Applied Energy 115 (2014) 190–204

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

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

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HIGHLIGHTS

- We quantify the benefits of controlled charging of plug-in hybrid electric vehicles.
- Costs are determined using an economic dispatch and unit commitment model.
- The model is based on New York ISO and allows for capacity expansion.
- We find controlled charging can significantly lower system costs.
- Controlled charging benefits are larger with high wind penetration.

ARTICLE INFO

Article history:
Received 25 April 2013
Received in revised form 3 September 2013
Accepted 7 October 2013

Keywords:
Dispatch
Capacity expansion
Plug-in hybrid electric vehicles
Controlled charging
Wind power integration

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 generation and 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 plug-in hybrid electric vehicle (PHEV) charging based on the NYISO system. We find that controlled charging cuts the cost of integrating PHEVs in half. The magnitude of these savings is ∼5% to 15% higher in a system with 20% wind penetration compared to a system with no wind power, and the savings are 50–60% higher in a system that requires capacity expansion.

1. Introduction

Electricity generation is responsible for over 40% of US 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]. As one of the fastest growing electricity sources in the United States [3], 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 [4].

Plug-in electric vehicles (PEVs), including plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), create additional electricity demand, resulting in additional air emissions from power plants [5,6]. But they have also been proposed as a

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http://dx.doi.org/10.1016/j.apenergy.2013.10.017

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 cost-savings and emissions-savings from adding V2G capabilities to the power system, given simplified ramping constraints for the power generation fleet [7]. However, it has been shown that the market for V2G in the energy market [8] and ancillary services market [9] 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 [10]. Controlled charging can also take advantage of the high levels of wind generation that commonly occur at night in the US. 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 [11], and Foley et al. find that off-peak charging can save vehicle owners nearly 30% of the charging costs [12]. Wang et al. evaluate different charging strategies of plug-in hybrid 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 [13], exaggerating variability by ignoring the complex effects of plant size and geographic diversity on mitigating wind generation correlation [14]. Sioshansi 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 [15]. 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 [16].

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 [17], 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 [18]. 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 the potential cost savings from controlled charging in scenarios with vs. without additional wind power in order to understand whether PEVs can provide 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. 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-min 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 US 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. Methods

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 US 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

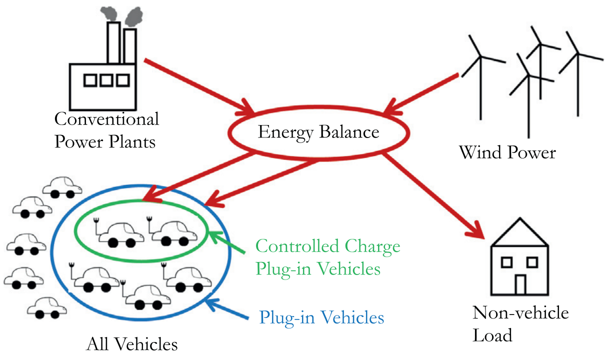

Fig. 1. System overview – energy is provided by conventional power plants and wind plants and must meet the demand from plug-in vehicles and non-vehicle load in each time step.

by wind[1,2]. Fig. 1 shows a graphical representation of the framework used.

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.

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

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 $x_{\tau c}^{\mathrm{CBIN}}$ 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 $x_{\tau h}^{\mathrm{HRBIN}}$ for the selected fleet. The distributions of plant capacities and heat rate 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}, $x_{\tau c}^{\mathrm{CBIN}}$, and $x_{\tau h}^{\mathrm{HRBIN}}$ 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

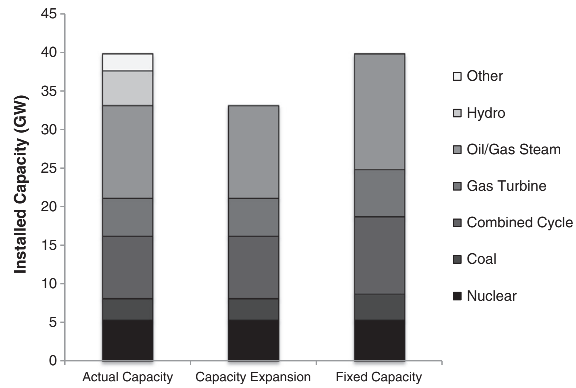

Fig. 2. Installed capacity of the actual capacity of the NYISO power plant fleet, Capacity Expansion Scenario, and the Fixed Capacity Scenario.

