NATIONAL ENERGY TECHNOLOGY LABORATORY

Vehicle to Grid Systems

November 6, 2009

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FINAL REPORT

November 6, 2009

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List of Acronyms and Abbreviations

kWh – kilowatt hours

PHEV – Plug-in hybrid electric vehicle

V2G – vehicle to grid energy transfer

V2G Deg – Coefficient relating battery degradation to battery use

LMP – locational marginal pricing

LMP_{BUY} – Buying price of electricity

LMP_{SELL} –Selling price of electricity

BOS – Boston, Massachusetts

ROC – Rochester, New York

PHL – Philadelphia, PA

NHTS – National Household Transportation Survey

RTP – Real Time Price

TND or T&D – Transmission and Distribution Charge

RTE – Round trip efficiency

RTO – Regional Transmission Organization

ISO – Independent System Operator

NYISO – New York Independent System Operator

ISO-NE – New England Independent System Operator

PJM - Pennsylvania New Jersey Maryland Interconnection LLC

DCH_{eff} – Discharge efficiency

CH_{eff} – Charge efficiency

BEV – Battery electric vehicle

UDDS – Urban Dynamometer Driving Schedule

m – mass

a – acceleration

ρ – density of air

v – vehicle velocity

C_d – coefficient of drag

A – frontal area of vehicle

C_{rr} – dimensionless coefficient of rolling resistance

g – acceleration of gravity

Δt – time step in seconds

V – Volt

A – Amp

DoD – Depth of Discharge

CCS – Carbon Capture and Sequestration

SRMC – Short Run Marginal Cost

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1. EXECUTIVE SUMMARY

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 LiFePO4/Graphite cells tested under combined driving and off-vehicle electricity utilization. For a 16 kWh (57.6 MJ) vehicle battery pack, the maximum annual profit with perfect market information and no battery degradation cost ranged from ~$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 $5,000 for a 16 kWh 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.

Current generation facilities have the potential to support electrification of personal transportation in the two RTO/ISOs examined, PJM and NYISO, if some sort of smart charging method to minimize the negative effects of adding load in an uncontrolled manner is employed. The increase in emissions associated with smart charging (as compared to uncontrolled charging) depends on the current generation mix and utilization rates. If coal generators are used to provide baseload generation during the night before electric vehicles are added to the load, adding vehicles is likely to result in natural gas or other facilities powering on to provide for charging load.

2. 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]. Benefits discussed in the literature 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 greatly vary 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]. V2G relies on dual purpose batteries where the capital cost of the battery is not assigned to the off-vehicle electricity use because the battery was purchased for driving. If load shifting or peak shaving is not economical the only wasted expenditures are the small cost of the controllers and converters, some of which will likely be installed in any case to enable off-peak charging. 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].

3. CHARACTERIZING LITHIUM BATTERIES FOR GRID ENERGY STORAGE IN PHEVS

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 in this report, 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.

3.1 TESTING OF USEABLE CAPACITY VS. BATTERY LIFETIME

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[7]. While these characteristics are well understood for the $LiC(Ni)O_2$/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 [8]. 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 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.

3.1.1 National Household Travel Survey (NHTS) Data

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 [9]. 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" [10]. 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 1. Because the three cities had similar median trips, the data from all three cities were combined to make a single trip profile (figure 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 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 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).

3.1.2 Urban Driving Dynamometer Schedule (UDDS) and Driving Energy Use Model

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 [11]. 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).

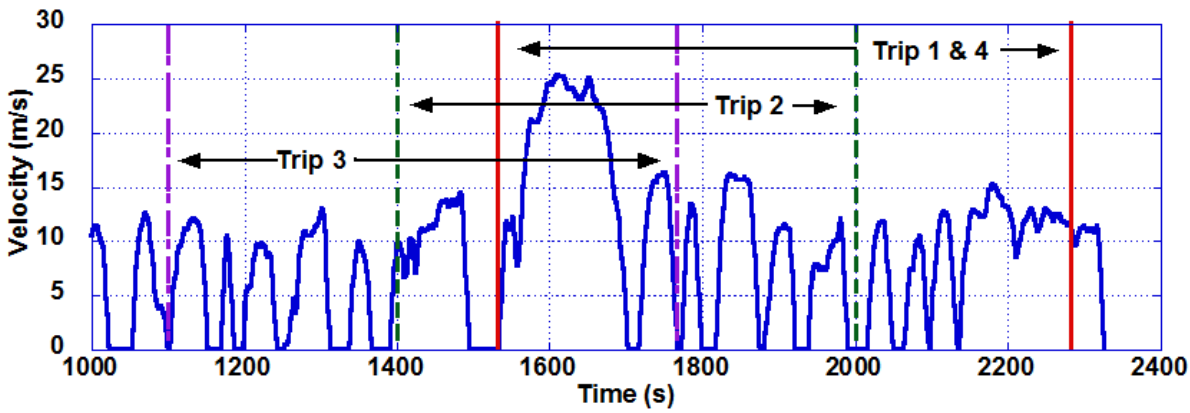

Figure 2 - Portions of urban dynamometer driving schedule (UDDS) were chosen to closely match driving profile shown in figure 1 in terms of duration and average velocity.

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 [12]. 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% [13]. The battery pack energy capacity was assumed to be 16 kWh (as in Chevrolet's proposed Volt) [14]. 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 [15]. 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.

Table 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	$F_{ar} = ½ \rho v^2 C_d A$	$½*1.23 \frac{kg}{m^3} * \left[10 \frac{m}{s}\right]^2 0.28*2.67m^2=45.8N$
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.

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

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

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 [16].

3.1.3 Cell Test Cycle

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 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 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

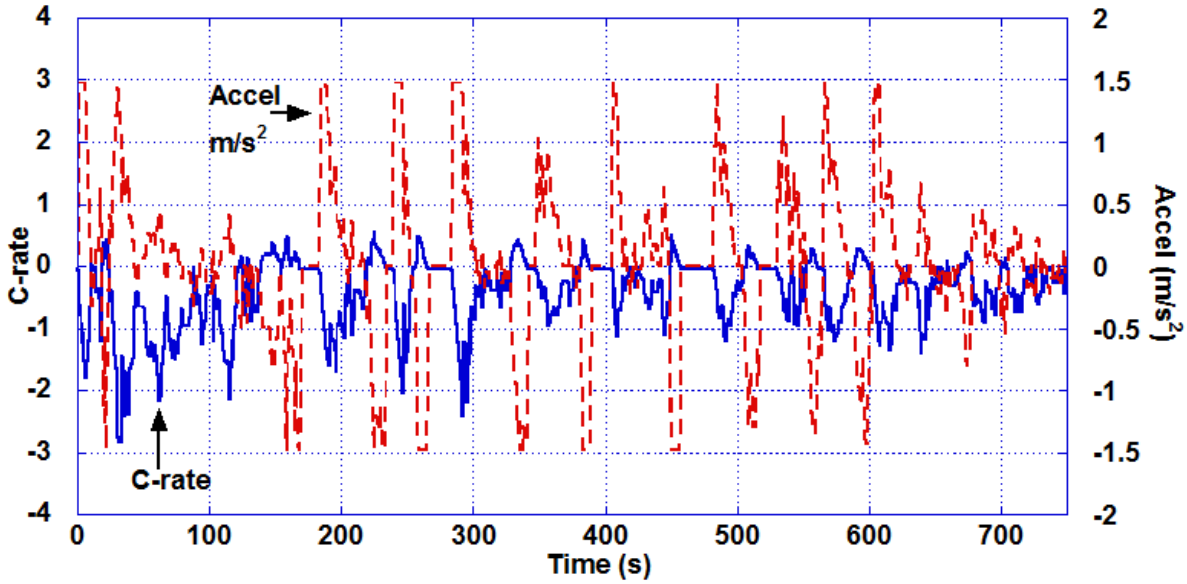

Figure 3 - Example of relationship between acceleration (red) and power required (in C-rate, blue) for trips 1 and 4. A negative C-rate corresponds to discharge rate from pack. Deceleration can lead to regenerative braking if it is significant - in this case, around 7% of the energy is regained via regenerative braking.

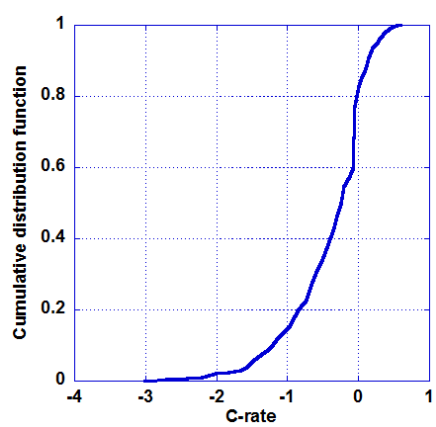

Figure 4 - Cumulative distribution function of power requirements for daily driving (all 4 trips). Given large pack size the current rates are low most of the time. The near-vertical portion is a result of times when velocity and acceleration are low and the base load to run accessories dominates the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

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. [17] A thermocouple was connected to one cell and temperature was monitored though 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 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 3.

