Cost and Emissions Impacts of Plug-In Hybrid Vehicles on the Ohio Power System☆

Ramteen Sioshansi*

Integrated Systems Engineering Department, The Ohio State University, 1971 Neil Avenue, Columbus, OH 43210, United States

Riccardo Fagiani*

Politecnico di Milano, Via Lambruschini, Milano, 20156, Italy

Vincenzo Marano*

Center for Automotive Research, The Ohio State University, 930 Kinnear Road, Columbus, OH 43212, United States

Abstract

Plug-in hybrid electric vehicles (PHEVs) have been promoted as a potential technology that can reduce vehicles' fuel consumption, decreasing transportation-related emissions and dependence on imported oil. The net emission and cost impacts of PHEV use are intimately connected with the electricity generator mix used for PHEV charging, which will in turn depend on when during the day PHEVs are recharged. This paper analyzes the effects of a PHEV fleet in the state of Ohio. The analysis considers two different charging scenarios—a controlled and an uncontrolled scenario—which offer the grid operator different levels of control over the timing of PHEV charging. The analysis shows that PHEV use could result in major reductions in gasoline consumption of close to 70% per vehicle compared to a conventional vehicle (CV) under both charging scenarios. Moreover, despite the high penetrations of coal in the Ohio power system, net CO_2 emissions from a PHEV could be up to 24% lower than that of a CV in the uncontrolled case, however CO_2 and NO_x emissions would increase in both scenarios.

Keywords: Plug-in hybrid electric vehicle, charging strategy, grid interaction

1. Introduction

Vehicle fleet electrification has increasingly been proposed as a potential solution to reduce transportation-related emissions. Using electricity as a transportation fuel will reduce the need for gasoline compared to a conventional vehicle (CV). Moreover, electrified transportation will shift emissions away from vehicle tailpipes, which tend to release emissions in population centers, to power plants, which are typically more remote and can typically have their emissions more-easily controlled. Moreover, electrified transportation will benefit from any future reductions in generation emissions and diversification of primary energy sources in the power sector. Thus grid-connected transportation solutions, such as electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs), will grow successively cleaner while the energy system as a whole becomes

☆The authors would like to thank Armin Sorooshian, SMART@CAR members, and two anonymous referees for helpful comments and suggestions. This work was supported by the SMART@CAR consortium. Any opinions and conclusions expressed in this paper are those of the authors and do not necessarily represent those of SMART@CAR members.

*Corresponding author

Email addresses: sioshansi.1@osu.edu (Ramteen Sioshansi), riccardo.fagiani@mail.polimi.it (Riccardo Fagiani), marano.8@osu.edu (Vincenzo Marano)

more secure. Even with today's carbon-intensive energy mix, the electrification of the transportation sector can produce an immediate reduction of greenhouse gases, an improvement in urban air quality and noise levels, and lower operating costs. Tomić and Kempton (2007) note that it will further create an explicit link between the power generation and transportation sectors, extending the range of sustainable renewable energy options that can propel the world's motor vehicles and improving power grid reliability with vehicle to grid services.

Currently PHEVs are considered the most reliable and easily-adoptable electrified vehicle technology. Unlike pure EVs, PHEVs do not require on-demand recharging—if the driver misses a charge, the vehicle can run on gasoline and operate as a standard hybrid electric vehicle (HEV). However, charging a large fleet of PHEVs could pose problems to the power grid operator, especially if vehicle charging is coincident with non-vehicle loads. Parks et al. (2007) note also that new generating capacity may be necessary to satisfy higher peak load on the grid and the existing transmission and distribution infrastructures may be insufficient to meet PHEV loads. An additional consideration is that the cost and emissions of PHEV use will be connected with the timing of PHEV charging and the generation mix in the system. For instance, if charging is coincident with non-PHEV loads, vehicle batteries may have to be charged using costly, less-efficient, and dirtier generators than if charging is delayed to lag other loads. Previous studies, including EPRI (2007); Stephan and Sullivan (2008); Samaras and Meisterling (2008); Marano and Rizzoni (2008); Sioshansi and Denholm (2009), have demonstrated that charging PHEVs during the night using excess generating capacity will result in minimal impacts on the power grid and lower charging costs. It has been suggested that this delaying of PHEV charging could be done by the grid operator in concert with power system operations. On the other hand, if instead PHEV owners could recharge vehicles whenever they are parked, this would result in some coordination losses and potential increases in peak loads but could reduce gasoline usage during midday trips.

The aim of this study is to estimate the effects of a fleet of PHEVs on the Ohio power system, in terms of load, cost, and emissions. Section 2 describes the model and data used in our analysis, with further modeling details given in Appendix A. Section 3 summarizes the results of our analysis, and section 4 concludes.

2. Model and Data

2.1. Model

The interactions of PHEVs and the power system are modeled through a power system and a vehicle model. Our analysis considers two charging scenarios—controlled and uncontrolled charging—which give the grid operator different levels of control over PHEV charging. Thus the power system and vehicle models interact differently under the two charging assumptions. All of the models are formulated using AMPL 12.1 and solved using cplex 12.1.

The controlled scenario assumes that the grid operator has near-total control in deciding when PHEVs should be recharged and co-optimizes PHEV charging loads with its non-PHEV loads and operation of the power system to minimize costs. Under the controlled scenario the grid operator has two constraints on PHEV charging decisions. One is that PHEVs can only be recharged when they are not being driven and are plugged in, and we assume that these driving and plugging decisions are made by the vehicle owners. The second restriction is that we require that each PHEV be fully recharged in time for the first vehicle trip each morning. Moreover, we assume that the grid operator's objective is to minimize the sum of generation costs and the cost of gasoline used by the PHEV fleet. Gasoline costs are included in the grid operator's objective function so that the grid operator would recharge a PHEV between two trips during the day if the cost of charging the battery is less than the gasoline it would otherwise have to burn on the subsequent trip. Thus the controlled scenario is modeled by integrating the power system and vehicle model and allowing the grid operator to coordinate decisions involving both.

The uncontrolled charging scenario is the complete opposite and assumes that all charging decisions are made by PHEV owners. Specifically, the uncontrolled scenario assumes that PHEV owners will plug-in and charge their vehicles whenever possible, given their driving habits. The grid operator has control over only the power system and commits and dispatches generators to minimize generation costs, while serving the exogenously determined PHEV and non-PHEV loads. Thus the uncontrolled scenario is modeled by using the vehicle mode to determine PHEV charging behavior, and then optimizing power system operations taking these charging decisions as exogenous parameters.

The power system is modeled using a unit commitment and dispatch model, which determines the hourly operation of each generating unit. The model is formulated as a mixed-integer program (MIP) and includes a three-part generation cost structure, consisting of startup, spinning, and variable generation costs, and load balance, minimum up- and down-time, minimum and maximum generation, and ramp-up and -down constraints. As is typical of unit commitment problems, the operation of the power system is optimized one day at a time, with the starting generation level and status of each generator determined by the previous day's optimization. Further details of the power system model are given in Appendix A and in Sioshansi and Denholm (2010).

