Energy 304 (2024) 132180

Contents lists available at ScienceDirect

Energy

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

Evaluating the potential for solar-plus-storage backup power in the United States as homes integrate efficient, flexible, and electrified energy technologies

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ARTICLE INFO

Handling Editor: Dr X Zhao

Keywords:
Backup power
Electric resilience
Energy efficiency
Load flexibility
Electrification
Solar
Storage

ABSTRACT

Adoption of residential behind-the-meter solar photovoltaic-plus-storage systems (PVESS) is driven, in part, by customer demand for backup power. However, there is limited understanding of how these systems perform over a range of building stock conditions that will evolve with future efficiency and electrification trends, posing challenges for identifying optimal electric resiliency investments. This study quantifies how residential energy consumption impacts the capability of PVESS to provide home backup power during long-duration power interruptions. We model statistically representative distributions of the residential building stock and estimate storage sizes required to provide backup power as a series of building envelope efficiency, load flexibility, and electrification measures are applied. For the baseline building stock, median storage size requirements range from 10 kWh in temperate weather conditions to 90 kWh in hot climates for a 3-day power interruption. Applying energy efficiency and temperature set-point adjustments reduce storage size requirements by 2–45 kWh (16%–53 %). In hot locations, heat pump retrofits reduce median storage sizing by an additional 10–30 kWh while in cold locations, they drive 10–50 kWh of storage capacity increase. Our results suggest that bi-directional EV charging may be essential to enabling PVESS backup of heating and cooling, given their typically large kWh sizes.

1. Introduction

Early adoption of behind-the-meter (BTM) solar photovoltaic + energy storage systems (PVESS for remainder of the paper) has been driven, to a significant degree, by customer concerns over electric system reliability and resilience [1–3]. Transmission and distribution networks are particularly vulnerable to severe storms and extreme heat [4–6], and customer concerns may reflect an expectation that severe weather events may become increasingly common given future climate change projections [7,8]. While PVESS investments are being made by individual customers on their own behalf, utilities may also need to make significant investments to maintain electric service resiliency to mitigate future climate risks [9,10]. Such trends underscore the importance of studying novel approaches to enhancing customer resiliency to electricity interruptions [11].

Today, most electric resiliency investments (e.g. infrastructure upgrades, tree trimming, protective equipment) are made by electric utilities and approved by their corresponding regulators [12]. Recent cost declines of solar and storage technologies over the last decade provide a new option for electric customers to meet their own resiliency needs [13–15]. BTM PVESS could therefore serve as an important substitute for traditional grid resilience investments [16], and some utilities have already begun to announce such programs [17]. Additionally, even if initially installed for resilience purposes, PVESS can provide a broader range of grid services once installed [18]. Understanding the backup power capabilities of PVESS in a variety of geographic contexts is therefore important to inform electricity system resiliency investments that are often made by public policies. Such research can also inform broader PVESS deployment forecasts that have historically been focused on non-resiliency drivers of PVESS adoption [19].

Recent work evaluated the technical capabilities of BTM PVESS for backup power during long-duration power interruptions [20]. That study implemented a novel and expansive analytical framework that

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https://doi.org/10.1016/j.energy.2024.132180
Received 12 March 2024; Received in revised form 29 May 2024; Accepted 22 June 2024
Available online 25 June 2024

Abbreviations

ACCA – Air conditioning contractors of America
AMY – actual meteorological year
BTM – behind-the-meter
COIN-OR – Computational infrastructure for Operations Research
DC – Washington DC
DER – Distributed energy resources
DFW – Dallas Ft. Worth
EV – electric vehicle
HP – heat pump
HSPF - Heating Seasonal Performance Factor
HVAC – heating ventilation air conditioning
kWh – kilowatt hour
LA – Los Angeles
NREL – National Renewable Energy Laboratory
NSRDB – National Solar Radiation Data Base
PVESS - Photovoltaic energy storage systems
RECS – Residential Energy Consumption Survey
SAM – System Advisor Model
SEER - Seasonal Energy Efficiency Ratio
SOC – state of charge
TMY – typical meteorological year
US – United States
VOLL – Value of lost load

Nomenclature

Y = size of storage system (kWh)
B_d = storage discharging, 15 min interval (kW)
D = Cost of discharging (i.e., degradation cost) ($/kWh)
SOC_k = state of charge of storage at time step k (kWh)
B_c = storage charging, 15 min interval (kW)
B_d = storage discharging, 15 min interval (kW)
η = storage efficiency (%)
L(k) = demand at time step k, 15 min interval (kW)
$E(k)$ = electricity shed from given demand profile at time step k, 15 min interval (kW)
S(k) = power generated from solar at time step k, 15 min interval (kW)
$D_{pv}(k)$ = curtailed PV production, 15 min interval (kW)

involved simulating PVESS backup power performance across a range of interruption conditions for a typical home in a variety of weather conditions, as well as across large and statistically representative distributions of building models within a selection of individual locations. That work highlighted the challenges associated specifically with providing backup power to heating and cooling loads, and the interdependencies with building envelope and equipment efficiency, electrification of heating loads, and behavioral conservation measures that customers may implement during power interruption events. Additional research on distributed resource applications to enhance customer electric resiliency has focused on microgrid deployments [21], individual case studies [22,23], or electric vehicle applications [24].

Importantly, however, these earlier analyses are based on the present-day building stock. Yet, buildings across the globe are in the midst of significant transformation, driven by technological advancement and policy goals [25,26]. Meeting decarbonization objectives cost-effectively will require substantial improvements in building energy efficiency [27] and large-scale electrification of building end-uses [28], including switching from fossil-based heating to efficient electric heat-pumps [29,30]. Buildings will also need to become significantly more flexible [31], to minimize the costs of transitioning to high renewable energy penetrations [32]. This transformation of the building stock, and the resulting changes in residential building electricity consumption patterns, will have potentially significant but diverse implications for PVESS-based backup power, depending on pre-existing building stock conditions, climate, and the timing and severity of power interruption events.

In this paper, we extend the previous literature to evaluate the technical potential for PVESS backup power as residential buildings become progressively more efficient, flexible, and electrified. To do so, we apply a series of building efficiency, load flexibility, and electrification measures to the baseline building stock, and evaluate the resulting impacts on required battery storage sizing for backup power during long-duration power interruptions. Such an approach allows us to evaluate how PVESS can mitigate customer concerns over electric system resilience. We focus on electricity system 'resilience', over reliability, in this paper given our focus on long-duration power interruptions. Prior work has defined mitigation of interruptions >24 h as resilience benefits, and we rely on the same definition here [33]. Our results illustrate key regional differences as well as a diversity of impacts across the building stock within each study location.

This work adds to the broader literature on PVESS backup power both in the novelty of its findings as well as the underlying methods. The literature review in Gorman et al., 2023 noted that prior work studying the resilience impacts of PVESS has consisted mostly of either the development of novel operation strategies for PVESS in individual case studies or analyses of the resilience impacts on the broader distribution network, rather than the impacts for the individual host customer who is typically the entity adopting (and financing) these investments [20]. Furthermore, prior research has thus far focused on the current residential building stock, without accounting for the significant change to building loads expected as a result of electrification and energy efficiency investments [34]. This paper fills these important gaps by providing generalizable findings about resilience impacts for host customers who might be considering corresponding building upgrades when choosing to install PVESS. These findings can inform decision-making by customers, building designers, developers, and technology vendors seeking to understand the capabilities of PVESS for individual customer-level backup power. This work can also inform building energy modeling and forecasting activities that aim to project customer adoption of PVESS, and require a characterization of the underlying distribution of its technical potential in backup power applications, and how that may evolve over time with changes in the underlying building stock [35].

2. Methods

This section is broken up into three subsections which describe our data, the implementation of the PVESS optimization program, and the parameters adjusted in our scenario analysis.