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 plants, 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 Fig. 2. 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 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."

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) data set [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. 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 details). 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].

[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]. For this paper, we model a system in which wind is the only renewable available.

[2] The model took between 5–10 h to run on an Intel i& processor running CPLEX using 20 day period with hourly data. Running the 15-min sensitivity cases over 20 days had a wide range of solve times, going up to 80 h 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.

[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.

Table 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/kW h)	Sim. ave HR (BTU/kW h)	Actual ave online year	Sim. ave online year
Coal	2767	2767	32	31	10,507	10,738	1970	1962
NGCC	8124	8124	103	103	8555	8584	1996	1995
NGCT	4885	4885	215	215	14,971	14,945	1976	1992
Oil/gas steam	11,723	11,723	32	32	11,341	11,763	1964	1963

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 Chevy Volt with a 16 kW h hour lithium ion battery of which 10.4 kW h 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 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 fee case allows the system operator to capture all of the cost savings). 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, 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 3000 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 2–18% of all vehicles in the US in 2025 depending on what policies are adopted [24].

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 [25]. 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.

2.5. 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 [26], 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 paper focus 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 generation 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 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 PHEVs with controlled charging.

2.6. Optimization

The optimization model minimizes capital and operating costs:

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

Table 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 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 90,000–1,350,000 plug-in electric vehicles.

Vehicle fleet characteristics	Minimum	Base case	Maximum
Battery size	5 kW h	16 kW h	24 kW h
Maximum charging rate	1.2 kW	7.4 kW	30 kW
Plug-in vehicle Penetration	1%	10%	15%

where $\mathcal{N}$ is the set of new conventional power plants; $\mathcal{E}$ is the set of existing conventional power plants; $\mathcal{C} = \mathcal{N} \cup \mathcal{E}$ is the combined set of existing and new conventional power plants; $\mathcal{W}$ is the set of (new) wind plants; $\mathcal{T}$ is the set of time steps in the sample period; c_i^{BLD} is the annualized cost for construction of plant i; y_i^{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:

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

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, $\mathcal{V}$ 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:

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

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:

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

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

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 [27]:

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

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:

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

where y_{it}^{ON} is the binary variable indicating whether or not plant i is on in timestep 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:

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

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

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

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

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

They are also subject to ramp rate limitations:

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

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

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:

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

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

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:

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

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 of 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:

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

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:

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

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 contained in the batteries of 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:

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

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:

$$x^{E}_{jt} \geqslant b_j w_j n^{EV} x^{EV}_{CTRL} \quad \forall j \in \mathscr{V}, \quad t \in \mathscr{T}^{AM}_{j}$$

where T^{AM}_{j} is the set of time steps each day when vehicle profile j leaves for the first trip of the day. Tables for all the variables and parameters as well as how the formulation was altered for the 15 min time step case can be found in Appendix B.

The optimization variables for this problem include $x^{E}_{jt}, x^{EV}_{CTRL}, x^{EV}_{jt}, x^{G}_{it}, x^{SD}_{it}, x^{SDC}_{it}, x^{NSR}_{it}, x^{SR}_{it}, x^{SU}_{it}, x^{SUC}_{it}, x^{W}_{t}, y^{BLD}_{i}, y^{ON}_{it}$.

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 Fig. 3, 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.

3.1. Cost savings

Our main results, summarized in Table 3, suggest that controlled charging can reduce system costs. Given a 10% penetration of PHEVs (totaling 900,000 PHEVs), controlled charging reduces

