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County-level assessment of behind-the-meter solar and storage to mitigate long duration power interruptions for residential customers

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HIGHLIGHTS

- Backup capability of solar and storage differs by region in the U.S.
- Small batteries can meet a limited set of critical loads in most counties.
- Electric cooling and heating loads are typically hardest loads to backup.
- Household building attributes like efficiency can impact results up to 20%
- Resiliency value needs to be high to motivate adoption of solar-plus-storage.

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ABSTRACT

Customer concerns over electric system resilience could drive early adoption of behind-the-meter solar-plus-storage (BTM PVESS), especially as wildfire, hurricane, and other climate-driven risks to electric grids become more pronounced. However, the resilience benefits of BTM PVESS are poorly understood, especially for residential customers, owing to lack of data and methodological challenges, making it difficult to forecast adoption trends. In this paper, we develop a methodology to model the performance of BTM PVESS in providing backup power across a wide range of customer types, geography / climate conditions, and long duration power interruption scenarios, considering both whole-building backup and backup of specific critical loads. We combine novel, disaggregated end-use load profiles across the continental United States with temporally and geospatially aligned solar generation estimates. We then implement a PVESS dispatch algorithm to calculate the amount of load served during interruptions. We find that PVESS with 10 kWh of storage can meet a limited set of critical loads in most United States counties during any month of the year, though this capability drops to meeting only 86% of critical load, averaged across all counties and months, when heating and cooling are considered critical. Backup performance is lowest in winter months where electric heat is common (southeast and northwest U.S.) and in summer months in places with large cooling loads (southwest and southeast U.S.). Winter backup performance varies by roughly 20% depending on infiltration rates, while summer performance varies by close to 15% depending on the efficiency of the central air-conditioning system. Differences in temperature set-points in Harris County correspond to a 40% range in winter backup performance and a 20% range in summer performance. Economic calculations show that a customer's resilience value of PVESS must be high to motivate adoption of these systems.

1. Introduction

The rapid cost declines of solar technologies over the last decade led to significant growth of both utility-scale solar power plants connected to the bulk transmission system as well as smaller "behind-the-meter" (BTM) systems sited at an individual electricity customer [1–3]. Similar

Abbreviations: BTM, Behind-the-meter; PVESS, Photovoltaic energy storage system.

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cost declines have occurred for Lithium-ion battery technologies [4], where there is high interest in utility-scale development, with a significant fraction of proposed battery projects co-located with a renewable power plant [5,6]. Paired BTM PVESS, however, is still a minority application in most regions, representing 10% of all U.S. BTM residential solar systems installed in 2021 [7].[1]

Industry observers note that early adoption of BTM solar-plus-storage (PVESS for remainder of the chapter) has been driven, to a significant degree, by customer concerns over electric system reliability and resilience [8].[2] As wildfire, hurricane, and other climate-driven risks to electric grids become more pronounced, those concerns are expected to grow [10]. In such scenarios, the vulnerability of transmission and distribution networks could increase and/or become more costly to maintain due to expensive adaptation activities like undergrounding transmission and distribution infrastructure [11]. Customer-sited backup power applications, therefore, could provide a key foothold for the BTM solar and storage industry and drive customer-adoption. But, the technical resilience benefits of BTM PVESS are poorly understood, owing to lack of data and methodological challenges.[3] Therefore, these benefits are often ignored or estimated in a simplified manner when building customer adoption models [12,13]. Some customer adoption studies assume PVESS can provide full backup during power interruptions, and do not consider heterogeneity across geographies, customer-types, interruption durations, and PVESS system sizes [14].

At the same time, there is active debate on the relative merits of promoting BTM over utility-scale technologies as the electric industry works towards decarbonization [15,16]. Past research has argued that given the relative expense of BTM compared to utility-scale applications, utility-scale technologies should be promoted to achieve rapid decarbonization of the electric grid in a cost effective manner [17,18]. Counterarguments emphasize that BTM technologies could defer and reduce fixed network costs of the electricity system [19]. Though the network benefits of BTM solar and storage are notoriously challenging to estimate [20,21], they should be considered in a cost-optimal plan [22]. As opposed to utility-scale technologies, the reliability and resilience benefits of BTM technologies for households are rarely quantified, in part due to the lack of data and methodological challenges mentioned above. Quantifying these benefits may affect the optimal balance between utility-scale and BTM resources and influence the ongoing debate of the relative merits of these technologies for decarbonization, affordability, and reliability/resilience.

In this paper, we model the performance of BTM PVESS in providing backup power across a wide range of residential customer types (e.g. single-family, mobile, and multifamily), geography / climate conditions (across the continental United States), and power interruption scenarios (e.g. long-duration interruptions of varying frequency, timing, and seasonality), considering both whole-building backup and backup of specific critical loads. Our approach provides an assessment of the technical potential of PVESS to enhance customer resilience. We do so by combining novel, disaggregated, and publicly available end-use load profiles across the continental United States with temporally and geospatially aligned solar generation estimates. We then implement a PVESS dispatch algorithm to calculate the amount of load served during differing long duration power interruptions.

[1] Hawaii is the only region in the United States that has seen significant pairing of BTM storage with solar, where upwards of 90% of new solar systems were paired with a battery in 2021.

[2] In the remainder of this paper, we will mostly use the term 'resilience' given our focus on long-duration interruptions. Prior work has defined mitigation of interruptions greater than24 h as resilience benefits, and we rely on the same definition in this paper [9].

[3] While backup benefits encompass both technical mitigation potential and corresponding economic valuation of the mitigated interruptions, we focus on technical mitigation potential in this paper.

Such analysis fills a literature gap by providing new information about the conditions PVESS technologies can be relied on to serve load during long-duration power interruptions. We find that PVESS with 10 kWh of storage can meet a limited set of critical loads in most United States counties during any month of the year, though this capability drops to meeting only 86% of critical load, averaged across all counties and months, when heating and cooling are considered critical. Backup performance is lowest in winter months where electric heat is common (southeast and northwest U.S.) and in summer months in places with large cooling loads (southwest and southeast U.S.). Furthermore, this paper contributes a unique dataset of county-level mitigation potential for PVESS that researchers in the resilience literature can use to assess the economic benefits of these systems to customers. The breadth of the results also enables public decision-makers at the state and federal level to design, target, and deploy policies that internalize the resilience benefits of PVESS. Finally, the information produced in this paper is useful to both researchers and industry practitioners forecasting future adoption of BTM PVESS systems as well as those evaluating the relative merits of utility-scale and BTM PVESS applications. We show that a customer's resilience value of PVESS must be high to motivate adoption of these systems.

2. Literature review

Past research on the resilience impacts of BTM technologies generally focused either on: (1) development of new optimization and operation methods of PVESS systems, assessing their viability within individual case studies or (2) resilience impacts of PVESS within the distribution system from the perspective of a utility or distribution system operator. Neither of these two approaches lend themselves to significant geographic and building-type heterogeneity, limiting a comprehensive understanding of the scale of applications for BTM PVESS to mitigate power interruptions and correspondingly assess future customer adoption trends.

