Electrical Power and Energy Systems 164 (2025) 110442

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

The power reliability event simulator tool (PRESTO): A novel approach to distribution system reliability analysis and applications

Sunhee Baik *, Juan Pablo Carvallo, Galen L. Barbose, Will Gorman, Cesca Miller, Michael Spears

Lawrence Berkeley National Laboratory. 1 Cyclotron Road, MS 90-4000, Berkeley, CA 94720, USA

A R T I C L E I N F O

Keywords:
Electricity reliability
Backup-power
Solar Photovoltaic Energy, Energy Battery Storage
Monte Carlo Simulation
Distributed Generation

A B S T R A C T

The growing interest in onsite solar photovoltaic and energy storage systems is partially motivated by customer concerns regarding grid reliability. However, accurately assessing the effectiveness of PVESS in mitigating these interruptions requires a comprehensive understanding of location-specific outage patterns and the ability to simulate realistic scenarios. To address the gap, we introduce the Power Reliability Event Simulation TOol (PRESTO), the first publicly available tool that simulates location-specific power interruptions at the county level. PRESTO allows for a more realistic assessment of system reliability by considering the unpredictability and location-specific patterns of power interruptions. We applied PRESTO in a case study of a single-family home across three U.S. counties, examining the performance of a solar photovoltaic system with 10 kWh of battery storage during short-duration power interruptions. Our findings show that this system reliably met 93 % of energy demand for essential non-heating and cooling loads, fully serving these loads in 84 % of events, despite the constraints of daily time-of-use bill management which limits the battery's state-of-charge reserve. However, when heating and cooling loads were included, system performance decreased significantly, with only 70 % of demand met and full service in 43 % of events. These results highlight the challenges of using solar photovoltaic and energy storage systems for short-duration outages, emphasizing the need to consider factors like battery size and grid charging strategies to improve reliability. Our study demonstrates the practical applications of PRESTO, providing valuable insights into potential mitigation strategies including grid charging and optimizing battery size.

1. Introduction

Customer interest in onsite solar photovoltaic and energy storage systems (PVESS) has been partially driven by reliability and resilience concerns [1]. Over time, concerns about grid reliability could intensify due to increasing climate impacts, wildfires, and greater use of variable generation sources [2]. Understanding the backup power capabilities of PVESS is crucial for guiding investments and early adoption as the industry grows. This understanding may also inform grid planning and policy-making, including predicting PVESS growth and prioritizing investments.

Applications for customer-sited backup power could serve as a pivotal entry point for the behind-the-meter solar and storage industry, fostering customer adoption. Despite the potential technical advantages of behind-the-meter PVESS for both reliability and resilience, a lack of data and complex methodologies hinder a comprehensive understanding. For instance, O'Shaughnessy, Ardani, Cutler and Margolis [3] analyze the value of distributed solar PV solely based on bill savings, while Hoff, Perez, and Margolis [4] distribute the value of uninterrupted emergency power from an average annual cost of outage-related disruptions across residential and commercial customers to estimate the value of uninterrupted emergency power. These approaches fail to capture the full picture of behind-the-meter PVESS benefits. While previous studies like Prasanna, McCabe, Sigrin, and Blair [5] have explored the reliability and resiliency benefits of PVESS systems, they often lack sufficient consideration for the diverse factors influencing these benefits. These factors include geographical variations, customer types, interruption durations, and the size of the PVESS system itself. Most recent work has focused on comprehensive nationwide evaluations of PVESS's ability to mitigate long-duration power interruptions at a

* Corresponding author.
E-mail address: shbaik@lbl.gov (S. Baik).

https://doi.org/10.1016/j.ijepes.2024.110442
Received 3 June 2024; Received in revised form 30 September 2024; Accepted 21 December 2024
Available online 28 December 2024

granular level [6]. However, a gap remains regarding PVESS effectiveness in addressing short-duration and routine interruptions. While long-duration interruptions, often stemming from major weather events, can be somewhat anticipated, allowing customers to proactively charge their batteries, short-duration disruptions present a more intricate challenge. These short-duration disruptions, which can recur multiple times throughout the year, exhibit varying durations but often follow discernible patterns. Yet, they remain less predictable due to their random frequency and duration, necessitating consideration of the battery's initial state of charge and its alignment with day-to-day operating schedules. Addressing these events requires a thorough examination of interruption patterns and a comprehensive analysis of how PVESS responds within specific contextual factors such as battery state of charge, solar production availability, and load.

This paper aims to demonstrate the application of the Power Reliability Event Simulation TOol (PRESTO), a publicly available model developed by Berkeley Lab, designed to simulate short-duration power interruption events at the county level with unprecedented accuracy. This tool represents a significant advancement in reliability assessment by incorporating location-specific data to generate realistic interruption scenarios. A separate storage dispatch model, developed in our previous research [6] is employed to simulate PVESS operation and backup performance for each of the large number of interruption events generated by PRESTO. The initial focus is on a typical single-family home in Maricopa County, Arizona, encompassing a limited set of scenarios related to system sizing, backup power configuration, and whether the customer charges their battery storage system from the grid during normal operating conditions. Comparative results for two counties in Massachusetts (Middlesex) and California (Los Angeles) are also presented, illustrating how regional differences in climate, interruption patterns, and retail rate structures can affect PVESS performance as a backup power source. The conclusions highlight several other important considerations for evaluating PVESS backup power capabilities. Beyond the specific case study, the paper emphasizes the broader applicability of PRESTO for reliability assessment in diverse geographical contexts. By providing a comprehensive framework for analyzing power reliability and PVESS effectiveness, PRESTO serves as a valuable tool for researchers, policymakers, and utility planners seeking to enhance grid reliability and resilience.

2. Literature review

Previous research has extensively examined the potential grid services offered by energy storage systems. Balducci et al. [7], building upon the framework introduced by Akhil et al. [8], categorized the services offered by energy storage into the following segments:

- Bulk energy: Dispatching energy storage services during peak demand events to provide capacity and resource adequacy services, reducing the need for new peaking power plants and engaging in energy arbitrage by trading in wholesale energy markets, buying during off-peak periods, and selling during high-price periods.
- Ancillary services: Balancing generation and load within the system through various services, such as regulation, load following, spin/non-spin service, frequency response, flexible ramping, voltage support, and black start service.
- Transmission services: Utilizing energy storage to store energy during uncongested periods, offering congestion relief, and reducing load on specific sections of the system, thus delaying transmission system upgrades.
- Distribution services: Employing energy storage to defer distribution system upgrades, provide volt-var control, and reduce energy consumption by lowering feeder voltage.
- Customer services: Using energy storage to lower customer charges during peak periods (time of use charge reduction), enhance reliability by minimizing power outages, and decrease the maximum power draw to avoid peak demand (demand charge reduction).

Several studies have evaluated the enhanced value of power system reliability. These assessments typically calculate power reliability benefits by multiplying the duration of power interruptions mitigated by energy storage with the value of unserved energy. For instance, Eyer and Corey [9] examined the reliability benefits of storage, assuming a 2.5-hour annual outage and a value of $20/MWh for unserved energy, resulting in an annual reliability benefit of $50/kW-year. Neubauer, Pesaran, Williams, Ferry, and Eyer [10] reported a combined power quality and reliability benefit of $135/kW-year in California, based on a 200 kW system experiencing around five reliability events and 10 power quality events annually. Similarly, Balducci, Jin, Wu, Leslie, Daitch and Marshall [11] assessed the outage mitigation potential of energy storage systems. Their approach considered the average number of customers affected by outages, historical outage frequency and duration data (based on the past two years' outage logs), and the value of lost load (VOLL) estimated for Washington state. The estimated benefits vary depending on factors such as energy storage size, the assumed number of outages, and the duration of each outage. The range of power reliability benefits assessed in the literature spans from $2/kW-year to $283/kW-year in 2015-dollar values [7].

Improving over these assumptions-based results, recent work employs simulation-based optimization approaches to estimate the benefits of PVESS, mostly for the resilience benefits. For instance, Benidris et al. [12] introduced resilience valuation metrics aimed at quantifying the value of resilience. These metrics entail the creation of an outage cost matrix, which considers outage duration, seasonality, and load type (essential, priority, and discretionary). The cost of service interruption resulting from extreme events is then estimated by multiplying the amount of load lost with the probability of a service interruption, factoring in both duration and season and the associated cost of interruption. This approach was applied to evaluate the resilience value of PVESS in Reno, where historical data were utilized to assess the likelihood and duration of extended power outages, augmented by sequential Monte Carlo simulations.

In a similar vein, Zhou, Tsianikas, Birnie, and Coit [13] utilized a simulation-driven optimization model to examine the economic and reliability advantages associated with PVESS. Their study involved simulating power disruptions using customer-centric reliability metrics (Customer Average Interruption Duration Index (CAIDI) and System Average Interruption Frequency Index (SAIFI)) alongside battery charging/discharging behavior during outages at the hourly level. The approach was implemented across various case studies involving diverse facilities (e.g., hospitals, hotels, primary schools, and small offices) in Islip, Long Island, NY, each characterized by different VOLL. The outcomes encompassed metrics such as the proportion of outage hours with met demands based on battery capacity, overall system costs corresponding to battery capacity, attained Loss of Load Probability (LOLP), and delved into the effects of additional variables, including battery pricing and sensitivity analyses encompassing increased LOLP, shifts in overall system costs, and adjustments in battery sizing scales.

Galvan, Mandal, and Sang [14] explored the reliability benefits of networked microgrids consisting of rooftop PV and energy storage systems. The research focused on a fixed scenario involving a three-hour power outage occurring between 17:00 and 20:00, representing the average outage duration in the U.S. and the estimated time for repair crews to restore service following moderate storm damage to a 33-bus radial distribution system. The study assessed five risk-mitigation strategies, ranging from conventional power distribution systems using tie-lines to maintain service during high-impact events, to microgrids deployed under various weather conditions. While the study successfully assessed the effectiveness of these strategies using resilience metrics—such as total customer-hours of outage, total customer energy not served, and total outage costs—it was limited by its reliance on a predetermined power interruption scenario. Consequently, the analysis did not consider the disaggregated impacts of outages or explore a range of scenarios based on historical power interruption data, which could have provided a more comprehensive understanding of the potential benefits of PVESS.

