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Residential PV-Storage System Optimization Under Self-Consumption

Abstract

Controversies around net energy metering threaten to disrupt the distributed solar photovoltaic (PV) markets in many US states. Residential PV systems are particularly dependent on net-metering for their economic viability because of the mismatch between residential load profiles and PV generation. However, with the cost of lithium-ion batteries rapidly falling, energy storage may soon provide an alternative to net-metering, allowing the residential PV market to persist without net-metering. This paper uses a nonlinear optimization model to determine the optimal sizing and operation of a residential PV + lithium-ion battery system under a variety of cost assumptions and rate structures. It is shown that the cost effectiveness of energy storage and PVs depends heavily on the specific retail rate structure considered. While much of the US is several years away from lithium-ion batteries becoming economic for residential applications, Hawaii is already nearing that threshold.

Introduction

Battles are being waged over net-metering in states across the US. While net-metering has formed the foundation for exponential growth of the distributed solar industry and for the creation of multibillion-dollar companies like Solar City, electric utilities argue that photovoltaic (PV) users are not paying their fair share of transmission and distribution costs. In 2013, at least eight state Public Utilities Commissions (PUCs) undertook reviews of their net-metering policies. In some states, such as Ohio and Arkansas, the PUCs considered expanding their net-metering programs. However, in most of these states, the PUCs considered eliminating or limiting net-metering, or adding additional charges to net-metering customers. In Idaho for instance, the PUC considered levying a monthly service charge and a monthly capacity charge on customers with net-metered systems. In Louisiana, the PUC considered reducing compensation for net-metered systems from the retail rate to the wholesale rate.[1]

Nowhere has the battle over net-metering been fiercer than in Arizona, where Arizona Public Service (APS), the state's largest utility, asked for massive fees to be imposed on net-metered customers. Thus far, most PUCs have sided with the solar industry and have maintained their net-metering policies. The Arizona PUC did impose a fee of $0.70/kw-month, however, this was only about 10% of what APS had requested.[2] While the solar industry appears to have largely won the first round of net-metering battles, the fight is far from over. It may not be long before PUCs begin to impose further restrictions on net-metering.

It is often argued that without net-metering, the distributed solar industry would grind to a halt. However, with the costs of energy storage rapidly decreasing, this may not always be the case. Net-metering is critical for residential PV systems because their generation does not align well with typical residential load profiles (See Figure 1). Thus without compensation for electricity
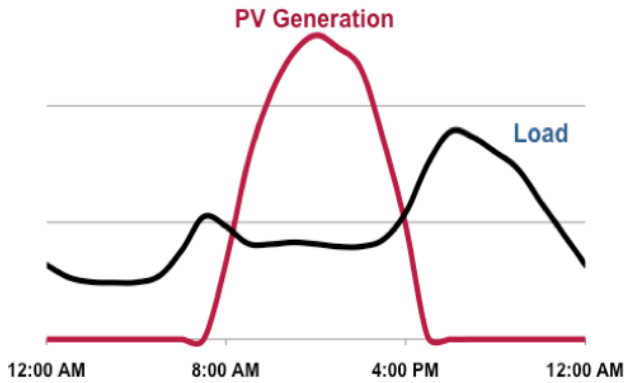
Figure 1 – Typical PV Generation and Residential Load Profiles

sent back to the grid, PV systems would have to be undersized in order to avoid wasting their excess generation during the middle of the day.

