September 2022

Evaluating the Capabilities of Behind-the-Meter Solar-plus-Storage for Providing Backup Power during Long-Duration Power Interruptions

Will Gorman[1], Galen Barbose[1], JP Carvallo[1], Sunhee Baik[1], Cesca Miller[1], Philip White[2], and Marlena Praprost[2]

[1]Lawrence Berkeley National Laboratory
[2]National Renewable Energy Laboratory

The study estimates the performance of behind-the-meter solar PV-plus-energy-storage-systems (PVESS) in providing critical-load or whole-building backup across a wide range of geographies, building types, and power interruption conditions. The study also considers a set of 10 historical long-duration power outage events and evaluates how PVESS could have performed in providing backup power during those specific events. The analysis is the first in what will be a series of studies by Berkeley Lab, in collaboration with the National Renewable Energy Laboratory, on the use of PVESS for backup power. This initial study is intended to provide a baseline set of performance estimates and to illustrate key performance drivers. This narrative summary provides a high-level overview of the analysis approach, key findings, and opportunities for future work. For further details, please refer to the full report.

Approach

Backup performance of PVESS is estimated by simulating battery storage dispatch during power interruption events, using modeled hourly end-use level building load and solar production profiles. The analysis covers three residential building types (single family, mobile homes, and multi-family) and three non-residential building types (hospitals, secondary schools, and big-box retail stores).

The focus of this analysis is on long-duration power interruptions, defined as lasting at least 1 day. The analysis is organized around two different approaches to representing power interruption events:

- Synthetic interruption events: This approach involves stipulating interruptions in each U.S. county and month of the year, using a common set of assumptions for the duration and timing of each monthly event. This approach aims to provide a standardized, geographically expansive analysis that allows for direct comparison across regions and seasons.
- Historical interruption events: This approach considers 10 historical long-duration interruption events, and simulates how PVESS would have performed in maintaining backup power for customers in a sample of affected counties. This approach aims to capture correlation between weather and interruption events while showcasing concrete examples of PVESS resilience capabilities.

Building end-use load profiles were generated using NREL's ResStock and ComStock models. For the synthetic interruption events, the analysis uses the public EULP dataset based on TMY3 weather, while the historical interruption events rely on a custom set of ResStock and ComStock simulations performed for the specific time periods and locations of each historical event. Solar generation profiles were developed using NREL's System Advisor Model. PV and storage system sizes are stipulated throughout the analysis based on a common set of conventions, with sensitivities performed to consider alternate sizing assumptions.

Battery storage dispatch was simulated using a script written in R, which dispatches storage to meet specified loads in each hour sequentially, given PV production, battery state-of-charge (SoC), and power constraints on the battery. The model prioritizes individual end uses, such that if the PVESS cannot meet all loads in an hour, individual loads are dropped in their entirety, starting with the lowest priority end-use.

Key Findings: Synthetic Event Analysis

The following are a few select findings, focusing on single-family detached homes. Unless otherwise noted, the results below are based on 3-day interruptions, starting on the median "net load" day each month, a PV system sized to generate 100% of each customer's annual energy consumption, 30 kWh of battery storage, and critical load backup that includes refrigeration, nighttime lights, computer/internet, well pump loads, heating, and cooling. The full report includes sensitivities around all of those varied assumptions.

Backup performance depends, first and foremost, on PVESS sizing and the set of critical loads selected for backup. Under a limited critical load scenario that *excludes* heating and cooling, a small PVESS with just 10 kWh of storage (at the lower end of sizes currently observed in the market) can fully meet backup needs over a 3-day outage in virtually all U.S. counties and any month of the year. If, instead, critical loads include heating and cooling, a PVESS of that size would meet 86% of critical load, averaged across all counties and months, while a larger PVESS with 30 kWh of storage (at the upper end of sizes currently observed in the market) would meet an average of 96% of critical load. Those results are shown by the dashed line in the left-hand panel of Figure 1 below, which represents the population-weighted average results across all U.S. counties. Larger amounts of storage, as might be provided by an electric vehicle, further increase performance, but with diminishing returns for a given PV size.

