



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

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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 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 ~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 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.

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1. 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].

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Nomenclature

List of symbols

| | |
|---|---|
| kWh | kilowatt hours |
| kWh _{Transacted} | the number of kWh transacted in a given discharge |
| 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 |
| BOS | Boston, MA |
| ROC | Rochester, NY |
| 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 |
| LMP _{BUY} | buying price of electricity |
| LMP _{SELL} | selling price of electricity |
| LMP _{BUY} (<i>t_{Bx}</i>) | buying price of electricity in hour <i>x</i> |
| LMP _{SELL} (<i>t_{Sx}</i>) | selling price of electricity in hour <i>x</i> |

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 justified largely 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.

2. Methodology

We examine energy arbitrage (buying low cost power to charge the battery pack and discharging the battery pack at high power prices) with PHEVs assuming that electricity sold will be replenished from the grid later in the evening so the battery pack is 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.

2.1. 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 to 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⁻¹ [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.

$$\text{profit}(\$) = \left((\text{LMP}_{\text{SELL}} + \text{T\&D}) \times \text{DCH}_{\text{eff}} - \frac{\text{LMP}_{\text{BUY}} + \text{T\&D}}{\text{CH}_{\text{eff}}} \right) \times \text{kWh}_{\text{Transacted}} - \text{degradation cost} \quad (1)$$

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.

2.2. Degradation cost

Degradation cost was calculated based on the multiple linear regression based on laboratory data from cycling LiFePO₄ cells described in [8]. While other chemistries, such as those based on the Li₄Ti₅O₁₂ 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/LiMn₂O₄ cost approximately \$58 kWh⁻¹ as compared to \$35 kWh⁻¹ for the graphite/LiMn₂O₄ analog (though the titanate system is currently exhibiting superior cycle life performance) [12]. 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 LiFePO₄ 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 [13].

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

$$\text{degradation cost} = \frac{\text{replacement cost} \times \text{V2G Deg}}{0.8 - 1} \times \text{percent of battery used} \quad (2)$$

Estimates of the current price of the Chevy Volt's battery pack range from \$5000 to \$11,000 [14]. However, it is a different battery chemistry from the battery we tested. We used a value of \$5000 (\$312 kWh⁻¹) and performed sensitivity analyses using the range \$2500 to \$20,000. With a \$5000 replacement cost, our laboratory measurements [8] predict a degradation cost of 4.2 ¢ kWh⁻¹ served.

2.3. Model

We use a sell-before-buy model. The battery pack begins a day fully charged. The time 8 a.m. to 4:59 p.m. 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 h 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 a.m. driving window. Appendix A 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 240 V single-phase, 30 A circuit infrastructure (7.2 kWh h⁻¹ 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

Table 1

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

| Year | Area | | ROC | | BOS | |
|------|--------|------|--------|------|--------|------|
| | PHL | | | | | |
| | Profit | kWh | Profit | kWh | Profit | kWh |
| 2003 | \$22 | 1286 | \$25 | 474 | N/A | N/A |
| 2004 | \$17 | 1120 | \$19 | 451 | \$12 | 252 |
| 2005 | \$110 | 2458 | \$71 | 1157 | \$19 | 1119 |
| 2006 | \$58 | 1471 | \$46 | 1037 | \$48 | 667 |
| 2007 | \$95 | 2223 | \$69 | 1210 | \$39 | 625 |
| 2008 | \$118 | 2264 | \$107 | 1650 | \$15 | 1128 |

Table 2

Lower bound annual profits for each area over years listed using 14 days backcasting averaging method and \$5000 battery replacement cost for a 16 kWh battery.

| Year | Area | | ROC | | BOS | |
|------|--------|------|--------|------|--------|-----|
| | PHL | | | | | |
| | Profit | kWh | Profit | kWh | Profit | kWh |
| 2003 | \$10 | 1123 | \$13 | 395 | N/A | N/A |
| 2004 | \$6 | 1009 | \$7 | 415 | \$10 | 267 |
| 2005 | \$72 | 2169 | \$33 | 978 | \$18 | 865 |
| 2006 | \$38 | 1384 | \$25 | 862 | \$28 | 508 |
| 2007 | \$57 | 1889 | \$28 | 988 | \$6 | 514 |
| 2008 | \$67 | 1998 | \$14 | 1202 | \$15 | 897 |

to use the vehicle for energy arbitrage. The vehicle is fully charged before 8 a.m. each morning.

