

# **Economics of Behind-the-Meter Solar PV and Energy Storage**

Submitted in partial fulfillment of the requirements for

the degree of

Doctor of Philosophy

in

Engineering & Public Policy

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August, 2016

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## **Acknowledgements**

This work was supported by academic funds from the Department of Engineering and Public Policy, by the program for Graduate Assistance in Areas of National Need (GAANN) of the U.S. Department of Education, by the Department of Energy under Awards DE-OE0000300 and DE-OE0000204, by the NSF center for Climate and Energy Decision Making Center (CEDM)(SES-0949710), and by the Carnegie Mellon Electricity Industry Center (CEIC). A portion of this work was also supported in collaboration with the Electric Power Research Institute (EPRI) under Award 1020211.

Very special thanks to my thesis committee, Granger Morgan (co-chair), Paulina Jaramillo (co-chair), Jay Whitacre, and Michael Dworkin for their guidance and support throughout the years. I am also grateful for conversations with Nadav Enbar and Steven Coley during my collaboration with EPRI. Many coffee shop meetings with David Luke Oates, Chin Yen Tee, and other peers were incredibly helpful to keep things rolling. Thank you to Debbie Kuntz for always providing sweets and support, Adam Loucks for unlimited sass and printing, and every other EPP administrative staff that made my four years very enjoyable. Finally, I am thankful for my family, especially my wife, Shawna Davis, for endless support.

## **Abstract**

In this thesis, I present three research papers that focus on the economics of behind-the-meter technologies for residential, commercial, and industrial customers. Each of these papers takes the perspective of the customer, where the value of the technology comes from reducing their electricity bill.

In Chapter 2, I assess whether solar photovoltaics are economically viable without subsidies for residential customers across the United States. I calculate the break-even electricity prices and installation costs and find that, at a state level, solar PV is only currently economically attractive in Hawaii without the use of subsidies. In order for widespread adoption of solar PV, I illustrate how the availability of favorable financing terms, installation costs at or below \$1.5/W, and the continuance of net energy metering policies are each critical.

In Chapter 3, I create a case study to better understand solar PV economics for commercial and industrial customers, who collectively account for the majority of annual electricity sales in the United States. While residential customers are billed based on the total amount of energy they consume, commercial and industrial customers are also billed according to their greatest 15-minute energy use in a month with a demand charge. I analyze the net present value of a solar PV investment using both simulated and measured load and solar data for a variety of commercial customers in North and South Carolina. I identify key factors that influence economic viability and find that solar PV is not presently economically viable for these customers without subsidies, but will be once installation costs drop to below \$1.25/W.

In Chapter 4, I evaluate the economics of using energy storage to further reduce demand charges for each of the customers examined in Chapter 3. Using a “black-box” approach, I apply several generic energy storage technical attributes of a high-energy lithium-ion battery to assess the ideal performance and maximum economic benefit of energy storage. I find that batteries with lower capacities are most profitable for the commercial and industrial customers examined using an optimistic algorithm, but require further cost reductions using a pessimistic algorithm.

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## Introduction

Concerns of climate change have led to policies and actions across many countries to reduce greenhouse gas emissions. In 2009, President Obama outlined the Climate Action Plan, which lists cutting carbon pollution as a major component to mitigating climate change due to human activity [1]. At the state level, 29 states have enacted Renewable Portfolio Standards to increase the amount of electricity coming from renewable sources [2].

Declining module prices paired with federal, state, and local subsidies have spurred solar photovoltaic (PV) installations in the US. In 2015, new solar PV generation capacity accounted for 29.4% of all new electric generating capacity in the US, exceeding natural gas capacity additions for the first time [3]. However, despite this rapid growth, solar PV only accounted for 0.6% of electricity generation in the US [4]. The Department of Energy's SunShot Initiative's mission is to make solar PV cost competitive with traditional energy sources by the end of the decade. Accordingly, the program set goals of achieving total installed system prices of \$1.5/W and \$1.25/W for residential and commercial systems, respectively, by 2020 [5]. Note, however, that as we move towards a cleaner electricity grid, electricity prices may increase at a rate higher than historical rates due to higher-cost generation technologies such as carbon capture and storage (CCS) for conventional fossil fuel power plants [6]. This provides additional incentive for behind-the-meter technologies aimed at reducing a customer's electricity bill. We assess the economics of solar PV for residential, commercial, and industrial customers for both current installation prices and SunShot Initiative's target prices. In addition, we examine the technical and economic potential for additional electricity bill savings through energy storage.

This thesis addresses the following research questions, divided into three chapters:

2. Is rooftop solar PV at socket parity without subsidies?
  - Where is rooftop solar PV economically viable for residential customers?
  - How do existing federal and state subsidies improve the economics of solar PV?
  - Does the optimal solar module type vary by location?
3. Evaluating solar photovoltaics socket parity for commercial and industrial customers: A North Carolina case study
  - Is solar for the commercial and industrial segment at socket parity, with and without the 30% federal investment tax credit?
  - What types of cost reductions are required to reach socket parity?
  - To what extent do key factors affect socket parity (e.g., rate structure, retail escalation, load profile, subsidy)?
  - Do hourly, simulated data adequately estimate demand charge reduction with solar PV?
4. Maximizing value of energy storage for commercial & industrial customers with demand charges
  - What are the levelized costs and benefits of stored electricity from a black box device?
  - Do actual technologies meet technical requirements?
  - If costs are not feasible, what conditions will need to occur for viability?

# **Is Rooftop Solar PV at Socket Parity Without Subsidies?**

## **1.1 Abstract**

Installations of rooftop solar photovoltaic (PV) technology in the United States have increased dramatically in recent years, in large part because of state and federal subsidies. In the future, such subsidies may be reduced or eliminated. From the homeowner's perspective, solar PV is competitive when it can produce electricity at a cost equivalent to the retail electricity rate, a condition sometimes referred to as "socket parity." In assessing the economic viability of residential solar PV, most existing literature considers only a few locations and fails to consider the differences in PV system cost and electricity prices that exist across the U.S. We combined insolation data from more than 1,000 locations, installation costs by region, and county-level utility rates to provide a more complete economic assessment of rooftop solar PV across the U.S. We calculated the break-even electricity prices and evaluated the reductions in installed costs needed to reach socket parity. Among the scenarios considered, we estimate that only Hawaii has achieved socket parity without the use of subsidies. With subsidies, six states reach socket parity, yet widespread parity is still not achieved. We find that high installation costs and financing rates are two of the largest barriers to socket parity.

## **1.2 Introduction**

As a result of falling installation prices and federal, state and local incentives, recent years have witnessed a remarkable proliferation of rooftop photovoltaic (PV) arrays. At the federal level, incentives include the 30% solar investment tax credit (ITC) and rules that require utilities to interconnect sources of distributed generation. Many local, regional, and state governments provide a variety of subsidies including rebates, low-interest loans, performance-based

incentives, grants, and various tax incentives [7]. Twenty-nine states, as well as Washington DC and three territories have renewable Portfolio Standards (RPS) that require that a percentage of electricity sold in the state come from qualifying renewable resources [8]. An additional eight states and one territory have renewable portfolio goals [8] with targets of renewable generation between 2-25% of total generation. While wind power has been the fastest growing renewable resource, and is expected to be the largest contributor to the RPS targets [9], solar is also playing a role, particularly because some state RPS programs require that a portion of solar power come from residential solar systems. Finally, many states have implemented net metering rules, which require distribution utilities to purchase surplus power produced by customers at retail rates, rather than the much lower wholesale prices at which the utilities buy most of their power [10].

Subsidies and incentives for PV have largely been motivated by an understanding of the need to decarbonize the energy system, and by a desire to reduce the other externalities that arise from burning fossil fuels [11], and by a more general belief that renewable energy resources contribute to "sustainability." The hope is that by subsidizing deployment, market size will increase and costs will be driven down through innovation and economies of scale. Indeed, recent years have witnessed a dramatic fall in solar PV module prices, largely as a result of Chinese module production and the decline of polysilicon prices (as seen in Figure A-1) that directly affect module costs [12]-[14]. Today, the average cost of a typical rooftop PV installation is around a third of what it was in 1998 [15]. A breakdown of these installation costs can be seen in Figure A-2. While electricity generated by PV still constitutes a very small fraction of total U.S. electricity generation, installations have grown rapidly, with capacity additions totaling over 4.5 GW in 2013 and nearly 4 GW during the first three quarters in 2014 (Figure A-3) [14], [16].

The recent growth in PV installations has sparked a growing number of news reports and press releases that argue that solar PV has already achieved "grid parity" or will reach grid parity in the near term [17]-[20]. Many of these articles reference an October 2014 market research report by Deutsche Bank's Vishal Shah and Jerimiah Booream-Phelps in which they argue that "...more than 10 US states are currently at grid parity and nearly all 50 states would be at grid parity by 2016 timeframe" [21]. Such news coverage typically neglects to report that this claim is based on the existence of the ITC and other policy mechanisms aimed at supporting the deployment of such renewables. There is uncertainty, however, about the long-term availability of such support. The ITC, for example, is set to expire for residential customers at the end of 2016. Similarly, many of the grants and tax credits available from states and counties have either fixed capacity and/or time frames such that they may not be available to customers in the next few years. For example, the Iowa personal tax credit for residential customers will expire at the end of 2016 with the conclusion of the federal ITC for residential customers [22] and the Maryland rebate program will expire when funds are exhausted [23]. Some states and electricity providers offer feed-in-tariffs (FITs) for renewable generation sold back to the power company at rates between 10-30 ¢/kWh [24]. These FITs aim to encourage rapid deployment of renewable energy and may over-compensate the solar system owner. Some utilities are thus beginning to instead design and implement value-of-solar tariffs that compensate system owners at rates comparable to retail electricity prices.

Claims of grid parity have also relied on the continued existence of net metering. A majority of the states with net metering policies also include caps on net-metered capacity, creating uncertainty about the future availability of net metering [25]. California utilities are now limiting



the availability of net metering to future customers pursuant to Assembly Bill No. 327 [26] and other states/utilities may adopt similar limits. For example, Kansas and Oklahoma are allowing utilities to create new rate classes for distributed generation customers [27], a change that could negatively affect the economics of solar PV dependent on how the tariffs are structured. On the other hand, Vermont is an example of a state that has raised previous caps on net-metering capacity [28]. These examples illustrate that net-metering programs for residential customers are in flux across the country, which creates more uncertainty about the future economic viability of rooftop solar PV.

While widely used [29]-[31], the phrase "grid parity" is ambiguous. In 2013, Bazilian et al. argued that the term "...has become outdated and is generally misleading." Most analysts have used the phrase to indicate a situation in which "the total cost to consumers of PV electricity, adding in as many of the realistic costs as possible" [32] is less than or equal to the cost of power purchased from the grid at retail rates. Unlike Shah and Booream-Phelps (2014), others such as Farrell (2012), have excluded subsidies from their definition of grid parity. Some have also defined "grid parity" based on a comparison of the average levelized cost of electricity (LCOE) of solar PV systems with the LCOE of other energy technologies [33]. Branker et al. (2011) demonstrate the need for proper and transparent valuations using the LCOE of solar on a locational basis as factors such as insolation, electricity rates, and installed costs vary geographically. Bazilian et al. (2013) suggest that an LCOE comparison is an inadequate metric of "grid parity" because it hides complex interactions between variables that affect the economics of solar PV systems. Similarly, Paul Joskow describes LCOE as a "flawed" metric for evaluating intermittent resources [34].

Since we are evaluating the economics of solar PV from the homeowner's perspective, and not for utility planning, we focus on the break-even electricity price required for socket parity. This method allows us to avoid making assumptions of future electricity prices, although increasing electricity prices will further improve the economics of solar PV. This method implicitly assumes that generation does not exceed the customer's instantaneous load or that excess generation can be valued at the retail electricity price. However, we explore the effect of these assumptions in a sensitivity analysis. The break-even electricity price is useful because a residential customer cares about the cost of electricity coming from their rooftop array as compared with the cost of the electricity they buy from their local utility. Hence, rather than "grid parity" we use the phrase "socket parity," which we define as occurring when the lifetime cost from the rooftop array is less than or equal to the lifetime price of purchasing electricity from the local distribution utility [35].

To evaluate socket parity, we developed an engineering-economic model that accounts for region-specific installation costs, solar radiation, and electricity prices. Under these assumptions, we evaluated whether residential solar PV systems are at socket parity without subsidies, expanding on the scope of previous work by modeling the economic viability of PV systems in over 1,000 locations across the U.S. Further, we systematically explored the effects of different parameters that influence the economic viability of solar PV including installation costs, financing costs, and annual maintenance costs.

## 1.3 Method

### 1.3.1 Break-even Electricity Price

Our model calculates the break-even electricity price for an investment in a rooftop solar PV installation using pessimistic, best, and optimistic scenarios for residential customers. The primary inputs to this calculation are the installation costs, financing parameters, and annual energy production. Installation costs vary by region of the country. Table A-1 provides the latest cost estimates for different regions including the median installation costs as well as the 20<sup>th</sup> and 80<sup>th</sup> percentile costs in each region in 2014, the latest year for which these data are available [36]. We used the median costs for our best estimate, and 20<sup>th</sup> and 80<sup>th</sup> percentile costs for our optimistic and pessimistic estimates, respectively. While this model is similar to NREL's System Advisor Model (SAM) [37], constructing a model outside of the SAM platform allowed comparisons across locations with input parameters that vary by location and allowed for a more robust sensitivity analysis. We assumed that annual operation and maintenance (O&M) costs are \$21/kW-year [38], and included an additional \$1,500 for inverter replacement in year 15 [39]. The inverter replacement cost may be an overestimate if in the future the price of inverters decreases more rapidly than it has in the past. However, this assumption does not significantly affect our results.

To model annual energy production, we used the Sandia PV Performance Model, which uses sun-earth geometry, insolation data, and module performance characteristics in order to simulate power output [40]. For each location, we assumed a south-facing PV array with a fixed tilt at an angle equivalent to the latitude for the most year-round solar energy [41]. We assumed a system size of 4 kW for all locations as this reflects the average size of residential installations and

largely avoids oversizing. Note that the median size of residential installations grew to 6 kW in 2014, however, the installation costs used in the analysis were for 4-6 kW systems. Thus, modeling a 6 kW system would not benefit from economies of scale and would not change our results [36]. For the base analysis, we used the performance characteristics of the crystalline silicon BP Solar BP3220N Module, as explained in more detail in the SI. We used the I-Power SHO-5.2 inverter provided in the Sandia Inverter Database that has a power rating of 5.2 kW, appropriate for a 4 kW system. The insolation data used in this analysis come from the National Solar Radiation Database, which provides typical meteorological year (TMY) data that contain hourly solar radiation values and meteorological elements for 1,011 station locations across the U.S. (excluding territories). These typical meteorological data characterize conditions at each site over longer periods of time and contain actual time-series meteorological measurements and modeled solar values, though some values may result from interpolations where measurements were not available [42]. Appendix A provides more details about this dataset and Figure A-4 provides the spatial distributions of the stations included in the database. Figure A-5 shows the annual energy produced from a 4 kW system with c-Si modules.

Additional parameters in the engineering-economic model include the financing terms, discount rate, and system degradation rate. The most affordable and widely recommended financing mechanism for homeowners wishing to purchase a solar PV system are non tax-deductible loans [43]. To model these loans, which unlike home equity loans do not allow for a tax break on the interests paid, we considered nominal interest rates between 4.7-8.4%, depending on the scenario. We also assumed loan terms of up to 20 years to approach the typical 25-year warranty of a solar PV system [43]. We used a discount rate of 7% as recommended by the Office of

Management and Budget (2014) and varied it between 0-10% for sensitivity. Lastly, we assumed the rate at which the module performance declines over time is 3% during the first year and 0.5% annually thereafter [44], [45]. Table 1 summarizes the financial assumptions for each of the scenarios. Note that this paper does not include an analysis of the monetized benefits that connectivity to the power system provides to customers who have solar PV systems, nor the cost imposed on the power system from intermittent solar output, which results in more variable system net load. Furthermore, we did not account for the social benefits associated with zero-emissions generating capacity (Siler-Evans et al., 2013).

**Table 1:** Scenarios for evaluating current economic viability of rooftop solar PV.

Variable	Pessimistic Estimate	Best Estimate	Optimistic Estimate
Installation Cost (\$/W)	80 <sup>th</sup> Percentile of 2014 Costs in Table A-1	Median of 2014 Costs in Table A-1	20 <sup>th</sup> Percentile of 2014 Costs in Table A-1
Nominal Loan Interest Rate	8.4%	6.5%	4.7%
Loan Term (years)	5	15	20

We calculate the break-even electricity price using the general form:

$$\begin{aligned}
 & BE_{Electricity\ Price} \\
 &= \frac{\sum_{y=0}^n \left( \frac{Capital\ Cost \times \frac{i_e(1+i_e)^n}{(1+i_e)^n - 1}}{(1+DR)^n} \right) + \sum_{y=0}^{Lifetime} \frac{Annual\ O\&M\ Cost(y)}{(1+DR)^y}}{\sum_{y=0}^{Lifetime} \frac{Annual\ Generation(y)}{(1+DR)^y}}
 \end{aligned}$$

where  $i_e$  is the effective annual interest rate of the loan,  $n$  is the term of the loan in years, and  $DR$  is the discount rate. Since loans are compounded monthly but the break-even electricity price equation relies on annual cash flows, the effective annual interest rate is defined as:

$$i_e = \left(1 + \frac{r}{m}\right)^m - 1$$

where  $r$  is the nominal interest rate and  $m$  is the number of compounding periods in the year. For this analysis,  $m = 12$ . While different from the traditional definition of LCOE that Joskow (2011) criticizes (provided in Appendix A), which does not conventionally include financing costs or changes in the capacity factor throughout the years, this equation is similar to what NREL's SAM documentation has termed LCOE [46]. To avoid confusions, we thus refer to this as the break-even electricity price.

As part of a sensitivity analysis, we explored the effects of existing federal and state subsidies. When including the federal ITC, we assumed that the tax credit is distributed over five years, as per the five-year compliance period [47]. A customer may, however, carry the ITC back one year or carry it forward 20 years [47]. When using the full ITC in the first year, the break-even electricity price decreases by less than one cent, on average. Most states, however, have a difference in break-even and retail electricity prices greater than one cent, such that using the full ITC in the first year is not critical. On the state level, we considered solar renewable energy certificates (SRECs), rebates, and loan programs as well as state personal tax credits and tax deductions as available from the Database of State Incentives for Renewable & Efficiency [48]. We assume that personal tax credits are distributed evenly over five years, unless the state's program requires a shorter period, in which case we assume the tax credit is used in full during the first year. For tax deductions, we use the state's average household income to determine the

annual tax benefit and distribute annually according to the guidelines of the tax deduction.

Appendix A includes details on the subsidies considered in this analysis.

### **1.3.2 Comparison with Current Electricity Prices**

The break-even price of electricity calculated with our engineering-economic model is the lifetime price of electricity that system owners need to receive (or avoid from the grid) in order to reach socket parity. While some residential customers may elect to enter a power purchase agreement (PPA), this financing option is not always allowed [49]. Similarly, while a new business model has been developed in California in which companies are leasing solar PV systems to residential customers [50], this paper focuses on customer-owned systems. The break-even electricity prices we estimate can thus allow customers to better compare the options of purchasing or leasing a solar PV system.

Our goal, however, is to identify locations where customer-owned residential solar PV systems have reached socket-parity. In order to identify these locations we thus need information about current electricity prices. We obtained utility price data for the latest year available (2012) from the Open Energy Information (OpenEI) database [51] and compared them with the break-even electricity price. Since multiple utilities may provide service to the same county, we developed a weighted-average electricity price for each county, based on the total energy sales of each utility across its service territory. Further, these rates are the “bundled” rates provided by OpenEI and are assumed to include generation, transmission, and distribution costs. Figure 1A shows the retail electricity price we derived for locations across the country. For further details about retail price heterogeneity, Figure A-6 in Appendix A shows that differences between highest and lowest electricity prices within each county can be up to about 10 ¢/kWh. In addition, Figure A-7

shows the highest electricity prices in each county, which are sometimes much higher than the weighted average retail price we used in our analysis. While we did not specifically analyze these outliers, the economics of solar PV improve when displacing higher retail costs.

### **1.3.3 Net Metering**

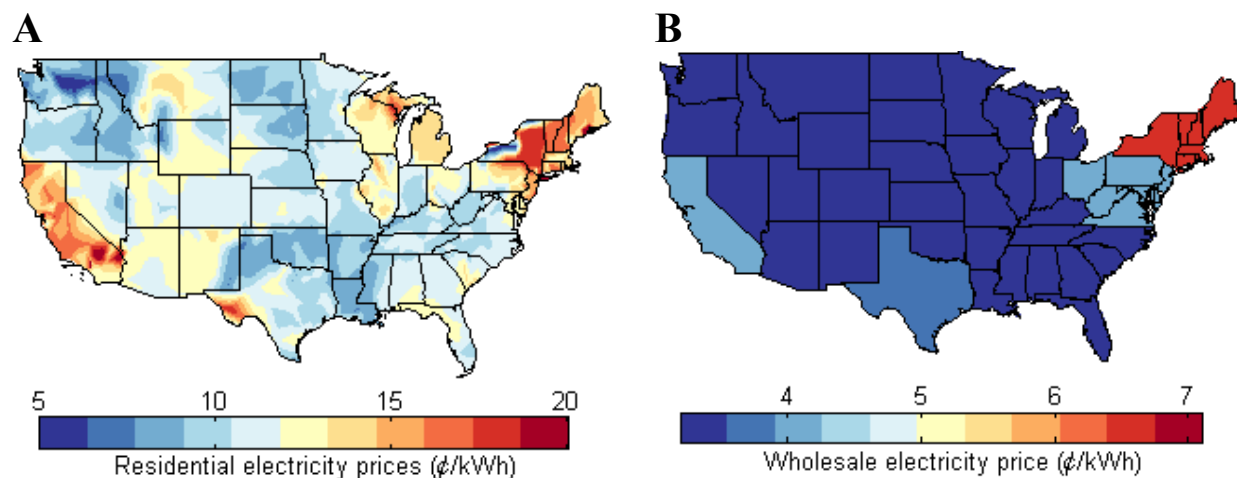
When a solar PV system produces power that exceeds the owner's simultaneous load, many utilities have net metering programs that credit customers at the residential retail rate for the energy from rooftop solar PV sent to the grid. However, this effectively constitutes a subsidy and in the future many utilities are likely to try to compensate producers of surplus power at wholesale prices, which are significantly lower than retail prices. While residential load profiles vary locally and across the U.S., we assumed that 30% of the annual energy produced by solar PV systems is exported back to the grid, which falls within the 20-40% range supported by both a study by LBNL as well as by the Solar Energy Industries Association [52], [53]. Thus, in order to account for potential changes in net metering benefits, we performed an additional analysis in which the electricity price we compare to the break-even electricity prices is a weighted average of the local retail rates previously described (weight is 70%) and the regional average wholesale prices shown in Figure 1B (weight is 30%) [54].

### **1.3.4 Alternative module technologies**

There have been suggestions that newer module technologies (i.e. thin-film) could perform better than the common crystalline silicon (c-Si) module type under certain climate conditions [55]-[57]. To better understand the effect of using the optimal module type for a given location, we compared the annual energy production from the common crystalline silicon (c-Si) module to various module types, including triple-junction amorphous silicon (3-a-Si), multi-crystalline silicon (mc-Si), Hetero-junction with Intrinsic Thin layer silicon (HIT-Si), and cadmium telluride



(CdTe) modules. We include these four particular alternative module types because they represent first and second-generation solar PV technologies at various levels of commercialization. Since region-specific installation costs for these alternative technologies are unavailable, we calculated the break-even electricity price by parametrically varying the installation costs nationally for each module type to assess differences between module types in economic terms.

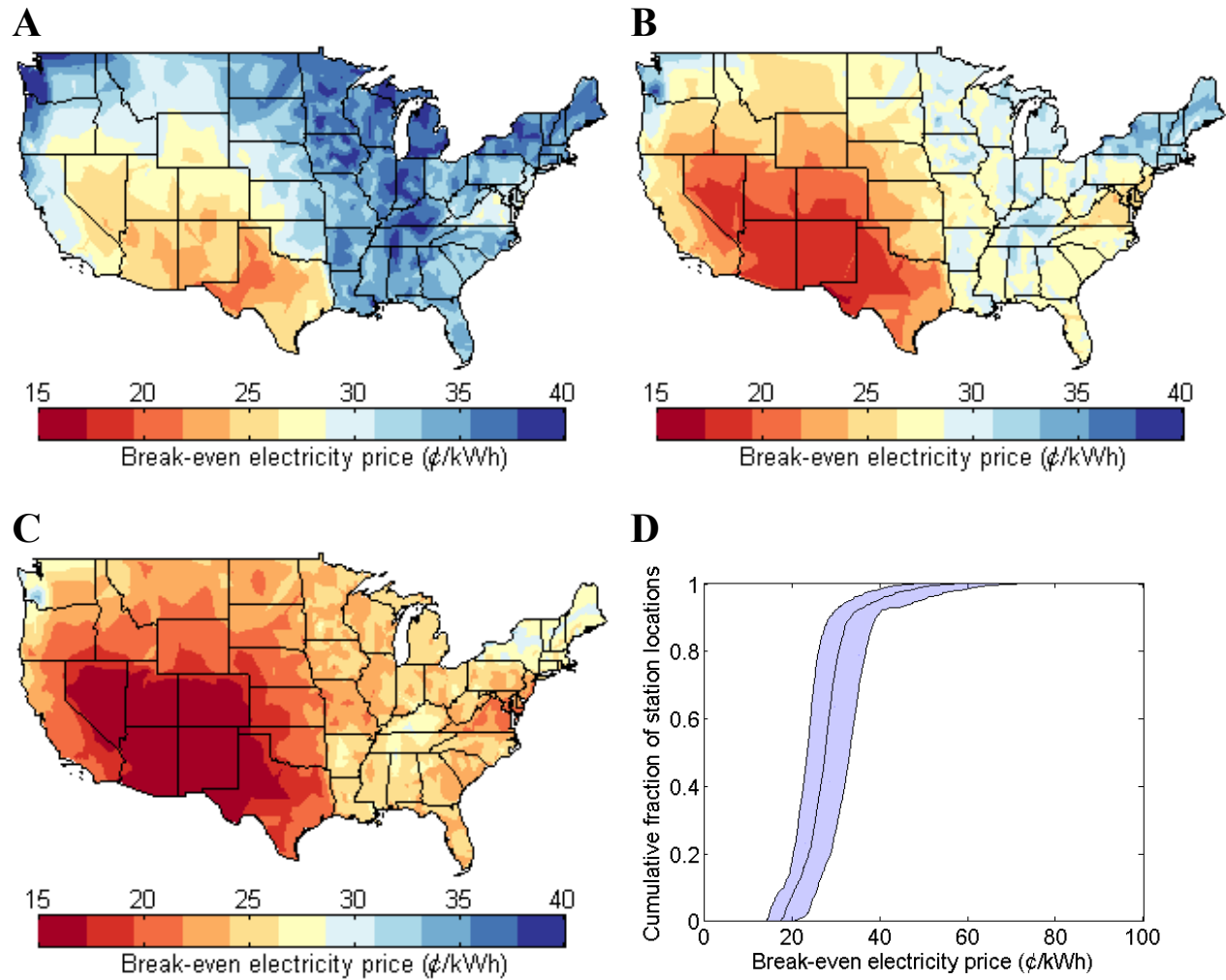


**Figure 1:** Residential (A) and wholesale (B) electricity prices used for comparison with estimated break-even electricity prices.