The vehicle model uses a combination of empirical driving pattern data and the ADVISOR Advanced Vehicle Simulator, described in Markel et al. (2002), to track the state of charge (SOC) of the PHEV batteries after each driving trip and provide charging requirement data to the power system model. The empirical driving data are based on a study of 227 instrumented vehicles in the metropolitan St. Louis, Missouri area, described in Gonder et al. (2007). Because this data is not publicly available, figure 1 shows the distribution of daily driving distances for the sample. This data tracks the second-by-second driving patterns of the vehicles. Our model assumes that the driving patterns of the PHEV fleet will correspond to this empirical driving data, and we assume that 1/227 of the PHEVs will drive according to each of the driving profiles. Moreover, to reduce computational complexity of the model, we assume that each vehicle corresponding to a driving profile will be charged identically—thus we only model charging decisions corresponding to 227 different driving profiles. The empirical driving data are used to determine when vehicles are driven and when they are plugged into the system for recharging. We assume that a vehicle must not be driven for an entire hour for it to be grid-connected during that hour. This implicitly assumes that PHEVs will have access to charging stations wherever they are parked. Importantly, we assume that in the controlled charging scenario the grid operator cannot influence driving patterns in order to time vehicle charging to reduce costs. Rather, the grid operator is constrained to charge vehicles when they are plugged in by the vehicle owner, but can optimize the timing of charging during these periods to minimize costs.

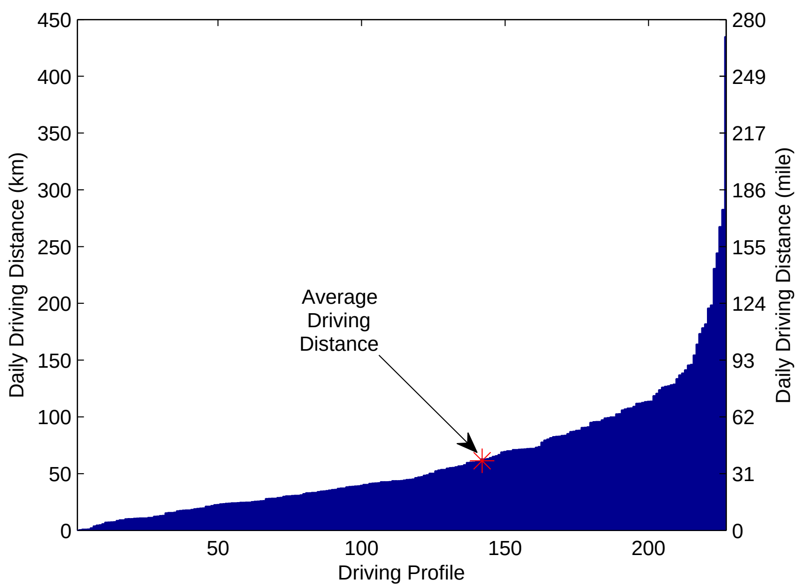

Figure 1: Daily driving distance of 227 driver profiles used. Average daily driving distance is about 61 km or 38 miles.

Table 1 summarizes the assumed characteristics of the PHEVs. We also assume that the PHEVs use an EV-type control strategy, in which the vehicle is driven in a charge-depleting (CD) mode when the

SOC is above 30%. While driving in this CD mode, the battery is the primary source of energy, with the gasoline engine only being used on a supplemental basis during high-power events. Once the SOC of the battery reaches 30%, the PHEV behaves much like a HEV and drives in a charge-sustaining (CS) mode, in which the average SOC of the battery remains close to 30%. The ADVISOR model is combined with the empirical driving data to determine how much gasoline and battery energy is used when the PHEVs are driven. Specifically, the ADVISOR model outputs the amount of battery energy (in Wh/km) and gasoline (in liter/km) used when a PHEV corresponding to each driving profile is driven in CD mode, and the amount of gasoline (in liter/km) used when it is driven in CS mode. In the controlled charging simulations, these parameters are explicitly included in the model to account for the relationship between gasoline and battery energy usage and charging decisions made by the grid operator. In the uncontrolled model, these parameters are used to determine the charging decisions made by PHEV owners, based on the SOC after each vehicle trip. We assume in both charging scenarios that the charging stations have a power capacity of 1.875 kW, making them a standard 120 V home circuit, and that there are 10% energy losses from vehicle charging.

Table 1: PHEV Characteristics

Characteristic	Value
Battery Capacity	9.4 kWh
Vehicle Mass	1488 kg
All-electric Range	60 km
Average Energy Use Over Drive Cycle	23 km/l and 59 Wh/km
CD-mode Electric Energy Use	0.183 kWh/km

2.2. Data

Our analysis models the PHEV fleet in the Ohio power system, using power system and vehicle data from 2007. The light-duty vehicle fleet in Ohio consisted of approximately 6.5 million vehicles in 2007, as reported by the U.S. Department of Transportation's Federal Highway Administration. We consider a case in which PHEVs represent 5% of the total light-duty vehicle fleet.

The state of Ohio is covered by two different electricity markets, that are administrated by PJM and the Midwest Independent System Operator (MISO), as well as a number of small regions that are not part of any organized market. Because PJM covers the largest area of Ohio, this analysis focuses on the area of Ohio that is in the PJM service territory. Our analysis models the operations of every generator in Ohio in 2007, as reported by the U.S. Department of Energy's Energy Information Administration (EIA). Nuclear plants are assumed to be non-dispatchable and always running at full capacity, thus their output is modeled as being constant and subtracted from the total load and no variable costs associated with nuclear units are included in the analysis. Our analysis does not model seasonally varying generator availability due to scheduled maintenance outages.

We model the cost of the other 411 dispatchable generators using a standard three-part cost structure consisting of startup, spinning, and variable generation costs. All three of these cost components are estimated as the product of the generator's heat rate and the cost of fuel. Fuel costs are estimated based on historical monthly fuel cost reports provided by the EIA. The EIA data also reports the maximum nameplate generating capacity of each unit. Heat rates are estimated using historical continuous emissions monitoring system (CEMS) data reported by the U.S. Environmental Protection Agency (EPA). The CEMS data reports hourly net electricity generation and fuel burned for each unit. The startup fuel of each generator is estimated by averaging the total cumulative energy burned each time the generator is started up until it begins producing energy. The spinning and variable generation fuel of each generator is then estimated by fitting the heat and generation data to a polynomial function. Finally, in order to model the power system using a linear MIP, we approximate the polynomial function of each generator as a step function. Figure 2 gives an example of the CEMS data and the approximation of the spinning and variable fuel use of a generator in the sample.

The CEMS data are also used to estimate the minimum generation level, ramp-up and -down limit, and minimum up- and down-times of each unit. The minimum generation level is estimated using the lowest non-zero generation level observed from each unit in the CEMS data.[1] Similarly, the ramp-up and -down limits are estimated based on the greatest observed increase and decrease in generation output between consecutive hours. Minimum up- and down-times are estimated as the shortest period between each unit being started up and shutdown. In order to estimate some of these parameters for baseload units, which are typically not cycled very much, we use several year's worth of historical CEMS data.

