Plug-in hybrid electric vehicles: battery degradation, grid support, emissions, and battery size tradeoffs

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Abstract

Plug-in hybrid electric vehicles (PHEVs) may become a substantial part of the transportation fleet on time scales of a decade or two. This dissertation investigates battery degradation, and how the introduction of PHEVs may influence the electricity grid, emissions, and petroleum use in the US. It examines the effects of combined driving and vehicle-to-grid (V2G) usage on the lifetime performance of relevant commercial Li-ion cells. The loss of battery capacity was quantified as a function of driving days as well as a function of integrated capacity and energy processed by the cells. The cells tested showed promising capacity fade performance: more than 95% of the original cell capacity remains after thousands of driving days worth of use. Statistical analyses indicate that rapid vehicle motive cycling degraded the cells more than slower, V2G galvanostatic cycling. These data are used to examine the potential economic implications of using vehicle batteries to store grid electricity generated at off-peak hours for off-vehicle use during peak hours. The maximum annual profit with perfect market information and no battery degradation cost ranged from ~US$140 to $250 in the three cities. If the measured battery degradation is applied, however, the maximum annual profit decreases to ~$10–120. The dissertation details the increase in electric grid load and emissions due to vehicle battery charging in PJM and NYISO with the current generation mix, the current mix with a $50/tonne CO_2 price, and this case but with existing coal generators retrofitted with 80% CO_2 capture. It also models emissions using natural gas or wind+gas. PHEV fleet percentages between 0.4 and 50% are examined. When compared to 2020 CAFE standards, net CO_2 emissions in New York are reduced by switching from gasoline to electricity; coal-heavy PJM shows somewhat smaller benefits unless coal units are fitted with CCS or replaced with lower CO_2 generation. NO_X is reduced in both RTOs, but there is upward pressure on SO_2 emissions or allowance prices under a cap. Finally the dissertation compares increasing the all-electric range (AER) of PHEVs to installing charging infrastructure. Fuel use was modeled using the National Household Travel Survey and Greenhouse Gasses, Regulated Emissions, and Energy Use in Transportation model. It was found that increasing AER of plug-in hybrids was a more cost effective solution to reducing gasoline consumption than installing charging infrastructure. Comparison of results to current subsidy structure shows various options to improve future PHEV or other vehicle subsidy programs.

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$\eta^{CD\text{-}E}$ – vehicle electric efficiency in charge depleting mode
$\eta^{CD\text{-}G}$ – vehicle gasoline efficiency in charge depleting mode
$\eta^{CS\text{-}G}$ – vehicle gasoline efficiency in charge sustaining mode
Δt – time step in seconds
ρ – density of air
v – vehicle velocity
a – acceleration
A – frontal area of vehicle
A – Amp
AEO – annual energy outlook published by energy information administration
AER – All electric range
BEV – Battery electric vehicle
BOS – Boston, MA
BTU – British thermal unit
CAFE – corporate average fuel economy
CD – charge depleting mode
CCS – Carbon Capture and Sequestration
CS – charge sustaining mode
CV – conventional vehicle
C_d – coefficient of drag
CH_{eff} – Charge efficiency
C_{rr} – dimensionless coefficient of rolling resistance
d^{CD} – distance in charge depleting mode
d^{CS} – distance in charge sustaining mode
DCH_{eff} – Discharge efficiency
DoD – Depth of discharge
E85 – an ethanol gasoline blend with 85% ethanol
EIA – Energy Information Administration
EVSE – Electric vehicle supply equipment
g – acceleration of gravity
Gal – gallons
GHG – greenhouse gas
GREET – Greenhouse Gasses, Regulated Emissions, and Energy Use in Transportation
HEV – hybrid electric vehicle
ICE – internal combustion engine
ISO – Independent System Operator
ISO-NE – New England Independent System Operator
kWh – kilowatt hours
LMP – locational marginal pricing
LMP_{BUY} – Buying price of electricity
LMP_{SELL} –Selling price of electricity
m – mass
mpg – miles per gallons
NHTS – National Household Travel Survey

NYISO – New York Independent System Operator
NPV – net present value
PHEV – Plug-in hybrid electric vehicle
PHL – Philadelphia, PA
PJM - Pennsylvania New Jersey Maryland Interconnection LLC
Quad – quadrillion BTUs
ROC – Rochester, NY
RTE – Round trip efficiency
RTO – Regional Transmission Organization
RTP – Real Time Price
SOC – State of charge
SRMC – Short Run Marginal Cost
SUV – sport utility vehicle
TND or T&D – Transmission and Distribution Charge
UDDS – Urban Dynamometer Driving Schedule
V – Volt
V2G – vehicle to grid energy transfer
V2G Deg – Coefficient relating battery degradation to battery use for arbitrage
VMT – vehicle miles travelled
W – Watt
Wh – Watt hour

Chapter 1 Introduction

1.1Overview and Motivation

Personal mobility enabled by automobiles has been woven into US culture for nearly a century. For example, soon after the automobile became widely available to U.S. citizens, the National Park Service (NPS) made a concerted effort to encourage automobile travel to and in National Parks [1]. The most visited section of the NPS system is a road. The Blue Ridge Parkway, authorized in 1933 by the National Industrial Recovery Act, consists of approximately 500 miles of scenic highway [1]. Nearly a century after its authorization the NPS's preferred alternative for managing the Parkway specifies that it "would be actively managed as a traditional, self-contained, scenic recreational driving experience [2]."

The ratio of automobiles to people climbed for most of the 20th century. Whether driving to work or traveling to one of the many National Parks, most US citizens interact with personal vehicles on a regular basis. Indeed proposals to increase tax on gasoline are often framed as unfair to ordinary persons because of the necessity to drive. There are costs associated with the widespread adoption of vehicles. It has linked the cost of transportation to petroleum prices and vehicle use in urban areas has ensured emissions are close to population centers concentrating localized negative environmental effects where people live. Plug-in hybrid electric vehicles (PHEVs) have the potential to mitigate some of these issues.

In the US, transportation uses nearly a third of the energy consumed annually (27.5 quads in 2010), 97% of which is provided by petroleum [3]. The light duty fleet accounted for 60% of this energy use and 45% of total US petroleum use in 2009 [4]. It appears that transportation will soon surpass the industrial sector as the largest energy consumer in the US (Figure 1.1).

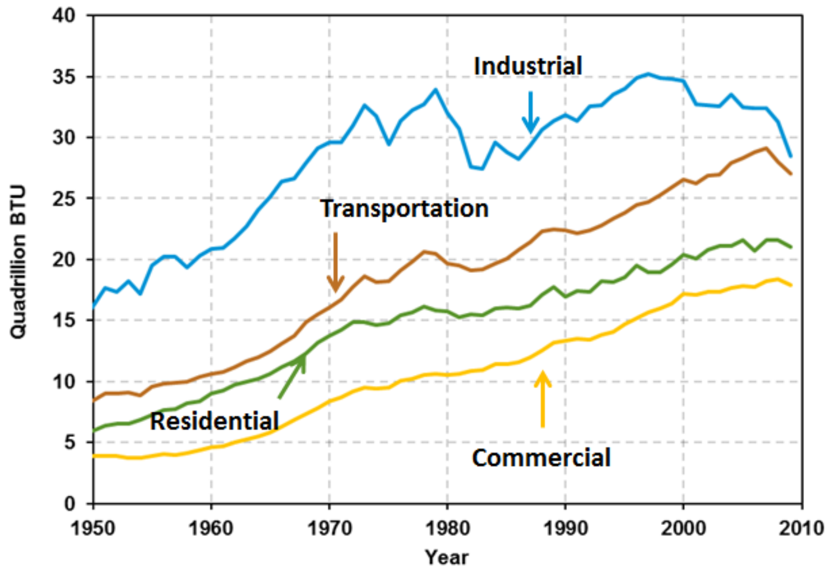

Figure 1.1 – Energy consumption in the US by sector since 1950 [5]

Despite increases in passenger car efficiency, there has been increasing fuel consumed from 1980 to 2004 (Figure 1.2). While an increase in light duty truck sales reduced fleet efficiency gains, overall fleet efficiency still increased each year [6]. An increase in vehicle miles travelled (VMT) per capita caused the observed increase in fuel consumed per capita (Figure 1.3).

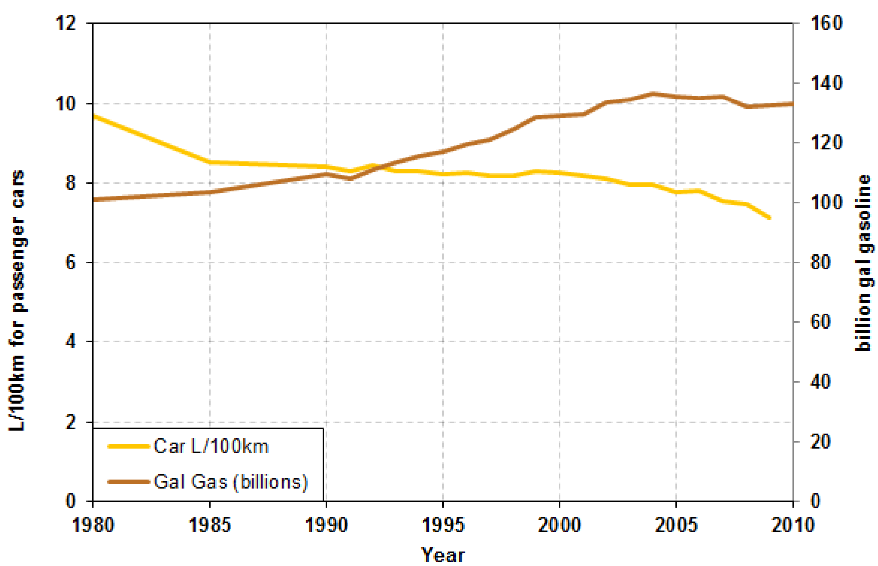

Figure 1.2 – Passenger car fleet efficiency and US gasoline consumption [6]

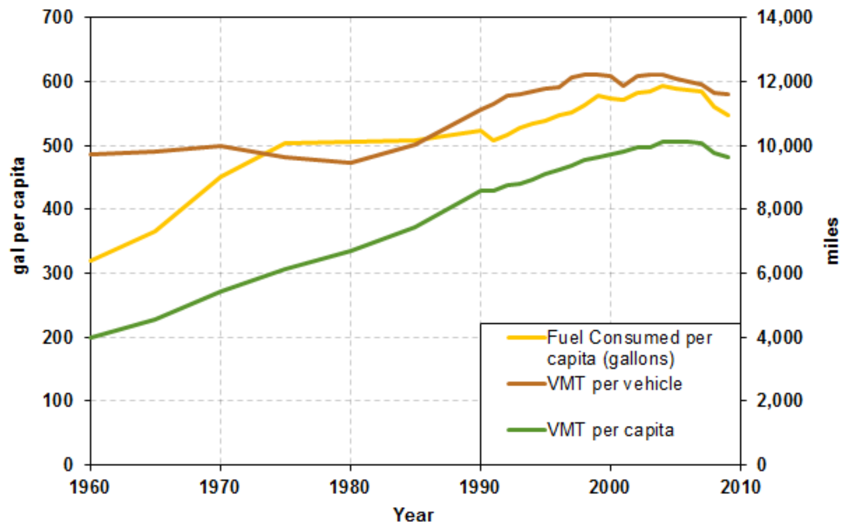

Figure 1.3 – The total VMT per capita has increased more than the VMT per vehicle as households purchased additional vehicles [7-9]

From 1960 to 1980 the VMT per capita rapidly increased, but VMT per vehicle held relatively steady as households purchased additional vehicles and decreased in size. It appears that in 2008 there was slowdown in adding vehicles because VMT per capita decreased, but VMT per vehicle held relatively steady. This can also been seen when comparing the number of vehicles per household, which increased in each subsequent National Household Travel Survey (formerly National Personal Travel Survey) until 2009 [10,11].

Oil is easily transported, so the specific country of origin is not important. However, having such an important sector of the economy so dependent on one type of fuel is an economic risk and seen as a threat to national security because if a producing country reduces output it affects all consuming countries not just those that purchased directly from those reducing production [12]. Economic downturns and increased fuel prices have coincided with a decrease of gasoline usage (Figure 1.4). The amount of money spent purchasing gasoline is still much higher in real terms than any time between 1990 and 2004. Regression of GDP growth on lagged petroleum prices has shown a statistically significant relationship [13-22]. Although recessions have also often been observed to follow oil price spikes there is still substantial debate about the magnitude of response in GDP growth [22].

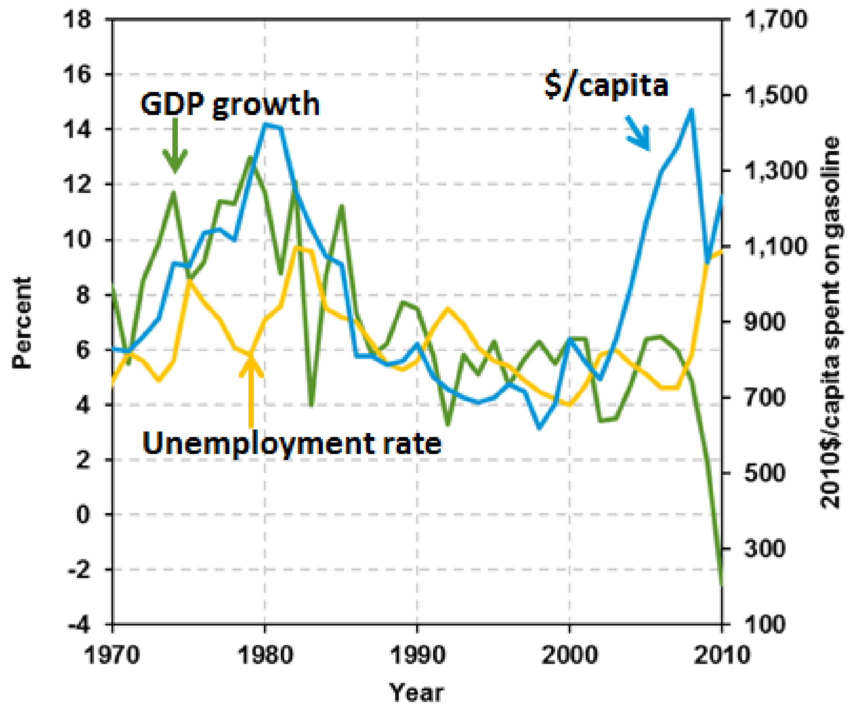

Figure 1.4 – Comparison of GDP growth, unemployment rate, and amount spent per capita on gasoline [23-26]

Consumers appear to show little short run elasticity to gasoline prices, and recent analysis of the 2006 price spike shows that the elasticity of demand has likely decreased from that seen in the price spike between 1975 and 1981 [27]. Gasoline prices climbed even higher in 2007 and have held at relatively high values since that time (Figure 1.5).

The cost of crude oil has fluctuated significantly in the last century (Figure 1.5). Although consumers may take into account expected fluctuations in gas prices, if they believe prices will remain high due to resource constraints, alternatives face a lower hurdle to compete. Hybrid electric vehicles move the fleet to more efficient vehicles, but as seen in the past that does not necessarily lead to reductions in petroleum use because of a rebound effect seen in terms if increased VMT. It is possible that the growth in VMT would slow because consumers have only a limited amount of time to drive, but increases in demand from developing nations will likely keep upward pressure on fuel prices for some time to come. Increasing fuel cost has led to slight reductions in per capita fuel use, but it is unlikely there is political will to implement a higher tax on fuel to further reduce consumption.

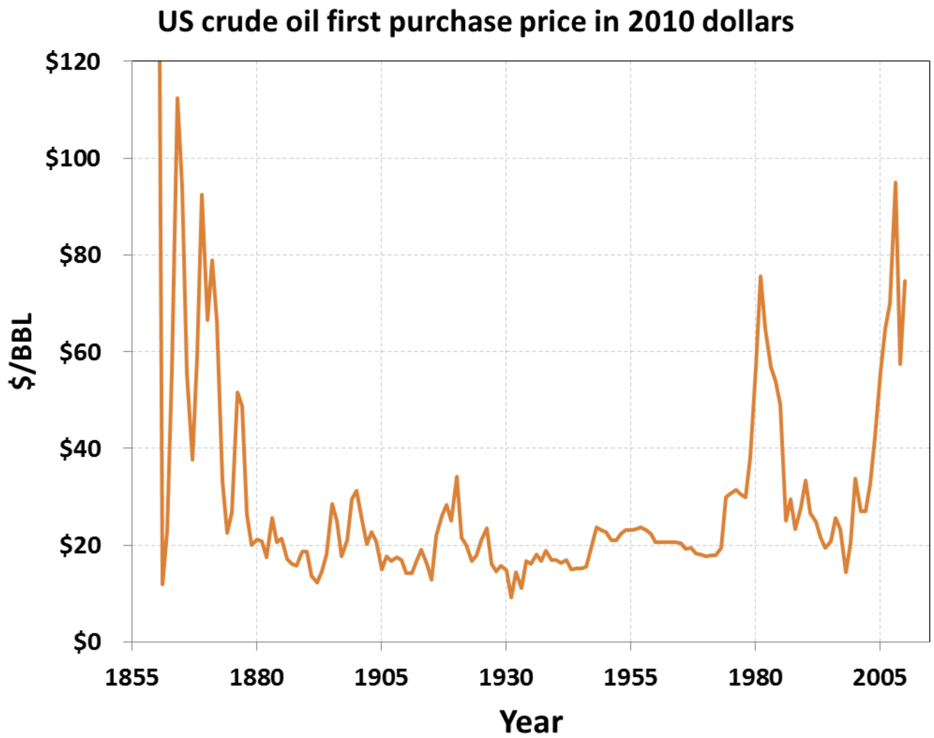

Figure 1.5 – First purchase price of oil taken from EIA adjusted via (1851 to 1890 - Consumer Price Index by Ethel D. Hoover; 1890 to 1912 - Cost of Living Index by Albert Rees; 1913- 2010 CPI) [28, 29, 30]

Burning petroleum in highway vehicles significantly contributes to total criteria pollutant emissions in the US: 53% of CO, 31% of NO_X, 24% of VOCs, 1.7% of PM2.5 in 2011 [31]. Transportation is also responsible for a significant proportion of US CO_2 emissions, 31% in 2009 [4].

There are policy options to reduce petroleum consumption without relying on taxes. Changing the fleet to use alternative sources of energy has the potential to drastically reduce petroleum consumption. Vehicles could be produced that run on biofuels, natural gas, or utilize electricity. An advantage of partially electrifying the transportation fleet is that it would provide for greater flexibility of primary fuel sources.

Electric vehicles are not a new idea. In 1900 of the 2370 automobiles in New York, Chicago and Boston 49% were steam powered (often burning kerosene), 34% were electric vehicles (EVs) and 17% gasoline [32]. At the time electrics enjoyed usability advantages. Steam vehicles took a long time to start and gasoline powered vehicles required cranking. However the low energy and power density of lead acid batteries combined with increased gasoline infrastructure, allowing longer trips, and reduction in both the price of petroleum (Figure 1.5) and gasoline vehicles, led to the demise of the electric vehicle [33].

In the late 1990s California passed legislation requiring 2% of model 1998 vehicles be zero emissions. This led automakers to introduce new electric vehicles [34]. General Motors introduced the EV1 using lead acid batteries in 1996. GM leased the vehicle and did not sell it. The first EV1 had a lead acid battery pack with capacity of 16.5 kWh and mass of 500kg [34]. This was later replaced with a nickel metal hydride battery pack with capacity 26.4kWh and mass 481 kg [35]. Eventually the EV1 was cancelled and the leased vehicles were crushed [36]. Other battery electric vehicle (BEV) projects from Toyota, Ford, Nissan (using NiMH and lead acid batteries) were also discontinued and 80% of the EVs sold in California were destroyed [37]. Gasoline prices were relatively low between 1985 and 2004, making it more difficult for EVs to compete.

Using onboard vehicle storage to help stabilize the electricity grid, termed vehicle-to-grid (V2G), was an idea proposed to help improve the value of early generation electrified vehicles [38]. While NiMH packs are better than lead acid packs in mass, volume, and cycle life, they were not enough in the late 1990s to make electrified vehicles gain mass market acceptance (Figure 1.6). As gas prices rise and batteries improve, electrified vehicles become more viable than they were. In late 2010 the Chevy Volt (a PHEV) and Nissan Leaf (a BEV) were introduced in the US market [36]. Both vehicles use lithium ion (Li-ion) battery packs. Due to the higher energy density these packs are both lighter and smaller. For example, the Volt's 16 kWh pack is roughly 1/3rd the size of the EV1's original 16.5 kWh pack [39].

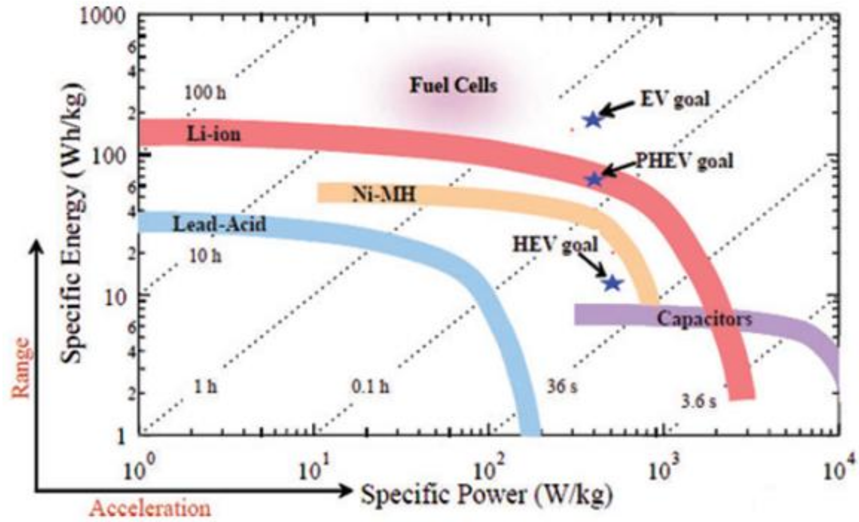

Figure 1.6 – Ragone plot comparing energy and power density of various battery types (adapted from [40])

With advances in battery technology and the introduction of PHEVs, it is important to examine their likely effects. This thesis investigates battery degradation, and how the introduction of PHEVs may influence the electricity grid, emissions, and petroleum use in the US.

1.2 Organization of Thesis and Research Questions

This thesis is divided into four chapters (2-5) that were written as research papers. A brief synopsis of the research conducted and key results for each chapter is included below.

Chapter two describes battery testing and measured degradation for $LiFePO_4$ batteries. At the time of the testing, these batteries were in contention for inclusion in the Chevy Volt. They were already being used in the Hymotion pack sold as an aftermarket addition to the Toyota Prius to convert it to a PHEV. Currently they are also included in the Fisker Karma PHEV and GM has signed an agreement to use them in an upcoming EV [41]. It was found that depth-of-discharge (DoD) alone was not the best predictor of the degradation of high-power $LiFePO_4$ A123Systems M1 cells. If cells exhibiting this property are used to create battery packs for PHEVs, then a PHEV can utilize a battery with lower rated capacity and use a greater proportion of the battery: however, doing so might make discharge rate and associated ohmic heating more of an issue. The current subsidy structure is based on total energy storage, not usable energy storage and would therefore not differentiate between a battery that allowed only 20% state-of- charge (SOC) swing and one that allowed 90%.

The dominant cell degradation method is not dependent upon depth of discharge. Instead the integrated number of lithium ions that have been intercalated/de-intercalated into the electrodes, regardless of the DoD at which these events occur seems to drive the degradation. Multiple regression analysis showed there was a significant difference in degradation when energy was used for driving and constant rate discharge.

This work also showed why the composition of a "test cycle" is important when attempting to quantify battery degradation. The percent capacity lost per normalized Wh or Ah processed is quite low: -6.0×10^{-3} % for driving support and -2.7×10^{-3} % for V2G support. Using constant discharge degradation to predict driving degradation is likely inaccurate, and a correction factor should be used if a more representative cycle cannot be tested. It is likely this difference is in response to polarity changes (corresponding to regenerative braking events in vehicles). Therefore, V2G modes that require charge and discharge from the battery (for example balancing intermittent resources) will lead to more rapid battery capacity fade and should be avoided to minimize battery capacity loss over many years of use. It appears that the cycle life of these cells is more than adequate to enable electrified transportation (>15 years simulated driving and 4 years real testing). However, because the tests were run at room temperature, it is possible that mechanical stress due to variations in temperature and accelerated aging from higher temperatures might reduce calendar life.

Chapter 3 focuses on the viability of using PHEVs for energy arbitrage. This was chosen as a topic because of it might improve the economics of PHEV ownership. Ancillary services such as frequency regulation were not considered because only a small number of vehicles will saturate that market [38]. Vehicle owners are unlikely to receive sufficient incentives from electricity arbitrage to motivate large-scale use of car batteries for grid support. Maximum annual profit with perfect market information and no battery degradation cost is \$142-\$249 in the three cities considered (Rochester NY, Boston MA, and Philadelphia PA) due to small variation in LMPs and the size of the battery pack. With degradation included, the maximum annual profit (even if battery replacement costs fall to \$5000 for a 16 kWh battery pack) is \$12-\$118; in the more realistic lower bound profit case, the annual profit is \$6 - \$72. If the difference between high and low LMPs grows in the future the value of energy arbitrage will increase, providing greater incentive to individuals or a hypothetical aggregator. However, any growth in electricity arbitrage will lower the gain, since vehicle owners will increase the presently low night demand and decrease peak demand, lowering the LMP spread.

Changes in net social welfare (change in consumer surplus less producer surplus) from energy arbitrage were also found to be small. The increase in net social welfare from battery storage was estimated to be equivalent to $8/vehicle/year based on Sioshansi and co-authors estimate of the net social welfare of energy storage in PJM during 2007 (for 4 GWh of total storage, about 380,000 16 kWh vehicles using 2/3 of their battery pack capacity for electricity) [42]. It is likely that the net social welfare provided by energy storage would increase at high levels of variable renewable power generation. If 25% of total U.S. generation were wind or solar, 10^{12} kWh, the integration cost would likely be on the order of 0.5 to 1 cent per kWh, then the integration cost mitigation would be $20 - $40/vehicle/year [43]. This assumes all 250 million vehicles participated in grid support and all integration costs could be mitigated by vehicle storage. Since not all vehicles could participate, the amount available per participating vehicle would be proportionally higher. In that case, there may be opportunities to transfer some of that benefit to the vehicle owner.

Avoiding the cost of new peaker plants is likely the largest potential grid benefit. A simple cycle natural gas turbine that is used 100 hours per year has fixed costs of approximately $50/kW, or 50¢/kWh. Add to that 10¢/kWh for fuel, for a total of 60¢/kWh, or $432 over the 100 hours the peaker would have run. Since these 100 hours are likely to be in 4 hour blocks on about 25 days of the year a vehicle owner could offset only roughly 2 hours of demand before the battery was depleted. Thus, the grid operator might be able to avoid ~$200 of peaking costs per participating vehicles. With such small monetary rewards, even a minimal barrier would likely preclude the use of batteries for energy arbitrage. Voiding the warranty on a very expensive component such as a traction battery is not a small risk. If the warranty for batteries was changed to reflect energy throughput instead of miles travelled it may be possible to overcome this hurdle. It is likely that manufacturers would rather have such a warranty as well to take into account differences in owner driving, but such a decision might face complaints from potential PHEV owners.

Chapter 4 focuses on use phase emissions of PHEVs. It investigates how a carbon price on electricity, charging strategies, battery size, and location would affect use phase emissions of PHEVs. Charging strategies change net emissions associated with PHEVs. In NYISO, the smart charging scenario (charging at night) resulted in lower or equal net emissions than home charging and lower than work charging. In PJM, smart charging generally causes higher emissions than other charging strategies because coal is often on the margin at night. In PJM there is a tradeoff between use of off-peak charging and increased emissions. Information about generation resources should be used in concert with pricing data to find the optimal charging strategy in individual RTOs. The natural gas, or gas and wind combined charging cases, will result in significant decreases to CO_2 and NO_X emissions.

Electric vehicles will place upward pressure on net SO_2 emissions. With the Cross State Air Pollution Rule (CSAPR) delayed by the courts there is uncertainty about the level of capped emissions. Net SO_2 emissions caused by vehicles will be less than 6% in NYISO and 2% in PJM, of the proposed 2014 CSAPR cap on electric generators under any of the reduced SO_2 scenarios (SO_2 allowances to states in question remained the same in CSAPR and under clean air transport rule) [44, 45].

A CO_2 price of $50/tonne on only electricity will not be effective at reducing net CO_2 emissions from a PHEV fleet unless it encouraged the use of CCS. PHEVs are likely to place upward pressure on SO_2 allowance prices if emission caps bind, or to increase emissions if the caps do not bind. PHEVs will probably reduce net CO_2 and NO_X emissions, but are unlikely to reduce net SO_2 emissions. In the end net emissions from PHEVs depend on the efficiency of the conventional vehicle fleet, PHEV CD (charge depletion, all-electric mode) mode efficiency, charging strategy, battery size, driving patterns, and generator mix used for charging.

Chapter 5 compares the policy decision to support increasing gasoline displacement through increasing all-electric range (AER) vs. installation of charging infrastructure. When comparing the option to increase PHEV AER or install charging points, it appears that under a set of assumptions strongly favorable to infrastructure increasing AER still achieves greater gasoline savings per dollar spent. The implied value of gasoline savings is the value placed on savings that would justify spending to enable a given vehicle scenario. Thus the higher the value the more expensive that option is in terms of gasoline savings. It was found that the maximum implied values of gasoline savings for increased AER for each class (cars, SUVs and trucks) was $1.97, $0.67, and $2.90, which was less than the minimum implied values when installing workplace infrastructure $3.27, $1.04, and $3.07 for respective classes.

This does not imply the current federal subsidy focused on increasing battery size is properly designed. The results of this study imply that the current subsidy structure favors large battery packs significantly and does not seem aligned with societal benefits. If all of the value in subsidizing PHEVs was allocated to gasoline savings it would imply that we subsidize 4 kWh battery PHEVs at $1.25 per gallon saved. At the same time 16 kWh battery PHEVs are subsidized at roughly $4.50 per gallon saved because each additional kWh of rated battery capacity is subsidized at $417 per kWh. Prior work suggests that large battery packs likely have worse life cycle emissions [46]. Aligning the subsidy to equally reward gasoline savings is preferable, but complicated because it is currently predicated on pack size instead of usable pack energy. As discussed in chapter 2, there are differences in battery degradation that means this subsidy might disadvantage a battery chemistry with higher costs per kWh even if the cost per usable kWh were lower. Because of this it would be preferable to subsidize based on usable battery energy instead of rated capacity. It is suggested that the best subsidy structure might be to target AER in a low power driving cycle such as the urban dynamometer driving cycle. This more carefully incentivizes automakers to provide vehicles that will displace gasoline with electricity and allows them the freedom to choose the design and battery chemistry they want.

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Chapter 2 Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilizations

2.1 Chapter Information

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2.2 Abstract

The effects of combined driving and vehicle-to-grid (V2G) usage on the lifetime performance of relevant commercial Li-ion cells were studied. We derived a nominal realistic driving schedule based on aggregating driving survey data from the National household travel survey and the Urban Dynamometer Driving Schedule, and used a vehicle physics model to create a daily battery duty cycle. Different degrees of continuous discharge were imposed on the cells to mimic afternoon V2G use to displace grid electricity. The loss of battery capacity was quantified as a function of driving days as well as a function of integrated capacity and energy processed by the cells. The cells tested showed promising capacity fade performance: more than 95% of the original cell capacity remains after thousands of driving days worth of use. Statistical analyses indicate that rapid vehicle motive cycling degraded the cells more than slower, V2G galvanostatic cycling. These data are intended to inform an economic model.

2.3 Introduction

One suggested benefit of plug-in hybrid electric vehicles (PHEVs) or battery electric vehicles (BEVs) is to provide electricity for off-vehicle use, "vehicle-to-grid" (V2G) services, when parked [1]. These benefits might include peak load shifting, frequency regulation and other ancillary services, smoothing variable generation from wind and other renewables, and providing distributed grid-connected storage as a reserve against unexpected outages. To determine the financial and technical feasibility of these applications, it is essential to quantify the effect of this kind of usage on battery degradation and performance. Most previous measurements have indicated that Li-ion battery capacity decreases as a result of cycling, and the magnitude of this loss is dependent on both the number of cycles and the depth of discharge (DoD) that the battery is subjected to during these cycles[2]. While these characteristics are well understood for the LiC(Ni)oO2/graphite based cells used in the consumer electronics market (as well as for lead acid and NiMH systems) , there is far less published data for the current and next generation of high rate cells that may see wide adoption in PHEV and BEV battery packs. Those data that have been published indicate it is possible to make Li-ion cells with much less capacity fade and dependence on depth of discharge than is commonly assumed [3]. However, these results are insufficient to determine the economics of V2G energy sales because they are from cycling that is not representative of battery use for driving and battery use for grid energy.

To provide more representative data, we examined the battery degradation of a battery cell already being implemented in the PHEV Hymotion battery pack (an aftermarket PHEV conversion), the A123 Systems ANR26650M1 cell. We have examined the response of multiple sets of these cells (from different lots) to gauge their behavior in both simulated driving and combined driving/V2G energy sales modes. Our ultimate goal is to determine the performance and financial costs associated with cycling for V2G energy use in combination with a typical PHEV driving duty cycle. Simulating the actual discharge pattern also has enabled us to determine if there is a difference between dynamic discharge (representing the driving) and constant discharge (energy arbitrage) using statistical analyses.

2.4 Experimental

2.4.1 Driving profile created with data taken from NHTS

The energy arbitrage potential of a vehicle battery depends on both the usable capacity and the fraction of the pack used for daily driving, while the lifetime cost of performing energy arbitrage will depend on how the pack degrades as a function of use mode. To experimentally quantify this, a nominal urban driving/V2G power profile and correlated battery test regime was derived by combing several common data sets. A representative urban commute driving duty cycle was constructed, using data from the 2001 National Household Travel Survey (NHTS) of 70,000 households [4]. To do this, we created a dataset from the NHTS day trip file tabulating the daily trip profile of a vehicle. The day trip file contains "data about each trip the person made on the household's randomly-assigned travel day" [5]. These trips include walking, taking public transportation, driving, or any other means of travel. We extracted only the trips taken by vehicles owned by households and eliminated trips taken at the same time by different members of the household in the same vehicle. This resulted in a new data set that tabulates the daily *vehicle* trips, instead of those of individual household members. The number of vehicles owned by the household is included in the day trip files, and only vehicles that were driven were used in the trip calculation.

The vehicle information dataset was then cross-referenced to append vehicle-specific information, such as the age, fuel economy, and other relevant information. Vehicle-specific information was used to check for potential trends that might indicate that the NHTS data would not apply to PHEVs; none were found. Three cities in the Northeastern quadrant of the United States were selected: Boston (BOS), Philadelphia (PHL), and Rochester NY (ROC). These cities were chosen because they are located in three different electricity markets and because they each had a high number of NHTS participants. The median number of trips taken on a given day by vehicles driven in each of the three cities was four (the mean was 4.46 for cities combined). For this reason, only vehicles which took four trips were thereafter considered in the determination of the representative profile. The median start time, duration, velocity, and distance of each trip in the three cities are listed in Table 2.1. Because the three cities had similar median trips, the data from all three cities were combined to make a single trip profile (Figure 2.1). The total distance traveled was 29 km (original data in miles) when combining all four trips. This is similar to the result obtained if the same analytical steps are applied to the entire NHTS dataset (total distance of 29 km; however trip start times and velocities vary).

Table 2.1 – Trip characteristics for 3 cities modeled and combined data used for battery testing

City	Trip	Start Time	Duration (min)	Average Trip Velocity (kph)	Distance (km)
BOS	1	8:48	14	38.6	7.2
	2	12:28	14.5	33.9	8.0
	3	15:00	10	32.2	6.4
	4	17:30	14.5	32.2	6.4
PHL	1	9:00	15	38.6	6.4
	2	12:04	11	38.6	6.4
	3	15:15	10	32.2	6.4
	4	17:00	15	32.2	8.0
ROC	1	8:43	15	45.1	9.7
	2	12:30	12	38.6	8.0
	3	15:40	10	38.6	6.4
	4	17:30	15	41.4	8.0
Combined	1	8:45	15	38.6	8.0
	2	12:16	12	38.6	6.4
	3	16:30	10	34.8	6.4
	4	17:20	15	38.6	8.0

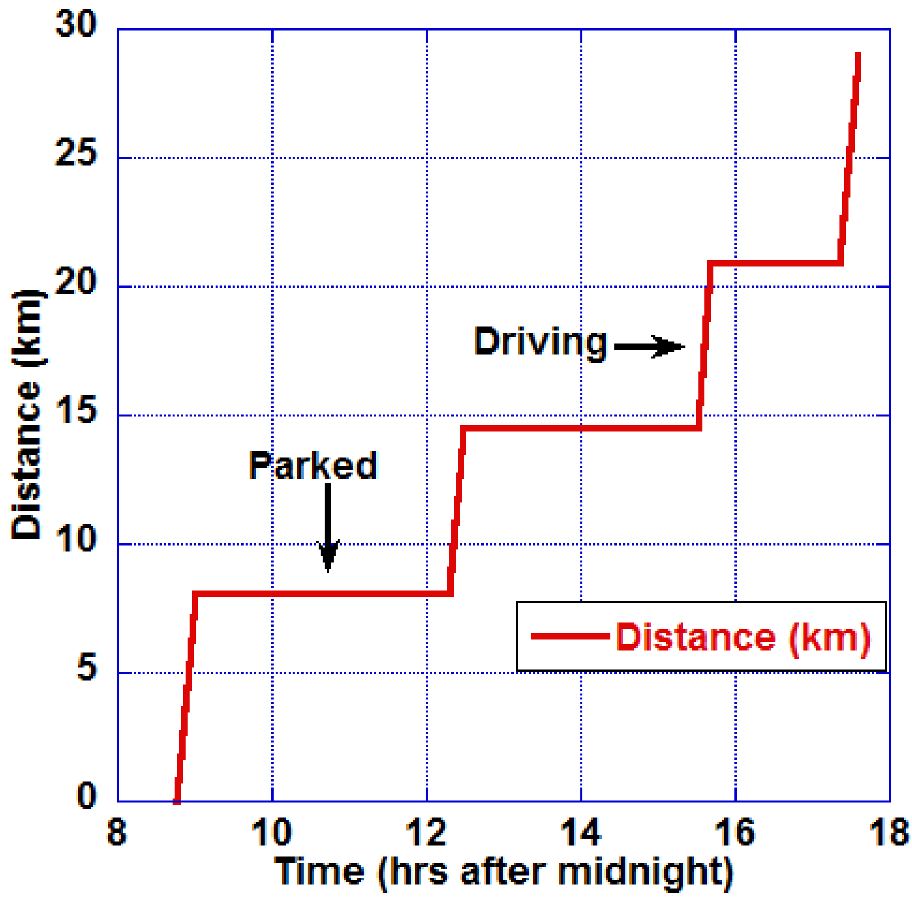

Figure 2.1 The daily driving profile used in cell testing. This profile is an aggregate of data taken from all 3 cities included in study. (Horizontal portions show when vehicle is parked, while diagonal portions represent driving).

2.4.2 Model constructed to replicate the energy use profile for driving

To determine the quantity and rate of energy transferred to and from a battery during driving conditions, we constructed a simple physics model that computed the energy needed to propel a typical vehicle through the NHTS trip profile. As an input to this model, the vehicle distance/velocity profile in each trip was created by sampling the Urban Dynamometer Driving Schedule (UDDS) and overlaying these segments into the average NHTS distance vs. time profile [6]. The 1370 second-long UDDS profile was doubled in length to allow contiguous selections to span from the end of original UDDS profile to the beginning. These selections were portions of the UDDS profile, and significant fractions were repeated multiple times (Figure 2.2).

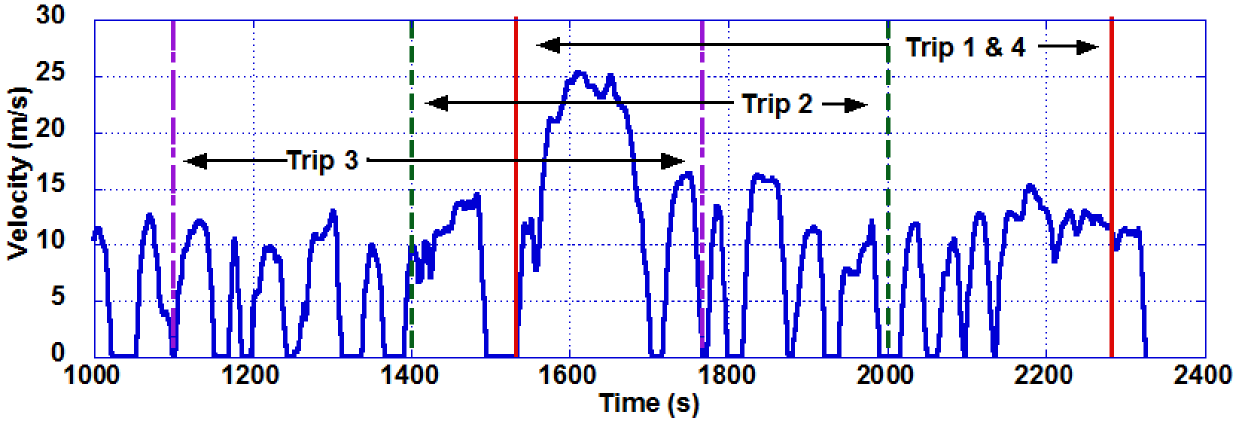

Figure 2.2 Portions of urban dynamometer driving schedule (UDDS) were chosen to closely match driving profile shown in Figure 2.1 in terms of duration and average velocity.

To calculate the power vs. time battery duty cycle needed to achieve this velocity/acceleration profile, the vehicle was assumed to have the physical characteristics of a 2008 Toyota Camry; the mass was 1588kg (3500 lbs), coefficient of drag of 0.28 and a frontal area of 2.7m^2. Rolling resistance of the tires was assumed to be 0.01 [7]. The efficiency of power transfer from regenerative braking to batteries was assumed to be 40%, the efficiency from battery to wheels was assumed to be 80% [8]. The battery pack energy capacity was assumed to be 16 kWh (as in Chevrolet's proposed Volt) [9]. The density of air was taken from the US standard atmosphere at sea level.

An 800 watt constant load was added to account for the power needed for all activities unrelated to movement such as heater, air conditioner, radio, lights and other accessories [10]. The total load every second was therefore obtained by adding the 800 watt load to the power necessary to achieve the velocity defined in the UDDS. The force needed as a function of time to achieve the UDDS target speed is a summation of the forces listed in Table 2.2.

Table 2.2 – Forces considered when calculating energy use for PHEV in charge depleting mode

Force Considered	Equation	Example: Velocity=10 m/s Acceleration=1m/s^2
Acceleration	F = ma	1590kg*1=1590N
Air resistance	$F_{ar} = \frac{1}{2}\rho v^2 C_d A$	$\frac{1}{2} * 1.23\frac{\text{kg}}{\text{m}^3} * \left[10\frac{\text{m}}{\text{s}}\right]^2$ $0.28 * 2.67\text{m}^2 = 45.8\text{N}$
Rolling Resistance	$F_{rr} = C_{rr}mg$	0.01*1590kg*9.8m/s^2=156N

If the acceleration is sufficiently negative (indicating braking), that its absolute value is greater than air resistance and rolling resistance combined, then regenerative braking is occurring and the power values for motion are given by equation 1. The regenerative value will be therefore be negative and indicates battery charging. Equation 2 describes the necessary power for cases where no regenerative braking occurs.

$$\text{power} = \left(ma + 1/2\rho v^2 C_d A + C_{rr}mg\right) 0.4 * v * \Delta t \qquad (1)$$

$$\text{power} = \frac{\left(ma + 1/2\rho v^2 C_d A + C_{rr}mg\right) * v * \Delta t}{0.8} \qquad (2)$$

Using this model, we compute that the vehicle would use 31% of its battery pack capacity to drive the derived 4-trip profile, with 0.28 kWh/mile being withdrawn from the battery on average. This value appears reasonable; the Electric Power Research Institute’s (EPRI) hybrid electric working group suggests 0.26 kWh/mile for a compact sedan [11].

The duty cycle profile derived from this model is used here as power-based "C-rate", the discharge power rate of a battery normalized to the total energy content. For example, for a 16 kWh battery a 16 kW load would be defined as having a discharge power with a 1 C-rate, 32 kW would be a 2 C-rate, etc. (in this case we are using power instead of the more common electronic current in Amps and Ah, for ease of calculation during economic analyses). By normalizing to cell energy and using a C-rate to determine power/current loads, the testing cycle can be run on any individual cell.

Under regenerative braking conditions, the battery pack will be charged if the deceleration provides more power than used by the constant base load (Figure 2.3). The cumulative distribution of power levels over a 24 hour period was calculated to illustrate the amount of time during the test cycle that the battery was under various loads (Figure 2.4). The near-vertical portion is due to the base load that is constant when there is nearly no force required for motion. As a result of the relatively large energy-to-power ratio for a battery pack of this size, the absolute value of the C-rate imparted to the battery exceeds 1 only 20% of the time. The maximum absolute C-rate value was 2.85. This value is modest compared to the demonstrated rate capability of the tested cells, which are qualified by the vendor to a C-rate of at least 20 C

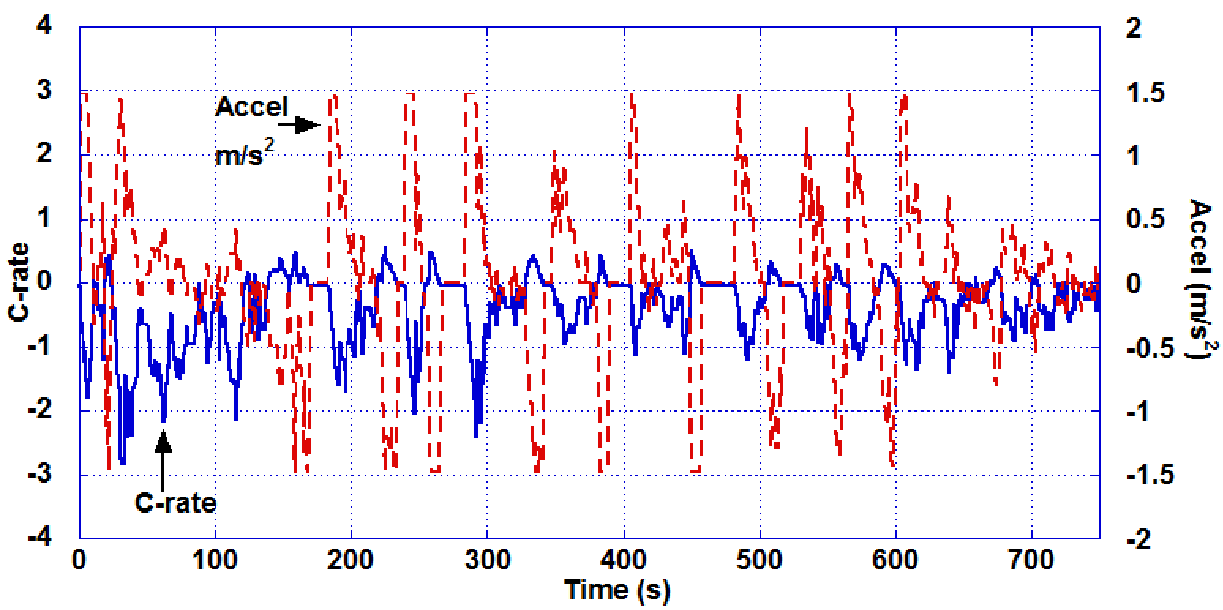

Figure 2.3 Example of relationship between acceleration and power required (in C-rate) for trips 1 and 4. A negative C-rate corresponds to discharge rate from pack. Deceleration can lead to regenerative braking if it is significant - in this case, around 7% of the energy is regained via regenerative braking.

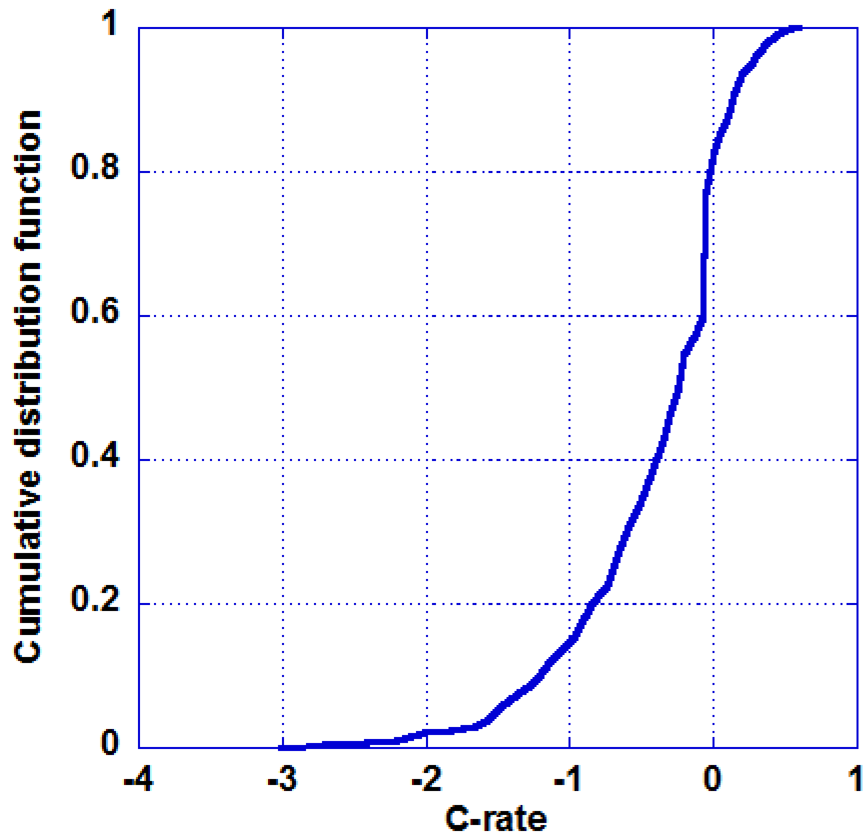

Figure 2.4 Cumulative distribution function of power requirements for daily driving (all 4 trips). Given large pack size the current rates are low most of the time. The near-vertical portion is a result of times when velocity and acceleration are low and the base load to run accessories dominates the power needs for vehicle.

