Estimating the Potential of Controlled Electric Vehicle Charging to Reduce Operational and Capacity Expansion Costs for Electric Power Systems with a Renewable Portfolio Standard

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Abstract

Electric power systems with substantial wind capacity require additional flexibility to react to rapid changes in wind farm output and mismatches in the timing of increased generation and increased demand. Controlled variable-rate charging of plug-in electric vehicles allows demand to be rapidly modulated, providing an alternative to using fast-responding natural gas plants for balancing supply with demand and potentially reducing costs of operation and new plant construction. We investigate the cost savings from controlled charging of electric vehicles, the extent to which these benefits increase in high wind penetration scenarios, and the trade-off between establishing a controlled charging program vs. increasing the capacity of generators in the power system. We construct a mixed integer linear programming model for capacity expansion, plant dispatch, and electric vehicle charging based on the NYISO system. We find that controlled charging can offer significant cost reductions in a system with 10% penetration of electric vehicles; however, the magnitude of these benefits is only slightly higher in a system a 20% renewable portfolio standard (RPS) compared to a system no RPS policy. In the systems examined, controlled vehicle charging reduces the costs of integrating electric vehicles but provides little additional cost benefits for integrating wind.

Keywords:

1. Introduction

Electricity generation is responsible for over 40% of U.S. CO_2 emissions [1], and producing electricity from traditional fossil fuel sources also creates other emissions that harm human health and the environment, such as NO_x and SO_2. Integrating low-emission power options, such as wind and solar power, will play a key role in reducing harmful emissions. Many states have recognized the need for more renewable energy production, and twenty-nine states have adopted renewable energy portfolio standards (RPS) requiring between 10% and 40% of generated power to come from renewable sources [2]. 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].

Plug-in electric vehicles create additional demand, resulting in additional air emissions from electricity generation [4], [5]. But they have also been proposed as a means for increasing grid flexibility in order to integrate renewables, with much emphasis on 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 additional 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 ancillary services is small, arbitrage potential is limited, and participation can significantly reduce battery life by increasing the total energy processed by the battery [7]. 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 plug-in electric vehicles – for example, following variations in wind supply. Such controlled charging can 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 electric vehicles. 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. Wang et. al. evaluate different charging strategies of plug-in vehicles in the Illinois power system and find significant cost savings 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 [8], exaggerating variability by ignoring the complex impacts of plant size and geographic diversity on mitigating wind generation correlation [9]. 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 [10]. They find that V2G could decrease system costs by around 0.5%.

Other work has focused on how 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 [11], 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 [12]. 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.

We seek to evaluate cost savings from controlled charging in scenarios with and without an RPS in order to understand whether electric vehicles can provide extra cost savings in systems with increased levels of wind power, or whether controlled charging only limits the impact of the vehicles themselves on the system. The interaction of electric vehicle 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 electric vehicles 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 electric vehicles) under alternative scenarios of high vs. low wind penetration in the power generation fleet, high vs. low electric vehicle penetration in the vehicle fleet, and high vs. low initial plant capacity. For this analysis, we develop a capacity expansion, unit commitment, and dispatch optimization model with detailed plant constraints. We use hourly and 15-minute time scales with perfect information of wind and load (no forecast error) to focus on capacity expansion and unit commitment decisions, and 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 system with sufficient capacity and those requiring investment in new capacity. We find that controlled charging does help to reduce system costs by about 2% in the scenarios examined with 10% EV 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. Methods

2.1 Model Overview

A mixed integer linear programming (MILP) capacity expansion model with hourly unit commitment and dispatch, plus hourly vehicle availability and charging rate finds the optimal combination of new power plants and controlled vehicle charging to meet demand at lowest costs. 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 hour and the level of output for each. The model also determines the rate of charging in each hour for each of a set of vehicles, where the set of vehicle driving profiles are selected to be representative of the U.S. vehicle population. The model assumes the penetration of plug-in vehicles that must be charged is 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 meet the load each hour, while keeping all plants within their operating constraints and satisfying a Renewable Portfolio Standards (RPS) that define a minimum percentage of overall power generation that must be supplied by wind[1]. Figure 1 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% [2]. We assume the RPS will be satisfied entirely by wind.

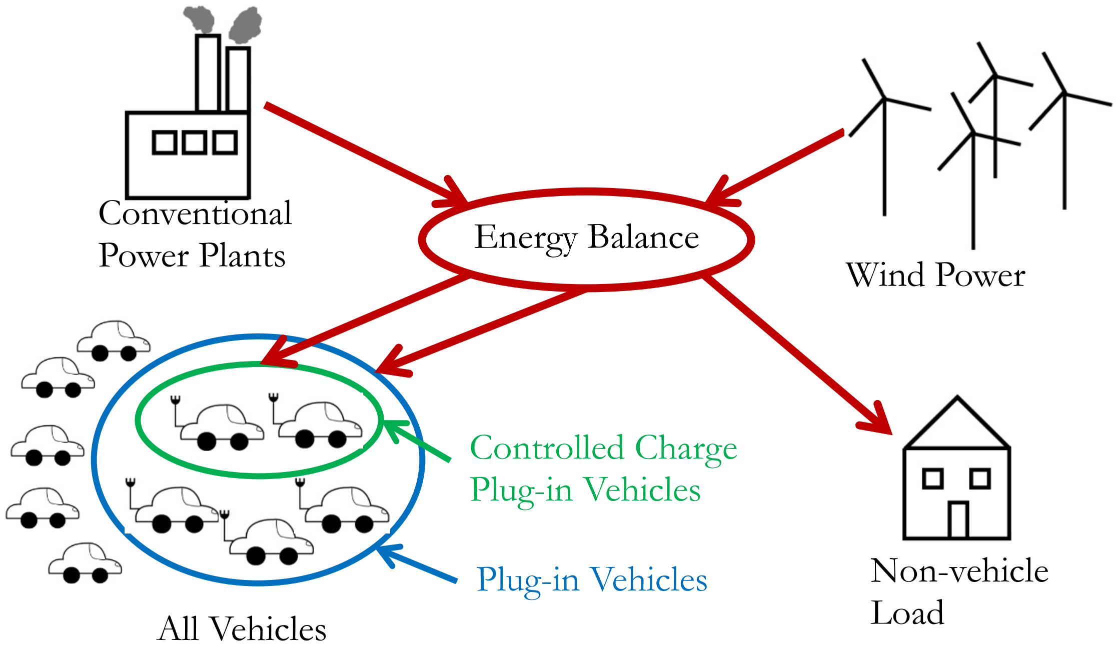

Figure 1: System Overview - Energy is provided by conventional power plants and wind plants and must meet the demand from plug-in vehicles and non-vehicle load in each time step.

2.2 Power Plant Fleets

We construct two different power plant fleet scenarios using the power plant fleet characteristics from the New York Independent System Operator (NYISO) area: one is used to examine a scenario with sufficient existing capacity to meet non-vehicle load (*Fixed Capacity Scenario*); and the second where capacity expansion is required regardless of electric vehicle penetration (*Capacity Expansion Scenario*). Because NYISO has significant amounts of hydro power for which operational data is unavailable, we construct the first power system by adding additional fossil fuel plants to make a fleet with the same total capacity as NYISO. In order to create a Capacity Expansion Scenario, we reduce the starting fleet by using only the existing nuclear, coal, oil and natural gas capacity from NYISO. Individual plant data were not available for all fossil fuel plants in NYISO, so the fleet was chosen from a sample of plants in NYISO, ERCOT and PJM with available data, optimizing to match capacity and heat rate distributions for each generation type in NYISO. 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 were taken from Ventyx [13], and power plant capacities and heat rates were taken from the National Electric Energy Data System (NEEDS) [14].