Similarly, Rosales-Asensio, de-Simón-Martín, Borge-Diez, Blanes-Peiró and Colmenar-Santos [15] developed a methodology to quantify the benefits of a PVESS of a large official building, considering both economic savings and resilience. Their study involved a life-cycle cost analysis of the microgrid with a large office building, evaluating its capacity to power critical loads during outages and estimating potential utility energy cost savings. The analysis provided detailed, disaggregated insights into the investments required for PV and energy storage systems, offering valuable information for making informed decisions at the organization level. Additionally, the study examined the probability of the microgrid sustaining outages of varying durations using stochastic simulations. However, these simulations assumed outages of 1 h to two weeks, distributed randomly throughout the year, without incorporating historical outage data specific to the region. This limitation may reduce the accuracy of the resilience assessment, potentially underestimating the true effectiveness of the PVESS. Moreover, the focus on large office buildings leaves unexplored the unique challenges and benefits of PVESS in residential settings, which may differ significantly and require further investigation.

While the studies above provide valuable insights into optimal PVESS sizing and resilience benefits, a significant challenge persists in comprehending the effects of power outages across diverse geographic regions. Outages, particularly short and localized events, can vary significantly in duration but often follow recognizable patterns, and simulating events following these patterns is crucial for accurate analysis. Previous studies often simplify this by relying on specific distributions with annual reliability metrics (e.g., Zhou et al.'s [13] use of the Poisson distribution) or solely basing outage probabilities due to specified types of events (e.g., only considering service interruptions due to extreme events; Benidris et al. [12]), which neglects real-world uncertainties. Accurate analysis of the benefits of PVESS requires highly detailed power outage profiles along with location-specific solar and load data, enabling the calculation of generation and dispatching power during outages at disaggregated temporal and spatial levels. Unfortunately, previous studies often lack this critical input data.

More recently, Gorman et al. [6] assessed the resilience benefits of PVESS for residential customers at the FIPS level. They employed stylized scenarios, including a 3-day synthetic interruption event that starts at 12 AM on the 50th percentile net-load day, a solar system sized to meet 100 % of annual load, and 10 kWh (5 kW) battery size with a 100 % beginning battery state of charge (SoC). Their key innovation was utilizing disaggregated end-use load profiles across the continental US, aligning them with geographically and temporally specific solar generation estimates. This allowed them to employ a PVESS dispatch algorithm and calculate loads served during outages with realistic solar profiles. The study analyzed performance across various customer types, geographic and climate conditions, and outage scenarios, all within a county-level framework.

While not directly linked to PVESS, studies have engaged in simulating power interruptions to evaluate system reliability and resilience. There have been resilience assessment studies focused on analyzing major outages resulting from extreme events to comprehend system resilience (e.g., [6]), understanding the impacts of such events [16], retrospective analysis of measures implemented during these events [17], and improving predictive capabilities or uncertainty quantification regarding such events [18]. In parallel, efforts have been made in reliability assessment either using stochastic simulation or using the historical data. For example, Najafi-Shad, Mollashahi, and Sadr [19] utilized historical feeder data to determine the distribution of outage durations and employed Monte Carlo simulations to model individual outage events and annual feeder outage durations. Similarly, Marcelino, Torres, Carvalho, Matos, and Miranda [20] developed a multi-objective optimization model aimed at maximizing distribution reliability by identifying optimal inspection plans that consider decision-makers' preferences, defining reliability in terms of reductions in metrics such as SAIFI and the System Average Interruption Duration Exceeding Threshold (SAIDET). However, these studies often rely on region-specific metrics provided directly by utilities or collaborators and assess reliability at an aggregated level (e.g., substations or equipment). This aggregated approach limits the ability to evaluate the effectiveness of risk-mitigation strategies at the individual customer level, highlighting a gap in the literature that warrants more granular analysis.

In summary, the review of previous studies underscores the ongoing efforts to analyze the reliability and resilience benefits of PVESS, as well as broader power system reliability and resilience. However, these studies have been limited, particularly in their geographical scope and their focus on aggregated data. Most analyses have concentrated on specific regions and have provided insights primarily at an aggregated level. While Gorman et al. [6] advanced the field by analyzing the impacts of DER at a disaggregated level across regions with varying outage characteristics, consumption profiles, and solar availability, their study was restricted to long-duration interruption events with fixed, non-stochastic start times. The efficacy of PVESS backup in mitigating stochastic, short-term interruptions remains understudied. This paper addresses this gap by offering a comprehensive examination of short-duration interruption patterns, supported by rigorous simulation and analysis. Our approach connects historical outage data with simulations of outages across U.S. counties, integrates these with building energy consumption and PV generation data, and evaluates the effectiveness of PVESS across a wide range of scenarios. This novel framework provides a more detailed understanding of PVESS performance at the disaggregated level, offering valuable insights into its role in enhancing system resilience.

3. Methods

This paper implements two processes in sequence, each with a methodological contribution. First, we develop the PRESTO model to generate realistic, county-specific short-duration outage scenarios across the continental US. Subsequently, we utilize these interruption datasets to evaluate the mitigation potential of PVESS against short outages using a high-resolution temporal analysis. This section provides a concise overview of both methodologies.

3.1. Model specifications of PRESTO

It is crucial to employ realistic profiles that accurately represent the timing, duration, and frequency of these disruptions to accurately evaluate the effectiveness of PVESS in mitigating short-duration power interruptions from a customer's perspective. To achieve this, we utilized PRESTO, a power outage simulation tool, and employed carefully curated inputs derived from historical interruption data. Fig. 1 visually outlines the process implemented by PRESTO, which will be further elaborated in the following text.

The foundation of our analysis lies in hourly interruption data for each county in the United States, spanning from July 2017 to November 2021. This comprehensive dataset was compiled from PowerOutage.US (POUS), a web scraper that gathers publicly available outage information from various utilities. The data is presented in an 8760 format, encompassing hourly counts of affected customers for each utility-county combination and hourly records of the maximum number of customers tracked and those without power.

From this rich dataset, we extracted valuable insights into the duration and extent of non-continuous interruption events in each county-month combination. Statistical analysis of the historical data played a pivotal role in designing and calibrating the inputs for PRESTO. We employed standard time-series decomposition techniques for each

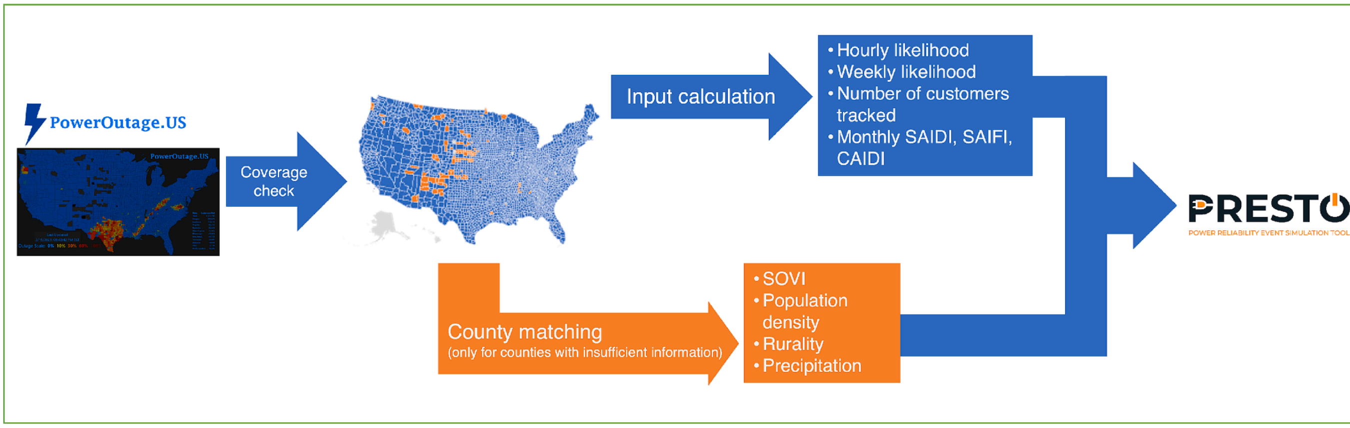


Fig. 1. Schematic illustrating the data curation process for PowerOutage.US (POUS) data to generate the default inputs for PRESTO, preparing them for simulation runs for all FIPS regions in the contiguous United States.

county to isolate seasonal and time-series trends versus and random components. The seasonal component, capturing several years of interruption patterns, reflects the long-term behaviour of county-level interruptions. Specifically, we calculated the weekly likelihood of an interruption throughout the year and the hourly likelihood for each month. Weekly interruptions were determined by the average percentage of customers affected during a specific week of the year, while hourly interruptions were based on the maximum percentage of customers affected during a specific hour of the day for each month. Leveraging the probabilistic functions to estimate the likelihood of individual customer within a given county throughout a year allows PRESTO to capture historical patterns in both the timing (e.g., seasonal and diurnal) and duration of interruptions. However, acknowledging the limitations of our analysis timeframe in capturing long-term reliability trends, we also allow users to input System Average Interruption Duration Index (SAIDI) and SAIFI values to adjust the likelihood of outages within PRESTO's simulations.