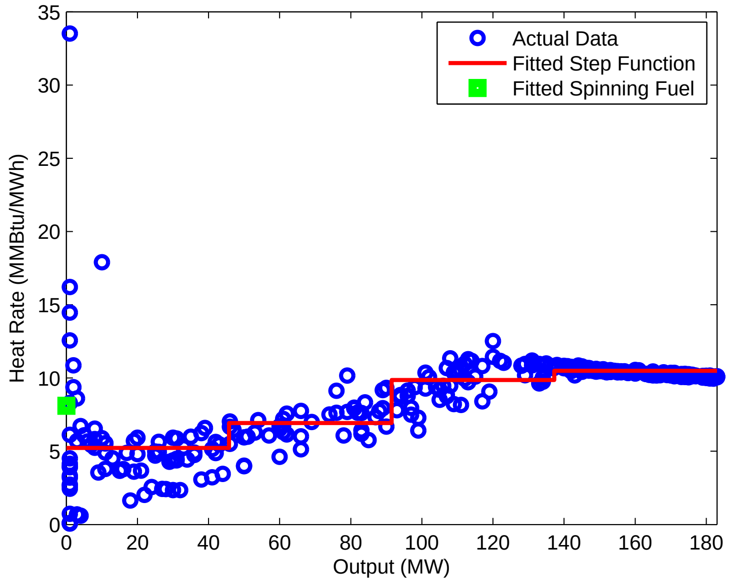

Figure 2: Actual heat rate and step-function approximation for a generator.

Since the Ohio power system is not isolated and is part of the PJM (as well as the MISO) system, we must also account for the fact that power system operations within Ohio will depend on the relative cost of energy that can be imported from or exported to the rest of the PJM system. The rest of the PJM market is accounted for in the power system models by allowing the Ohio grid operator to buy and sell energy from the rest of the market, at a price that will be a function of the amount of energy transacted. The energy price function in each hour is approximated by using actual historical bids into the PJM market. As shown in figure 3, the energy price function is derived from the bids based on their merit order. The actual historical PJM load is used to shift the market price function horizontally, and the shifted function is used to determine the price of net energy transactions between Ohio and the rest of the PJM market. In order for the model to be a linear MIP, the energy price function is approximated by a step function, as shown in the figure.

This approach to modeling the exchange of energy between Ohio and neighboring regions does present some difficulties. For one, as discussed above, some areas of Ohio are part of the MISO system. As such, these regions will trade energy primarily with that market as opposed to PJM. If there are persistent differences in energy prices between the MISO and PJM markets, our model will not capture potentially more economic energy exchanges with the MISO market that may be available to the Ohio grid operator. If, however, market participants are able to trade across market boundaries, either bilaterally or through an organized market, one would expect such price differences to be small due to the potential for price arbitrage. Another issue with this approach is that it does not account for transmission constraints and congestion, which could limit the exchange of energy between Ohio and the rest of the market, or could increase or decrease the cost of those exchanges, since we use a single system-wide energy price function. Finally, because the publicly available PJM bid data does not reveal the identity or location of bidders, we are not able to remove bids

[1] Because some generators produce a negligible amount of energy when being started up, we exercise some discretion in removing these data points when estimating each generator's minimum generation level.

from Ohio generators from the energy price function. We partially mitigate this issue by using the aggregate PJM load, which includes the Ohio load and will account for Ohio bids used to serve the aggregate PJM load, to shift the market price function.

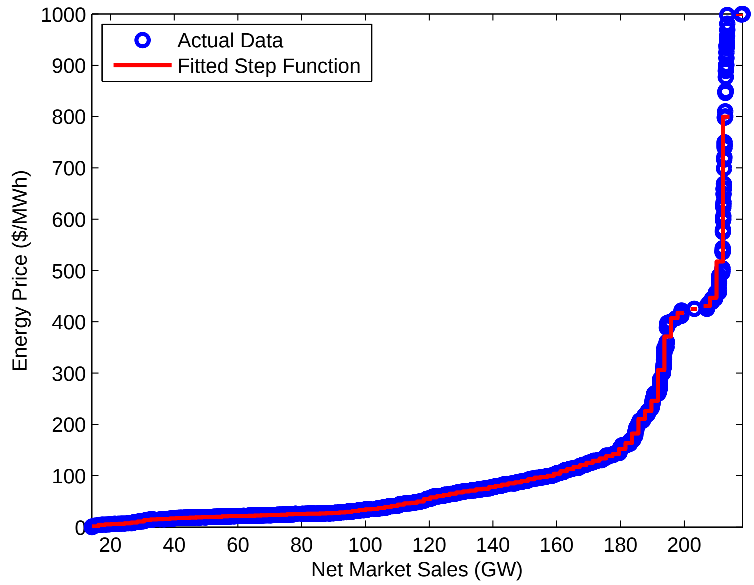

Figure 3: Actual market price bid data and step-function approximation for one day.

Our analysis considers emissions from two sources, generators and vehicle tailpipes, and three type of emissions, CO_2, SO_2, and NO_x. Generator emissions are further broken down into the emissions of generators in Ohio and those in the rest of the PJM market. The emissions of Ohio generators are estimated using input-based emissions rates, which give mass of each pollutant per unit of fuel burned, as opposed to output-based emissions rates, which give mass of each pollutant per MWh of electricity produced. The advantage of using an input-based emissions rate is that it will capture differences in emissions rates due to generator startup and spinning fuel burned, as well as differences in generator heat rates from part-load operations. An output-based emissions rate will not capture these factors. Generator emissions rates are estimated using the CEMS data, which provides hourly historical emissions and combining this with fuel burned data to estimate input-based emissions rates.

Emissions from generators in the rest of the PJM market are estimated by using historical hourly marginal fuel mix data.[2] This data indicates what types of generators, classified by fuel type, are marginal in each hour. We then assume that when PHEV charging loads are added in Ohio, any resulting changes in generation from the rest of the PJM system will be attributable to different generating fuels in this same proportions as the marginal fuel mix. Thus we assume in our calculations that the addition of the PHEV charging loads in Ohio will have a negligible effect on the generating technologies that are marginal in the rest of the PJM system. We combine this marginal fuel mix data with estimates of output-based emissions rates for each generating fuel to determine the net change in emissions in the rest of the PJM system. These output-based emissions rates are estimated by using CEMS data, which gives actual historical net generation and emissions, for generators in PJM that are not located in Ohio.

Vehicle tailpipe emissions are estimated using a combination of emissions regulations and the chemical composition of gasoline. Since CO_2 emissions are not controlled they are estimated at 2.35 kg/liter of gasoline burned (about 8.87 kg/gallon), based on the carbon content of gasoline. For SO_2 emissions, we assume that the chemical content of gasoline will exactly comply with the EPA's Tier2 requirement of 0.045 g/liter of gasoline burned (about 0.17 g/gallon). Tier2 also requires NO_x emissions to be less than

[2]This data is publicly available at http://www.monitoringanalytics.com/data/marginal_fuel.shtml.

0.05 g/km (about 0.07 g/mile). We assume that the emission controls in CVs and HEVs will be designed to exactly meet these requirement. PHEVs emissions are estimated from HEV emissions based on a linear reduction in HEV emissions, which is in proportion to the reduction in gasoline consumption of a PHEV relative to an HEV.

3. Results

3.1. Effects of PHEV Charging on the Load Profile

As it typical of many power systems, the Ohio system load had two seasonal peaks in 2007: one in the winter and the other in the summer. These peaks are caused, primarily, by heating and lighting loads in the winter and cooling loads in the summer. The higher of these peaks is during the summer, owing to the fact that a substantial portion of building heating uses fossil fuels, such as natural gas or oil, whereas nearly all building cooling uses electricity.

