Plug-in Hybrid Electric Vehicles Can Be Clean and Economical in Dirty Power Systems☆

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Abstract

Plug-in hybrid electric vehicles (PHEVs) that are driven and charged in 'dirty' power systems, with high penetrations of coal and other polluting generation fuels, may yield higher net emissions than conventional vehicles (CVs). We examine the implications of imposing a constraint on PHEV recharging that forces emissions from PHEVs to be no greater than those from a comparable CV. We use the Texas power system, which has a mix of coal- and natural gas-fired generation and has been shown to yield higher emissions from PHEVs than CVs, as a case study. Our results show that imposing the emissions constraint results in most of the PHEV charging loads being shifted from coal- to cleaner natural gas-fired generators. There is, however, virtually no increase in generation or PHEV driving costs due to efficiency benefits that are possible through coordination of unit commitment and PHEV charging decisions.

Keywords: Plug-in hybrid electric vehicle (PHEV), emissions, unit commitment

1. Introduction

Plug-in hybrid electric vehicles (PHEVs) have been offered as alternatives that can reduce driving costs relative to conventional and hybrid electric vehicles (CVs and HEVs). These savings stem from the fact that PHEVs have larger batteries than HEVs that can be charged from the electric power system, and give the vehicles a limited 'electric-only' driving range. Due to the abundance of low-cost generating capacity, especially overnight, electricity can be a less costly transportation fuel than gasoline, when the relative driving efficiencies of electric motors and internal combustion engines are taken into account. The actual cost savings from PHEV use will depend on the generation mix in the power system. This is because of differences in the cost of generating fuels, for instance between coal and natural gas. Diurnal PHEV charging patterns will also affect charging costs, because different generation fuels are marginal and would serve the charging loads at different times of day. PHEV economics in a number of power systems in the United States has been examined, including by Parks et al. (2007), who model the Xcel service territory in Colorado, Sioshansi and Denholm (2010), who model the ERCOT (Texas) power system, Sioshansi et al. (2010), who model the state of Ohio, and Wang et al. (2010), who model the PJM system. EPRI (2007a,b) examines the impacts of PHEVs across the United States over a 40-year period from 2010 to 2050. These analyses all show PHEVs to be less costly alternatives, on the basis of driving cost, than CVs and HEVs.

The net emissions impacts of PHEVs, when accounting for emissions associated with vehicle charging loads, are more mixed and will again depend on the generation mix of the power system and the timing of PHEV charging. Parks et al. (2007) show that PHEVs in Colorado will yield lower CO_2, SO_2, and NO_x emissions than HEVs and CVs. EPRI (2007a,b) shows that while PHEVs will yield substantially lower greenhouse gas (GHG) emissions than HEVs and CVs, they will have more modest effects on NO_x and SO_2 and can lead to increases in mercury and particulate emissions. McCarthy and Yang (2010) model PHEV GHG emissions in California, showing the range of possible emissions rates depending on the timing of PHEV charging. Hajian et al. (2009) show similar GHG reductions in Alberta, Canada, and also examine the effect of varying amounts of wind generation being added to the system. Elgowainy et al. (2009) model GHG emissions from PHEVs in three North American Electric Reliability Corporation regions, which encompass major metropolitan areas. Their results show differences in GHG emissions between the different regions, but that PHEVs will offer GHG reductions relative to CVs and HEVs. Sioshansi and Denholm (2009) model PHEV emis-

sions in Texas, and show that while CO_2 and NO_x emissions will be lower than a CV, net SO_2 emissions would be more than 50 times higher than a CV due to the use of coal-fired generation for PHEV charging. Sioshansi et al. (2010) model PHEVs in Ohio, which has a coal-dominated power system, and show similar SO_2 increases as well as higher NO_x emissions.

Emissions of SO_2 and NO_x in the United States are capped by Federal legislation and regulations, including Title IV of the Clean Air Act and the NO_x State Implementation Plan (SIP) Call. As such, total emissions of these species may not be able to increase with the introduction of PHEVs.[1] Thus, increases in SO_2 and NO_x emissions due to PHEV charging in systems such as ERCOT or Ohio would have to be offset by reductions elsewhere. Otherwise a constraint would have to be imposed on PHEV charging to ensure that the added loads do not yield higher emissions. In the short term, when the generator set is fixed, the market would react to such a restriction through emissions dispatch. In the case of ERCOT or Ohio, loads that would be served using coal-fired generation would instead be served with natural gas-fired generators. This type of emissions dispatch has been observed in other instances in which emissions regulations have come into force on the electric power industry. Heslin and Hobbs (1989); Talaq et al. (1994) survey and evaluate the costs and benefits of different operational strategies, including emissions dispatch, which can be used to meet such emissions restrictions. Jackson et al. (1993); El-Keib et al. (1994) model the impacts of the Clean Air Act on generator dispatch in the United States. Delarue and D'haeseleer (2007, 2008) explore emissions dispatch as a result of the European Union Emission Trading Scheme (EU ETS), and describe conditions that are necessary for such switching to occur. Delarue et al. (2007, 2008) examine historical EU ETS allowance price data to demonstrate that emissions dispatch took place as a result of the GHG regulations. They also estimate the potential for additional emissions reductions from emissions dispatch with higher allowance prices.

Using the model developed by Sioshansi and Denholm (2009, 2010), we examine the impact of imposing an emissions constraint on PHEV charging in the ERCOT system. We consider two different PHEV charging and emissions constraint scenarios. The charging scenarios that we model are one in which the utility or system operator (SO) can control PHEV charging, and another in which the charging decisions are made by vehicle owners in an uncontrolled fashion. These two scenarios are hereafter referred to as the controlled and uncontrolled charging cases, respectively. The emissions constraint scenarios that we consider are one in which total emissions from the generator fleet cannot increase with the introduction of PHEVs, and another in which reductions in tailpipe emissions (due to lower relative gasoline use by PHEVs) can offset increases in generator emissions. We hereafter refer to these two as the non-offset and offset emissions constraint scenarios, respectively. We compare these two cases to one in which there is no constraint on emissions to estimate the cost of PHEV charging having to comply with SO_2 and NO_x regulations. Our results show that imposing the constraint results in nearly all of the PHEV charging load being served by higher-cost and cleaner natural gas-fired generation, as opposed to some coal-fired generation that is used without the constraint. There is, however, virtually no increase in generation or PHEV driving costs, due to the ability of the SO to coordinate power system unit commitment and PHEV charging decisions to yield generation efficiency gains.

The remainder of this paper is organized as follows: section 2 describes the model and data used in our analysis, section 3 summarizes our results, and section 4 concludes.

2. Model and Data

2.1. Model and Data Overview

Our analysis is based on the unit commitment and vehicle driving model that Sioshansi and Denholm (2009, 2010) develop. The model takes the power system and PHEV fleet characteristics and driving patterns as fixed. In the controlled charging case, the model determines the commitment and dispatch of the generator set as well as when to recharge the PHEVs to minimize the sum of generation and PHEV driving costs. PHEV driving costs are included in the objective function to provide the SO with a proper incentive to recharge the PHEV fleet. Moreover, we also impose a constraint that requires each PHEV battery to be fully recharged in time for the first trip each morning. In the uncontrolled scenario the charging patterns are fixed and the model only determines the commitment and dispatch of the generator set. All of the models are formulated using AMPL 12.1 and are solved using Cplex 12.1 with default settings. We model CO_2, SO_2, and NO_x emissions in our analysis and consider generator and tailpipe emissions sources.