The first area of literature uses case study analyses of particular buildings and locations in order to demonstrate novel methods for optimal PVESS system sizing and/or to show how including reliability/resilience value impacts PVESS cost-effectiveness. For instance, Laws et al explore the economic and resiliency benefits associated with a hybrid system comprising solar PV and energy storage for commercial buildings and critical infrastructure sites [23]. Anderson et al estimate resiliency value of PVESS plus diesel systems for businesses in New York City, suggesting the potential to reduce $2.5 billion in business losses [23] while other studies have focused on households during extreme and rare weather events [24]. These studies are often extended to achieve additional goals, such as determining the storage size to meet a reliability targets [25], to maximize utility bill savings and resiliency benefits [26], to minimize the lifecycle cost of energy [27], to explore the tradeoffs between interruption probability and storage capacity [28], to consider fuel source vulnerability [29], or to incorporate social equity values [30]. Work exploring the benefits of introducing load control technologies or controlled electric vehicle charging that increase the value of PV has also been performed [31,32]. In general, these studies often rely on stylized scenario analysis [23,33] or statistical models and simulations [24,27,34], but such approaches are tied to the characteristics of reference events and input parameters, which are location-specific.

These studies have improved our understanding of the potential for PVESS-based backup, but their focus makes it challenging to describe variation across regions, interruption conditions, customer-types, building stock, and specific end-uses of electricity. Cole et al is perhaps the most geographically expansive analysis, studying PVESS capabilities across 18 different hurricane events in the southeast, but focus on the supply of a constant, flat load [36]. Furthermore, only a small number of studies in this literature evaluate critical load scenarios. Some of these studies do not specify how they develop a "critical" demand scenario [33,35] or solely rely on a flat percentage of total load

[37–39]. Manz et al identify refrigeration and lighting as critical loads, but instead of explicitly modeling heating and cooling loads, create a generic 'baseline' heating/cooling power consumption [40]. More recent work has been done to understand how end-customers might prioritize various end-uses [41,42], but it has remained challenging to implement such sensitivities in PVESS analysis due to the need to have sufficiently disaggregated demand profiles.

A subset of this literature has also evaluated PVESS capability to serve end-consumers with a wider geographic coverage, though the lens of grid defection [43–45]. Hittinger et al find that grid defection is cost prohibitive for the customer when relying on BTM PVESS, results that are corroborated by Gorman et al and Hanser et al under a variety of scenarios. A few studies find that adding BTM fossil-fuel based systems could make grid defection more likely [46]. All these studies find that the PVESS system sizes required for grid defection are often quite large due to the constraint to provide year-round electricity service. Given these large sizes, it is difficult to apply results from these studies to understand PVESS capabilities to provide backup during power interruptions with smaller system sizes that are currently more commonly adopted [47].

Compared to the case-study approaches discussed above, the distribution system literature that evaluates the system reliability/resiliency impacts of BTM PVESS adoption focuses on the electric utility, rather than individual end-consumer, perspective. A wide literature has evaluated the distribution impact of high PV penetrations on distribution feeders, focused on issues of hosting capacity, voltage support, protection coordination, voltage flicker, and short circuiting [21,48]. Seguin et al. catalogs major findings from these studies [49]. More recent studies have begun evaluating more expansive DER technologies such as electric vehicles and battery storage and their corresponding impacts on the distribution system [50–52]. Carvallo et al models the capability of BTM PVESS form both the distribution utility and customer perspective. However, their results are focused effects on system-aggregated metrics such as system average interruption duration index (SAIDI), system average interruption frequency index (SAIFI), and customer average interruption duration index (CAIDI). They find reductions in the SAIDI from 2 to 12%, depending on PVESS penetration levels but focus on a specific set of locations in Indiana, making it hard to generalize there results across diverse geographic conditions [9,53].

Given that BTM solar-plus-storage adoption is often driven by end-customer procurement decisions [54], it is difficult to take the results from this system-oriented resiliency literature and apply them to customer adoption models. Much of the literature studying the adoption of distributed energy resources focuses on cost, demographic, and community/network effects [55–57]. While these studies are predominantly focused on distributed PV adoption, new methods are being developed to forecast BTM storage adoption [14,58]. Sigrin et al apply historical co-adoption of PVESS to forecast adoption in the future, citing limited research on distributed storage adoption while Prasanna et al apply an economic model that takes into account the value for backup power based on regionally distributed SAIDI and SAIFI metrics, assuming that a PVESS system could avoid all potential interruptions [14].

3. Methods

This section is broken up into three subsections which describe our data collection efforts, the implementation of the PVESS dispatch algorithm, and the parameters that we include in our scenario analysis.

3.1. Data collection

Our research approach requires three hourly 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 hourly interval given the correlation of weather events with likelihood of power outage [59]. 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. Fig. 1 provides a schematic summarizing how these key data sources flow into our corresponding PVESS evaluation methodology.

For load profiles, we use a foundational dataset of more than 500,000 residential building models generated by the National Renewable Energy Laboratory's (NREL) ResStock simulation tool [60]. These building models use a wide range of empirical data to inform statistical representations of the United States building stock, covering a variety of residential building types, end-uses, and characteristics [61]. These statistical representations are created with Census, Residential energy consumption survey (RECS), and actual electricity consumption datasets. Overall, ResStock reports annual energy uncertainty of its aggregated models within the 3–6% range and peak demand uncertainty within the 3–9% range [60]. We focus on detached single-family homes for our base case analysis but also assess the capability of PVESS systems to serve mobile homes and multifamily dwellings. Multifamily dwellings are modeled as individual units within ResStock. To create an aggregate building profile, we sum 10 individual unit load profiles within a particular region that have the same HVAC technologies.

The ResStock model generates the full collection of building models using probabilistic distributions of more than 100 building stock characteristics (e.g. building insulation, HVAC technology type, square footage, heating fuel). For computational tractability, we select a single building model per county that is closest to the statistical median in terms of annual electricity consumption while ensuring that the selected building has the same end-use characteristics that are most common within that county (e.g. electric heating, air conditioning presence).[4] For counties with fewer than 10 building samples for a given building type, we aggregate the building models into their associated Public Use Microdata Areas (PUMA) region and apply the same selection process as above. In the case of single-family detached homes, this applies primarily to a number of sparsely populated rural counties; for other building types, this aggregation occurs more frequently. In the results

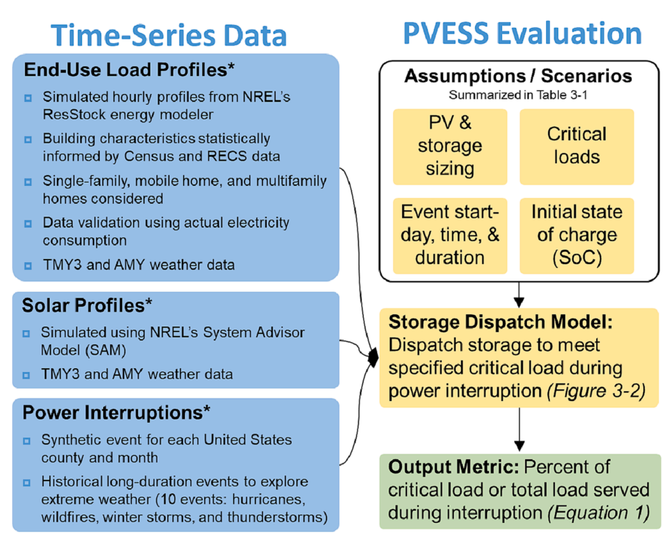

Fig. 1. Schematic summarizing key data sources and corresponding use in PVESS evaluation methodology.