Energy storage may soon provide a viable alternative to net-metering by shifting PV generation from mid-day to the evening. A recent study by the Rocky Mountain Institute titled "The Economics of Grid Defection" found that with the cost of lithium-ion batteries r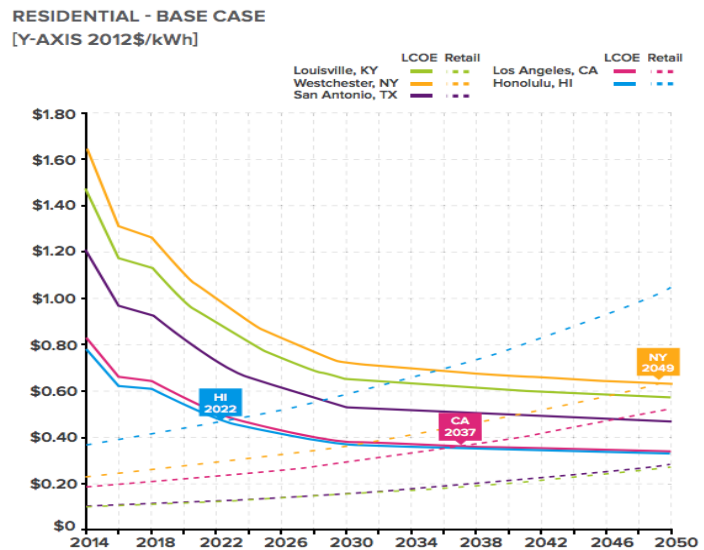apidly falling, completely disconnecting from the grid may soon be an economically viable option. The study found that even with conservative assumptions about technology improvement, off-grid solar+battery systems will be cheaper than buying electricity at retail rates in California by 2037 (see Figure 2). However, when more aggressive technology assumptions, consistent with recent progress, were applied, it was found that off grid systems will be economic in California by 2020, and in much of the rest of the United States in the following decade.[3]

Unless utilities opt for high monthly charges on all residential customers, however, disconnecting from the grid is unlikely to become the cheapest option. Doing so requires battery systems to be significantly oversized to cover long periods without sunlight. Instead, customers, even with limited or no net-metering, are likely to remain grid connected, sizing their battery system to shift PV generation to the evening, but using the grid on cloudy

Figure 2 – Project Levelized Cost of Energy from PV+Storage vs. Projected Residential Retail Rates (from RMI Report)

days. This paper examines the factors that drive the economics of such an arrangement and seeks to determine at what price lithium ion batteries could effectively replace net-metering. It also examines how the batteries would be operated, and what impact this transition would likely have on utility revenues.

System Setup and Input Data

The base case model assumes a grid tied, AC-coupled, PV and Lithium-ion battery system as shown in Figure 3. Electricity generated by the PV system is converted to AC by micro-inverters, and can then be used to power loads, can be converted back to DC in order to charge the battery, or can be sent back to the grid without compensation.

Figure 3 – System Layout

In order to characterize this system, a number of data inputs including PV output, load profiles, rate structures, and efficiencies of the various components were required. Hourly solar generation profiles and typical residential load profiles were generated based on Typical Meteorological Year 3 (TMY3) data. The hourly solar generation was simulated using the National Renewable Energy Laboratory (NREL's) System Advisor Model (SAM). Load profiles were taken from the OpenEI database of residential load profiles. [4]
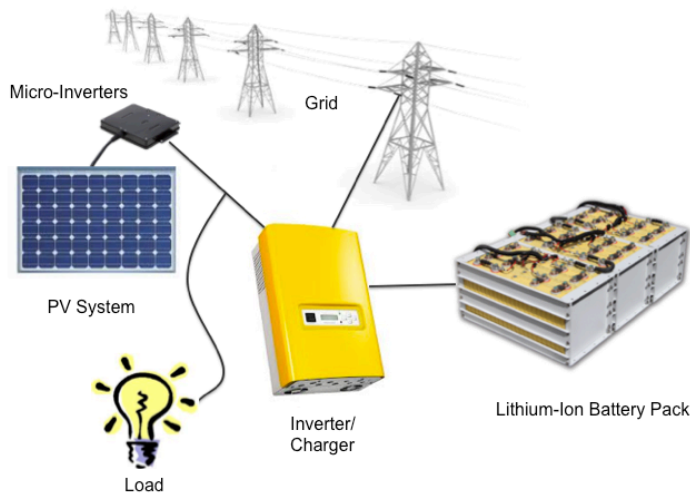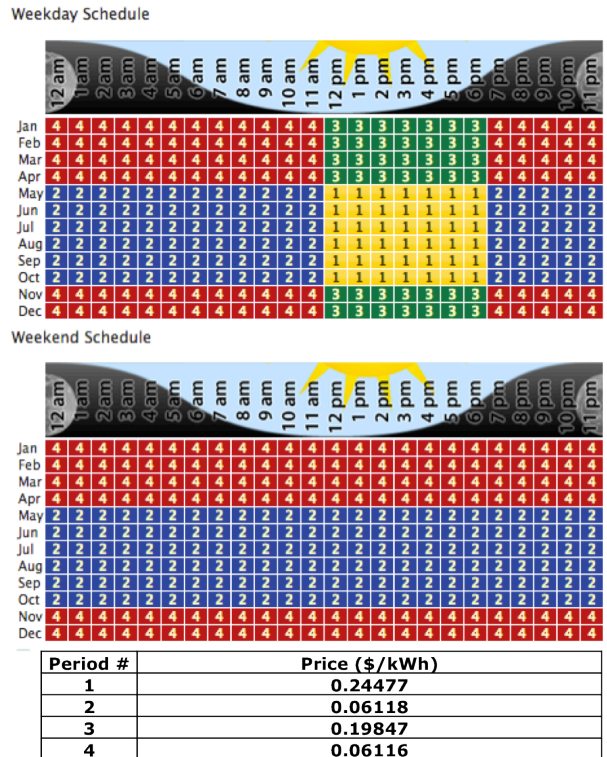
The base model uses TMY3 data from Phoenix Arizona, within the service territory of APS. It also assumes an APS residential time of use (TOU) rate structure shown in Figure 4.[5] It assumes 93% charging efficiency, and a 93% discharging efficiency (including the inverter). The efficiency of the micro-inverters is not considered, since the PV production outputs of SAM already take into account inverter losses. A discount rate of 5% is applied in the base case and a PV lifetime of 20 years is assumed.