We use the same model data, which are based on the ERCOT system, that Sioshansi and Denholm (2009, 2010) use. The generator set, operating constraints, and cost data, as well as the non-PHEV loads are based on actual data from 2005. The generator set, operating constraint, and cost data are obtained from Ventyx and Platts, which are proprietary data vendors. We include SO_2 allowance costs in computing generation costs, and obtain historical SO_2 allowance costs from Platts. The load data are obtained from ERCOT. We model generator emissions using input-based emissions rates, which compute emissions based on the amount of fuel burned. This use of input-based emissions rates allows us to capture emissions due

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[1] If emissions are already below the cap without PHEVs, then emissions could increase. Since SO_2 allowances have historically been traded and auctioned at strictly positive prices, this suggests that the SO_2 cap is binding. Similarly, the introduction of NO_x regulations have led to reductions in NO_x emissions, also suggesting that the NO_x cap is binding.

to generator startups and differences in generator efficiencies when operated at part load. We estimate emissions rates using continuous emissions monitoring systems data obtained from the United States Environmental Protection Agency (EPA).

We model a case in which 1% of the light duty vehicle fleet in ERCOT are PHEVs. This amounts to 75,750 PHEVs, based on vehicle registration data reported by the United States Department of Transportation's Federal Highway Administration for the year 2005.[2] We assume that the PHEV fleet is driven according to empirical driving data detailed by Gonder et al. (2007), and that the actual driving patterns are fixed based on these data. These data provide second-by-second driving data for 227 study participants, which were obtained using the global positioning system. Figure 1 shows the distribution of average daily driving distances among the 227 study participants, as well as the average daily driving distance of the study population. We assume that the vehicle fleet we model is uniformly distributed between these 227 driving profiles and that all of the vehicles corresponding to each driving profile charge identically in each hour. The empirical driving data are used to determine the hours in which the PHEVs corresponding to each driving profile are driven, and when they are plugged into the grid. We assume that a PHEV is grid-connected in an hour if it is not driven for the entire hour. The driving data are combined with the ADVISOR vehicle simulation tool, which is described by Markel et al. (2002), to determine gasoline and battery energy usage for each of the driving profiles. Table 1 summarizes the assumed characteristics of the PHEVs in the fleet, which are used by Parks et al. (2007). We assume that the PHEVs operate using an electric vehicle-type control. Under such a control, PHEVs are initially driven in a charge-depleting (CD) mode, which uses electricity as the primary transportation fuel. Once the state of charge (SOC) of the battery reaches a preset minimum level, which we assume to be 30%, the PHEV switches to charge-sustaining (CS) mode. When driven in CS mode, the PHEV behaves much like an HEV, using gasoline as the primary transportation fuel and keeping the SOC at the minimum. Once the PHEV enters CS mode, it will remain there until the battery is recharged using grid energy. We assume that all charging stations have a power capacity of 5 kW, and that charging incurs 5% transmission and distribution losses and 10% inverter losses.

Our model is formulated to minimize the sum of all generation costs (*i.e.* the cost of serving the PHEV and non-PHEV loads) and PHEV gasoline costs. Gasoline costs are computed using estimates of gasoline use when the PHEVs are driven in CD and CS modes, obtained from the ADVISOR model, and retail gasoline prices. The gasoline prices
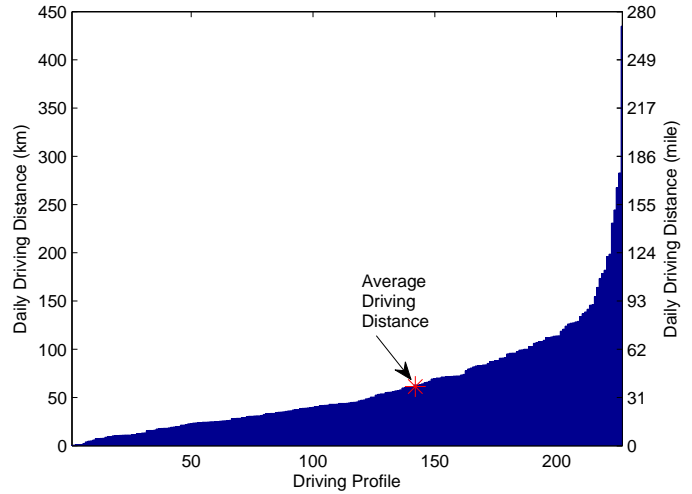
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[2]The data reports vehicle registrations by state. We assume that 85% of the vehicles in Texas are driven within the ERCOT power system, based on the fact that ERCOT serves approximately 85% of the state's population. Thus the 75,750 PHEVs corresponds to 0.85% of light-duty vehicles registered in the state of Texas.

Figure 1: Average daily driving distance of driving profile data used.

Table 1: PHEV Characteristics

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

are based on weekly average prices for the state of Texas in 2005, as reported by the United States Department of Energy's Energy Information Administration. We also use the ADVISOR model to estimate gasoline usage by CVs driven with the same driving profiles that we use to model the PHEVs. Following Parks et al. (2007), we assume that the CVs are comparably sized to the PHEVs and have a fuel economy of about 25 miles per gallon or 11 kilometers per liter. These gasoline usage estimates are combined with the retail price data to estimate the driving cost of a CV, which we use as a benchmark to estimate cost savings associated with PHEV use.

We estimate tailpipe emissions using both the chemical composition of gasoline and relevant environmental regulations. CO_2 emissions are based on the carbon content of gasoline, which gives emissions of about 2.35 kg/liter of gasoline burned. Tailpipe emissions of SO_2 will depend on the sulfur content of gasoline, which will in turn depend on gasoline refining. The EPA's Tier2 rule, which is described by EPA (2000), requires the sulfur content of gasoline to be below 30 ppm. We assume that refiners will exactly meet this requirement, which will give an emissions rate of 0.045 g/liter of gasoline burned. Tailpipe emissions of NO_x will depend to a large extent on vehicle designs, since NO_x emissions can be controlled. Tier2 requires tailpipe emissions of NO_x to be below 0.043 g/km driven. We assume that vehicle manufacturers will design

3

CVs to exactly meet this requirement. Following EPRI (2007b); Sioshansi and Denholm (2009), we assume that HEVs will also be designed to exactly meet this requirement. We then estimate tailpipe emissions from PHEVs based on the percentage reduction in gasoline used by a PHEV relative to a comparable HEV using the same driving profile. This gives an NO_x emissions rate of about 0.673 g/liter of gasoline burned for a PHEV.