2.1. Datasets for optimization analysis

Our research approach requires three timeseries data: (1) disaggregated end-use load profiles, (2) solar production profiles, and (3) power interruption profiles. Critically, we ensure that these data sets are temporally and geospatially aligned at an 15-min interval given the correlation of weather events with likelihood of power outage [5]. To do so, we rely on a consistent set of typical meteorological year (TMY3) and actual meteorological year (AMY) weather data that are used to simulate both end-use load profiles and solar production profiles. Using both weather data sources allows us to compare more recent weather than used to construct the TMY3 dataset, and potentially allows us to observe more extreme weather conditions. Still, our analysis relies primarily on

TMY3, which selects actual weather data from the most typical month of a given historical period, relying on both average and extreme weather (i.e. the selection tries to match a distribution of temperature outcomes rather than solely the median outcome) [36]. More information on both the temperature and solar radiation data inputs are provided in supplementation data Figs. 9–1 and 9–2.

Our analysis relies on a large and statistically representative set of end-use level building models that, in the baseline case, reflect the present-day distribution of building envelope and equipment characteristics across the entire stock of U.S. single-family detached homes. Focusing on a set of ten climatically diverse study locations, the analysis evaluates PVESS backup performance across 170,000 unique building load profiles, allowing for robust insights into the effects of building stock transformations on PVESS backup power capabilities. These building load profiles are simulated using the National Renewable Energy Laboratory's (NREL) ResStock simulation tool to create a statistically representative sample of 1000 baseline building models for each location studied (Fig. 1) [37]. The baseline building models for each location are based on probabilistic distributions of more than 100 building stock characteristics (e.g. building insulation, HVAC technology type, square footage, heating fuel), reflecting characteristics of the present-day building stock [38]. Those probabilistic distributions are derived from a wide range of empirical data, including the U.S. Census, the U.S. Energy Information Administration's Residential Energy Consumption Survey (RECS), and whole-building interval meter data from residential utility customers [38]. More information about the probability distributions for the housing characteristics can be found in an online data repository [39].

We then modify these baseline buildings by applying a series of building envelope efficiency (e.g., insulation and air sealing), electrification (e.g., heat pumps, water heaters, dryers, and cooking equipment), and load flexibility (temperature set-point adjustments) measures. Building envelope efficiency measures reduce median annual energy consumption in our buildings across the 10 locations by 3–12 %. Our load flexibility measure is implemented by applying 5 °F increase (cooling) and 6 °F decrease (heating) in temperature set points. In addition, we studied several heat pump configurations that incorporate different efficiency and sizing assumptions. Heat pumps are modeled with performance and capacity curves with outdoor temperature as the dependent variable (find more information in Supplemental data Table 9–2). Our electrification measure involves electrifying water heating and cooking with heat pump water heaters and induction stoves.

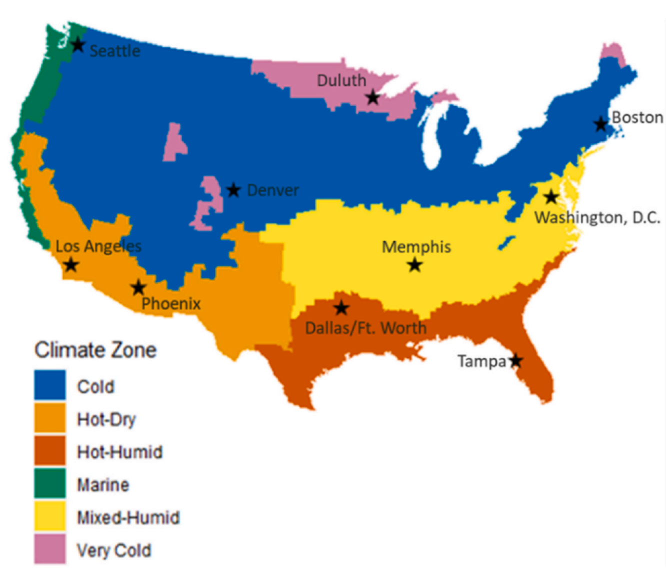

Fig. 1. Department of Energy Building America Climate Zones, with stars indicating our focus locations within the study.

For computational tractability, we select 10 locations across the country with differing climate and solar insolation levels (see Fig. 1). Overall, we model 17 building measure bundles, yielding a total of 170,000 unique building load profiles (17 measure bundles x 10 locations x 1000 homes/location). A more detailed table that explains the difference between all 17 measures is provided in the Supplemental data Table 9–2 and corresponding text.

To produce solar generation profiles, we apply the same weather data that are used in the underlying ResStock building simulations to ensure geospatial and temporal alignment. In total, 10 weather locations were used, and the corresponding weather data combines both ground based measurement data and solar radiation data from NREL's National Solar Radiation Data Base (NSRDB) [40]. Then, we use NREL's System Advisor Model (SAM), which outputs AC solar production profiles. For these simulations, we use default system losses from NREL's SAM tool of 14 % and an inverter efficiency of 96 % and assume a 1.2 inverter loading ratio, 180 azimuth, fixed-roof system with tilt equal to the latitude of the weather station location [41,42]. We size the solar system to meet 100 % of each building's annual load, subject to available roof area. The presumption is that PV systems are sized for reasons other than backup power (e.g., to minimize utility-bills). Such assumption is consistent with current installation practices in most markets [43] though PV systems sized for resilience purposes could be larger [44]. The roof constraint assumes that only 70 % of total roof area is available to the PV, though this constraint rarely binds as most modeled solar systems take up less than half of the total roof area (see Fig. 9–5 in supplemental data).

Finally, we simulate power interruption profiles by defining the start date, start time, and duration of each interruption event. The interruption start date is defined for each individual building model based on the daily net-load (i.e., gross load – PV production calculated for each day of analysis). For our base-case interruption scenario, the interruption begins on the 90th percentile net-load day, which corresponds to the day with the 36th highest net load out of the 365 days in the year. We default to starting the interruption at midnight. The interruption durations then extend for a specified number of days (in the base-case, a 3-day power interruption is assumed).

When studying resilience issues within the electricity sector, it has previously been shown that extreme weather conditions are more important to consider over typical or average conditions [45–48]. Given that concern, we replicate our analysis using AMY data. However, using AMY data is significantly more data intensive given the need to model more than a decade of 15-min load and solar intervals; therefore, we only modeled two locations to assess if TMY3 data understates the impact of extreme weather: (1) Boston (to represent cold-weather locations) and Phoenix (to represent hot-weather locations). We perform calculations using TMY3 weather data for all locations and 11 years of historical AMY data (2011–2021) for Boston and Phoenix. Comparisons of results using those different sets of weather data are provided in the discussion section.

2.2. Optimization and dispatch model used to size PVESS

Across all residential buildings and scenarios, the analysis employs a linear optimization model to determine the minimum required battery storage size needed to provide backup power over the corresponding power interruption event. Fig. 2 provides a graphical representation of how the linear optimization model connects with the key data inputs summarized in the previous section to calculate our results. An illustrative time-series figure for each location is provided in the Supplemental data Fig. 9–6.

Since we aim to understand the technical capability of a PVESS to provide backup, we limit the operation of the system to solely provide backup during interruption events. We develop the optimization model to solve for the minimum storage size (in kWh) required to serve specified critical loads over the duration of a given power outage, ensuring

