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Backup power or bill savings? How electricity tariffs impact residential solar-plus-storage usage in the United States

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ABSTRACT

Adoption of paired solar-plus-storage systems has accelerated in recent years, driven by both the demand for backup power and a desire to manage utility bills. Tradeoffs between those two uses can arise through the reserve setting on the battery storage system, which serves to maintain a minimum state of charge in case of a power interruption. Our paper applies an economic framework to evaluate this tradeoff in terms of changes in bill savings and customer reliability value across reserve levels, considering how those tradeoffs depend on the underlying electricity rate structure and levels. The analysis is based on a representative set of load profiles, solar profiles, tariff designs, and stochastic power interruption events across ten different regions in the United States. We find that the opportunity cost of holding storage capacity in reserve, in terms of foregone bill reductions, outweighs any gains in reliability value from mitigated power interruptions in the majority of customer situations. Higher storage reserve levels increase total customer value only in specific circumstances, such as for customers with inferior reliability (10x average interruptions), with a very high value of lost load ($50/kWh), and with tariff or interconnection rules that disallow grid charging. However, even this result is dampened when considering tariff designs with higher price differentials that increase the opportunity cost of holding storage in reserve (e.g. import/export or time-of-use rates). Allowing grid charging in tariffs essentially eliminates the necessity to hold any storage in reserve in all sensitivity cases explored.

1. Introduction

The adoption of residential solar photovoltaic and energy storage systems (PVESS hereafter) is driven by customer electricity bill savings and demand for backup power (Alipour et al., 2022; Energy Sage, 2024). Over the past decade, regulators have increasingly implemented time-differentiated electricity tariffs, providing an economic incentive for customers to shift the timing of their electricity consumption (Faruqui et al., 2020; Trabish, 2022). Moreover, some jurisdictions have adopted tariffs that encourage customer self-consumption, partly due to the growth of distributed energy resources (Barbose, 2024; Benalcazar et al., 2024; Cambini and Soroush, 2019).

These tariff designs aim to align the usage of customer-sited energy technologies with improved grid outcomes, and storage technologies are particularly well-suited to respond to these new residential price signals, by providing a means for customers to arbitrage between higher and lower retail prices (e.g., peak and off-peak prices under a time-of-use tariff, or import and export prices under a net billing tariff). Prior research has explored how individual customers are making PVESS investments for private benefit, though better tariff designs can provide greater public value (Forrester et al., 2022).

Concurrently, customer concerns regarding electric system reliability and resilience have grown (Brown, 2022; Brown and Muehlenbachs, 2023; EnergySage, 2022) as electricity networks have become increasingly vulnerable to severe storms and extreme heat events (Burillo et al., 2019; Mukherjee et al., 2018; Shield et al., 2021). By providing power locally, PVESS technologies offer customers backup power capabilities (Barbose et al., 2021, 2024; Gorman, 2022), and there is a sizeable body of research examining the technical capabilities of PVESS to provide backup power (Marqusee and Stringer, 2023; Mitra and Vallem, 2012; Waseem et al., 2009).

Many of these studies consider individual case studies in particular geographies (Anderson et al., 2016; Kosai and Cravioto, 2020; Wang et al., 2019). Others consider synergistic utilization of PVESS with other distributed energy resources to provide backup power (Ani, 2016; Sanni et al., 2021). Our recent work evaluates these capabilities for lengthy duration power interruptions, finding that geographic context and the penetration of electrification and energy efficiency technologies are critical, given the importance of heating and cooling demand during

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Abbreviations

DC – Washington, DC
DER – Distributed energy resources
DFW – Dallas-Fort Worth
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
SOC – state of charge
US – United States
VoLL – Value of lost load

Nomenclature

S_{TOU} = the savings from installing storage under TOU tariffs ($)
$C_{off,pv-only}$ = the annual off-peak period net consumption with on PV installed (kWh)
$C_{off,PVESS}$ = the annual off-peak period net consumption with PV and storage installed (kWh)
P_{off} = the off-peak price ($/kWh)
$C_{on,pv-only}$ = the annual on-peak period net consumption with on PV installed (kWh)
$C_{on,PVESS}$ = the annual on-peak period net consumption with PV and storage installed (kWh)
P_{on} = the on-peak price ($/kWh)
S_{NB} = the savings from installing storage under net billing tariffs ($)
$I_{pv-only}$ = annual imports with PV installed (kWh)
I_{PVESS} = annual imports with PV and storage installed (kWh)
P_I = the import price ($/kWh)
$E_{pv-only}$ = annual exports with PV installed (kWh)
E_{PVESS} = annual exports with PV and storage installed (kWh)
P_E = the export price ($/kWh)

power interruptions (Gorman et al., 2023, 2024).

Deploying PVESS to provide both bill savings and backup power, however, presents a fundamental tradeoff. The unpredictable nature of many power interruptions (Jaech et al., 2019) could necessitate maintaining storage capacity in reserve, in order to ensure power availability during grid outages. However, this practice reduces the storage unit's capacity to manage utility bills throughout the year and, by extension, limits its ability to provide grid value. At the extreme, a high reserve setting would result in the storage unit sitting idle, waiting to provide backup during a power interruption, providing no meaningful bill savings or associated grid value. Conversely, a low storage reserve setting risks insufficient power during an interruption, particularly during nighttime interruptions when solar generation is unavailable. The fundamental question is, how should a customer set their storage reserve level? This paper aims to evaluate how electricity tariff design impacts this operational tradeoff from the perspective of a customer adopting PVESS. We do so by developing an analytical framework and a corresponding model to compare the decrease in annual bill savings with the increase in annual reliability value that results from holding storage capacity in reserve throughout the year. The bill savings decrease results from the inability of storage being held in reserve to arbitrage time-differential tariffs. Conversely, the reliability value increases as a result of the ability of the storage unit to provide more backup power in the case of an unpredictable power interruption.

Tariff designs interact with our above research question in two main ways. First, PVESS backup power performance, particularly for short-duration outages, is dependent on the storage unit's initial state of charge (SoC) at the beginning of the interruption event (Gorman et al., 2023), which is a function of storage's charging and discharging behavior under the prevailing tariff design (Costa et al., 2022). Second, the impact of a storage unit's reserve level on customer bill savings also depends on tariff design, as the depth of discharge can vary under different rate structures, which could imply more marginal impacts of higher reserve levels if the tariff already does not encourage full storage discharge behavior.