2.2. Emissions-Unconstrained Model Formulation

We first give the formulation of the model in the case in which emissions are unconstrained. We use the following notation in the formulation:

T: set of hours in planning horizon;

I: set of generators;

V: set of PHEV driving profiles;

M_v: number of PHEVs driven according to driving profile v;

$C_{i,t}(\cdot)$: generator i's non-decreasing stepped variable generating cost function in hour t;

$N_{i,t}$: generator i's noload cost in hour t;

$SU_{i,t}$: generator i's startup cost in hour t;

K_i^-: generator i's minimum operating point;

K_i^+: generator i's maximum operating point;

R_i^-: generator i's rampdown limit;

R_i^+: generator i's rampup limit;

τ_i^-: generator i's minimum down-time;

τ_i^+: generator i's minimum up-time;

D_t: non-PHEV load in hour t;

$\overline{p}$: power limit of PHEV charging station plug;

$\overline{e}$: maximum energy level of PHEV battery;

$\underline{e}$: minimum energy level of PHEV battery;

π_t^g: cost of gasoline in hour t;

ce: charging efficiency (including transmission, distribution, and inverter losses) of PHEV battery;

$dist_{v,t}$: distance driving profile v drives in hour t;

cd_v^e: average net battery energy usage of driving profile v when operating in CD mode;

cd_v^g: average gasoline usage of driving profile v when operating in CD mode;

cs_v^g: average gasoline usage of driving profile v when operating in CS mode;

$\phi_{v,t}$: binary parameter indicating whether the battery of a PHEV driven according to driving profile v must be fully recharged in hour t;

$q_{i,t}$: generation provided by generator i in hour t;

$u_{i,t}$: binary variable indicating if unit i is online in hour t;

$s_{i,t}$: binary variable indicating if unit i is started-up in hour t;

$h_{i,t}$: binary variable indicating if unit i is shutdown in hour t;

$L_{v,t}$: ending energy level of battery of PHEV with driving profile v in hour t;

$ch_{v,t}$: energy charged into battery of PHEV with driving profile v in hour t;

$cd_{v,t}$: distance driven in CD mode by PHEV with driving profile v in hour t;

$cs_{v,t}$: distance driven in CS mode by PHEV with driving profile v in hour t; and

$\widetilde{cd}_{v,t}$: binary variable indicating whether SOC of PHEV with driving profile v is above minimum at end of hour t.

The objective of the model is to minimize the sum of generation and PHEV gasoline costs:

$$\min \sum_{t \in T} \left\{ \sum_{i \in I} [C_i(q_i) + N_i u_{i,t} + SU_i s_{i,t}] \right. \tag{1}$$
$$\left. + \sum_{v \in V} \pi_t^g M_v [cd_v^g cd_{v,t} + cs_v^g cs_{v,t}] \right\},$$

subject to the following constraints:

$$\sum_{i \in I} q_{i,t} = D_t + \sum_{v \in V} M_v ch_{v,t}/ce, \quad \forall\, t \in T; \tag{2}$$

$$K_i^- u_{i,t} \le q_{i,t} \le K_i^+ u_{i,t}, \qquad \forall\, i \in I, t \in T; \tag{3}$$

$$R_i^- \le q_{i,t} - q_{i,t-1} \le R_i^+, \qquad \forall\, i \in I, t \in T; \tag{4}$$

$$\sum_{y=t-\tau_i^+}^{t} s_{i,y} \le u_{i,t}, \qquad \forall\, i \in I, t \in T; \tag{5}$$

$$\sum_{y=t-\tau_i^-}^{t} h_{i,y} \le 1 - u_{i,t}, \qquad \forall\, i \in I, t \in T; \tag{6}$$

$$s_{i,t} - h_{i,t} = u_{i,t} - u_{i,t-1}, \qquad \forall\, i \in I, t \in T; \tag{7}$$

$$u_{i,t}, s_{i,t}, h_{i,t} \in \{0,1\}, \qquad \forall\, i \in I, t \in T; \tag{8}$$

$$L_{v,t} = L_{v,t-1} + ch_{v,t} - cd^e cd_{v,t}, \quad \forall\, v \in V, t \in T; \tag{9}$$

$$cd_{v,t} + cs_{v,t} = dist_{v,t}, \qquad \forall\, v \in V, t \in T; \tag{10}$$

$$\widetilde{cd}_{v,t} \ge \frac{L_{v,t} - \underline{e}}{\overline{e} - \underline{e}}, \qquad \forall\, v \in V, t \in T; \tag{11}$$

$$cs_{v,t} \le dist_{v,t}(1 - \widetilde{cd}_{v,t}), \qquad \forall\, v \in V, t \in T; \tag{12}$$

$$\underline{e} \le L_{v,t} \le \overline{e}, \qquad \forall\, v \in V, t \in T; \tag{13}$$

4

$$L_{v,t} = \overline{e} \text{ if } \phi_{v,t} = 1, \qquad \forall \ v \in V, t \in T; \quad (14)$$

$$0 \leq ch_t \leq \begin{cases} 0, & \text{if } dist_{v,t} > 0 \\ \overline{p}, & \text{otherwise} \end{cases}, \quad \forall \ v \in V, t \in T; \quad (15)$$

$$0 \leq cd_{v,t}, cs_{v,t}, \qquad \forall \ v \in V, t \in T; \quad (16)$$

$$\widetilde{cd}_{v,t} \in \{0,1\}, \qquad \forall \ v \in V, t \in T. \quad (17)$$

Constraint (2) is the hourly load-balance constraint, which ensures that PHEV and non-PHEV loads are exactly met. Constraints (3) and (4) are hourly generation bounds and ramping limits, respectively. Constraints (5) and (6) impose minimum-up and -down times when generators are started up and shutdown, while constraint (7) defines the startup and shutdown variables in terms of the $u_{i,t}$ variables. Constraint (8) imposes integrality on these variables. Constraint (9) defines the ending energy level in each PHEV battery in terms of the previous level and charging and driving decisions. Constraint (10) ensures that each PHEV drives the required distance in each hour. Constraint (11) defines the $\widetilde{cd}_{v,t}$ variables in terms of the ending charge level of the battery—if the charge level is above the minimum then $\widetilde{cd}_{v,t}$ is forced equal to one. Constraint (12) forces a PHEV to operate in CD mode if the charge level of the battery is above the minimum. Constraint (13) imposes the minimum and maximum energy levels of the PHEV batteries and constraint (14) requires each PHEV battery to be recharged in time for the first trip of each morning. Constraint (15) imposes the power capacity of the charging plug, and also constrains a PHEV to not be charged in any hour in which it is being driven. Constraint (16) imposes non-negativity on the driving variables, and constraint (17) imposes integrality on $\widetilde{cd}_{v,t}$.

The emissions-unconstrained model is given by objective function (1) and constraints (2) through (17). In the controlled charging case $q_{i,t}, u_{i,t}, s_{i,t}, h_{i,t}, L_{v,t}, ch_{v,t}, cd_{v,t}, cs_{v,t}$, and $\widetilde{cd}_{v,t}$ are all decision variables, reflecting the fact that the SO can control the charging of the PHEV fleet. In the uncontrolled case, however, $L_{v,t}, ch_{v,t}, cd_{v,t}, cs_{v,t}$, and $\widetilde{cd}_{v,t}$ are exogenously fixed, and only $q_{i,t}, u_{i,t}, s_{i,t}$, and $h_{i,t}$ are decision variables. In the uncontrolled case we follow the assumption made by Sioshansi et al. (2010) that drivers will immediately charge their vehicles whenever they are not being driven. Because solving this problem using a year-long optimization horizon is intractable, we simplify the model by solving it one day at a time using a rolling two-day optimization horizon. This use of a two-day horizon ensures that generator commitments at the end of each day account for the fact that there will be loads to serve in the future. Without the use of a two-day horizon, generators may be shutdown at the end of each day, incurring expensive generator cycling costs.