2.3 Electric Vehicle Fleet

We model a fleet of plug-in hybrid electric vehicles using the National Highway Travel Survey (NHTS) data set [15], which contains data for one day of driving for approximately 900,000 different passenger cars across the United States. While load from uncontrolled vehicles is calculated from all passenger vehicles in the dataset, the controlled-charging scenarios use 20 representative driving profiles for computational tractability (weighted profiles were selected to match the characteristics of the overall data set -- see Appendix A for more detail). We assume the vehicles only charge after their last trip of the day and must be either full or maximally charged by their first trip of the 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 (preventing additional battery degradation). We assume vehicle owners receive a set annual fee for participating in the controlled charging program, with the system operator determining how many vehicles will be paid for participation. We perform a sensitivity analysis to examine a range of vehicle characteristics, shown below in Table 1, as well as different vehicle penetration levels and payment to vehicle owners.

Table 1: 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. The range of charge rates come 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%

2.4 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 [16]. 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 data to hourly resolution for model tractability. We then add wind sites from the EWITS data set to our model in order of highest capacity factor. We investigate an RPS 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 could 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 and Western Wind and Solar Data are the only existing public sources for a time series prediction of future wind production with future wind sites already selected. Although the meso-scale weather model used to produce the wind speed data in these datasets under-predicts high-frequency variability of wind speeds, the effect on the modeled power output is small for small wind plants, and roughly equivalent to filtering that should take place from geographic diversity within large wind plants [17].

2.5 Load Data

We use five minute demand data for the New York ISO in 2006, again converted to hourly resolution. As load is predicted to remain within 1% of its current level by 2025 [18], this 2006 data is used as non-vehicle load without any scaling. In the future, more areas can be tested in this model by using the corresponding EWITS and load data. It is important to use load and wind data from the same time and place to account for temporal and geographical correlations.

To ensure a reasonable computation time, we chose four different seasonal periods of five days each to capture periods of high and low load (including the year's peak load), while keeping the average load over the four periods equal to the average load of the year, 19 GW. Given the wind plants needed to meet the 20% RPS standard over the course of the entire year (when run as must-take), the wind generation from the modeled wind plants in these four periods is both sufficient to meet the RPS standard within the twenty days without building additional wind plants, and has an average power within 10% of the annual average wind power. 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 electric vehicles with controlled charging.

2.6 Optimization

The optimization model minimizes new power systems cost required to meet vehicle and non-vehicle demand, annualized capital costs of building new plants, operating costs of new and existing plants, and compensation to plug-in vehicle owners to participate in a controlled charging program. 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 output of the model includes the percent of vehicles participating in controlled charging, the charging schedule for each driving profile, the power plant generation schedule, and the number of additional plants to be built by fuel type.

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 in every time step, while satisfying the RPS over the twenty days. In addition to meeting the load, the system must also provide sufficient spinning and non-spinning reserves, as defined in Appendix B, and meet the 15% reserve margin above peak load recommended by FERC.

Every power plant has its own set of operating constraints. The nuclear plants have a constant generation level. All fossil fuel plants have a maximum output capacity, ramp rate limitations, and minimum on and off times. The wind power plants have a generation potential at each time step based on the wind behavior modeled in the EWITS database. Wind curtailment is not explicitly penalized in the objective function, and anywhere from zero to of the full potential wind generation may be used in each time step, as long as the RPS 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 RPS, 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 may change within a single time step but must not exceed the power limit of the circuitry and must keep the battery between its minimum and maximum states of charge. Vehicles may only charge at home after the last trip of the day. Further, vehicles are driven in charge depleting mode (using electricity as the sole propulsions source) until the battery has reached its minimum state of charge, as assumed by Sioshansi and Denholm [10]. The full mathematical formulation of the mixed-integer linear optimization model is defined in Appendix B.

3. Results

Controlled charging of electric vehicles reduces peak load and can reduce wind curtailment. A sample dispatch for the 20% RPS case is shown in Figure 2 below 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 show that controlled charging significantly lowers the peak demand in the first three periods and reduces wind curtailment and coal plant ramping.