Degradation of the battery is modeled using the equation: *cycle life = 1,000,000 * (Depth of Discharge*100)* $^{-1.45}$. This formulation was obtained by curve fitting data provided in a report by the Pacific Northwest National Laboratory.[6]

Period #	Price ($/kWh)
1	0.24477
2	0.06118
3	0.19847
4	0.06116

Figure 4 - APS Residential Time of Use Rate Structure

Other factors such as the degradation of the PV system, operation and maintenance (O&M) costs, and utility rate escalation are neglected in this analysis. The net present value of a system is determined based on capital expenditures for the PV and battery systems and savings from decreased electricity bills, and does not include the value of any reliability or backup power services that could be provided by the battery system.

The major data inputs and their sources are summarized in Table 1.

Input Name	Value/Description	Data Source
Rate Structure	Cost of electricity during each hour of the year. See Figure 4 for more details.	OpenEI[7]
PV Generation	Hourly PV generation	Simulated with SAM using TMY3 weather files[8]
Load Profile	Hourly electricity demand	OpenEI[9]
Battery Degradation	Lifecycle of the battery depends on how it is cycled. This effect was modeled with the equation: *cycle life = 1,000,000 * (Depth of Discharge *100)* $^{-1.45}$	Pacific Northwest National Laboratory[10]

The Model

Given these inputs, as well as values for the installed cost of PVs and battery systems, the model seeks to determine the optimal PV and storage system sizing and the optimal operation of the battery over the course of a year. The model, presented below, is a storage model with continuous variables, a nonlinear objective function and nonlinear constraints. The model assumes perfect knowledge of future PV generation and electricity load. The inherent uncertainty present in both of these parameters can be better managed with machine learning than with optimization.

The condensed mathematical form of the model is as follows:

$$\text{Maximize f(x)} = \left(\sum_{d=0}^{364} \sum_{h=0}^{23} P_{d,h} * L_{d,h} - P_{d,h} * E_{d.h}^{p} \right) - CRF_{PV} * C_{PV} - CRF_B * C_B$$

Subject to:

$$\forall\ d \in \{0...365\} \text{ and } h \in \{0...23\} : S_{d,h} \leq S_B * DOD_d$$
$$\forall\ d \in \{0...365\} \text{ and } h \in \{0...23\} : E_{d,h}^{in} = E_{d,h}^{out}$$
$$\forall\ d \in \{0...365\} \text{ and } h \in \{0...23\} : S_{d,h} \geq 0$$
$$\forall\ d \in \{0...365\} : DOD_d \leq 1$$

With Decsion Variables:

$E_{d,h}^{t}$ is the electricity flowing to the battery in hour h of day d (kWh)

$E_{d,h}^{f}$ is the electricity flowwing out of the battery in hour h of day d (kWh)

$E_{d,h}^{w}$ is the energy wasted (i.e. sent back to the grid without compensation) (kWh)

