Electric Vehicles and the Grid:
Interactions and Environmental and Health Impacts

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Abstract

The societal benefit of electric vehicles depends heavily on how they interact with the electric power system. In this thesis, I investigate the impact of electric vehicles based on this interaction in order to determine the possible benefits of controlling electric vehicle charging and how they compare to other vehicle options based on optimization models of electricity systems. I estimate the cost reductions from controlled charging of electric vehicles in the New York power system both with and without a high wind penetration and with and without the need for capacity expansion. In this power system, controlled charging can reduce the generation costs associated with charging the vehicles in half, with slightly higher cost reductions in high wind scenarios. I also estimate the cost reductions along with the changes in carbon and criteria air pollutant emissions due to controlled charging in the PJM power system. I examine both current and future grid scenarios, several plug-in vehicles types, and a high wind penetration scenario. Again I find that controlled charging can significantly reduce the costs of charging the vehicles, on the order of 30% of the generation costs to meet the charging demand. However, the environmental and health damages from the emissions cause total social costs to be higher with controlled charging in most cases. Finally, using the charging emissions from PJM, I evaluate the lifecycle emissions of plug-in, hybrid, and conventional vehicles in this region to determine which has lower environmental and health damages. I find that given the representative vehicles studied, plug-in electric vehicles have higher lifecycle damages than hybrids in PJM in 2010 but have lower lifecycle damages in a forecasted 2018 PJM power system.

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Chapter 1: INTRODUCTION

Electric vehicles are seen as a promising technology for reducing the environmental and health impacts of transportation systems. Passenger vehicles are responsible for 17% of US greenhouse gas emissions [1] as well as 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]. Electric vehicles have been promoted through both federal and state policies such as the Zero Emissions Vehicle (ZEV) mandate, Corporate Average Fuel Economy (CAFE) standard and tax incentives, but may not reduce emissions in all circumstances.

Electric vehicles have also been proposed as a means of incorporating more renewable energy into the electricity system, which accounts for a further 40% of US greenhouse gas emissions, 71% of SO_2 emissions, and 14% of NO_x emissions [3][4]. Electric vehicles could help reduce these emissions by providing additional flexibility to deal with the inherent variability of many renewable resources like wind and solar generation. Renewable energy is also being encouraged by federal policies, such as the production tax credit, and state renewable portfolio standards. These polices have supported the rapid deployment of wind power, which is now the fastest growing source of energy in the country [5]. As this resource grows, it will be important to understand both how electric vehicles can help mitigate wind power's inherent variability and how adding increasing amounts of wind to the grid will change the costs and emissions of charging electric vehicles.

The total impact of electric vehicles depends on their interaction with the power grid, as shown by Michalek et. al [6]. Some studies, such as Michalek et al. and Tessum et al. [7], rely on average emission rates from the regions studied to estimate the emissions attributable to vehicle charging. Average emission rates can be very useful to bound the possible impacts of electric vehicle charging but cannot be used to calculate how costs and emissions will be different with and without the additional load from electric vehicle charging. These marginal costs and emissions are important for evaluating whether or not electric vehicles and controlled charging should be incentivized by policy. Marginal costs and emissions can be captured by top-down regression analysis of historical data to measure the effect of marginal load on emissions at different times of day in different seasons, such as those created by Siler-Evans et al. [8] and Graff Zivin et al.[9] and used by Graff Zivin and Tamayoa et al. [10]. Alternatively, bottom-up models can determine how power plant operations will change when adding charging load from electric vehicles, such as those used by Sioshansi et al. [11], Peterson et al. [12], Choi et al. [13] and many others. The top-down models have the advantage of being able to capture the effects of trading energy between regions, transmission constraints, and other details of the power system that can be hard to capture in a bottom-up model. However, because top-down models are based on historical data, they can only be used to analyze scenarios that are similar to what has occurred in the past. The existing top-down studies also do not capture the costs associated with generating the electricity. A general comparison of top-down vs. bottom-up approaches for analyzing the interaction of electric vehicle charging with the electricity system is included in Table 1.1 below. The work in this thesis is based on a bottom-up optimization model of the power system in order to both optimize electric vehicle charging with power generation while minimizing operational costs and to examine future scenarios, such as high wind penetration, for which no historical data is available. Using this modeling framework, I investigate how electric vehicles can reduce the costs and emissions impacts of their own charging, their interaction with high wind penetrations, and how their lifecycle emissions compare to other vehicle options. A detailed comparison of my work to other relevant bottom-up studies is included with each chapter.

Table 1.1 Comparison of top-down regression model vs. bottom-up optimization approaches for assessing cost and emissions implications of marginal vehicle load

	Top-down	**Bottom-up**
Inputs	Aggregate historical hourly load and emissions for each region of interest	Marginal costs and operational constraints for every power plant and hourly load for a given region
Outputs	Charging emissions for entire country	Charging emissions and costs for one region
System constraints included	Trading between regions and transmission constraints	Trading cannot be fully captured Transmission constraints can be included given sufficient data but increase computation time
Possible scenarios	Load levels present in historical data with identical power systems Charging based on time of day	Any power system for which plant data is available with any load level Charging based on time of day or optimized with power plant operation

Chapter two focuses on the impact of when electric vehicles are charged on the cost of generating the electricity to meet this extra demand in a power system based on the New York power system, with and without the addition of 20% wind power. I compare an uncontrolled, convenience charging scenario (vehicle owners plug in their vehicles as soon as they get home at the end of the day) with a controlled charging scenario (the charging of the vehicles between the last trip of the day and the first trip of the next day is optimized along with the operation of the power plants). The optimization is done using a capacity expansion, unit commitment and economic dispatch model. This model determines the operation of every power plant in each hour to satisfy load while minimizing total costs, ensuring power plants are operating within their physical constraints, and certain system-wide constraints, such as maintaining sufficient reserves, are met. The model also determines which plants to build if there is insufficient capacity to meet load or reserve requirements. I consider a scenario in which capacity expansion is necessary with and without high wind penetration, as well as the base case scenario with sufficient starting capacity. I find that controlling electric vehicle charging can cut the cost of generating the power for charging by around 50%. These savings increase slightly in the high wind scenario and more substantially when controlling charging also changes capacity expansion decisions.

In chapter 3, I again look at the impact of controlled charging, this time in the PJM power system instead of in New York. In addition to calculating how controlled charging will change power generation costs, I also examine the resulting change in emissions from vehicle charging and the health and environmental impacts of these emissions. Once again, the operation of the power system under each charging scenario is determined using a unit commitment and economic dispatch model, this time the PJM Hourly Open-source Reduced-Form Unit Commitment Model (PHORUM) developed at CMU by Roger Lueken [14]. By using a model predictive control approach in this study, larger time periods can be studied, but the model cannot assess capacity expansion scenarios. Instead, I look at both the current PJM system and a future scenario based on predictions made by the EPA for what power plants will be part of the system in 2018, along with their emission rates and marginal costs. I also include a scenario with 20% wind penetration. In this system, I find that controlled charging reduces generation costs by around 30%, again slightly higher with high wind penetration. However, most of the reductions in cost come from shifting to coal and the increase in CO_2, and especially SO_2, emissions leads to higher social damages than those cost reductions in most cases.

Chapter 4 builds on the charging emissions results from chapter 3 to calculate the total lifecycle emissions of different plug-in electric vehicles and the damages resulting from those emissions and to compare them to the lifecycle emissions and damages of conventional and hybrid vehicles in the PJM power system. The emissions from the rest of the lifecycle, including tailpipe emissions, vehicle and battery manufacturing, coal production, gas production, and oil production and refining, come from Argonne National Lab's GREET model [15][16]. I evaluate the health and environmental impacts of the lifecycle emissions of each vehicle type in order to determine which has the lowest impact on society in both the current and future PJM system, as in chapter 3. I find that of the representative vehicle types tested in the current PJM system, plug-in electric vehicles have higher social damages from lifecycle emissions than hybrid vehicles and only the smallest battery size can have lower damages than conventional vehicles. In the future PJM power system, plug-in electric vehicles have lifecycle damages that are lower than hybrid vehicles by about the same amount that hybrid vehicles' lifecycle damages are lower than conventional vehicles. Table 1.2 below summarizes the study in each chapter.

This thesis contributes an analysis of the social impact of controlled charging and electric vehicles compared to other vehicle options considering the health and environmental damages from criteria air pollutants in addition to carbon emissions, based on a detailed grid model. The results of this thesis can be used to help policy makers judge the circumstances in which controlled charging should be encouraged and what the near term benefits of electric vehicles will be in the PJM power system.

Table 1.2: Summary of each chapter. PHEV = plug-in hybrid electric vehicle, PEV = plug-in electric vehicle, HEV = hybrid electric vehicle, CV = conventional vehicle

	Chapter 2	**Chapter 3**	**Chapter 4**
Research Questions	• Can controlled charging reduce the cost of charging PHEV's? • How do these costs change when capacity expansion is necessary? • How do these costs change with high wind penetration?	• Can controlled charging reduce the impact of charging PEV's in terms of operational costs and emissions? • How are costs and emissions affected by an evolving power plant fleet and high wind penetration?	• How do the lifecycle emissions and damages from emissions of PEV's compare to those of HEV's and CV's? • How does this comparison change as the grid evolves and with high wind penetration?
Vehicles Included	PHEV-5, PHEV-35, PHEV-60	PHEV-10, PHEV-35, PHEV-265	PHEV-10, PHEV-35, PHEV-265, HEV, CV
Region of Study	New York	PJM Interconnection	PJM Interconnection
Year	2010	2010 and 2018	2010 and 2018
Time Period Modeled	20 days representing year	1 year	1 year
Capacity Expansion	Yes	No	No
Pollutants Included	None	CO_2, SO_2, $PM_{2.5}$, NO_X, VOCs	CO_2, SO_2, $PM_{2.5}$, NO_X, VOCs
Key Findings	Controlled charging cuts the cost of charging electric vehicles in half	Controlled charging reduces the cost of charging electric vehicles by 30% but increases total social costs due increases in power plant emissions	PEV's studied have higher lifecycle damages in 2010 PJM but lower lifecycle damages in 2018 PJM

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Chapter 2: OPERATIONAL AND CAPACITY COST IMPACTS OF CONTROLLED ELECTRIC VEHICLE CHARGING IN POWER SYSTEMS WITH HIGH WIND PENETRATIONS

This chapter is based on research published in A. Weis, J. Michalek, and P. Jaramillo. "Estimating the Potential of Controlled Plug-in Hybrid Electric Vehicle Charging to Reduce Operational and Capacity Expansion Costs for Electric Power Systems with High Wind Penetration" *Applied Energy*. 115 (2014). 190-204

2.1 Introduction

One method for potentially reducing the impact of plug-in electric vehicles, as well as aiding in the integration of wind power, is to control electric vehicle charging. This chapter focuses on how controlled charging impacts operational and capacity costs in a power system based on New York, with and without high wind scenarios. Controlled charging can affect what power plants are used to meet the additional demand created by electric vehicles in addition to which power plants are most economical to build when the power system lacks sufficient capacity. Charging that can respond to provide additional flexibility to manage fluctuations in wind power generation. This flexibility becomes increasingly important as federal and state policies encourage the build out of the wind power in order to reduce the emissions from electric power sector. Twenty-nine states have adopted renewable energy portfolio standards (RPS) requiring between 10% and 40% of generated power to come from renewable sources [1]. As one of the fastest growing electricity sources in the United States [2], wind can be expected to meet a large proportion of the renewable portfolio standards. To compensate for the increased amounts of these inherently–variable sources of electricity, the power grid requires additional flexibility to manage fluctuations in generation. For systems incorporating high levels of wind power, ramping natural gas combustion turbine plants in response to changes in output from variable resources has typically provided this flexibility. Recent research has shown that ramping gas turbines to manage the variability of wind power can increase NO_x emissions and reduce the greenhouse gas benefits associated with wind power production [3].

Much of the previous research on using electricity vehicles as a means for increasing grid flexibility in order to integrate renewables has studied the possibility of using the vehicles for grid storage via a bidirectional electrical connection between the vehicle and the electricity grid, referred to as vehicle-to-grid (V2G). For example, Lund and Kempton calculate the cost-savings and emissions-savings from adding V2G capabilities to the power system, given simplified ramping constraints for the power generation fleet [6]. However, it has been shown that the market for V2G in the energy market [7] and ancillary services market [8] is small, arbitrage potential is limited, and participation can significantly reduce battery life by increasing the total energy processed by the battery [9]. V2G systems also require a substantial investment in power electronics, control software, and additional grid infrastructure. As an alternative, electricity demand can be partially managed by modulating the charging rate of PEVs – for example, following variations in wind supply. Such an approach does not increase the energy processed by the battery, and it is possible that such an approach could actually extend battery life by lowering average charge rates and thus heat generation [9]. Controlled charging can also take advantage of the high levels of wind generation that commonly occur at night in the U.S. At these times, other load is likely to be low, and coal plants would likely need to be cycled, adding costs and emissions that could be saved with smart charging of PEVs. Alternatively, ramping of thermal plants could be reduced by building excess wind capacity, curtailing wind energy when it is not needed, and taking it when most cost effective for the system.

Previous work has shown the benefit of controlled charging in power systems with wind power. Dallinger et. al show that excess renewable energy in periods of low load can be significantly reduced through optimized charging in California and Germany [10], and Foley et. al find that off-peak charging can save vehicle owners nearly 30% of the charging costs [11]. Wang et. al. evaluate different charging strategies of plug-in hybrid vehicles in the Illinois power system and find significant cost reductions with controlled charging. They assume the rest of the power system is static and use a simple scaling of existing wind data to model new wind construction [12], exaggerating variability by ignoring the complex effects of plant size and geographic diversity on mitigating wind generation correlation [13]. Sioshanshi and Denholm analyze a system based on the Electric Reliability Corporation of Texas (ERCOT) in its current form, with 10% wind generation, to calculate the additional benefit of V2G over controlled charging, again allowing only operation of existing power plants to vary [14]. They find that V2G could decrease system costs by around 0.5%. Instead of holding existing capacity fixed as in these studies, we consider a case in which new capacity needs to be built to meet required system reserve margins. As discussed by De Jonge et. al., it is important to consider the capacity expansion in the context of all the operational constraints of the power plants [15].

Other work has focused on how controlled charging can be used as balancing power in systems with high wind penetration by modeling forecasting error for wind and load instead of evaluating detailed operating constraints. A study by the Pacific Northwest National Laboratory estimates the number of vehicles necessary to provide a complete response to the balancing signal [16], capturing the high frequency behavior of the wind and vehicle charging but ignoring other types of flexibility already present in the grid. Druitt and Früh also focus on how controlled electric vehicle charging can provide balancing power at high wind penetrations [17]. They use a simplified scheduling of conventional generation, which ignores many operating constraints, and develop a model based on historic prices to estimate economic effects. Still other work has evaluated how including controlled electric vehicle charging as part of the electricity system can increase the amount of renewables that can be integrated, as summarized by Wei et al. [18]

We seek to evaluate the potential cost reductions from controlled charging in scenarios with vs. without additional wind power in order to understand whether PEVs can provide cost reductions in systems with increased levels of wind power, or whether controlled charging only limits the impact of the vehicles themselves on the system. We focus on PHEVs, which do not require changes in current driving patterns, since PHEVs can operate using gasoline for long trips. The interaction of PHEV charging with the grid is complex, and a complete understanding requires evaluating the power system in a range of circumstances and at a variety of time scales. We examine the benefit of controlled charging of PHEVs relative to convenience charging (vehicle charges at maximum rate upon arrival), delayed charging (vehicle begins charging at maximum rate just in time for its next use), and no charging (no PHEVs) under alternative scenarios of high vs. low wind penetration in the power generation fleet, high vs. low PHEV penetration in the vehicle fleet, and high vs. low initial power generating capacity. For this analysis, we develop a capacity expansion and unit commitment with economic dispatch optimization model with detailed plant constraints. We use hourly data for wind and load and assume perfect information (no forecast error) to focus on capacity expansion and unit commitment decisions. We then compare results using a 15-minute resolution to test the importance of sub-hourly trends. We study a period of 20 days selected to be representative of the year. We do not evaluate the entire range of power plant fleets that exist in the U.S. but instead focus on comparing the difference between a system with sufficient capacity and one requiring investment in new capacity.

In the remaining sections we present our detailed methods, results, and conclusions. We find that controlled charging does help to reduce system costs by about 2% in the scenarios examined with 10% PHEV penetration. However, the additional benefit of controlled charging in high wind-penetration scenarios is much smaller. Thus the benefits of controlled charging are general to power systems and not specific to wind integration under the scenarios examined. We also examine the tradeoff between adding new capacity to the system versus controlled charging in order to accommodate high wind penetration scenarios, finding that controlled charging reduces the number of combined cycle gas plants that would otherwise be built.

2.2 Methods

2.2.1 Model Overview

We pose a mixed integer linear programming (MILP) capacity expansion model with hourly unit commitment and dispatch, plus hourly vehicle availability and charging rates, to find the optimal combination of new power plants and controlled vehicle charging to meet demand at lowest costs subject to operation constraints. Capacity expansion optimizes which power plants should be added to the system, if any. Unit commitment and dispatch determine which plants will be on in each time period and the level of output for each. As part of the cost minimization, the model also determines the charge rate in each hour for each set of available vehicles, where the set of vehicle driving profiles are selected to be representative of the U.S. vehicle population. The model treats the penetration of plug-in vehicles that must be charged as exogenous, and the grid operator can choose a percentage of the vehicles to participate in a controlled charging program for a given annual payment. We vary the number of vehicles present in the system and the amount of the annual payment to vehicle owners in a sensitivity analysis. The model constrains electricity generation to match the load in each time step, while keeping all plants within their operating constraints and satisfying a wind penetration goal that defines a minimum percentage of overall power generation that must be supplied by wind[1][2]. **Error! Reference source not found.** shows a graphical representation of the framework used.

[1] As the cheapest renewable energy source by levelized cost, wind is likely to make up the bulk of power installed to meet RPS. Some RPS policies include specific set-asides for solar power, but these are very small: 0.2%-2.5% [1]. For this paper, we model a system in which wind is the only renewable available.

[2] The model took between 5-10 hours to run on an Intel i& processor running CPLEX using 20 day period with hourly data. Running the 15-minute sensitivity cases over 20 days had a wide range of solve times, going up to 80 hours for each charging scenario. Because solve time for MILP problems is nonlinear with the number of variables, it was not feasible to use smaller time steps or more days for all of the sensitivity cases analyzed

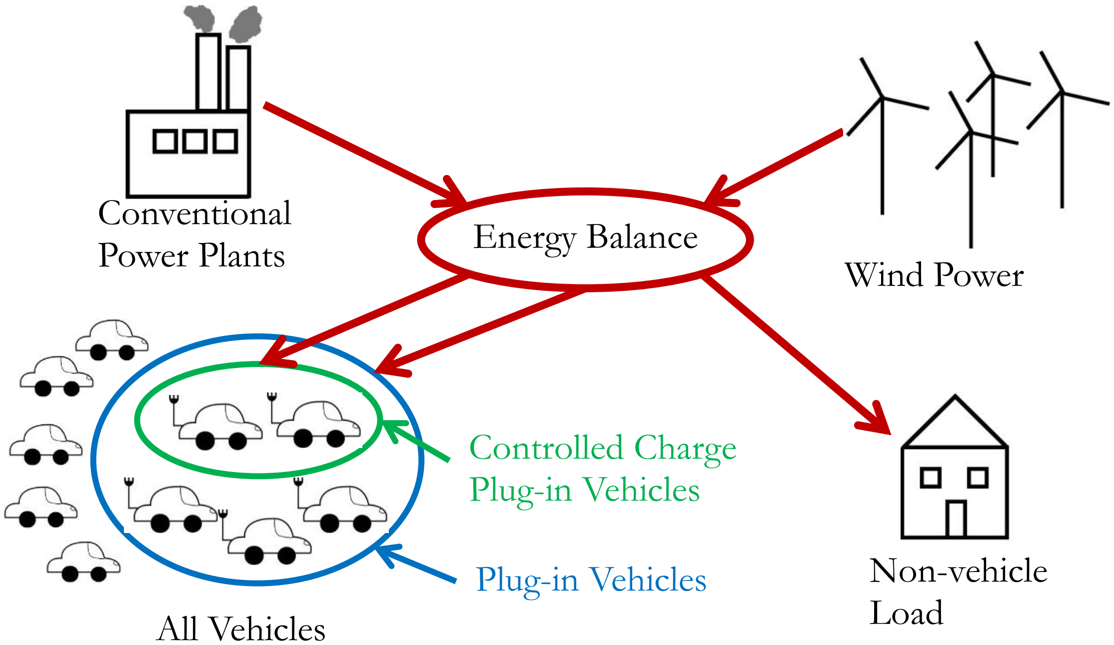

Figure 2.1 System Overview - Energy is provided by conventional power plants and wind plants and must meet the demand from plug-in vehicles and non-vehicle load in each time step.

2.2.2 Power Plant Fleets

We construct two different power plant fleet scenarios using power plant fleet characteristics from the New York Independent System Operator (NYISO) area: the first scenario with sufficient existing capacity to meet vehicle and non-vehicle load (*Fixed Capacity Scenario*); and the second where capacity expansion is required regardless of PHEV penetration (*Capacity Expansion Scenario*). Because NYISO has significant amounts of hydroelectric power for which operational data is unavailable, we construct the Capacity Expansion Scenario by eliminating the hydro capacity from NYISO and using only existing nuclear, coal, oil, and natural gas capacity as the initial state of the fleet. For the Fixed Capacity Scenario we replace the hydro capacity with fossil fuel plants roughly proportional to the existing fossil fuel mix. Individual plant data were not available for all fossil fuel plants in NYISO, so the fleet was chosen from a sample of similar plants in NYISO, ERCOT and PJM with available data. The plants were selected using an optimization that minimizes the difference between actual fleet characteristics and the selected fleet characteristics.

$$\text{minimize} \sum_{\tau} \left| K_{\tau}^{\text{TOT}} - x_{\tau}^{\text{TOT}} \right| + w_1 \sum_{\tau} \sum_{c \in \mathscr{C}_\tau} \left| K_{\tau c}^{\text{BIN}} - x_{\tau c}^{\text{CBIN}} \right| + w_2 \sum_{\tau} \sum_{h \in \mathscr{H}_\tau} \left| H_{\tau h} - x_{\tau h}^{\text{HRBIN}} \right|$$

where total capacity of plants of each plant type τ is K_{τ}^{TOT} for the actual fleet and x_{τ}^{TOT} for the selected fleet. The number of plants in each capacity bin $c \in \mathscr{C}_\tau$ for fuel type τ is K_{τ}^{BIN} for the actual fleet and $x_{\tau c}^{\text{CBIN}}$ for the selected fleet, and similarly the capacity of plants in each heat rate bin $h \in \mathscr{H}_\tau$ for fuel type τ is $H_{\tau h}$ for the actual fleet and $x_{\tau h}^{\text{HRBIN}}$ for the selected fleet. The distributions of plant capacities and heat rates were defined using four evenly spaced bins for each plant type. The optimization variables are how many of each of the sample plants are included in the selected plant fleet and x_{τ}^{TOT}, $x_{\tau c}^{\text{CBIN}}$, and $x_{\tau h}^{\text{HRBIN}}$ are calculated from this selected fleet. We found that relative weights of $w_1 = 300$, and $w_2 = 100$, respectively for these three factors in the objective function gave a good fleet representation for these fuel types. The fuel types that could be modeled in this way for NYISO were bituminous coal, natural gas combined cycle, natural gas combustion turbine, and oil/gas steam, whereas nuclear was modeled as a single capacity and heat rate. The resulting fleets are shown by plant type in Figure 2.2.

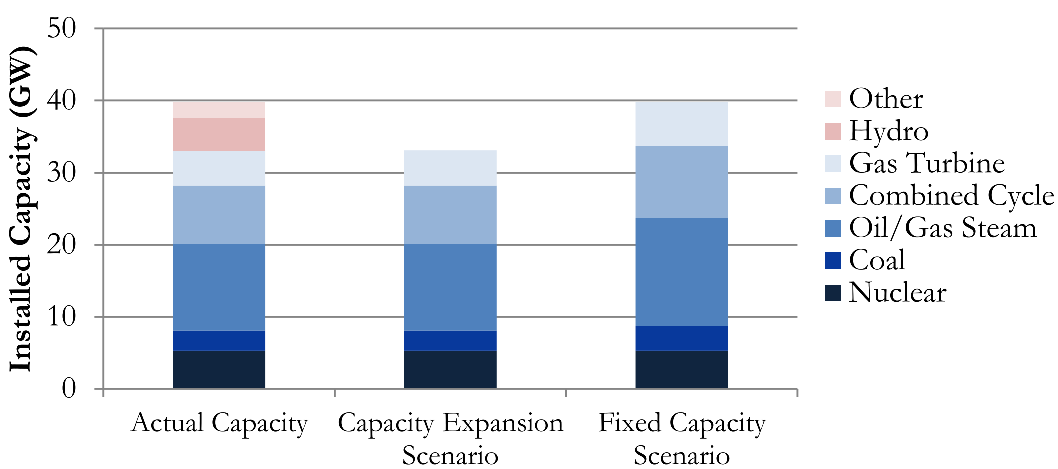

Figure 2.2: Power plant fleets derived from NYISO's actual capacity.