There is a robust body of research that analyzes bill savings opportunities from the adoption of PVESS, but it rarely incorporates interactions with backup power capability. Some of this literature focuses on the customer economics of behind-the-meter storage dispatch considering varying retail tariff designs (Darghouth et al., 2019). Other research focuses on developing novel optimization algorithms to control the utilization of these distributed energy resources given different rate designs (Bloch et al., 2019; Varghese and Sioshansi, 2020; Yang et al., 2023). None of the above papers aims to integrate the use case of backup power. However, a subset of this literature does incorporate the economic value of enhanced customer resilience by converting the mitigation of lost load into a dollar value and maximizing the sum of bill savings and resilience value (Chatterji et al., 2021; Laws et al., 2018). Still, these papers focus on optimal system sizing, rather than aiming to understand the customer decision to reserve a portion of their storage unit in the case of a power outage (Mishra et al., 2022; O'Shaughnessy et al., 2018).

For long-duration outage events caused by extreme weather, customers may be able to anticipate interruptions and charge their batteries in advance, obviating the need for a high reserve setting (Schmitz et al., 2020). Low probability, random interruption events are much more difficult to anticipate, and there has been limited research evaluating how unpredictable (and often relatively short) power interruptions will impact customer PVESS usage decisions (e.g., through setting some minimum storage reserve level). Rather, most of the above research aims to assess optimal design parameters to meet a specified level of power reliability (Mitra and Vallem, 2012) or to develop predictive control algorithms that aim to anticipate interruption events and thus provide automated PVESS usage rather than assess customer decision-making (Hunter-Rinderle et al., 2023).

Neither the literature evaluating the technical capabilities nor the bill saving opportunities of PVESS considers a customer's operational decision to keep storage in reserve under differing electricity tariff designs. Understanding the drivers of the tradeoff between operating PVESS to maximize reliability value versus bill savings has implications for the overall asset utilization of the customer-sited storage fleet and is influenced by utility tariff design and interconnection rules (Gautier et al., 2021; Simeone et al., 2023; Valova and Brown, 2022), but little research in this area has been done to date.

We fill this gap by developing a two-stage storage dispatch model to compare residential bill savings and reliability value across a range of storage reserve levels, electricity tariff designs, and a wide set of climates and geographies, leveraging hourly simulated solar and end-use level load profiles. We simulate stochastic power outages, based on historical outage observations across the U.S., to create a distribution of possible outage events (Baik et al., 2025). Such an approach allows us to rigorously assess how power interruption timing aligns with solar production, load, tariff structure, and constraints on grid charging and discharging in the choice to hold storage in reserve.

Overall, we find that the customer reliability value is relatively insensitive to storage reserve level. As a result, the opportunity cost of holding storage capacity in reserve, in terms of foregone bill savings, almost always outweighs any gains in reliability value from mitigated power interruptions in most of the sensitivity cases we analyze. Thus, the key conclusion from this work is that customers are generally better off, financially, by maintaining as low a reserve setting as possible. Our conclusions are sensitive to the underlying storage degradation model. Given our assumptions about storage degradation, discussed more in the methods section, our results are most applicable to modern battery chemistries (e.g. Lithium iron phosphate (LFP)).

2. Methods

This section is split into four subsections, which describe our methodological framework, data used, the implementation of the two-part PVESS bill savings and interruption event dispatch algorithm, and the parameters adjusted for our sensitivity analysis.

2.1. Framework to compare reliability value and bill savings value

Behind-the-meter storage capacity can be used for bill savings or reserved for backup power to mitigate a potential future power outage. Fig. 1 provides a simple back-of-the-envelope comparison between the marginal value of setting aside 1 kWh of storage for reserve vs. the value of instead using that 1 kWh of capacity to manage utility bills. In this simple comparison, the marginal bill savings are larger than the reliability value. However, rigorously comparing the two customer values requires consideration of outage timing and how that aligns with solar production and load, rate structure, and constraints on storage grid charging and discharging. The rest of the methods section outlines how we design this more rigorous comparison and describes the key sensitivity analyses we perform that vary from the parameter assumptions in Fig. 1.

2.2. Datasets for simulation

Our research approach requires three time-series 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 the likelihood of power outage. To do so, we rely on a consistent set of 2018 annual meteorological year (AMY) weather data that are used to simulate both end-use load profiles and solar production profiles.

We leverage building load profiles from the National Renewable Energy Laboratory's (NREL) ResStock simulation database for 10 U.S. study locations, selecting representative load profiles for detached single-family homes for each location. Our study locations are Seattle, Los Angeles, Phoenix, Denver, Duluth, Memphis, Dallas-Fort Worth, Tampa, Washington, DC, and Boston (Los Angeles, Dallas-Fort Worth, and Washington, DC are abbreviated to LA, DFW, and DC, respectively). Reducing the scope to ten locations allows us to make the research study computationally tractable while still covering a diverse set of climate conditions (hot, cold, and temperate), solar insolation levels (sunny/cloudy and lower/higher latitude), and building stock conditions (e.g. high prevalence of electric-resistance based heating in the southeast and northwest U.S.).

ResStock is a large and statistically representative set of end-use level building models that reflect the present-day distribution of building envelope and equipment characteristics across the entire stock of U.S. single-family detached homes. Their collection of load profiles is built from 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 (Wilson et al., 2022). 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 (Wilson et al., 2022). From the set of roughly 1000 building models per location available from ResStock, we select three representative models corresponding to the median, 20th (low-usage), and 80th percentile (high-usage) annual consumption (in kWh) amounts (see Supplemental Table 4 for key building characteristics for each model by location). More information about the probability distributions for the housing characteristics can be found in an online data repository (NREL, 2024).

We size the solar system to meet 100 % of the annual energy consumption of the underlying building model, subject to available roof area. The NREL ResStock metadata files provide roof area data. The roof constraint assumes that only 70 % of the total roof area is available to PV panels, though this constraint never binds for the specific representative building models selected in this study. In our baseline case, our modeled solar systems take up 20–50 % of a building's roof area (see supplemental Figure 11 and Fig. 12). Solar generation is simulated with 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-degree azimuth, and tilt equal to the latitude of the weather station location (Barbose et al., 2024; Blair et al., 2018). We leverage the same weather data that is used in the underlying ResStock building simulations to ensure geospatial and temporal alignment. Sizing for storage is based on typical commercially available sizes (see section 2.4)

Finally, we simulate stochastic power interruption events for each location using Berkeley Lab's power reliability event simulator model (PRESTO).[1] PRESTO uses historical county-level hourly power interruption data from PowerOutage.US (POUS) to stochastically simulate power interruption events that reflect the actual timing, duration, and frequency of interruptions over the empirical training period from roughly 2017 to 2021 (Baik et al., 2025). These data allow us to calculate the system average interruption frequency index (SAIFI), which represents the average number of times a customer experiences an outage during the year, and the system average interruption duration index (SAIDI), which represents the total number of minutes of interruption the average customer experiences in the year. Both metrics are