2.3. Emissions-Constrained Model Formulation

We analyze the emissions-constrained case using the same basic model, but add a new set of constraints that limit emissions of CO_2, SO_2, and NO_x to not increase as a result of adding the PHEV charging loads. We consider two emissions-constrained cases. In the first, we assume that the reductions in tailpipe emissions due to PHEV use can offset increases in generator emissions. Thus in this case we constrain total emissions with the PHEV fleet (consisting of the sum of generator emissions and tailpipe emissions from the PHEVs) to be less than total emissions with a CV fleet of the same size (consisting of the sum of generator emissions without any PHEV and tailpipe emissions from the CVs). The second emissions-constrained case assumes that tailpipe emissions cannot offset increases in generator emissions. Thus in this case we constrain generator emissions with PHEVs to be no greater than generator emissions without PHEVs.

In order to give the formulation of this model, we first define the following notation:

Λ: set of pollutants to be constrained;

$\xi_i(\cdot)$: generator i's non-decreasing stepped generation heat rate function;

ξ_i^N: spinning fuel used by generator i;

ξ_i^S: startup fuel used by generator i;

$\rho_{i,\lambda}$: emissions of pollutant λ emitted per unit of fuel burned by generator i;

γ_λ: emissions of pollutant λ emitted per unit of gasoline burned by a PHEV;

ω_λ^G: total annual emissions of pollutant λ from all generators without any PHEVs in the system; and

ω_λ^V: total annual emissions of pollutant λ from a CV fleet which is the same size as the PHEV fleet.

In the case in which tailpipe emissions can offset generator emissions, the model would include the following set of constraints:

$$\sum_{t \in T} \left\{ \sum_{i \in I} \rho_{i,\lambda} [\xi_i(q_{i,t}) + \xi_i^N u_{i,t} + \xi_i^S s_{i,t}] \right.$$
$$\left. + \sum_{v \in V} \gamma_\lambda M_v [cd_v^g cd_{v,t} + cs_v^g cs_{v,t}] \right\} \quad (18)$$
$$\leq \omega_\lambda^G + \omega_\lambda^V, \qquad \forall \ \lambda \in \Lambda;$$

whereas in the other case the emissions constraints would be:

$$\sum_{t \in T} \sum_{i \in I} \rho_{i,\lambda} [\xi_i(q_{i,t}) + \xi_i^N u_{i,t} + \xi_i^S s_{i,t}] \quad (19)$$
$$\leq \omega_\lambda^G, \qquad \forall \ \lambda \in \Lambda.$$

Adding either constraint set (18) or (19) to the model couples the 365 days of the year together, making the model intractable to solve. We apply Lagrangian relaxation, which is described by Wolsey (1981), to relax these coupling constraints. If we let $\eta_\lambda \geq 0$ denote the Lagrange multiplier associated with the constraint on pollutant λ, then the objective function of the relaxed problem becomes:

$$
\min \sum_{t \in T} \left\{ \sum_{i \in I} [C_i(q_i) + N_i u_{i,t} + SU_i s_{i,t} \right. \tag{20}
$$
$$
+ \sum_{\lambda \in \Lambda} \eta_\lambda \rho_{i,\lambda} (\xi_i(q_{i,t}) + \xi_i^N u_{i,t} + \xi_i^S s_{i,t})]
$$
$$
+ \sum_{v \in V} [\pi_t^g M_v (cd_v^g cd_{v,t} + cs_v^g cs_{v,t})
$$
$$
\left. + \sum_{\lambda \in \Lambda} \eta_\lambda \gamma_\lambda M_v (cd_v^g cd_{v,t} + cs_v^g cs_{v,t})] \right\},
$$

in the case in which tailpipe emissions can offset generator emissions. In the other case, in which tailpipe emissions cannot offset generator emissions, the objective function is:

$$
\min \sum_{t \in T} \left\{ \sum_{i \in I} [C_i(q_i) + N_i u_{i,t} + SU_i s_{i,t} \right. \tag{21}
$$
$$
\left. + \sum_{\lambda \in \Lambda} \eta_\lambda \rho_{i,\lambda} (\xi_i(q_{i,t}) + \xi_i^N u_{i,t} + \xi_i^S s_{i,t})] \right\}.
$$

The relaxed problem, which consists of objective function (20) or (21) and constraints (2) through (17) can be more easily solved, since it decouples into 365 subproblems, corresponding to each day. These problems can be solved using the same rolling two-day optimization horizon. We use a subgradient algorithm to solve for a near-optimal set of η_λ that give a solution satisfying the emissions constraints with a small duality gap.

3. Results

We begin our analysis by first considering an emissions-unconstrained case, in which the sum of generator and tailpipe emissions of SO_2 and NO_x can increase with the introduction of the PHEV fleet. This case could arise if there are offsetting reductions in SO_2 and NO_x reductions elsewhere in the economy. Otherwise, we use the results of this case as a baseline to estimate the cost of PHEV charging complying with emissions caps, without relying on such offsetting reductions.

3.1. Emissions-Unconstrained Case

3.1.1. PHEV Costs

Table 2 compares generation costs with and without PHEVs in the emissions-unconstrained case. The first row

of the table gives the total annual generation costs under the different scenarios, while the second gives the incremental cost (between the PHEV and no-PHEV cases) when PHEVs are added to the system. These incremental costs represent the added cost to the power system of serving PHEV charging loads. The final row of the table normalizes these costs based on the size of the PHEV fleet, to give the charging cost on a per-vehicle basis. As expected, these charging loads are more expensive in the uncontrolled case since PHEV charging is not co-optimized with power system operations.

Table 2: Annual generation costs with CVs and PHEVs in the emissions-unconstrained case.

	CVs	PHEVs	
		Controlled	Uncontrolled
Total ($ mil.)	12,470	12,476	12,488
Incremental ($ mil.)		7	19
Per-vehicle ($)		92	248

Table 2 summarizes annual CV and PHEV driving costs, which consist of vehicle charging and gasoline costs, in the emissions-unconstrained case. The PHEV charging costs are the incremental generation costs given in table 2, while the gasoline costs of the PHEV fleet are given by the system optimization and ADVISOR models. The costs reported in the table are only for the fleet of 75,750 CVs and PHEVs that we compare to each other, and as such do not represent the driving cost of the *entire* light-duty vehicle fleet in ERCOT. The table provides costs for the PHEV and CV fleets, as well as on a per-vehicle basis. Table 2 shows that PHEVs yield a significant driving cost savings relative to CVs, although greater cost reductions are possible with proper coordination of charging and power system operation decisions in the controlled charging case. With controlled charging, PHEVs are 67% less costly than CVs as opposed to only a 54% savings with uncontrolled charging.

Table 3: Annual CV and PHEV driving costs in the emissions-unconstrained case.

	CVs	PHEVs	
		Controlled	Uncontrolled
Fleet Costs ($ mil.)			
Electricity	0	7	19
Gasoline	91	23	23
Total	91	30	42
Per-Vehicle Costs ($)			
Electricity	0	92	248
Gasoline	1,196	302	301
Total	1,196	393	549

It is important to stress that the electricity costs reported in table 3 represent the *social* cost of PHEV charging, and not necessarily the private cost incurred by PHEV owners. This is because the private cost of PHEV charging will depend on how electricity tariffs are set. If, for instance, PHEV charging loads are priced the same as non-PHEV loads, then the private cost of PHEV driving

will be lower than the costs in table 3. This is because the incremental generation cost when PHEVs are added to the system will be socialized across PHEV and non-PHEV loads.

