OPERATIONS RESEARCH
Vol. 60, No. 2, May-June 2012, pp. 1–11
ISSN 0030-364X | EISSN 1526-5463 | 12 | 2 | 0001

INFORMS
DOI 10.1287/opre.1120.1038

Modeling the Impacts of Electricity Tariffs on Plug-in Hybrid Electric Vehicle Charging, Costs, and Emissions

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Plug-in hybrid electric vehicles (PHEVs) have been touted as a transportation technology with lower fuel costs and emissions impacts than other vehicle types. Most analyses of PHEVs assume that the power system operator can either directly or indirectly control PHEV charging to coordinate it with power system operations. This paper examines the incentives of individual drivers making charging decisions with different electricity tariffs, and compares the cost and emissions impacts of these charging patterns to the ideal case of charging controlled by the system operator. Our results show that real-time pricing performs worst among all of the tariffs we consider, since linear prices are inherently limited in signaling efficient use of resources in a system with non-convexities. We also show that controlling overnight PHEV charging is significantly more important than limiting midday vehicle charging.

Key words: plug-in hybrid electric vehicles, environment, pricing

1. Introduction

Recent events, including the high prices of oil and gasoline in 2008, have increased commercial interest in plug-in hybrid electric vehicles (PHEVs). PHEVs are similar to current hybrid electric vehicles (HEVs) but differ in that they have a larger battery that can be charged using grid electricity. This larger battery allows a PHEV to drive a certain distance using electricity as its primary transportation fuel until the battery reaches a minimum state of charge (SOC). Once the battery has reached this minimum SOC the vehicle behaves much like an HEV, using gasoline or another liquid fuel as its primary energy source. A number of studies, including the works of Denholm and Short (2006), EPRI (2007a), Parks et al. (2007), Lemoine et al. (2008), Stephan and Sullivan (2008), Sioshansi and Denholm (2009, 2010), Sioshansi et al. (2010a), and Wang et al. (2010), examine the impacts of integrating PHEVs into the power system. These studies show that PHEVs can have lower total fuel costs and net emissions (when the cost and emissions of charging loads are taken into account) than HEVs and conventional vehicles (CVs).

One implicit assumption in these analyses and most discussions of PHEVs is that PHEV charging is coordinated with power system operations. Absent such coordination, PHEV impacts could be quite different. For instance, because different generation fuels are marginal at different times of day, the cost and emissions impacts of PHEVs could vary depending on when they are charged. Many studies, including the works of Denholm and Short (2006), EPRI (2007a), Parks et al. (2007), Stephan and Sullivan (2008), and Sioshansi and Denholm (2009, 2010), assume that the system operator (SO) will be able to control PHEV charging and co-optimize it with power system operations.

Some, including Collins and Mader (1983), Lemoine et al. (2008), and Mohseni and Stevie (2009), advocate using an indirect market-based approach to controlling PHEV charging. Under such a scheme charging decisions are left to individual consumers but electricity price tariffs are designed to encourage PHEV owners to make charging decisions similar to what SO control of charging would yield. For instance, a time-of-use (TOU) rate, which charges a lower price for energy during certain hours of the day, could provide PHEV owners with an incentive to delay PHEV charging from the early evening, when they arrive home, to overnight hours. Real-time pricing (RTP), which dynamically sets prices based on the real-time marginal cost of energy, could provide PHEV owners with even finer grained price signals. Although electricity tariffs provide indirect control of PHEV charging, detailed analyses of such schemes are scant. Wang et al. (2010) use a mathematical program with equilibrium constraints (MPEC) model to examine PHEV charging and the resulting price patterns under a variety of tariff schemes. Their results show that RTP can reduce the impact of PHEVs on power system costs compared to a time-invariant electricity tariff. One limitation of an MPEC-based analysis, which this paper highlights, is that it neglects non-convexities of power systems. Because linear energy prices do not properly signal non-convexities, RTP may yield inefficiencies that would not be apparent in an MPEC-based analysis, which assumes convexity.[1]

This paper presents a detailed analysis of PHEV charging patterns under a variety of electricity pricing tariffs using a non-convex unit commitment model. We show that RTP performs worse than other simpler electricity tariffs in terms of both the net cost and emissions impacts of PHEVs. The poor performance of RTP stems exactly from the non-convex nature of power system operations and the inability of linear electricity prices to properly signal the impact of PHEV charging decisions on the system. The remainder of the paper is organized as follows: § 2 describes the model and data underlying our analysis, § 3 summarizes our results, and § 4 concludes.

2. Model, Data, and Tariff Structures

This study is based on the power system and vehicle driving models that Sioshansi and Denholm (2009, 2010) develop. The power system is modeled as a unit commitment problem, while the vehicle model determines PHEV driving and charging decisions. We examine five different charging cases in our analysis. The first is a controlled charging scenario, in which the SO co-optimizes power system operation and vehicle charging decisions to minimize the sum of power system and PHEV driving costs. The other four assume that PHEV owners make charging decisions autonomously to minimize total driving costs under three different electricity tariffs: fixed (time-invariant), TOU, and RTP rates. Our case study considers the impacts of the PHEV fleet over an entire year, which we model at hourly time steps. We use data from the Electricity Reliability Council of Texas (ERCOT) power system in 2005 and examine a case with a small PHEV fleet that constitutes 1% of the total light-duty vehicle fleet in ERCOT.

2.1. Power System Model

The power system is modeled as a unit commitment problem, which optimizes generator commitments and dispatch to minimize total generation costs subject to power system and unit operation constraints. We first define the following parameters of the model:

- T: number of hours in the planning horizon of the problem;
- I: number of generators in the power system;
- C_i^{SU}: startup cost of generator i;
- C_i^N: spinning cost of generator i;
- $C_i(\cdot)$: non-decreasing stepped variable generation cost function of generator i;
- K_i^-, K_i^+: minimum and maximum per-hour generation level of generator i when it is online, respectively;
- R_i^-, R_i^+: maximum amount by which the generating output of generator i can decrease and increase between subsequent hours, respectively;
- K_i^{sp}, K_i^{ns} generator i's per-hour spinning and non-spinning reserve capabilities, respectively;

- τ_i^-, τ_i^+: minimum number of hours generator i must remain offline and online after being shutdown or started up, respectively;
- D_t^n, D_t^p: non-PHEV and PHEV load in hour t, respectively; and
- ρ^{sp}, ρ^{ns}: fraction of the total hourly load that must be available as spinning and non-spinning reserves, respectively.

We also define the following variables:

- $u_{i,t}, s_{i,t}, h_{i,t}$: binary variables indicating whether generator i is online, started up, and shutdown in hour t, respectively;
- $q_{i,t}$: amount of generation provided by generator i in hour t; and
- $k_{i,t}^{sp}, k_{i,t}^{ns}$: amount of spinning and nonspinning reserves provided by generator i in hour t, respectively.