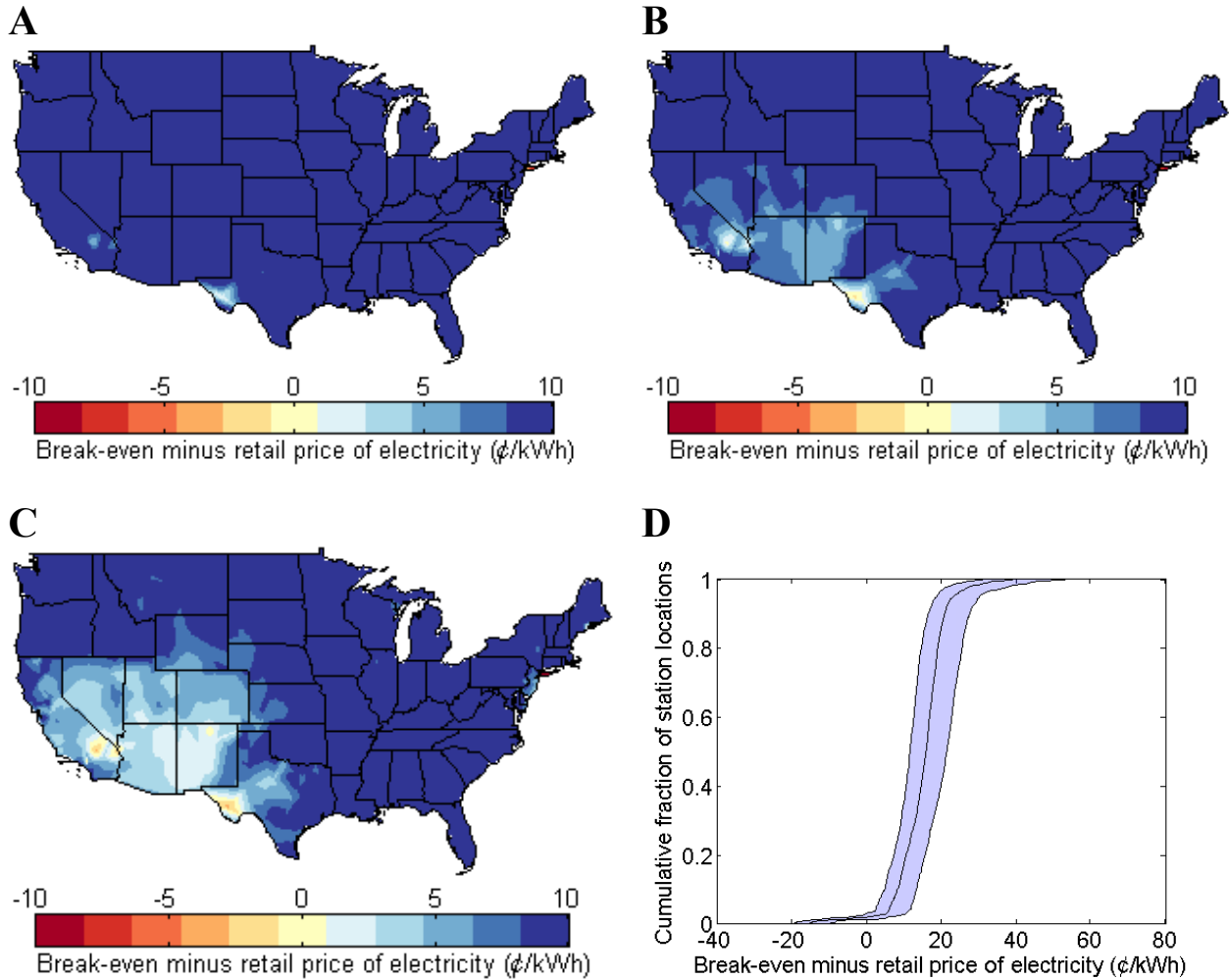
#### 1.4 Results and Discussion

When evaluating the current economics of solar PV without subsidies, we considered pessimistic, best, and optimistic parameters, as defined in Table 1. Figure 2 shows the break-even electricity prices for installations across the country for these scenarios. Not surprisingly, the break-even electricity price is lowest for states in the Southwest that have high insolation. To put these prices in perspective, Figure 3 shows the difference between the break-even and current retail electricity prices (weighted at the county level as previously described), as well as the cumulative distribution of these differences. Only Hawaii, not shown in the map, achieves statewide socket parity across any scenario due to high retail electricity prices and high

insolation. Figure 3D suggests that residential solar PV has yet to reach widespread socket parity when considering customer-owned investments without the use of subsidies, with less than 5% of locations at parity regardless of the scenario.



**Figure 2:** Pessimistic (A), Best (B), and Optimistic (C) break-even electricity prices for a 4 kW system as well as the cumulative distribution of these prices (D). The cumulative distribution shows the break-even electricity prices for the pessimistic estimate (right-most line), best estimate (middle line), and optimistic estimate (left-most line). These graphs (and later graphs) contain coloring spills across state borders that are an artifact of the smoothing algorithm used over the more than 1,000 sites in this analysis.



**Figure 3:** Pessimistic (A), Best (B), and Optimistic (C) estimates of the difference between break-even and current retail electricity prices as well as the cumulative distribution of these differences (D). Positive numbers reflect how far away a location is from reaching socket parity, while negative numbers are locations that have already reached socket parity. The cumulative distribution shows the difference between break-even and current retail electricity prices for the pessimistic estimate (right-most line), best estimate (middle line), and optimistic estimate (left-most line).

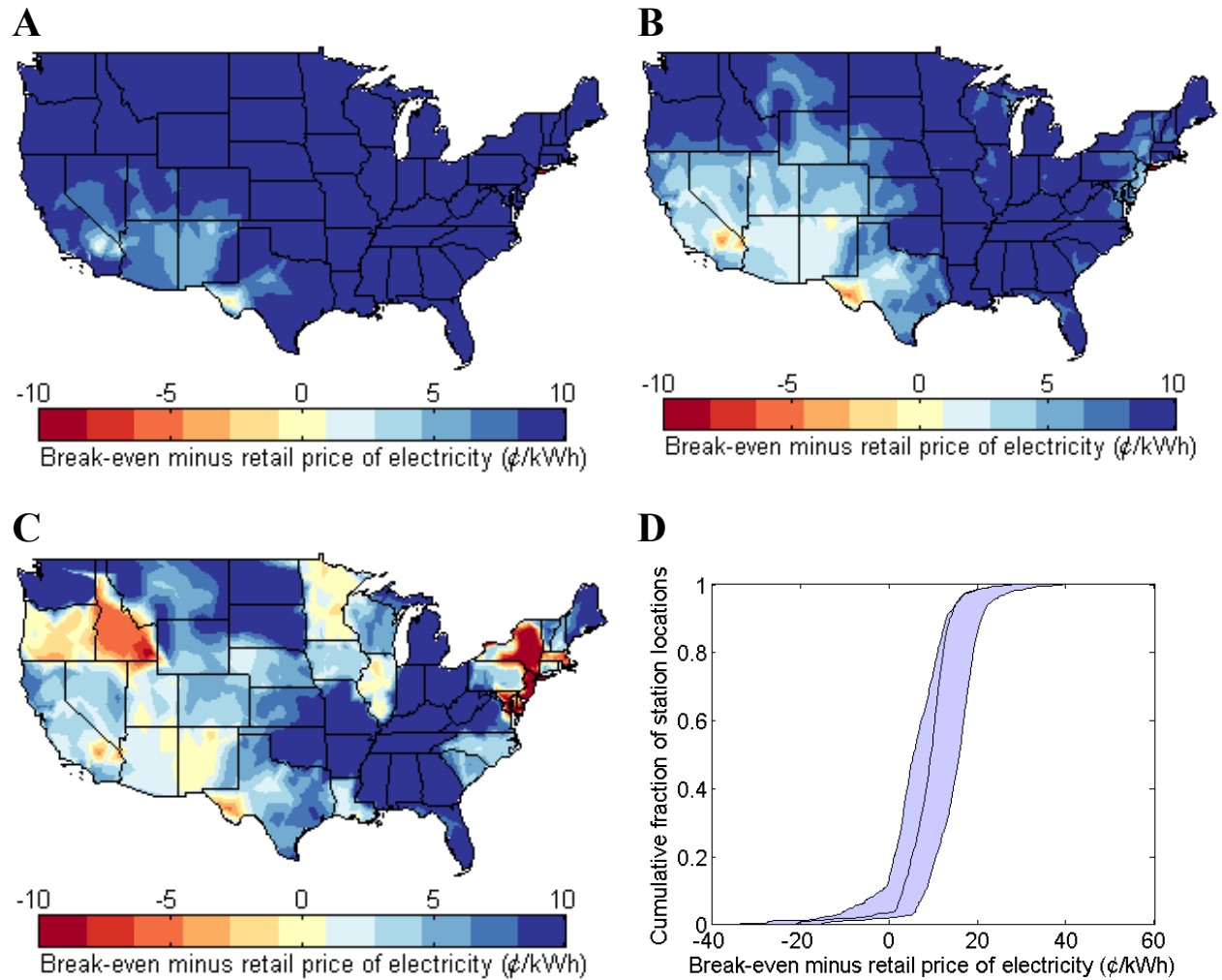
### 1.4.1 Sensitivity Analysis

To better understand the influence of the variables that drive the break-even electricity price, we used the best estimate as the base case and individually varied the nominal interest rate and loan term (0-8.4%, 5-30 years), installation cost (20<sup>th</sup>-80<sup>th</sup> percentile), discount rate (0-10%), and maintenance costs (annual and inverter replacement). No additional states achieve widespread socket parity when changing any one parameter between the upper and lower bounds. When

using a 0% nominal interest rate (a highly subsidized loan), 10-20% of locations within Alaska, California, New Mexico, and New York achieved socket parity. It may seem surprising that parts of Alaska would reach parity, but this is primarily driven by retail electricity prices exceeding 40 ¢/kWh.

#### **1.4.2 Effect of Subsidies**

In the best estimate scenario, only Hawaii has achieved socket parity. Even in the optimistic scenario of 20<sup>th</sup> percentile 2014 installation costs financed with a 20-year, 4.7% loan, widespread socket parity has not been achieved (only 3% of locations nationwide have achieved socket parity). Given that widespread parity at current installation costs without subsidies is unlikely, we considered the economics of these solar PV systems with the federal ITC alone, as well as the combination of the federal ITC and existing state subsidies. In Figure 4 the difference in break-even and retail electricity prices for these scenarios shows that federal and state subsidies improve the economic viability of residential PV systems in several states (some of which are subsidized more than what is necessary to reach socket parity), yet widespread parity is still not achieved. Further, if the federal ITC does in fact expire at the end of 2016 for residential customers and state and local subsidies remain uncertain, it may take longer to achieve widespread socket parity.



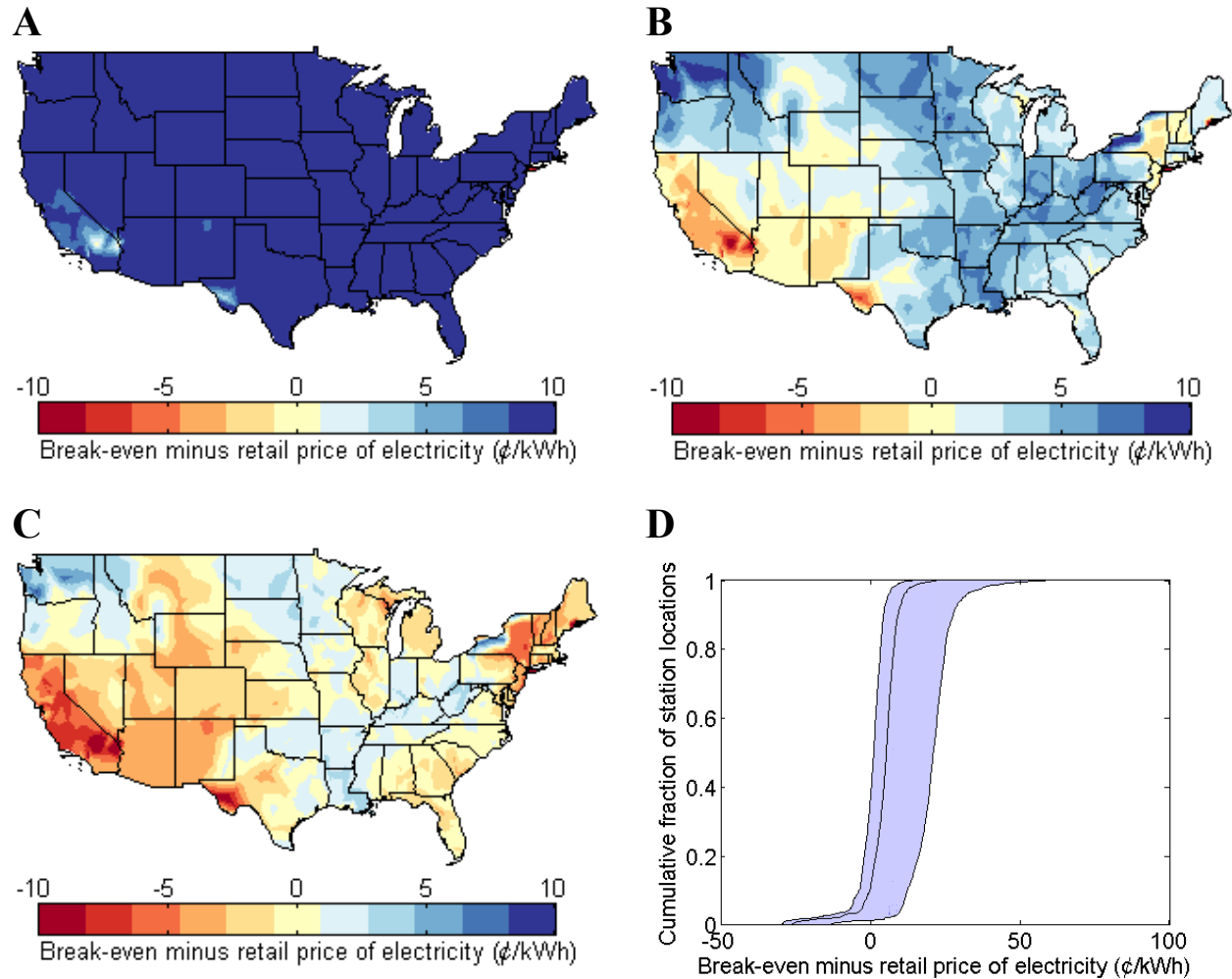
**Figure 4:** Difference between break-even and retail electricity prices for the best estimate scenario without subsidies (A) with the federal ITC (B), with the combination of the federal ITC and state subsidies (C), and a cumulative distribution of the break-even electricity prices for all locations in the model (D) without subsidies (right-most line), with federal ITC (middle line), and with both the federal ITC and state subsidies (left-most line).

### 1.4.3 The SunShot Initiative

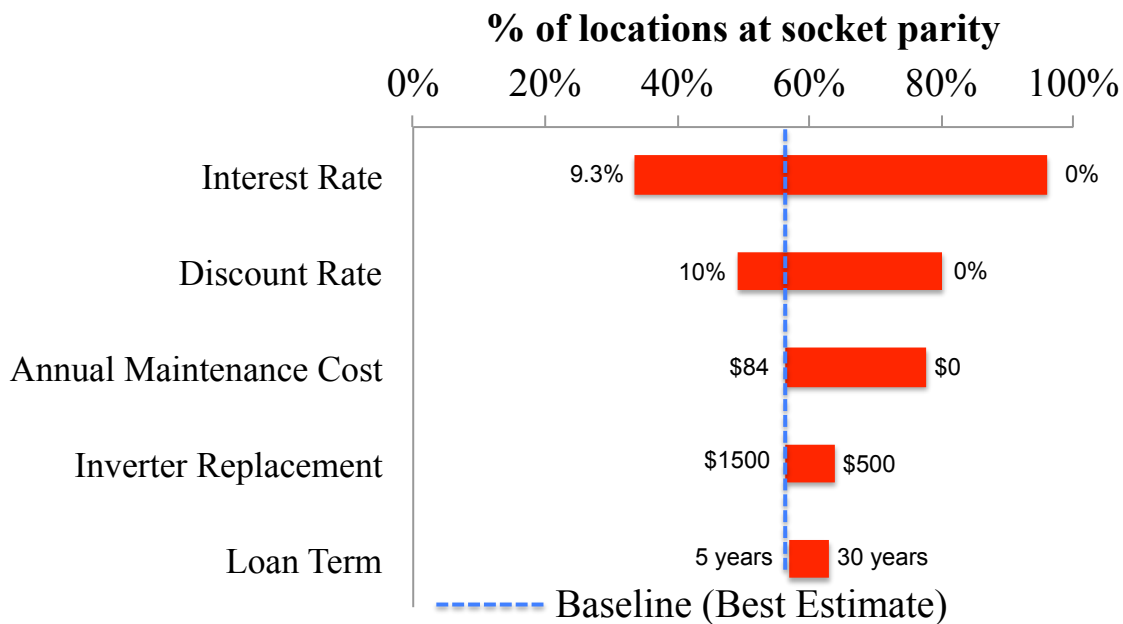
The Department of Energy's SunShot Initiative calls for installation costs for residential systems of \$1.5/W by 2020 [5]. This target is significantly lower than the system costs in our base case scenarios. The fact that residential installed costs in Germany averaged \$2.13/W in 2013 [36] suggests that the SunShot target may be feasible. Figure 5 shows the difference between break-even and retail electricity prices with installation costs of \$4.5/W (2014 national average for 4-6 kW systems), the 2013 Germany benchmark, and the SunShot Initiative target. In addition to locations in the Southwest, lower installation costs bring locations in the Northeast to socket parity due to high retail electricity prices. Meanwhile, Florida, nicknamed the "sunshine state", barely reaches socket parity with current electricity prices, even at the SunShot target costs.

To examine how the financial assumptions in our model affect the break-even electricity price of the system under the SunShot target installation cost, we perform a sensitivity analysis varying the key assumptions in our model while assuming a uniform installation cost of \$1.5/W across the country. The model was most sensitive to the interest rate, discount rate, and annual maintenance costs, as seen in Figure 6. Of these variables, the homeowner only has control of the annual maintenance costs and interest rate when financing a system. The annual maintenance cost was varied between \$84 and \$0 (note that inverter replacement costs are still included at year 15). Thus, if a homeowner can self-provide all required maintenance (washing if needed and cleaning debris off panels), then the economics of a solar PV investment can be improved considerably: 78% of sites in the best case scenario would achieve socket parity without other subsidies, while 98% would achieve socket parity if state and federal subsidies continued to be available. Similarly, securing a loan with a low interest rate is very valuable. The firm SolarCity

has recognized the business opportunity for providing loans with low interest rates with their MyPower solar loans that offer interest rates as low as 4.5% to customers in select states [58]. As we progress towards the SunShot Initiative’s 2020 goal, financing at low rates can significantly improve the economics of a residential solar PV investment, especially if government subsidies are not available.



**Figure 5:** Difference in break-even and retail electricity prices for the best estimate scenario for (A) 2014 national average installed costs of \$4.5/W, (B) 2013 German average of \$2.13/W, (C) SunShot Initiative goal of \$1.5/W, and (D) a cumulative distribution of each for all locations in the model at \$4.5/W (right-most line), at \$2.13/W (middle line), and at \$1.5/W (left-most line).

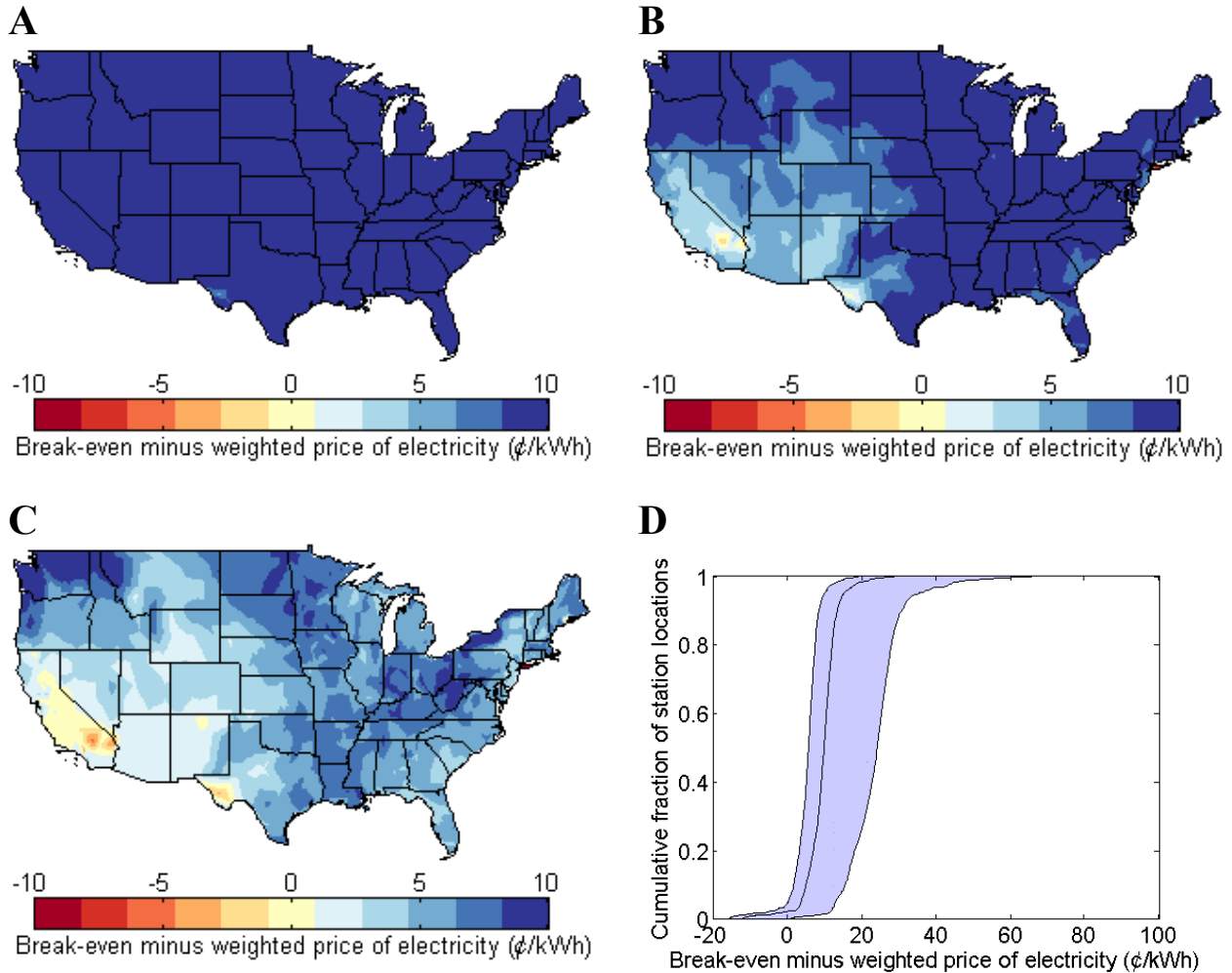


**Figure 6:** Percentage of stations at socket parity in sensitivity analysis using the best estimate scenario as the baseline and the SunShot Initiative's 2020 residential installed cost target of \$1.5/W.

#### 1.4.4 Net Metering and Displaced Costs of Energy

As previously noted, the continuation of net metering programs is uncertain in the future as utilities may compensate solar PV owners for any excess generation only at the wholesale electricity prices. To account for this possibility, we compared the break-even price of electricity for the systems with a weighted average of retail and wholesale electricity prices, assuming 30% of electricity produced by the residential solar PV systems is sold to the grid. Figure 7 shows the results of this comparison. Even with SunShot installation costs, if 30% of electricity produced by the solar PV system were sold to the grid at wholesale prices, most of the United States would not achieve socket parity. This highlights the effect that net metering has on the economics of solar PV for residential customers as well as the importance of avoiding oversizing the solar PV system relative to a customer's load.





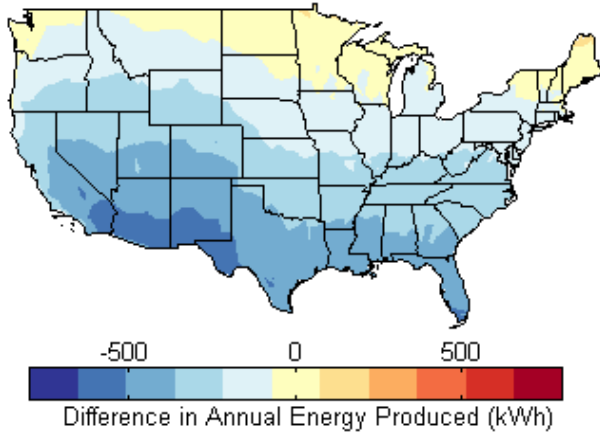
**Figure 7:** Difference in break-even and weighted (retail/wholesale) electricity prices for the best estimate scenario for (A) current installed costs (B) 2013 German average of \$2.13/W, (C) SunShot Initiative goal of \$1.5/W, and (D) a cumulative distribution of each for all locations in the model at current installed costs (right-most line), at \$2.13/W (middle line), and at \$1.5/W (left-most line).

In addition to net metering, there are some utilities (particularly those in California) that implement tiered pricing for residential customers. For customers with high levels of energy consumption, a solar PV system can displace electricity at rates much higher than the average retail electricity price. Similarly, net metering with time-of-use rate tariffs can provide an opportunity to shift consumption to off-peak times and receive credit for generation at peak rates. This has the potential to improve the economics for solar PV, but is highly dependent on the customer's load as well as the structure of the tariff.

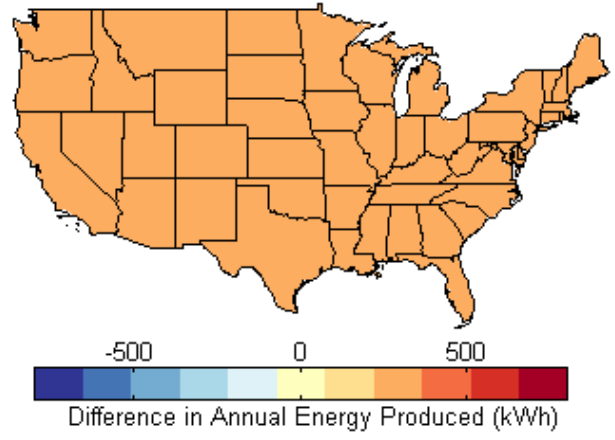
### 1.4.5 Alternative Module Types

While c-Si is the most common PV module type, a number of other solar technologies may be viable in the future. These technologies have different performance characteristics that, under some conditions, may allow them to produce more energy than c-Si modules. Figure 8 shows the differences in annual energy production from a c-Si module and four other module types, each scaled to 4 kW. This figure suggests that there are regional differences in the annual energy production of the alternative module types, probably arising in part from their varying temperature sensitivities. Generally, higher temperatures result in decreased module performance. Note that 3-a-Si, and HIT-Si modules consistently outperformed c-Si modules, with the differences in annual output increasing with higher temperatures [59]. The mc-Si module performed similarly to the c-Si module as the difference in annual output between the two modules is negligible. On the other hand, CdTe modules always underperform the c-Si module, however, the gaps in performance decrease as temperatures increase. Because these alternative modules are at different stages of development and deployment, their competitive position may change in the future and there may be additional benefits not captured in our model. For example, alternative modules may produce less variable power; or their production may be more coincident with daily peak demand.

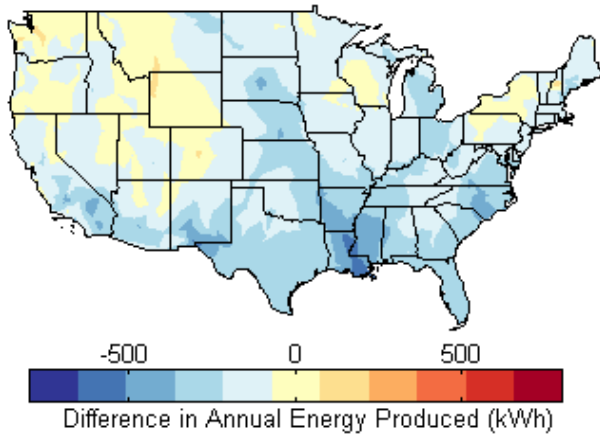
3-a-Si



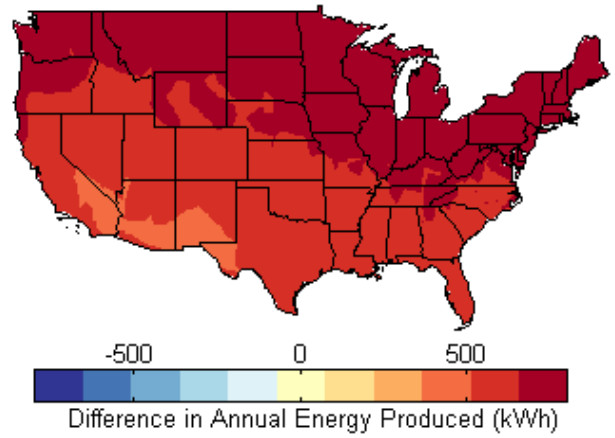
mc-Si



HIT-Si



CdTe

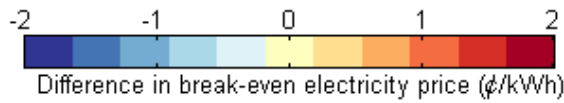
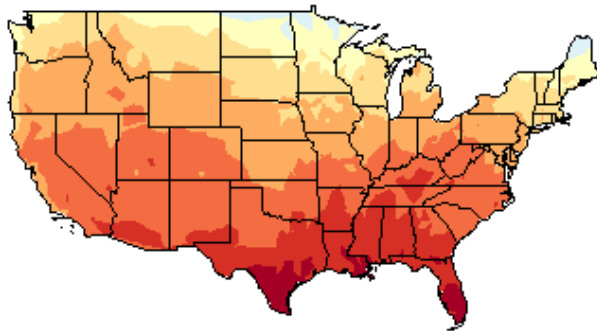


**Figure 8:** Difference in annual energy production (kWh) between c-Si modules and the 3-a-Si, mc-Si, HIT-Si, and CdTe modules. Positive values indicate that c-Si modules produce more energy.