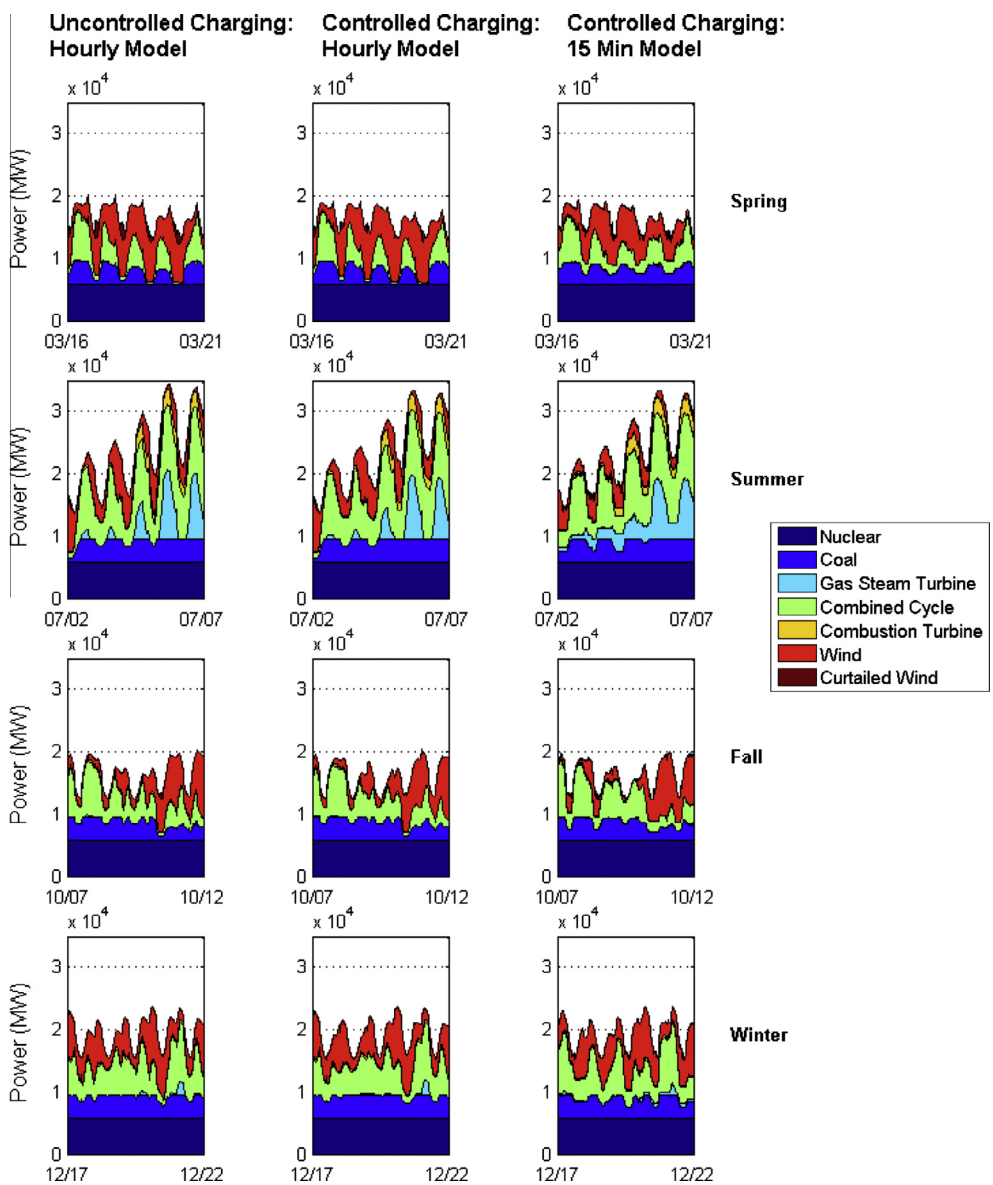

Fig. 3. Seasonal dispatch in the Fixed Capacity Scenario given 10% vehicle penetration and a 20% wind penetration for uncontrolled charging in the hourly model, controlled charging in the hourly model, and controlled charging in the fifteen minute model.

Table 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%

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 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 savings 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 found in Appendix C.

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 we allow charging only at home, availability of workplace or public charging might increase the flexibility and value of controlled charging (though the availability of low cost plants will continue to encourage most charging at night at 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 under-estimate 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 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.

We examined the sensitivity of the cost savings 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, as described further in Appendix B. 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 Fig. 4. 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.