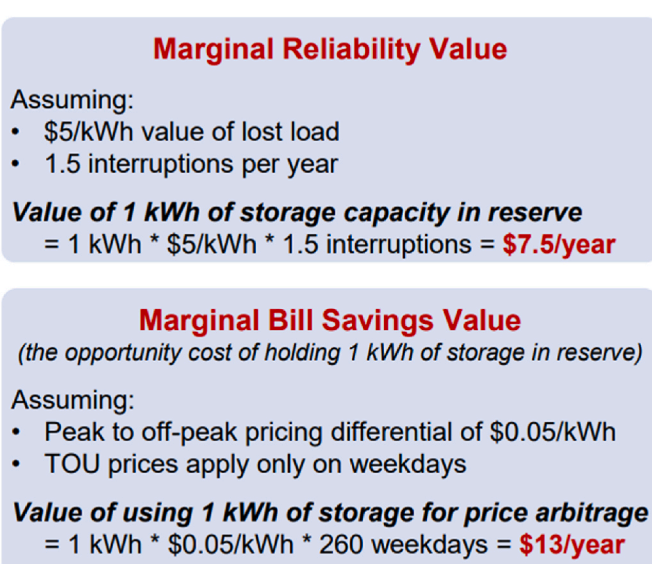

Fig. 1. A back-of-the-envelope comparison of marginal reliability value and marginal bill savings value.

[1] https://presto.lbl.gov/home.

critical inputs to characterizing a distribution of customer interruptions across different locations.

We run 1500 simulation years per location using default POUS data, with each simulation yielding an hourly time-series of interruption events for the year. Of course, future power interruption trends may differ from historical data, given changes to weather patterns. However, over the past decade, key U.S.-wide reliability metrics have shown limited variation, particularly when focused on short-duration interruption events, which is the focus of this paper (EIA, 2024). A detailed description of PRESTO's stochastic simulation process is provided in Baik et al. (2025), where the full model framework is documented, including how it draws event timing, frequency, and duration from empirically derived distributions.

Table 1 summarizes the key outage characteristics for each location for our base case assumptions (more details on basic interruption statistics found in Supplemental Table 5). Two key features are worth noting. First, not all simulation years have a power interruption. Second, in some locations (DFW, LA), the average duration per event is quite long, due to long-duration events that occurred within our historical period (see supplemental Figure 13 - 16 for full distributions of interruption durations, start hour, and start season). We also include sensitivity analyses where we increase interruption frequency by 2x and 10x in each location, while maintaining the same average duration per event. These sensitivities, in part, allow us to consider the impact of a future where interruptions might increase, as well as how the results might differ in cases where customer expectations for interruptions are much higher than their baseline experience.

2.3. Dispatch models used to simulate PVESS usage

We develop two independent but connected models to calculate, respectively, the annual bill savings from operating storage on a day-to-day basis over the year and the reliability value from operating storage during power interruption events. An overview of the analysis structure and corresponding data inputs and outputs is depicted in Fig. 2.

The annual dispatch model simulates storage dispatch over every hour of the year to calculate utility bill savings from storage utilization (beyond the savings from the PV system alone). Dispatch occurs sequentially hour by hour in response to retail electricity price signals and subject to the specified storage reserve level (and other key constraints, noted below). We consider two types of tariff structures, time-of-use (TOU) and net billing (NB). For TOU, storage charges during off-peak periods and discharges during peak periods are subject to grid charging and discharging constraints (discussed in the next section). For NB, storage charges from surplus solar and discharges to meet the net load. For all tariff structures, the storage unit charges and discharges as soon as possible, subject to loads, PV generation, storage reserve setting, storage power constraints, and round-trip efficiency. An illustrative dispatch profile is shared in Supplemental Fig. 19.

We assume 85 % round-trip efficiency and a 2-h storage duration, which corresponds to typical current residential storage systems (Barbose et al., 2024). We apply constraints on the discharge and charge rates of the storage such that they do not exceed the kW capacity of the storage within the hour, which is determined by dividing the kWh energy limit of the storage by the 2-h duration. The key outputs from the model are annual bill savings from storage and an hourly 8760 storage SoC timeseries. We then calculate bill savings from storage by taking the difference in the utility bill relative to the corresponding PV-only case (see Eq. (1) and Eq. (2)).

$$S_{TOU} = \left(C_{off,pv-only} - C_{off,PVESS}\right)^{*}P_{off} + \left(C_{on,pv-only} - C_{on,PVESS}\right)^{*}P_{on} \quad (1)$$

Where.

S_{TOU} = the savings from operating storage under TOU tariffs ($)
$C_{off,pv-only}$ = the annual off-peak period net consumption with only PV installed (kWh)
$C_{off,PVESS}$ = the annual off-peak period net consumption with PV and storage installed (kWh)
P_{off} = the off-peak price ($/kWh)
$C_{on,pv-only}$ = the annual on-peak period net consumption with only PV installed (kWh)
$C_{on,PVESS}$ = the annual on-peak period net consumption with PV and storage installed (kWh)
P_{on} = the on-peak price ($/kWh)

$$S_{NB} = \left(I_{pv-only} - I_{PVESS}\right)^{*}P_{I} + \left(E_{PVESS} - E_{pv-only}\right)^{*}P_{E} \quad (2)$$

Where.

S_{NB} = the savings from operating storage under net billing tariffs ($)
$I_{pv-only}$ = annual imports with only PV installed (kWh)
I_{PVESS} = annual imports with PV and storage installed (kWh)
P_{I} = the import price ($/kWh)
$E_{pv-only}$ = annual exports with only PV installed (kWh)
E_{PVESS} = annual exports with PV and storage installed (kWh)
P_{E} = the export price ($/kWh)

The interruption-event dispatch model simulates PVESS dispatch during the stochastic power interruption events produced by PRESTO to determine the amount of energy supplied by the PVESS system during the interruption events, which is converted to dollar terms with a value of lost load (VoLL) assumption. The interruption event dispatch model dispatches storage in each hour sequentially during each power interruption, given PV production, storage SoC, and storage power constraints. Fig. 3 shows the decision tree used to determine the dispatch of the PVESS system during interruption events. We do not consider behavioral adjustments from households that might result from an interruption (e.g., reducing demand to save energy for high-priority uses). Such a choice, however, could serve to reduce the reliability value of the PVESS overall as there becomes less energy to serve by the system overall.

We apply the same storage constraints on the discharge and charge rates of storage as in the annual dispatch model. Storage SoC at the beginning of each interruption event is passed from the annual dispatch

Table 1
Summary of Simulated Power Interruptions for each Study Location in the Base Case.