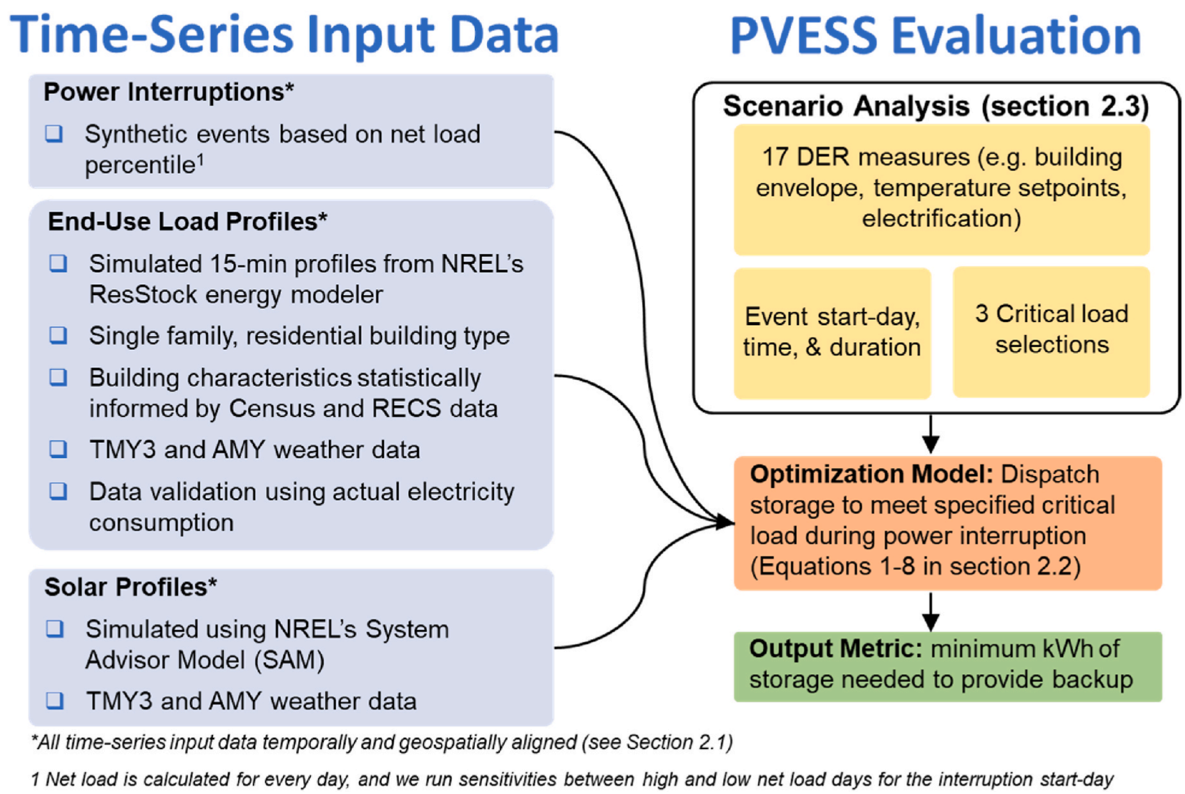

Fig. 2. Schematic summarizing key data sources and corresponding use in PVESS evaluation methodology.

load is met for each 15-min time interval during the interruption. To calculate the minimum size of storage, we develop a linear objective function, a variety of linear constraints, and a specific electric demand and solar profile. The key variables are the size of storage system, the storage's state of charge, and power going into or out of storage in one-time step (t = 15 min). We treat storage system size (Y) as the decision variable.[1] We do not treat inverter size (e.g. power capability of storage) as a decision variable because, for a back-up power system, it is dictated by customer demand – which is an exogenous assumption in our model framework – rather than PV or storage size. Furthermore, we do not implement a minimum or maximum state of charge, effectively meaning that the optimization program solves for "useable" capacity. The below equations mathematically describe the objective function. The battery degradation cost (D) is included in the objective function to eliminate the error of simultaneous discharging and charging of the battery which can result if no cost is placed on discharging.

$$\text{Objective function}: Minimize(\ Y + B_d * D) \qquad \text{(Eq. 1)}$$

Where.

Y = size of storage system (kWh)
B_d = storage discharging, 15 min interval (kW)
D = Cost of discharging (i.e., degradation cost) ($/kWh)

We implemented several operational constraints on the system, shown below in equations (2)–(8). The storage constraints are defined in equations (2)–(6). For simplicity, we assume that the storage can charge or discharge its full capacity in each 15-min time step and has a 92 % one-way storage efficiency. The main operational constraint placed on the PVESS is the demand balancing equation (Eq. 7). This equation sets the rule that the energy consumption must match the energy production during a given time step. The left-hand side represents household energy use while the right-hand side represents energy production (i.e., positive terms for storage discharging, solar energy production, or avoided consumption due to our reliability constraint) and energy consumption (i.e., negative terms for storage charging or curtailed solar production). The final constraint establishes the bound on how much electricity can be shed due to our reliability constraint (Eq. (8)).

$$\text{Beginning state of charge}: SOC_0 = Y * SOC_b \qquad \text{(Eq. 2)}$$

$$\text{Storage state of charge}: SOC_{k+1} = SOC_k + \left[\frac{\eta B_C(k)}{4} - \frac{B_d(k)}{\eta * 4}\right] \qquad \text{(Eq. 3)}$$

$$\text{State of charge range}: 0 \le SOC_k \le Y \qquad \text{(Eq. 4)}$$

$$\text{Power in rate}: 0 \le B_C(k) \le Y \qquad \text{(Eq. 5)}$$

$$\text{Power out rate}: 0 \le B_d(k) \le Y \qquad \text{(Eq. 6)}$$

$$\text{Demand balance}: L(k) = B_d(k) - B_C(k) + S(k) + E_l(k) - D_{pv}(k) \qquad \text{(Eq. 7)}$$

$$\text{Reliability constraint}: \sum E_l(k) \le 0 \qquad \text{(Eq. 8)}$$

Where.

SOC_k = state of charge of storage at time step k (kWh)
B_c = storage charging, 15 min interval (kW)
B_d = storage discharging, 15 min interval (kW)
η = storage efficiency (%)
Y = size of storage system (kWh)
L (k) = demand at time step k, 15 min interval (kW)

[1] We also place a small cost on discharging electricity from the storage unit to ensure that the optimization algorithm does not generate inappropriate solutions with discharging and charging simultaneously.

$E_l(k)$ = electricity shed from given demand profile at time step k, 15 min interval (kW)
S (k) = power generated from solar at time step k, 15 min interval (kW)
$D_{pv}(k)$ = curtailed PV production, 15 min interval (kW)

In the framework above, we assume that future demand for electricity and future solar production is known. We use the optimization solver, Computational Infrastructure for Operations Research (COIN-OR, or "Clp"). This solver is used for linear programming. The optimization model is implemented utilizing the Julia programming language and the package JuMP [49].

The primary metric for our analysis is the median required storage size needed to meet load at every single time step during our defined power interruption across all modeled buildings in each location. As noted above, we have results from over 170,000 individual building models, given we simulate 1000 building models for each of the 10 geographic locations and 17 different building measures. We estimate the entire distribution of battery sizes for the entire building stock but focus on the median required storage size in each location and for a given building measure to better highlight how changes to our building measures impact battery sizes for the typical residential home. We still share full distributions of results, where relevant.

2.3. Scenario and sensitivity analysis description

Our analysis focuses on how required battery sizing is affected by the timing and duration of power interruption events (including coincidence with extreme weather events), the set of building loads included for backup power, and a variety of building measures. Table 1 summarizes the key parameters we adjust in our analysis. Our baseline interruption scenario involves a 3-day interruption event that starts at 12am on the 90th percentile net-load day (i.e. the day with the 36th highest net load out of the 365 days in the year). We assume that the storage unit has a 100 % beginning storage state of charge at the time of the interruption. Though we present results with both whole-home backup and limited critical load backup (no heating and cooling), most of our results focus on PVESS capabilities to meet critical loads with heating and cooling. The load measures in this study principally impact heating/cooling loads, hence our focus on critical-load backup with heating and cooling.

Our critical load assumptions are informed by a set prior literature that focused on the Value of Lost Load (VoLL). In particular, past research has surveyed customers in the northeast asking about load prioritization during interruption time periods.[2] The top 7 categories selected by respondents in rough order of prioritization were lighting, refrigeration, chargers, computers, TV, heaters, and air conditioning [50,51]. Informed by this literature, we designate 6 out of 15 disaggregated end-use types in the ResStock building simulations as critical: refrigeration, interior lighting,[3] a limited set of plug loads,[4] well pumps, space heating, cooking ranges, water heating, and space cooling. End-uses that we deem non-critical are fans (bath, ceiling), clothes dryer/washers, pool equipment, dish washers, exterior lighting, and full plug loads (other ancillary equipment like televisions, microwaves, humidifiers are unfortunately not disaggregated beyond a generic 'plug load' category in ResStock). We also consider a limited critical load case without heating and cooling demand. A visual representation of these assumptions is depicted in Fig. 9–3 in the supplemental data

Table 1
Summary of parameters and scenarios considered for the scenario analysis.