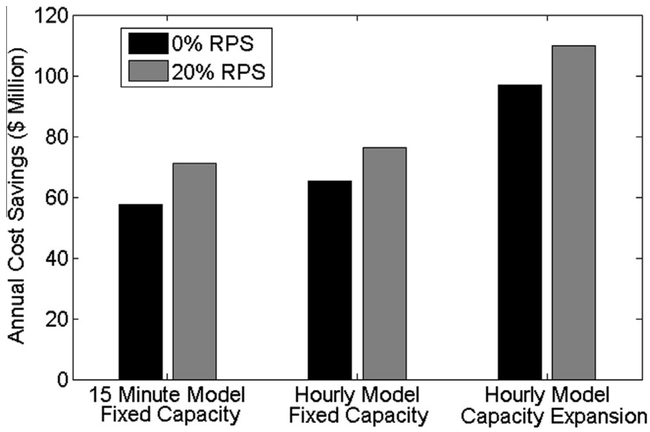

Fig. 4. Annual cost savings due to controlled charging for different models given 0% and 20% wind penetration.

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 min [28].

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 Fig. 5. 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.

Increasing the maximum charge rates has diminishing returns, as shown in Fig. 6. 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 kW h batteries to 24 kW h batteries, we see cost reductions differ from the base case by $1–$35 million dollars per year depending on the scenario due to the competing effects discussed above.

3.2. Capacity and generation mix

Fig. 7 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 utilized 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.

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.

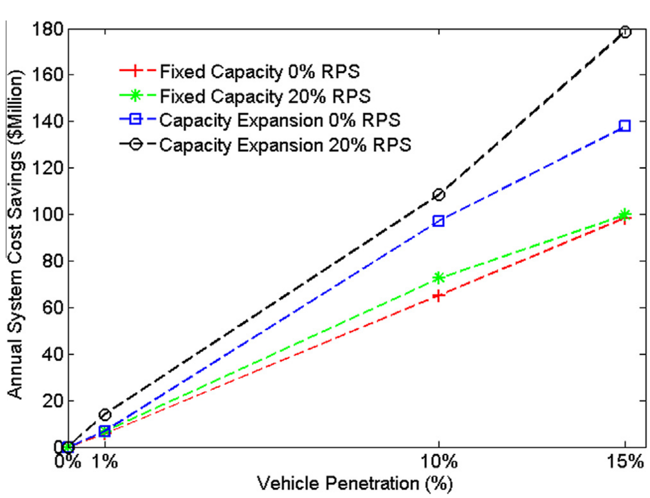

Fig. 5. Sensitivity of the maximum annual system cost savings possible through 100% controlled electric vehicle charging compared to uncontrolled charging for a range of vehicle penetrations from 0% to 15% of a 9 million passenger vehicle fleet.

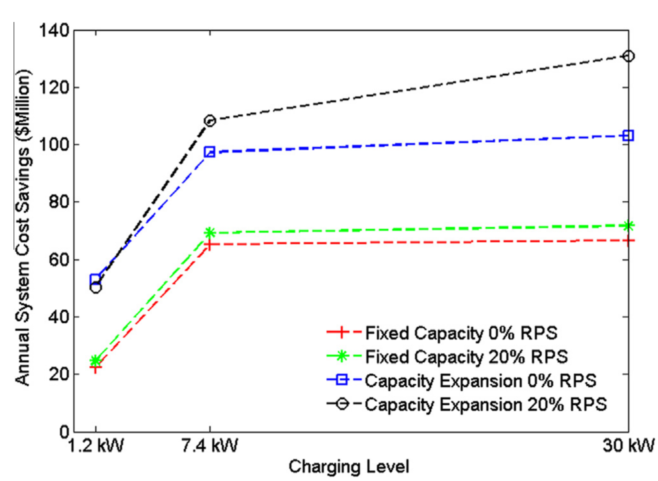

Fig. 6. Sensitivity of the maximum annual system cost savings possible through 100% controlled electric vehicle charging compared to uncontrolled charging for Level 1 (1.2 kW), Level 2 (7.4 kW), and Level 3 (30 kW) charging. Only Level 1 and 2 are likely to be used in residential settings in the foreseeable future.