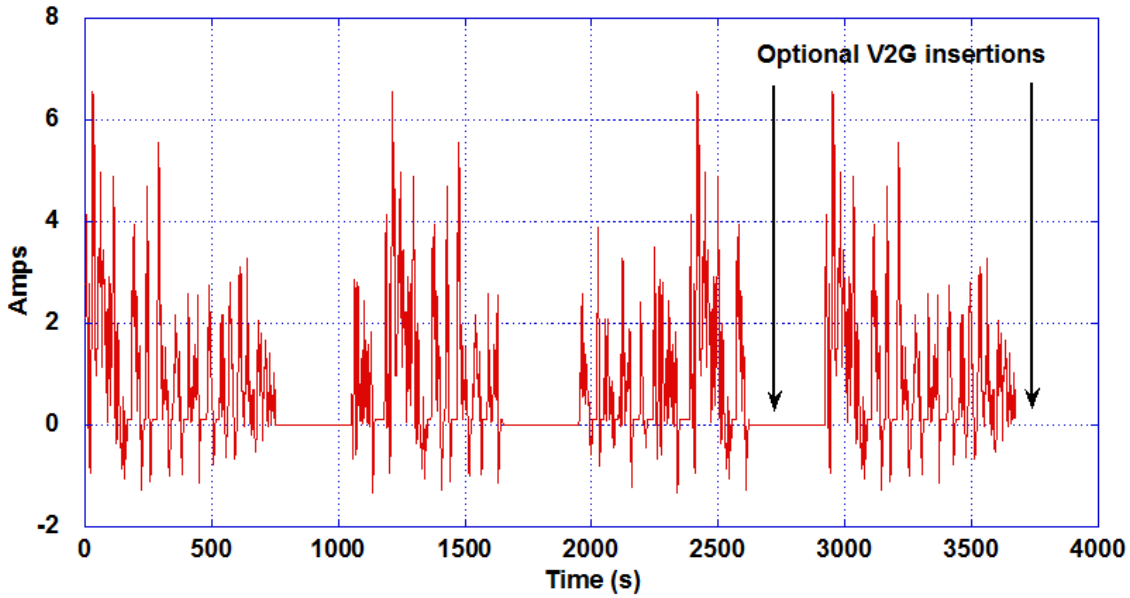

Figure 5 - Test current profile used to simulate driving day for cells showing all trips. The times after trips 3 and 4 when V2G discharge was simulated are indicated.

Table 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.

3.1.4 Cell Testing Results and Discussion

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 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 6c). It is possible 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.

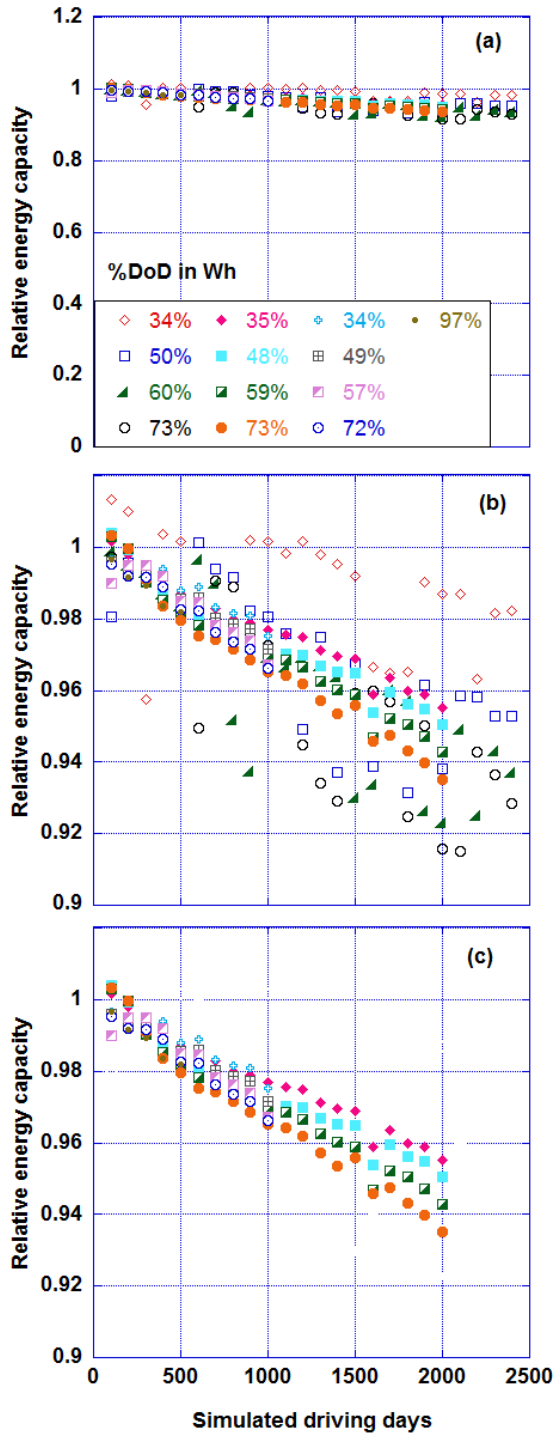

Figure 6 - Degradation of cells versus driving days simulated (a) full range, (b) same information zoomed, (c) with highly variable cells from lot 1 dropped.

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 7), where DoD is a key variable [18]. 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.

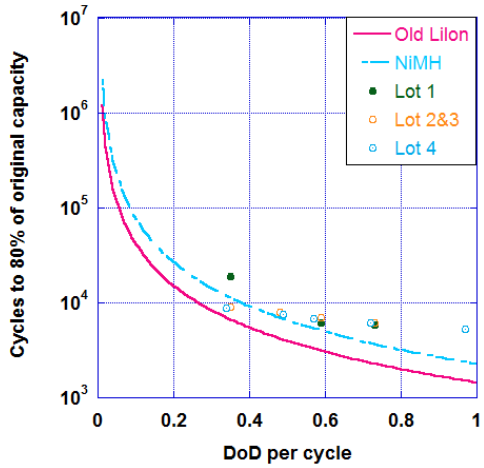

Figure 7 - Laboratory results overlaid onto VARTA curves illustrating more linear response in cycle life as a function of depth of discharge for the cells tested.

Figure 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 8b).

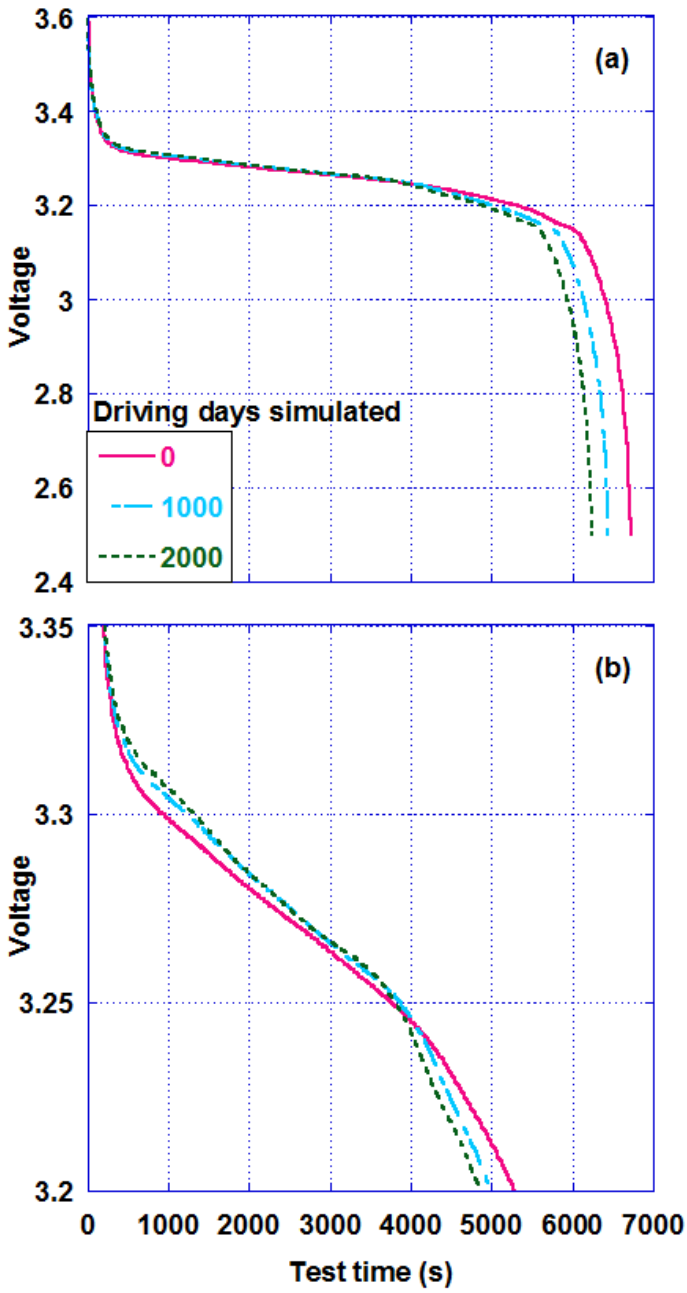

Figure 8 - Voltage profiles of a cell that reached an ultimate DoD value of 73% each driving day. The initial, 1000th and 2000th baseline discharge curves are shown.

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 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 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 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.