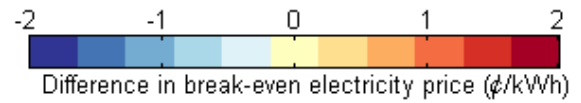
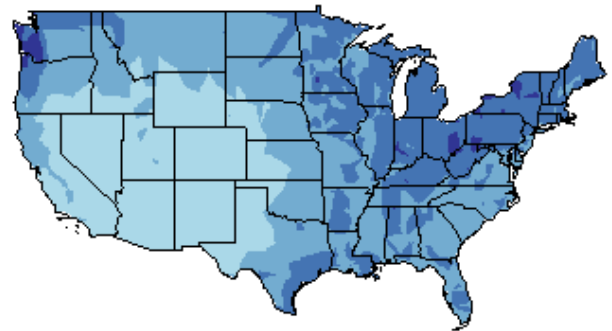
Because costs of these modules are less clear, we estimate break-even electricity prices for these systems at different installation costs. Figure 9 shows the difference in break-even electricity prices between the c-Si module and the four other module types if each module cost \$4/W.

Positive (red) numbers indicate that the alternative module is more cost effective than the c-Si module.

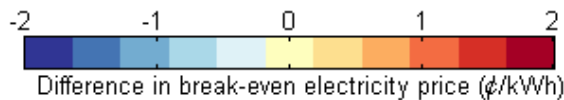
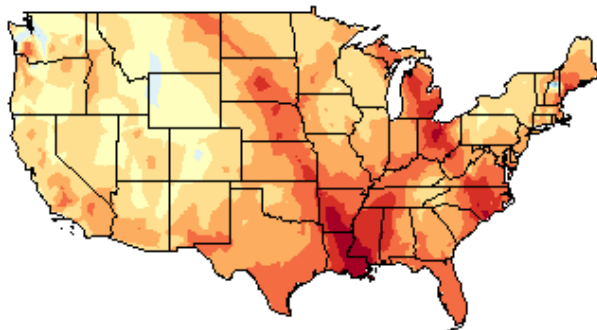
3-a-Si



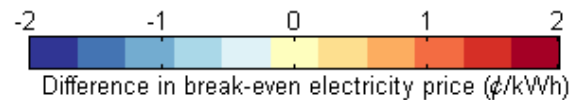
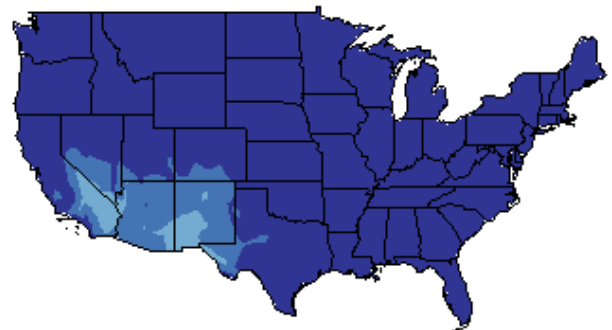
mc-Si



HIT-Si



CdTe



**Figure 9:** Difference in break-even electricity price (¢/kWh) between c-Si modules and the 3-a-Si, mc-Si, HIT-Si, and CdTe modules if all modules cost \$4/W. Positive values indicate that the alternative module is more cost effective than the c-Si module.

## **1.5 Conclusions and Policy Implications**

In summary, our results suggest that socket parity without subsidies has not yet become a reality in the lower 48 states. For residential solar systems to reach socket parity, continued installation-cost reductions are critical, along with the availability of low-interest loans and the ability to reduce or eliminate annual maintenance costs. Further, socket parity is highly dependent on how much, and at what rate, excess electricity is sold back to the grid. While net metering programs can improve the economics of residential solar PV, they represent a financial burden for most utilities because they can purchase electricity at lower prices in the wholesale market, and because utilities must continue to cover the operation and maintenance costs of the distribution systems to which solar PV systems are connected (Kind, 2013).

When examining potential benefits of using less common solar PV module technologies, we found that the ideal module type varies by climate, in part due to varying temperature sensitivities. Because ours is an engineering-economic analysis performed from the perspective of the homeowner, it does not consider potential societal benefits of increased solar PV penetration. Similarly, this assessment does not account for the value of reducing dependencies on foreign and local fuels that historically have been subject to price volatility. Together these benefits may provide sufficient incentive for maintaining at least some government subsidies.

Until the SunShot cost targets are achieved, continued subsidies can support the growth needed to meet state and federal goals of increased renewable generation. As shown in Figure 4, subsidies have enabled some states to achieve socket parity that would not otherwise occur with current installed costs. However, these state subsidies may yield varying amounts of public benefit. If the goal is to encourage more installations, smaller subsidies in states closer to parity may achieve that goal more efficiently than subsidizing installations in states not close to parity.

Similarly, if the goal is to achieve the greatest public health benefits by reducing air emissions from the power system, then subsidies in states with a “dirtier” electricity mix may provide more benefit than subsidies in states with a “cleaner” electricity mix [60]. Given different goals, it may be necessary to reallocate subsidies instead of providing the same level of support throughout every location, as the ITC does. Once the SunShot cost target is reached, policy-makers should consider what timing is most appropriate for the reduction or elimination of additional financial support for solar PV systems. The analysis in this paper should be helpful in informing that decision-making process.

## ACKNOWLEDGMENTS

This work was supported by academic funds from the Department of Engineering and Public Policy, by the program for Graduate Assistance in Areas of National Need (GAANN) of the U.S. Department of Education, by the Department of Energy under Awards DE-OE0000300 and DE-OE0000204, by the NSF center for Climate and Energy Decision Making Center (CEDM) (SES-0949710), and by the Carnegie Mellon Electricity Industry Center (CEIC). Results and conclusions are the sole responsibility of the authors and may not represent the views of the funding sources.

# Evaluating Solar PV for Commercial and Industrial Customers

## 1.6 Abstract

Commercial and industrial (C&I) customers, who collectively account for the majority of annual electricity sales in the U.S., may be poised to adopt larger amounts of solar photovoltaics (PV) as the resource's costs continue to decline and potential rate reforms unfold. To better understand the outlook for this market segment, we create a case study to gain insight about the financial viability of grid-connected, behind-the-meter solar PV. Tariffs for C&I customers typically include demand charges. To assess the degree to which such customers are at “socket parity”—the point at which the total cost of ownership for unsubsidized solar PV equals the associated offset in the retail electricity bill—we analyze the net present value (NPV) of a solar PV investment using simulated load and solar data for a variety of commercial customers in North Carolina. We find that these customers do not currently achieve socket parity without subsidies. We expand the analysis to identify key factors that influence economic viability using 59 measured C&I load profiles and 16 simulated load profiles. In sensitivity analyses, we explore the effect of data resolution and find that data with only hourly-resolution can result in an overestimate of savings on demand charges.

## 1.7 Introduction

Declining installation costs for solar photovoltaics (PV) paired with federal, state, and local subsidies have spurred the resource's recent growth in the United States, though at differing rates among customer segments. Over the last two years, installed capacity has grown more rapidly among utility and residential customers than commercial/industrial (C&I) customers [61]. Third-party ownership models (predominately leasing arrangements) have driven much of the growth in the residential segment. These models overcome barriers facing customer-owned solar

systems including the homeowner's lack of available capital and inability to fully exploit tax credits. As with solar PV leasing companies, C&I customers tend to have greater access to capital than individual residential customers, can make better use of tax credits, and can take advantage of accelerated depreciation of their solar PV systems. Many are also better able to exploit economies of scale in solar PV pricing. For the first half of 2015, U.S. average installed prices for solar PV were \$3.35/W for a 5-kW system and \$2.34/W for a 1-MW system [62]. However, the uptake of PV among C&I customers has slowed (up by 4% between Q3 2014 and Q3 2015) while it has been rapidly growing for residential customers (up by 69% between Q3 2014 and Q3 2015) [61]. The different tariff structures that apply to the two sectors may partly explain this difference in trends.

Tariffs for residential customers are predominantly based on volumetric energy charges ( $\text{¢/kWh}$ ) and a fixed customer charge ( $\text{\$/month}$ ). A volumetric energy charge is based on the cumulative energy (kWh) consumed by a customer each month, either at a flat rate (fixed  $\text{¢/kWh}$ ) or a tiered rate (e.g.,  $10\text{¢/kWh}$  for the first 5,000 kWh,  $8\text{¢/kWh}$  for additional energy thereafter). A customer charge is typically a fixed monthly charge for all customers on each tariff (e.g.,  $\text{\$15/month}$ ). Additionally, tariffs for C&I customers typically also include demand charges ( $\text{\$/kW}$ ), which are based on the customer's monthly peak demand—usually the highest 15-minute average—and can be set at a flat rate (fixed  $\text{\$/kW}$ ) or a tiered rate (e.g.,  $\text{\$10/kW}$  for the first 5,000 kW,  $\text{\$8/kW}$  for additional kW thereafter). These demand charges can constitute a large portion of the bills to C&I customers. As a result, load profile characteristics can be a stronger driver of the economics of solar PV for C&I customers than for residential customers,



since the reduction in costs of electricity from C&I solar PV systems is highly dependent in the system's ability to reduce peak demand, which may not coincide with peak solar output.

Net energy metering (NEM) programs can improve the economics of grid-connected solar PV. These arrangements allow customers to receive a credit, either the retail or wholesale price of electricity, for solar PV generation that exceeds their simultaneous demand. However, NEM programs are generally more beneficial for residential customers who typically operate under energy-only tariffs that have no demand charges. Further, residential customers tend to consume less energy per square foot than commercial customers and have more rooftop availability per square foot of floor space [63]. As a result, residential customers tend to have greater solar PV-to-load ratios (the ratio of the annual energy produced by a solar PV system compared to the annual energy consumed by a customer [52]) than C&I customers, resulting in larger reductions of the monthly retail electricity bill. While many C&I customers can also participate in NEM programs, their higher energy use per square foot of roof space can restrict higher solar PV-to-load ratios. This limits the amount of excess solar generation they can produce beyond their own load and thus also limits the benefits of NEM programs for C&I customers.

Despite these differences, as PV costs continue to decline, state and national incentive programs evolve, and potential tariff reform unfolds, C&I customers, who account for 62% of annual electricity sales in the U.S. [64], may be poised to adopt greater amounts of solar. In light of that, additional assessment of the financial viability of grid-connected, behind-the-meter solar PV is needed to attain a broader understanding of the market segment's outlook.

Previous studies have evaluated the economics of solar PV systems for commercial customers using simulated reference commercial building load profiles and solar generation based on data for a typical-meteorological year (TMY) [65]-[67]. These studies have found retail rates and rate structures to be the biggest drivers of PV system economic value. In this paper, we expand on previous work by using the same simulated commercial load profiles and TMY data used in other papers, to compare with *measured* load and solar PV data for several C&I customers in a case study set in Raleigh, North Carolina. We perform a sensitivity analysis on modeled parameters to assess the relative effect that individual parameters have on reaching socket parity (i.e. becoming cost competitive in the absence of subsidies). Furthermore, while most studies have used load and solar data that have hourly resolution, we explore the effects of data resolution to better understand the extent to which hourly load and solar data can adequately estimate solar PV's ability to reduce demand charges, which are typically based on 15-minute intervals.

## **1.8 Methods**

### **1.8.1 PV socket parity analytical approach and general assumptions**

To assess the economic viability of solar PV for C&I customers, we estimate the net present value and break-even installation costs (\$/W) of grid connected solar PV systems. Equation 1 highlights the definition of NPV, which we estimate using current installation costs for C&I-scale solar PV systems. In order to compare the economics for systems of different sizes, we calculate the normalized NPV by dividing the NPV by the system size. We also evaluate the break-even installation cost as it represents the installation cost at which the NPV of the system equals zero. We note that while other studies [32], [68] report the levelized cost of electricity (LCOE) for solar PV, which provides a simple, comparative evaluation of life cycle technology

energy production costs, this metric is less appropriate for assessing whether C&I customers are at or near socket parity since it does not capture the benefits of potentially displaced demand charges.

**Equation 1: Net Present Value Equation**

$$NPV = \sum_{y=1}^{Lifetime} \frac{DS(y) + ES(y) - PMT(y) - TotalOpEx(y) + TaxReductions(y)}{(1 + d)^y}$$

Where,

- *DS* is the annual demand savings from the customer’s utility bill.
- *ES* is the annual energy savings from the customer’s utility bill.
- *PMT* is the amortized annual loan payment.
- *TotalOpEx* includes annual operation and maintenance costs, inverter replacement costs, insurance payments, and property tax.
- Tax reductions include the depreciation of the PV system (using the 5-year Modified Accelerated Cost Recovery System [MACRS] [69]) and all costs included within *TotalOpEx*.  
Note that while states and local municipalities may offer tax exemptions for solar PV projects, these are not considered in this analysis.
- *d* is the nominal discount rate.

Our economic calculations for PV socket parity in North Carolina rely on a number of model parameter assumptions described in

Table 2.

**Table 2:** Model assumptions for economic analysis of solar PV for C&I customers in North Carolina.

Parameter	Value
Nominal Loan Rate, Term, and Debt Fraction	5%, 10 years, 100%
Nominal Discount Rate	10%
Analysis Period	25 years
Federal Income Tax Rate	28%
State Income Tax Rate	5% [70]
Property Tax Rate	0.4% (of installed cost) [71]
Sales Tax	6.75% [72]
Insurance Rate	0.5% of installed cost [73]
Depreciation	5-year MACRS
Annual Operation & Maintenance	\$20/kW-year [38]
Solar PV Degradation Rate	0.75% annually [32]
Inverter Replacement	\$0.12/W, years 10 and 20 [65]
Federal ITC	0%, 10%, 30%
State and Local Incentives	Not Included
Installation Cost	10 kW: \$3.35/W <sub>DC</sub> ; 200 kW: \$2.75/W <sub>DC</sub> ; 500 kW: \$2.5/W <sub>DC</sub> ; 1.2 MW: \$2.34/W <sub>DC</sub> [62]
Nominal Electricity Price Escalation Rate	3% annually [74]
Price of Excess Generation	No value

*Note: Installation Cost is the price the owner pays for installation, including all parts and labor, without any incentives.*

## 1.8.2 Solar and load data

### 1.8.2.1 DOE reference building load profiles

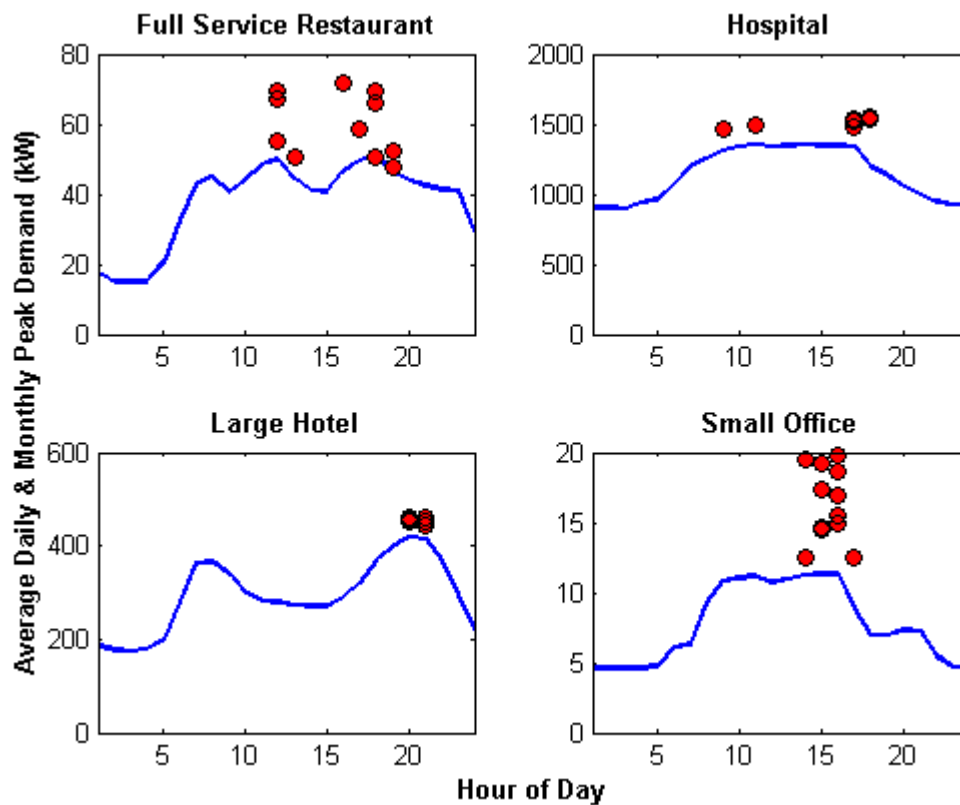
The U.S. Department of Energy (DOE) has created 16 reference building load profiles for commercial customers [75] using hourly, simulated data. We begin by using these reference profiles to examine the range of economic performance of solar PV systems for commercial customers in Raleigh, North Carolina. This provides a baseline for comparison in a subsequent analysis that uses multiple measured loads. The simulated load profiles span a variety of customer load profile types and are useful for illustrating the effect that different rate tariff structures may have on a variety of customer load profiles given that commercial customers are segmented by their billing demand (modeled as their peak annual demand without solar PV).

Figure 10 shows the load characteristics of four of the DOE's 16 reference commercial load profiles (selected to show diversity in load profiles). Appendix B includes the figure for the rest of the DOE's 16 reference commercial load profiles. The full service restaurant has three daily peaks that correspond to breakfast, lunch, and dinner times. The hospital has a fairly stable load, but with higher loads during the daytime. The large hotel has a peak in the morning and a peak in the evening, reflecting guest activity. The small office has higher mid-day demand during work hours. When combined with tariffs that include demand charges, these load profiles affect the economics of solar PV because the potential savings depend on the ability of PV to reduce peak demand. For some customer load profiles that have peak demand during times when the sun is not shining (or is low in the sky during early morning or evening hours)—such as the hospital or large hotel in Figure 10—the ability for solar PV to offset demand charges decreases, thus diminishing the value of solar investment.

#### ***1.8.2.2 Simulated PV system profiles***

In this paper we simulate solar PV output to evaluate the NPV and break-even installation costs of solar PV systems for the DOE reference commercial buildings. To develop simulated profiles of solar PV, we rely on the Sandia PV Performance model [40]. This model employs the same TMY data used to construct the DOE reference building load profiles in order to match load with correlated PV output. To evaluate the economic viability of solar PV for the DOE reference commercial buildings, we model a 4-kW PV system using Sandia's default model parameters. We include the performance characteristics of the crystalline silicon BP Solar BP3220N module and the I-Power SHO-5.2 inverter, fixed tilt angles at latitude tilt, and south facing PV system orientation. In addition, we assume an annual system degradation of 0.75% and a system lifetime of 25 years. We then linearly scale the output from the Sandia model to a 10-kW system to

represent the size of a small commercial PV system while avoiding excess generation for all DOE reference commercial profiles. Furthermore, in order to examine the effects of system size and NEM, we linearly scale the output to various system sizes (as measured by PV capacity) to model a range of PV-to-load ratios. Finally, for the analyses for buildings with higher average demand, we scale up the simulated solar PV data to a 200-kW system with the tilt of an actual solar plant in NC. Table B-1 in Appendix B provides details of the simulated output scaled to 200 kW<sub>DC</sub>.



**Figure 10:** Average annual load profiles for 4 DOE reference buildings in Raleigh, North Carolina. The lines show the average daily demand (or load profile), while the dots report the magnitude of peak demand in each month and the hour in which it occurred.

### 1.8.2.3 Measured load and solar data in North Carolina

An inherent limitation of simulated low-frequency load data is its inability to accurately capture potential demand savings as demand charges for C&I customers are typically calculated based

on the customer's peak 15-minute or 30-minute average monthly demand (kW). Sub-hourly measurements of demand may be either greater than or less than the hourly average demand. In this paper we include an analysis of the economic viability of solar PV using 15-minute resolution load data from 2013 for 59 C&I customers located in North and South Carolina. This analysis allows us to refine our case study in North Carolina in order to confirm (or disprove) the analysis based on the DOE building profiles. Furthermore, to investigate the sensitivity to the temporal resolution of the data, we perform a sensitivity analysis using the measured NC load and solar data at various resolutions. However, we use hourly averages of the measured data when comparing simulated and measured load profiles to remove the effect of data resolution. Table B-2 summarizes the characteristics of the measured load data used for the case study.

In addition to empirical load data, we rely on one-minute resolution PV output data collected in 2013 from a 1.2-MW<sub>DC</sub> solar PV plant in North Carolina, that we scale linearly down to a 200-kW system. Pairing the measured load data with same-year measured solar data is important because the simulated solar data described in the previous section is not specific to the actual weather in 2013. Although the commercial customers for whom we have empirical data are not located at the same site as our measured solar PV data, we assume that weather patterns are sufficiently similar such that the load characteristics are the primary differentiating factor. Table 3 and Table B-1 provide information about the PV system characteristics and the available data. Since data were only available for one year, we model the plant's lifetime production by replicating the full year of measured data and degrading production by 0.75% per year throughout the system's expected life. While one year of measured data may not reflect actual climatic variation that may occur over the lifetime of the system, the measured and simulated PV



systems have the same capacity factor, thus allowing for a more direct comparison of measured and simulated loads

**Table 3:** Summary of measured data used in analyses.

Location	Type	Resolution	Year	Description
North Carolina	Solar	One-minute	2013	1.2-MW <sub>DC</sub> ground-mounted plant located in Raleigh. Faces 180 degrees south at an angle of 35 degrees.
North Carolina	Load	15-minute	2013	59 load profiles for C&I customers located in areas of North and South Carolina (Ashville, Charlotte, Greensboro, and Greenville)

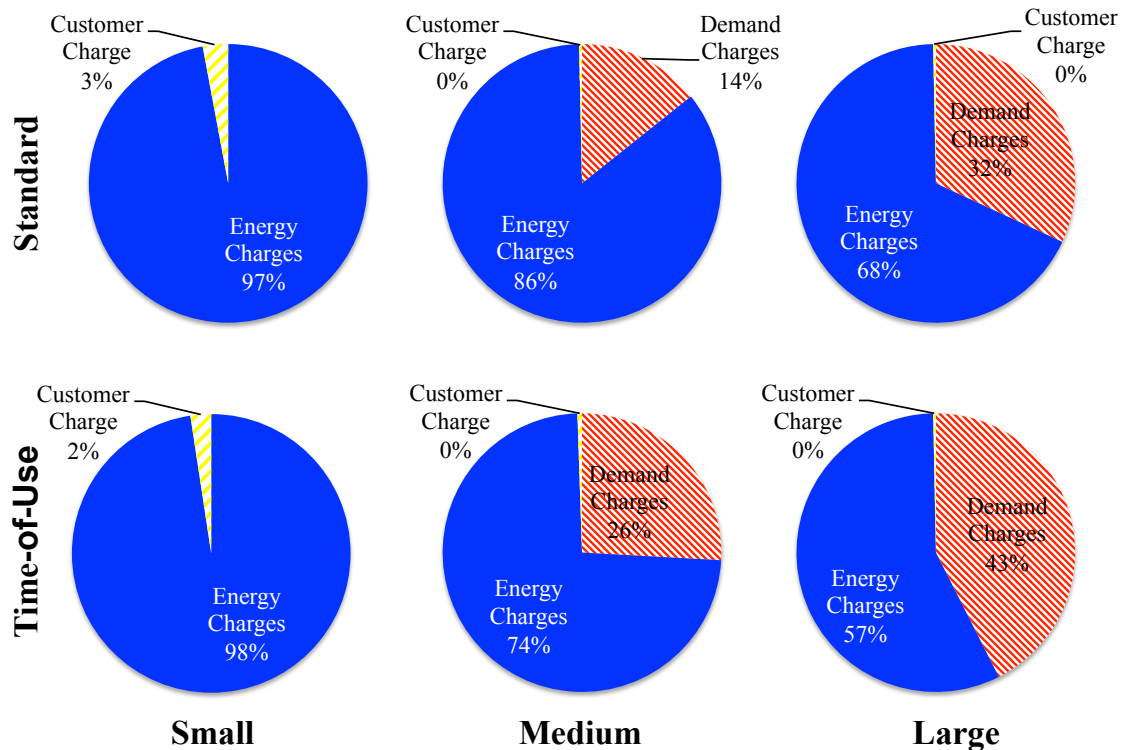
#### **1.8.2.4 Reference Tariffs**

The structure of the tariff for C&I customers is a key driver of the economic performance of solar PV systems. Table 4 summarizes the different types of tariffs used in this analysis, based on the retail electricity tariffs [76] for C&I customers in North Carolina which differ for the different customer classes within the C&I sector. Note that tiered rates are based on a declining block schedule. For example, in one tariff energy rates are 10.808 ¢/kWh for the first 750 kWh, 9.168 ¢/kW for the next 1,250 kWh, and 8.722 ¢/kWh for additional energy consumed thereafter. Another tariff includes demand rates that are \$11.23/kW for the first 5,000 kW, \$10.26/kW for the next 5,000 kW, and \$9.29/kW for additional demand thereafter. Demand ratchets are designed to increase demand charges for customers that have fluctuating monthly peak demand by establishing a minimum demand charge based on the previous 11 billing months. For example, if a customer in North Carolina has a very high peak demand in December and low peak demand in July, then the July bill may actually be based on a defined percentage of the December peak demand if such percentage exceeds the demand charge associated with the peak demand in July. Detailed information about how the minimum demand charge is calculated can be found in the tariffs available on the Duke Energy website.

**Table 4:** Description of the different types of tariffs used in this analysis.

<b>NORTH CAROLINA TARIFFS</b>		
<b>Customer Class</b>	<b>Standard Tariff</b>	<b>Time-of-Use Tariff</b>
Small General Service <30 kW	Energy (tiered), Customer charge	Energy (flat, time blocks, seasons), Customer charge
Medium General Service 30-1,000 kW	Energy (flat), Demand (flat w/ ratchet), Customer charge	Energy (flat, time blocks, seasons), Demand (time blocks, seasons), Customer charge, Min bill calculation
Large General Service >1,000 kW	Energy (flat), Demand (tiered w/ ratchet), Customer charge	Energy (time blocks, seasons), Demand (tiered, time blocks, seasons), Customer charge, Min bill calculation

For analyses that rely on simulated load data, we associate the 16 DOE reference commercial building profiles with the different relevant tariffs in North Carolina. We assign one reference building to small general service, 12 to medium general service, and three to large general service based on annual peak demand as summarized in the SI. Figure 11 provides a breakdown of the average monthly customer electric bill for the 16 DOE reference profiles averaged across each of three customer segments (small, medium, large) for the standard and time-of-use (TOU) tariffs. For the analyses that use measured load data, we assign 9 commercial customers and 31 industrial customers to the large general service and 11 commercial customers and 8 industrial customers to the medium general service based on annual peak demand. Note that all of these customers are known to operate on a TOU tariff.