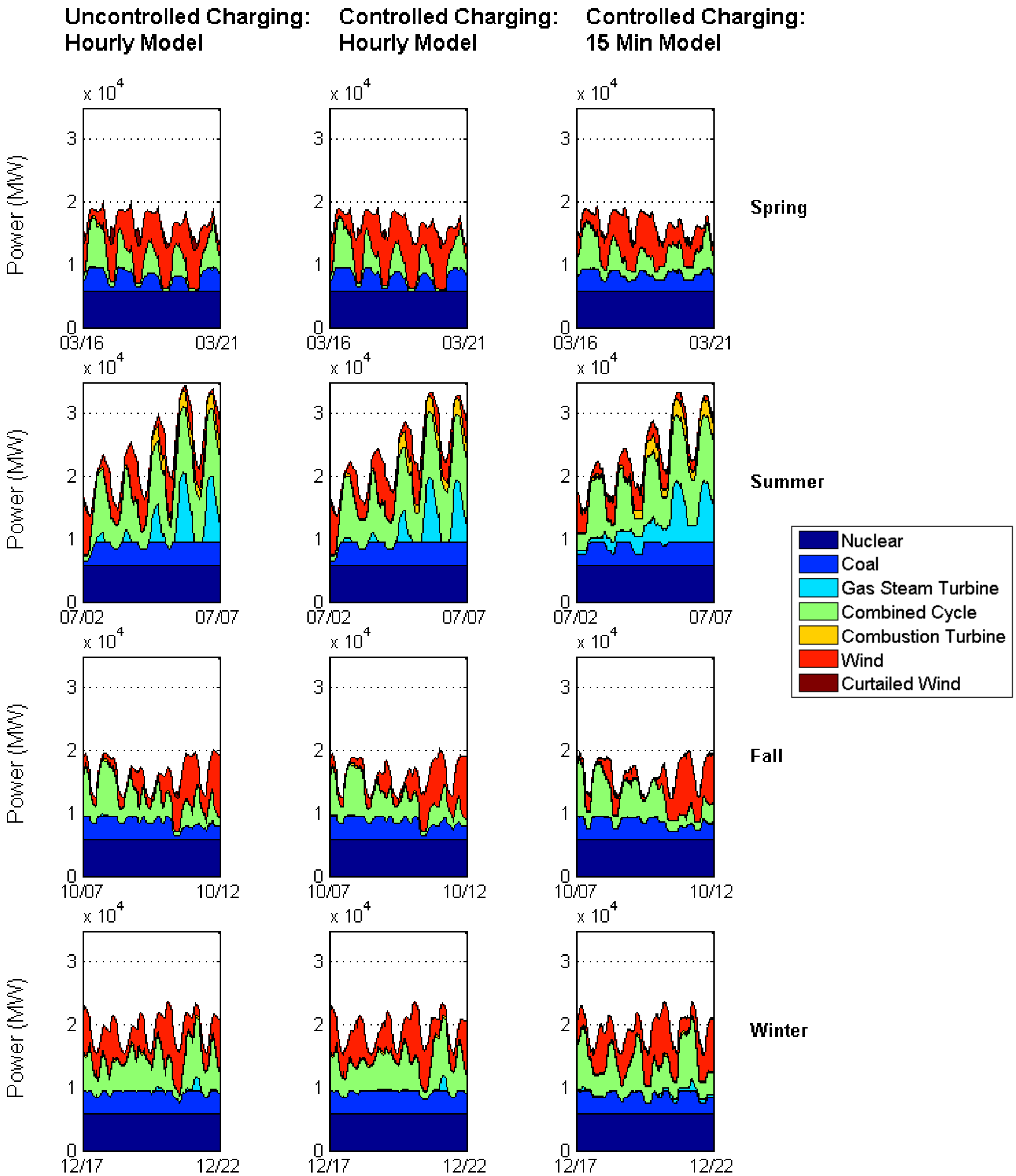

Figure 2: Seasonal dispatch in the Fixed Capacity Scenario given 10% vehicle penetration and a 20% RPS for uncontrolled charging in the hourly model, controlled charging in the hourly model, and controlled charging in the fifteen minute model.

3.1 Cost Savings

Our main results, summarized in Table 2, suggest that controlled charging can reduce system costs. Given a 10% penetration of electric vehicles of the total 9 million New York vehicles, controlled charging reduces power generation by $65-$100 million dollars a year compared to the uncontrolled charging scenario. Controlled vehicle charging allows for shifting generation to cheaper plants and to off-peak hours. As shown in Table 2, 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 with a stagnant non-vehicle load, the additional vehicle load can be accommodated without building any new capacity, as the New York 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% RPS, controlled charging offers slightly greater cost reduction compared to the same system without wind. However, these savings are much smaller than the savings associated with shifting vehicle load and eliminating the need for capacity expansion through controlled charging. A detailed breakdown of the costs for each payment level in each scenario can found in the Appendix C.

Table 2: Comparison of cost savings from controlled electric vehicle charging in the Fixed Capacity Scenario and Capacity Expansion Scenario for a 0% and 20% RPS, 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 allowing for maximal charge; and Controlled Charging, which uses the 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 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% RPS	20% RPS	0% RPS	20% RPS
A. System Costs with No Electric Vehicles (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%

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. Avoiding incomplete charging of vehicles when vehicle trips and wind generation are uncertain may require safety margins that limit the flexibility of controlled charging. On the other hand, controlled charging may provide additional value to the grid when accounting for the forecasting error of the wind generation, as vehicle charging can be changed on time scales much faster than the ramping constraints of conventional power plants. Additionally, ignoring transmission constraints may over- or under-estimate this value depending on the difference between the distribution of electric vehicles and other flexible resources in congested areas of the grid. It is possible that controlled charging of electric vehicles 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.

We examined the sensitivity of the cost savings to several different important input assumptions, the first of which was 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 described further in Appendix B. This model did not include the option of capacity expansion so that each day's dispatch could be optimized sequentially. This allowed for a manageable run times even with four times as many variables per day. Total system costs for a 10% vehicle penetration (with uncontrolled charging) were ~2% higher in the fifteen minute model given a 0% RPS and ~7% higher given a 20% RPS compared to the hourly model. Higher costs were 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 3. The higher time resolution of the data leads to a lower peak demand in the uncontrolled charging case. This effect overwhelms any additional cost savings 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% RPS 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. 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 has been shown to saturate with a relatively small number of vehicles [7]. 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 [19].

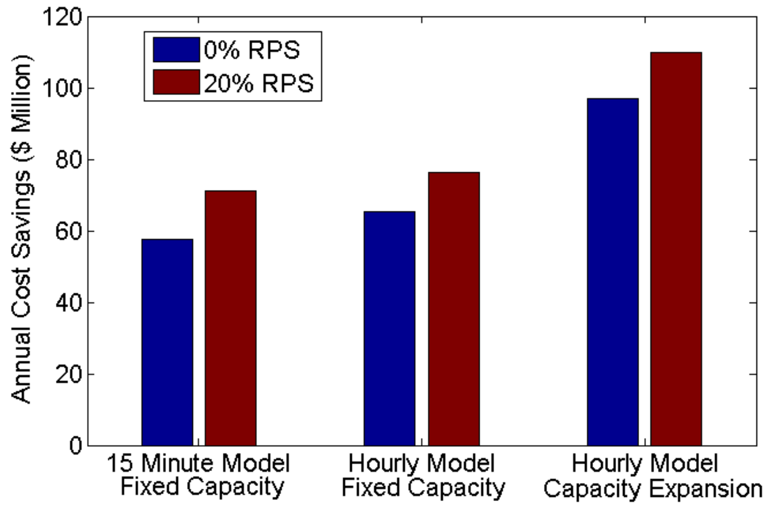

Figure 3: Annual cost savings due to controlled charging for different models given 0% and 20% renewable portfolio standards.

We also investigated the sensitivity of the results to changes in the parameters of the electric vehicle fleet. The potential cost savings from controlled charging is approximately linear with the penetration of electric vehicles, as shown in Figure 4. Regardless of the vehicle penetration, controlled charging is worth more in scenarios with high RPS and capacity expansion. In the Capacity Expansion Scenario with 20% RPS, 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% RPS 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.

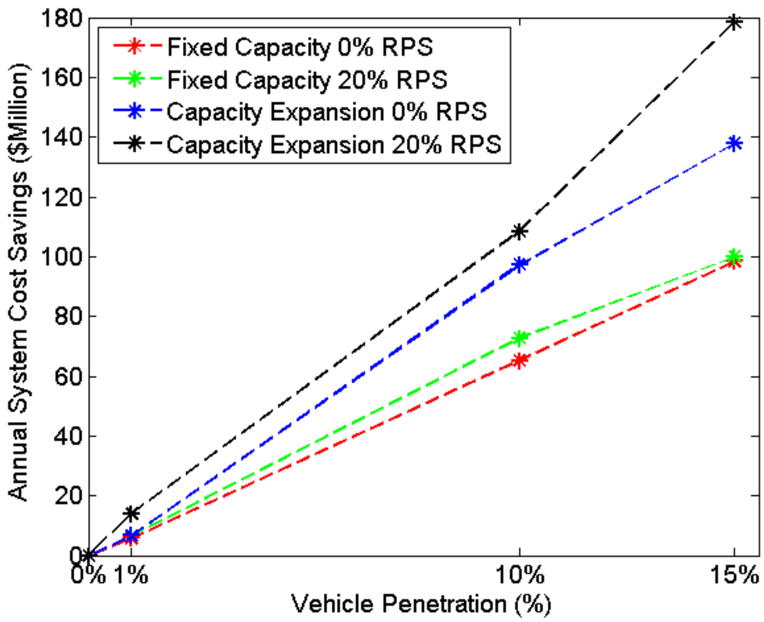

Figure 4: Sensitivity of the maximum annual system cost savings possible through 100% controlled electric vehicle charging compared to uncontrolled charging for a range of vehicle penetrations from 0% to 15% of a 9 million passenger vehicle fleet.