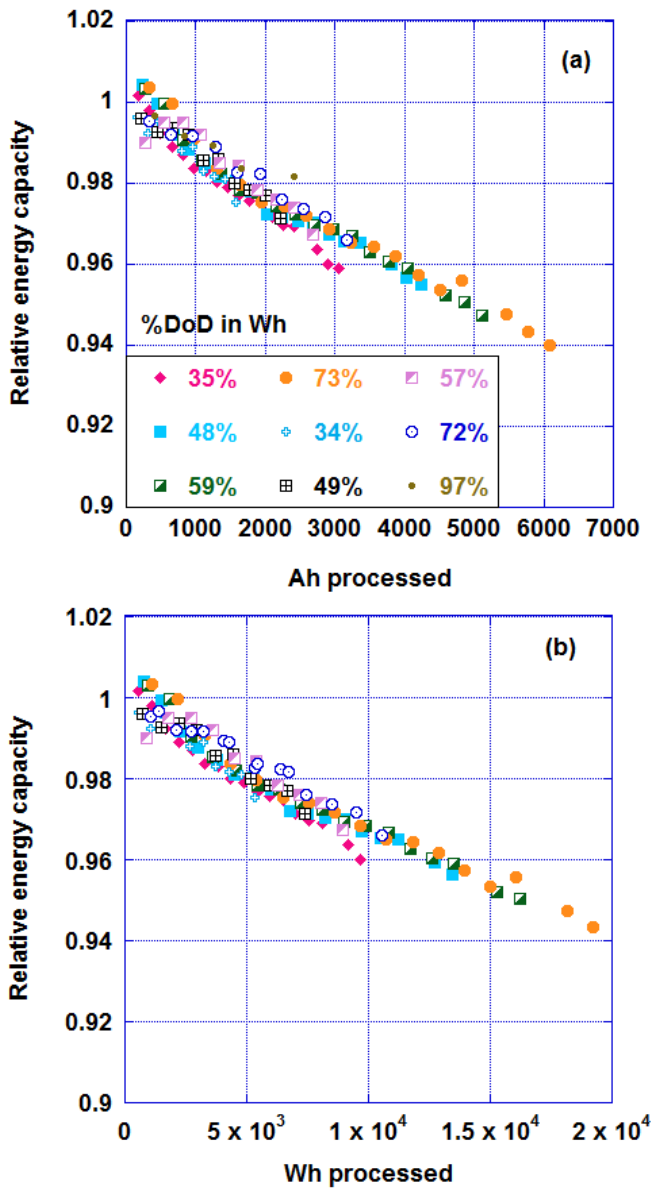

Figure 9 - Degradation as a function of (a) capacity (Ah) processed by cell or (b) energy (Wh) processed by cell for all but lot 1 cells. Both appear linearly related, as expected given the nominally linear discharge profile of the LiFePO4/graphite system.

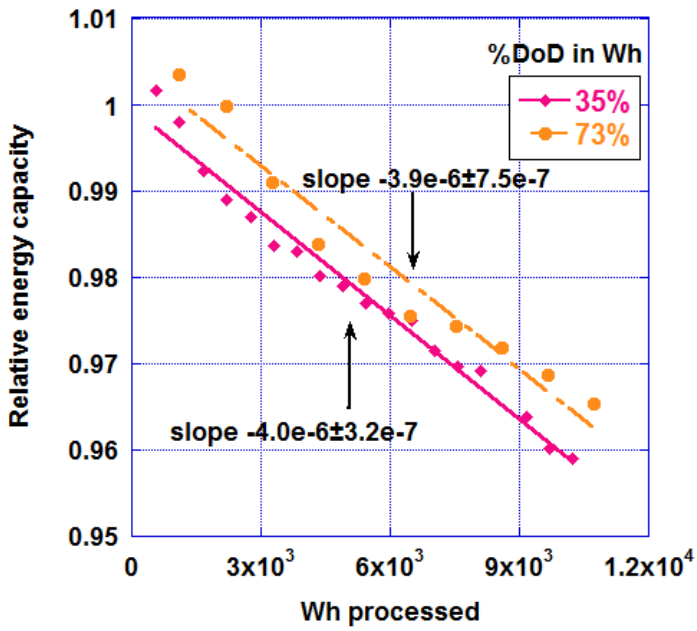

Figure 10 - Capacity degradation as a function of energy processed for two cells tested with contrasting end-of-cycle depth of discharge values (35% and 73% DoD). The slight observed difference would indicate less degradation for higher DoD/cycle cell, however the 95% confidence interval of slopes overlaps for these fits, so they are not statistically discernable.

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 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 [19].

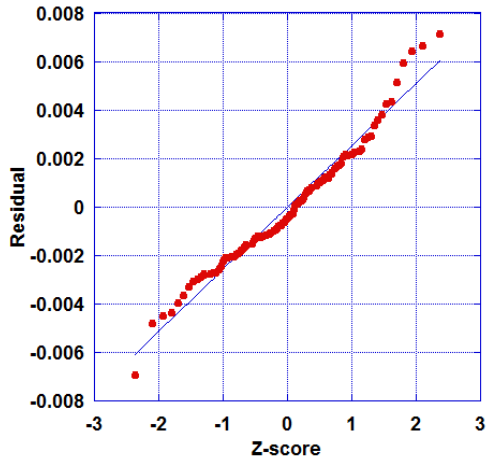

Figure 11 - Q-Q plot shows errors are normally distributed for multiple linear regression. The line represents expected values for a normal distribution.

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 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 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 [20].

Table 4

Example 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%	

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.

3.2 ECONOMIC MODELS OF SALES STRATEGIES IN THREE ISO/RTOs

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 was obtained for three different 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 [21] are available to construct driving profiles in each of these metropolitan areas. 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 profits 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 [22].

We model energy arbitrage by owners to offset their own electricity consumption during high priced periods. According to the EIA average residential customers consume 936 kWh/month or just over 30kWh/day, thus a 16 kWh battery has the potential to provide just over half a day's energy needs[23]. 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.

3.2.1 Sales Strategy Models

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 [11]). 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.

3.2.2 Private Benefits of Grid Sales

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 or TND) cost of 7 ¢/kWh [24] 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 to be 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.

$$\text{Proft}(\$) = \left(\left(\text{LMP}_{\text{SELL}} + \text{TND}\right) * \text{DCH}_{\text{eff}} - \frac{\left(\text{LMP}_{\text{BUY}} + \text{TND}\right)}{\text{CH}_{\text{eff}}} \right) * \text{kWh}_{\text{Transacted}} - \text{Degradation Cost} \tag{3}$$

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.

Degradation cost was calculated based on the multiple linear regression based on laboratory data from cycling $LiFePO_4$ cells described in [25]. The cost associated with using energy from the battery pack is given in equation 4. Note that the V2G degradation coefficient is negative.

$$\text{Degradation Cost} = \frac{\text{Replacement Cost} * \text{V2G Deg}}{(0.8 - 1)} * \text{Percent of Battery Used} \tag{4}$$

Estimates of the current price of the Chevy Volt's battery pack range from $5,000 to $11,000 [26]. 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 predict a degradation cost of 4.2¢/kWh served.

3.2.3 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 5). The maximum annual profit ($118) occurred in the Philadelphia area in 2008. A vehicle owner in Boston, even with perfect information, would have see profits of $12 to $48, depending on the year.

Table 5

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	$12	252
2005	$110	2,458	$71	1,157	$19	1,119
2006	$58	1,471	$46	1,037	$48	667
2007	$95	2,223	$69	1,210	$39	625
2008	$118	2,264	$107	1,650	$15	1,128

The lower bound of profit estimated without perfect information resulted in profits that reached their maximum in Philadelphia in 2005 (table 6). 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 [27]. 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 6

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	$10	267
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

3.2.4 Sensitivity Analysis

We performed sensitivity analyses on the effect of battery pack replacement cost on profit (Figures 12 - 13). The median value and yearly maximum and minimum for the period 2003-2008 are shown for upper and lower bound scenarios.

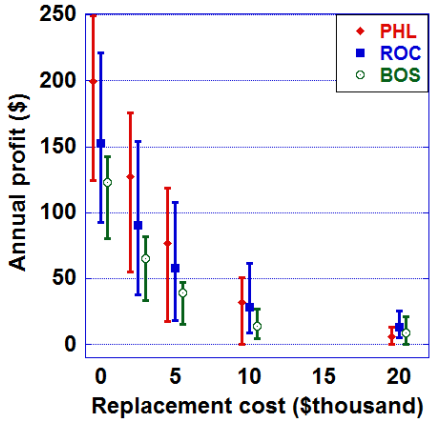

Figure 12 - V2G energy arbitrage profit sensitivity to battery pack replacement cost with perfect information in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for battery replacement costs of $0, $2,500, $5,000, $10,000, and $20,000.

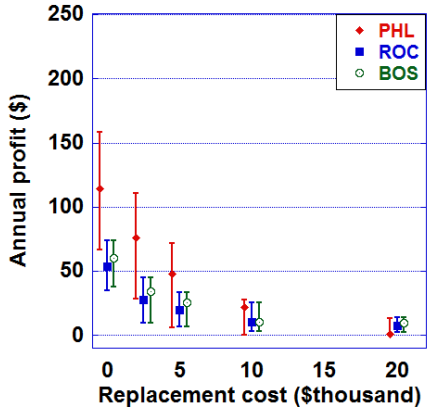

Figure 13 - V2G energy arbitrage profit sensitivity to battery pack replacement cost with 14 day backcasting method in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is 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 (figures 14-15). 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 (figures 16-17). It was similar in range of values, and in rate of change of those values, but the rate does appear slightly lower.