City (PRESTO County)	Percent of years with at least one interruption	Average interruptions per year	Average duration per interruption event (hours)
Boston (Middlesex)	48 %	0.98	19.61
DC (Fairfax)	67 %	0.76	9.29
Denver (Jefferson)	73 %	0.84	3.97
DFW (Tarrant)	48 %	0.49	34.69
Duluth (St. Louis)	68 %	0.79	5.81
LA (Los Angeles)	29 %	0.29	39.51
Memphis (Shelby)	79 %	1.04	5.75
Phoenix (Maricopa)	99 %	2.22	6.77
Seattle (King)	71 %	0.87	12.97
Tampa (Hillsborough)	71 %	0.84	9.63

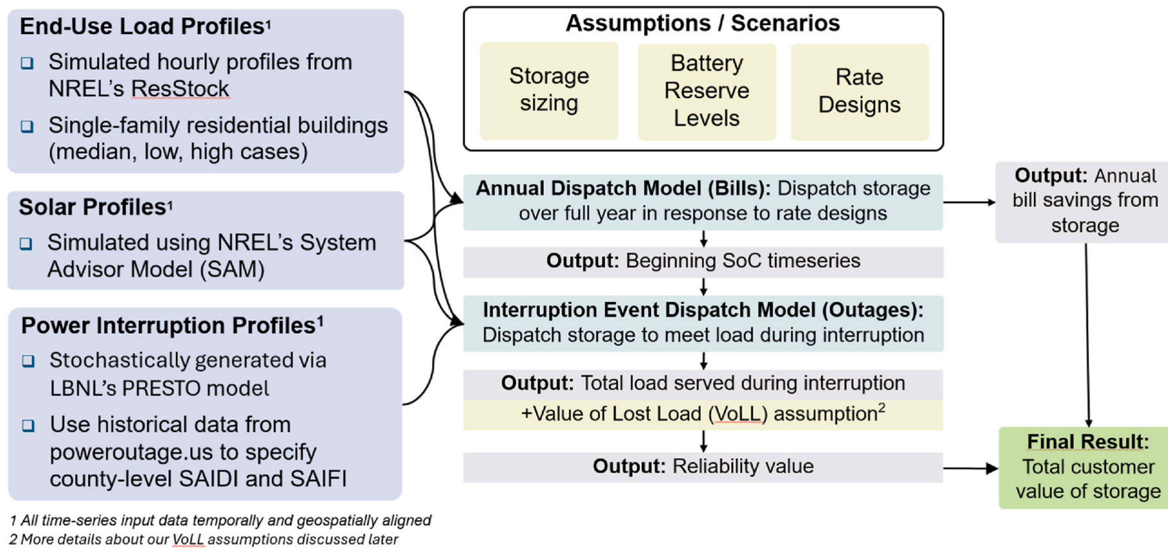

Fig. 2. Schematic summarizing key data sources and corresponding use in both the bill savings and power interruption dispatch algorithms.

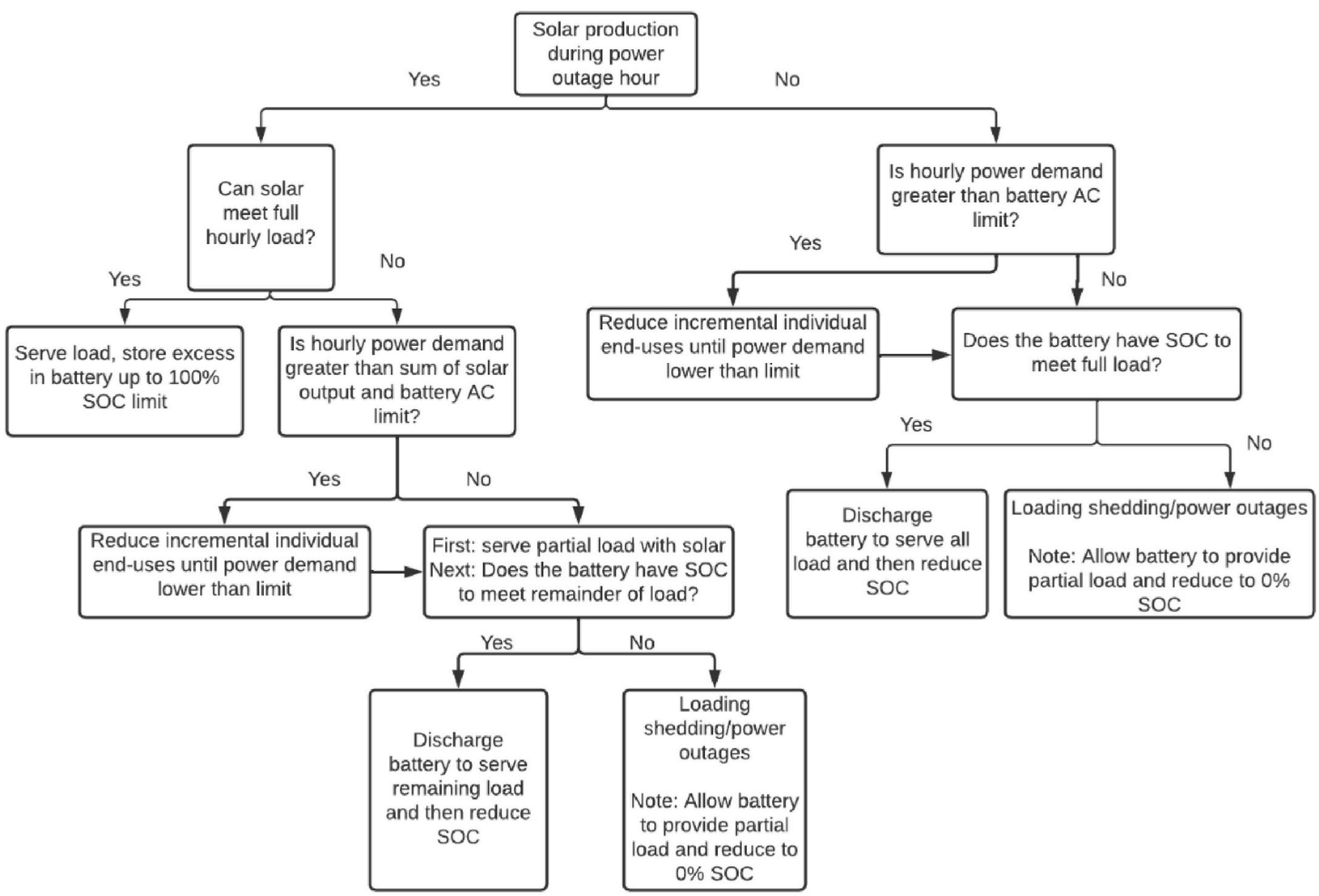

Fig. 3. PVESS dispatch logic implemented to model usage of the storage unit during power interruptions.