Table 3 shows that the difference in PHEV driving costs between the controlled and uncontrolled charging scenarios is almost entirely due to differences in generation costs. The uncontrolled scenario yields some small gasoline cost savings, since the uncontrolled scenario results in slightly more midday recharging of about 0.05 kWh per vehicle daily than controlled charging. This difference amounts to only an annual per-vehicle reduction in gasoline cost of $0.95, however. Figure 2 shows the average hourly per-vehicle charging profiles over the course of the year under the two charging cases. As expected, the uncontrolled charging scenario results in the bulk of overnight recharging taking place between 4 and 10 pm, after most commuters arrive home. With the controlled scenario, however, this charging is delayed to later hours overnight when lower-cost baseload generating capacity is available.
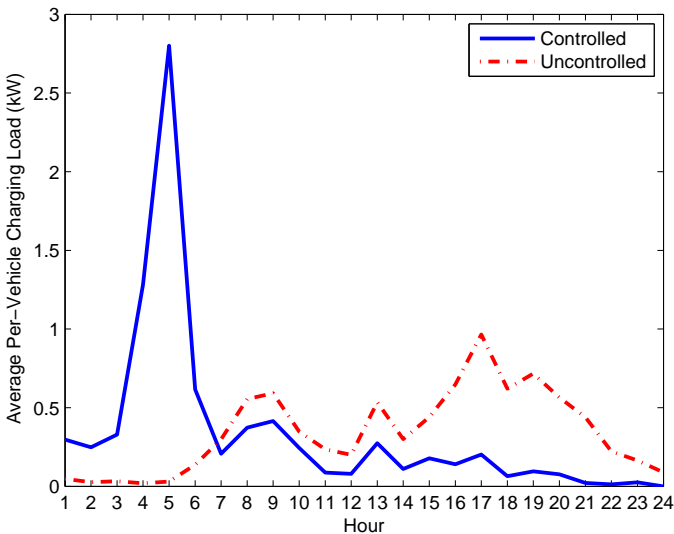

Figure 2: Average hourly per-vehicle charging load (kW) in the emissions-unconstrained case.

Table 4 shows the effect of these differences in the timing of PHEV charging on the breakdown and heat rate of the charging load. The first two rows of the table show the breakdown of the incremental generating load between natural gas- and coal-fired generators under the two charging scenarios. The incremental generating load is defined as the change in generation between the PHEV and no-PHEV case. The table shows that significantly more of the PHEV charging load is served by coal-fired generation under the controlled charging scenario, as a result of the delaying of overnight charging. Almost all of the charging is done using natural gas-fired generation in the uncontrolled case, by contrast, since natural gas is the marginal generating fuel virtually all of the time in late-afternoon and early-evening hours.

Table 4: Breakdown and average heat rate of annual incremental generating load with addition of PHEVs in the emissions-unconstrained case.

	Charging Scenario	
	Controlled	Uncontrolled
Incremental Generating Load (%)		
Natural Gas	73.42	96.72
Coal	26.58	3.28
Incremental Heat Rate (kJ/kWh)		
Natural Gas	3,289	8,976
Coal	11,355	12,207

The last two rows of the table show the average heat rate of the incremental charging load. This is defined as the difference in fuel burned between the PHEV and no-PHEV case, divided by the difference in generation between those cases. The table shows that generation of the charging load in the controlled scenario is significantly more efficient than under uncontrolled charging. These high efficiencies in the controlled case are due to the ability of the SO to time PHEV charging in such a way to shift non-PHEV loads to more efficient generators, and is also observed by Sioshansi and Denholm (2010).

Table 5 demonstrates this effect of the PHEV charging load by breaking the natural gas-fired generators into two sets—those with a net increase and those with a net decrease in generation between the PHEV and no-PHEV cases. The table shows the net change in generation and fuel burned for these two sets of generators between the PHEV and no-PHEV cases. It also shows the average heat rate, which is defined as the change in fuel burned divided by the change in generation. The table shows that non-PHEV loads are shifted between the two sets of generators. This is because the addition of the PHEV charging loads necessitates or allows the SO to shift loads to generators that it could not use without the PHEV loads, due to constraints on generator operations. In the controlled charging case, about 634 GWh of non-PHEV load is shifted over the year from natural gas-fired generators with an average heat rate of about 11,000 kJ/kWh to generators with an average heat rate of about 9,000 kJ/kWh, giving the high incremental generating efficiency. The 634 GWh of shifted generation can also be normalized by the 8,760 hours of the year, showing that on average about 72 MW of power is shifted in each hour from less- to more-efficient generators. The SO is able to do similar generation shifting in the uncontrolled charging case, but since it does not have the same flexibility in optimizing the timing of PHEV charging, the effect is somewhat muted with less load being shifted and a smaller difference between the heat rates of generators that the load is shifted to and from. Similar load shifting is done among coal-fired generators, although to a lesser extent. The PHEV charging loads allow 2,392 MWh and 412 MWh of non-PHEV loads to be shifted from less- to more-efficient coal-fired generators in the controlled and uncontrolled cases, respectively.

The differences in the generation mix and heat rates

Table 5: Net change in annual total generation and fuel consumed, and average heat rate of natural gas-fired generators with net generation increase and decrease with addition of PHEVs in the emissions-unconstrained case.

| | Charging Scenario | |
	Controlled	Uncontrolled
Net Generation Increase		
Δ Generation (MWh)	811,022	508,847
Δ Fuel Burned (TJ)	7,276	4,971
Heat Rate (kJ/kWh)	8,972	9,769
Net Generation Decrease		
Δ Generation (MWh)	-633,577	-273,720
Δ Fuel Burned (TJ)	-6,692	-2,861
Heat Rate (kJ/kWh)	10,563	10,454

between the controlled and uncontrolled charging cases shown in table 4, explain the drastically different PHEV charging costs in the two cases.

3.1.2. PHEV Emissions

Table 6 summarizes generator emissions of CO_2, SO_2, and NO_x in the emissions-unconstrained case. CO_2 emissions are reported in megatonnes, whereas the other pollutants are given in tonnes. The table shows the total emissions of each pollutant with and without PHEVs. It also shows, in the two PHEV cases, the incremental emissions, which is defined as the change in the emissions (relative to the non-PHEV case) when PHEV charging loads are added to the system. Table 7 estimates total emissions attributable to the CV and PHEV fleets. The generator emissions are the incremental emissions reported in table 6. The emissions are, again, only for the fleet of 75,750 CVs and PHEVs that we compare to one another, and as such the values reported do not give total emissions attributable to the entire light-duty vehicle fleet in ERCOT.