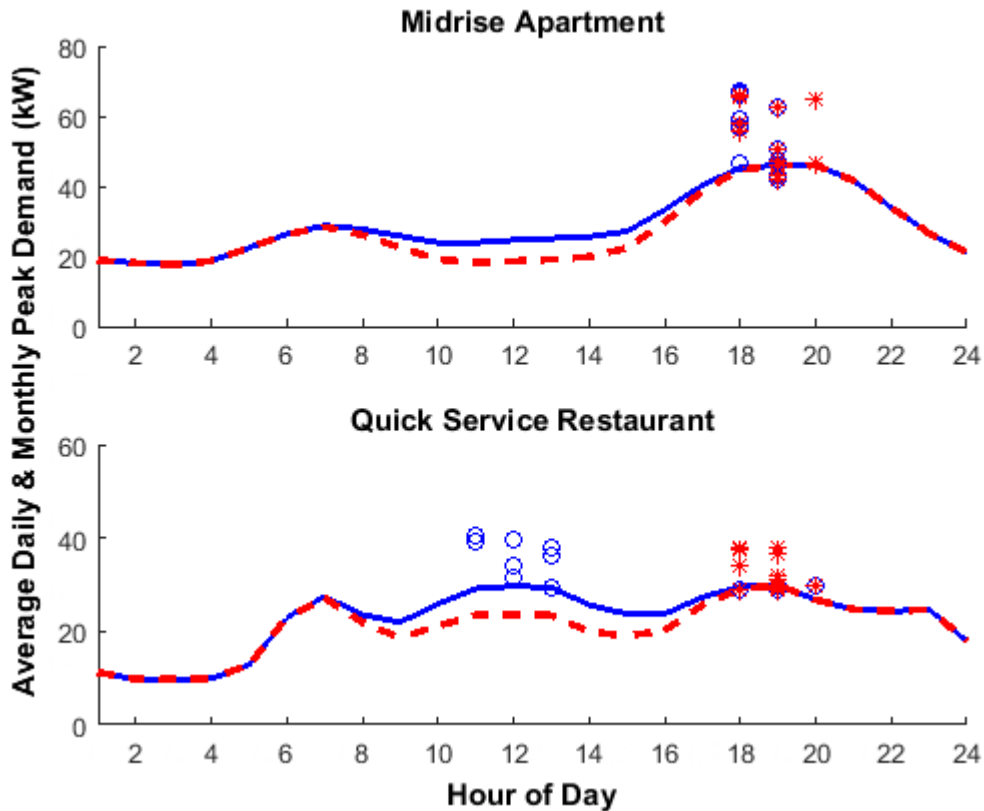


**Figure 11:** Breakdown of electric bills under standard and time-of-use tariffs for small, medium, and large commercial customers (based on 16 DOE reference commercial load profiles).

## 1.9 Results and discussion

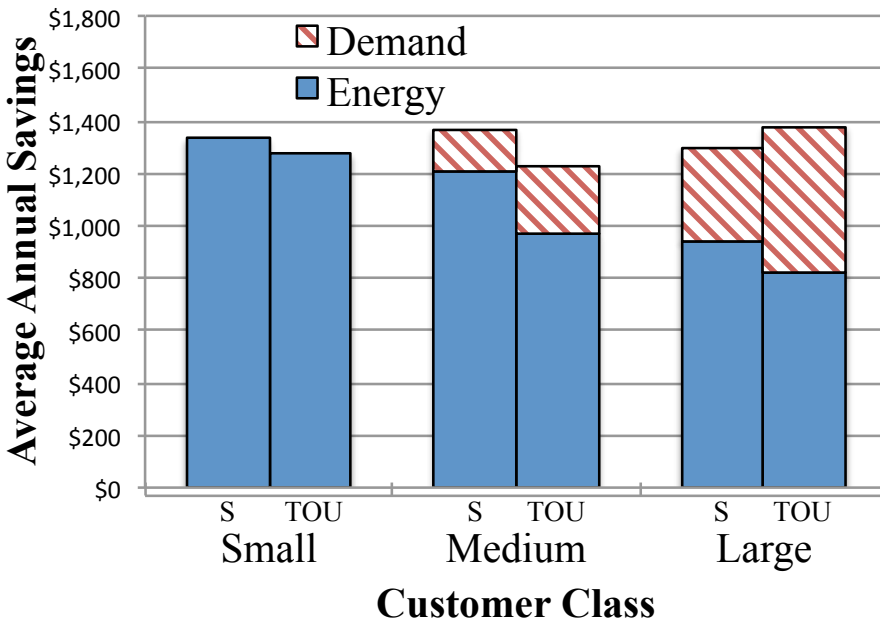
### 1.9.1 The economics of PV across multiple commercial building types

As previously mentioned, a solar PV system's ability to reduce and displace peak demand, and thus reduce demand charges, is dependent on the characteristics of the load and the coincidence of solar generation with the time of peak customer demand. Figure 12 shows two of the 16 DOE reference commercial building profiles with similarly sized loads but with peak demands that occur at different times. For the midrise apartment, a 10-kW solar PV system does not significantly reduce or displace the monthly peak demand. In contrast, for the quick service restaurant, a 10-kW solar PV system reduces and displaces most of the monthly peak demand.



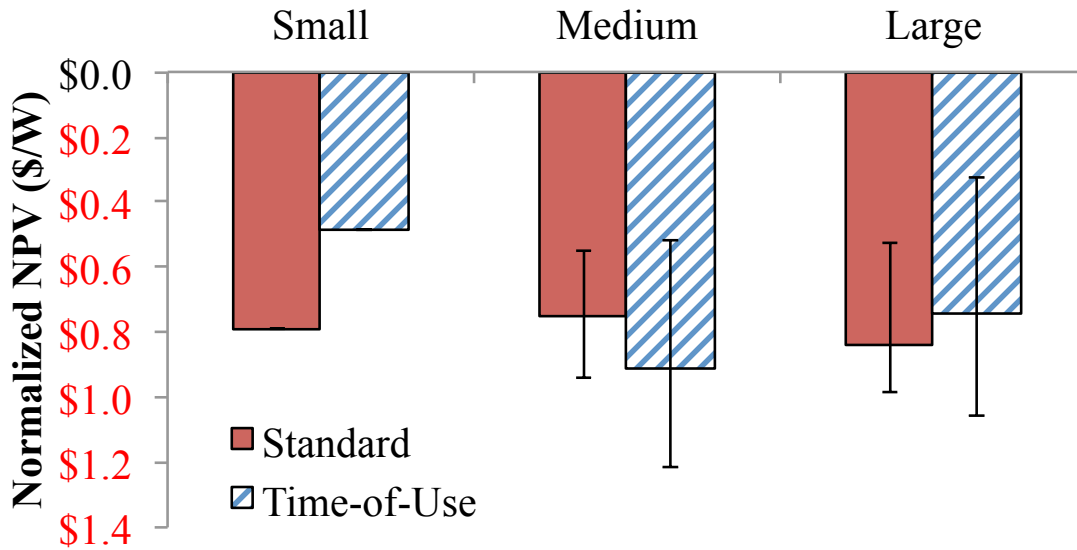
**Figure 12:** Average daily demand and monthly peak demand for midrise apartment (top) and quick service restaurant (bottom). The lines illustrate average daily demand with and without solar (dotted and solid lines, respectively). Circles indicate the time and magnitude of the average monthly peak demand without the solar array. Stars indicate the time and magnitude of the average monthly peak demand with the solar array.

Figure 13 shows the breakdown of annual savings for each customer rate class using the 16 DOE reference buildings with a 10-kW solar PV system and the North Carolina tariffs for C&I customers. We separate the results between energy and demand savings for each customer rate class. Demand savings ranged from ~10% to 40% of total annual savings for medium and large customers. Compared to medium customers, large customers have greater demand savings and lower energy savings for both the standard and TOU tariffs described in Table 4.



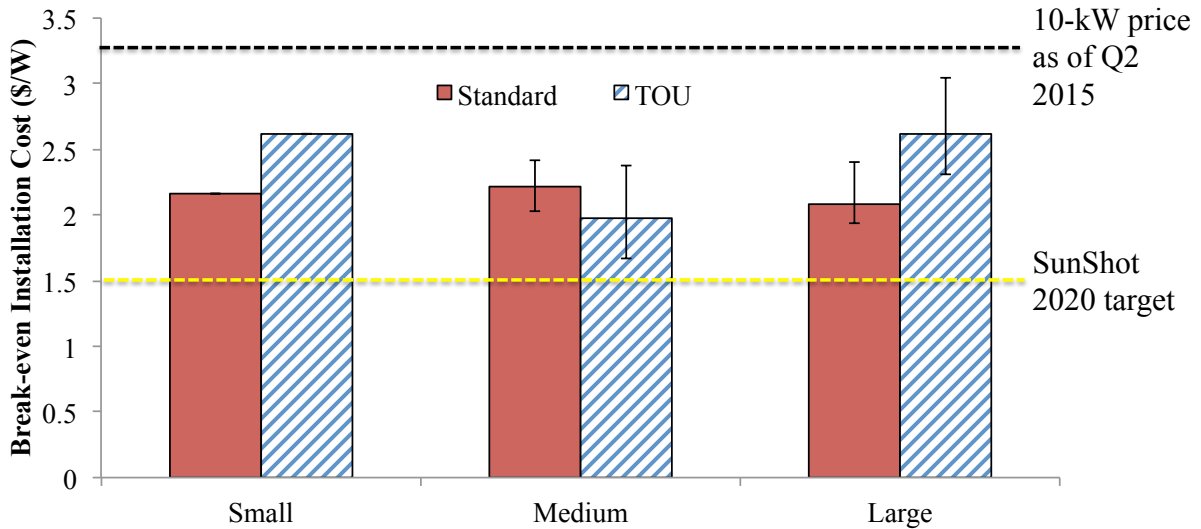
**Figure 13:** Average annual energy (solid) and demand savings (striped) from a 10-kW solar PV system for customers on standard (S) and TOU tariffs for each customer rate class.

In Figure 14, we show the average normalized NPV by customer rate class of a 10-kW PV system applied to each of the DOE reference load profiles. Due to smaller sample sizes for small and large customers, Figure 14 is primarily intended to convey the range of values within each rate class rather than to directly compare across customer rate classes. For all customer rate classes and types examined, the economic viability of solar PV is below a normalized NPV of \$0/W, indicating that these systems have not reached socket parity under the assumptions made in this analysis. The NPVs are fairly consistent across all customers under the default tariffs. On the other hand, the range in normalized NPVs is greater for customers under the time-of-use tariffs, though still negative. While the TOU tariffs may provide an opportunity for solar PV to reduce demand and energy charges, actual savings depend on how well the load and solar PV generation align, and are not presently sufficient to cover the costs of the PV system without subsidies.



**Figure 14:** Normalized NPV (without subsidies) of a 10-kW system by customer rate class and tariff type. The bars show the range of NPV for all loads within each rate class size. There is only one customer in the small category.

To determine the installation cost required for solar PV to reach socket parity under current tariffs, we conducted a break-even analysis, as illustrated in Figure 15, for a 10-kW solar PV system on each of the DOE profiles without subsidies. The lowest break-even cost across all 16 profiles is about \$1.50/W, which is the same as the SunShot Initiative’s 2020 cost target for residential systems (similar capacity). While PV is not currently at socket parity without subsidies for any of the DOE commercial profiles under the selected tariffs in North Carolina, we project that they will reach parity if the SunShot Initiative’s cost targets are met, tariff structures remain unchanged, and tariff rates increase 3% annually. Appendix B includes the results of a similar analysis that include the effect of the federal ITC, which results in a positive NPV for about half of the customers.



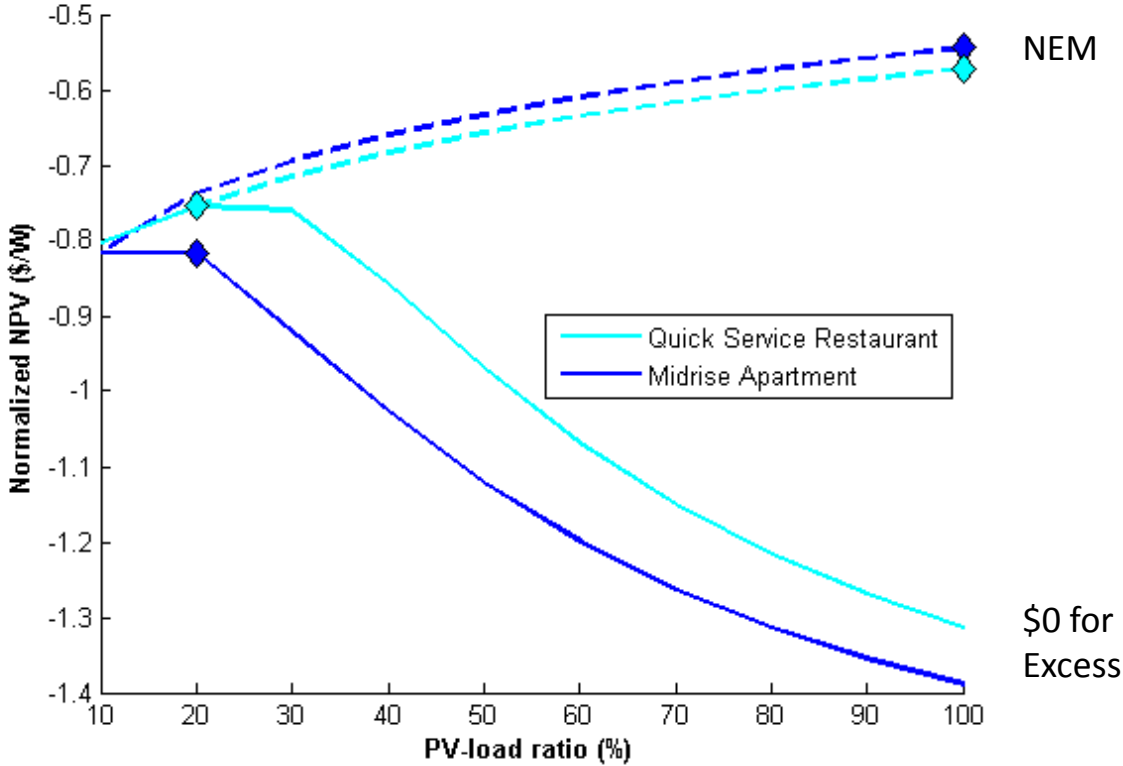
**Figure 15:** Break-even installation costs (without subsidies) for a 10-kW solar PV system for each of the DOE commercial reference building load profiles by customer rate class and tariff type.

### 1.9.2 Optimal system sizing and the effects of NEM

To better understand how system sizing affects the economics of solar PV for commercial customers, in Figure 16 we report the normalized NPV for a range of solar PV-to-load ratios for the DOE quick service restaurant and midrise apartment profiles. We selected these two loads for comparison because the magnitudes of their average and peak demand are similar, yet they have very different load profiles (as seen in Figure 12). In addition to examining the differences in economics for various solar PV-load ratios, we assess the effects of NEM. Results show NPV values with (dotted lines) and without (solid lines) NEM credited at the full energy rate. The installation costs vary according to system size. Appendix B provides the installation cost curve used for cost assumptions of various installation sizes.

Points shown as diamonds indicate the optimal PV-to-load ratios, which occur at the maximum normalized NPV for each building type. As a reminder, we estimate the PV-to-load ratios by linearly scaling the simulated output from the Sandia PV model. These points illustrate the fact

that there is a wide range of optimal PV-to-load ratios depending on whether excess generation is valued at the full energy rate or not at all. As illustrated, NEM incentivizes larger PV system sizes to take advantage of economies of scale in PV installation costs. Without NEM, optimal sizing requires a balance of increasing demand charge savings without too much excess generation (which is credited at \$0 in this example). The large gap between normalized NPV for higher PV-to-load ratios, suggests that installing larger solar PV systems may only be advantageous if there is greater certainty that NEM will continue to be available and if the installed system qualifies for NEM (as some programs have individual and aggregate capacity limits).

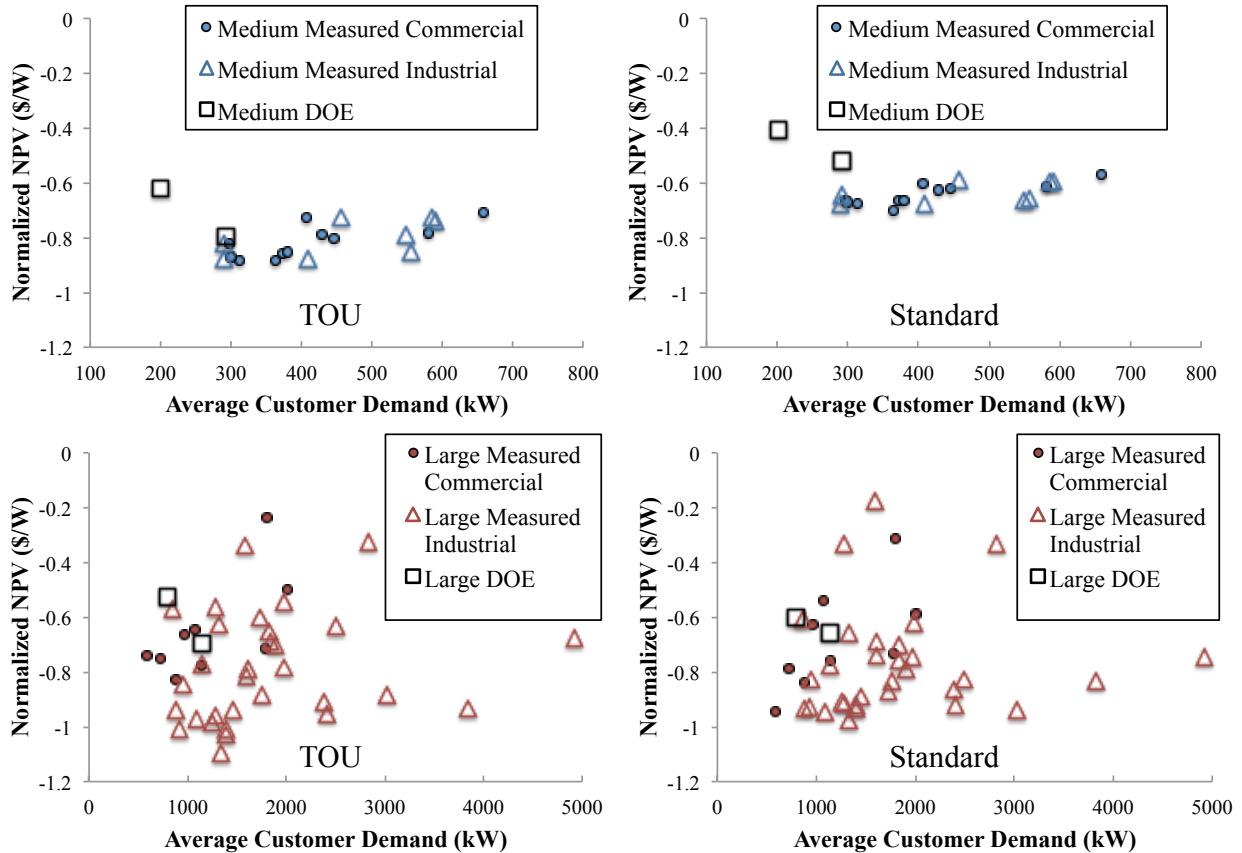


**Figure 16:** Normalized NPV with optimal solar PV-to-load ratios for two medium DOE reference customer profiles. The dotted lines represent NPV values that credit excess generation (w/ NEM) valued at the full energy price. The solid lines represent NPV values that do not credit excess generation (w/o NEM).



### **1.9.3 Comparing solar PV economics for commercial customers with measured data**

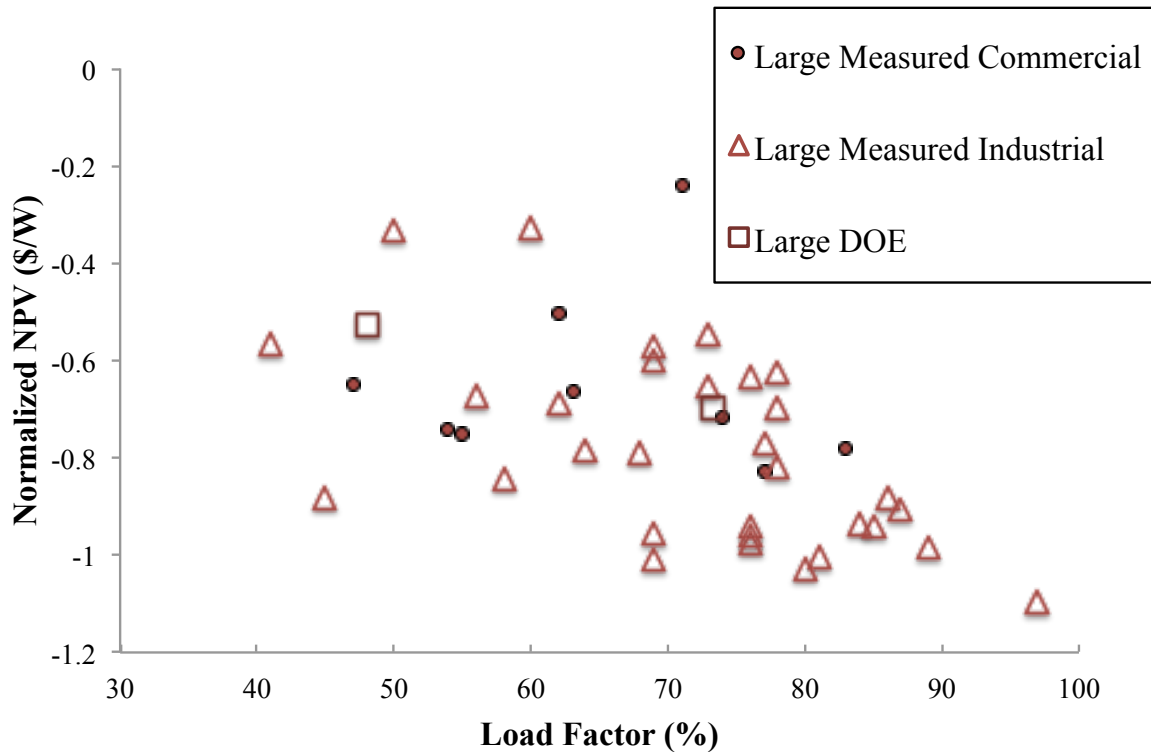
Figure 17 illustrates the normalized NPV for each of the measured 59 customer load profiles according to applicable tariffs described in Table 4, matched with measured solar output from a 1.2-MW PV plant scaled to a 200-kW system. In order to avoid the implications of net metering policies, we use only load profiles (measured and simulated DOE) where the customer can self-consume all generation from a 200-kW PV system. Thus, there is no excess generation that goes to the grid and the value of PV is based on demand and energy savings resulting from a reduced net load. It is notable that the range in normalized NPV for medium customers is smaller than for large customers. This is consistent for both commercial and industrial customers, suggesting that the tariff rather than customer type drives the larger variation in NPVs within the large tariffs. Note too that the measured data (consisting of both commercial and industrial customers) spans a wider range of average demand than the DOE data (consisting of only commercial buildings). Figure 17 also shows that the NPVs are slightly more favorable under the standard tariffs than the TOU tariffs. However, this is because customers are already able to achieve electricity bill reductions (without solar PV) by switching to the TOU tariffs. Thus, while solar PV may contribute to lower additional savings under the TOU tariffs, the annual electricity costs (with or without solar PV), are lower under the TOU tariffs than the standard tariffs for 54 out of 59 of the measured loads.



**Figure 17:** Normalized NPV and average customer demand (without solar PV) for measured commercial load (round), measured industrial load (triangle), and simulated DOE load (square). A simulated 200-kW solar PV output is used for all DOE points and the measured solar PV output data is scaled to a 200-kW solar PV system for all measured data points. The top two graphs show customers on the medium general service TOU and standard tariffs, and the bottom two graphs show customers on the large general service TOU and standard tariffs.

In order to better understand the variance in NPV among large customers (both commercial and industrial), we explore whether certain load characteristics are indicators of improved economic viability of solar PV for customers under the TOU tariff. To begin, in Figure 18 we report normalized values of NPV versus the original load factors (before the addition of PV). Load factors are calculated as the average annual demand divided by the annual peak demand. The results show a downward trend for both commercial and industrial customers, indicating that solar PV tends to be less valuable for customers with higher load factors. This is expected as customers with higher load factors inherently have flatter demand curves and thus a greater

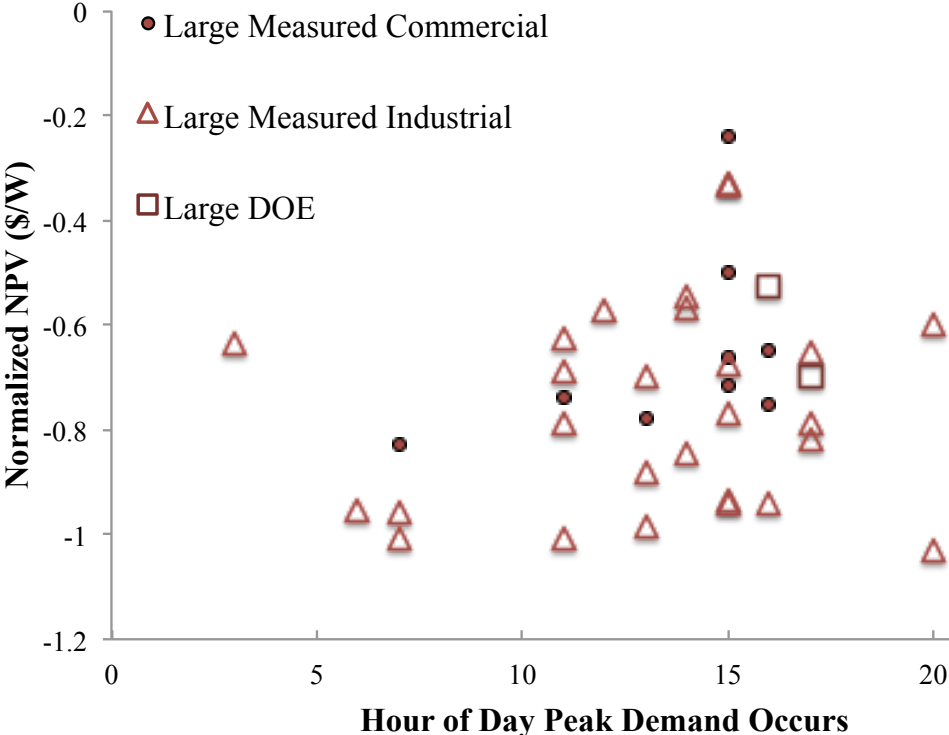
probability that nighttime demand is similar to daytime demand. As a result, daytime solar PV production would be less effective at lowering the monthly peak demand.



**Figure 18:** Normalized NPV and original load factor (without solar PV) for measured commercial loads (round), measured industrial loads (triangle), and simulated DOE loads (square) under large TOU tariff. A simulated 200-kW solar PV output is used for all DOE points and the measured solar PV output data is scaled to a 200-kW solar PV system for all measured data points.

In Figure 19, we report the normalized NPV versus the hour of the day at which the peak demand most often occurs (without solar PV). This hour was calculated by finding the hour of the day that monthly peak demand occurs most often (defined as the mode of distribution of peak hours) throughout the year. As expected, customers with peak demands occurring during the day tend to have a higher normalized NPV. Combining information about the load factor and typical peak demand hours provides better insight into the economic viability of solar PV for large C&I customers. For example, customers with peak demands between 10 a.m. to 4 p.m. (during middle of the day) and load factors lower than 70% have an average normalized NPV of  $-\$0.6/W$ . In

contrast, customers with peak demands outside of these hours and with load factors above 70% have an average normalized NPV of  $-\$0.9/\text{W}$ . Therefore, these characteristics can help inform C&I customers whether solar PV is more likely to be a better investment (particularly once installation costs reach the SunShot Initiative’s goals).