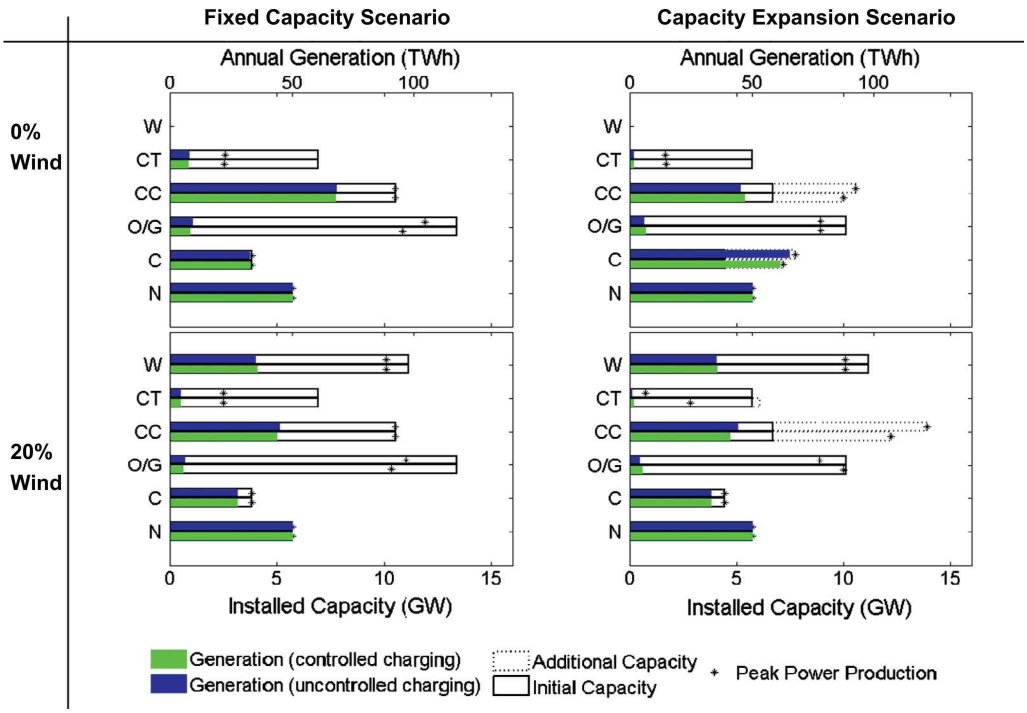

Fig. 7. Comparison of capacity and generation data with and without controlled electric vehicle charging by generator type for each scenario. The following abbreviations are used for the generation types: W – Wind, CT – Gas Combustion Turbine, CC – Gas Combined Cycle, O/G – Oil/Gas Steam, C – Coal, N – 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.

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 (Fig. 7). 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.

4. Conclusions

In our test systems, controlled charging of PHEVs reduces the costs of integrating PHEVs into the electricity system 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-h 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 (see cost data in Appendix C). 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/kW h 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.

Acknowledgements

The authors would like to thank Bri-Mathias Hodge for his feedback and guidance on our modeling efforts and to David Luke Oates for technical assistance. This work was supported through the RenewElec Project (http://www.renewelec.org) by the Doris Duke Charitable Foundation, the Richard King Mellon Foundation, the Electric Power Research Institute, and the Heinz Endowment. Additional funding was provided by the National Science Foundation CAREER Award #0747911 and the National Science Foundation Graduate Research Fellowship Program. Findings and recommendations are the sole responsibility of the authors and do not necessarily represent the views of the sponsors.

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 Household 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 hybrid 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 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