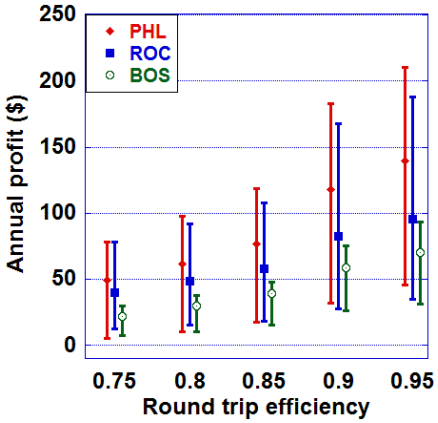

Figure 14 - V2G energy arbitrage profit sensitivity to round trip efficiency (RTE) with perfect information in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for RTE of 0.75, 0.80, 0.85, 0.90, and 0.95.

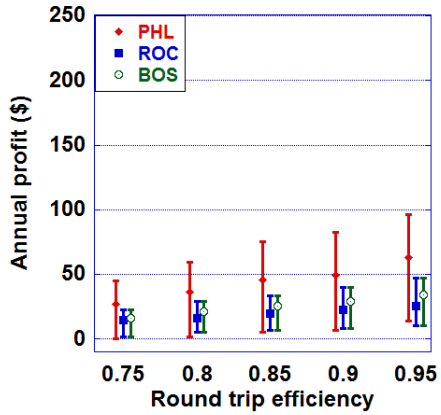

Figure 15 - V2G energy arbitrage profit sensitivity to RTE with 14 day backasting method in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for RTE of 0.75, 0.80, 0.85, 0.90, and 0.95.

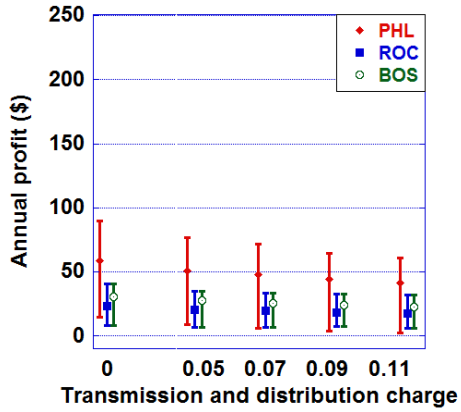

Figure 16 - V2G energy arbitrage profit sensitivity to Transmission and Distribution (T&D) charges with perfect information in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for T&D charges of 0, 0.05, 0.07, 0.09, and 0.11 ¢/kWh.

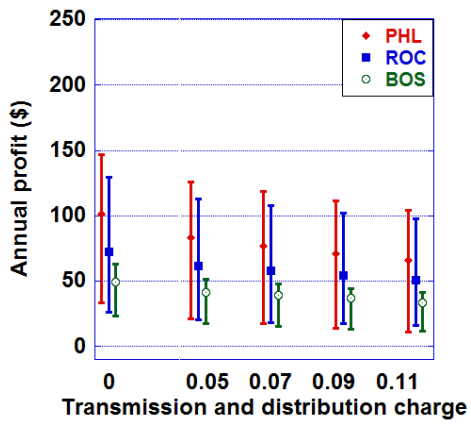

Figure 17 - V2G energy arbitrage profit sensitivity to T&D charges with 14 day backcasting method in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for T&D 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 18).

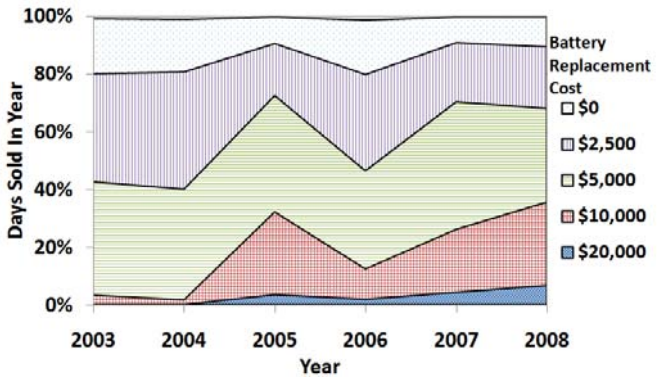

Figure 18 - Percent of days in Philadelphia area of PJM that energy arbitrage is profitable given different battery replacement costs and perfect information

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 (figures 19-20). 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).

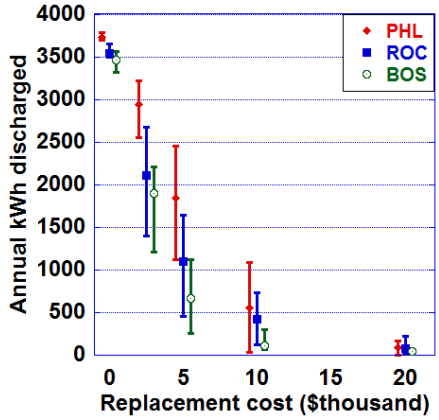

Figure 19 - V2G energy arbitrage quantity sensitivity to battery pack replacement cost with perfect information in the three cities studied. The symbol indicates the median annual kWh discharged for the years studied and the range indicates the most and least kWh discharged. The arbitrage in each city is calculated for battery replacement costs of $0, $2,500, $5,000, $10,000, and $20,000.

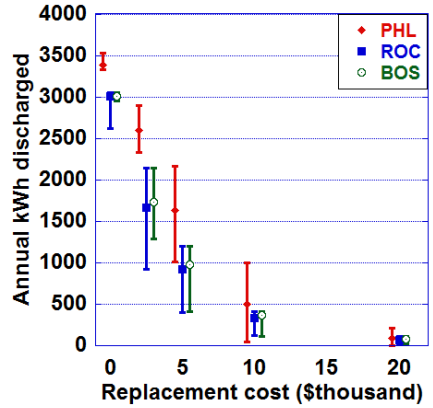

Figure 20 - V2G energy arbitrage quantity sensitivity to battery pack replacement cost with 14 day backcasting method in the three cities studied. The symbol indicates the median annual kWh discharged for the years studied and the range indicates the most and least kWh discharged. The arbitrage in each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

3.2.5 Summary

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.

Ancillary services such as frequency regulation are not discussed here because only a small number of vehicles will saturate those markets (for California, less than 200,000 vehicles for regulation and a comparable number for spinning reserve) [28]. While first movers in these markets may receive revenues much larger than the energy revenues discussed here, the number of vehicles that can benefit is typically less than 1% of the total.

4. ANALYZING THE EFFECTS OF PHEVS AND EREVS ON PJM AND NYISO GRIDS

Given the long lead-time for new generation, it is important for grid operators and planners to have an idea of changes in load patterns associated with integration of large numbers of PHEVs, EREVs, and EVs. We used publically available data on heat rates and fuel prices to create short-run marginal cost (SRMC) generation dispatch curves, and used these to help bound the effect of vehicles that will be plugged into the grid. These curves allow predictions about differences in load to be converted to estimates of differences in carbon emissions and generator energy payments.

4.1 GENERATOR DISPATCH ORDER CURVES

We created short-run marginal costs for generators and ordered the generators into generator dispatch order curves using the Emissions & Generation Resource Integrated Database (eGRID) 2007, which contains data from 2005 [29]. We combined that with regionally appropriate fuel cost and quality data from the same year [30]. A dispatch order curve was created for PJM and NYISO (figures 21-22) 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 CO_2 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 NOx seasonal shutdowns to simplify modeling.

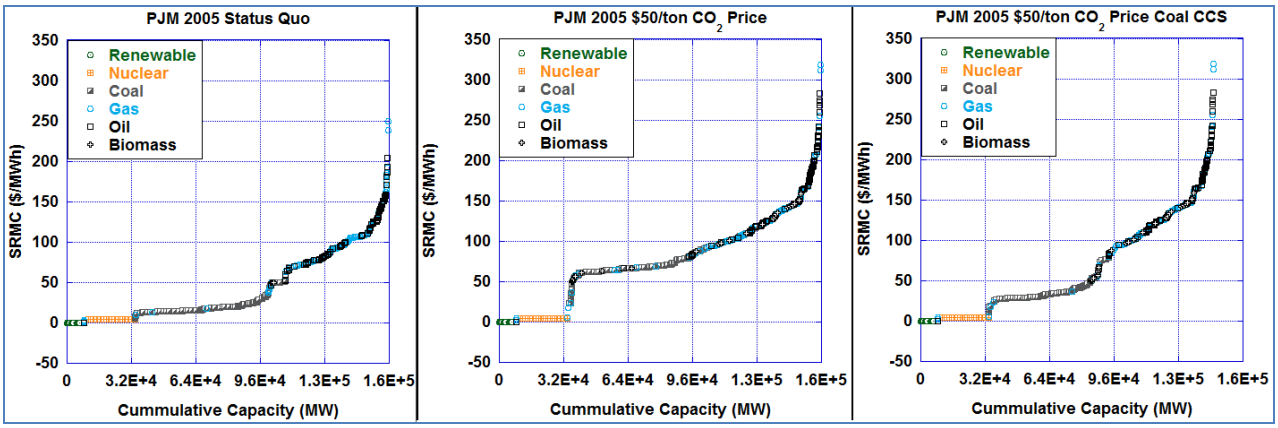

Figure 21- PJM modeled generator dispatch order curves for 2005 using eGRID data. The three dispatch curves represent the status quo, a $50/ton CO_2 price, and adding CCS to coal plants in the hypothetical CO_2 price scenario.