PRESTO stochastically generates interruption events over a large number (1,000–20,000) of simulation years, allowing a user to develop probabilistic assessments of the impacts of power interruptions. For each simulated year, PRESTO:

- Calculates the scaling factor: To ensure the interruption generators do not produce excessive outages, we apply a scaling factor to adjust SAIFI values in subsequent calculations, which are determined heuristically:

  0.7783×j=112SAIFIj-0.055 if j=112SAIFIj>0.3, 0.4679×j=112SAIFIj-0.652 if j=112SAIFIj≤0.3where SAIFIj is the average of monthly SAIFI for the selected FIPS region over the five year
- Draws interruption frequency (num_int): The interruption frequency is drawn from a truncated normal distribution, which s defined as $round\left(TruncNorm\left(\sum_{j=1}^{12} SAIFI_j \bullet scalingfactor,\right.\right.$

  $$\left.\left.\sum_{j=1}^{12} SAIFI_j \bullet scalingfactor^2, 0, 365\right)\right)$$

  . This ensures that the simulated interruption frequency is consistent with historical observations.
- Assigns a week: A week is assigned to each event based on weekly likelihoods, which are determined from the seasonal decomposition as probability weights

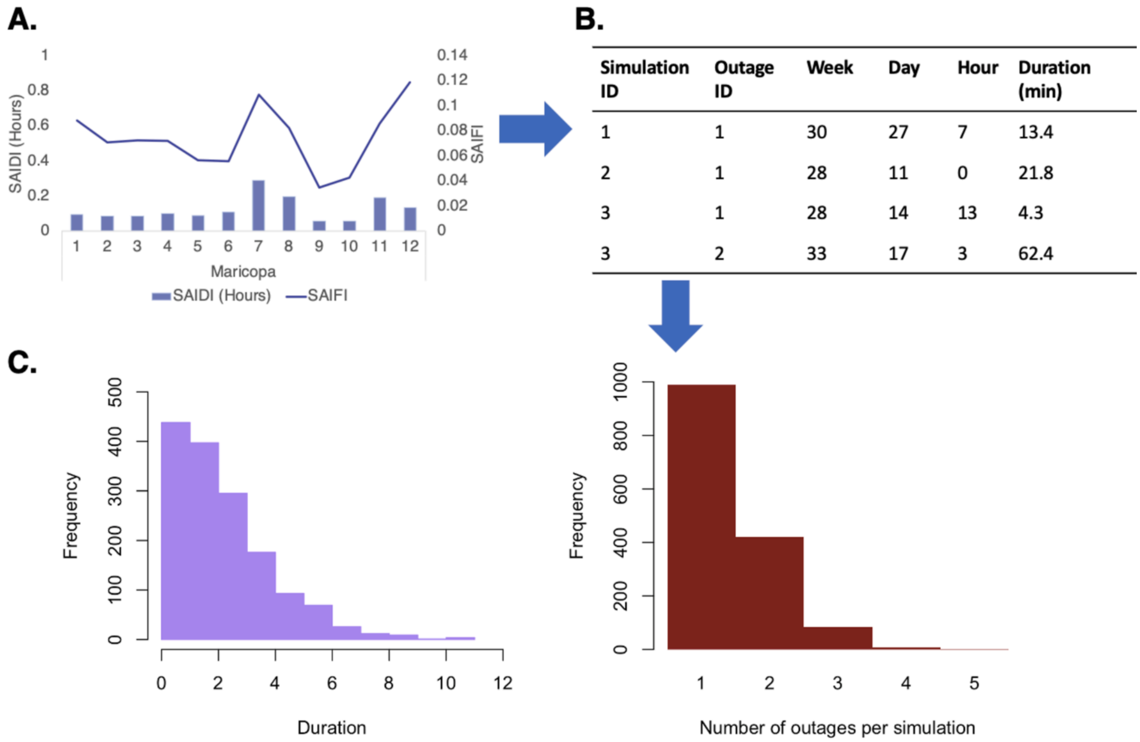
  (i.e., Discretew1,w2,…w53, pw1,pw2,…,pw53 where w is week of a year and pwi denotes probability weights determined by regional weekly likelihoods). This captures the seasonal patterns in interruption frequency.
- Assigns a start hour of the power interruption (hour-of-day): An hour-of-day is assigned to each event based on the month for a given week, using the corresponding hour-of-day monthly vector of likelihoods

  (i.e., Discretehm1,hm2,…hm24, pm1,pm2,…,pm24 where m is the month of the selected week, hmj denotes the likelihood of an outage starting at hour j of the day within month m). This is also determined from the seasonal decomposition and captures the diurnal patterns in interruption frequency.
- Draws duration: The interruption duration is drawn from a calibrated probability distribution based on a truncated normal distribution. The distribution is determined by the monthly CAIDI divided by the number of generated power interruptions from the second step to ensure that the simulated interruption durations are consistent with historical observations $TruncNorm\left(\frac{CAIDI_m}{num_{int}}, CAIDI_m{}^2, 0, +\infty\right)$.

PRESTO is written in TypeScript and designed to run in the Node.js environment. It leverages the comprehensive stdlib library, a standard library for JavaScript and Node.js, which provides a rich set of statistical and mathematical functions.

The training dataset for PRESTO is derived from the POUS dataset, compiling outage data from various utilities spanning mid-2017 to late 2021, with continuous monitoring for 96 % of counties (2,985 out of 3,106 FIPS regions) for over a year. To address the 3.8 % of regions (121 regions) lacking consistent POUS tracking, a matching approach is employed, pairing regions with insufficient data with similar counties based on factors such as population density, degree of rurality, the Social Vulnerability Index (SOVI), and precipitation patterns. Fig. 2 shows how monthly SAIDI and SAIFI data (top left, Fig. 2 Panel A) is used by PRESTO to simulate power interruption profiles for a selected county over 1,000 years (top right, Fig. 2 Panel B). This simulation helps us understand the inherent distribution of interruption characteristics, such as duration and frequency (bottom, Fig. 2 Panel C).

By meticulously constructing realistic interruption profiles that faithfully represent the timing, duration, and frequency of power outages, we have established a solid foundation for evaluating the effectiveness of PVESS in alleviating these disruptions from a customer's perspective. This approach accurately captures historical patterns in both the timing (e.g., seasonal and diurnal) and duration of interruption events at the county level, providing a comprehensive framework for assessing the impact of PVESS on customer experience. In this study, we integrate PRESTO with a storage dispatch model developed in our previous research [6] to simulate PVESS operation and backup performance across numerous interruption events. However, it is important to emphasize that PRESTO's utility extends beyond this particular application, as it can also generate interruption profiles crucial for broader



Simulation ID	Outage ID	Week	Day	Hour	Duration (min)
1	1	30	27	7	13.4
2	1	28	11	0	21.8
3	1	28	14	13	4.3
3	2	33	17	3	62.4

Fig. 2. Illustration of how monthly SAIDI and SAIFI, along with other inputs, generate power interruption profiles and distribution of interruption characteristics in PRESTO.

analyses like reliability assessments at disaggregated temporal/spatial levels and identifying communities in need of additional investments.

3.2. PVESS evaluation during power interruptions

Leveraging the power interruptions simulated using PRESTO, we evaluated the efficacy of PVESS for residential customers using the PVESS dispatch algorithm introduced by Gorman et al. [6]. Our methodology involves utilizing four essential time-series datasets as inputs to the PVESS dispatch model during power interruption events:

- Load profiles are generated using NREL's ResStock model for selected counties. The ResStock model generates a comprehensive set of building models by utilizing probabilistic distributions of over 100 building stock characteristics, including insulation, HVAC technology, square footage, and heating fuel [21]. A representative single-family detached home was chosen based on the median values for annual energy consumption in each county. Simulated load profiles for those homes are resolved at a 15-minute interval basis and disaggregated into individual end-uses.
- Solar generation profiles are derived for temporal and geospatial alignment, drawing from weather data used in the foundational ResStock building simulations. This involves merging ground-based measurements with solar radiation data from NREL's National Solar Radiation Data Base (NSRDB) [22]. Subsequently, NREL's System Advisor Model (SAM) is employed to generate hourly AC solar production profiles that ensure the annual PV generation matches the building's overall annual consumption profile [23].
- Power interruption profiles are created with PRESTO. PRESTO utilizes county-level hourly outage data (POUS data for the period of mid-2017 through late 2021) to calibrate functions, generating annual outage time series with stochastic attributes. These functions are fine-tuned to match real data statistics, ensuring the simulated short-duration interruptions align with actual conditions.
- Simulating PVESS operation during power interruptions requires information about the battery's SoC at the beginning of the interruption event. To generate those initial SoC estimates, we use NREL's ReOPT model to simulate battery storage operation under blue-sky conditions, assuming that customers take service under the local utility's existing time-of-use (TOU) rate and operate storage in response to TOU rate structures [24]. In the baseline set of scenarios, grid charging is not permitted, but grid exports are allowed.

Refer to Fig. 3 below for a comprehensive overview of how the primary data sources are integrated into the corresponding PVESS evaluation methodology.

4. Case study design

The primary objective of this paper is to assess the potential of PVESS to mitigate short-duration power interruptions in typical residential buildings within specific study regions. We consider residential PVESS systems with a fixed battery size (representing typical sizing observed in the U.S. market today)[1], paired with a photovoltaic (PV) system sized to meet 100 % of the customer's annual load (also typical in the U.S. market).[1] The analysis includes a limited set of scenarios related to storage system sizing, backup power configuration, and whether the customer charges the battery storage system from the grid during normal operating conditions. The analysis also presents comparative results across several regions to illustrate how differences in climate,

[1] In accordance with Gorman et al. [6], default PV system sizing prioritizes roof constraints over annual load requirements. For each representative single-family home, roof area was calculated by dividing the building's square footage by its number of stories. For single-family and mobile homes with slanted roofs, a standard panel density of 160 W/m^2 (0.01486 kW/ft^2) and a 98 % ground-coverage ratio are assumed. The final PV system size for each home was then determined as the minimum of either the roof-limited capacity or the capacity required to meet 100 % of the annual load.

