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Optimal Battery Sizing for Storm-Resilient Photovoltaic Power Island Systems

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ABSTRACT

Photovoltaic systems with battery storage are analyzed from the perspective that they can operate as a local power island in circumstances of storm-damage or other grid outage. The specific focus is to determine the optimal battery size for a given solar array size, taking into account reasonable day-to-day and seasonal sunlight variations as well as efficiency losses when converting from DC to AC for connection to the grid, or for provision of power during island mode. Three locations in the United States are used as case studies (Newark NJ, Boulder CO, and Tucson AZ). These provide a wide range of sunlight characteristics and illustrate variability factors that will be similar to many locations in continental North America. The analysis of the probability distributions for sunlight brightness then allow for the establishment of a 95% confidence rating for the steady-state power output from a specific combined battery and solar array configuration when faced with a grid interruption. This rating system can be used as a guide for designing systems for future installation.

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Introduction

Photovoltaic systems with battery storage have long been critical for those who live in remote places or want to be completely “off the grid”. Many studies have looked at balancing system design with known demand profiles for remote locations around the world [1-10], but the system optimum is strongly affected by the particular load profile and power generation mix (and variability). Still, stand-alone PV+battery systems have typically only been a very small fraction of PV systems installed. Most residential installations are actually grid-tied, which means that under conditions of local usage extra solar-generated power is fed back to the grid at large. In addition, these residential systems don’t typically have any local storage options; the solar is used when it is generated and any shortage or excess relative to the local need is moderated by the grid connection: the grid itself serves as storage. This widely distributed renewable generation has taken hold in California, New Jersey, Germany, and a number of other localities around the world. However, the recent “superstorm” events (Sandy and others) have exposed a key weakness of these systems: that the typical residential inverters used do not have “islanding” capability, which forces the vast majority of the solar generation capacity to be turned OFF when the grid goes down. Thus, a widely distributed power generation resource (that could be particularly valuable during storm recovery) is restricted because of the simplicity of the common strategy for installation. This has naturally led to calls for the design and installation of combined PV+battery systems with an inverter having islanding capability and some systems like this have already been fielded.

Previous studies that have examined optimal matching between intermittent renewable generation and local storage provide excellent guidance when considering how to design battery backup power for grid-tied solar generation with the aim of providing storm resiliency[10-40].

One example of a probabilistic method is the work of Samimi et al.[38] who have used a cloudiness index that accounts for the weather variability, though they distilled these factors into representative monthly averages and aggregated these into likelihoods of many back-to-back days of cloudy weather in those months during the 20-year scope. Their treatment was different than the present work as we have to be prepared for a grid interruption that might happen any time of the year and not be of unlimited duration. Similarly, Ahmad[39] provides a statistical treatment that allows for projections of repeated bad-weather days, but it is based on monthly average numbers that then are limited to specific seasons rather than the entire year, which is our present focus.

Further, many of the previous works have examined complicated load/demand configurations, but they have not examined the sizing strategy for a battery backup system for a power island during grid outage, where during regular grid operation the battery might also find use for load shifting, energy arbitrage[41-43] and frequency regulation[44-46] revenue generation. In fact, recognizing that storm/grid outages are relatively sparse it should be expected that these other revenue streams would be the most critical for installation cost-benefit analysis. Still, it is necessary to make sure that the battery size is large enough to ensure the operation of critical equipment during any outage. Since the island-mode power supply is limited by the day-time generation of solar electricity we focus on the relative size that the storage system would need to have in proportion to the solar array size. For this comparison, we quantify the solar resource and its variability, which provides information on the expected energy capture and thus the required sizing for the batteries needed for a reasonable power-islanding installation. Conversely, the analysis here is able to show the likely night-time power output that a system would be able to provide, again considering the variability of natural sunlight, seasonally and regionally – subject to the either the PV array or battery capacity mutual limitations.