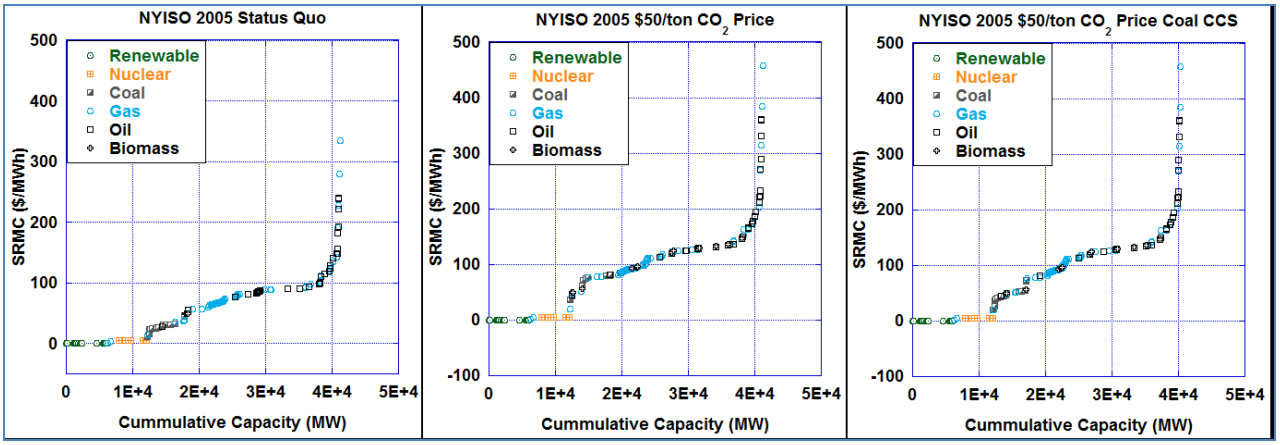

Figure 22– NYISO modeled generator dispatch order curves for 2005 using eGRID data. The three dispatch curves represent the status quo, a $50/ton CO_2 price, and adding CCS to coal plants in the hypothetical CO_2 price scenario.

The eGRID database does not appear to have CO_2 emissions consistently reported for biomass generators. Many of the generators co-fire coal or natural gas but are reported as having zero carbon emissions. It is possible that this is because there are disagreements on how to count carbon emissions from biomass, but it will affect the dispatch order in a carbon price scenario. Given the small amount of biomass generation it is not a large problem, but if the share of biomass generation increases it will be important to include carbon emissions. Other dual fuel plants were rated based on the percent of fuel of each type used in the year (according to eGRID database).

4.1.1 Dispatch Changes Due to PHEVs and EREVs

Four levels of PHEV market penetration were modeled in PJM and NYISO, to examine grid effects from the early adoption stage to a stage in which a majority of vehicles are PHEVs. We estimated the number of vehicles in PJM and NYISO by scaling the number of vehicles in

the United States by the ratio of electricity retail sales in each area to the electricity retail sales in the entire US[1]. These numbers were then rounded (table 7).

Table 7

Region	Number of PHEVs			
PJM	170,000	2,500,000	12,000,000	25,000,000
NYISO	40,000	600,000	3,000,000	6,000,000
Approximate Percent of Vehicles	0.38%	5.8%	29%	58%

We used the analysis of Lemoine et al. [31] as a starting point. They did not use trip survey data, but rather assumed that each vehicle requires 4.1 kWh each time it is charged (twice a day). We modified their procedure as follows: the charge rate is increased to 7.2 kWh so that it is comparable to the battery testing described in section 1. For this reason each vehicle can be recharged in less than one hour. Reducing the charging time increases the peak load added by PHEVs.

For each scenario of PHEV penetration, three different charging strategies were modeled. The first modeled charging strategy termed “Evening Charging” charges one third of the vehicles every hour between the hours of 6pm and 8pm. This models a case in which vehicles arrive home in a staggered pattern and are immediately plugged in. In the second charging scenario (the modified Lemoine et al. “Double Charging”), owners plug their PHEVs, assumed to be depleted by the morning commute, in when they get to work in the hours of 8-9 am then again when they get home between 6 pm and 8 pm to recharge for another 4.1 kWh.

The final charging scenario (“Smart Charging”) is designed to smooth out the valley of the load curve by charging a variable number of vehicles to different hours in the night. This is based on the yearly average for each hour of the 24 hour day. An example of "smart charging" is shown for PJM in figure 23[2].

[1] Finding the number of registered vehicles in PJM is challenging because PJM is not defined by political boundaries of states.

[2] It should be emphasized that figure 23 represents a custom charging scenario not based on the yearly average as with the program described in section 2. Given a yearly average as a basis, the load curve will not appear completely flat while vehicles are charging.

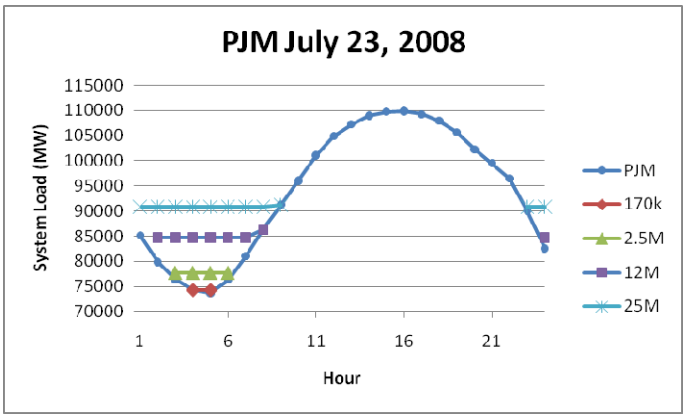

Figure 23 – PJM load curve for July 23, 2008. The base load curve is shown with modifications resulting from smart charging various numbers of PHEVs.

The smart charging scenario excluded hours during the workday (7 am to 8 pm), but none of the modeled numbers of PHEVs attempted to charge in those hours so this constraint did not bind. It is possible that if the fleet moved to 100% PHEVs then this constraint might increase nightly load enough to create a small peak where the valley was on certain days.

Changes in CO_2 emissions refer only to the electricity sector, not net emissions. Thus, savings in CO_2 emissions from not using gasoline are not accounted for. The focus instead is on how charging strategies effect emissions. Generator energy payments are estimated by taking the SRMC of the last MW delivered in a given hour and multiplying by the number of MWh delivered in that hour.

Once the charging strategies were complete, we added the load from PHEVs as described above to the hourly reported load for the entire ISO/RTO through the 2005 year. The program cycles through all 8760 hours and adds the appropriate load on the given hours to reflect the charging scenarios. These new loads are then combined with the generator dispatch order curves to predict the SRMC every hour in the year for each of PHEV charging scenarios. The CO_2 emissions are also recorded for each plant. The final output includes the modeled load, SRMC, and CO_2 emissions for each scenario in every hour of the year.

4.1.1.1 Integration of PHEVs with no Carbon Price

We added PHEVs to the grid with no CO_2 price in this scenario. Only the number of vehicles is varied to determine the effect on load, estimated yearly generator energy payments, generation mix and CO_2 emissions (Tables 8 and 9). It is important to note double charging results in twice the additional load so increases are not directly comparable to evening charging and smart charging.

Table 8

Load characteristics in PJM 2005 with no carbon price					
Charging Strategy	Number of PHEVs	Yearly Energy Million MWh	Estimated Yearly Generator Energy Payments Billion $	Yearly Million Tons CO_2	Estimated Added Yearly Generator Energy Payments Million $
None	0	685	18.4	372	N/A
Double Charging	175k	685	18.4	372	44
	2.5M	692	19.1	379	700
	12M	720	23.3	407	5,000
	25M	759	33.1	437	15,000
Evening Charging	175k	685	18.4	372	30
	2.5M	688	18.8	375	450
	12M	703	21.0	389	2,700
	25M	722	26.2	404	7,800
Smart Charging	175k	685	18.4	372	700
	2.5M	688	18.5	376	110
	12M	703	19.0	390	610
	25M	722	20.0	409	1,600

Table 9

Load characteristics in NYISO 2005 with no carbon price					
Charging Strategy	Number of PHEVs	Yearly Energy Million MWh	Estimated Yearly Generator Energy Payments Billion $	Yearly Million Tons CO_2	Estimated Added Yearly Generator Energy Payments Million $
None	0	166	8.94	46.4	N/A
Double Charging	40k	166	8.95	46.5	17
	600k	168	9.19	47.5	250
	3M	175	10.3	51.5	1,300
	6M	184	11.6	57.6	2,700
Evening Charging	40k	166	8.95	46.4	8.4
	600k	167	9.06	46.9	130
	3M	171	9.59	48.9	660
	6M	175	10.3	52.0	1,300
Smart Charging	40k	166	8.94	46.4	5.1
	600k	167	9.02	47.3	85
	3M	171	9.27	49.2	330
	6M	175	10.4	54.2	1,500

The percentage change is helpful in comparing values more easily. Tables 10 and 11 show the percentage change from the case with no PHEVs[3]. The changes in load are very similar in PJM and NYISO. There are significant differences in yearly generator energy payments. It appears that, without smart charging, large numbers of PHEVs will significantly change the price of electricity in PJM. However, with smart charging the increase in NYISO is greater than in PJM. This most likely reflects a greater difference in pricing between on and off peak in PJM as compared to NYISO. NYISO also shows a greater increase in yearly CO_2 emissions with PHEV penetration (PHEVs do not cause a large enough change in demand to require large amounts of new generation, so the current generation mix is used).