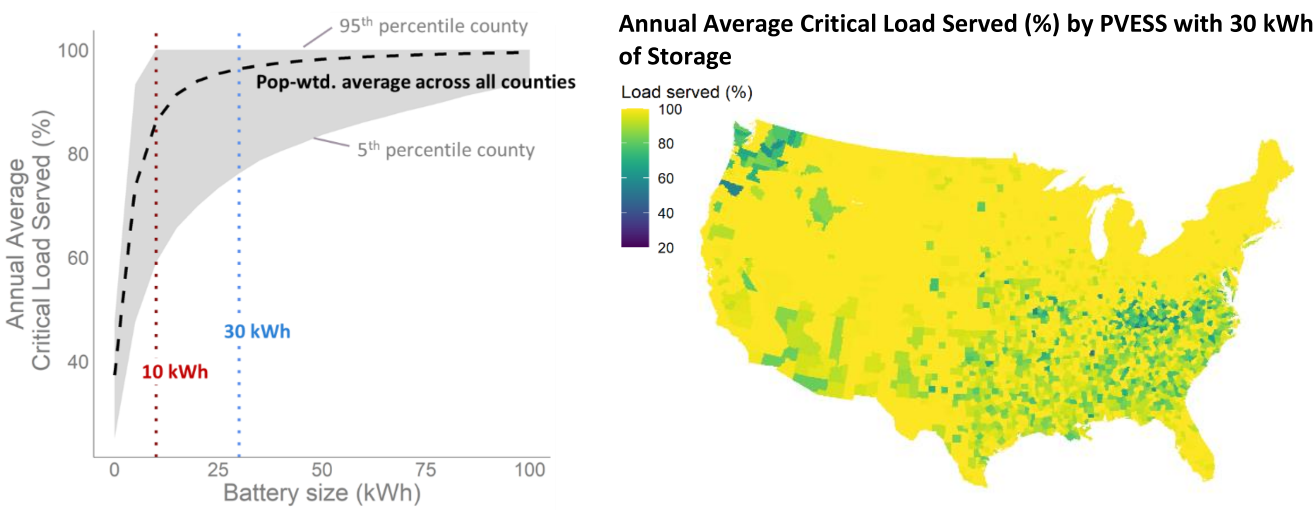

Figure 1. PVESS Backup Performance for Single-Family Residential Buildings
Notes: The figures are based on an analysis of the median home in each county (in terms of annual electricity consumption), and show the percent of critical load (with heating and cooling) served for each county-median home, averaged over 12 monthly outages. The figure on the left shows how backup performance varies with battery sizing, with results denoted in

terms of the population-weighted average and percentile range across counties, while the figure on the right shows the geographical distribution in backup performance by county.

Backup coverage of heating and cooling loads varies considerably *across* regions, depending on climate and building stock characteristics. The numbers above mask considerable regional variability in backup performance, as reflected by the percentile bands in the left-hand panel of Figure 1, and shown more directly in the right-hand panel. In particular, performance tends to be lowest in regions where electric heating is common (the southeast and northwest) and in regions with large cooling loads (the southwest and parts of the southeast). Naturally, these regions can also see considerable seasonal variability in backup performance. Important to note is that these results are based on the existing U.S. building stock, where electric space heating consists primarily of electric resistance-based heating, rather than heat pumps.

Backup performance can also vary considerably *within* individual regions, based on variation in the underlying building stock. The study evaluated backup performance among a statistically representative sample of modeled homes in six geographically diverse counties. One county with a particularly high level of variability in backup performance was Harris County, Texas. As shown in Figure 2, backup performance for PVESS with a fixed quantity of storage (in this case 30 kWh) is generally lower for higher-usage homes. Differences in consumption levels, in turn, reflect a variety of underlying building conditions. For example, among homes with electric resistance heating, a median of 77% of winter critical load is served, compared to 96% for those with heat pumps and 100% for those with fossil heating. Winter backup performance also varies by roughly 20% depending on infiltration rates (the "leakiness" of the home), while summer performance varies by close to 15% depending on the efficiency of the central air-conditioning system. Finally, differences in temperature set-points correspond to a 40% range in winter backup performance and a 20% range in summer performance.