Because of the missing data, the fleets used in this analysis are not meant to exactly replicate the New York system, but rather serve as a test system with realistic plant distributions matched to a realistic load. Average ramp rates and minimum generation levels by generation type, along with the individual plant heat rates and total capacity for the sample of plants used, were taken from Ventyx [19], and the distribution of power plant capacities and heat rates for NYISO were taken from the National Electric Energy Data System (NEEDS) [20]. A comparison of the resulting characteristics for the Fixed Capacity Scenario and actual NYISO fleet is shown in Table 2.1. We are able to obtain a similar fleet according to measurable characteristics. The only large difference is the average age of the natural gas combustion turbine plants due to the available data to choose from. The simulated fleet is newer, but because the average heat rate remains very close to that of the actual fleet, there should not be a large impact on total operational cost. The newer gas plants may be somewhat more flexible, but on the hourly time scale, combustion turbine plants have excess ramping capability.

Table 2.1: Comparison between the coal, natural gas, and oil/gas steam plants in the actual NYISO fleet and the simulated fleet in terms of capacity installed, number of units, average heat rate, and online year.

Type	Actual MW	Sim. MW	Ref. # Units	Sim. # Units	Actual Ave HR (BTU/kWh)	Sim. Ave HR (BTU/kWh)	Actual Ave Online Year	Sim. Ave Online Year
Coal	2,767	2,767	32	31	10,507	10,738	1970	1962
NGCC	8,124	8,124	103	103	8,555	8,584	1996	1995
NGCT	4,885	4,885	215	215	14,971	14,945	1976	1992
Oil/Gas Steam	11,723	11,723	32	32	11,341	11,763	1964	1963

2.2.3 Plug-in Hybrid Electric Vehicle Fleet

We model a fleet of plug-in hybrid electric vehicles using the National Household Travel Survey (NHTS) dataset [21], which contains data for one day of driving for approximately 900,000 different passenger cars across the United States. We use time of arrival and departure from home and distance traveled from all vehicles in the dataset, weighted by vehicle to be nationally representative, to compute uncontrolled electricity demand in the convenience charging (charge upon arrival at home) and delayed charging (charge just before departure) cases. In order to create a tractable controlled charging model while maintaining a representative dynamic vehicle load for the power system, a sample of 20 profiles were selected and optimally weighted to best match the aggregate characteristics of the entire 900,000 profiles available in the NHTS of passenger cars. These aggregate characteristics were evaluated for each hour and included the average number of miles driven in that hour, the average cumulative number of miles driven until that hour, the percent of vehicles at home, and the percent of vehicles parked. 20 vehicle profiles were randomly selected from the NHTS data set; the characteristics of the resulting fleet were compared to those of the full NHTS data set using the distance metric below; and this process was repeated one million times, retaining only the set of 20 that minimizes the distance metric.

$$\text{distance metric} = \sum_t \left(\Delta h_t^{\,2} + \Delta p_t^{\,2} + \Delta o_t^{\,2} + \Delta d_t^{\,2} + \left(\frac{\Delta a_t}{\max_t(a_t)}\right)^2 + \left(\frac{\Delta c_t}{\max_t(c_t)}\right)^2 \right)$$

where Δh_t and Δp_t are the difference in the percent of drivers in the sample vs. the full data set at home and parked at time step *t*, respectively, and Δa_t and Δc_t are the difference in average miles and cumulative miles, respectively, at time step *t*. The distance terms are normalized so that all six terms will be of comparable scale. Each of the 20 vehicles was weighted by a variable w_i, $i \in \{1,2,\ldots,20\}$, $w_i \in [0,1]$, $\Sigma_i w_i = 1$; w_i was optimized to minimize the distance metric above. This process was repeated 1 million times and the best match optimally weighted profile of 20 vehicles was retained. The weighted sample can be thought of as a case where some selected vehicle profiles are representative of a larger portion of the full NHTS dataset than others.

As shown in Figure 2.3, the final sample of 20 weighted profiles does not perfectly match the aggregate characteristics of all passenger vehicles. However, it much more closely matches the aggregate data than 20 randomly chosen profiles and according to the distance metric shown below, it is just as close as 200 randomly chosen profiles and allows for a feasible computation time. While we track day-to-day differences in wind and load, we assume that vehicle travel patterns are the same every day (due to lack of data on daily variability).

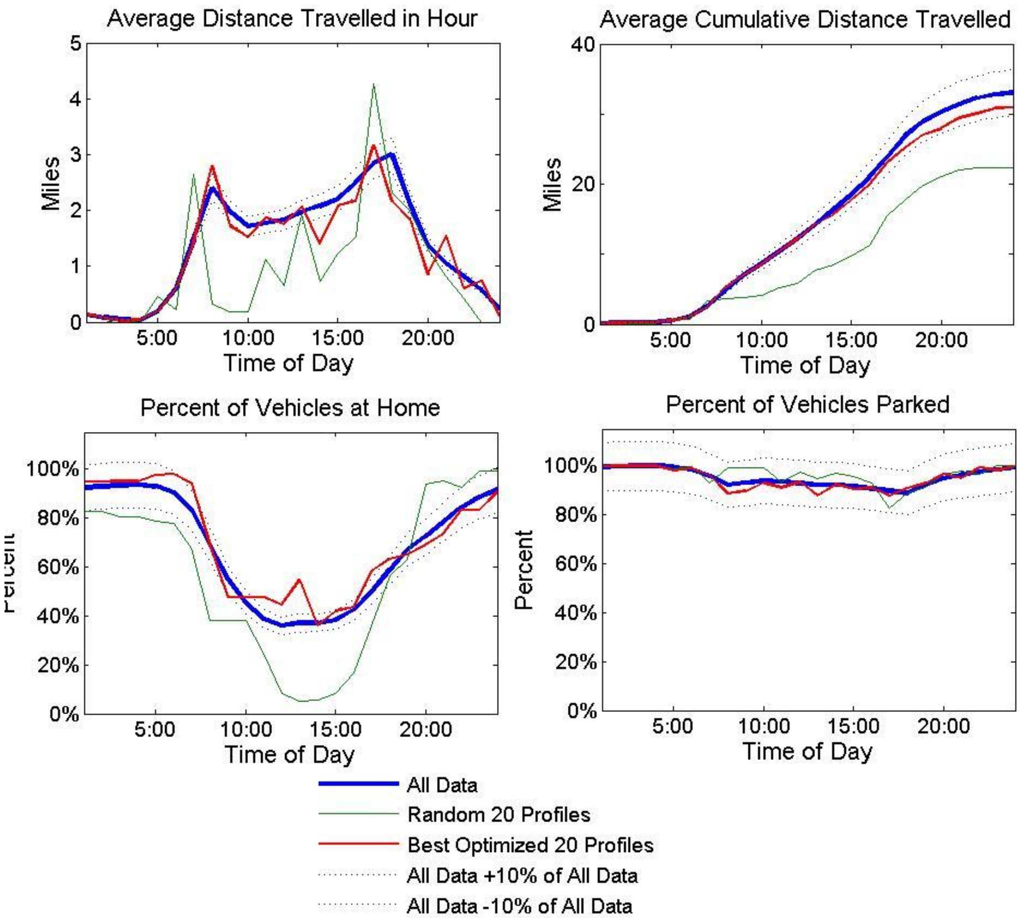

Figure 2.3: Aggregate characteristics for all passenger vehicles in the NHTS dataset and best match 20 optimally weighted vehicle profiles drawn from the NHTS dataset over 1 million random draws. The percent of vehicles at home dips during the day, and only a small percentage of the fleet is driving at any time.

The PHEVs we study operate in charge-depleting mode until the battery reaches its minimum state of charge or all the miles are driven (sometimes called extended-range electric vehicles (EREVs), like the Chevy Volt). Any remaining miles are driven in charge-sustaining (extended-range) mode, powered by the gasoline engine[3]. This allows all drivers to retain their existing driving patterns, regardless of the electric range of the vehicle. The base-case vehicle is modeled after the

[3] We do not consider blended-operation PHEVs, like the PHEV Prius, which use a blend of gasoline and electricity in charge depleting mode. In our model, which focuses on electricity consumption, a blended-operation PHEV would function equivalently to a higher-efficiency EREV PHEV, since the partial use of gasoline offsets some electricity use in charge depleting mode.

Chevy Volt with a 16 kWh hour lithium ion battery of which 10.4 kWh are useable. We assume the vehicles only charge after their last trip of the day and must be fully charged by their first trip of the next day if controlled by the system operator in the controlled charging program. The charging program alters the rate of charge for each vehicle but does not withdraw power from the battery. Charging for a portion of a time step is equivalent to charging for the entire time step at a lower rate. We model different levels of controlled charging program costs, ranging from $0-$400/vehicle/year. These assumed costs would have to cover both payments to the vehicle owners as well as any infrastructure costs, with the system operator determining how many vehicles will be paid for participation (the zero cost case assumes the system operator captures all of the cost reductions). We perform a sensitivity analysis to examine supply solutions at different participation fee levels and leave as future work an estimate of the vehicle owner demand curve. We also perform sensitivity analysis to examine a range of vehicle characteristics, shown below in Table 2.2, as well as different vehicle penetration levels and payment to vehicle owners. The growth rate of PHEV penetration is very uncertain, but the governor of New York was quoted as saying "the number of plug-in electric vehicles on the road in New York State could increase from less than 3,000 today to 30,000-40,000 in 2018 and one million in 2025," [22] which would be around 10% of the approximately 9 million passenger vehicles in New York in 2008 [23]. Additionally, EIA estimates that PHEV's could account for 2% to 18% of all vehicles in the U.S. in 2025 depending on what policies are adopted [24].

Table 2.2: Ranges of values used to reflect the uncertainty in the characteristics of the future plug-in vehicle fleet. The base case for the battery size comes from the Chevy Volt, allowing for roughly 35 miles of driving on electric power, with minimum and maximum battery sizes allowing for 5 miles and 60 miles of electric driving, respectively. Vehicles with larger and smaller batteries are assumed to have the same ratio of useable kWh to total kWh as the base case (65%). The range of charge rates comes from the three standard levels of electric vehicle charging. Level 1 charging can be achieved from a normal household 120 V plug and is used as the minimum. Level 2 charging requires a 240 V outlet, such as those used by larger household appliances, but is more convenient for vehicle owners and is used as the base case. Level 3 charging requires higher voltage and current levels than typically available on the household level but is possible at future service stations and is the upper bound on vehicle charge rates. Total fleet size in New York is 9 million passenger vehicles, and the range of 1% - 15% plug-in vehicle penetration represents 90,000 to 1,350,000 plug-in electric vehicles.

Vehicle Fleet Characteristics	Minimum	Base case	Maximum
Battery Size	5 kWh	16 kWh	24 kWh
Maximum Charging Rate	1.2 kW	7.4 kW	30 kW
Plug-in Vehicle Penetration	1%	10%	15%

2.2.4 Wind Power Data

We use modeled wind production data for all potential land-based wind sites in New York reported in the Eastern Wind Integration and Transmission Study (EWITS) dataset [26]. EWITS lists all the sites in the Eastern Interconnect that would be needed in order to reach a 30% RPS and contains ten-minute modeled wind plant output for these sites for 3 years from 2006 to 2008. We convert the ten-minute power data to hourly resolution for model tractability by averaging the six data points given for each hour. We then add wind sites from the EWITS data set to our model in order of highest capacity factor. We investigate wind penetration rates that range from 0% to 20% to allow for additional wind plants to be built in all scenarios without making use of offshore wind, as it is uncertain that offshore wind sites will be widely utilized by 2025.

We use modeled wind data instead of measured output data from existing wind sites so that wind capacity can be expanded beyond existing levels. Because wind production is dependent on local weather patterns and geography, existing empirical wind data cannot be easily scaled up to include new sites. The EWITS dataset is the only existing public sources for a time series simulation of wind production for potential wind sites in this area of the country.

2.2.5 Load Data

We use five-minute power demand data for the New York ISO in 2006, again converted to hourly resolution by averaging the twelve data points given for each hour. As load is predicted to remain within 1% of its current level by 2025 [27], this 2006 data is used as non-vehicle load without any scaling. It is important to use load and wind data from the same time and place to account for temporal and geographical correlations. While this chapter paper focuses on a model based on the characteristics of the New York System, the method developed could later be applied to other systems around the country. This additional analysis, however, is beyond the scope of this paper.

To ensure a reasonable computation time, we chose four different periods of five days each to capture the different shape of the load curve in different seasons and include the year's peak load, while keeping the average load over the four periods equal to the average load of the year, 19 GW. Six of the 20 days are weekend days. Given the wind plants needed to meet the 20% penetration over the course of the entire year (when run as must-take), the wind output from the modeled wind plants in these four periods is both sufficient to meet the wind penetration goal (scaled within the twenty days) without building additional wind plants, and has an average power within 10% of the average wind power for the entire year. Within each of the four periods, plant-operating constraints apply. The model's capacity expansion variables apply simultaneously across all four periods, along with the percent of PHEVs with controlled charging.

2.2.6 Optimization

The optimization model minimizes capital and operating costs:

$$\text{minimize} \underbrace{\sum_{i \in \mathscr{W} \cup \mathscr{N}} c_i^{\text{BLD}} y_i^{\text{BLD}}}_{\text{New Plant Construction}} + \underbrace{c^{\text{EV}} n^{\text{EV}} x_{\text{CTRL}}^{\text{EV}}}_{\substack{\text{Payments to} \\ \text{PHEV Owners}}} + \underbrace{\sum_{t \in \mathscr{T}} \left(\sum_{i \in \mathscr{C}} \left(x_{it}^{\text{SUC}} + x_{it}^{\text{SDC}} + c_i^{\text{F}} h_i x_{it}^{\text{G}} \right) \right)}_{\text{Cost of Plant Operations}}$$

where $\mathscr{N}$ is the set of new conventional power plants; $\mathscr{E}$ is the set of existing conventional power plants; $\mathscr{C} = \mathscr{N} \cup \mathscr{E}$ is the combined set of existing and new conventional power plants; $\mathscr{W}$ is the set of (new) wind plants; $\mathscr{T}$ is the set of time steps in the sample period; c_i^{BLD} is the annualized cost for construction of plant *i*; $\mathrm{y}_i^{\mathrm{BLD}}$ is the binary variable determining whether or not plant *i* is constructed; c^{EV} is the annual payment to each vehicle owner participating in the controlled charging program; n^{EV} is the total number of PHEVs; $x_{\mathrm{CTRL}}^{\mathrm{EV}}$ is the percentage of PHEVs are that are controlled; x_{it}^{SUC} and x_{it}^{SDC} are the start-up and shut-down costs, respectively, of plant *i* in time step *t*, c_i^{F} is the fuel cost of plant *i*, h_i is the heat rate of plant *i*, and x_{it}^{G} is the power output of the plant *i* in time step *t*. We vary the value of the annual payment to each participating vehicle owner with a sensitivity analysis to understand the willingness to pay of the system operator. The willingness to accept controlled charging by vehicle owners is unknown and is outside the scope of this paper.

The constraints are typical for economic unit commitment and dispatch models with plug-in vehicles, but they are adapted to allow for additional binary variables to represent new power plant construction and a variable for the percentage of plug-in vehicles participating in the controlled charging program. The overall system must meet the existing non-vehicle load plus the vehicle load of both the controlled and uncontrolled vehicles in every time step:

$$x_t^{\mathrm{W}} + \sum_{i \in \mathscr{C}} x_{it}^{\mathrm{G}} = L_t + \sum_{j \in \mathscr{V}} x_{jt}^{\mathrm{EV}} + (1 - x_{\mathrm{CTRL}}^{\mathrm{EV}}) n^{\mathrm{EV}} v_t^{\mathrm{UCTRL}} \quad \forall t \in \mathscr{T}$$

where x_t^{W} is the amount of wind energy used in time step *t*, x_{jt}^{EV} is the total amount of energy consumed to charge all vehicles of profile *j* in time step *t*, $\mathscr{V}$ is the set of all PHEV profiles, and v_t^{UCTRL} is the fixed amount of uncontrolled charging that occurs for vehicle profile *j* in time step *t*. The wind penetration goal must be met over the 20 days:

$$\sum_{t\in\mathcal{T}} x_t^{\mathrm{W}} \geq E^{\mathrm{RPS}}\left(\sum_{t\in\mathcal{T}}\left(x_t^{\mathrm{W}}+\sum_{i\in\mathcal{C}} x_{it}^{\mathrm{G}}\right)\right)$$

Where E^{RPS} is the percent wind energy required by the penetration goal. In addition to meeting the load, the system must also provide sufficient spinning and non-spinning reserves:

$$\sum_{i\in\mathcal{C}}\left(x_{it}^{\mathrm{SR}}+x_{it}^{\mathrm{NSR}}\right) \geq R^{\mathrm{TR}}\left(x_t^{\mathrm{W}}+\sum_{i\in\mathcal{C}} x_{it}^{\mathrm{G}}\right) \quad \forall t\in\mathcal{T}$$

$$\sum_{i\in\mathcal{C}} x_{it}^{\mathrm{SR}} \geq R^{\mathrm{SR}}\left(x_t^{\mathrm{W}}+\sum_{i\in\mathcal{C}} x_{it}^{\mathrm{G}}\right) \quad \forall t\in\mathcal{T}$$

Where x_{it}^{SR} and x_{it}^{NSR} are the spinning reserves and non-spinning reserves provided by plant *i* in time step *t*, and R^{SR} and R^{TR} are the spinning and total reserve requirements as a percentage of the generation. The system must also meet the 15% reserve margin above peak load recommended by NERC for power systems with predominantly thermal generators [26]:

$$\sum_{i\in\mathcal{E}} k_i + \sum_{i\in\mathcal{N}} k_i y_i^{\mathrm{BLD}} \geq (1+R^{\mathrm{RM}})L^{\mathrm{PEAK}}$$

Where R^{RM} is the reserve margin, L^{PEAK} is the peak load for the year, and k_i is the capacity of plant *i*. Every power plant has its own set of operating constraints. All the conventional plants have a maximum output capacity:

$$x_{it}^{\mathrm{G}}+x_{it}^{\mathrm{SR}} \leq y_{it}^{\mathrm{ON}} k_i \quad \forall i\in\mathcal{C}, \forall t\in\mathcal{T}$$

Where y_{it}^{ON} is the binary variable indicating whether or not plant *i* is on in time-step *t*. x_{ik}^{SU} and x_{ik}^{SD} are continuous start-up and shut-down variables for each plant that are restricted to be between 0 and 1 and forced to be only 0 or 1 by their relationship to y_{it}^{ON} and the start-up and shut-down costs:

$$x_{it}^{\mathrm{SU}}-x_{it}^{\mathrm{SD}} = y_{it}^{\mathrm{ON}}-y_{i(t-1)}^{\mathrm{ON}} \quad \forall i\in\mathcal{C}, \forall t\in\mathcal{T}\setminus\mathcal{T}_1$$

$$x_{it}^{\mathrm{SUC}} \geq c_i^{\mathrm{SU}} x_{it}^{\mathrm{SU}} \quad \forall i \in \mathscr{C}, \forall t \in \mathscr{T}$$

$$x_{it}^{\mathrm{SDC}} \geq c_i^{\mathrm{SD}} x_{it}^{\mathrm{SD}} \quad \forall i \in \mathscr{C}, \forall t \in \mathscr{T}$$

Where c_i^{SU} and c_i^{SD} is the cost for one start-up and shut-down for plant *i* respectively and $\mathscr{T}_1$ is the first time step for each five day sequence. Each plant has a minimum generation level (when on) m_i:

$$x_{it}^{\mathrm{G}} \geq m_i y_{it}^{\mathrm{ON}} \quad \forall i \in \mathscr{C}, t \in \mathscr{T}$$

They are also subject to ramp rate limitations:

$$x_{it}^{\mathrm{G}} + x_{it}^{\mathrm{SR}} \leq x_{i(t-1)}^{\mathrm{G}} + r_i^{\mathrm{UP}} y_{i(t-1)}^{\mathrm{ON}} \Delta + m_i (y_{i(t)}^{\mathrm{ON}} - y_{i(t-1)}^{\mathrm{ON}}) \quad \forall i \in \mathscr{C}, \forall t \in \mathscr{T} \setminus \mathscr{T}_1$$

$$x_{i(t-1)}^{\mathrm{G}} - r_i^{\mathrm{DWN}} y_{i(t)}^{\mathrm{ON}} \Delta - m_i (y_{i(t-1)}^{\mathrm{ON}} - y_{i(t)}^{\mathrm{ON}}) \leq x_{it}^{\mathrm{G}} \quad \forall i \in \mathscr{C}, \forall t \in \mathscr{T} \setminus \mathscr{T}_1$$

Where r_i^{UP} and r_i^{DWN} are the maximum amount the plant can ramp up or down in a time step respectively and Δ is the length of a time step. Plants have to stay on for a minimum number of time steps δ_i^{ON} once turned on, and off a minimum number of time steps δ_i^{OFF} once turned off:

$$\sum_{k=t-\delta_i^{\mathrm{ON}}+1}^{t} x_{ik}^{\mathrm{SU}} \leq y_{it}^{\mathrm{ON}} \quad \forall i \in \mathscr{C}, \delta_i^{\mathrm{ON}} \leq t \leq T^{\mathrm{END}}$$

$$\sum_{k=t_i-\delta_i^{\mathrm{OFF}}+1}^{t} x_{ik}^{\mathrm{SD}} \leq (1 - y_{it}^{\mathrm{ON}}) \quad \forall i \in \mathscr{C}, \delta_i^{\mathrm{OFF}} \leq t \leq T^{END}$$

T^{END} is the last time step in the associated five day contiguous sequence. The wind power plants have a generation potential at each time step based on the wind behavior modeled in the EWITS database:

$$x_t^{\mathrm{W}} \leq \sum_{i \in \mathscr{W}} p_{it} y_i^{\mathrm{BLD}} \quad \forall t \in \mathscr{T}$$

Where p_{it} is maximum amount of wind that could be generated by a wind plant *i* in time step *t*. Wind curtailment is not explicitly penalized in the objective function, and anywhere from zero to the full potential wind generation may be used in each time step, as long as the penetration goal is satisfied. Because the initial capacity of wind is the minimum number of wind plants that can generate enough wind energy over the 20 day time period to meet the penetration goal, if the system operator chooses to curtail, additional wind capacity must be installed to make up for the lost energy, incurring additional capital costs.

Vehicle charging levels must not exceed the power limit of the circuitry:

$$x_{jt}^{\mathrm{EV}} \leq l_j p_{jt} w_j n^{\mathrm{EV}} x_{\mathrm{CTRL}}^{\mathrm{EV}} \quad \forall j \in \mathscr{V}, t \in \mathscr{T}$$

Where l_j is the maximum charge rate for the vehicle j, p_{jt} is the percent of the time step *t* that the vehicle is parked at home at the end of the day and thus available to charge, and w_j is percent of total electric vehicles that are of profile *j*. The charging must keep the battery between its minimum and maximum states of charge:

$$b_j^{\mathrm{LO}} b_j w_j n^{\mathrm{EV}} x_{\mathrm{CTRL}}^{\mathrm{EV}} \leq x_{jt}^{\mathrm{E}} \leq b_j^{\mathrm{HI}} b_j w_j n^{\mathrm{EV}} x_{\mathrm{CTRL}}^{\mathrm{EV}} \quad \forall j \in \mathscr{V}, t \in \mathscr{T}$$

Where b_j^{LO} is the minimum SOC and b_j^{HI} is the maximum SOC, both expressed as percentages, b_j is the total size of the battery, and x_{jt}^{E} is the total amount of energy added to all the vehicles of profile *j* during time step *t*. Vehicles are driven in charge depleting mode (using electricity as the sole propulsions source) until the battery has reached its minimum state of charge or all the miles for the day have been driven, which is calculated ahead of time. The energy stored in the batteries of each vehicle profile depends on how much energy they had in the last period, the charging, and the discharging due to driving:

$$x_{jt}^{\mathrm{E}} = x_{j(t-1)}^{\mathrm{E}} + x_{jt}^{\mathrm{EV}}\Delta - d_{jt} w_j n^{\mathrm{EV}} x_{\mathrm{CTRL}}^{\mathrm{EV}} \eta^{\mathrm{ELEC}} \quad \forall j \in \mathcal{V}, t \in \mathcal{T}$$

Where s is the length of the time step and d_{jt} the distance in miles driven in electric mode. Every car is required to have the battery filled by the first trip of the next day:

$$x_{jt}^{\mathrm{E}} \geq b_j w_j n^{\mathrm{EV}} x_{\mathrm{CTRL}}^{\mathrm{EV}} \quad \forall j \in \mathcal{V}, t \in \mathcal{T}_j^{\mathrm{AM}}$$

Where $\mathcal{T}_j^{\mathrm{AM}}$ is the set of time steps each day when vehicle profile j leaves for the first trip of the day.