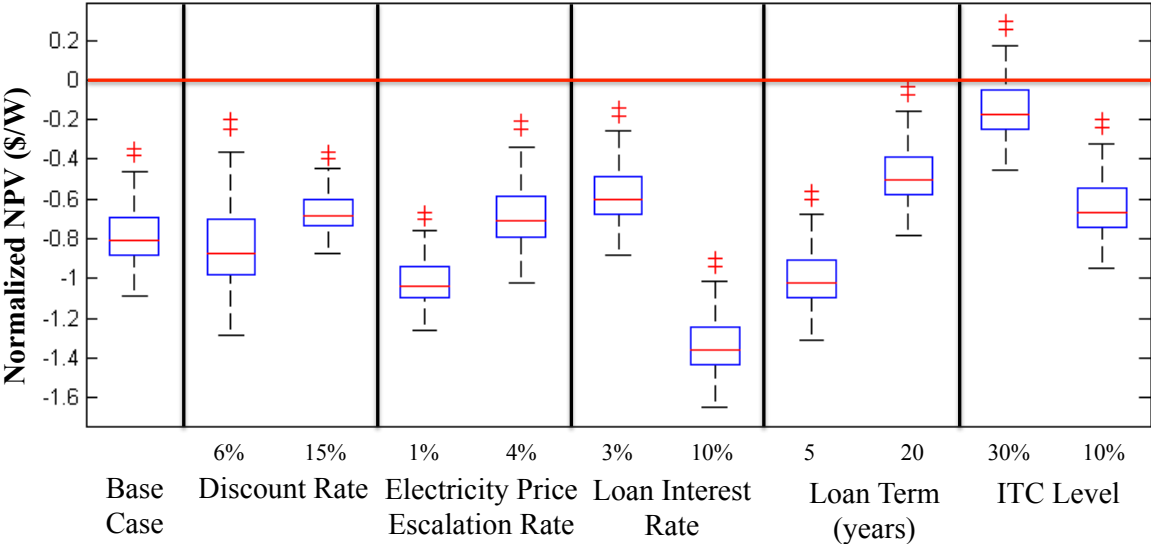


**Figure 19:** Normalized NPV and the hour at which the peak demand most often occurs (without solar PV) for measured commercial loads (round), measured industrial loads (triangle), and simulated DOE loads (square). A simulated 200-kW solar PV output is used for all DOE points and the measured solar PV output data is scaled to a 200-kW solar PV system for all measured data points.

**1.9.4 Additional sensitivity analyses**

Figure 20 provides results from a sensitivity analysis that explores how various parameters can affect calculated normalized net present values. Here, normalized NPV is calculated using all 59 North Carolina measured load profiles paired with measured solar data from a 1.2 MW plant linearly scaled down to 200 kW. Each customer is able to completely self-consume the PV generation. As shown in Figure 20, the model is highly sensitive to the loan interest rate and loan

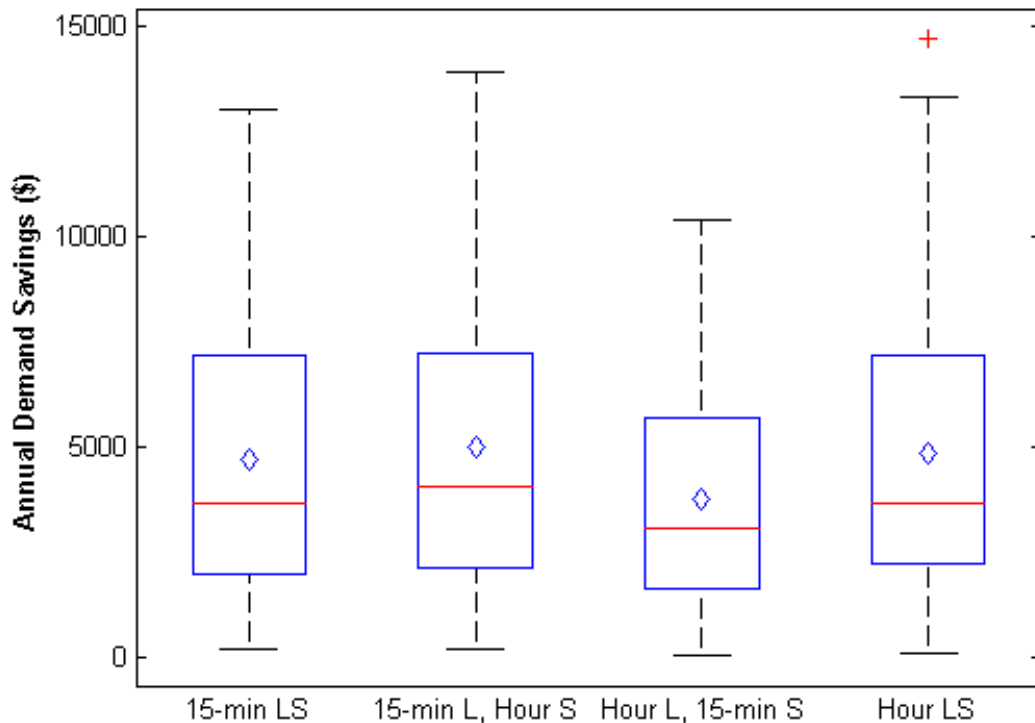
term. These parameters are customer-specific and highlight the importance of securing the best financing option. Few scenarios result in socket parity at current installation costs. The break-even installation costs for these customers range between \$1.10/W and \$2.40/W (provided in Appendix B). Thus, if installation costs drop to the SunShot Initiative’s 2020 goal to install commercial PV systems at \$1.25/W, solar PV will likely be at socket parity for most customers in this dataset.



**Figure 20:** Sensitivity analyses of normalized NPV for North Carolina C&I measured data across the ranges shown within each panel.

To explore the effects of data resolution, Figure 21 shows the annual demand savings using different data resolutions. Overall, the box plots show similar average demand savings yet there is a wide range in demand savings across the customers. The leftmost box plot shows the customer’s actual demand savings, which are calculated using 15-minute solar PV and load data. We calculate the percent difference between the actual and estimated demand savings for each resolution combination (provided in Appendix B). We find that using hourly averages of the measured solar data overestimates annual demand savings by 7% on average with 15-min load data (second box plot) and 5% on average with hourly averages of the measured load data

(rightmost box plot). These percentages translate into average overestimations of the NPV by 3% and 1%, respectively. In contrast, using 15-minute solar data with hourly averages of the measured load data underestimates annual demand savings by approximately 20%, underestimating NPV by 10% (third boxplot). The ranges in annual demand savings for each resolution combination vary, extending both above and below the range of actual annual demand savings. This means that the higher variation in the net load seen by the electricity meter can result in either higher or lower demand charges than if the meter only saw hourly-averaged net load. While the average percent difference between modeled and actual annual demand savings is relatively low, Figure 21 illustrates that the effect of data resolution varies widely across load profiles and is most sensitive to the resolution of the load data. If there are significant changes to tariffs such that demand charges comprise a larger portion of the bill, these differences may become more important.



**Figure 21:** Annual demand savings calculated using different combinations of solar (S) and load (L) data resolution. Actual demand savings (15-minute load and solar data) are shown in the leftmost box plot. The central red lines indicate the median; the bottom and top edges of the boxes indicate the 25th and 75th percentiles, respectively; the

whiskers extend to the most extreme data points not considered outliers; the outliers are plotted individually using the '+' symbol; the blue diamonds indicate the means.

### **1.10 Conclusion**

This paper aims to evaluate the economic viability of PV systems for commercial and industrial buildings using simulated and measured load and solar output data. Among the measured load profile characteristics examined, customers with higher load factors (higher average demand relative to peak demand) typically appear to face less favorable solar PV economics than customers with lower load factors. This is expected as customers with higher load factors have flatter demand curves and greater probability that nighttime demand is similar to daytime demand. As a result, daytime solar PV production will be less effective at lowering the monthly peak demand. Lastly, as expected, customers with peak demand occurring during daylight hours typically face more favorable economics than those with peak demand occurring when the sun is not shining. In addition, we demonstrate that the time resolution of measured data results in differences in calculated demand savings, with hourly data resolutions overestimating demand savings, on average.

When additional data are available, the analytic approach illustrated here could be applied to other locations and allow further investigation of different types of tariffs and demand calculations. This is especially important as rate reforms may significantly change a customer's monthly bill, with or without solar PV. In addition, information on leasing options and available power purchase agreements could be used to further compare PV economics for C&I customers. Since demand charges and TOU tariffs are more prominent in the C&I sector, it may also be advantageous to, in the future, explore other potential ways to increase annual demand and energy savings—for example, making adjustments to the tilt and orientation of modules in a

solar PV array, increasing energy efficiency measures, participating in demand response programs, and/or using behind-the-meter storage.

While the additional analyses previously described could provide more refined results, there are some general conclusions that are likely to remain. Results of this analysis suggest that C&I customers in North Carolina are not at PV socket parity without subsidies. Overall, using simulated load and solar data, unsubsidized break-even installation costs are found to range between \$1.50/W and \$2.80/W for a 10-kW solar PV system under applied tariffs for these customers. A sensitivity analysis using measured load and solar data indicates break-even installation costs to be between \$1.10/W and \$2.40/W for a 200-kW system. Thus, if the SunShot Initiative's 2020 goal of \$1.25/W for commercial systems is met, the majority of C&I customers examined in this paper will, in the future, achieve socket parity. While this paper focused on North Carolina, some of these results are likely generalizable. Most importantly it is clear that in addition to reducing capital costs, appropriate solar PV sizing and tariff design structures drive the economic viability of these systems.

### **1.11 Acknowledgements**

This work was supported by academic funds from Carnegie Mellon University's Department of Engineering and Public Policy, by The Electric Power Research Institute (EPRI) under Award 1020211, by the program for Graduate Assistance in Areas of National Need (GAANN) of the U.S. Department of Education, by the Department of Energy under Awards DE-OE0000300 and DE-OE0000204, by the center for Climate and Energy Decision Making through a cooperative agreement between the National Science Foundation and Carnegie Mellon University (SES-0949710), and by the Carnegie Mellon Electricity Industry Center (CEIC). Results and conclusions are the sole responsibility of the authors and may not represent the views of the funding sources.

Special acknowledgements to EPRI's Nadav Enbar and Steven Coley who assisted in the development of this paper.



# **Maximizing value of energy storage for commercial & industrial customers with demand charges**

## **1.12 Abstract**

Energy storage has quickly gained attention over the past few years with the rapid adoption of solar photovoltaic (PV) systems. One of the greatest economic opportunities for energy storage is demand charge reduction. By using a “black-box” approach, we apply several generic energy storage technical attributes to assess the ideal performance and maximum economic benefit of energy storage. We establish upper bounds with a perfect 24-hour same-day forecast and lower bounds with a basic algorithm. This analysis features high-resolution load and solar PV generation data and general performance characteristics from a lithium-ion battery. We find that batteries with lower capacities are most profitable for the commercial and industrial customers examined using an optimistic algorithm, but require further cost reductions using a pessimistic algorithm. We also highlight differences in energy storage economics based on the rates and structure of electricity tariffs.

## **1.13 Introduction**

During recent years, deployment of solar photovoltaics (PV) has grown significantly in regions of the U.S. In previous work, we examined “socket parity” for residential customers throughout the country as well as for commercial and industrial customers in North Carolina using high-resolution solar PV and load data. With the future of net energy metering (NEM) being uncertain [77]-[79], the economics of solar PV are at risk in many locations, especially when trying to reduce a larger proportion of electricity bills. To reduce susceptibility to changes in NEM policies, commercial and industrial customers are better poised to install solar PV systems large

enough to take advantage of economies of scale in pricing yet avoid generating power beyond what the customer can self-consume. For customers with high electricity costs due to location or load characteristics, there are opportunities to achieve further bill savings with energy storage.

Previous literature evaluating the economics of energy storage typically relies on simulated load data with hourly resolution, perfect load forecasts, and/or limit analyses to a single customer. For example, a report by the Rocky Mountain Institute uses the simulated hourly load of a large hotel in San Francisco to estimate the potential for peak demand reduction [80]. However, actual loads may have sub-hourly variations in load that can result in higher demand charges (which are typically measured on 15-minute intervals). Other studies examine energy storage for multiple customers using high-resolution data but rely on either perfect 24 or 48-hour load/solar PV forecasts, which may yield optimistic results [81], [82]. By using high-resolution load data for several commercial and industrial customers paired with high-resolution measurement data from a solar PV plant, we create a robust case study to examine the technical and economic potential for a “black-box” energy storage device.

By using a “black-box” approach, we incorporate generalized performance characteristics to assess the economics of energy storage. We use a perfect 24-hour same-day forecast to capture ideal performance and maximum economic benefit, as well as a basic algorithm with no forecasting to establish a conservative estimate. We then compare these technical and economic specifications to existing technologies and help establish targets for technology performance and cost. This analysis features high-resolution load and solar PV generation data and general performance characteristics from a lithium-ion battery. These findings should be instructive to

utilities, regulators, and policy makers interested in understanding the economics of load defection and distributed energy systems.

## **1.14 Methods**

In order to model the economics of a black-box energy storage device, we use measured load and solar PV data along with electricity tariffs as inputs to our model. We assume performance characteristics of a high-energy lithium-ion battery and use either a 24-hour same-day forecast or a basic algorithm with no forecasting to plan energy storage behavior for demand charge reduction. Economic outputs of the model provide insight to optimal energy storage sizing and the required installed costs for a break-even investment.

### **1.14.1 Load and solar PV data**

We use 15-minute resolution measured load and solar PV data from 2013. The measured load data consist of 59 commercial and industrial customers located in North and South Carolina, with characteristics provided in Appendix C. For the measured solar PV data, we use one-minute resolution PV output data collected in 2013 from a 1.2-MW<sub>DC</sub> solar PV plant in North Carolina. We linearly scale the output to a 200-kW system in order to avoid excess generation for any of the measured loads. In this analysis, we use the net load (load with solar PV) for each of the 59 profiles.

### **1.14.2 Reference tariffs**

All of the customer loads used in this analysis operate under a time-of-use (TOU) scenario. According to tariffs downloaded from Duke Energy Progress, these loads would be eligible for either the large or medium general service TOU tariff. The primary components of these tariffs include the customer charge (a fixed, small portion of the bill), demand charge (based on the greatest 15-minute load during the month), and energy charge (with on-peak and off-peak rates).

### 1.14.3 Assumptions

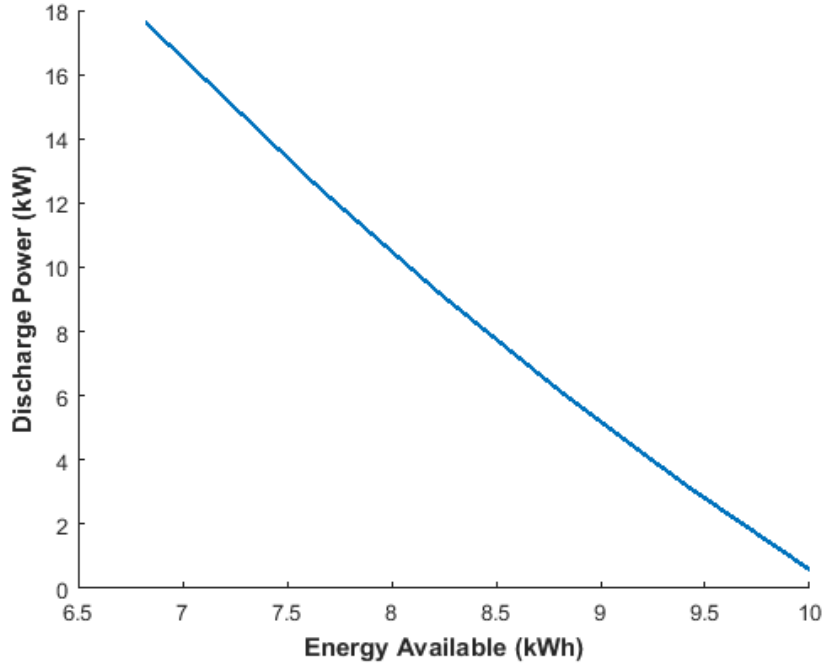
Key parameter assumptions for a black-box storage device are listed in Table 5. In this analysis, we consider a battery with performance characteristics of high-energy lithium-ion batteries, represented by the Ragone analysis shown in Figure 22. The Ragone plot shows the relationship between available energy and discharge rate, which allows us to calculate the efficiency of a battery at different discharge rates. Table 6 provides additional assumptions for economic analyses. Since battery lifetimes may exceed ten years due to limited cycling, we assume that the battery is financed with a loan term of ten years or the battery lifetime, whichever is less. We conduct a break-even analysis to identify the total installed cost per kWh for energy storage required for a break-even investment, however, for the remainder of analyses we use the capacity costs listed in Table 6 as the total installed cost.

**Table 5:** Key parameter assumptions for black box storage device.

<b>Parameter</b>	<b>Value</b>
<b>Usable Capacity</b>	Varies parametrically
<b>Charge Energy Efficiency</b>	90%
<b>Available Discharge Energy</b>	Varies (based on Ragone analysis)
<b>Max Charge Rate</b>	0.5 x usable capacity
<b>Battery Lifetime</b>	600 equivalent full cycles

**Table 6:** Assumptions for economic analyses. Note that all rates are nominal and capacity costs are per kWh of usable capacity.

<b>Parameter</b>	<b>Value</b>
<b>Discount Rate</b>	7%
<b>Loan Interest Rate</b>	7%
<b>Loan Term</b>	Minimum of battery lifetime or 10 years
<b>Total Installed Cost</b>	\$300/kWh
<b>Electricity Price Escalation Rate</b>	3%



**Figure 22:** Nominal Ragone relationship based on typical low-cost, high-energy lithium-ion battery performance extrapolated to show the energy available as a function of discharge power for a 10-kWh battery [83].

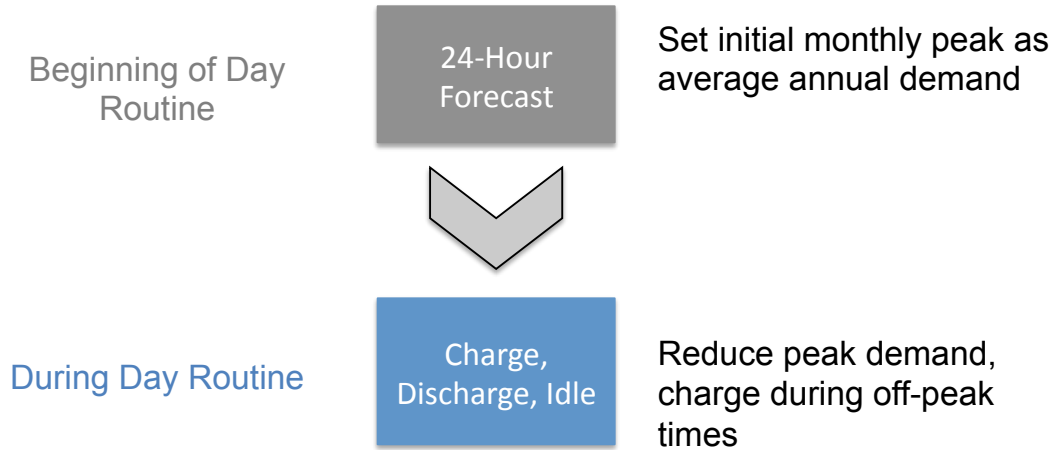
#### 1.14.4 Algorithms

In this paper, we employ two different energy storage algorithms. The first of which establishes an ideal case given perfect 24-hour information. The second algorithm is basic and does not rely on any forecasting in order to establish a lower-bound estimate.

##### *1.14.4.1 24-hour optimization algorithm*

To determine an upper bound for storage economics, we optimize the behavior of a battery using a perfect same-day forecast (up to 24 hours). Note that while demand charges are based on the greatest 15-minute load during the month, it is unlikely that any charge controller will be able to accurately predict either the load or solar PV more than one or two days in advance. Figure 23 shows an overview of the algorithm that incorporates Equations 1-5 to schedule discharge for the day ahead.  $L_i$  represents the load (or net load) and  $S_i$  represents the planned storage discharge for each 15-minute interval of the day.  $E_i$  denotes the amount of energy that will be required from

the battery, operating at efficiency  $\eta_i$  (determined by analysis according to the Ragone plot), for each 15-minute interval of the day. Figure 24 shows the charging, discharging, and idling decisions of the battery. When  $L_i$  is greater than the existing monthly peak demand, the battery discharges energy according to the optimally scheduled discharge. The rate of the optimal discharge varies as it depends on the amount of energy required to reduce the 15-minute demand to the level of the existing monthly peak demand. During off-peak pricing, the battery charges until full capacity if  $L_i$  is less than the existing monthly peak demand.



**Figure 23:** Overview of algorithm for perfect same-day forecast.

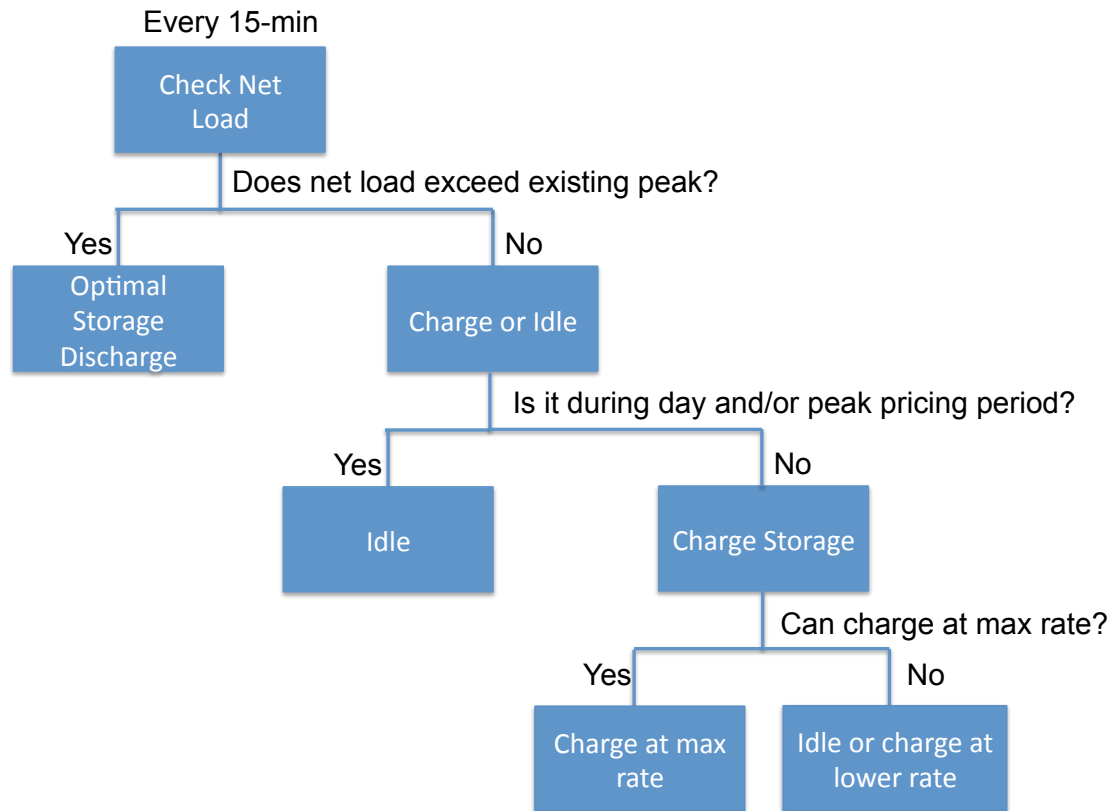
$$\min \max (L_i - S_i) \text{ such that} \quad (1)$$

$$\sum_{i=1}^T E_i \leq C_{\text{Usable}} \quad (2)$$

$$\eta_i = \frac{f(S_i)}{C_{\text{Usable}}} \quad (3)$$

$$E_i = \frac{S_i}{4} (1 + (1 - \eta_i)) \quad (4)$$

$$\forall i, E_i > 0 \quad (5)$$



**Figure 24:** Algorithm for every 15 minutes during the day for perfect same-day forecast.

#### ***1.14.4.2 Basic algorithm***

To provide a lower bound for storage economics, we implement a basic algorithm that, unlike the perfect same-day forecast, has only one discharge rate and does not use any forecasting of the net load. As a result, the battery may discharge all of its energy prior to the time of the day when the monthly peak demand occurs. For each 15-minute period, the battery either discharges at 0.5C (the rate of half the usable capacity) when the net load exceeds the existing monthly peak demand or charges according to the same algorithm depicted in Figure 24. We chose the discharge rate of 0.5C after conducting a parametric analysis on discharge rates ranging from 0.25C to 4C, available in Appendix C. A 0.5C discharge rate provides the greatest average benefit-cost ratio across the range of usable capacities and reflects an approximately 2-hour

discharge. According to Figure 22, a 10-kWh battery discharging at 5 kW would actually have about 9 kWh available (90% efficiency).

### 1.14.5 Performance metrics

For this analysis, we focus on three economic metrics: levelized benefit of electricity (LBOE), levelized cost of stored electricity (LCOSE), and net present value (NPV). In addition, we also consider the benefit-cost ratio (BCR) in sensitivity analyses, which we define as the LBOE divided by the LCOSE.

#### 1.14.5.1 LBOE and LCOSE

LBOE provides context of the economic viability for energy storage while the LCOSE allows comparisons to the levelized cost of electricity from current technologies and serves as a target for future technologies. The calculations of these are provided in Equations 6-7, where  $r$  is the discount rate and  $N$  is the loan term.

$$LBOE = \frac{\sum_{y=1}^N \frac{\sum_{m=1}^{12} \text{Demand Charge Savings} + \text{Energy Charge Savings}}{(1+r)^y}}{\sum_{y=1}^N \frac{\sum_{m=1}^{12} \text{Energy Discharged}}{(1+r)^y}} \quad (6)$$

$$LCOSE = \frac{\sum_{y=1}^N \frac{\text{Annual Loan Payment}}{(1+r)^y}}{\sum_{y=1}^N \frac{\sum_{m=1}^{12} \text{Energy Discharged}}{(1+r)^y}} \quad (7)$$

#### 1.14.5.2 NPV

Calculating the NPV (Equation 8) helps provide significance to the benefits and costs of energy storage and allows for an easier comparison across various scenarios in sensitivity analyses. In addition, we calculate the NPV of a combined investment in solar PV and energy storage.

$$NPV = \sum_{y=1}^N \frac{\sum_{m=1}^{12} (\text{Demand Charge Savings} + \text{Energy Savings}) - \text{Annual Loan Payment}}{(1+r)^y} \quad (8)$$



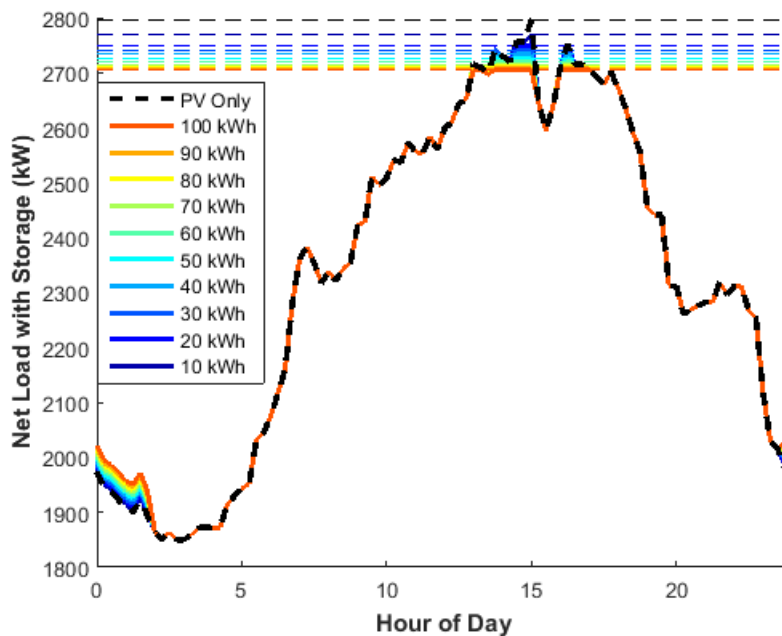
## 1.15 Results and discussion

Due to the nature of commercial and industrial electricity tariffs, it is generally most profitable for a customer to deploy energy storage to reduce demand charges. Depending on the load characteristics of a customer, reducing the monthly peak demand may require a relatively small amount of energy. As a result, the LBOE can be much higher than for customers on TOU tariffs without demand charges (energy charges only). Energy arbitrage has benefits on the order of 10-20 ¢/kWh given the difference in peak and off-peak energy rates and the efficiency of an energy storage device. However, these benefits are lower than the LCOSE for batteries today (~20¢/kWh to greater than \$1/kWh [84]). Reducing peak demand, on the other hand, can be highly profitable because demand rates are typically on the order of \$10-20/kW. Thus, a kWh of peak demand reduction would yield benefits between of at least \$10-20 or more if the peak demand only lasts 15 minutes.