Increasing the maximum charge rates has diminishing returns, as shown in Figure 5. 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 on charge depleting mode. This increases the value of controlled charging to the system to a certain extent, as the uncontrolled peak load becomes more and more expensive. However, this benefit is limited because the more miles on charge depleting mode, the less flexibility there is to move charging to a later time as more of the hours need to be used. 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.

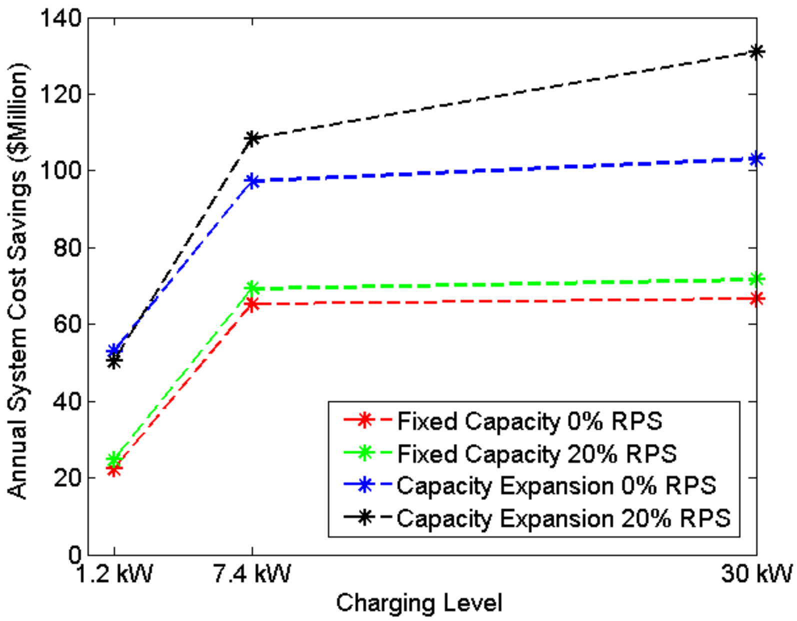

Figure 5: Sensitivity of the maximum annual system cost savings possible through 100% controlled electric vehicle charging compared to uncontrolled charging for Level 1 (1.2 kW), Level 2 (7.4 kW), and Level 3 (30 kW) charging. Only Level 1 and 2 are likely to be used in residential settings in the foreseeable future.

3.2 Capacity and Generation Mix

Figure 6 summarizes plant capacity and generation results for four cases. In the Fixed Capacity Scenario with no RPS, 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 in cases with no RPS is utilized nearly continuously with very few startups and shutdowns. Not surprisingly, in the Fixed Capacity Scenario under a 20% RPS, controlled charging results in reduced generation from all fossil fuel plants types, replacing it with wind generation.

In the Capacity Expansion Scenario, controlled charging results in reduced plant construction: when there is no RPS fewer gas combined cycle and coal plants are built, and for a 20% RPS, 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 RPS, controlled charging slightly shifts the generation from coal to natural gas and oil. Under a 20% RPS, 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 6). 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 RPS 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 RPS. 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 RPS. 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.

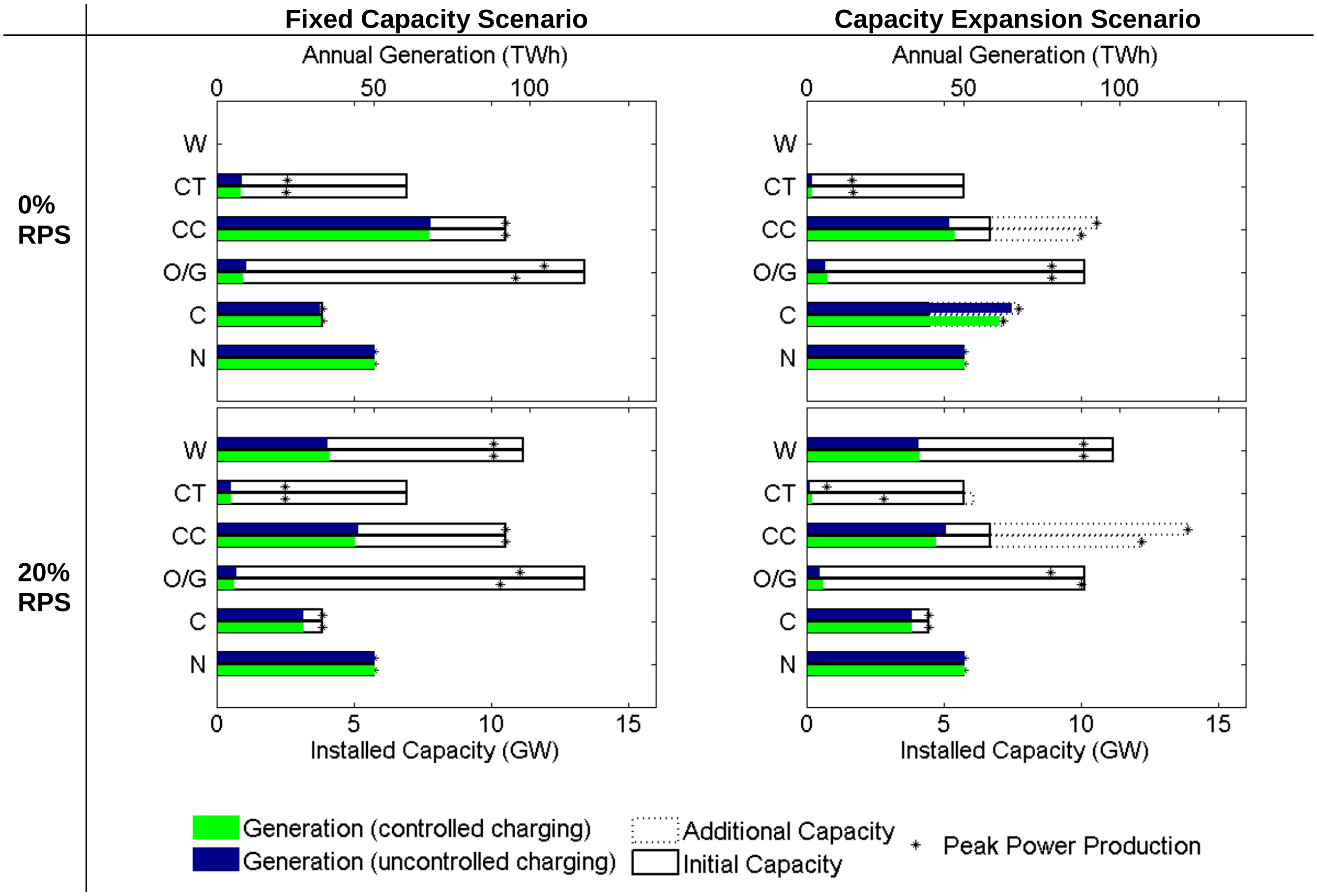

Figure 6: Comparison of capacity and generation data with and without controlled electric vehicle charging by generator type for each scenario. The following abbreviations are used for the generation types: W- Wind, CT – Gas Combustion Turbine, CC – Gas Combined Cycle, O/G – Oil/Gas Steam, C – Coal, 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.