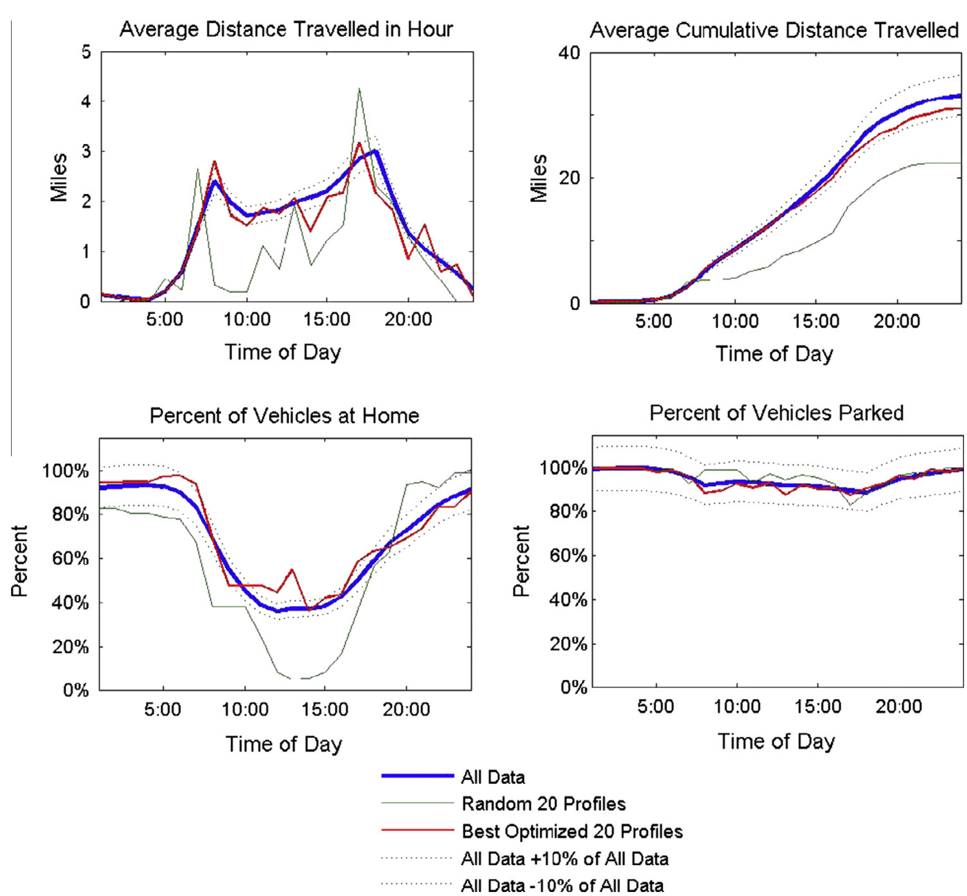

Fig. A.1. Aggregate characteristics for all passenger vehicles in the NHTS dataset and best match 20 optimally weighted vehicle profiles drawn from the NHTS dataset over 1 million random draws. The percent of vehicles at home dips during the day, and only a small percentage of the fleet is driving at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

Table B.1
Optimization variables.

Symbol	Description	Domain	Units
x_{jt}^{E}	Sum of usable energy remaining in all vehicles in controlled charging program of type j in time step t	$\mathbb{R}_+$	MW h
x_{CTRL}^{EV}	Percentage of plug-in vehicles in the controlled charging program	[0,100]	%
x_{jt}^{EV}	Sum of power to charge all vehicles in controlled charging program of type j in time step t	$\mathbb{R}_+$	MW
x_{it}^{G}	Power generated in time step t by plant i	$\mathbb{R}_+$	MW
x_{it}^{SD}	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_{it}^{SDC}	Shut-downs for plant i in time step t	$\mathbb{R}_+$	NA
x_{it}^{NSR}	Non-spinning reserve power for plant i in time step t	$\mathbb{R}_+$	MW
x_{it}^{SR}	Spinning reserve power for plant i in time step t	$\mathbb{R}_+$	MW
x_{it}^{SU}	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_{it}^{SUC}	Start-up cost for plant i in time step t	$\mathbb{R}_+$	NA
x_{t}^{W}	Total wind generation taken in time step t	$\mathbb{R}_+$	MW
y_{i}^{BLD}	Binary decision = 1 if plant i is built, 0 otherwise	{0,1}	NA
y_{it}^{ON}	Binary decision = 1 if plant i is on at time i, 0 otherwise	{0,1}	NA

Table B.2
Model parameters.

Symbol	Description	Base value	Sensitivity values	Units
b_j	Battery capacity of vehicle j	16	5, 24	kW h
b^{AM}	Battery charge requirement in the morning	100/Max possible[a]	–	%
b_j^{HI}	Battery higher limit for vehicle j	100	–	%
b_j^{LO}	Battery lower limit for vehicle j	30	–	%
c_i^{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/year
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%	%
h_i	Heat rate for plant i	Ventyx	–	Btu/MW h
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
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^{RM}	Reserve margin over peak load	15%	–	%
r_i^{DWN}	Ramp down rate for plant i	Ventyx	–	MW/h
r_i^{UP}	Ramp up rate for plant i	Ventyx	–	MW/h
v_t^{UCTRL}	Charging power to all uncontrolled plug-in hybrid electric vehicles at time t	NHTS database	–	MW
w_j	Weighting factor for vehicles that are of type j	NHTS sample	–	%
Δ	Length of time step	1	0.25	h
δ_i^{OFF}	Minimum time off for plant i	WECC	–	# Time steps
δ_i^{ON}	Minimum time on for plant i	WECC	–	# Time steps
η^{ELEC}	Efficiency of vehicle in electric mode	.3	–	kW h/mile