2.4.3 Cell acquisition and cycling

Thirteen cells were purchased at three separate times, and came from four different fabrication lots. Due to equipment limitations, testing start dates were staggered as new equipment became available. All testing was conducted with Arbin BT2000 series battery cyclers. The inception of testing of the first 4 cells (lot 1) was followed after 3 months by 4 more cells (lots 2 & 3), in turn followed by 5 more cells (lot 4) after another 4 months. Cells from lot 1 underwent 2400 cycles, lot 2 and 3 completed 2000 cycles and lot 4 had reached 1000 cycles when this paper was submitted. Again, each cycle in this case represents a single driving day, so some of these cells were tested the equivalent of at least 5 driving years.

The cells were not thermally controlled and were kept at the lab ambient temperature, which varied from 24˚ to 27˚C, but was most commonly approximately 25˚C. Data published by the manufacturer indicating good cell stability and uniformity up to at least 40˚C imply that the cell temperatures used in this testing were not high enough to cause excess degradation, nor were they variable enough to significantly affect the data. [12] A thermocouple was connected to one cell and temperature was monitored through several full driving cycles; the cell temperature did not increase significantly, as expected from these cells, which have been engineered for high rate applications and so do not heat up significantly under the nominally low C rates experienced.

The cells were subjected to one of five different driving day testing cycles. Test cycle 1 corresponded to driving only and is shown in Figure 2.5, while each of the other 4 cycles consisted of the same daily duty cycle, with varying amounts of additional V2G discharge in the afternoon hours.. The V2G discharge consisted of a specific time at a galvanostatic C/2 rate (1.15 A in this case), and in and a cutoff voltage of 2.5 V was used to avoid over-discharge. A C/2 discharge rate was chosen to represent V2G simulation because it scales to an approximate 8 kW rate of withdrawal from the 16 kWh pack. The rate might be forced lower depending on the infrastructure available in the home; a 240V, 30A circuit could maintain only 7.2 kW of energy transfer. This implies the rate of discharge will likely be below C/2 slightly unless a special circuit is installed. Each cycle began with a 1 C galvanostatic charge of 2.3 A until cells reached a voltage of 3.6 V followed by a 5 minute rest. Then trips 1-3 were executed with 5 minute rests between each. The V2G discharge then was conducted. The driving only cells had no V2G discharge (3 cells, one each from lots 1, 2, and 4). Test cycle 2 had one V2G discharge of 1.15 A for 995 s (3 cells, one each from lots 1, 2, and 4). Test cycle 3 had one V2G discharge lasting 1715 s (3 cells, one each from lots 1, 2, and 4). Test cycle 4 had 2 V2G discharges and was the same as test cycle 3 with an additional V2G discharge after trip 4 held until the cell voltage dropped to 3.2 V (3 cells, one each from lots 1, 3 and 4). Test cycle 5 extended the second V2G discharge until 2.5 V (1 cell from lot 4). This test regimen is indicated in Table 2.3.

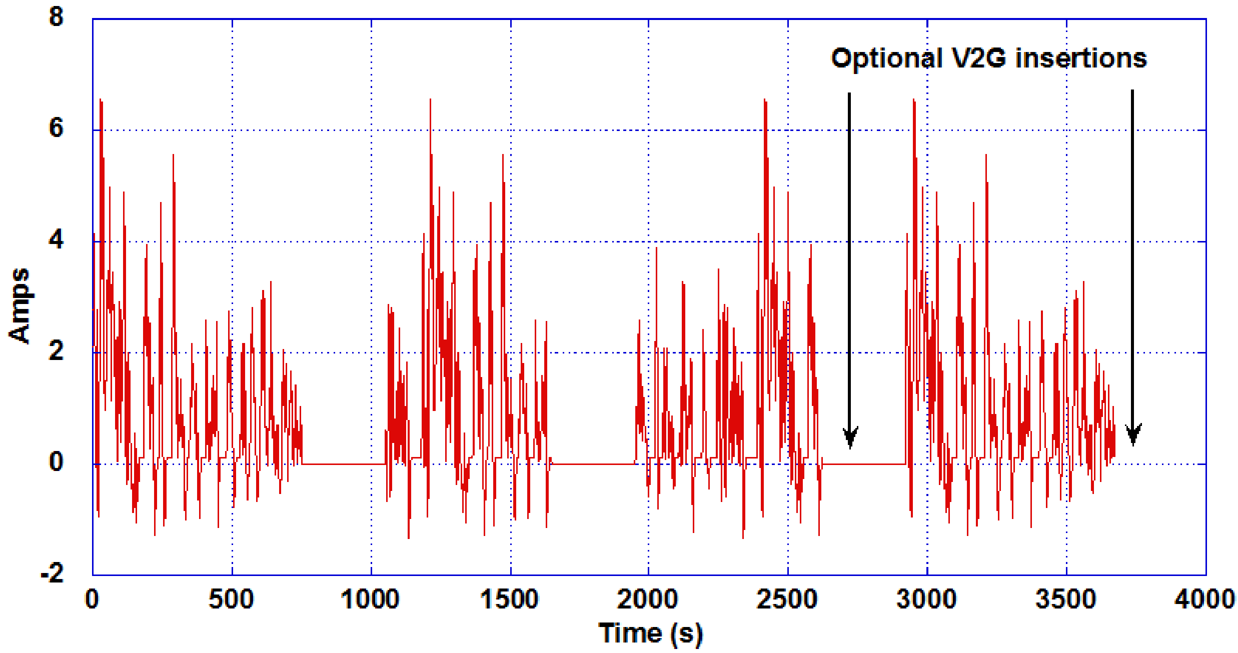

Figure 2.5 – Test current profile used to simulate driving day for cells showing all trips. The times after trips 3 and 4 when V2G discharge was simulated are indicated.

Table 2.3 – Testing regimens used on cells

Test cycle	Length of first V2G Discharge (s)	Voltage at end of second V2G discharge
1	0	NA
2	995	NA
3	1715	NA
4	1715	3.2
5	1715	2.5

The duration of the rest period the end of each driving day simulation was adjusted such that each test case, regardless of the degree of V2G discharge, lasted 3 hours. This regimen was repeated for 100 cycles, and then the cells were put through a C/2 charge/discharge "measurement" cycle to 100% state of charge/discharge to measure cell capacity. This started with charging the cell 1.15 A until it reached a voltage of 3.6V. Then the voltage was held constant until the current tapered to 0.01A to ensure the cells were fully and equally charged. After a 5-minute rest the cells were discharged at 1.15 A rate until voltage fell below 2.5 V (i.e. 100% DoD). The capacity measured through this discharge was defined as the cell capacity at that point in the testing. To avoid biasing the results with differing rest periods between test cycle and baseline cycle the baseline check automatically began 5 minutes after completion of the 100 test cycles.

2.5 Results and Analyses

The cells from different lots did not behave identically. Lot 1 showed a significant degree of variation in capacity retention as the cells were cycled (Figure 2.6 a-b), with cells increasing and decreasing in capacity as they were cycled, although the overall trend was downward. Lots 2 - 4 showed remarkable consistency in degradation (Figure 2.6c). It is possible (and believed by the author) that the unusual scatter observed in the data from lot 1 is somehow linked to the integrity of the BT2000 test unit used for these cells (on which only these 4 cells have been tested), though such a link has not been quantified. For this reason they are not used in the final statistical analysis.

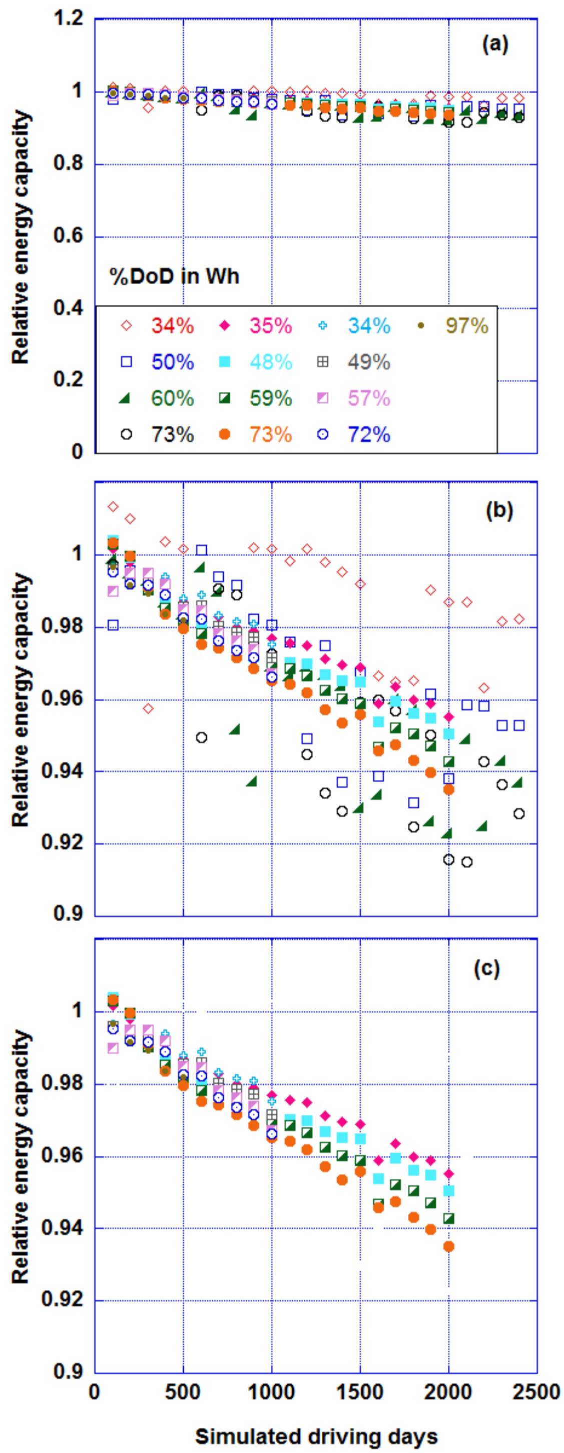

Figure 2.6 Degradation of cells versus driving days simulated (a) full range, (b) same information zoomed, (c) with highly variable cells from lot 1 dropped.

Because the cells from different lots might have undergone different formation (at the factory) before testing started it was necessary to find a way to determine an initial capacity in a consistent manner. One common approach is to measure capacity after a specific number of identical low rate cycles. We considered this unsuitable because we felt it was desirable to avoid running a large number of cycles on the battery in an attempt to normalize them and thus decrease capacity by an unknown amount. The next alternative we considered was to measure the capacity after an arbitrary number of cycles, but with 5 different possible test cycles this was also unsatisfactory. Instead, we performed a linear regression on each cell data set to back-predict their initial capacity in terms of cycles tested. This capacity was then used to determine the relative loss as a function of cycles instead of using a numerical value for the total energy content. A linear regression of relative capacity degradation vs. cycles was then used to predict when the cell would reach 80% of original capacity. This information was used to predict the cycle life vs. DoD/cycle.

Overlaying the values on the VARTA Automotive plot shows that DoD/cycle appears to have a smaller effect on degradation with these cells compared to those reported previously, particularly given that a single “cycle” in this case was representative of an entire day’s worth of driving. This appears to indicate that the portion of a cell's capacity used, or the ultimate depth of discharge, is not as important with A123 systems based cells as with the cells on VARTA plot labeled old LiIon and NiMH (Figure 2.7), where DoD is a key variable [13]. As the degree of discharge per driving day increases, the predicted cycle life does not fall as rapidly as conventional data analysis commonly predicts. For example, in cells discharged to 95% DoD per cycle, our measurements predict that 5300 cycles will be needed before reaching 80% of initial capacity instead of around 1500 cycles as indicated by the VARTA data. Also, daily cycles with shallower DoD values do not appear to increase cycle life as significantly as those indicated from the VARTA analyses. This suggests that a greater portion of the cell capacity could be used during each cycle than would be suggested by the VARTA plot if applied to this chemistry.

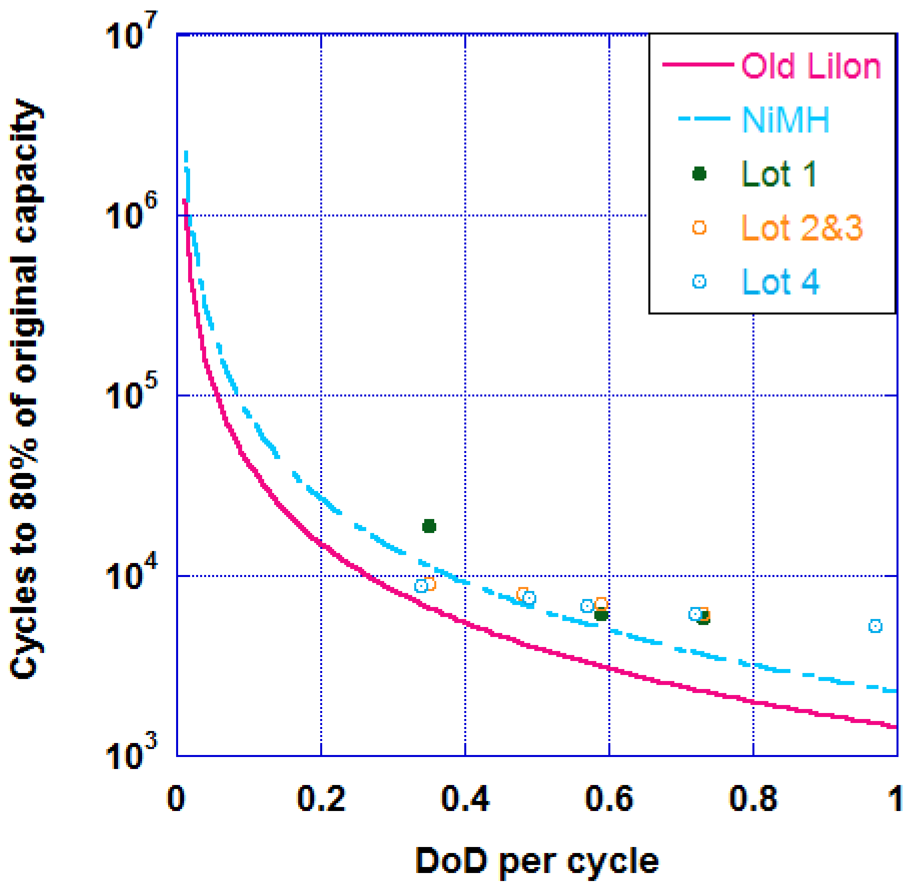

Figure 2.7 Laboratory results overlaid onto VARTA curves illustrating more linear response in cycle life as a function of depth of discharge for the cells tested.

Figure 2.8 shows data for a C/2 discharge of the same cell (from lot 3) after 0, 1000, and 2000 simulated driving days. The potential profile in the voltage plateau region was essentially unchanged after 2000 cycles, indicating that internal resistance did not change significantly, as the differential in cell polarization under discharge before and after the 2000 cycles was imperceptible. The decrease in delivered capacity after cycling is manifested as a departure from the discharge plateau after 1.82 Ah of discharge for the heavily cycled cell, vs. 1.91 Ah for the uncycled cell (Figure 2.8b).

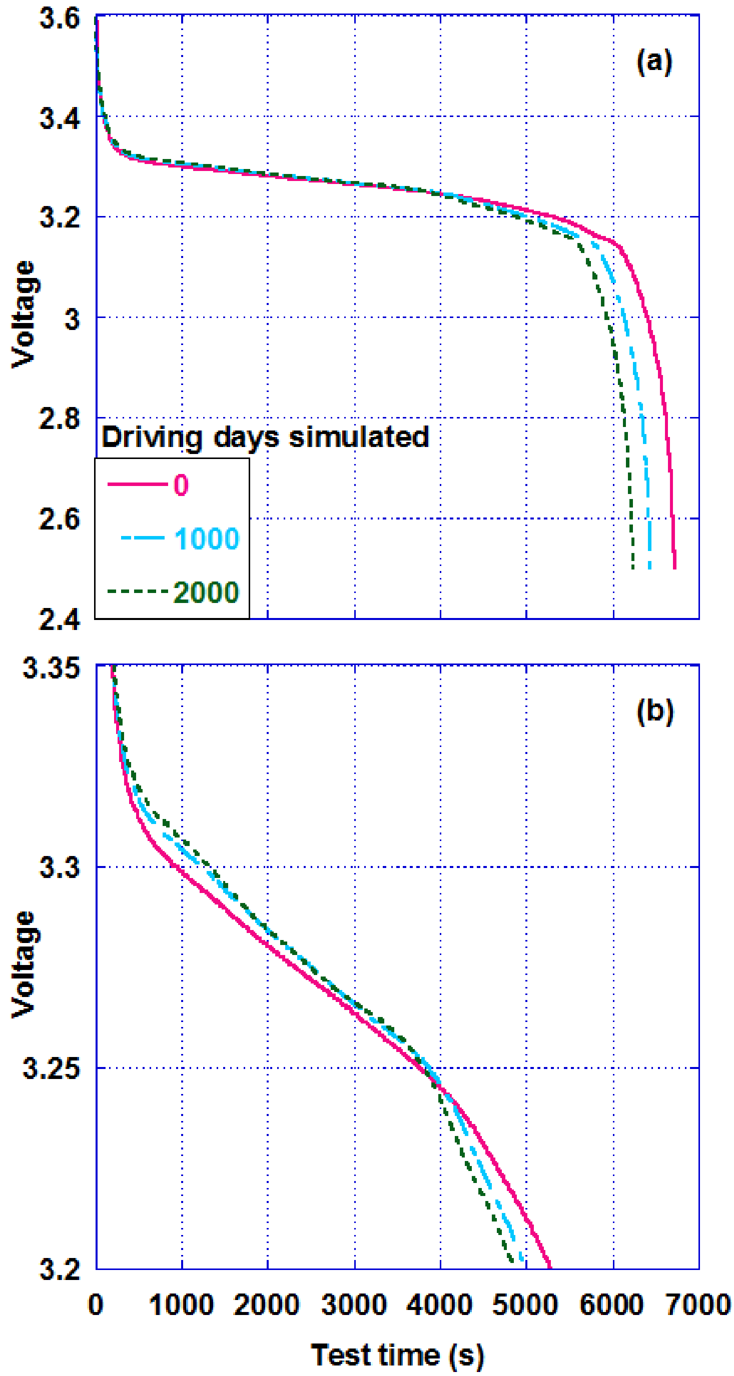

Figure 2.8 Voltage discharge profiles of a cell that reached an ultimate DoD value of 73% each driving day. The initial, 1000th and 2000th baseline discharge curves are shown.

The test profiles used on these cells were very different from those typically published (i.e. potential-limited galvanostatic charge/charge at intermediate rates), so a different approach is used here to quantify the capacity fade as a function of battery use. Simple accounting for the

%DoD at end of cycle DoD does not accurately represent the amount of energy processed by a cell per cycle. For example, the ratio of charging from regenerative braking to discharging produced by the model was 0.076; if 100% energy efficiency is assumed, then at least 14% more energy is exchanged during a driving cycle beyond the energy associated with the indicated DoD value. To this end, percent initial capacity was related to the total capacity (in Ah) processed by each cell, a value that included the discharge for driving, charging from regenerative braking, charging during the evening to recharge the battery for the next day, baseline check. This value can be directly related to the moles of Lithium ions transferred between the electrodes during use.

Data collected from cell lot 1 showed inconsistencies, again, consistent with the capacity versus cycle life for these cells. However, the second set of cells, lots 2 – 4, showed a high level of consistency in degradation with respect to integrated Ah processed; the cells appear to degrade in response almost exclusively to capacity processed as opposed to the number of cycles, or the DoD per cycle (Figure 2.9a). The sample analysis based on energy processed (in Wh) showed marginally better results and were more directly applicable to modeling the energy arbitrage potential of the cells (Figure 2.9b). There appeared to be a slight difference in slope between cells. Those with greater energy arbitrage discharge appeared to degrade slightly slower. Comparing two specific cells from lot 2 over a similar range of energy processed shows a different but statistically insignificant slope (at the 95% level) (Figure 2.10). Adding cells from lot 4 tightens the 95% confidence interval lessening the overlap of the two slopes, at the 95% level, but they are still not statistically different.

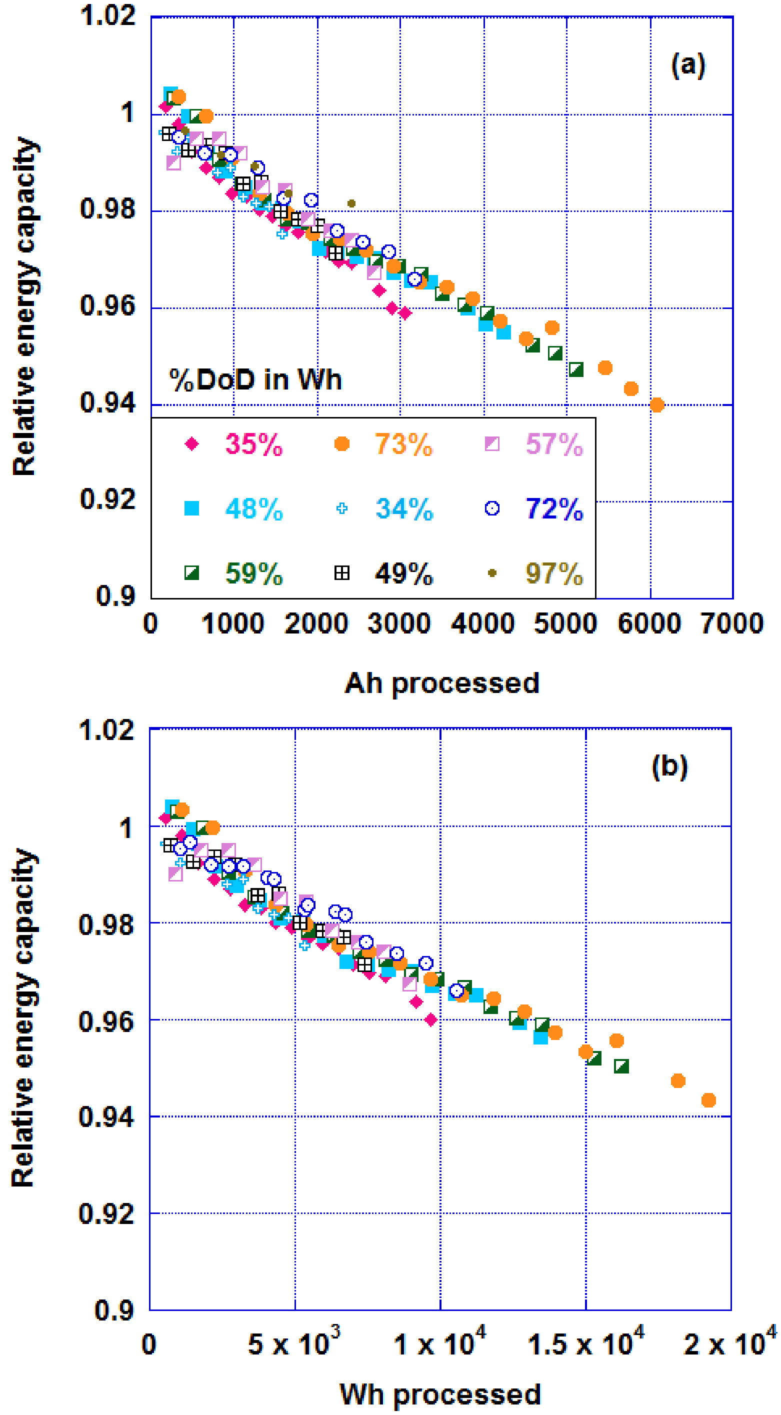

Figure 2.9 Degradation as a function of (a) capacity (Ah) processed by cell or (b) energy (Wh) processed by cell for all but lot 1 cells. Both appear linearly related, as expected given the nominally linear discharge profile of the LiFePO4/graphite system.

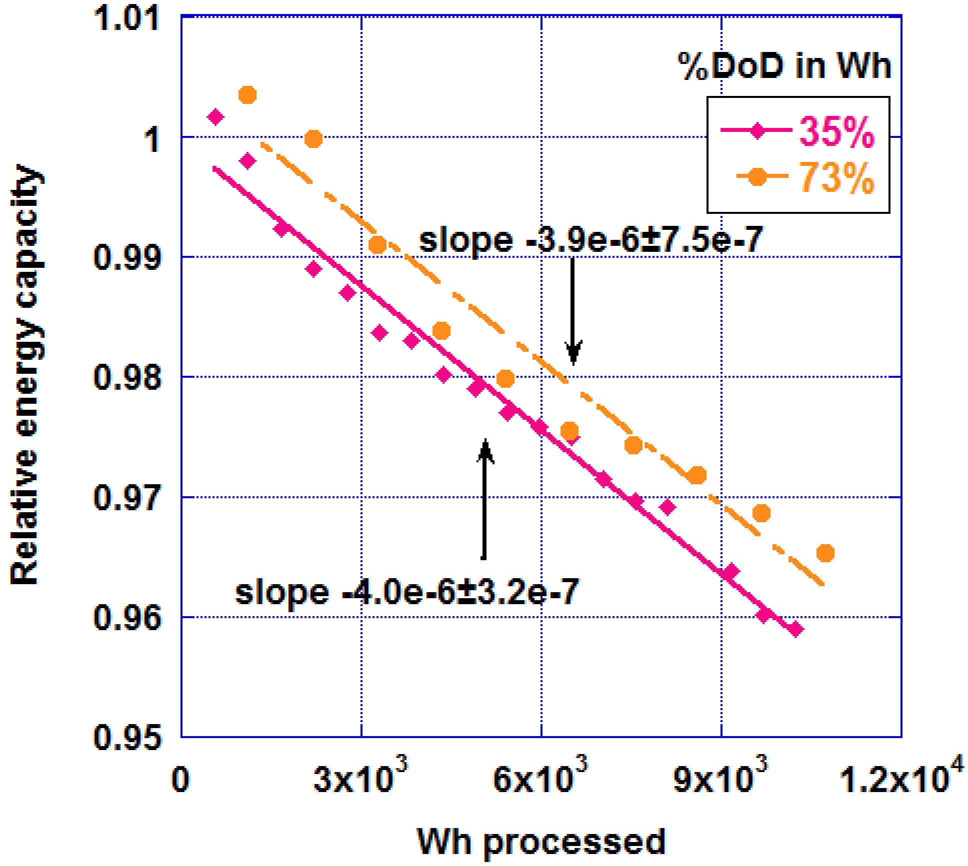

Figure 2.10 Capacity degradation as a function of energy processed for two cells tested with contrasting end-of-cycle depth of discharge values (35% and 73% DoD). The slight observed difference would indicate less degradation for higher DoD/cycle cell, however the 95% confidence interval of slopes overlaps for these fits, so they are not statistically discernible.

To investigate this further, a multiple linear regression was conducted to relate the degradation of the cells to the type of cycling incurred. The first step was to break the total Wh processed by each cell in different categories of charge and discharge. It was assumed that these different cycling regimes could be represented by driving discharge, driving recharge (from regenerative braking), energy arbitrage discharge, and recharge. The first two are dynamic, while the last two categories are constant rate. The values were normalized to the initial capacity of each cell to remove variation from differing initial capacity. Regenerative braking recharge was highly correlated with the driving discharge because the simulation had a specific ratio of regenerative braking to driving discharge as defined by the UDDS. Therefore, regenerative braking was dropped from the multiple linear regression analysis. Only driving discharge and energy arbitrage discharges were considered for the multiple linear regression, because the other values could be almost perfectly predicted if these values were known. The errors of the resulting regression appear to follow the assumption of normality, as shown in Figure 2.11, which indicates that a multiple linear regression can be used without fear that the errors follow a pattern that would indicate some hidden underlying process [14].

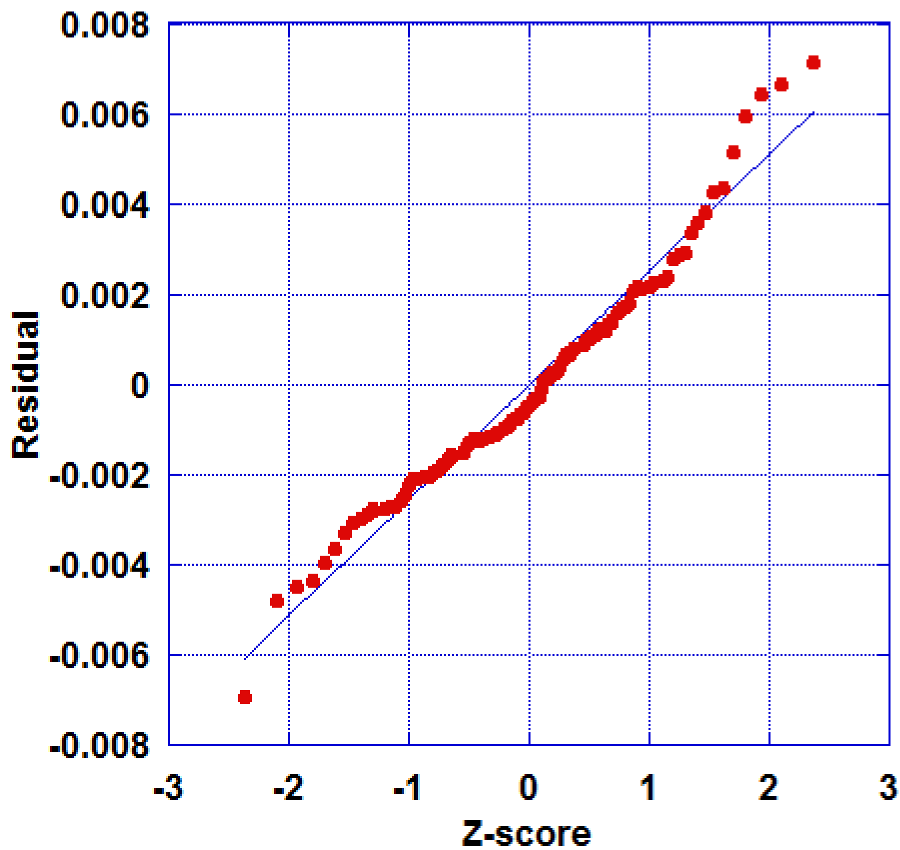

Figure 2.11 Q-Q plot shows errors are normally distributed for multiple linear regression. The line represents expected values for a normal distribution.

The resulting regression appeared linear (adjusted R^2=0.96). The relative size of the coefficients implies that the battery usage associated with driving causes more loss in cell capacity per Wh processed than usage associated with V2G load shifting (lower rate, more controlled discharges) (Table 2.4). The confidence intervals are small enough that there is no overlap as indicated by the high absolute value of the t-stat. The regression relates percent capacity loss to energy discharged driving, energy discharged for arbitrage, and initial capacity. An example is shown in Table 2.5, where we illustrate how a given quantity of energy processed in a particular mode can be used to predict the percent capacity loss. Because all cells underwent the same cycling associated with driving, the differences in these coefficients relates not just to the difference in degradation from dynamic discharge versus constant discharge, but also to other hidden variables such as cell aging, which is thought to be minimal over the approximately 12 months of testing performed for this study [15].

Table 2.4 – Results of multiple linear regression

Coefficient	Value	t-stat	Confidence Interval
Wh discharged driving	-5.99E-5	-34.9	1.71E-6
Wh discharged arbitrage	-2.71E-5	-14.6	1.85E-6
Constant	1.00	2120	4.7E-4

Table 2.5 – Examples using results of multiple linear regression to calculate battery capacity degradation

Coefficient	Value	Normalized	Multiplied by Coefficient
Wh discharged driving	3000 Wh	462	-0.027
Wh discharge arbitrage	1500 Wh	231	-0.0062
Initial Capacity	6.5 Wh	1	
Capacity Remaining	97%		

2.6 Discussion/Conclusions

The loss of capacity as a function of driving days shown in Figure 2.6 indicates that the degradation of these high-power $LiFePO_4$ - based cells does not follow the same pattern as commonly used previous reported results and models [16,17]. These data reveal that in bench top testing of simulated driving conditions, the cell DoD does not does not have nearly as great an effect on lifetime as previously reported values for other battery chemistries (commonly those based on layered metal oxide cathodes such as $LiMO_2$ where M is some combination of Co, Ni, and Mn) [14, 15, 18]. This result implies that a $LiFePO_4$/graphite– based PHEV battery pack with properly matched cells can be cycled through a very broad state of charge range without incurring any significant increase in capacity loss as a function of Ah or Wh processed. In principle, a PHEV can utilize a smaller battery and use a greater proportion of the battery, however doing so might make discharge rate and associated ohmic heating more of an issue.

After 2000 cycles the low rate discharge potential profile appears very similar to that collected before cycling started, and a very small fraction of the initial capacity has been lost. This observation is consistent with the hypothesis that only a minimal Solid Electrolyte Interphase (SEI) layer must be forming during cycling of these cells, and that the mechanical cycling of the electrodes does not induce loss of connection and capacity fade . The tendency for increased I^2R cell heating after many cycles is not present (due to the relatively low C-rates encountered), and so failure mechanisms associated with this effect are minimal.

The comparison between capacity fade as a function of cycle number and Ah processed provides several key insights to the processes at work in these batteries. First, the dominant cell degradation method is not dependent upon depth of discharge, or rate of discharge (at least up to the 3C spikes encountered in this test regimen). For example, if only the data shown in Figure 2.6 were used to examine capacity loss, the conclusion might be drawn that degradation was indeed a function of depth of discharge. However we show in Figure 2.9 that, in fact, the cycle DoD and relative fraction of low-rate galvanostatic cycling vs. acceleration/regenerative braking current pulses are not important even over thousands of driving days. Rather, it is the integrated number of lithium ions that have been intercalated/de-intercalated into the electrodes, regardless of the DoD at which these events occur. Nevertheless, there are still other factors of importance. The multiple regression shows there is a difference between driving energy withdrawn and constant discharge. With the low rate constant discharge associated with roughly half the degradation of the dynamic discharge (-6.0E-3% and -2.7E-3% for 1 normalized Wh). For this reason, using constant discharge degradation to predict driving degradation is likely inaccurate, and correction factor attributed to the kind of cycling encountered is prescribed.

The literature commonly indicates that the dominate mechanisms for capacity loss in Li-ion cells are (1) the formation of a resistive and progressively Li-consuming interfacial layer between the functional graphite at the anode and the electrolyte, and (2) the physical degradation of active materials and electrode structures [19]. Our data indicate a much lower loss of capacity as a function of cycles and Ah processed, a result consistent with the use of high performance nanostructured electrode (cathode) materials that are much more physically stable during use and so do not degrade. The remaining loss in capacity is likely due to anode interfacial film of Li_2O/LiF/Li_2CO_3/Other formation [20]. In most interpretations, the loss of capacity is correlated to amount of Li that has reacted to form the SEI and so is no longer functional in the battery function. The fact that we observed little to no relationship between DoD and capacity fade supports the idea that the SEI formation at the anode occurs at the same rate regardless of state of charge and degree of graphitic lithiation. A recent capacity degradation model is consistent with this hypothesis; the anode potential was not varied significantly during simulation and so depth of discharge was not nearly as important as the time-integrated current of Li-ions the SEI was driven to process during cycling [17]. Higher rate cycling causes more rapid capacity loss. This is also consistent with the literature in several ways: at higher rates greater overpotentials are observed at the electrode surfaces and will therefore slightly enhance the rate SEI formation. Local heating at the electrode surface at high rates could also increase the rate of SEI formation. It should also be noted that the cells were kept at room temperature throughout the test mainly for convenience. It is acknowledged, however, that the rate of capacity loss would almost certainly have been greater for cells kept at elevated temperatures during testing. Elevated and variable temperature testing will be conducted in our labs to explore this possibility.

2.7 Summary

The composition of a test "cycle" is important when quantifying battery degradation, and using depth of discharge (DoD) per cycle as an independent variable when studying capacity fade can be misleading in cases where each cycle is laden with rapid discharge and charge events. Analyses performed here show that the strongest indicator of capacity fade for the type of cell tested (A123Systems M1 Cell) was the integrated capacity or energy processed, regardless of the DoD experienced. Furthermore, statistical analyses show that using a PHEV battery for V2G energy incurs approximately half the capacity loss per unit energy processed compared to that associated with more rapid cycling encountered while driving, and DoD was not important in either case except as a reflection of energy processed. The percent capacity lost per normalized Wh or Ah processed is quite low: -6.0×10^{-3} % for driving support and -2.70×10^{-3} % for V2G support. These values show that several thousand driving/V2G driving days incur substantially less than 10% capacity loss regardless of the amount of V2G support used. However, V2G modes that are more intermittent in nature will lead to more rapid battery capacity fade and should be avoided to minimize battery capacity loss over many years of use.

2.8 Acknowledgements

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Chapter 3 The economics of using plug-in hybrid electric vehicle battery packs for grid storage

3.1 Chapter Information

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3.2 Abstract

We examine the potential economic implications of using vehicle batteries to store grid electricity generated at off-peak hours for off-vehicle use during peak hours. Ancillary services such as frequency regulation are not considered here because only a small number of vehicles will saturate that market. Hourly electricity prices in three U.S. cities were used to arrive at daily profit values, while the economic losses associated with battery degradation were calculated based on data collected from A123 Systems $LiFePO_4$/Graphite cells tested under combined driving and off-vehicle electricity utilization. For a 16kWh (57.6 MJ) vehicle battery pack, the maximum annual profit with perfect market information and no battery degradation cost ranged from ∼US$140 to $250 in the three cities. If the measured battery degradation is applied, however, the maximum annual profit (if battery pack replacement costs fall to $5000 for a 16kWh battery) decreases to ∼$10–120. It appears unlikely that these profits alone will provide sufficient incentive to the vehicle owner to use the battery pack for electricity storage and later off-vehicle use. We also estimate grid net social welfare benefits from avoiding the construction and use of peaking generators that may accrue to the owner, finding that these are similar in magnitude to the energy arbitrage profit.

3.3 Introduction

Legislation enacted in 2008 provides a subsidy in the form of tax credits for purchasers of plug-in-hybrid electric vehicles (PHEVs) to increase market acceptance [1]. Subsidies may be economically justified if they support private investments that have social benefits. One suggested benefit has been that PHEVs could provide services to the electricity sector (vehicle-to-grid or V2G services) [2]. These benefits might include peak load shifting, smoothing variable generation from wind and other renewables, and providing distributed grid-connected storage as a reserve against unexpected outages. Hybrid electric vehicles, battery electric vehicles, and plug-in hybrid electric vehicles (PHEVs) rely on batteries located in the vehicle to store energy.

One of the fundamental properties of electricity markets is the lack of cost-effective storage [3]. Without storage, meeting peak demand requires underutilized investment in generators and transmission lines. Because of the costs of meeting peak demand, the difference between daily peak and off-peak costs can vary greatly throughout the year (wholesale markets see this as a price difference; a small but increasing number of retail customers also see this as a price difference). If the difference is small on a given day, single purpose storage facilities either make minimal revenue or sit unused and depreciating. Single purpose battery energy storage facilities have not proven economical except in niche applications such as delaying a distribution system upgrade [4]. A plausible conjecture is that V2G, that relies on dual purpose batteries where the initial capital cost of the battery is not assigned to the off-vehicle electricity use because the battery was purchased for driving, will be more economic for grid support than batteries whose capital cost must be amortized for grid use. With vehicle batteries, if load shifting or peak shaving is not economical the only wasted expenditure is the cost of the controllers and converters, some of which will likely be installed in any case to enable off-peak charging (although additional electronics would be required for V2G). This possibility, along with quick battery reaction times, has made V2G applications to stabilize or slow fluctuations from intermittent sources (such as wind or solar) a subject of research interest [5]. V2G has the potential to diminish the need for rapid ramping of following generators to match variable power sources. Rapidly ramping generators may not be the lowest cost generators, and ramping can lead to increases in pollution [6].

Here we examine the net revenue that a vehicle owner could receive from V2G energy sales to estimate whether this would provide an attractive incentive for owners to participate in V2G operations as a dual use for the battery pack whose capital cost has been largely justified by transportation. V2G services could be sold in an organized market as ancillary services (spinning reserve and regulation), as energy sales to the grid (running the meter backwards), or their value could be captured as avoided grid electricity purchases (running the meter slower). The first two incur transaction costs and grid costs, while the third does not; it is the third we examine here. Net revenue, as used here, is the net of avoided grid energy purchases from using the energy stored in the vehicle battery pack less the cost of grid electricity used to charge the battery pack and the cost associated with shortening the battery pack's lifetime by cycling for such energy use.

3.4 Methodology

We examine energy arbitrage (buying low cost power to charge the battery pack and discharging the battery pack at high power price times) with PHEVs assuming that electricity sold will be replenished from the grid later in the evening so the battery pack is be full in the morning. Hourly historical locational marginal pricing (LMP) data were obtained for three cities: Boston (BOS), Rochester NY (ROC) and Philadelphia (PHL). Each city is in a different electricity market and good data from the 2001 National Household Travel Survey (NHTS) of 70,000 households [7] are available to construct driving profiles in each of these metropolitan areas [8]. The three cities have annual mean temperatures that are not far enough from the national average of 11.6 C to materially affect the modeled battery state of charge: Boston is 10.7 C, Rochester is 8.7 C, and Philadelphia is 12.4 C [9].

LMP data are available for the years from 2003 to 2008 for Rochester and Philadelphia; the first full year of Boston data is 2004. The LMPs (plus a transmission and distribution charge) provided the cost for buying the electricity, and the maximum potential profit for avoiding electricity purchase, or for selling the electricity in the absence of transaction costs. We model a vehicle with a 16 kWh battery pack, as used in Chevrolet's proposed Volt [10].

We model energy arbitrage by owners to offset their own electricity consumption during high priced periods. This simplifies consideration of transaction costs. On the other hand, it ignores possible social benefits such as increased rates of utilization of utility investments or other benefits that might accrue to society if PHEV owners used their vehicles in a widespread fashion for energy arbitrage. Thus, it is an analysis of the economic benefits to individuals providing energy arbitrage services, although we use coarse estimates of the net social welfare to bound additional revenue below.

3.4.1 Revenue

We calculate the revenue from energy arbitrage based on LMP data from the PECO, Genesee, and Boston nodes of PJM, NYISO, and ISO-NE. These nodes serve Philadelphia, Rochester, and Boston, respectively. LMP data from 2003-2008 are used to calculate the maximum revenue possible from energy arbitrage (2004-2008 for Boston). For this model, we assume the PHEV owner is under a real time pricing (RTP) tariff. We add a transmission and distribution (T&D) cost of 7 ¢/kWh [11] to the hourly nodal price to estimate the RTP. The net effect of the T&D costs is small given high round trip efficiency (RTE). We use an RTE of 85% as our base case.   The discharge efficiency (DCH_{eff}) and charge efficiency (CH_{eff}) were both assumed equal and the square root of 0.85 so that they result in 85% RTE (our laboratory measurements showed DC-DC energy efficiency of cells only in excess of 95% for discharge/charge cycles). It is assumed the PHEV owner is a price taker. The results therefore estimate the incentive for owners, in a RTP scenario, to choose to use their PHEV for energy arbitrage.

We estimated the profit possible from energy arbitrage by subtracting the degradation cost and the cost of buying electricity from that of selling it to offset the owner's use and multiplying by the number of kWhs transacted and adjusting for efficiency.

$$\text{Profit}(\$) = \left(\left(\text{LMPSELL} + \text{T\&D}\right) * \text{DCH}_{\text{eff}} - \frac{\text{LMP}_{\text{BUY}} + \text{T\&D}}{\text{CH}_{\text{eff}}} \right) * \text{kWh}_{\text{Transacted}} - \text{Degradation Cost} \tag{1}$$

The kWh transacted by a profit-maximizing PHEV owner depends on the percent of the battery pack energy available after driving, the battery pack size, and the marginal cost of degradation associated with additional withdrawal from the battery pack. The variable cost of battery degradation depends on the amount of energy withdrawn. Thus, the objective function for the transaction optimization considers revenue and variable costs (battery degradation), but not fixed costs necessary for using a PHEV for energy arbitrage because the capital cost of the battery pack and charging station are considered here to be sunk costs.

3.4.2 Degradation Cost

Degradation cost was calculated based on the multiple linear regression based on laboratory data from cycling $LiFePO_4$ cells described in [12]. While other chemistries, such as those based on the $Li4Ti_5O_{12}$ anode, have been considered for vehicle use, their low cell voltage, relatively poor energy density, and higher expense per unit energy make their use less likely in the near term. For example, a recent analysis indicates that the electrode materials for a Lithium Titanate/$LiMn_2O_4$ cost approximately $58/kWh as compared to $35/kWh for the graphite/$LiMn_2O_4$ analog (though the titanate system is currently exhibiting superior cycle life performance) [13]. Not surprisingly, the major automotive companies have elected to use Li-ion cell chemistries based on graphite anode materials and either lithium-transition metal-oxide or lithium iron phosphate cathode material. For this reason, we have selected a $LiFePO_4$ based chemistry, as produced by A123 Systems. This company is currently producing after market PHEV battery packs, as well as partnering with Chrysler as a battery supplier for its line of EV and extended range vehicles, and has also recently partnered with GE [14].

The cost associated with using energy from the battery pack is given in equation 2. Note that the V2G degradation coefficient is negative.

$$\text{Degradation Cost} = \frac{\text{Replacement Cost} * \text{V2G Deg}}{(0.8-1)} * \text{Percent of Battery Used} \qquad (2)$$

Estimates of the current price of the Chevy Volt's battery pack range from $5,000 to $11,000 [15]. However, it is a different battery chemistry from the battery we tested. We used a value of $5,000 ($312/kWh) and performed sensitivity analyses using the range $2,500 to $20,000. With a $5,000 replacement cost, our laboratory measurements [8] predict a degradation cost of 4.2¢/kWh served.

3.4.3 Model

We use a sell-before-buy model. The battery pack begins a day fully charged. The time 8 AM to 4:59 PM is reserved exclusively for driving (the driving profiles used are given in section 2.1 of [8]). Discharging for household electricity and charging are allowed in other hours. The battery pack is fully charged at the lowest cost hours (charging requires 2.2 hours for a fully discharged 16 kWh battery pack using the infrastructure constraint discussed below). No discharge is permitted between the time charging finishes and the start of the 8 AM driving window. The appendix contains details of the model.

To estimate the portion of battery pack capacity a profit-maximizing consumer would choose to devote to energy arbitrage on a given day, we use two different methods. The first method uses perfect information to find an upper bound on profit. In this model, owners know what the RTP will be in the future; they pick the most expensive LMP hour to use the battery pack for home energy use ("sell") and the cheapest hour after to recharge. When the amount of energy to exchange exceeds the capability of the assumed 240V single-phase, 30A circuit infrastructure (7.2 kWh/h exchanged) the use is restricted to 7.2 kW per unit time available. Then the next least or most expensive hour is considered in steps until the battery pack is completely discharged or it is no longer profitable to use the vehicle for energy arbitrage. The vehicle is fully charged before 8 AM each morning.

The second method uses knowledge of the real time prices in the previous two weeks to predict the hours that would be least expensive to recharge; this estimates a reasonable lower bound on profit. The predicted price in each hour of the coming day is the average price seen in that hour over the previous 14 days. Using this prediction for the cost of recharge and knowledge of the actual RTP in an hour when selling is contemplated; the model determines whether selling in a given hour would be profitable. If so, it uses battery pack energy for home energy use. Of course, it sometimes mispredicts the cost of recharging, and the net revenue is less than if perfect information were available. The profit is then calculated as the revenue less cost to charge and less the additional battery degradation cost from energy arbitrage.

3.5 Results

The yearly profits from the years of 2003-2008 using perfect information, a $5,000 battery pack cost, and our measured battery degradation are shown below (Table 3.1). The maximum annual profit ($118) occurred in the Philadelphia area in 2008. A vehicle owner in Boston, even with perfect information, would have seen profits of $12 to $48, depending on the year.

Table 3.1 – Upper bound annual profits for each area over years listed with perfect information and $5000 battery replacement cost for a 16kWh battery

Year	Area							
	PHL			ROC			BOS	
	Profit	kWh		Profit	kWh		Profit	kWh
2003	$22	1,286		$25	474		N/A	N/A
2004	$17	1,120		$19	451		$19	252
2005	$110	2,458		$71	1,157		$48	1,119
2006	$58	1,471		$46	1,037		$39	667
2007	$95	2,223		$69	1,210		$15	625
2008	$118	2,264		$107	1,650		$39	1,128

The lower bound of profit estimated without perfect information resulted in profits that reached their maximum in Philadelphia in 2005 (Table 3.2). Even with perfect information the maximum annual profit was $118 per year. The 2007 profit in the more realistic lower bound case represents 5%, 2%, and 0.5% of the average residential customer's yearly electricity bill in 2007 in RHL, ROC, and BOS, respectively [16]. Profit would not increase greatly with a larger battery because the limitation of the local circuit infrastructure (240 V, 30 A) would curtail the rate at which power could be used (sold) during high priced periods.

Table 3.2 – Lower bound annual profits for each area over years listed using 14 day backcasting averaging method and $5000 battery replacement cost for a 16kWh battery

Year	Area							
	PHL			ROC			BOS	
	Profit	kWh		Profit	kWh		Profit	kWh
2003	$10	1,123		$13	395		N/A	N/A
2004	$6	1,009		$7	415		$5	198
2005	$72	2,169		$33	978		$18	865
2006	$38	1,384		$25	862		$28	508
2007	$57	1,889		$28	988		$6	514
2008	$67	1,998		$14	1,202		$15	897

3.6 Sensitivity Analysis

We performed sensitivity analyses on the effect of battery pack replacement cost on profit (Figure 3.1-Figure 3.2). The median value and yearly maximum and minimum for the period 2003-2008 are shown for upper and lower bound scenarios.