$E_{d,h}^{p}$ is the quantity of electricity purchased from the grid in hour h of day d (kWh)

S_{PV} is the size of the PV array (kW)

S_B is the total inital storage capacity of the battery (kWh)

DOD_d is the depth of discharge in day d (%)

With Defined Variables:

$S_{d,h}$ is the quantity of energy stored in hour h of day d (kWh)
→ $\forall\ d \in \{0...364\} S_{d,0} = 0$
→ $\forall\ d \in \{0...364\}$ and $h \in \{0...23\} : S_{d,h} = S_{d,h-1} + E^t_{d,h} * \eta^t_B - E^f_{d,h}$
$E^{in}_{d,h}$ is the electricity flowing into the home (from PVs, battery, or grid) in hour h of day d (kWh)
→ $\forall\ d \in \{0...364\}$ and $h \in \{0...23\} : E^{in}_{d,h} = E^{PV}_{d,h} + E^p_{d,h} + E^f_{d,h} * \eta^f_B$
$E^{out}_{d,h}$ is the electricity flowing out of, or being used by the home (kWh)
→ $\forall\ d \in \{0...364\}$ and $h \in \{0...23\} : E^{out}_{d,h} = L_{d,h} + E^t_{d,h} + E^w_{d,h}$
CRF_B is the capital recover factor for the battery pack
→ $CRF_b = \frac{r(r+1)^{T_b}}{(r+1)^{T_b}-1}$
T_b is the lifetime of the battery pack (years)
→ $T_b = D_{Max}/D_{yr}$
D_{Max} is the max number of times that the battery can be cycled before reaching the end of its useful life
→ $D_{Max} = \dfrac{365}{\sum\limits_{d=0}^{364} \frac{1}{1,000,000*(DOD_d*100)^{-1.452}}}$
C_{PV} is the installed cost of the PV system ($)
→ $C_{PV} = C^{kWh^{-1}}_{PV} * S_{PV}$
C_B is the installed cost of the battery ($)
→ $C_B = C^{kWh^{-1}}_B * S_B$

And With Parameters:

$P_{d,h}$ is the price of electricity in hour h of day d ($/kWh)
η^t_B is the efficiency with which electricity is converted into chemical energy in the battery
η^f_B is the efficiency with which electricity is withdrawn from the battery
$E^{PV}_{d,h}$ is the PV production in hour h of day d (kWh)
$L_{d,h}$ is the electricity load during hour h of day d (kWh)
T_{pv} is the lifetime of the PV array (years)
D_{yr} is the number of cycles per year
r is the discount rate
$C^{kWh^{-1}}_B$ is the installed cost of batteries per kWh ($/kWh)
$C^{kW^{-1}}_{PV}$ is the cost of PV per capacity ($/kW)
CRF_{PV} is the capital recovery factor for the PV array
→ $CRF_{PV} = \frac{r(r+1)^{T_{pv}}}{(r+1)^{T_{pv}}-1}$

A few features of the model deserve additional attention:

- The model forces the battery to be emptied completely each night. This assumption greatly reduces the computational intensity of the model, as it allows the model to optimize the operation of the battery over the course of each day separately. It also simplifies the calculation of depth of discharge for each day. Simulations run with a simplified linear formulation of the model suggest that this assumption is reasonable. The simplified linear model found that the battery would nearly always be empty at night even when the constraint was removed. Using this simplified model it was also found that the effect of this constraint on the objective function is negligible, however this assumption could break down for very cheap batteries and PVs or extremely high retail electricity rates. In these cases it could become optimal to oversize both systems and store excess PV generated electricity for use on cloudy days.

- A second simplifying assumption applied in most of the model runs is that the battery has no charging rate or discharging rate limitations. Because the battery is usually charged or discharged over the course of several hours, this assumption has little effect on the results. In a sensitivity analysis, it was found that power limitations of the battery had no effect on the objective function value or the system sizing, as long as the battery was able to fully charge within four hours and fully discharge within four hours.

- The model runs for only one year and annualizes the capital costs of the battery and PV system by using capital recovery factors (CRFs). While the model would ideally choose whether or not to replace the battery in each year of a multi-year simulation, this would require the introduction of binary variables, which cause the SNOPT solver to fail. Because the model only runs for one year and capital costs are annualized, all objective function values reported are annual.