Table 6: Annual generation emissions of CO_2 (Mt), SO_2 (t), and NO_x (t) in the emissions-unconstrained case.

| | CVs | PHEVs | |
		Controlled	Uncontrolled
CO_2 Emissions (Mt)			
Total	195.354	195.452	195.471
Incremental		0.098	0.117
SO_2 Emissions (t)			
Total	452,942	453,237	452,970
Incremental		295	28
NO_x Emissions (t)			
Total	130,167	130,143	130,248
Incremental		-24	81

Table 7 shows that the PHEV charging loads will increase generator emissions of CO_2 in both the controlled and uncontrolled charging cases, but that the decrease in tailpipe emissions from PHEVs more than offset these increases, giving a net decrease in CO_2 emissions relative to CVs. It may be counterintuitive that generator emissions of CO_2 are higher with uncontrolled charging than in the controlled case, despite the greater use of natural gas in the uncontrolled scenario, since natural gas has an input-based CO_2 emissions rate of about 51 kg/GJ as opposed to

Table 7: Annual emissions of CO_2 (Mt), SO_2 (t), and NO_x (t) attributable to CVs and PHEVs in the emissions-unconstrained case.

| | CVs | PHEVs | |
		Controlled	Uncontrolled
CO_2 Emissions (Mt)			
Generator	0	0.098	0.117
Tailpipe	0.363	0.091	0.091
Total	0.363	0.189	0.208
SO_2 Emissions (t)			
Generator	0	295	28
Tailpipe	7	2	2
Total	7	297	30
NO_x Emissions (t)			
Generator	0	-24	81
Tailpipe	104	26	26
Total	104	2	107

91 kg/GJ for coal. This result is due to the much higher incremental heat rate of the natural gas generators in the uncontrolled case, as shown in table 4. This higher heat rate implies that significantly more natural gas must be used for generation in the uncontrolled case, giving the higher CO_2 emissions. This result also highlights the importance of using an input-based emissions rate to properly estimate generator emissions, due to differences in generating efficiency and energy used for generator startups. When these factors are taken into account, the output-based CO_2 emissions rate of incremental natural gas generation (which is defined as the difference in CO_2 emissions divided by the difference in generation between the PHEV and no-PHEV cases) is 169 kg/MWh in the controlled charging case as opposed to 458 kg/MWh with uncontrolled charging.

Table 7 shows that the increase in generator emissions of SO_2 more than outweighs the decrease in tailpipe emissions, meaning that PHEVs will result in greater net SO_2 emissions than CVs. The difference in generator emissions of SO_2 is driven entirely by the significantly greater use of coal-fired generation in the controlled charging case—natural gas has an SO_2 emissions rate of 0.003 kg/GJ as opposed to an average emissions rate of 0.302 kg/GJ for coal generators in ERCOT. Since more than a quarter of the charging load is served by coal in the controlled case, the much higher emissions rate of coal yields higher SO_2 emissions. Indeed, despite the fact that only 3% of the charging load is served by coal in the uncontrolled case, the high emissions rate of coal yields higher net SO_2 emissions than CVs in this case as well.

Table 7 also shows that net NO_x emissions will decrease relative to CVs with controlled PHEV charging, but will slightly increase with uncontrolled PHEVs. Moreover, generator emissions of NO_x will decrease in the controlled charging case, despite the fact that more electricity is being generated. This reduction in generator emissions of NO_x is a consequence of the load shifting that gives the low incremental heat rate in the controlled charging case, and is also observed by Sioshansi and Denholm (2009). The natural gas-fired generators that have a net decrease in generation between the PHEV and no-PHEV case have an

average NO_x emissions rate of about 0.039 kg/GJ, while the generators with a net increase in generation have an average emissions rate of about 0.026 kg/GJ. This reduction in NO_x emissions is somewhat coincidental, in that the more-efficient generators to which the non-PHEV loads are shifted happen to have lower NO_x emissions rates. Indeed, although the same type of generation shifting is done in the uncontrolled case, the loads are shifted from natural gas generators with an average emissions rate of 0.029 kg/GJ to generators with a higher average emissions rate of 0.031 kg/GJ.

Figure 3 summarizes the effect of these changes in generation and tailpipe emissions on net annual per-vehicle emissions of CVs and PHEVs. The values in the figure are taken from table 7, and normalized by the 75,750 vehicles in the simulated fleets. CO_2 emissions are reported in tonnes, while SO_2 and NO_x emissions are given in kilograms. The figure shows that PHEVs will result in lower CO_2 and higher SO_2 emissions than a CV under both charging scenarios, and that NO_x emissions from PHEVs will be lower with controlled and higher with uncontrolled charging. Table 7 and figure 3 can also be used to compared PHEV emissions to emissions from CVs with different fuel efficiencies, since we model CO_2 and SO_2 emissions as scaling linearly in fuel use. NO_x emissions will not, however, be affected by fuel economy since we assume that CVs are designed to exactly meet the Tier2 NO_x requirement of 0.043 g/km.
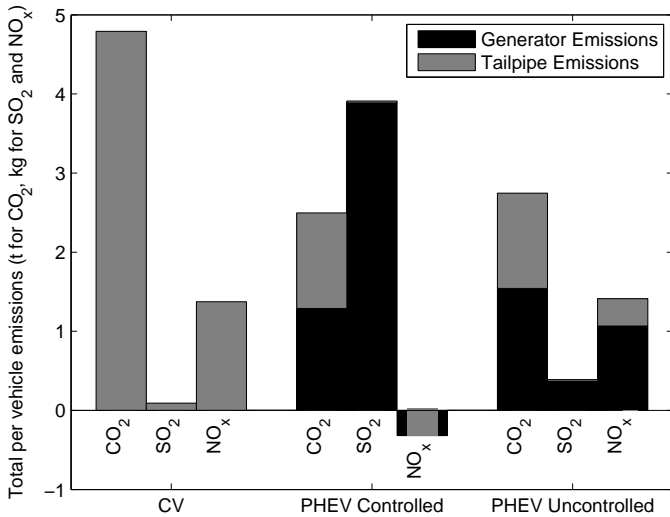

Figure 3: Net annual per-vehicle emissions of CO_2 (t), SO_2 (kg), and NO_x (kg) from CVs and PHEVs in the emissions-unconstrained case.

3.2. Emissions-Constrained Cases

As discussed above, because of current SO_2 and NO_x limits, emissions of these species cannot increase with the introduction of PHEVs, unless there are offsetting emissions reductions elsewhere in the economy or something else causes the emissions caps to be relaxed. As such, we now consider two cases in which emissions are constrained not to increase with the introduction of PHEVs. We first consider a case in which reductions in tailpipe emissions (relative to CVs) due to PHEV use can offset increases in generation emissions. We also consider a case in which such offsetting cannot be done, which means that generator emissions cannot increase. Because of the limited flexibility in how the SO can meet the emissions constraints in the short-run, the effect of imposing these constraints will be to shift PHEV charging loads to generators with lower emissions rates.

3.2.1. Offset Emissions-Constrained Case

Table 7 and figure 3 show that with controlled charging only SO_2 emissions from PHEVs will be higher than those from CVs, and that only SO_2 and NO_x emissions will be greater with uncontrolled charging. Thus the Lagrange multiplier on the CO_2 constraint can be neglected (*i.e.* fixed equal to zero) in the both cases, and the Lagrange multiplier on the NO_x constraint can be neglected in the controlled case. Moreover, because we allow offsetting in this case, the right-hand side of constraints (18) will consist of the sum of generator emissions without PHEV charging and tailpipe emissions from the CV fleet, which are given in tables 6 and 7. Table 8 summarizes the total upper bounds on the three pollutants.

Table 8: Emissions upper bounds in the offset emissions-constrained case.