4. Conclusions

In our test systems, controlled charging of electric vehicles reduces systems costs and reduces the impact of integrating the vehicles in to the electricity system by 50-70%, depending on the scenario. Cost reductions that result from employing controlled vehicle charging are estimated at $70-$100 million/year, given a 10% electric vehicle penetration, perfect information, no transmission constraints, and a 1-hour resolution. Larger cost reductions can be found in systems requiring capacity expansion 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. When capacity expansion is needed together with substantial wind integration, controlled charging may provide additional reductions in plant construction requirements; however, the effect of controlled charging on overall systems costs is not much greater in high-wind power systems compared to low wind systems. This suggests that system operators should not rely on controlled vehicle charging to significantly help reduce 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 tractability issues.

In most of our scenarios, at 10% electric vehicle penetration or higher, controlled charging provides enough system benefits to pay some vehicle-owners $100/vehicle/year to participate (see cost data in Appendix C). A payment of $100/vehicle/year may be attractive enough for some vehicles owners 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. The cost benefits of controlled charging scale fairly linearly with the number of electric vehicles, 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 electric vehicle penetrations.

Building additional wind plants beyond RPS requirements 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 to the grid.

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Appendix A: Selecting Representative Driving Profiles

The capacity expansion, unit commitment, and dispatch model uses driving profiles to determine the state of charge of the plug-in vehicles in the model. Representative driving profiles are chosen from the 2009 National Highway Travel Survey (NHTS) data set, which contains data for one day of driving from approximately 900,000 different passenger cars across the United States. These profiles include information for each vehicle on all trips taken during that day, including distance traveled, starting and stopping times, and starting and stopping locations, so that plug-in vehicle expected battery state of charge can be tracked throughout the day with a variety of different location-dependent charging schemes. Vehicles in the controlled charging program are allowed to charge when parked at home after the last trip of the day and must be fully charged (or charged as much as possible if complete charging during the time window is impossible with the modeled charging infrastructure) by the first trip of the day. Uncontrolled vehicles begin charging after arriving home for the last time that day and charge at the maximum rate until fully charged or leaving for the first trip of the next day. Each vehicle discharges its battery throughout the day based on the number of miles driven until the battery reaches its minimum state of charge.

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.

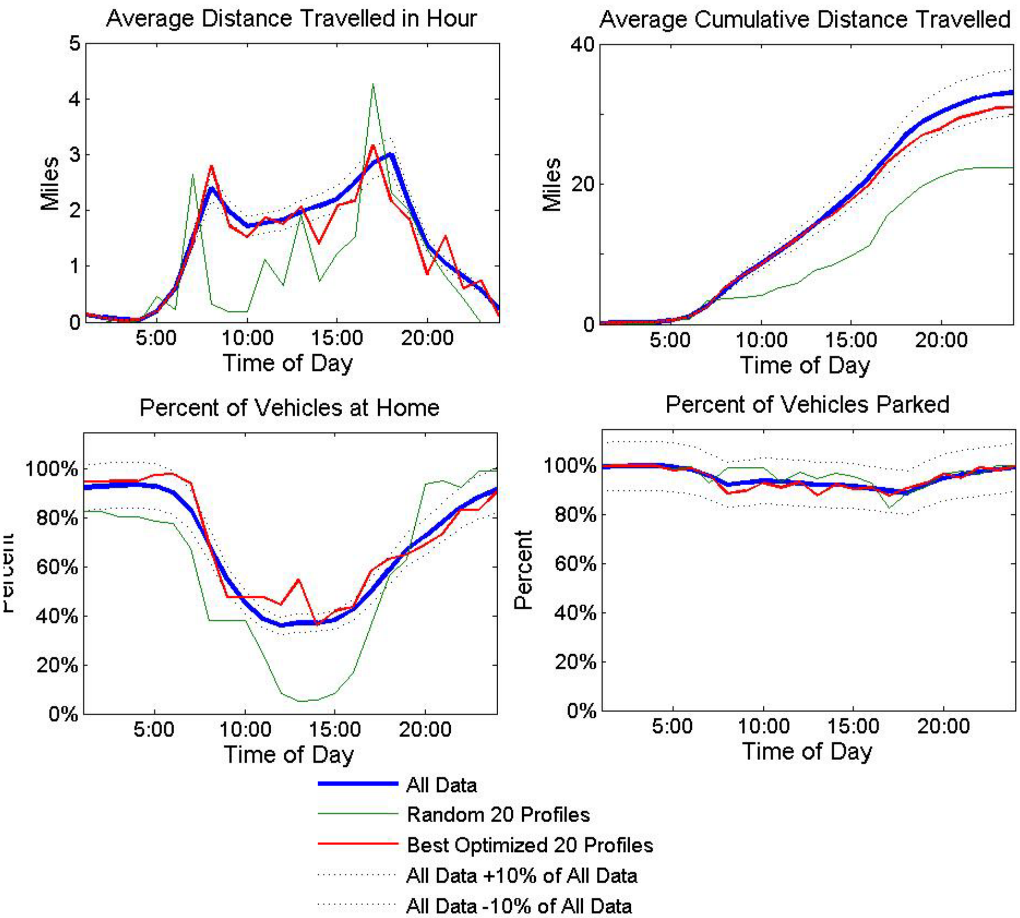

Figure A.1: Aggregate characteristics for all passenger vehicles in the NHTS dataset and best match 20 optimally weighted vehicle profiles drawn from the NHTS dataset over 1 million random draws. The percent of vehicles at home dips during the day, and only a small percentage of the fleet is driving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

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 A.1, 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).

Appendix B: Optimization Model

Hourly Model

The main optimization model includes capacity expansion and unit commitment, minimizing new plant construction costs and the cost of plant operations, in addition to the payment made to plug-in hybrid vehicle owners in exchange for having their vehicles participate in the controlled charging program.

The model contains the following sets of plants, vehicles, and time steps:

P is the set of all plants, which are partitioned into wind plants $\mathrm{P_W}$ and conventional plants $\mathrm{P_C}$, so that $\mathrm{P_C} \cup \mathrm{P_W} = \mathrm{P}$ and $\mathrm{P_C} \cap \mathrm{P_W} = \varnothing$. Conventional plants are similarly partitioned into existing plants that are fixed and new plants that the optimizer may choose to build: $\mathrm{P_C^{NEW}} \cup \mathrm{P_C^{EXT}} = \mathrm{P_C}$. All wind plants are assumed to be new and are built in order of capacity factor to meet the RPS.

$\mathrm{P_{GT}^{NEW}} \subseteq \mathrm{P_C^{NEW}}$ and $\mathrm{P_{GT}^{EXT}} \subseteq \mathrm{P_C^{EXT}}$ indicate the gas turbine power plants.

E is the set of all plug-in vehicles.

T is the set of all time steps. $\mathrm{T}_j^{\mathrm{AM}} \subseteq \mathrm{T}$ contains the time steps at which plug-in vehicle *j* must be fully charged (or charged as much as possible) each day. $\mathrm{T}_j^{\mathrm{AM}}$ is taken as the start of the first trip of the day for each vehicle profile.