Scenario	Assumption
Building Measure	17 different measures considering load flexibility, energy efficiency, and electrification (see Supplemental Tables 9–2 for details and labels for analyzed building measures)
Backup Load	• Limited critical load (no heating/cooling) • Critical load (w/heating/cooling) • Whole-home
Interruption start day (based on net load percentile within month)	Range from 1st percentile to 99th percentile
Interruption length (days)[a]	1; 2; 3; 4; 5; 6; 7

[a] Results for this scenario are shared in the supplemental information.

3. Results

Our results section is split between two scenarios: storage system sizing for the (1) baseline (present-day) building stock and (2) the building stock with the energy efficiency, load flexibility, and electrification measures.

3.1. Baseline building stock

For the baseline building stock, the median required storage size across all modeled buildings ranges from 10 kWh in LA to 90 kWh in DFW and Phoenix (Fig. 3). While we focus mostly on medians in this

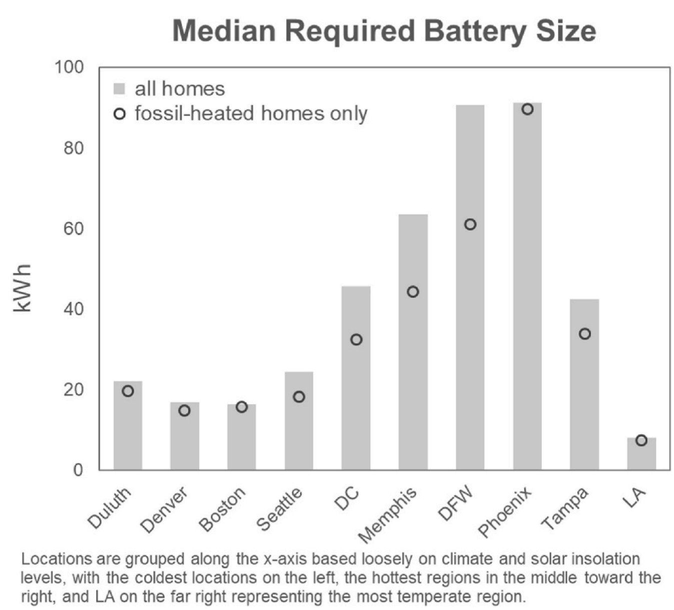

Fig. 3. Storage size needed to maintain power during the 3-day interruptions with baseline building stock. Critical-Load scenario includes heating and cooling loads. Assumes 100 % beginning storage state of charge.

[2] In both studies, the authors asked the respondents to select electric appliances they would like to use *within a 20 Amp limitation*, which was determined after testing several combinations of electric appliances that cover bare necessities (i.e., critical demands).

[3] Critical lighting load is defined as interior light usage from 5pm to 12am.

[4] The ResStock model does not provide detailed plug load disaggregation. Therefore, we define our critical plug load as a constant 70 W demand, accounting for the typical usage of low demand computer, internet, and phone charger end-uses.

section, required storage sizing varies widely across individual homes in each location (see Fig. 6 for the distribution of results across all 1000 building models per location). Electric-resistance heating is highly energy intensive and providing backup power to homes with electric resistance heating over a 3-day interruption would require extremely large batteries in most locations (see Supplemental Fig. 9–8). The fat tail of the distribution in Supplemental Fig. 9–7 highlights the extent of electric resistance heating in Memphis and DFW.

Fig. 4 shows that there is a linear relationship between the required storage size and the net critical load over the interruption event. The relationship implies a 1.1 kWh increase in storage size for each kWh increase in net load during an outage event across all locations and building models, aligning with storage charging and discharging inefficiencies. This basic relationship underlies many of the results presented later in this paper and can also serve as a useful heuristic for sizing storage systems. Deviations above the trend line (see insert in Fig. 4) are cases where the load shape/timing during the interruption impacts storage sizing, solar curtailment occurs, and/or the storage power constraint binds.

3.2. Impacts of set-point adjustments, energy efficiency, and electrification

In Fig. 5, we sequentially vary individual measures to show the incremental impacts of set-point adjustments, building envelope efficiency, heat pump retrofits, and full building electrification on changing the minimum storage size for all 10 locations studied. Our set-point adjustment measure reduces required storage size across all locations. The largest reductions (14–25 kWh) are in the five locations with hot summers and/or with a concentration of electric-resistance heating (DC, Memphis, DFW, Tampa, Phoenix). Effects in other locations are negligible, due to mild summers and fossil-based heating. Building envelope measures further reduce storage sizing across all locations similarly to the set-point adjustment measure. Set-point adjustments in cold weather locations become more impactful once heat pumps are installed: 8–14 kWh reduction in median storage size when heat pumps are installed, compared to 1–3 kWh when the baseline building stock is analyzed. In contrast, in hot-weather locations, the impact of set-point adjustments is lower (though still meaningful) once heat pump and building envelope measures are installed: 4–8 kWh reduction in storage sizing vs. 14–25 kWh in the baseline building stock. Similar results occur for the energy efficiency measures (see Fig. 9–15 in the supplemental data for more detail).

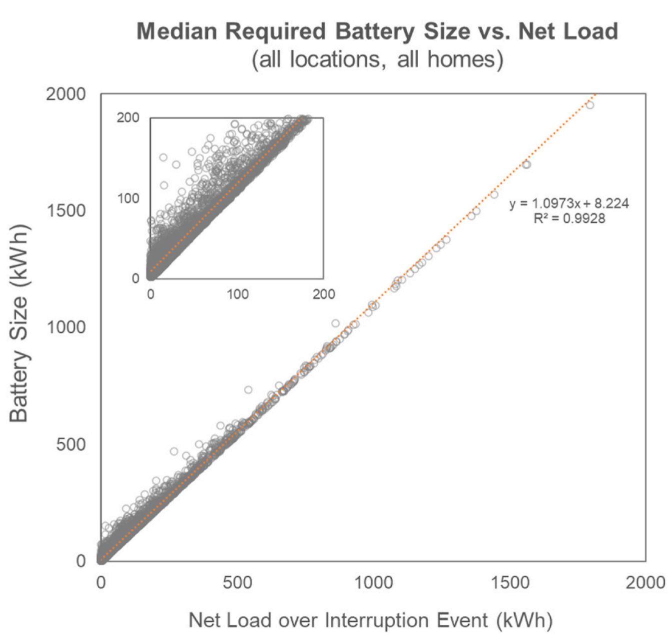

Fig. 4. Correlation between required storage size and net load of the power outage event with the baseline building stock.

Heat pump retrofits have different directional impacts on battery sizing depending on the location. In hot locations (Phoenix, Tampa, DFW, Memphis), heat pump retrofits reduce median storage sizing by ~10–30 kWh, due to replacement of inefficient air conditioning. In cold locations where fossil-based heating is used in the current building stock, heat pump retrofits necessitate larger batteries (10–30 kWh more in Denver, Boston, Seattle; 50 kWh more in Duluth). Our electrification measure has negligible impact on storage sizing, given the small energy consumption by these loads over the duration of an interruption event. Required median storage size declines in some locations from replacing inefficient electric end-uses and the side-effect of heat-pump water heaters to reduce internal building cooling loads (e.g., in DFW, Phoenix, and Tampa).

As previously noted, required storage sizing varies widely across homes in each location. Fig. 6 shows corresponding shifts in the underlying distribution that result from the building measures analyzed. Efficiency and (to a lesser extent) load flexibility measures tend to compress these distributions (blue line in Fig. 6). Heat pump retrofits compress the distributions in hot climates and in regions with a high concentration of electric-resistance heating in the baseline stock (e.g., Memphis and DFW). However, in fossil-heated cold climates, heat pumps significantly widen the distributions (e.g., Duluth, Denver, Boston). Furthermore, the building measure impacts the season which drives storage sizing decision given that the net load calculation updates with the changing load profile resulting from a new building measure. DFW, Boston, Memphis, and Washington DC have summer power interruption start days in 20–40 % of their baseline residential building stock. That percentage is reduced to 0 % of the building stock when moving from the baseline to all measures building stock scenario (see Figs. 9 and 10 in the supplemental data section). All other locations' interruption start day season distribution does not change due to the building stock scenario, with the winter season driving most of the interruption start days. Phoenix is the only area that retains a large majority of summer season system sizing once the all building measures scenario is applied.