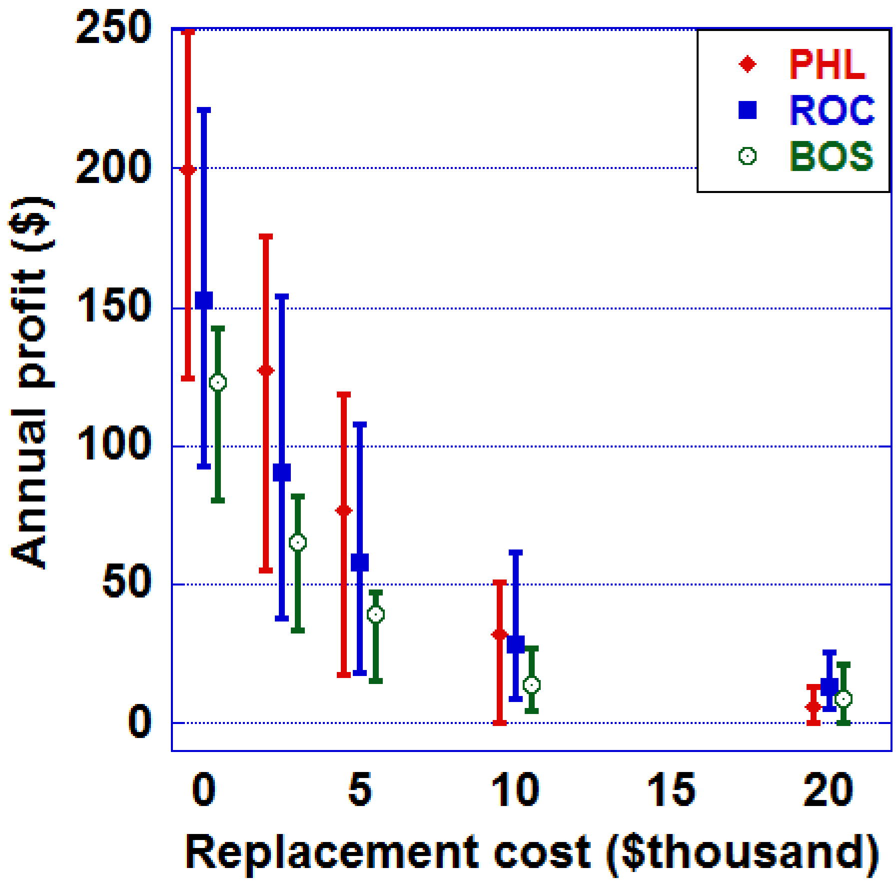

Figure 3.1 V2G energy arbitrage profit sensitivity to battery pack replacement cost with perfect information in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for battery replacement costs of $0, $2,500, $5,000, $10,000, and $20,000.

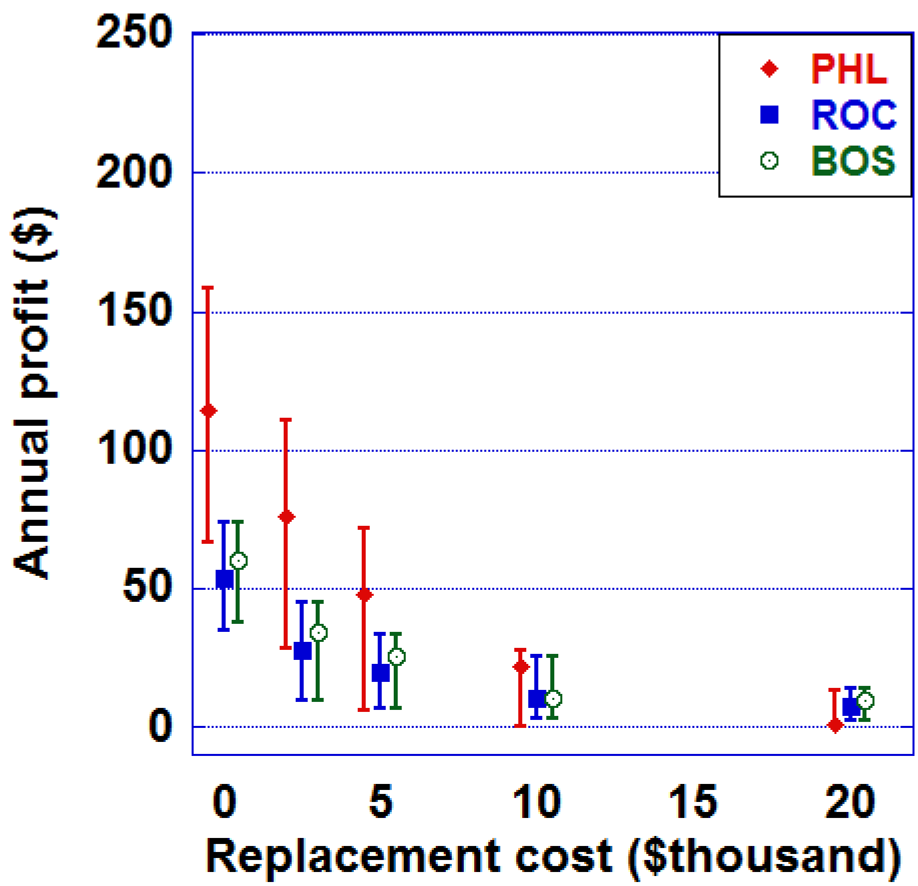

Figure 3.2 V2G energy arbitrage profit sensitivity to battery pack replacement cost with 14 day backcasting method in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for battery replacement costs of $0, $2,500, $5,000, $10,000, and $20,000.

Profit drops rapidly with increasing battery pack cost until replacement cost reaches $10,000 then becomes asymptotic near zero profit. With the battery pack replacement cost set to zero, the cost of degradation is also zero. This yields the maximum profit given no marginal cost of degradation. The median for the six years is $200 in the most profitable city (Philadelphia), a 17% decrease in the average Pennsylvania annual electricity bill. In the least profitable (Boston), the profit in the median year represents 10% of the average Massachusetts electric bill. The difference in buying and selling LMPs necessary for profitable arbitrage is a function of battery pack replacement price and the buying LMP. The response of profit to varying battery degradation costs thus is reflective of the distribution of LMPs in the various RTOs. The difference between peak and off peak is higher in PJM than the other RTOs, but the lower value in Philadelphia at high battery replacement costs reflects fewer extremely high price events in PJM that would justify use of the battery pack if replacement costs were high. In the lower bound Boston becomes more profitable than Rochester for this reason.

T&D costs and RTE had a small effect on annual profits. Lower round-trip efficiency incurs extra T&D costs; at 100% RTE, the T&D charges cancel out completely. Sensitivity analysis of RTE shows that it reduces profit in an approximately linear fashion (Figure 3.3-Figure 3.4). The perfect information annual profit decreases more rapidly than the backcasting model. RTE (the AC-DC conversion efficiency) is important because it occurs twice for energy arbitrage. An increase in efficiency of AC-DC conversion of 2.7% would increase the RTE from 85% to 90% average annual profits by $33 over the 6 year period for PHL and ROC. T&D had a similar though smaller effect over the range of values tested (Figure 3.5-Figure 3.6).

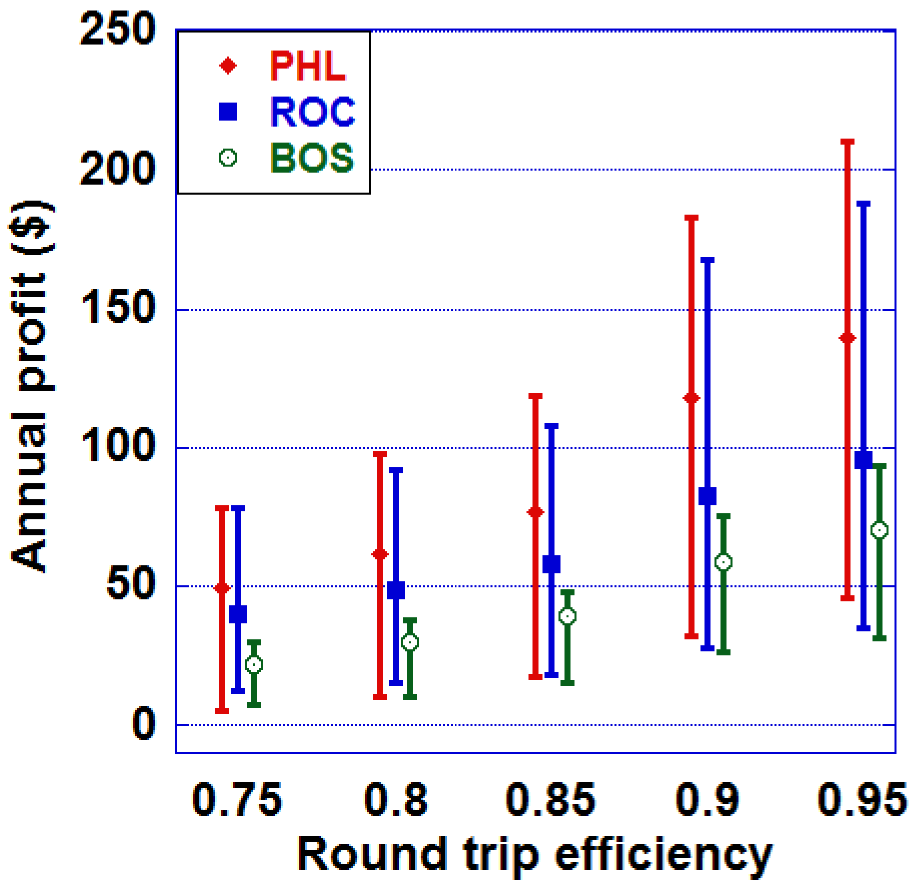

Figure 3.3 V2G energy arbitrage profit sensitivity to round trip efficiency (RTE) with perfect information in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for RTE of 0.75, 0.80, 0.85, 0.90, and 0.95.

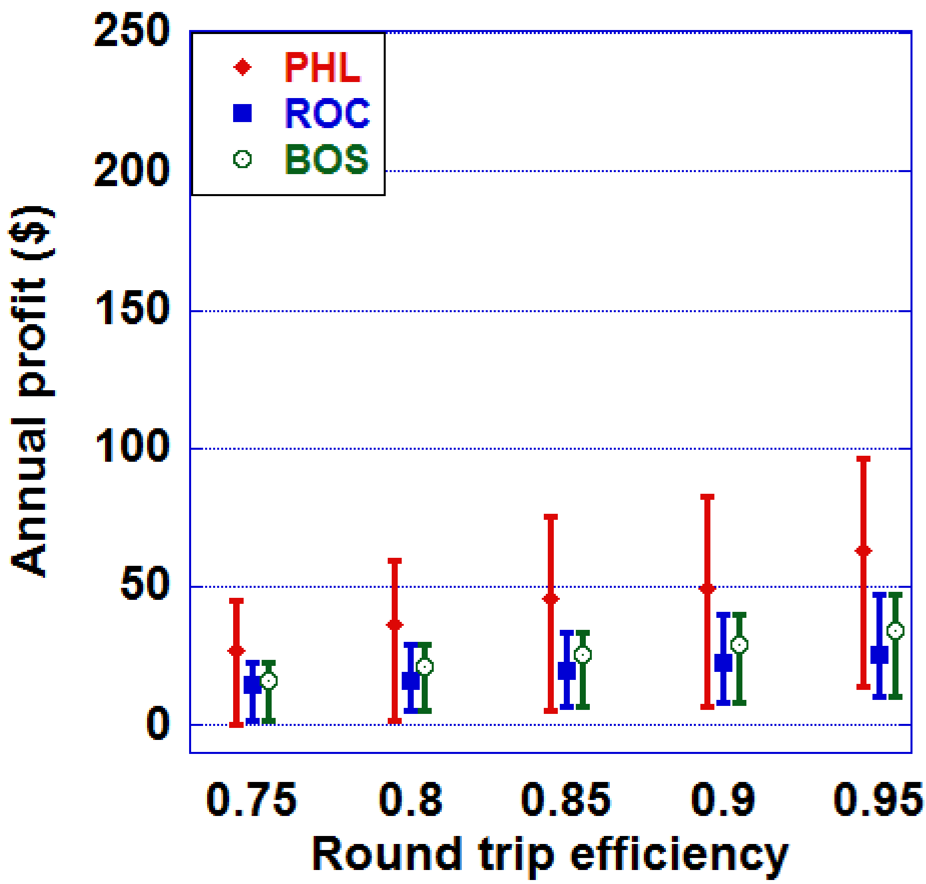

Figure 3.4 V2G energy arbitrage profit sensitivity to RTE with 14 day backcasting method in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for RTE of 0.75, 0.80, 0.85, 0.90, and 0.95.

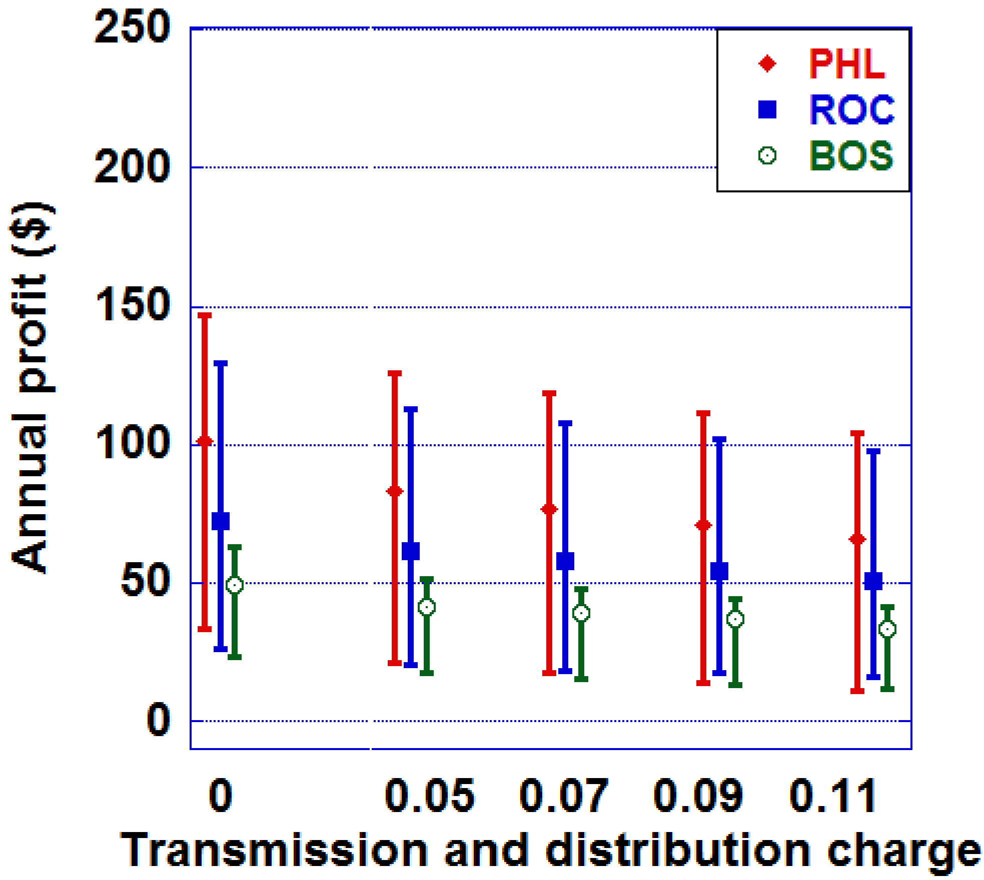

Figure 3.5 V2G energy arbitrage profit sensitivity to Transmission and Distribution charges with perfect information in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for T&D charges of 0, 0.05, 0.07, 0.09, and 0.11 ¢/kWh.

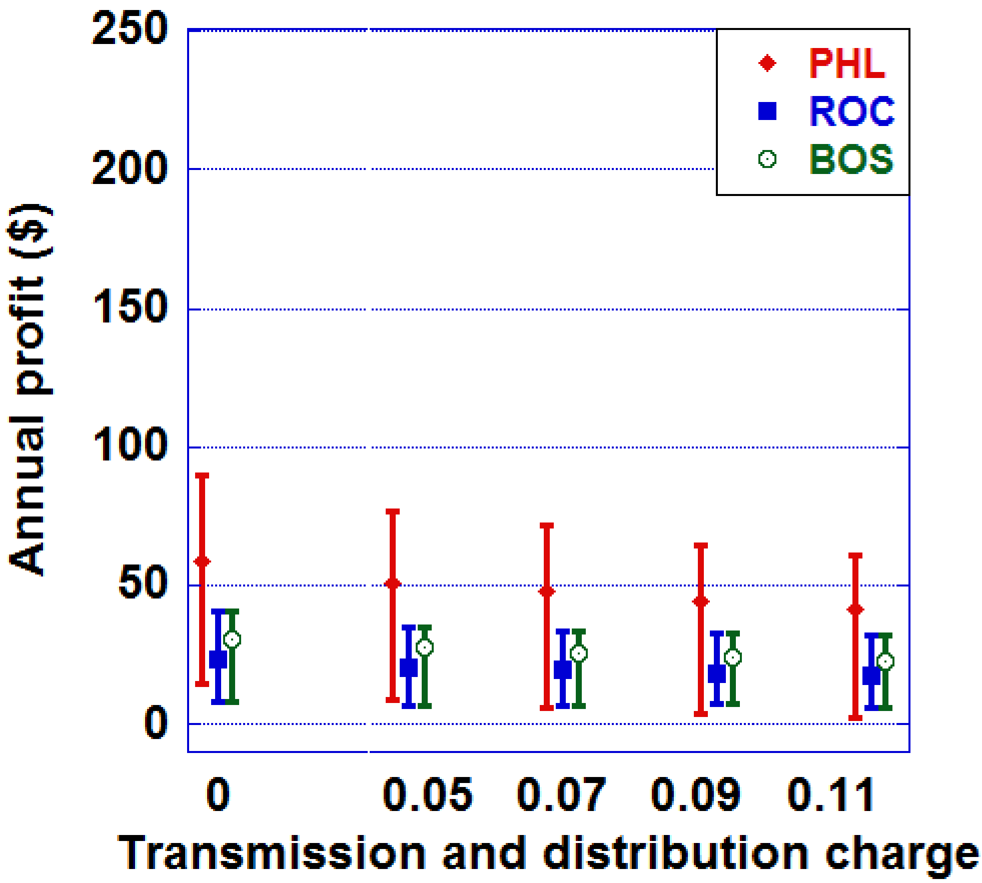

Figure 3.6 V2G energy arbitrage profit sensitivity to T&D charges with 14 day backcasting method in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for T&D charges of 0, 0.05, 0.07, 0.09, and 0.11 ¢/kWh.

Whether vehicle owners will make their energy available for sale on a particular day is of interest to grid operators. Given the base case assumptions ($5,000 battery replacement cost and 85% RTE, 7.2 kW infrastructure wiring), it was profitable in the Philadelphia area to participate in energy arbitrage 56% of the days in the years 2003-2008 (Figure 3.7). This decreases to 38% if battery pack replacement cost is $10,000. The difference between perfect information and the more realistic backcasting method does not affect the number of kWh discharged as strongly as profit (Figure 3.8-Figure 3.9). On average for all replacement costs and locations the number of kWh offered for arbitrage based on backcasting method was 89% of the number offered based on perfect information (we note that backcasting profit was only 51% of that for perfect information).

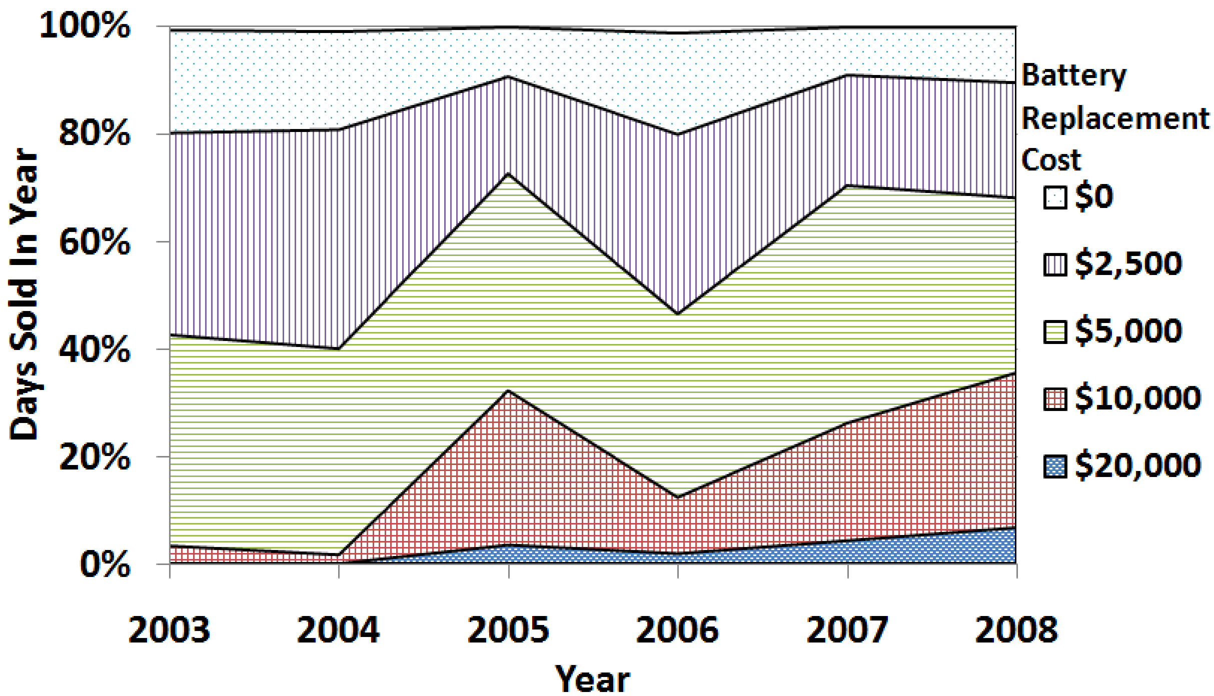

Figure 3.7 Percent of days in Philadelphia area of PJM that energy arbitrage is profitable given different battery replacement costs and perfect information.

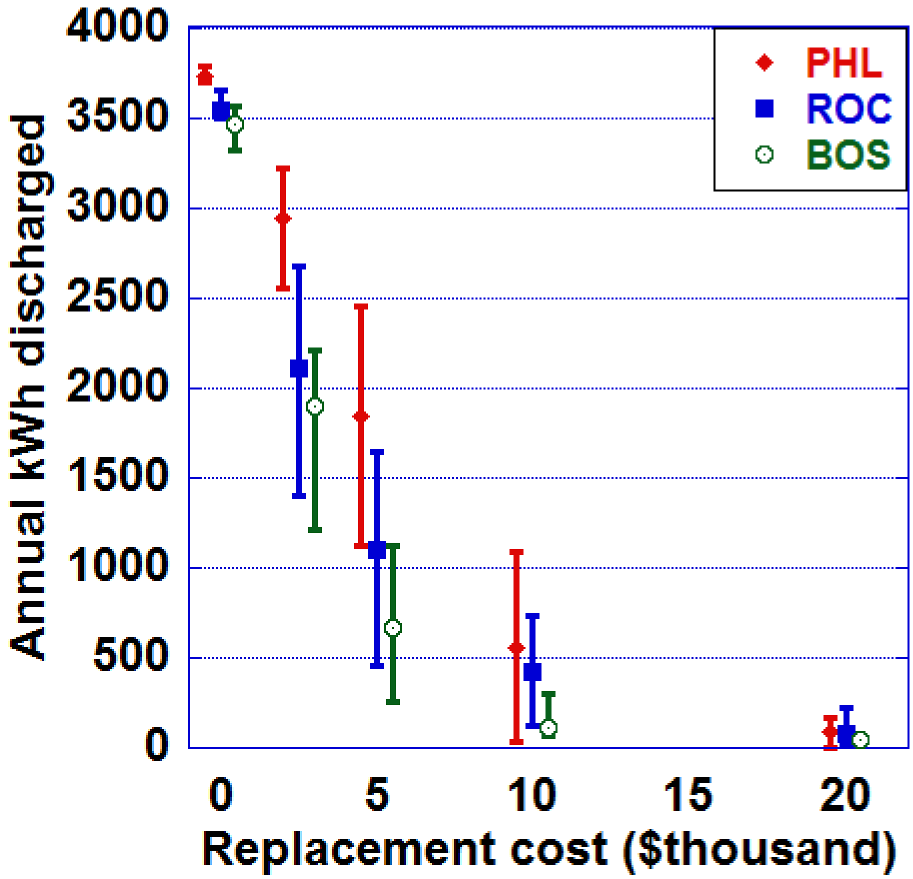

Figure 3.8 V2G energy arbitrage quantity sensitivity to battery pack replacement cost with perfect information in the three cities studied. The symbol indicates the median annual kWh discharged for the years studied and the range indicates the most and least kWh discharged. The arbitrage in each city is calculated for battery replacement costs of $0, $2,500, $5,000, $10,000, and $20,000.

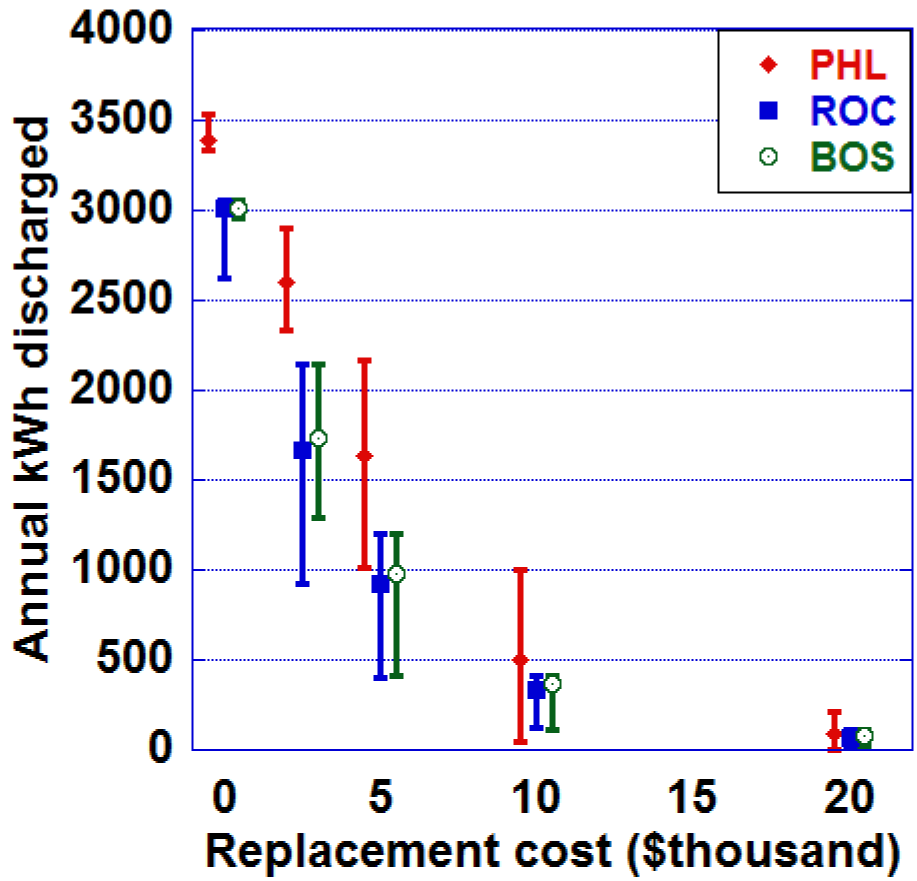

Figure 3.9 V2G energy arbitrage quantity sensitivity to battery pack replacement cost with 14 day backcasting method in the three cities studied. The symbol indicates the median annual kWh discharged for the years studied and the range indicates the most and least kWh discharged. The arbitrage in each city is calculated for battery replacement costs of $0, $2,500, $5,000, $10,000, and $20,000.

3.7 Conclusion

The results suggest that vehicle owners are not likely to receive sufficient incentives from electricity arbitrage to motivate large-scale use of car batteries for grid support. The maximum annual profit even with perfect market information and no battery degradation cost is $142-$249 in the three cities considered due to the relatively small variation present in LMPs, 230 V 30A infrastructure, and the size of the battery pack. With degradation included, the maximum annual profit (even if battery replacement costs fall to $5000 for a 16 kWh battery pack) is $12-$118; in the more realistic lower bound profit case, the annual profit is $6 - $72. If the difference between high and low LMPs grows in the future the value of energy arbitrage will increase, providing greater incentive to individuals or a hypothetical aggregator. However, any growth in electricity arbitrage will lower the gain, since vehicle owners will increase the presently low night demand and decrease peak demand, lowering the LMP spread.

Could some of the grid's contribution to social welfare from battery storage (change in consumer surplus less producer surplus) justify subsidies to provide sufficient incentives for the owner to use PHEV and BEV batteries for grid support? Sioshansi and co-authors [17] estimate the net social welfare of energy storage in PJM during 2007 to be equivalent to $8/vehicle/year (for 4 GWh of total storage, about 380,000 16 kWh vehicles using 2/3 of their battery pack capacity for electricity). Walawalkar and co-authors find that the effect of demand response in PJM gives similar low net social welfare per kWh [18]. It is possible that the net social welfare provided by energy storage may increase at high levels of variable renewable power generation. Various estimates of the integration cost of variable renewable power to 15-25% of total generation indicate costs on the order of 0.5 to 1 cent per kWh [19]. Suppose 25% of total U.S. generation were wind or solar, 10^{12} kWh. Then the integration cost mitigation would be $20 - $40/vehicle/year if all 250 million vehicles participated in grid support and all integration costs could be mitigated by vehicle storage. Of course, not all vehicles would participate, so the amount available per participating vehicle may be proportionally higher. In that case, there may be opportunities to transfer some of that benefit to the vehicle owner. However, not all the integration cost would be captured by battery owners. The largest potential grid benefit is the avoided cost of new generation plants to meet peak demand. The battery/wiring system is capable of meeting 7.2 kWh of load in a peak hour. A simple cycle natural gas turbine that is used 100 hours per year has fixed costs of approximately $50/kW, or 50¢/kWh. Add to that 10¢/kWh for fuel, for a total of 60¢/kWh, or $432 over the 100 hours the peaker would have run. A specific vehicle owner would not be able to help the grid avoid all $432, since those 100 hours are likely to be in 4 hour blocks on only 25 days and the vehicle's battery would discharge for only a bit less than 2 hours. Thus, the vehicle owner might be able to avoid ~$200 of peaking costs. In states with traditional regulated electricity, the public utility commission might elect to avoid paying the utility to install and run a peaker, instead giving some of the avoided cost to V2G owners. In restructured states, the ISO/RTO may pay an aggregator to provide V2G power instead of paying a generator a capacity payment; the aggregator would then pay some of their revenue to the vehicle owner. In the absence of such incentives, it is unlikely that large-scale grid energy storage in PHEVs will be attractive to vehicle owners.

3.8 Acknowledgements

The authors thank Lester B. Lave and Mitchell J. Small for helpful discussions. This work was funded in part by the National Energy Technology Laboratory of the Department of Energy, the Alfred P. Sloan Foundation and the Electric Power Research Institute under grants to the Carnegie Mellon Electricity Industry Center (CEIC), and the U.S. National Science Foundation through the Climate Decision Making Center at Carnegie Mellon University under grant SES-0345798. This paper does not necessarily reflect the views of any of the funding agencies. No funding agencies had any role in the collection, analysis or interpretation of data; in the writing of the report; or in the decision to submit the paper for publication.

3.9 Appendix: Model

Hours required to recharge from driving

Driving Discharge*Battery Size=0.341*16=5.47kWh

Infrastructure:

Capacity=240V*30A=7.2kW

Time and Energy needed to recharge:

$DCH_{eff}=CH_{eff}=\sqrt{0.85}$

$$\frac{\text{Driving Discharge} * \text{Battery Size}}{CH_{eff}} = \frac{5.47\text{kWh}}{\sqrt{0.85}} = 5.93\text{kWh}$$

$$\frac{5.93\text{kWh}}{7.2\text{kWh}} = 0.82 \text{ hours}$$

Buying for driving recharge:

Minimize $\dfrac{\text{LMP}_{\text{Buy}}(t_{B1}) + \text{TND}}{\text{CH}_{\text{eff}}} * \text{kWh}$

$17 \leq t_{B1} \leq 31$ (Corresponds to 5pm to 7am)

Selling:

Maximize $\left[\left(\text{LMP}_{\text{Sell}}(\text{t}_{\text{s1}}) + \text{TND}\right) * \text{DCH}_{\text{eff}} - \dfrac{\text{LMP}_{\text{Buy}}(t_{B1}) + \text{TND}}{\text{CH}_{\text{eff}}} \right] * \text{Percent} * \text{Battery Size}$

$17 \leq t_{s1} \leq t_{B1}$

$$\left[\left(\text{LMP}_{\text{Sell}}(\text{t}_{\text{s}}) + \text{TND}\right) * \text{DCH}_{\text{eff}} - \frac{\text{LMP}_{\text{Buy}}(t_{B1}) + \text{TND}}{\text{CH}_{\text{eff}}} \right] * \text{Percent} * \text{Battery Size} >$$

$$\text{Degradation Cost} = \frac{\text{Battery Replacement Cost} * \text{V2G Deg}}{(0.8 - 1)} * \text{Percent}$$

$$\text{Percent} \leq \frac{(1 - 0.82) 7.2 * \text{CH}_{\text{eff}}}{\text{Battery Size}} = \mathbf{0.729}$$

Percent<1-Driving Discharge

Choose Next Buying hour:

$$\min \frac{\text{LMP}_{\text{Buy}}(t_{B2}) + \text{TND}}{\text{CH}_{\text{eff}}} * \text{kWh}$$

$17 \le t_{B2} \le 31$ (Corresponds to 5pm to 7am)

$t_{B2} \ne t_{B1}$

Decide Whether to Sell (and hence buy in the hour just chosen):

$$\text{Maximize}\left[\left(\text{LMP}_{\text{Sell}}(\text{t}_{\text{s1}}) + \text{TND}\right) * \text{DCH}_{\text{eff}} - \frac{\text{LMP}_{\text{Buy}}(t_{B2}) + \text{TND}}{\text{CH}_{\text{eff}}}\right] * \text{Percent} * \text{Battery Size}$$

$17 \le t_{s1} \le t_{B2}$

$17 \le t_{s1} \le t_{B1}$

$$\text{Percent} \le \frac{(1)7.2\text{kWh} * \text{CH}_{\text{eff}}}{\text{Battery Size}} = \mathbf{0.4148}$$

$$\text{Percent} \le \frac{\dfrac{7.2\text{kWh}}{\text{Battery Size}} - (0.729) * \text{DCH}_{\text{eff}}}{\text{CH}_{\text{eff}}} = 0.4152$$

Percent<1-Driving Discharge-0.0729

Other constraints same as above (namely revenue>cost)

Choose Next Buying hour:

$$\min \frac{\text{LMP}_{\text{Buy}}(t_{B3}) + \text{TND}}{\text{CH}_{\text{eff}}} * \text{kWh}$$

$17 \le t_{B3} \le 31$ (Corresponds to 5pm to 7am)

$t_{B3} \ne t_{B2} \ne t_{B1}$

Decide Whether to Sell (and hence buy in the hour just chosen):

$$\text{Maximize}\left[\left(\text{LMP}_{\text{Sell}}(\text{t}_{\text{s1}})+\text{TND}\right)*\text{DCH}_{\text{eff}}-\frac{\text{LMP}_{\text{Buy}}(t_{B3})+\text{TND}}{\text{CH}_{\text{eff}}}\right]*\text{Percent}*\text{Battery Size}$$

$17 \le t_{s1} \le t_{B3}$

$17 \le t_{s1} \le t_{B2}$

$17 \le t_{s1} \le t_{B1}$

$$\text{Percent} \le \frac{(1)7.2\text{kWh}*\text{CH}_{\text{eff}}}{\text{Battery Size}} = 0.4148$$

$$\text{Percent} \le \frac{\frac{7.2\text{kWh}}{\text{Battery Size}}-(0.729)*\text{DCH}_{\text{eff}}-(0.4148)*\text{DCH}_{\text{eff}}}{\text{CH}_{\text{eff}}} = \mathbf{3.21E\text{-}4}$$

Percent<1-Driving Discharge-0.0729-0.4148

Other constraints same as above (namely revenue>cost)

Decide whether to get new selling hour (and hence buy in the hour just chosen):

$$\text{Maximize}\left[\left(\text{LMP}_{\text{Sell}}(\text{t}_{\text{s2}})+\text{TND}\right)*\text{DCH}_{\text{eff}}-\frac{\text{LMP}_{\text{Buy}}(t_{B3})+\text{TND}}{\text{CH}_{\text{eff}}}\right]*\text{Percent}*\text{Battery Size}$$

$17 \le t_{s2} \le t_{B3}$

$17 \le t_{s2} \le t_{B2}$

$17 \le t_{s2} \le t_{B1}$

$t_{S2} \ne t_{S1}$

$$\text{Percent} \le \frac{(1)7.2\text{kWh}*\text{CH}_{\text{eff}}}{\text{Battery Size}} = 0.4148$$

$$\text{Percent} \leq \frac{\frac{7.2\text{kWh}}{\text{Battery Size}}}{CH_{eff}} = 0.488$$

Percent<1-Driving Discharge-0.0729-0.4148-3.21E-4

Other constraints same as above (namely revenue>cost)

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[1]The American Recovery and Reinvestment Act (ARRA), H.R.1 of the 111th Congress, provides a minimum tax credit of $2500 per vehicle is increased by $417 per kWh in excess of 4 kWh, to a maximum of $7500. Full credits for plug-in hybrids will be given to the first 250,000 sold PHEVs. Aftermarket conversions of HEVs to PHEVs are eligible for a credit of 10% of conversions costs up to $40,000.
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Chapter 4 Net air emissions from electric vehicles: The effect of carbon price and charging strategies

4.1 Chapter Information

Authors: Scott B. Peterson, Jay F. Whitacre, and Jay Apt

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4.2 Abstract

Plug-in hybrid electric vehicles (PHEVs) may become part of the transportation fleet on time scales of a decade or two. We calculate the electric grid load increase and emissions due to vehicle battery charging in PJM and NYISO with the current generation mix, the current mix with a \$50/tonne CO_2 price, and this case but with existing coal generators retrofitted with 80% CO_2 capture. We also examine all new generation being natural gas or wind+gas. PHEV fleet percentages between 0.4 and 50% are examined. Vehicles with small (4 kWh) and large (16 kWh) batteries are modeled with driving patterns from the National Household Travel Survey. Three charging strategies and three scenarios for future electric generation are considered. When compared to 2020 CAFE standards, net CO_2 emissions in New York are reduced by switching from gasoline to electricity;, coal-heavy PJM shows somewhat smaller benefits unless coal units are fitted with CCS or replaced with lower CO_2 generation. NO_X is reduced in both RTOs, but there is upward pressure on SO_2 emissions or allowance prices under a cap.

4.3 Introduction

Mass-market electric vehicles have recently been introduced in the USA, following the introduction in China of the BYD plug-in hybrid electric vehicle (PHEV) in 2008. Here we use the term PHEV to denote both plug-in hybrid vehicles and extended-range electric vehicles (EREVs). Vehicle gasoline consumption can be displaced by electric power generation. The net air emissions of such displacement depend on the fleet gasoline mileage, PHEV fleet electric mileage, and electric generation mix at the time vehicle charging takes place. Moving emissions to the electricity sector has advantages, but the resulting environmental quality depends on net changes in emissions.

Existing electricity generation assets can likely support a significant number of PHEVs (*1*-*3*). Previous work has predicted reductions in NO_X and CO_2 emissions when comparing PHEVs to conventional vehicles (CVs), but the magnitude varies and depends on PHEV and generation mix assumptions (*4*-*9*). Pollutant concentration has been estimated to decline in densely populated areas, but may increase near generators (*6*, *7*). The majority of these models suggest an increase in SO_2 emissions; however one comes to a contrasting conclusion based on assumptions that rely on aggressive new emissions control technology (*8*). SO_2 emissions from USA power plants in 2008 and 2009 respectively were 7.9 and 5.6 million short tons, well under the Acid Rain Program cap of 8.95 MT for 2010 (*10*).

In modeling PHEV effects on the electric grid, it is important to know when vehicles will charge, and how much energy they will need. Only one of the previous analyses (*5*) uses driving data to predict the energy needed for recharging and the time when that recharging will likely take place. Those that do not use driving data make assumptions that strongly influence their results (e.g. assuming that a specific percentage of miles are driven using only battery energy, or that all vehicles require the same charge and arrive at designated times at charging points). Variation in assumptions can lead to significant changes in conclusions. For example, if the required charge is changed from 4.8 to 12 kWh and the charge rate is changed from 1.2 to 7.2 kW (variations that are within reasonable ranges) then the peak-added load from all vehicles arriving at specific assumed hours could more than double system load (*1*). Another simplification is modeling only one type of PHEV; if all SUVs were replaced with small cars, emissions would decline significantly regardless of whether those small cars were PHEVs or CVs.

Use of data from surveys of travel that log vehicle type and driving data allows both time and energy requirements to be predicted. We use publicly-available data to predict net emissions from PHEVs under different CO_2 scenarios. Vehicle electricity use is predicted using multiple PHEV types, different charging strategies, battery sizes, CV efficiencies, charge depleting (CD, all-electric mode) efficiencies and charge sustaining (CS, gasoline mode) efficiencies of the vehicles.

To model the electric power generation fleet, we consider four approaches. First, we model a scenario in which the generation capacity needed to charge PHEVs has the same attributes as the generation capacity currently available. Second, we model replacement or retrofit of current coal generators with CO_2 capture and sequestration (CCS). Third, we model all new generation as natural gas (assuming 45% efficiency, a heat rate of 7600 BTU/kWh) (*11*). Finally, we model all new generation as 30% wind, 70% natural gas by energy. We also consider the implications of a binding cap on SO_2 emissions.

We estimate that PHEVs are likely to have lower net emissions of NO_X and CO_2 than a conventional vehicle fleet, given current (10.7 liters/100 km) efficiencies. When compared to 2020 CAFE standards (6.7 liters/100 km), net CO_2 emissions in New York are greatly reduced by switching from gasoline to electricity, but coal-heavy PJM shows lower benefits unless coal units are fitted with CCS or replaced with lower CO_2 generation. NO_X is reduced in both RTOs, but SO_2 increases unless a cap binds (discussed below). A $50/tonne CO_2 price applied only to combustion emissions in the electric sector will have a negligible short-term effect on net CO_2 emissions from PHEVs.

4.4 Methods

4.4.1 Estimating the additional electric load from electric vehicles

To model the incremental increase in electricity load from the addition of PHEVs, we used the day trip file from the 2009 national household travel survey (NHTS) (*12*). This file was analyzed to enumerate the trips taken by vehicles in the survey. The NHTS data file contains trip frequency, length, start and end time, mode, and vehicle attributes (make, model, year) from 150,000 USA households. We used the data to model vehicles trips taking into account the battery state of charge. To reflect the range of the current U.S. federal subsidy structure for reported battery capacity, we modeled a small battery of 4 kWh and a large battery of 16 kWh for passenger cars (*13*). Batteries for other vehicle classes were scaled by their charge depleting (CD) mode efficiencies resulting in "small" batteries of 4, 5.27, and 5.58 kWh and “large" batteries of 16, 22.1, and 22.3 kWh for cars, vans, and SUVs/light trucks respectively. Using the trip distances from the NHTS data, we modeled the amount of electricity necessary to move the vehicle assuming two different sets of CD efficiencies. The first, referred to as 2005, assumes 0.19, 0.24, and 0.34 kWh/km for cars, vans, and SUVs/light trucks respectively. The second, referred to as 2020, assumes 0.12, 0.16, and 0.23 kWh/km for cars, vans, and SUVs/light trucks respectively. These values include losses in transmission and are consistent with estimates from other sources *(14-17*). The lower efficiency case was compared to current conventional vehicles, and the higher case to a fleet meeting 2020 CAFE standards of 35 mpg. Charge rate was assumed to be 7.2 kW, but a lower charge rate (1.4 kW) was not found to change load characteristics significantly for small battery PHEVs (supporting information).

The total distance travelled in electric mode was constrained by a limit that allowed vehicles to use 75% of battery capacity. Once the battery was depleted, gasoline was assumed to provide motive force for the charge sustaining (CS) mode travel. The arrival times for vehicles were then used to predict the times of day when grid load from PHEVs would occur, given different charging strategies (described in the displaced gasoline section below). More information about this method is available in the supporting information.

Since the boundary of PJM is not coincident with state boundaries, we estimated the number of vehicles in PJM by using statewide vehicle registrations for states that are mostly in PJM (*18*). The ratio of vehicles per GWh of annual load for each state was combined in a weighted average to yield an estimate of 30 million vehicles in PJM. We used 10.5 million vehicles in NYISO (*18*). The PHEV market share of this fleet was modeled at three levels: 0.45% (corresponding to a goal of 1 million PHEVs nationwide (*19*)) 10, and 25%.

4.4.2 Generator Dispatch

We used the method described in (*20*) to construct monthly short-run marginal cost (SRMC) curves for each electric power generator in PJM and NYISO from EPA eGRID data (*21*) and DOE fuel cost and heat content data (*22*). The monthly SRMC curves allow seasonal NO_X emission calculations. The effects of a price on CO_2 were modeled as in (*20*). Here we do not model the effects of transmission constraints, nor of the additional emissions when generators are started and ramped to full power. We also modeled the effects of replacing all coal generation with coal generators that capture 80% of emitted CO_2, using a 20% energy penalty to de-rate the nameplate capacity.   We adopted the assumption that coal plants equipped with CCS reduced SO_2 emissions by 98% (*23*).

The hourly load with and without electric vehicles was combined with the SRMC curve to determine the market clearing price. The generators predicted to bid in at or below the market clearing price make up the generation fleet that in each hour. Once the dispatched generators were determined in each hour, CO_2, NO_X, and SO_2 emissions from the eGRID database for each generator were used to predict emissions from the additional load in response to PHEVs.

4.4.3 Displaced Gasoline

Reductions in gasoline consumption from using a PHEV depend on the CD and CS mode efficiencies and the miles travelled in each mode. The miles travelled in CD mode depends on the size of the PHEV battery. The net change in gasoline usage can then be determined, using the efficiency of conventional vehicles. Given large batteries, petroleum consumption could be reduced by 65-90% for every conventional vehicle replaced with a PHEV, depending on the number of charges in the day and the efficiency of the vehicle in charge depleting mode. Small batteries could reduce consumption by 25-50%.

Subtracting the distance travelled in CD mode from the total distance travelled by the vehicle yields the distance travelled in CS mode and the miles displaced from regular gasoline travel. We assume that the efficiency in CS is equal to that of the CV fleet so any increase in CV fleet efficiency increases the CS efficiency. This efficiency determines the amount of fuel used by PHEVs and CVs. This choice was made because, although PHEVs have the ability to use regenerative braking to increase efficiency, they carry additional weight compared to conventional cars, and thus will likely be less efficient in CS mode than a hybrid electric vehicle (HEV) such as the Prius. When a consumer chooses a PHEV instead of a conventional vehicle both will likely have similar technology and therefore more efficient PHEVs will coexist with more efficient conventional vehicles. Because of this the lower efficiency CD mode values are combined with 2005 new vehicle efficiency, and the higher efficiency CD values are compared to 2020 new car efficiency (assumed to be 35mpg). This assumption is used throughout this work.

The changes that will allow the CV fleet to meet the 2020 CAFE standards will also increase efficiency of PHEVs. Advances in aerodynamics and body weight reduction are as applicable to PHEVs as CVs. Drive train and engine efficiency improvements will also increase PHEV efficiency, though improvements will not necessarily yield identical efficiency increases in CVs and PHEVs. If a lighter, more efficient engine is developed for CVs it could be incorporated in PHEVs as a range extender.

4.4.4 Net Emissions

Reductions in gasoline consumption from using a PHEV depend on the CD and CS mode efficiencies and the miles travelled in each mode. The miles travelled in CD mode depends on the size of the PHEV battery. The net change in gasoline usage can then be determined, using the efficiency of conventional vehicles. Given large batteries, petroleum consumption could be reduced by 65-90% for every conventional vehicle replaced with a PHEV, depending on the number of charges in the day and the efficiency of the vehicle in charge depleting mode. Small batteries could reduce consumption by 25-50%.

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4.5 Results

We show results for a 10% PHEV market share of the light-duty vehicle fleet. Other PHEV market shares are included in the supporting information, but results are similar except for the lowest 0.45% level (with fewer PHEVs charging, the specific plant used to charge them becomes uncertain).

Compared to 2005 gasoline fleet efficiency levels, all charging strategies and CD mode efficiencies yield reduction of CO_2 emissions. If the 2020 conventional vehicle fleet efficiency target of 35 MPG is compared to the 2020 CD efficiency, net CO_2 emissions drop significantly in switching from gasoline to electricity in NYISO, but less in PJM because of the differences in generation, unless CCS generation is used.

Home charging occurs near peak system load, smart charging near minimum system load, and work charging occurs both near peak system load (at the same time as home charging) and earlier in the day when most vehicles are arriving at work. These differences in timing result in changes in generator mix and thus emissions. In PJM, home charging results in the greatest CO_2 reductions with no CO_2 price and relies more on natural gas generation. In NYISO, smart charging results in greater CO_2 reductions because of the large number of natural gas generators predicted to be used to meet demand.

Few qualitative changes are observed between small and large battery sizes. Large batteries increase the magnitude of emissions changes, but do not change the sign except in the case of NO_X emissions in NYISO with work or home charging. Large batteries are also more sensitive to charge rate (see supporting information).