[4] To do so, we characterize key end-use characteristics for each region by calculating the percentage of buildings with A/C and percent of buildings with electric space heating.

section, we often present population weighted averages that are not significantly impacted by this aggregation. Geospatial results, however, are coarser in rural areas as a result of the aggregation.

While we focus on the 'typical' consumption for building models across the U.S., for a select number of high-population counties, we present a distribution of results across the entire building stock within that county. Such analysis allows us to estimate the range of capabilities of BTM PVESS within a single geographic territory. These focus locations and corresponding climate zones[5] are shared in Figure 11-2 in the Supplemental Information section.

To produce solar generation profiles, we apply the same weather data that are used in the underlying ResStock building simulations in order to ensure geospatial and temporal alignment. In total, 889 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) [62]. Then, we use NREL's System Advisor Model (SAM), which outputs AC solar production profiles. For these simulations, we use default system losses 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.

Finally, we develop two distinct approaches to simulating power interruption profiles: (1) synthetic profiles and (2) historical profiles. Our synthetic profiles are simulated as interruption events that occur in every month at a pre-determined start date and start time. These synthetic profiles allow us to assess the capability of PVESS systems to provide power across different seasons and are used solely in tandem with TMY weather conditions. To determine the start day of a synthetic interruption within a given month, we calculate the daily net load for each building model and develop scenarios where we choose a specific percentile of net load for the interruption window (e.g. 50th percentile or 90th percentile). We default to starting the interruption at midnight, though explore a sensitivity where we adjust the start time to different times throughout the day (e.g. hours 6, 12, 18).

While the synthetic approach allows us to compare our geographies and building models in a consistent way, they are limited in their ability to assess the provision of backup power of BTM PVESS systems during extreme weather events. To complement the synthetic profiles, we identify 10 historical, wide-spread, weather-driven power outages and develop historical interruption profiles that align with the empirical experience of outages during those events. We focus on 4 event types: (1) Hurricanes (Harvey (2017), Irma (2017), Florence (2018), Michael (2018), and Isaias (2020)); (2) wildfires (California (2019)); (3) winter storms (Washington state (2019) and Oklahoma (2020)); and (4) thunderstorm (Iowa (2020) and Texas (2020)). For each of these events, we select four representative counties that ensure diversity of experience during the interruption event, focusing on the most populous, most vulnerable (based on the U.S. Federal Emergency Management Agency's social vulnerability index [63]), most impacted rural (using U.S. Department of Housing and Urban Development designations), and longest duration interruption counties. We also limit the selections to counties experiencing a minimum interruption duration of 48 h. The set of counties selected through this process are listed in the Supplementary Material section (Table 11-1).

To determine the start and end-times for each county-event, we use data from Poweroutage.us, which collects utility outage management system reporting that tracks the total number of customers who lost power during these extreme weather events by county [64]. Start and end-times for each event are based on a threshold of 10% of customers experiencing an interruption within a specific county. For our analysis of historical extreme weather events, we simulate new building load profiles for a subset of counties and years using the AMY weather data.

[5] Climate zones are shaded to represent high-level climatic differences across regions in the United States.

3.2. PVESS dispatch and evaluation

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.[6] Fig. 2 shows the decision tree that is used to determine the dispatch of the PVESS system. We assume a 92% one-way battery efficiency and a 2 h duration battery. We apply constraints on the discharge and charge rates of the battery such that they do not exceed the kW capacity of the battery within the hour, which is determined by dividing the kWh energy limit of the battery by the 2 h duration. We assume an AC coupled system such that the maximum power of the PVESS is the PV's AC capacity plus the battery power constraints mentioned above.[7] The energy limit of the battery is a parameter we adjust, discussed below in the scenario analysis subsection below. An illustrative time-series figure for a single-site which represents our dispatch approach is provided in Fig 11-5 in the Supplemental Information.

In order to describe and compare the performance of the PVESS system across all modeled scenarios, we focus on a simple customer centric metric: percent load met (adjusting for load scenario of interest). This metric is defined by the below equation and is based entirely on dispatch data calculated for our interruption events. Importantly, the load demanded and load served vary by our specific load scenario (i.e. full load, critical load, limited critical load) of focus, described in greater detail below.[8]

$$P = \frac{E_s}{E_o} \tag{1}$$

Where,
P = percent load met (%).
E_s = load served during interruption (kWh).
E_o = load demanded during interruption (kWh).

3.3. scenario analysis

Table 1 summarizes the adjustable parameters in our analysis. Our baseline scenario involves the single family detached building model, a 3-day synthetic interruption event that starts at 12am on the 50 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. Importantly, we do not perform detailed sensitivities of potential battery degradation (e.g. during cold-weather conditions) or the potential physical destruction of the PVESS during extreme weather events. Our battery sizing assumptions, therefore, refer to the amount of usable/available capacity at the time of the interruption, which may be less than the nameplate capacity of the battery given degradation.

Though we present results with both full load and critical load assumptions, the majority of our results focus on PVESS capabilities to meet critical loads. In our comparison of different residential building types, we update our default PV system sizing assumption to being based

[6] We do present a scenario analysis which adjusts the beginning state of charge of the battery to explore potential impacts of using the PVESS system for other use cases besides backup power.

[7] We are limited in our capability to model more granular power constraints at the minute-to-minute level given the time scale of the NREL load profiles. We performed a sensitivity analysis using 15-minute data on a subset of our results and found limited implications on the power constraints. We do still observe power constraints (rather than just solely energy constraints) binding in our results, especially for electric heating end-use scenarios.

[8] The realism of such load scenarios would require that these end-uses can be disconnected independently and/or controlled in a disaggregated manner within a house-level circuit.