The power system model is then formulated as minimizing total generation costs:

$$\min_{q,k^{sp},k^{ns},u,s,h} \quad \sum_{t=1}^{T} \sum_{i=1}^{I} (C_i(q_{i,t}) + C_i^N u_{i,t} + C_i^{SU} s_{i,t}), \tag{1}$$

subject to the following constraints:

$$\sum_{i \in I} q_{i,t} = D_t^n + D_t^p; \qquad \forall\, t = 1, \ldots, T \tag{2}$$

$$\sum_{i \in I} k_{i,t}^{sp} \geq \rho^{sp} \cdot (D_t^n + D_t^p); \qquad \forall\, t = 1, \ldots, T \tag{3}$$

$$\sum_{i \in I} (k_{i,t}^{sp} + k_{i,t}^{ns}) \geq (\rho^{sp} + \rho^{ns})(D_t^n + D_t^p); \qquad \forall\, t = 1, \ldots, T \tag{4}$$

$$K_i^- u_{i,t} \leq q_{i,t}; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{5}$$

$$q_{i,t} + k_{i,t}^{sp} \leq K_i^+ u_{i,t}; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{6}$$

$$q_{i,t} + k_{i,t}^{sp} + k_{i,t}^{ns} \leq K_i^+; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{7}$$

$$0 \leq k_{i,t}^{sp} \leq K_i^{sp}; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{8}$$

$$0 \leq k_{i,t}^{ns} \leq K_i^{ns}; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{9}$$

$$R_i^- \leq q_{i,t} - q_{i,t-1}; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{10}$$

$$q_{i,t} - q_{i,t-1} + k_{i,t}^{sp} + k_{i,t}^{ns} \leq R_i^+; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{11}$$

$$\sum_{y = t - \tau_i^+}^{t} s_{i,y} \leq u_{i,t}; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{12}$$

$$\sum_{y = t - \tau_i^-}^{t} h_{i,y} \leq 1 - u_{i,t}; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{13}$$

$$s_{i,t} - h_{i,t} = u_{i,t} - u_{i,t-1}; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I \tag{14}$$

$$u_{i,t}, s_{i,t}, h_{i,t} \in \{0, 1\}; \qquad \forall\, t = 1, \ldots, T,\ i = 1, \ldots, I. \tag{15}$$

Constraint (2) ensures loads are exactly met and constraints (3) and (4) enforce the spinning and non-spinning reserve requirements. Constraints (5) and (6) impose minimum and maximum generation limits, while constraint (7) ensures that the 'potential' generation of a generator offering non-spinning reserves does not violate the maximum generating capacity if its non-spinning reserves are called in real-time. Constraints (8) and (9) are bounds on spinning and non-spinning reserves each generator can provide, constraints (10) and (11) are ramping constraints, and constraints (12) and (13) are minimum up- and down-time constraints. Constraint (14) defines the $s_{i,t}$ and $h_{i,t}$ variables in terms of the $u_{i,t}$ variables, and constraint (15) is the integrality restriction.

We model all of the dispatchable generators that were interconnected with the ERCOT system in 2005. Nuclear generators are assumed to operate as must-run generators, and as such are not modeled directly in the unit commitment (rather their nameplate capacity is subtracted from the total load in defining D_t^n). Generator costs are estimated based on heat rates and emission permit and fuel prices, obtained from Global Energy Decisions and Platts. Load data are obtained from ERCOT. We use mesoscale modeled wind data produced by 3TIER to represent available wind energy in each hour, which is assumed to have a marginal cost of zero. We assume that ERCOT has a 4.5% spinning reserve requirement, and a 9% total reserve requirement. We also assume, based on estimates of Boswell and Raish (2005), transmission and distribution losses of 5% for system loads. Following Sioshansi and Denholm (2009, 2010) we model the power system one day at a time using a two-day planning horizon. The second day is included in the planning horizon to ensure that sufficient generating capacity is kept online at the end of each day to meet the following day's load (as opposed to cycling units on and off, which may happen with a one-day planning horizon).

2.2. Vehicle Model

The vehicle model captures PHEV driving and charging decisions, and provides hourly aggregate PHEV fleet charging loads as inputs to the power system model. The vehicle model assumes that PHEV driving patterns are exogenously given and determines how many kWh of energy should be charged into each PHEV in each hour to minimize the total cost of gasoline and electricity used for driving that PHEV. The model is based on the ADVISOR vehicle simulation tool, developed by Markel et al. (2002), and driving pattern data based on an empirical study of 227 drivers, described by EWGCC (2003a,b) and Gonder et al. (2007). Further details of the driving patterns are given in the e-companion. We assume that the PHEV fleet we model is uniformly distributed between these 227 driving profiles. The empirical driving data are used to determine the hours in which the PHEVs are driven. Specifically, we assume that PHEV driving patterns are fixed based on these empirical data, and that drivers do not adjust the timing of vehicle trips in reaction to electricity price patterns. We similarly assume that in the controlled charging scenario (*i.e.* the scenario in which the SO controls the timing of PHEV charging) the SO only controls when PHEVs are charged between vehicle trips, and does not control when PHEVs are driven. The driving data are also used to determine the hours in which PHEVs are plugged in for charging. Following the work of Sioshansi and Denholm (2009, 2010) we assume that a PHEV is grid-connected in an hour if it is not driven for the entire hour. This implicitly assumes that charging stations are available wherever PHEVs park.

The ADVISOR model and empirical data are also used to determine gasoline and battery energy usage when the PHEVs are driven. We assume that the PHEVs use an electric vehicle-type control strategy[2] in which electricity is used as the primary energy source during an initial all-electric range. While driving in this range the PHEV operates in a charge-depleting (CD) mode, until the battery reaches its minimum SOC. Once the battery is at its minimum SOC the PHEV operates in a charge-sustaining (CS) mode, using gasoline as the primary transportation fuel. The PHEV continues to operate in CS mode and the battery remains at this minimum SOC until it is charged using grid energy.

Since the driving patterns of PHEVs corresponding to the 227 different profiles can differ, we use 227 instances of the charging model to optimize charging for each profile. We let v index over the set of driving profiles, and define the following parameters in formulating the vehicle model:

- $\overline{p}$: power limit on PHEV charging station;
- $\underline{e}, \overline{e}$: minimum and maximum charge levels of the PHEV battery, respectively;
- ϵ: net efficiency of PHEV battery charging;
- π_t^g, π_t^e: cost of gasoline and electricity in hour t, respectively;
- b_v^{cd}: net battery energy used when a PHEV with driving profile v is driven in CD mode;

- $\gamma_v^{cd}, \gamma_v^{cs}$: gasoline used when a PHEV with driving profile v is driven in CD and CS modes, respectively; and
- $\delta_{v,t}^{tot}$: total distance a PHEV with driving profile v is driven in hour t.

We also define the following variables:

- $l_{v,t}$: storage level of the battery of a PHEV with driving profile v at the end of hour t;
- $r_{v,t}$: energy charged into the battery of a PHEV with driving profile v in hour t;
- $d_{v,t}^{cd}, d_{v,t}^{cs}$: distance driven in CD and CS modes by a PHEV with driving profile v in hour t, respectively; and
- $a_{v,t}$: binary variable indicating whether the battery of a PHEV with driving profile v is above the minimum SOC at the end of hour t.