The analysis thus far assumed interruptions begin on the 90th percentile net-load day (challenging but not extreme conditions). Sizing the storage instead for less or more extreme conditions significantly impacts the required storage size, especially for homes with large electric heating/cooling loads (Fig. 7). For that reason, sensitivity to interruption timing is most acute for cold-weather homes with electric heat (all measures cases) and for inefficient hot-weather homes (baseline building stock case). Efficiency and load flexibility can reduce that sensitivity, effectively extending the range of interruption conditions over which a given PVESS can provide backup power. For example, incremental storage capacity needed when sizing based on a 90th rather than a 99th percentile net-load day is reduced from 65 kWh to 20 kWh in DFW or from 45 kWh to less than 5 kWh in Tampa. The ultimate decision on which sizing criteria will be up to individual households in collaboration with system installers.

In many backup power applications today, customers back up a limited set of critical loads that exclude heating and cooling loads. For limited critical load backup without heating and cooling, storage sizes are quite small (<15 kWh) across all locations and are largely unaffected by the set of building measures (circles in Fig. 8). Whole-home backup requires about 30 kWh more storage, on average, compared to what is needed for backup of just critical loads with heating and cooling; that difference is largely unaffected by the set of load measures (triangles in Fig. 8).

4. Discussion

The results above focus on the technical impacts on PVESS sizing

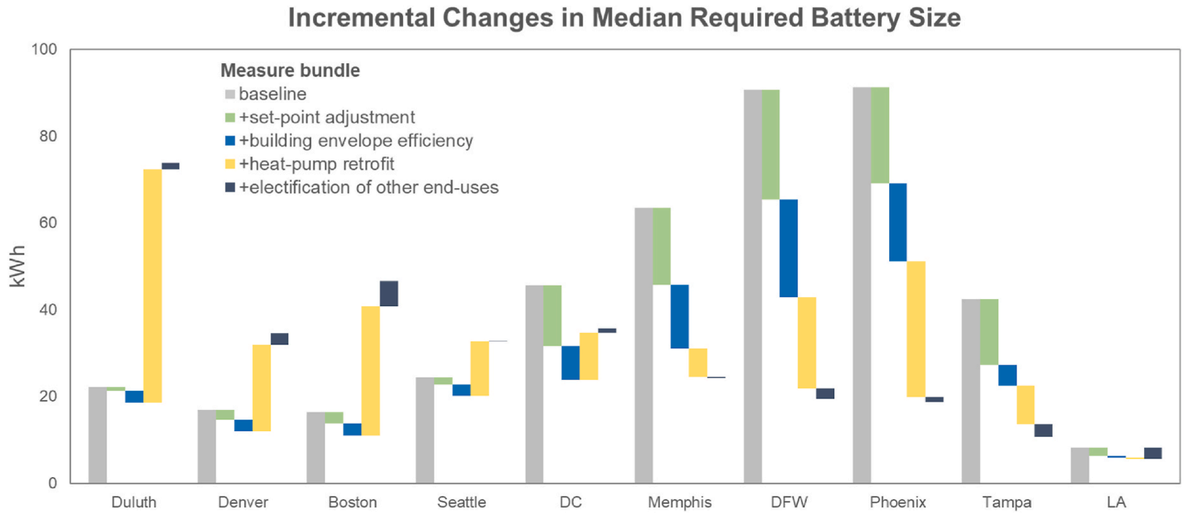

Fig. 5. Waterfall chart showing impacts on median storage sizing as different efficiency and electrification measures are sequentially added.

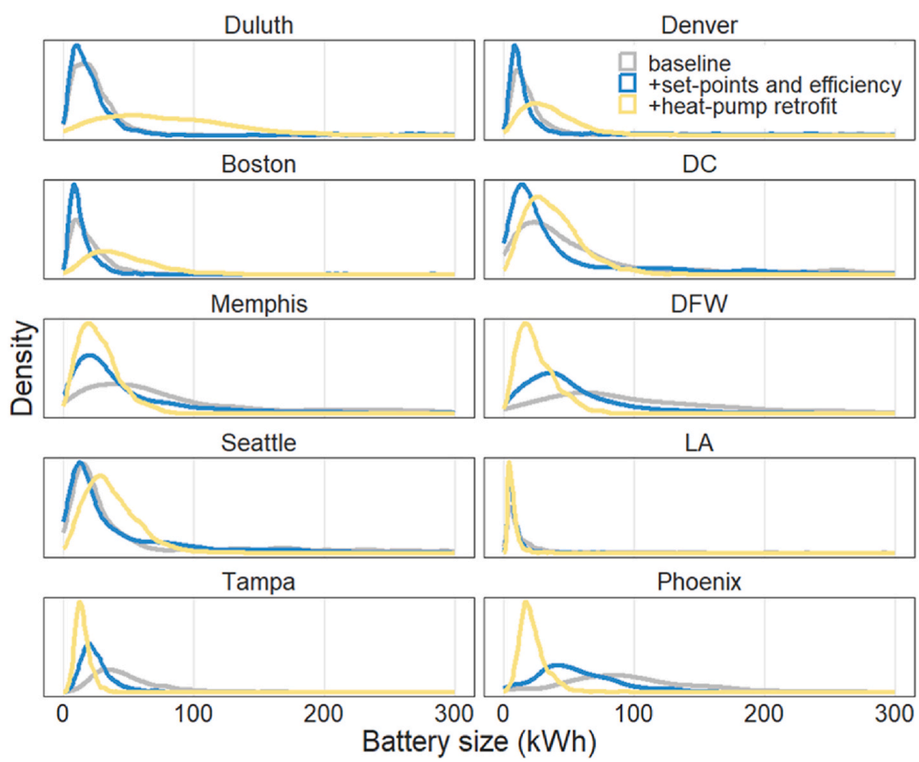

Fig. 6. Distribution in Required Storage Size across Homes in Each Location for three building measures: (1) baseline, (2) set-points and efficiency upgrades, and (3) heat-pump retrofits.

decisions when providing backup power under a variety of end-use load assumptions. However, such results do not provide an indication of the market potential for this new backup power option amongst the residential customer class. A 30 kWh storage system is at the upper end of the size range of what is typically observed in the residential market today [14]. We can determine what percentage of homes within our distribution of household building models would be able to technically meet their backup power needs with a system of that size, under our base-case power interruption conditions.

Fig. 9 shows that a 30 kWh system could provide complete mitigation of power interruptions to some portion of the existing building stock, ranging from 6 % of homes in Phoenix to 90 % of homes in LA. However, through some combination of set-point adjustments, building envelope efficiency upgrades and (in hot climates) heat pump retrofits, this potential market for full mitigation can be raised to at least ~60 % of homes in all 10 regions. Such a high percentage suggests that the technical capabilities highlighted in this paper could serve a sizable portion of the residential building stock in the 10 locations studied. In places dominated by cooling loads, the heat pump retrofit increases the addressable market (e.g. Phoenix, Tampa) whereas in places dominated by heating loads, that retrofit significantly decreases the addressable market (e.g. Duluth, Denver, Boston). Of course, any customer's decision to install a backup PVESS would entail economic considerations that incorporate a customers' value of electric resiliency or value of lost load. Such analyses were out of scope for this paper.