The formulation is as follows:

Minimize the cost of annualized capital investments, payments to vehicle owners, and the operating costs in each time step:

$$\text{minimize } \underbrace{\sum_{n \in \mathrm{P_C^{NEW}}} c_n^{\mathrm{BLD}} \mathrm{y}_n^{\mathrm{BLDC}} + \sum_{w \in P_{\mathrm{W}}} c_w^{\mathrm{BLD}} \mathrm{y}_w^{\mathrm{BLDW}}}_{\text{New Plant Construction}} + \underbrace{c^{\mathrm{EV}} n^{\mathrm{EV}} \mathrm{x}_{\mathrm{CTRL}}^{\mathrm{EV}}}_{\substack{\text{Payments to}\\ \text{PHEV Owners}}} + \underbrace{\sum_{t \in \mathrm{T}} \left(\sum_{i \in \mathrm{P_C}} \left(\mathrm{x}_{it}^{\mathrm{SUC}} + \mathrm{x}_{it}^{\mathrm{SDC}} + c_i^{\mathrm{F}} h_i \mathrm{x}_{it}^{\mathrm{G}} \right) \right)}_{\text{Cost of Plant Operations}}$$

With respect to:

$$w.r.t. \left\{ \mathrm{x}_{jt}^{\mathrm{CDM}}, \mathrm{x}_{jt}^{\mathrm{CSM}}, \mathrm{x}_{t}^{\mathrm{CW}}, \mathrm{x}_{jt}^{\mathrm{E}}, \mathrm{x}_{\mathrm{CTRL}}^{\mathrm{EV}}, \mathrm{x}_{jt}^{\mathrm{EV}}, \mathrm{x}_{it}^{\mathrm{G}}, \mathrm{x}_{it}^{\mathrm{NSR}}, \mathrm{x}_{it}^{\mathrm{SDC}}, \mathrm{x}_{it}^{\mathrm{SR}}, \mathrm{x}_{it}^{\mathrm{SUC}}, \mathrm{x}_{t}^{\mathrm{W}}, \mathrm{y}_{jt}^{\mathrm{CDM}}, \mathrm{y}_{i}^{\mathrm{BLDC}}, \mathrm{y}_{w}^{\mathrm{BLDW}}, \mathrm{y}_{it}^{\mathrm{ON}} \right\}$$

$$\forall n \in \mathrm{P_C^{NEW}}, w \in \mathrm{P_W^{NEW}}, i \in \mathrm{P_C}, j \in \mathrm{E}, t \in \mathrm{T}$$

Symbol	Description	Domain	Units
x^{E}_{jt}	Sum of usable energy remaining in all vehicles in controlled charging program of type *j* in time step *t*	$\square_{+}$	MWh
x^{EV}_{CTRL}	Percentage of plug-in vehicles in the controlled charging program	[0,100]	%
x^{EV}_{jt}	Sum of power to charge all vehicles in controlled charging program of type *j* in time step *t*	$\square_{+}$	MW
x^{G}_{it}	Power generated in time step *t* by plant *i*	$\square_{+}$	MW
x^{SD}_{it}	Shut-down variable for the minimum on/off constraints for plant *i* at time *t*. Formulation forces this to 1 (plant shutting down) or 0 (plant not shutting down)	[0,1]	NA
x^{SDC}_{it}	Shut-downs for plant *i* in time step *t*	$\square_{+}$	NA
x^{NSR}_{it}	Non-spinning reserve power for plant *i* in time step *t*	$\square_{+}$	MW
x^{SR}_{it}	Spinning reserve power for plant *i* in time step *t*	$\square_{+}$	MW
x^{SU}_{it}	Start-up variable for the minimum on/off constraints for plant *i* at time *t*. Formulation forces this to 1 (plant starting up) or 0 (plant not starting up)	[0,1]	NA
x^{SUC}_{it}	Start-up cost for plant *i* in time step *t*	$\square_{+}$	NA
x^{W}_{t}	Total wind generation taken in time step *t*	$\square_{+}$	MW
y^{BLDC}_{i}	Binary decision =1 if plant *i* is built, 0 otherwise	{0,1}	NA
y^{BLDW}_{w}	Binary decision =1 if wind plant *i* is built, 0 otherwise	{0,1}	NA
y^{ON}_{it}	Binary decision =1 if plant *i* is on at time *i*, 0 otherwise	{0,1}	NA

Subject to:

System Constraints

Balancing Load and Generation

$$x^{W}_{t} + \sum_{i \in P_C} x^{G}_{it} = L_t + \sum_{j \in E} x^{EV}_{jt} + (1 - x^{EV}_{CTRL}) n^{EV} v^{UCTRL}_{t} \forall t \in T$$

Wind generation must meet RPS standard

$$\sum_{t} x^{W}_{t} \geq E^{RPS} \left(\sum_{t} x^{W}_{t} + \sum_{i \in P_C} x^{G}_{it} \right)$$

Required total reserves (spinning plus non-spinning)

$$\sum_{i \in \mathrm{P_C}} \left(\mathrm{x}_{it}^{\mathrm{NSR}} + \mathrm{x}_{it}^{\mathrm{SR}} \right) \geq R^{\mathrm{TR}} \left(\sum_{t} \mathrm{x}_{t}^{\mathrm{W}} + \sum_{i \in \mathrm{P_C}} \mathrm{x}_{it}^{\mathrm{G}} \right) + R^{\mathrm{W}} \mathrm{x}_{t}^{\mathrm{W}} \forall t \in \mathrm{T}$$

Required spinning reserves

$$\sum_{i \in \mathrm{P_C}} \left(\mathrm{x}_{it}^{\mathrm{SR}} \right) \geq R^{\mathrm{SR}} \left(\sum_{t} \mathrm{x}_{t}^{\mathrm{W}} + \sum_{i \in \mathrm{P_C}} \mathrm{x}_{it}^{\mathrm{G}} \right) + R^{\mathrm{W}} \mathrm{x}_{t}^{\mathrm{W}} \forall t \in \mathrm{T}$$

Plant Operating Constraints

Wind generation must be less than or equal to potential wind generation

$$\mathrm{x}_{t}^{\mathrm{W}} \leq \sum_{w \in \mathrm{P_W}} p_{wt} \mathrm{y}_{w}^{\mathrm{BLDW}} \forall t \in \mathrm{T}$$

Conventional plants generation limits

The capacity of plants that are on can be used for generation and spinning reserves.

$$\mathrm{x}_{it}^{\mathrm{G}} + \mathrm{x}_{it}^{\mathrm{SR}} \leq \mathrm{y}_{it}^{\mathrm{ON}} k_i \forall i \in \mathrm{P_C}, \forall t \in \mathrm{T}$$

Non-spinning reserve comes only from plants that are off but can start quickly, i.e. gas turbines

$$\mathrm{x}_{it}^{\mathrm{NSR}} \leq (\mathrm{y}_{it}^{\mathrm{BLDC}} - \mathrm{y}_{it}^{\mathrm{ON}}) k_i \forall i \in \mathrm{P_{GT}^{NEW}}, \forall t \in \mathrm{T}$$

New plants can only be on if they are built.