The vehicle charging model for driving profile v is formulated as minimizing the sum of total electricity and gasoline costs associated with driving:

$$\min_{l,r,d^{cd},d^{cs},a} \quad \sum_{t=1}^{T} [\pi_t^e \cdot r_{v,t}/\epsilon + \pi_t^g \cdot (\gamma_v^{cd} \cdot d_{v,t}^{cd} + \gamma_v^{cs} \cdot d_{v,t}^{cs})] \tag{16}$$

subject to the following constraints:

$$l_{v,t} = l_{v,t-1} + r_{v,t} - b_v^{cd} \cdot d_{v,t}^{cd}; \qquad \forall\, t = 1, \ldots, T \tag{17}$$

$$d_{v,t}^{cd} + d_{v,t}^{cs} = \delta_{v,t}^{tot}; \qquad \forall\, t = 1, \ldots, T \tag{18}$$

$$a_{v,t} \geq \frac{l_{v,t} - \underline{e}}{\overline{e} - \underline{e}}; \qquad \forall\, t = 1, \ldots, T \tag{19}$$

$$d_{v,t}^{cs} \leq \delta_{v,t}^{tot}(1 - a_{v,t}); \qquad \forall\, t = 1, \ldots, T \tag{20}$$

$$\underline{e} \leq l_{v,t} \leq \overline{e}; \qquad \forall\, t = 1, \ldots, T \tag{21}$$

$$0 \leq r_{v,t} \leq \overline{p}; \qquad \forall\, t = 1, \ldots, T \tag{22}$$

$$r_{v,t} = 0; \qquad \forall\, t = 1, \ldots, T \;:\; \delta_{v,t}^{tot} > 0 \tag{23}$$

$$0 \leq d_{v,t}^{cd}, d_{v,t}^{cs}; \qquad \forall\, t = 1, \ldots, T \tag{24}$$

$$a_{v,t} \in \{0, 1\}; \qquad \forall\, t = 1, \ldots, T \tag{25}$$

Constraint (17) defines the ending charge level of the battery in each hour based on the starting charge level and driving and charging decisions in each hour. Constraint (18) ensures that the vehicle drives the necessary distance in each hour. Constraint (19) defines the $a_{v,t}$ binary variable in terms of the SOC of the battery, while constraint (20) ensures that the PHEV only drives in CD mode when the SOC is above its minimum. Constraint (21) restricts the charge level of the battery to be between its upper and lower bounds, while constraint (22) enforces the power capacity of the vehicle charging station. Constraint (23) ensures that the battery is only charged when the vehicle is not being driven and is grid-connected, while constraints (24) and (25) are non-negativity and integrality restrictions.

We assume that the PHEVs are compact cars with a battery capacity of 9.4 kWh and a minimum SOC of 30%, implying that $\underline{e} = 2.82$ kWh. These assumptions mean the PHEVs have an all-electric range of about 35.9 km, depending upon the driving behavior. Our vehicle characteristic assumptions are based on the work of Gonder et al. (2007), and further details are given in the e-companion. Following Sioshansi and Denholm (2009, 2010) we assume that the charging stations have a power capacity of 5 kW, making them an average of a 120 V/10 A home circuit and a 240 V/30 A appliance circuit. The gasoline costs in the driving model are based on historical weekly retail gasoline prices in Texas for 2005, as reported by the U.S. Department of Energy's Energy Information Administration. Electricity prices are determined based on the tariff structures considered, and are discussed in more detail in § 2.3.

The total light-duty vehicle fleet size (consisting of both PHEVs and non-PHEVs) is taken from 2005 Texas vehicle registration information reported by the U.S. Department of Transportation's Federal Highway Administration. We assume that of all of the vehicles in Texas, 85% are driven within and interconnect with the ERCOT control area based on the fact, reported by Baldick and Niu (2005), that ERCOT serves approximately 85% of Texas's retail electric customers. We model a case in which 1% of the light-duty fleet in ERCOT are PHEVs, implying a total of 75,750 PHEVs. Since we assume that these PHEVs are evenly divided between the 227 driving profiles, there are about 333.7 PHEVs that drive and charge according to each driving profile. Thus, the aggregate charging load of the PHEV fleet in each hour, which is an input of the power system model, is defined as:

$$D_t^p = \eta \cdot \sum_{v=1}^{227} r_{v,t}/\epsilon, \tag{26}$$

where η is the number of PHEVs corresponding to each driving profile.

2.3. Tariff Structures

We model PHEV charging under six different charging scenarios: a controlled charging scenario, in which the SO makes charging decisions, and five uncontrolled charging scenarios with different retail electricity rates in which charging decisions are made by PHEV owners. The retail rates we consider are fixed rates, fixed rates with a rebate for delayed charging (hereafter referred to as the 'delay rebate' tariff), TOU pricing, and RTP.

The controlled charging scenario assumes that the SO co-optimizes power system operations and the charging of PHEVs to minimize the total cost of electricity generation and gasoline used for vehicle driving (the cost of electricity used for PHEV charging is accounted for in the generation costs). Thus, this scenario is modeled by assuming that the SO has control over the power system variables $(q, k^{sp}, k^{ns}, u, s, h)$ and the vehicle charging variables $(l, r, d^{cd}, d^{cs}, a)$. The SO's objective function is given by:

$$\min_{q,k^{sp},k^{ns},u,s,h,l,r,d^{cd},d^{cs},a} \quad \sum_{t=1}^{T} \left\{ \sum_{i=1}^{I} [C_i(q_{i,t}) + C_i^N u_{i,t} + C_i^{SU} s_{i,t}] + \eta \cdot \sum_{v=1}^{227} \pi_t^g \cdot (\gamma_v^{cd} \cdot d_{v,t}^{cd} + \gamma_v^{cs} \cdot d_{v,t}^{cs}) \right\}.$$

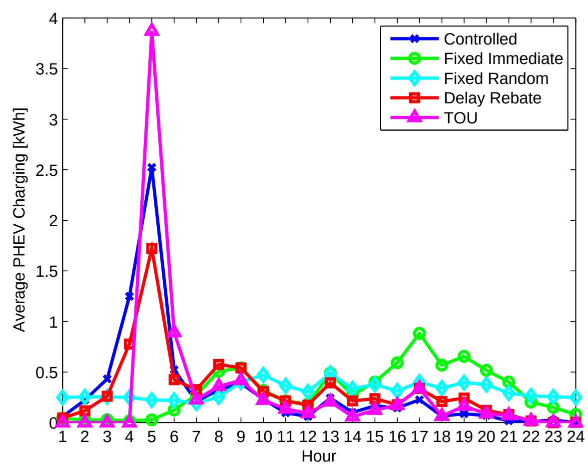
This objective function is optimized subject to constraints (2) through (15), constraints (17) through (26), and another constraint that requires each PHEV battery to be fully charged in time for the first trip of the morning. This daily charging constraint, along with the inclusion of gasoline costs in the SO's objective function, are intended to ensure that the SO has incentives to charge PHEV batteries.