- In order to calculate the CRF of the battery, it is necessary to determine the battery lifetime. The battery lifetime, in turn, depends on how the battery is cycled. The dependence of the battery life on the number of cycles, and the dependency of the CRF on the lifetime are both nonlinear, leading to a nonlinear objective function.

- As discussed above, the cycle life of the battery is assumed to be given by *cycle life = 1,000,000 * (Depth of Discharge *100)* [-1.45]. This formulation is based on data presented in a 2008 report by the Pacific Northwest National Laboratory.[11] Because lithium-ion batteries have seen significant improvement over the past six year, these values may no longer be accurate. For this reason, the sensitivity of results to this cycle life assumption is further investigated in a later section. Additionally, it is not clear what depth of discharge should be used in the equation above. Three options were considered: the maximum depth of discharge over the course of the year, the average depth of discharge over the course of the year, or the sum of daily degradations over the course of the year.

While each of these options is examined further in a later section, the results presented in this paper were obtained using the last of these three options. This option results in the formulation:

$$CycleLife = \frac{365}{\sum_{d=0}^{364} \frac{1}{1,000,000*(DOD_d*100)^{-1.452}}}$$

To see the motivation for this formulation, imagine the following scenario:
- The depth of discharge of the first cycle is 72.2%, thus the cycle life should be 2000 cycles, and 1/2000 of the battery life has been used up.
- The depth of discharge of the second cycle is 54.6%, implying a cycle life of 3000 cycles. Thus another 1/3000 of the battery life has been used up.

Over the course of these two days, 1/1200 of the battery life has been used up. If the battery continues to be cycled in this fashion, we would expect it to last for 2/(1/1200) = 2400 cycles. The equation shown above is simply the application of this logic to an entire year.

- Finally, because the battery is emptied each night, the depth of discharge for a given day is just the extent to which the battery if filled. This allows the operation of the battery to be regulated by the constraint $S_{d,h} \leq S_B * DOD_d$. This constraint is nonlinear.

Results

Base Case: Phoenix Arizona

The initial application of the model was to Phoenix Arizona, within the service territory of APS, the epicenter of the battle over net-metering. If net-metering were removed today, with current after-incentive installed PV costs of around $2.50/watt and lithium ion battery costs of around $500/kWh, the model finds an optimal solution of installing 1.1 kW of PVs and no battery system.[12, 13] The optimal PV system is so small because of the misalignment between generation and load. In practice, the cost of such a small PV systems would be dominated by permitting, labor, and other soft costs, resulting in a higher price. Thus if net-metering were removed today, residential solar installations would likely cease in Arizona.

A second optimization was run for the year 2025. In this scenario residential solar costs were assumed to fall to the current utility scale cost of around $2/watt, lithium-ion battery costs fall to the DOE 2022 target of $125/kWh, and electricity rates increase by 3% per year.[14, 15] The results are summarized in Table 2. These results suggest that lithium-ion batteries would not completely replace the benefits of net-metering (a PV system under net-metering would likely be larger than 2.43 kW), however, at these prices, battery storage could make PVs a viable option even without net-metering. In this 2025 case, customer bills would decrease by 63.4% and utility revenues would decrease by a corresponding amount. However, since the utility's peak demand is also lowered, further analysis would be required in order to determine the impact on utility profit.

Table 2 – APS comparison of current scenario and 2025 scenario

	2014	2025
After Incentive PV Cost ($/W)	2.50	2.00
After Incentive Battery Cost ($/kWh)	500	125
Utility Rate Escalation	1	$(1.03)^{11} = 1.38$
Objective Function Value ($)	39.59	529.84
Optimal PV Size (kW)	1.1	2.4
Optimal Battery Size (kWh)	0	22.0
Decrease in Electricity Bill (%)	19.3	63.4

In order to better understand the influence of battery cost and PV cost on battery and PV sizing, a sensitivity analysis was performed, varying PV price between $1.00/W and $4.00/W and battery price between $100/kWh and $400/kWh. The results are presented in Figures 5 through 7.