Table 10

Percentage change in load characteristics in PJM 2005 no carbon price				
Charging Strategy	Number of PHEVs	Yearly Energy	Estimated Yearly Generator Energy Payments	Yearly Tons CO_2
Double Charging	175k	0.07%	0.24%	0.13%
	2.5M	1.1%	3.8%	2.0%
	12M	5.3%	27%	9.4%
	25M	11%	81%	17%
Evening Charging	175k	0.04%	0.17%	0.07%
	2.5M	0.55%	2.5%	0.96%
	12M	2.6%	14%	4.5%
	25M	5.5%	42%	8.8%
Smart Charging	175k	0.04%	0.04%	0.07%
	2.5M	0.55%	0.58%	1.0%
	12M	2.6%	3.3%	4.8%
	25M	5.5%	8.7%	10%

[3] The load change is not identical because rounding in the number of PHEVs made it so that it was not a perfect ratio between PJM and NYISO.

Table 11

Percentage change in load characteristics in NYISO 2005 no carbon price				
Charging Strategy	Number of PHEVs	Yearly Energy	Estimated Yearly Generator Energy Payments	Yearly Tons CO_2
Double Charging	40k	0.07%	0.19%	0.15%
	600k	1.1%	2.8%	2.3%
	3M	5.4%	15%	11%
	6M	11%	30%	24%
Evening Charging	40k	0.04%	0.09%	0.06%
	600k	0.54%	1.4%	1.0%
	3M	2.7%	7.4%	5.4%
	6M	5.4%	15%	12.2%
Smart Charging	40k	0.04%	0.06%	0.12%
	600k	0.54%	0.95%	1.9%
	3M	1.9%	3.7%	6.1%
	6M	5.4%	17%	17%

The generation mix for each scenario is shown in tables 12 and 13. In PJM where there is a great deal of coal generation it is possible that the percent of coal used to meet load can increase in certain scenarios. Using smart charging uses more coal during the night. Hydroelectric, wind and solar are assumed to have a SRMC of $0 so they are always used first to the fullest extent possible.

Table 12

Generation mix in PJM 2005 with no carbon price							
Charging Strategy	Number of PHEVs	Renewable	Nuclear	Coal	Gas	Oil	Biomass
None	0	8.0%	32.1%	54.2%	2.8%	2.8%	0.2%
Double Charging	175k	8.0%	32.1%	54.2%	2.8%	2.8%	0.2%
	2.5M	7.9%	31.7%	54.5%	2.8%	2.8%	0.2%
	12M	7.6%	30.5%	55.4%	3.4%	2.8%	0.3%
	25M	7.2%	28.9%	54.3%	5.9%	3.2%	0.5%
Evening Charging	175k	8.0%	32.1%	54.2%	2.8%	2.8%	0.2%
	2.5M	7.9%	31.9%	54.3%	2.8%	2.8%	0.2%
	12M	7.8%	31.3%	54.6%	3.3%	2.9%	0.3%
	25M	7.6%	30.4%	54.2%	4.4%	3.0%	0.4%
Smart Charging	175k	8.0%	32.1%	54.2%	2.8%	2.8%	0.2%
	2.5M	7.9%	31.9%	54.4%	2.8%	2.8%	0.2%
	12M	7.8%	31.3%	55.2%	2.8%	2.7%	0.2%
	25M	7.6%	30.4%	56.3%	2.8%	2.7%	0.2%

Table 13

Generation mix in NYISO 2005 with no carbon price							
Charging Strategy	Number of PHEVs	Renewable	Nuclear	Coal	Gas	Oil	Biomass
None	0	31.6%	28.4%	19.9%	17.4%	1.3%	1.4%
Double Charging	175k	31.5%	28.4%	19.9%	17.4%	1.3%	1.4%
	2.5M	31.2%	28.1%	19.9%	18.0%	1.4%	1.4%
	12M	29.9%	27.0%	19.2%	20.2%	2.3%	1.5%
	25M	28.5%	25.6%	18.2%	21.2%	5.1%	1.4%
Evening Charging	175k	31.5%	28.4%	19.9%	17.4%	1.3%	1.4%
	2.5M	31.4%	28.3%	19.8%	17.7%	1.4%	1.4%
	12M	30.7%	27.7%	19.4%	18.7%	2.1%	1.4%
	25M	29.9%	27.0%	18.9%	19.2%	3.6%	1.3%
Smart Charging	175k	31.5%	28.4%	20.0%	17.4%	1.3%	1.4%
	2.5M	31.4%	28.3%	20.2%	17.4%	1.3%	1.4%
	12M	31.0%	27.9%	20.8%	17.6%	1.3%	1.4%
	25M	29.6%	26.7%	16.5%	25.0%	1.5%	0.7%

4.1.1.2 Potential PHEV Effects on Dispatch Stacks With \$50/ton CO_2 Price

In this scenario, the PHEVs are added to the grid with a \$50/ton CO_2 price. The percentage change is in relation to the values in the first lines of table 14 and 15 for PJM and NYISO, not to the "no carbon price" scenario described in the previous section. The load remains unchanged, as it is not modeled as responsive to price. Only the estimated energy payments and the tons of CO_2 emitted change in response to changes in the dispatch order curves (figures 21 and 22).

Table 14

Load characteristics in PJM 2005 with carbon price of $50/ton					
Charging Strategy	Number of PHEVs	Yearly Energy Million MWh	Estimated Yearly Generator Energy Payments Billion $	Yearly Million Tons CO_2	Estimated Added Yearly Generator Energy Payments Million $
None	0	685	51.6	347	N/A
Double Charging	175k	685	51.6	347	62
	2.5M	692	52.5	354	980
	12M	720	57.4	381	5,800
	25M	759	67.3	411	16,000
Evening Charging	175k	685	51.6	347	34
	2.5M	688	52.1	350	540
	12M	703	54.6	363	3,100
	25M	722	59.9	379	8,400
Smart Charging	175k	685	51.6	347	20
	2.5M	688	51.9	350	310
	12M	703	53.1	365	1,600
	25M	722	55.2	385	3,600

Table 15

Load characteristics in NYISO 2005 with carbon price of $50/ton					
Charging Strategy	Number of PHEVs	Yearly Energy Million MWh	Estimated Yearly Generator Energy Payments Billion $	Yearly Million Tons CO_2	Estimated Added Yearly Generator Energy Payments Million $
None	0	166	14.6	34.2	N/A
Double Charging	40k	166	14.6	34.3	19
	600k	168	14.9	35.5	300
	3M	175	16.3	40.7	1,700
	6M	184	18.1	47.5	3,600
Evening Charging	40k	166	14.6	34.3	10
	600k	167	14.7	34.8	160
	3M	171	15.5	37.5	900
	6M	175	16.4	40.9	1,900
Smart Charging	40k	166	14.6	34.2	9.2
	600k	167	14.7	34.7	150
	3M	171	15.1	36.1	540
	6M	175	16.1	41.6	1,600

Table 16

Percentage change in load characteristics in PJM 2005 with carbon price of $50/ton				
Charging Strategy	Number of PHEVs	Yearly Energy	Estimated Yearly Generator Energy Payments	Yearly Tons CO_2
Double Charging	175k	0.07%	0.12%	0.15%
	2.5M	1.1%	1.91%	2.1%
	12M	5.3%	11%	9.8%
	25M	11%	31%	19%
Evening Charging	175k	0.04%	0.07%	0.07%
	2.5M	0.55%	1.1%	1.0%
	12M	2.6%	6.0%	4.8%
	25M	5.5%	16%	9.3%
Smart Charging	175k	0.04%	0.04%	0.08%
	2.5M	0.55%	0.61%	1.1%
	12M	2.6%	3.1%	5.2%
	25M	5.5%	7.0%	11%

Table 17

Percentage change in load characteristics in NYISO 2005 with carbon price of $50/ton				
Charging Strategy	Number of PHEVs	Yearly Energy	Estimated Yearly Generator Energy Payments	Yearly Tons CO_2
Double Charging	40k	0.07%	0.13%	0.24%
	600k	1.1%	2.0%	3.7%
	3M	5.4%	12%	19%
	6M	11%	24%	39%
Evening Charging	40k	0.04%	0.07%	0.12%
	600k	0.54%	1.1%	1.8%
	3M	2.7%	6.2%	9.6%
	6M	5.4%	13%	20%
Smart Charging	40k	0.04%	0.06%	0.09%
	600k	0.54%	1.1%	1.4%
	3M	1.9%	3.7%	5.7%
	6M	5.4%	11%	21%

The carbon price decreases the difference in on- and off-peak prices in PJM, and thus makes the charging strategy less important. It would still be quite costly not to use smart charging, but the energy payments increase by only 13% with evening charging vs. 11% with smart charging in the 25M case. With no carbon price that same comparison is 9% vs. 42%.