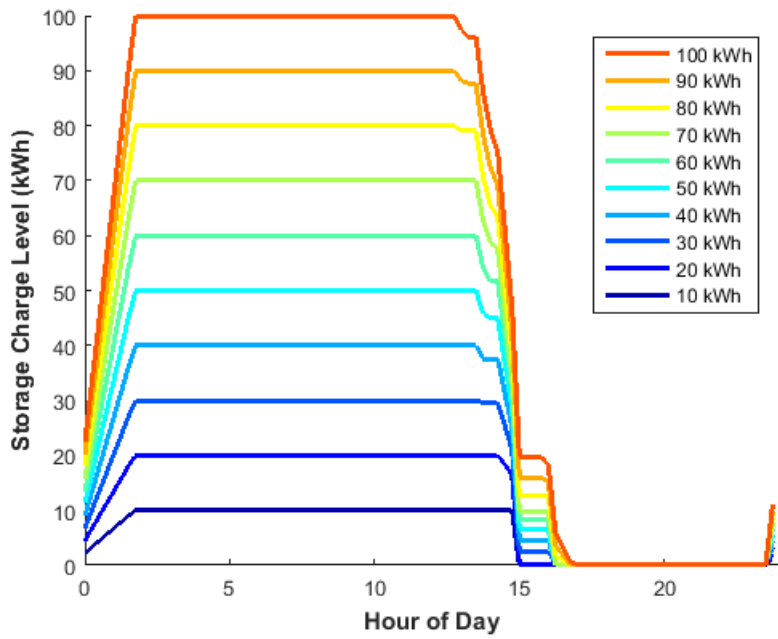
### 1.15.1 Perfect same-day forecast

To begin, we use a single load profile to illustrate detailed behavior. Details about this load can be found in Appendix C listed as building 10. In Figure 25 **Error! Reference source not found.**, we show the behavior of a battery with various usable capacities for a day on which the monthly peak demand occurs. The dotted black line at the top shows the level of the peak demand given the load with solar PV only. Batteries are able to reduce this peak demand to a lower level, indicated by the corresponding dotted lines. The batteries then charge during off-peak pricing periods when the net load (load - solar - storage discharge) can remain less than the peak demand.

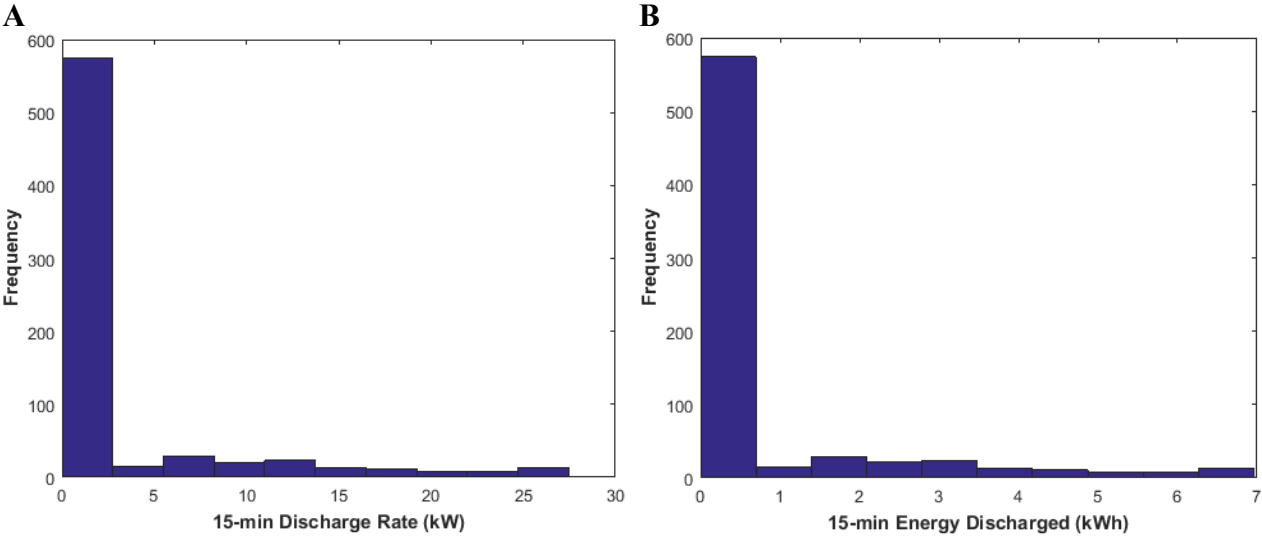
**Error! Reference source not found.** Figure 26 shows the state of charge of the batteries on the same day. Each of the batteries modeled fully discharge during the time of the peak demand to achieve the greatest peak demand reduction. Figure 27A illustrates the frequency of different discharge rates for a 10-kWh battery, with the majority of discharge rates below 2.5 kW. This indicates that there are not many 15-minute periods when the battery must discharge at higher rates. Similarly, Figure 27B shows the frequency of energy discharged for each 15-minute period throughout the year. Rarely does the battery discharge most of its capacity in a single 15-minute period. To better understand the cycling behavior of the battery, in Figure 28**Error! Reference source not found.** we show a frequency plot of the state of charge (SOC) swing. This illustrates that for most times when the energy storage is used, it discharges 100% of its energy prior to charging back to full capacity. This characteristic is important for battery type selection, as some technologies degrade more quickly and are less efficient when discharging at low capacity.



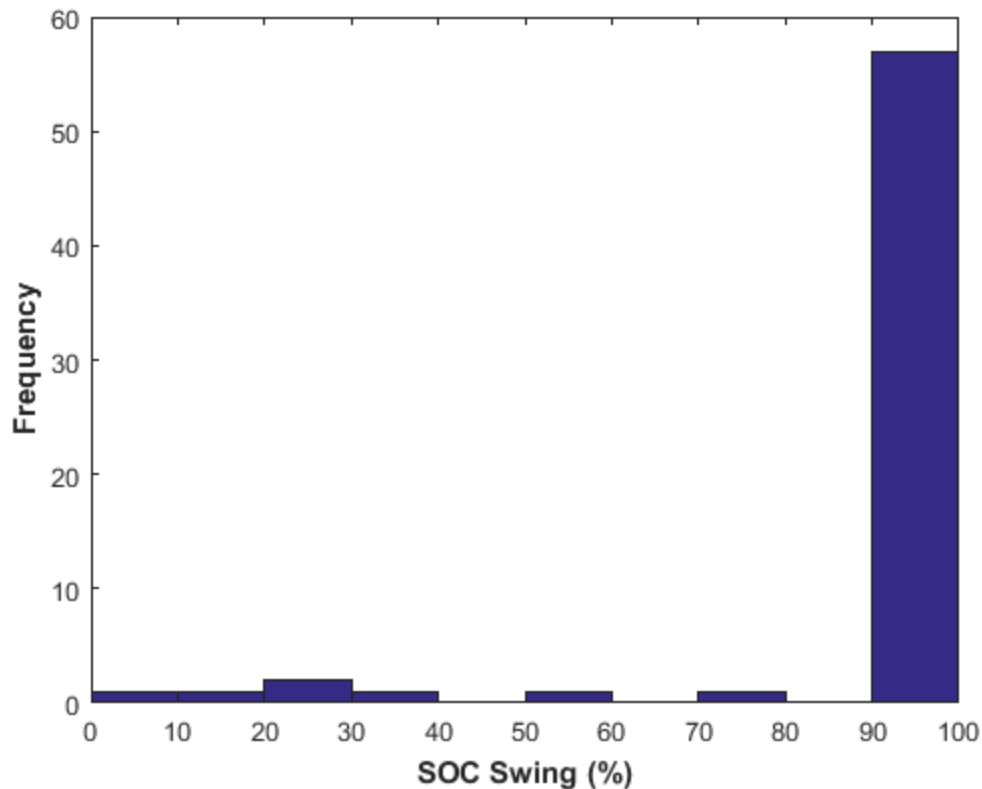
**Figure 25:** Net load with storage during peak day in month of June for single net load with various storage capacities using the 24-hour perfect same-day forecast.



**Figure 26:** Charge level during peak day in month of June for single net load with various energy storage capacities using the 24-hour perfect same-day forecast.



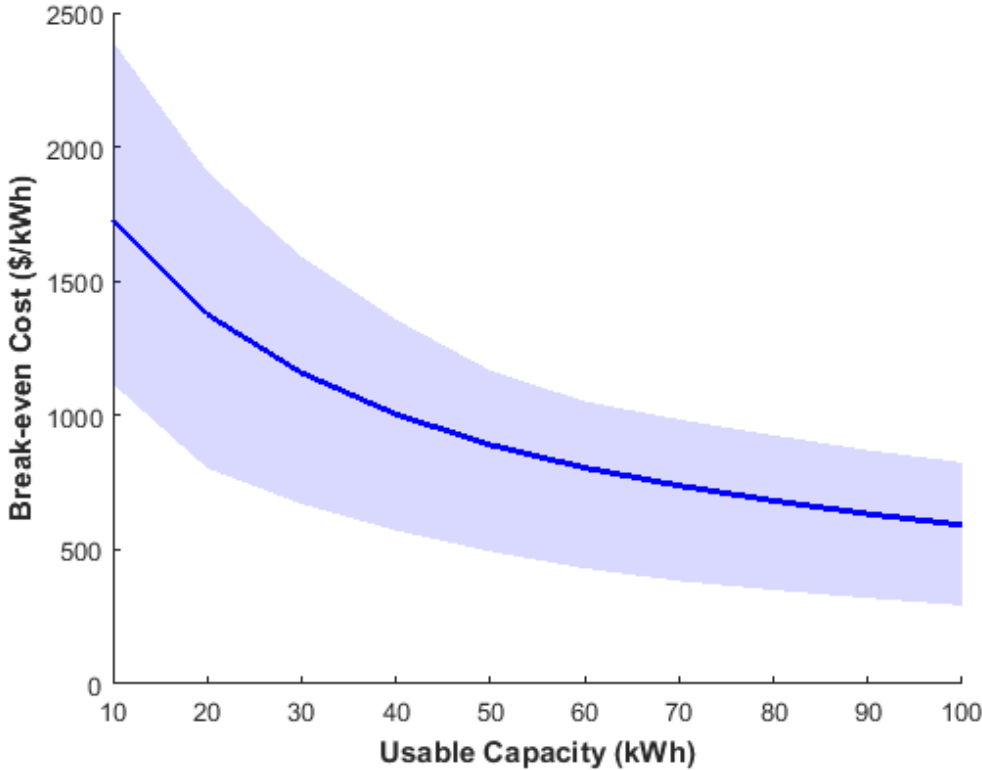
**Figure 27:** Frequency of annual (A) discharge rates and (B) energy discharged for single net load with a 10-kWh battery for one year using the 24-hour perfect same-day forecast.



**Figure 28:** Frequency of annual SOC swings for single net load with a 10-kWh battery for one year using the 24-hour perfect same-day forecast.

With capital costs and balance of system (BoS) costs for energy storage declining, we first show the break-even total installed cost for an energy storage device across the 59 commercial and industrial customers. Figure 29 shows break-even costs from \$590/kWh to \$1700/kWh across all capacities, on average, which suggests that if the total installed cost of energy storage can fall below these costs, these customers would be motivated to install energy storage. For a 10-kWh battery, the 75<sup>th</sup> percentile of break-even costs range between \$1,100/kWh and \$2,400/kWh. To put this in perspective, Tesla estimated battery costs of \$200/kWh to \$300/kWh in 2014 and the Rocky Mountain Institute estimates BoS costs at about two-thirds of the total installed cost of the system [85]. This translates to total installed costs of \$600/kWh to \$900/kWh, which falls within the range of average break-even costs for all capacities considered, and well below the 75<sup>th</sup> percentile range for 10-kWh batteries. Further, the U.S. Advanced Battery Consortium predicts

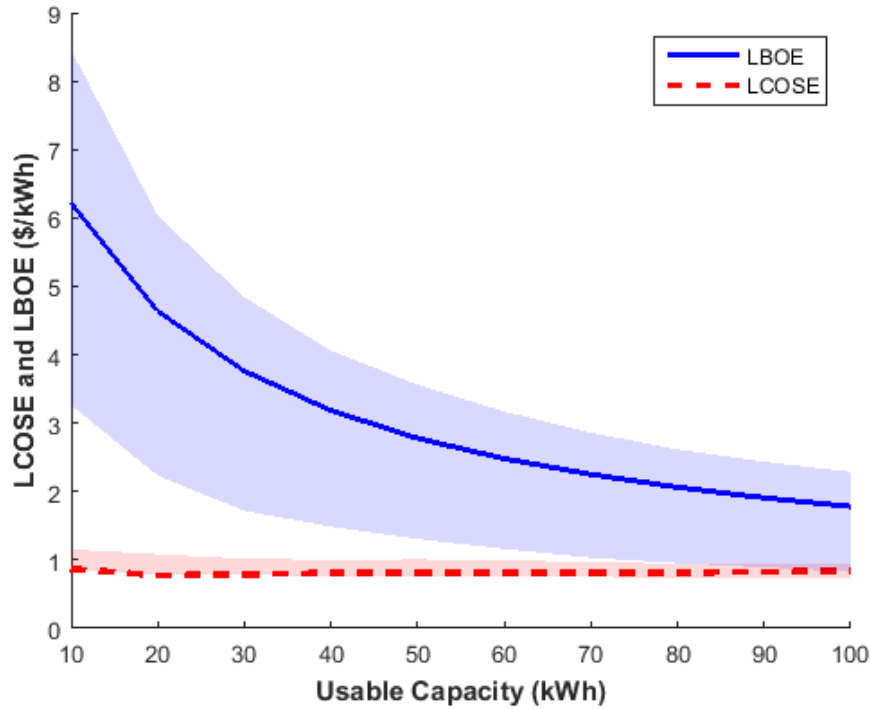
battery costs of \$100/kWh by 2020, which would potentially translate to a total installed cost of \$300/kWh [86].



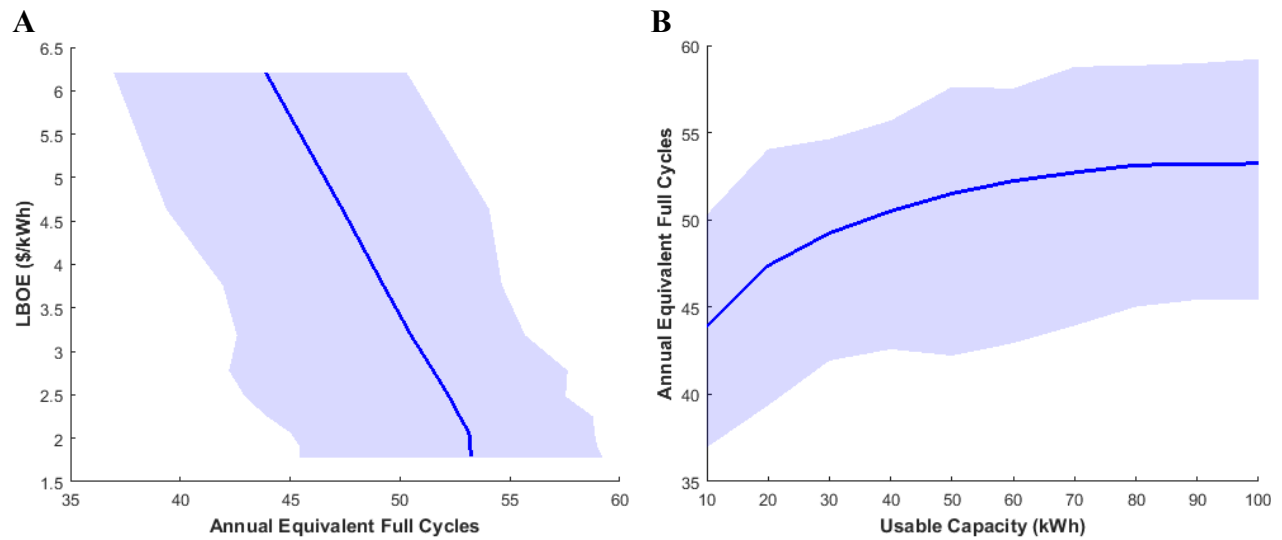
**Figure 29:** Break-even total installed cost for energy storage with various capacities. Shaded area represents the 25<sup>th</sup>-75<sup>th</sup> percentile of results.

In Figure 30 **Error! Reference source not found.**, we show both the LCOSE and LBOE for a battery used to reduce the monthly peak demand. There is a large gap between the LCOSE and LBOE for lower capacities, indicating that lower capacities are most profitable and additional capacity has decreasing benefit. This occurs because peak demand reductions can be made with small energy requirements. While a higher capacity battery yields greater demand savings, it must discharge more energy during the month to maintain the lower peak demand. In Figure 31A **Error! Reference source not found.**, we show that LBOE diminishes with increased annual number of full equivalent cycles just as it did with higher usable capacities. Figure 31B shows

that the average number of equivalent full cycles over ten years would be around 440 cycles for a 10-kWh battery and 530 cycles for a 100-kWh battery, on average. These results help illustrate performance requirements and suggest that these batteries could actually continue to operate and provide savings to a customer after the ten-year timeframe considered in this analysis.

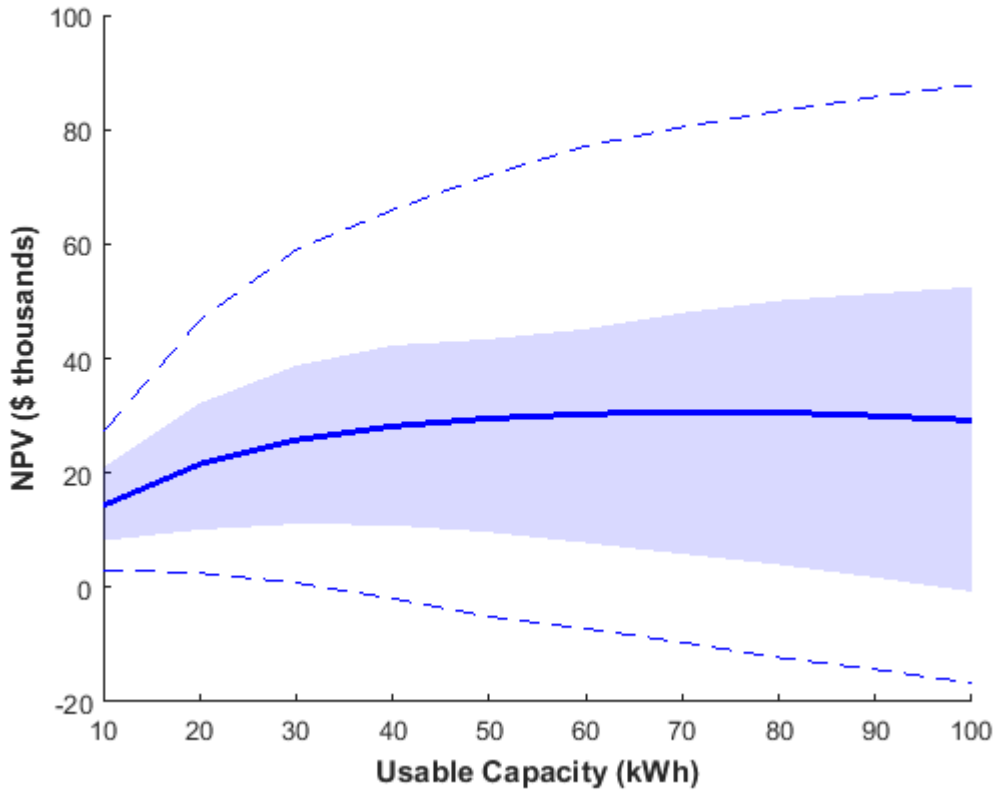


**Figure 30:** LCOSE and LBOE for a battery of various capacities for 59 commercial and industrial loads with a 200-kW PV system. Battery is optimally dispatched according to a 24-hour perfect same-day forecast. Shaded areas represent the 25<sup>th</sup>-75<sup>th</sup> percentile of results.



**Figure 31:** (A) LBOE versus annual equivalent full cycles for various energy storage capacities and (B) annual equivalent full cycles for various energy storage capacities for 59 loads. Shaded areas represent the 25<sup>th</sup>-75<sup>th</sup> percentile of results.

While LBOE declines with increasing usable capacity, Figure 32 **Error! Reference source not found.** shows that the NPV of energy storage actually continues to increase until a certain capacity threshold (around 70 kWh for these loads, on average) and then decreases. However, the average customer would likely elect to install a 10 to 20-kWh battery system to yield the most benefit while hedging against any financial risks. On the other hand, from the perspective of a company that helps finance an energy storage system for multiple customers, it would be most profitable to install 10-kWh battery systems for each of the customers to achieve the highest return on investment.



**Figure 32:** NPV for various energy storage capacities with the mean (solid line), 25<sup>th</sup>-75<sup>th</sup> percentile (shaded area), and 5<sup>th</sup>-95<sup>th</sup> percentile (dotted lines).

### 1.15.2 Basic algorithm

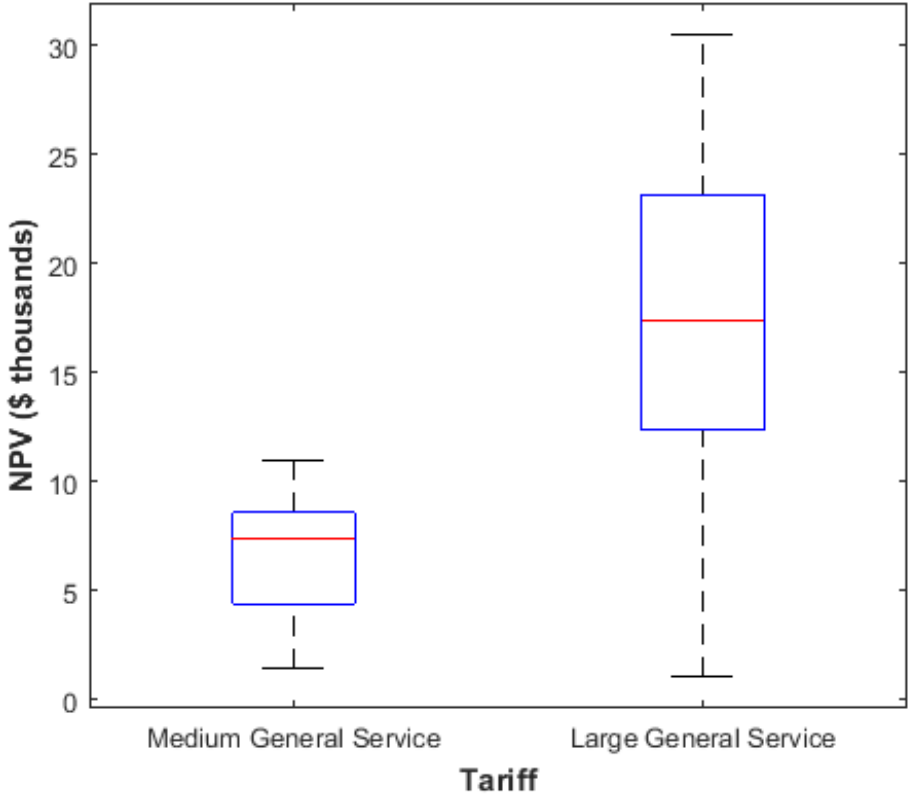
Figure 33

### 1.16 Effects of tariffs

With behind-the-meter energy storage, a customer benefits through electricity bill savings. These savings, however, are dependent on the rates and structure of the tariff. When using energy storage to reduce the monthly peak demand, the demand charge rate can impact economic viability. The tariff used in this analysis for large customers has demand charge rates of \$17.96/kW to \$18.93/kW for the months of June through September and of \$12.82/kW to \$13.79/kW for the months of October through May (actual values dependent on magnitude of peak demand during the on-peak time period). In contrast, the tariff used for medium customers



has a year-round demand charge rate of \$9.90/kW during the on-peak time period. In Figure 34, we show that the NPV of a 10-kWh battery system tends to be at least 2.5 times as much for large customer than medium customers. While this makes sense, it does highlight that energy storage may not be as profitable for customers with lower demand charge rates.



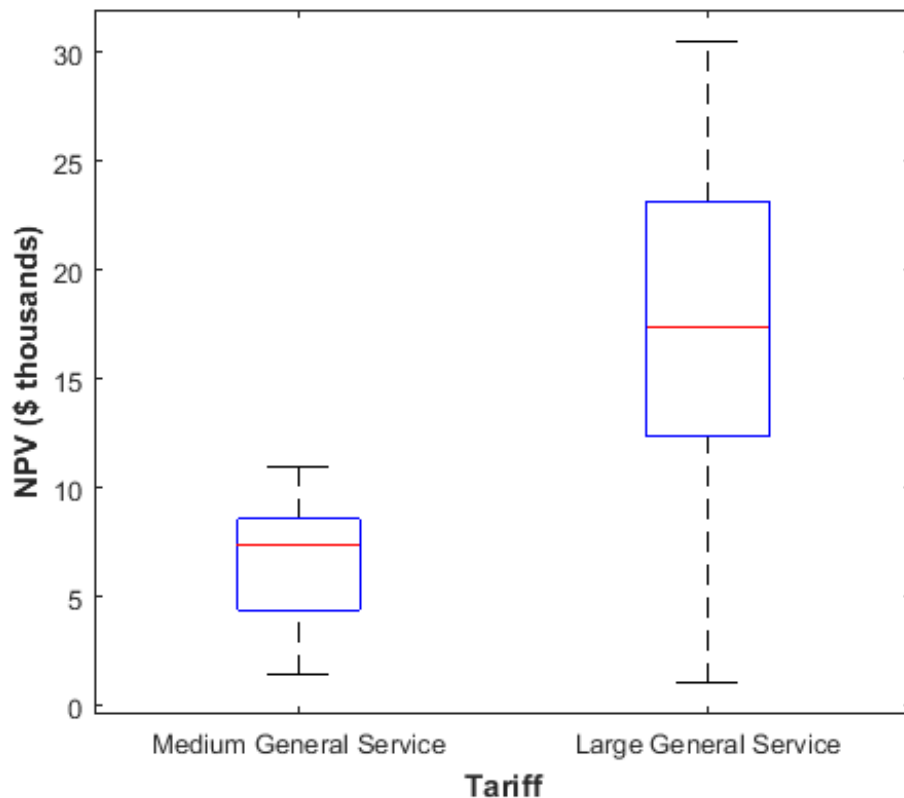
**Figure 34:** NPV for a 10-kWh energy storage device for the 19 medium customers (annual peak demand less than 1,000 kW) and 40 large customers (annual peak demand greater than or equal to 1,000 kW). The central red lines indicate the median; the bottom and top edges of the boxes indicate the 25<sup>th</sup> and 75<sup>th</sup> percentiles, respectively; and the whiskers extend to the most extreme data points not considered outliers.

shows energy storage economics when using a basic algorithm, providing a lower-bound estimate of economic viability. Compared to the upper-bound estimate using a perfect-24 hour forecast, the NPV and total installed break-even costs using the basic algorithm are much lower. The mean NPV in Figure 33

**1.17 Effects of tariffs**

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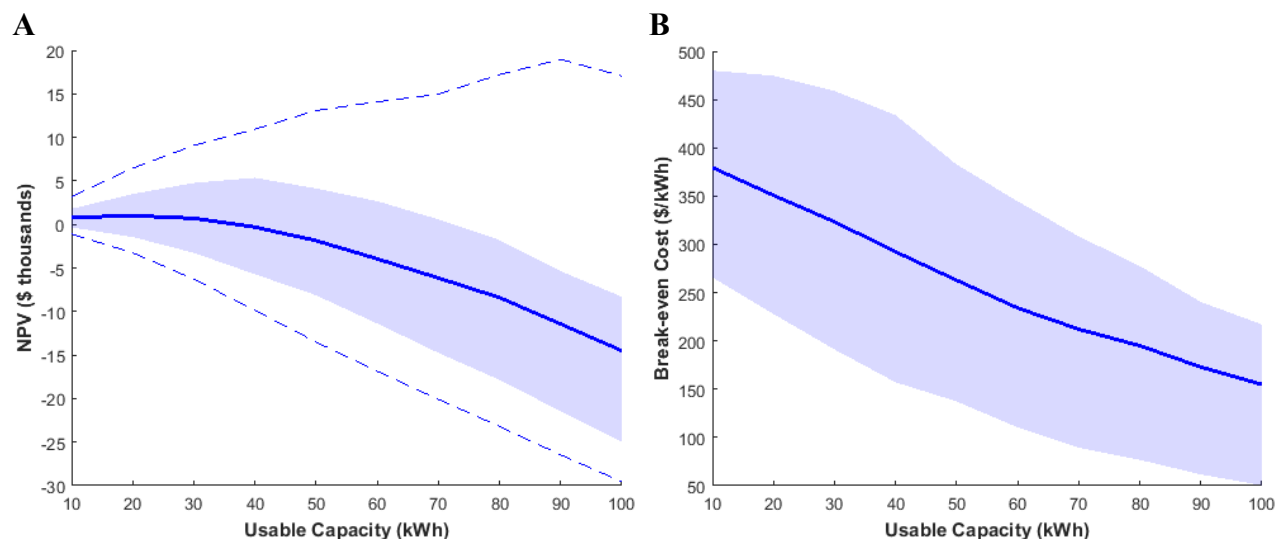
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A decreases beyond about 20-kWh capacities. With this algorithm, a customer should prefer to install a battery system with 10-kWh capacity. The significance here is that even with a basic

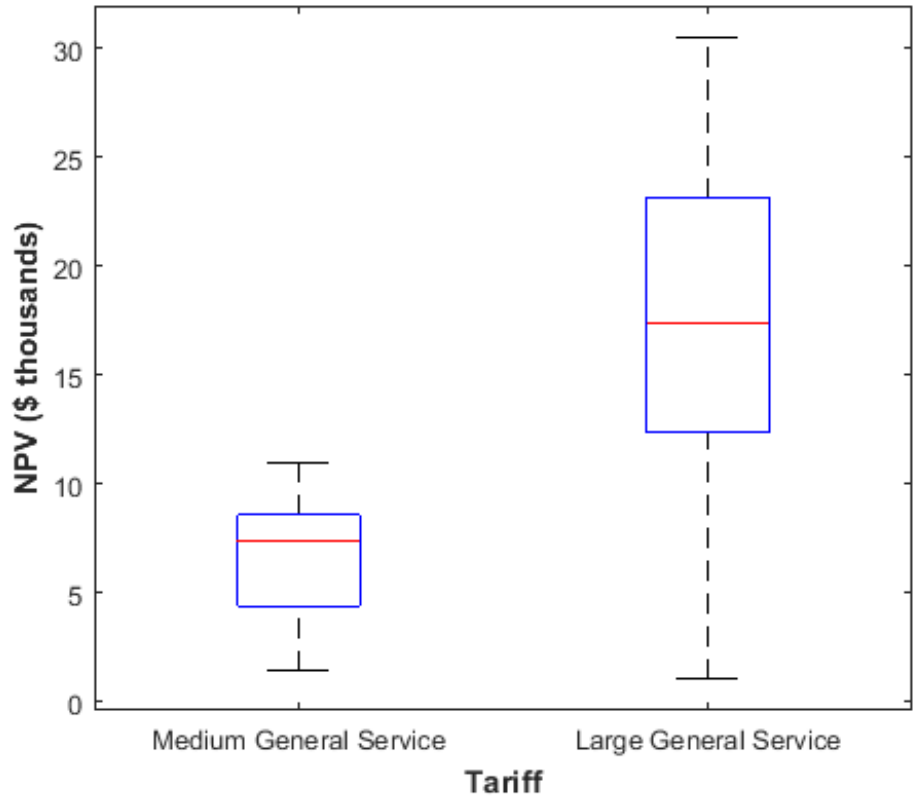
algorithm, lower-capacity energy storage is currently viable, on average, for the commercial and industrial customers modeled, but further cost reductions would help reduce financial risk.