Background

As a starting point for this analysis it is useful to examine the standard data for sunlight that have been logged and publicly provided by the National Renewable Energy Lab (NREL). The most detailed data come from the Typical Meteorological Year (TMY3) database where 24-hour by 365-day datasets are available for numerous specific locations in the United States[47]. To illustrate both the analysis technique and the regional variability of sunlight three specific locations are examined in the present paper: Tucson AZ (a very sunny desert location), Boulder CO (a higher altitude, mid-latitude location), and Newark NJ (a mid-latitude, cloudier location); the basic conclusions will be generalizable to many similar locations and the process can be carried out for more extreme locations working with the appropriate TMY3 datasets. The third generation meteorological data, "TMY3", provide hourly sunlight intensity values with broad utility, ranging from ETR (the extraterrestrial radiation measured on a plane parallel to the local earth's surface, but outside of the atmospheric scattering), to GHI (the global horizontal irradiance, combining both direct and scattered light hitting a level local reference plane), DNI (the direct normal irradiance, being the sunlight coming directly from the sun and hitting a plane normal to the light path), the wind speed, air temperature and many other data. The DNI is used in combination with the diffuse light fraction to help design tracking systems and algorithms, while for many fixed solar installations (guided by roof pitch and inclination) some alternative manipulation of these quantities must be performed [48-52]. For the present analysis we simply take GHI as a quantitative representative measure of the sunlight brightness, recognizing that perhaps 10-20% improvement in output might result for selected southward-tilted well-designed arrays. However, since the emphasis here is the relative *matching* between the solar output and the battery size, any improvement in solar array installation output would indicate the need for an identical proportional increase in battery capacity.

While the TMY3 database provides for hourly insolation data, we are mainly interested in the daily totals since the battery system must store the daily captured energy for delivery during the night, essentially providing continuous steady output for some kind of emergency equipment or electrical need in the event of grid outage. Working with these numbers it is easy to calculate the nominal expected output from PV modules as the standard testing conditions (STC) are defined using uniform illumination with spectrally balanced light having intensity of 1000 W/m^2. So, taking the daily insolation total (GHI) and dividing by the STC intensity gives an effective number of "sun hours" to scale a module or array's output[53], as shown in equation (1):

$$j^{th}\ daily\ total = \sum_{i=1}^{24} GHI_{j,i} \qquad (1)$$

Figure 1 shows this daily GHI summation expressed as kWh/m^2/day, which is quantitatively equivalent to the effective sun hours for each day. Data are provided for the entire model year for each of the three locations. Clearly the daily weather conditions cause dramatic swings in available energy collection from PV installations (as emphasized by the widest scatter seen in New Jersey and the least in sunny Arizona). At the same time there are strong seasonal variations that are occurring.

The expected daily energy output from a PV array is found by multiplying that day's effective hours of sunlight times the array's DC nameplate rating. The usable AC output is downgraded based on expected inverter losses, possible downtime, surface layer soiling, and other factors. NREL's online PV power calculating tool, PVWATTS 2.0, has suggested a default factor of 0.77 for this overall DC-to-AC conversion efficiency[54]. Some improvement relative to this downgrading will likely be possible if the power management system is designed to interface with the battery management unit directly (DC-to-DC) when charging the battery. However, the battery output must also eventually be converted to AC for local island utilization. The specific configuration of the necessary power electronics and their optimization is beyond the scope of the present analysis. As we look more specifically at the matching of the battery and the PV array, it must be recognized that the (effective sun hours)*(PV Array rating) will deliver an expected quantity of energy that needs to be stored. But this must then be trickled gradually over the many hours of darkness, essentially limiting the power "rating" that might be given any array+battery configuration for the needs of emergency equipment operation, etc.

In the next sections we discuss two limiting cases of the PV array+battery configuration, where either the battery capacity or the sunlight availability are the limiting factors in determining the emergency power that a system can deliver when the grid goes down. For the purposes of comparison we apply the inverter, battery round-trip, and other inefficiencies as one factor after examining the idealized PV+Battery energy availability limits only.