The second method uses knowledge of the real time prices in the previous 2 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. Results

The yearly profits from the years of 2003 to 2008 using perfect information, a \$5000 battery pack cost, and our measured battery degradation are shown below (Table 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 \$12–48, depending on the year.

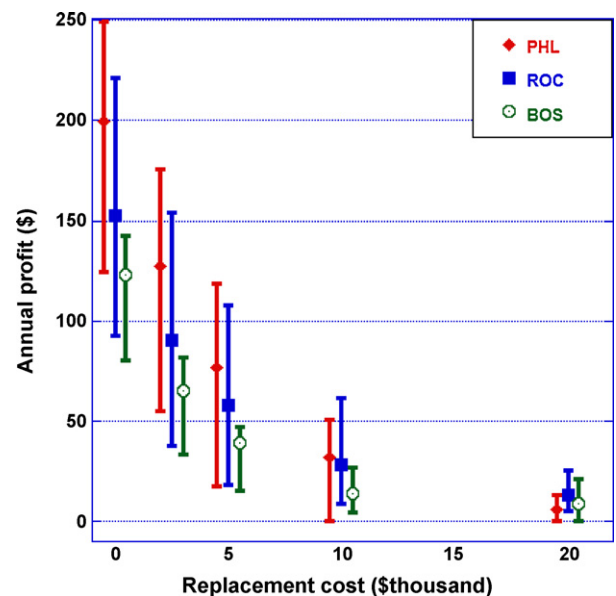


Fig. 1. V2G energy arbitrage profit sensitivity to battery pack replacement cost with perfect information in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for battery replacement costs of \$0, \$2500, \$5000, \$10,000, and \$20,000.

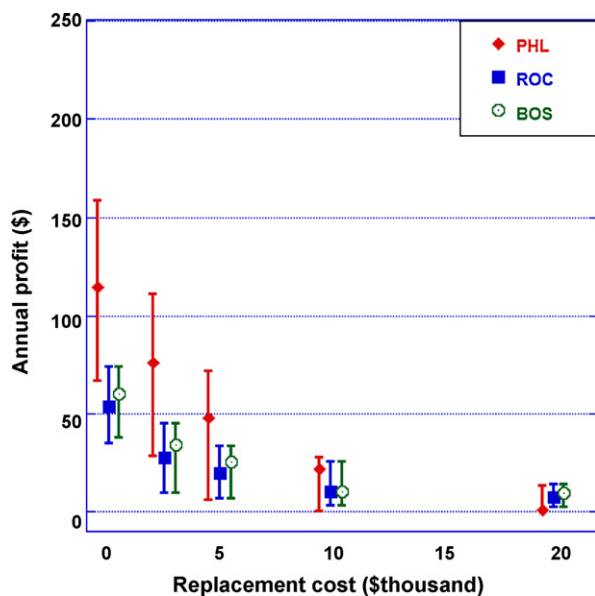


Fig. 2. V2G energy arbitrage profit sensitivity to battery pack replacement cost with 14 days backcasting method in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for battery replacement costs of \$0, \$2500, \$5000, \$10,000, and \$20,000.

The lower bound of profit estimated without perfect information resulted in profits that reached their maximum in Philadelphia in 2005 (Table 2). 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 [15]. 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.