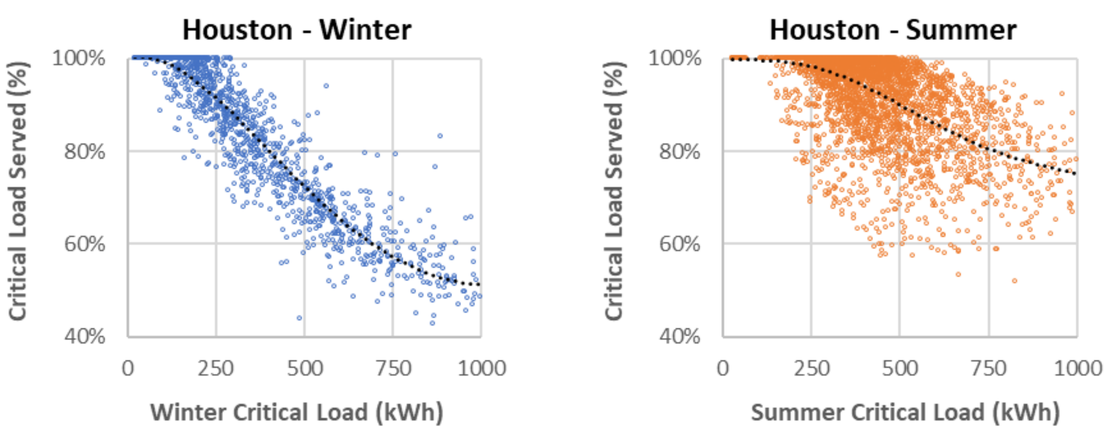

Figure 2. Backup performance across individual modeled homes in Harris County, TX.
Notes: Each dot in the figures represents the results for a single home and shows average critical load served during interruptions in winter (left) and summer (right) months. PV systems are sized to generate 100% of each customer's annual electricity consumption.

Backup performance for homes with electric heat or high cooling loads is quite sensitive to weather variability. For example, in counties with high penetration of electric heat, an average of 53% of critical load during winter months would be met if outages begin on the worst day each month, compared to 96% if outages begin on the best day (the left-hand panel of Figure 3). A similar, though less dramatic, trend can be observed for homes with high cooling loads. In this analysis, the best and worst days each month are defined within a typical meteorological year and refer to the days with the lowest or highest "net load" (i.e., the difference between load and PV generation); even greater variability would occur under more extreme weather conditions.

Backup performance is fairly insensitive to outage duration beyond 1-day. As shown in the right-hand panel of Figure 3 below, backup performance declines as outage duration increases, though the effect is relatively modest, given the ability of the PV system to recharge the batteries each day. On average across all counties and months, backup performance drops from 100% of critical load served for a 1-day outage to 92% for a 10-day outage.