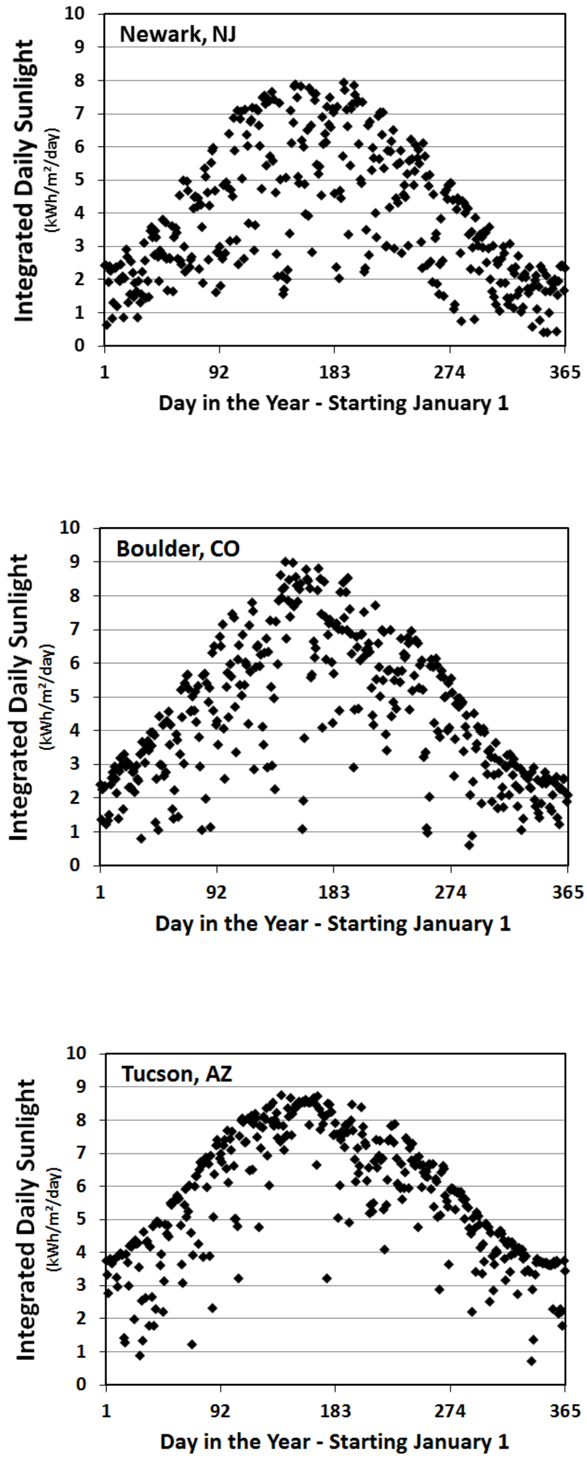

Figure 1: Daily integrated global horizontal irradiance (GHI) at ground level for (top) Newark, NJ, (middle) Boulder, CO, and (bottom) Tucson, AZ.

Case 1: Sunlight Limited Operation

As battery prices get lower and the requirements for power backup from battery storage grows there will be more situations where larger batteries are installed and thus may more frequently encounter situations where the smoothly operating steady-state power will be limited more by the sun's integrated intensity than by the battery's storage capacity. This might be especially true in winter times when sunlight is less intense.

In this simple limit we might expect that any day's accumulated solar energy capture would need to be spread evenly over the applicable 24 hour period – and the effective steady-state output power ("SSP") (scaled to the solar array rating ("PV")) would simply be:

$$\frac{SSP}{PV} = \frac{(sun\ hours)}{24} = Capacity\ Factor \qquad (2)$$

If we use the daily sums presented in **Figure 1** and replot them as a probability distribution we can find ratings that satisfy confidence limits at various levels. **Figure 2** shows these probability distributions, where each day's Capacity Factor is plotted (Y-axis) versus the fraction of days in the model year that have lower Capacity Factor (X-axis). This ratio can be applied to any PV array size to give a workable steady state operating power output. The X-axis in **Figure 2** is defined as the probability that a randomly chosen day will *not* have enough sunlight to provide the specified steady state power. If larger powers are required for a given solar array size there is progressively more likelihood that the integrated sunlight would be too low. **Table 1** is built by reading the specific Capacity Values from Figure 2 , taken at probabilities of 0.05, 0.25, 0.50, and 0.75, being the fractions of days with less output. These then translate to the 95%, 75%, 50%, and 25% confidence levels for providing the needed power for the night following a randomly chosen day of power outage, for the three geographical locations and their specific historical distributions. It is not surprising that the more sunny locations will have higher ratios as this limiting case is defined by the sunlight availability and assuming that the battery is big enough to spread that captured energy through the day and night.