Under fixed rates the price of charging energy is time-invariant and the charging patterns are determined exogenously using the vehicle model, consisting of objective function (16) and constraints (17) through (25). As discussed in the e-companion, electricity is a significantly less-costly source of transportation energy when accounting for the relative efficiencies of internal combustion and electric engines. Thus fixed rates would result in PHEV owners always preferring to use electricity as opposed to gasoline for driving. If a PHEV is parked longer than it would take for it to be fully charged, there is not a unique cost-minimizing charging profile. Thus we consider two different charging profiles: one in which PHEV owners charge their vehicles immediately when they grid connect, which we refer to as the 'fixed immediate' scenario, and another in which charging is uniformly spread over the time during which it is parked, which we refer to as the 'fixed random' scenario. Once the charging profiles are determined, the power system model, consisting of objective function (1) and constraints (2) through (15), is solved to determine power system operations, using equation (26) to fix the charging loads.

The delay rebate scenario assumes time-invariant electricity rates, but that PHEV owners are given an incentive for allowing the SO to control PHEV charging between the last trip of the day and the first trip of the following morning. This scenario represents a case in which PHEV owners have controllable charging stations at home and a financial incentive to allow the SO to control charging. Because of the time-invariant electricity rate this scenario results in PHEV owners charging their vehicles whenever they are plugged in midday but, due to the incentive, allowing the SO to delay PHEV charging overnight between the last and first trip of each day. We model this case in the same way as the controlled scenario, except that charging variables for each driving profile between trips in the middle of the day are fixed based on the fixed immediate scenario.

The TOU scenario assumes that PHEV owners face time-variant electricity rates that are set *ex ante*. We assume that the tariff has a simple form, with two different electricity rates that apply to charging loads during different hours. Figure 1 shows the average per-vehicle diurnal charging profiles under the controlled charging scenario and with the fixed and delay rebate tariffs. We assume that the TOU tariff is designed to incent charging patterns that closely approximate controlled charging. This is done by setting a lower electricity price between 5 am and 7 am and a higher price in the remaining hours. Since electricity is a less-costly transportation fuel than gasoline, we do not need to explicitly determine the rates levied in the TOU tariff—we must simply identify the hours in which the price of electricity will be lower. The effect of this tariff, which is shown in figure 1, is that there is still midday vehicle charging, but overnight charging is delayed to between 5 am and 7 am to exploit the lower electricity price.

Figure 1 Average hourly per-vehicle PHEV charging [kWh] with controlled charging and fixed, delayed rebate, and TOU tariffs.



RTP assumes that drivers pay a time-variant price that is set dynamically based on the actual hourly marginal cost of energy for vehicle charging. Specifically, we assume that the prices are set equal to the dual variables associated with load-balance constraints (2) in the SO's power system model.

2.4. Emissions Model

Our analysis considers three different emissions—CO_2, SO_2, and NO_x. Since NO_x is an ozone precursor, we divide NO_x emissions into those during an ozone season (May through September) and those during a non-ozone season (the remaining months). Four separate emissions sources are considered in our analysis: generator, upstream-generator, tailpipe, and refinery emissions. Generator emissions are estimated using input emissions rates, which specify the mass of each pollutant released per unit of fuel burned. Input-based rates are preferred to output-based rates, which give emissions per unit of electricity generated, since they capture differences in the efficiency of generators operated at part-load and emissions associated with generator startups. The rates are estimated using continuous emissions monitoring system data for 2005 obtained from the U.S. Environmental Protection Agency (EPA). To capture differences in the efficacy of emissions controls when generators are operated at part-load, we model NO_x emissions using an emissions rate that is a function of the operating point of a generator, as described by Sioshansi and Denholm (2009). We also use two NO_x emissions rate estimates—one for the ozone season and the other for the non-ozone season. This reflects the fact that emissions controls may only be used when NO_x restrictions are put into place during the ozone season. Upstream-generator emissions include emissions associated with the extraction and transportation of generator fuels, and are based on estimates of Spath et al. (1999) and Denholm et al. (2005).

Tailpipe emissions are direct vehicle emissions due to gasoline combustion. CO_2 emissions are based on the carbon content of gasoline, and are estimated at about 2.34 kg per liter of gasoline. We use the EPA's Tier2 requirement, described in EPA (2000), that gasoline sulfur content be below 30 ppm to estimate tailpipe emissions of SO_2, which amounts to about 0.044 g per liter of gasoline. Tier2 also requires that tailpipe emissions of NO_x be below 0.044 g per km driven. In computing tailpipe emissions of NO_x we assume that CVs and HEVs will be designed to exactly meet this requirement. Following EPRI (2007b) and Sioshansi and Denholm (2009), tailpipe emissions of NO_x from PHEVs are derived from HEV emissions using a linear reduction based on the reduction in gasoline consumption, where gasoline usage by HEVs are derived using the same driving profile data and vehicle simulator model. Refinery emissions account for gasoline refining and transportation, and are estimated using the GREET model described by Wang et al. (2007).

3. Results

3.1. Cost Impacts of PHEVs

Table 1 summarizes annual generation costs with and without the PHEV fleet under the different charging scenarios. The total generation costs include all of the costs in objective function (1). The incremental cost for each scenario is computed as the difference in total generation costs with and without PHEVs, and is given as a total and per-vehicle value. The table shows that controlled charging minimizes generation costs—*e.g.* a fixed tariff more than doubles charging costs. Figure 1 shows the important difference in the controlled and fixed tariff charging profiles—a fixed tariff results in more charging between 4 pm and 10 pm, after drivers arrive home, whereas controlled charging tends to delay this until later in the evening between 1 am and 6 am of the following day.

Table 1 Annual generation costs with and without PHEVs under different charging scenarios.

Scenario	Total [$ billion]	Incremental Total [$ million]	Incremental Per-Vehicle [$]
No PHEVs	12.434		
PHEVs			
Controlled	12.442	8	116
Fixed Immediate	12.455	21	277
Fixed Random	12.452	18	243
Delay Rebate	12.446	12	166
TOU	12.452	18	240
RTP	12.461	27	366

These differences in diurnal charging patterns result in different generation mixes being used to serve the charging loads. The two primary generating fuels in ERCOT in 2005 were coal and natural gas, which accounted for about 20% and 71%, respectively, of system capacity. Because of this mix and fuel costs, natural gas tends to be the marginal generating fuel during the day and early evening whereas coal is marginal overnight.[3] Table 2 summarizes the breakdown of fuels used for the PHEV charging load. This breakdown is defined as the incremental change in generation between the PHEV and no-PHEV cases. The table shows that about 78% of the charging load is served by natural gas-fired generation in the controlled case as opposed to at least 93% with a fixed tariff. These differences contribute to the higher generation costs with a fixed tariff—natural gas-fired generation in ERCOT has an average cost of nearly \$88/MWh as opposed to only \$19/MWh for coal.

Table 2 Breakdown of generation fuels use for PHEV charging loads.