Because of these seasonal differences in the underlying energy needs driving the load peaks, the controlled and uncontrolled charging scenarios yield different charging and load patterns on a seasonal basis. For instance, figure 4 shows the hourly load both with and without PHEV charging on a summer day. The data are from August 8, which has the highest summer load (without PHEV charging) of 2007. With uncontrolled charging, the bulk of PHEV charging takes place in the late afternoon and early evening hours, when most drivers finish commuting from work to home. This has the effect of both increasing the peak load, in this case in hour 17, and extending the peak into hour 18. Controlled charging, on the other hand, delays charging from when drivers arrive home to hours later in the evening, which smooths the overnight load. In the middle of the day, both controlled and uncontrolled charging give similar amounts of midday charging between vehicle trips.

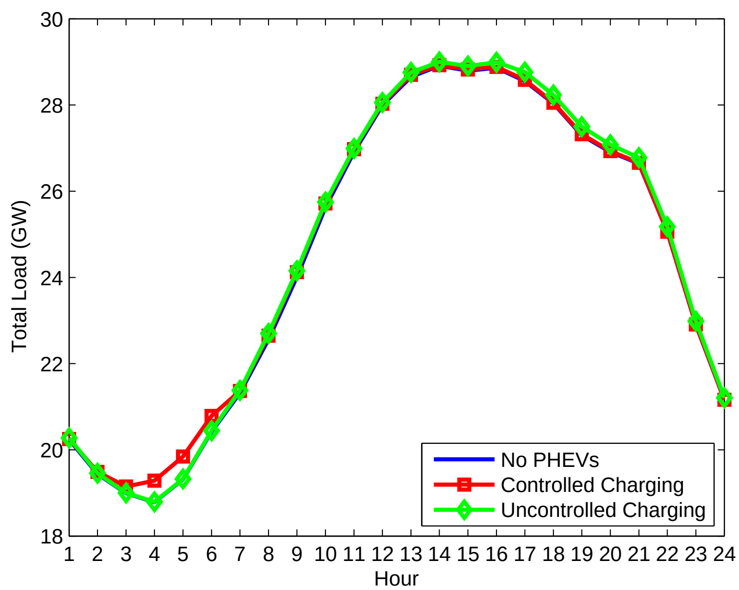

Figure 4: Load profile on 8 August with and without PHEV charging.

Figure 5 shows the hourly load with and without PHEV charging on a winter day. The data are from February 6, which is the day with the highest winter peak without PHEV charging. Again, with uncontrolled charging the afternoon peak is increased due to the coincidence of heating and lighting loads with commuters arriving home. We also see that controlled charging would result in the delaying of this charging until the early morning hours when many generators would otherwise sit idle. Figure 6, which shows the total hourly charging of PHEVs, highlights the effects of the differences in seasonal load profiles on PHEV charging. With uncontrolled charging, the driving and charging patterns are assumed the same. With controlled charging, on the other hand, we see that the grid operator would opt for a fair amount of recharging between hours 15 and 17 in the winter to exploit the availability of committed generating capacity. Moreover, in the summer the grid operator would provide more PHEV charging immediately after the morning commute due to the lack of a morning peak, whereas this is not done in the winter.

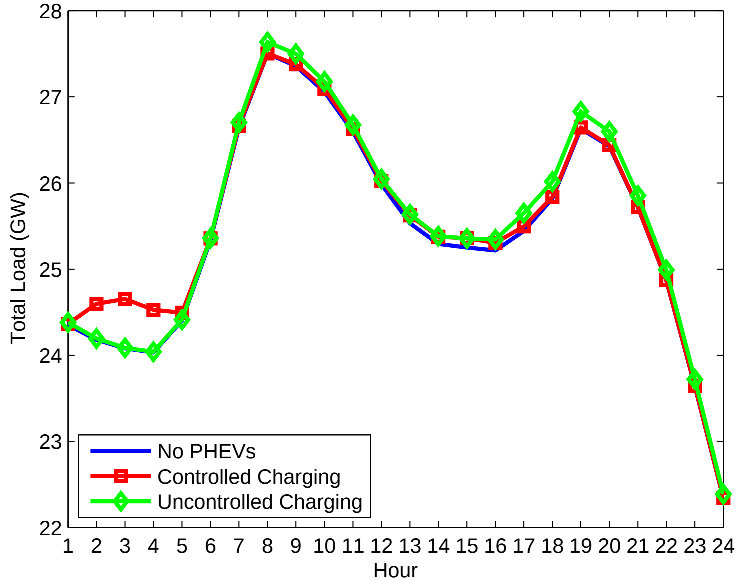

Figure 5: Load profile on 6 February with and without PHEV charging.

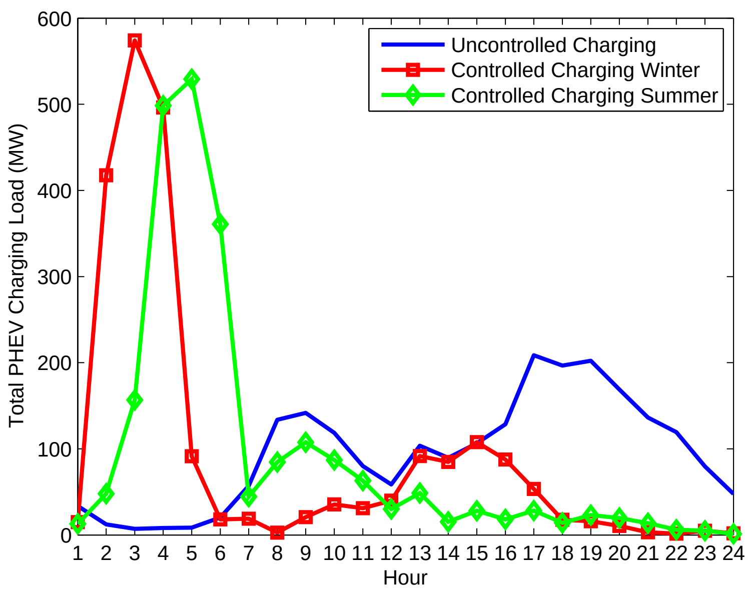

Figure 6: PHEV charging profile with controlled and uncontrolled charging on 8 August and 6 February.

These differences in the timing of PHEV charging, between the controlled and uncontrolled cases, coupled with diurnal patterns in what types of generators are marginal, will affect the mix of generating fuels used to serve the PHEV charging loads. Table 2 presents the breakdown of generating fuels used by Ohio generators to serve the PHEV charging load in the two charging cases. The breakdown of PHEV charging loads is computed by determining the increase in the output of each type of generator between the PHEV and no-PHEV cases and normalizing by the total increase in generating loads. The table shows that the charging loads are served primarily by natural gas- and coal-fired generators, although there are negligible increases of less than 1% in generation from fuel oil-fired generators. The noticeable difference in the charging loads between the two cases is that much more vehicle charging is done using natural gas in the uncontrolled case. In the controlled charging case, the grid operator can delay PHEV charging at the end of the day to overnight hours, during which low-cost coal-fired generation is marginal and available. Conversely, in the uncontrolled case PHEV owners begin charging immediately upon arriving home in the late afternoon and early evening, and as such more of their charging loads are served by higher-cost natural gas-fired generators that are marginal during these hours.