As expected, the objective function value increases as PVs and batteries get cheaper. The less intuitive results appear in Figures 6 and 7. As shown in figure 6, a very large battery system becomes optimal when batteries are very cheap and PVs are expensive. In this situation, the batteries are used primarily for arbitraging the difference in price between the different periods of the TOU rate. Perhaps an even more counterintuitive result is shown in Figure 7. The optimal PV size is largest when the cost of batteries is around $200/kWh, but decreases with cheaper, or more expensive batteries. This result is a product of the specific rate structure being considered. As can be seen in Figure 6, there is no opportunity for energy arbitrage with batteries costing more than $150/kWh, thus the value of PVs is higher when batteries cost $200.
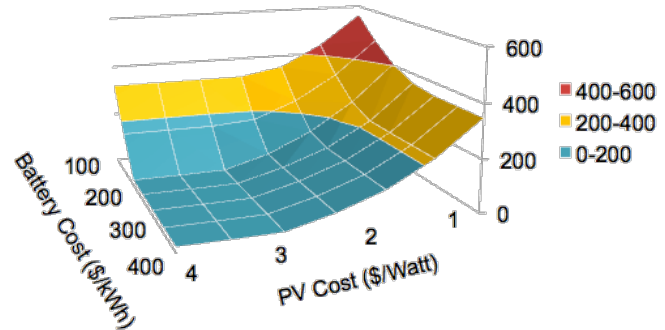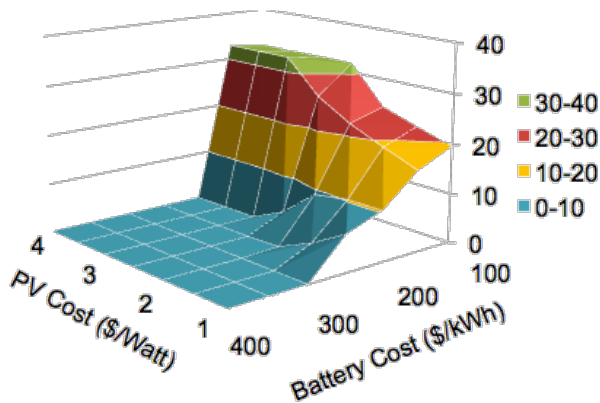

Figure 5 - Objective Function ($)

Figure 6 - Optimal Battery Size (kWh)
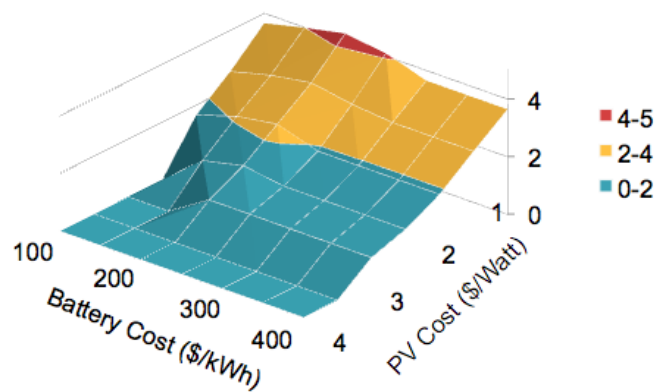

Figure 7 - Optimal PV Size (kW)

Flat Rates: Hawaii

Because many of the conclusions of the APS analysis were highly dependant on the specific rate structure considered, a second location and rate structure were chosen as a point of comparison. The RMI Report identifies Hawaii as the first place where off grid systems will become economic.[16] Thus a similar analysis was undertaken for Hawaii. This analysis is especially pertinent for Hawaii because residential solar installations are beginning to overwhelm the grid in many locations. Last year, Hawaiian Electric Company (HEC), Hawaii's largest utility abruptly halted the interconnection of new residential systems on Oahu, claiming that their system could not handle more solar. Energy storage, however, might provide a way around this dilemma without major investments in centralized infrastructure.[17]

While HEC offers a variety of rate structures, a flat rate of $0.351/kWh, the average residential retail price, was used to approximate HEC's very gradual tiered rate structure. Because there is only a $0.03 difference between the lowest and highest tier, this is a reasonable approximation.[18]