$$\mathrm{y}_{nt}^{\mathrm{ON}} \leq \mathrm{y}_{n}^{\mathrm{BLDC}} \forall n \in \mathrm{P_C^{NEW}}, \forall t \in \mathrm{T}$$

Plants have to operate above minimum generation

$$\mathrm{x}_{it}^{\mathrm{G}} \geq m_i \mathrm{y}_{it}^{\mathrm{ON}} \forall i \in \mathrm{P_C}, t \in \mathrm{T}$$

Ramp rate limits for a plant already in operation. If in the process of starting up or shutting down, the plant goes to min gen. The time requirement for ramping up to and down from min gen is built into the minimum on and off times. Spinning reserves have to be possible to reach in the time step. These reserves are only used when there is too little generation, so they are not included when considering ramping down.

$$\mathrm{x}_{it}^{\mathrm{G}} + \mathrm{x}_{it}^{\mathrm{SR}} \le \mathrm{x}_{i(t-1)}^{\mathrm{G}} + r_i^{\mathrm{UP}} \mathrm{y}_{i(t-1)}^{\mathrm{ON}} s + m_i (\mathrm{y}_{i(t)}^{\mathrm{ON}} - \mathrm{y}_{i(t-1)}^{\mathrm{ON}}) \forall i \in \mathrm{P_C}, t \in \mathrm{T}$$

$$\mathrm{x}_{i(t-1)}^{\mathrm{G}} - r_i^{\mathrm{DWN}} \mathrm{y}_{i(t)}^{\mathrm{ON}} s - m_i (\mathrm{y}_{i(t-1)}^{\mathrm{ON}} - \mathrm{y}_{i(t)}^{\mathrm{ON}}) \le \mathrm{x}_{it}^{\mathrm{G}} \forall i \in \mathrm{P_C}, t \in \mathrm{T}$$

Start-up and Shutdown Costs

$$\mathrm{x}_{it}^{\mathrm{SUC}} \ge c_i^{\mathrm{SU}} (\mathrm{y}_{it}^{\mathrm{ON}} - \mathrm{y}_{i(t-1)}^{\mathrm{ON}}) \forall i \in \mathrm{P_C}, \forall t \in \mathrm{T}$$

$$\mathrm{x}_{it}^{\mathrm{SDC}} \ge c_i^{\mathrm{SD}} (\mathrm{y}_{i(t-1)}^{\mathrm{ON}} - \mathrm{y}_{it}^{\mathrm{ON}}) \forall i \in \mathrm{P_C}, \forall t \in \mathrm{T}$$

Minimum on and off times

$$\sum_{k=t-o_i+1}^{t} x_{ik}^{\mathrm{SU}} \le \mathrm{y}_{it}^{\mathrm{ON}} \forall i \in \mathrm{P_C}, o_i \le t \le \mathrm{T}^{END} \forall i \in \mathrm{P_C}, t \in \mathrm{T}$$

$$\sum_{k=t_i-f_i+1}^{t} x_{ik}^{\mathrm{SD}} \le_i (1 - \mathrm{y}_{it}^{\mathrm{ON}}) \forall i \in \mathrm{P_C}, f_i \le t \le \mathrm{T}^{END} \forall i \in \mathrm{P_C}, t \in \mathrm{T}$$

Vehicle Constraints

Vehicle charge rate is limited by charging level, the number of vehicles controlled, and the portion of the hour the vehicle is at home

$$\mathrm{x}_{jt}^{\mathrm{EV}} \le l_j p_{jt} w_j n^{\mathrm{EV}} \mathrm{x}_{\mathrm{CTRL}}^{\mathrm{EV}} \forall j \in \mathrm{E}, t \in \mathrm{T}$$

The energy stored in the vehicle batteries must stay within the battery limits

$$b_j^{\mathrm{LO}} b_j w_j n^{\mathrm{EV}} \mathrm{x}_{\mathrm{CTRL}}^{\mathrm{EV}} \le \mathrm{x}_{jt}^{\mathrm{E}} \le b_j^{\mathrm{HI}} b_j w_j n^{\mathrm{EV}} \mathrm{x}_{\mathrm{CTRL}}^{\mathrm{EV}} \forall j \in \mathrm{E}, t \in \mathrm{T}$$

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

$$\mathrm{x}_{jt}^{\mathrm{E}} = \mathrm{x}_{j(t-1)}^{\mathrm{E}} + \mathrm{x}_{jt}^{\mathrm{EV}} s - d_{jt} w_j n^{\mathrm{EV}} \mathrm{x}_{\mathrm{CTRL}}^{\mathrm{EV}} \eta^{\mathrm{ELEC}} \forall j \in \mathrm{E}, t \in \mathrm{T}$$

Net battery energy requirement at the beginning of the first trip of the day

$$\mathrm{x}_{jt}^{\mathrm{E}} \ge b^{\mathrm{AM}} b_j w_j n^{\mathrm{EV}} \mathrm{x}_{\mathrm{CTRL}}^{\mathrm{EV}} \forall j \in \mathrm{E}, t \in T^{\mathrm{AM}}$$

Fifteen Minute Model

For the fifteen minute model, most of the constraints remain the same, but everything regarding capacity expansion is cut out of 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 $\mathrm{x}_{\mathrm{CTRL}}^{\mathrm{EV}}$ 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 savings.

Minimize the cost operating costs in each time step:

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

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 RPS requirement is also dropped because it can only be used across all time periods at once. Instead, we assume that the RPS 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 the 20% RPS standard. Because of the low marginal cost of wind, most of this wind energy will be utilized 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 the hour while generation levels are free to change every fifteen minutes.

Model Parameters

Symbol	Description	Base Value	Sensitivity Values	Units
b_j	Battery capacity of vehicle *j*	16	5, 24	kWh
b^{AM}	Battery charge requirement in the morning	100/max possible*	-	%
b_j^{HI}	Battery higher limit for vehicle *j*	100	-	%
b_j^{LO}	Battery lower limit for vehicle *j*	30	-	%
c_n^{BLD}	Capital cost of each new plant *i*	EIA 2011 Reference Case	-	$/year
c^{EV}	Payment to vehicle owner for participation in controlled charging program	$0	$100, $200, $300	$/vehicle/yr
c_i^{F}	Fuel cost of plant i	EIA 2011 Reference Case	-	$/Btu
d_{jt}	Distance driven by each vehicle of type *j* in time *t*	NHTS Sample	-	Miles
E^{RPS}	RPS energy requirement	10%	0%, 20%	%
f_i	Minimum time off for plant *i*	WECC	-	# time steps
h_i	Heat rate for plant *i*	Ventyx	-	Btu/MWh
k_i	Size of each plant *i*	Ventyx	-	MW
L_t	Non-vehicle load at time *t*	NYISO	-	MW
l_j	Charge limit of vehicle *j*	9.6	1.2, 30	kW
m_i	Minimum generation for plant *i*	Ventyx	-	%
n^{EV}	Number of plug-in vehicles total	10%	1%, 15%	% of total vehicles
o_i	Minimum time on for plant *i*	WECC	-	# time steps
p_{wt}	Wind power potential at time *t* from each wind plant	EWITS data	-	MW
p_{jt}	Percent of time step vehicle type *j* is home	NHTS sample	-	%
R^{SR}	Spinning reserve requirement	3%	-	%
R^{TR}	Total reserve requirement	6%	-	%
R^{W}	Extra spinning reserves based on a percentage of the wind power at time *t*	5%	-	%
r_i^{DWN}	Ramp down rate for plant *i*	Ventyx	-	MW/hr
r_i^{UP}	Ramp up rate for plant *i*	Ventyx	-	MW/hr
s	Length of time step	1	0.25	hr
v_t^{UCTRL}	Charging power to all uncontrolled electric vehicles at time *t*	NHTS database	-	MW
w_j	Weighting factor for vehicles that are of type *j*	NHTS sample	-	%
η^{ELEC}	Efficiency of vehicle in electric mode	.3	-	kWh/mile

*Vehicles which cannot be charged completely during their longest period at home are always charged for that entire time period.