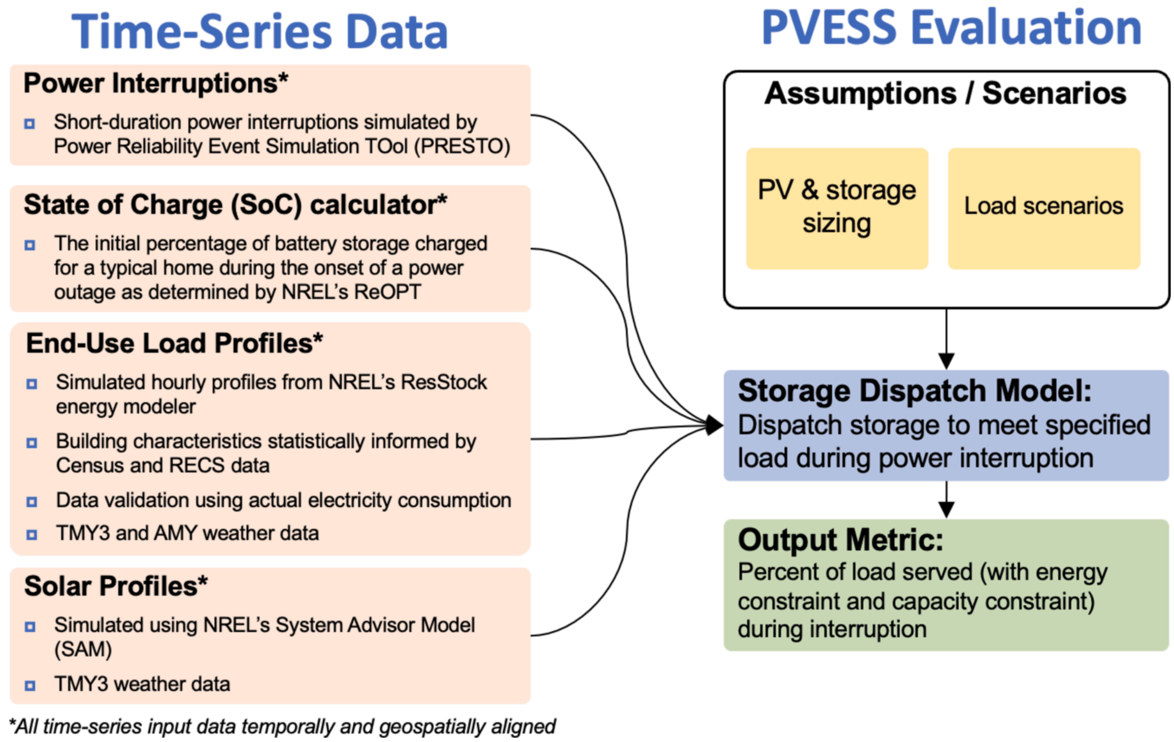


Fig. 3. Schematic representation of PVESS evaluation methodology.

interruption patterns, and retail rate structures can affect PVESS performance as a backup power source.

For the case study presented here, we used the PRESTO model to simulate power outages over 1,000 representative years for three US counties: Maricopa County, Arizona; Middlesex County, Massachusetts; and Los Angeles County, California. The analysis focuses on a typical single-family home in Maricopa County, Arizona. For Maricopa County, the model generated 1,520 interruption events over 1,000 simulation years, corresponding to an average interruption frequency of 1.52 events per year. As shown in the top left panel of Fig. 4, most of these interruption events were relatively short, with a median of 1.8 h and a mean of 2.2 h. Most of the power interruptions had high beginning SoC with an average of 77 % and median of 88 % (the bottom left panel of Fig. 4). As shown in the right panel, most of these interruptions occurred during the early morning hours in July and August, aligning with historical trends observed in POUS (highlighted in dotted box in the heatmap).

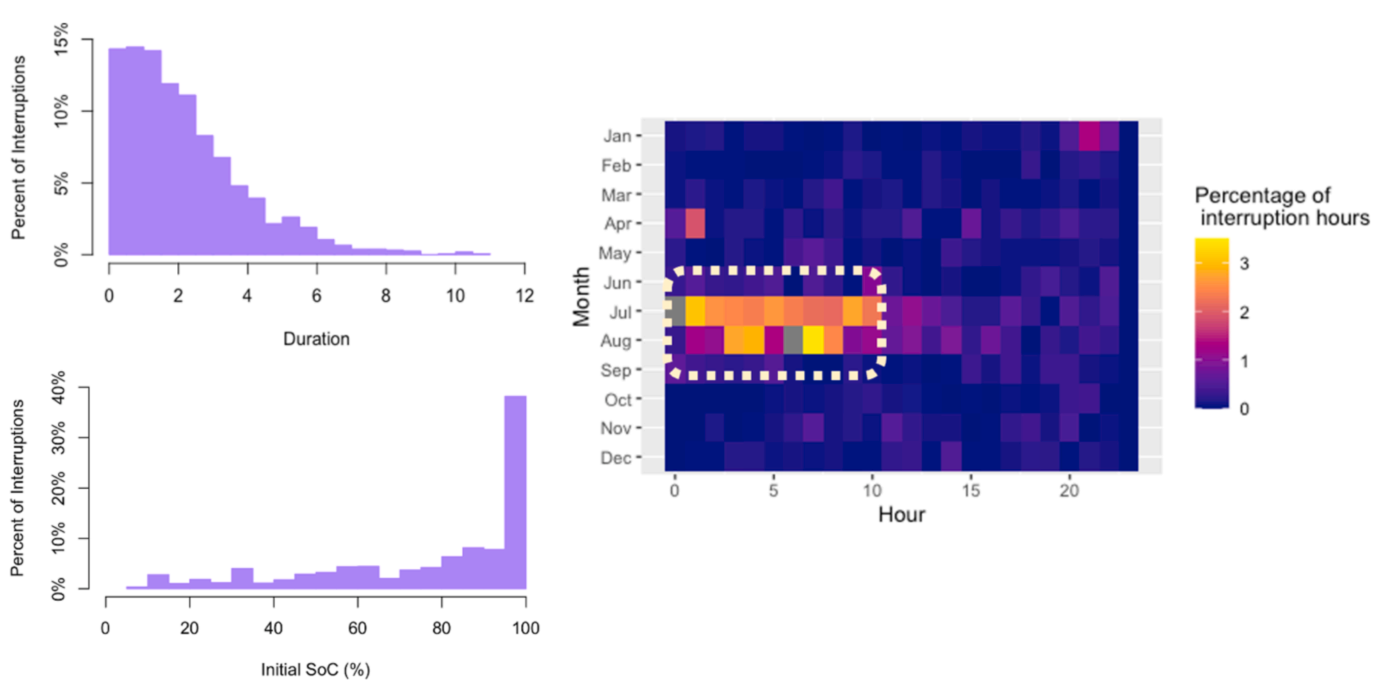


Fig. 4. Histogram of interruption duration for the set of simulated interruption events in Maricopa County, Arizona (top left), beginning SoC when the interruption events start (bottom left), and heatmap showing the timing of those events (right).

5. Results

In this section, we present our findings regarding the performance of PVESS during short-duration power interruptions, examining the following four research questions:

- How well does the PVESS perform across different backup load configurations?
- How does PVESS backup power performance vary in response to event duration, the initial battery SoC, and event timing?
- How can PVESS backup performance be improved?
- How does the performance of PVESS vary across different regions?

Our base case focuses on a PVESS consisting of a PV system sized to meet the customer's annual electricity consumption paired with a 10-kWh battery – at the smaller end of the size range commonly observed in today's market, which corresponds to a single LG Chem RESU10H, one of the more common residential batteries, while a Tesla PowerWall has a somewhat larger storage capacity of 13.5 kWh. The base case assumes exclusive solar charging of the battery, with no grid charging,[2] to serve full critical loads which includes refrigeration, nighttime lighting, essential plug-in devices, and heating and cooling equipment (full critical load hereafter). The customer manages its battery to minimize electricity costs under the local utility's time-of-use rate. Additionally, no battery capacity is reserved for potential power interruptions beyond a minimum of 5 % SoC.

5.1. How well does the PVESS perform across different backup load configurations?

We considered three backup load configurations: (i) a limited critical load case that powers refrigeration, nighttime lighting, and essential plug-in devices; (ii) a full critical load case that additionally powers heating and cooling equipment; and (iii) a whole-home backup case that powers all available loads.

Fig. 5 illustrates the distribution of backup performance across all 1,520 simulated power interruption events in Maricopa County for each of the three critical load configurations described above. As depicted in the figure, the system meets less than 100 % of backup load in 16 % of interruptions for limited critical load backup, 48 % for full critical load backup, and 57 % for whole-home backup. These results assume a conservative scenario with no load flexibility during outages. This likely underestimates real-world performance. In practice, we can improve backup performance by reducing energy use during outages (e.g., lowering thermostats). Additionally, programming the battery to reserve more charge, installing a larger battery, or charging it from the grid during off-peak hours can further enhance backup capability. We explore those latter two approaches through scenario analyses presented later.

The cumulative distributions show that a PVESS with a 10 kWh battery cannot fully mitigate the impact of short, localized power interruptions in a county in the Southwest U.S., at least under the conservative assumptions implicit in our base-case. We examine the factors contributing to these instances of reduced load servicing and illustrate the potential efficacy of several mitigation strategies.

5.2. How does the performance of PVESS vary depending on the duration of power interruptions, the initial battery SoC, and the timing of power interruptions?

The effectiveness of PVESS in providing backup power during short-duration power outages may depend on when and how long the interruption occurs. We first explored the relationship between the backup performance with interruption duration. As can be seen from left of Fig. 6, the modelled PVESS serves approximately 80 % of the full critical load on average even for outages lasting less than an hour, signifying the sensitivity to the beginning battery SoC and temporal alignment with solar output. However, backup performance declines as outages lengthen. While the backup performance generally declines with duration and the percentage of critical load served reaches 62 % at the 8-hour mark, there is an upturn after 8 h. By the 10-hour mark, the system manages to meet 68 % of the full critical load. This upturn at the 8-hour mark is likely due to the specific characteristics of this region. As the right panel of Fig. 4 shows, many outages were simulated during nighttime in July. After several hours, sunrise occurs, and the PV system starts generating power, improving backup performance.