model to the interruption event dispatch model, and the system is configured for whole-home backup, such that backup load served is maximized. If the PVESS cannot meet all loads in an hour, individual end-uses are dropped, starting with the lowest priority load, until remaining loads are fully served. We determine the total load met in kWh for each interruption event. We then sum the total amount of load met for all interruptions that occur for one simulation year of the PRESTO simulation. We calculate the total reliability value by multiplying the load served by the VoLL assumption (see Eq. (3)). The VoLL assumption is further discussed in the next section. Finally, total value from storage is calculated by adding the reliability value to the bill savings under the particular rate design and sensitivity case being analyzed (see Eq. (4)).

$$R = L^{*}VoLL \quad (3)$$

$$T = R + S_X \quad (4)$$

Where,

R = the reliability value from adding storage ($)
L = annual load served for all interruptions occurring for one simulation-year (kWh)
$VoLL$ = value of lost load ($/kWh)
T = Total value from adding storage ($)
S_x = bill savings from either the TOU or net billing cases ($)

The above dispatch models are designed to compare annual bill savings to annual reliability value and thus do not consider storage degradation. Degradation could impact our conclusions in three ways: (1) cycling-driven degradation of storage capacity that could reduce annual bill savings or reliability value over the working life of the storage asset; (2) cycling-driven degradation reducing the lifespan of the storage system resulting in forgone reliability value in later years of the storage asset's life; and/or (3) increased maintenance costs due to storage cycling. For our analysis, the critical question is how much incremental degradation is realized from cycling storage versus having the storage unit sit idle. Mishra et al. find that for some more common storage chemistries (e.g., LFP), there is a limited difference in degradation between daily cycling and idling applications, suggesting that the lifespan of those storage systems is not significantly different when considering cycling vs. idling use-cases (Mishra et al., 2020). For lithium nickel manganese cobalt (NMC) storage chemistries, however, they find that cycling does significantly reduce the storage system's useful life. Thus, our results would vary depending on the specific storage chemistries being analyzed and their corresponding degradation profile. We assume no incremental degradation from cycling storage; and thus our findings apply most directly to LFP technologies, which are currently the standard choice for Tesla's Powerwall model.

2.4. Base case and sensitivity-analysis parameters

This paper assesses how changing residential tariff structures and grid charging/discharging rules impact the amount of storage a customer should hold in reserve to maximize their value from storage dispatch. Our focus on the residential case allows us to explore a wider variety of sensitivities specific to that customer class than would be possible if needing to incorporate the heterogeneous set of rate designs (e.g., with demand charges) and load profiles of commercial and industrial customers. Table 2 summarizes the key modeled tariff structures and grid charging/discharging constraints we adjust in our analysis to answer this research question. Under all tariff structures, storage generates bill savings by arbitrage between high and low prices. For net billing, the arbitrage is between import and export prices, and for TOU, the arbitrage is between on-peak and off-peak prices, where on-peak is defined as the period from 3 to 7 pm on weekdays. Storage dispatch is also impacted by grid charging and discharging constraints, where the default case assumes that storage charges only from surplus solar and discharges only to meet the net load. We consider TOU variants that allow grid charging and/or grid discharging (see Table 2).

Table 2
Summary of Modeled tariff structures and grid charging/discharging constraints.

Tariff Structure Variant	Grid Charging	Grid Discharging
Net billing	No	No
TOU self-consumption	No	No
TOU grid charging	Yes	No
TOU grid discharging	No	Yes
TOU front-of-the-meter	Yes	Yes

The key assumptions that we vary throughout the analysis are present in Table 3. Base price refers to either the off-peak period price (for TOU rates referred to as P_{off}) or the export price (for NB referred to as P_E). A higher base price increases the cost of round-trip storage efficiency losses. Price arbitrage differential refers to the price differential between on-peak and off-peak or between import and export prices. The base-case price arbitrage differential is intentionally small (5 cents/kWh), to focus initially on cases where the results are driven more strongly by reliability value compared to bill savings. We do not consider any price elasticity of demand as a result of these price changes. Instead, we hold demand fixed in relation to price but do consider static sensitivity cases with higher and lower demand profiles.

The base-case and sensitivity VoLL assumptions are taken from the literature (Baik et al., 2021; Gorman, 2022). The average lower bound of the VoLL estimates is $4.91/kWh, while the upper bound averages $11.70/kWh. Some recent studies suggest residential VoLLs >$40/kWh. Therefore, our study focuses on a base-case VoLL of $5/kWh, with sensitivities at $10/kWh (2x base case) and $50/kWh (10x base case). Supplemental Fig. 17 shows a compilation of VoLL estimates from the cited papers. Given the high costs of behind-the-meter storage today, it is likely that customers who are adopting batteries have a high VoLL (Gorman et al., 2023). Our high-VoLL sensitivities should therefore be given extra weight if readers are interested in understanding the behavior of early adopters of these technologies in particular.

The base-case interruption frequency for each county is based on historical interruption data obtained from PowerOutage.US for 2017–2021. The 10x sensitivity case is informed by (Dunn et al., 2019), which finds that variability in interruptions can span orders of magnitude within a utility service territory. Importantly, increasing the number of interruptions results in more utilization of the energy being held in reserve by the customer over the year because there are thus more opportunities to use that reserve capacity to mitigate the energy lost at the beginning of the interruptions modeled.

The base-case storage size roughly corresponds to the most-typical storage size observed within the market today, whereas the larger storage size in the sensitivity case may be more reflective of how a customer would size its storage for whole-home backup (Barbose et al., 2024). The base-case customer load profile is based on the ResStock building model with the median annual electricity consumption for the county. The solar sizes are driven by the customer load profiles, as discussed in section 2.2. These size ranges are specified in Table 3 and for each location in Supplemental Fig. 11.

Finally, for both the base and sensitivity cases, we vary the storage reserve level assumption between 5 % and 95 % in increments of 15 %. This reserve level is a key input into the annual dispatch model as it constrains the amount of storage available for charging and discharging and thus impacts the storage's SoC profile, which is the key input to the interruption event model.

Table 3
Base-case assumptions and sensitivities.