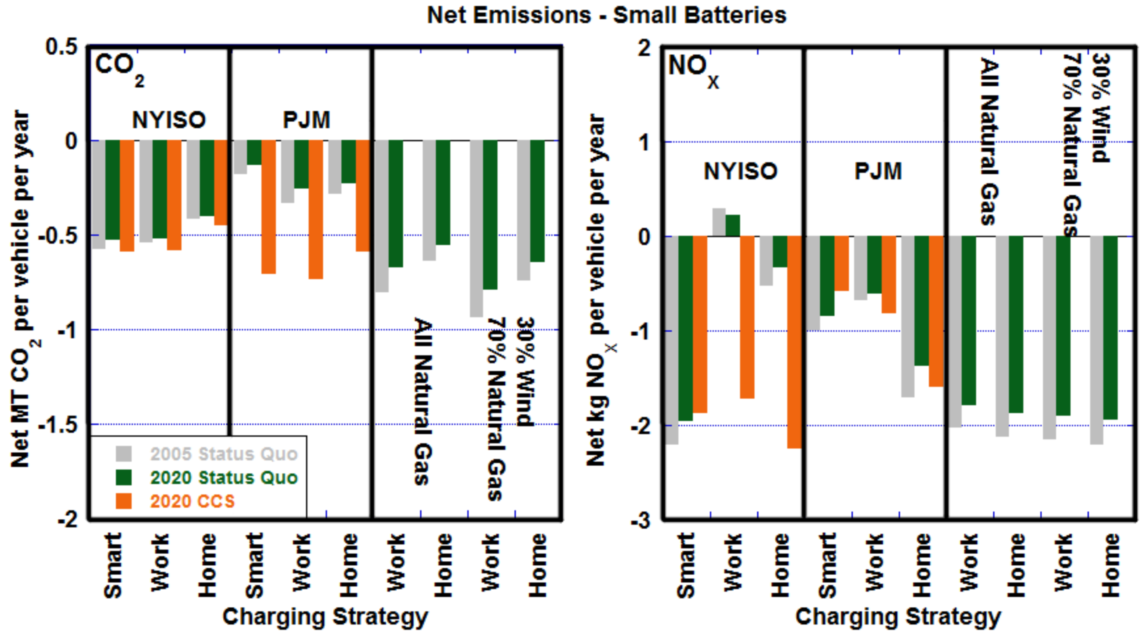

Figure 4.1: Net metric tons of CO_2, and net kg of NO_X emitted per vehicle-year given PJM and NYISO generation mix and all natural gas and 30% wind / 70% natural gas (in the latter two cases the charging strategy is not relevant because the emissions are independent of the time a vehicle charges and represent charging twice or only once). For comparison, the predicted emissions per conventional vehicle using 2005 (22 mpg) and 2020 (35 mpg) efficiencies are 4.1 and 2.6 MT CO_2, and 10 and 6.4 kg NO_X. Emissions for 2005 fleet and 2020 fleet are compared given the status quo (no CO_2 price) as well as a \$50/tonne CO_2 price in conjunction with CCS installed on coal plants given 2020 efficiencies. A similar figure for large batteries is included in the supporting information.

4.5.1 CO_2 emissions

Without a CO_2 price there is no incentive to use a generator with lower CO_2 emissions. Both current and future PHEVs are predicted to result in net decreases of emissions in all charging strategies and both RTOs. In NYISO home charging does not decrease CO_2 emissions as much as smart or work charging because it is displacing gasoline with plants near the peak, often using oil (discussed below). Smart charging relies on 86% natural gas in NYISO, whereas home charging uses only 44% natural gas. In NYISO work and smart charging have similar CO_2 emissions. PJM shows nearly the opposite result with smart charging having significantly lower reductions in CO_2 emissions (relying on 98% coal). Home and work charging in PJM exhibit similar levels of CO_2 emissions.

Adding a \$50/tonne CO_2 price does not significantly alter the plants used to meet a given load. The no-PHEV load is adjusted using a -0.1 price elasticity of demand. By itself, this causes a significant decrease in emissions (*20*). No price elasticity was applied to demand associated with PHEVs, since it is likely that in an era with large penetration of PHEVs that the combination of gasoline price, electricity price, battery price, and (possibly) subsidies that encourage large-scale adoption will make the substitution of electricity for gasoline attractive. Emissions associated with PHEVs are compared to emissions given the no-PHEV load and a \$50/tonne CO_2 price (supporting information); there was very little effect.

We modeled the effects of converting only coal plants to CCS. Under the CCS scenario, smart charging in PJM relies on 91% coal, and 4% natural gas, with 5% oil and biomass. The percentage from coal is smaller than the non-CCS cases because CCS reduces the net capacity of coal plants. In NYISO, the generation mix for PHEV load is 6.4% coal, 88% natural gas, 2.7% oil, 0.4% biomass, and 2.3% renewable. In PJM, CO_2 emissions savings are roughly doubled from the no-CCS case, while in NYISO there is only a slight reduction compared to the status quo.

Using only natural gas generators (at 45% efficiency) to charge PHEVs, means that charging time does not affect emissions. Thus, the smart charging scenario is not included. Net emissions of CO_2 are reduced by 0.55-0.69 tonnes compared to 2005 CVs and by 0.47-0.57 tonnes compared to 2020 CVs. Reductions in the wind case are larger. In PJM net emissions of CO_2 are likely to be reduced 4-62%. In NYISO, net emissions of CO_2 are likely to be reduced 9-42%.

4.5.2 NO_X emissions

At the outset, we note that there is insufficient experience with PHEVs to reliably predict certain aspects of their operational NO_X emissions (e.g. cold starts). Thus, our results apply to vehicles in the CD mode, but CS mode operations require additional data (such as the chosen control strategy of manufacturers). CO_2 price does not directly affect NO_X emissions. However, coal generators emit more NO_X per MWh produced on average than other generators (*24*), so any increase in natural gas compared to coal reduces NO_X. Emissions of NO_X decline in all scenarios except work charging in NYISO because high-emission generators being used at a specific time in the day to charge PHEVs in NYISO. Both home and work charging increase peak demand because the uncontrolled charge after vehicles arrive home closely coincides with system peak load.

Smart charging in NYISO results in the greatest reductions of NO_X. This relies heavily on natural gas that has low NO_X emission rates. Home charging uses the same energy as smart charging, but takes place largely in the evening near peak load (supporting information). In PJM home charging based on the current generation mix and short-run marginal costs would be 55% coal, 33% natural gas, 10% oil and 2% biomass. Using the 2005 generation mix of NYISO. this load would be met with a mostly oil generators: the marginal units for home charging in NYISO would be 1% coal, 44% natural gas, 54% oil and 0.5% biomass. Oil use in New York reached a 15-year high in 2005 (16% of generation). Dual-fuel generation represents the majority of marginal units in New York City, Long Island, and Albany (25). In 2008, high oil price and low natural gas price drove these units to use 6 times more gas than in 2005 (supporting information), and oil represented only 3% of generation. It is reasonable to expect that recent shale gas exploitation will keep oil use low in New York in the next decade, Thus, our "all natural gas" scenario is likely to better represent future NYISO emissions from charging PHEVs than the 2005 data.

Adding a \$50/ton CO_2 price significantly decreases the no-PHEV load. This is especially important in NYISO. Instead of seeing increases of NO_X ranging from 0.22-0.29 kg per vehicle-year as in the status quo case reduction of 1.5-1.6 kg per vehicle-year are expected.

In the CCS scenario there is little change in NO_X emissions. For amine-based carbon capture (added to coal plants in our model) to function ,the amount of SO_2 and NO_2 must be below 10 ppm, but NO_2 makes up very little of the NO_X emissions from a power plant (*23*). IGCC and chilled ammonia systems also require low SO_2. CCS decreases the electricity output of coal plants per MMBTU of fuel (due to the energy penalty of CCS), but the NO_X/MMBTU remains roughly constant decreasing only 1% (*21*). Thus, the NO_X/MWh generated by coal plants would increase without additional emission controls. This is especially noticeable in the PJM smart charging scenario that relies heavily on coal. NO_X emissions are still reduced compared to a CV.

Using only natural gas causes significant reductions in NO_X emissions. This model does not reflect any increase in emissions from gas generators ramping to follow wind (26), so NO_X emissions from the electricity generation fall by 30%. NO_X emissions will decline between 7 and 43% in PJM and 5-70% in NYISO except in the work charging scenario. In either case NO_X emissions are likely to decrease significantly for each PHEV that displaces a CV.

4.5.3 SO_2 emissions

Unlike the other pollutants, net SO_2 emissions increase in most scenarios (Figure 4.2a). National 2005 electric sector emissions were 9.4 million tonnes of SO_2, compared to combined emissions for highway vehicles of 0.13 million tonnes (Figure 4.2), reflecting the low sulfur content of motor fuels in the United States. Even with 25% PHEVs, neither RTO would exceed current SO_2 emissions caps established under the Acid Rain Program, because the annual SO_2 emissions have declined in 2008 and 2009 (*27*) to 88% and 63% of the 2010 cap, respectively. The decline is likely due to actions taken in anticipation of the now-voided Clean Air Interstate Rule and demand reductions associated with the recent recession. The highest increase in SO_2 emissions from the electricity sector from our model was 0.17 million tonnes in PJM (with smart charging, large batteries, low efficiency CD mode, and 25% PHEVs), comparable to the current total emissions from highway vehicles using liquid fuels.

The proposed Clean Air Transport Rule (CATR) would greatly reduce the allowable SO_2 emissions in both NYISO and PJM, making results such as those in Figure 4.2a unlikely in the 28 capped states unless the CATR is not implemented. We now consider the introduction of PHEVs when generators have complied with the 2014 CATR. SO_2 emissions must decrease below those in 2005 by 77% in NYISO to comply. PJM is not made up of a single state; the weighted average of reductions necessary in Pennsylvania, Ohio, Maryland, Virginia, West Virginia, Delaware, and New Jersey was estimated to be 83%. These reductions were then applied to SO_2 emissions factors for plants in each RTO and the model was rerun (Figure 4.2b). With the electric generation reductions necessary to meet the CATR, net vehicle emissions in NYISO are near zero and those in PJM are always lower than 0.9 kg per vehicle-year for small batteries.

We emphasize that under CATR, while per-vehicle net SO2 emissions increase, total emissions from electric generating units in the capped states cannot. Thus, if CATR goes into effect as proposed, and we assume emissions in the RTOs are just under the cap without PHEVs, the additional generation would cause an upward pressure on SO_2 allowance prices. EPA estimates that the marginal cost of SO_2 allowance prices in Pennsylvania near the cap limit will be ~$22 per additional thousand tonnes (*28*). Thus, for 0.9 kg/vehicle-year, the approximately 840 tonnes of additional SO_2 emissions from charging vehicles in Pennsylvania would increase the SO_2

allowance prices by ~$19/tonne (EPA estimates that the allowance price will be ~$2300/tonne at the proposed Pennsylvania 2014 cap limit of 128,542 tonnes).

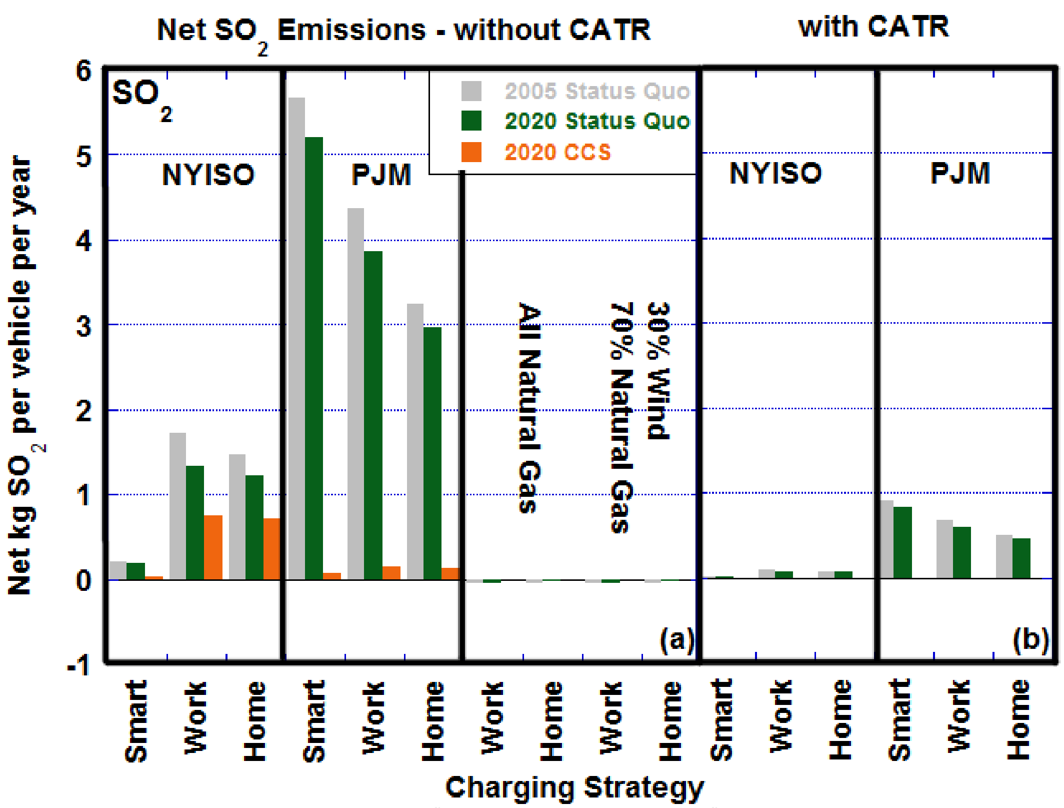

Figure 4.2: Net kg SO_2 emitted per vehicle-year given (a) PJM and NYISO generation mix of 2005, as well as all natural gas and 30% wind / 70% natural gas, and (b) PJM and NYISO with generator emissions factors for SO_2 reduced to comply with CATR. For comparison, the predicted annual emissions per conventional vehicle using 2005 (22 mpg) and 2020 (35 mpg) efficiencies are 0.20 and 0.13 kg SO_2. Emissions for 2005 fleet and 2020 fleet are compared given the status quo (no CO_2 price) as well as a $50/tonne CO_2 price in conjunction with CCS installed on coal plants. Different charging strategies are modeled to determine the timing of PHEV charging. A similar figure for large batteries is included in the supporting information.

SO_2 emissions would not change significantly in response to a CO_2 price alone except for an increase in the NYISO smart charging case. However, CCS will require SO_2 emissions to be reduced significantly to avoid contamination during portions of the capture process for IGCC or amine capture. Thus, the net SO_2 emissions in the CCS cases are closer to zero (*23*). Using only natural gas or a combination of natural gas and wind both results in essentially no change to net SO_2 emissions.

4.6 Discussion

Net emissions from PHEVs depend on the efficiency of the conventional vehicle fleet, PHEV CD (charge depletion, all-electric mode) mode efficiency, charging strategy, battery size, driving patterns, and generator mix used for charging. In all cases, net CO_2 emissions decline. In most cases, NO_X emissions decline (NO_X emissions in NYISO increase when combined with work charging, because of the heavy reliance during 2005 on oil to accomplish this charging and specific plants being used; natural gas has supplanted oil in most NYISO units recently). With large batteries, NO_X emissions are unchanged. Even in a RTO with cleaner generation overall, the marginal units might have higher emissions factors; in PJM, the plants charging near peak emit less NO_X than those in NYISO. Using only natural gas, or gas and wind combined, will result in significant decreases to CO_2 and NO_X emissions. It is also possible that there would be some improvements to grid stability and a decreased need for balancing fluctuations in wind generation if variable charging of PHEVs is coordinated with changes in wind output.

Electric vehicles will place upward pressure on net SO_2 emissions. With the Clean Air Interstate Rule vacated by the courts and the final rule promulgation of CATR delayed by EPA, there is uncertainty about the level of capped emissions. Net SO_2 emissions caused by vehicles will be less than 6% in NYISO and 2% in PJM, of the proposed 2014 CATR cap on electric generators under any of the reduced SO_2 scenarios. We note that the upstream (largely refinery) emissions displaced by decreasing gasoline use are ~ 0.45 kg SO_2 per vehicle-year (supporting information). This is more than half of the SO_2 emissions reduction required to comply with CATR. However, it is possible that the associated upstream refining emissions will also decrease when CATR is implemented.

Choosing a charging strategy can change the resulting net emissions associated with PHEVs. In NYISO, the smart charging scenario generally resulted in lower or equal net emissions than home charging and lower than work charging, resulting in lower emissions. In PJM, smart charging generally causes higher emissions because coal is often on the margin at night. In PJM there is a tradeoff between use of off-peak charging and increased emissions. RTOs and LSEs should be aware of possible tradeoffs between cost and emissions before encouraging particular charging strategies. Information about generation resources should be used in concert with pricing data to find the optimal charging strategy in individual RTOs.

4.7 Conclusion

There are strong arguments in favor of electrification of the transportation sector in addition to net emissions. Combining numerous mobile emission sources into a far small number of stationary sources offers opportunities for cost-effective emissions reduction that may not otherwise be feasible in the transportation sector, and the location of emissions is likely to be moved farther from densely populated areas. If PHEV cars displace light trucks, SUVs, and vans from the fleet, emissions will be further reduced from the values reported here.

Enacting a CO_2 price of $50/tonne will not be effective at reducing net CO_2 emissions from a PHEV fleet. PHEVs are likely to place upward pressure on SO_2 allowance prices if emission caps bind, or to increase emissions if the caps do not bind. PHEVs will probably reduce net CO_2 and NO_X emissions, but are unlikely to reduce net SO_2 emissions.

4.8 Acknowledgments

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4.9 Supporting Information

4.9.1 Timing and magnitude of additional load from PHEVs

The national household transportation survey (NHTS) was used as the basis for estimating the timing and magnitude of additional load from PHEVs (*1*). The NHTS day trip file was divided according to month, and by weekday and weekend. Then the resulting trip data was reorganized to list the vehicle trips for the day. Estimation of the driving distribution was conducted for weekday (Monday-Friday) and weekend days due to significant changes in driving patterns. These data were used to list vehicle trips by trip length (some are zero length for cars not used during a day), for each month, with weekend days separated from work-week days. We modeled that the vehicles operate entirely on electric propulsion until they reach the design limit of energy in the pack (assumed as 75% of the rated capacity). Thereafter the vehicle continues in charge sustaining mode for the rest of the driving, using gasoline for propulsion (PHEV) or charge sustaining (EREV). The NHTS data on use of cars, vans, and light trucks allowed us to model the charging load based on the relative proportions of those vehicle types. The electricity use for all trips was based on vehicle efficiency. Added load is based on battery state and an assumed 7.2 kW circuit infrastructure (240V single-phase, 40A de-rated for continuous use). The charger is assumed to by 92% efficient. A separate run was conducted assuming 1.4 kW rate charging and similar emissions results were achieved for small batteries.

Not all vehicles are driven on a given day so all vehicles, whether driven or not, were included in the total number. The vehicle trips were modeled on a monthly basis. Therefore it was assumed that the load added by PHEVs was identical on weekdays throughout a given month and also that all weekends in a month are identical.

Four different levels of PHEV market penetration were modeled. The first is based on the goal of having 1 million PHEVs nationwide (0.45%) (2). The others are 10%, 25%, and 50%. For every number of PHEVs modeled the entire NHTS day trip file was run. To model a specific percentage the file was looped multiple times until the desired number of vehicles to constitute the correct percentage was reached or surpassed. This was done to avoid omitting the vehicles near the end of the dataset on the last loop in each case otherwise. In all cases the charging time is limited both by the time the vehicle is available to charge and the charge needed based upon the reported distance driven prior to charging.

The timing of vehicle charging varies depending on the strategy modeled. An example is shown (Figure 4S.1 and Figure 4S.2) for the highest and lowest load days in PJM. The example includes a fleet of 50% PHEVs to illustrate the timing. The timing of smart charging is based on the average load during the given month and therefore may not perfectly flatten load during every night. The lowest load day of the year was a weekend and therefore it is unsurprising that the PHEV load leads to an increase over existing load.

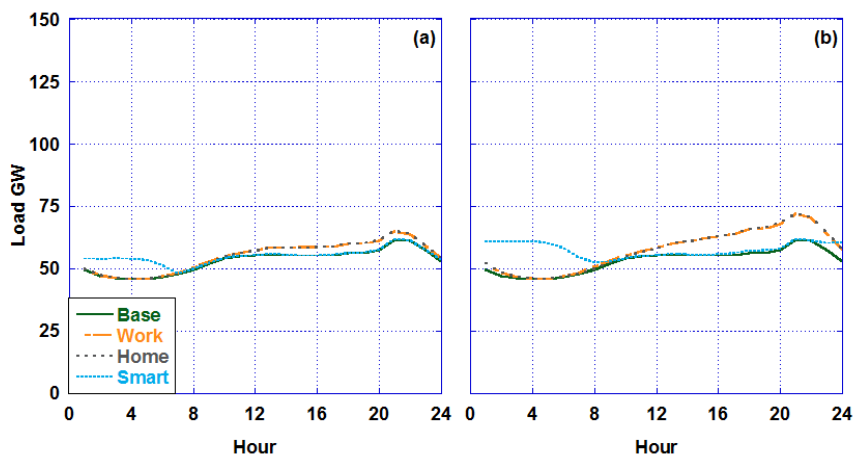

Figure 4S.1: Load on day of minimum hourly demand(Sunday, April 10, 2005) in PJM, 50% PHEVs with (a) small batteries and (b) large batteries

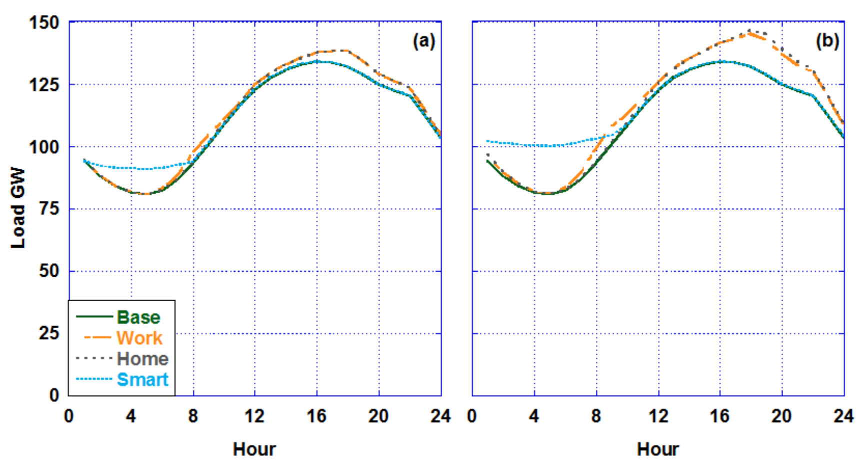

Figure 4S.2: Load on day of maximum hourly demand(Tuesday, July 26, 2005) in PJM, 50% PHEVs with (a) small batteries and (b) large batteries

Work and home charging are quite similar throughout the year so it is possible to show the average added load per PHEV used. Results for home charging are shown in Figure 4S.3. The average hourly load per PHEV driven is shown given different charge depleting mode efficiencies, battery sizes (a and b for small, c and d for large) and separating weekends and weekdays (a and d for weekday, b and c for weekend). It is clear from the figure that many of the small battery PHEVs are depleted upon arrival at their destination. This can be observed by noting the small difference between current and 2020 efficiencies. With large batteries the difference is much greater because a significant number of vehicles do not entirely deplete their battery.

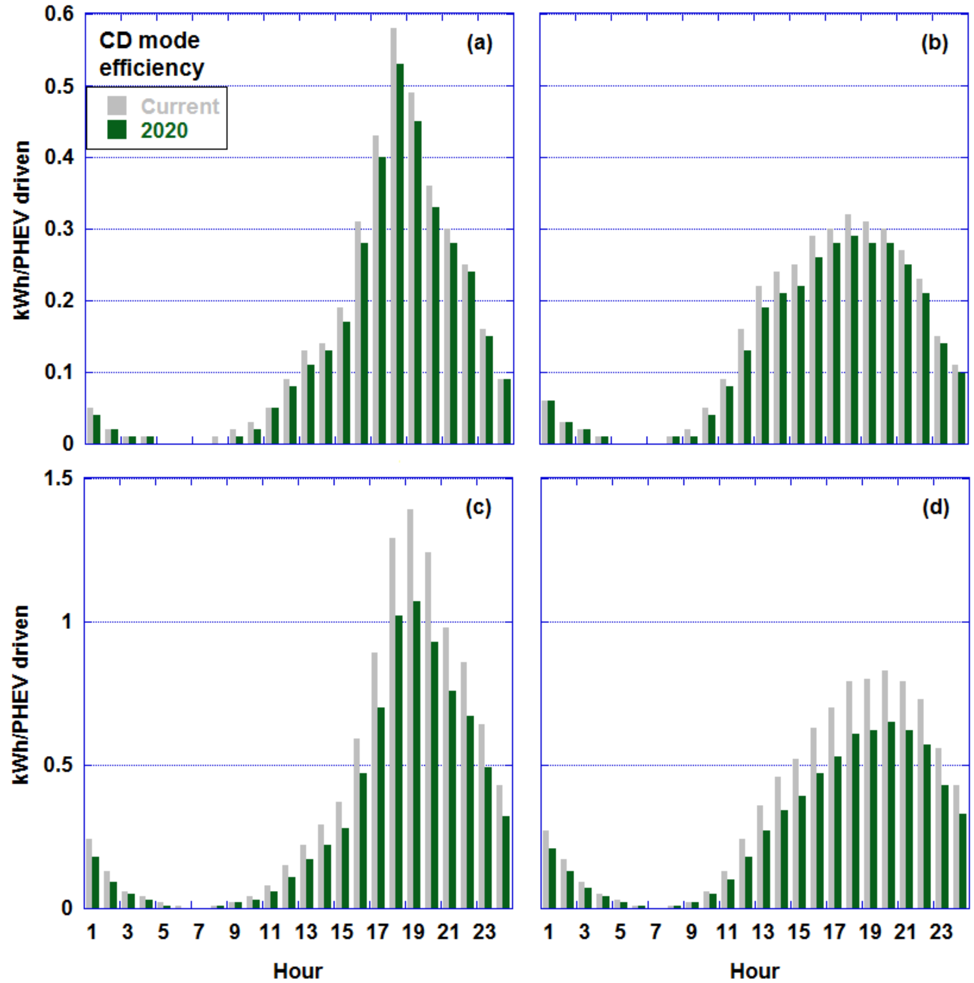

Figure 4S.3: Load per PHEV driven given home charging for (a) small batteries on a weekday, (b) small batteries on a weekend, (c) large batteries on a weekday, (d) large batteries on a weekend.

Figure 4S.4 shows results for work charging and is otherwise similar to Figure 4S.3. It is notable that the small battery cases can charge the battery in one hour so the magnitude of load is also indicative of the timing of vehicle arrival. With large batteries this is no longer the case.

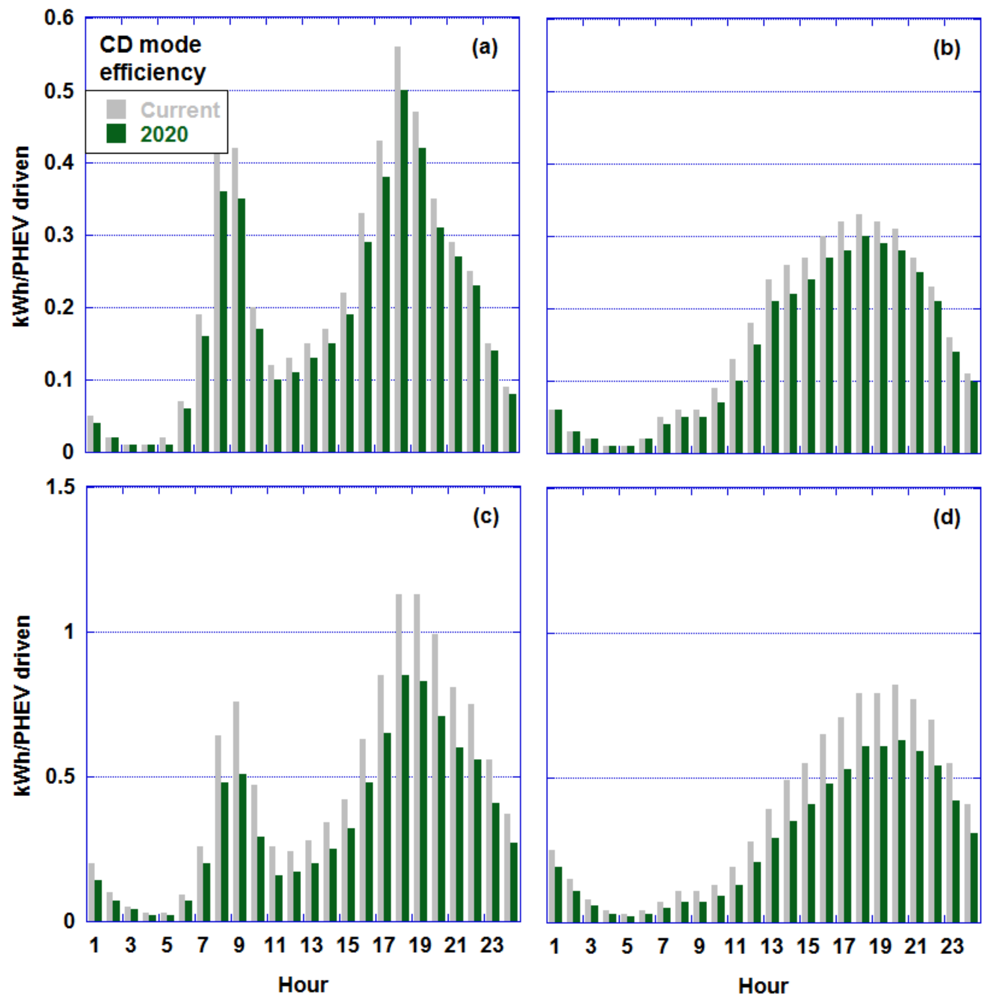

Figure 4S.4: Load per PHEV driven given work charging for (a) small batteries on a weekday, (b) small batteries on a weekend, (c) large batteries on a weekday, (d) large batteries on a weekend.

If a slower charge rate is used then the load curves do change. Figure 4S.5 and Figure 4S.6 show load changes when charging infrastructure is varied. What is most notable is the load given small batteries is very similar. This results in similar emissions and means that charge rate is not greatly relevant for small batteries. This is a response to the varied nature of vehicle arrival times. The natural distribution means that peaks from arrival and short charge times largely do not matter. With large batteries a low charge rate does greatly change the load profile by lowering peak additional load and spreading it across the day. However such low charge rates are unlikely with large batteries. In some cases this limits the ability of vehicles to actually charge their battery. The lower efficiency rate is used to maximize demand associated with PHEVs.

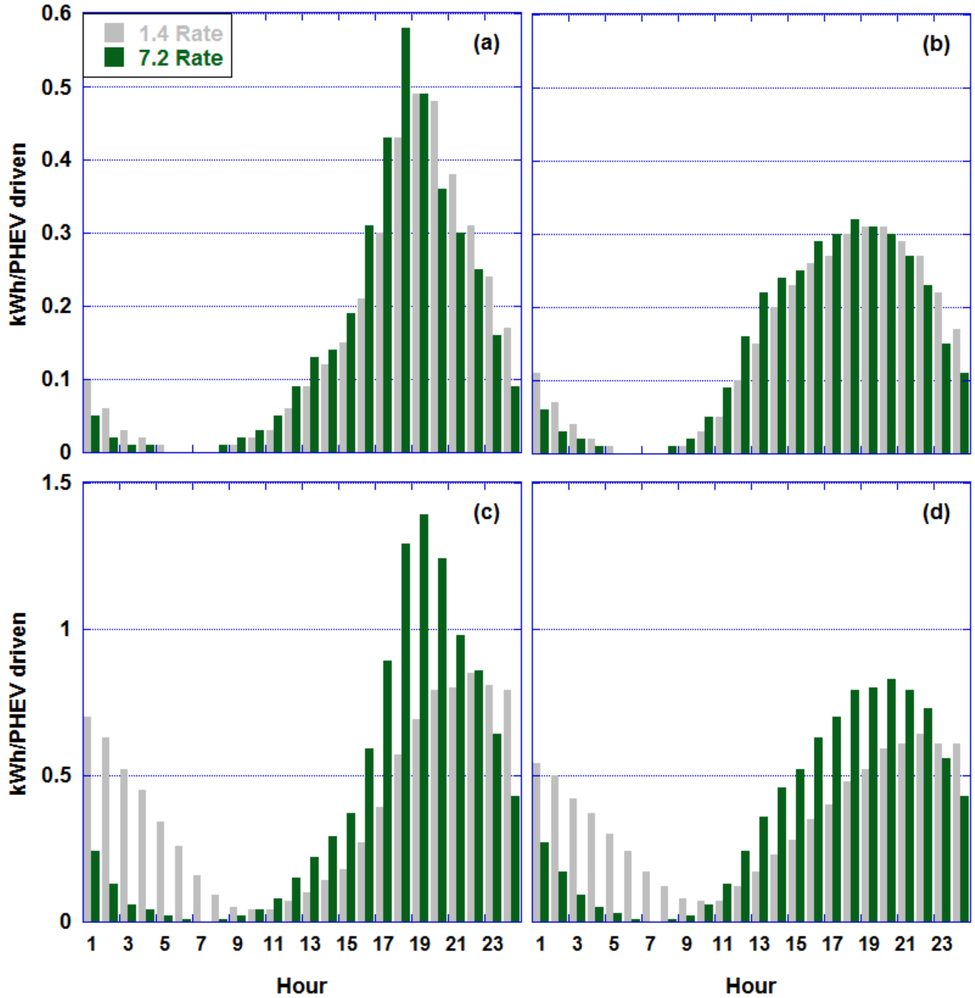

Figure 4S.5: A comparison of load given home charging with lower efficiency vehicles and two separate charge rates for (a) small batteries on a weekday, (b) small batteries on a weekend, (c) large batteries on a weekday, (d) large batteries on a weekend.

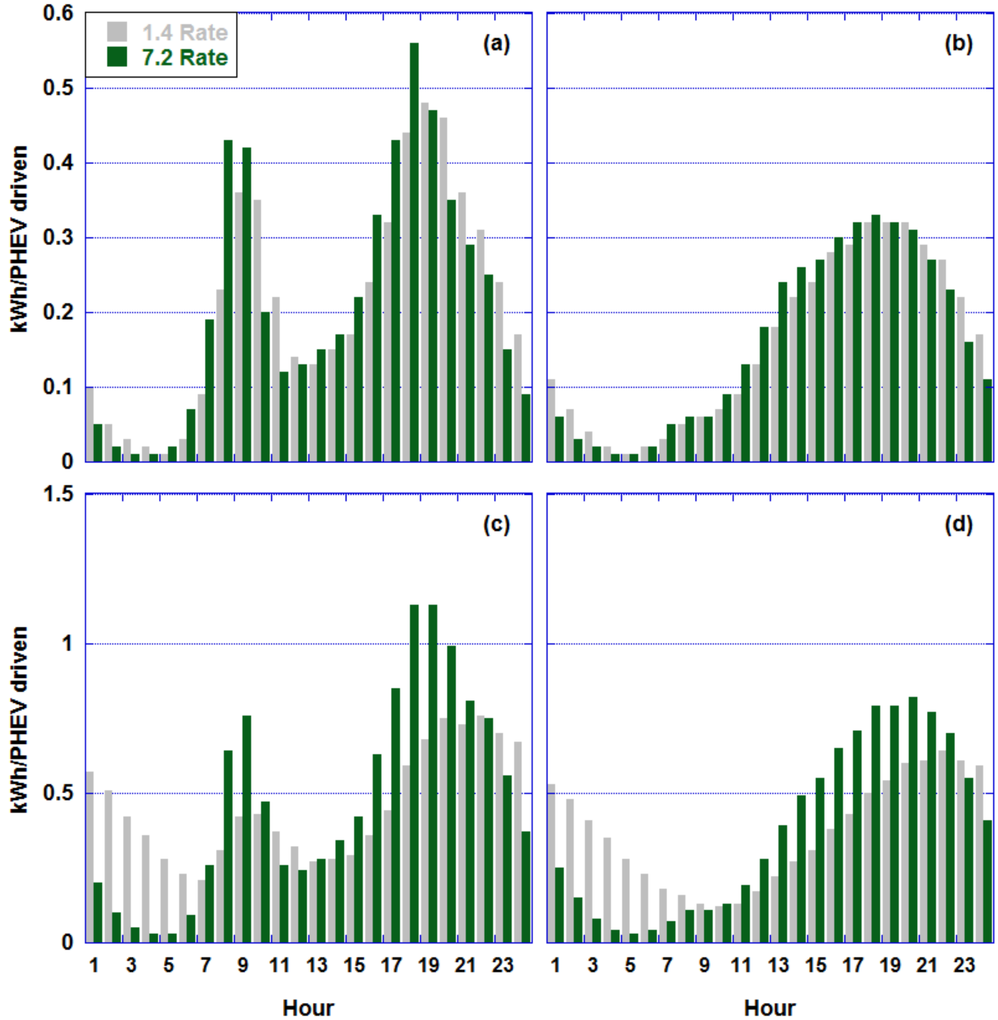

Figure 4S.6: A comparison of load given work charging with lower efficiency vehicles and two separate charge rates for (a) small batteries on a weekday, (b) small batteries on a weekend, (c) large batteries on a weekday, (d) large batteries on a weekend.

4.9.2 Generator Dispatch

We used the method described in (*3*) to construct monthly short-run marginal cost (SRMC) curves for each electric power generator in PJM and NYISO from EPA eGRID data (*4*) and DOE fuel cost and heat content data (*5*). We combined that with regionally appropriate fuel cost and quality data from the same year. A dispatch order curve was created for PJM and NYISO using the 2005 data and reported annual generator availability.

We modeled the effect of a CO_2 price using the CO_2 emissions data included in the eGRID database. Adding a CO_2 price increases the short run marginal cost (SRMC) of generators with listed CO2 emissions and can change the dispatch order slightly. The change is more noticeable in PJM where a large part of the generation mix is low cost coal than in NYISO. We also modeled the effect of a CO_2 price on dispatch mixes where the coal generators are replaced with coal generators that capture 80% of their CO_2 and sequester it. The effects of the plant use of electric power for capture, compression, pipeline shipment, and injection of the carbon dioxide were modeled by de-rating the plant output by 20% of current nameplate generation capacity. We assume there are no forced or unforced outages, and no constraints due to NO_X seasonal shutdowns to simplify modeling. The monthly SRMC curves allow seasonal NO_x emission calculations (for plants that repot separate emissions factors in eGRID database). An example SRMC curve created based on the yearly average capacity for PJM is shown in Figure 4S.7. Given a scheduled no-PHEV load the plants with minimal SRMC that meet the load are used. PHEV load is then added onto the no-PHEV load for each hour and the additional plants needed are determined along with their related emissions.

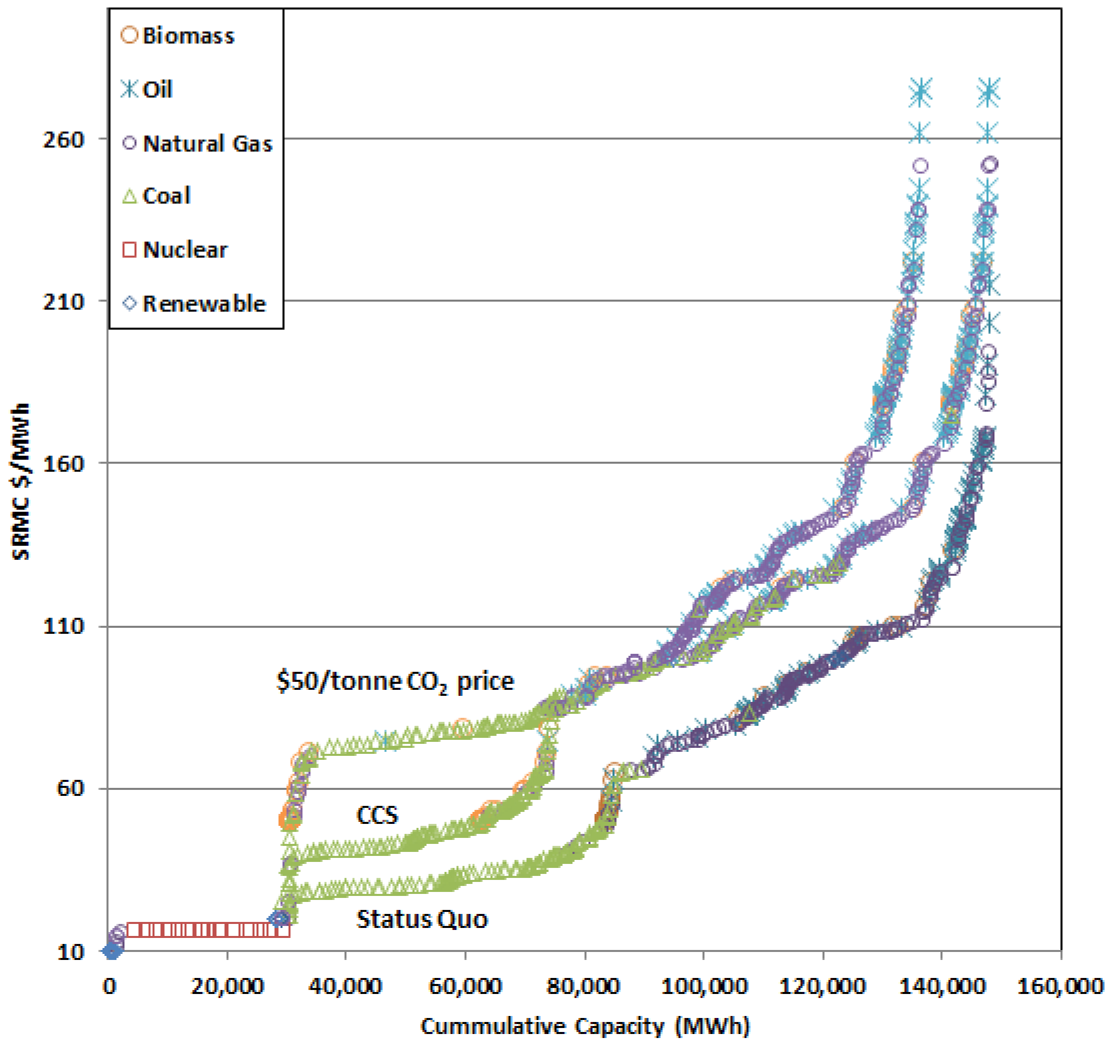

Figure 4S.7: SRMC curve for PJM based on yearly averages. Three different curves are shown for the three different carbon scenarios. Adding CCS decreased the SRMC of coal plants compared to a $50/tonne CO_2 price, but also results in a decrease in overall system capacity.

The effects of a price on CO_2 were modeled as in (3). The hourly load with and without electric vehicles was combined with the SRMC curve to determine the market clearing price. The generators predicted to bid in at or below the market clearing price make up the generation fleet that in each hour. Once the dispatched generators were determined in each hour, CO_2, NO_x, and SO_2 emissions from the eGRID database for each generator were used to predict emissions from the additional load in response to PHEVs.

Here we do not model the effects of transmission constraints, nor of the additional emissions when generators are started and ramped to full power. However eGRID records emissions from plants throughout the year and thus should include emissions associated with ramping plants up and down. Plants that ramp up and down, or start often should have relatively higher emissions rates. The predicted number of plant starts does not increase a great deal in response to the added load from PHEVs and is shown in Table 4S.1 for large batteries in NYISO and PJM. It is possible given smart charging the number of plants starts will actually likely decline. With smaller batteries the changes in plant starts are also smaller.

Table 4S.1 – Generator starts with large batteries

Charging Strategy	%PHEVs	Percent Change	
		NYISO	PJM
Work Charging	0.44%	0.12%	0.16%
	10%	1.9%	9.4%
	25%	7.6%	29.3%
Home Charging	0.44%	0.11%	0.12%
	10%	2.8%	8.4%
	25%	9.0%	25.6%
Smart Charging	0.44%	-1.7%	-0.9%
	10%	-13%	-10%
	25%	-28%	-23%

Figure 4S.8 and Figure 4S.9 show the modeled plants starts with and without PHEVs in PJM. The eGRID data should reflect actual emissions from plants. As seen in the figures the plants that are cycling due to changes in load throughout the day are the same plants that are cycling more or less often in response to PHEVs. Because of this it is assumed that their emissions factors already largely take into account the cycling that the plants undergo.

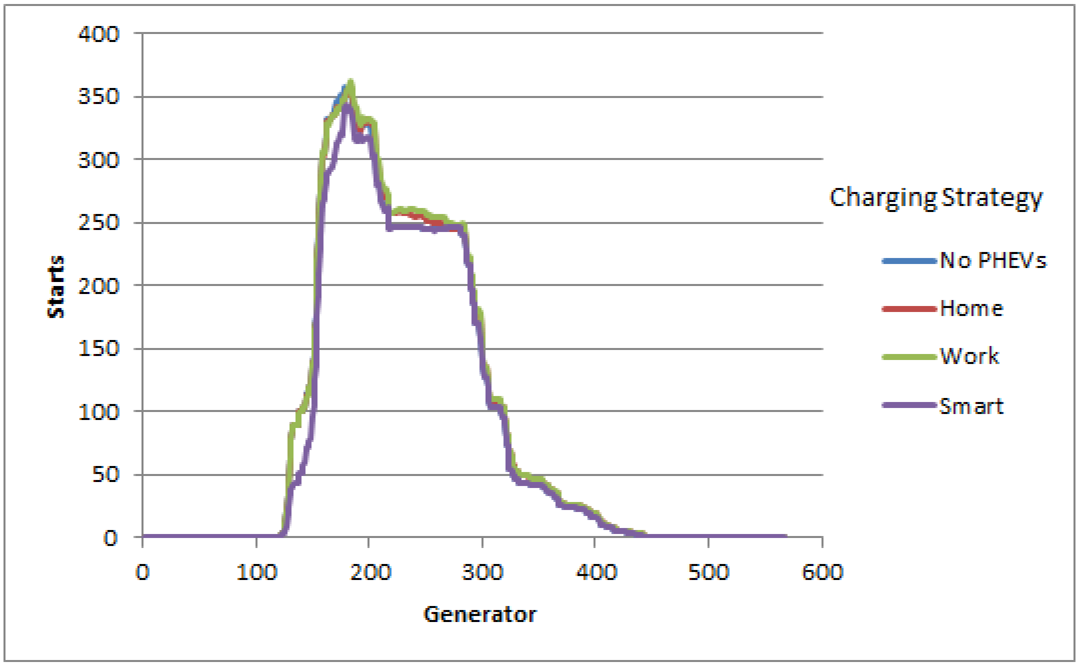

Figure 4S.8: Modeled plant starts in PJM given 10% PHEVs and small batteries

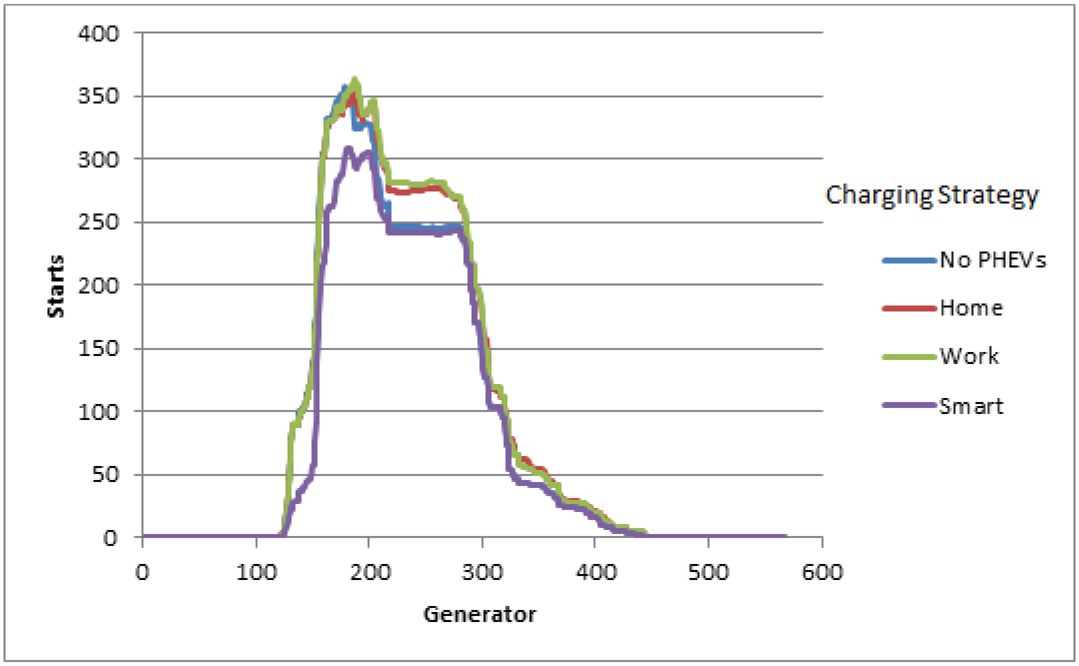

Figure 4S.9: Modeled plant starts in PJM given 10% PHEVs and large batteries

This model does not account for regional flows between power control areas. In 2005 net imports accounted for 10% of NYISO load (4). Net exports accounted for 6% of PJM generation (4). Because only the load in each area was accounted for, the model under or over estimates the amount of pollution depending on where the excess generation occurred. This difference explains a great deal of the variation between the reported and modeled emissions in each power control area. The two did not solely transfer power between markets though. So the emissions characteristics of the imports and exports are not clear. According to a letter from the director of system and resource planning for NYISO the majority of imports came from Canada and were mostly hydroelectric and nuclear generation (*6*).

Table 4S.2 – Comparison of modeled emissions and reported emissions in 2005

	Million Tons CO_2	Tons SO_2	Tons NO_X
PJM reported	460	2,900,000	740,000
PJM modeled	410	2,900,000	670,000
Diff	-10%	-1%	-9%
NYISO reported	61	180,000	66,000
NYISO modeled	59	200,000	74,000
Diff	-3%	11%	12%

We also modeled the effects of replacing all coal generation with coal generators that capture 80% of emitted CO_2, using a 20% energy penalty to de-rate the nameplate capacity. We adopted the assumption that coal plants equipped with CCS reduced SO_2 emissions by 98% (*7*).

4.9.3 Generator fuel mix used for charging

The generation mix used to charge PHEVs depends on the charging time of day shown previously. The specific plants used were estimated following a previously described method (8). Figure 4S.10 through Figure 4S.12 show the mix of fuel types predicted to be used for charging PHEVs given different numbers of PHEVs, charging strategies, and carbon scenarios. Only the medium charge depleting mode efficiency values are shown since there were only negligible changes in response to changing the charge depleting efficiency.