The analysis of critical load provision during short-duration power interruptions, categorized by capacity (kW) and energy (kWh) limitations, reveals that the backup performance of PVESS is primarily driven by energy limits, rather than high power needs of specific appliances (see right of Fig. 6). Even for brief outages, around 11 % of remaining critical loads may remain unserved, possibly due to low SoC at the onset of the interruptions, and further explored in subsequent sections. The percent load not served due to energy constraints steadily increased and reached 30 % for outages lasting 7 h, and then decreased to 22 % at 10 h. These patterns reveal that PVESS performance depends on energy and capacity needs on the load side, as well as characteristics of the interruption itself and the SoC of the battery upon interruptions.

We then examined the impact of the initial SoC of the battery on backup performance. As shown from the left side of Fig. 7, the backup performance remains relatively constant for initial SoC up to approximately 50 %. Beyond this threshold, the backup performance improves with increasing SoC. However, even at 100 % initial SoC, the system still falls short of meeting all critical load requirements, which stems from either insufficient system capacity or the presence of critical loads exceeding available energy. The results also suggest a compounding relationship between interruption duration and initial SoC to explain PVESS reliability performance. The right side of Fig. 7 illustrates this relationship by categorizing events into three groups based on percent load not served: shallow shortfalls (less than 20 % unserved load, represented in black), moderate shortfalls (20 % to 40 %, represented in red), and deep shortfalls (greater than 40 %, represented in blue). The figure shows that shallow and moderate shortfalls are driven primarily by the initial SoC, since the curve is relatively flat regardless of duration. In contrast, the occurrence of deeper shortfalls depends on the combination of SoC and duration. The blue linear fit shows that short-duration interruptions that have ~60 % SoC can produce deep shortfalls, and longer duration interruptions can produce equally deep shortfalls even when SoC is higher. In other words, PVESS ability to mitigate interruptions is driven by SoC, but interruption duration will worsen interruptions more than SoC will.

Lastly, the results presented in Fig. 8 show how backup performance is impacted by the timing of the interruption, which itself correlates to a number of underlying performance drivers (critical load levels, solar insolation, and battery SoC). As noted previously, most of the simulated power interruptions occurred during early morning hours in July and August. As shown in Fig. 8, backup performance during those hours averaged roughly 75 %. While the initial SoC during those interruptions was generally low (at least in our base case, with no overnight grid charging), critical loads also tend to be low during those hours of the day, leading to relatively high performance. The highest overall performance levels tend to occur during midday hours, when solar generation is strong. In contrast, the lowest backup performance occurs during early evening hours in warm months of the year. That reflects a confluence of high energy demand during early evening hours (due to high air-conditioning load), low SoC (because the battery discharged during the peak TOU period, which runs from 3-8 pm), and little or no

[2] The assumption of no grid-charging is partially meant to reflect limitations previously imposed by the federal investment tax credit, which was available to battery storage only if charged primarily from solar (or other renewables), as well as limitations on grid charging that may be imposed by the utility, the battery software, or third-party owners of the system.

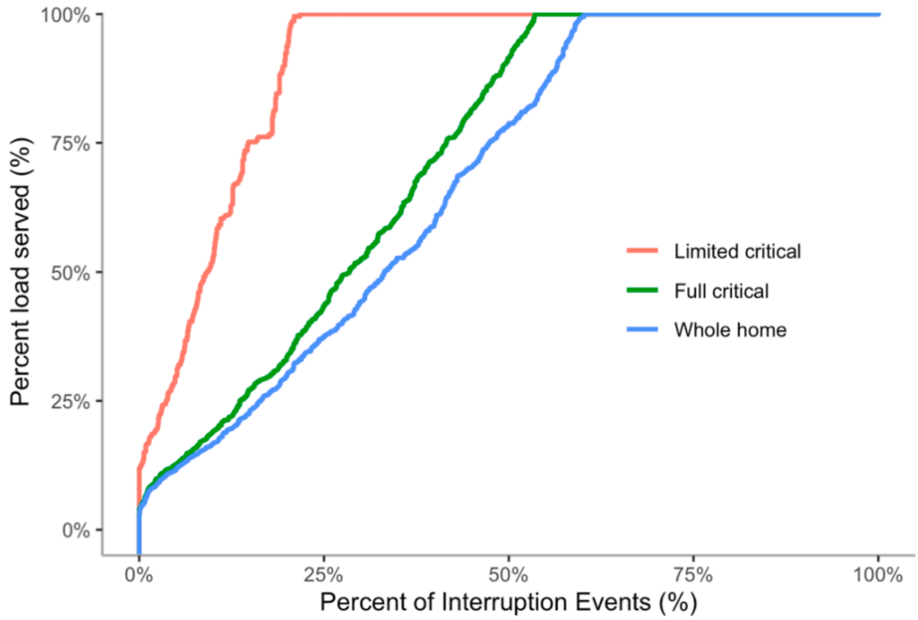


Fig. 5. Cumulative distributions of percent load served during short-duration power interruptions in Maricopa with 10kWh batteries without grid charging at a 5% reliability threshold for limited critical (red), full critical (green), and whole-home loads (blue).

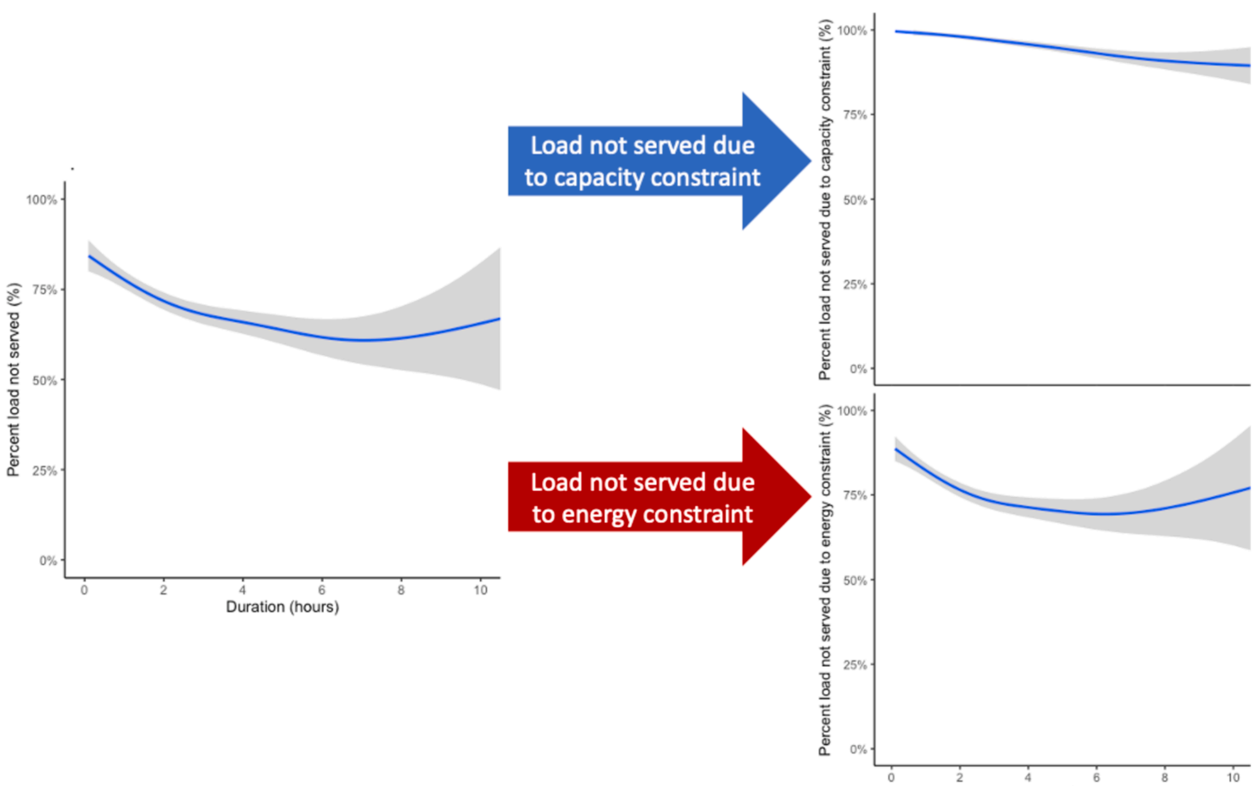


Fig. 6. Percentage of load lost (left) and percent load lost due to capacity constraints (right, top) and energy constraints (right, bottom) in relation to interruption duration for a full critical load backup scenario in a median single-family home in Maricopa County, Arizona. Blue lines represent the fitted trendlines and gray areas represent the confidence intervals.

solar insolation available to recharge the battery.

In summary, our analysis suggests that duration, initial SoC, and timing all contribute to PVESS backup performance. More importantly, these results demonstrate that mitigating short-duration interruptions is not trivial, given that the battery is operating at a non-100 % SoC and that the interruption randomness prevents customers from taking any demand-side mitigation measure in advance. Given that the PVESS could not fully meet all critical demands even in short-duration outages, implementing strategies such as predictive battery management—allocating reserves for periods with higher forecasted loads—or installing larger-size batteries could enhance the effectiveness of PVESS during power interruptions. We turn to examine the impact of some of these strategies in the next subsection.