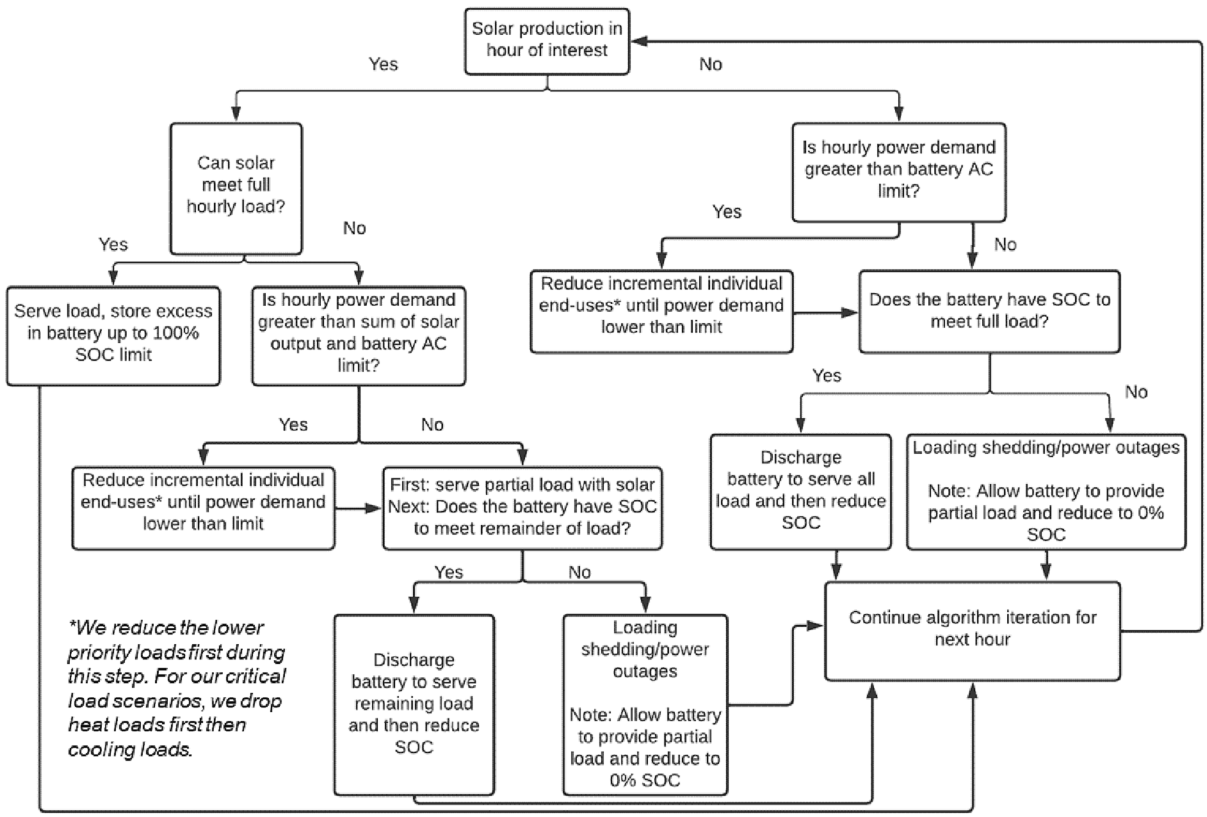

Fig. 2. Decision tree to control state of charge (SOC) of the battery.

Table 1
Summary of parameters and scenarios considered for synthetic interruption events.

Scenario	Assumption
Building types	Single family detached; Mobile home; Multifamily
Interruption length (days)*	1; 3; 7
Load scenario	Critical load (no heating/cooling); Critical load (w/ heating/cooling); Full load
Beginning SOC (% of total kWh of battery)	0%; 50%; 100%
Interruption start time	12am; 6am; 12pm; 6pm
Interruption start day (based on net load percentile within month)	Worst; median; best
Solar sizing	Solar generation is 50%; 100% of annual load; Roof area constraint
Battery sizing	10 kWh; 30kWh

* Only applies to synthetic events.

on a roof constraint rather than PV sizing based on annual load.[9] This decision relates to the fact that multi-family buildings will be constrained by the space limitations to site PV. Roof area is provided by *meta*-data within the ResStock dataset.

Our critical load assumptions are informed by a set prior literature that focused on the Value of Lost Load (VoLL). In particular, Baik et al. survey customers in the northeast asking about load prioritization during interruption time periods.[10] The top 7 categories selected by respondents in rough order of prioritization were lighting, refrigeration, chargers, computers, TV, heaters, and air conditioning [41,42]. Informed by this literature, we designate 6 out of 15 disaggregated end-use types in the ResStock building simulations as critical: refrigeration, interior lighting[11], a limited set of plug loads[12], well pumps, space heating, and space cooling. End-uses that we deem non-critical are fans (bath, ceiling, range), clothes dryer/washers, pool equipment, cooking ranges, dish washers, water heating, exterior lighting, extra refrigerator/freezer, 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 critical load case without heating and cooling demand. Fig. 11-2 within the supplemental information shows the percentage of total annual load represented by these two critical load cases.

4. Results

Our results section is split between three main levels: (1) The median consumption ResStock household for each county across the entire U.S., (2) All ResStock households within a subset of 6 counties in the U.S., and (3) 10 historical wide-spread power outage events. The first two sections rely on the Synthetic power interruption methodology while the last

[9] Roof constraint calculated as follows: Take square feet of building model and divide by the number of stories of the building model to get roof area. We assume a 160 W/m^2 (0.01486 kW/ft^2) PV panel density and a ground-coverage ratio of 98% for single-family and mobile homes (slanted roofs) and 70% for multi-family (flat roofs). The ultimate PV size is the lessor of PV sized based on roof area or PV sized based on meeting 100% annual load.

[10] 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).

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

[12] 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 focuses on actual power interruptions experienced between 2017 and 2021.

4.1. Median-building analysis

In the vast majority of counties, the PVESS with 10 kWh of storage can provide full power for our minimum set of critical loads that ignore heating/cooling demand (i.e. include refrigeration, limited interior lighting, computer / internet, and well-pumps). With our largest PV sizing assumption, the entire set of limited critical loads are met in 93% of counties. However, Fig. 3 shows that the base PVESS configuration cannot provide power for the majority of U.S. counties once including heating and cooling loads are included (maps on the left of Fig. 3). In this scenario, a PVESS with 10 kWh of battery could supply 100% of annual power demand to just 6% of counties. In our whole-home backup scenario (maps on the right of Fig. 3), this drops to 0% of counties. There are clear seasonal and regional trends, where performance in summer months is lowest in regions with high cooling loads (i.e. southwest and southeast) while performance in winter months is lowest in regions with electric heating (southeast and northwest, especially in rural counties).

In order to understand the sensitivity in choice of critical loads, we focus on a set of locations with representative climate/end-use combinations and simulate how our base PVESS configuration can fully backup incremental additions to the critical load profile. Fig. 4 shows that the base PVESS configuration can fully backup incremental additions of refrigeration, lighting, computer / internet, and well-pump loads for these locations. We also report the key heating and cooling technology used in the representative building model studied. Heating and cooling loads go partially unserved in areas with relatively hot or cold weather. Los Angeles is the only location within this set where all critical load is served. Locations with electric heat have particularly high levels of unserved energy, a result which aligns with the geographic result in Fig. 3. Unserved heating load can even occur for buildings with fossil-based systems due to the usage of energy by the furnace fan, though these unserved loads are relatively small.