PJM shows little change in dispatch mix with a $50 carbon price. Some gas and biomass generators have displaced coal plants, but otherwise the pattern appears very similar to the previous section. In NYISO there is a greater change in the dispatch mix. Gas plants displace

more coal, or a greater proportion of coal. It is likely that this is because fuel for coal plants is cheaper in PJM than in NYISO while gas prices are similar and it is easier for gas plants with similar fuel costs to underbid coal generators paying a relatively higher CO_2 price. We emphasize that these results are for the current generation capital stock, since the added demand of PHEVs in even the majority penetration scenario is low.

Table 18

Generation mix in PJM 2005 with \$50/ton CO_2							
Charging Strategy	Number of PHEVs	Renewable	Nuclear	Coal	Gas	Oil	Biomass
None	0	8.0%	32.1%	51.4%	4.7%	2.8%	1.0%
Double Charging	175k	8.0%	32.1%	51.5%	4.7%	2.8%	1.0%
	2.5M	7.9%	31.7%	51.8%	4.8%	2.8%	1.0%
	12M	7.6%	30.5%	52.6%	5.6%	2.8%	1.0%
	25M	7.2%	28.9%	51.8%	8.1%	3.0%	1.0%
Evening Charging	175k	8.0%	32.1%	51.4%	4.7%	2.8%	1.0%
	2.5M	7.9%	31.9%	51.6%	4.8%	2.8%	1.0%
	12M	7.8%	31.3%	51.9%	5.2%	2.8%	1.0%
	25M	7.6%	30.4%	51.5%	6.5%	2.9%	1.0%
Smart Charging	175k	8.0%	32.1%	51.4%	4.7%	2.8%	1.0%
	2.5M	7.9%	31.9%	51.7%	4.7%	2.8%	1.0%
	12M	7.8%	31.3%	52.6%	4.6%	2.7%	1.0%
	25M	7.6%	30.4%	53.9%	4.5%	2.7%	1.0%

Table 19

Generation mix in NYISO 2005 with \$50/ton CO_2							
Charging Strategy	Number of PHEVs	Renewable	Nuclear	Coal	Gas	Oil	Biomass
None	0	31.6%	28.4%	12.2%	25.9%	1.2%	0.7%
Double Charging	175k	31.5%	28.4%	12.2%	25.9%	1.2%	0.7%
	2.5M	31.2%	28.1%	12.4%	26.3%	1.3%	0.7%
	12M	29.9%	27.0%	12.9%	27.4%	2.0%	0.7%
	25M	28.5%	25.6%	12.6%	27.9%	4.6%	0.8%
Evening Charging	175k	31.5%	28.4%	12.2%	25.9%	1.2%	0.7%
	2.5M	31.4%	28.3%	12.3%	26.1%	1.3%	0.7%
	12M	30.7%	27.7%	12.5%	26.6%	1.8%	0.7%
	25M	29.9%	27.0%	12.3%	26.8%	3.3%	0.8%
Smart Charging	175k	31.5%	28.4%	12.2%	25.9%	1.2%	0.7%
	2.5M	31.4%	28.3%	12.3%	26.1%	1.2%	0.7%
	12M	31.0%	27.9%	12.7%	26.6%	1.2%	0.7%
	25M	29.6%	26.7%	13.8%	28.0%	1.2%	0.7%

4.1.1.3 Potential PHEV Effects on Dispatch Stacks Including Low Carbon Coal Generators

In this section, we model coal generators with carbon capture and sequestration (CCS) systems. This, in combination with a $50/ton CO2 price, is used to construct a new generation order dispatch stack for PJM and NYISO (figures 21-22). We model that retrofitting coal plants with CCS would involve a 20% derating of the current nameplate capacity and capture 80% of CO_2 emissions.

Table 20

Load characteristics in PJM 2005 with carbon price of $50/ton and CCS on coal generators					
Charging Strategy	Number of PHEVs	Yearly Energy Million MWh	Estimated Yearly Generator Energy Payments Billion $	Yearly Million Tons CO_2	Estimated Added Yearly Generator Energy Payments Million $
None	0	685	38.9	81.8	N/A
Double Charging	175k	685	38.9	82.0	92
	2.5M	692	40.4	84.0	1,500
	12M	720	48.4	94.7	9,600
	25M	759	64.8	119	26,000
Evening Charging	175k	685	38.9	81.9	52.8
	2.5M	688	39.7	83.1	840
	12M	703	44.0	88.9	5,100
	25M	722	52.6	99.7	14,000
Smart Charging	175k	685	38.9	81.9	16
	2.5M	688	39.1	82.6	270
	12M	703	40.6	85.6	1,700
	25M	722	43.5	89.8	4,600

Table 21

Load characteristics in NYISO 2005 with carbon price of $50/ton and CCS on coal generators					
Charging Strategy	Number of PHEVs	Yearly Energy Million MWh	Estimated Yearly Generator Energy Payments Billion $	Yearly Million Tons CO_2	Estimated Added Yearly Generator Energy Payments Million $
None	0	166	13.6	18.3	N/A
Double Charging	40k	166	13.6	18.4	24
	600k	168	14.0	19.2	360
	3M	175	15.6	23.1	2,000
	6M	184	17.5	29.5	3,900
Evening Charging	40k	166	13.6	18.4	12
	600k	167	13.8	18.8	190
	3M	171	14.6	21.0	1,000
	6M	175	15.6	24.2	2,000
Smart Charging	40k	166	13.6	18.3	8.7
	600k	167	13.7	18.6	120
	3M	169	14.1	19.2	460
	6M	177	15.7	22.1	2,100

Table 22

Percentage change in load characteristics in PJM 2005 with carbon price of $50/ton and CCS on coal generators				
Charging Strategy	Number of PHEVs	Yearly Energy	Estimated Yearly Generator Energy Payments	Yearly Tons CO_2
Double Charging	175k	0.07%	0.24%	0.16%
	2.5M	1.1%	3.9%	2.7%
	12M	5.3%	25%	16%
	25M	11%	67%	44%
Evening Charging	175k	0.04%	0.14%	0.10%
	2.5M	0.55%	2.2%	1.5%
	12M	2.6%	13%	8.7%
	25M	5.5%	35%	22%
Smart Charging	175k	0.04%	0.04%	0.06%
	2.5M	0.55%	0.69%	0.95%
	12M	2.6%	4.4%	4.6%
	25M	5.5%	12%	9.8%

Table 23

Percentage change in load characteristics in NYISO 2005 with carbon price of $50/ton and CCS on coal generators				
Charging Strategy	Number of PHEVs	Yearly Energy	Estimated Yearly Generator Energy Payments	Yearly Tons CO_2
Double Charging	40k	0.07%	0.18%	0.00%
	600k	1.1%	2.6%	0.29%
	3M	5.4%	14%	4.5%
	6M	11%	28%	26%
Evening Charging	40k	0.04%	0.08%	61%
	600k	0.54%	1.4%	0.16%
	3M	2.7%	7.3%	2.7%
	6M	5.4%	15%	14%
Smart Charging	40k	0.04%	0.06%	32%
	600k	0.54%	0.89%	0.08%
	3M	1.9%	3.4%	1.3%
	6M	6.6%	15%	4.6%

With CCS-retrofitted coal plants in the smart charging scenario the CO_2 emissions decline with the maximum number of PHEVs in comparison to evening charging. This reflects the use of other generators during the evening to charge that do not capture emissions. Smart charging uses a mix of renewable, nuclear, and low carbon coal in these cases.

Retrofitting coal generators with CCS makes them more competitive under a carbon price, and increases the use of coal generators, but it also decreases their nameplate capacity. Thus, even if they are less expensive to dispatch than other generators their percent in the generation mix will still decline when load surpasses their derated nameplate capacity.

Table 24

Generation mix in PJM 2005 with \$50/ton CO_2 price and CCS on coal Generators							
Charging Strategy	Number of PHEVs	Renewable	Nuclear	Coal	Gas	Oil	Biomass
None	0	8.0%	32.1%	51.5%	5.2%	2.9%	0.3%
Double Charging	175k	8.0%	32.1%	51.5%	5.3%	2.9%	0.3%
	2.5M	7.9%	31.7%	51.7%	5.4%	2.9%	0.3%
	12M	7.6%	30.5%	51.5%	7.0%	3.0%	0.4%
	25M	7.2%	28.9%	49.3%	10.5%	3.6%	0.5%
Evening Charging	175k	8.0%	32.1%	51.5%	5.3%	2.9%	0.3%
	2.5M	7.9%	31.9%	51.5%	5.4%	2.9%	0.3%
	12M	7.8%	31.3%	51.3%	6.2%	3.0%	0.4%
	25M	7.6%	30.4%	50.3%	8.1%	3.3%	0.4%
Smart Charging	175k	8.0%	32.1%	51.5%	5.2%	2.9%	0.3%
	2.5M	7.9%	31.9%	51.7%	5.2%	2.9%	0.3%
	12M	7.8%	31.3%	52.7%	5.1%	2.9%	0.3%
	25M	7.6%	30.4%	53.7%	5.2%	2.8%	0.4%

Table 25

Generation mix in NYISO 2005 with \$50/ton CO_2 price and CCS on coal Generators							
Charging Strategy	Number of PHEVs	Renewable	Nuclear	Coal	Gas	Oil	Biomass
None	0	31.6%	28.4%	15.6%	22.3%	1.5%	0.6%
Double Charging	175k	31.5%	28.4%	15.6%	22.3%	1.5%	0.6%
	2.5M	31.2%	28.1%	15.6%	22.8%	1.6%	0.7%
	12M	29.9%	27.0%	15.1%	24.8%	2.6%	0.7%
	25M	28.5%	25.6%	14.3%	25.5%	5.3%	0.7%
Evening Charging	175k	31.5%	28.4%	15.6%	22.3%	1.5%	0.6%
	2.5M	31.4%	28.3%	15.5%	22.6%	1.6%	0.6%
	12M	30.7%	27.7%	15.2%	23.4%	2.3%	0.7%
	25M	29.9%	27.0%	14.8%	23.8%	3.8%	0.7%
Smart Charging	175k	31.5%	28.4%	15.6%	22.3%	1.5%	0.6%
	2.5M	31.4%	28.3%	15.8%	22.4%	1.5%	0.7%
	12M	31.0%	27.9%	16.1%	22.9%	1.5%	0.7%
	25M	29.6%	26.7%	16.5%	25.0%	1.5%	0.7%

4.1.2 Effect of Carbon Price on Dispatch Stacks

The previous sections did not explore the change in baseline load characteristics for different carbon scenarios. This section focuses on the percent change in estimated generator energy payments and CO_2 emissions, created by a carbon price and CCS.