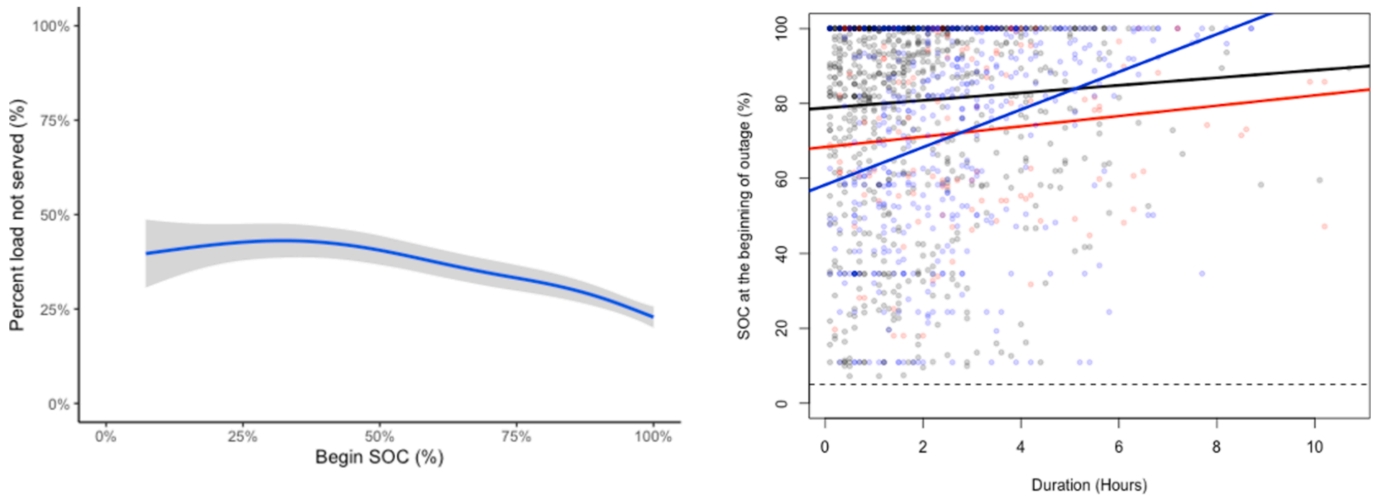


Fig. 7. (Left) Percentage of lost load in relation to the initiating SoC in Maricopa County, Arizona. (Right Initial SoC vs. power interruption duration in Maricopa County. Black indicates shallow shortfall (≥80 % load served), red indicates moderate shortfall (60–80 % load served), and blue indicates deep shortfall (<60 % load served). The dotted horizontal line represents the reliability threshold of 5 %, and the solid lines represent the linear relationship between the initial SoC and interruption durations.

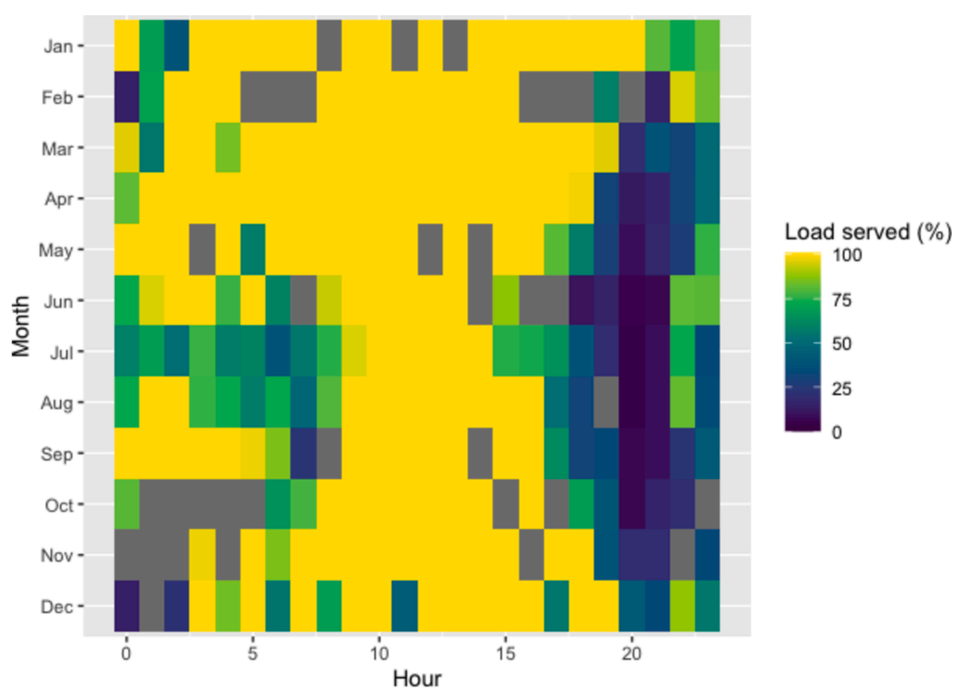


Fig. 8. Heatmaps of the percentage of load served during simulated power interruptions in Maricopa with a 10 kWh battery without grid charging.

5.3. *How can the backup performance of PVESS be improved?*

As previously outlined, several strategies could be implemented to improve the backup performance of PVESS. In this analysis, we examined two of them. Firstly, we assumed that customers have the option to install larger batteries, as demonstrated in our consideration of a PVESS equipped with 30 kWh of battery storage—representing the upper range of typical residential systems observed in the market today. Secondly, we explored a scenario where the customer charges the battery from the grid during normal day-to-day operations, deviating from the exclusive reliance on PV generation.

As Fig. 9 below illustrates, both strategies significantly enhance performance relative to a PVESS equipped with 10 kWh battery storage without grid charging. The 10 kWh battery without grid charging serves all critical demands for 52 % of simulated power interruptions, while the 10 kWh battery with grid charging covers 83 %. The average percentage of load served increases from 88 % (with a 10 kWh battery and no grid charging) to 94 % when grid charging is allowed. Examining the minimum percentage of load served, which represents the most severe event in the simulated power interruptions, allowing grid charging with a 10 kWh battery results in a 9 % increase in load served.

Similarly, increasing battery size from 10 kWh to 30 kWh increases the percentage of interruptions where all critical demand is served from 52 % to 79 %. The average percentage of load served with a 30 kWh battery reaches 99 % from an original 88 % with a lower capacity battery. The minimum percentage of load served increases from 4.3 % in the 10 kWh case to 17 % in the 30 kWh case. An interesting finding is that performance does not increase in proportion to the size of the battery for percent interruptions with full mitigation and for average load served. However, the worst-case scenarios do improve by around

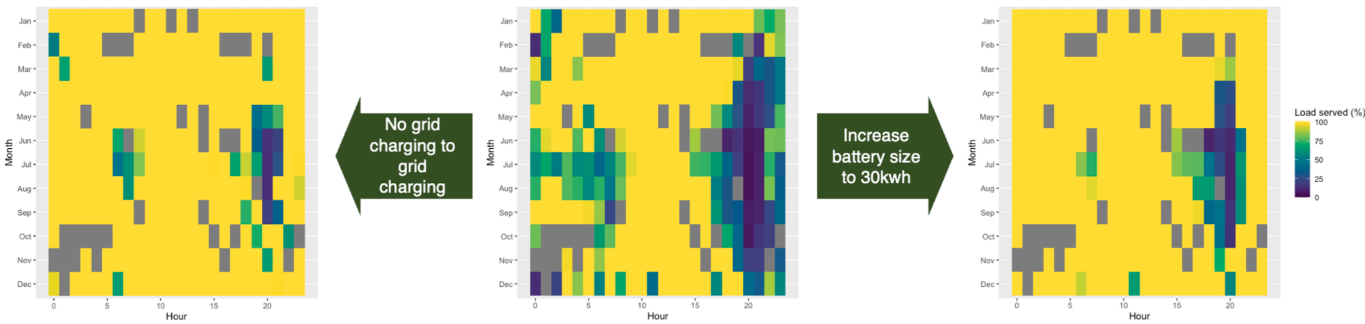


Fig. 9. Heatmaps of the percentage of load served during simulated power interruptions in Maricopa with a 30 kWh battery without grid charging (left) and a 10 kWh battery with grid charging (right). The heatmaps show the percentage of load served for each month and starting hour of interruption.

Table 1
Median and 10th to 90th percentiles of percent load served during short-duration power interruptions in Maricopa, Los Angeles, and Middlesex. We assumed the critical load backup scenario in a median single-family home for a 10 kWh battery storage without grid charging.

Region	Across all year		Summer (Jun-Sep)		Winter (Dec-Feb)	
	Percent of Load Served (Median with 10th-90th percentiles)	Fraction of events with 100 % coverage	Percent of Load Served (Median with 10th-90th percentiles)	Fraction of events with 100 % coverage	Percent of Load Served (Median with 10th-90th percentiles)	Fraction of events with 100 % coverage
Maricopa, AZ	100 % (21 %-100 %)	52 %	88 % (20 %-100 %)	45 %	100 % (29 %-100 %)	89 %
Los Angeles, CA	100 % (48 %-100 %)	79 %	100 % (41 %-100 %)	71 %	100 % (54 %-100 %)	92 %
Middlesex, MA	100 % (46 %-100 %)	72 %	100 % (33 %-100 %)	71 %	100 % (31 %-100 %)	87 %

the same scaling factor for battery capacity. This suggests that a higher battery capacity may not dramatically improve load met, but reduce the frequency of poor performance.

In summary, both strategies substantially improve backup performance. Grid charging allows the system to meet critical demands during more outage events by increasing the available energy. On the other hand, a larger battery proves more effective in handling all outage scenarios, even the most severe situations. However, it's important to acknowledge that even with these improvements, the PVESS system may not fully back up heating and cooling in all situations. Further exploration of strategies like adjusting thermostats or selectively turning off high-power appliances during outages could also improve backup performance of PVESS.

5.4. *How does the performance of PVESS vary across different regions?*

The backup performance of PVESS can vary across regions as a result of underlying differences in interruption patterns, tariff structures, solar production, and load profiles. To illustrate the potential significance regional differences, we analyzed PVESS backup performance in typical single-family homes across three counties: Los Angeles (CA) representing marine climate, Maricopa (AZ) embodying hot-dry climate, and Middlesex (MA) representing a cold climate. The comparison is based on the same base-case assumptions used previously and focuses on a backup configuration that includes critical loads with heating and cooling.

As summarized in Table 1 below, the backup performance across year is higher in Los Angeles and Middlesex counties (with full backup provided in 79 % and 72 % of interruption events, respectively), compared to Maricopa (52 %). However, upon closer examination of performance during summer and winter months, Middlesex displays less improvement during winter. This discrepancy can be attributed to two factors. First, Los Angeles and Middlesex has significantly lower cooling loads during summer. Second, despite none of the analyzed homes have electric heating, all regions experience lower solar production in winter. Given Middlesex's higher latitude, it is particularly susceptible to this reduced solar output, resulting in relatively lower enhancements in backup performance during winter.