	Charging Load Breakdown [%]	
Scenario	Natural Gas	Coal
Controlled	77.8	22.2
Fixed Immediate	99.6	0.4
Fixed Random	93.6	6.4
Delay Rebate	83.2	17.0
TOU	79.6	20.4
RTP	61.7	38.3

The delay rebate tariff reduces generation costs relative to a fixed tariff by delaying overnight charging. Figure 1 shows that the delay rebate and fixed immediate scenarios result in similar midday charging profiles, but most of the late afternoon charging loads are shifted to early morning hours of the following day with the delay rebate. There is less overnight charging done with the delay rebate compared to the controlled case, however, since PHEVs tend to have a higher SOC at the end of the day. Nonetheless, the control allowed by the delay rebate reduces the amount of natural gas-fired generation used compared to a fixed tariff, giving the cost savings.

TOU pricing alleviates some of the cost increases from a fixed tariff, although not as effectively as the delay rebate. The tiered structure of TOU prices incents PHEV owners to reduce midday charging and to delay charging at the end of the day. Midday charging is reduced because drivers will only want to charge their vehicles with enough electricity for any subsequent midday driving trips, in order to exploit the lower rate levied overnight. After the final vehicle trip of the day, drivers opt to delay charging until 5 am to 7 am, as their driving habits allow, to take advantage of the lower price of electricity during those hours.

Comparing diurnal charging patterns with the delay rebate and TOU tariffs reveals tradeoffs in terms of how they compare to the controlled and fixed price cases. A TOU tariff reduces midday charging and delays charging overnight compared to a fixed tariff, but the ‘blunt’ nature of the tiered prices yields a peak in vehicle recharging at 5 am, which is much higher than under controlled charging. The delay rebate tariff, by contrast, results in greater midday charging but allows better coordination between charging and power system operations overnight. Sioshansi and Denholm (2009) show that with controlled charging the SO can time PHEV charging to allow the use of more efficient generators to serve the non-PHEV load. Without the PHEV loads these more efficient generators could not be used due to the interaction of minimum load, ramping, and minimum up- and down-time constraints. Table 3 shows these effects by summarizing the average incremental heat rate, which is defined as the difference in fuel burned between the PHEV and no-PHEV cases divided by the change in generation, under the different scenarios. The table shows that the controlled and delay rebate cases have low heat rates compared to the other scenarios, due to the coordination between charging and generator commitments overnight. These heat rates and the low generation costs in the controlled and delay rebate cases show that from an efficiency standpoint, coordinating PHEV charging with generator commitment is more important than curtailing midday vehicle charging.

Table 3 Average incremental generator heat rate.

Scenario	Heat Rate [kJ/kWh]
Controlled	5,714
Fixed Immediate	10,446
Fixed Random	9,361
Delay Rebate	7,076
TOU	10,209
RTP	16,211

Surprisingly, RTP performs poorly compared to the other tariffs on the basis of generation costs. Table 4 summarizes how generation costs breakdown between the three cost components, showing that while variable generation costs are lower with RTP than all of the other cases considered, generator startup costs are higher. This shows that RTP is able to properly signal the marginal cost of energy to PHEV owners, but does not convey the non-convex startup cost component. As discussed by O'Neill et al. (2005), this is an inherent limitation of using linear prices in a system with non-convexities, such as power systems. The RTP charging patterns force an average of about 6.4 generator startups per day, as opposed to between 2.4 and 2.7 startups in the other scenarios. These additional generator startups also explain the significantly higher incremental heat rate with RTP compared to the other scenarios shown in table 3.

Table 4 Breakdown of generation cost with PHEV charging loads added.

	Cost Component [$ million]		
Scenario	Variable	Spinning	Startup
Controlled	10,613	1,813	15.561
Fixed Immediate	10,660	1,778	16.205
Fixed Random	10,659	1,777	15.516
Delay Rebate	10,654	1,778	15.017
TOU	10,655	1,781	16.538
RTP	10,543	1,873	45.712

Although PHEVs increase generation costs, there is a countervailing reduction in gasoline consumption. Table 5 summarizes average annual per-vehicle charging and gasoline costs for PHEVs and CVs. The charging costs are the per-vehicle costs reported in table 1. The table shows that PHEVs have lower driving costs than CVs under all of the charging scenarios, but that the cost savings from PHEV use vary considerably between the cases. It is important to note that the generation costs in table 5 are the incremental cost of adding the charging load. Since we have not specified what exact rates would be levied on charging energy, except in the RTP case, these costs may not be borne by PHEV owners. Thus, these values represent the social cost of PHEV use, as opposed to the private cost to PHEV owners.

Table 5 Annual per-vehicle driving costs [$] of CVs and PHEVs under different charging scenarios.

Scenario	Cost Component Gasoline	Electricity	Total
CV	1,193	0	1,193
PHEV			
Controlled	308	116	424
Fixed Immediate	299	277	576
Fixed Random	299	243	542
Delay Rebate	299	166	465
TOU	299	240	539
RTP	302	366	668

3.2. Emissions Impacts of PHEVs

Figures 2 through 4 summarize the breakdown of annual net per-vehicle emissions of CO_2, SO_2, and NO_x, respectively. Figure 2 shows that PHEVs have lower CO_2 emissions than CVs under all of the charging scenarios, but that CO_2 emissions vary between the cases. The differences in CO_2 emissions are largely due to the amount of coal used to serve the charging load—coal releases about 92 kg of CO_2 per GJ as opposed to about 51 kg/GJ from natural gas—although generator efficiencies also play a role. The effect of generator efficiencies is seen by noting that the fixed immediate case gives higher generator CO_2 emissions compared to the controlled, fixed random, and delay rebate cases, despite using less coal-fired generation. This is because of the higher incremental generator heat rate in the fixed immediate case, which is shown in table 3. As such, even though the fixed immediate case uses natural gas for PHEV charging, the less-efficient generators that are used completely offsets the emissions benefit of using natural gas. When efficiency differences are taken into account, the output-based emissions rate of the additional natural gas-fired generation in the fixed immediate case is about 539 kg/MWh, as opposed to only 318 kg/MWh with the delay rebate. RTP yields the highest generator CO_2 emissions due, in part, to this phenomenon. Table 2 shows that RTP has the most coal-fired generation among the cases we consider. However, the fuel used for generator startups yields an incremental heat rate of about 19,080 kJ/kWh for natural gas-fired generators, giving an incremental output-based emissions rate of about 936 kg/MWh.

Figure 2 Total annual per-vehicle emissions of CO_2 [tonnes] from CVs and PHEVs under different charging scenarios.