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

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, $i \in \{1, 2, \ldots, 20\}$, $w_i \in [0,1]$, $\sum_i w_i = 1$; 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 Fig. A.1, the final sample of 20 weighted profiles does not perfectly match

Table C.1
Costs given a 0% wind penetration and 10% vehicle penetration with different levels of payment to PHEV owners for controlled charging in the Fixed Capacity 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.[a] 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

[a] 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.

Table C.2
Costs given a 20% wind penetration and 10% vehicle penetration with different levels of payment to PHEV owners 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% wind penetration and 10% vehicle penetration with different levels of payment to PHEV owners 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% wind penetration and 10% vehicle penetration with different levels of payment to PHEV owners 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

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 variables and parameters

See Tables B.1 and B.2.

B.1. Fifteen minute model

For the fifteen minute model, 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 h window, save the first 24 h of data as the optimal operation for that day, move the window forward 24 h and run another 48 h 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 h 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^{EV}_{CTRL} 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:

$$\text{minimize } \underbrace{\sum\nolimits_{t\in\mathcal{T}^{48}}\left(\sum\nolimits_{i\in\mathcal{G}}\left(x^{SUC}_{it}+x^{SDC}_{it}+c^{F}_{i}h_{i}x^{G}_{it}\right)\right)}_{\text{Cost of Plant Operations}}$$

No additional plants are provided to be built, so the constraint requiring plants to be built in order to be turned on is dropped.

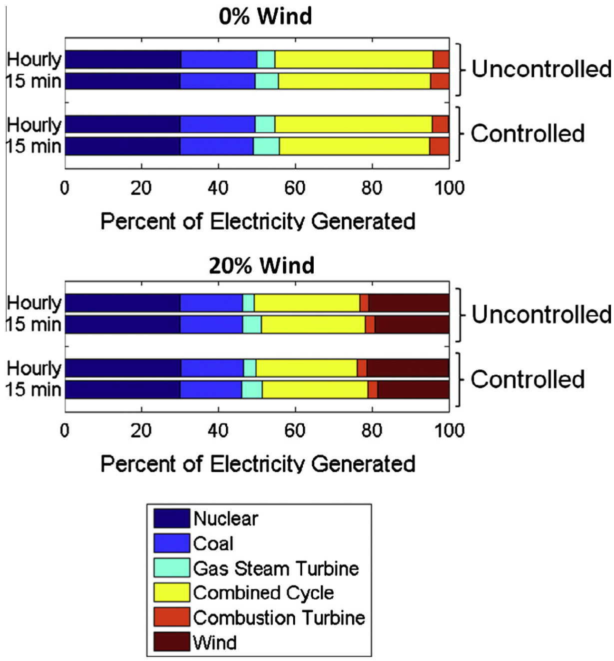

Fig. C.1. Comparison of resulting generation mixes between the hourly and fifteen minute model.

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.

Appendix C. Additional results

C.1. Detailed cost breakdown

In Tables C.1–C.4, the operational and capital costs are broken down for each scenario. In each case, the higher the payment that the grid operator is assumed to pay to each individual vehicle owner, the lower the number of vehicles it is optimal for the grid operator to include in the charging program.

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

Table C.5
Capacity factor for each generation type given a 0% wind penetration and 10% vehicle penetration with different levels of payment PHEV owners 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% wind penetration and 10% vehicle penetration with different levels of payment to PHEV owners 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

Table C.7
Capacity factor for each generation type given a 0% wind penetration and 10% vehicle penetration with different levels of payment to PHEV owners 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% wind penetration and 10% vehicle penetration with different levels of payment to PHEV owners 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

Table D
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 min 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 [14] 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

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.

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% wind penetration compared to a 0% wind penetration (see Fig. C.1 and Tables C.5–C.8).

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.

Appendix D. Assumptions

Table D discusses the assumptions made in the study and the expected direction and magnitude of bias they might give the results.

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