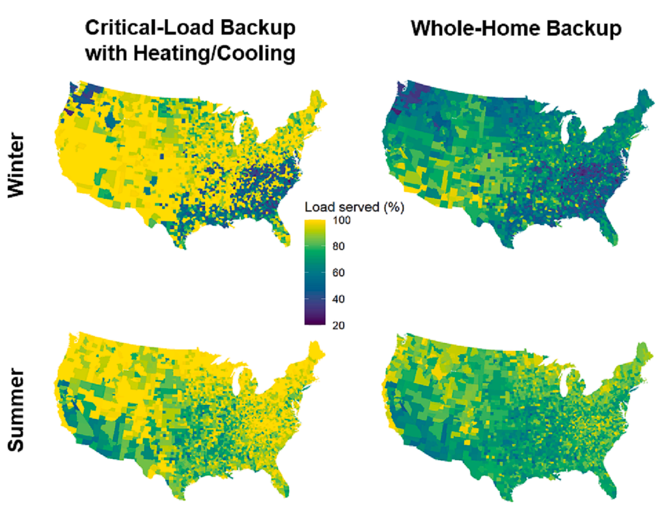

Fig. 3. Average percent of total load served during the 3-day interruptions simulated in each month, aggregated to the average of winter and summer seasons for the county-median home. Critical-Load scenario includes heating and cooling. Assumes PV sized to 100% of annual load, 100% beginning SOC, 10 kWh battery.

Fig. 5 shares the impact of increasing battery sizes and interruption event duration on the capability of the PVESS to meet critical load year-round. Fig. 3 and Fig. 4assumed a 10 kWh battery, based on current installation sizes [47]. Systems with larger batteries can naturally better maintain critical loads. Tripling the size from 10 to 30 kWh leads to a 10% increase in the critical load served year-round (86% to 96%). A PVESS system with a 100 kWh battery, which might be more representative of a household with an electric vehicle backup system, could serve 99.5% of critical load across all counties. However, backup performance is limited by PV production, which is shown by the decreasing marginal returns to increased battery sizes in Fig. 5. Furthermore, we show that as interruption duration increases, backup performance declines. The longer duration of the interruption, the higher the probability of an especially low solar or high load day. In these cases, the initial stored energy is depleted in the battery and the ability to meet critical load becomes more limited by daily PV generation. These effects are especially pronounced for counties in the lower end of the distribution.

Given the relatively low ability for a 10-kWh battery system to serve critical load with heating and cooling, we present the remainder of the results with a PVESS incorporating a 30-kWh battery. Fig. 6 compares results between single-family, mobile, and multi-family homes by climate zone. Load served is generally similar between the three building types. More information about variation in annual consumption and PV system sizes between these building types and geographic results can be found in the Supplemental Information (see Fig. 11-3, 11-4, 11-10, 11-11).

4.2. Distributions within the building stock of select High-population counties

For a subset of high-population counties, we simulate our results for all single-family detached ResStock building models. Fig. 7 shows that PVESS capability to provide year-round backup of critical load varies significantly across the building stock distribution in Houston and Phoenix. Alternatively, we find that the median in Seattle, Chicago, LA, and Boston is centered at a truncated distribution of 100% of load served. Our use of medians in Section 4.1 likely understates the variability across and within counties, given that some counties have longer lower tails while others have much narrower distributions clustered at 100%. However, as we show in Fig. 7, the median result for some counties contains the majority of the distribution. This result happens in locations with limited electricity-driven HVAC loads (e.g. low air conditioning need and/or fossil-fuel based heating technologies).

Fig. 8 shows two counties with higher variability in backup performance (Phoenix and Houston). In these two counties, backup performance declines the greater the amount of critical load to serve, given fixed battery sizing. Scatter around those trends reflects differences in customer load profile shapes. Differences in critical load levels reflect a number of fundamental drivers: (1) Building size, (2) Heating and cooling equipment type (especially electric vs. gas heating), (3) Efficiency levels, and (4) Occupant/behavioral factors (e.g., set points). For example, among homes with electric resistance heating in Houston, a median of 77% of winter critical load is served, compared to 96% for those with heat pumps and 100% for those with fossil heating. Winter backup performance also varies by roughly 20% depending on infiltration rates (the "leakiness" of the home), while summer performance varies by close to 15% depending on the efficiency of the central air-conditioning system. More information about variation in performance is shared in the discussion section (see Fig. 11) and the Supplemental Information (see Figs. 11-8 and 11-9).

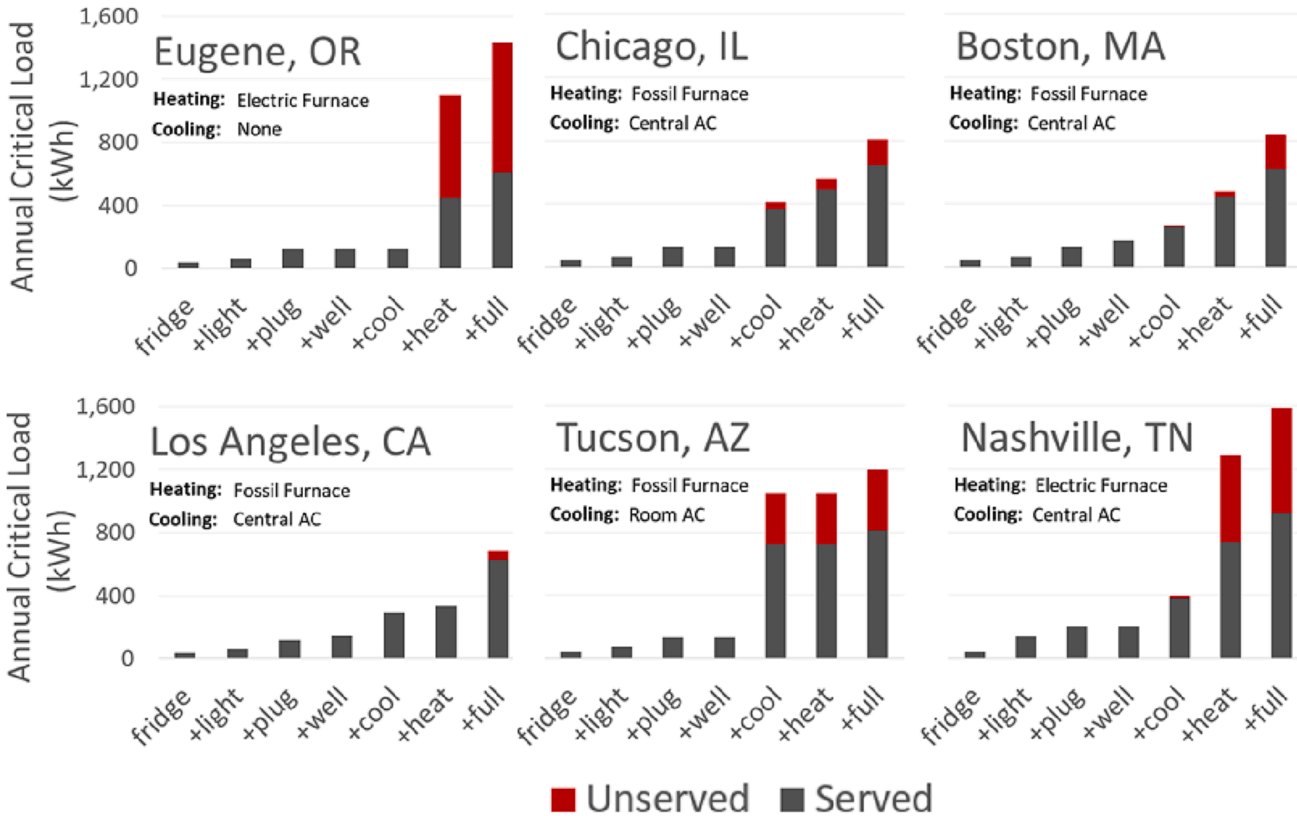

Fig. 4. Served and unserved load over all 12 3-day monthly interruptions, as end-uses are incrementally added to the set of critical loads. Assumes PV sized to 100% of annual load, 100% beginning SOC, 10 kWh battery.