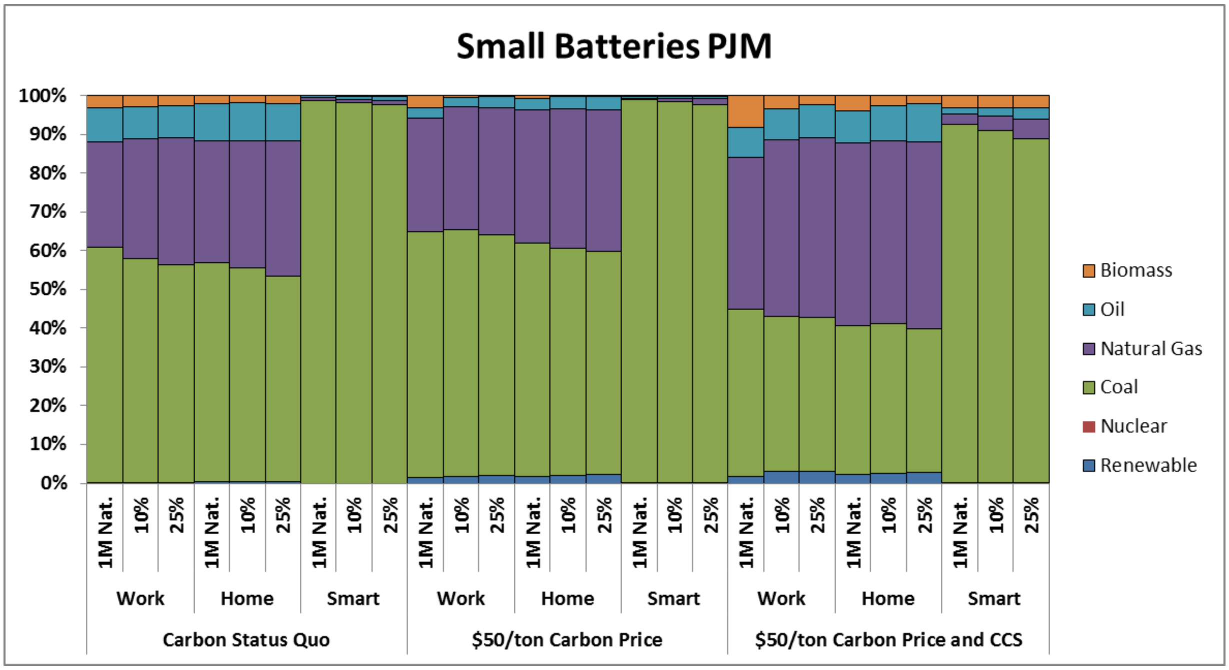

Figure 4S.10: Generation mix used to charge in PJM given small batteries and PHEV numbers ranging from 1 million nationwide to 50% of the fleet. Coal declines as number of PHEVs grows because coal generators are already used to their capacity. 2005 generation mix assumed.

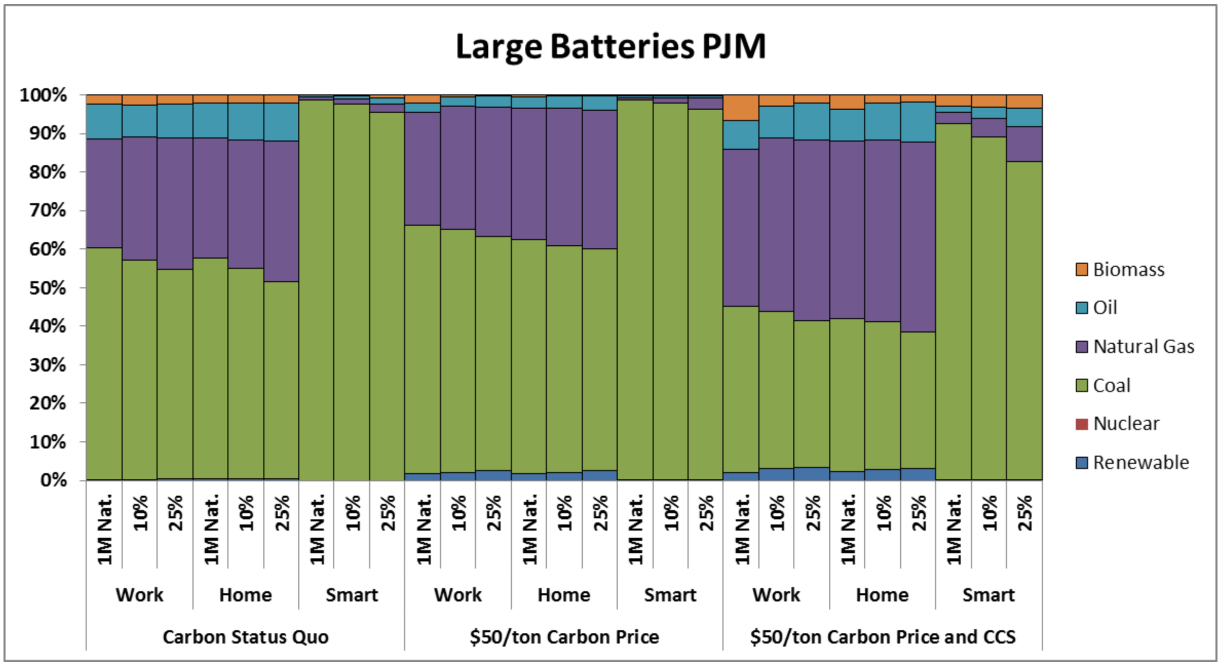

Figure 4S.11: Generation mix used to charge in PJM given large batteries and PHEV numbers ranging from 1 million nationwide to 50% of the fleet. Introduction of a carbon price increases the amount of coal used for PHEVs because generators previously used to meet the no-PHEV load are now available for charging PHEVs due to predicted declines in load associated with increased prices. 2005 generation mix assumed.

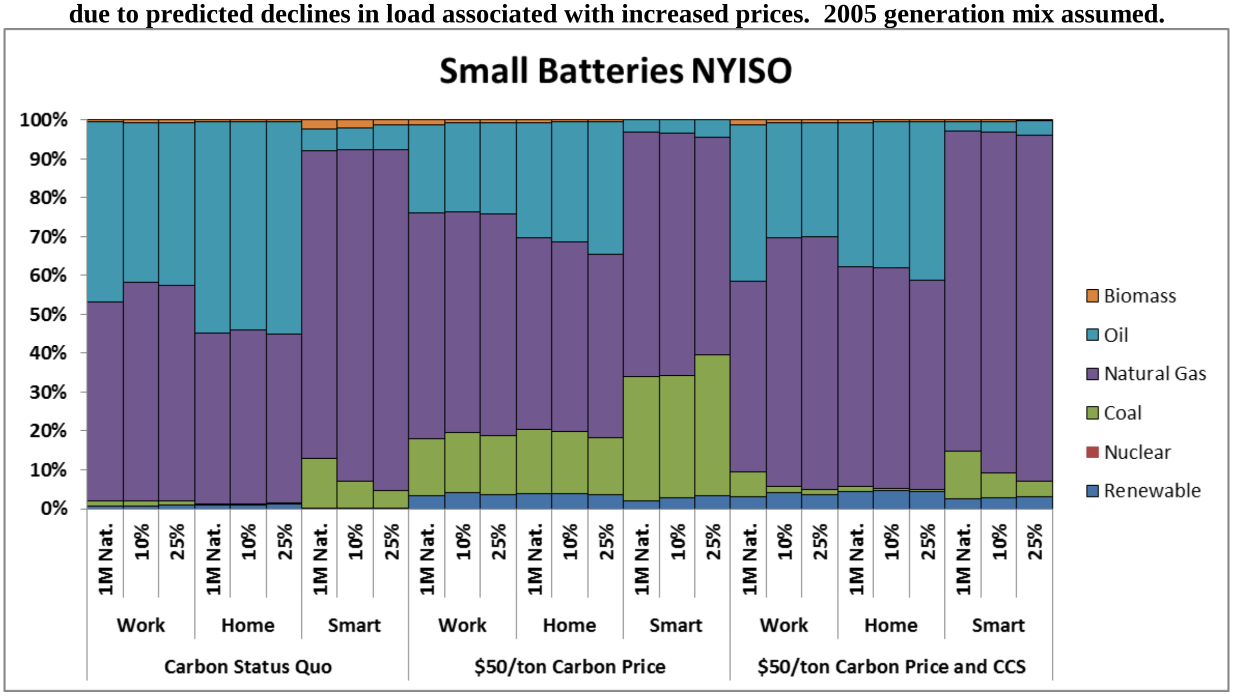

Figure 4S.12: Generation mix used to charge in NYISO given small batteries. Coal use for PHEVs predicted to increase given a carbon price. 2005 generation mix assumed.

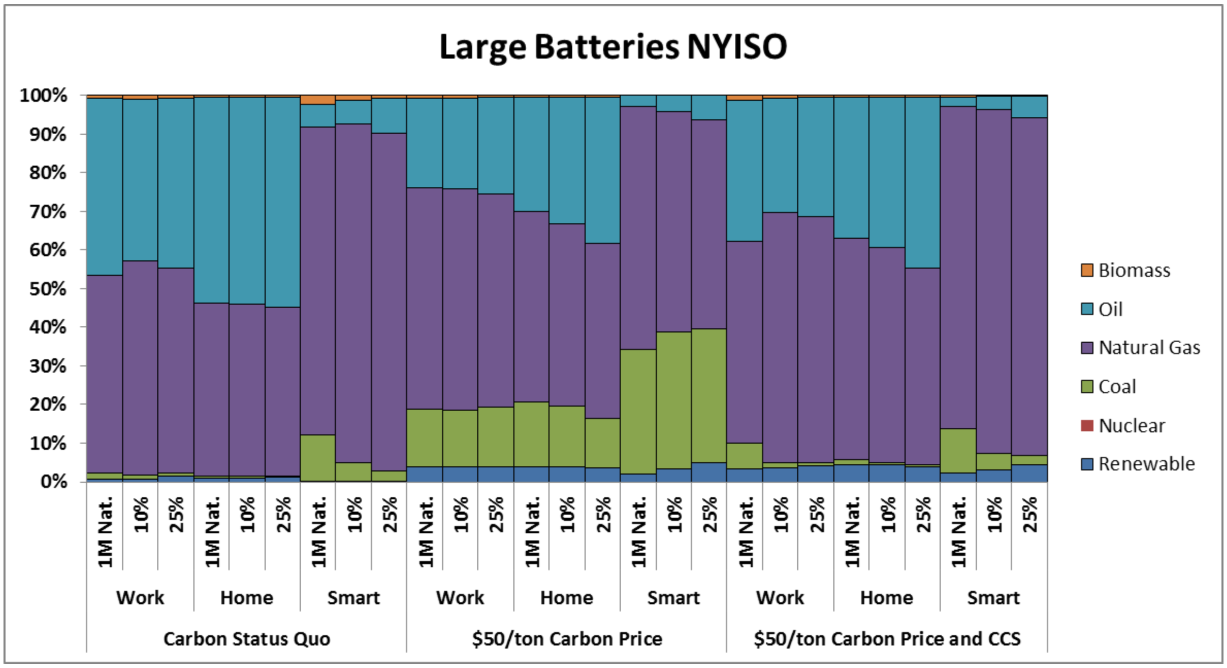

Figure 4S.13: Generation mix used to charge in NYISO given large batteries. Coal use for PHEVs predicted to increase given a carbon price. 2005 generation mix assumed.

The marginal fuel postings for PJM in 2005 were used to compare with these results (Figure 4S.14). These include imports which were not taken into account in the dispatch model. They also include the effects of congestion in the grid which dictates each power plant cannot necessarily serve each load. Overall the results indicate that coal is on the margin a good deal of the time throughout the year.

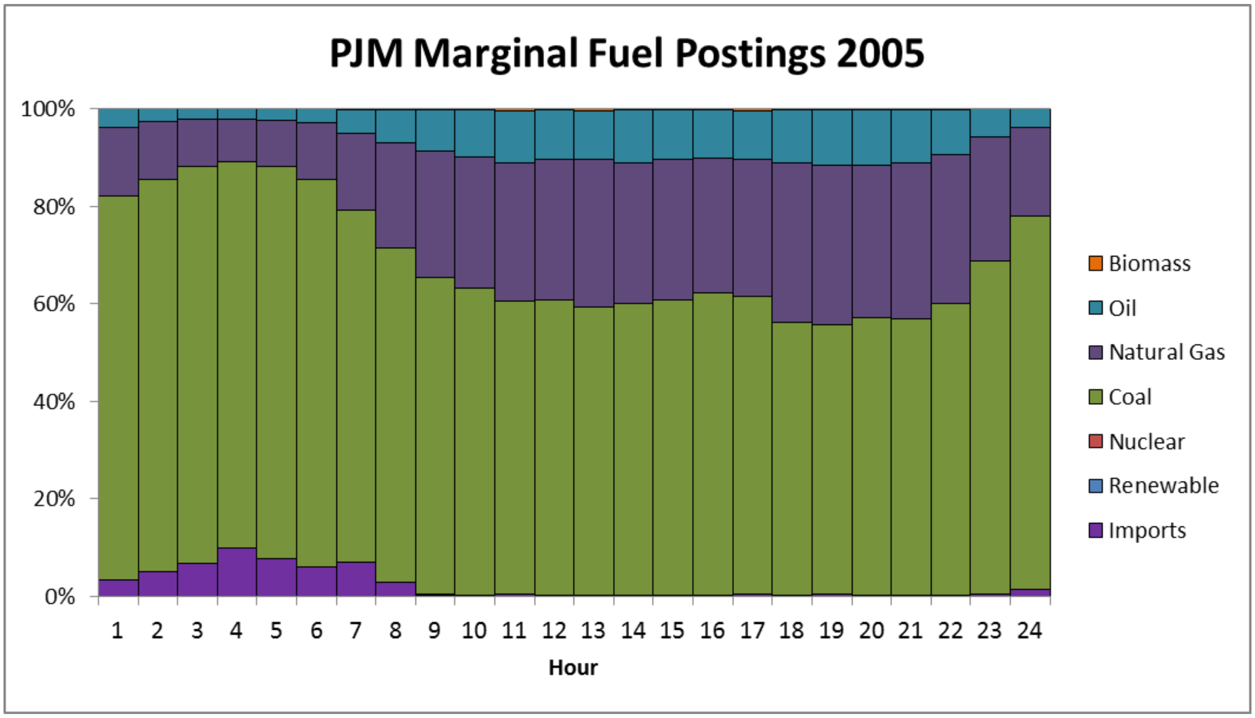

Figure 4S.14: Marginal fuel postings from 2005 in PJM showing high percentage of time coal is on the margin. The marginal fuel is coal more than 50% of the time throughout the day.

4.9.4 Effect of a carbon price on emissions

The effect of a carbon price was modeled assuming that the price elasticity of demand is -0.1. The changes predicted in response to a carbon price for load, and emissions are shown in Table 4S.3 and Table 4S.4. In both the CCS and carbon price no-PHEV load decreases in response to price changes. A carbon price results in decreased emissions (predictable given a decreased load), but with CCS some pollutants increase due to the lower electricity output per BTU of fuel consumed by coal plants. NYISO has fewer coal plants so the increase of emissions from coal plants with CCS does not outweigh other emissions savings.

Table 4S.3 – Comparison of no-PHEV load and emissions under carbon scenarios in PJM

Carbon Scenario	Change in Load	Change in CO_2	Change in NO_x	Change in SO_2	Change in CH_4	Change in N_2O	Change in Hg
$50/ton Carbon Price	-8.3%	-23%	-24%	-19%	-11%	-23%	-26%
$50/ton Carbon Price and CCS	-4.9%	-79%	5.3%	-83%	17%	6.3%	3.6%

Table 4S.4 – Comparison of no-PHEV load and emissions under carbon scenarios in NYISO

Carbon Scenario	Change in Load	Change in CO_2	Change in NO_x	Change in SO_2	Change in CH_4	Change in N_2O	Change in Hg
$50/ton Carbon Price	-3.5%	-18%	-40%	-34%	-16%	-29%	-34%
$50/ton Carbon Price and CCS	-3.4%	-47%	-32%	-76%	-11%	-19%	-2.9%

4.9.5 Additional emissions from the electricity sector due to charging

Figure 4S.15 through Figure 4S.17 show emissions per additional MWh of load from PHEVs and include pollutants not discussed in the main text. The increase is measured from the no-PHEV case. This distinction is important because the emissions overall for the carbon price or CCS case might be lower than the status quo case for a given number of PHEVs, but the increase in emissions in response to adding PHEVs might be larger for those cases than the carbon status quo case. This section does not reflect net emission changes including offset petroleum usage. The charts show the average emissions per additional MWh of load combining small batteries, large batteries, and all three different charge depleting efficiencies. Uncertainty bars indicate the maximum and minimum among those options. The x-axis is labeled to indicate the percent of vehicles that are PHEVs and the charging strategy used for PHEVs. By normalizing the emissions to the MWh of load the difference in charging twice in work charging and other charging strategies which only charge one time is reduced. It is apparent that emission rates in some combinations of charging strategies, carbon scenarios, are more sensitive to the number of PHEVs being charged than others.

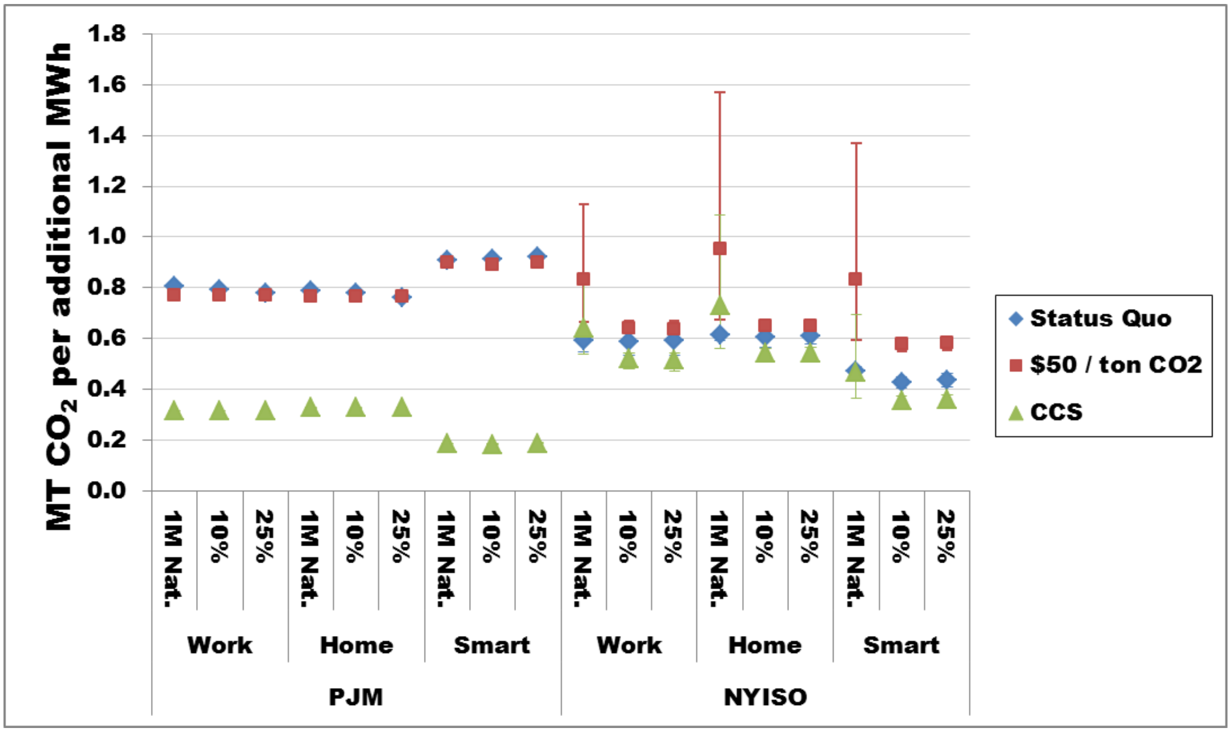

Figure 4S.15: Metric tons carbon dioxide emitted to charge various numbers of PHEVs in PJM and NYISO. Markers indicate average value while error bars indicate the minimum and maximum value predicted given any combination of battery size and charge depleting efficiency covered in the paper. 2005 generation mix assumed.

The emissions of CO_2 shown here are reflected in the net emissions results in the main paper which found higher net emission of CO_2 with a $50/ton carbon price. Different numbers of PHEVs do not appear to influence the emissions given either a carbon price or CCS in PJM.

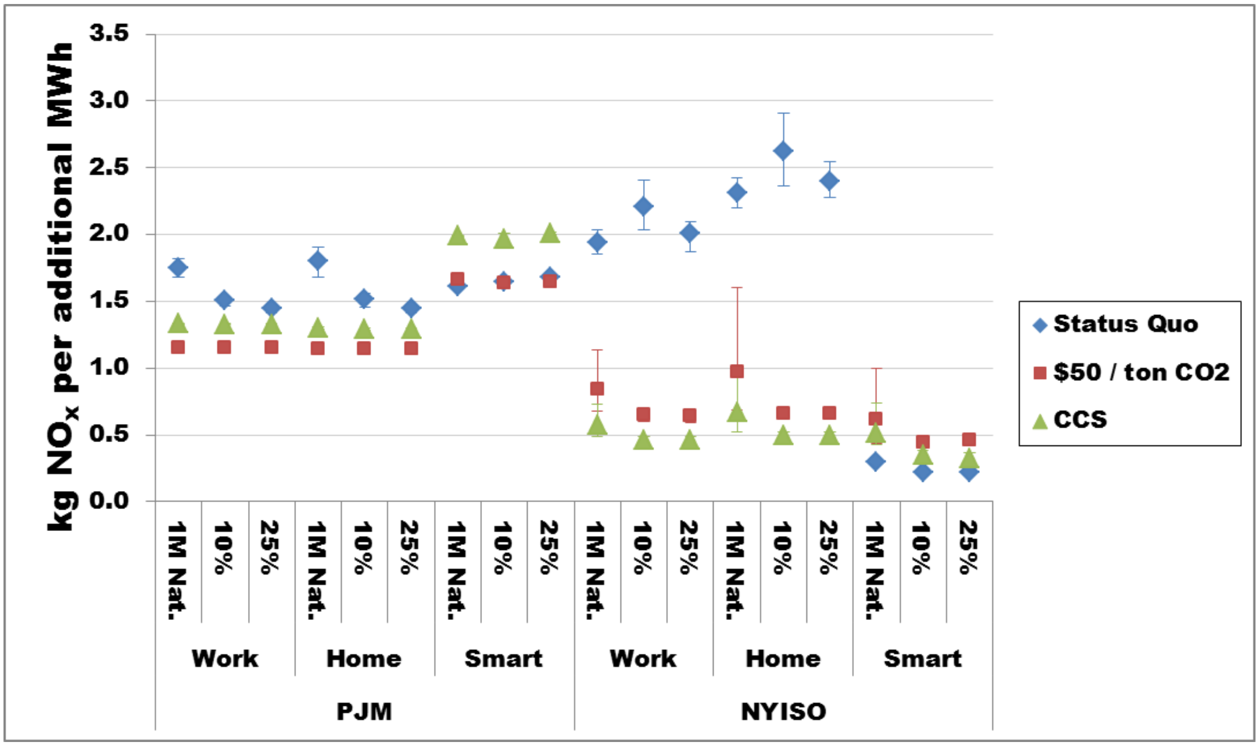

Figure 4S.16: Kilograms of NOx emitted per MWh to charge various numbers of PHEVs in PJM and NYISO. Markers indicate average value while error bars indicate the minimum and maximum value predicted given any combination of battery size and charge depleting efficiency covered in the paper. 2005 generation mix assumed.

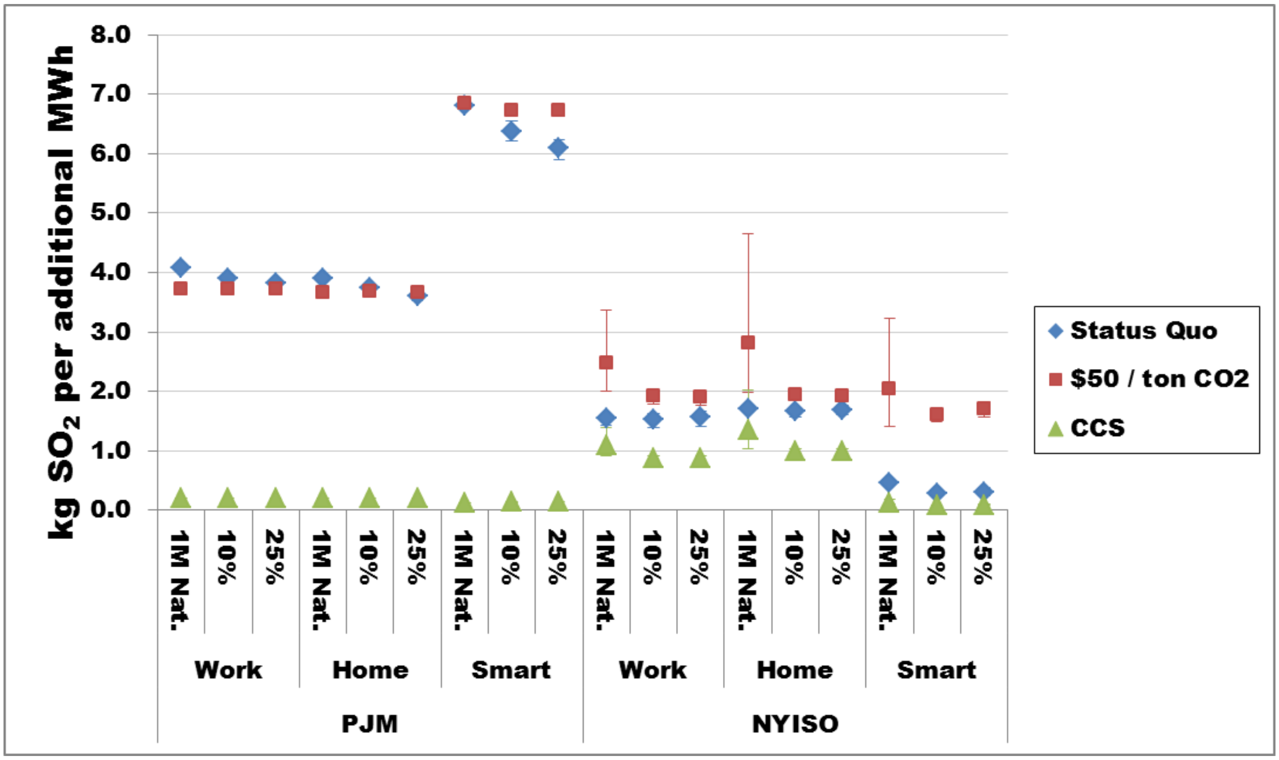

Figure 4S.17: Kilograms of SO_2 emitted per MWh to charge various numbers of PHEVs in PJM and NYISO. Markers indicate average value while error bars indicate the minimum and maximum value predicted given any combination of battery size and charge depleting efficiency covered in the paper. 2005 generation mix assumed.

4.9.6 Emissions from gasoline

The distance traveled in CS mode is recorded for each vehicle along with the total distance travelled by vehicles. The total distance can be considered the conventional fleet and gasoline consumption is calculated based on the efficiencies described in the main text and shown below (table S5). The same is done for PHEVs using the distance in CS mode to calculate gasoline consumption by PHEVs. The same efficiency values are used for CS mode travel and vehicles that PHEVs replace. This is done for a number of reasons. The increase in weight associated with creating a PHEV will decrease efficiency to some extent. Also the comparison does not exclude hybrids. Hybrids will get boosts from regenerative braking and effectively run in CS mode constantly. Hybrids will also be more efficient than similar PHEVs running in CS mode. To achieve the 2020 CAFE standards it will likely be necessary to have a significant number of hybrids in the fleet. This does mean that the estimates of displaced emissions may be lower than actually observed especially if PHEVs are replacing CVs instead of HEVs.

Table 4S.5 – Fuel efficiency (l/100km)

Vehicle Type	Current	2020 (35 MPG fleet)
Car	9.1	5.9
Van	12	7.6
SUV	13	7.8
Truck	13	7.8

The liters of gasoline consumed are multiplied by the factors reported in the EPA documents cited in the main text and reported again in Table 4S.6.

Table 4S.6 – Emissions Factors

Pollutant	kg/l gasoline
CO_2	2.3
SO_2	1.1e-4
NO_x	5.8e-3

The difference between emissions from total and CS miles can be used to find the reduction in pollution from mobile sources attributable to partial electrification of the distance travelled.

4.9.7 Net emissions per PHEV

Figure 4S.18 through Figure 4S.21 show net emissions of CO_2, NO_x, and SO_2 per vehicle-year given PJM and NYISO generation mix. The number of PHEVs modeled varies from 0.4% to 50% of the vehicle fleet. For comparison, the predicted emissions per conventional vehicle using 2005 and 2020 efficiencies are 3.7 and 2.3MT CO_2, 9.3 and 5.8 kg NOx, and 0.18 and 0.11 kg SO_2. Columns represent medium charge depleting (CD) mode efficiency and uncertainty bars represent high and low CD efficiency. Emissions for 2005 fleet and 2020 fleet are compared given the status quo (no carbon price) as well as a $50/ton CO_2 price and a $50/ton CO_2 price in conjunction with CCS installed on coal plants. Different charging strategies are modeled to determine the timing of PHEV charging as discussed previously in the supporting information.

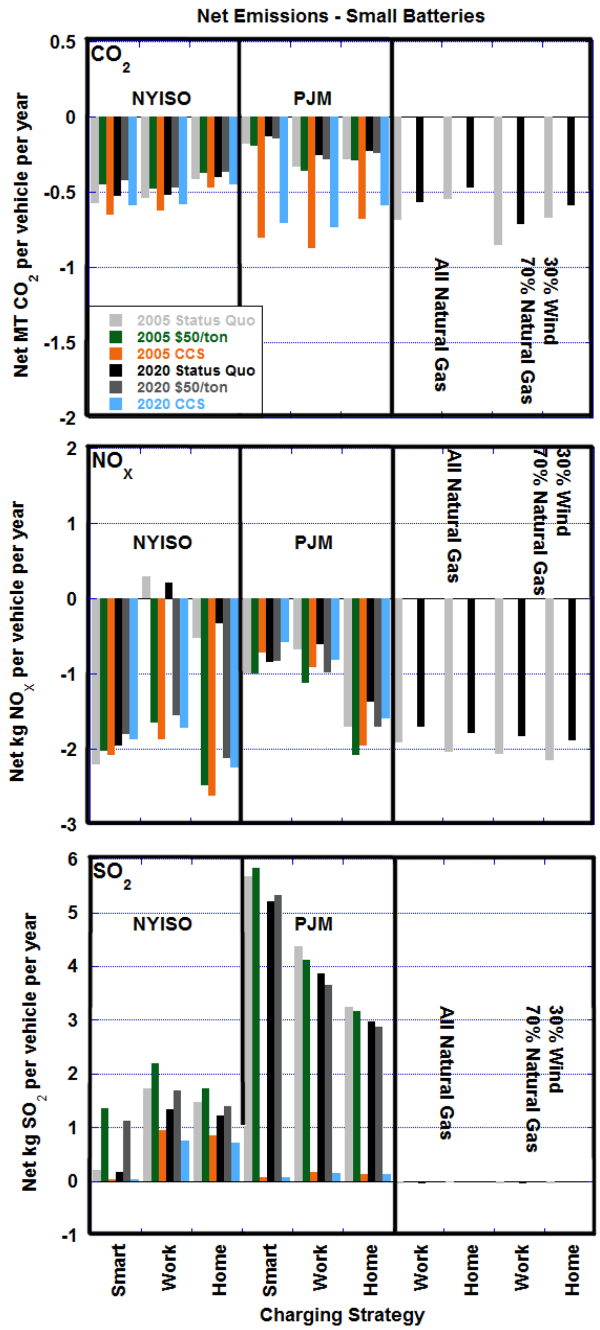

Figure 4S.18: Net emissions given 10% PHEVs and small batteries. Net metric tons of CO_2, and net kg of NO_x and SO_2 emitted per vehicle-year given PJM and NYISO generation mix as well as all natural gas and 30% wind combined with natural gas. For comparison, the predicted annual emissions per conventional vehicle using 2005 (22 mpg) and 2020 (35 mpg) efficiencies are 4.1 and 2.6 MT CO_2, 10 and 6.4 kg NO_x, and 0.20 and 0.13 kg SO_2. Emissions for 2005 fleet and 2020 fleet are compared given the status quo (no carbon price) as well as a \$50/ton CO2 price and a \$50/tonne CO2 price in conjunction with CCS installed on coal plants. Different charging strategies are modeled to determine the timing of PHEV charging. 2005 generation mix assumed.

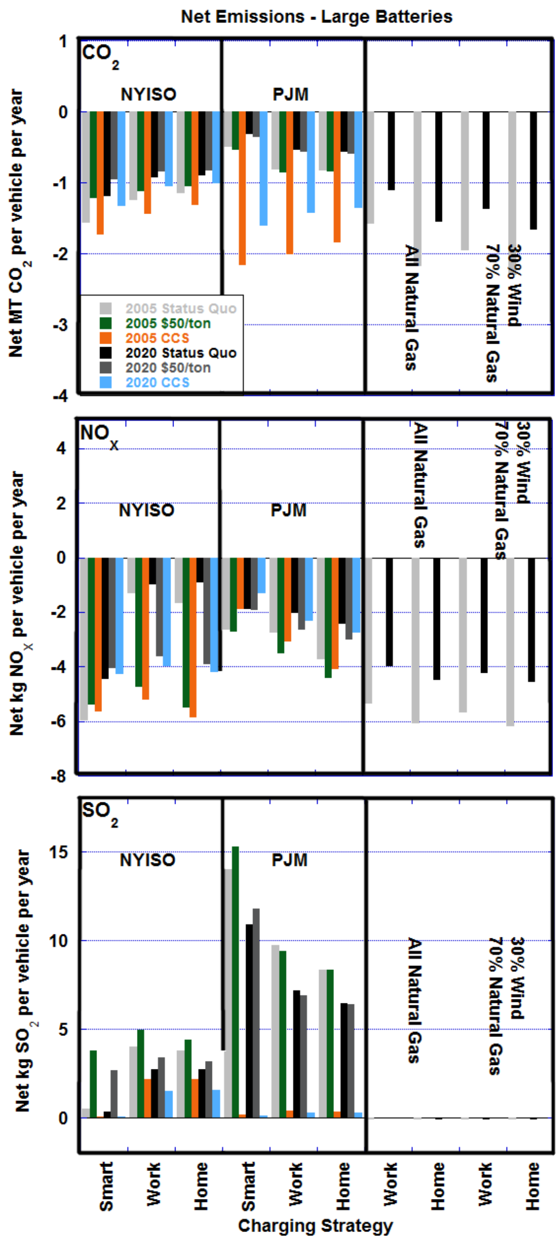

Figure 4S.19: Net emissions given 10% PHEVs and large batteries.Net metric tons of CO_2, and net kg of NO_x and SO_2 emitted per vehicle-year given PJM and NYISO generation mix as well as all natural gas and 30% wind combined with natural gas. For comparison, the predicted annual emissions per conventional vehicle using 2005 (22 mpg) and 2020 (35 mpg) efficiencies are 4.1 and 2.6 MT CO_2, 10 and 6.4 kg NO_x, and 0.20 and 0.13 kg SO_2. Emissions for 2005 fleet and 2020 fleet are compared given the status quo (no carbon price) as well as a $50/ton CO2 price and a $50/tonne CO2 price in conjunction with CCS installed on coal plants. Different charging strategies are modeled to determine the timing of PHEV charging. 2005 generation mix assumed.

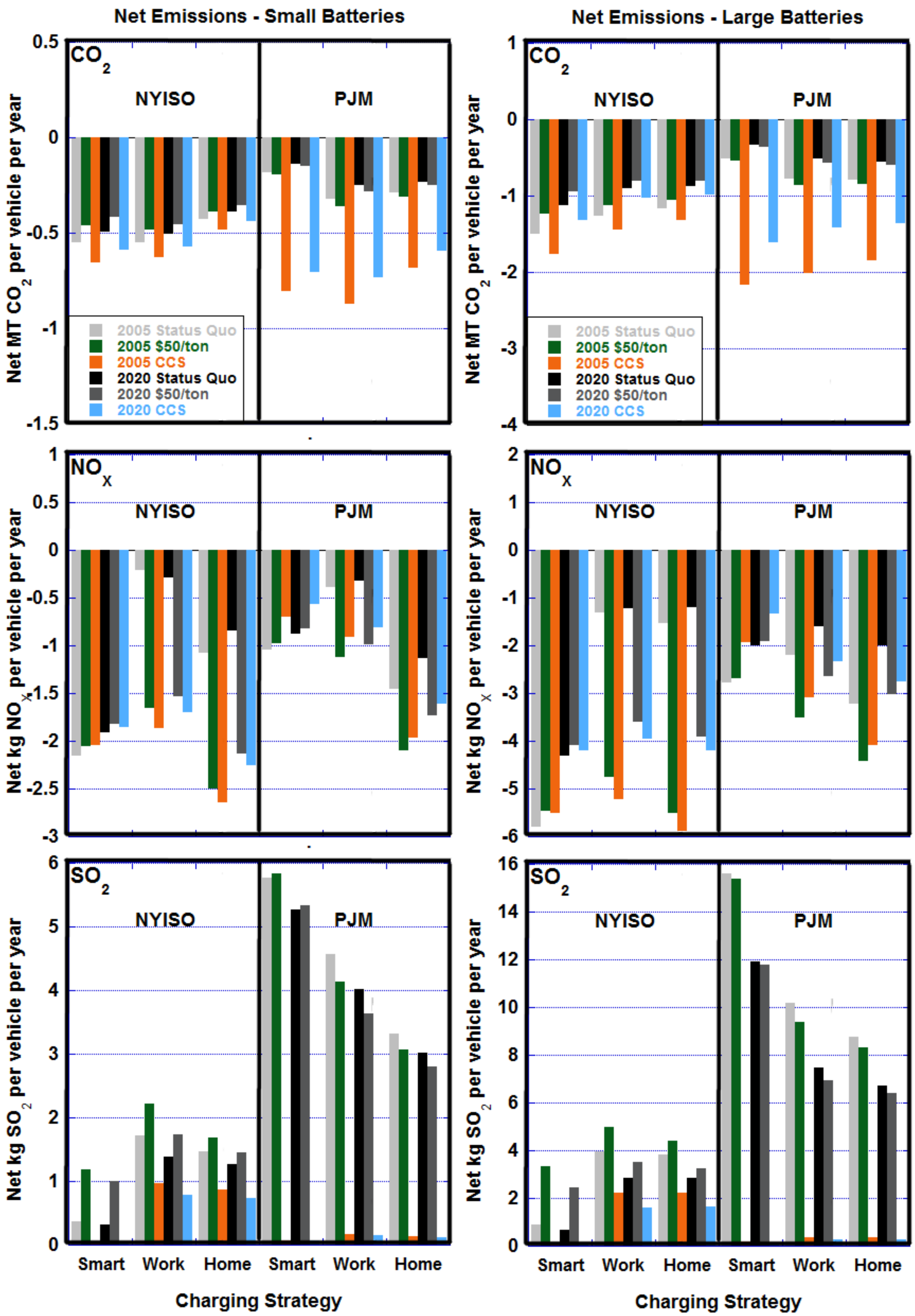

Figure 4S.20: Net emissions per vehicle given 0.44% PHEVs 2005 generation mix assumed.

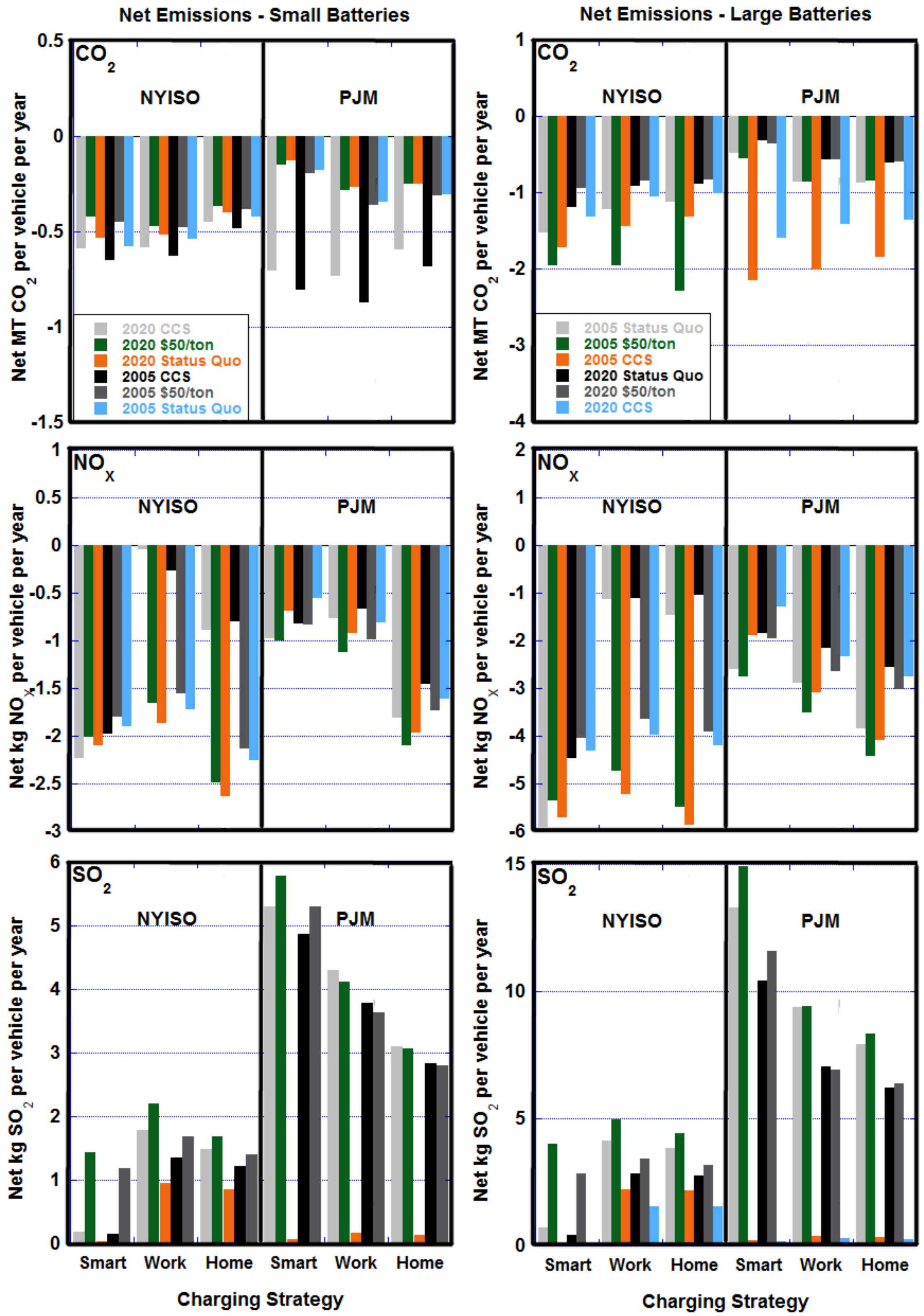

Figure 4S.21: Net emissions per vehicle given 25% PHEVs 2005 generation mix assumed.

4.9.8 Sensitivity to natural gas prices

The high petroleum use in NYISO was likely a response to low prices for petroleum relative to natural gas prices (Figure 4S.22). Natural gas prices have fluctuated more than coal prices recently. Because of this the model was also run assuming gas cost $4.90 / mmbtu.

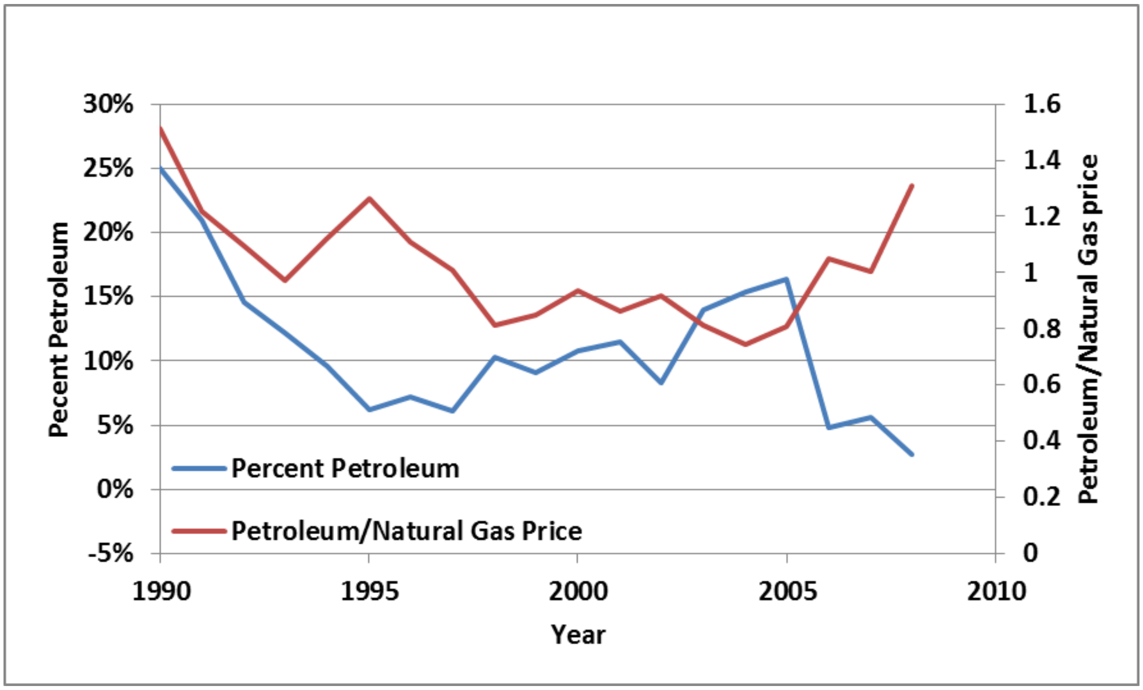

Figure 4S.22: Percent petroleum used for generation in NYISO compared to the ratio of petroleum to natural gas prices per BTU. There is clearly anti-correlation between the ratio of petroleum to natural gas prices and the percent petroleum (9, 10).

The results are shown below for the 2005 gas prices and lower gas prices assuming a 10% PHEV fleet.

Table 4S.7 – Net CO_2 emissions MT/vehicle-year in PJM given 2005 natural gas prices

Battery		2005 Status Quo	2005 $50/tonne	2005 CCS	2020 Status Quo	2020 $50/tonne	2020 CCS
Small	Smart	-0.18	-0.19	-0.81	-0.13	-0.15	-0.71
	Work	-0.33	-0.36	-0.87	-0.26	-0.28	-0.73
	Home	-0.28	-0.29	-0.68	-0.23	-0.24	-0.59
Large	Smart	-0.49	-0.55	-2.2	-0.32	-0.36	-1.6
	Work	-0.82	-0.86	-2.0	-0.54	-0.57	-1.4
	Home	-0.83	-0.84	-1.8	-0.57	-0.59	-1.4

Table 4S.8 – Net CO_2 emissions MT/vehicle-year in PJM given 490 cents/Mbtu natural gas prices

Battery		2005 Status Quo	2005 $50/tonne	2005 CCS	2020 Status Quo	2020 $50/tonne	2020 CCS
Small	Smart	-0.23	-0.34	-0.80	-0.18	-0.28	-0.70
	Work	-0.44	-0.30	-0.85	-0.35	-0.23	-0.71
	Home	-0.35	-0.24	-0.66	-0.29	-0.19	-0.58
Large	Smart	-0.65	-0.90	-2.1	-0.44	-0.64	-1.6
	Work	-1.0	-0.72	-1.9	-0.74	-0.47	-1.4
	Home	-1.0	-0.72	-1.8	-0.72	-0.49	-1.3

Table 4S.9 – Net CO_2 emissions MT/vehicle-year in NYISO given 2005 natural gas prices

Battery		2005 Status Quo	2005 $50/tonne	2005 CCS	2020 Status Quo	2020 $50/tonne	2020 CCS
Small	Smart	-0.58	-0.45	-0.65	-0.53	-0.42	-0.59
	Work	-0.54	-0.48	-0.63	-0.52	-0.47	-0.58
	Home	-0.41	-0.37	-0.47	-0.40	-0.37	-0.45
Large	Smart	-1.6	-1.2	-1.7	-1.2	-0.95	-1.3
	Work	-1.2	-1.1	-1.4	-0.93	-0.84	-1.1
	Home	-1.2	-1.1	-1.3	-0.90	-0.83	-1.0

Table 4S.10 – Net CO_2 emissions MT/vehicle-year in NYISO given 490 cents/Mbtu natural gas prices

Battery		2005 Status Quo	2005 $50/tonne	2005 CCS	2020 Status Quo	2020 $50/tonne	2020 CCS
Small	Smart	-0.39	-0.58	-0.64	-0.33	-0.50	-0.56
	Work	-0.47	-0.47	-0.65	-0.38	-0.37	-0.54
	Home	-0.38	-0.35	-0.50	-0.32	-0.29	-0.42
Large	Smart	-1.1	-1.6	-1.7	-0.75	-1.1	-1.3
	Work	-1.1	-1.1	-1.5	-0.76	-0.74	-1.0
	Home	-1.1	-1.0	-1.4	-0.76	-0.72	-1.0

With no carbon price net emissions of CO_2 generally decline in response to a lower natural gas prices in PJM. In NYISO the opposite holds true because the no-PHEV load then uses more of the natural gas leaving the PHEV load to relying on dirtier plants. Cheaper natural gas would also allow a CO_2 price to be more effective as seen in PJM, however it is unlikely natural gas prices will remain low compared to coal if demand significantly increases. In NYISO where many plants are dual fuel plants running on petroleum or natural gas it is likely that natural gas will continue to be cheaper and the preferred fuel.

4.9.9 Upstream emissions

The paper focuses only on use phase emissions. Upstream emissions from both PHEVs and the vehicles they will be displacing are significant. Data on upstream emissions associated with lithium-ion batteries being used in PHEVs is not yet common. For example in the GREET model the description of the battery data states the following (11):

> We collected data from another source and calculated the energy required for assembly and testing of an Ni-MH battery to be approximately 35.2 million Btu/ton of battery material; the data revealed that battery testing requires significant amounts of electricity (Gaines 2006). The large discrepancy between the values for Ni-MH batteries is troubling, and even the other values have been questioned because the energy required for vehicle assembly is much lower. We decided to use the Li-ion value from Ishihara et al. (1999) and the Ni-MH value from Gaines (2006) as default values for GREET 2.7, but we hope to find publicly available data that could replace these sources. By using our default values, the resulting energy requirement for Pb-Ac assembly is 27.5 million Btu/ton of battery material

This highlights some of the problems associated with attempting to specify the emissions associated with a relatively new product. Testing of batteries need not require using huge amounts of energy as it is entirely feasible to feed energy back into the grid when discharging batteries instead of simply wasting the energy as heat. Then the only losses are the efficiency losses associated with charge and discharge cycles and conversion and synchronization to the grid. Using the GREET data and assuming 140Wh/kg energy density the emissions associated with battery assembly are shown below (tables S11-S12).