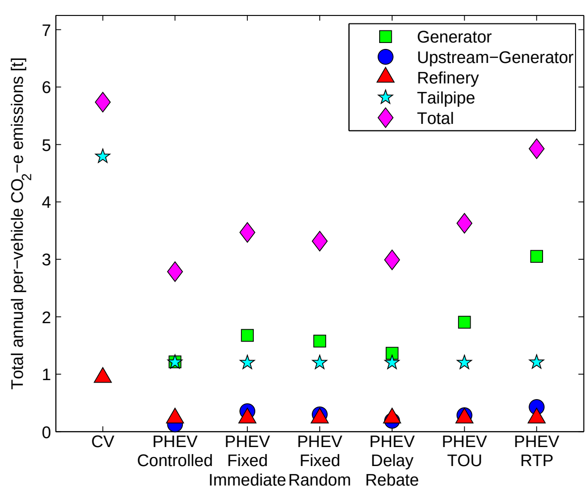


Figure 3 Total annual per-vehicle emissions of SO_2 [kg] from CVs and PHEVs under different charging scenarios.

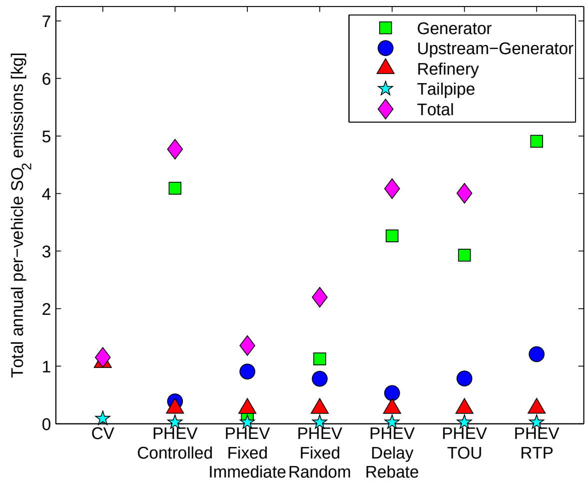


Figure 4 Total annual per-vehicle emissions of NO_x [kg] from CVs and PHEVs during the ozone and non-ozone seasons under different charging scenarios.

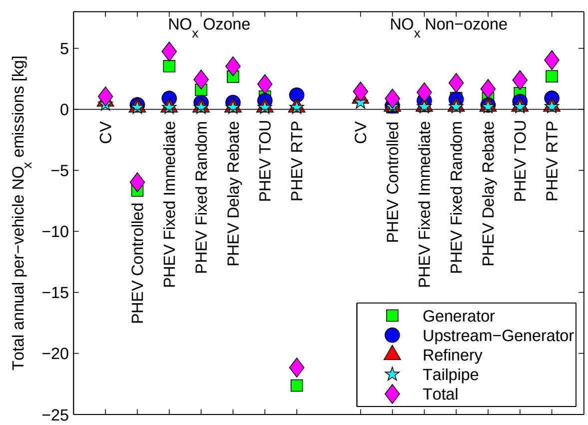


Figure 3 shows that increases in generator SO_2 emissions completely swamp gasoline-related reductions, resulting in higher net SO_2 emissions from PHEVs than CVs. The fixed immediate case has the lowest SO_2 emissions due to almost all of the charging load being served by natural gas and the relatively low sulfur content of natural gas. Coal in ERCOT releases between about 0.4 and 1.4 kg of SO_2 per GJ as opposed to about 0.0007 kg/GJ from natural gas. The higher SO_2 emissions in the other scenarios are due to coal serving larger portions of the PHEV charging load. These SO_2 results are somewhat specific to ERCOT and the eastern U.S., due to the relatively high sulfur content of coal from these regions. Parks et al. (2007) model PHEV-related emissions in Colorado, and they find that up to a third of the charging load is served by coal-fired generation. Nevertheless, their analysis shows that net SO_2 emissions from PHEVs would be below CV and HEV emissions, due to the significantly lower sulfur content of the coal from the western U.S. that is used in Colorado.

Figure 4 shows net NO_x emissions, broken down between the ozone and non-ozone seasons. Generator emissions of NO_x decrease in the controlled and RTP cases, despite the fact that more electricity is generated. This implies that PHEV use reduces NO_x emissions in these cases. These reductions in generator NO_x emissions are due to the effect of the PHEV charging loads on changing the set of generators that are committed. In the controlled case the SO is able to coordinate charging and system operation decisions to commit more efficient generators, whereas generators must be cycled with RTP since the linear energy price does not signal generator commitment costs. Table 6 summarizes this effect of the PHEV loads on generator NO_x emissions by breaking the generators into two sets: those with a net increase in generation when PHEVs are added, and those with a net decrease. The table shows that when PHEVs are added in the controlled and RTP cases, nearly 2 TWh and 4 TWh, respectively, of load is shifted from one set of generators to another. The table shows that these loads are shifted to generators with lower NO_x emissions rates. The table also includes the average incremental heat rate of the two generator sets, showing that loads are shifted to lower-heat-rate generators in the controlled case whereas RTP has the opposite effect. These NO_x reductions are somewhat serendipitous, in that the load shifting is done purely for economic reasons to minimize generation costs. Figure 4 also shows that the NO_x reductions are concentrated during the ozone season, during which the effect of NO_x would be greatest. In the other charging scenarios PHEVs have higher net NO_x emissions than CVs. The differences in generator emissions among these cases are primarily due to the limited delaying of PHEV charging loads in the fixed random, delay rebate, and TOU cases.

Table 6 Net annual change in generation [GWh], fuel burned [GJ], and NO_x emissions [t] for generators with a net decrease and net increase in generation between PHEV and no-PHEV cases, under controlled charging and RTP.

Controlled Charging

	Net Decrease Generators	Net Increase Generators
Δ Generation [GWh]	-1,903	2,137
Δ Fuel Burned [GJ]	-20,308,949	21,643,437
Δ NO_x Emissions [t]	-1,095	604
Input NO_x Emissions Rate [g/GJ]	53.9	27.9
Output NO_x Emissions Rate [g/MWh]	575.4	282.6
Heat Rate [kJ/kWh]	10,672	10,128

RTP

	Net Decrease Generators	Net Increase Generators
Δ Generation [GWh]	-4,088	4,321
Δ Fuel Burned [GJ]	-45,120,802	48,904,973
Δ NO_x Emissions [t]	-2,943	1,433
Input NO_x Emissions Rate [g/GJ]	65.2	29.3
Output NO_x Emissions Rate [g/MWh]	719.9	331.6
Heat Rate [kJ/kWh]	11,037	11,318

4. Discussion and Conclusions

Comparing net PHEV costs and emissions under the different scenarios shows that charging decisions, and the effect of electricity tariffs on them, can greatly influence the impacts of PHEV use. Depending on the timing of PHEV charging, different generating fuels or technologies may be marginal. Our results show that although RTP may intuitively be the most attractive tariff, the inability of linear prices to signal non-convex generator costs cause it to perform worse than the other tariffs—including a fixed price—on every metric, except for NO_x emissions. This finding is important in light of a number of analyses, including those of Denholm and Short (2006), EPRI (2007a), Parks et al. (2007), and Sioshansi and Denholm (2009, 2010), that assume the SO can indirectly control charging through RTP.