Table 2: PHEV charging load generation mix

Generation	Percent of PHEV Charging Load (%)	
Fuel	Controlled Charging	Uncontrolled Charging
Bituminous Coal	85	78
Sub-bituminous Coal	11	5
Natural Gas	4	17

3.2. Emissions Impacts of PHEV Charging Scenarios

PHEVs are intended to reduce transportation-related emissions by using electricity instead of gasoline as an energy source. The net emissions impact of PHEV use will, however, be closely related to the generation mix in the power system in question and the mix of generating technologies used to serve the vehicle-charging load. In a system with high penetrations of renewable or nuclear energy, the net emissions associated with PHEVs can be very low, as opposed to a predominantly coal-based system, which would yield higher PHEV emissions. In most systems the diurnal charging pattern will also be an important factor, since different generating fuels can be marginal at different times of day. In Ohio, for instance, that controlled charging will result in much of the charging taking place during periods with low loads. As such, table 2 shows that nearly all of the charging load will be served by baseload coal-fired generators. A significant portion of uncontrolled charging, on the other hand, is done during the afternoon and is covered with more natural gas-fired generation.

Figure 7 summarizes the annual per-vehicle emissions of a PHEV with controlled and uncontrolled charging, and contrasts it with emissions from a comparably sized CV. The results show that PHEVs will yield some reductions in CO_2 relative to CVs, but that SO_2 and NO_x emissions will rise dramatically, due to high generator emissions of these species. The CO_2 reductions are smaller with controlled charging due to the greater use of coal-fired generation in that scenario, as shown in table 2. Uncontrolled charging, on the other hand, uses more natural gas-fired generation for PHEV charging, which gives the close to a 24% reduction in CO_2 emissions compared to controlled charging and CVs. The high penetration of coal-fired generation in Ohio also leads to the high SO_2 and NO_x emissions, as coal generators in Ohio tend to have high SO_2 and NO_x emissions rates. As with CO_2 emissions, since uncontrolled charging results in less coal-fired generation being used, PHEVs release less SO_2 and NO_x in the uncontrolled case.

Figure 7 also suggests that if the primary goal of PHEV use is to reduce emissions, then uncontrolled charging (or the grid operator replicating the uncontrolled charging profile) would be preferred, since emissions of all of the criteria pollutants are lower than with controlled charging. This result is not, however, universally true and the emissions impacts will be highly sensitive to the generation mix. For example, in countries such as France or Switzerland, where hydroelectricity and nuclear are more abundant, controlled charging may be preferred since more hydroelectricity and nuclear may be used for vehicle charging if power system operations and charging are tightly coordinated. For this reason, using PHEVs in these countries may be more beneficial from a net emissions standpoint than countries such as the United States and Germany, which have a large mix of coal-fired generation.

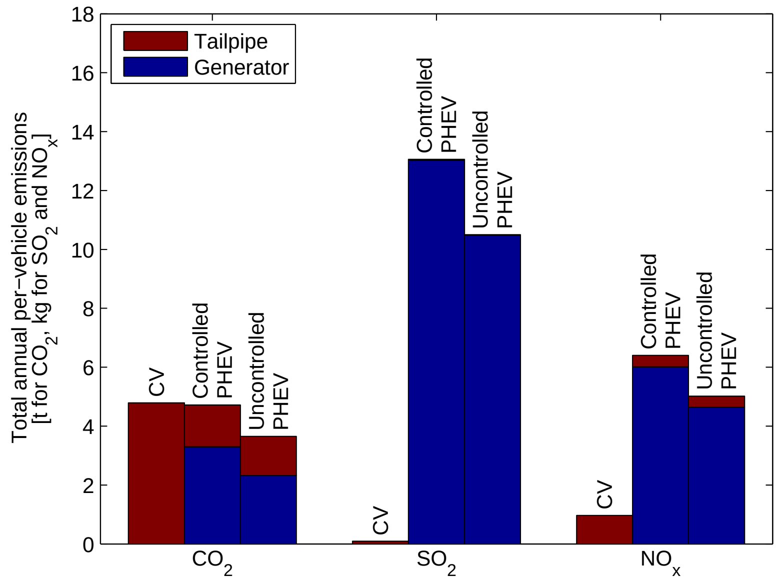

Figure 7: Annual per-vehicle emissions of CO_2 (tonnes) and SO_2 and NO_x (kg).

3.3. PHEV Ownership Cost

An analysis of PHEV ownership costs must tradeoff the generally higher capital cost of a PHEV (compared to a CV or even an HEV) and the lower relative driving cost of a PHEV, due to reduced gasoline consumption, the lower cost of electricity as a transportation fuel, and potential operations and maintenance cost savings. Moreover, PHEVs may be subject to incentives or subsidies, in order to incentivize their use. Our analysis will focus on capital and fuel costs only, neglecting the other potential value streams associated with PHEV use, since these other costs and values are difficult to estimate without commercially available PHEVs.

The architecture of a PHEV is differentiated from that of an HEV by its ability to further displace fuel usage by charging off-board electrical energy from the electric power system while not being driven. To accommodate the increased dependence on electric power while maintaining an appropriate vehicle weight, the PHEV uses a battery pack with a larger capacity and a smaller internal combustion engine and fuel tank. Also, an inverter-integrated charging plug is needed to connect the enhanced battery pack to a standard electrical socket for recharging purposes. Since all PHEVs produced in the future are expected to offer at least 220 V charging capability, the estimated cost to install an additional outlet in an accessible location to the PHEV is included in this cost analysis. Currently, conventional vehicles exhibit the least-expensive initial cost of about $21,390, which is not expected to vary significantly in the future (in terms of real cost, excluding inflation). Sentech (2008) suggests that PHEVs will experience a more dramatic cost reduction from current cost estimates of $51,388 to about $27,668. With these cost reductions, PHEVs are expected to have a price premium of approximately $6,200 in the future relative to conventional vehicles.

Tables 3 and 4 summarize the per-vehicle and total impact of PHEV use on gasoline consumption. Table 3 shows that PHEV use can result in substantial fuel savings of close to 1500 liters (400 gallons) annually. Moreover, the table shows that uncontrolled PHEV charging yields slightly greater gasoline reductions than the controlled case, due to the greater midday recharging and distance driven using grid electricity in the uncontrolled scenario. Table 4, which summarizes total gasoline consumption by the entire light-duty vehicle fleet (including non-PHEVs), shows that the 5% penetration of PHEVs assumed will decrease total vehicle fleet gasoline consumption by about 3.5%.

Although PHEV use reduces gasoline consumption, there will be an increase in electricity demand. Figure 8 summarizes total annual generation costs, broken down by the cost of in-state generation and net purchases from the rest of the PJM market, with and without the PHEV fleet. The figure shows that both

Table 3: Annual per-vehicle gasoline usage

Type	Gasoline usage (liters)
CVs	2040
Controlled PHEVs	606
Uncontrolled PHEVs	564

Table 4: Annual total gasoline usage

		Gasoline Savings	
	Total Usage (million liters)	Million Liters	%
CVs	13143		
Controlled PHEVs	12681	462	3.5
Uncontrolled PHEVs	12670	477	3.6

with and without PHEV charging loads, Ohio has a negative cost from market transactions—implying that Ohio is a net exporter of energy due to the lower cost of generation in Ohio compared to the rest of the PJM market. Moreover, the figure shows that the net impact on generation costs of PHEV use is a mere 0.1% increase, with uncontrolled charging resulting in slightly higher generation costs due to the lack of coordination between charging and power system operation decisions.