We also analyzed how our building measure scenarios impact the

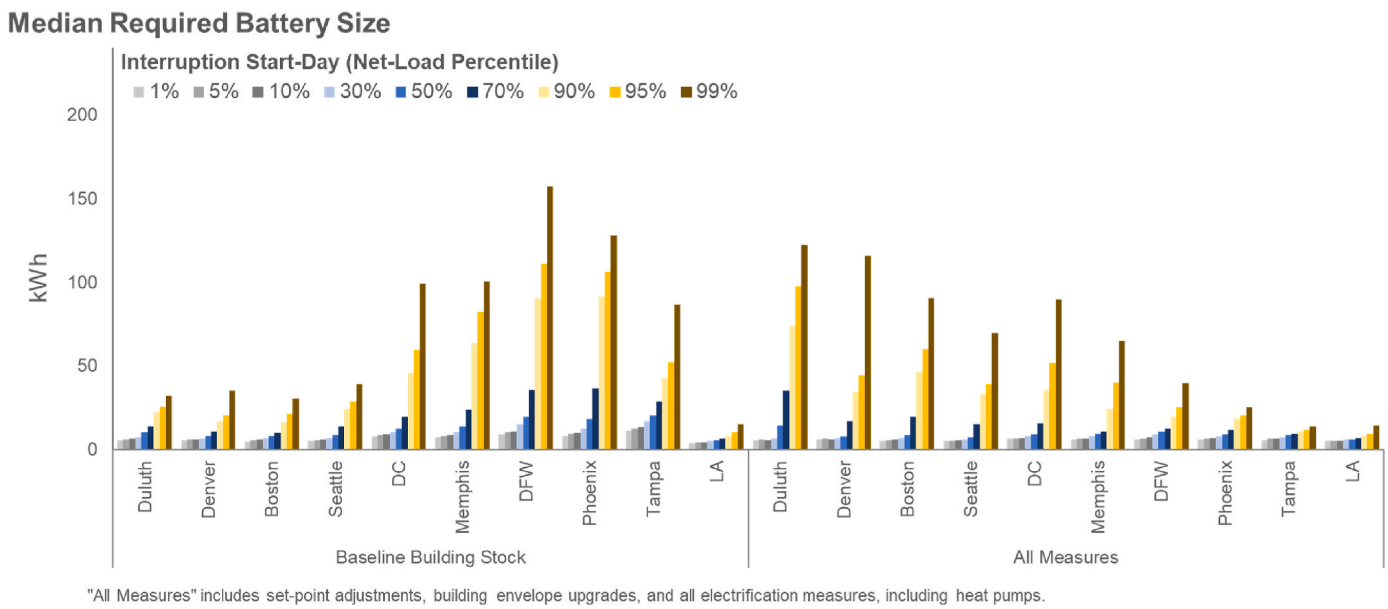

Fig. 7. Sensitivity of median results to interruption start day. The interruption start day is defined for each individual building model based on the daily net-load. This figure explores variation away from our baseline assumption of the 90th percentile netload day.

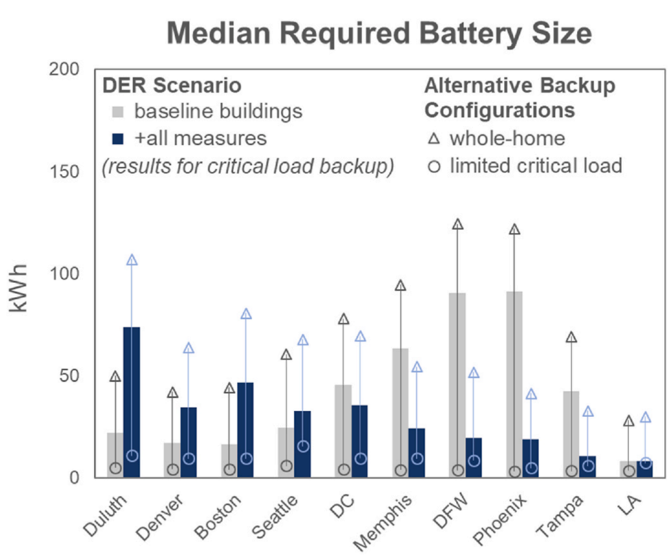

Fig. 8. Impact of backup load scenarios on median building results.

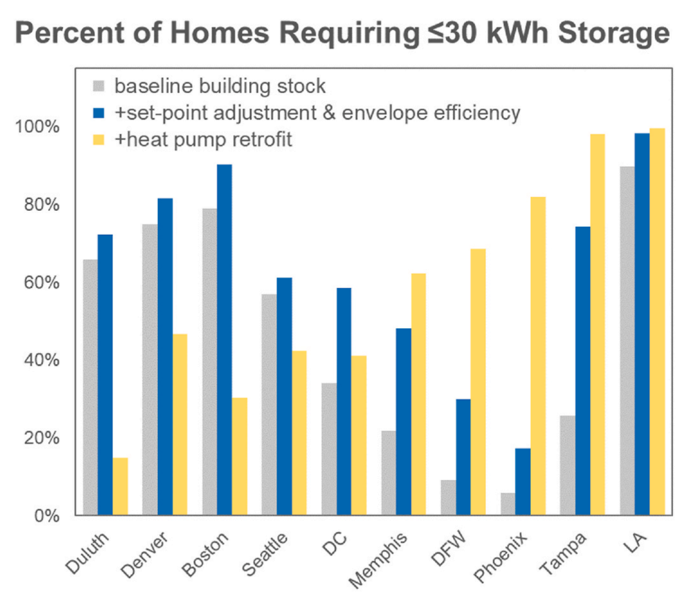

Fig. 9. Breakdown of distribution of homes that require storage less than 30 kWh across various load measures.

number of days a 30 kWh PVESS could provide backup power to the residential building models. In Phoenix, moving from the baseline building measures to the all measures case increases backup potential from 1 to 7 days. In cold locations, electrifying space heating tends to have the opposite effect and shortens the backup period for a 30 kWh PVESS in Denver and Boston from 7+ days to 2 days. Required storage sizing scales more-or-less linearly with interruption duration (right insert Fig. 9–13 in the supplemental data), as daily PV generation typically is not enough to fully replenish the storage, so initial state of charge gets drawn down over the course of the event.

We did not explicitly model electric vehicles (EVs) in this study, in part because while they could potentially be an additional load for the PVESS to serve, they could also be a large source of energy storage for backup power (see Fig. 9–17 in the supplemental data), but also because current EV charging methods and data sources are based on typical operating rather than power interruption conditions, when customers' driving behavior could differ significantly [52]. Our results illustrate several cases where the large kWh sized batteries in bi-directional EVs could be essential to enabling full mitigation of interruptions via PVESS: Customers with heat pumps in cold-weather locations, especially for extreme cold-weather events/locations or, more generally, customers with particularly high consumption levels (relative to the medians in each location). Future work would need to consider how driving and charging behavior may differ significantly from the norm during a long-duration power interruption and how customers might balance deploying an EV for backup power use versus for serving driving demand. Our results provide valuable information to policymakers and market participants considering storage sizes required to effectively manage electricity demand during power interruption scenarios.

When replicating our analysis using AMY data from 2011 to 2021 (see Fig. 10), Phoenix shows slightly larger required storage sizes, for interruptions starting on either the 90th or 99th percentile net-load day

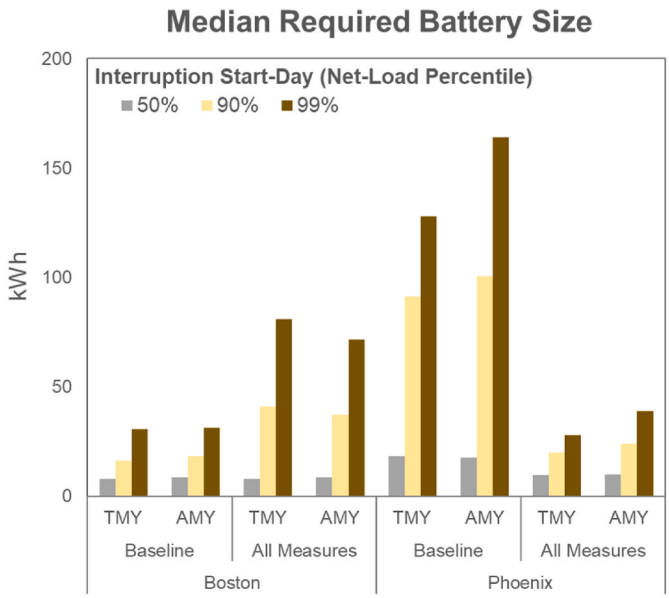

Fig. 10. Median required storage size by interruption start-day comparing TMY3 and AMY datasets. The interruption start day is defined for each individual building model based on the daily net-load. This figure explores variation away from our baseline assumption of the 90th percentile netload day.