Comparing the delay rebate and TOU cases shows the relative impacts of midday and overnight charging on generation costs. The TOU tariff reduces midday charging but yields a peak in overnight charging, whereas the delay rebate allows SO control of charging overnight. The fact that the TOU tariff results in much higher costs suggests that coordinating overnight charging is more important in minimizing PHEV costs. Midday charging could become a more important factor, however, with a larger PHEV fleet. This is because midday charging could contribute to or extend the system peak, and may necessitate generation, transmission, or distribution expansions. Our analysis does not account for transmission constraints, which Wang et al. (2010) show can cause locational differences in charging costs. We do not account for distribution-level constraints either, which Mohseni and Stevie (2009) suggest can become an issue due to possible clustering of PHEV owners.

Although the fuel mix used to serve the charging load will influence PHEV emissions, generator efficiencies can also play a role. The fixed immediate case has higher generator CO_2 emissions than the controlled, fixed random, and delay rebate cases, due to high heat rates of the incremental natural gas-fired generators. This finding also reinforces the importance of using input- as opposed to output-based rates to accurately model emissions.

While the particular cost and emissions values reported here are specific to ERCOT, the results are illustrative of issues that will arise in integrating electrified vehicles into power systems. In 2005 coal and natural gas were the predominant marginal generating fuels in ERCOT. Texas now has close to 10 GW of wind, which is about 10% of installed capacity. Increased renewable penetrations can have mixed effects on PHEV impacts. At lower penetrations, adding more renewables to ERCOT will tend to displace higher-cost natural gas-fired generation. This will yield more hours in which coal is the marginal generating fuel. Thus PHEV-related costs could decrease while emissions increase, relative to the case that we examine. Moreover, if coal is the marginal generating fuel in a greater number of hours, there would likely be smaller cost and emissions differences between the charging scenarios than we estimate. At higher penetrations, there will increasingly be hours during which renewable generation is marginal. Coordinating vehicle charging with availability of excess renewable energy can substantially reduce PHEV impacts compared to our estimates, since these technologies have zero or low marginal costs and emissions. Better coordination between PHEV charging and power system operations may also prove beneficial in terms of renewable integration, as shown by Marano and Rizzoni (2008) and Papavasiliou and Oren (2008). While there are presently many hours in which wind is marginal in ERCOT, these arise due to transmission constraints that prevent wind from west Texas being delivered to load centers in the east. Since PHEVs are unlikely to be in the west in significant numbers they may, at present, have a limited ability to absorb excess renewable energy. Thus the impact of the additional wind will likely be to decrease the cost and increase the emissions of PHEVs relative to our estimates based on 2005 system data. Further analyses of PHEVs, which incorporate extremely high renewable penetrations, greater system transmission capacity, and ERCOT's newly adopted nodal congestion management system, will be necessary to examine these effects. Since our focus is the effect of electricity tariffs on PHEV impacts, we do not focus on modeling these future interactions between PHEVs and renewables.

On the other hand, EPRI (2007a) considers the effect of PHEV loads on long-term generation investments and finds that coal may make a large portion of the future generation mix. Given coal's low cost but high carbon and sulfur content, this could result in PHEVs having lower costs and higher emissions under all of the charging scenarios than we have estimated here. Moreover, if sufficient coal capacity is installed in ERCOT, coal may become the marginal generating fuel during a greater number of hours, which could reduce the cost and emissions differences between the charging scenarios.

Regardless of the underlying generating mix, flexibility in scheduling charging loads will generally allow for more efficient commitments, due to intertemporal generator constraints. PHEV impacts will tend to be more sensitive to the timing of charging loads in systems that have different marginal generating fuels by time of day. Such systems are common in the U.S. and abroad. In other systems, the marginal generating fuel will not vary but the generating technology may. For instance, in California natural gas-fired generation is almost always marginal. Nevertheless, McCarthy and Yang (2010) show that PHEV costs and emissions will vary depending on when they are charged, which determines whether combined- or open-cycle generators serve the charging load.

Another question that warrants further investigation is the interaction between tariff design and PHEV use. We use exogenous driving patterns that do not respond to tariffs in our analysis. If customers become accustomed to persistent electricity price patterns they may adjust their driving habits to exploit lower-cost energy. Such changes in driving patterns would likely be second-order effects, however, since drivers ultimately have constraints on when vehicle trips must be made during the day. Thus our use of exogenous driving patterns is a reasonable assumption, although more detailed study of PHEV driving patterns may reveal interesting price responsive effects. Our vehicle model assumes that drivers rationally optimize charging decisions to minimize driving costs. While this is likely a sound assumption, it can neglect the effects of cost allocation on charging decisions. For instance, complimentary use of charging stations at workplace parking lots can incentivize midday as opposed to overnight charging—such behavior has been observed in an empirical study of PHEV use conducted at The Ohio State University. In such a case midday charging with TOU and RTP tariffs would be higher than our results show. Conversely, drivers may not have access to charging stations midday, in which case vehicles would only be charged overnight. Our comparison of the delay rebate and TOU cases suggest, however, that midday charging is less important than overnight charging in determining the impacts of PHEVs. We assume that the charging stations have a power capacity of 5 kW, which is a mixture of a standard and appliance outlet. If PHEVs instead connect to a standard 1.2 kW wall outlet, the differences in impacts between the charging scenarios would likely be reduced. This is because the tighter constraint on PHEV charging will limit the extent to which charging profiles could differ between the scenarios. On the other hand, differences in the aggregate PHEV charging load will increase with the size of the PHEV fleet. Thus our assumption of a higher power capacity can be thought of as a worst-case scenario, compared to having all vehicles charge using standard wall sockets.

Finally, it is important to note that we only consider four price tariffs, and that there may be others that would be more effective in mitigating the adverse effects of PHEVs that we find. For instance, we assume that the TOU tariff has two price tiers and is designed to yield charging profiles that mirror the controlled case. In doing so, the tariff yields a spike in the charging loads when the lower-price tier comes into effect. A tariff with multiple tiers or combining the two-tier tariff with the uniform charging assumption of the fixed random case may provide better results. This charging spike could also be alleviated by refining the charging model to better account for actual consumer charging decisions and intertemporal dynamics. A latent response model could better reflect consumer behavior, since they may not immediately respond to prices. Such a modeling approach could alleviate some of the issues this analysis highlights with respect to TOU and RTP tariffs. Nevertheless, the scenarios that we consider represent a wide swath of possible tariffs and highlight their pros and cons.

Endnotes

1. O'Neill et al. (2005), Sioshansi et al. (2008), and Sioshansi et al. (2010b) provide a detailed discussion of the types of non-convexities inherent in power systems and the limitations and inefficiencies associated with linear prices applied in electricity markets.
2. Tulpule et al. (2010) discuss energy control strategies as they relate to PHEVs.
3. Our analysis uses fuel prices from 2005, during which natural gas averaged \$9.17/GJ. Natural gas prices have since dropped by close to 40%. Even with these price reductions, coal-fired generation

is still considerably less expensive than natural gas, and the marginal generation patterns would not be affected.

Acknowledgments
The author would like to thank Shmuel Oren, Paul Denholm, Armin Sorooshian, Tony Markel, the editors, and two referees for helpful comments and suggestions. Tony Grasso of the Public Utility Commission of Texas provided invaluable assistance in gathering ERCOT market and system data.