The optimization variables for this problem include x_{jt}^{E}, $x_{\mathrm{CTRL}}^{\mathrm{EV}}$, x_{jt}^{EV}, x_{it}^{G}, x_{it}^{SD}, x_{it}^{SDC}, x_{it}^{NSR}, x_{it}^{SR}, x_{it}^{SU}, x_{it}^{SUC}, x_t^{W}, y_i^{BLD}, y_{it}^{ON}.

The formulation was altered slightly to allow for the examination of the effect of a 15-minute time period. Most of the constraints remain the same, but everything regarding capacity expansion is removed from the objective function and constraints. Additionally, instead of executing the full twenty day period at once, we optimize over a 48 hour window, save the first 24 hours of data as the optimal operation for that day, move the window forward 24 hours and run another 48 hour optimization. This is repeated until optimal operation has been found for all 20 days. This shorter optimization window allows for a greater time resolution in the data while retaining similar run times. The new objective function used for each 48-hour period is shown below. By removing the payment to vehicle owners from the objective function, we assume a $0/vehicle/year payment in all cases and separately dictate $x_{\mathrm{CTRL}}^{\mathrm{EV}}$ as 1 or 0. For the sensitivity analysis, we are only interested in the extremes of all vehicles being controlled or none to understand the largest possible cost reductions.

Minimize the cost operating costs in each time step:

$$\text{minimize} \underbrace{\sum_{t\in\mathcal{T}^{48}}\left(\sum_{i\in\mathcal{C}}\left(x_{it}^{\text{SUC}}+x_{it}^{\text{SDC}}+c_i^{\text{F}}h_i x_{it}^{\text{G}}\right)\right)}_{\text{Cost of Plant Operations}}$$

No additional plants are provided to be built, so the constraint requiring plants to be built in order to be turned on is dropped. The wind penetration target requirement is also dropped because it can only be used across all time periods at once. Instead, we assume that the wind penetration functions simply as a requirement to build sufficient wind capacity so that 20% of the energy could be generated by wind. The model uses the same set of wind farms as used in the hourly model with 20% wind penetration. Because of the low marginal cost of wind, most of this wind energy will be used without a hard constraint. Constraints are added to hold the unit commitment variables constant through a single hour so that plants can only be turned off or turned on each hour, while generation levels are free to change every fifteen minutes.

2.3 Results and Discussion

We find that controlled charging of PHEVs reduces peak load and can reduce wind curtailment. A sample dispatch for the 20% wind penetration case is shown in

Figure 2.4, both with and without controlled charging in the Fixed Capacity Scenario (where the initial power plant fleet capacity is sufficient to meet all load). The figure shows that controlled charging significantly lowers the peak demand in the first three periods and reduces wind curtailment and coal plant ramping.

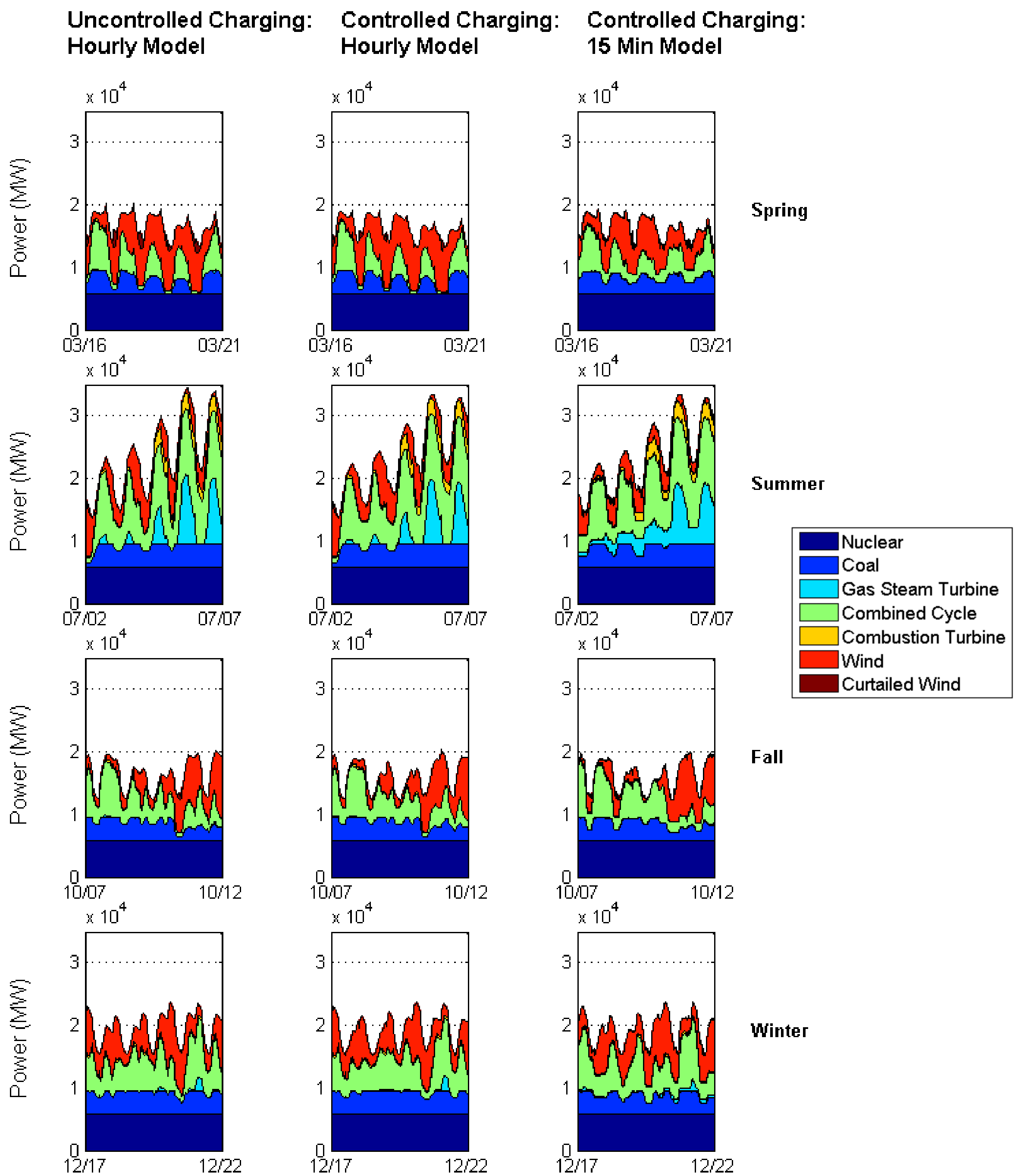

Figure 2.4: Seasonal dispatch in the Fixed Capacity Scenario given 10% vehicle penetration and a 20% wind penetration for uncontrolled charging in the hourly model, controlled charging in the hourly model, and controlled charging in the fifteen minute model.

2.3.1 Cost Reductions

Our main results, summarized in Table 2.32.3, suggest that controlled charging can reduce system costs. Given a 10% penetration of PHEVs (totaling 90,000 PHEVs), controlled charging reduces power generation costs by \$65-\$110 million dollars a year compared to the uncontrolled charging scenario, representing 1.5%-2.3% of total system costs and 54%-73% of the cost of integrating PHEVs. Controlled vehicle charging allows for shifting generation to cheaper plants and to off-peak hours. As shown in Table 2.3, controlled charging is most valuable in the Capacity Expansion Scenario, as the controlled charging program offers the opportunity to change which types and how many new power plants are built, in addition to influencing plant operation. In the Fixed Capacity Scenario, the additional vehicle load can be accommodated without building any new capacity, as the system is already operating with more capacity than required by the 15% reserve margin. In all cases, delayed charging is able to capture some, but not all, of the cost reductions offered by controlled charging. It is interesting to note that, regardless of the capacity scenario, when there is a 20% wind penetration, controlled charging offers 6%-13% greater cost reduction compared to the same system without wind. Thus, most of the cost reductions can be captured even when there is no wind in the system, and savings are somewhat higher but not dramatically higher in a system with significant wind generation. A detailed breakdown of the costs for each payment level in each scenario can be found in Table 2.4.

Table 2.3: Comparison of cost savings from controlled PHEV charging in the Fixed Capacity Scenario and Capacity Expansion Scenario for a 0% and 20% wind penetration, given different charging scenarios: Uncontrolled Charging, which uses the entire set of vehicles from the NHTS and begins as soon as the vehicle arrives home for the day; Delayed Charging, which also uses the entire set of vehicles from the NHTS and begins charging as late as possible before the vehicle leaves for the next day's trip while still achieving maximal charge; and Controlled Charging, which uses the weighted set of 20 representative vehicles and optimally charges each vehicle as part of the dispatch optimization, given a $0 payment to vehicle owners for participation. The maximum savings are calculated as the difference between the Uncontrolled and Controlled Charging system costs. The system costs for each system without plug-in hybrid electric vehicles are given as a reference, and reduction in vehicle integration costs is found by dividing the difference in costs between uncontrolled charging vs. controlled charging with difference in costs between uncontrolled charging vs. no vehicles.

	Fixed Capacity Scenario (Starting Capacity: 34,700 MW)		Capacity Expansion Scenario (Starting Capacity: 27,500 MW)	
	0% Wind Penetration	20% Wind Penetration	0% Wind Penetration	20% Wind Penetration
A. System Costs with No PHEVs (Reference)	3.56 $billion/year	4.42 $billion/year	4.05 $billion/year	4.89 $billion/year
B. System Costs with Uncontrolled Charging	3.69 $billion/year	4.53 $billion/year	4.20 $billion/year	5.04 $billion/year
C. System Costs with Delayed Charging	3.65 $billion/year	4.49 $billion/year	4.18 $billion/year	4.98 $billion/year
D. System Costs with 100% Controlled Charging and $0 Payment to Vehicle Owners	3.62 $billion/year	4.46 $billion/year	4.10 $billion/year	4.93 $billion/year
Maximum Cost Savings with Controlled Charging [B-D]	65 $million/year	69 $million/year	97 $million/year	110 $million/year
Operational Cost Savings %, Capital Cost Savings %	100%, 0%	100%, 0%	-27%, 127%	30%, 70%
Reduction in Vehicle Integration Costs with Controlled Charging [(B-D)/(B-A)]	54%	63%	66%	73%

Table 2.4: Costs for 10% vehicle penetration with different levels of payment to PHEV owners for controlled charging in each wind penetration and capacity expansion scenario. Overnight new capital costs include the cost of building wind capacity in order to meet the wind penetration goal as well as any additional plants. Annualized new capital costs represent the cost each year given the lifetime of each plant (50 years for coal, 30 years for gas, and 20 years for wind) and a 5% discount rate[4]. Annualized new system costs are the sum of the annualized new capital costs, annual vehicle program costs, and annual operating costs.

Wind Penetration	Capacity Expansion	Vehicle Payment ($/vehicle/year)	Percent Controlled (%)	Overnight New Capital Cost (billion $)	Annualized New Capital Costs (billion $)	Annual Vehicle Program Costs (million $)	Annual Operating Costs (billion $)	Annualized New System Costs (billion $)
0%	No	0	100%	4.5	0.29	0	3.3	3.6
		100	48%	4.5	0.29	43	3.4	3.7
		200	0%	4.5	0.29	0	3.4	3.7
20%	No	0	100%	25	2.0	0	2.5	4.5
		100	0%	25	2.0	0	2.5	4.5
0%	Yes	0	100%	10	0.65	0	3.5	4.1
		100	37%	11	0.74	0.03	3.4	4.2
		200	7.2%	12	0.77	0.01	3.4	4.2
		300	0%	12	0.8	0	3.4	4.2
20%	Yes	0	100%	30	2.3	0	2.6	4.9
		100	94%	30	2.3	0.085	2.6	5.0
		200	0%	31	2.4	0	2.6	5.0

There are limitations to these results. On one hand, they may overestimate the value of controlled charging by assuming perfect knowledge of vehicle trips and wind generation. Ensuring full charge of vehicles each day when vehicle trips and wind generation are uncertain may require safety margins that limit the flexibility of controlled charging, and implementable controllers with limited information about future states will have lower savings than optimal solutions under perfect information. On the other hand, controlled charging may provide additional value to the grid when accounting for the forecasting error of wind generation, as vehicle charging can be changed on time scales much faster than the ramping constraints of conventional power plants. Additionally, while

[4] The discount rate is highly uncertain because it depends on what else could have been invested in instead of the power plants. The IEA uses provides annualized costs of power plants using both a 5% and 10% discount rate [29] while the Office of Management and Budget suggests using a 7% discount rate [30] and experts consulted suggested rates between 3% and 10%. A higher discount rate would mean that investments in new power plants would be more expensive and therefore increase the value of controlled charging. Future work can examine a range of discount factors to understand the sensitivity to this parameter.

we allow charging only at home, availability of workplace or public charging might increase the flexibility and value of controlled charging (although current load patterns create the highest availability of low cost plants at night when vehicle owners are likely to be home). Except for the wind power, we assume that power plants are not limited by availability because with a limited number of sample days it is difficult to predict which plants might be offline. This assumption could overestimate the flexibility in the system and therefore underestimate the benefits of controlled charging. However, with the exception of nuclear plants, none of the plant types run 100% of the time, so we do not expect cost estimates to be substantially affected by plant downtime. This assumption also does not change the value in the Capacity Expansion Scenario, as reserve margins do not take availability into account but only reference peak load and total capacity. We also do not consider the costs maintaining wind farms or replacing them if they fail. While these costs could significantly increase the total costs of wind farms, it should not significantly impact the interaction of vehicle charging and wind. Electric vehicles would not change any of these costs and if less wind is on the system it could only decrease the modest difference between the value of controlled charging with high vs. low wind penetrations. Additionally, we ignore transmission constraints, which may over- or under-estimate this value depending on the distribution of PHEVs and other flexible resources in congested areas of the grid. It is possible that controlled charging of PHEVs could provide additional value by mitigating transmission congestion, but they may be unable to absorb wind energy if separated from wind resources by congested areas of the grid. The results from this model do give a good estimate of the operational cost savings possible considering time scales greater than an hour. And because the cost reductions result largely from shifting peak load, they should remain relatively unchanged with more detailed models. A summary of the model assumptions and the estimated direction they might affect the results is show below in Table 2.5.

Table 2.5: Model Assumptions. (-) represents assumptions that we believe result in our model underestimating the benefits of controlled charging. (+) represents assumptions that can result in our model overestimating the benefits.

Assumption	Justification	Expected Direction of Bias of the Value of Controlled Charging
No transmission constraints	No data available	(-) In our model, uncontrolled charging does not increase congestion and controlled is given no chance to relieve this and other congestion in the system.
Perfect information for demand and wind	Limited forecasting data available for the future wind sites, and this would require assumptions about the structure of future reserve markets to value the service.	(-) Controlled charging may be able to help forecasting error.
Hourly time steps	Increasing the time step to 15 minutes does not qualitatively change the results, and use of hourly time steps allows many more scenarios to be examined. The variability of wind decreases with frequency [31] so substantial differences at smaller time steps are unlikely.	(-) Some of the fast balancing that can be performed by controlled charging is missed, but we expect it to be small.
Battery can be charged anywhere between 0 and its maximum charge rate	While instantaneous changes in charge rate may be limited, at an hourly time scale, the desired average charge rate can be achieved without technical challenges.	We do not expect this assumption to be unrealistic at the time scales examined.
We focus on extended range plug-in hybrid electric vehicles instead of vehicles with blended operation	Although not the case for every PHEV, the Chevy Volt depletes the battery before extending the range with the gasoline motor as opposed to operating in a blended mode. Like previous studies [12][14], we assume our PHEV's operate as an extended range vehicle like the Chevy Volt.	(+) blended operation PHEVs result in somewhat smaller electricity demand for the same battery size, reducing the impact of uncontrolled charging and the potential for controlled charging to reduce this impact. We expect this to be a small effect, as a blended mode is more common in vehicles with smaller batteries where daily driving patterns are likely to use the entire battery even in blended mode. Modeling blended-operation PHEVs requires assumptions about vehicle control strategies, but there is no reason to believe these small differences in electricity consumption would qualitatively change results.
Controlled charging does not significantly reduce battery life	Degradation is complex, so we cannot be certain, but we expect that controlled charging will not decrease battery life and may increase it. Barre et.al. review the literature on lithium-ion battery aging mechanisms and find that cycle number is the most important factor, but voltage, temperature, and change in SOC can also play a factor [10]. Controlled charging does not change the number of cycles, and because it lowers the average C-rate, may decrease average charging voltage and temperature and therefore potentially extend battery life. Controlled charging also changes how long batteries remain at low SOC vs. high SOC while plugged in. Some chemistries have been shown to degrade faster at high SOC, so again controlled charging may extend battery life by leaving batteries at low SOC longer before charging rather than charging immediately upon arrival.	(-) the benefits of controlled charging may be larger if the reduced average C-rate of controlled charging results in extended battery life. However, it is not known whether variation in C-rate or SOC profile may have other positive or negative effects on battery life.

20 days are used to represent the calendar year	Necessary due to computational constraints in order to examine a wide variety of sensitivity cases.	This could shift the results in either direction, but we expect the differences to be small since the average load and wind match the annual averages and the peak and minimum load conditions are captured.

We examined the sensitivity of the cost reductions to several different important input assumptions, the first of which is the hourly time scale. We optimized grid operations over the same twenty-day period with a fifteen-minute time scale using a modified version of the optimization model designed to handle larger problems, without capacity expansion, by optimizing each day's dispatch sequentially. This allowed for manageable runtimes even with four times as many variables per day, while obtaining solutions close to the optimal solution of the original model. Total system costs for a 10% vehicle penetration with uncontrolled charging were ~2% higher in the fifteen minute model given a 0% wind penetration, and ~7% higher given a 20% wind penetration compared to the hourly model. Higher system costs are expected especially in the high wind case because there is more total ramping to accommodate the shorter time scale examined. The cost reductions associated with controlled charging are slightly lower in the fifteen-minute model, as shown in Figure 2.5. The higher time resolution of the data leads to a lower peak demand in the uncontrolled charging case. This effect overwhelms any additional cost reductions that might occur at fifteen-minute time resolution due to additional flexibility, and indicates that the cost reduction estimates at hourly resolution are optimistic. Both time resolutions produce similar trends between 0% and 20% wind penetration given the same initial generation capacity. These results suggest that the hourly time scale used in the base case is likely sufficient resolution -- it does not miss a major source of benefits from controlled charging at higher resolution. Although it is possible that even shorter time scales may allow for controlled charging to provide more benefit through participation in the regulation market, this requires more extensive communication infrastructure, and this market is expected to saturate with a relatively small number of vehicles [9]. In addition, the fifteen minute load control framework is similar to many existing demand response programs that use one-way radio controlled switches and cycle loads roughly every 15 minutes [28].

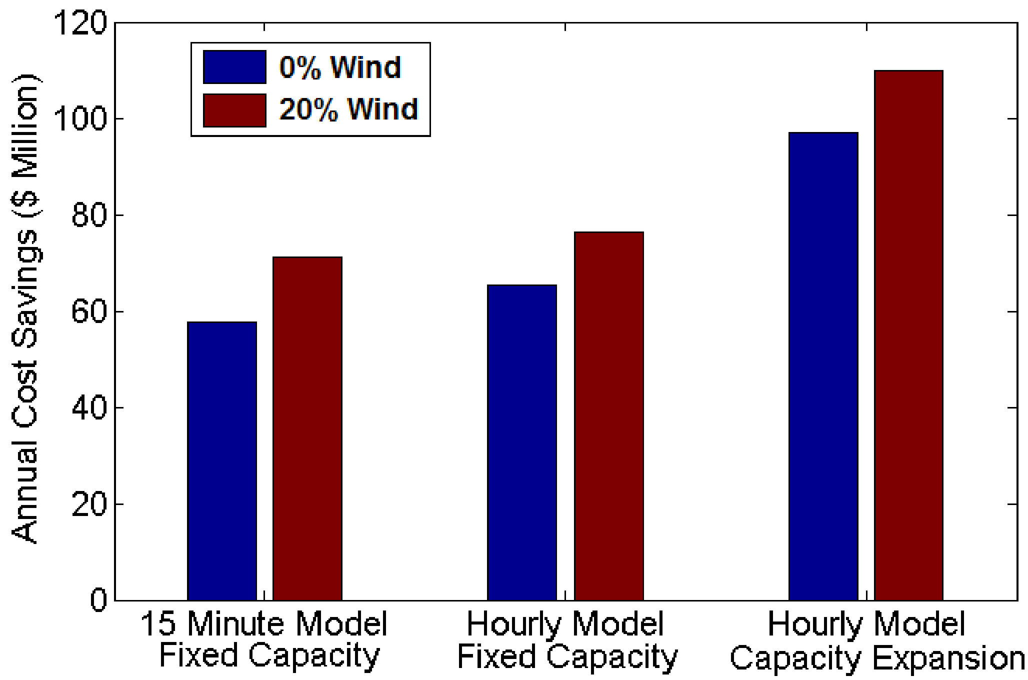

Figure 2.5: Annual cost savings due to controlled charging for different models given 0% and 20% wind penetration.

We also investigated the sensitivity of the results to changes in the parameters of the PHEV fleet. The potential cost savings from controlled charging is approximately linear with the penetration of PHEVs, as shown in Figure 2.6. Regardless of the vehicle penetration, controlled charging is worth more in scenarios with high wind penetration and capacity expansion. In the Capacity Expansion Scenario with 20% wind penetration, the cost reduction is slightly higher than the linear trend at the 15% vehicle penetration because controlled charging prevents construction of an additional gas plant. The Fixed Capacity Scenario with 20% wind penetration has a slightly higher cost reduction at 10% vehicle penetration than the linear trend because it has the most switching away from gas turbine generation.

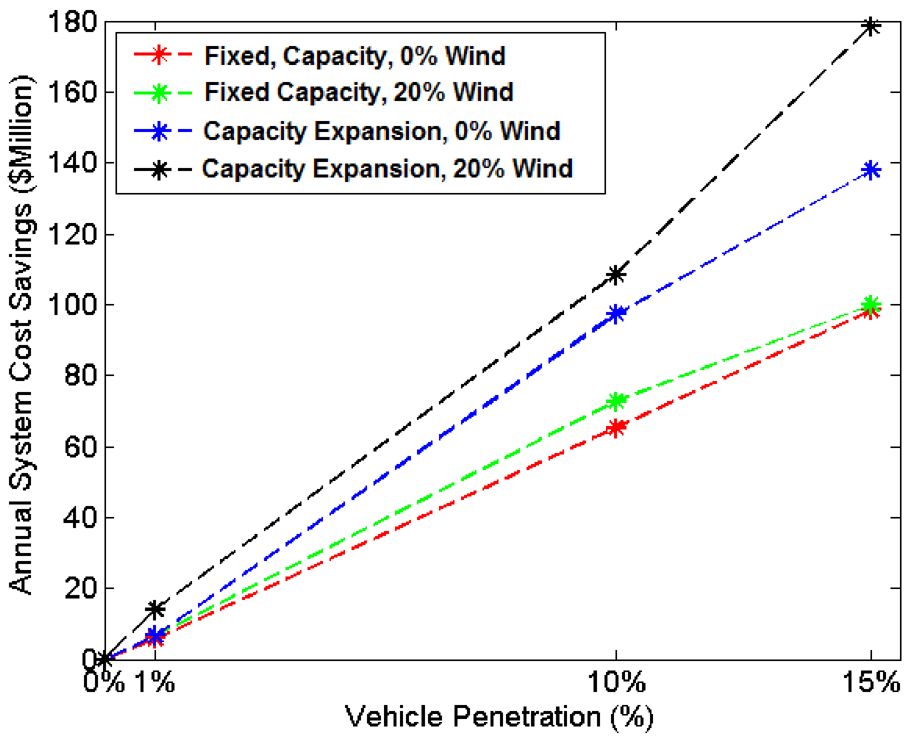

Figure 2.6: Sensitivity of the maximum annual system cost savings possible through 100% controlled electric vehicle charging compared to uncontrolled charging for a range of vehicle penetrations from 0% to 15% of a 9 million passenger vehicle fleet.

Increasing the maximum charge rates has diminishing returns, as shown in Figure 2.7. Level 1 charging restricts the peak power that occurs with uncontrolled charging, so controlling the charging is much less valuable. In the uncontrolled charging scenarios, increasing to Level 3 charging from Level 2 charging only minimally increases the peak load because the total amount all vehicles can be charged is limited by battery size and total driving distance. As battery size increases, the vehicles are able to drive more miles per day in charge depleting mode. This increases the value of controlled charging to the system somewhat, as the uncontrolled peak load becomes more and more expensive. However, this benefit is limited because the more miles traveled in charge depleting mode, the less flexibility there is to move charging to a later time, since much of the time spent parked is needed for charging. Examining a range of 5 kWh batteries to 24 kWh batteries, we see cost reductions differ from the base case by $1 to $35 million dollars per year depending on the scenario due to the competing effects discussed above.