Parameter	Base Case	Sensitivities
Base price (P_{off} or P_E)	$0.10/kWh	$0.20/kWh
Price arbitrage differential (add differential to P_{off} or P_E to get P_{on} or P_I)	$0.05/kWh	$0.10, $0.15, and $0.20/kWh
Value of Lost Load (VoLL)	$5/kWh	$10 and $50/kWh
Interruption frequency	Historical county-average	2x and 10x the base-case values
Storage size	10 kWh	30 kWh
Customer load profile	County median kWh from ResStock	20th and 80th percentile customers based on kWh
Solar size	4–10 kW, depending on location	High-load: 6–15 kW Low-load: 3–7 kW

3. Results

3.1. Base case

Fig. 4 depicts the annual bill savings (left image) and annual reliability value (right image) for all tariffs in the Memphis study area. The left image of the graph shows that for the TOU self-consumption tariff and TOU grid charging cases, bill savings taper gradually at low reserve levels, as daily cycling depth is constrained by grid discharging limits, and there is not enough peak-period net load to fully discharge the battery. Under NB and TOU cases that allow grid discharging, there is a more linear decrease in bill savings as reserve levels increase.

The right image in Fig. 4 shows that the annual average reliability value is relatively insensitive to reserve levels, albeit with a slightly more pronounced slope for the NB and TOU grid discharging cases. For the other three tariff cases, the reliability value is effectively flat, reflecting a few key factors. First, for many locations, a significant share of simulation years has no interruption (see Table 1 and the description of simulation year creation in Section 2.2). A second critical factor is that the net load available to serve is typically relatively low (see Supplemental Figs. 21 and 22). The final, and most complex factor, is that the initial SoC at the onset of power interruptions under tariffs that allow grid charging tends to be relatively high, regardless of reserve level, because storage will be fully charged during most hours of the day.

In contrast, for tariffs where storage can discharge fully but charges only from solar (e.g., net billing), the initial SoC is sensitive to reserve level. Under the TOU self-consumption tariff, the initial SoC is less sensitive to reserve level due to shallower discharge during daily arbitrage. See Supplemental Fig. 20 for a depiction of these initial SoC trends for Memphis.

To simplify the presentation of the remainder of the results, we primarily focus on the NB and TOU self-consumption rate design, given that results from the other tariff cases fall in between the NB and TOU self-consumption cases. Fig. 5 reports the same information as the prior figure, but now for all locations. The left image of Fig. 5 shows that all locations have similar decreasing bill savings trends, though the slopes and levels differ by location. Under both tariffs, grid charging/discharging constraints can be more or less binding depending on solar, load levels, and load shapes, hence the observed spreads across locations.

Combining the results from the above two graphs, Fig. 6 shows that total customer value declines monotonically with reserve levels, as any gain in reliability value is more than offset by the decline in bill savings. Customer value under our base-case assumptions is therefore maximized by maintaining low storage reserves. That said, the decline under the TOU self-consumption tariff is relatively modest compared to NB, given the much smaller drop in bill savings. Customers are therefore nearly indifferent to changes in reserve level, at least up to some point.

The preceding results reflect average values across all 1500 stochastic interruption simulation years for each location. Fig. 7 shows that the same trends hold even under worse-than-average interruption years, with one modest exception. In this figure, we reduce the line chart from Fig. 6 to a single value plotted by the bar segment, representing the change in customer value with an increase in reserves from 20 % to 80 % (see Supplemental Fig. 24 for a visual depiction of this transmutation). Thus, negative values indicate that the total value declines with higher reserves. The key added feature to Fig. 7 is the error bands, which show the range in value-change across stochastic simulation years from PRESTO. Under worse-than-average interruption years, the reliability value will tend to be higher, and potentially also more sensitive to reserve level. However, even in those years, represented in the figure by the upper bound of the error bands, total customer value still tends to decline with increasing reserves, as the added reliability value still does not offset the loss in bill savings. The sole exception is for the TOU self-consumption tariff in Seattle, where total customer value in some years may be modestly higher if reserves are increased.

3.2. Sensitivity to higher interruption frequency and higher VoLLs

The above results considered base case interruption frequencies and VoLLs, reflective of average reliability conditions and customers. However, customers adopting PVESS technologies for reliability reasons may be more likely to either live in relatively unreliable areas (i.e., with a greater than average interruption frequency compared to other areas within the same county) and/or have a relatively high VoLL.

Fig. 8 shows that total customer value increases with reserve level if VoLL and interruption frequency are sufficiently high. In Fig. 8, we apply progressively higher interruption frequency (SAIFI) and VoLL assumptions to the Memphis NB case. Doubling SAIFI and VoLL does not materially change the results from the base case: low reserves are still best. Only with the highest (10x) SAIFI and VoLL assumptions is the reliability value sufficiently sensitive to reserve level that the average total customer value increases with higher reserves. In contrast, under TOU structures where the initial SoC typically remains high regardless of reserve level (e.g., TOU front-of-the-meter and TOU grid charging), the gain in customer value is negative, even with aggressive VoLL and SAIDI

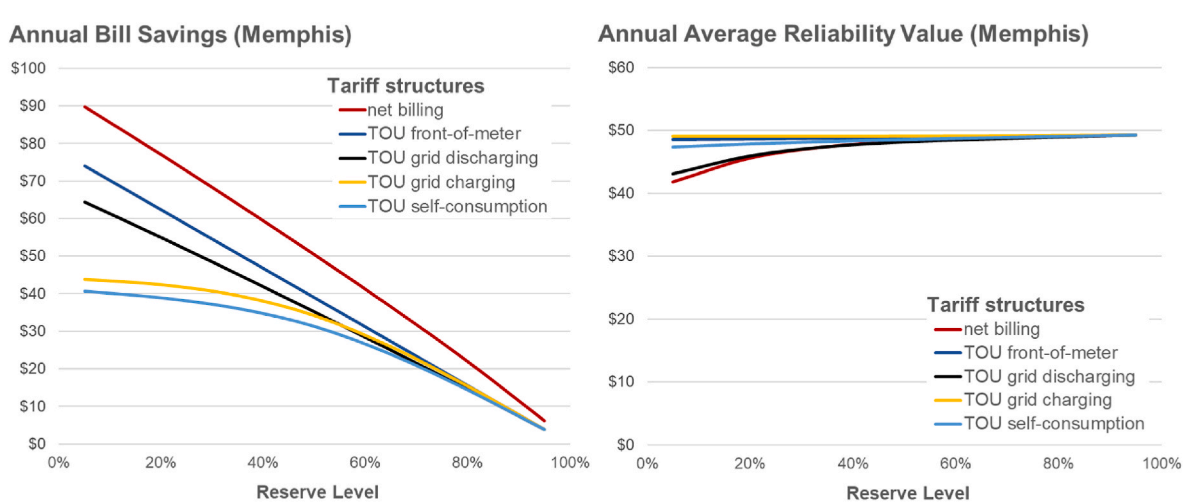

Fig. 4. Annual bill savings in dollars (left image y-axis) compared to annual reliability value in dollars (right image y-axis) as the storage reserve level is changed under base case assumptions (10 kWh storage, median load profile, $5/kWh VoLL) in Memphis for all tariff designs ($0.10/kWh base price with $0.5/kWh price arbitrage differential).