Given this very high, flat rate structure, batteries may already provide a viable alternative to net-metering. At a battery cost of $400/kWh, the optimal battery size is 6.2 kWh and the optimal PV size is 4.07 kW. Figure 8 shows the optimal PV size as a function of battery price. Not only does this graph demonstrate the potential of batteries to allow for large residential PV systems in Hawaii, but it also demonstrates that unlike with the APS TOU rate structure, optimal PV size shows a simple negative correlation with battery cost.
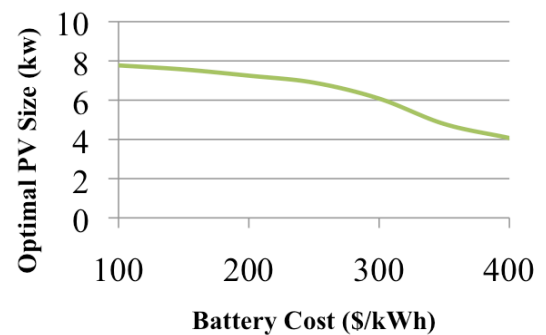

Figure 6 – Hawaii Dependence of Optimal PV Size on Battery Cost (assumes PV price of $2.50/W installed)

Sensitivity to Formulations of Cycle Life

As previously discussed, the formulation of battery degradation used to obtain the results above involved calculating the degradation that occurred during each day, and then summing these values. However, two other formulations were also considered for calculating the cycle life of the battery. They involve utilizing the maximum DOD or the average DOD. In order to compare these three methods, each was run for the Arizona Base Case, with a PV cost of $1.50/watt and a battery cost $200/kWh. The distribution of DODs over the course of a year is shown in Figure 9 for each of these assumptions.
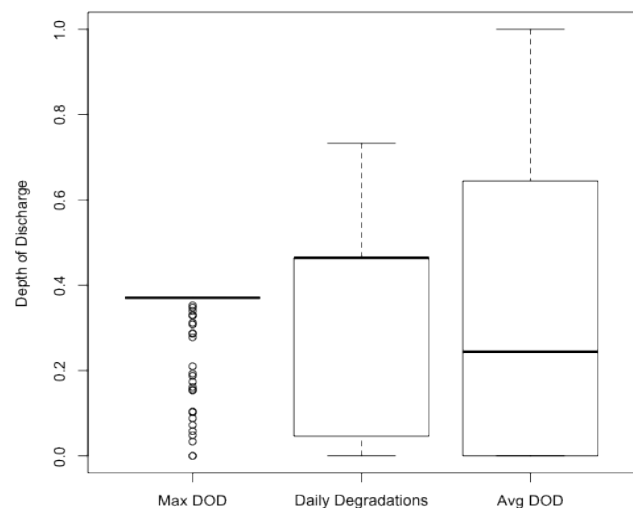

Figure 7 – Daily Variation in Depth of Discharge

As can be seen from the figure, calculating the cycle life based solely on the maximum DOD causes the battery to be cycled to the max DOD nearly every day. Using the average DOD has the opposite effect, causing wide variation in how the battery is cycled. On weekends and during the winter, it tends to be cycle very little, while in the summer it often exhibits a DOD of 100%. Finally, the Daily Degradation model exhibits an intermediate level of variation, but never fully cycles the battery.

The sensitivity of other optimization outputs to the degradation formulation is displayed in Table 3. The important takeaway is that while the objective function value varies by less than 40%, these different approaches to modeling degradation lead to greater differences in the optimal size and operation of the battery.

Table 3 – Comparison of Different Cycle Life Formulations

	Max DOD	Daily Degradations	Avg DOD
Objective Function Value ($)	152.36	186.47	219.45
Optimal PV Size (kW)	2.47	2.86	2.76
Optimal Battery Size (kWh)	0.27	7.45	15.65
Lost Utility Revenue (%)	33.6	50	62.1
Cycle Life	5271	5272	5799

A second concern about the model's treatment of battery degradation is that the data used are derived from a 2008 report. Newer lithium-ion batteries may have longer cycles lives, however, newer data is not readily available. The one available data point comes from A123 systems, which claimed that its battery could be cycled at 100% DOD approximately 8000 times.[19] This claim is based on laboratory testing and is likely an overstatement, however, in order to evaluate the sensitivity of results to changes in this 2008 data, the Daily Degradation version of the model was run with the same inputs as above, except with the cycle life increased by a factor of 2. Thus *cycle life = 2,000,000 * (Depth of Discharge *100)* $^{-1.45}$.