Results also differ across counties as a result of interruption patterns. In both Los Angeles and Middlesex counties, the PRESTO model produced power interruptions that occur with relatively equal probability across hours of the day, and thus the average SoC on the battery at the beginning of the interruption is higher than in Maricopa, where the interruptions are more concentrated in early morning hours, when the battery SoC tends to be low (see Fig. 10 below). Lastly, TOU rate structures also differ across these counties, which can impact the battery SoC when interruptions occur given the optimal bill saving PVESS dispatch. In particular, the TOU rate applicable in Middlesex County has a broad peak period from 8 am to 9 pm, which leads to more diffuse charging and discharging patterns, compared to the TOU structures in the other two counties, where peak period rates are concentrated in a much smaller number of hours.

6. Discussion

The presented findings provide a foundational understanding of the backup capabilities of PVESS for short-duration power interruptions through a comprehensive analysis drawn from probabilistic functions constructed based on the historical outage data. These results are useful for researchers, analysts, and electric system planners. Firstly, in a conservative scenario with a 10 kWh battery, PVESS can effectively support customers with minimal critical demands in most instances. However, PVESS performance during short-duration interruptions to back up critical loads that include heating and cooling loads is much lower than when heating and cooling are not considered. Secondly, the

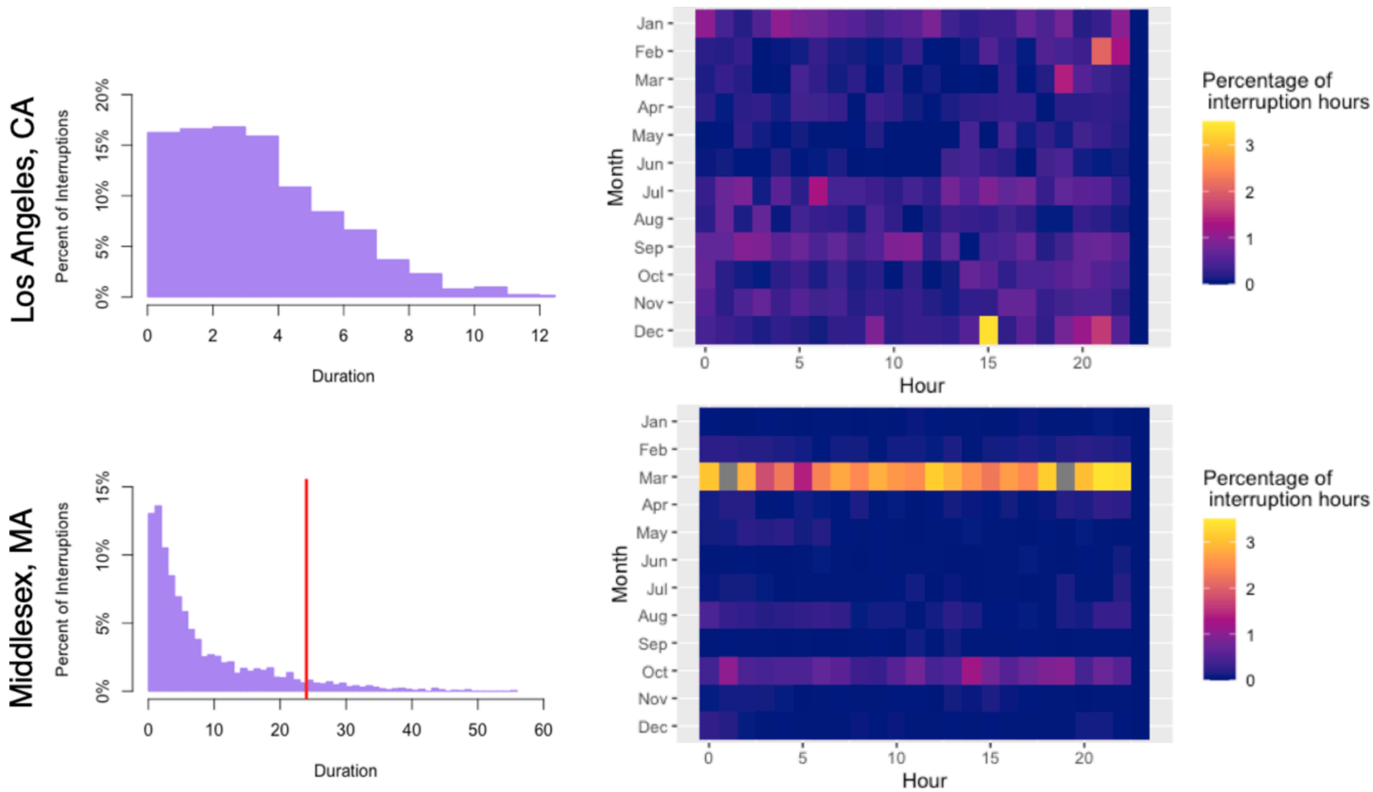


Fig. 10. Histogram of interruption duration for the set of simulated interruption events (left) and heatmap showing the timing of those events (right) in Los Angeles (top) and Middlesex (bottom).

Table 2
Summary of the simulated power interruption durations and the kWh mitigated by installing PVESS with a 10kWh battery in the three study regions.

County	Duration of power interruptions across the simulated year				kWh lost load mitigated annually with PVESS with 10 kWh battery storage and a 5 % reliability threshold			
	Min	Median	Mean	Max	Min	Median	Mean	Max
Maricopa, AZ	0	2.9	3.4	12.5	0	3.4	7.8	60.5
Los Angeles, CA	0	5.1	5.5	22	0	3.1	4.2	26.0
Middlesex, MA	0	19.8	22.0	95.5	0	12	13.8	63.3

performance of PVESS depends on geographic location, end-uses, outage occurrence patterns, and battery consumption patterns. This highlights the need for regional analysis to accurately assess backup capabilities. Finally, several strategies can enhance home resilience against outages. Allowing grid charging – which is disallowed in many jurisdictions as a way to incentivize pairing with rooftop solar – greatly enhances mitigation performance at a low cost. Higher capacity batteries can achieve slightly better results, but likely at a much higher cost. We did not examine demand response approaches, but these are likely to allow for improved performance at relatively low costs as well.

This paper focuses on the technical capabilities of PVESS in mitigating short-duration power interruptions. However, customer deployment and operation decisions will be driven in part by the economic benefits that these reliability enhancements bring to households. Recent surveys show that customers' concerns about grid reliability and resilience are key drivers of PVESS adoption [1]. We estimate the monetary value of these reliability benefits for the three regions considered in this study, to understand how this particular value stream impacts the overall customer-economics of PVESS. In this calculation, we focused on whole-home backup scenarios because this aligns with the methodology used to derive the residential value of lost load estimates that rely on willingness-to-pay for whole-home backup services [25]. We calculated the mitigated power interruption costs by multiplying the total loads served in each simulation year by the value of lost load estimates for each state, derived from the ICE calculator.[3]

The regions analyzed in this study mostly experience short and infrequent power interruptions, as evidenced by the simulated number and total duration of short-duration power interruptions per year (Table 2). These regions experience an average of 3 to 22 h of power outages per year. For a PVESS with a 10 kWh battery and a reliability threshold of 5 %, representative households can mitigate 68 % to 83 % of the potentially lost demand, on average.

The average cost savings from avoided outages appear modest under the base case (10 kWh battery, no grid charging), ranging from $17 to $40 annually (refer to the first three columns of Table 3). However, a closer examination of the distribution of annual reliability benefits reveals a significantly wider range of potential savings, with maximum benefits reaching up to $180 (see the middle three columns of Table 3). In Middlesex, extended outage durations yielded the highest savings,

[3] https://icecalculator.com/interruption-cost. Adjusting for inflation using the Bureau of Labor Statistics' consumer price index, we converted the ICE calculator's value of lost load estimates to 2022 dollars [25]. This resulted in estimates of $3.09/kWh, $2.96/kWh, and $4.00/kWh for Maricopa, Middlesex, and Los Angeles, respectively.

Table 3
Summary of the value of the annual mitigated lost load for PVESS with a 10kWh battery system and no grid charging, a PVESS with a 10kWh battery system with grid charging, and a PVESS with a 30kWh battery system and no grid charging.

County	10kWh, no grid charging			10kWh, grid charging			30kWh, no grid charging		
	Median	Mean	Max	Median	Mean	Max	Median	Mean	Max
Maricopa, AZ	$10.5	$24.0	$187	$17.2	0$.29.5	$197	$15.6	$40.8	$217
Los Angeles, CA	$12.3	$16.7	$103.8	$13.7	$17.9	$105.3	$14.8	$19.5	$121.6
Middlesex, MA	$34.3	$39.5	$181	$39.1	$43.1	$206	$43.2	$48.7	$234.6

while in Maricopa, the peak coincided with periods of high energy demand driven by air conditioning use and limited solar irradiation. Strategies that improve the backup performance of PVESS can increase these benefits. Specifically, allowing grid charging increases average savings by 7.5 % to 22 %, and installing larger batteries increases average savings by 17 % to 23 % with a higher upfront investment in storage capacity (see the last three columns of Table 3). Comparing the mitigated value of lost load to PVESS costs[4] reveals that economic benefits from mitigating short-duration interruptions can improve the economics of PVESS by 1.3 % to 2.5 % of the total PVESS costs, or by 2.5 to 5.4 % of the storage cost on average. Furthermore, considering the mitigation of resilience events like the 2019 Public Safety Power Shutoff, Hurricane Michael, and winter storms, strengthens the economic case for PVESS systems [6].