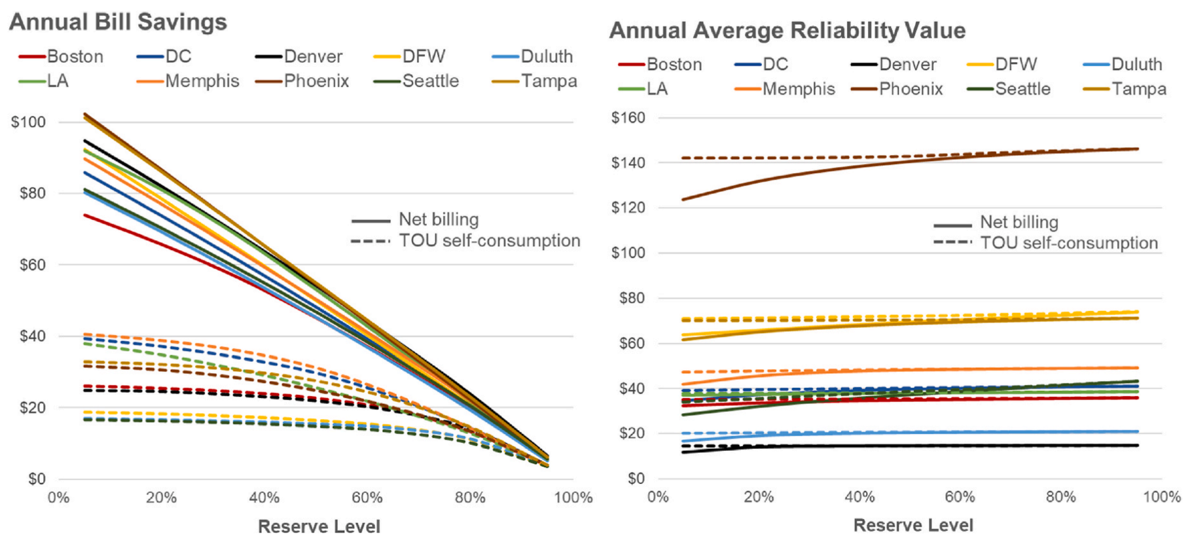

Fig. 5. Annual bill savings in dollars (left image y-axis) compared to annual reliability value in dollars (right image y-axis) as the storage reserve level is changed under base case assumptions (10 kWh storage, median load profile, $5/kWh VoLL) for all locations ($0.10/kWh base price with $0.5/kWh price arbitrage differential).

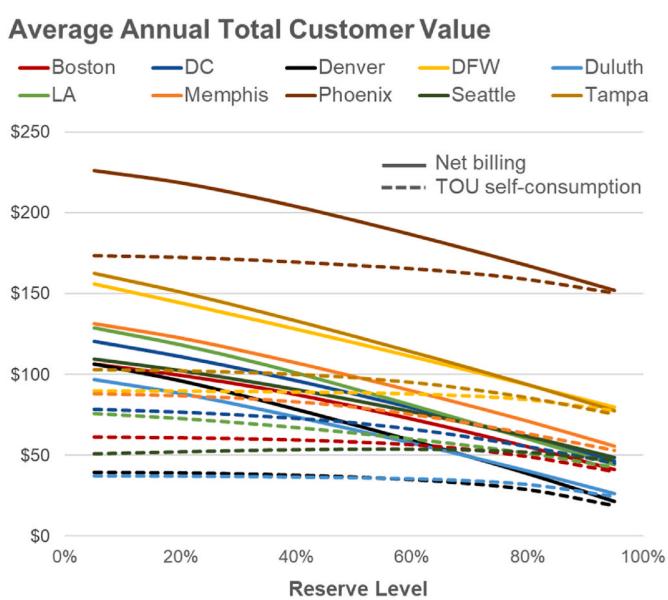

Fig. 6. Average annual total customer value (annual bill savings plus annual reliability value) for all locations for two tariff designs under base case assumptions (10 kWh storage, median load profile, $5/kWh VoLL) and all locations ($0.10/kWh base price with $0.5/kWh price arbitrage differential) as the storage reserve level is changed.

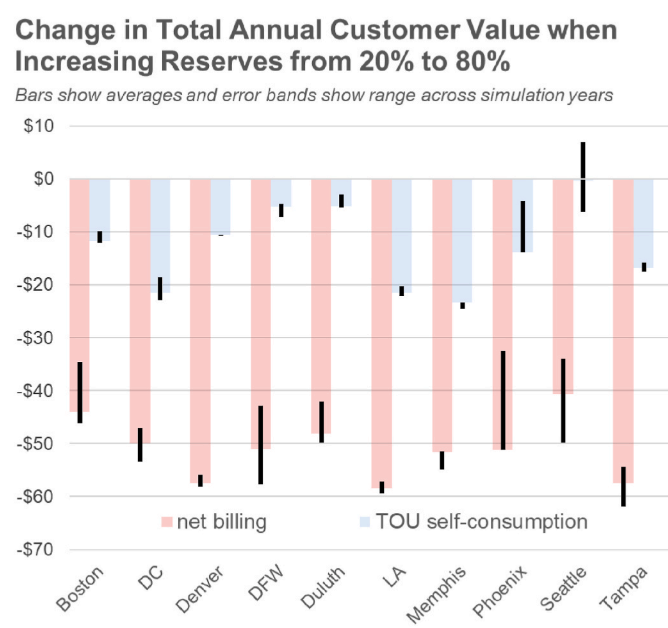

Fig. 7. Change in Total Annual Customer Value (annual bill savings plus annual reliability value) when Increasing Reserves from 20 % to 80 % under base case assumptions (10 kWh storage, median load profile, $5/kWh VoLL) for all locations ($0.10/kWh base price with $0.5/kWh price arbitrage differential).

values.

We also compare the baseline results for the NB tariff to cases where interruptions and VoLLs are increased by 2x and 10x across all locations. As with Memphis, other locations show that doubling the interruption conditions and VoLL does not materially change the results from the base case: i.e., low storage reserves are still optimal. Only with the highest (10x) interruption and VoLL assumptions combined is the reliability value sufficiently sensitive to reserve level such that average total customer value increases with higher reserves. In these cases, increasing storage reserve levels from 20 % to 80 % increases the total annual customer value in almost all study locations. The most dramatic effects occur in Phoenix, due to relatively frequent interruptions in its base case that are more significantly impacted by the 10x multipliers for interruptions and VoLL values. See Supplemental Fig. 18 for more details.