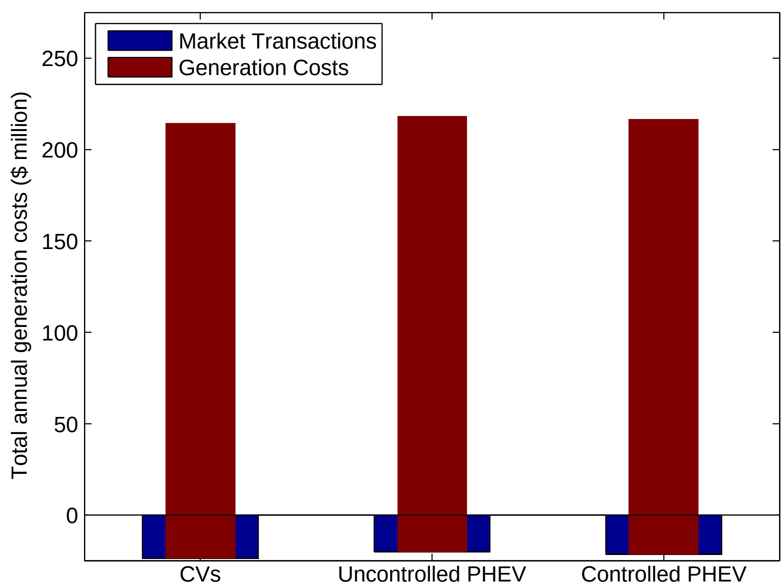

Figure 8: Annual generation cost ($ million).

How these generation cost increases may be passed onto ratepayers, and specifically to PHEV owners, is difficult to determine, since it is not clear what retail electricity rates will be charged when PHEVs enter the market and whether PHEVs will be given different electricity rates. In 2007, retail residential electricity rates averaged about \$0.111/kWh in Ohio, based on data reported by the EIA. While the cost of energy contributes to determining this retail rate, there are non-energy related charges, such as fixed cost recovery, transmission and distribution costs, and metering, that are included in these tariffs as well. Our simulations show that adding the PHEV charging loads increase the annual cost of all generation (of PHEV and non-PHEV loads) by about \$0.0032/kWh and \$0.0024/kWh in the uncontrolled and controlled cases, respectively. Since utilities would need to recover these additional generation costs, it is plausible to assume that if PHEVs pay the same retail price of electricity as non-PHEV charging, then retail rates would increase by this amount above the \$0.111/kWh average.

It is worth noting, however, that policymakers may opt to levy a different rate on PHEV charging for a number of reasons. One is that it may be desirable to charge a lower rate to incentivize PHEV adoption. It has even been suggested that lower rates should be provided to PHEV owners who allow the grid operator to control charging, thereby providing PHEV owners with an incentive to give the grid operator this type of control. On the other hand, it has also been suggested that PHEV owners be charged higher electricity rates in order to recover gasoline excise and other taxes that are used to fund transportation infrastructure improvements. Because PHEV owners will use less gasoline, the cost of these taxes would be borne disproportionately by CV and (to a lesser extent) HEV owners, and state and federal governments may not receive sufficient tax revenues for these types of projects. For example, Lemoine et al. (2008) estimate that PHEV charging loads in California would require taxes of about \$0.04/kWh in order to recover lost tax revenues that a comparable CV would provide from gasoline taxes. Finally, it is worth noting that the generation cost increases of \$0.0024/kWh to \$0.0032/kWh given above assume that the costs associated with PHEV are allocated to all (PHEV and non-PHEV) loads, which may not be desirable since the incremental cost of PHEV charging can be non-trivially high. Without PHEV charging loads, the total generation costs average about \$0.0127/kWh. When PHEV charging loads are added, the incremental generation costs, which are defined as the increase in total generation costs divided by the increase in total generation, are \$0.1953/kWh and \$0.0924/kWh in the uncontrolled and controlled cases, respectively. Given the high cost of these incremental loads, especially in the uncontrolled case, it may be desirable to allocate a relatively high portion of these charging costs to PHEV owners.

Due to this uncertainty in the electricity rates, this cost analysis is done by parameterizing electricity rates. Similarly, although the average retail price of gasoline in Ohio in 2007 was \$2.27/gallon (as reported by the EIA), gasoline prices soared to much higher levels in 2008. Although prices have dropped from the highs seen then, this is largely attributed to the recent global recession with many expecting prices to rebound as economic activity increases. Thus, the price of gasoline is also parameterized in the analysis. Furthermore, this cost analysis focuses on the uncontrolled charging scenario (to determine gasoline and electricity usage), since this is the most likely scenario when PHEVs first enter the vehicle fleet.

Figure 9 summarizes the effect that retail gasoline and electricity prices would have on the fuel cost of PHEVs and the percentage savings in these costs relative to a CV. With 2007 costs of \$0.114/kWh for electricity and \$2.27/gallon for gasoline, a PHEV achieves a close to a 45% reduction in fuel costs relative to a CV. Even in the 'worst' scenario, with a high electricity price of more than \$0.15/kWh and a low gasoline cost of close to \$2/gallon, PHEVs would still yield substantial savings of more than a third due to the much higher efficiency of an electric engine relative to an internal combustion engine. Higher gasoline prices of \$4/gallon or higher, such as those seen in 2008, would give PHEVs an even greater fuel cost advantage.

3.4. Payback Time of PHEVs

Payback time is an important factor in determining whether future consumers will decide to buy a PHEV. The basic tradeoff facing the consumer is the higher upfront capital cost of a PHEV relative to the stream of driving cost savings due to reduced gasoline costs. Figures 10 and 11 summarize the payback time of a PHEV, as a function of the gasoline, electricity, and purchase price of a PHEV. The payback time is defined as how long it would take for a PHEV, through lower fuel costs, to have the same cumulative ownership cost as a comparable CV. If a buyer owns a PHEV for longer than this payback period, she will have a lower cost from PHEV ownership than from a CV.