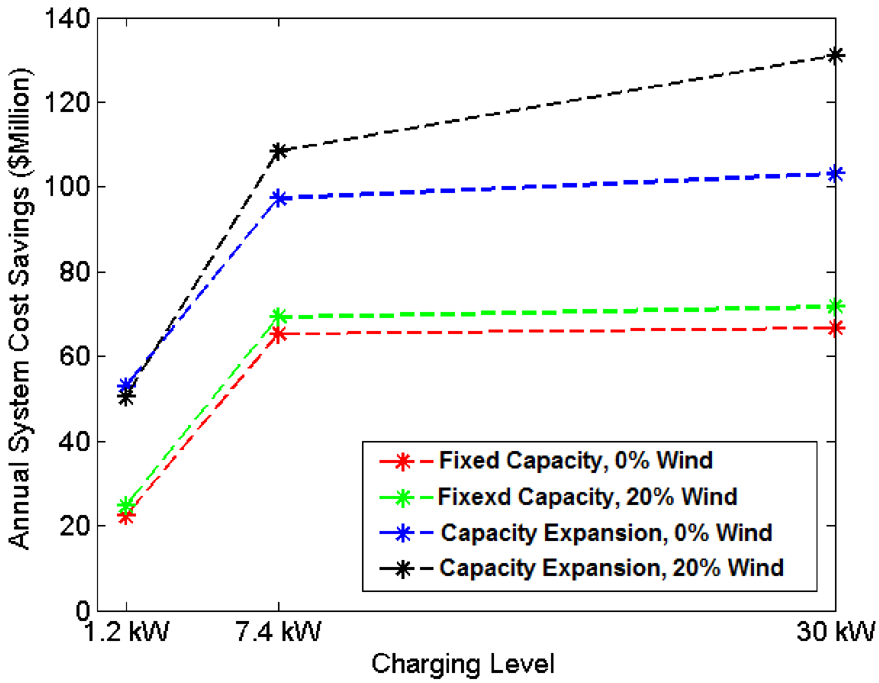

Figure 2.7: Sensitivity of the maximum annual system cost savings possible through 100% controlled electric vehicle charging compared to uncontrolled charging for Level 1 (1.2 kW), Level 2 (7.4 kW), and Level 3 (30 kW) charging. Only Level 1 and 2 are likely to be used in residential settings in the foreseeable future.

2.3.2 Capacity and Generation Mix

Figure 2.8 summarizes plant capacity and generation results for four cases. In the Fixed Capacity Scenario with no wind, controlled charging reduces generation from gas-combined cycle and oil/gas steam plants and increases generation from coal plants slightly, bringing coal plants to very high utilization levels. The lack of both the cheap energy from wind and its variability means that any coal capacity is used nearly continuously with very few startups and shutdowns. Not surprisingly, in the Fixed Capacity Scenario under a 20% wind penetration, controlled charging results in reduced generation from all fossil fuel plants types, replacing it with wind generation.

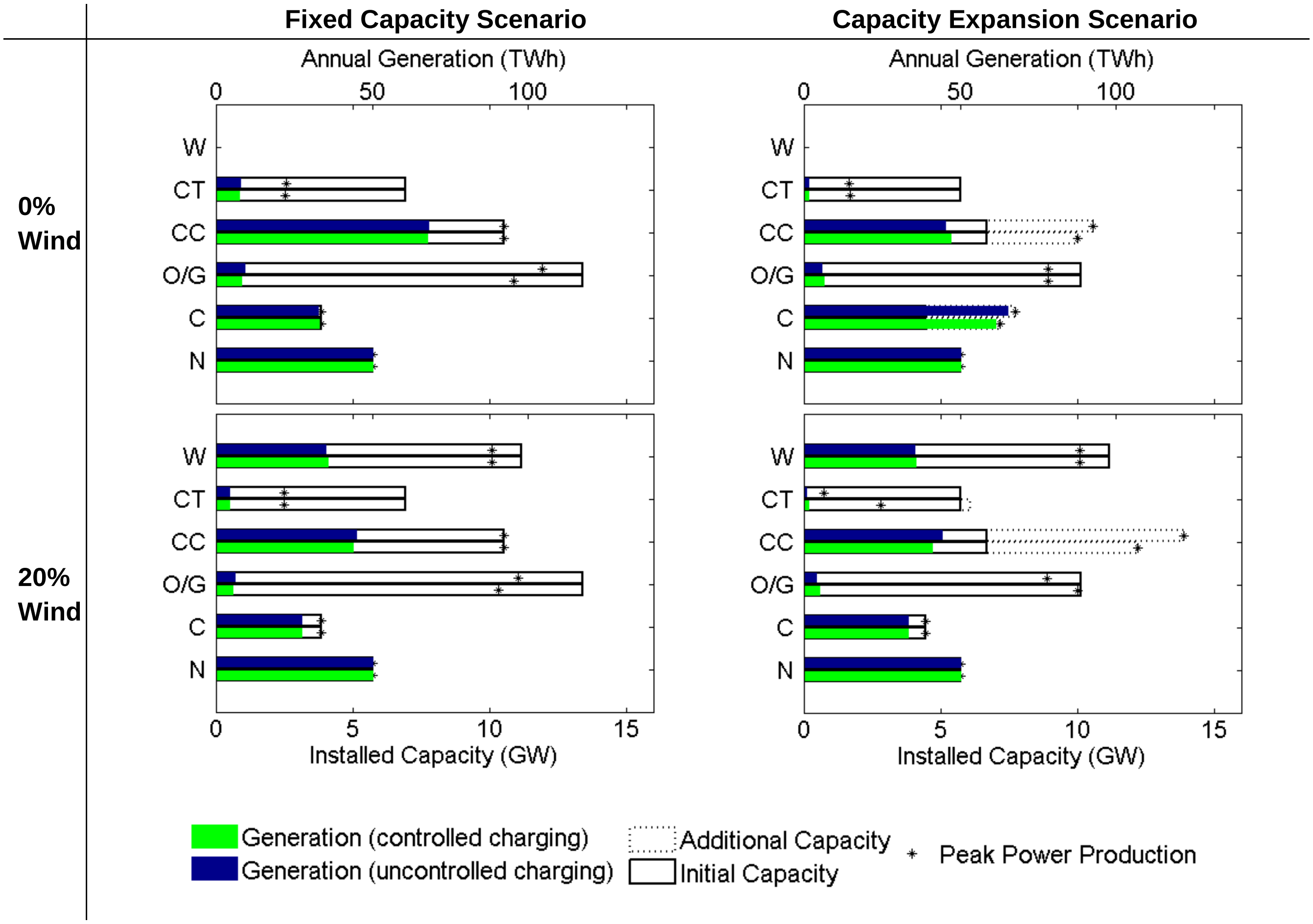

Figure 2.8: Comparison of capacity and generation data with and without controlled electric vehicle charging by generator type for each scenario. The following abbreviations are used for the generation types: W- Wind, CT – Gas Combustion Turbine, CC – Gas Combined Cycle, O/G – Oil/Gas Steam, C – Coal, N – Nuclear. Generation axis is scaled so that average capacity factor can be seen as percent of installed capacity bar filled with generation. Peak power production is calculated based on hourly data.

In the Capacity Expansion Scenario, controlled charging results in reduced plant construction: when there is no wind, fewer gas combined cycle and coal plants are built; and for a 20% wind penetration, no additional coal plants are built because of the abundance of low cost and high variability wind. Instead, most additional capacity is combined cycle gas. Given controlled charging, far fewer combustion plants are built compared to the uncontrolled charging scenario, and in exchange a small number of gas turbine plants are built to meet reserve margin and ramping requirements. These plants have higher operating costs than coal and combined cycle plants but have the lowest capital costs.

Controlled charging in the Capacity Expansion Scenario also shifts generation to allow for cheaper capacity expansion options. With no wind, controlled charging slightly shifts the generation from coal to natural gas and oil. Under a 20% wind penetration, controlled charging reduces gas combined cycle generation and slightly increases oil/gas steam generation to allow for reduced construction of combined cycle plants.

In both the Fixed Capacity Scenario and the Capacity Expansion Scenario, wind curtailment is reduced with controlled charging, but the curtailment that occurs even without controlled charging is a very small percentage of total wind generation, as seen by the slight difference in wind generation between the controlled and uncontrolled scenarios (Figure 2.8). Because plants have specified capacities and are added discretely until the wind generation potential is greater than the 20% of all load required by the penetration goal over the course of a year, a small amount of wind generation from the last plant added is extra and may be curtailed by the system operator while still meeting the penetration goal. Any larger amount of curtailment requires building additional wind plants. Curtailing the extreme peaks of wind production could help in reducing system costs by reducing the ramping and shut downs of conventional power plants. These cost reductions would have to exceed the capital costs of the new wind plants to make up for the energy lost in the curtailed peaks in order to meet the wind penetration goal. We find that regardless of the cost of controlled charging, it is never cost effective in the cases examined here to build extra wind plants in order to add flexibility to the system through the option of wind curtailment.

The generation mix remains fairly similar between the hourly and fifteen-minute model, as shown in Figure 2.9. The most noticeable differences are the increased use of oil/gas steam turbines and combustion turbines with the fifteen-minute model, and a corresponding decrease in the use of combined cycle plants. Wind energy is also used less with the fifteen minute model because we dropped the hard wind energy constraint in order to perform each day's optimization separately to save computation time with larger number of time steps. Using the same wind capacity as in the Fixed Capacity Scenario hourly model, the fifteen-minute model had only 19% wind by energy.

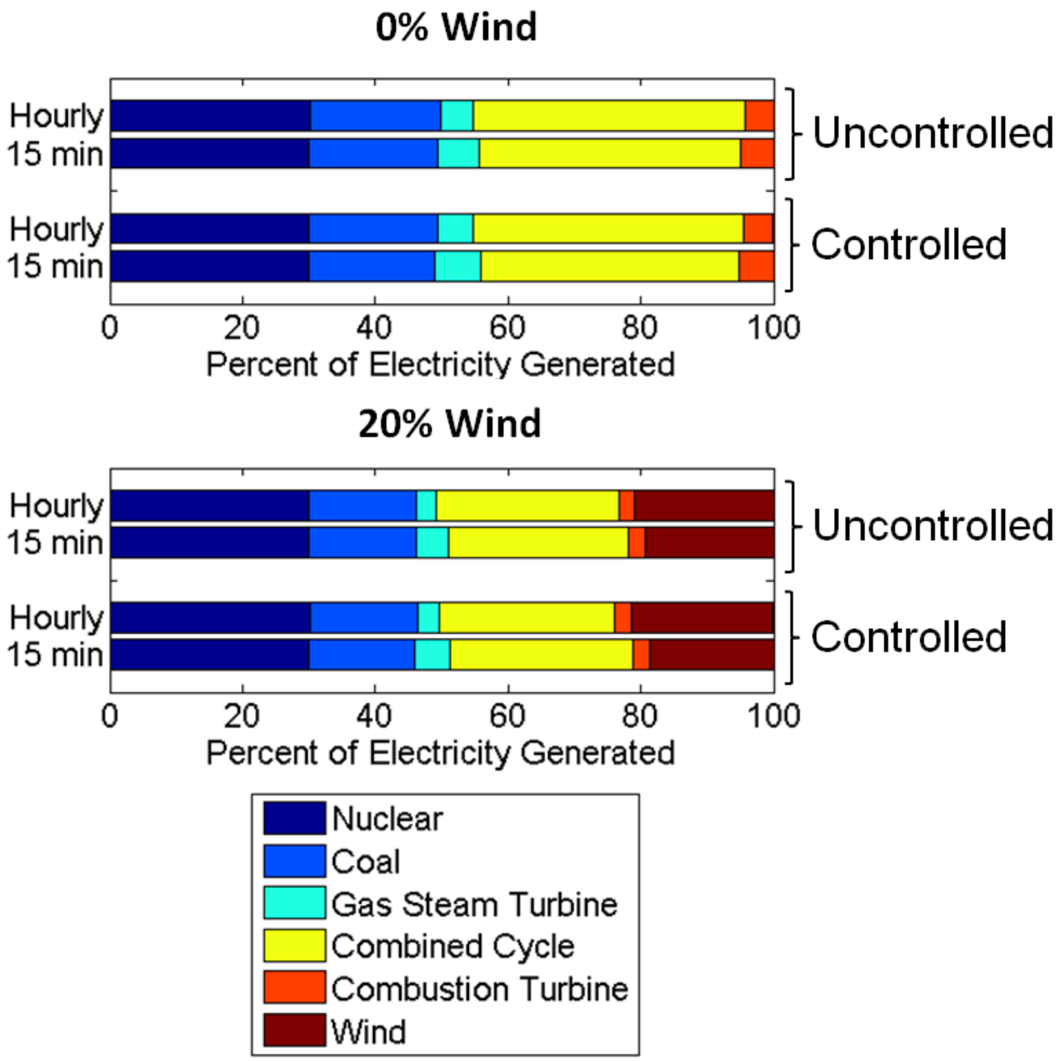

Figure 2.9: Comparison of resulting generation mixes between the hourly and fifteen minute model.

2.4 Conclusions

In our test systems, controlled charging of PHEVs reduces the costs of generating electricity to charge PHEVs by 54-73% depending on the scenario. Cost reductions that result from employing controlled vehicle charging are estimated at $65-$110 million/year, given a 10% PHEV penetration, perfect information, no transmission constraints, and a 1-hour resolution. Cost reductions 50%-60%

larger can be found in our cases requiring capacity expansion than in those without because controlled charging reduces the need for new plant construction and provides flexibility in deciding which plants to build. Capacity expansion may be needed in systems where coal plants are forced to retire due to emissions regulations or when significant load growth is expected. Cost reductions 6%-13% larger can be found in our cases with a 20% wind penetration than in those with a 0% wind penetration because of the additional value of controlled charging in managing wind variability. This suggests that controlled charging may offer some additional support for wind integration; however, system operators should not rely on controlled vehicle charging to dramatically cut wind integration costs. This result holds when examining sub-hourly time resolution. However, the potential of controlled charging in high wind penetration scenarios could vary when considering load and wind forecasting error and transmission constraints. Such considerations were not modeled here due to data availability and model tractability issues. Controlled charging could provide additional benefits by providing very fast ramping capability to balance solar PV systems, and could also not be needed as much given the flexibility of some new renewable sources like geothermal and small scale hydro, but these effects should be small due to the small amount of capacity being installed.

In most of our scenarios, at 10% PHEV penetration or higher, controlled charging provides enough system benefits to save $100/vehicle/year for many vehicles. These savings may be sufficient to provide a large enough payment for some vehicles owners to be willing to participate in a controlled charging program with an average savings of up to 0.2 cents/kWh of charging, as long as the necessary equipment can be obtained by the vehicle owner or system operator at low cost. Both the installation and maintenance costs of the controlled charging system would have to come out of the $100/vehicle/year. The cost benefits of controlled charging scale fairly linearly with the number of PHEVs, so if the equipment costs per vehicle are low enough and the overhead costs of program are kept low, a controlled charging program could pay for itself even at low PHEV penetrations. We do not, however, model the vehicle owner's willingness to participate in the program, as this is a behavioral question beyond the scope of our analysis.

Building additional wind plants beyond the penetration goal in order to allow curtailment and mitigate extreme generation fluctuation is not cost effective in our model. Although the energy lost by curtailing peaks is minimal and therefore requires little additional capacity to make up for it, the high capital cost of wind farms outweighs any benefit of flexibility to the grid.

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Chapter 3: Emissions and Cost Implications of Controlled Electric Vehicle Charging in the US PJM Interconnection

This chapter is based on a working paper: A. Weis, J. Michalek, P. Jaramillo and R. Lueken, "Emissions and Cost Implications of Controlled Electric Vehicle Charging in the US PJM Interconnection." Department of Engineering and Public Policy, Carnegie Mellon University.

3.1 Introduction

While controlled charging can significantly reduce the operational costs of charging electric vehicles, as shown in the previous chapter, these cost savings largely come from shifting some gas generation to coal generation. This creates significant emissions consequences, especially in the emissions of SO_2. In this chapter, we again examine the operational cost savings from controlled electric vehicle charging, but also quantify how emissions and the environmental and health damages from emissions are changed. Several previous studies have evaluated the emission benefits of controlled vs. uncontrolled electric vehicle charging. Table 3.1 provides a summary of this literature. One of these studies, Choi et. al [1], examined lifecycle emissions, while Lund and Kempton [2], Hadley and Tsvetkova [3], McCarthy and Yang [4], and Peterson et. al. [5] 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. Additionally, Hadley and Tsvetkova and McCarthy and Yang do not explicitly evaluate the effects of controlled charging, only the effect of shifting charging to different times of day. We build on previous work and provide new insights about the costs and benefits of vehicle electrification under controlled vs. uncontrolled charging schemes. We include operating constraints of the electric grid and estimate system operating costs and the economic value of emissions damages from generating the electricity used for charging plug-in electric vehicles. 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. The first grid scenario is based on the current 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.

Table 3.1: Previous literature comparing the effect of controlled and 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 [2]	2008	Denmark	Charging emissions	Supply curve with min gen	Yes	CO_2	No
Hadley and Tsvetkova* [3]	2008	US	Charging emissions	Supply curve	No	CO_2, SO_2, NO_X	No
McCarthy and Yang* [4]	2010	California	Charging emissions	Supply curve	No	CO_2	No
Peterson et al. [5]	2011	PJM and NYISO	Charging emissions	Supply curve	No	CO_2, SO_2, NO_X	No
Choi et. al [1]	2013	Eastern Inter-connect	Lifecycle emissions	Unit commitment and capacity expansion	Yes	CO_2	No
This chapter		PJM	Charging emissions	Unit commitment	Yes	CO_2, SO_2, $PM_{2.5}$, NH_3, NO_X, VOCs	Yes

*These studies do not explicitly compare controlled and uncontrolled charging, but it does examine the difference in emissions for charging at different times of day.

3.2 Methods

3.2.1 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 [6] (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 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 charging is optimized for minimum cost and can occur any time between the last trip of the day and the first trip of the next day as long as the battery is fully charged for the next trip.

3.2.2 Optimization of the Power System

In order 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 [7][8]. This model uses mixed integer linear programing to minimize the costs of operating the power plants 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. Each day is optimized using a 48-hour window, and then the model steps forward 24 hours, optimizes the following 48 hour window, and repeats.

The objective function minimizes the operating costs of all generators in the system:

$$\underset{\mathbf{x}}{\text{minimize}} \sum_{t \in \mathscr{T}} \left(\sum_{i \in \mathscr{C}} \left(x_{it}^{\text{SUC}} + x_{it}^{\text{G}} \left(c_i^{\text{F}} h_i + c_i^{\text{OM}} \right) \right) \right)$$

Where $\mathscr{T}$ is the set of all time steps in the 48 hour periods, $\mathscr{C}$ is the set of all generators, x_{it}^{SUC} is the start-up cost for the generator *i* in time step *t*, x_{it}^{G} is the power generated by generator *i* in time period *t*, c_i^{F} is the cost fuel, h_i is the head rate, and c_i^{OM} is the variable operation and maintenance cost for generator *i*.

The optimization is subject to similar constraints as those in chapter 2. The generation must meet the load in each region in each time period:

$$x_{rt}^{\mathrm{W}} + \sum_{i \in \mathscr{C}_r} x_{it}^{\mathrm{G}} + \sum_{l \in \mathscr{L}_r} x_{r,l}^{\mathrm{T}} = L_{rt} + R_r + y_{\mathrm{CTRL}}^{\mathrm{EV}} \sum_{j \in \mathscr{V}} x_{jrt}^{\mathrm{EV}} + (1 - y_{\mathrm{CTRL}}^{\mathrm{EV}}) n_r^{\mathrm{EV}} v_{rt}^{\mathrm{UCTRL}} \quad \forall r \in \mathscr{R}, \forall t \in \mathscr{T}$$

Where $\mathscr{C}_r$ is the set of generators in region r, $\mathscr{L}_r$ is the set of transmission lines connecting to region *r,* $\mathscr{V}$ is the set of all vehicle profiles, and $\mathscr{R}$ is the set of all regions in PJM. x_{rt}^{W} is the wind power taken from wind generators in region *r,* $x_{r,l}^{\mathrm{T}}$ is the power flowing into region *r* across power line *l*, and x_{jrt}^{EV} is the charging power to vehicle profile *j* from region *r* in time period *t.* L_t is the non-vehicle load in region *r* and time period *t* and R_r is level of reserves required in region *r.* $y_{\mathrm{CTRL}}^{\mathrm{EV}}$ is a binary parameter which is 1 if charging is controlled in the scenario and 0 if uncontrolled. n_r^{EV} is the number of electric vehicles in region *r* and v_{rt}^{UCTRL} is the uncontrolled charging load of one vehicle.

Wind generation used by the system cannot exceed the total wind potential:

$$x_{rt}^{\mathrm{W}} \le W_{rt} \forall r \in \mathscr{R}, \forall t \in \mathscr{T}$$

Where W_{rt} is the wind potential in region *r* in time period *t.*

The system is also subject to the physical constraints of the power plants. Each plant's maximum capacity cannot be exceeded:

$$x_{it}^{\mathrm{G}} \le y_{it}^{\mathrm{ON}} k_i \quad \forall i \in \mathscr{C}, \forall t \in \mathscr{T}$$

Where y_{it}^{ON} is a binary variable describing if the plant is on or off and k_i is the capacity of plant *i*. Similarly, the plant must be operated above its minimum generation level if on:

$$x_{it}^{\mathrm{G}} \ge y_{it}^{\mathrm{ON}} m_i \quad \forall i \in \mathscr{C}, t \in \mathscr{T}$$

Where m_i is the minimum generation level of plant *i*.

The plants incur start-up costs when turned on:

$$x_{it}^{\mathrm{SUC}} \geq c_i^{\mathrm{SU}} \left(y_{it}^{\mathrm{ON}} - y_{i(t-1)}^{\mathrm{ON}} \right) \quad \forall i \in \mathscr{C}, \forall t \in \mathscr{T}$$

Where c_i^{SU} is the cost of starting up for plant *i*.

Changes in generation levels have to comply with plant ramp rates:

$$x_{it}^{\mathrm{G}} \leq x_{i(t-1)}^{\mathrm{G}} + r_i^{\mathrm{UP}} y_{i(t-1)}^{\mathrm{ON}} \Delta + m_i (y_{i(t)}^{\mathrm{ON}} - y_{i(t-1)}^{\mathrm{ON}}) \quad \forall i \in \mathscr{C}, \forall t \in \mathscr{T} \setminus \mathscr{T}_1$$

$$x_{i(t-1)}^{\mathrm{G}} - r_i^{\mathrm{DWN}} y_{i(t)}^{\mathrm{ON}} \Delta - m_i (y_{i(t-1)}^{\mathrm{ON}} - y_{i(t)}^{\mathrm{ON}}) \leq x_{it}^{\mathrm{G}} \quad \forall i \in \mathscr{C}, \forall t \in \mathscr{T} \setminus \mathscr{T}_1$$

Where r_i^{UP} is the ramp rate of plant *i*, r_i^{DWN} is the ramp rate down, and Δ is the length of the time step.

Plants also have to stay on for a specified period of time δ_i^{ON} once turned on and stay off for a specified period of time δ_i^{OFF} when turned off:

$$\sum_{n=t-\delta_i^{\mathrm{ON}}+1}^{t} \left(y_{in}^{\mathrm{ON}} - y_{i(\mathrm{n}-1)}^{\mathrm{ON}} \right) \leq y_{it}^{\mathrm{ON}} \quad \forall i \in \mathscr{C}, \delta_i^{\mathrm{ON}} \leq t \leq T^{\mathrm{END}}$$

$$\sum_{n=t_i-\delta_i^{\mathrm{OFF}}+1}^{t} \left(y_{i(\mathrm{n}-1)}^{\mathrm{ON}} - y_{in}^{\mathrm{ON}} \right) \leq (1 - y_{it}^{\mathrm{ON}}) \quad \forall i \in \mathscr{C}, \delta_i^{\mathrm{OFF}} \leq t \leq T^{END}$$

Controlled vehicle charging has to be kept below the maximum charge rate:

$$x_{jrt}^{\mathrm{EV}} \leq l_j p_{jt} w_j n_r^{\mathrm{EV}} \quad \forall j \in \mathscr{V}, t \in \mathscr{T}$$

Where l_j is the maximum charge rate for a single vehicle, p_{jt} is what percent of time step *t* the vehicle profile *j* is parked at home, and w_j is the percent of electric vehicles with profile *j*.