(no difference for 50th). Results for Boston show the opposite trend (TMY3-based sizing > AMY-based sizing). Directional differences between the hot-weather and cold-weather location might suggest the impact of a changing climate, since TMY3 data rely on data through 2005, while our AMY data is for the most recent decade (i.e., weather patterns have generally become warmer). On balance, though, our storage sizing results were not significantly different, suggesting that TMY3 data can still be relied upon when applied in resilience settings. More important is the choice of net load percentile as suggested in Fig. 7. Nevertheless, a changing climate might pose more serious challenges in the future as TMY3 data becomes more outdated.

5. Conclusions

In this paper, we analyzed the performance of PVESS in providing backup power across a wide range of geographies and load scenarios. Our approach provides an assessment of the technical potential of PVESS to enhance customer resilience within the residential sector. Our results relied on load profiles statistically representative of the current United States building stock, and given deep decarbonization policy goals, evaluated the impact of energy efficiency, load flexibility, and electrification measures on the PVESS system size required to provide backup power over long-duration power interruptions. We were able to capture the inherently interactive nature of the various measures analyzed.

In hot-weather climates, the set of efficiency, flexibility, and electrification measures reduce the battery sizing needed for backup power over a 3-day interruption from a median (across all homes in each location) of roughly 90 kWh for the baseline building stock to 20 kWh once all measures are applied. Given typical residential PVESS sizing observed in the market today, these load measures would increase the addressable market for PVESS backup power in those locations from less than 10 % of homes today to more than 60 % in a future with highly efficient, flexible, and electrified homes. This result illustrates, in part, the value of pairing PVESS with building efficiency upgrades and smart home controls. Conversely, in cold weather locations, the switch from fossil-based heating to electric heat pumps leads to a substantial increase in backup power battery sizing, even after accounting for load reductions from building envelope efficiency and load flexibility measures. In one cold weather location, for example, the median required battery size rises from less than 20 kWh in the baseline stock to 50 kWh once all load measures are applied. Maintaining existing fossil-based heating systems as a backup heating source in cold-weather locations may therefore be necessary in some cases, if households expect to rely on PVESS for backup power during long-duration power interruptions. We found that PVESS backup power for homes with electric-resistance heat is impractical; replacing with a heat pump is effectively a prerequisite. Electrified cooking and water heating have marginal impacts on backup storage sizing.

Though our results focused on median system sizes across the distribution of building models, we did show that the required storage sizing does varies widely across homes in each location, given the variety of building characteristics in the residential building stock. We also found that our results were quite sensitive to the interruption start day, with some locations having a 10x change in median system size when moving from a typical weather day to an extreme weather day. Efficiency and load flexibility can reduce that sensitivity, effectively extending the range of interruption conditions over which a given PVESS can provide backup power. Nevertheless, identifying the preferred sizing criteria for will be a difficult decision for homeowners and system installers.

Bi-directional EVs may be essential to enabling PVESS backup power in some circumstances, given their typically large kWh sizes compared to our storage system sizing findings, but future research would need to consider how electric vehicle transport demands would compete with the household backup power use case in the event of a long duration interruption. Future research could also evaluate load flexibility beyond temperature set point changes, especially as it pertains to non-heating and cooling demands. Finally, this paper was focused exclusively on long-duration interruption events, which can be extremely costly for electric consumers, but are also the least common form of power interruption experienced by customers in the United States. Future work should consider how stochastic, short-term interruptions may be met by PVESS backup, especially considering economic operations that PVESS might be performing leading up to a power interruption event. Such work could incorporate estimates of the VoLL to provide estimates of the economic resiliency value of PVESS across short- and long-duration interruption events.

CRediT authorship contribution statement

Will Gorman: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Galen Barbose:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Cesca Miller:** Formal analysis, Data curation. **Philip White:** Software, Methodology, Formal analysis, Data curation. **Juan Pablo Carvallo:** Funding acquisition, Conceptualization. **Sunhee Baik:** Data curation.

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.

The authors do not have any competing interests to declare.

Data availability

Data will be made available on request.

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 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 on an earlier draft were provided by Jeff Marqusee (NREL) and Ted Burhans (SEPA).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2024.132180.