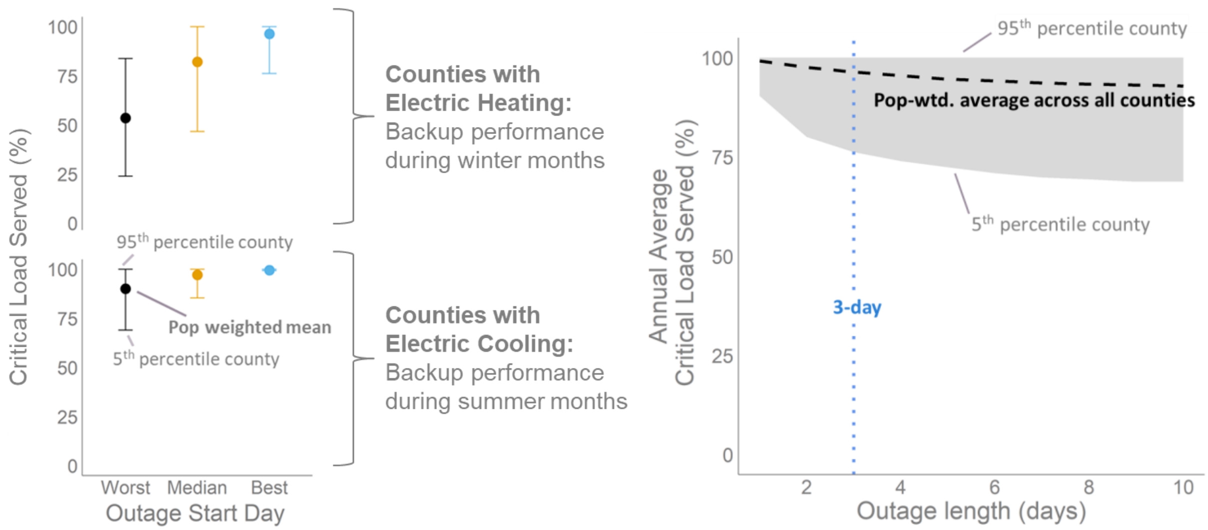

Figure 3. PVESS Backup Performance Sensitivity to Outage Timing (left) and Duration (right)
Notes: The figures are based on an analysis of the median home in each county (in terms of annual electricity consumption), and show the percent of critical load served for each county-median home, averaged over all 12 monthly outages. The figure on the left shows how backup performance varies depending on the specific day in each month on which the interruption begins. The figure on the right shows how performance varies with the duration of the monthly interruptions.

The findings highlighted above represent just a fraction of the full report, which provides more details on those findings, explores additional performance drivers (such as the initial SoC on the battery and alternate PV sizing assumptions), and presents results for whole-building back-up and for other residential and non-residential building types.

Key Findings: Historical Event Analysis

While the preceding findings are based on a series of hypothetical interruptions, the study also considered how PVESS would have performed in providing backup power during a sample of actual historical events. For reasons of data availability, the events were selected from the years 2017-2020 and include five hurricanes (Harvey, Irma, Florence, Michael, and Isaias), a Public Safety Power Shutoff (PSPS) event in California, winter storms in Washington state and Oklahoma, and thunderstorms in Iowa and Texas. For each event, the analysis focused on a subset of affected counties, including where possible a populous county, a rural county, a county with a high social vulnerability index, and a county that experienced a particularly long-duration outage. For each county, a statistically representative sample of end-use level loads profiles were generated for each building type.

As with the synthetic event analysis, the findings below focus on single-family residential homes; the full report includes results for the other modeled residential and non-residential building types.

In 7 of the 10 events, the majority of homes would have been able to maintain critical loads, using a PVESS with 30 kWh of storage. This is shown by the median values in the box-and-whiskers plots in Figure 4. Moreover, in four of the events (Michael, PSPS, TX Thunderstorm, and IA Derecho), all modeled homes would have been able to fully maintain critical load. That said, significant variability across homes can exist. In the case of the two winter storms, while all critical load was served in the median case, a sizeable fraction of customers—those with electric heating—saw much lower backup performance. Also of note is that no consistent trend emerged across the county types, as indicated by the county median performance levels shown in Figure 4.