The amount of energy left in the batteries x_{jrt}^{E} of vehicle in each regions and profile and time step must be tracked from time period to time period based on the amount of charging and the number of miles driven d_{jt}:

$$x_{jrt}^{\mathrm{E}} = x_{jr(t-1)}^{\mathrm{E}} + x_{jrt}^{\mathrm{EV}} \Delta - (d_{jt} w_j n_r^{\mathrm{EV}}) / \eta^{\mathrm{ELEC}} \quad \forall j \in \mathscr{V}, r \in \mathscr{R}, t \in \mathscr{T}$$

The amount of energy also must be constrained to be less than the total usable capacity of the batteries b_j:

$$0 \le x_{jrt}^{\mathrm{E}} \le b_j w_j n_r^{\mathrm{EV}} \quad \forall j \in \mathscr{V}, t \in \mathscr{T}$$

Finally, the batteries must be fully charged by morning:

$$x_{jrt}^{\mathrm{E}} = b_j w_j n_r^{\mathrm{EV}} \quad \forall j \in \mathscr{V}, r \in \mathscr{R}, t \in \mathscr{T}_j^{\mathrm{F}}$$

Where $\mathscr{T}_j^{\mathrm{F}}$ is the set of time steps during each 48 hour period when that particular vehicle profile makes its first trip of the day.

The reduced-form portion of the model title refers to the 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 reserve requirement is added to the load, treating the system as though reserves are always used. This simplification decreases the run time by a factor of 10, 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, since 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 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 [7]. However, this simplification does suggest that total generation and emissions for any given scenario represent an upper bound.

3.2.3 Data

3.2.3.1 Power Plant Fleet

The power system used in this study is based on PJM in 2010. The data for the power plants comes largely from the NEEDS dataset (v.4.10) [9] but also includes data on power plant operating parameters from other sources like Energy Information Administration (EIA) and PJM reports [7]. In order 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 [7]. It divides the PJM system into 5 transmission-constrained regions connected by six transmission interfaces, as shown in **Error! Not a valid bookmark self-reference.**. Each transmission interface consists of several actual transmission lines PJM identified as causing about half of the congestion costs [10]. 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.

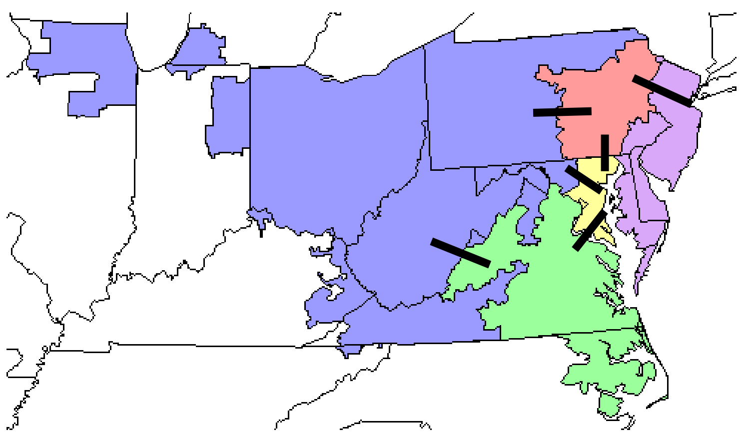

Figure 3.1: PJM power system divided into five transmission-constrained regions with simplified, power-limited transmission constraints between regions, represented by the black bars.

For scenarios 1-3 we use power plant emission rates from the 2010 eGRID dataset for CO_2, SO_X, and NO_2 emissions [11] and the 2005 NEI dataset for VOCs and PM 2.5 emissions [12] divided by the generation from eGRID 2005 (although more recent years are available, 2005 is the most recent year for which NEI data could be matched to our other power plant data). 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 missing plants 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 [13]. 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). The transmission constraints remain unchanged in PHORUM as we do not have any further data on how they will evolve over time. 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 its exact effects will be.

In order 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 [14]. The EWITS data set contains 5-minute 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.

3.2.3.2 Non-Vehicle Load

In order to model the effect of vehicle load on the dispatch of power plant, we need to account for the baseline non-vehicle load. For the 2010 scenarios (scenarios 1, 2, and 3) we used hourly load data for PJM for 2010 [15]. 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 US electricity load in 2018 by the total US electricity load in 2010 [16].

3.2.3.3 Plug-in Vehicle Fleet

Vehicle driving profiles are the basis for estimating the demand for electricity for vehicle charging. We modeled the driving profiles using data from the National Household Travel Survey [17]. This dataset contains all the trips travelled in one day for each vehicle in 100,000 households across the United States, giving the start and finish time, location, and distance travelled for each trip. We assume that uncontrolled charging happens at home starting immediately after the last trip of the day and is executed 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 twenty 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 described in chapter 2. Further, for this analysis we considered a 10% electric vehicle penetration of the passenger vehicle fleet (chapter 2 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.

3.2.4 Valuation of Health and Environmental Damages

The output of PHORUM includes hourly generation from all the 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 [18]. This model estimates the location-specific marginal monetary damages caused by 5 air pollutants (SO_2, NO_X, NH_3, $PM_{2.5}$, and VOCs) given a change in emissions from a reference case. This reference case is based on the total emissions from the National Emissions Inventory from the year being modeled. The model quantifies health damages based on air quality, exposure, and dose response models. The model outputs include damage values (in $/ton) for each pollutant based on the county from which it is emitted. Further, the damages vary depending on the height of the source of the emissions (ground level vs. stack height). The damages stem largely from health effects, calculated using a $6 million value of statistical life, but also include reductions in recreational use, agricultural yields, and other damages. AP2 damage values are available for 2002, 2005, 2008, and 2011. However, only the 2005 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 as well.

3.3 Results and Discussion

We find that controlling the charging of plug-in electric vehicles can significantly reduce the cost of generating electricity for vehicle charging, with savings ranging between 23% and 34% depending on the scenario, as shown in

Table 3.2. The cost reductions come from lowering fuel, operating, maintenance, and start-up costs through changes in plant dispatch. The cost reductions are smaller than the 50% cost reductions found in chapter 2 because the modeled PJM system included existing flexible storage plants while the modeled New York system only include fossil, nuclear, and wind plants.

Table 3.2: 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 3.2 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 otherwise would have been lost through curtailment, further reducing operating costs. 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 compared to controlled charging due to efficiency losses from storing and retrieving energy.

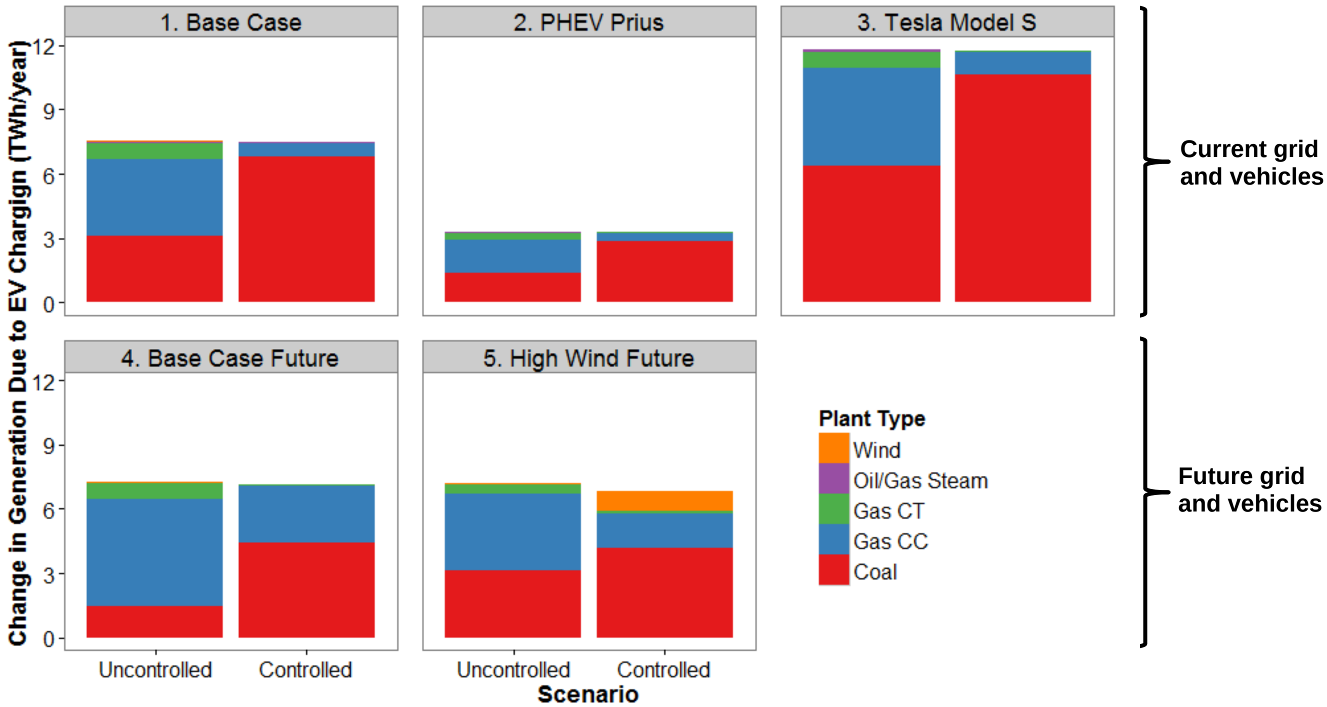

Figure 3.2: Change in system generation due to electric vehicle charging for controlled and uncontrolled charging for a 10% electric vehicle penetration. The current grid scenarios are based on the 2010 PJM power system with the 2010 GREET PHEV$_{35}$ as the base case vehicle. The future grid scenarios are based on the 2018 PJM grid as predicted by the EPA with the 2015 GREET PHEV$_{35}$ as the vehicle. CC = Combined Cycle, CT = Combustion Turbine.

Figure 3.3 shows the resulting changes in emissions when controlled charging takes place. The shift towards more coal generation when there is controlled charging causes an increase in emissions of CO_2, SO_2, NO_X, and $PM_{2.5}$ in scenarios 1-4. These results are consistent with those found by Peterson et al. [4] who also reported increased CO_2, SO_2, and NO_X emissions with smart charging compared to home charging in PJM. In these scenarios, VOC and NH_3 decrease with controlled charging. 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 when there is a 20% wind penetration. Controlled charging in this high wind scenario continues to drive an increase in SO_2 and NO_X emission compared to uncontrolled charging as a result of slightly increased coal generation during off-peak charging hours. The total increase in coal generation is smaller, however, so while CO_2 and

$PM_{2.5}$ from coal plants increase with controlled charging, greater use of wind power cuts enough CO_2 and $PM_{2.5}$ emissions from gas plants to result in a net reduction of these emissions. Figure 3.4 provides a breakdown of the total emissions by fuel type for the high wind scenario.

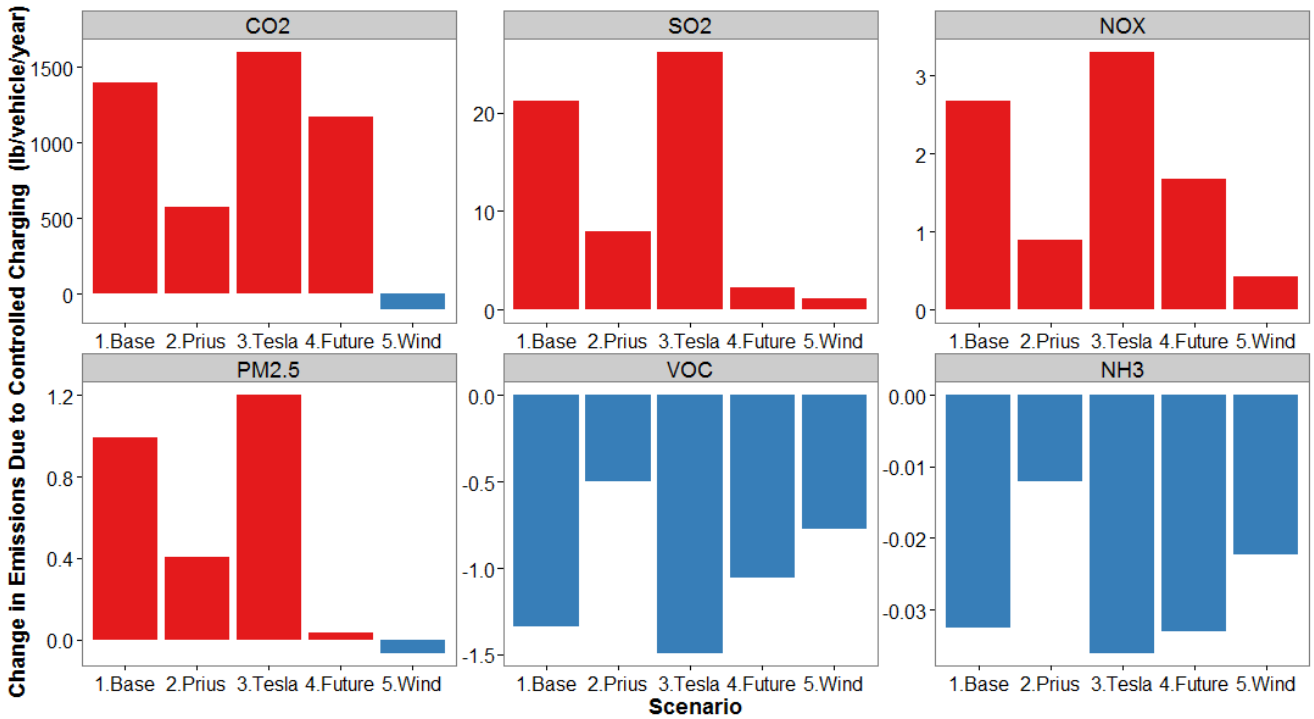

Figure 3.3: Average change in emissions due to controlled vs. uncontrolled charging per vehicle per year in PJM. Increases in emissions due to controlled charging are shown in red; decreases in emissions due to controlled charging are shown in blue.

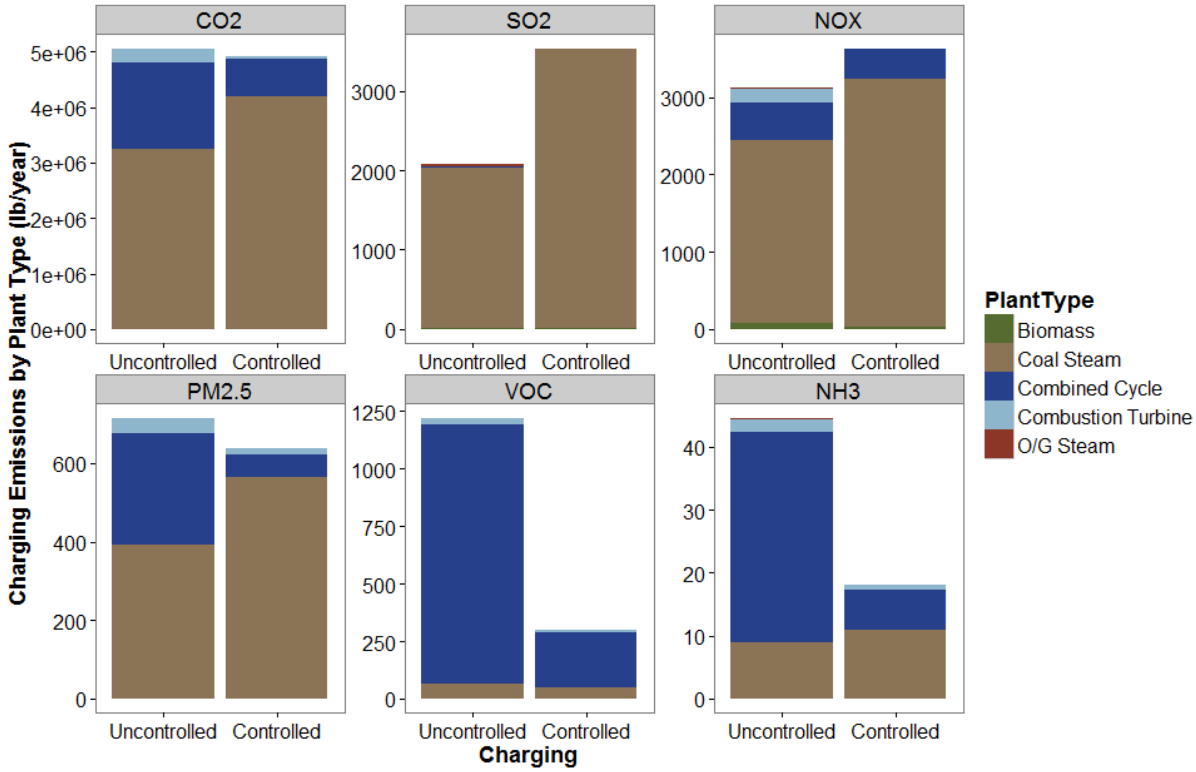

Figure 3.4: Total charging emissions in PJM for uncontrolled and controlled charging by plant type in the high wind scenario for a 10% electric vehicle penetration.

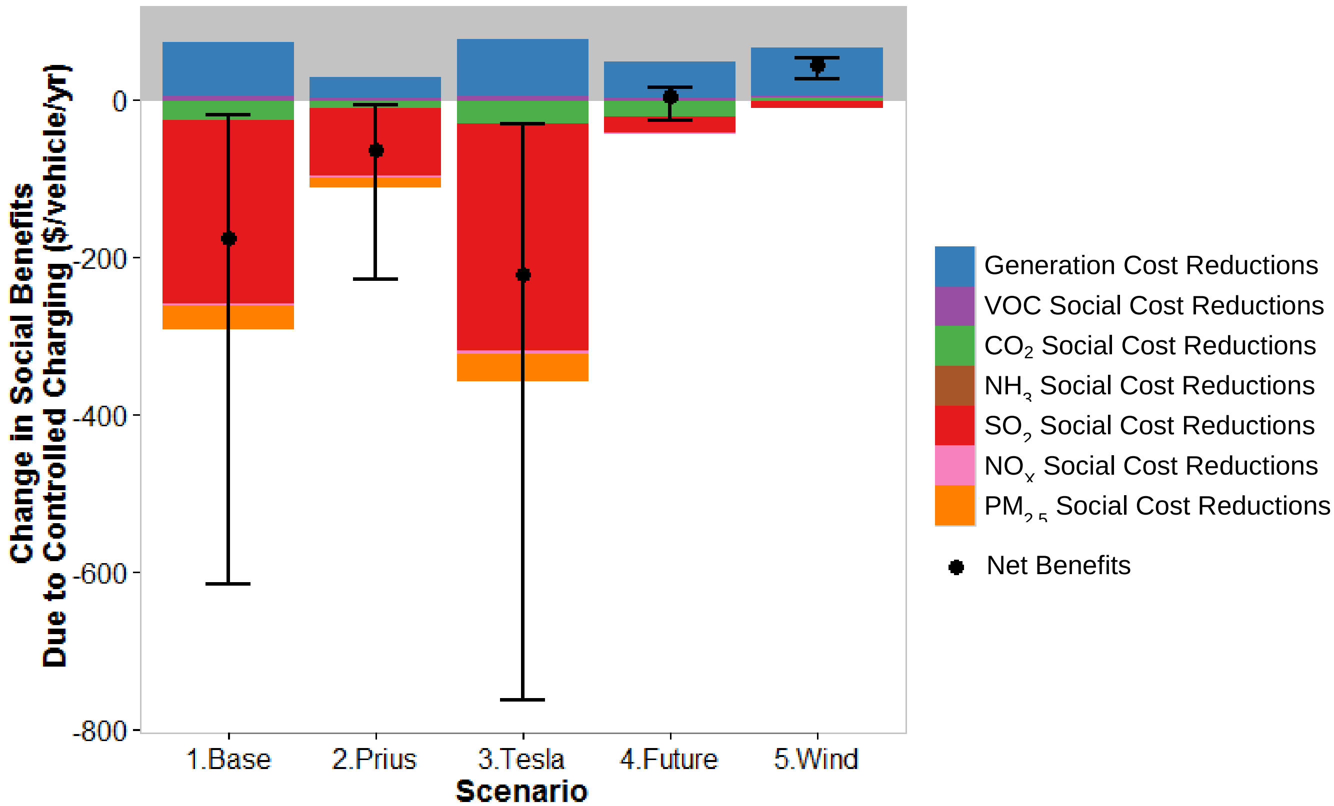

Figure 3.5: Change in annual social benefits due to controlled charging compared to uncontrolled charging ($$_{2010}$). Stacked bars show the change in generation cost combined with the median damages by pollutant assuming the 2010 social cost of carbon given by the OMB ($31 in $$_{2010}$). Black dots show the reductions in net social benefit due to controlled charging with error bars representing a 95% confidence interval, reflecting uncertainty in emissions damages.

Figure 3.5 summarizes total social benefits from changes in generation cost and emissions due to controlled charging. Error bars display a 95% confidence interval for net benefits. In scenarios 1-3 the entire confidence interval is negative, indicating high confidence that increased social costs from controlled charging emissions outweigh reductions in generation costs. 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 increased emissions costs.

As previously mentioned, the results in Figure 3.5 are based on AP2 damages for 2005, which is the only year for which AP2 includes uncertainty. In order to test the robustness of these results, we also evaluated the changes in emission damages using AP2 point estimate values from 2002, 2008, and 2011, shown in Figure 3.6. Our conclusions are robust for scenarios 1 through 4 regardless of which year's AP2 data we use. For the high wind scenario (Scenario 5), the results are consistent when using AP2 damages for 2002 and 2008. However, using AP2 damages for 2011 results in increased emission damages from controlled charging that exceed the reductions in generation costs. The period between 2008 and 2011 saw a significant reduction in SO_2 emissions from the power sector, which affected the background concentrations. This period also underwent shifts in population densities and thus exposure trends. The combination of these two trends results in higher marginal damages for 2011. Nonlinear properties of the dose-response functions as well as nonlinearities in atmospheric chemistry not currently included in the AP2 model, combined with further changes to emission concentrations and populations may make future marginal damages change in either direction.

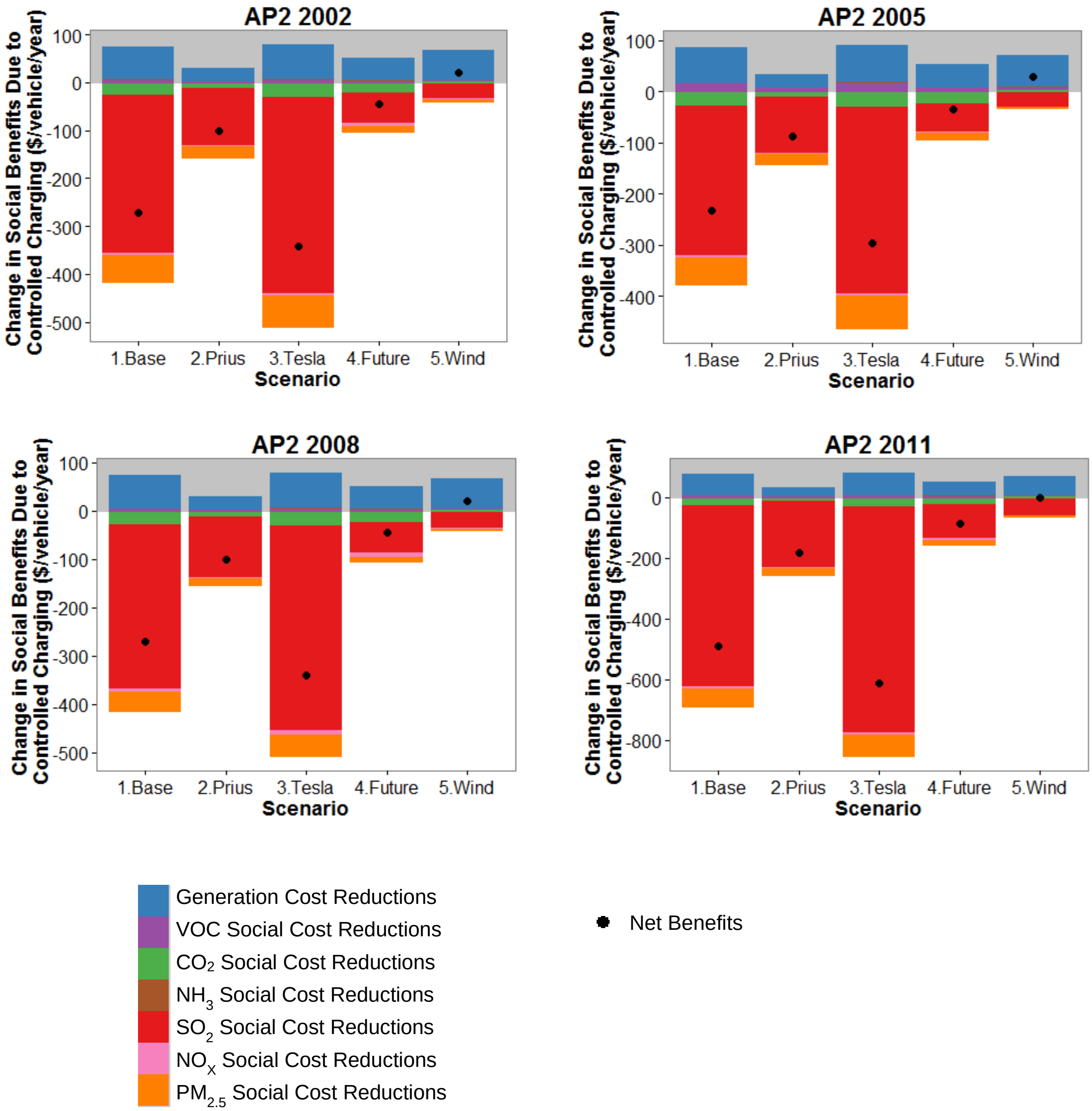

Figure 3.6: Change in annual social benefits due to controlled charging compared to uncontrolled charging ($\$_{2010}$) for each AP2 year. Stacked bars show the change in generation cost combined the median damages by pollutant assuming the 2010 social cost of carbon given by the OMB ($31 in $2010).