Table 26

Load characteristics in PJM 2005 with carbon scenarios and no PHEVs		
Carbon Scenario	Estimated Yearly Generator Energy Payments ($)	Yearly Tons CO_2
$50/ton CO_2 Price	181%	-6.8%
$50/ton CO_2 Price and CCS	112%	-78.0%

PJM contains a large number of coal generators. Even with a $50/ton CO_2 price, these generators are still dispatched before most natural gas generators. Thus, there is only a small effect on carbon emissions, but a large change in the SRMC of the last dispatched generator throughout the year. Adding CCS to coal plants (for example, encouraged by a carbon performance standard) has a far greater effect on CO_2 emissions than simply adding a carbon price.

Table 27

Load characteristics in NYISO 2005 with carbon scenarios and no PHEVs		
Carbon Scenario	Estimated Yearly Generator Energy Payments ($)	Yearly Tons CO_2
$50/ton CO_2 Price	63%	-26%
$50/ton CO_2 Price and CCS	52%	-60%

NYISO has a smaller percentage of coal generators in the dispatch stack so adding CCS does not have as dramatic an effect on the SRMC or the CO_2 emissions in comparison to a carbon price. The patterns in CO_2 emission reductions are similar for large numbers of PHEVs. The change in estimated yearly generator energy payments is also similar when the carbon scenario changes.

4.2 POTENTIAL FOR REDUCED GRID LOAD

This section attempts to bound the capacity of PHEVs to reduce peak grid load. According to NHTS data, over 30% of vehicles are not driven on a given day. When only vehicles 5 years and newer are included, the number of undriven vehicles still exceeds 20%. For this reason, we assumed that on any given day 20% of PHEVs would not be driven. Because the capacity of energy storage in PHEVs is quite large in relation to load only the 6% of vehicles being PHEVs was considered (600k in NYISO and 2.5M in PJM).

For a lower bound estimate it was assumed that the entire fleet was made up of vehicles with 4 kWh batteries (the lowest amount of storage that currently qualifies for a federal subsidy).

The fleet vehicles were allowed to discharge 75% of the energy in their batteries. This reflects the assumption that vehicle manufacturers will recommend that the owner deplete batteries completely for fear of excess degradation. This means 3 kWh could be discharged for driving, or peak shaving (versus 4.1 kWh assumed in the prior section). The round trip efficiency (RTE) of energy to and from battery was assumed to be 85%, with the charging efficiency the square root of the RTE. This means the load from driving vehicles was reduced over the cases described in the previous sections, because there are less vehicles driving (20% less) and the batteries in the vehicles are smaller. The daily energy needed to recharge a fleet as described here is roughly 1600 MWh in NYISO and 6500 MWh in PJM (compared to 2,500 and 10,000 MWh in the previous sections).

It was assumed that any vehicle driven was completely depleted and unable to contribute to energy arbitrage. The remaining 20% of the fleet were allowed to contribute 75% of the energy in their batteries. Because of the RTE, for every 1 kWh received by the grid 1.18 kWh must be withdrawn later in the evening. Leveling grid load is not achievable in the "double charging" or "evening charging" scenarios. Thus, this analysis considers only smart charging. This analysis also discharges only in the most expensive hour (averaged for the year for each ISO/RTO). This lowered the SRMC in that hour, but increased it later in the night when the vehicles were recharged.

The upper bound assumed the vehicle fleet was made up of vehicles with 16 kWh battery packs. It also assumes that 4.1 kWh are used driving on average (as in the previous sections). This means that the 80% of vehicles that were driven can also contribute to reducing peak load. Other constraints remain as in the lower bound case.

Table 28

Potential for reduced grid peak load in PJM 2005

Carbon Scenario	V2G Scenario	Yearly Energy Million MWh	Estimated Yearly Generator Energy Payments Billion $	Yearly Million Tons CO_2	Estimated Added Yearly Generator Energy Payments Million $
Status Quo	None	685	18.4	372	N/A
	Lower Bound	687	18.4	374	20
	Upper Bound	689	18.1	376	-280
$50/ton CO_2 Price	None	685	51.6	357	N/A
	Lower Bound	687	51.7	359	180
	Upper Bound	689	51.6	361	82
$50/ton CO_2 Price and Coal CCS	None	685	38.9	81.8	N/A
	Lower Bound	687	39.0	82.3	100
	Upper Bound	689	38.6	82.2	-230

In PJM it appears using PHEVs to reduce the peak load reduces the estimated yearly generator energy payments for the upper bound case except when a carbon price is set. The change in price is a reflection of the dispatch curve. Where there are steep drops in the SRMC if the energy arbitrage pushes the load past this point there is potential for savings. The lack of difference with smaller use of PHEVs and a carbon price means that the hours chosen do not have sufficient differences in SRMC to overcome the 15% RTE energy penalty associated with energy arbitrage.

In NYISO it does not appear that load shifting with PHEV energy arbitrage is effective at reducing estimated yearly generator payments. This likely occurs because of the shape of the NYISO dispatch curve with CCS and a carbon price. There is a jump at around 17,000 MW. Apparently involving vehicles in energy arbitrage reduces the load enough that it falls off the shoulder a significant number of days in the year. This shoulder is not as noticeable in the other carbon scenarios and thus reducing the peak is not as effective at changing the SRMC. The lack of savings when using vehicles implies that a better algorithm should be applied to determine the number of vehicles to use, and the amount to discharge. This also represents only 6% integration of PHEVs. If the 29% PHEV integration was used it could displace all load over an hour period.

Table 29

Potential for reduced grid peak load in NYISO 2005

Carbon Scenario	V2G Scenario	Yearly Energy Million MWh	Estimated Yearly Generator Energy Payments Billion $	Yearly Million Tons CO_2	Estimated Added Yearly Generator Energy Payments Million $
Status Quo	None	166	8.94	46.4	N/A
	Lower Bound	167	8.98	47.0	48
	Upper Bound	167	8.97	47.7	34
$50/ton CO_2 Price	None	166	14.6	34.2	N/A
	Lower Bound	167	14.7	34.5	93
	Upper Bound	167	14.8	34.7	180
$50/ton CO_2 Price and Coal CCS	None	166	13.6	18.3	N/A
	Lower Bound	167	13.7	18.4	66
	Upper Bound	167	13.6	18.3	37

4.3 NET SOCIAL WELFARE

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 [32] 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 [33]. 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 [34]. 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.

Capturing the full benefit will require the more sophisticated planning outlined in section 2.2 instead of the more simplistic model outlined in section 3.2. Still it is clear that PHEVs have the potential to store vast amounts of energy.

4.4 SUMMARY

Significant electrification of the transportation fleet is possible with generating assets. Smart charging can reduce generator energy payments considerably. It is important that as the fleet of vehicles charging expands smart charging is used. This will help contain cost increases. Increases in CO_2 emissions from charging during low load periods do not increase greatly over uncontrolled charging in PJM. In NYISO there is a greater sensitivity to smart charging. A carbon price without CCS technology increases costs significantly and depending on the generation mix may not reduce CO_2 emissions by a similar rate. It is likely that including demand response to increased prices for electricity would reduce CO_2 emissions more than changes in generation mix due to new prices for running plants. Using vehicles for peak shaving will be possible, but a simple average yearly methodology will not yield worthwhile results.

5. RECOMMENDATIONS FOR RESEARCH TARGETED AT MINIMIZING ENVIRONMENTAL AND COST TRADEOFFS

A fruitful area for future research is finding a better smart charging algorithm. This will minimize the base rate cost increases associated with integrating a large number of PHEVs. The estimates used here, for when PHEVs will be charged without a smart charging strategy, are not necessarily precise. Using actual data describing driving patterns could provide greater insight into the effect of large numbers of PHEVs on the grid. Adding CCS to coal power plants, and ensuring that replacements for old plants have CCS, has the potential to greatly reduce CO2 emissions and the SRMC with a carbon price. These changes are capital intensive and benefit-cost analysis comparing a broader scope than this report would be useful in making decisions. Analysis using a changing generation capital stock with the PHEV penetrations discussed here would also be useful.

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