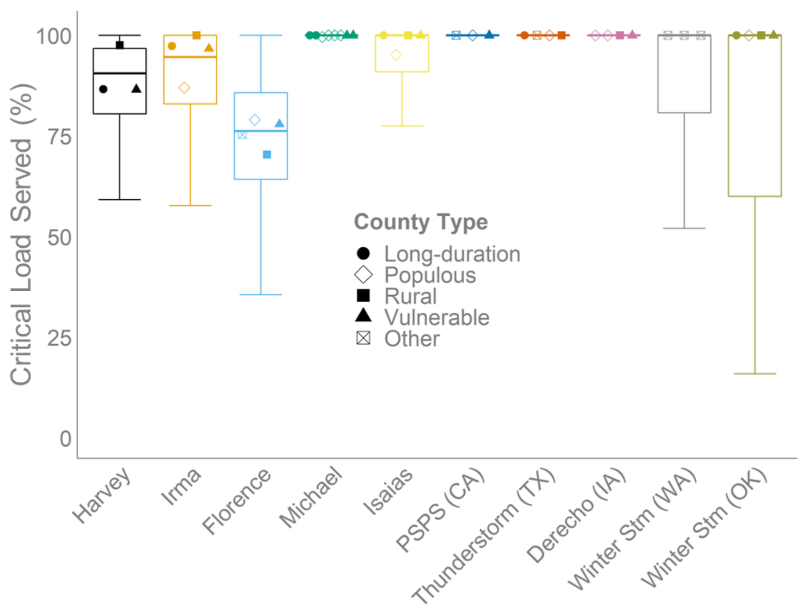

Figure 4. PVESS Backup Performance across 10 Historical Long-Duration Outage Events
Notes: Box-and-whiskers plots show the distribution across all modeled homes (500 per county multiplied by the number of affected counties selected). The icons show median values across homes in each of the selected counties, identified by their county-type. See report for details on the specific counties selected.

Backup performance during the hurricane events is driven by solar insolation patterns and the length of the outage. As shown in Figure 4, the hurricane events were the lowest performing among the various event types sampled, and performance varied considerably across those events. A defining feature of many of the hurricane events was that they often include periods of reduced solar insolation levels as a result of cloud cover. Of the five hurricane events analyzed, backup performance was lowest for Hurricane Florence, where almost no PV generation occurred over the first three days of the ~8-day outage. As shown in Figure 5. In comparison, Hurricane Harvey also had three days of limited solar insolation; however, it was a much longer duration outage, and therefore the average backup performance over the event as a whole was higher than for Florence. Hurricane Irma had a similar duration as Florence, but just a single day of reduced solar insolation, leading to the higher levels of backup performance.

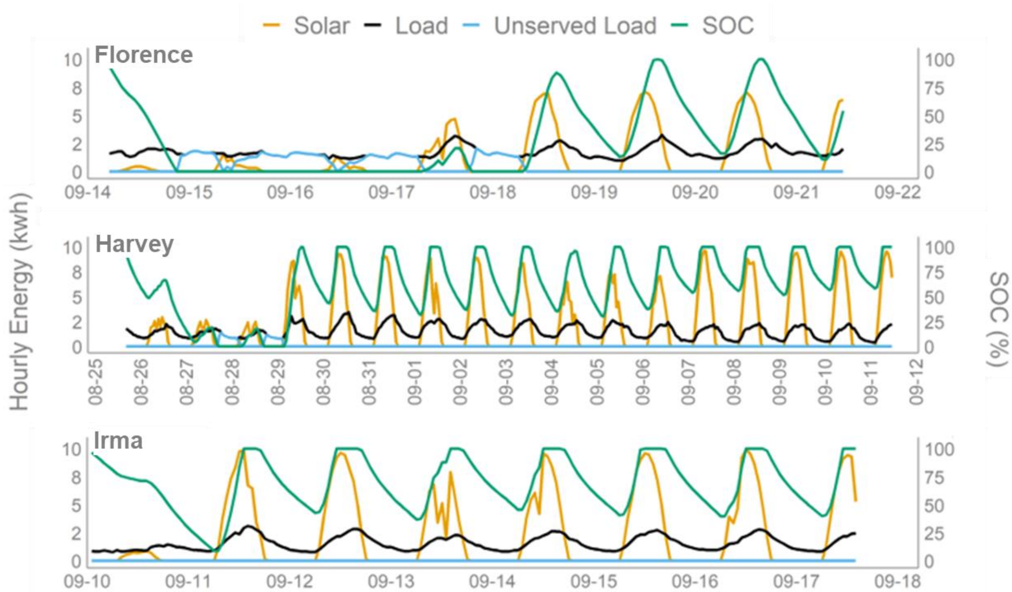

Figure 5. Time series results for Hurricanes Florence, Harvey, and Irma
Notes: These charts show time series values for solar PV production, total load, unserved load, and the battery SoC. These results are for the median home in the selected populous county for each event, and a PVESS with 30 kWh of storage.