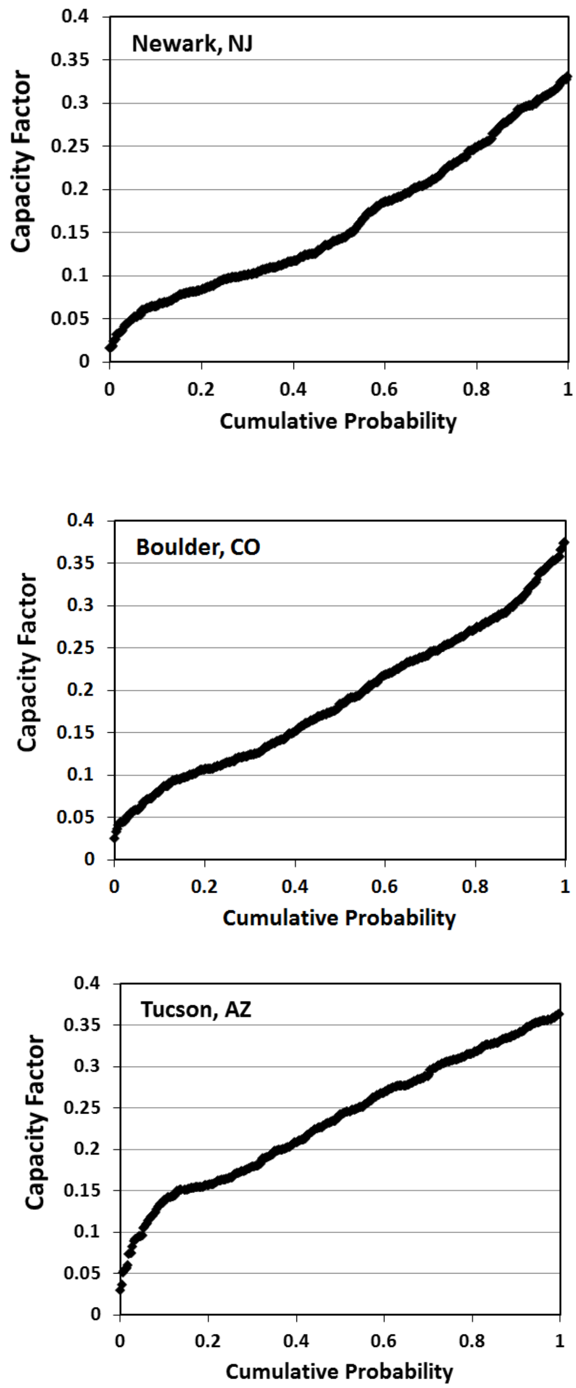

Figure 2: Probability distribution of the capacity factor calculated for each day's integrated sunlight through a full calendar year: (top) Newark, NJ, (middle) Boulder, CO, and (bottom) Tucson, AZ.

Table 1: Threshold system output power in relation to PV array size (Limiting Capacity Factor) for selected confidence levels for the three chosen locations. Percentage values indicate probabilities that the integrated sunlight would be high enough to provide the steady-state power output defined by the ratio given in equation (2).

	Rating Factor Required to give the Indicated Confidence of Power Delivery during a Grid Outage			
	95%	75%	50%	25%
Newark, NJ	**0.050**	**0.096**	**0.142**	**0.229**
Boulder, CO	**0.059**	**0.115**	**0.183**	**0.257**
Tucson, AZ	**0.096**	**0.166**	**0.242**	**0.307**

Clearly, if the battery is large enough then there may be many days where the possible delivered power will be higher, even substantially higher, but Table 1 provides the lower threshold "rating" to provide high enough confidence for powering critical equipment during grid outage. And, to confidently have battery capacity to provide the needed output the battery capacity, "BC", should be large enough to receive nearly the full day's energy, at least for the lower end of the probability distribution:

$$BC_{required} \geq (sun\ hours)_{lower} * PV \qquad (3)$$

where, the chosen "lower" value would be defined by the steady-state-power being targeted, as defined in equation (2). And, similarly, if a specific emergency power load needs to be provided but the Capacity Factor rating shown in Table 1 is low then one would conclude that a larger solar array size would be needed.

Case 2: Battery Capacity Limited Operation

Probably the more common installation configuration for the near-term future is one where the battery capacity will be relatively undersized in comparison to the available sunlight/PV-array size, even for the darker days of winter. Battery costs have been getting lower, but they remain relatively expensive especially in comparison with other backup energy sources such as diesel generators, for example. In these circumstances the battery is easily recharged to its full capacity every day, but then discharges during the night-time hours. Because the following morning will likely provide plentiful directly-generated PV output, the battery system power rating can be defined in rough terms relative to the amount of energy safely discharged[*] (BC_{max}) divided by the duration of the night-time (t_{night} in hours), to yield a nominal steady-state system power rating (SSP):

$$SSP = \frac{BC_{max}}{t_{night}} \qquad (4^{**})$$

This energy balance can be described with reference to **Figure 3.** Two sequential days of solar intensity are mapped to illustrate the algorithm that was used for finding the night-time duration. The falling brightness associated with the end of day 1 (“dusk”) is fitted with a straight line and similarly the rising sunlight brightness as the second day starts (“dawn”) is fitted with a second straight line. For the present work we have found that excellent dawn and dusk fits have been achieved by picking the steepest point when fitting 5-hour linear regressions of the GHI(t) hourly data. The two lines drawn in **Figure 3** are lines calculated in this manner. **Figure 3** also contains a representative steady-state power line. The area below that line during the night-time (the yellow area) then gives the energy amount that must be stored in the battery from the previous