**Figure 33:** (A) NPV and (B) total installed break-even costs for various energy storage capacities. Shaded areas represent the 25<sup>th</sup>-75<sup>th</sup> percentiles and dotted lines represent 5<sup>th</sup>-95<sup>th</sup> percentiles.

### 1.18 Effects of tariffs

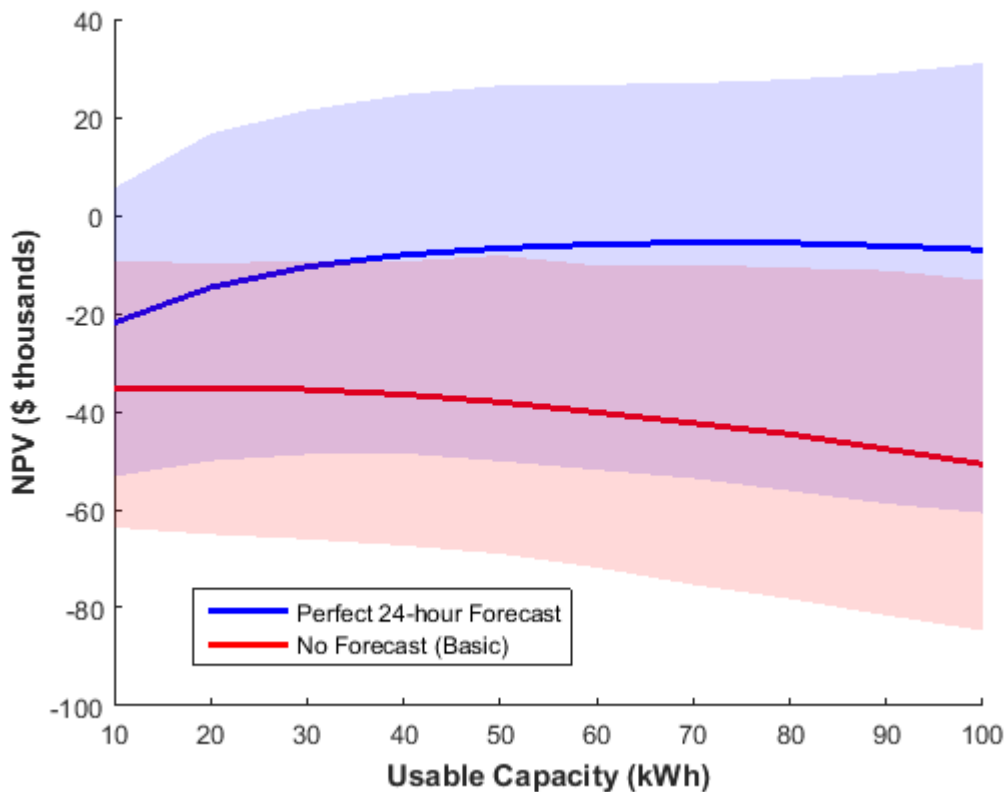
With behind-the-meter energy storage, a customer benefits through electricity bill savings. These savings, however, are dependent on the rates and structure of the tariff. When using energy storage to reduce the monthly peak demand, the demand charge rate can impact economic viability. The tariff used in this analysis for large customers has demand charge rates of \$17.96/kW to \$18.93/kW for the months of June through September and of \$12.82/kW to \$13.79/kW for the months of October through May (actual values dependent on magnitude of peak demand during the on-peak time period). In contrast, the tariff used for medium customers has a year-round demand charge rate of \$9.90/kW during the on-peak time period. In Figure 34, we show that the NPV of a 10-kWh battery system tends to be at least 2.5 times as much for large customer than medium customers. While this makes sense, it does highlight that energy storage may not be as profitable for customers with lower demand charge rates.



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### 1.18.1 Combined economics for solar PV and energy storage

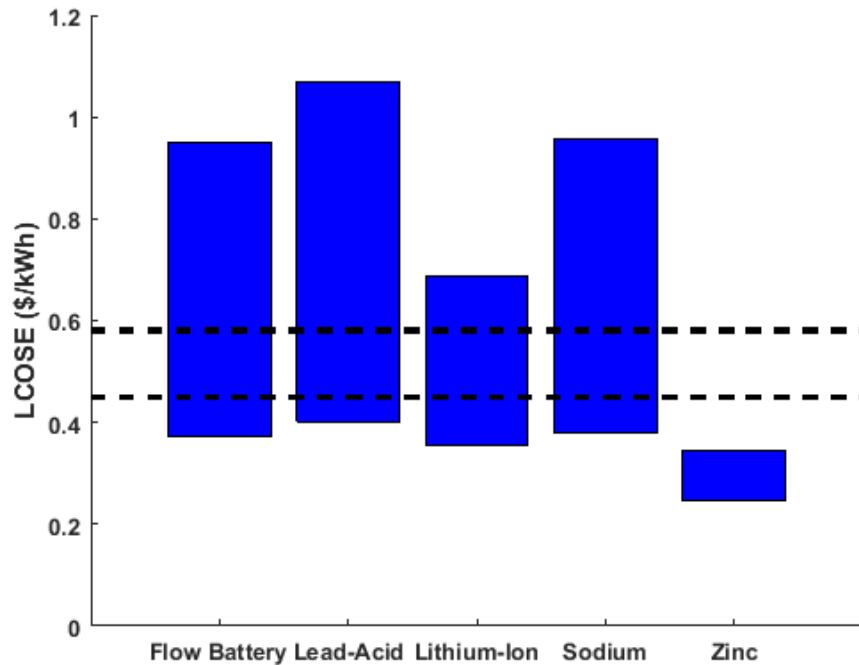
In Figure 35 **Error! Reference source not found.**, we combine the NPV of a 200-kW solar PV system with the NPV of various energy storage capacities. Details about financial assumptions for the solar PV system, which include the 30% federal investment tax credit (ITC), are provided in Appendix C. While the combined NPVs are sometimes positive for the perfect-24 forecast algorithm, the basic algorithm requires that solar PV installation costs and/or energy storage costs decrease in order to allow for a positive NPV. This supports the need for the ITC for solar PV until break-even costs occur.



**Figure 35:** Combined NPV of energy storage and a 200-kW solar PV system financed separately with ITC for both the perfect 24-hour forecast (top) and basic (bottom) algorithms.

### 1.18.2 Comparisons to existing technologies

In Figure 36, we show how the LCOSE of our modeled black-box storage device compares to existing energy storage technologies. Each of the ranges of existing technologies includes levelized costs at or below our range, suggesting that these technologies are capable of being economically viable. With respect to technical performance, high-energy lithium-ion batteries are well suited to this application due to their higher energy efficiency. Other technologies can be competitive if they are able to achieve similar energy efficiencies or reduce costs such that additional capacity can be installed to compensate for lower energy efficiency.



**Figure 36:** Comparison of the range of LCOSE for the black-box storage device (dotted lines) to existing technologies. We derive the range of LCOSE for the black-box storage device as the mean values across all customers for a 10-kWh (upper bound) and a 100-kWh battery (lower bound). Ranges in LCOSE for existing technologies (for PV integration) adapted from [84].

### 1.19 Conclusion

In this paper we examine the economics of a “black-box” energy storage device for commercial and industrial customers in North Carolina. By using high-resolution load and solar PV generation data, we are able to assess energy storage economics for reducing demand charges. We find that batteries with lower capacities can be profitable for the customers examined whether using a same-day 24-hour perfect forecast or employing a basic algorithm with no forecasting. We also estimate average break-even total installed costs for a 10-kWh battery of \$1,700/kWh for with a same-day 24-hour perfect forecast and \$380/kWh with a basic algorithm. This suggests that low-capacity energy storage would be viable for most of these customers with an advanced charge controller today, and for customers with a basic charge controller by 2020. Considering the current technologies available, we find that high-energy lithium-ion batteries

may be well suited for this application both in cost and performance but that other technologies can be competitive with improved energy efficiencies and lowered costs.

We illustrate that energy storage economics are dependent on the rates and structure of electricity tariffs. Energy storage can be highly profitable under tariffs with high rates for peak demand, where storage can be valuable with minimal discharged energy. While solar PV currently has a negative NPV for customers modeled in this analysis, 2020 cost targets for solar PV would yield a positive investment of solar PV and energy storage for these customers.

### **1.20 Acknowledgements**

This work was supported by academic funds from Carnegie Mellon University's Department of Engineering and Public Policy, by the program for Graduate Assistance in Areas of National Need (GAANN) of the U.S. Department of Education, by the Department of Energy under Awards DE-OE0000300 and DE-OE0000204, by the center for Climate and Energy Decision Making through a cooperative agreement between the National Science Foundation and Carnegie Mellon University (SES- 0949710), and by the Carnegie Mellon Electricity Industry Center (CEIC). Results and conclusions are the sole responsibility of the authors and may not represent the views of the funding sources.

## Conclusion

As the U.S. continues to strive for a cleaner electricity mix, large amounts of solar PV will reduce the total load on the grid and thus help cut daytime carbon emissions. The scalability of solar PV and the convenience of being installed on rooftops, makes solar PV a prime candidate for distributed generation, where it can offset a customer's load and other nearby loads. In order for solar PV to become a more significant source of electricity for the U.S., however, it is important for the technology to become cost-competitive without subsidies, a condition we refer to as socket parity for behind-the-meter applications. While we focus on historical electricity price escalation rates, these may be conservative, as they do not reflect a carbon price. Thus, if electricity prices increase above historical rates due to the implementation of higher-cost technologies, solar PV and energy storage become more valuable for a customer.

In Chapters 2 and 3, we show that solar PV has not achieved widespread socket parity with respect to present electricity rates for residential customers across the continental U.S., or for commercial and industrial customers in a North Carolina case study, without subsidies.

However, with the availability of low-interest loans, we expect that investments in solar PV will be viable for most residential, commercial, and industrial customers across the country once the SunShot Initiative's 2020 cost target is met. Until then, continued subsidies can support the growth needed to meet state and federal goals of increased renewable generation. Given different goals, it may be necessary to reallocate subsidies instead of providing the same level of support in all locations, as the ITC does. Once the SunShot cost target is reached, policy-makers should consider what timing is most appropriate for the reduction or elimination of additional financial



support to promote the additional deployment of solar PV systems. The analyses in Chapters 2 and 3 should be helpful in informing that decision-making process.

In Chapter 3, we find that a commercial or industrial customer's load factor and time of peak demand have large consequences for the economic viability of solar PV. Customers typically face more favorable economics if they have lower load factors (lower average demand relative to peak demand) and when a customer's peak demand occurs during daylight hours. In addition, we demonstrate that the time resolution of measured data can result in differences in calculated demand savings, with hourly data resolutions likely, on average to, overestimate demand savings. We also show that in addition to reducing capital costs, appropriate solar PV sizing and tariff designs drive the economic viability of these systems.

In Chapter 4, we examine the economics of a "black-box" energy storage device for commercial and industrial customers in North Carolina where value is primarily derived from reductions in demand charges. We find that batteries with lower capacities can be profitable for the customers examined using a same-day 24-hour perfect forecast, but may require further cost reductions when employing a basic algorithm with no forecasting. Considering the current technologies available, we find that high-energy lithium-ion batteries are well suited for this application both in cost and performance but that other technologies can be competitive with improved energy efficiencies and lowered costs. When combining the economics of solar PV and energy storage, the NPV is negative for most customers examined. However, once solar PV achieves socket parity on its own, commercial and industrial customers can reduce their electricity bills in a profitable way with solar PV and energy storage.

Overall, this thesis supports the conclusion that achieving the SunShot Initiative's 2020 cost targets would yield widespread solar PV socket parity for residential, commercial, and industrial customers. For customers who face demand charges, low-capacity energy storage can be profitable when shaving a customer's monthly peak demand. Further, having both technologies may reduce a customer's vulnerability to changes in net metering policies or rate structures.

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# Appendix A: Supporting Information Paper 1

## A-1. Background Data

Figure A-1 shows reductions in solar module prices over a four-year period, characterized by a sharp decline in the first two years, followed by a small increase and leveling off in the last two years. This figure also shows that a reduction in the costs of polysilicon supported a reduction in module prices. Figure A-2 then shows the contribution of module prices to the total installation costs of solar PV systems, as reported by the National Renewable Energy Laboratory (NREL) in 2012, the latest year for which these detailed data are available.

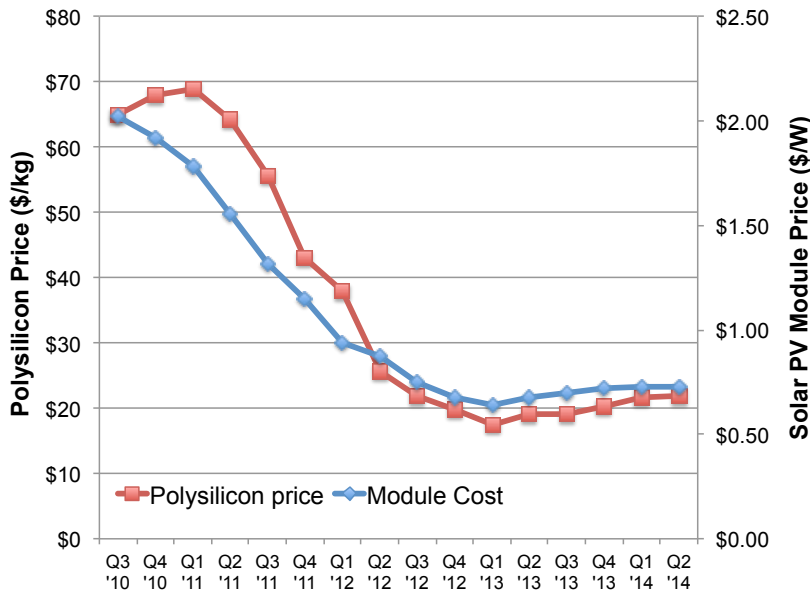
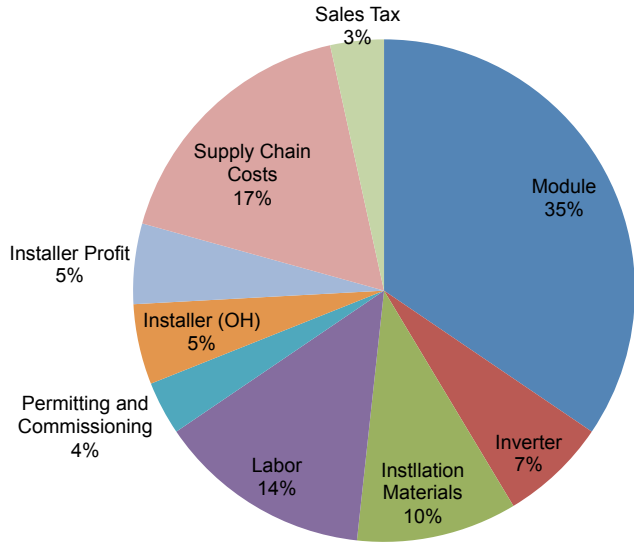
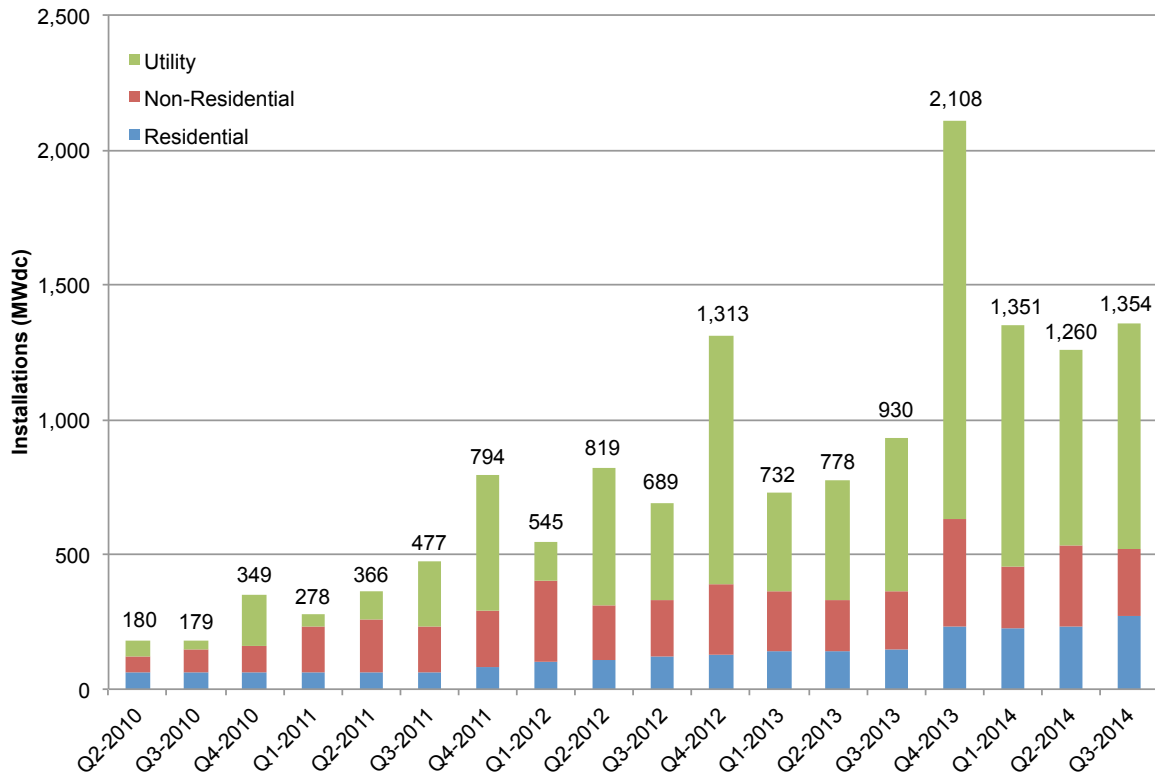


Figure A-1: U.S. polysilicon and solar module wholesale prices, Q3 2010 – Q2 2014 [12]-[14].





**Figure A-2:** Breakdown of solar PV installation costs. Adapted from the National Renewable Energy Laboratory [87].



**Figure A-3:** Solar PV installations, 2010-2014. Adapted from GTM Research/SEIA: U.S. Solar Market Insight® [14], [16].

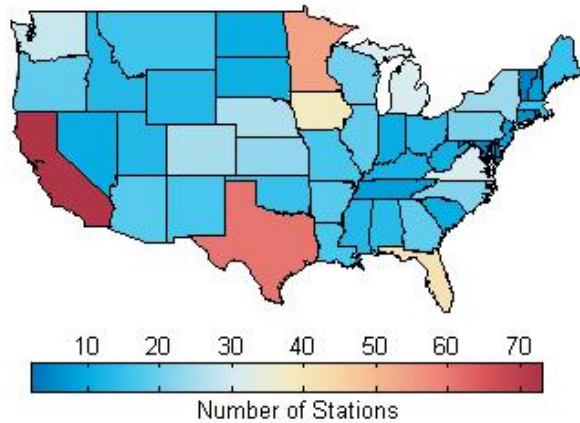
## **A-2. Model Data**

### **A-2.1 Insolation Data**

The insolation data used in this analysis came from the National Solar Radiation Database, which provides typical meteorological year (TMY) data that contain hourly solar radiation values and meteorological elements for 1,011 station locations across the U.S. (excluding territories).

These typical meteorological data characterize conditions at each site over longer periods of time and contain actual time-series meteorological measurements and modeled solar values, though some values may result from interpolations where measurements were not available [42].

According to Wilcox and Marion (2008) the selected typical months for each station “were chosen using statistics determined by considering five elements: global horizontal radiation, direct normal radiation, dry bulb temperature dew point temperature, and wind speed. These elements are considered the most important for simulating solar energy conversion systems and building systems.” While these data are not designed for meteorological extremes, they contain natural diurnal and seasonal variations and represent a year of typical climatic conditions for a location [42]. Figure A-4 shows the spatial distribution of the stations in this database across the lower 48 states. These stations serve as the locations for calculating the break-even price of electricity.



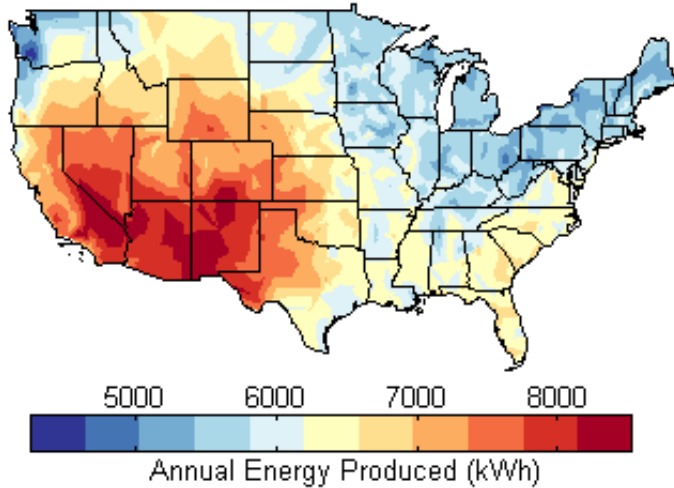
**Figure A-4:** Number of stations within each of the lower 48 states.

We selected the crystalline silicon BP Solar BP3220N Module because crystalline silicon modules are widely used and this module was one of the most recently manufactured crystalline silicon modules provided in the Sandia Module Database from the PV\_LIB toolbox.

Additionally, this module was the best performing module among crystalline silicon modules.

Note that this module was scaled to a 4 kW system using the maximum power point of the module, calculated as the product of the cited voltage and current at the maximum power point.

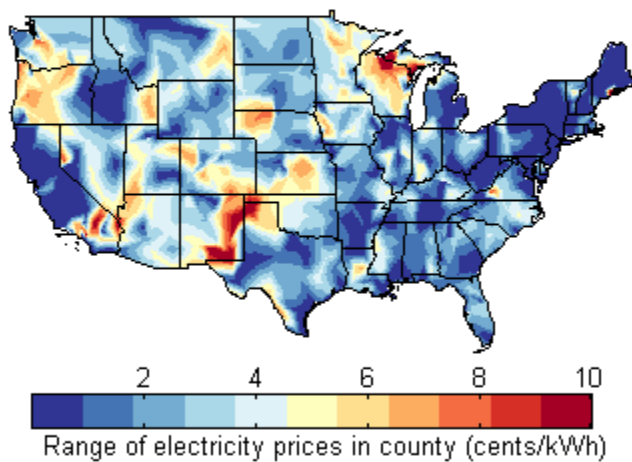
This same method was applied to the alternative module types, where for each module type we selected the module with the highest annual energy output across all locations. We used the best modules available in order to show whether state of the art residential PV systems are at socket parity.



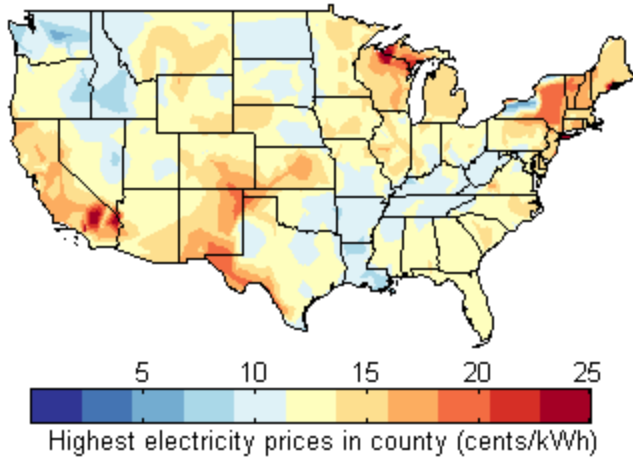
**Figure A-5:** Annual energy produced by from a 4 kW system.

### A-2.2 Electricity Price Data

It is important to note that electricity prices can vary within a county, which directly affects the economics of solar PV. Customers with electricity rates higher than the county average would have improved economics for their solar PV system, but might also be better off switching electricity providers, if possible. Conversely, electricity rates lower than county average would negatively affect solar PV economics.



**Figure A-6:** Difference between highest and lowest electricity prices within each county.



**Figure A-7:** Highest electricity price in each county.

### **A-2.3 Installation Costs**

System costs came from an NREL report that lists costs on a state level for those with 15 or more observations [36]. We then aggregated these costs into regions using weighted averages by the reported number of installations in each state within the region [36]. These regions were defined as follows:

Northeast: CT, MA, ME, NH, NY, RI, and VT

Mid-Atlantic: DE, MD, NJ, OH, PA, WV, and VA

Southeast: AL, AR, FL, GA, KY, LA, MS, NC, SC, and TN

Midwest: IA, IL, IN, KS, MI, MN, MO, ND, NE, OK, SD, and WI

Southwest: AZ, CO, NV, NM, and UT

Northwest: ID, MT, OR, WA, and WY

**Table A-1:** Regional installation costs (\$/W) of solar PV systems in 2014. Values based on data from NREL PV Pricing Trends [36]. \*Information not available. Applied the average range for 4-6 kW systems.