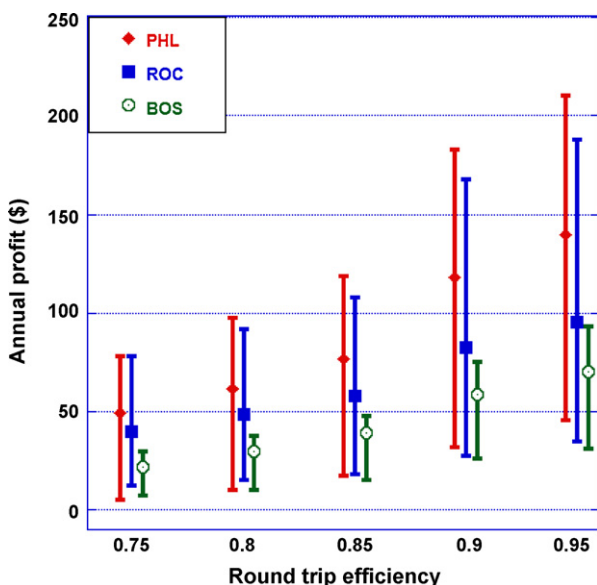


Fig. 3. V2G energy arbitrage profit sensitivity to round-trip efficiency (RTE) with perfect information in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for RTE of 0.75, 0.80, 0.85, 0.90, and 0.95.

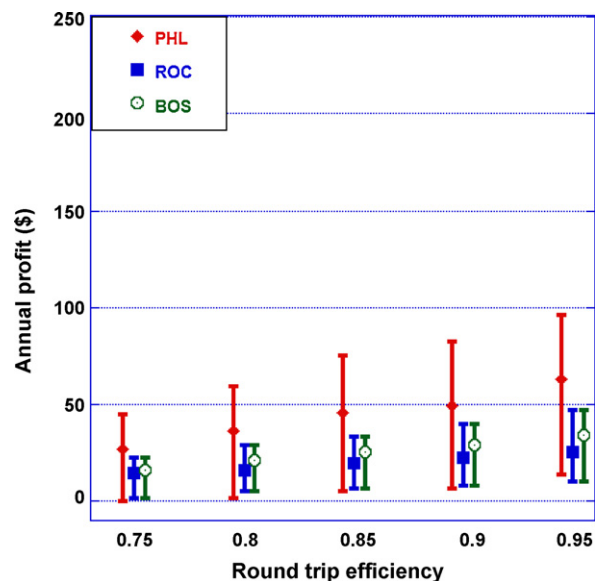


Fig. 4. V2G energy arbitrage profit sensitivity to RTE with 14 days backcasting method in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for RTE of 0.75, 0.80, 0.85, 0.90, and 0.95.

4. Sensitivity analysis

We performed sensitivity analyses on the effect of battery pack replacement cost on profit (Figs. 1 and 2). The median value and yearly maximum and minimum for the period 2003–2008 are shown for upper and lower bound scenarios.

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 without battery degradation for the 6 years is \$200 in the most profitable city

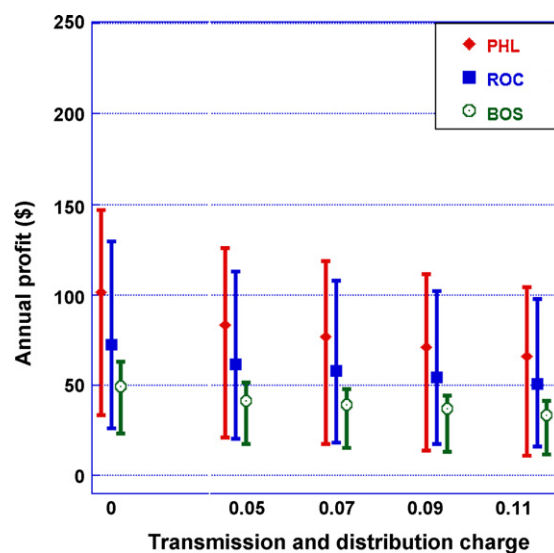


Fig. 5. V2G energy arbitrage profit sensitivity to transmission and distribution (T&D) charges with perfect information in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for T&D charges of 0, 0.05, 0.07, 0.09, and 0.11 ¢ kWh^{-1} .