Figure 10 shows payback times for PHEVs that have incremental costs of \$6000 above that of a CV, whereas figure 11 considers a case with a higher purchase price premium of \$10000. The figures show that the payback time will be highly sensitive to all three costs factors. If PHEVs have a cost premium of \$6000 above a CV, which is in line with the cost estimates given by Sentech (2008), then the payback time of a PHEV will be less than six years if gasoline prices are on average greater than \$4/gallon and electricity prices less than \$0.15/kWh—fuel prices that were seen in the United States in the summer of 2008 before the global economic slowdown suppressed prices. Given that many vehicle buyers expect an investment in a fuel-efficient car to pay for itself within a few years, this less than six-year payback time could make PHEV adoption feasible. With a cost premium of \$10000, however, the payback period can increase to close to

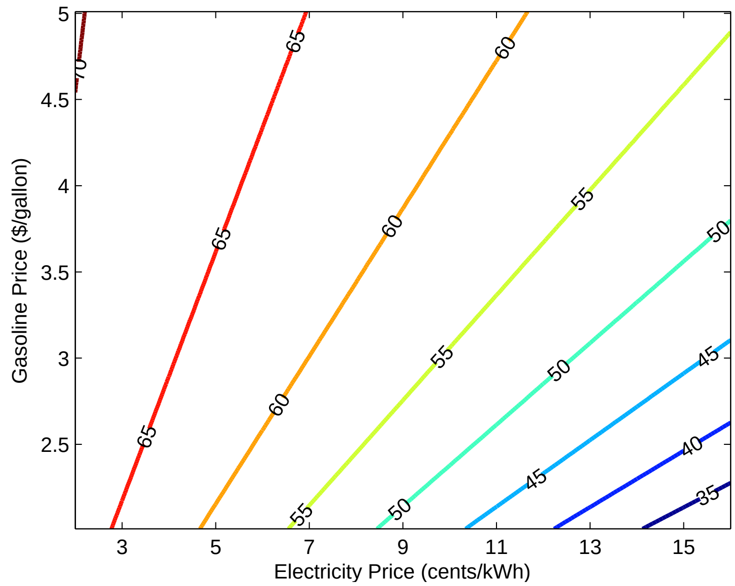

Figure 9: Fuel cost savings of a PHEV relative to a CV, as a percentage of CV fuel costs.

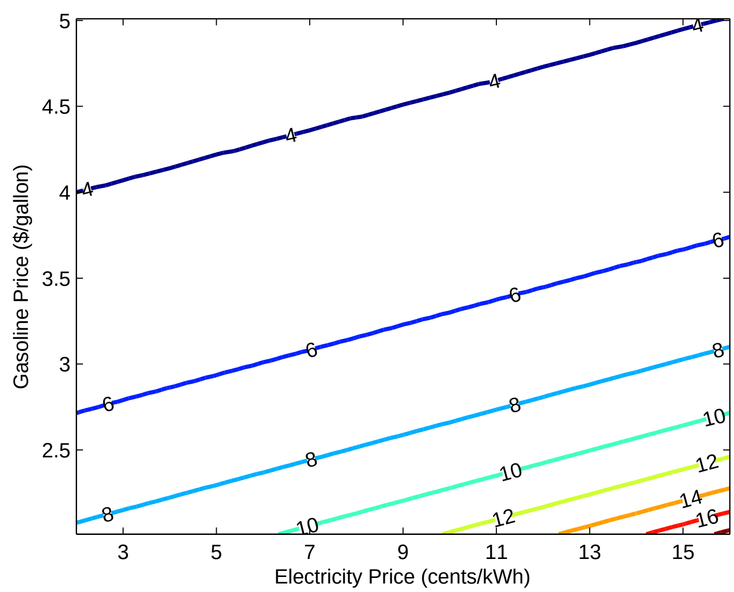

Figure 10: Payback time of a PHEV with an additional purchase price of $6000.

nine years, making PHEV adoption must less attractive to potential buyers. Thus it is evident that the manufacturing cost of PHEVs will be critical in ensuring consumer adoption.

It also bears mentioning that this analysis excludes a number of other important factors that could affect the economics of PHEV purchases. One is the effect of the discount rate. Following Denholm and Letendre (2007), figures 10 and 11 show payback times assuming undiscounted cost streams. If consumers have high discount rates, however, this could increase the payback time by a few years. Another factor we have not accounted for is the effect of any future climate or carbon regulation on the price of generating fuels, gasoline, and electricity. Carbon regulation could be expected to have a major impact on the cost of electricity in Ohio, given the high penetration of coal-fired generation in the state. If these regulations are

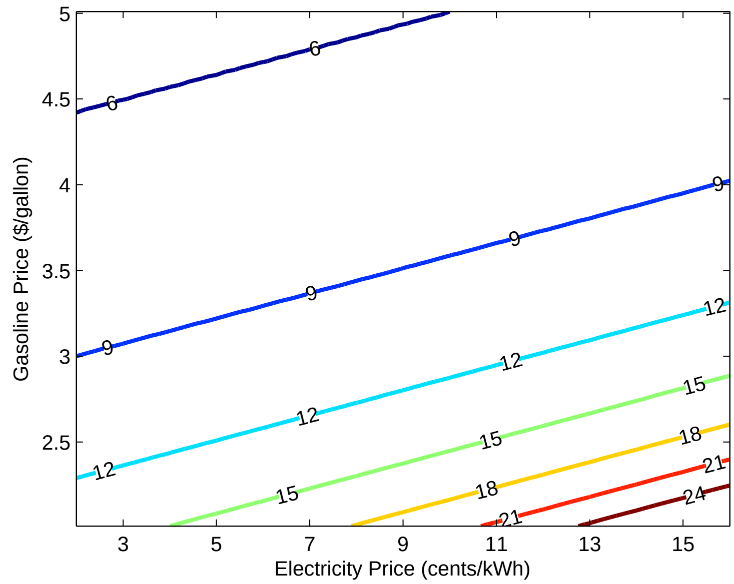

Figure 11: Payback time of a PHEV with an additional purchase price of $10000.

applied disproportionately to generators, this could increase the payback time of a PHEV by decreasing the fuel cost savings of a PHEV. On the other hand, if carbon regulations are also imposed on gasoline, this could increase the cost of gasoline and potentially increase the fuel cost advantage of a PHEV relative to a CV. For example, a coal generator with a heat rate of about 10 MMBtu/MWh releases roughly 872 kg of CO_2 per MWh of electricity generated. A PHEV could travel an average of about 5464 km (or 3395 miles) with a MWh of electricity in CD mode, meaning that coal-generated electricity produces roughly 0.16 kg of CO_2 per km driven. A CV that averages about 11 km per liter (about 26 miles per gallon), on the other hand, would produce roughly 0.21 kg of CO_2 per km driven. Thus, if carbon regulations are applied to both electricity and gasoline, this could further increase the cost advantage of a PHEV relative to a CV, reducing the payback time.

4. Conclusions

This paper models and examines the interactions between PHEVs and the Ohio power grid. The analysis is based upon a combination of a unit commitment model of the power system and a vehicle driving model. The model considers two different charging scenarios: one in which the power grid has a great deal of flexibility in coordinating charging decisions with power system operations, and another in which charging decisions are made entirely by PHEV owners. The analysis shows that due to the high penetration of coal-fired generation and the high emissions rates of these generators, SO_2 and NO_x would increase with PHEV use, whereas CO_2 emissions would decrease. If the goal of PHEV use is primarily emissions reductions, then an uncontrolled charging scenario would be preferred, since it yields lower emissions and a cost increase of only about $0.0008 per kWh generated relative to controlled charging. This strategy leads to an annual decrease of about one tonne of CO_2 per PHEV.

With an uncontrolled strategy, however, PHEV charging will increase peak loads on the grid because of the coincidence between summer afternoon cooling loads and when vehicle drivers could be expected to arrive home and plug their vehicles in. With our assumption of a 5% penetration level of PHEVs, this had a negligible impact. If, however, PHEVs represented 30% of light-duty vehicles, uncontrolled charging would increase the summer peak load by more than 3%. This increase in the peak load could necessitate more generating capacity being installed in the system, which could increase PHEV-related costs and emissions. These issues with uncontrolled charging could potentially be overcome if more exotic electricity tariffs, such as time-of-use rates or real-time pricing, which can provide PHEV owners with indirect incentives to coordinate their charging behavior with power system operations, are used. The potential impacts of these types of tariffs have not, however, been explored in detail, and is a topic of future work.