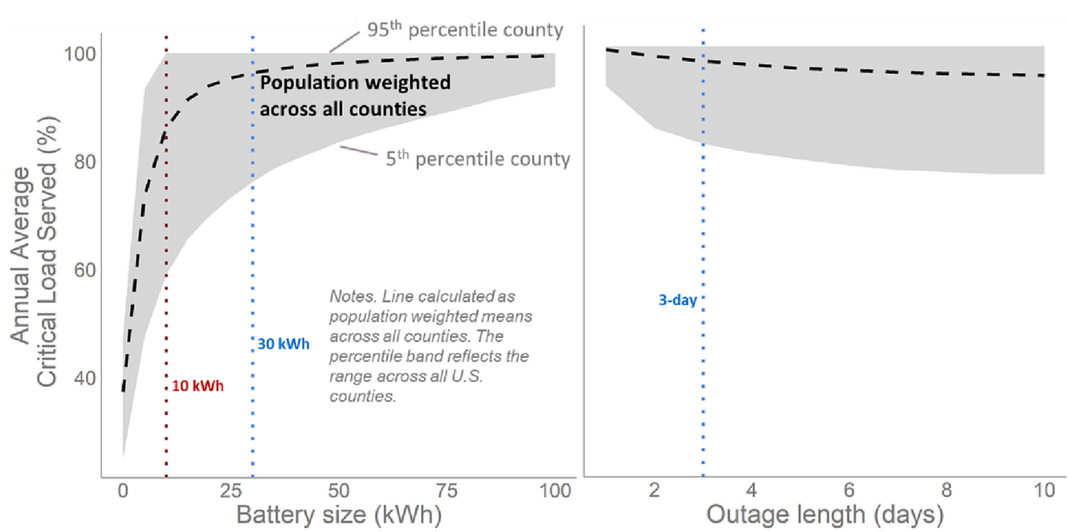

Fig. 5. Annual average critical load served under varying battery size and event durations. Assumes PV sized to 100% of annual load, 100% beginning SoC.

4.3. *Historical event case study*

For historical results, we simulate 500 single-family building models for each county within the sample. Fig. 9 reports the distribution of results for each event. Each dot represents a distinct county, and the dot's shape corresponds to the criteria by which that county was identified amongst the sample of counties impacted by each historical event. We find that the default system would have supplied full backup for the majority of building models in the Thunderstorm (TX), PSPS (CA), Derecho (IA), and Hurricane Michael events. The worst distributions of load served occur for the two winter storm events and Hurricane Florence. The large range of experience in Oklahoma is driven by the large portion of electric heating represented in that state (25% of single-family building models), which drives the low end of performance of PVESS during the winter event.

The relatively poor performance represented by Hurricane Florence is driven by the lack of solar production in the first three days of the ~ 8-day outage event as shown in Fig. 10. The lack of solar production

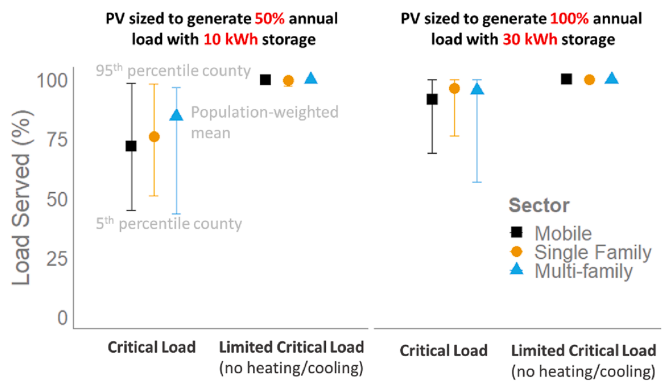

Fig. 6. Comparison of residential building types. Assumes PV sized based on the roof constraint, 100% beginning SOC, 30 kWh battery per unit.

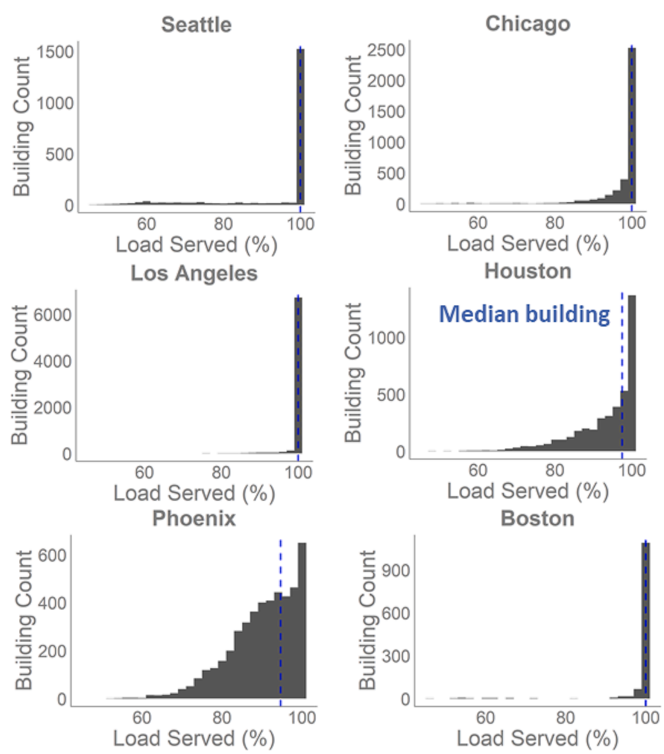

Fig. 7. Distribution in percent of critical load served across all modeled single-family homes in ResStock with dashed indicating median building result presented in section 4.1. Assumes PV sized to 100% of annual load, 100% beginning SOC, 30 kWh battery.

results in quick depletion of the 30 kWh beginning state of charge of the battery in order to meet cooling demands. In comparison, Hurricane Harvey also had three days of limited solar insolation; however, it was a much longer duration outage, and therefore the average backup performance over the event as a whole was higher than for Florence. Hurricane Irma had a similar duration as Florence, but just a single day of reduced solar insolation, leading to the higher levels of backup performance.