Table 4S.11 – Emissions associated with battery assembly for small batteries

Battery size kWh	Tons CO2	kg NOX	kg SO2
4	0.08	0.09	0.20
5.16	0.11	0.12	0.25
5.33	0.11	0.12	0.26
5.33	0.11	0.12	0.26

Table 4S.12 – Emissions associated with battery assembly for small batteries

Battery size kWh	Tons CO2	kg NOX	kg SO2
16	0.34	0.36	0.79
20.65	0.44	0.46	1.02
21.33	0.45	0.48	1.05
21.33	0.45	0.48	1.05

These emissions increases from battery creation are quite small in comparison to the emissions savings for CO_2 and NO_X. In one year it is likely the emissions savings over gasoline will surpass the additional emissions associated with battery creation. Emissions of SO_2 are likely to increase, and increase further according to this, but once again the magnitude is similar to one year's use phase emissions. These emissions will likely decrease as the electricity grid becomes cleaner since many are associated with electricity use. The yearly gallons of gasoline displaced per PHEV depends on the number of charges and battery size and is shown below.

Table 4S.13 – Liters saved per vehicle and upstream emissions (well-to-pump)

Battery Size	Charging strategy	Annual liters gasoline saved	kg SO2	kg Nox	MT CO2
Small	Home	580	0.45	0.91	0.32
	Work	740	0.58	1.16	0.41
Large	Home	1550	1.2	2.43	0.86
	Work	1690	1.3	2.65	0.94

The annual upstream emissions from gasoline production are significant and the savings associated with displacing the gasoline are as well, but there are upstream emissions from the electricity produced to displace the gasoline. A complete life cycle assessment is beyond the scope of this work and will not be conducted.

1 *National Household Travel Survey*, U.S. Department of Transportation: Washington, DC, 2010; http://nhts.ornl.gov/download.shtml
2 Remarks of Senator Barack Obama—as prepared for delivery, New Energy for America, Michigan State University, Monday, August 4th, 2008, Lansing, Michigan
3 Newcomer, A; Blumsack S. A.; Apt, J; Lave, L. B.; Morgan, M. G. Short Run Effects of a Price on Carbon Dioxide Emissions from U.S. Electric Generators. *Environ. Sci. Technol.* **2008**. *42* (9), 3139-3144.
4 *Emissions & Generation Resource Integrated Database (eGRID)*, U.S. Environmental Protection Agency: Washington, DC, 2007 http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html
5 *Cost and Quality of Fuels for Electric Plants 2004 and 2005*, U.S. Department of Energy : Washington, DC, 2006.
6 Chao, H. New York state department of environmental conservation comments of the NYISO on initial report of the RGGI emissions leakage multi-state staff working groups to the RGGI agency heads. 2007.
7 Integrated Environmental Control Model (IECM), Version 6.2.4, Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh. Available: http://www.cmu.edu/epp/iecm/.

8 Newcomer, A; Blumsack S. A.; Apt, J; Lave, L. B.; Morgan, M. G. Short Run Effects of a Price on Carbon Dioxide Emissions from U.S. Electric Generators. *Environ. Sci. Technol.* **2008**. *42* (9), 3139-3144.
9 Electric power industry generation by primary energy source, 1990 through 2008 (megawatthours). available http://www.eia.doe.gov/cneaf/electricity/st_profiles/sept05ny.xls
10 Electric power delivered fuel prices and quality for coal, petroleum, natural gas, 1990 through 2008. available http://www.eia.doe.gov/cneaf/electricity/st_profiles/sept06ny.xls
11 Burnham, A.; Wang, M; Wu, Y. Development and applications of GREET 2.7 – the transportation vehicle-cycle model. Argonne National Labs, Argonne, IL 2006.

Chapter 5 Relative Cost of Reducing U.S. Gasoline Consumption via Increased Plug-in Hybrid All-electric Range vs. Charging Infrastructure

5.1 Chapter Information

Authors: Scott Peterson and Jeremy Michalek

5.2 Abstract

Electric vehicle policies in the United States currently include subsidies based on battery size and subsidies for installing charging stations in public places. We compare increasing the all-electric range (AER) of plug-in hybrid electric vehicles (PHEVs) to installing charging infrastructure as alternate methods to reduce gasoline consumption. Fuel use was modeled using the National Household Travel Survey and Greenhouse Gasses, Regulated Emissions, and Energy Use in Transportation model. It was found that increasing AER of plug-in hybrids was a more cost effective solution to reducing gasoline consumption than installing charging infrastructure. Comparison of results to current subsidy structure shows that subsidy does not align with fuel savings.

5.3 Introduction

The 1975 Energy Policy Conservation Act enabled CAFE standards to be created in response to the Arab oil embargo. This standard attempted to increase the efficiency of the fleet by setting efficiency standards for passenger cars (starting in 1978). As time passed efficiency requirements increased and eventually other vehicles were included in the standards, but then they remained static for many years. In 2007 the Energy Independence and Security Act was passed "to move the United States toward greater energy independence and security." This act required the combined fuel economy average for model year 2020 to reach 35 mpg, but stipulated penalties only if manufacturers fell below 92% of the standard. The act also allows manufacturers to trade credits which could allow one manufacturer to specialize in fuel efficient vehicles and another to make gas guzzlers. Certain vehicle types, such as flex-fuel vehicles (those that run on E85) are attributed an increase in fuel economy, but this bonus declines to 0 by 2019. It also provided loan guarantees for advanced battery research and grant programs for plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) to help make electric vehicles feasible. The date has since been moved forward from 2020 to 2016 [1].

At the end of 2010 General Motors introduced the Volt and Nissan introduced the Leaf. The Volt is the first mass market PHEV in the Unites States, and the Leaf is a BEV. Other automakers plan to introduce PHEVs and BEVs in the U.S. soon. These types of vehicles use electricity to displace gasoline from the transportation sector.

While BEVs may seem the easiest solution to displacing gasoline with electricity, there are significant drawbacks. High rate charging for the recently released Nissan Leaf allows the battery to be charged to 80% in 30 minutes. This is still slow compared to refilling a gas tank and requires new infrastructure. This would mean stopping every 70 miles for approximately 30 minutes. There are battery chemistries that would allow for quicker charging, but they are more expensive, and completely replacing conventional vehicles (CVs) would still likely require changes in infrastructure (such as new transmission, sub-transmission, and distribution lines). While there are enough generation assets to supports a significant fleet of BEVs this does not mean that current infrastructure could support charging of BEVs along interstates in rural areas which would be necessary for BEVs to fully replace CVs [2-5]. It is possible that in the future the necessary infrastructure will be in place to support a fleet mostly made up of BEVs, but in the short term this is unlikely. This research will focus on PHEVs because they can more easily replace current vehicles and can benefit from charge points without a large disbenefit if a charge point is unavailable.

PHEVs differ from BEVs because they can continue operating as a gasoline hybrid when their battery is depleted. Unlike a hybrid electric vehicle (HEV) like the Prius that uses a battery as a buffer to store braking energy, PHEVs also have the ability to store electricity from the grid on-board and use it to displace gasoline while driving. Drivers will not need to change their habits. Long trips can still be undertaken without waiting for charging (as in a BEV), and short trips can be taken using less or no gasoline depending on PHEV design. These advantages do not come without a penalty. PHEVs require an internal combustion engine (ICE) like a HEV or CV and large batteries (similar to BEVs). A PHEV designed for 40 miles of electric range will weigh and cost more than a BEV with similar range. It will also weigh and cost more than a conventional vehicle with similar performance and interior space. Additional battery capacity can also be underutilized if a vehicle does not travel far enough in a normal day.

A great deal of the cost increase in PHEVs is related to the large on-board battery. To help overcome this obstacle policymakers have provided incentives based on battery size. The American Recovery and Reinvestment Act of 2009 provides a tax credit of $2,500 for per plug-in hybrid electric vehicle sold and an additional $417 for each additional kWh of traction battery capacity in excess of 4 kWh (capped at $7,500 for vehicles with a gross vehicle weight less than 14,000 pounds) [6]. This subsidy for a specific manufacturer's vehicles declines to 50% then 25% in a "phaseout" period, which begins in the second calendar quarter after that manufacturer has sold 200,000 vehicles, and lasts four calendar quarters [6]. Each additional kWh of storage results in diminishing returns in terms of reduction in gasoline usage.

The US Department of Energy (DOE) granted $37 million for installing 4,600 charge points in specific markets around the nation (over $8,000 per charge point) [7]. DOE also granted $99.8 million to fund the EVProject which is installing 14,000 level 2 (208-240V) chargers, and a variety of other infrastructure and monitoring equipment (making the cost calculation for a specific charge point troublesome) [8]. While BEVs would require a large number of charge points if they were to displace gasoline vehicles, PHEVs can benefit from a smaller number. This is because a PHEV does not require a charge point, but if a charge point is available then more gasoline could be displaced with electricity using a given PHEV. If PHEVs benefit significantly from charge points then they could help justify installations that could also be used by BEVs. Charge points could help small battery PHEVs displace a greater amount of gasoline. This research investigates whether subsidies for increased all-electric trange (AER) is an efficient way to spend future incentives for PHEVs or if funding to subsidize installation of charge points away from home would be more effective at decreasing gasoline consumption.

5.4 Methodology

The goal of this paper is to determine whether subsidies are more efficient at reducing gasoline consumption when targeted to incentivize increased vehicle all-electric range (AER) or when targeted to increased charging infrastructure deployment. To do this we first calculate fuel use accounting for both gasoline and electricity use by PHEVs with AERs ranging from 5-25 miles with a variety of charging strategies. Second, we estimate the necessary charging infrastructure to enable each charging strategy. Finally we use estimates of cost and gasoline displacement to compare across options.

5.4.1 Fuel use model

This work uses two main data sources. The first is the National Household Travel Survey 2009 (NHTS) which lists travel information from diaries of over 150,000 households [9]. The NHTS day trip file which is used lists trips taken by the household on a randomly assigned day. The second is the Department of Energy's Greenhouse Gasses, Regulated Emissions, and Energy Use in Transportation (GREET) Model, version1.8d [10]. The GREET model assesses energy use in transportation and includes simulations for passenger cars, SUVs, and light trucks with over 80 fuel systems and technologies. This paper uses the estimates of vehicle efficiency in charge depleting (CD) and charge sustaining mode (CS), taken from GREET 1.8d 2015. Combining these efficiency numbers with vehicle travel patterns from the NHTS day trip file allows the prediction of estimated gasoline and electricity consumption from PHEVs with an AER ranging from 5-60 miles relative to a reference conventional vehicle. Base case assumptions are shown in Table 5S.12 of the supporting information and described below.

The GREET data assume that PHEVs with AERs less than or equal to 25 miles utilize a split powertrain and blended control strategy, while PHEVs with AER in excess of 25 miles utilize a serial hybrid design, which is far less efficient in charge sustaining mode (the Chevy Volt with AER 37 does not use a serial design [11]). This assumption causes the model to have a dip in overall vehicle efficiency and increase in cost when moving from an AER of 25 to 30 miles (Figure 5.3). To avoid the serial powertrain assumption, we consider only AERs less than 30 miles; however, our results shown later suggest that AER values above 30 miles are not competitive with the shorter AER ranges on a cost per gallon saved metric regardless of powertrain assumption in all sensitivity scenarios.

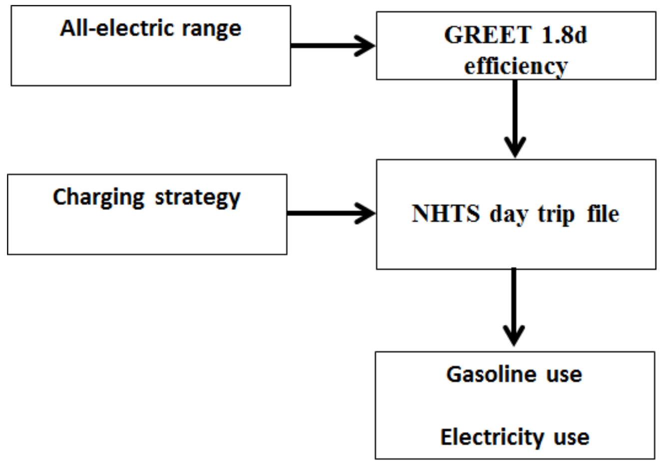

Figure 5.1 – Basic fuel use model overview

The NHTS data were processed according to the same methodology described in previous work with changes as described below [4]. The daily vehicle travel data were extracted and weighted according to the vehicle weights assigned in the sample. To estimate the timing of fuel savings, vehicles are partitioned by age and vehicle class because their travel varies significantly along both dimensions (Figure 5.2, Figure 5.3). Changes in efficiency as vehicles age were ignored. PHEV battery capacity will decline with age, which would shorten AER if manufacturer control strategy does not increase the allowable state of charge swing. Whether PHEVs will encounter more or less engine wear depends on how PHEVs use their engine. If the engine speed is partially decoupled from the wheel speed using the electric motor to compensate, this could prolong engine life by enabling the engine to run mostly at steady state. On the other hand if the engine starts and stops often and revs to follow vehicle power demand then engine wear could increase. We consider cars, SUVs, and trucks (vans were ignored because data were unavailable for efficiency and cost, but they make up the smallest portion of the classes mentioned here). The total distance traveled in CD and CS mode for each vehicle under each charging strategy scenario is calculated. Then the energy consumption of each vehicle in the sample is calculated using the previously mentioned GREET efficiency in charge depleting and charge sustaining mode estimates and assuming vehicles began each day fully charged and charge completely after the last trip of the day.

Hypothetical charging scenarios were included to determine how much additional gasoline consumption could be substituted with electricity by charging vehicles at times in addition to the default once per day at home after the last trip of the day. Vehicles were allowed to charge if they were parked at least 30 minutes at a location. Each charging pattern is described in Table 5.4. The total electricity use f^{ELEC} and gasoline use f^{GAS} are calculated for vehicle class c, vehicle AER β, and charging scenario γ. These values are then summed over each year a of vehicle life of the average NHTS-computed CD and CS mode gasoline and electricity consumption among all vehicle profiles associated with a vehicle of class c, age a, and surveyed on a weekend WE or weekday WD in the NHTS data set as shown in Equation set 5.1: where a is vehicle age in years, L is the vehicle life assumed in our model (12 years base case), j indexes the vehicle driving profiles taken from the NHTS day trip file, $J_{a,c,\text{WE}}$ is the set of NHTS vehicle profiles of age a and class c surveyed on a weekend, $J_{a,c,\text{WD}}$ refers to those surveyed on a weekday, $|J_{a,c,\text{WE}}|$ is the number of NHTS vehicles of age a and class c surveyed on a weekend, $|J_{a,c,\text{WD}}|$ is the number of vehicles of age a and class c surveyed on a weekday, and $\eta^{\text{CD-E}}$, $\eta^{\text{CD-G}}$, and $\eta^{\text{CS-G}}$ are the vehicle's electrical efficiency in CD mode (mi/kWh), gasoline efficiency in CD mode (mi/gal), and gasoline efficiency in CS mode (mi/gal) as estimated by GREET (shown in tables 5.1 - 5.3 below).

$$f_{ca}^{\text{ELEC}}(\beta,\gamma) = 104\frac{\sum_{j\in J_{a,c,\text{WE}}} d_j^{\text{CD}}(\beta,\gamma)}{|J_{a,c,\text{WE}}|\eta_c^{\text{CD-E}}} + 261\frac{\sum_{j\in J_{a,c,\text{WD}}} d_j^{\text{CD}}(\beta,\gamma)}{|J_{a,c,\text{WD}}|\eta_c^{\text{CD-E}}}$$

$$f_{ca}^{GAS}(\beta,\gamma) = 104\left(\frac{\sum_{j\in J_{a,c,\text{WE}}} d_j^{\text{CD}}(\beta,\gamma)}{|J_{a,c,\text{WE}}|\eta_c^{\text{CD-G}}} + \frac{\sum_{j\in J_{a,c,\text{WE}}} d_j^{\text{CS}}(\beta,\gamma)}{|J_{a,c,\text{WE}}|\eta_c^{\text{CS-G}}}\right) + 261\left(\frac{\sum_{j\in J_{a,c,\text{WD}}} d_j^{\text{CD}}(\beta,\gamma)}{|J_{a,c,\text{WD}}|\eta_c^{\text{CD-E}}} + \frac{\sum_{j\in J_{a,c,\text{WD}}} d_j^{\text{CS}}(\beta,\gamma)}{|J_{a,c,\text{WD}}|\eta_c^{\text{CS-E}}}\right)$$

$$f_c^{\text{ELEC}}(\beta,\gamma,L) = \sum_{a=1}^{L} f_{ca}^{\text{ELEC}}(\beta,\gamma)$$
$$f_c^{\text{GAS}}(\beta,\gamma,L) = \sum_{a=1}^{L} f_{ca}^{\text{GAS}}(\beta,\gamma)$$

Equation set 5.1

Table 5.1 - $\eta^{\text{CD-E}}$ in mi/kWh for 2015 vehicles from GREET 1.8d

AER	5	10	15	20	25
Car	5.2	5.2	5.3	5.3	5.3
SUV	4.5	4.5	4.5	4.5	4.5
Truck	4.9	4.9	4.9	4.8	4.8

Table 5.2 - $\eta^{CD\text{-}G}$ in mi/gallon for 2015 vehicles from GREET 1.8d

AER	5	10	15	20	25
Car	74	74	78	82	82
SUV	54	54	56	58	58
Truck	41	41	42	42	42

Table 5.3 - $\eta^{CS\text{-}G}$ in mi/gallon for 2015 vehicles from GREET 1.8d

AER	CV	HEV	5	10	15	20	25
Car	27	38	43	43	43	42	42
SUV	20	28	28	28	28	28	28
Truck	18	24	25	25	25	25	25

The functions $d^{CD}{}_j$ and $d^{CS}{}_j$ use the NHTS data to compute the distance that a vehicle with AER of β under charging scenario γ traveling on vehicle day trip profile j would travel in CD mode and CS mode, respectively. We examine $\beta \in \{5,10,15,20,25\}$ miles and $\gamma \in$ {home evening, home all, work home evening, work home all, all stops}, where the charging scenarios are described in Table 5.4.

Table 5.4 – Charging scenarios

Charging Scenario	Brief Description
Home evening	Vehicle charges after arriving home on last trip of the day
Home all	Vehicle charges anytime it is parked at home for at least 30 minutes
Work home evening	Vehicle charges when it first arrives at work and is parked for at least 30 minutes and at home after last trip of the day
Work home all	Vehicle charges anytime it is parked at either home or work for at least 30 minutes
All stops	Vehicle charges anytime it is parked anywhere for at least 30 minutes

The procedure for computing d^{CD} and d^{CS} for each vehicle in the set of a given age, AER, charging scenario, class, and weekday or weekend (set $\{a, \beta, \gamma, c, \text{WE}, \text{WD}\}$) starts by assuming each vehicle begins the day fully charged. The vehicle is tracked through all reported trips and it is assumed it operates first in CD mode, where it consumes both electricity and gasoline, switches to CS mode once the battery drops to its target state of charge (SOC) (40% of battery energy remaining according to GREET), and fully recharges after the last trip of the day. We use trip distances and times specified in the NHTS dataset and assume a constant efficiency per VMT from GREET ($\eta^{CD\text{-}E}$, $\eta^{CD\text{-}G}$, and $\eta^{CS\text{-}G}$). For each trip if a vehicle's battery is above the target SOC then the total battery energy required to complete a trip is calculated. If the battery has enough energy, the SOC is decremented by the energy requirements of the trip. If the SOC is too low to complete the trip in CD mode then the SOC is decremented to the target SOC and the portion of the trip not travelled in CD mode is travelled in CS mode. If the vehicle battery is at the target SOC at the beginning of a trip the entire trip is travelled in CS mode. When a vehicle parks, the time between trips is calculated and if it is greater than or equal to 30 minutes then the vehicle can charge if the designated charging scenario allows charging at the location the vehicle is reported parked.

GREET also accounts for reduction in real-world efficiency compared to test cycle efficiency, where the AER is rated. This means that simulated AER may be shorter than rated AER (but this is especially likely for the serial hybrid configuration that is not included in this analysis). Vehicles that are not driven on the survey day have a d^{CD} and d^{CS} of zero, but are included so that the average total mileage found when simulating the trips (found by adding d^{CD} and d^{CS} of all vehicles in a set and dividing by the total number in that set) and fuel use estimates properly reflect all vehicles in NHTS (that are classed as car, SUV, or truck). The resulting daily consumption is multiplied by either 104 for weekends or 261 for weekdays and summed to convert to annual consumption for a given age, AER, and charging scenario. The NHTS file does not specify if travel was on a holiday, nor are vacation days specified and such days should be accounted for on average weekday travel. Calculating fuel use by CVs and HEVs is accomplished in the same manner, but total mileage is used instead of tracking d^{CD} and d^{CS} separately since these vehicles do not use separate fuels.

The results of total distance travelled annually by all vehicles in a set of given age and class divided by the number of vehicles (both driven and not driven) in that set is shown in Figure 5.2. To simulate the life of a vehicle it was assumed that it was driven in a manner consistent with reported NHTS data for a vehicle of its age and class as found previously. Thus, for the base case of a 12 year vehicle lifetime it is assumed a car drives roughly 14,000 miles in the first year, 13,000 in the next year and so on for each year until it reaches year 12 (Figure 5.2). Calculation of fuel consumption uses each vehicle age and class separately so any changes in travel patterns as vehicles age are accounted for. However, it was found that the primary reason that vehicle miles traveled (VMT) declined with age was that the vehicle was less likely to be driven on a given day. It was found that older vehicles, that were driven, generally followed similar driving patterns to their newer counterparts. The total consumption numbers for each AER, vehicle class, and vehicle age are reported in the supporting information for the base case.

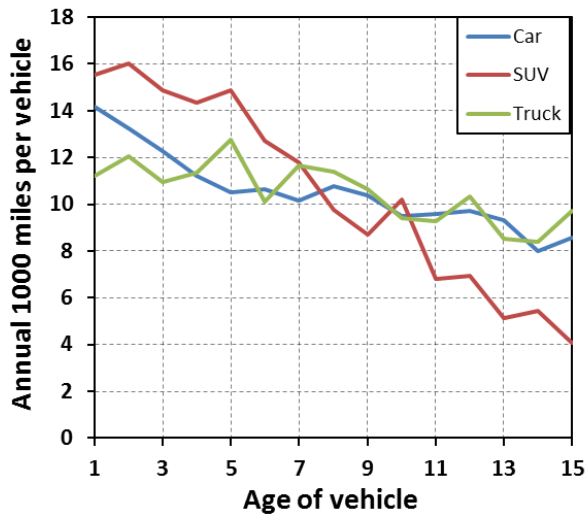

Figure 5.2 – Change in annual VMT with vehicle age as found from NHTS data

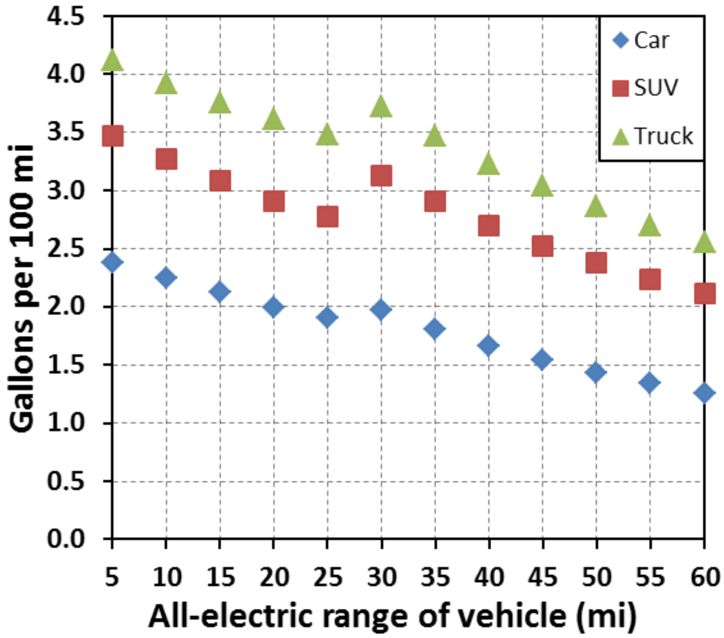

Figure 5.3 – Comparison of vehicle gasoline consumption over 12 year life and all-electric range of vehicles using GREET 1.8d 2015 efficiency numbers (AER on x-axis corresponds to GREET AER) gasoline use includes both CD and CS travel

5.4.2 Infrastructure estimates

Because the amount of shared charging infrastructure required per PHEV to enable work and all stops charging scenarios will vary tremendously with the number of PHEVs in operation, we attempt to estimate an infrastructure case that is favorable to charging points. The first assumption is that charging infrastructure is based on widespread PHEV adoption and charger installation; thus a new charge point would not need to be installed every time a person moves, changes jobs, goes on a different errand and so on. If charging infrastructure offers less value than increasing AER in this optimistic case it will be even worse with low PHEV penetration, requiring more chargers per vehicle. To make these optimistic estimates the number of charges for each charging strategy was tabulated when the fuel use model was run with NHTS data (as described in fuel use model section). The total number of charges per vehicle driven in the work charging case was compared to the home evening only charging case to determine how many additional charges occurred when a vehicle was parked at work. Similarly the total number of charges per vehicle in the all stops charging case was compared to the work home all stops case to determine the number of additional charges at locations other than home or work. Since every trip uses some energy, the number of charges does not change with AER. The average additional charges were weighted by the number of vehicles of a given age and class in the sample to determine the number of additional charge points used to estimate charging infrastructure. The NHTS includes only data that generally describes the location such as home, work, place of worship, shopping and so on. It is acknowledged that this lack of information could lead to errors in the estimated number of charge points needed. Over counting could result when a vehicle parks at the same location twice in the day (if it is not work or home), it could also occur because the same charge point could serve more than one vehicle if they parked at different times in the day. Undercounting will occur because averaging does not account for peak demand, vehicles could charge at work, leave and return to find the charge point occupied or a vehicle surveyed on a given day might not travel to work (on a holiday for example), but the next day it could. We are likely undercounting infrastructure needs to enable charging scenarios and thus results are purposefully favorable toward infrastructure.

The weekday or weekend set of vehicles was used depending on which resulted in a greater demand for charge points. Using these average values instead of estimating peak demand for charge points once again makes the estimates more favorable for charging infrastructure. It was found that charging at work resulted in 0.47 additional charges per driven vehicle on a weekday compared to home evening charging only. According to NHTS data, only about 67% of vehicles were driven on a given weekday. Thus about 30% of PHEVs surveyed could charge at work on a weekday (0.67*.47). The number of additional chargers to enable work charging was set at 0.3 per PHEV to reflect this. Similarly, it was found that on weekends all stops charging resulted in an additional 1.5 charges per PHEV driven compared to work home all charging. However, only about 60% of vehicles are driven on a weekend so an additional 0.9 chargers per PHEV was assumed necessary to enable all stops charging (using weekday numbers would result in 0.76).

5.4.3 Cost estimates

We created lifetime cost estimates by combining available cost estimates for vehicles, fuel, and infrastructure as described below. There are two cases considered. The first, our base case, examines the problem by assuming that a single entity purchases all vehicles, charging stations, and fuel. The second case, consumer behavior, attempts to reflect consumer behavior by tallying costs for vehicles and fuel separate from charge points and using a higher discount rate to reflect observed and estimated consumer behavior.

The costs of charging infrastructure are varied over a range shown in the table below and include installation and equipment costs and are lower in the base case than has been observed thus far for charging away from home [7, 12]. Installation costs can vary tremendously. Plugging into an outlet at home with the included cord is free. Installing a machine to take credit cards or other forms of payment, deal with potential vandalism, and withstand exposure to the elements for charging a vehicle away from home is likely more expensive regardless of charge rate. If a home owner had to install a new panel or get a new meter to accommodate charging it would obviously be more expensive than simply adding a circuit to an existing panel. Retrofitting charge points into some commercial settings could also be very expensive. Public charge points would utilize some amount of electricity even when not charging and would need maintenance, but neither of these costs is included in the model. The base case charging rates were assumed to be 1.4 and 7.7 kW for home and away charging because higher rates had minimal usefulness (see supporting information).

Table 5.5 – Charging infrastrucutre cost estimates [7]

	Low	Base Case	High
Home 1.4 kW	$25	$75	$550
Home 7.7 kW	$500	$1,125	$4,000
Away 1.4 kW	$1,050	$3,000	$9,000
Away 7.7 kW	$2,500	$5,000	$15,000
Away 38.4 kW	$11,000	$20,000	$50,000

Lifetime cost premium for different options are found as follows. Vehicle costs are taken from the 2015 average case estimated by Argonne National Labs in their 2011 report on potential of technologies in the light duty vehicle fleet to reduce petroleum consumption, hereafter referred to as LDVFC [13]. These are manufacturing costs and report the additional cost compared to a CV. All vehicle costs from this report were multiplied by 1.5 to account for markup [14]. Any differences in vehicle maintenance cost are ignored. Lifetime gasoline and electricity use is estimated from the previously described fuel use model. Fuel costs are taken from the EIA

Annual Energy Outlook (AEO) 2011 that lists retail prices including taxes, using their "traditional high oil price" case as our base case and including other cases in supporting information [15]. Fuel costs are taken starting in the year corresponding to vehicle age using the assumption that vehicles are purchased in the year 2015 as defined in the vehicle cost numbers. Fuel costs occur through time so an NPV calculation is used to bring all costs to consistent value. The NPV for each vehicle class, AER, and each charging scenario is calculated using a 5% discount rate (in the base case), as shown in Equation set 5.2. Then the change in NPV compared to a CV is calculated (lifetime cost premium) for each AER and vehicle class. Negative lifetime cost premium values indicate lifetime savings.

$$\text{Lifetime Cost Premium} = \text{NPV}_{\text{PHEV}} - \text{NPV}_{\text{CV}}$$

$$\text{NPV}_{\text{PHEV}} = DP + \sum_{t=1}^{L_t} \frac{\left(PMT(C_c, i_L, L_t)\right)}{\left(1+r_d\right)^t} + \sum_{a=1}^{L} \frac{\left(f_{\text{ca}}^{\text{ELEC}}(\beta,\gamma)P_t^{ELEC} + f_{\text{ca}}^{\text{Gas}}(\beta,\gamma)P_t^{GAS}\right)}{\left(1+r_d\right)^a} + C_{CH}$$

$$\text{PMT} = \frac{C_c i_L}{1-\left(1+i_L\right)^{L_t}}$$

$$\text{NPV}_{\text{CV}} = \sum_{t=1}^{L} \frac{\left(d_{ct} \middle/ \eta_{\text{c}} \left|J_{t,c}\right|\right) P_t^{GAS}}{\left(1+r_d\right)^t}$$

Equation set 5.2

Where *DP* is down payment (100% of additional cost of vehicle of class *c* in base case), r_d is discount rate and t is year of vehicle life, P_t^{ELEC} is the price of electricity from AEO 2011 report for a given year, and P_t^{GAS} is the price of gasoline from AEO report for a given year. PMT is the annual payment (0 in base case), C_c is additional cost of a vehicle of class *c* and home charging infrastructure over a CV of class *c* minus the down payment, i_L is loan rate, and L_t is loan period in years and C_{CH} is the cost of charging infrastructure away from home.

Studies about alternative vehicle purchase, conducted using surveys, have found consumer discount rates of 21-49%, but generally agree that in the near term the most likely value is nearer to the lower part of the range [16,17]. One problem with such surveys is that it has been shown that consumers are unlikely to understand a NPV calculation [18]. It has been posited that when making an actual purchase a consumer might seek out expert information regarding NPV style results [19]. This idea is supported by findings suggesting that implicit consumer discount rates decline as purchase price increases. A study conducted looking at refrigerator purchases found that consumer had a discount rate of about 45% [25]. There is a possibility that some of these refrigerators were purchased by landlords, or others that were not paying the utility costs and therefore had little incentive to purchase an efficient model (principal-agent problem). Other studies focusing on retirement plans instead of appliance purchases found lower discount rates ranging from 1.3-25.7% which may be attributed to the greater value (perhaps supporting the idea that an individual thinks more carefully about a financial decision of larger amount) [20-23]. These studies also found that in general those with higher incomes and education levels exhibited lower discount rates. It is possible that studies focusing on retirement decisions are biased toward higher income households who exhibit lower discount rates. The newer of these studies examined the military drawdown of the early 1990s and the decision service members faced about accepting either a lump sum payment or annuity. It found that discount rates varied considerably among service members depending on whether they were enlisted or officers [23]. It was found that officers had a discount rate of 11.5% and enlisted has a discount rate of 25.7%. In aggregate the discount rate was 17.5%. Given that surveys regarding purchase of alternative vehicle found an implied discount rate in the low 20% range and that the actual decision regarding retirement resulted in an implied rate of 17.5%, the consumer behavior case used a value of 20%.

It has been reported that over 80% of new vehicles were purchased using a loan (between 1998 and 2003) and that the median loan had a period of 60 months and rate of 8.7% with down payment of 14% [24]. Twenty percent of new vehicles are not purchased on a loan. Our consumer behavior case assumes conditions that are in some sense averaged, where consumers take a 60 month loan at 8.7% with a 31% down payment.

In the consumer behavior case consumers purchase vehicles and fuel using a discount rate of 20% (and are assumed to have knowledge of charging infrastructure that will be available), charge points are still purchased outright (presumably by government), so no discount rate is applied, and the total cost is found by adding the cost of charge points, vehicle and fuel despite two separate groups making the purchases. Once again if the lifetime cost premium is negative it implies the PHEV fuel costs relative to the reference CV are low enough to offset the increase in vehicle cost and cost of chargers.

In all cases it is assumed that for adoption of a given AER vehicle or charging strategy a subsidy would be required to make the scenario equal in lifetime cost premium to the lowest cost option. While it is not assured that lifetime cost parity or savings will necessarily induce consumers to adopt a vehicle, for the purposes of comparison it is assumed. There are non-monetary reasons that may tilt some consumers toward such a purchase, and others away. At the same time consumers often exhibit surprisingly high discount rates and gravitate toward purchasing whatever costs less in the beginning regardless of lifetime costs [25].

5.5 Results

These results assume that the traction battery lasts the lifetime of the vehicle for PHEVs. Figure 5.4 summarizes these results for the base case. Figure 5.5 shows the results for the consumer behavior case. Home evening and home all stops charging are averaged (shown with diamonds) and the error bars indicate the results for home all and home evening. The same is true for work home evening and work home all charging (shown by squares). AER increases to the right in the figure and is labeled on the all stops charging case. Lifetime cost premium on the x-axis relates how the cost of adopting each scenario and varies from that of a conventional vehicle. It is made up of the cost of the vehicle, charging infrastructure, and NPV of fuel costs over vehicle lifetime. Minimum lifetime cost is the point farthest to the left. Lowest lifetime gasoline consumption is shown by the lowest point on the graph. If a point (such as AER 5 and work charging) is to the right and higher to any other point on the graph it is dominated and should not be considered as a way to reduce fuel consumption by a decision maker. If lifetime cost premium is negative the selected choice would result in lifetime savings compared to CV. It is assumed that the minimum subsidy to enable any scenario can be found by the difference between its cost and the lowest cost option (furthest to the left on the graphs).

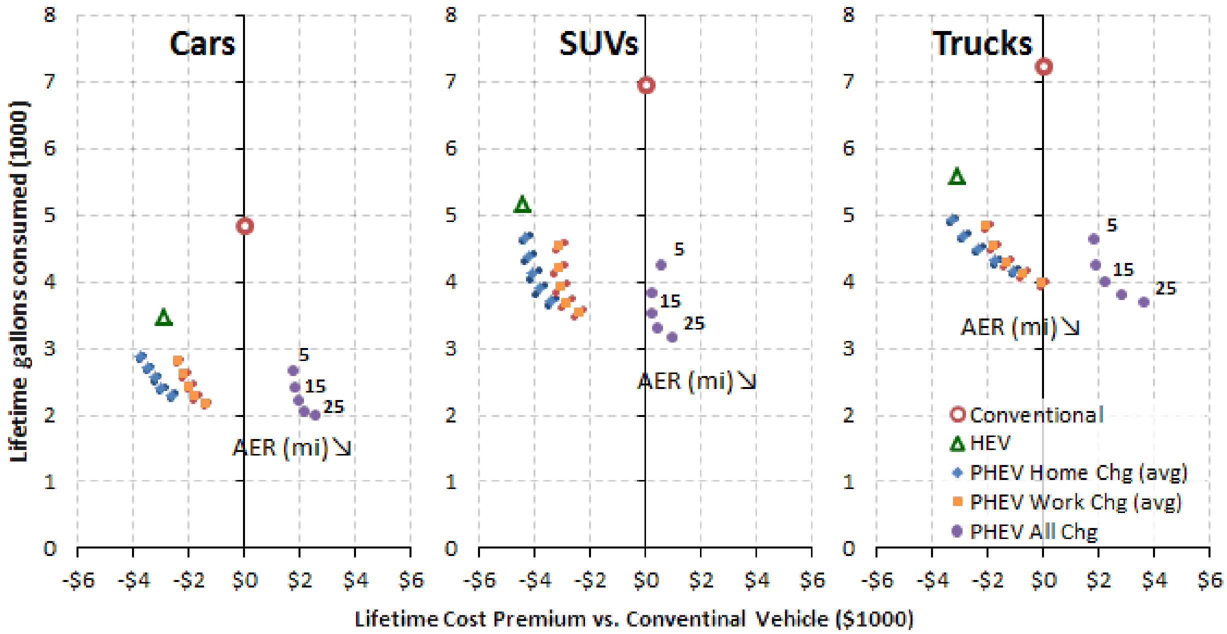

Figure 5.4 – Base case results. Cost of vehicle, chargers, and NPV of fuel costs over vehicle lifetime compared to CV. The minimum necessary subsidy can be found by comparing the cost premium of any point to the lowest cost point. Increasing AER is consistently preferred over work charging. All stops charging is significantly more expensive. Given a 12 year vehicle life, AEO traditional high oil price, GREET 1.8d 2015 efficiency, 2015 average vehicle costs from LDVFC with 50% markup, and a 5% discount rate on fuel purchases. Vehicles and chargers purchased outright. Open circles represent CVs, open triangles HEVs, and diamonds show results for PHEVs using and average of home evening and home all with error bars indicating the difference between those values, squares show the average of work home evening and work home all charging with error bars indicating the difference between those values. Filled circles show the results for all stops charging. AER values increase in 5 mile increments from 5 to 25 and are labeled on all stops charging scenario for clarity.

Calculating the difference between options can be used to compare the valuation of gasoline savings necessary to justify paying more for a different option. For example, in the base case using a passenger car, shown in Figure 5.4, a PHEV5 has the lowest lifetime cost. The PHEV10 is $275 more expensive over vehicle lifetime and saves 165 gallons of gasoline. If the entire value of the subsidy were attributed to effects from gasoline savings this would imply a value of $1.66 per gallon saved. To pay for additional charging infrastructure they would require $21.7 per gallon saved using PHEV5 or $10 per gallon using PHEV25.

The consumer behavior case is shown in Figure 5.5. Using a higher discount rate, the same results are found in terms of AER and charging infrastructure, however not all PHEV options results in lifetime savings. In the case of trucks only PHEV5 decreases lifetime cost compared to

CVs. HEVs for SUVs and trucks are the lowest lifetime cost options. If gasoline savings were valued at $0.92/gallon or it would make sense to pay owners to move from a HEV SUV to a PHEV5. In a more realistic early adoption scenario the infrastructure to enable charging at workplaces would be more expensive because more charging points would be necessary per PHEV. Enabling charging at all stops of over 30 minutes would likely be even more expensive during early adoption since there is less predictability of where the owner a PHEV might travel compared to workplace charging.

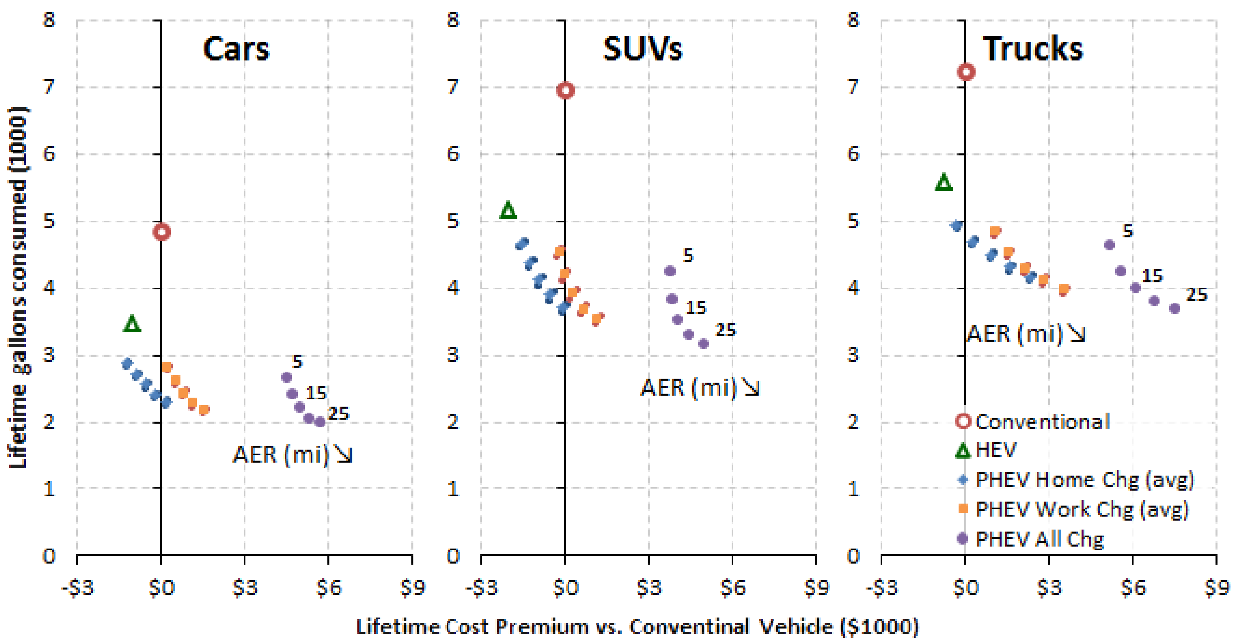

Figure 5.5 –Consumer behavior case. Discount rate at 20% for vehicle and fuel. Chargers purchased up front, other values the same as Figure 5.4. Minimum necessary subsidy for adoption of given scenario can be found by comparing a point to the point farthest to the left (PHEV5 for cars, HEV for SUV, and SUV for truck)

We summarize the results presented in figures 5.4 and 5.5 as follows. First, PHEVs save gasoline over conventional vehicles in all cases. Second, PHEV cars save gasoline and total lifetime costs over conventional cars, in both the base case and the case where consumers exhibit a 20% discount rate. Third, subsidizing charge points at work or elsewhere increases total cost without saving more gasoline (unless the additional charge points lead to larger rates of PHEV adoption). Fourth, PHEVs save gasoline compared to HEVs, and subsidizing AER saves gasoline at the cost of approximately $2 per gallon saved.

If gasoline prices are lower than AEO prediction in the future it will not change the preference of increasing AER compared to installing charge points (see supporting information). It would simply shift all points to the right relative to conventional vehicles. This might necessitate a subsidy to encourage the adoption of HEVs and PHEVs, but would not justify spending on charging infrastructure.

5.6 Limitations

Not all vehicle owners will have access to off street parking, or their own garage. While vehicle owners who are home owners with a garage are likely to pay for home charge points themselves, they are extremely unlikely to pay for those at other locations with the possible exception of a workplace charger. The likely entities that would pay for charge points (or receive a subsidy to install charge points) would be property owners where the charge point is installed, electric utilities, or charge point network operators. This study does not explicitly consider any charge point maintenance costs, but operators will have to sell the electricity for enough to pay for the installation, maintenance, and any profit. The higher charge rates assumed for charging away from home may result in ohmic heating and a decrease of charging efficiency for smaller AER vehicles (resulting in higher electricity costs and greater battery degradation). The desire for profit could lead to consumers facing a higher electricity price when charging away from home, but given the lower rates paid by large customers it is also possible that consumers could pay the same or less and the party operating the charge point could still make a profit. Charge points might last longer than vehicles as well so that in the long run fewer charge points per vehicle would need to be installed, but as discussed previously when PHEVs are being introduced there will need to be far more installed.

Paying for the installation of charge points does not encourage their use or investigation about where is an effective site for a charge point. If a group's business was in selling electric vehicle supply equipment (EVSE) then they would want to install charge points as cheaply as possible so they could sell the most EVSEs with a given grant. If the company that installs them will profit from electricity sales they are incentivized to install them in locations where vehicle owners want to charge. Another feasible scenario is vehicle manufacturers trying to promote the installation of charge points so that they are always within a certain distance of each other. They might never be used, but their availability might make purchasers of BEVs more comfortable while driving with the knowledge that a charge point is somewhere relatively nearby (reducing range anxiety).

Current subsidies for vehicles are given in the form of tax credits to purchasers. There are other alternatives such as a direct payment regardless of tax liability or even payments to manufacturers. Funding manufacturers directly for vehicle research is not a new idea, but subsidies targeted at vehicle purchasers make more sense because they incentivize companies to actually sell products instead of simply build up patent portfolios.

We assume a single owner purchases a vehicle and drives it until they get rid of it with no salvage value. Given consumers discount rates often seen a salvage value of $3,000 in year 8 might only be worth $700 (at 20%) or $335 in year 12.

This paper considers only AERs from 5-25. The results would change if higher range AERs were considered. The jump in cost (from LDVFC) and decrease in CS mode efficiency (from GREET), when moving to a serial hybrid at AER 30, makes charge points more competitive but it is unlikely such vehicles would be widely produced (see supporting information).

This methodology considers only gasoline savings and does not consider the possible desire to improve the technology of PHEVs by incentivizing their adoption. Nevertheless this limitation should not affect the results of the study unless the technology of EVSEs needs to be improved more than PHEVs.

Because the percent markup over manufacturing costs is held constant it means the markup on higher AER vehicles is higher in dollar terms than HEVs and those vehicles with smaller AER. It is feasible that at some point consumers could purchase different AER versions of the same vehicle, which might reduce markup. If a constant increase over manufacturing cost were assumed instead vehicles of greater AER would offer higher lifetime savings compared to base case (see supporting information).

There are obviously other factors affecting vehicle adoption rates. HEVs were not originally found to be cost competitive with CVs in the past yet individuals adopted them [26]. This implies that some people place value on more than the monetary savings from reduced gasoline consumption. It is likely that some small group of people will likewise place value on driving on electricity instead of gasoline beyond the savings associated with fuel costs. This will not be enough to lead to mass adoption, but could help during the learning phase as PHEVs become more commonplace.

The vehicle cost estimates from LDVFC do not include a breakdown by component so the precise increase in vehicle cost associated with the traction battery is not clear [13]. However a case assuming that the cost differential between a HEV and PHEV is made up of traction battery is included in the supporting information. Most warranties currently appear to be 8 years for the traction battery so it is assumed the battery will last 8 years in the supporting information [27-29]. It was found that in the truck case work place charging with AER of 20 was superior to home charging with AER 25.

This paper does not include valuation of air quality benefits derived from displacing gasoline with electricity. These benefits would depend on a variety of factors and were judged beyond the scope of this paper (the type of pollutant considered, the location of power generation compared to population centers, prevailing weather patterns, etcetera.).

5.7 Summary and Discussion

In all cases the maximum AER of 25 is reached in this study before charging infrastructure is considered. When comparing the option to increase PHEV AER or install charging points it appears that under a set of assumptions strongly favorable to infrastructure increasing AER still achieves greater gasoline savings per dollar spent. Comparing the subsidy necessary to make an option equal to the lowest cost option we find the following. The maximum subsidy per gallon saved for increased AER for each class (cars, SUVs and trucks) is \$1.97, \$0.67, and \$2.90, which is less than the minimum subsidy per gallon saved when installing workplace infrastructure \$3.27, \$1.04, and \$3.07 for respective classes.

Convincing owners to plug in when they are parked for short times may be difficult which would decrease cost effectiveness of charging infrastructure. Whether it is worth plugging in at home any time a person parks for more than 30 minutes to save 100 gallons over the life of the vehicle is questionable. The same issue arises when parking away from home. Taking the time to conduct a transaction, to pay for electricity, would make consumers less likely to charge when parking for short periods. Integrating parking charges and electricity charges into one payment, or utilizing some sort of automated payment system would be desirable if the infrastructure already being installed is to be used. Under the home all charging strategy, increasing home charge rates from 1.4 to 3.8 kW results in a maximum increase of 2.5% in CD miles travelled by fleet with AER of 15 (AERs that are smaller and larger see less increase in CD mode travel). Increasing to 7.7 from 1.4 kW for home charging results in a maximum increase of 3% in CD miles travelled for a fleet with AER 20. That is mainly because smaller AER vehicles can be charged quickly even with a low rate charger and larger AER vehicles generally do not need as many interim charges through the day. More information on charge rate comparisons is included in the supporting information.

Using assumptions strongly favorable to charging infrastructure, the maximum subsidy to make lifetime cost equivalent to lowest cost option, when increasing AER, was 5-40% less than the minimum cost for installing charging infrastructure depending on vehicle class. Using the metric of gasoline saved per dollar spent it makes more sense to use federal subsidies to encourage increased AER instead of installing charging infrastructure, however this does not imply the current federal subsidy structure is well designed. In the base case PHEVs have a lower lifetime cost than HEVs in all cases except the SUV case. The SUV case would require a payment of $0.12 per gallon saved to make a HEV and PHEV5 equivalent in the base case. A median estimate for externality benefits of saving a gallon of gasoline that includes the cost of oil supply disruptions ($0.09) and monopsony effect ($0.22) is $0.31 per gallon saved [30,31]. In the consumer behavior case this value would need to be increased to $0.92 per gallon saved to make a consumer ambivalent between a SUV HEV and PHEV5.

If all of the value in subsidizing PHEVs was allocated to gasoline savings it would imply that we subsidize 4 kWh battery PHEVs at $1.25 per gallon saved. At the same time 16 kWh battery PHEVs are subsidized at roughly $4.50 per gallon saved (Figure 5.6). When comparing the gasoline savings in the results from this paper to the actual federal subsidy structure it is clear that federal subsidies are not currently aligned with the goal of decreased gasoline consumption. What could justify these differences in subsidies?