Study Limitations and Opportunities for Future Work

This analysis required a variety of simplifying assumptions and methodological choices, given data availability and the need to maintain a tractable study scope. Some of these simplifications may tend to over-state backup performance under real-world conditions, while others may tend to under-state it. Listed below are some of the most important limitations of the analysis, some of which will be addressed through follow-on analyses. A number of additional limitations are noted in the full report.

- *Use of "percent of critical load served" as the performance metric*. This metric was chosen for its ease of computation and interpretability, but other metrics can and have been used in similar analyses, such as the time to failure, building internal temperature, or PVESS size required to maintain critical load.
- *Use of hourly interval data.* Some electric end-uses, such as electric heat and air-conditioning, can have high instantaneous power draw that may exceed the instantaneous power output capabilities of the PVESS. This analysis included a limited set of sensitivity cases using 15-minute interval data, and found no meaningful difference from the hourly-based results. To fully capture the effects of these power constraints, more granular (e.g., 1-minute interval) data would likely be needed.
- *Use of TMY-based load and solar data*. The synthetic event analysis relied on load and solar generation profiles generated from weather files for a Typical Meteorological Year (TMY). Although TMY data for any given location and month may contain a substantial level of variability, it does not capture "extreme" weather conditions (either historical or projected future extremes). The historical event analysis was included in this study partly to reflect a more extreme set of conditions.
- *Focus on existing building stock.* This analysis was deliberately focused on analyzing backup performance for the existing building stock across the U.S. Future studies will consider how the results may differ with changes in building efficiency, electrification, and load flexibility.
- *Ignores snow cover*. The analysis does not account for snow accumulation that may occur during winter events. This can be a notoriously complex factor to account for, given that how it depends not just on

climatic and physical characteristics, but behavioral factors as well (i.e., whether and how frequently the building occupant removes the snow, which itself may depend on the power interruption).

- *Ignores potential for physical damage to the PV panels or batteries*. The analysis assumes that the PVESS can continue to operate as designed throughout each event. Under real-world conditions, this may not be the case (e.g., due to hail, flooding, or other weather-related damage to the system)
- *Does not consider temperature set-backs*. This analysis assumes that building occupants maintain normal temperature set-points during each interruption, but most likely occupants would adjust their set-points to some reduced level of heating or cooling service.
- *Does not consider single-room cooling and heating*. Along similar lines as the above, this analysis assumes that occupants continue to heat or cool their entire home throughout the duration of each event. In cases of extreme weather, occupants may opt to heat or cool only a single-room (e.g. using a portable room A/C or space heater), assuming those appliances are on-hand during the event.
- *Does not consider pre-cooling/heating strategies*. For some customers and events, a significant amount of PV generation is curtailed over the course of an interruption period. This occurs when the battery reaches a full SoC and PV generation exceeds load. If the controls were available, a customer could use that curtailed PV to pre-cool or pre-heat their home, thereby reducing load during later hours when the battery is being discharged to meet load.

Acknowledgements

This work was funded by the U.S. Department of Energy's Solar Energy Technologies Office, under Contract No. DE-AC02-05CH11231 (Award Number 38425). For their support of and feedback on this work, we thank Caroline MacGregor, Rebecca Glaser, Ammar Qusaibaty, Michele Boyd, and Becca Jones-Albertus of the U.S. DOE. For comments and input on this analysis, we thank members of our technical advisory committee: Geoff Oxnam and Nate Mills (American Microgrid Solutions), Seth Mullendore (Clean Energy Group), Aric Saunders (Electriq Power), Spencer Fields (EnergySage), Steve Campbell (GRID Alternatives), Alex Bazhinov (Lumin), Kiera Zitelman (NARUC), Tolu Omotoso (NRECA), Tom Stanton (consultant, formerly NRRI), Elena Krieger and Patrick Murphy (PSE Healthy Energy), Steven Rymsha (SunRun), and Damon Franz (Tesla). Additional review comments were provided by Brian Gerke and Miguel Heleno (LBNL), Jeremiah Miller (SEIA), and Bethel Tarekegne (PNNL).

Disclaimer and Copyright Notice