[*] In this regard “safely” is primarily used to denote the acceptable range of charge-discharge that doesn’t cause notable damage or lifetime reduction to the battery. Conditions of battery overcharge or complete discharge can cause physical damage and in some extreme cases even risk fire or other catastrophic failure. Most manufacturers will build safety factors into the battery management systems that can help keep systems working for many cycles without worry.

day to provide for operation during the full night. Thus, the battery capacity (BC) required for a given steady-state power (SSP) average requirement can be found using the dusk and dawn regressions as:

$$BC = \frac{SSP}{2}\left(\frac{SSP-2B_{dawn}}{M_{dawn}} - \frac{SSP-2B_{dusk}}{M_{dusk}}\right) \quad (5)$$

where the factors M_{dawn}, B_{dawn}, M_{dusk}, *and* B_{dusk} correspond to the slopes and intercepts of the linear regressions for light intensity. Conversely, the maximum steady state power, SSP_{max}, can be determined based on what would just barely drain the battery at the time when the next day's sunlight will take over sufficient power generation, which is a simple quadratic equation found by inverting equation (5).

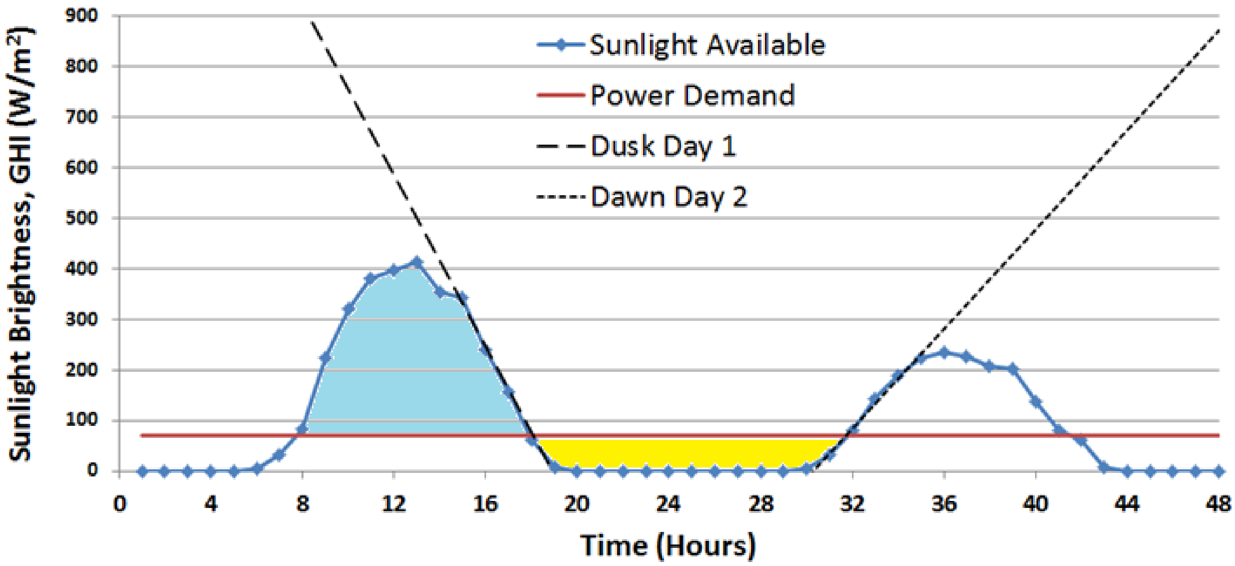

Figure 3: Two sequential days with illustration of night-time power gap that must be supplied by the battery (integrated area shown in yellow).