These findings suggest that expected reliability benefits will not offset the cost of a PVESS system or justify the battery addition, which is a relatively expected result. Customers leverage several other value streams – most importantly TOU arbitrage – to justify investment in PVESS. However, these results show that accounting for the economic benefits of mitigating short-duration interruptions could improve the economics of these systems by 5 %-15 %. Furthermore, for regions experiencing frequent or extended power interruptions, particularly during periods of high energy demand and limited solar irradiation or for customers with high VOLL, the potential economic value of reliability benefits can become more compelling.

7. Conclusion, Limitations, and future research Directions

Power disruptions, though often brief, can cause significant disruptions to daily life and business operations. To accurately assess the potential of PVESS in mitigating these disruptions, a comprehensive understanding of interruption patterns and their statistical properties is crucial. This study presents the PRESTO model, a novel tool for simulating short-duration power interruptions at the county level, expanding upon previous analyses focused on long-duration events [6]. By accurately reflecting the statistical characteristics of historical interruptions, PRESTO allows for a detailed evaluation of PVESS performance and economic viability in various residential scenarios. Our findings demonstrate that, under conservative scenarios with a 10 kWh battery charged solely by solar and maintaining a 5 % reserve, PVESS met critical backup loads in 43–84 % of simulated interruptions in Maricopa, Arizona, depending on specific household load selections. The case study underscores the impact of factors such as outage duration, initial battery state of charge, and interruption timing on PVESS effectiveness. While these results are promising, further research is needed to disaggregate these influences and develop predictive systems for dynamic battery management.

Our case study is limited by the scope of the input data. Specifically, the calculation of SAIDI and SAIFI at a disaggregated level relies on data from the POUS, while the energy simulation results at the end-use levels and granular solar data are also specific to the U.S. Consequently, our case study is confined to the United States. However, the methodology we developed is versatile and can be applied globally, provided that granular historical power interruption data (sourced from local utilities or data collection platforms such as Powercut105 for the United Kingdom, Entso-E Transparency Platform for European countries, and data scraped via ElectricityMap for global regions), as well as corresponding electricity consumption and solar generation data, are available. This adaptability allows for potential application of our approach in various regions worldwide.

A primary objective is to highlight PRESTO's potential as a valuable tool for evaluating the performance and economic viability of PVESS backup power systems under various scenarios and conditions. By filling a critical knowledge gap, we comprehensively examine PVESS's capability to provide backup power during short, stochastic, and localized interruptions. Our methodology effectively simulates these interruptions, assesses state of charge while considering tariff structures and load profiles, and evaluates PVESS's mitigation potential across diverse residential settings.

Future research could involve a more expansive and robust assessment that would necessitate a broader geographical scope, particularly toward regions experiencing frequent and prolonged power interruptions. This expansion will allow for a more robust assessment of the technical potential and economic benefits achievable through PVESS or storage systems in mitigating power interruptions. Additionally, research should explore the trade-off between using solar generation for bill savings and reserving capacity for backup power, aiming to identify optimal battery operation and sizing strategies. Beyond reliability, future studies and tools should incorporate diverse benefit streams like bill savings, renewable energy credits, and enhanced resilience to offer a more comprehensive assessment of PVESS economics and return on investment potential.

CRediT authorship contribution statement

Sunhee Baik: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Juan Pablo Carvallo:** Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Galen L. Barbose:** Writing – original draft, Validation, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis. **Will Gorman:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Cesca Miller:** Data curation. **Michael Spears:** Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[4] To estimate the annual cost of PVESS, we leveraged Berkeley Lab's Tracking the Sun database for PV and PVESS costs, EnergySage's 2023 Solar and Storage Marketplace Report [26] for energy storage costs, and NREL's Annual Technology Baseline [27] for the cost assumptions. For a more objective comparison, we solely considered overnight costs, independent of individual creditworthiness. Additionally, we incorporated annual fixed operation and maintenance (O&M) expenses across the system's 25-year lifespan. However, we excluded battery degradation and potential replacement costs, focusing solely on the initial battery system investment.

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). The authors thank Ammar Qusaibaty, Michele Boyd, and Becca Jones-Albertus from the Solar Energy Technologies Office for their support of this work, as well as members of Berkeley Lab's technical advisory group for their ongoing input on research into PVESS backup power applications.

Data availability

Data will be made available on request.

References

[1] EnergySage (2021). Solar Installer Survey - 2021 Results. Available at: https://www.energysage.com/data/#2021-survey.
[2] Brockway AM, Dunn LN. Weathering adaptation: grid infrastructure planning in a changing climate. Clim Risk Manag 2020;30:100256.
[3] O'Shaughnessy, E. J., Ardani, K. B., Cutler, D. S., & Margolis, R. M. (2017). Solar Plus: A Holistic Approach to Distributed Solar PV (No. NREL/TP-6A20-68371). National Renewable Energy Lab.(NREL), Golden, CO (United States).
[4] Hoff TE, Perez R, Margolis RM. Maximizing the value of customer-sited PV systems using storage and controls. Sol Energy 2007;81(7):940–5.
[5] Prasanna, A., McCabe, K., Sigrin, B., & Blair, N. (2021). Storage futures study: Distributed solar and storage outlook: Methodology and scenarios (No. NREL/TP-7A40-79790). National Renewable Energy Lab.(NREL), Golden, CO (United States).
[6] Gorman W, Barbose G, Carvallo JP, Baik S, Miller CA, White P, et al. County-level assessment of behind-the-meter solar and storage to mitigate long-duration power interruptions for residential customers. Appl Energy 2023;342:121166.
[7] Balducci PJ, Alam MJE, Hardy TD, Wu D. Assigning value to energy storage systems at multiple points in an electrical grid. Energ Environ Sci 2018;11(8): 1926–44.
[8] Akhil, A. Huff, G., Currier, A., Kaun, B., Rastler, D., Chen, S., Cotter, A., Bradshaw, D., & Gauntlett, W. (2015). DOE/EPRI Electricity Storage Handbook in Collaboration with NRECA. Albuquerque, NM, 2015, pp.29, 149-166.
[9] Eyer J, Corey G. Energy storage for the electricity grid: benefits and market potential assessment guide. Sandia Natl Lab 2010;20(10):5.
[10] Neubauer, J., Pesaran, A., Williams, B., Ferry, M., & Eyer, J. (2012). Techno-economic analysis of PEV battery second use: Repurposed-battery selling price and commercial and industrial end-user value (Vol. 1, No. NREL/CP-5400-53799). National Renewable Energy Lab.(NREL), Golden, CO (United States).
[11] Balducci, P. J., Jin, C., Wu, D., Leslie, P., Daitch, C., & Marshall, A. (2013). Assessment of energy storage alternatives in the puget sound energy system (No. PNNL-23040). Pacific Northwest National Lab.(PNNL), Richland, WA (United States).
[12] Benidris M, Bhusal N, Abdelmalak M, Gautam M, Egan M, Groneman S, et al. Quantifying resilience value of solar plus storage in city of reno. In: 2021 Resilience Week (RWS). IEEE; 2021. p. 1–6.
[13] Zhou J, Tsianikas S, Birnie III DP, Coit DW. Economic and resilience benefit analysis of incorporating battery storage to photovoltaic array generation. Renew Energy 2019;135:652–62.
[14] Galvan E, Mandal P, Sang Y. Networked microgrids with roof-top solar PV and battery energy storage to improve distribution grids resilience to natural disasters. Int J Electr Power Energy Syst 2020;123:106239.
[15] Rosales-Asensio E, de Simón-Martín M, Borge-Diez D, Blanes-Peiró JJ, Colmenar-Santos A. Microgrids with energy storage systems as a means to increase power resilience: an application to office buildings. Energy 2019;172:1005–15.
[16] Abdelmalak M, Cox J, Ericson S, Hotchkiss E, Benidris M. Quantitative resilience-based assessment framework using eagle-i power outage data. IEEE Access 2023; 11:7682–97.
[17] Wu D, Zheng X, Xu Y, Olsen D, Xia B, Singh C, et al. An open-source extendable model and corrective measure assessment of the 2021 texas power outage. Adv Appl Energy 2021;4:100056.
[18] Arora P, Ceferino L. Probabilistic and machine learning methods for uncertainty quantification in power outage prediction due to extreme events. Nat Hazards Earth Syst Sci 2023;23(5):1665–83.
[19] Najafi-Shad S, Mollashahi M, Sadr SM. A new evaluation method for customer outage costs using long-term outage data and Monte Carlo simulation. Int J Electr Power Energy Syst 2024;159:110061.
[20] Marcelino CG, Torres V, Carvalho L, Matos M, Miranda V. Multi-objective identification of critical distribution network assets in large interruption datasets. Int J Electr Power Energy Syst 2022;137:107747.
[21] Wilson, E. J., Parker, A., Fontanini, A., Present, E., Reyna, J. L., Adhikari, R., ... & Li, Q. (2022). End-use load profiles for the US building stock: Methodology and results of model calibration, validation, and uncertainty quantification (No. NREL/TP-5500-80889). National Renewable Energy Lab.(NREL), Golden, CO (United States).
[22] Sengupta M, Xie Y, Lopez A, Habte A, Maclaurin G, Shelby J. The national solar radiation data base (NSRDB). Renew Sustain Energy Rev 2018;89:51–60.
[23] National Renewable Energy Laboratory (2020). System Advisor Model. Available at: https://sam.nrel.gov/.
[24] Anderson, K. H., Cutler, D. S., Olis, D. R., Elgqvist, E. M., Li, X., Laws, N. D., ... & Walker, H. A. (2017). REopt: A platform for energy system integration and optimization (No. NREL/TP-7A40-70022). National Renewable Energy Lab. (NREL), Golden, CO (United States).
[25] Sullivan SC, Barthlott C, Crosier J, Zhukov I, Nenes A, Hoose C. The effect of secondary ice production parameterization on the simulation of a cold frontal rainband. Atmos Chem Phys 2018;18(22):16461–80.
[26] EnergySage (2024). 2023 EnergySage Solar and Storage Marketplace Report.
[27] National Renewable Energy Laboratory (2021). Annual Technology Baseline. Available at: https://atb.nrel.gov/electricity/2021/data.