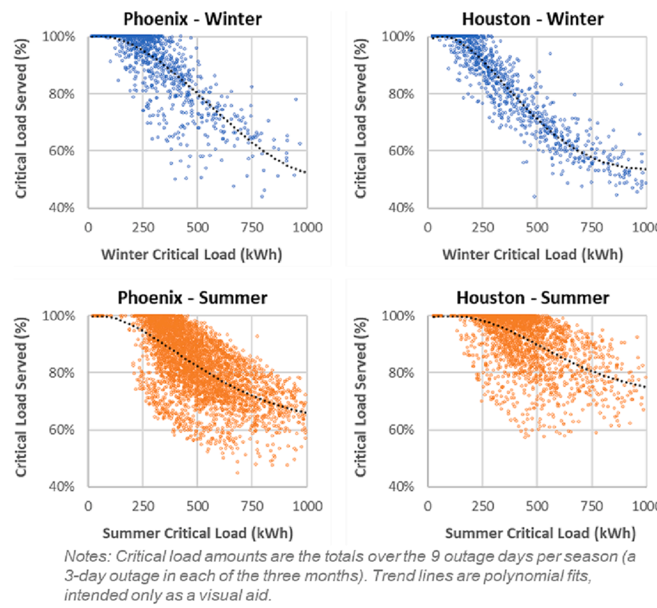

Fig. 8. Percentage of critical load served based on amount of critical load.

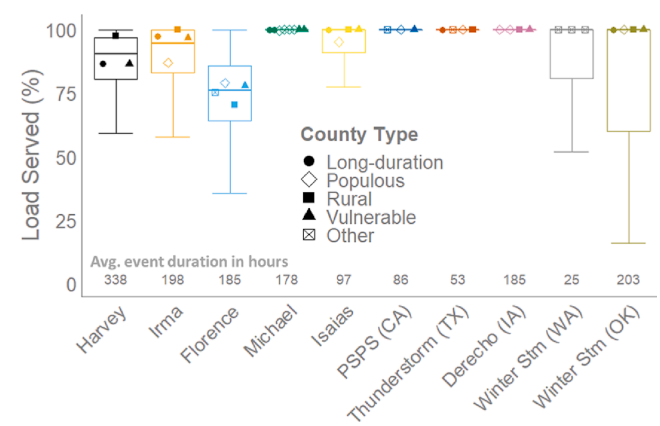

Fig. 9. Backup power performance across all counties and historical extreme power interruption events, assuming 30 kWh battery and critical load scenario. Assumes PV sized to 100% of annual load, 100% beginning SOC, 30 kWh battery.

5. Discussion

The above results establish a baseline understanding of the capabilities of PVESS to provide backup power across a range of geographies and building stock conditions and have important implications for researchers, analysts, and/or electric system planners trying to forecast the adoption of PVESS for backup. First, assuming that PVESS can fully backup a customer experiencing long-duration interruptions is incorrect and varies geographically. Second, we show that the specific electric end-use requirements demanded of a PVESS backup power system will drive the resiliency capability of the system. Across all of our scenarios, PVESS could provide power to refrigeration, nighttime lighting, internet

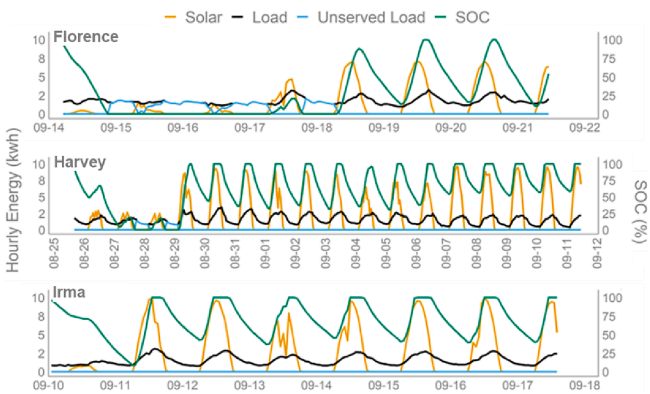

Fig. 10. Time series results for Hurricanes Florence, Harvey, and Irma with median home. Assumes critical load with cooling, PV sized to 100% of annual load, 100% beginning SOC, 30 kWh battery.

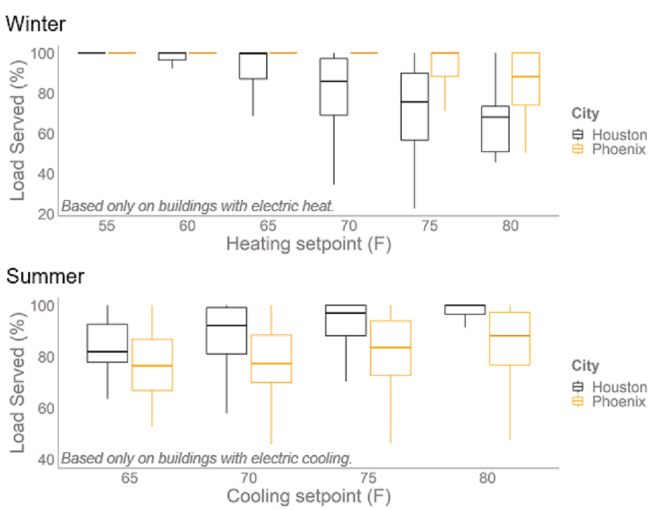

Fig. 11. Relationship between heating (top) and cooling (bottom) set-point and percent load met by PVESS. Assumes PV sized to 100% of annual load, 100% beginning SOC, 30 kWh battery. Cooling analysis based on summer months; heating analysis based on winter months. Only consider building types with electric heating or electric cooling.

/ computer loads, and well-pumps without any shed load. However, heating and cooling demand are much more difficult to backup with a PVESS system and oftentimes cannot be fully served during interruption conditions under typical operating conditions. Last, we find that PVESS could mitigate interruptions for a significant fraction of the building stock during prominent wide-spread interruption events over the last 5 years, but customers who adopt PVESS do take on weather risk if the sun is not available during the event, as shown in Hurricane Florence.

We only considered typical operating conditions without load flexibility. In the case of an interruption event, though, households will be able to adjust their thermostat set points to limit the energy demanded. Though deriving the amount of possible flexibility was out of scope for this analysis, we could analyze the relationship between our load served metric and heating and cooling temperature setpoints in the select locations where we simulated all building models in ResStock. Fig. 11 presents this relationship for Houston and Phoenix[13] building models and shows that load served is positively correlated with cooling setpoint and negatively correlated with heating set point. Each observation in this figure is an individual building model, and we include the entire distribution of homes modeled in the Houston and Phoenix areas. Differences in temperature set-points between these homes correspond to a 40% range in winter backup performance and a 20% range in summer performance in Houston (~10% range in Phoenix for both winter and summer performance).

Understanding the capability of PVESS to serve heating and cooling is important because there are situations when our prioritized critical loads (i.e., refrigeration, lighting, internet / computer, well pumps) might vary depending on the context of the power interruption event. For instance, during the Winter Storm Uri, many homes that rely on electricity to heat their homes might have re-prioritized end-uses towards electric heating given health risks posed by deadly low temperatures [65].

Notably, we found that load served is not just limited by energy but also power constraints. Though we were unable to model sub-minute electric demand, we still identified times when the AC power limit of the PVESS reduced the capability to serve load. This limitation is particularly acute for electric heating, which depending on the technology type can draw up to 20 kW or more demand (e.g. electric baseboard). This constraint was binding even though we only had access to hourly load data; it is likely that we would find it even more challenging to serve the power component of heating demand, especially in regions where the default heating technology is electric baseboard heat. Future technology solutions that offer modulation of high-power loads might be required if households want to use PVESS to backup electric heating.