Unfortunately, this is only a retrospective knowledge of the power availability based on knowing when the next day's sunlight will be bright enough to take over. For confident future predictions it is necessary to examine the probability distribution of night-time durations and use these to make a battery capacity choice. This is still a coupled fit because the required steady-state power as presented in **Figure 3** governs directly the area under the curve, but the probability distribution of adjacent dusk-dawn fits also plays a role because the trapezoidal area of energy required gets wider (essentially requiring the energy be spread over a somewhat longer time) as the desired steady-state power is increased. However, in this limit of small battery capacity compared to the sunlight we get simply take the low power limit. **Figure 4** shows this probability distribution of night-time durations for each of the chosen locations. These numbers provide a slight underestimate since many PV system/inverter combinations might have a low light level threshold before any energy output can be collected. The seasonal variation in the night-time duration is well known, but the sunlight intensity effects when real weather patterns are factored in add some noise. However, the full year probability distribution is the defining term because a storm outage could happen randomly any time during the year.

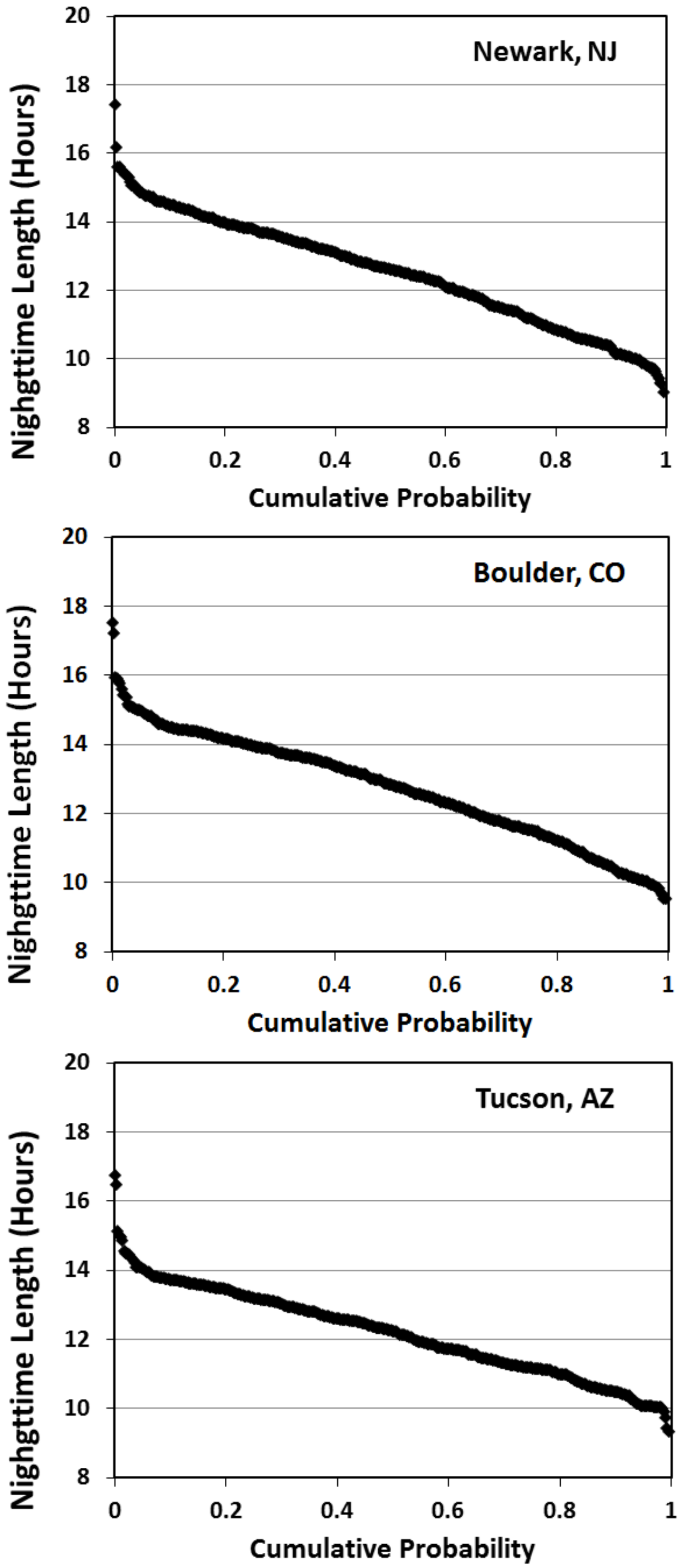

Figure 4: Cumulative probability distributions for the nighttime length: (top) Newark, NJ, (middle) Boulder, CO, and (bottom) Tucson, AZ.