Appendix C: Additional Results

C.1 Detailed Cost Breakdown

Table C.1: Costs given a 0% RPS and 10% vehicle penetration with different levels of payment to electric vehicles for controlled charging in the Fixed Capacity Scenario. Overnight new capital costs include the cost of building wind capacity in order to meet the RPS 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. Annualized new system costs are the sum of the annualized new capital costs, annual vehicle program costs, and annual operating costs.

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	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

Table C.2: Costs given a 20% RPS and 10% vehicle penetration with different levels of payment to electric vehicles for controlled charging in the Fixed Capacity Scenario.

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	100%	25	2.0	0	2.5	4.5
100	0%	25	2.0	0	2.5	4.5

Table C.3: Costs given a 0% RPS and 10% vehicle penetration with different levels of payment to electric vehicles for controlled charging in the Capacity Expansion Scenario.

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	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

Table C.4: Costs given a 20% RPS and 10% vehicle penetration with different levels of payment to electric vehicles for controlled charging in the Capacity Expansion Scenario.

Vehicle Payment ($/vehicle/year)	Percent Controlled (%)	Overnight Capital Cost (billion $)	Annualized New Capital Costs (billion $)	Annual Vehicle Program Costs (million $)	Annual Operating Costs (billion $)	Annualized New System Costs (billion $)
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

C.2 Generation Mix

The generation mix remains fairly similar between the hourly and fifteen minute model. 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 RPS energy constraint in order to performing 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.

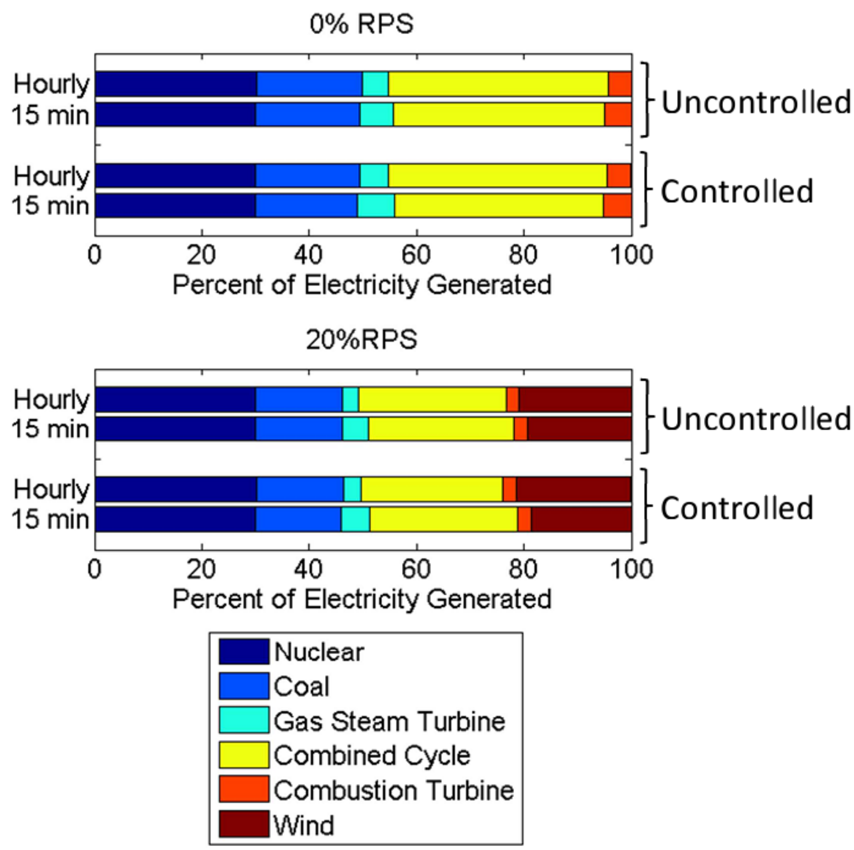

Figure C.1: Comparison of resulting generation mixes between the hourly and fifteen minute model.

C.3 Capacity Factors

In the Fixed Capacity Scenario, combined cycle plants have a lower capacity factor when charging is controlled. All conventional power plants except for nuclear which is held at 100% of its capacity at all times have a lower capacity factor under 20% RPS compared to a 0% RPS.

Table C.5: Capacity factor for each generation type given a 0% RPS and 10% vehicle penetration with different levels of payment to electric vehicles for controlled charging in the Fixed Capacity Scenario.

Vehicle Payment ($/vehicle/year)	Percent Controlled (%)	Nuclear	Coal	Oil/gas steam	Gas combined cycle	Gas combustion turbine
0	100%	100%	98%	7%	73%	12%
100	48%	100%	97%	7%	73%	12%
200	0%	100%	97%	8%	74%	12%

Table C.6: Capacity factor for each generation type given a 20% RPS and 10% vehicle penetration with different levels of payment to electric vehicles for controlled charging in the Fixed Capacity Scenario.

Vehicle Payment ($/vehicle/year)	Percent Controlled (%)	Nuclear	Coal	Oil/gas steam	Gas combined cycle	Gas combustion turbine	Wind
0	100%	100%	81%	4.4%	47%	6.5%	36%
100	0%	100%	82%	4.9%	48%	6.6%	36%

In low initial capacity scenarios combined cycle plants have a higher capacity factor with controlled charging as the controlled charging allowed for fewer combined cycle plants to be built.

Table C.7: Capacity factor for each generation type given a 0% RPS and 10% vehicle penetration with different levels of payment to electric vehicles for controlled charging in the Capacity Expansion Scenario.

Vehicle Payment ($/vehicle/year)	Percent Controlled (%)	Nuclear	Coal	Oil/gas steam	Gas combined cycle	Gas combustion turbine
0	100%	100%	97%	7.0%	54%	2.8%
100	37%	100%	96%	7.0%	50%	2.3%
200	7.2%	100%	96%	6.2%	49%	2.4%
300	0%	100%	96%	6.1%	49%	2.4%

Table C.8: Capacity factor for each generation type given a 20% RPS and 10% vehicle penetration with different levels of payment to electric vehicles for controlled charging in the Capacity Expansion Scenario.

Vehicle Payment ($/vehicle/year)	Percent Controlled (%)	Nuclear	Coal	Oil/gas steam	Gas combined cycle	Gas combustion turbine	Wind
0	100%	100%	86%	5.3%	38%	2.2%	36%
100	94%	100%	85%	5.1%	39%	2.0%	36%
200	0%	100%	85%	4.4%	36%	1.2%	36%