Another very important aspect of PHEV use is the potential to reduce oil consumption, thereby decreasing dependence on foreign sources of energy and avoiding problems associated with oil price instability. Our results show that a single PHEV can save more than 70% of the gasoline that would be consumed by a comparable CV. Since electricity is a much cheaper transportation fuel than gasoline this will also yield a substantial reduction of vehicle operation costs of close to 40% assuming the low electricity and gasoline prices in 2007 remained. These fuel cost savings will also lead to shorter payback times for PHEV owners of less than six years, depending on the capital cost premium of a PHEV above a CV.

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Appendix A. Mathematical Formulation

Appendix A.1. Power System Model

The power system model is a standard unit commitment problem, which minimizes total generation costs, subject to unit and system operating constraints—including a load-balance constraint that ensures the total load in each hour is served. In the uncontrolled charging scenario, the power system model takes the PHEV and non-PHEV loads as exogenous parameters, whereas in the controlled case PHEV charging will be endogenous decision variables from the vehicle model.

In order to give the mathematical formulation of the model, we first define the following notation:
Problem Parameters:

- T: number of hours
- I: generator index set
- $C_i(q_i)$: generator i's non-decreasing stepped variable generating cost function
- N_i: generator i's noload cost
- SU_i: generator i's startup cost

- K_i^-, K_i^+: generator i's minimum and maximum operating points, respectively
- R_i^-, R_i^+: generator i's rampdown and rampup limits, respectively
- τ_i^-, τ_i^+: generator i's minimum down- and up-time, respectively
- D_t^n, D_t^p: non-PHEV and PHEV load in hour t, respectively
- $M(p)$: cost of net energy purchases from the rest of the PJM market

Decision Variables:

- $q_{i,t}$: generation provided by generator i in hour t
- $u_{i,t}, s_{i,t}, h_{i,t}$: binary variables indicating if unit i is up, started-up, and shutdown in hour t, respectively
- p_t: net energy purchases from the rest of the PJM market in hour t

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

$$\min_{q,u,s,h,p} \sum_{t \in T} \left(\sum_{i \in I} (C_i(q_i) + N_i u_{i,t} + SU_i s_{i,t}) + M(p_t) \right)$$

subject to the following constraints:

$$\begin{aligned}
&\sum_{i \in I} q_{i,t} + p_t = D_t^n + D_t^p && \forall\, t \in T && \text{// load-balance} \\
&K_i^- u_{i,t} \le q_{i,t} \le K_i^+ u_{i,t} && \forall\, i \in I, t \in T && \text{// generator output limits} \\
&R_i^- \le q_{i,t} - q_{i,t-1} \le R_i^+ && \forall\, i \in I, t \in T && \text{// generator ramping limit} \\
&\sum_{y=t-\tau_i^+}^{t} s_{i,y} \le u_{i,t} && \forall\, i \in I, t \in T && \text{// generator minimum up time} \\
&\sum_{y=t-\tau_i^-}^{t} h_{i,y} \le 1 - u_{i,t} && \forall\, i \in I, t \in T && \text{// generator minimum down time} \\
&s_{i,t} - h_{i,t} = u_{i,t} - u_{i,t-1} && \forall\, i \in I, t \in T && \text{// generator state transitions} \\
&u_{i,t}, s_{i,t}, h_{i,t} \in \{0, 1\} && \forall\, i \in I, t \in T && \text{// integrality of commitment variables}
\end{aligned}$$

Appendix A.2. Vehicle Model

The vehicle model minimizes total gasoline costs, subject to driving constraints which ensure that the battery state of charge (SOC) remain within appropriate limits, the vehicle is only recharged when it is grid connected, and all vehicle trips are taken. Because the PHEV fleet is modeled by assuming that the vehicles drive and charge according to the 227 driving profiles in the empirical driving data, each driving profile will have distinct parameter values and variables associated with it. Thus, for instance, each driving profile will have a set of values, $dist_t$, specifying the distance that a PHEV with that profile is driven in each hour (although this is not explicitly shown in the notation). We first define the following notation:
Problem Parameters:

- T: number of hours
- $\overline{p}$: power limit of PHEV charging station plug
- $\overline{e}, \underline{e}$: maximum and minimum SOC of PHEV battery, respectively

- π^g: cost of gasoline
- ce: charging efficiency of PHEV battery
- $dist_t$: distance PHEV drives in hour t
- cd^e: average net battery energy usage (measured in Wh/km) when driven in CD mode
- cd^g, cs^g: average gasoline usage (measured in l/km) when driven in CD and CS modes, respectively

Decision Variables:

- SOC_t, ch_t: ending SOC and energy charged into PHEV battery in hour t, respectively
- cd_t^m, cs_t^m: distance driven in CD and CS mode, respectively, in hour t
- $\widetilde{cd}_t$: binary variable indicating whether battery SOC is above minimum at end of hour t

The vehicle model is formulated as minimizing the sum of gasoline costs associated with driving:

$$\min_{SOC, ch, cd^m, cs^m, \widetilde{cd}} \sum_{t \in T} \pi^g \cdot (cd^g cd_t^m + cs^g cs_t^m)$$

subject to the following constraints:

$$\begin{array}{lll}
SOC_t = SOC_{t-1} + ch_t - cd^e cd_t^m & \forall\, t \in T & // \text{ battery charge balance} \\
cd_t^m + cs_t^m = dist_t & \forall\, t \in T & // \text{ driving requirement} \\
\widetilde{cd}_t \geq \dfrac{SOC_t - \underline{e}}{\overline{e} - \underline{e}} & \forall\, t \in T & // \text{ CD mode definition} \\
cs_t^m \leq dist_t(1 - \widetilde{cd}_t) & \forall\, t \in T & // \text{ CD to CS mode transition} \\
ch_t = 0 & \forall\, t \in T \mid dist_t > 0 & // \text{ no recharging when driving} \\
\underline{e} \leq SOC_t \leq \overline{e} & \forall\, t \in T & // \text{ variable bounds} \\
0 \leq ch_t \leq \overline{p} & & \\
0 \leq cd_t^m, cs_t^m \leq dist_t & & \\
\widetilde{cd}_t \in \{0, 1\} & \forall\, t \in T & // \text{ variable integrality}
\end{array}$$

Appendix A.3. Integration of Models

In the uncontrolled scenario, the vehicle model is used to determine the charging decisions made by the individual PHEV owners. Essentially, the vehicle model is used to determine how much electric energy is used during each driving trip and how much energy will be put into the battery once the vehicle is parked and plugged in. These charging patterns are then input into the power system model as exogenous parameters.

In the controlled scenario, the vehicle and power system models are integrated together. Thus, the grid operator controls both power system operations and charging decisions, subject to the constraints of the above models and an added constraint that each vehicle must be fully recharged before the first trip of each day. The objective function of this integrated model is to minimize the sum of total generation and gasoline costs incurred by the PHEV fleet.