Using this distribution it is possible to predict the different confidence values of steady-state power output based on choosing the night-time durations from the low-probability end of the distribution (mostly winter based), depending on the required confidence that power would be sustained:

$$SSP = \frac{BC}{(Night\ duration)_{@confidence}} \qquad (6)$$

Table 2 gives the cutoff night-time durations for the different confidence levels for the geographically distinct locations we have chosen as examples. The entries in Table 2 are read directly from Figure 4 at cumulative probability values of 0.05, 0.25, 0.50, and 0.75 (which again relate to the respective 95%, 75%, 50%, and 25% confidence levels in this case for providing the needed power through a randomly chosen night time length).

Table 2: Night-time duration cut-off values required to ensure the noted confidence levels for calculating steady-state power outputs for given battery capacities using Equation (6).

	Night-time Duration (Hours) where the Stated Percentage of Randomly Chosen Night-time Durations are Shorter.			
	95%	75%	50%	25%
Newark, NJ	**14.9**	**13.8**	**12.6**	**11.2**
Boulder, CO	**15.0**	**14.0**	**12.8**	**11.5**
Tucson, AZ	**14.1**	**13.2**	**12.2**	**11.2**

Discussion

In the above sections we have examined the two limiting cases where either the battery capacity or the sunlight availability would limit the probabilities of system power outputs at several levels of confidence. Now it is possible to merge the two limits and establish what this means for optimum battery size selection, and essentially examine where the cross-over from one limit to the other occurs. **Figure 5** gives this overlay for the four different confidence levels examined in **Tables 1** and **2**. We see the expected general behavior: that at small battery size the expected steady-state output power will grow in proportion to the battery size (the blue slanted lines). However, after some cross-over point the sunlight availability takes over and limits the system output (the level black lines) to be a constant. **Figure 5** has four lines plotted in with the indicated confidence levels, illustrating the point that solar based installations are inherently variable and it is difficult to know when a grid outage might occur – as the variability is controlled mostly by the winter-to-summer seasonal changes.

Because of the sunlight limits at higher battery capacity then it becomes less and less cost effective to install larger batteries past the crossover point shown in **Figure 5**. In some regards the crossover point is the most likely optimum point – reaping the most value from the solar array, but also limiting the investment in the battery pack within the constraint of system matching requirements.

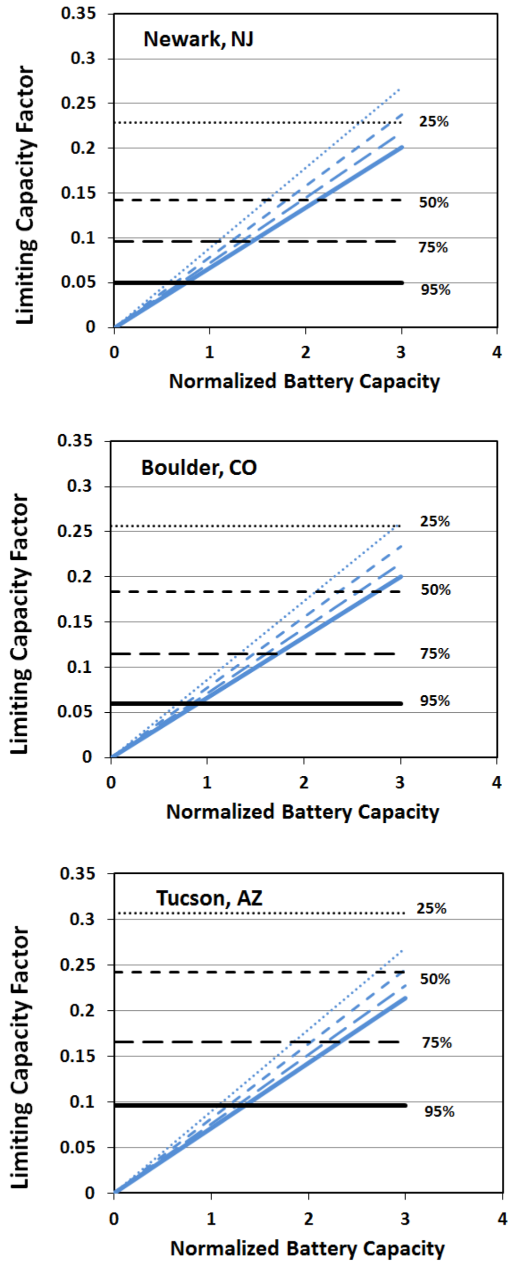

Figure 5: Limiting system capacity factor as a function of normalized battery capacity for different confidence levels as labeled. The battery capacity is normalized by the PV rated peak power and is equivalent to hours of storage at peak power. The level black lines are limited by sunlight availability; the sloped blue lines are limited by battery capacity. The lower of the two lines controls system performance: (top) Newark, NJ, (middle) Boulder, CO, and (bottom) Tucson, AZ.