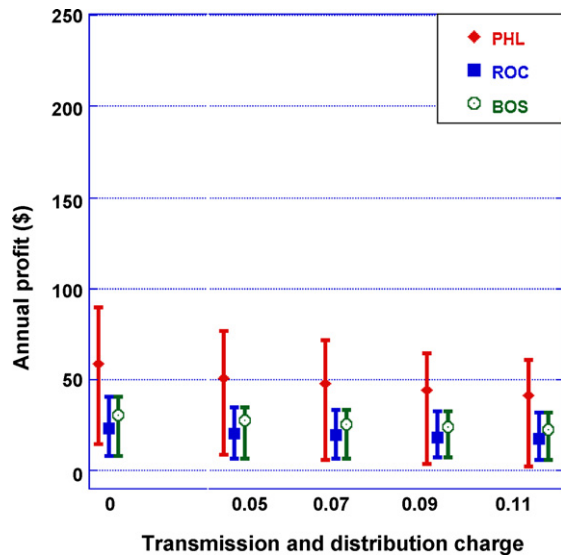


Fig. 6. V2G energy arbitrage profit sensitivity to T&D charges with 14 days back-casting method in the three cities studied. The symbol indicates the median annual profit for the years studied and the range indicates the most and least profitable years. The profit in each city is calculated for T&D charges of 0, 0.05, 0.07, 0.09, and 0.11 ¢ kWh^{-1} .

(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 (Figs. 3 and 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

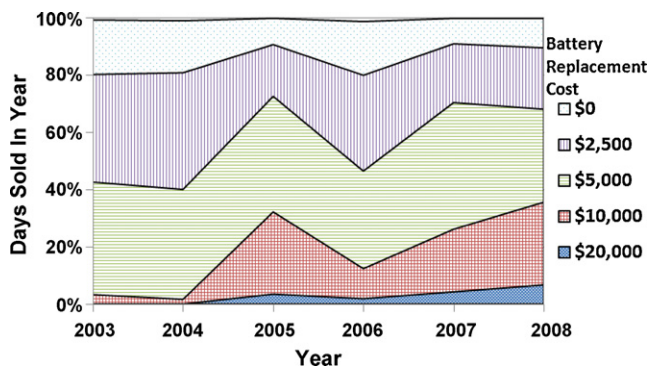


Fig. 7. Percent of days in Philadelphia area of PJM that energy arbitrage is profitable given different battery replacement costs and perfect information.

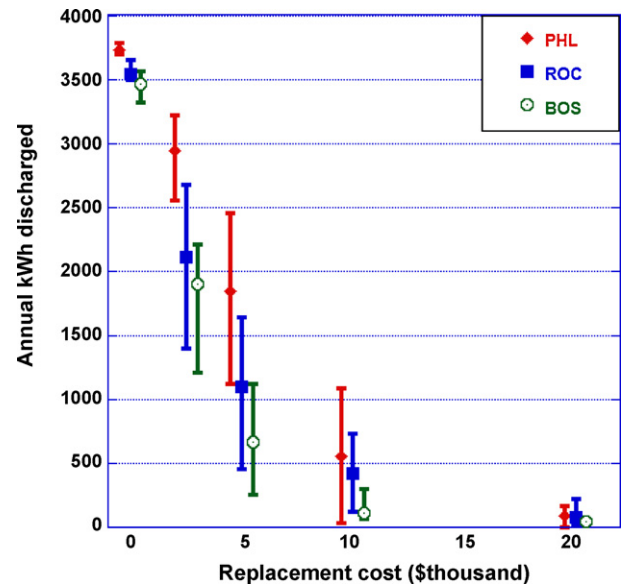


Fig. 8. V2G energy arbitrage quantity sensitivity to battery pack replacement cost with perfect information in the three cities studied. The symbol indicates the median annual kWh discharged for the years studied and the range indicates the most and least kWh discharged. The arbitrage in each city is calculated for battery replacement costs of \$0, \$2500, \$5000, \$10,000, and \$20,000.

a similar though smaller effect over the range of values tested (Figs. 5 and 6).

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 (\$5000 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 (Fig. 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 (Figs. 8 and 9).