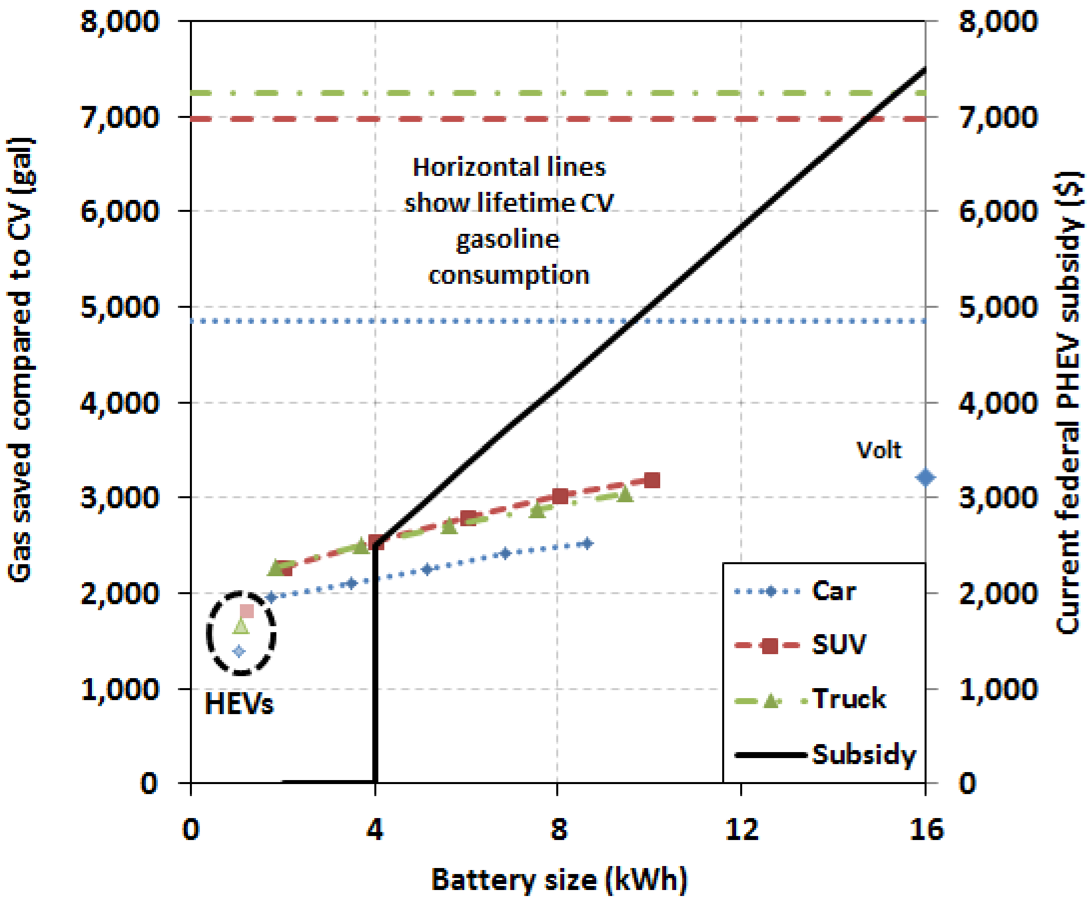

Figure 5.6 – Comparison of current federal subsidy to base case assumptions showing fuel savings over vehicle life (home evening charging). An estimate based on EPA Chevy Volt reported efficiency is also included for comparison [32]. The federal subsidy significantly favors larger battery packs. Hybrid electric vehicles (HEVs) are also shown in the circle.

The first possible explanation is the externality of emissions from transportation. The change in net air emissions in the use phase is largely proportional to the amount of petroleum displaced by electricity, though the charge timing could result in varying magnitude of the emissions changes [4]. It is also likely that emissions will move away from populated areas in proportion to the amount of electricity displacing gasoline [33, 34]. However larger batteries entail higher upstream emissions per vehicle and such packs are more likely to be underutilized. Based on prior work we expect life cycle analysis to favor shorter range AER vehicles [35]. So ignoring emissions effects actually implies that the subsidy predicted only based on gasoline savings slightly favors higher AER vehicles.

Another explanation could be technology development. Is there a reason to think that larger batteries would help advance technology more than smaller batteries? It does not appear there is reason to believe advancements in battery technology will improve with larger battery PHEVs. This is because larger battery PHEVs will see lower power demands from cells comprising the battery and have more room to degrade as time passes. However it is possible that larger battery based PHEVs could spur drivetrain development. Overall there is not a clear case that larger battery PHEVs help advance technology more than smaller battery based PHEVs.

The remaining possibility is that a subsidy could be designed to increase employment. There is also no clear reason that subsidizing larger battery packs at a higher value per gallon saved would encourage higher employment than subsidizing smaller battery packs at an equal level per gallon saved.

Given that the current subsidy seems misaligned we offer preferable policy alternatives. Calculating lifetime gasoline savings based on vehicle rated efficiencies could be used to set subsidies, but it is acknowledged that such a calculation requires significant assumptions which could be controversial. The first option is to subsidize additional battery capacity at $80-100 per kWh instead of $417 per kWh. This would more closely align the subsidy with gasoline savings and would also reduce the cost of the subsidy program if it remained based on a fixed number of vehicles sold. However, a subsidy based on the rated kWh capacity of the pack would still penalize a vehicle allowing a greater SOC swing. While the Volt allows 65% swing (similar to GREET assumptions of 60% SOC swing) some battery chemistries and manufacturers appear to allow more (Leaf and i-Miev EPA fuel economy ratings imply they allow far more than 65% SOC swing) [36, 37]. To avoid biasing manufacturer battery selection it would be preferable to subsidize based on usable battery capacity instead of rated capacity [38].

Another possible alternative which also encourages technology development for PHEVs would be to subsidize based on actual AER (instead of equivalent AER) in a specific low demand drive cycle, such as the urban dynamometer driving schedule (UDDS). Compared to the current subsidy this would directly incentivize automakers to design PHEVs in a manner that focuses on displacing gasoline with electricity. Automakers would be free to choose any battery chemistry they thought would be best and have no incentive to pick a battery that enabled them to get a larger capacity pack at a constant price point. For example, it would encourage including batteries with high enough power capabilities in small pack PHEVs to operate using electricity in low demand situations. This would ensure battery technology improvements were incentivized as well. Automakers could still provide differentiation of performance to consumers in blended mode, or by including a higher power rated pack, but if the consumer were willing to drive no more aggressively than the UDDS they could operate the vehicle entirely in electric mode during CD mode travel. Consumers could also benefit from such a subsidy as it would make understanding AER easier when comparing across vehicle options.

HEVs and PHEVs with low AER and only home charging generally provide the largest gasoline savings per dollar spent, offering both lower costs and lower gasoline consumption than CVs, depending on the consumer's discount rate. It is therefore possible that incentivizing a larger number of consumers to purchase HEVs or low-AER PHEVs would save more gasoline under a fixed policy budget than incentivizing a relatively smaller number of consumers to purchase high-AER PHEVs [35]. However, given a fixed market of electrified vehicle adopters, if more gasoline savings is needed than what can be achieved with a HEVs and low-AER PHEVs, additional savings can be achieved per vehicle more efficiently by paying for additional AER than by paying for extra charging infrastructure.

Looking forward as battery prices decrease and the AER resulting in maximum lifetime cost savings increases the value of plugging in each time a vehicle stops will also decline. Although the recently announced DC quick charger from Nissan costs far less than in the past ($9,900), it requires three phase AC input [39]. The actual installation costs of such units are likely to be substantial. Co-locating fast chargers to save on trenching and other installation costs would increase the likelihood of transformer upgrades and other costly changes to the distribution system. However, installing charging infrastructure would also provide employment opportunities for local workers, whereas increasing AER would provide employment for workers in the supply chain for battery manufacturing.

5.8 Conclusions

Increased PHEV AER is more cost effective at reducing gasoline consumption than public infrastructure investment, even under optimistic assumptions. Federal subsidies for charging infrastructure should be analyzed based on the benefit to BEVs because PHEVs are unlikely to gain a substantial benefit regardless of AER. Our results call into question the design of the current PHEV subsidy and suggest that there are a number of policy options that will likely achieve the similar goals more efficiently. It would be preferable to align the subsidy to value gasoline savings equally across the different PHEV options unless there is specific reason cited to avoid this. These subsidy options are subsidizing based on: actual AER in a low demand drive cycle, usable battery capacity, or battery size aligned to fuel savings. Gasoline savings from charging infrastructure are not cost competitive with efforts to increase the AER of PHEVs.

5.9 Acknowledgements

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5.10 Supporting information

5.10.1 Acronyms

η^{CD-E} – vehicle electric efficiency in charge depleting mode

η^{CD-G} – vehicle gasoline efficiency in charge depleting mode

η^{CS-G} – vehicle gasoline efficiency in charge sustaining mode

AEO – annual energy outlook published by energy information administration

AER – all electric range

BEV – battery electric vehicle

CAFE – corporate average fuel economy

CD – charge depleting mode

CS – charge sustaining mode

CV – conventional vehicle

d^{CD} – distance in charge depleting mode

d^{CS} – distance in charge sustaining mode

E85 – an ethanol gasoline blend with 85% ethanol

EIA – Energy Information Administration

EVSE – Electric vehicle supply equipment

GHG – greenhouse gas

GREET – Greenhouse Gasses, Regulated Emissions, and Energy Use in Transportation

HEV – hybrid electric vehicle

ICE – internal combustion engine

kWh – kilowatt hour

LDVFC – Potential of technologies for displacing gasoline consumption by light-duty vehicles through 2045

mpg – miles per gallons

NHTS – National Household Travel Survey

NPV – net present value

PHEV – plug-in hybrid electric vehicle

PTC – production tax credit

VMT – vehicle miles travelled

WD – weekday designator

WE – weekend designator

5.10.2 Consumption tables by class and age

These tables list the annual fuel consumption calculated with fuel use model as described in main text for each vehicle class and age.

Table 5S.6 – Annual fuel consumption for cars (gallons gasoline per vehicle)

	Grid Independent		PHEV AER (miles)				
Age	CV	HEV	5	10	15	20	25
1	521	372	314	299	284	269	257
2	486	347	293	279	265	251	240
3	451	322	272	258	244	231	221
4	411	294	247	234	221	209	199
5	386	276	231	219	207	195	186
6	391	280	234	222	210	198	189
7	372	266	222	210	197	185	177
8	397	284	237	224	211	198	189
9	382	273	227	214	202	189	181
10	349	250	208	195	183	172	163
11	351	251	208	196	183	171	163
12	356	254	212	200	188	177	169
13	341	244	202	189	178	167	159
14	294	210	173	162	151	141	134
15	314	224	187	176	166	156	149

Table 5S.7 – Annual electricity consumption for cars (kWh per vehicle)

	PHEV AER (miles)				
Age	5	10	15	20	25
1	333	631	879	1,088	1,280
2	308	583	812	1,007	1,185
3	298	563	783	968	1,136
4	282	531	736	909	1,068
5	273	512	709	871	1,015
6	280	522	720	885	1,033
7	282	525	720	882	1,027
8	296	554	762	933	1,087
9	295	550	753	919	1,063
10	282	522	713	869	1,007
11	293	541	737	898	1,040
12	280	515	702	854	988
13	291	535	721	869	1,001
14	265	484	656	793	913
15	246	452	615	748	864

Table 5S.8 – Annual fuel consumption for SUVs (gallons gasoline per vehicle)

	Grid Independent		PHEV AER (miles)				
Age	CV	HEV	5	10	15	20	25
1	759	562	516	490	465	442	424
2	786	582	535	506	481	457	437
3	728	539	494	467	442	419	401
4	701	519	475	449	425	402	384
5	727	539	491	463	437	413	394
6	623	461	420	395	372	351	335
7	576	426	387	363	341	321	305
8	476	353	320	299	280	263	250
9	426	316	287	269	253	239	228
10	499	369	336	316	297	281	267
11	333	247	222	207	193	181	172
12	338	251	227	212	198	186	176
13	252	187	167	154	143	133	125
14	265	196	177	165	155	146	140
15	200	148	132	122	114	106	100

Table 5S.9 – Annual electricity consumption for SUVs (kWh per vehicle)

	PHEV AER (miles)				
Age	5	10	15	20	25
1	399	754	1,063	1,323	1,546
2	412	784	1,106	1,382	1,618
3	398	756	1,064	1,327	1,551
4	390	742	1,042	1,297	1,515
5	428	806	1,128	1,402	1,637
6	372	702	986	1,224	1,426
7	363	682	954	1,180	1,369
8	307	580	815	1,010	1,170
9	266	499	696	860	996
10	306	574	801	992	1,154
11	238	438	606	742	852
12	224	422	589	728	844
13	197	363	497	610	705
14	182	337	462	561	639
15	158	286	390	477	545

Table 5S.10 – Annual fuel consumption for trucks (gallons gasoline per vehicle)

	Grid Independent		PHEV AER (miles)				
Age	CV	HEV	5	10	15	20	25
1	617	475	428	411	397	384	372
2	668	514	462	442	426	411	397
3	606	466	418	400	385	372	360
4	628	483	432	412	396	381	368
5	702	540	484	464	446	430	416
6	557	428	381	361	345	330	317
7	647	497	444	423	406	390	377
8	630	484	431	410	392	376	362
9	588	452	401	380	362	347	334
10	520	400	355	336	320	305	293
11	512	394	348	329	312	298	286
12	573	441	390	369	351	336	323
13	470	362	318	300	284	270	260
14	464	357	312	293	277	264	253
15	538	414	364	342	325	310	298

Table 5S.11 – Annual electricity consumption for trucks (kWh per vehicle)

	PHEV AER (miles)				
Age	5	10	15	20	25
1	242	459	657	835	984
2	275	525	754	960	1,130
3	259	490	697	882	1,031
4	286	542	769	968	1,132
5	301	569	812	1,026	1,201
6	285	537	762	959	1,116
7	306	575	813	1,022	1,189
8	312	586	829	1,044	1,216
9	312	585	826	1,032	1,196
10	277	519	736	927	1,083
11	289	540	762	950	1,100
12	319	593	830	1,035	1,199
13	279	521	733	912	1,045
14	297	546	756	928	1,064
15	331	610	842	1,038	1,189

5.10.3Sensitivity Analysis

This section examines a variety of different assumptions as shown in Table 5S.12. An examination of possible changes in value when including battery replacement in year 8 of vehicle lifetime is included.

Table 5S.12 – Base case assumptions and ranges considered in sensitivity analysis

Parameter	Base value	Range of sensitivity
Fuel costs	AEO 2011 traditional high oil price [1]	Reference case, GHG price economy wide
Vehicle cost	LDVFC 2015 Average with 50% markup[2]	No markup, low and high from LDVFC with 50% markup
Charger cost	As defined in Table 5.5 of main document	As defined in Table 5.5 of main document
Charge rate (kW)	1.44 at home and 7.68 when away	1.44 ,3.8, 7.68 Home 1.44, 7.68, 38 kW Away
Vehicle efficiency	GREET 1.8d 2015 [3]	GREET 1.8d 2010-2020
Discount rate	5%	0, 50%
Vehicle life	12 years	8, 15
Vehicle loan (years)	5	0, 5 years
Loan rate	8.74%	0
Down payment	31%	0, 100%
Chargers per PHEV required to enable work charging	0.3	0.2, 0.6
Chargers per PHEV required to enable all stops charging	0.9	1.5

Table 5S.13 – Sensitivity summary table

Scenarios	Cost Minimum Vehicle			$/gal implied by								
				Lowest cost PHEV			Work Charging			AER increase		
	Car	SUV	Truck	Car	SUV	Truck	Car	SUV	Truck	Car	SUV	Truck
Base case	PHEV5	HEV	PHEV5	0.00	0.12	0.00	21.66	11.11	11.85	1.66	0.37	1.67
AEO reference	PHEV5	HEV	HEV	0.00	1.23	0.77	22.74	12.21	12.94	2.75	1.48	2.76
AEO GHG economywide	PHEV5	HEV	HEV	0.00	1.20	0.68	22.88	12.25	12.97	2.89	1.51	2.79
No markup	PHEV5	PHEV20	PHEV5	0.00	0.00	0.00	21.66	4.84	11.85	0.41	0.60	0.23
Low Vehicle cost	PHEV5	PHEV10	PHEV5	0.00	0.00	0.00	21.66	6.42	11.85	1.02	0.10	0.83
High vehicle cost	PHEV5	HEV	CV	0.00	1.64	0.26	21.66	11.11	11.85	4.44	2.41	4.43
Discount rate 0	PHEV5	PHEV15	PHEV5	0.00	0.00	0.00	21.03	4.12	5.85	0.39	0.68	0.89
Discount rate 50%	CV	CV	CV	0.51	0.48	1.09	23.12	12.89	13.76	3.12	2.14	3.57
8 yr vehicle life	PHEV5	HEV	HEV	0.00	0.99	0.84	32.71	15.80	19.21	3.35	1.25	3.73
15 yr vehicle life	PHEV5	HEV	PHEV5	0.00	0.01	0.00	17.58	9.60	9.20	1.06	0.11	0.92
Low charger cost	PHEV5	HEV	PHEV5	0.00	0.02	0.00	9.78	4.22	4.60	1.66	0.37	1.67
High charger cost	PHEV5	HEV	HEV	0.00	1.06	0.42	69.18	38.64	40.86	1.66	0.37	1.67
0.2 chargers for work	PHEV5	HEV	PHEV5	0.00	0.12	0.00	13.74	6.52	7.02	1.66	0.37	1.67
0.6 chargers for work	PHEV5	HEV	PHEV5	0.00	0.12	0.00	45.42	24.87	26.36	1.66	0.37	1.67
1.5 chargers for all	PHEV5	HEV	PHEV5	0.00	0.12	0.00	21.66	11.11	11.85	1.66	0.37	1.67
Battery replacement	PHEV5	HEV	HEV	0.00	1.46	0.93	21.66	11.11	11.85	3.36	1.74	3.62
2010 GREET efficiency	PHEV5	PHEV20	PHEV5	0.00	0.00	0.00	13.81	3.87	8.47	0.09	1.38	0.59
2020 GREET efficiency	PHEV5	PHEV5	PHEV5	0.00	0.00	0.00	24.22	13.17	12.32	2.10	0.90	1.76
Low charge rate	PHEV5	HEV	PHEV5	0.00	0.12	0.00	12.19	5.63	6.10	1.66	0.37	1.67
High charge rate	HEV	HEV	HEV	0.32	2.19	1.32	93.09	52.55	55.46	1.58	0.28	1.58
Consumer Behavior	PHEV5	HEV	HEV	0.00	0.92	0.73	22.58	12.21	13.06	2.10	1.06	2.32
Cash payment	PHEV5	HEV	HEV	0.00	1.32	1.10	22.58	12.21	13.06	2.59	1.45	2.88
No down payment	PHEV5	HEV	HEV	0.00	0.73	0.55	22.58	12.21	13.06	1.88	0.88	2.07

5.10.3.1 Base Case Results

We show Base case results first for comparison to other sensitivity cases shown below (Figure 5S.1).

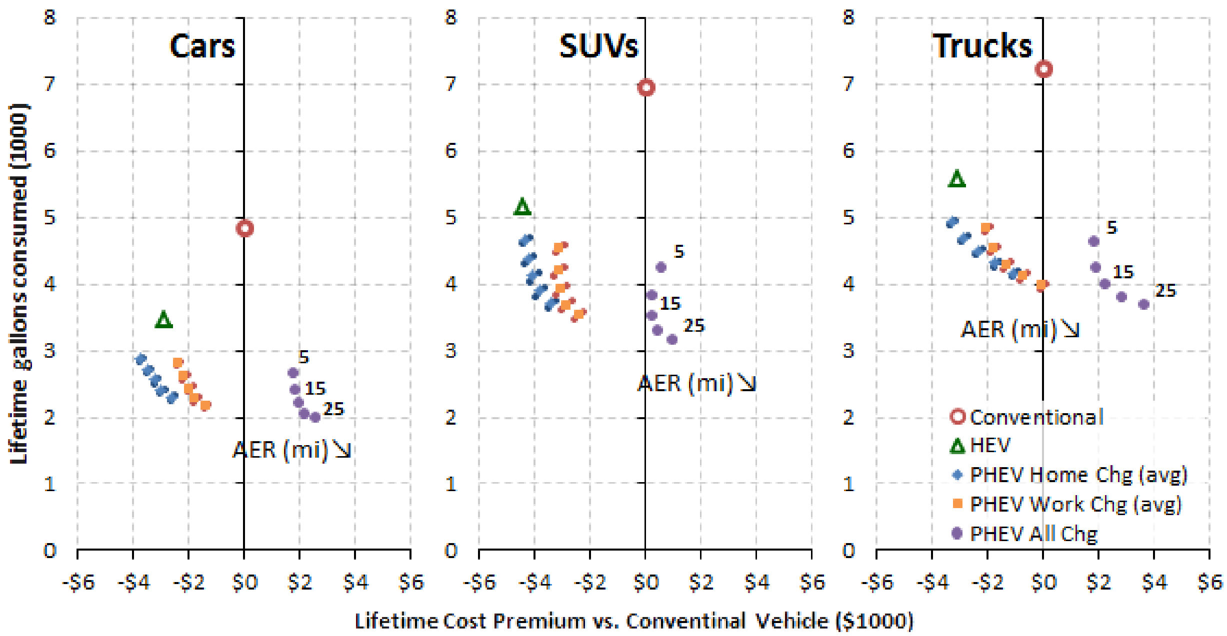

Figure 5S.1 – Base case results. Cost of vehicle, chargers, and NPV of fuel costs over vehicle lifetime compared to CV. The minimum necessary subsidy can be found by comparing the cost premium of any point to the lowest cost point. Increasing AER is consistently preferred over work charging. All stops charging is significantly more expensive. Given a 12 year vehicle life, AEO traditional high oil price, GREET 1.8d 2015 efficiency, 2015 average vehicle costs from LDVFC with 50% markup, and a 5% discount rate on fuel purchases. Vehicles and chargers purchased outright. Open circles represent CVs, open triangles HEVs, and diamonds show results for PHEVs using and average of home evening and home all with error bars indicating the difference between those values, squares show the average of work home evening and work home all charging with error bars indicating the difference between those values. Filled circles show the results for all stops charging. AER values increase in 5 mile increments from 5 to 25 and are labeled on all stops charging scenario for clarity.

5.10.3.2 Fuel Costs

The fuel costs from AEO reference case (Figure 5S.2) and AEO greenhouse gas economy wide (Figure 5S.3) scenarios are shown below. Lower petroleum prices result in most of the vehicles being more expensive, but with other base case assumptions they still result in lifetime cost savings compared to CVs. Increasing AER still dominates the option to install charge points.

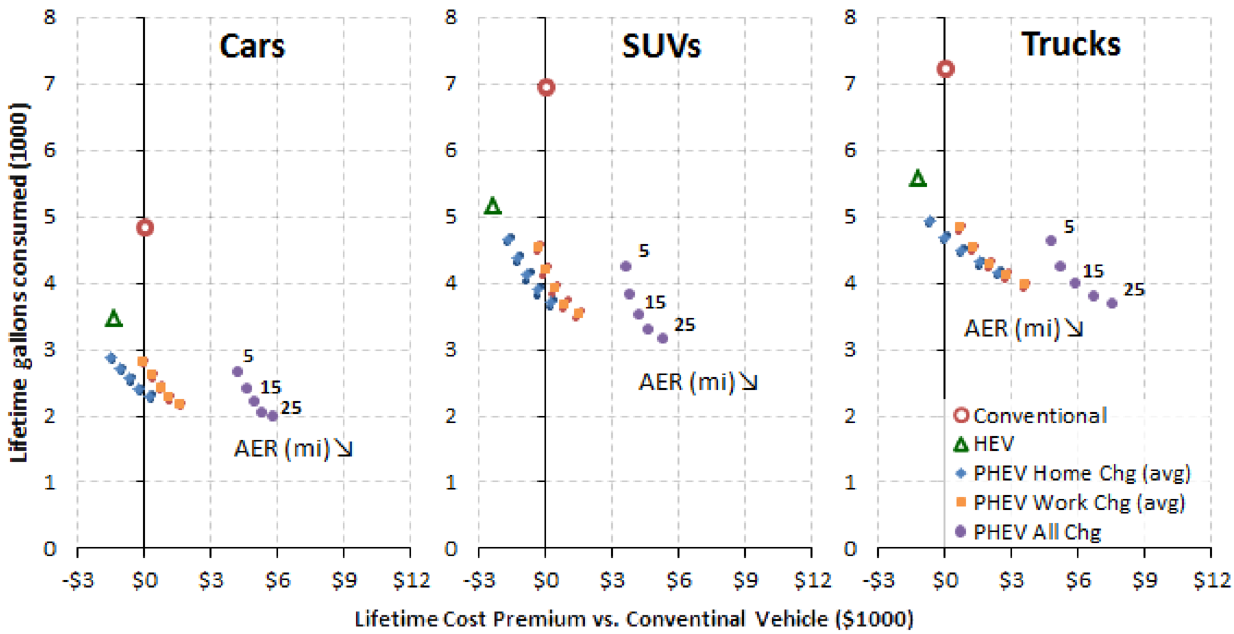

Figure 5S.2 – Using fuel costs from AEO reference case scenario instead of traditional high oil price case

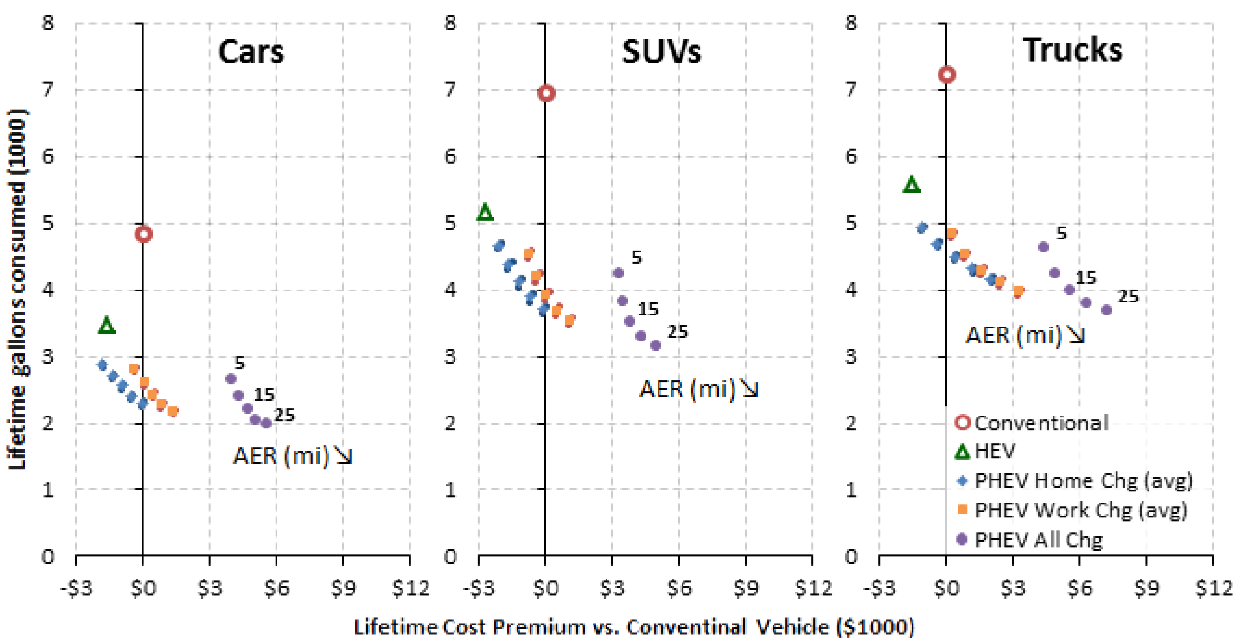

Figure 5S.3 – Using fuel costs from AEO greenhouse gas price economy wide scenario instead of traditional high oil price case

5.10.3.3 Vehicle Costs

Removing the markup on manufacturing costs shows how vehicles would compare if markup were not proportional to vehicle cost, but instead was a constant value (Figure 5S.4). It is possible that if consumers are allowed to purchase different AER options on the same vehicle the markup may not be proportional. If this were the case the largest change is in the SUV case where the results are inverted and a PHEV20 is the lowest lifetime cost compared to CV. Reducing vehicle costs obviously increases the distance between options to increase AER and install charging infrastructure (Figure 5S.5). Increasing the vehicle costs makes work charging infrastructure preferable after AER of 15 is reached in the truck case and makes the SUV of AER 25 about equal to work charging (Figure 5S.6).

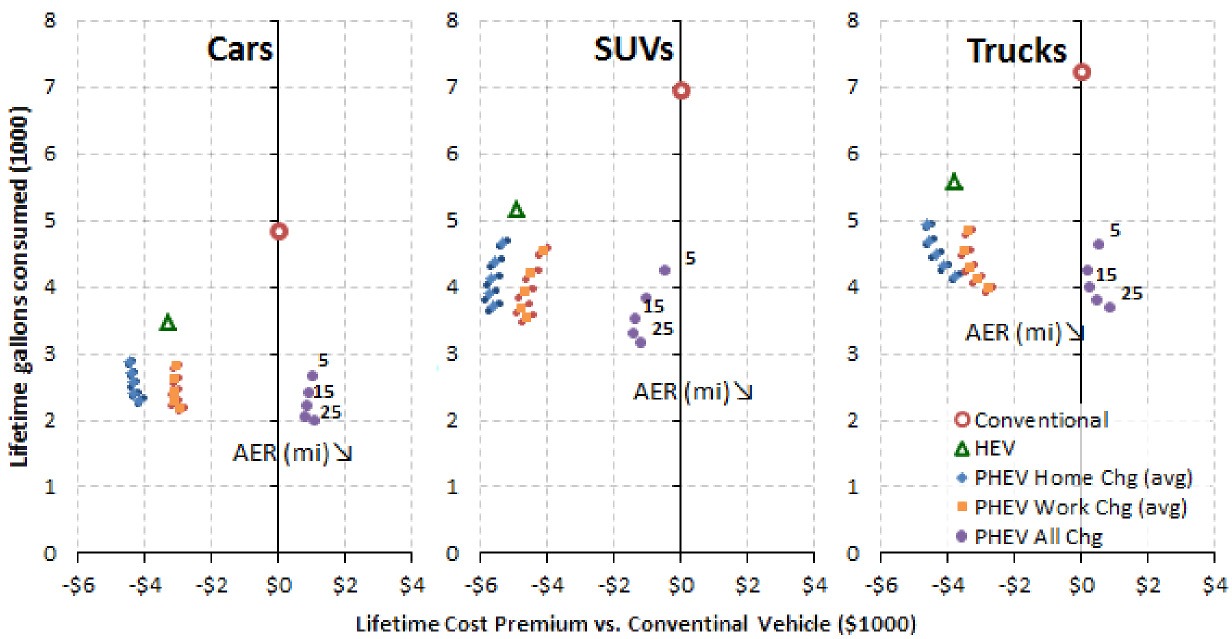

Figure 5S.4 – No markup on manufacturing costs instead of 50% markup in base case

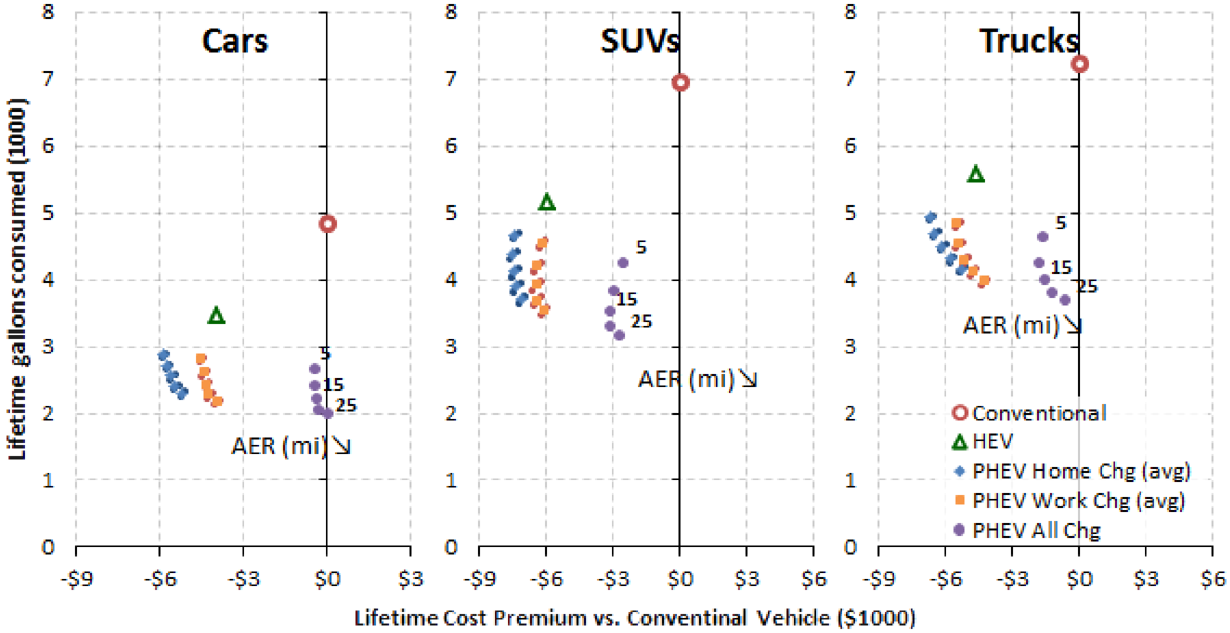

Figure 5S.5 –LDVFC 2015 low cost case

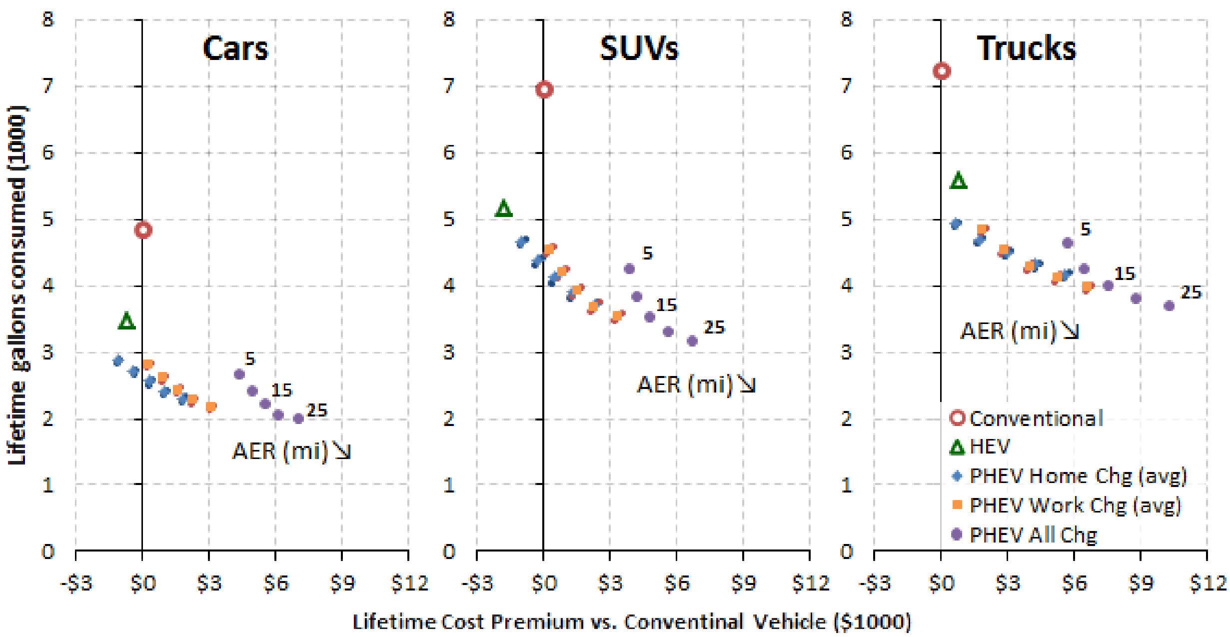

Figure 5S.6 – LDVFC 2015 high cost case

5.10.3.4 Discount Rate

Discount rates tend to vary tremendously for consumers. Value of 0% is shown below in Figure 5S.7. A higher discount rate of 50% is shown in Figure 5S.8. Increased AER range is still preferred to charging infrastructure.

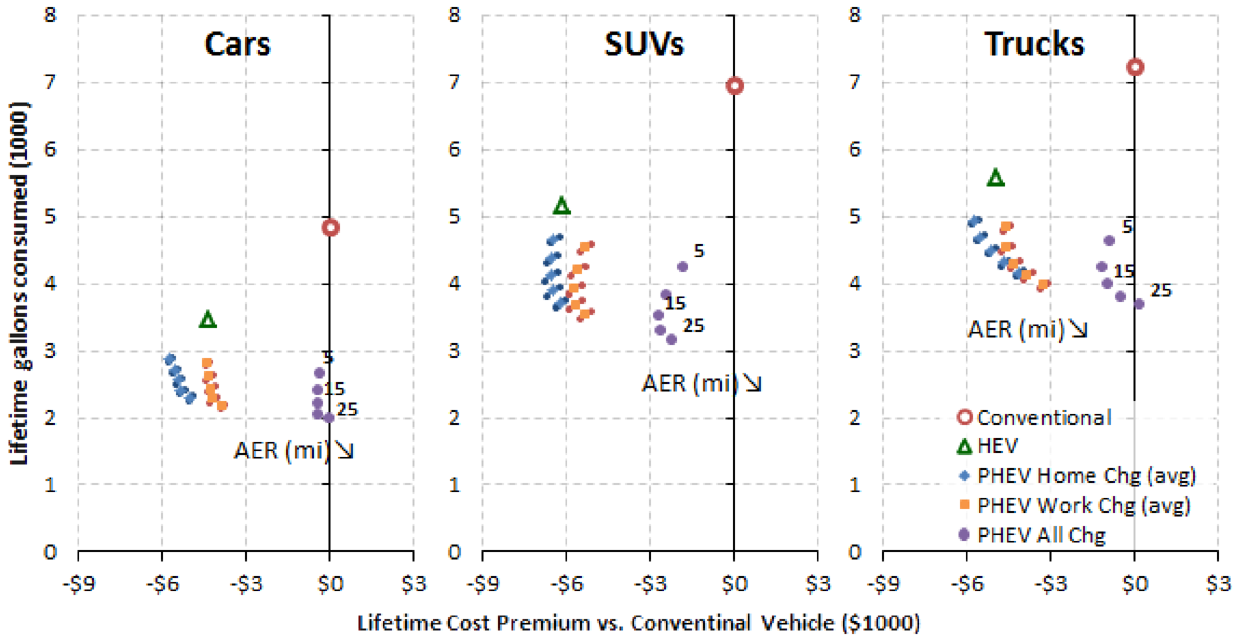

Figure 5S.7 – Discount rate 0% instead of 5% in base case.

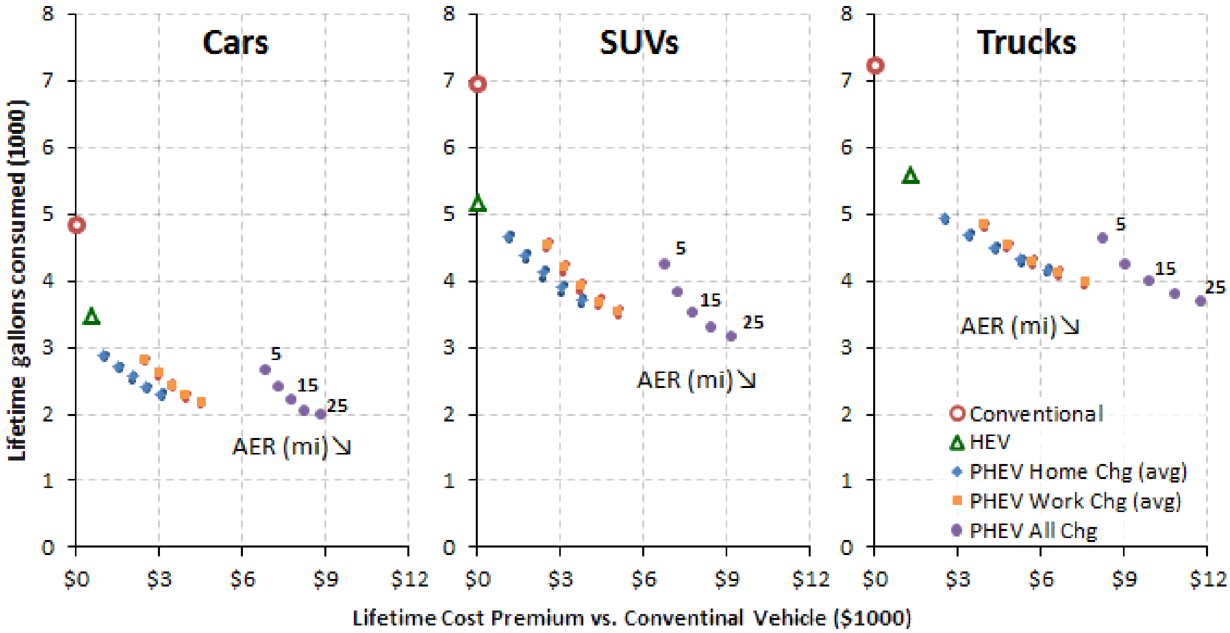

Figure 5S.8 – Discount rate 50% instead of 5% in base case.

5.10.3.5 Vehicle Life

Shortening vehicle lifetime decreases the amount of fuel savings possible and thus the value of HEVs and PHEVs declines (Figure 5S.9). Increasing vehicle lifetime increases the fuel savings and the value of all points (Figure 5S.10).

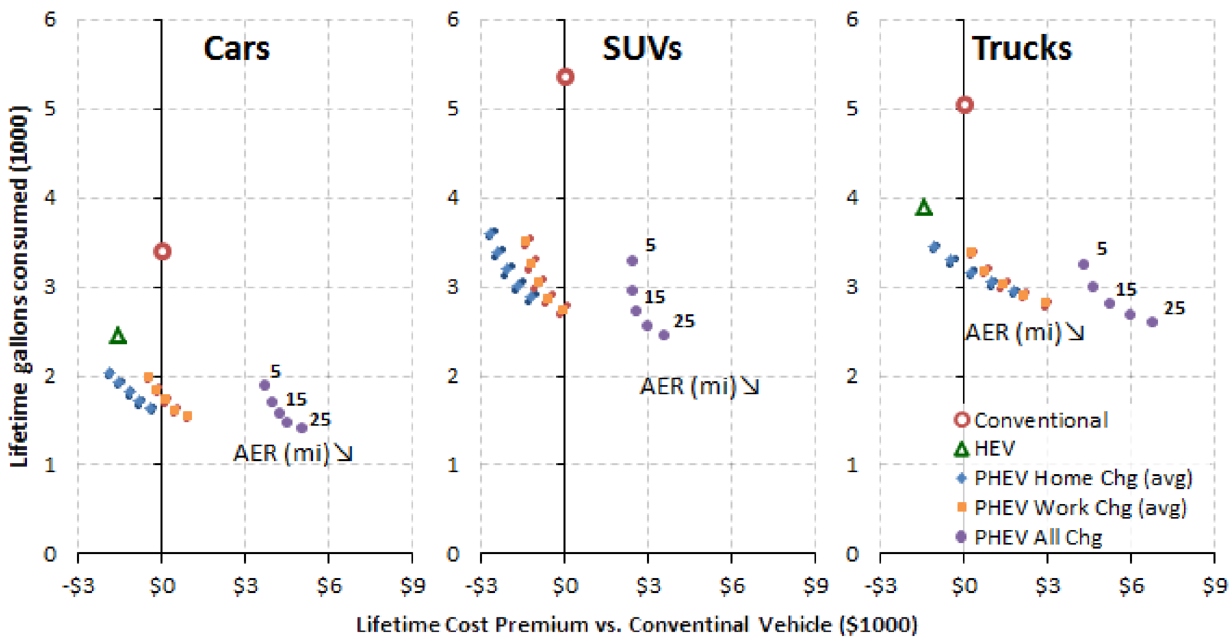

Figure 5S.9 – Eight year vehicle lifetime instead of 12 years as in base case

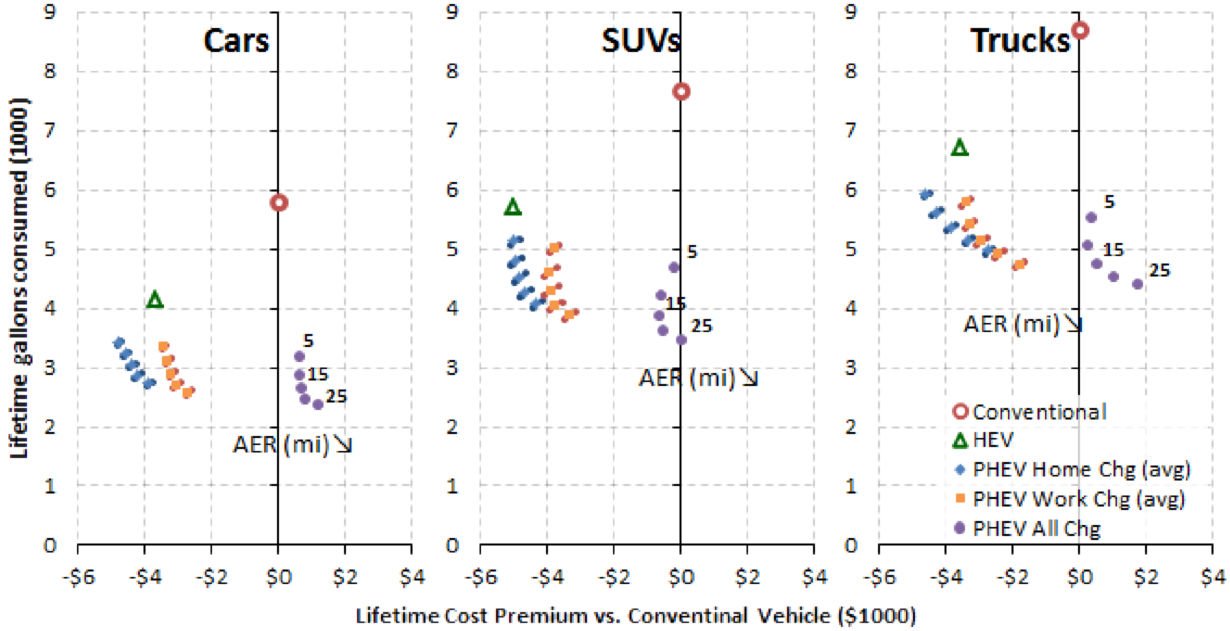

Figure 5S.10 – Fifteen year vehicle lifetime instead of 12 years as in base case.

5.10.3.6 Charger Costs

If charger costs are significantly lower (Figure 5S.11), charging is more competitive with increasing AER. In this case AER for cars reaches 25 still, but SUVs only reach 20 before work charging is preferred and trucks only reach 10 before work charging is preferred. If charger costs are higher (Figure 5S.12) then the charging options show a greater lifetime cost.

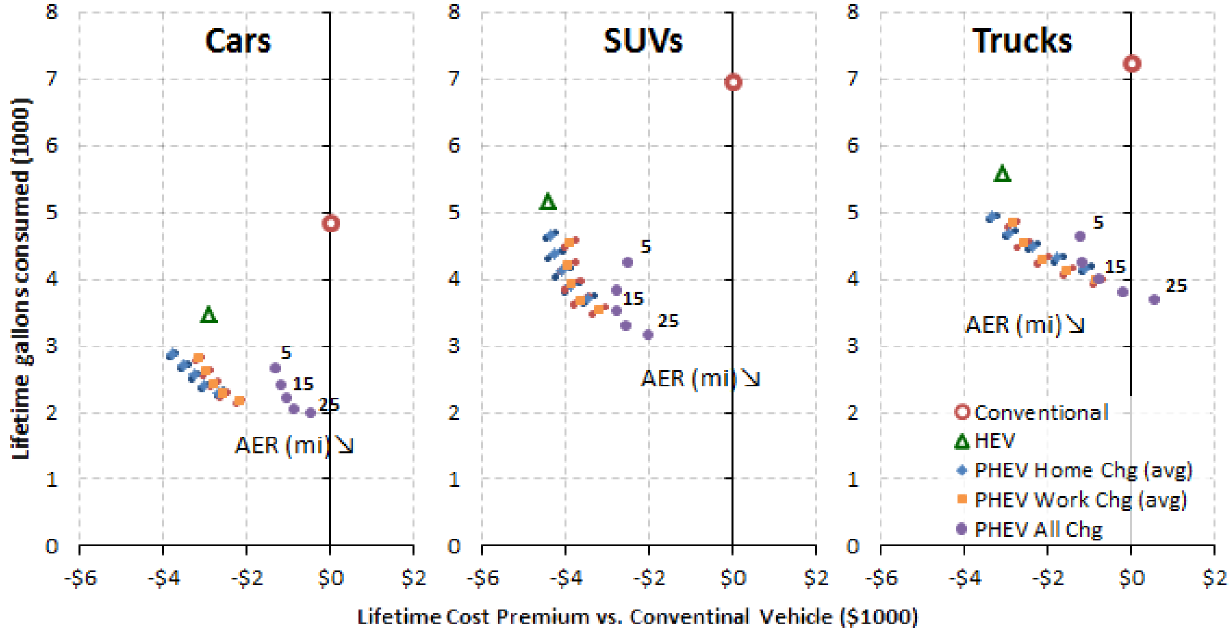

Figure 5S.11 – Low charger costs ($25 for 1.4kW at home, $2500 for 7.7kW away from home)

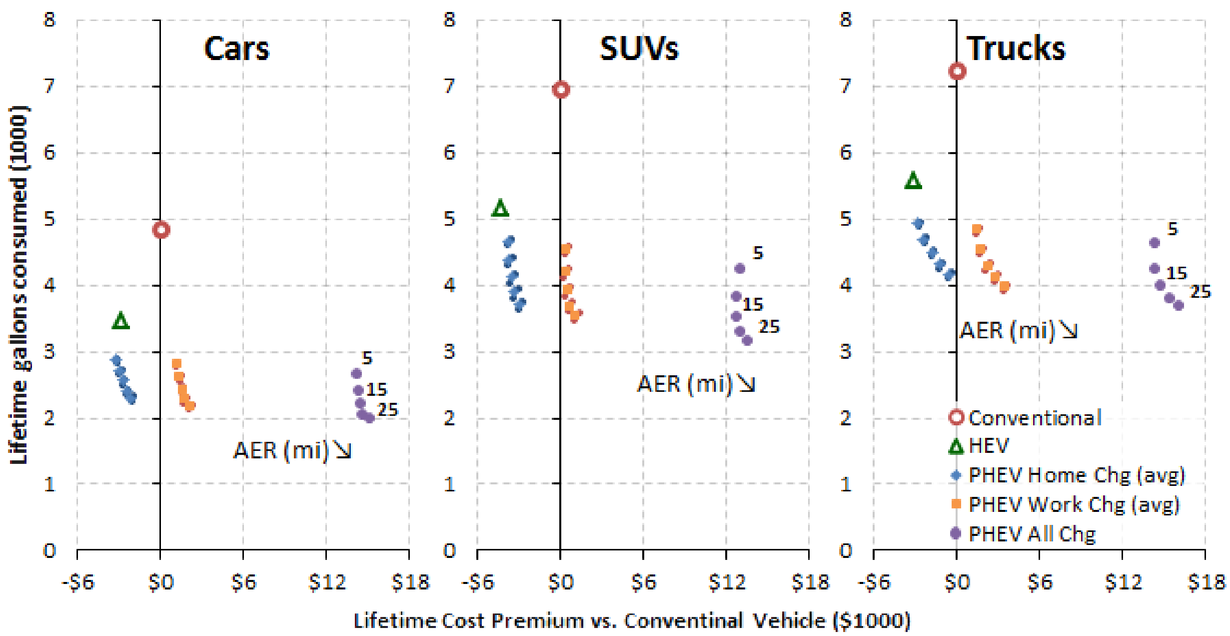

Figure 5S.12 – High charger costs ($550 and for 1.4kW at home, $15,000 for 7.7kW away from home)

5.10.3.7 Chargers necessary to enable charging strategy

If fewer installations could provide for work charging of the fleet then work charging is more competitive with increased AER and surpasses increased AER in the truck case for AER of 20 and 25 (Figure 5S.13). In other cases AER is still preferred. In the opposite case with 0.6

chargers per PHEV work chargers are far less competitive (Figure 5S.14). Increasing the ratio of chargers, to enable all stops charging, increases the difference in cost between work and all stops charging significantly (Figure 5S.15).