This change causes the optimal cycle life to increase from 5272 cycles to 7335 cycles while the battery is cycled more fully. It also results in a significantly higher optimal battery size and objective function value of 15.4 kWh and $294.02 respectively. The optimal size of the PV system decreases slightly to 2.59 kW. This implies that the effect of a longer-lived battery depends greatly on the rate structure in which it is deployed. More generally, these results suggest that the battery degradation rate can have a major impact on the optimization results and it would be extremely useful to have more up-to-date data.

Robustness and Problems with Convergence

Because the model is highly nonlinear, it is not guaranteed to find the global optimal solution. A sensitivity script was run to test the model's robustness with various default values of the decision variables. The model converged to the same optimal solution in nearly all cases. However, in rare cases, the solver was unable to satisfy the criteria for an optimal solution. Nonetheless, in these cases, the model returned a solution that was very similar or identical to the optimal solution.

Other challenges were observed when running the PV and battery price sensitivity script. For certain values of the input parameters, the model was unable to verify that it had reached a local optimal solution. For some of these points, SNOPT was unable to improve the objective function value, but could not satisfy the convergence criteria. For others, the model ran for long periods of time without improving the objective function and was eventually forced to return its current solution. These cases did not follow a clear pattern, however, they tended to occur only for high PV and/or storage system costs associated with objective function values of approximately zero. And, while these model runs did not necessarily find optimal values, they did return values that were consistent with observed trends. Because these convergence failures were rare and did not appear to significantly impact the results, they were not examined further.

Future Research

The greatest potential flaw in this optimization model lies in its treatment of degradation. As previously discussed, the way that degradation is modeled has a significant impact on the optimal size of a battery to be installed. A better characterization of degradation would require more up-to-date data, and a clearer understanding of the underlying chemistry and physics of a lithium ion battery. A more accurate formulation would also take into account temperature and calendar life. Because of the secrecy of the battery industry, this data may be difficult to obtain. However, such data would allow for more rigorous and meaningful academic evaluations of optimal battery deployment.

Another way that the model could be improved would be to add the capability to consider tiered rate structures. Such rate structures, which exist in many states including California, can provide a strong incentive for installing residential PV systems, and with modification, this model could help to examine how these rate structures would effect the cost effectiveness of energy storage.

A third addition to the model would be to allow electricity flowing into the grid to be reimbursed at the wholesale rate. It has often been suggested, and several PUCs have considered the idea, that distributed generators should be compensated at the avoid cost (i.e. the wholesale rate) rather than at the retail rate. This is an intermediate step that PUCs may choose to take rather than completely eliminating net-metering. In such a scenario, PVs would be more cost effective than they would be with the complete elimination of net-metering, however, energy storage would be less cost effective. With modification, this model could help to quantify the effect of such a policy on PVs and energy storage.

Finally, without modifying the model, there are numerous additional sensitivity analyses that could be run and rate structures that could be considered. One potential application would be a comparison with the RMI study to determine how the timeline for economic grid connected residential storage compares with the timeline for off-grid systems. Energy storage systems would also likely perform well under real-time pricing, which could be simulated by expressing a specific electricity price for each hour or even each 15-minute period of the year.

Conclusions

It is clear from the model results presented above that lithium ion batteries, with costs around $500/kWh cannot currently serve as a replacement for net-metering in Arizona. However, with battery prices projected to reach $200/kWh by 2020 and to continue declining for the foreseeable future, the day may come when energy storage will represent a real alternative.[20] Depending on how utilities handle the expansion of distributed solar, customers may opt to fully disconnect from the grid, as described in the RMI report. However, if net-metering is simply removed, the optimal response for customers may be to install undersized storage systems that decrease, but do not completely eliminate their dependence on the grid.

The best choice for future utility customers may depend heavily on their precise rate structures and locations. In cases with high flat rate structures, the optimal solution and its dependence on PV and battery costs may be relatively intuitive. However for more complex rate structures, the optimal solution for customers may be less clear. Thus utilities and their regulators will need to consider energy storage carefully in establishing rate structures. The long-term fate of net-metering is uncertain, but the challenges that distributed generation poses to utilities are likely to persist even if net-metering is limited or removed. The future evolution of the electric utility and the electricity grid will depend on how utilities respond.

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