Region	20 <sup>th</sup> Percentile	Median	80 <sup>th</sup> Percentile
Northeast	3.8	4.5	5.0
Mid-Atlantic	3.3	3.9	4.6
Southeast	3.9	4.5	5.5
Midwest	3.4	4.2	5.3
Southwest	2.9	3.7	5.0
Northwest	3.6	4.2	5.1
Texas	3.0	3.4	4.0
California	3.9	4.6	5.6
Hawaii*	3.7	4.5	5.7
Alaska*	3.7	4.5	5.7

### A-2.3 Levelized Cost of Electricity

The levelized cost of electricity (LCOE) is a common metric used to compare the economic performance of different energy technologies. This metric generally includes capital costs, fuel costs, fixed and variable operations and maintenance (O&M) costs, and an average capacity factor of a plant over its lifetime. The LCOE includes financing costs by incorporating a discount rate in the capital recovery factor used to convert capital costs to annual costs over the life of the

entire system. Equation A-1 shows the conventional form of calculating the LCOE. In recent years, there has been some criticism of LCOE. Bazilian et al. (2013) suggest that an LCOE comparison is an inadequate metric of “grid parity” because it hides complex interactions between variables that affect the economics of solar PV systems. Similarly, Paul Joskow describes LCOE as a “flawed” metric for evaluating intermittent resources [34]. In this paper, we thus refrained from using the traditional definition of the LOCE. Instead we modeled the breakeven electricity price that a residential PV system owner has to receive over the life of the system in order to recover all the costs over the life of the system. While the equation used to model the breakeven price of electricity may look similar to the LCOE equation, it differs in that it accounts for financing cost and discount rate separately. Further, it accounts for the fact that the loan term may be different than the life of the system. Finally it accounts for changes in the capacity factor of the system throughout the life of the system.

$$LCOE \left( \frac{\$}{MWh} \right) = \quad \quad \quad \text{(Eq. A-1)}$$

$$\frac{\text{Capital Cost} \times CRF}{\text{System Capacity (MW)} \times CF \times 365 \times 24} + \text{Fixed O\&M Costs} \left( \frac{\$}{MWh} \right) + \text{Fuel Costs} \left( \frac{\$}{MWh} \right)$$

where  $CRF$  is the capital recovery factor (defined in Equation S2) and  $CF$  is the average capacity factor over the life of the system.

$$CRF = \frac{DR(DR-1)^y}{(DR-1)^y - 1} \quad \quad \quad \text{(Eq. A-2)}$$

where  $DR$  is the real discount rate and  $y$  is the life of the system (in years).

#### **A-2.4 Subsidies Included in Analysis**

Federal: 30% tax credit, distributed over 5 years

State:

##### *Rebate Programs*

Oregon: Modeled as \$0.75/W

New York: Modeled as \$0.70/W across state

Connecticut: \$0.54/W

Wisconsin: \$0.6/W

Illinois: \$1.5/W

Maryland: \$1,000 (per installation/household)

New Hampshire: \$0.75/W

Delaware: \$0.85/W

##### *Tax Credits*

Kentucky: \$3/W with max of \$500, used in installation year

Massachusetts: 15% with max of \$1000, used in installation year

Montana: \$1,000 per household, used in installation year

Rhode Island: 25%, must be used in installation year

Hawaii: 35%, distributed evenly over 5 years

New York: 25% with max of \$5,000, distributed evenly over 5 years

Arizona: 25% with max of \$1,000, distributed evenly over 5 years

Louisiana: 50% with max of \$25,000, distributed evenly over 5 years

Iowa: 18% with max of \$5,000, distributed evenly over 5 years

Maryland: \$8.5/MWh for 20 years



New Mexico: 10% with max of \$9,000, distributed evenly over 5 years

North Carolina: 35% with max of \$10,500, distributed evenly over 5 years

Oregon: \$1.7/W with max of \$6,000, distributed evenly over 5 years

South Carolina: 25% with max of \$3,500, distributed evenly over 5 years

Utah: 25% with max of \$2,000, distributed evenly over 5 years

*Tax Deductions*

Idaho: 40% in first year, 20% per year for next 3 years, \$5k per year limit. Assumed the state average household annual income of \$46,783<sup>1</sup>;

Annual tax calculated as  $\$1093.18 + (\text{AverageHouseholdIncome} - \$21,436) * 0.074$ ;<sup>2</sup>

*Premium Rates/Production Incentives (on top of electricity prices)*

Kentucky: 2 cents/kWh for first 10 years

Washington: 15 cents/kWh for first 5 years

*Solar Renewable Energy Credits (SRECs) (\$/MWh)*

New Jersey:

Year	1	2	3	4	5	6	7	8	9	10	11	12	13
	\$323	\$315	\$308	\$300	\$293	\$286	\$279	\$272	\$266	\$260	\$253	\$250	\$239

DC: \$480/MWh for 25 years

Maryland: \$160/MWh for 25 years

Massachusetts:

Year	1	2	3	4	5	6	7	8	9	10
	\$285	\$285	\$271	\$257	\$244	\$232	\$221	\$210	\$199	\$189

<sup>1</sup> <http://www.deptofnumbers.com/income/idaho/>

<sup>2</sup> Tax rates according to Idaho income tax: <http://tax.idaho.gov/i-1039.cfm#sub1>

Ohio: \$40/MWh for 11 years

Pennsylvania: \$43.5/MWh for 25 years

#### *Feed-in-Tariff*

Rhode Island: 37.75 cents/kWh

#### *Loan Programs*

New York: 3.49%, 15 yr, max of \$25k

Idaho: 4%, 5 yr, max of \$15k

Nebraska: 2.5%, 10 yr

Minnesota: 6.032%, 10 yr, max of \$20k

Ohio: 3% off interest rate for 7 years

Connecticut: 6%, 10 yr

Iowa: Interest-free for 50% of cost for 20 years

#### *Net Metering Programs*

The following states are assumed to credit all energy produced at full retail rate:

WA, AK, AZ, AR, CA, CO, CT, DE, DC, FL, GA, HI, IL, IN, IA, KS, KY, LA, ME,  
MD, MA, MI, MN, MO, MT, NE, NV, NH, NJ, NM, NY, NC, ND, OH, OK, OR, PA,  
RI, SC, UT, VT, VA, WV, WI, WY

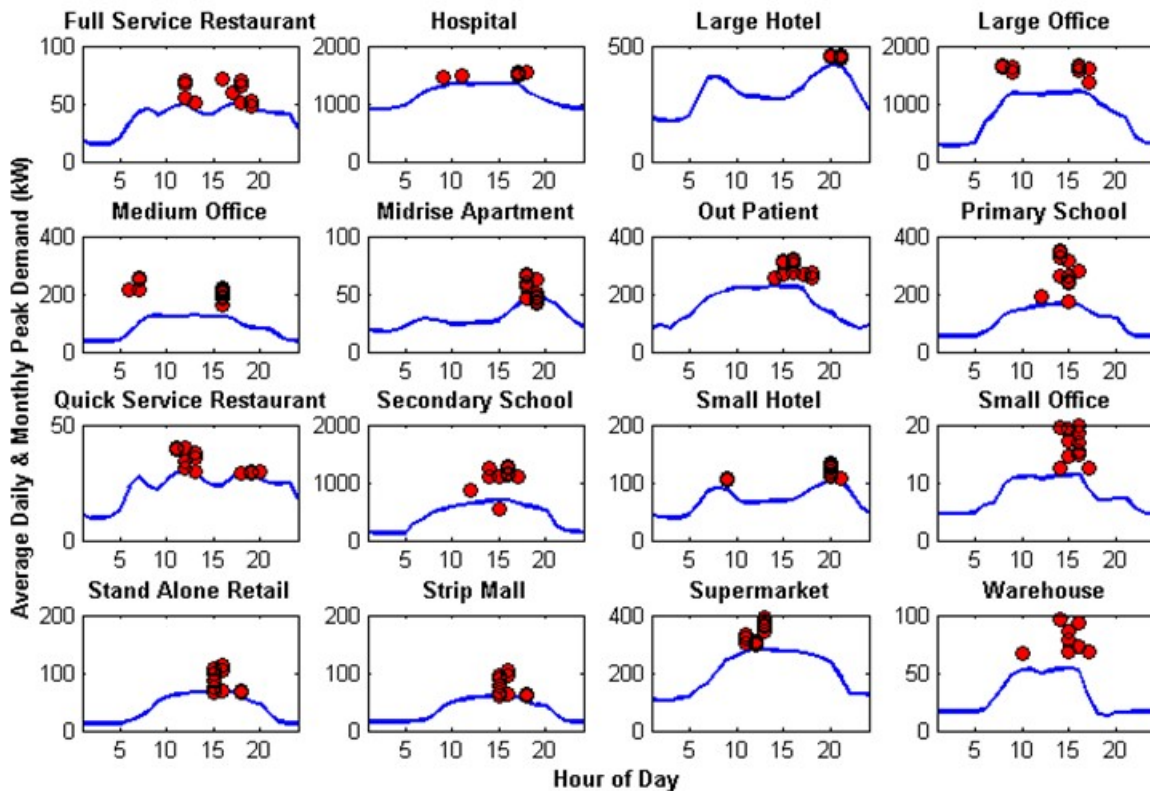
## Appendix B: Supporting Information Paper 2

**Table B-1:** Summary of measured and simulated solar data.

Location	Resolution	Year	Tilt (degrees)	System Size	Peak Output	Capacity Factor
Raleigh, NC	One-minute (measured)	2013	35	1.2 MW <sub>DC</sub> *	996 kW	15.6%
Raleigh, NC	Hourly (simulated)	TMY3	35	200 kW <sub>DC</sub>	198	15.6%

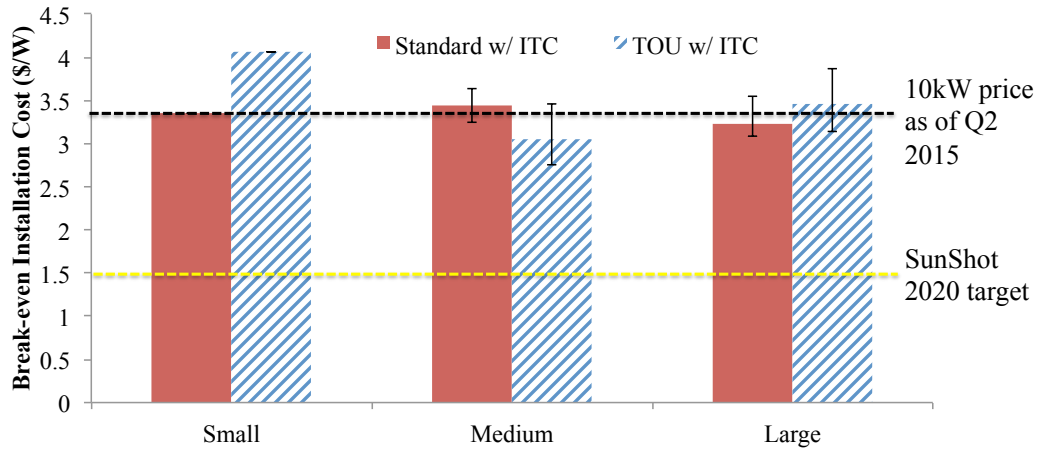
Note: \*Data scaled to 200 kW<sub>DC</sub> for sensitivity analysis. \*\* TMY3 = Typical meteorological year.

### Supplemental Graphs for DOE Reference Building Analysis



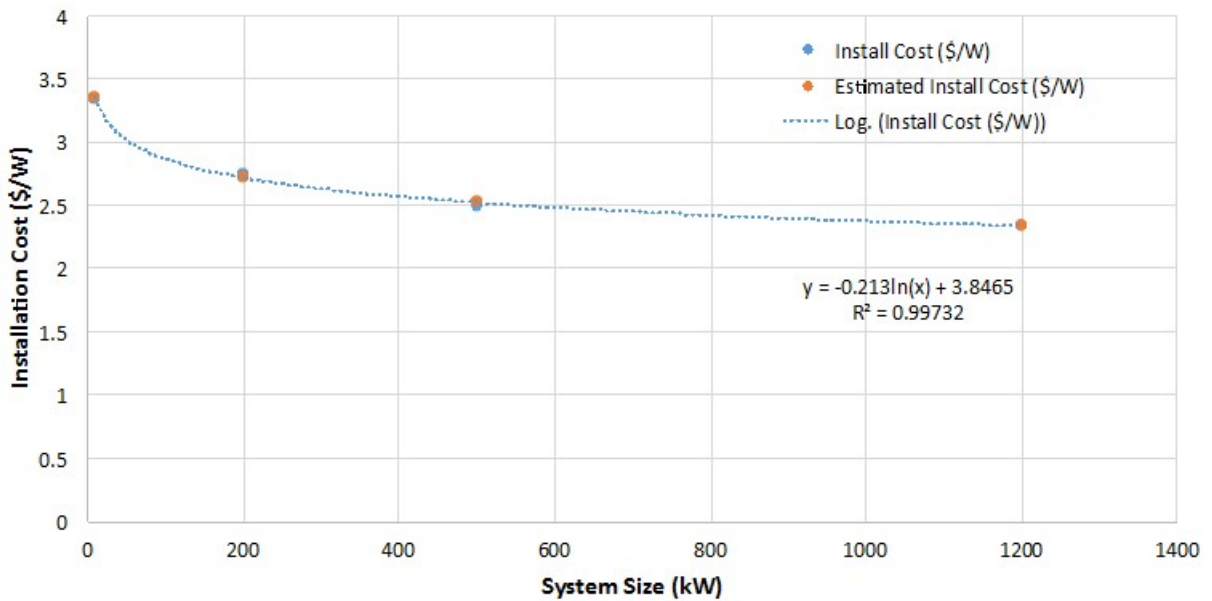
**Figure B-1:** Load characteristics of the 16 DOE reference commercial building load profiles.

Note: The blue lines illustrate average daily demand. The red circles are the magnitude of the peak demand each month and the hour in which it occurred.



**Figure B-2:** Break-even installation costs (with federal ITC) for a 10 kW solar PV system for each of the 16 DOE commercial reference building load profiles under both the standard and TOU tariffs.

*Installation Price Curve*



**Figure B-3:** Installation price curve used to inform analysis of optimal PV system size and effect of NEM

Summary Tables

**Table B-2:** North Carolina measured load profiles

Building Number	Peak Demand (kW)	Average Demand (kW)	Load Factor	Business Type	Current Tariff	Tariff Rate Class	Mode of Peak Hour	Break-even Installation Cost (\$/W)*
1	423	211	0.5	COM	TOU	MGS	16	1.4
2	767	327	0.43	COM	TOU	MGS	8	1.4
3	958	406	0.42	COM	TOU	MGS	15	1.5
4	437	270	0.62	COM	TOU	MGS	5	1.6
5	893	429	0.48	COM	TOU	MGS	11	1.6
6	443	297	0.67	COM	TOU	MGS	12	1.3
7	557	373	0.67	COM	TOU	MGS	15	1.4
8	439	380	0.86	COM	TOU	MGS	12	1.4
9	372	337	0.91	COM	TOU	MGS	16	1.6
10	1334	729	0.55	COM	TOU	MGS	16	1.5
11	1536	973	0.63	COM	TOU	MGS	15	1.4
12	473	364	0.77	COM	TOU	MGS	15	1.4
13	806	580	0.72	COM	TOU	MGS	13	1.4
14	3247	2014	0.62	COM	TOU	MGS	15	1.4
15	2290	1076	0.47	COM	TOU	MGS	16	1.3
16	1368	1140	0.83	COM	TOU	MGS	13	1.3
17	1087	587	0.54	COM	TOU	LGS	11	1.6
18	378	313	0.83	COM	TOU	LGS	16	1.6
19	2424	1785	0.74	COM	TOU	MGS	15	1.4
20	2520	1801	0.71	COM	TOU	MGS	15	1.5
21	912	659	0.72	COM	TOU	LGS	14	1.8
22	1140	880	0.77	COM	TOU	LGS	7	1.8
23	470	299	0.64	COM	TOU	LGS	13	1.5
24	608	446	0.73	COM	TOU	LGS	17	1.6
25	2448	1900	0.78	IND	TOU	LGS	13	1.3
26	2506	1733	0.69	IND	TOU	MGS	20	1.3
27	3283	2493	0.76	IND	TOU	MGS	3	1.4
28	1114	861	0.77	IND	TOU	MGS	1	1.3
29	1145	924	0.81	IND	TOU	LGS	11	1.5
30	1494	1144	0.77	IND	TOU	LGS	15	2.0
31	441	235	0.53	IND	TOU	MGS	11	1.7
32	1416	1255	0.89	IND	TOU	LGS	13	1.5
33	1560	1246	0.8	IND	TOU	MGS	18	1.4
34	1436	1095	0.76	IND	TOU	MGS	22	1.5

35	538	319	0.59	IND	TOU	LGS	12	0.7
36	1372	1329	0.97	IND	TOU	MGS	24	1.5
37	1032	881	0.85	IND	TOU	MGS	15	1.5
38	8855	4923	0.56	IND	TOU	MGS	15	1.5
39	6848	3805	0.56	IND	TOU	MGS	22	1.1
40	6784	3030	0.45	IND	TOU	MGS	22	1.3
41	298	225	0.76	IND	TOU	MGS	15	1.3
42	449	261	0.58	IND	TOU	MGS	11	1.3
43	354	228	0.64	IND	TOU	LGS	7	1.7
44	338	216	0.64	IND	TOU	MGS	13	1.0
45	418	286	0.68	IND	TOU	LGS	18	1.8
46	653	515	0.79	IND	TOU	LGS	15	1.7
47	896	409	0.46	IND	TOU	LGS	15	1.3
48	684	456	0.67	IND	TOU	LGS	11	1.2
49	395	261	0.66	IND	TOU	MGS	1	1.2
50	2016	1393	0.69	IND	TOU	LGS	7	1.5
51	1901	1451	0.76	IND	TOU	MGS	16	1.5
52	1742	1396	0.8	IND	TOU	LGS	20	1.1
53	1699	1287	0.76	IND	TOU	LGS	7	1.1
54	401	266	0.66	IND	TOU	LGS	15	1.2
55	3197	1585	0.5	IND	TOU	MGS	15	1.3
56	288	227	0.79	IND	TOU	LGS	6	1.1
57	1632	950	0.58	IND	TOU	LGS	14	1.3
58	968	731	0.75	IND	TOU	LGS	15	1.9
59	4589	3837	0.84	IND	TOU	LGS	15	1.4
60	950	585	0.62	IND	TOU	LGS	14	1.3
61	447	339	0.76	IND	TOU	MGS	15	1.3
62	413	267	0.64	IND	TOU	MGS	9	1.5
63	403	250	0.62	IND	TOU	MGS	10	1.4
64	4752	2831	0.6	IND	TOU	MGS	15	1.4
65	2966	1834	0.62	IND	TOU	MGS	11	1.3
66	403	291	0.72	IND	TOU	MGS	9	1.3
67	420	290	0.69	IND	TOU	MGS	16	1.3
68	422	277	0.66	IND	TOU	MGS	15	1.3
69	1688	1322	0.78	IND	TOU	MGS	11	1.4
70	2040	1328	0.65	IND	TOU	MGS	13	1.4
71	1235	855	0.69	IND	TOU	MGS	12	1.6
72	3072	1971	0.64	IND	TOU	MGS	17	1.4
73	2724	1984	0.73	IND	TOU	LGS	14	1.2
74	358	263	0.73	IND	TOU	LGS	16	1.3
75	351	215	0.61	IND	TOU	LGS	14	1.1

76	592	415	0.7	IND	TOU	LGS	13	1.2
77	816	354	0.43	IND	TOU	MGS	13	1.4
78	650	494	0.76	IND	TOU	LGS	14	2.1
79	454	378	0.83	IND	TOU	MGS	12	1.3
80	418	310	0.74	IND	TOU	LGS	17	1.4
81	3144	1281	0.41	IND	TOU	MGS	14	1.4
82	878	591	0.67	IND	TOU	LGS	15	1.4
83	451	247	0.55	IND	TOU	MGS	14	1.6
84	3504	2412	0.69	IND	TOU	MGS	6	1.4
85	391	232	0.59	IND	TOU	MGS	15	1.3
86	533	307	0.58	IND	TOU	MGS	15	1.3
87	2040	1757	0.86	IND	TOU	LGS	13	2.2
88	2736	2381	0.87	IND	TOU	LGS	22	1.6
89	872	549	0.63	IND	TOU	MGS	11	1.5
90	781	557	0.71	IND	TOU	MGS	15	1.4
91	2369	1610	0.68	IND	TOU	MGS	11	1.4
92	2050	1600	0.78	IND	TOU	LGS	17	1.3
93	1476	1241	0.84	IND	TOU	MGS	17	1.3
94	2498	1826	0.73	IND	TOU	LGS	17	1.8

Note: \* Calculated using measured load and solar data.

Table B-3: DOE load profiles

Building Name	Peak Demand (kW)	Average Demand (kW)	Load Factor	Business Type	Tariff Rate Class	Mode of Peak Hour	Break-even Installation Cost (\$/W)*
Full Service Restaurant	72	38	53%	COM	MGS	19	2.1
Hospital	1556	1140	73%	COM	LGS	17	1.9
Large Hotel	461	293	64%	COM	MGS	20	1.9
Large Office	1655	796	48%	COM	LGS	16	2.0
Medium Office	258	85	33%	COM	MGS	16	2.1
Midrise Apartment	67	29	43%	COM	MGS	19	2.0
Out Patient	320	161	50%	COM	MGS	15	2.3
Primary School	353	106	30%	COM	MGS	15	2.5
Quick Service Restaurant	40	23	56%	COM	MGS	13	2.1
Secondary School	1272	416	33%	COM	LGS	16	2.3

<b>Small Hotel</b>	135	70	52%	COM	MGS	20	1.9
<b>Small Office</b>	20	8	39%	COM	SGS	16	2.2
<b>Stand Alone Retail</b>	114	39	34%	COM	MGS	15	2.3
<b>Strip Mall</b>	103	35	34%	COM	MGS	15	2.3
<b>Supermarket</b>	390	201	52%	COM	MGS	13	2.6
<b>Warehouse</b>	96	30	31%	COM	MGS	15	2.4

Note: \* Values for standard tariff.



## Appendix C: Supporting Information Paper 3

**Table C-1:** Details of measured load profiles.

Building Number	Peak Demand (kW)	Average Demand (kW)	Load Factor (%)	Business Type	Current Tariff	Tariff Rate Class	Mode of Peak Hour
1	958	406	42	COM	TOU	MGS	15
2	893	429	48	COM	TOU	MGS	11
3	443	297	67	COM	TOU	MGS	12
4	557	373	67	COM	TOU	MGS	15
5	439	380	86	COM	TOU	MGS	12
6	1334	729	55	COM	TOU	MGS	16
7	1536	973	63	COM	TOU	MGS	15
8	473	364	77	COM	TOU	MGS	15
9	806	580	72	COM	TOU	MGS	13
10	3247	2014	62	COM	TOU	LGS	15
11	2290	1076	47	COM	TOU	LGS	16
12	1368	1140	83	COM	TOU	MGS	13
13	1087	587	54	COM	TOU	MGS	11
14	378	313	83	COM	TOU	LGS	16
15	2424	1785	74	COM	TOU	LGS	15
16	2520	1801	71	COM	TOU	MGS	15
17	912	659	72	COM	TOU	MGS	14
18	1140	880	77	COM	TOU	MGS	7
19	470	299	64	COM	TOU	LGS	13
20	608	446	73	COM	TOU	LGS	17
21	2448	1900	78	IND	TOU	MGS	13
22	2506	1733	69	IND	TOU	MGS	20
23	3283	2493	76	IND	TOU	MGS	3
24	1145	924	81	IND	TOU	MGS	11
25	1494	1144	77	IND	TOU	LGS	15
26	1416	1255	89	IND	TOU	LGS	13
27	1436	1095	76	IND	TOU	LGS	22
28	1372	1329	97	IND	TOU	LGS	24
29	1032	881	85	IND	TOU	LGS	15
30	8855	4923	56	IND	TOU	LGS	15
31	6784	3030	45	IND	TOU	LGS	22
32	896	409	46	IND	TOU	MGS	15
33	684	456	67	IND	TOU	MGS	11

34	2016	1393	69	IND	TOU	MGS	7
35	1901	1451	76	IND	TOU	MGS	16
36	1742	1396	80	IND	TOU	MGS	20
37	1699	1287	76	IND	TOU	MGS	7
38	3197	1585	50	IND	TOU	LGS	15
39	1632	950	58	IND	TOU	LGS	14
40	4589	3837	84	IND	TOU	LGS	15
41	950	585	62	IND	TOU	MGS	14
42	4752	2831	60	IND	TOU	MGS	15
43	2966	1834	62	IND	TOU	MGS	11
44	403	291	72	IND	TOU	MGS	9
45	420	290	69	IND	TOU	MGS	16
46	1688	1322	78	IND	TOU	MGS	11
47	1235	855	69	IND	TOU	LGS	12
48	3072	1971	64	IND	TOU	MGS	17
49	2724	1984	73	IND	TOU	LGS	14
50	3144	1281	41	IND	TOU	MGS	14
51	878	591	67	IND	TOU	MGS	15
52	3504	2412	69	IND	TOU	MGS	6
53	2040	1757	86	IND	TOU	LGS	13
54	2736	2381	87	IND	TOU	MGS	22
55	872	549	63	IND	TOU	MGS	11
56	781	557	71	IND	TOU	MGS	15
57	2369	1610	68	IND	TOU	LGS	11
58	2050	1600	78	IND	TOU	LGS	17
59	2498	1826	73	IND	TOU	LGS	17

### Solar PV system financing assumptions

We assume that the 200-kW solar PV system with an installation cost of \$2.7/W is financed separately with a 5% loan interest rate over 10 years (on par with PACE financing). We also assume that the customer can fully utilize the 30% investment tax credit (ITC) for solar PV and depreciate the asset using the 5-year MACRS schedule.

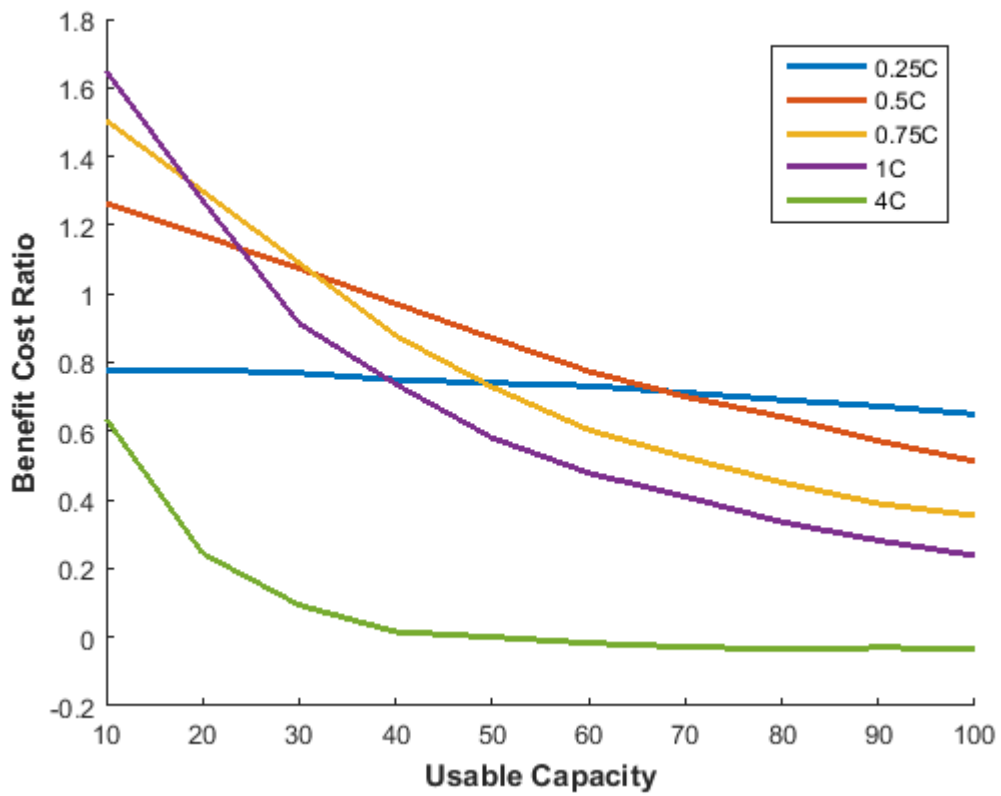


Figure C-1: Benefit cost ratio for various usable capacities with the basic algorithm using different discharge rates.