Pollutant	Upper Bound
CO_2 (Mt)	195.717
SO_2 (t)	452,949
NO_x (t)	130,271

Table 9 summarizes the emissions, Lagrange multipliers, and system cost in the emissions-constrained case. The emissions shown are the sum of generator and PHEV tailpipe emissions, and are all less than the upper bounds given in table 8. The costs shown are the sum of generation and PHEV gasoline costs. Interestingly, these costs are lower than the costs in the emissions-unconstrained case. In the emissions-unconstrained case, the sum of generation and PHEV gasoline costs are \$12,499 million and \$12,511 million in the controlled and uncontrolled charging cases, respectively. These cost reductions give the negative duality gaps[3] shown in table 9.

These negative duality gaps indicate that the solutions found in the emissions-unconstrained case are not MIP-optimal, and that there are other solutions which are near-optimal in terms of cost but differ in terms of emissions. Guan et al. (2003) show that unit commitment problems

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[3]The duality gap is defined as the difference in costs between the emissions-constrained and emissions-unconstrained cases, as a percentage of the costs in the emissions-unconstrained case. This is a standard metric used to measure how near-optimal a solution is. See Wolsey (1981) for further discussion.

Table 9: Total generation and gasoline emissions and cost, and Lagrange multipliers in the offset emissions-constrained case.

	Controlled	Uncontrolled
Emissions		
CO_2 (Mt)	195.489	195.492
SO_2 (t)	452,938	452,574
NO_x (t)	130,058	130,086
η_λ (\$/kg)		
CO_2	0	0
SO_2	0.18739	0.21897
NO_x	0	0
Total Cost (\$ mil.)	12,498	12,508
Duality Gap (%)	-0.01	-0.02

are $\mathcal{NP}$-hard, and as such they are rarely (if ever) solved to complete optimality by SOs or utilities. For example, Streiffert et al. (2005) explain that since PJM has a short time window after receiving bids from the market to determine the day-ahead dispatch and commitment of the system, the unit commitment model is solved for a fixed period of time and the best solution (in terms of cost) found within that window is used. This solution that is used by PJM is rarely, if ever, completely optimal and will instead be within a fraction of a percent of optimal. We use a similar approach in solving our simulation models, since by default Cplex will terminate when it finds a solution that has a duality gap of 0.01%. Johnson et al. (1997); Sioshansi et al. (2008) demonstrate that these different near-optimal solutions to a unit commitment problem can vary in terms of which generators are started up. Our findings here show that these different near-optimal solutions can yield different system emissions as well.

Indeed, the subgradient algorithm that we use to find our final emissions-constrained solution yields several intermediate solutions, all of which are very near-optimal and yield different emissions. Tables 10 and 11 show the difference in cost and emissions between the emissions-unconstrained solution and each of these intermediate solutions found by the subgradient algorithm. These tables highlight the fact that the commitment and dispatch of the power system and resulting emissions can be rather sensitive to the choice of near-optimal solution. These solutions are all similar in terms of cost, however, since they are all within 0.033% of the final emissions-constrained solution.

Table 10: Difference in total generation and gasoline cost and CO_2, SO_2, and NO_x emissions between emissions-unconstrained case and intermediate solutions of subgradient algorithm in in offset emissions-constrained case with controlled charging.

Iteration	Difference from Emissions-Unconstrained Case			
	Cost (\$ mil.)	CO_2 (t)	SO_2 (t)	NO_x (t)
1	1.74	-38,659	-335	-79
2	1.51	-34,160	-296	23
3	0.83	-43,501	-325	-120
4	0.74	-52,378	-352	-127
5	-0.43	-56,104	-333	-79

Almost all of the emissions reductions are obtained

Table 11: Difference in total generation and gasoline cost and CO_2, SO_2, and NO_x emissions between emissions-unconstrained case and intermediate solutions of subgradient algorithm in in offset emissions-constrained case with uncontrolled charging.

Iteration	Difference from Emissions-Unconstrained Case			
	Cost (\$ mil.)	CO_2 (t)	SO_2 (t)	NO_x (t)
1	1.28	-36,847	-351	-64
2	-1.94	-53,940	-343	-113

by the shifting of loads to generators with lower emissions rates. Although the SO is assumed to have flexibility in timing when PHEVs are charged in the controlled charging scenario, the average hourly charging pattern in the emissions-constrained case is nearly identical to that shown in figure 2 for the emissions-unconstrained case. There are five days on which the charging load is slightly lower in the emissions-constrained case. This indicates that it is preferable to use gasoline as opposed to midday PHEV recharging on these days, but these differences are extremely small in net.

Table 12 summarizes the breakdown of the incremental generating load in the emissions-constrained case. The table shows that when the emissions constraint is imposed, almost all of the PHEV charging load in the controlled charging case is served using natural gas-fired generation. In the uncontrolled case, on the other hand, 126% of the incremental load uses natural gas. This indicates that both the PHEV and a portion of the non-PHEV load must be shifted from coal- to natural gas-fired generators. The last two rows of table 12 also show the incremental heat rate in the emissions-constrained case. These rows highlight the fact that the load shifting done when the emissions constraints are imposed yields the same type of efficiency gains we observe with controlled charging in the emissions-unconstrained case. Essentially, the added cost that the Lagrange multiplier imposes on emissions forces the SO to find another near-optimal solution to the unit commitment problem that uses more natural gas-fired generation. The higher cost of natural gas, relative to coal, is offset by the fact that the SO is able to use more-efficient natural gas generators, which yields a very small cost difference when the emissions constraint is imposed. Indeed, comparing the heat rates in table 12 to those in table 4 shows that the SO is able to achieve efficiency gains in the emissions-constrained case compared to the unconstrained case.

Table 12: Breakdown and average heat rate of annual incremental generating load with addition of PHEVs in the offset emissions-constrained case.

	Charging Scenario	
	Controlled	Uncontrolled
Incremental Generating Load (%)		
Natural Gas	97.31	126.15
Coal	2.69	-26.15
Incremental Heat Rate (kJ/kWh)		
Natural Gas	3,552	7,732
Coal	752	12,675

Table 9 also shows that the NO_x constraint is satisfied in the uncontrolled charging case, despite the Lagrange multiplier on the associated constraint being zero. This is because the shifting of loads that is done as a result of the Lagrange multiplier on SO_2 emissions also results in lower NO_x emissions, due to the fact that the generators with high SO_2 emission rates also happen to have high NO_x emission rates. Indeed, both CO_2 and NO_x emissions are reduced with controlled and uncontrolled charging, despite having Lagrange multipliers of zero on both of those constraints.

3.2.2. Non-Offset Emissions-Constrained Case

When reductions in tailpipe emissions due to PHEV use cannot offset increases in generation emissions, we impose constraint (19) which restricts generator emissions not to increase with the addition of PHEV charging loads. Thus the right-hand side of the emissions constraints will be given by generator emissions in the CV case. Table 6 shows that in the controlled charging case generator emissions of CO_2 and SO_2 increase with the introduction of PHEVs, whereas in the uncontrolled case emissions of all three species increases. Table 13 summarizes the final set of Lagrange multipliers in the non-offset emissions-constrained case. Comparing this set of multipliers to those in table 9 shows that a cost on SO_2 emissions alone is not sufficient to reduce CO_2 emissions to the necessary levels, and positive Lagrange multiplier values on CO_2 are needed in both the controlled and uncontrolled charging cases. NO_x emissions are, however, reduced despite having a Lagrange multiplier of zero, which shows that the generation shifting done to reduce CO_2 and SO_2 emissions also reduces NO_x.