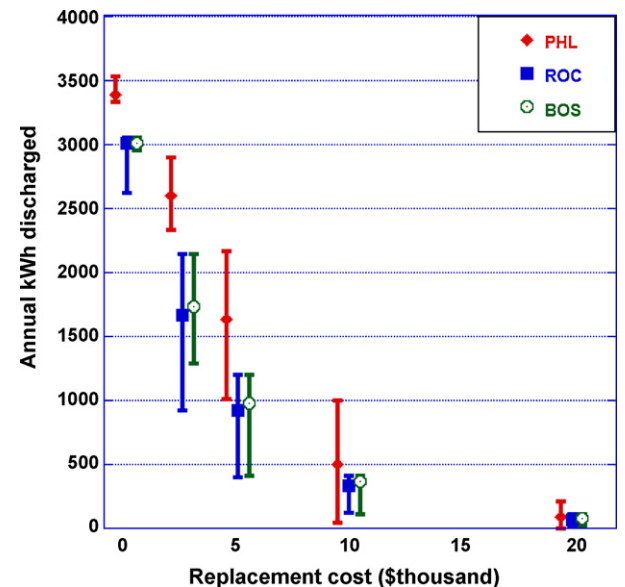


Fig. 9. V2G energy arbitrage quantity sensitivity to battery pack replacement cost with 14 days backcasting method in the three cities studied. The symbol indicates the median annual kWh discharged for the years studied and the range indicates the most and least kWh discharged. The arbitrage in each city is calculated for battery replacement costs of \$0, \$2500, \$5000, \$10,000, and \$20,000.

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).

5. 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 energy storage. 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 30 A 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 would increase, providing greater incentive to individuals or a hypothetical aggregator. However, if a large number of vehicle owners engage in arbitrage the profit would decrease, 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) [16]. 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.

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 et al. [17] estimate the net social welfare of energy storage in PJM during 2007 to be equivalent to \$8 per vehicle per year (for 4 GWh of total storage, about 380,000 16 kWh vehicles using 2/3 of their battery pack capacity for electricity). Walawalkar et al. 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 0.5–1 ¢ kWh⁻¹ [19]. Suppose 25% of total U.S. generation were wind or solar, 10¹² kWh. Then the integration cost mitigation would be \$20–40 vehicle⁻¹ year⁻¹ 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. A 30 A 240 V 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 h year⁻¹ has fixed costs of approximately \$50 kW⁻¹, or 50 ¢ kWh⁻¹. Add to that 10 ¢ kWh⁻¹ for fuel, for a total of 60 ¢ kWh⁻¹, or \$432 over the 100 h the peaker would have run. A specific vehicle owner would not be able to help the grid avoid all \$432, since those 100 h are likely to be in 4 h blocks on only 25 days and the vehicle's battery would discharge for only a bit less than 2 h. Thus, the vehicle owner might be able to avoid ~\$200 of peaking costs in a year. 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.

To summarize, there may be \$300–400 of annual net social welfare benefits that can be transferred to the owner of an electric vehicle. In the absence of such incentives, it is unlikely that large-scale grid energy storage in PHEVs will be attractive to a large number of vehicle owners.

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Appendix A. Model

- Hours required to recharge from driving:

$$\text{driving discharge} \times \text{battery size} = 0.341 \times 16 = 5.47 \text{ kWh}$$

- Infrastructure:

$$\text{capacity} = 240 \text{ V} \times 30 \text{ A} = 7.2 \text{ kW}$$

- Time and energy needed to recharge:

$$\text{DCH}_{\text{eff}} = \text{CH}_{\text{eff}} = \sqrt{0.85}$$

$$\frac{\text{driving discharge} \times \text{battery size}}{\text{CH}_{\text{eff}}} = \frac{5.47 \text{ kWh}}{\sqrt{0.85}} = 5.93 \text{ kWh}$$

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

- Buying for driving recharge:

$$\text{Minimize } \frac{\text{LMP}_{\text{Buy}}(t_{B1}) + \text{T\&D}}{\text{CH}_{\text{eff}}} \times \text{kWh}$$

$$17 \leq t_{B1} \leq 31 \text{ (corresponds to 5 p.m. to 7 a.m.)}$$

- Selling:

$$\text{Maximize } \left[(\text{LMP}_{\text{Sell}}(t_{s1}) + \text{T\&D}) \times \text{DCH}_{\text{eff}} - \frac{\text{LMP}_{\text{Buy}}(t_{B1}) + \text{T\&D}}{\text{CH}_{\text{eff}}} \right]$$