Our representation of the future PJM grid is not intended 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 very small, and we cannot be certain they will be positive, as the marginal damages from emissions change over time. It is also important to note that controlled charging does allow increased use of wind resources, which would thus support efforts to meet the penetration targets set in state Renewable Portfolio Standards (RPS). However, if the policy goal of the RPS is to reduce emissions, then despite the increased use of wind resources, controlled charging does not necessarily support this policy goal.

There are several important limitations to our model. We look at the average impact of a vehicle in PJM based on 10% electric vehicle penetration, but because there are transmission constraints in the system, the emissions and health effects caused by additional charging load would in practice vary somewhat across the region. The simplified transmission constraints used in PHORUM only capture roughly 50% of the congestion in the PJM system and do not take into account how the transmission constraints might change in the future. Additional congestion could prevent controlled charging from using all of the wind energy we estimate, or the use of cheaper plants in general, but controlled charging could also help relieve congestion and allow for greater reductions in generation costs. The imperfect transmission constraints could also imply error in the predicted location of emissions. This could imply a greater uncertainty in the damages values than is represented in **Error! Reference source not found.**, which only includes the uncertainties from within the AP2 model. This additional uncertainty is difficult to quantify. Higher levels of congestion would also increase the variance in emissions associated with vehicle charging across PJM.

We assume perfect knowledge of load and wind generation over each 48-hour period. Because vehicle charge rates could be changed on a faster time scale than the operational limits of power plants, controlled charging could provide additional value in correcting for forecasting error. On the other hand, since we assume that we know the exact schedule of all electric vehicles, the results may overestimate of the operational value of controlled charging. However, as electric vehicles become more widely adopted in each region, their behavior should become easier to predict.

Our model also does not take into account other environmental constraints that might impact power plant operation, such as the National Ambient Air Quality Standards (NAAQS). In 2010, some regions within PJM were in nonattainment of the NAAQS. To check if vehicle charging would affect nonattainment, the resulting power plant emissions from uncontrolled and controlled vehicle charging added to the existing electricity demand were run through the AP2 air quality model to find the resulting concentrations. We found slightly increased concentrations in some counties that were already in nonattainment compared to the concentrations without vehicle charging. States with regions in nonattainment have State Implementation Plans to address the problem, which may affect the way plants can be dispatched in the future. We also do not include emission caps in our modeling. These caps link operational decisions between all time periods within the year modeled, and even between years because power plants can bank unused allowances. In 2010, the Acid Rain Program (ARP) and Clean Air Interstate Rule (CAIR) limited power plant SO_2 emissions in PJM. Emissions were well below the budget set by the ARP, but power plants subject to CAIR exceeded the 3.6 million ton annual budget by 0.8 million tons, indicating that they used banked allowances from the APR [19]. Power plants only used 1 million out of a total of 16 million available banked allowances, so operational decisions were likely not significantly influenced by the opportunity cost of using these allowances. NO_X is also regulated by CAIR, but the cap has not been binding for any of the years that it has been in place [20]. It is uncertain if any caps will be binding in 2018. Starting in 2015, the Cross-state Air Pollution Rule (CSAPR) replaced CAIR in setting the SO_2 emission limits, tightening the cap 1.8 million tons below the CAIR level by 2017. It is possible that because power plants must reduce their emissions to comply with the MATS, emissions will already be below the cap. In this case, power plant operations would remain unaffected. On the other hand, if emissions were high enough to make the cap binding, then any additional generation for vehicle charging would have to come from low-emission sources and increase the SO_2 prices by increasing the pressure on the cap. In this case, charging generation could not switch from gas to coal unless the coal plants were retrofitted with emission controls that eliminated SO_2 emissions. Controlled charging could reduce health damages in addition to generation costs by switching from the less efficient gas plants available in peak hours with more efficient gas plants that would have capacity available night. Damages could still increase with controlled charging by changing the location of SO_2 emissions to areas with larger populations even as the total magnitude stayed constant.

There are also limitations to using the marginal damages of pollutants from one year to estimate what the damages will be in the future. Changes in background air pollutant concentrations and non-linear effects of atmospheric chemistry that may occur as a result of cleaner power plants, as well as shifts in population, may also result in significant changes in the values of the marginal damages associated with one ton of pollutant. It is thus important to improve social costs models that can include these effects. These limitations notwithstanding, several key conclusions emerge from this analysis.

Controlled electric vehicle charging may reduce the generation cost of electric vehicle charging significantly but may nevertheless produce net social costs in the PJM grid due to increased use of inexpensive, high emission coal plants. Even in a future 2018 system, coal remains a significant resource in PJM, which would continue to drive increased pollution damages from controlled charging at night. These health and environmental damages, especially those associated with SO_2, outweigh the reductions in generation cost associated with controlled charging except in the high wind case. The addition of large amounts of wind to the PJM system may make controlled charging more desirable from an operation cost perspective, but we still expect higher environmental and health damages than with uncontrolled charging. In general, controlled charging has potential for reducing generation costs, but its societal impact depends 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 optimization are substantial and should be considered when making policy decisions to avoid large increases in human health and environmental costs.

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Chapter 4: Lifecycle Emissions and Impacts of Plug-in Electric Vehicles in PJM

This chapter is based on the working paper: A. Weis, P. Jaramillo, and J. Michalek, "Lifecycle Impacts of Plug-in Electric Vehicles in the PJM Interconnection" Department of Engineering and Public Policy, Carnegie Mellon University.

4.1 Introduction

The benefits and costs of controlled charging can be determined solely through the interaction of vehicle charging with the electricity grid, as done in chapters 2 and 3. However, in order to evaluate the impacts of plug-in electric vehicles relative to other passenger vehicle options, such as hybrids and conventional internal combustion engine vehicles, we need to consider the entire lifecycle of the vehicles. This allows us to account for the differing upstream fuel and manufacturing emissions. However, the charging emissions remain critical to determining which vehicle will have the lowest total impact [1]. This chapter contributes an analysis of lifecycle emissions, including vehicle and battery manufacturing, using a bottom-up unit commitment and economic dispatch model of the grid to evaluate criteria air pollutant and emissions and their societal damages.

Only the recent study by Choi et al. [2] has also used a detailed optimization model of the power system that includes the physical constraints of power plants to evaluate the lifecycle emissions of electric vehicles. All other studies that attempt to evaluate the impact of future changes to the electricity mix do so by assuming scenarios with a single generation type such "all renewables" and "all gas," as is done by Michalek et al. [1] and Tessum et al [3]. Choi et al. include the evolution of the grid through capacity expansion, but they only evaluate carbon emissions. Including the physical power plant constraints becomes increasingly important to determine what plants will be on the margin at different times of day as the grid evolves to incorporate more renewables. For example, with no ramping constraints, wind will never be on the margin since it has the lowest marginal cost. The Tessum et al.study has a "2020 average mix scenario," but the generation mix is from 2007. This study does use a state-of-the-science air quality model to evaluate the resulting concentrations and damages across the country. Our study uses a simpler air quality mode which allows us to evaluate the impact of emissions in each county separately. As discussed in the thesis introduction, studies using past average emissions rates or technology specific emissions rates give us bounding cases but cannot tell us how electric vehicles will interact with specific future grid scenarios, or how different charging patterns will affect emission and damages. Studies by Graff Zivin et al. [4] and Tamayao et al. [5] can capture the complexities of the current electricity grid by using top-down regression models. However, because the regressions used are based on historical data, these models also cannot be used to predict what might happen to emissions when significant changes occur to the system. Table 4.1 below compares this chapter with other relevant, peer-reviewed LCA studies on total vehicle lifecycle emissions in the United States.

Table 4.1: Comparison of literature addressing the lifecycle emissions of plug-in electric vehicles in the United States that include vehicle manufacturing emissions. This chapter combines a consideration of a wide range of emissions and their damages with a detailed model of the electricity grid, unlike previous work.

Author	Year	Power System	Power System Model	High Wind Scenarios?	Emissions Considered	Calculation of damages?	Charging patterns?
Samaras and Meisterling [6]	2008	United States	Average emissions with sensitivity	No	CO_2 Eq	No	No
Michalek et. al. [1]	2011	United States	Average emissions with sensitivity	No	CO_2, CO, SO_2, $PM_{2.5}$, NH_3, NO_X, VOCs	Yes	No
MacPherson et. al. [7]	2012	United States and by region	Average emissions	No	CO_2 Eq	No	No
Ma et. al. [8]	2012	California	Marginal emission factors	No	CO_2	No	No
Choi et. al [2]	2013	Eastern Interconnect	Unit commitment and capacity expansion	Yes	CO_2	No	Yes
Tamayao et. al. [5]	2014	United States by region	Marginal emissions factors	No	CO_2	No	Yes
Tessum et. al [3]	2014	United States	Average emissions	Yes	CO_2 Eq, O_3, $PM_{2.5}$	Yes	No
This Study		PJM	**Unit commitment**	**Yes**	**CO_2 Eq, CO, SO_2, $PM_{2.5}$, NO_X, VOCs**	**Yes**	**Yes**

4.2 Methods

4.2.1 Lifecycle Boundary

This chapter estimates the lifecycle emissions of CO_2, CO, SO_2, $PM_{2.5}$, NO_X, and VOCs for each vehicle type, including the emissions from vehicle and battery manufacturing, in addition to the well-to-wheel emissions of the vehicle fuel. For conventional and hybrid vehicles, the well-to-wheel emissions include the upstream fuel emissions from petroleum drilling and refining, as well as the tailpipe emissions. For plug-in hybrid electric vehicles, it also includes the emissions created by burning fuel in power plants to charge the vehicle, and the upstream emissions from coal and natural gas production. The scope of the lifecycle inventory is shown below in Figure 4.1. We do not consider end of life emissions in this study. We assume a total vehicle life of 160,000 miles, as done in [1].

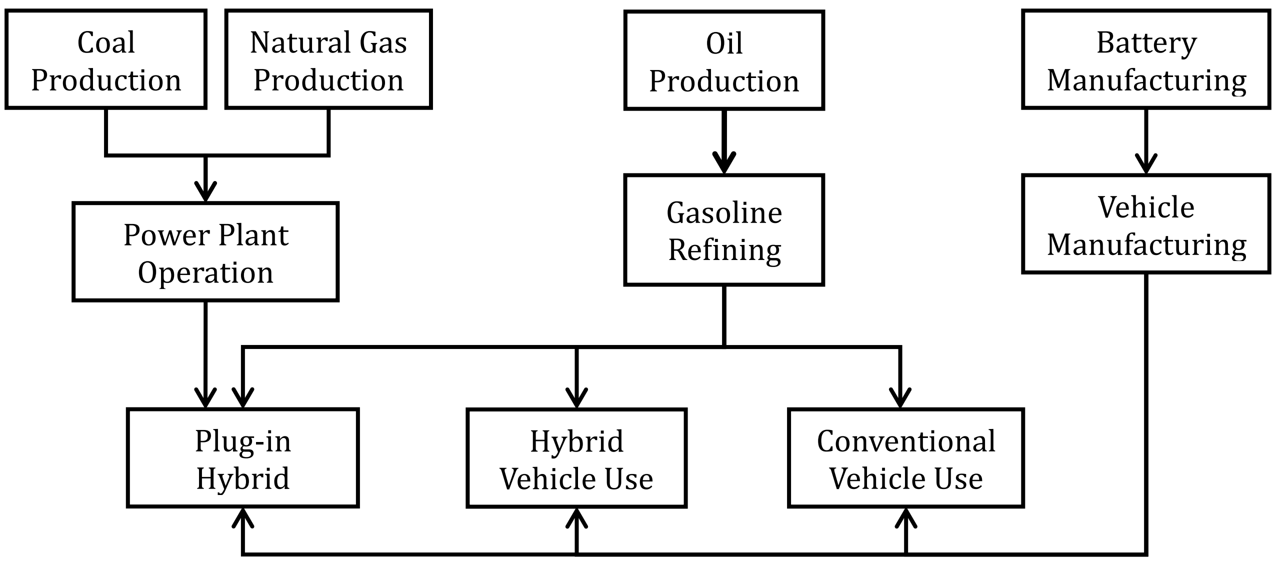

Figure 4.1: Lifecycle Inventory for plug-in hybrid, hybrid, and conventional vehicles.

4.2.2 Vehicle and Power Grid Scenarios

We use two sets of scenarios, one based on the current power system in PJM and one based on a possible future PJM power system, to compare lifecycle emissions and damages of plug-in hybrid electric vehicles with conventional and hybrid gasoline vehicles:

Table 4.2: Scenarios for lifecycle emissions and damages comparison

Scenario	Power System Data	Conventional Vehicle	Hybrid Vehicle	Plug-in Electric Vehicles
1. Current (2010)	2010 PJM	2010 GREET ICEV	2010 GREET HEV	2010 GREET PHEV-10 (Plug-in Prius-sized) 2010 GREET PHEV-35 (Volt-sized) 2012 BEV-265 (Tesla-sized)
2. Future (~2018)	EPA forecasted 2018 PJM With and without high wind	2015 GREET ICEV	2015 GREET HEV	2015 GREET PHEV-35 (Volt-sized)

For each scenario, data was used to represent 2010 and 2018 respectively as accurately as possible, given data availability. Data for most vehicles come from the Argonne National Laboratory's 2013 GREET 1 and 2 models [9][10]. The electric range and efficiency for the Tesla-sized large electric range PHEV's is for the 2012 Tesla Model S on fueleconomy.gov [11]. For the future grid scenarios, we use 2015 GREET plug-in hybrid, hybrid, and conventional gasoline vehicles, as this was the latest model year available in GREET. Electricity grid data for 2010 is taken from the NEEDS data set and other sources, and updated for the future grid scenarios with new and retired power plants, as done in chapter 3. The additional wind generation for the future grid comes from NREL's Eastern Wind Integration and Transmission Study dataset [12]. We add wind sites in order of capacity factor to reach the 3% wind penetration forecasted by the EPA for 2018 for PJM for the base case future scenario. We increase the number of sites to reach a 20% wind penetration for the high wind scenario.

4.2.3 Lifecycle Inventory

We determine the lifecycle emissions for each stage shown in Figure 4.1 for each vehicle type based on a 160,000 mile lifecycle. A summary of the data used for each stage is shown in Table 4.3 below and explained in more detail in the following sections.

Table 4.3: Data for the lifecycle emissions for each stage

Stage	Emission Rate	Source	Other Assumptions	Source
Power Plant Operation	Ton/year	Unit commitment model	Driving patterns Vehicle efficiency	NHTS GREET 1, fueleconomy.gov
Tailpipe	Grams/mile	GREET 1	Driving patterns	NHTS
Vehicle	Ton/lifetime	GREET 2		
Battery manufacturing	Ton/lifetime	GREET 2		
Oil Production	Ton/mile	GREET 1		
Gasoline Refining	Ton/mile	GREET 1		
Coal Production	Ton/MWh	GREET 1	MWh hours produced	Unit commitment model
Natural Gas Production	Ton/MWh	GREET 1	MWh hours produced	Unit commitment model

4.2.3.1 Power Plant Operation Emissions

Power system emissions are determined by calculating the extra electricity load added to system from vehicle charging and modeling the power plant response to the added load. Vehicle charging load is determined from vehicle parameters and driving patterns taken from the National Household Travel Survey (NHTS) data [13], as done in chapters 2 and 3. These data provide the distance driven during each trip throughout the day surveyed as well as the time of each trip. We use the distance driven in a day, the vehicle efficiency, and the electric range of the vehicle to calculate both how many miles are driven in charge-depleting vs. charge-sustaining mode and the total charging load per day. We assume that all plug-in hybrid electric vehicles drive as many miles as possible in charge-depleting mode before switching to charge-sustaining mode. We also assume that all vehicles are charged at home after the last trip of the day and are fully charged by the first trip of the next day. For each scenario, we calculate the hourly charging load for both uncontrolled and controlled charging. Uncontrolled charging load is calculated assuming that the vehicles begin charging as soon as they arrive home after the last trip of the day at the maximum charge until fully charged. Controlled charging is optimized with power plant operations using 20 representative vehicle profiles as described in chapter 3. The charging can occur any time between the last trip of the day and the first trip of the next day and at any charging power at or below the maximum charge rate, as long as vehicles are fully charged by the end of this period. Charging in all scenarios is limited to Level 2 (7.2 kW) charging.

The resulting emissions from vehicle charging are calculated using a unit commitment and economic dispatch model of the PJM power system that minimizes the cost of generating electricity while meeting all loads. This model is based on PHORUM (PJM Hourly Open-source Reduced form Unit commitment Model), developed at Carnegie Mellon [14]. It is modified to include variables and constraints for the additional vehicle charging load, as done in chapter 3. Charging load is added to the existing non-vehicle electricity load by assuming electric vehicles make up 10% of the vehicle fleet in PJM. The vehicles are distributed throughout the system proportional to population. The model is run with and without both types of charging load, and the resulting change in generation and emissions at each power plant is attributed to vehicle charging.

4.2.3.2 Tailpipe Emissions

Tailpipe emissions are determined by the number of miles driven in gasoline or charge-sustaining mode and the emission rates per mile. All vehicle types are assumed to drive 160,000 miles over their lifetime, with plug-in electric vehicle miles divided between charge-sustaining and charge-depleting modes of operation as discussed in section 4.2.3.1 above. The emission rates per mile are taken from the GREET 2 model [10] and shown in Table 4.4 below. While the two plug-in vehicles with smaller batteries are assumed to burn some gasoline in charge-depleting mode as given by the GREET model, we assume that the Tesla-sized vehicle operates without any tailpipe emissions.

Table 4.4: Tailpipe emissions in grams per mile from GREET 1

Vehicle	CO_2 Eq	VOC	CO	NO_X	$PM_{2.5}$	SO_2
2010 CV	350	0.17	2.9	0.12	0.012	0.0052
2010 HEV	250	0.12	2.9	0.10	0.012	0.0037
2010 PHEV-10 CS (Plug-in prius)	240	0.12	2.9	0.10	0.012	0.0036
2010PHEV-10 CD (Plug-in prius)	120	0.04	1.0	0.036	0.0025	0.0019
2010 PHEV-35 CS (Volt)	310	0.12	2.9	0.10	0.012	0.0047
2010PHEV-35 CD (Volt)	20	0.01	0.17	0.0058	0.00041	0.00030
2010 BEV-265 CD (Tesla)	0	0	0	0	0	0
2015 CV	320	0.17	2.9	0.12	0.012	0.0048
2015 HEV	230	0.12	2.9	0.10	0.012	0.0034
2015 PHEV CS (Volt)	260	0.12	2.9	0.10	0.012	0.0040
2015 PHEV CD (Volt)	19	0.0073	0.18	0.0062	0.00043	0.00029

4.2.3.3 Upstream Emissions

Upstream emissions for gasoline are determined using emission rates per mile and the total number of miles per lifecycle. Argonne National Laboratory's GREET 1 model [9] provides the emission rates for oil drilling and refining, and each vehicle is assumed to drive a total of 160,000 miles per lifecycle. Upstream emissions for vehicle and battery manufacturing are given by the GREET 2 model [10].

Upstream emissions for coal and gas are determined by emission rates per MWh for each fuel type and the total additional power generated by each fuel type for each vehicle type and type of charging. The upstream emissions per MWh of power generated for each fuel type are taken from the GREET 1 model. The power generated for vehicle charging is an output of unit commitment model described above in section 4.2.3.1. We only consider coal and natural gas upstream emissions from the electric power sector as coal and gas make up the majority of generation attributable to vehicle charging as shown in chapter 3. In addition, coal and gas have the largest upstream emissions. Wind generation provides the only other significant contribution to vehicle charging and has no upstream fuel emissions. Upstream emissions for each lifecycle stage from the GREET model are given in Appendix A.

4.2.4 Lifecycle Damages

Damages from CO_2 emissions are calculated using the social cost of carbon for regulatory impact used by the EPA [15]. The social cost of carbon is calculated in the aforementioned report for three different discount rates: 2.5%, 3%, and 5%. We use the 3% discount rate average value for 2010 as our base value for all scenarios.

Damages from SO_2, $PM_{2.5}$, NO_X, and VOCs are calculated using the AP2 model [16], which estimates the marginal health and environmental damages for emissions of each criteria air pollutant in each county in the United States. This model has many uncertain parameters, including the value of a statistical life, which is used to translate morbidity and mortality from air pollution into dollar damages. Results from a Monte Carlo analysis of the damages in each county are given for the baseline year 2005. As a base case, we assume that these 2005 marginal damages per unit emission in each location apply also to the current (2010) and future (2018) scenarios. We use the distribution of results from the Monte Carlo analysis to characterize the uncertainty within the AP2 model. Damages from vehicle charging are calculated based on the change in power plant operations in each location over the year resulting from increased charging load. Tailpipe emissions from all vehicles are assigned to counties proportional to population, with the assumption that the vehicles are operated within that county. Emissions from vehicle and battery manufacturing are located in automobile and parts manufacturing counties, weighted by the number of automotive manufacturing workers, as done in [1]. Coal, oil, and natural gas upstream emissions are located in the US counties with extraction and refineries, weighted by the production in each county, as done in [17]. The resulting cumulative probability distribution of damages from manufacturing, coal, oil and gas production, and oil refining are shown below in Figure 4.2: Cumulative probability distribution of damages for upstream production emissions by pollutant type. Identical probability distributions are used for vehicle and battery manufacturing. The damage calculations assume that all emissions and damages occur in the United States, when in fact some of these processes occur outside of US borders. These emissions would incur different damages, depending on the existing concentrations and populations in those areas. All damages, except for vehicle and battery manufacturing, are divided among the years of operation. The damages are then discounted back to the year of manufacturing using a 3% discount rate, to be consistent with the calculation of CO_2 damages.

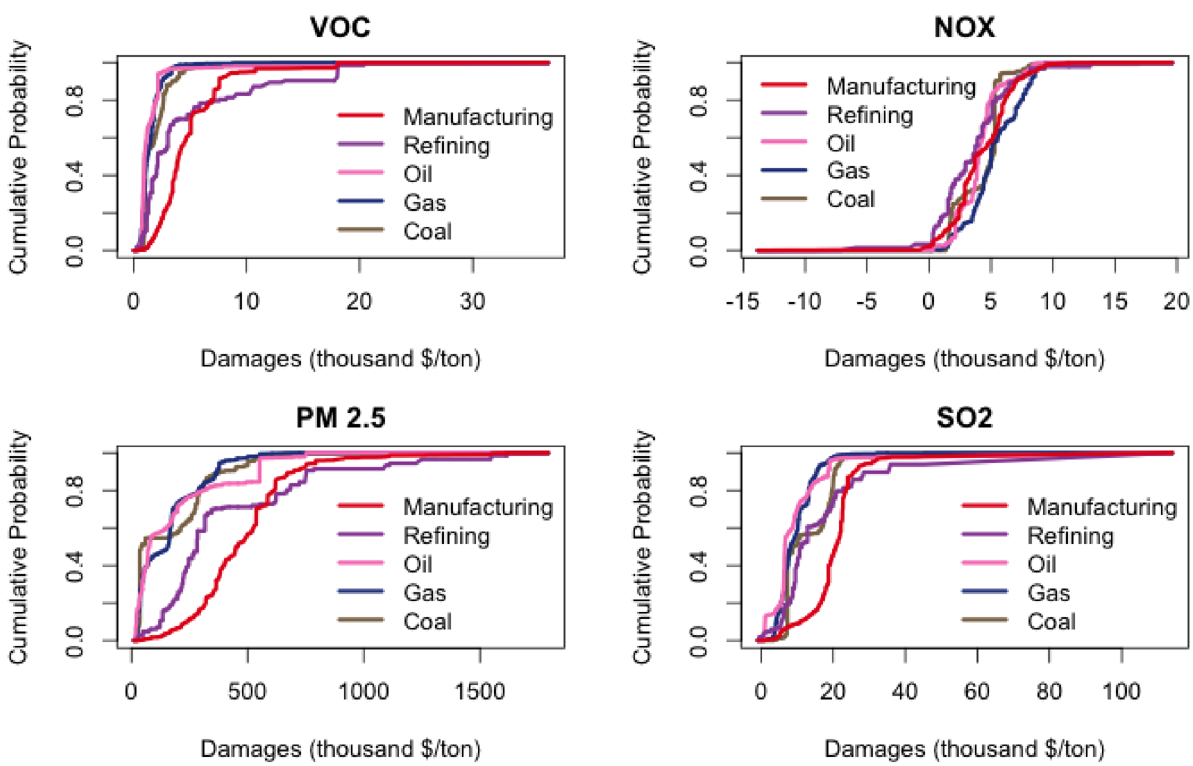

Figure 4.2: Cumulative probability distribution of damages for upstream production emissions by pollutant type. Identical probability distributions are used for vehicle and battery manufacturing.