References

[1] EnergySage. EnergySage's solar installer suvery. results. Energy Sage; 2022. 2021.
[2] Brown DP, Muehlenbachs L. The value of electricity reliability: evidence from battery adoption. Resoures for the Future Working Paper. Resoures for the Future Working Paper 2023:2.
[3] Brown DP. Socioeconomic and demographic disparities in residential battery storage adoption: evidence from California. Energy Pol 2022;164:112877. https://doi.org/10.1016/j.enpol.2022.112877.
[4] Burillo D, Chester MV, Pincetl S, Fournier E. Electricity infrastructure vulnerabilities due to long-term growth and extreme heat from climate change in Los Angeles County. Energy Pol 2019;128:943–53. https://doi.org/10.1016/j.enpol.2018.12.053.
[5] Mukherjee S, Nateghi R, Hastak M. A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S. Reliab Eng Syst Saf 2018;175:283–305. https://doi.org/10.1016/j.ress.2018.03.015.
[6] Shield SA, Quiring SM, Pino JV, Buckstaff K. Major impacts of weather events on the electrical power delivery system in the United States. Energy 2021;218:119434. https://doi.org/10.1016/j.energy.2020.119434.
[7] Brockway AM, Dunn LN. Weathering adaptation: grid infrastructure planning in a changing climate. Clim Risk Manag 2020;30:100256. https://doi.org/10.1016/j.crm.2020.100256.
[8] Ebi KL, Vanos J, Baldwin JW, Bell JE, Hondula DM, Errett NA, et al. Extreme weather and climate change: population health and health system implications. Annu Rev Publ Health 2021;42:293–315. https://doi.org/10.1146/annurev-publhealth-012420-105026.
[9] Larsen PH. A method to estimate the costs and benefits of undergrounding electricity transmission and distribution lines. Energy Econ 2016;60:47–61. https://doi.org/10.1016/j.eneco.2016.09.011.
[10] Fant C, Boehlert B, Strzepek K, Larsen P, White A, Gulati S, et al. Climate change impacts and costs to U.S. electricity transmission and distribution infrastructure. Energy 2020;195:116899. https://doi.org/10.1016/j.energy.2020.116899.
[11] Tian M-W, Talebizadehsardari P. Energy cost and efficiency analysis of building resilience against power outage by shared parking station for electric vehicles and demand response program. Energy 2021;215:119058. https://doi.org/10.1016/j.energy.2020.119058.
[12] Omb, Nreca, Eei, Nasuca, Schwartz L. Utility investments in resilience of eletricity systems. Lawrence Berkeley National Laboratory; [n.d].
[13] Barbose G, Darghouth N, O'Shaughnessy E, Forrester S. Tracking the sun: pricing and design trends for distributed photovoltaic systems in the United States. 2022 Edition. Lawrence Berkeley National Laboratory; 2022.
[14] Barbose G, Elmallah S, Gorman W. Behind the meter Solar+Storage: market data and trends. Lawrence Berkeley National Laboratory; 2021. https://doi.org/10.2172/1810087.
[15] Gorman W. The quest to quantify the value of lost load: a critical review of the economics of power outages. Electr J 2022;35:107187. https://doi.org/10.1016/j.tej.2022.107187.
[16] Sanni SO, Oricha JY, Oyewole TO, Bawonda FI. Analysis of backup power supply for unreliable grid using hybrid solar PV/diesel/biogas system. Energy 2021;227:120506. https://doi.org/10.1016/j.energy.2021.120506.
[17] Green Mountain Power. Resilient Neighborhood. Green Mt power resilient neighborhood. 2023. https://greenmountainpower.com/news/resilient-neighborhood/.
[18] Zhang Y, Ma T, Yang H. A review on capacity sizing and operation strategy of grid-connected photovoltaic battery systems. Energy Built Environ 2024;5:500–16. https://doi.org/10.1016/j.enbenv.2023.04.001.
[19] Hassan Q, Algburi S, Sameen AZ, Al-Musawi TJ, Al-Jiboory AK, Salman HM, et al. A comprehensive review of international renewable energy growth. Energy Built Environ 2024. https://doi.org/10.1016/j.enbenv.2023.12.002. S2666123323001186.
[20] Gorman W, Barbose G, Pablo Carvallo J, Baik S, Miller C, 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. https://doi.org/10.1016/j.apenergy.2023.121166.
[21] Gilani MA, Kazemi A, Ghasemi M. Distribution system resilience enhancement by microgrid formation considering distributed energy resources. Energy 2020;191:116442. https://doi.org/10.1016/j.energy.2019.116442.
[22] Kosai S, Cravioto J. Resilience of standalone hybrid renewable energy systems: the role of storage capacity. Energy 2020;196:117133. https://doi.org/10.1016/j.energy.2020.117133.
[23] Bhayo BA, Al-Kayiem HH, Gilani SIU, Khan N, Kumar D. Energy management strategy of hybrid solar-hydro system with various probabilities of power supply loss. Sol Energy 2022;233:230–45. https://doi.org/10.1016/j.solener.2022.01.043.
[24] Mehrjerdi H. Resilience oriented vehicle-to-home operation based on battery swapping mechanism. Energy 2021;218:119528. https://doi.org/10.1016/j.energy.2020.119528.
[25] Creutzig F, Roy J, Lamb WF, Azevedo IML, Bruine De Bruin W, Dalkmann H, et al. Towards demand-side solutions for mitigating climate change. Nat Clim Change 2018;8:260–3. https://doi.org/10.1038/s41558-018-0121-1.
[26] Arowoiya VA, Moehler RC, Fang Y. Digital twin technology for thermal comfort and energy efficiency in buildings: a state-of-the-art and future directions. Energy Built Environ 2024;5:641–56. https://doi.org/10.1016/j.enbenv.2023.05.004.
[27] Altieri D, Patel MK, Lazarus J, Branca G. Numerical analysis of low-cost optimization measures for improving energy efficiency in residential buildings. Energy 2023;273:127257. https://doi.org/10.1016/j.energy.2023.127257.
[28] Li X, Lepour D, Heymann F, Maréchal F. Electrification and digitalization effects on sectoral energy demand and consumption: a prospective study towards 2050. Energy 2023;279:127992. https://doi.org/10.1016/j.energy.2023.127992.
[29] Walker IS, Less BD, Casquero-Modrego N. Carbon and energy cost impacts of electrification of space heating with heat pumps in the US. Energy Build 2022;259:111910. https://doi.org/10.1016/j.enbuild.2022.111910.
[30] Wilson EJ, Christensen CB, Horowitz SG, Robertson JJ, Maguire JB. Energy Efficiency Potential in the U.S. Single-Family Housing Stock 2017. https://doi.org/10.2172/1414819.
[31] Loengbudnark W, Khalilpour K, Bharathy G, Voinov A, Thomas L. Impact of occupant autonomy on satisfaction and building energy efficiency. Energy Built Environ 2023;4:377–85. https://doi.org/10.1016/j.enbenv.2022.02.007.
[32] Langevin J, Harris CB, Satre-Meloy A, Chandra-Putra H, Speake A, Present E, et al. US building energy efficiency and flexibility as an electric grid resource. Joule 2021;5:2102–28. https://doi.org/10.1016/j.joule.2021.06.002.
[33] Carvallo JP, Collins M, Bieler S, Mueller J, Gehbauer C, Larsen P. Indiana 21st century energy policy: emerging technologies on the electricity distribution system. Lawrence Berkeley National Laboratory; 2020.
[34] Browning M, McFarland J, Bistline J, Boyd G, Muratori M, Binsted M, et al. Net-zero CO2 by 2050 scenarios for the United States in the energy modeling forum 37 study. Energy Clim Change 2023;4:100104. https://doi.org/10.1016/j.egycc.2023.100104.
[35] Willems N, Sekar A, Sigrin B, Rai V. Forecasting distributed energy resources adoption for power systems. iScience 2022;25:104381. https://doi.org/10.1016/j.isci.2022.104381.
[36] Wilcox S, Marion W. Users manual for TMY3 data sets. Tech Rep 2008;58.
[37] Present E, White P, Adhikari R, Merket N, Wilson E, Fountanini A. End-Use savings Shapes, public dataset release for residential round 1. National Renewable Energy Lab; 2022.
[38] Wilson E, Parker A, Fontanini A, Present E, Reyna J, Adhikari R, et al. End-use load profiles for the U.S. Building stock: methodology and results of model calibration. Validation, and Uncertainty Quantification 2022. https://doi.org/10.2172/1854582.
[39] NREL. ResStock housing characteristics. 2024. https://github.com/NREL/resstock/tree/develop/project_national/housing_characteristics.
[40] 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. https://doi.org/10.1016/j.rser.2018.03.003.
[41] Barbose G, Darghouth N, O'Shaughnessy E, Forrester S. Tracking the sun 2023 edition: pricing and design trends for distributed photovoltaic systems in the United States. Berkeley, CA: Lawrence Berkeley National Laboratory (LBNL); 2023.
[42] Blair N, DiOrio N, Freeman J, Gilman P, Janzou S, Neises T, et al. System advisor model (SAM) general description (version 2017.9.5). National Renewable Energy Lab; 2018.
[43] Energy Sage. Solar and storage marketplace report 2023. Energy Sage; 2023.
[44] Simpkins T, Anderson K, Cutler D, Olis D. Optimal sizing of a solar-plus-storage system for utility bill savings and resiliency benefits. In: 2016 IEEE power energy soc. Innov. Smart grid technol. Conf. ISGT. Minneapolis, MN, USA: IEEE; 2016. p. 1–6. https://doi.org/10.1109/ISGT.2016.7781237.
[45] Busby JW, Baker K, Bazilian MD, Gilbert AQ, Grubert E, Rai V, et al. Cascading risks: understanding the 2021 winter blackout in Texas. Energy Res Social Sci 2021;77:102106. https://doi.org/10.1016/j.erss.2021.102106.
[46] Jufri FH, Widiputra V, Jung J. State-of-the-art review on power grid resilience to extreme weather events: definitions, frameworks, quantitative assessment methodologies, and enhancement strategies. Appl Energy 2019;239:1049–65. https://doi.org/10.1016/j.apenergy.2019.02.017.
[47] Panteli M, Mancarella P. Influence of extreme weather and climate change on the resilience of power systems: impacts and possible mitigation strategies. Elec Power Syst Res 2015;127:259–70. https://doi.org/10.1016/j.epsr.2015.06.012.
[48] Moreno R, Panteli M, Mancarella P, Rudnick H, Lagos T, Navarro A, et al. From reliability to resilience: planning the grid against the extremes. IEEE Power Energy Mag 2020;18:41–53. https://doi.org/10.1109/MPE.2020.2985439.

[49] Dunning I, Huchette J, Lubin M. JuMP: a modeling language for mathematical optimization. https://doi.org/10.1137/15M1020575; 2015.

[50] Baik S, Davis AL, Park JW, Sirinterlikci S, Morgan MG. Estimating what US residential customers are willing to pay for resilience to large electricity outages of long duration. Nat Energy 2020;5:250–8. https://doi.org/10.1038/s41560-020-0581-1.

[51] Baik S, Davis AL, Morgan MG. Assessing the cost of large-scale power outages to residential customers. Risk Anal 2018;38:283–96. https://doi.org/10.1111/risa.12842.

[52] Yip A, Hoehne C, Jadun P, Ledna C, Hale E, Muratori M. Highly resolved projections of passenger electric vehicle charging loads for the contiguous United States. National Renewable Energy Laboratory Technical Report. 2023.