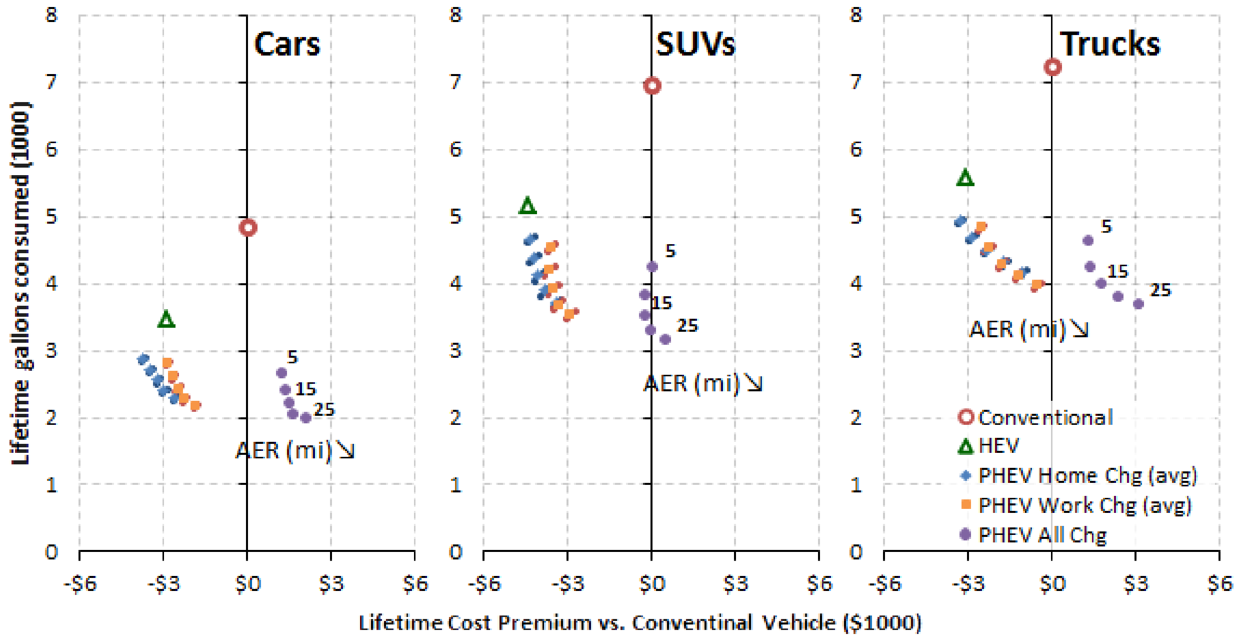

Figure 5S.13 – Lower ratio of chargers to enable work charging (0.2 per PHEV instead of 0.3)

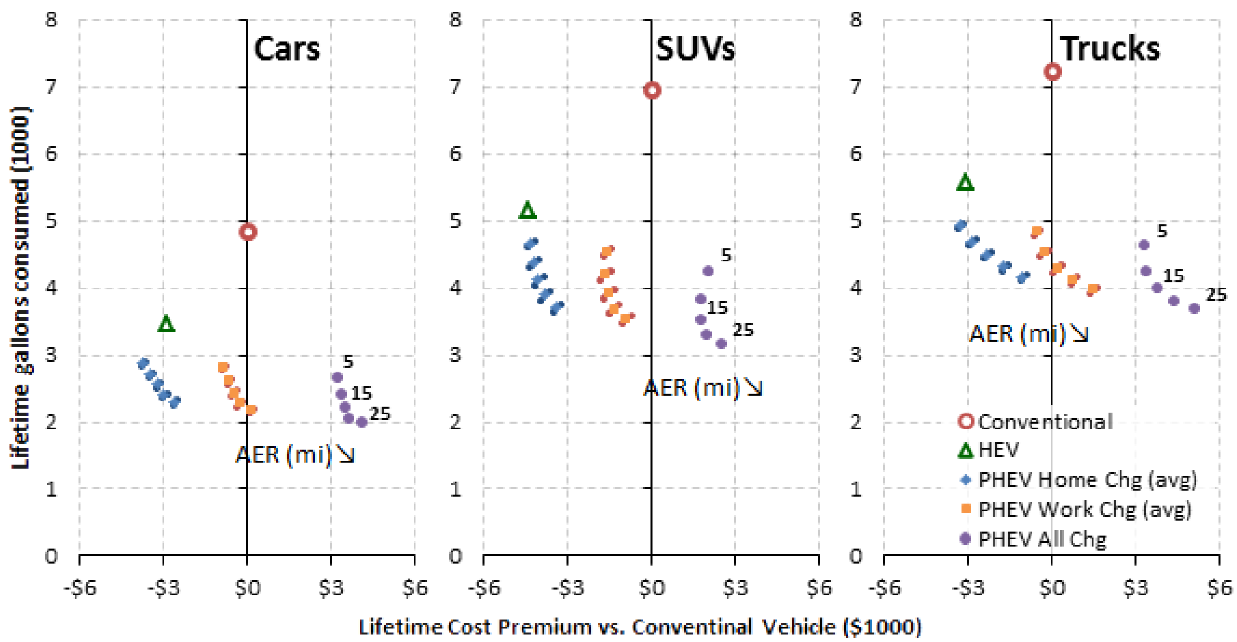

Figure 5S.14 – Higher ratio of work chargers (0.6 per PHEV instead of 0.3)

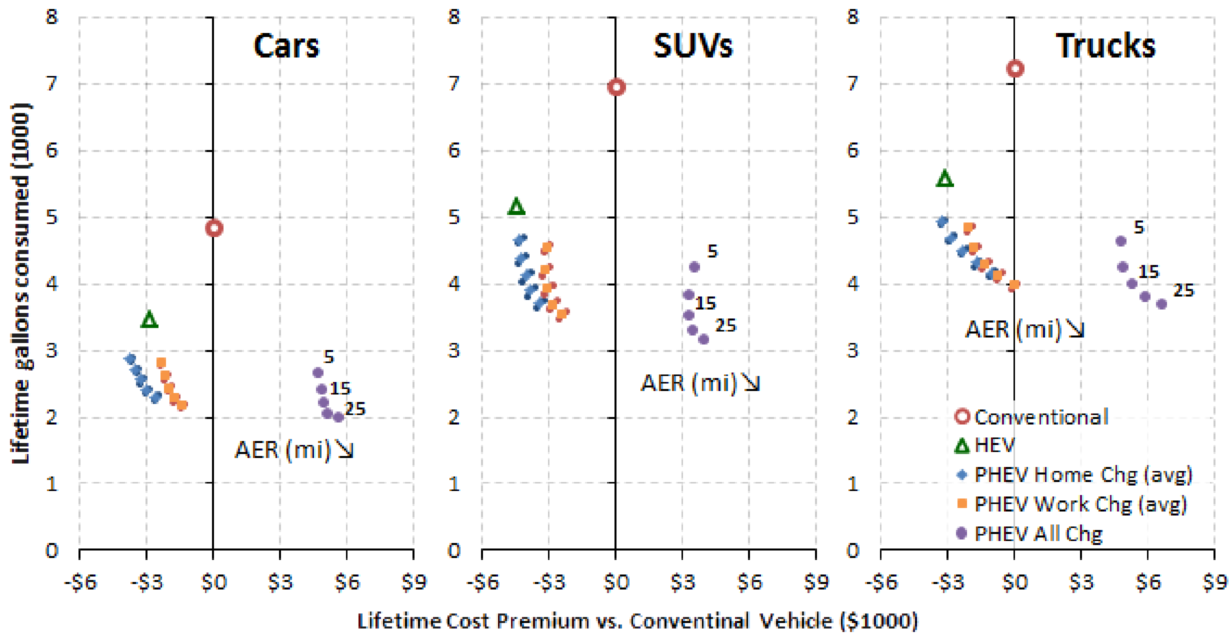

Figure 5S.15 – Higher ratio of chargers to enable all stops charging (1.5 per PHEV instead of 0.9)

5.10.3.8 Battery Replacement

It is likely that battery replacement will be necessary at some point in a vehicles lifetime especially if small AER PHEVs utilize a higher percentage of their batteries at higher c-rates. Currently it appears that battery replacement warranties are 8 years and 100,000 miles (Volt allows 30% capacity degradation before warranty replacement) [4-6]. Figure 5S.16 shows results for battery replacement in year 8 of vehicle lifetime assuming costs above HEV can be attributed entirely to battery. Battery replacement makes truck cases of AER 20 and 25 inferior to work charging. Other cases remain the same.

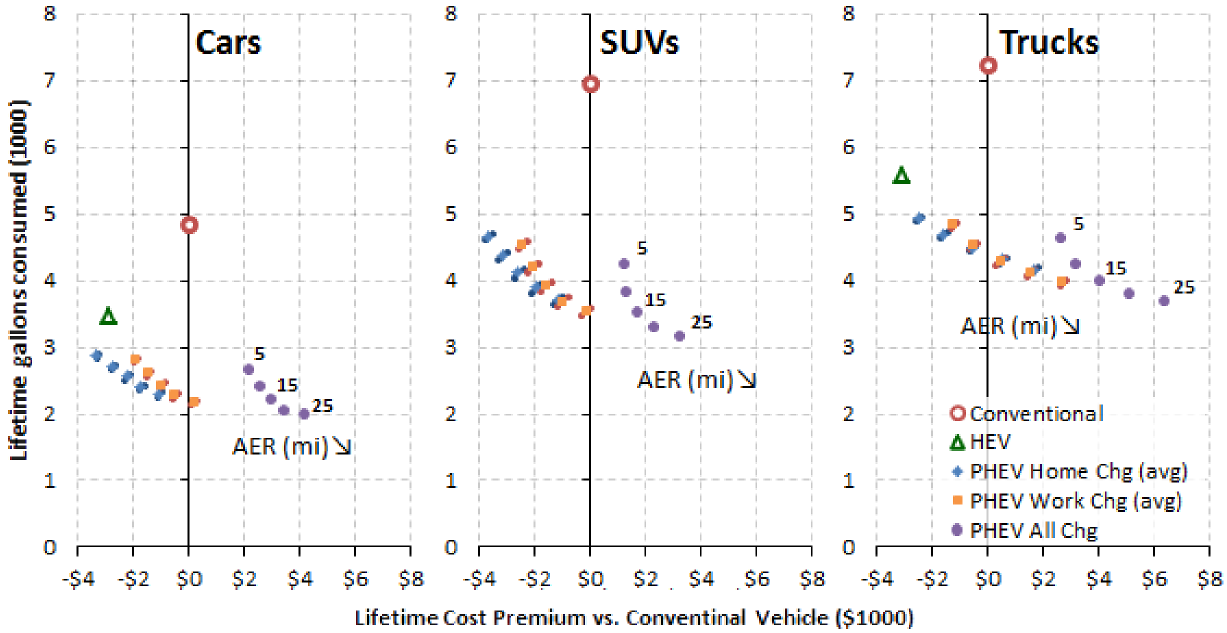

Figure 5S.16 – Battery replacement in year 8 assuming all increase in cost above HEV is attributed to battery cost

5.10.3.9 Vehicle Efficiency

Using GREET 2010 efficiency numbers reduces the efficiency of the CV being compared and actually improves the lifetime cost savings of PHEV cases (Figure 5S.17). The more efficient CVs in the GREET 2020 case result in the opposite effect (Figure 5S.18). Neither of these cases changes vehicle costs to match vehicle efficiencies.

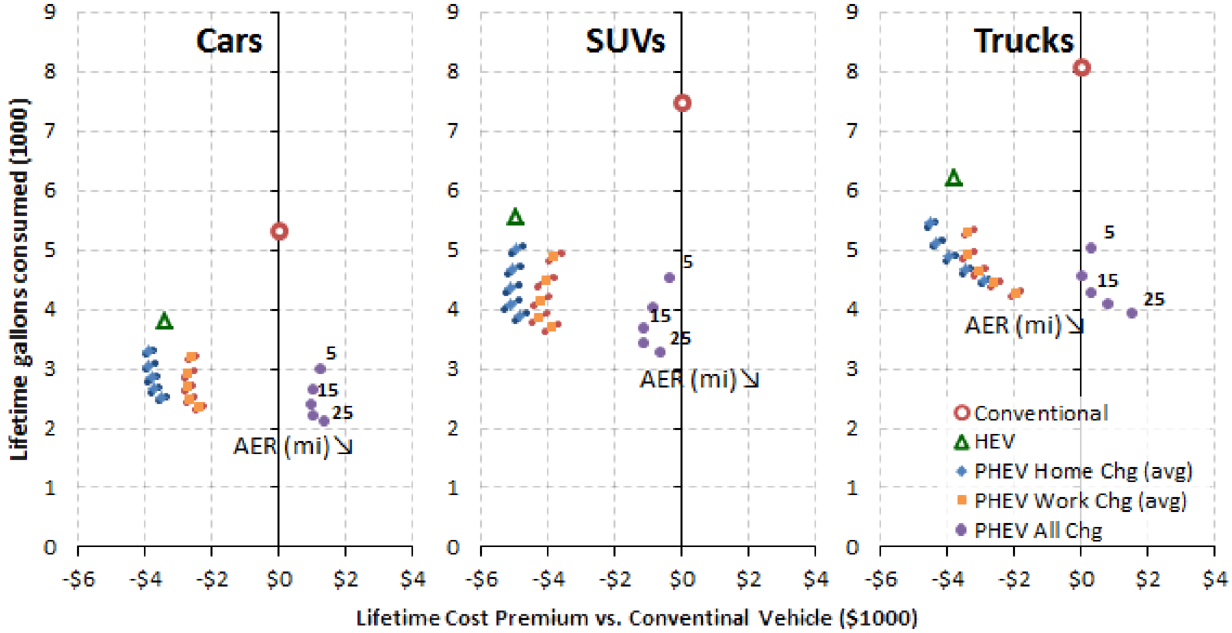

Figure 5S.17 – Vehicle efficiency using GREET 2010 instead of 2015

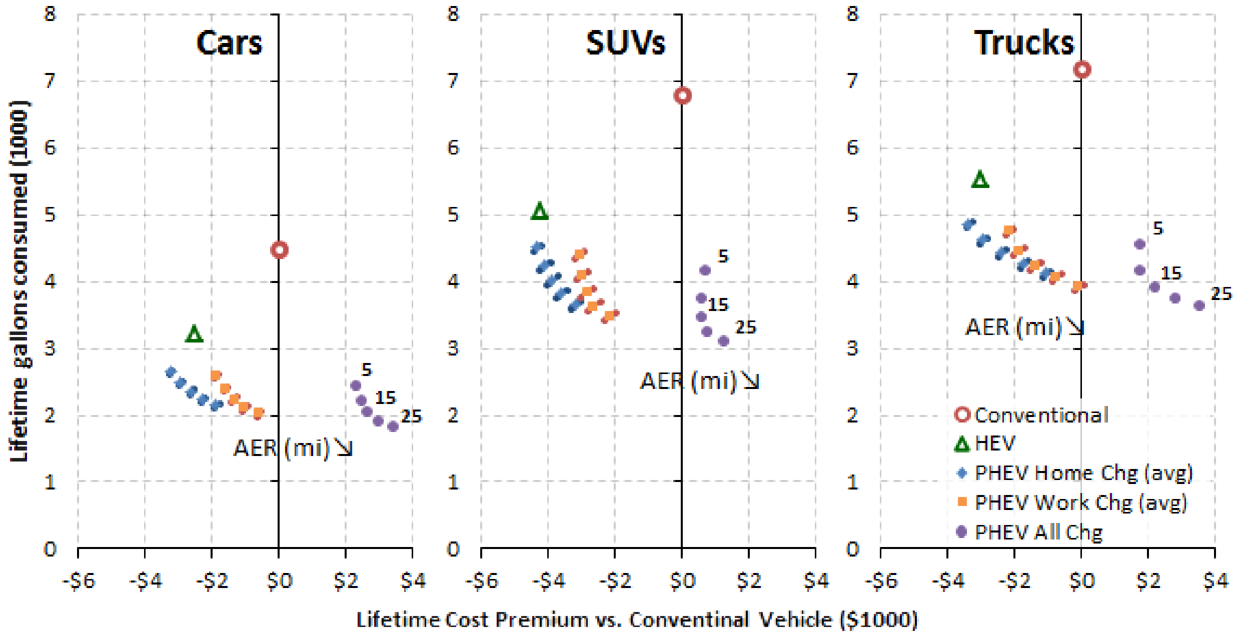

Figure 5S.18 – Vehicle efficiency using GREET 2020 instead of 2015

5.10.3.10 Charge Rate

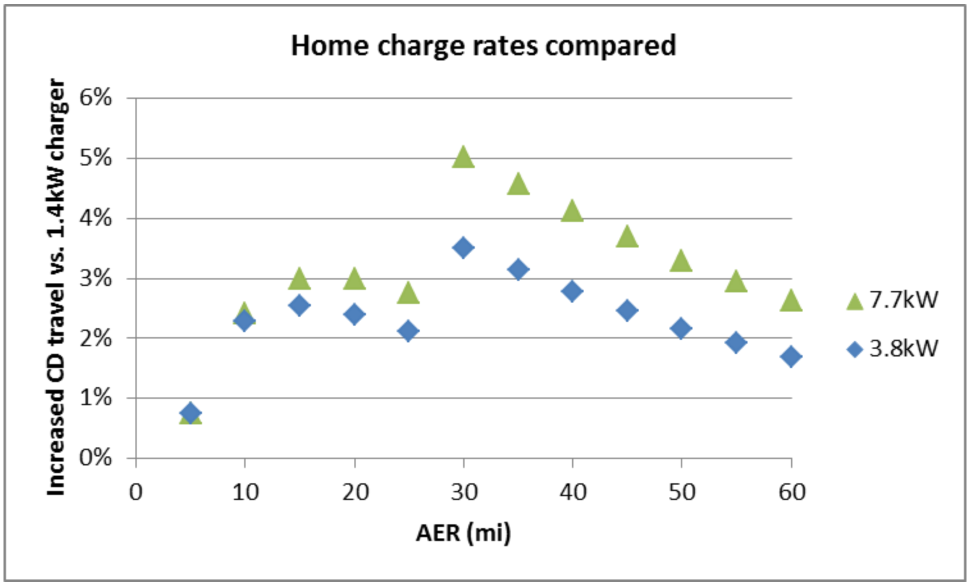

Figure 5S.19 – Home all stops charging rates compared

Increasing the charge rate at home results in only modest gains for PHEVs with small AERs (Figure 5S.19). A large part of this is because with a 30 minute minimum charge time a PHEV with AER 5 can usually charge the battery up completely. As AER increases the difference in charge rate becomes more apparent because it takes longer to charge a large depleted pack than a small depleted pack. As pack size continues to increase though there is a good chance that the battery will not be depleted during interim charges in the day. This can be seen by the slow decrease in the difference between 7.7 and 3.8kW rates. The largest increase in miles travelled in CD mode occurs at AER of 15 and is less than 3%.

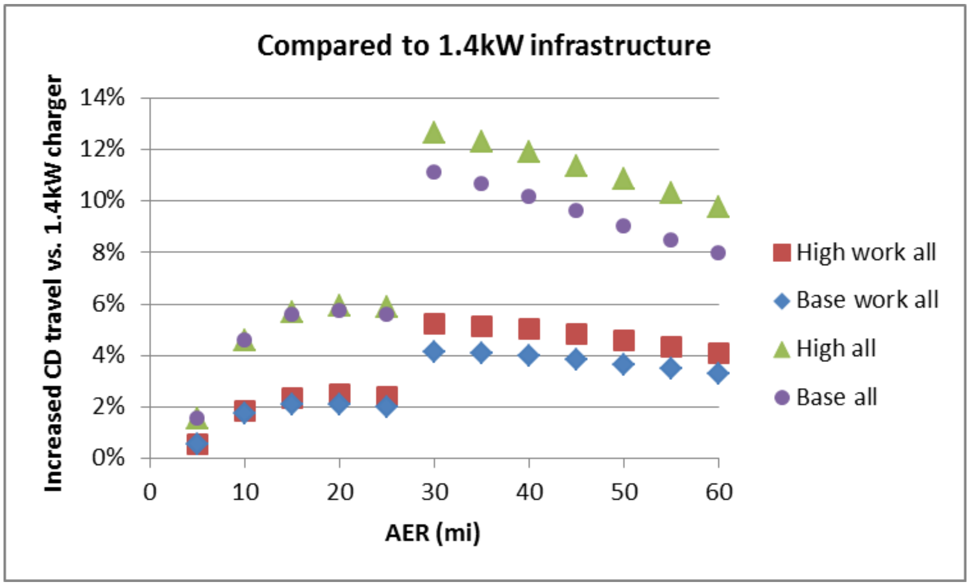

Figure 5S.20 – Illustration of charge rate effectiveness at increasing CD mode travel in a given charging strategy. High refers to 38kW charging stations away from home and 7.7kW charging at home. Base refers to 7.7kW charging stations away from home and 1.4kW charging at home. Chart compares the increase from charge rates above 1.4kW.

This chart (Figure 5S.20) compares the increase in miles travelled in CD mode when charge rates are increased from 1.4 kW in various charging scenarios. For example the Base all case refers to charging at 7.7kW every stop of greater than 30 minutes when away from home and 1.4kW when at home, the increase refers to the alternative of charging at a 1.4kW rate away from home and at home. All stops charging shows a greater increase than work charging (around 6% for AER range 5-25). This makes sense because vehicles are usually parked for longer periods at work so the charge rate is not as important. If PHEVs utilize electricity faster in CD mode charge rates will likely be more important. This explains why serial PHEVs gain far more benefit from charge points. If the small AER hybrids behaved more like serial hybrids they would likewise see increases greater than 10%. Work charging for AERs between 5 and 25 sees less than a 3% increase in CD miles. This chart shows that high rate charging (38kW vs. 7.7kW for base case charge points away from home) does not offer much benefit for small AER PHEVs. The vehicles would also be unlikely to take advantage of such high charging rates without damaging their batteries. As the AER increases the difference between high rate and base case charging hold fairly steady in the all stops charging scenarios, but in work charging they converge. Both all stops and work charging show decreasing benefit from the interim charges as AER increases and more vehicles can complete their travel with only one charge.

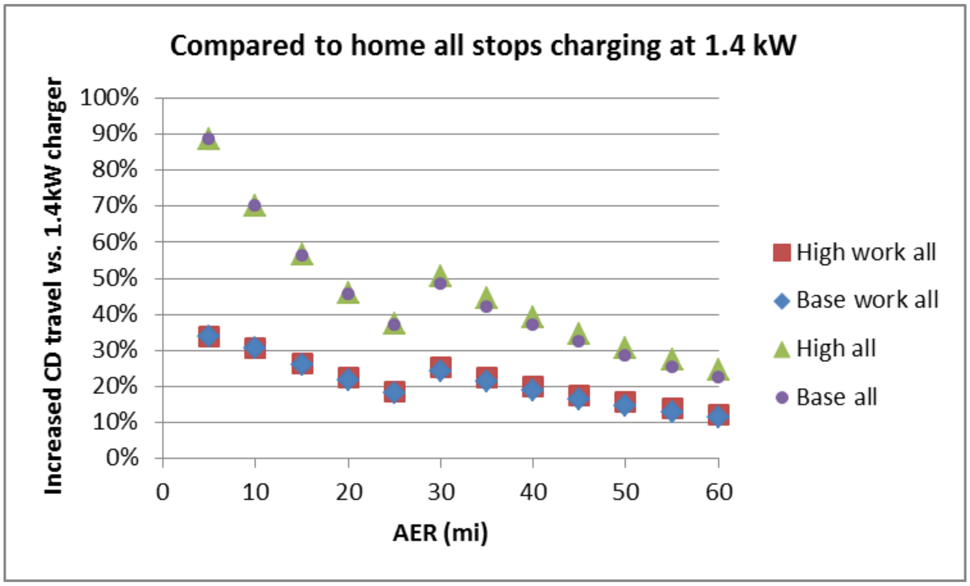

Figure 5S.21 – Comparison of charge rates across charging strategies

As expected from the results in the main paper all stops charging increases travel in CD mode significantly (Figure 5S.21). Increasing charge rates to 38kW from 7.7kW offers only marginal benefit to small AER PHEVs which likely cannot use such high charge rates in any case. These results suggest that the base case using 7.7kW chargers while away from home and 1.4kW chargers at home captures most of the benefit of charging throughout the day. A 1.4kW rate can be accomplished by any outlet in an owner's garage and PHEVs come with a cord to utilize such an outlet. Installing a charge point in the home is likely an unnecessary and currently costly decision. The reason that a 7.7kW rate was chosen away from home for the base case is that the infrastructure costs are driven by installation and equipment costs. If an owner can charge for free in a regular outlet then it is obviously beneficial to them, but if a charge point is installed that takes payment and controls electricity flow the marginal cost to install a 7.7kW instead of 1.4kW charger is likely to be quite small. Also a 3% increase in CD miles compared to the home work all charging strategy is bigger than a 3% increase in the home all stops charging strategy. Values for low and high charge rates are shown in Figure 5S.22 and Figure 5S.23. The cost differential in charge rates results in changes to slope.

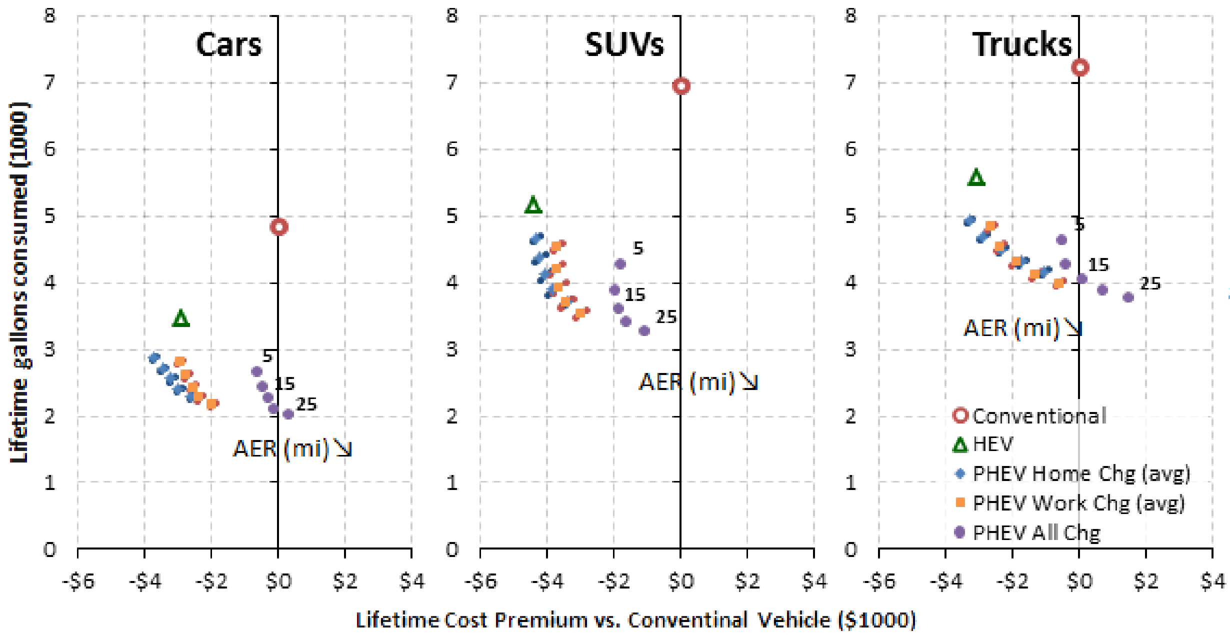

Figure 5S.22– Low charge rates (1.4kW) everywhere.

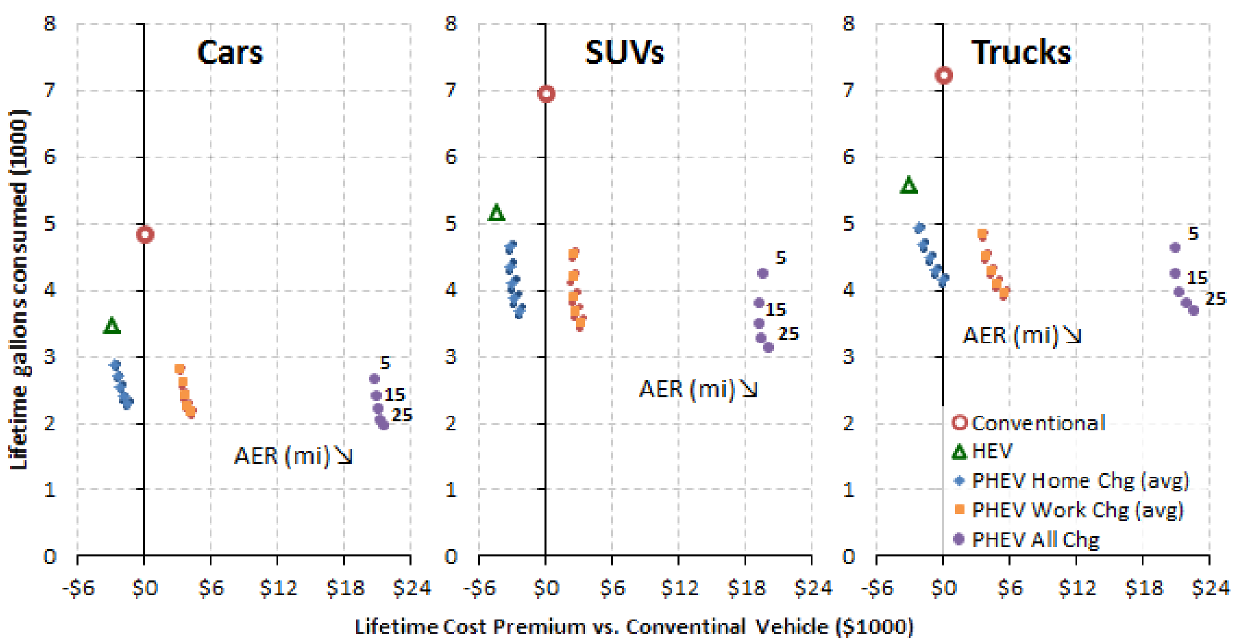

Figure 5S.23 – High charge rates (38kW away from home and 7.7kW at home)

5.10.3.11 Vehicle Loan and Down Payment

This section is based on the consumer behavior case because it involves a loan. Purchasing without a loan decreases the value of all points (Figure 5S.24). Paying for the entire vehicle on loan increases the value of all points since the discount rate is higher than loan rate in base case

(Figure 5S.25).

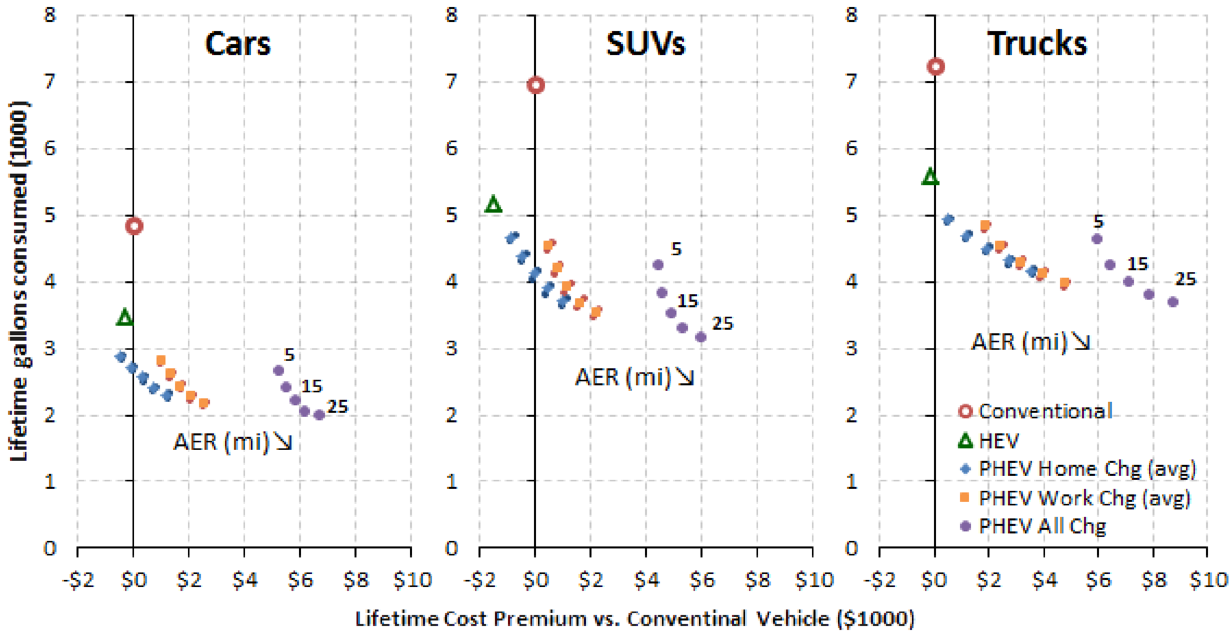

Figure 5S.24 – Full payment (100% down payment or no loan) instead of a five year loan

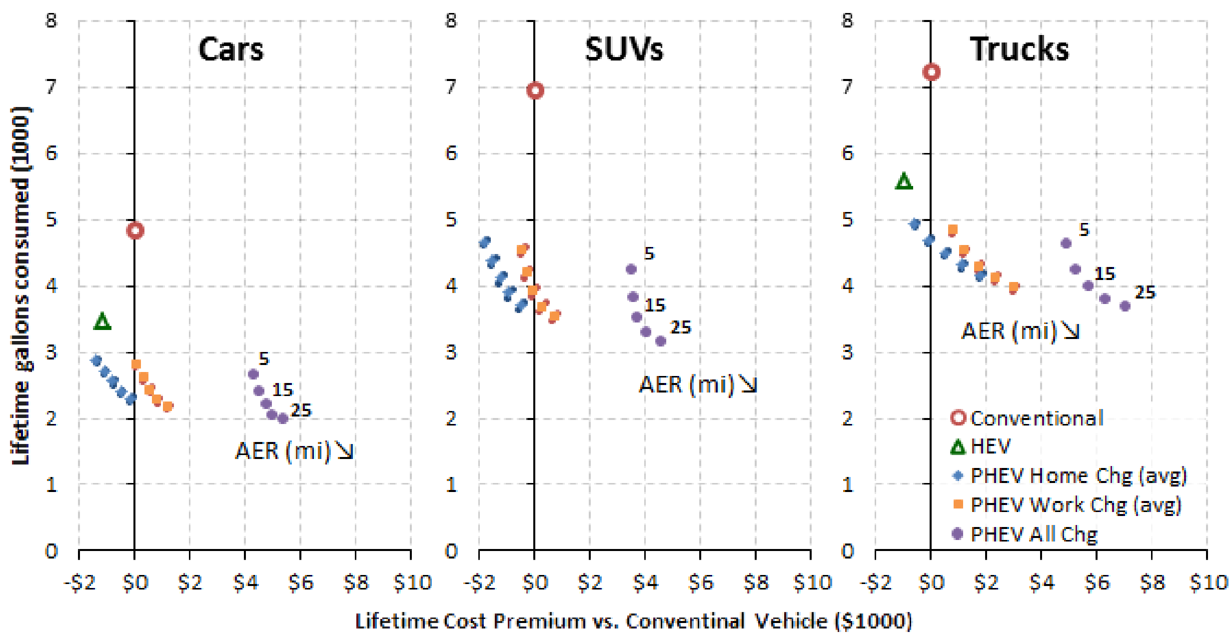

Figure 5S.25 – Zero down payment instead of 31% down payment as in base case.

5.10.4 Vehicle Aging

As vehicles age the probability that a given vehicle is driven on a given day declines. The NHTS data was analyzed to find the probability of a vehicle being driven on a given day. A binomial distribution was used to model the likelihood of a vehicle being driven and one standard deviation is shown on charts below (Figure 5S.26, Figure 5S.27). While consecutive years show overlap there is a definite trend toward declining chances of a vehicle being driven as it ages. The entire dataset was analyzed and weekend and weekday values of the probability of being driven were compared. The probability that the differences observed on weekends and weekdays were due to random chance was too small to report.

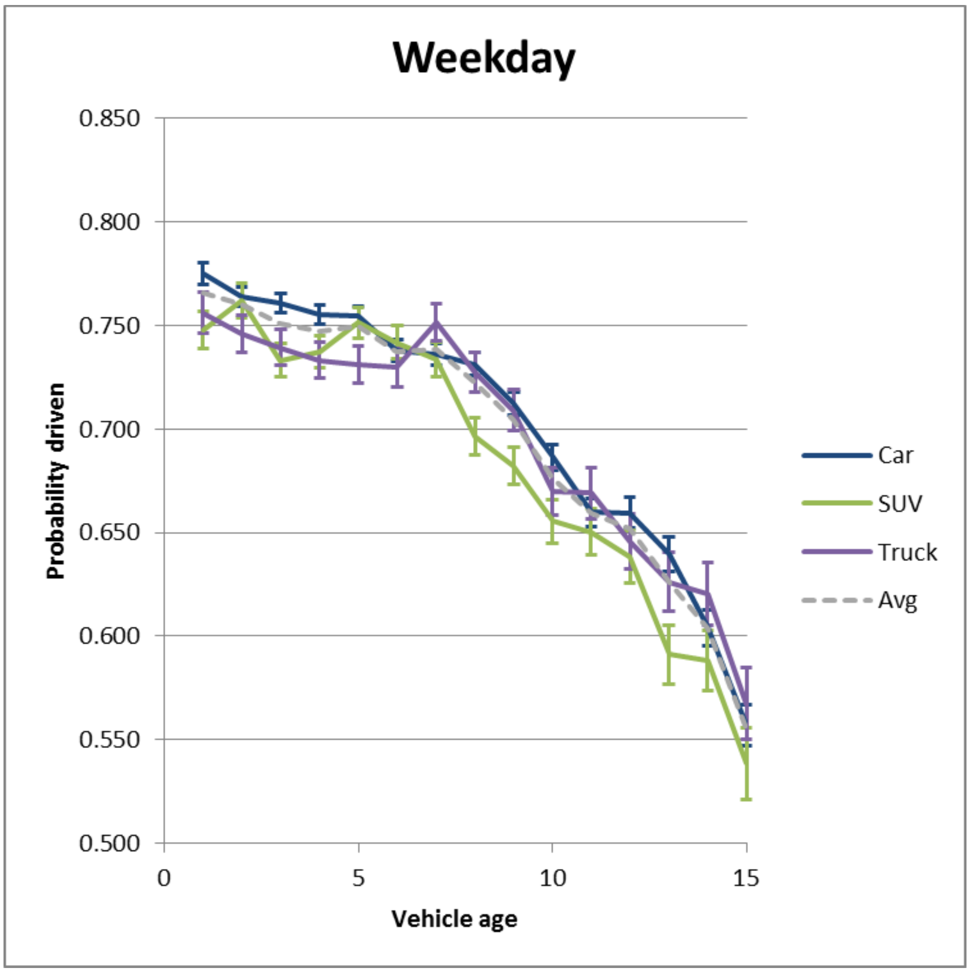

Figure 5S.26 – Likelihood of vehicle being driven on a given weekday versus vehicle age . Standard deviation shown in error bars is taken form a binomial distribution of weekday data

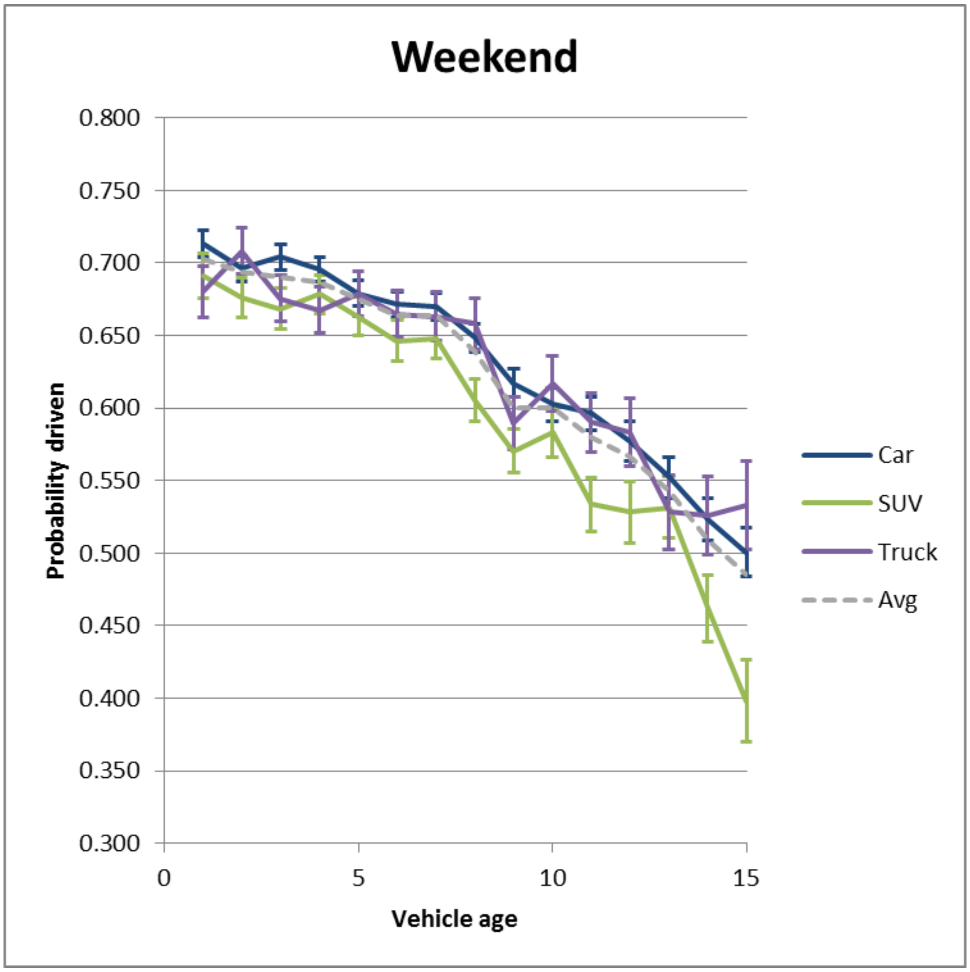

Figure 5S.27 – Likelihood of vehicle being driven on a given weekend versus vehicle age. Standard deviation shown in error bars is taken form a binomial distribution of weekend data

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1. Annual Energy Outlook 2011. US Department of Energy: Washington, DC, 2011. http://www.eia.gov/forecasts/aeo/ (accessed November 29, 2011).
2. Potential of technologies for displacing gasoline consumption by light-duty vehicles through 2045. US Department of Energy: Washington, DC, 2011. http://www.autonomie.net/publications/fuel_economy_report.html (accessed November 29, 2011).
3. The Greenhouse Gasses, Regulated Emissions, and Energy Use in Transportation (GREET) Model, version1.8d. US Department of Energy: Washington, DC, 2010
4. 2010. *2011 Chevrolet Volt Limited Warranty and Owner Assistance Information Book*. General Motors. http://www.chevrolet.com/assets/pdf/owners/manuals/2011/2011_chevrolet_volt_warranty.pdf.
5. 2010. *2011 Leaf Warranty Information Booklet*. Nissan. http://www.mynissanleaf.com/wiki/images/c/c3/2011-leaf-warranty-booklet.pdf.
6. Toyota Prius Plug-in Warranty Coverages. http://www.toyota.com/prius-plug-in/warranty.html.

Chapter 6 Conclusions

This research investigated ways to increase the benefits of PHEVs and examine some potential pitfalls. Partially electrifying the transportation sector has the potential to greatly reduce petroleum use and shift much of the energy needs of the light duty fleet to the electricity sector. Electrifying the transportation sector enables previously infeasible emissions control strategies because power plants are stationary. There are still some likely negatives of adoption PHEVs besides their initial cost. For example, SO_2 emissions are likely to increase without regulatory action. Battery technology is far from the energy and power density of internal combustion engines, even given the enhanced efficiency of an electrified drivetrain [1]. However, batteries are continuing to close the gap and do not need to match the ICE when a PHEV architecture is being considered. Much like the pursuit of solar cells with greater efficiency we may already be at a point where cost reductions should be pursued instead of increases in energy and power density, or battery lifetime. Already commercial vehicles are being sold using a PHEV architecture and many more are set to be introduced. Hopefully by examining some of these issues ahead of time emissions can be further reduced and any subsidies encouraging the use of PHEVs can be shaped to more efficiently allocate funding toward goals that are beneficial to society.

Currently available cells have promising capacity fade performance and allow for a broad state-of-charge (SOC) swing. The current federal subsidy is designed in a way that incentivizes picking cells with lower cost per rated capacity and penalizes cells that have higher cost per rated capacity even if the cost per usable capacity is lower. Manufacturers might also choose to limit the SOC swing to increase the longevity of their battery (even if they degrade in response to energy throughput decreasing the SOC swing would increase the battery lifetime if a vehicle switches to CS mode once depleted). This chapter suggests that a subsidy based on usable pack energy would make far more sense than one based on rated capacity. It would remove an incentive to pick a battery that does not necessarily align with societal benefits associated with reduced gasoline consumption. It would also encourage manufacturers to increase the SOC swing allowed.

The benefits from energy arbitrage are unlikely to significantly change the economics of PHEV adoption. It is extremely unlikely for vehicle owners to participate in the market on their own. There are benefits however, and an aggregator might participate in the market. Instead of using vehicles to provide energy to the grid using them as dispatchable load likely makes more sense in the near term. This still captures some of the benefits of energy arbitrage and would result in increased generation utilization. It is also possible that it could help with integration of renewable resources.

Use phase emissions of PHEVs are sensitive to charge time and net emissions could double if a vehicle were charged at different times. In some areas it would make sense to charge during periods of low demand because the emissions and cost would both be reduced. Other areas face a more difficult decision and will face a tradeoff in costs and emissions. Information about generation resources should be used in concert with pricing data to find the optimal charging strategy in individual RTOs. A carbon price on electricity alone would be ineffective at reducing vehicle related emissions. It seems that PHEVs will increase SO_2 emissions unless there is regulatory action, but CO_2 and NO_X emissions are both likely to decline in the use phase compared to conventional vehicles (CVs). The natural gas, or gas and wind combined charging cases show that the total emissions decrease for CO_2 and NO_X is roughly 20-30% even with very clean generation and 5-20% with existing generation assets. Emissions of SO_2 are very sensitive to regulations. In 2011 the electricity sector emitted 4.7 million tonnes of SO_2 far below the cap of 8.6 million tonnes [2]. These emissions will increase significantly if electrified vehicles replace conventional vehicles and there are no regulatory changes. The court delayed cross-state air pollution rule would force significant reductions in SO_2 emissions and mean that if states were operating at the emissions cap that any electricity used to displace gasoline would actually result in net decreases to SO_2 emissions.

When attempting to encourage the adoption of PHEVs subsidizing increased all-electric-range for vehicles is more cost effective than spending money on charging infrastructure. The current subsidy appears to be misaligned with societal benefits. Because it subsidizes rated battery size it could lead to distortions in the market. It encourages automakers to pick batteries with a high rated capacity to cost ratio and does not encourage a wide SOC swing. This means automakers are encouraged to design vehicles with large batteries and low SOC swing to allow for battery degradation. If the subsidy targets large batteries under the premise that such PHEVs will lead to greater technological learning then the subsidy could target actual all-electric range rated on a low demand drive cycle instead and achieve the same sort of goals. It also avoids the possibility of subsidizing a vehicle that is inefficient and happens to have a battery with a higher rated or even usable energy capacity. If the subsidy was designed on the premise that larger batteries means more petroleum is displaced then this work shows that the subsidy increases with battery size too quickly or starts too low.

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1. 2011. *Electric Vehicles*. Washington, DC: US Environmental Protection Agency. http://www.fueleconomy.gov/feg/evtech.shtml.
2. 2011. *National Emissions Inventory (NEI) Air Pollutant Emissions Trends Data*. Washington, DC: US Environmental Protection Agency. http://www.epa.gov/ttn/chief/trends/.