In addition to the uncertainty included in the Monte Carlo analysis, there is uncertainty in all of the damages due to unquantified errors in the AP2 model, including a simplified air quality model and uncertainty in assumed dose-response relationships. Other uncertainties remain in both the magnitude of emissions and damages specific to each lifecycle stage, as summarized in Table 4.5.

Table 4.5: Uncertainty unaccounted for in the lifecycle analysis of criteria air pollutant emissions and associated damages specific to each lifecycle stage.

Lifecycle Stage	Unaccounted for uncertainty in emissions	Unaccounted for uncertainty in damages
Electric vehicle charging	Type of power plant dispatched Use of average emission rate	Location of power plant dispatched
Tail pipe emissions	Driving Style Climate Representative vehicle types	Location of driving Distribution of EV adoption
Vehicle and battery manufacturing	Changes in electricity system emissions	Manufacturing that occurs outside of the US Location of battery manufacturing compared to vehicle manufacturing
Upstream for coal, oil, and gas	Use of average emission rate	Production that occurs outside of US Future production methods

4.3 Results

4.3.1 Lifecycle Emissions

In the current PJM grid, the plug-in electric vehicles studied have higher lifecycle emissions than the HEV for most pollutants, including CO_2, SO_2, NO_X, and $PM_{2.5}$. While battery emissions do play a small role, the electricity sector emissions have the largest role in increasing these pollutants. Plug-in electric vehicles do reduce VOC and CO emissions compared with both hybrid and conventional vehicles; both the Prius and Volt-sized plug-in vehicles are able to reduce CO2 emissions compared to conventional vehicles. In the future PJM grid, plug-in vehicles reduce $PM_{2.5}$ emissions in addition to VOC and CO emissions, and Prius and Volt-sized electric vehicles can reduce NO_X emissions in addition to CO_2 emissions relative to conventional vehicles. Figure 4.3 below shows the breakdown of estimated emissions by lifecycle stage for each scenario in the two different grid systems.

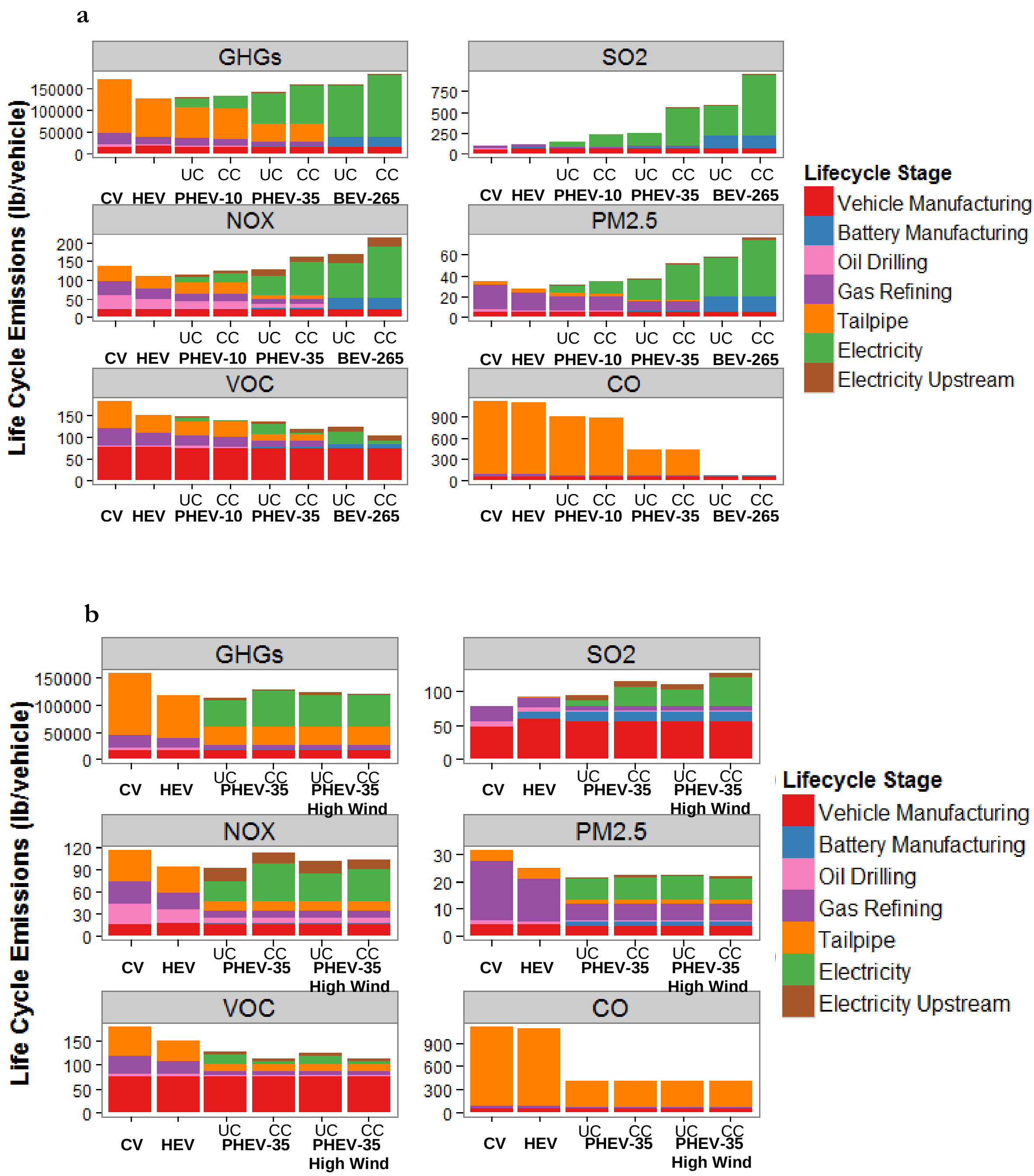

Figure 4.3: Lifecycle emissions by pollutant and lifecycle stage for each vehicle type in the current (a) and future (b) PJM grid. UC stands for uncontrolled charging and CC stands for controlled charging for the electric vehicles.

4.3.2 Lifecycle Damages

4.3.2.1 Expected Values

Plug-in electric vehicles have higher expected lifecycle damages than hybrid vehicles in the current PJM scenario in all cases examined, as shown in Figure 4.4. Their expected damages are also higher than those of conventional vehicles, except for the case of the PHEV-10 with controlled charging. The electricity generation damages come largely from the SO_2 emissions of the coal plants used to charge the vehicles in off-peak hours. Controlled charging increases lifecycle damages relative to uncontrolled charging because of the increases in emissions from higher levels of coal generation, as found when examining charging emissions alone in chapter 3. Uncertainty is not presented here because common sources of uncertainty create correlated uncertainty across scenarios, so error bars would be misleading. Instead, uncertainty and robustness are characterized in Section 4.3.2.2.

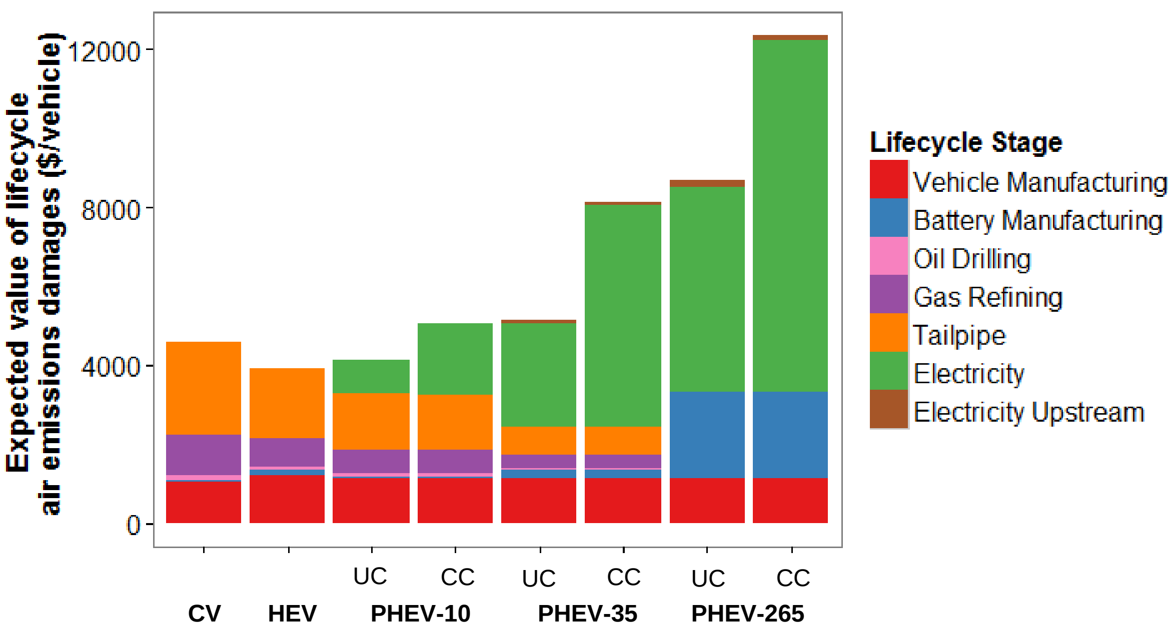

Figure 4.4: Expected value of lifecycle damages for each vehicle type in the current PJM grid. UC stands for uncontrolled charging and CC stands for controlled charging for the electric vehicles.

In the future scenario, shown in Figure 4.5, plug-in vehicles are able to reduce lifecycle damages by a few hundred dollars over their lifetime, when compared with hybrid vehicles. Plug-in vehicles perform most favorably when the least amount of coal is used for their charging, as is the case with uncontrolled charging without high wind penetrations. In this case, lifecycle damages were reduced by around $400 per vehicle compared to hybrid vehicle lifecycle damages. Continued use of coal generation for some of the charging limits the benefits of plug-in electric vehicles relative to hybrid vehicles, even with high wind penetrations.

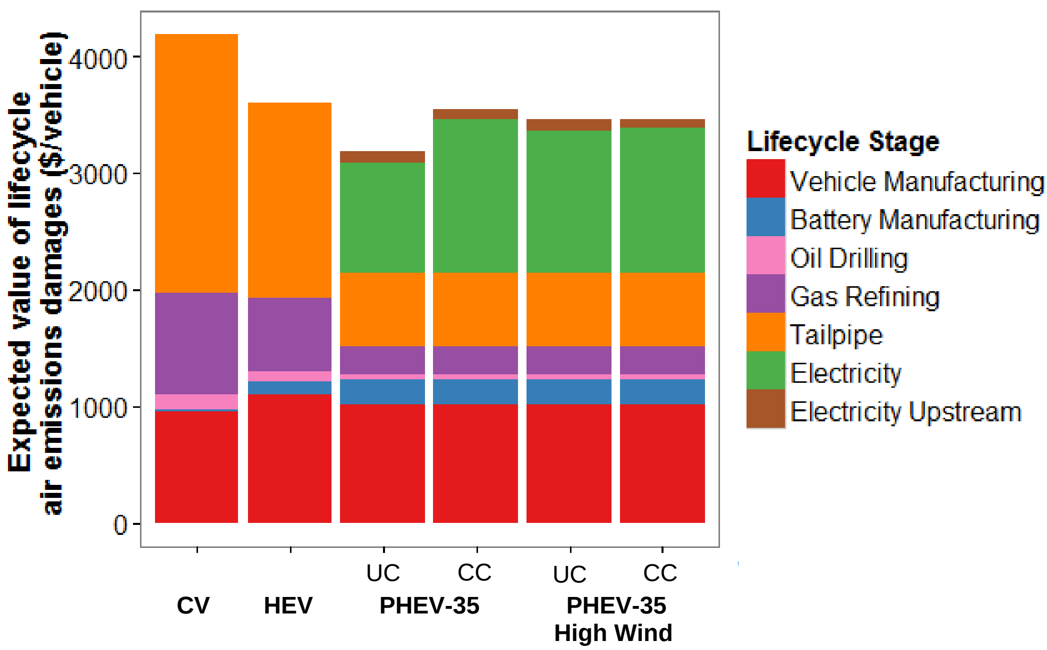

Figure 4.5: Expected value of lifecycle damages in the future PJM grid. The high wind scenario has 20% of demand met by wind. UC stands for uncontrolled charging and CC stands for controlled charging for the electric vehicles.

4.3.2.2 Uncertainty and Robustness

To characterize uncertainty and robustness of these results, we use the Monte Carlo analysis results from the AP2 model and assess the probability that each vehicle technology has higher lifecycle air emissions damages than the HEV. Table 4.6 reveals that the conclusions above are robust, especially in the current grid. This is because most of the uncertainty in the AP2 model comes from the uncertainty in the value of a statistical life, which is held constant across scenarios.

This uncertainty only changes the magnitude of the difference between hybrids and other vehicles, never the sign. The CDF for the probability that each vehicle's lifecycle damages are higher than those of the HEV is shown in Figure 4.6 and Figure 4.7 below.

Table 4.6: Robustness of results for the damage difference between hybrid vehicles and each other vehicle type. CV = conventional vehicle.

Scenario	Charging	Probability Damages Are Larger than for HEV's	Mean Change in Lifecycle Damages Compared to HEV's
CV – Current Grid		100%	$650
PHEV-10 – Current Grid	Uncontrolled	81%	$210
	Controlled	98%	$1100
PHEV-35 – Current Grid	Uncontrolled	95%	$1200
	Controlled	99%	$4200
BEV-265 – Current Grid	Uncontrolled	99%	$4800
	Controlled	99%	$8400
CV –Future Grid		99%	$580
PHEV-35 – Future Grid	Uncontrolled	4%	-$420
	Controlled	28%	-$60
PHEV-35 – Future Grid with High Wind	Uncontrolled	17%	-$150
	Controlled	18%	-$150

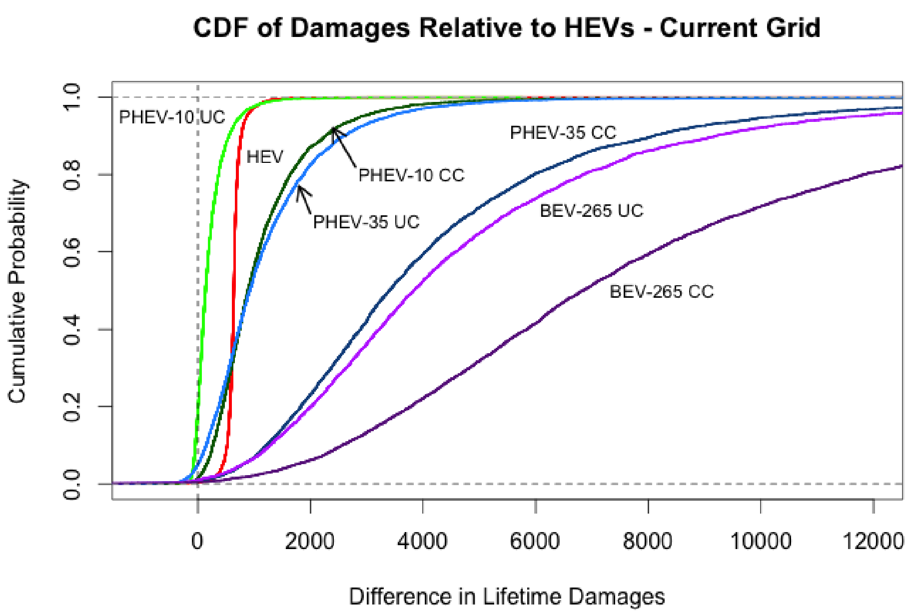

Figure 4.6: CDF of damages of each vehicle type relative to hybrid vehicles in the current (2010) PJM grid. UC = uncontrolled charging; CC = controlled charging, CV = conventional vehicle.

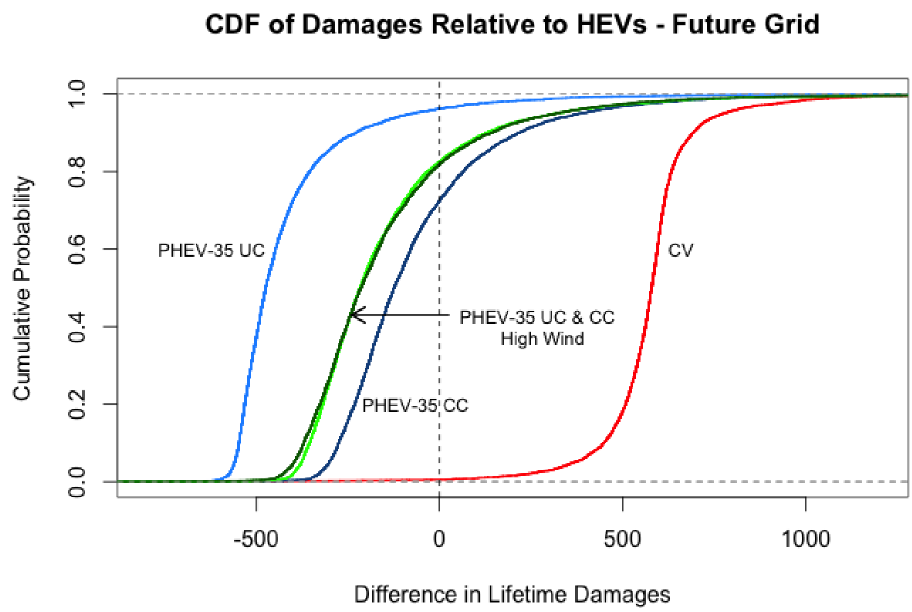

Figure 4.7: CDF of damages of each vehicle type relative to hybrid vehicles in the future (2018) PJM grid. The high wind scenario has 20% of electricity load met by wind generation. UC stands for uncontrolled charging; CC stands for controlled charging.

We also evaluate how sensitive our results are to the assumption that vehicles are distributed proportional to population. It seems possible that electric vehicles will be adopted more heavily in urban counties where charging infrastructure will be more concentrated. 88% of the population of PJM is already in urban counties so we examine an even stronger case of assuming the electric vehicles, as well as the conventional and hybrid vehicles they are compared to, are adopted only in counties in metropolitan areas with 1 million residents or more. This affects the distribution of the additional charging load to the five different transmission regions in PJM. It also affects the location of the tailpipe emissions. However, the total effect on the lifecycle damages is small. Figure 4.8 below shows the lifecycle damages in the current grid for volt-sized vehicle compared to conventional and hybrid vehicles. The conclusions remain the same as when vehicles are distributed proportional to population.

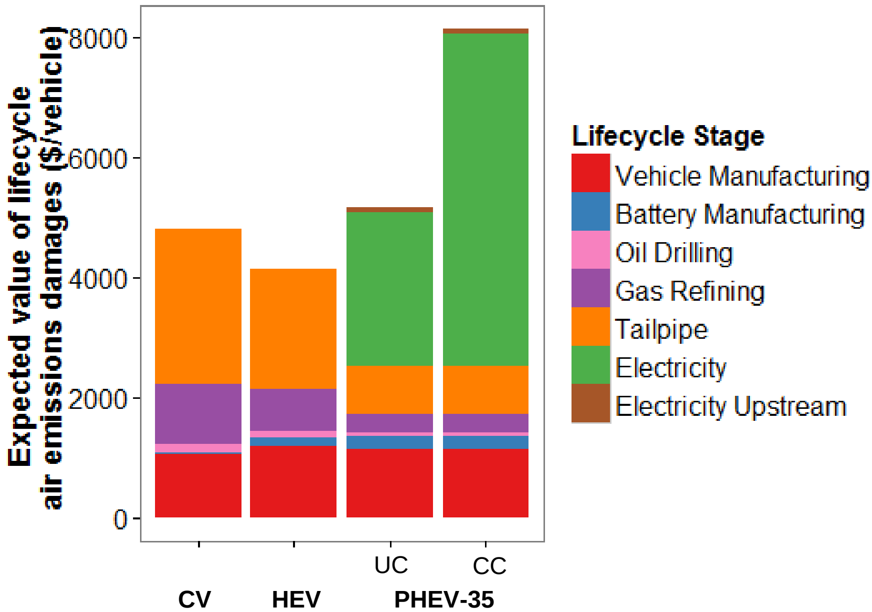

Figure 4.8: Expected value of lifecycle damages in the current PJM grid with all vehicles adopted proportional to population in metro areas of 1 million residents or more. UC stands for uncontrolled charging and CC stands for controlled charging for the electric vehicles.

4.4 Discussion and Conclusions

We find that electric vehicles are unlikely to reduce air emission damages of passenger car transportation significantly in the current scenario (2010), but they are likely to reduce damages in the future scenario (2018). However, as we show in Table 3, this analysis misses sources of uncertainty outside of the AP2 model, and we discuss these factors qualitatively. The emissions rates from every stage of the lifecycle have uncertainty we are unable to quantify. We use a point estimate of the emissions for each representative vehicle. These emissions and the electric efficiency of the PEV's would change with different driving styles and climate zones. Different driving styles could affect damages either way. PJM's relatively cold climate is likely to cause EV efficiency to decrease on average relative to hybrid and conventional vehicles and damages to increase. Additionally, a comparison between specific vehicle models instead of these representative GREET vehicles might result in different outcomes. We use annual average emission rate for each power plant, but the real emission rates could vary as different load and wind scenarios cause different amounts of ramping.

Higher levels of wind generation and uncontrolled charging are likely to increase ramping. Controlled charging could help reduce ramping, and therefore lower emission rates. The vehicle and battery manufacturing emissions are dependent on the grid mix, but we only use a point estimate calculated using GREET's US average grid mix. As the power plant fleet evolves and has lower emission rates on average, we expect these upstream emissions to decrease as well. Finally, the emission rates for the upstream fossil fuel production are point estimates for the US average production as an estimate of the marginal emissions of producing one more unit of each type of fossil fuel for the power plants or vehicles.

The unit commitment and dispatch model also contributes uncertainty to our results. We have reasonable confidence about the type of generation used to meet load in the unit model because power plants within each plant type have similar marginal costs. However, we are less certain of the location of the emissions. We may be choosing a plant in a different county than would have actually been dispatched since we only account for 50% of congestion. The location of the power plant determines the number of people exposed and the existing ambient concentrations around those exposed, therefore affecting the damages of those emissions. The unit commitment model also uses fixed hourly exports and imports from neighboring regions from 2010 operations. PJM exported 4.5% of its generation and imported 3.4% of its load in 2010. Some of this trading was likely on the margin and would affect the lifecycle emissions of electric vehicle charging by changing the generation and emissions of power plants in the neighboring regions that are not included in the model. However, the magnitude of this effect is difficult to quantify as we know neither how often the imports and exports are on the margin nor the emission rates of the affected power plants.

We assume that the damages per unit emitted in each county in 2010 and 2018 are the same as in 2005 because we lack a full distribution of damage estimates for other years. As a sensitivity analysis, however, we calculate the lifecycle damages using the 2011 AP2, as shown in Figure 4.10 and Figure

4.9 below. Total damage values using the 2011 AP2 values are higher than with the 2005 values, but the conclusions remain the same: electric vehicles increase damages in the current grid compared to hybrid electric vehicles, but decrease damages in the 2018 grid.

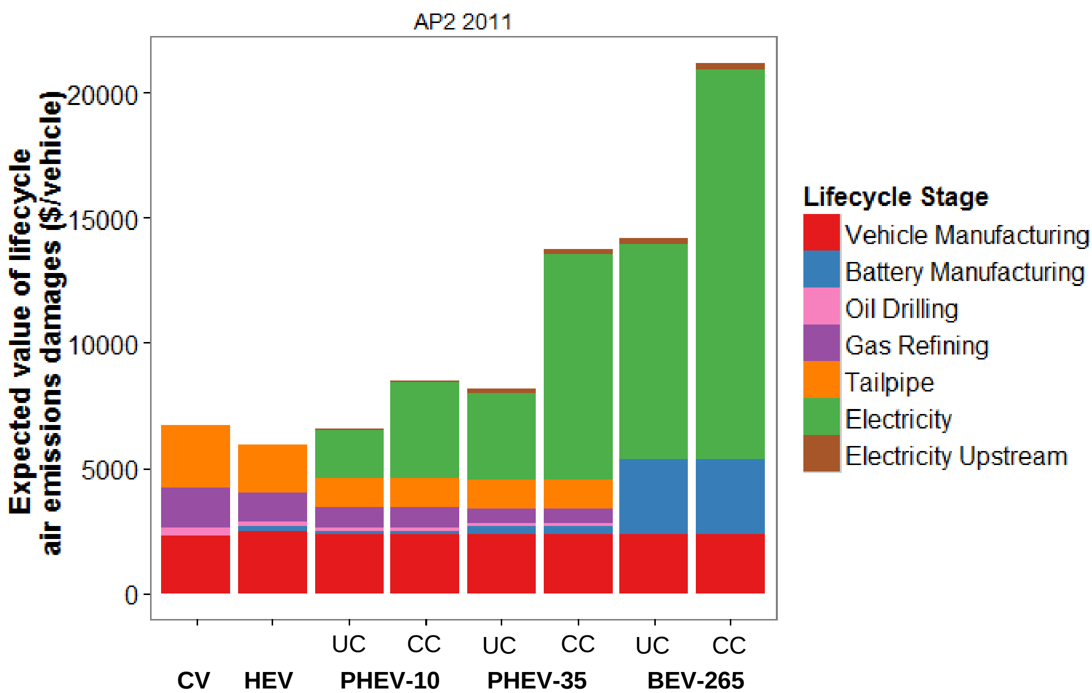

Figure 4.9: Expected value of lifecycle damages in the current PJM grid given 2011 AP2 damage values. UC stands for uncontrolled charging and CC stands for controlled charging for the electric vehicles.