$$\times \text{percent} \times \text{battery size}$$

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

$$\left[(\text{LMP}_{\text{Sell}}(t_s) + \text{T\&D}) \times \text{DCH}_{\text{eff}} - \frac{\text{LMP}_{\text{Buy}}(t_{B1}) + \text{T\&D}}{\text{CH}_{\text{eff}}} \right] \\ \times \text{percent} \times \text{battery size}$$

$$\text{degradation cost} = \frac{\text{battery replacement cost} \times \text{V2G Deg}}{0.8 - 1} \\ \times \text{percent}$$

$$\text{percent} \leq \frac{(1 - 0.82)7.2 \times \text{CH}_{\text{eff}}}{\text{battery size}} = \mathbf{0.729}$$

percent < 1 – driving discharge

- Choose next buying hour:

$$\min \frac{\text{LMP}_{\text{Buy}}(t_{B2}) + \text{T\&D}}{\text{CH}_{\text{eff}}} \times \text{kWh}$$

$$17 \leq t_{B2} \leq 31 \text{ (corresponds to 5 p.m. to 7 a.m.)}$$

$$t_{B2} \neq t_{B1}$$

- Decide whether to sell (and hence buy in the hour just chosen):

$$\text{Maximize} \left[(\text{LMP}_{\text{Sell}}(t_{s1}) + \text{T\&D}) \times \text{DCH}_{\text{eff}} - \frac{\text{LMP}_{\text{Buy}}(t_{B2}) + \text{T\&D}}{\text{CH}_{\text{eff}}} \right] \\ \times \text{percent} \times \text{battery size}$$

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

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

$$\text{percent} \leq \frac{(1)7.2 \text{ kWh} \times \text{CH}_{\text{eff}}}{\text{battery size}} = \mathbf{0.4148}$$

$$\text{percent} \leq \frac{(7.2 \text{ kWh/battery size}) - (0.729) \times \text{DCH}_{\text{eff}}}{\text{CH}_{\text{eff}}} = 0.4152$$

percent < 1 – driving discharge – 0.0729

Other constraints same as above (namely revenue > cost).

- Choose next buying hour:

$$\min \frac{\text{LMP}_{\text{Buy}}(t_{B3}) + \text{T\&D}}{\text{CH}_{\text{eff}}} \times \text{kWh}$$

$$17 \leq t_{B3} \leq 31 \text{ (corresponds to 5 p.m. to 7 a.m.)}$$

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

- Decide whether to sell (and hence buy in the hour just chosen):

$$\text{Maximize} \left[(\text{LMP}_{\text{Sell}}(t_{s1}) + \text{T\&D}) \times \text{DCH}_{\text{eff}} - \frac{\text{LMP}_{\text{Buy}}(t_{B3}) + \text{T\&D}}{\text{CH}_{\text{eff}}} \right] \\ \times \text{percent} \times \text{battery size}$$

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

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

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

$$\text{percent} \leq \frac{(1)7.2 \text{ kWh} \times \text{CH}_{\text{eff}}}{\text{battery size}} = 0.4148$$

$$\text{percent} \\ \leq \frac{(7.2 \text{ kWh/battery size}) - (0.729) \times \text{DCH}_{\text{eff}} - (0.4148) \times \text{DCH}_{\text{eff}}}{\text{CH}_{\text{eff}}} \\ = \mathbf{3.21\text{E} - 4}$$

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):

$$\text{Maximize} \left[(\text{LMP}_{\text{Sell}}(t_{s2}) + \text{T\&D}) \times \text{DCH}_{\text{eff}} - \frac{\text{LMP}_{\text{Buy}}(t_{B3}) + \text{T\&D}}{\text{CH}_{\text{eff}}} \right] \\ \times \text{percent} \times \text{battery size}$$

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

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

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

$$t_{s2} \neq t_{s1}$$

$$\text{percent} \leq \frac{(1)7.2 \text{ kWh} \times \text{CH}_{\text{eff}}}{\text{battery size}} = 0.4148$$

$$\text{percent} \leq \frac{7.2 \text{ kWh/battery size}}{\text{CH}_{\text{eff}}} = 0.488$$

percent < 1 – driving discharge – 0.0729 – 0.4148 – 3.21E – 4

Other constraints same as above (namely revenue > cost).

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