Table 13: Lagrange multipliers (\$/kg) in the non-offset emissions-constrained case.

	Controlled	Uncontrolled
CO_2	0.00220	0.00220
SO_2	0.18739	0.21897
NO_x	0	0

Table 14 shows generator, tailpipe, and total emissions in the non-offset emissions-constrained case. The table shows that generator emissions of the three species are all reduced compared to the CV case, and when tailpipe emissions are taken into account total emissions of all three pollutants also drop. Table 15 summarizes generation and gasoline costs when the emissions constraint is imposed. Comparing these costs to those in tables 2 and 3 shows that imposing the emissions constraint in the non-offset case results in no cost increase. There is, in fact, a slight generation and total cost decrease, which does not appear in table 15 due to rounding. The emissions and cost reductions are achieved in much the same way as in the case with offsetting of emissions. About 170% and 196% of the incremental load is served by natural gas-fired generators in the controlled and uncontrolled charging cases, respec-

tively. The fact that these values are both greater than 100% indicates that both PHEV charging and non-PHEV loads are also shifted from coal- to natural gas-fired generators. The higher cost of natural gas as a generating fuel is offset by efficiency gains the SO is able to exploit by committing more efficient generation—the average incremental heat rate of natural gas-fired generators is about 4,896 kJ/kWh and 7,701 kJ/kWh in the controlled and uncontrolled charging cases, respectively.

Table 14: Emissions in the non-offset emissions-constrained case.

	Controlled	Uncontrolled
CO_2 (Mt)		
Generator	195.253	195.269
Tailpipe	0.091	0.091
Total	195.344	195.360
SO_2 (t)		
Generator	452,428	452,084
Tailpipe	2	2
Total	452,430	452,084
NO_x (t)		
Generator	129,715	129,751
Tailpipe	26	26
Total	129,741	129,777

Table 15: Cost in the non-offset emissions-constrained case.

Cost (\$ mil.)	Controlled	Uncontrolled
Generation	12,476	12,488
Gasoline	23	23
Total	12,499	12,511

4. Conclusions

The net emissions and cost impact of PHEVs and other electrically driven vehicles will generally be quite sensitive to a number of factors. One of these is the generation mix of the power system in which they charge. Another is the time of day that they are charged and the extent to which charging decisions can be co-optimized with power system operations. PHEV charging in 'dirty' power systems, such as Texas, could yield net increases in emissions of some pollutants. This will, of course, depend on the regulatory framework within which PHEVs are deployed. If emissions are capped, then PHEVs cannot increase generator emissions.

Our results suggest that if a power system has enough efficient natural gas-fired generating capacity (or any other technology with low emissions rates) to serve the PHEV charging loads, PHEVs could be cost-effectively accommodated without a net increase in emissions. This is because unit commitment problems can have many near-optimal solutions, which have very similar costs but differ in terms of the commitment and dispatch of individual generators and total emissions. Since SOs and utilities do not solve unit commitment problems to optimality, our results show that the operation of the power system can be guided toward a lower-emission dispatch without much (if any) cost

increase. Indeed, our emissions-constrained solutions are all lower-cost than the emissions-unconstrained one. If the unit commitment problem is solved to complete optimality, then there would by definition be a cost increase when the emissions constraints are imposed. We can, however, bound any such cost increase since we know that the solutions found by Cplex must be within 0.01% of optimal. If the unit commitment problem is solved to complete optimality then annual generation costs will increase by at most $1.1 million when the emissions caps are imposed, which represents at most a 0.01% increase in costs.[4] Thus the cost of meeting the emissions constraints would be trivial, regardless of whether the unit commitment problem is solved to optimality. These results are dependent, however, on properly penalizing emissions in the objective function of or 'finessing' the unit commitment model to ensure a near-optimal low-emissions solutions is used. Since SOs and utilities may use different termination criteria in their unit commitment models than those we assume, the actual cost impacts of such emissions restrictions may differ from the specific values that we report. Nevertheless, our result that the restrictions can be met with only a trivial cost impact would still apply.

In our case study the SO is able to meet the emissions constrains by shifting charging and non-charging loads from coal- to natural gas-fired generators. The higher cost of natural gas as a generating fuel is offset by efficiency gains that the SO is able to achieve by better coordinating unit commitment decisions with the PHEV charging loads. Table 16 summarizes the annual per-vehicle driving costs and emissions of CVs and PHEVs. The driving costs consist of gasoline costs for the CV and gasoline and charging costs for the PHEVs. The emissions consist of tailpipe emissions for the CV and the sum of tailpipe and generator emissions for the PHEVs. The table shows that PHEVs can be made significantly cleaner than CVs without any increase in driving costs.

Table 16: Annual per-vehicle charging and gasoline cost and emissions of CVs and PHEVs.

	Cost ($)	CO_2 (kg)	SO_2 (g)	NO_x (g)
CV	1,196	4,792	91	1,374
Contr. PHEV				
Uncons.	393	2,496	3,910	32
Offset	381	1,780	-54	-1,442
Non-offset	391	-127	-6,772	-5,629
Uncontr. PHEV				
Uncons.	549	2,747	390	1,411
Offset	512	1,823	-4,863	-1,070
Non-offset	544	84	-11,313	-5,153

The negative duality gaps that we find when the emissions constraints are imposed also point to an inefficiency that will generally occur as a result of the SO or utility having to rely on near-optimal unit commitment solutions. The price of SO_2 permits averaged $997/t and ranged between $712/t and $1,752/t during the year 2005. Thus the reduction in generator emissions of SO_2 that we simulate in the emissions-constrained cases amount to an annual savings of between about $214,000 and $1.6 million, based on these permit prices. These savings are included in the costs reported in tables 9–11, and 15, but further point to the fact that generation emissions can be slightly reduced with little or no added cost depending on the unit commitment solution selected.

We do not make any explicit assumptions regarding what policy or regulation levers are used to achieve these low-emission outcomes. Algorithmically, Lagrangian relaxation works by imposing costs, given by the Lagrange multipliers, on CO_2, SO_2, and NO_x emissions, as suggested by Gjengedal (1996). Thus the Lagrangian relaxation and subgradient algorithm find the emissions-constrained solutions through a price-based mechanism, and this can be likened to a tax or cap-and-trade program. However, our model fundamentally only assumes that upper bounds are imposed on emissions. If current SO_2 caps are not relaxed with the addition of vehicle charging loads and the NO_x SIP Call or a similar program is extended to ERCOT, then the non-offset emissions-constrained case should theoretically occur. The offset emissions-constrained case could occur if SO_2 and NO_x emissions caps are relaxed based on reduced tailpipe emissions from PHEVs, however there are currently no such exemptions in the relevant laws or regulations.

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[4]The $1.1 million cost increase would occur if the cost of the optimal unconstrained solution is 0.01% less than the near-optimal solution and the emissions-constrained solutions we have found are optimal. This could occur in theory, since our solutions in the unconstrained case are only guaranteed to be within 0.01% of optimal, while the emissions-constrained solutions may be optimal.

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