As noted in the introduction, the normal solar array AC output estimates take into account a number of inefficiencies, which, in aggregate, may reduce the output by more than 20%. And, further, the battery in the system will contribute some round-trip losses. So the steady-state power projections made in Figure 5 must be downgraded by these factors before confident useful AC output power values can be quoted. As with all engineering systems, it is imperative that the range of behavior and the interplay between the parameters be fully understood before system specifications are promised.

Inherent in this variability analysis is that the least sunny days limit the expected operation when one wants to establish a high level of confidence about the output. However, this immediately indicates that many days will have more sunlight and during daylight hours one might be able to utilize more power than the steady-state minimum found above. In many cases, we can reallocate our usage to conform to the possible daylight abundance. To build on this concept, it is recommended that future “power island” systems be designed with versatile energy management systems that can highlight situations of abundant solar availability and steer emergency workers to charge batteries and other gear when the sun shines – and conversely to economize on power usage during the night-time.

The present analysis has been performed using the flat-surface integrated irradiance (the “Global Horizontal Irradiance” or “GHI” which is consistent with many installations. However, for arrays on steeply pitched southward-facing roofs it may be possible to boost the winter season integrated sunlight, though losing some of the available sunlight during the summer. This can be used to level the winter-summer solar power swings shown before in **Figure 1** and used in another group’s statistical analysis balancing stochastic demands against the variable input [55]. This tilting effect is one reason that solar power units powering remote street signs along highways are often tilted more than one might expect as the optimal value for the local latitude. To the extent that this boosts the winter values, then it would be expected that the confident steady-state ratings might be somewhat higher than predicted by the present analysis.

It is interesting to find that the three dramatically different climate locations ended up with relatively similar steady-state power outputs – especially in the battery limited case (see **Table 2**). Basically, the worst-case tail of the distribution controls the high-confidence-level rating projections; and, this part of the distribution is dominated by winter time behaviors (having a combination of latitude and weather pattern influences). In the battery-limited cases the extra abundance of sunlight in a desert location like Tucson might simply mean that there would be more *excess* power during the daylight hours for situations of storm outage or other power interruption – while still limited by the battery for the night-time output ratings. In the sunlight-limited case we expect the latitude will have a noticeable effect and this is confirmed in Table 1 by the significantly better results for Tucson, while Boulder and Newark are more similar to each other (though also demonstrating that the weather is better in Boulder than Newark!). As noted above, there are presently cost limitations which may make it difficult to install battery systems as large as suggested by the crossover points in **Figure 5**. In these circumstances it may be necessary to use a variety of different revenue streams to justify large scale energy storage in conjunction with existing solar arrays to enable the power islands (which might only be used for relatively rare storm outages). Large battery systems can earn value by shifting demand from daytime to nighttime when electricity costs will be different, this can also apply to bi-directional charge/discharge taking advantage of these price differentials as so-called energy arbitrage [41, 42]. Further, batteries can serve as power loads/providers that have value for frequency regulation ancillary services [41, 44-46]. The difficulty with these additional revenue streams is that they may have implications for the state-of-charge (SOC) of the battery at the moment when the grid-power is interrupted. However, evaluating the likely SOC throughout the day is highly dependent on the algorithm and the cost-driver factors that play into it. Developing criteria for recommended minimum state-of-charge criteria could be useful, but will also have financial consequences if it reduces the amount of energy buy/sell can take place, etc. These algorithm development angles are beyond the present paper's scope.

Another area worthy of future algorithm development would cover the question of more extended power interruptions. The present work develops the power that can be achieved for a single randomly selected day in a particular climate. When the grid outage lasts longer, as it has for the occasional superstorm we have experienced, we must evaluate day-to-day weather correlation probabilities and develop algorithm contingencies where energy might be retained from one daily capture period to the next, giving a possibly higher net steady-state output power.

Conclusions

The present work has examined the Typical Meteorological Year database for sunlight brightness throughout the year and performed a probabilistic analysis for evaluating the expected output power from a PV+battery system. Large and small battery limits were examined and overlaid to find a nominal optimum point for system design subject to the available sunlight variability.

Acknowledgements

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