In this paper, we focused on the technical capabilities of PVESS rather than the economic value of such resiliency enhancements to a household. The future adoption of PVESS, however, will be driven by how customers value reliable electric service as well as their expectations of future interruption conditions. To provide insight into these values, we converted our load served metric into a cost of served energy metric using Equation (2) below. The cost of served energy metric is an economic indicator which represents the levelized cost of providing energy via PVESS during an interruption and is calculated by taking an annualized cost of the PVESS system[14] net of any bill savings[15] and dividing it by the load served by the PVESS over all interruption events for a household in a year. It is important to note that the load served provided in this analysis is based on the portion of total load, rather than critical load, that can be served by the PVESS system.

$$CoSE = \frac{A - B}{E_s + (SAIDI^{*}L)} \tag{2}$$

Where,

CoSE = cost of served energy ($/kWh).

A = annualized capital cost of PVESS system ($/yr).

B = annual bill savings ($/yr).

E_s = load served by PVESS during annual interruption events for a household, considering total load case (kWh/yr).

SAIDI = 2020 System Average Interruption duration index (hrs).

L = average consumption (kwh / hr).

[13] Other cities were ignored because as Fig. 7 shows, these cities had limited deviations from full load served in our default PVESS scenario.

[14] Annual cost calculated assuming a 5% discount rate, 20-year lifetime, battery cost of $1,000/kWh and solar cost of $3,000/kW. We assume a 30 kWh battery and set the PV system size equal to the size assumed in our various historical event case studies (PV sized to meet 100% annual energy consumption). We ignore any upfront capital-cost subsidies in these calculations.

[15] Given that the majority of locations in the United States offer limited time-of-use arbitrage rates, we assume a use case where all of the energy generated by the PV system can be used to offset the local utility's retail electric price. Such a price would incorporate distribution, transmission, and generation deferral value but might ignore emissions avoided.

Table 2
Breakdown of the cost of served energy ($/kWh) between the historical events with variation depending on assumption of the expected number of events per year.

Expected Number of events over PVESS lifetime	2020 Thunderstorm (TX)	2019 PSPS (CA)	2020 Derecho (IA)	2018 Florence (NC)	2017 Harvey (TX)	2017 Irma (FL)	2020 Isaias (NY)	2018 Michael (FL)	2020 Winter Stm (OK)	2019 Winter Stm (WA)
2 (1-in-10 years)	$260.18	$134.63	$115.70	$126.47	$41.08	$62.38	$153.49	$153.75	$152.16	$726.96
20 (Every year)	$54.13	$17.46	$12.26	$14.94	$4.45	$6.47	$16.69	$16.53	$18.28	$98.38
40 (2 times a year)	$28.79	$8.87	$6.15	$7.55	$2.24	$3.24	$8.39	$8.30	$9.25	$50.18

This metric can be compared to research measures and industrial applications of the value of lost load (VoLL) assuming that the load served during the annual interruption events represents a household's expectation for future annual interruption events. For our historical case studies, this assumption is reasonable if these historic events represent the majority of lost energy due to annual interruptions for a particular household. Such a simplifying assumption is poor for the synthetic interruption event analysis; therefore, we do not analyze this metric using those analyses.[16] We slightly augment the load served numbers by applying System Average Interruption Duration Index metrics, excluding major event days, provided via EIA 860.[17]

Table 2 calculates the median cost of served energy for the 10 historical events we modeled in our analysis. Each row varies the expectation for how frequent such a wide-spread outage event might occur over the course of the assumed 20-year lifetime of the PVESS system. Details of the calculation, including system cost, assumed retail rate, bill savings, SAIDI metrics, and load served are shared in Table 11-2 in the Supplemental Information.

The above numbers can be compared to average VoLL estimates provided by researchers studying resiliency events, which tend to be between $1–5/kWh for the residential customer class [41,66,67]. While most of these events are outside of the VoLL range from the literature, others are closer. Overall, the economic results suggest that the resilience value of PVESS must be high for a sizable fraction of customers to adopt these systems.

Of course, estimating the likely number of major outage events in the future is challenging, making it difficult to determine which row in Table 2 should be used. Serious events like Hurricanes are less likely than the PSPS events in California, for instance, but future researchers could focus on estimating such probabilities regionally to refine the above calculations. Moreover, the *risk aversion* of PVESS adopters will induce them to pay a premium in case frequencies of events are higher than researchers may estimate. Similarly, these customers may have personal VoLLs that are higher than the average VoLL ranges determined by researchers and cited above.

6. Conclusions and open research questions

In this paper, we analyzed the performance of BTM PVESS in providing backup power across a wide range of customer types, geography / climate conditions, and power interruption scenarios, considering both whole-building backup and backup of a specific set of critical loads. Our approach provides an assessment of the technical potential of PVESS to enhance customer resilience. The synthetic interruption analysis showed that that PVESS can meet a limited set of critical loads that includes refrigeration, nighttime lighting, well-pumps, and internet / computer load for a majority of U.S counties if a customer was exposed to a 3-day interruption in each month, and had a 10 kWh battery installed with a PV system is sized to meet 100% of annual load. However, we find that providing heating and cooling demand is much more difficult, with only 86% of critical load met, on average, in this larger demand scenario. Backup performance for PVESS with a fixed quantity of storage is generally lower for higher-usage homes. Differences in consumption levels, in turn, reflect a variety of underlying building conditions. For instance, backup performance is lowest in winter months where electric heat is common (southeast and northwest U.S.) and in summer months in places with large cooling loads (southwest and southeast U.S.). Winter backup performance varies by roughly 20% depending on infiltration rates, while summer performance varies by close to 15% depending on the efficiency of the central air-conditioning system.

Our results relied on load profiles which are statistically representative of the current United States building stock. However, deep decarbonization policy goals suggest that the building stock will electrify beyond levels observed in our study. Though we did find signs of how electrification might pose difficulties for PVESS in providing reliable services to end-customers, future research should more precisely consider load profiles which incorporate more electrification. Such electrification might certainly pose challenges to home back-up via increasing electricity demand; however, other electrification trends could support customer resiliency. For instance, our battery size scenario of 100 kWh, which might loosely represent electric vehicle backup, increased the number of counties that can meet critical load to 94%.

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 should also evaluate load flexibility with more detail, especially as it pertains to heating and cooling demand. Finally, our paper was focused exclusively on long-duration interruption events, which can be highly costly, but are the least common form of interruption experience 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 up to a power interruption event. Such work could incorporate estimates of the VoLL to provide estimates of the resiliency value of PVESS across short- and long-duration interruption events.

CRediT authorship contribution statement

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

[16] A customer's expectation for annual outages is likely not tied to a 3-day outage event occurring every month of the year.

[17] These have a limited impact on the overall results as given SAIDI metrics only represents between 1 and 4 h of additional outages compared to major event outages between 25 and 380 h. However, the relative impact of SAIDI increases when assuming a lower number of expected major events.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2023.121166.

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