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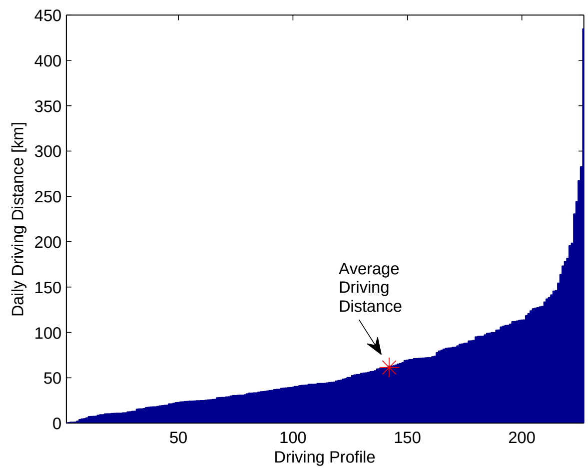
Details of Vehicle Modeling and Charging Assumptions

EC.1. Vehicle Data

Vehicle driving patterns are based on a household travel survey conducted by the East-West Gateway Coordinating Council, details of which are given by EWGCC (2003a,b). The vehicle survey uses global positioning system data to track the second-by-second driving patterns of 227 vehicles over the course of a number of days. The PHEV fleet that we model is assumed to be uniformly divided into groups corresponding to the 227 surveyed vehicles. We further assume that PHEVs within each of the 227 groups have identical charging profiles. We assume that for a PHEV to be grid-connected in an hour it must not be driven for the entire hour. This assumption reduces potential charging time by about 18% compared to if we allow PHEVs to connect for less than an hour at a time. Figure EC.1 shows the distribution of the total daily distance driven among the 227 driving profiles. The median and mean daily driving distances are about 44 km and 61 km, respectively.

Figure EC.1 Distribution of total daily distance driven [km] among the 227 driving profiles.



The batteries in the PHEVs are assumed to have a 9.4 kWh energy capacity, which will yield a CD driving range of about 35.9 km, depending on the vehicle class and driving behavior. EPRI (2001, 2005) and Tate et al. (2008) provide further details regarding battery energy requirements for PHEVs. Table EC.1 summarizes the PHEV characteristic assumptions used in the analysis. For purposes of comparison, the Chevrolet Volt, which is a PHEV, has a 16 kWh battery pack giving it an EPA-tested all-electric driving range of about 56 km. The Nissan Leaf is a pure electric vehicle with a 24 kWh battery pack and an EPA-tested driving range of about 117 km. Further details of the PHEV assumptions are given by Gonder et al. (2007), to which interested readers are referred.

Table EC.1 PHEV characteristic assumptions.

Characteristic	Value
Battery Energy Capacity	9.4 kWh
Vehicle Mass	1488 kg
CD-Mode Range	35.9 km
Energy Use Over Average Drive Cycle	23 km/l and 59 Wh/km
CD-Mode Electric Energy Use	0.183 kWh/km

EC.2. Charging Assumpion

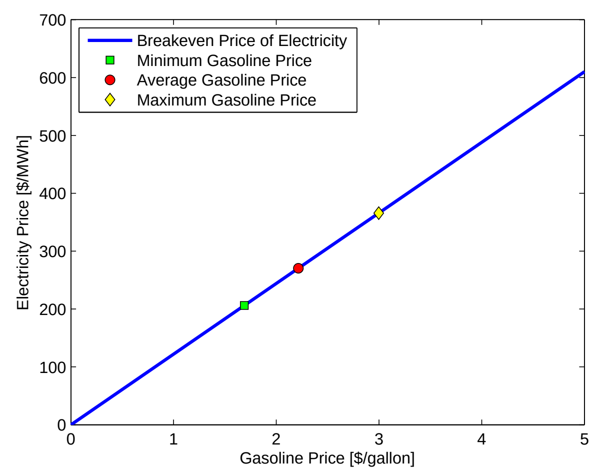
We assume in the fixed rate, delay rebate, and TOU cases that vehicle charging decisions are made by PHEV drivers, using the vehicle model, consisting of objective function (16) and constraints (17) through (25).

Under the fixed tariff, the electricity prices, π_t^e, in the objective function are the same in every hour. Typically, fixed retail rates are determined on an annual or less-frequent basis and are set such that the total expected revenues earned from energy sales cover expected costs associated with electricity service. For the purposes of our analysis, the specific value of the energy price does not need to be determined. This is because with a fixed tariff, PHEV owners will only be concerned with whether electricity is a more economic transportation fuel than gasoline. If it is, then it will be cost-minimizing for them to recharge their vehicles whenever possible, due to the time-invariant electricity tariff. Figure EC.2 shows the breakeven price of electricity as a transportation fuel, as a function of the price of gasoline. The breakeven price is defined as:

$$\frac{\pi_t^g \cdot (\gamma^{cs} - \gamma^{cd})}{b^{cd}}, \tag{EC.1}$$

and specifies the price of electricity, below which electricity is a less-expensive transportation fuel than gasoline. Equation (EC.1) includes the parameters γ^{cs}, γ^{cd}, and b^{cd}, which account for the relative efficiency of driving in CD mode as opposed to CS mode, which in turn depends on the efficiencies of the electric and internal combustion engines in the PHEV. The figure shows that for the range of gasoline prices in 2005, so long as the retail price of electricity is below \$206/MWh, electricity is a more economic transportation fuel. Given the fact that retail electricity rates in Texas in 2005 averaged \$73.67/MWh, PHEV owners would always opt to recharge their vehicle batteries whenever they are grid-connected.

Figure EC.2 Breakeven price of electricity [\$/MWh].



Midday charging behavior under the delay rebate tariff will be identical to the fixed rate tariff, since PHEV owners are assumed to pay a time-invariant electricity price. Because consumers receive a rebate for allowing the SO to control charging between the last trip of each night and the first trip of the following morning, we assume the PHEV owners will give the SO this control.

In the TOU pricing scenario different hours of the day have different prices that are set *ex ante*. We assume that the TOU tariff will consist of two different pricing blocks, with a comparably lower rate levied on charging loads between 5 am and 7 am and higher rates on charging during other hours. As with a fixed tariff, the actual prices would be determined such that expected energy revenues equal expected costs. We can again appeal to the high breakeven cost of electricity shown in figure EC.2, which implies that the exact electricity prices do not need to be determined. So long as 'reasonable' electricity prices below \$206/MWh are levied during the two periods, electricity will necessarily be a more economic transportation fuel than gasoline. Thus we model vehicle charging with the TOU tariff by using small arbitrary values for π_t^e during the low-price hours, and relatively high values for π_t^e during the high-price hours in objective function (16). The net effect of the TOU tariff will be that during hours in which the price of electricity is high, PHEV owners will only recharge their vehicle batteries to provide enough energy for any subsequent vehicle trips before the low-price period. During the low-price period, PHEV owners will fully recharge their vehicle batteries to exploit the relatively low price.