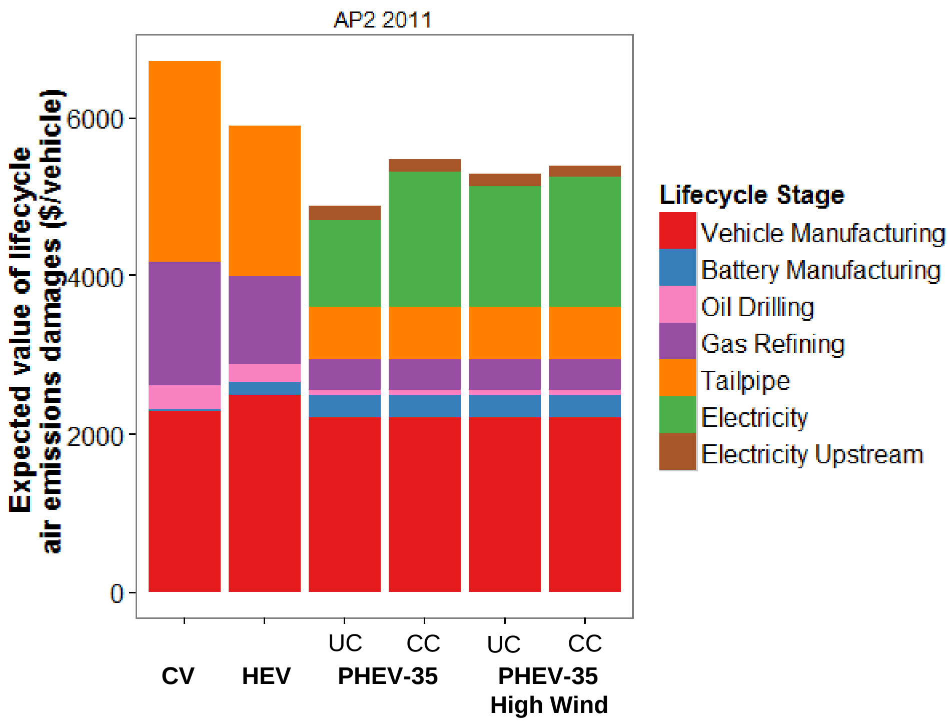

Figure 4.10: Expected value of lifecycle damages in the future PJM grid given AP2 2011 damages values. The high wind scenario has 20% of demand met by wind. UC stands for uncontrolled charging and CC stands for controlled charging for the electric vehicles.

While we present the lifecycle reductions in CO emissions for reference, we do no evaluate any lifecycle damages from that particular pollutant. There is some evidence that long-term CO exposure might have a causal relationship with some heart problems [18], CO emissions are not included in the AP2 model. The existing evidence is insufficient to understand how the health impacts change depending on where the pollutant is emitted. Additionally, CO emissions do not seem to be a pressing health concern to EPA. The primary quality standards have remained at the same level since 1984, with no areas of the country currently in nonattainment, and the secondary standards were revoked "due to lack of evidence of adverse effects on public welfare at or near ambient concentrations" [19].

As in chapter 3, the results could be affected by policies not included in this analysis. If the CSAPR SO2 cap becomes binding by 2018, electric vehicles would not increase the emissions of

SO_2 from the electricity grid, although the additional load would create additional pressure on the cap and increase SO_2 prices. Any additional cost to comply with CSAPR because of vehicle charging is not include in the lifecycle costs presented in this study. In Figure 4.12 and 4.11 below, we show the breakdown of lifecycle damages by pollutant instead of by lifecycle stage, with SO_2 broken into the emissions associated with charging the vehicle from the electricity grid and those from the rest of the lifecycle. The SO_2 damages from charging are already much lower in the future grid case because of reduced coal generation and stronger emission controls on the remaining coal plants. With a binding SO_2 cap, it is possible these damages would be completely eliminated as no additional SO_2 emissions could come from the electricity grid. However, the exact effects of a binding SO_2 cap are difficult to predict. Under the cap, emissions could still theoretically be shifted to areas with higher damages due to electric vehicle charging. A binding SO_2 cap could also reduce more than just the charging damages as some of the upstream emissions also come from the electricity grid, further decreasing the total damages of all vehicles types.

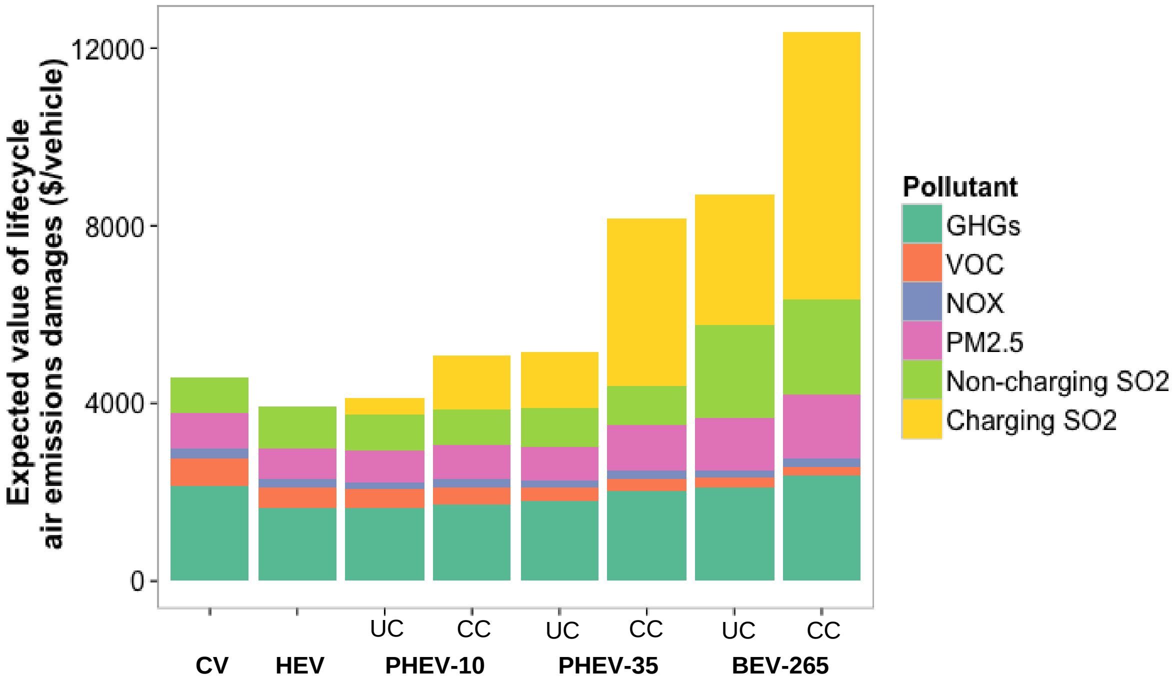

Figure 4.11: Expected value of lifecycle damages in the current PJM grid broken down by pollutant. The damages for each pollutant are from all lifecycle stages except for those of SO2 which are broken down into the damages from power plant emissions for vehicle charging and those from every other lifecycle stage. UC stands for uncontrolled charging and CC stands for controlled charging for the electric vehicles.

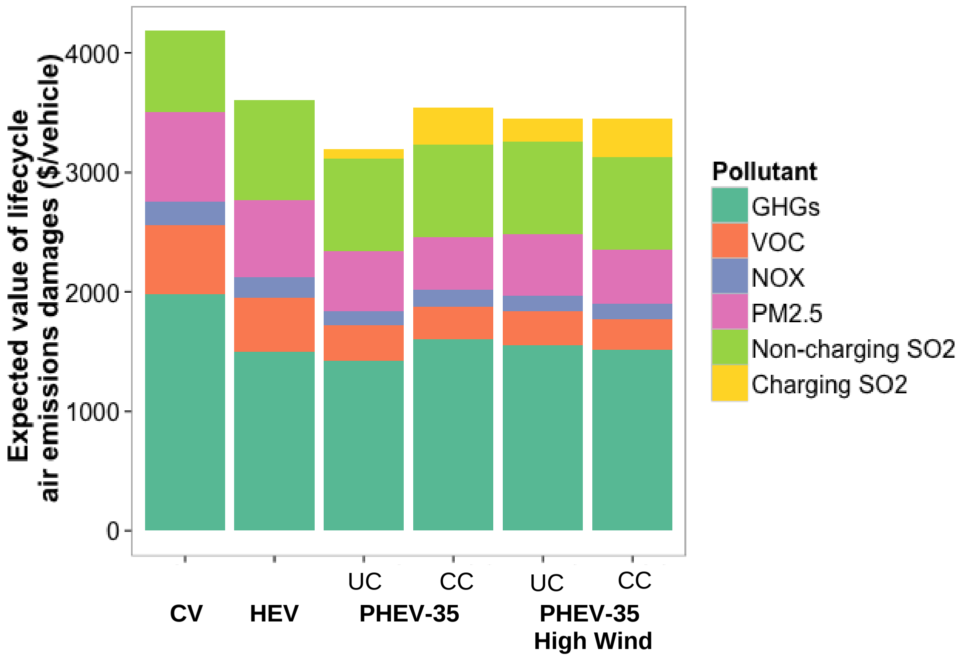

Figure 4.12: Expected value of lifecycle damages in the future PJM grid broken down by pollutant. The damages for each pollutant are from all lifecycle stages except for those of SO2 which are broken down into the damages from power plant emissions for vehicle charging and those from every other lifecycle stage. The high wind scenario has 20% of demand met by wind. UC stands for uncontrolled charging and CC stands for controlled charging for the electric vehicles.

The CAFE fuel economy standard may also influence the lifecycle emissions of electric vehicles. This standard includes incentives to encourage the adoption of electric vehicles, but these incentives interact with the rest of the policy to change the lifecycle emissions and damages attributable to adding electric vehicles to the transportation system. Compliance with the CAFE fuel economy standard is based on a sales-weighted fuel economy average from each vehicle manufacturer, and it is expected that the standard will be binding for all manufacturers. Starting in 2012, the policy has encouraged manufacturers to sell electric vehicles by counting each sale of an electric vehicle as multiple sales when calculating compliance, as well as by not including any charging emissions in the calculation. For every electric vehicle sold, these extra incentives allow the manufacturer to meet a less stringent standard for the rest of the fleet, increasing the total emissions of the vehicle fleet over its lifetime. Jenn et al. have analyzed the impact of these incentives for a variety of electric vehicle models and calculated the net increases in CO_2 emissions for each additional electric vehicle sold [21] [22]. When we include the damages from the additional CO_2 emissions for a Chevy Volt sold in 2018 with the rest of lifecycle damages, as shown in Figure 4.11, the plug-in electric vehicles have higher lifecycle damages than hybrid vehicles. In fact, the plug-in vehicle lifecycle damages may even exceed those of the 2018 conventional vehicle. The less efficient vehicles that are sold because of each electric vehicle sale will also likely have higher emissions of criteria air pollutants, further increasing the lifecycle damages.

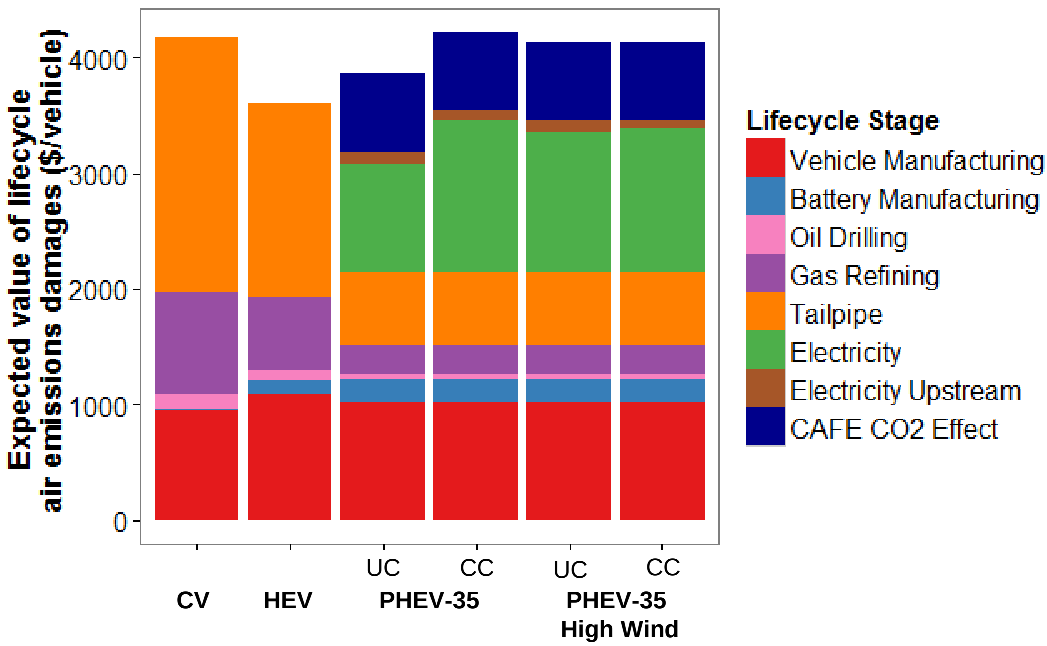

Figure 4.13: Expected value of lifecycle damages in the future PJM grid from the individual vehicle lifecycle plus the extra CO_2 emissions resulting from the incentives for plug-in vehicles in the CAFE standard. The high wind scenario has 20% of demand met by wind. UC stands for uncontrolled charging and CC stands for controlled charging for the electric vehicles.

Our results for the current PJM grid are consistent with those from Tessum et al. using the 2007 electricity mix [3]. In both studies plug-in electric vehicles increase damages relative to gasoline vehicles. Michalek et al. found that plug-in vehicles with larger battery sizes had higher damages than hybrids, while plug-in vehicles with smaller batteries had lower damages. [1] None of the plug-in vehicles in our study, regardless of battery size, had lower damages than hybrids in the current grid due to the large amounts of coal on the margin in PJM compared to the average mix used in Michalek et al. Both Michalek et al. and Tessum et al. find that plug-in electric vehicles can reduce damages once all renewables are used for electricity generation. This is a useful bounding case but not a scenario likely to occur soon. While no prediction of the future grid will be completely accurate, our detailed model is able show that even in one of the power systems in the country with the most coal generation currently, electric vehicles could reduce transportation health and environmental damages in the near future, long before a zero-carbon electricity mix is achieved. The total savings are small compared to the incentives given for purchasing electric vehicles, which include the $7,500 federal incentive and additional incentives provided by some states [20]. The transformation of the transportation system could also lead to long-term benefits that are not quantified in this analysis. We are also able to use our model to understand the lifecycle emissions and damage consequences of uncontrolled, convenience charging compared to controlled charging. Until higher wind penetrations are reached in the PJM power system, controlled charging will make it more difficult for electric vehicles to have lower environmental and health damages than hybrids. While policies to encourage the adoption of electric vehicles in PJM may benefit society in the near future, encouraging controlled charging or other nighttime charging may be detrimental to human health and the environment at the present time.

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Appendix 4.A

Table 4.7: Current Grid Upstream Emission Rates

		[g/mile]	[g/mile]	[g/lifetime]	[g/lifetime]
Vehicle	Pollutant	Feedstock	Fuel	Manufacturing	Battery
CV	CO2	2.909	68.15	6934715	38815
CV	GHGs	13.01	76.26	7380994	44087
CV	VOC	0.01489	0.1154	34103.74	23.609
CV	CO	0.02322	0.09573	23717.98	44.806
CV	NOX	0.1028	0.1062	9579.742	76.507
CV	PM2.5	0.005854	0.06749	2273.367	32.168
CV	SO2	0.03247	0.07537	24164.06	513.684
HEV	CO2	2.078	48.68	7528739	25114
HEV	GHGs	9.296	54.47	7764506	270435
HEV	VOC	0.01064	0.08239	34300.65	79.979
HEV	CO	0.01658	0.06838	26307.65	342.143
HEV	NOX	0.0734	0.07588	10000.93	384.041
HEV	PM2.5	0.004182	0.04821	2327.763	75.479
HEV	SO2	0.02319	0.05383	30253.39	4841.256
PHEV-35 CD	CO2	0.1679	3.933	6831070	1001589
PHEV-35 CD	GHGs	0.7512	4.402	7261228	1063130
PHEV-35 CD	VOC	0.00086	0.006658	33922.92	346.947
PHEV-35 CD	CO	0.00134	0.005525	24060.44	652.405
PHEV-35 CD	NOX	0.005933	0.006131	9371.553	1538.657
PHEV-35 CD	PM2.5	0.000338	0.003896	2161.458	693.235
PHEV-35 CD	SO2	0.001874	0.00435	27826.22	7109.536
PHEV-35 CS	CO2	2.603	60.97	6831070	1001589
PHEV-35 CS	GHGs	11.64	68.23	7261228	1063130
PHEV-35 CS	VOC	0.01332	0.1032	33922.92	346.947
PHEV-35 CS	CO	0.02077	0.08565	24060.44	652.405
PHEV-35 CS	NOX	0.09197	0.09505	9371.553	1538.657
PHEV-35 CS	PM2.5	0.005238	0.06039	2161.458	693.235
PHEV-35 CS	SO2	0.02905	0.06744	27826.22	7109.536
PHEV-10 CD	CO2	1.0278	24.07329	6831070	308181.2
PHEV-10 CD	GHGs	4.597359	26.93936	7261228	327116.9
PHEV-10 CD	VOC	0.005261	0.040748	33922.92	106.7529
PHEV-10 CD	CO	0.008202	0.033816	24060.44	200.74
PHEV-10 CD	NOX	0.036311	0.037525	9371.553	473.4329
PHEV-10 CD	PM2.5	0.002068	0.023842	2161.458	213.3031
PHEV-10 CD	SO2	0.01147	0.026625	27826.22	2187.55
PHEV-10 CS	CO2	1.97087	46.16334	6831070	308181.2
PHEV-10 CS	GHGs	8.815969	51.65936	7261228	327116.9

PHEV-10 CS	VOC	0.010088	0.078139	33922.92	106.7529
PHEV-10 CS	CO	0.015728	0.064846	24060.44	200.74
PHEV-10 CS	NOX	0.06963	0.071959	9371.553	473.4329
PHEV-10 CS	PM2.5	0.003966	0.04572	2161.458	213.3031
PHEV-10 CS	SO2	0.021995	0.051056	27826.22	2187.55
PHEV-265	CO2	0	0	6831070	9698078
PHEV-265	GHGs	0	0	7261228	10293961
PHEV-265	VOC	0	0	33922.92	3359.381
PHEV-265	CO	0	0	24060.44	6317.037
PHEV-265	NOX	0	0	9371.553	14898.34
PHEV-265	PM2.5	0	0	2161.458	6712.381
PHEV-265	SO2	0	0	27826.22	68839.45

Table 4.8: Future Grid Upstream Emission Rates

		[g/mile]	[g/mile]	[g/lifetime]	[g/lifetime]
Vehicle	Pollutant	Feedstock	Fuel	Manufacturing	Battery
CV	CO2	4.532139	61.91715	6603110	36820.06
CV	GHGs	13.47098	69.00923	7042621	42065.6
CV	VOC	0.012887	0.104636	34058.25	23.34857
CV	CO	0.019713	0.086027	23529.38	43.7169
CV	NOX	0.074936	0.085321	7163.69	59.31664
CV	PM2.5	0.004428	0.060759	1837.551	29.39731
CV	SO2	0.022662	0.060058	21406.72	490.349
HEV	CO2	3.237242	44.22653	6944454	235671.4
HEV	GHGs	9.622128	49.29231	7398739	254670.1
HEV	VOC	0.009205	0.07474	34251.13	77.89123
HEV	CO	0.014081	0.061448	26101.29	333.8068
HEV	NOX	0.053526	0.060943	7431.508	274.8561
HEV	PM2.5	0.003163	0.043399	1864.907	55.14613
HEV	SO2	0.016187	0.042898	27287.33	4712.265
PHEV-35 CD	CO2	0.27701	3.784459	6495775	958329.3
PHEV-35 CD	GHGs	0.823364	4.217937	6918927	1018991
PHEV-35 CD	VOC	0.000788	0.006395	33876.58	337.0062
PHEV-35 CD	CO	0.001205	0.005258	23868.03	598.6426
PHEV-35 CD	NOX	0.00458	0.005215	6965.205	1070.002
PHEV-35 CD	PM2.5	0.000271	0.003714	1727.86	610.9333
PHEV-35 CD	SO2	0.001385	0.003671	25054.97	6604.766
PHEV-35 CS	CO2	3.764227	51.42608	6495775	958329.3
PHEV-35 CS	GHGs	11.1885	57.3165	6918927	1018991
PHEV-35 CS	VOC	0.010703	0.086907	33876.58	337.0062
PHEV-35 CS	CO	0.016373	0.071451	23868.03	598.6426
PHEV-35 CS	NOX	0.062239	0.070864	6965.205	1070.002
PHEV-35 CS	PM2.5	0.003677	0.050464	1727.86	610.9333
PHEV-35 CS	SO2	0.018822	0.049882	25054.97	6604.766

Chapter 5: CONCLUSION

The integration of electric vehicles into the electricity grid offers several possibilities for reducing costs and lowering emissions. I use bottom-up optimization models of power systems based on New York and PJM to examine the impacts of controlled charging of electric vehicles. I find that controlled charging can be used to reduce the generation costs of charging electric vehicles by 30-50%, and a 20% wind scenario provides modest additional benefits. However, given an electric power system that is optimized only for the direct costs incurred by power generators, controlled charging may increase emissions by causing generation to shift from gas plants to coal plants. By monetizing the health and environmental damages from the change in emissions, I show that controlled charging should not be encouraged by public policy in the current PJM grid, as the increase in damages from increased coal generation outweighs the reduction in generation cost. Even as the grid evolves as predicted by the EPA until 2018, controlled charging still leads to higher damages than the electricity generation cost reductions. Controlled charging may be in the public interest once the use of wind generation increases to 20% of the load or more, when small reductions in damages can be added to the generation cost reductions. These results are specific to the power system studied. In a system with all gas plants or all coal plants, marginal costs would be driven by efficiency, and controlled charging could reduce both costs and emissions by shifting generation from less efficient, more expensive power plants to more efficient, cheaper plants.

My bottom-up modeling of a specific region also allows me to estimate the lifecycle emissions and damages of plug-in electric vehicles in the near future. Previous work has shown that electric vehicles likely increase damages in the current grid, but would decrease damages with 100% renewables. By explicitly modeling a plausible future grid, I am able to show that electric vehicles can reduce damages in PJM before a 100% renewable grid has been achieved. Although the damage reduction remains small in the power system predicted by the EPA for PJM in 2018, it does mean that by the near future, investments in electric vehicles and electric vehicle infrastructure for long-term benefits could possibly be achieved without harming public health in the short-term. Again, these results are dependent on the power system studied. Other parts of the country, such as California, rely very little on coal generation. These regions will have lower lifecycle damages for electric vehicles due to much lower charging emissions. Systems with even higher levels of wind generation that would otherwise be curtailed could also have much lower charging emissions, especially if using controlled charging.

My main results suggest that policies encouraging the adoption of plug-in electric vehicles over hybrids in PJM may not be as harmful as previously feared. However, the way in which these policies are implemented will determine if total social damages really are reduced. The current incentives for plug-in electric vehicles built in to the CAFE fuel economy standards starting in 2012 will likely lead to higher lifecycle damages for plug-in electric vehicles compared to hybrid vehicles. On the other hand, other energy policies may have an opposite effect. A binding SO_2 cap or more extensive coal retirements from an existing source CO_2 standard would likely strengthen the relative advantage of plug-in electric vehicles compared to hybrids.

This study is also able to show that while in general further decarbonization of the grid is important to reduce the damages from electric vehicles, current Renewable Portfolio Standards of around 20% may not significantly affect the lifecycle damages of electric vehicles. At this level of wind penetration, most of the wind generation is already being used to meet existing load and very little can be used for vehicle charging. It is important for policy makers to keep in mind that not all public policies aimed at reducing power system emissions will automatically result in lower lifecycle emissions and damages of electric vehicles.