3.3. Sensitivity to higher tariff differentials and base prices

Importantly, the trends in Figs. 8 and Supplemental Fig. 18 retain the modest base-case differential between import and export prices (in NB cases) and on- and off-peak prices (in TOU cases) of $0.05/kWh. Raising the differential between these prices increases the opportunity cost of holding additional storage capacity in reserve, offsetting to varying degrees the effects of modifying the reliability and VoLL assumptions. Fig. 9 shows that in half of the study locations, a price differential of $0.20/kWh increases the opportunity cost enough to fully offset the reliability benefits of maintaining high reserves, even under the 10x interruption and VoLL assumptions for the NB case. In the other locations, where reliability value is more sensitive to reserve levels,

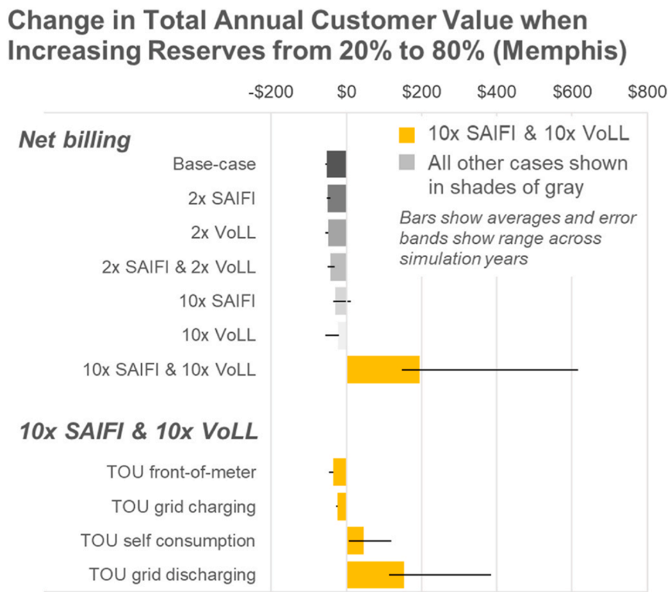

Fig. 8. Change in Total Annual Customer Value (annual bill savings plus annual reliability value) when increasing reserves from 20 % to 80 % in the Memphis location for a variety of the sensitivity cases considered (base-case, increase power interruptions, increased VoLL, different rate designs).

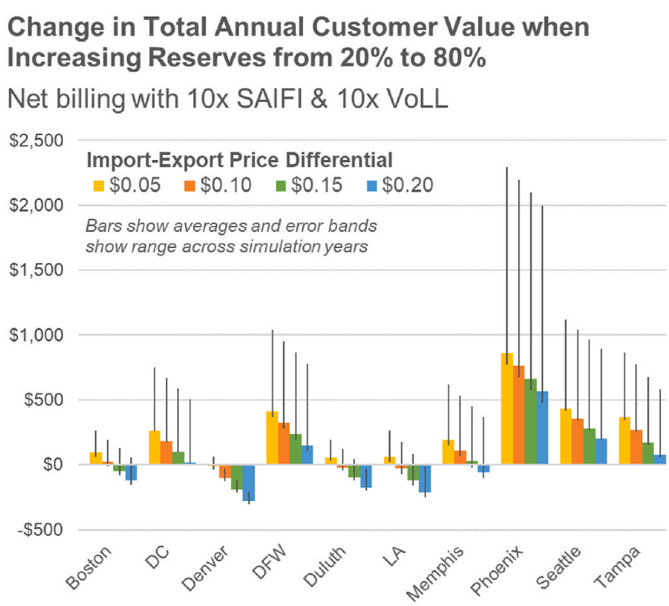

Fig. 9. Change in total annual customer value (annual bill savings plus annual reliability value) when increasing reserves from 20 % to 80 % and when increasing the import-export price differential under net billing tariff with 10x increases to power interruption and VoLL assumptions.

customer value is still greatest with high reserves. We chose this 20-cent value to correspond roughly to the most aggressive end of price differentials in current rate offerings by U.S. utilities, though there are examples of even larger differentials (Faruqui and Tang, 2023). The patterns and trends outlined and discussed above hold across all additional tariff sensitivities, though with a different impact on the magnitude of outcomes. These results are shown in the supplemental information section, where a complete treatment of all sensitivities across all locations is shared in Supplemental Figs. 27–31.

In Fig. 10, we show how a higher base price impacts annual bill savings and total annual customer value. Higher base prices increase the cost of round-trip efficiency losses for storage, and thus serve to reduce the overall bill savings resulting from price arbitrage. This effect impacts our results by making bill savings less sensitive to reserves (left image of Fig. 10). Nevertheless, we still find that the reduction in bill savings due to increased storage reserve levels still outweighs the added reliability value resulting from increased storage reserve levels in most locations and tariff designs. Additional sensitivities that correspond to changes in customer demand are presented in Fig. 26, but did not significantly impact the change in bill savings or reliability value when increasing reserve levels.

4. Conclusions

In this paper, we analyzed the tradeoff between operating behind-the-meter storage to provide maximum reliability value in the case of a power interruption (by setting a high storage reserve level) versus using that same storage asset to arbitrage retail tariffs and provide corresponding annual bill savings. We focused on power interruptions that are unpredictable, infrequent, and often relatively short. To maintain readiness to respond to these types of events, a customer will typically set its storage to maintain some minimum capacity in reserve in case of an interruption, which reduces the capacity available for managing utility bills. To quantify this economic tradeoff, we utilize the PRESTO tool to stochastically simulate power interruption events and then compare changes in customer reliability value and bill savings across varying reserve levels. This study intends to inform product decisions and business models, as well as regulatory rate design and interconnection rules that require an understanding of the different sources of value that behind-the-meter storage can provide to the host customer and tradeoffs therein.

One central, and unexpected, finding from this analysis is that customer reliability value is relatively insensitive to reserve level. As a result, the opportunity cost of holding storage capacity in reserve, in terms of foregone bill savings, almost always outweighs any gains in reliability value from mitigated power interruptions when considering modern LFP storage chemistry degradation models. We found this to be true both on average and in more extreme years among our stochastic simulations for each location, including years with relatively severe interruptions. As a result, the key conclusion from this work is that customers are generally better off, financially, by maintaining as low a reserve setting as possible (and as allowed by the battery manufacturer's warranty). This finding is robust across all tariff structures and most sensitivities considered, including those related to rate level, customer load level, and storage sizing. We did not explicitly model household risk aversion within our methodological framework, which could make PVESS adopters pay a premium for reliability and therefore place more value on the backup power use case. However, we believe that our high VoLL sensitivity case does, to a significant extent, incorporate this aspect of decision making by placing a particularly high economic cost to losing electricity service.

Furthermore, we did not consider a detailed degradation model, as those models vary widely depending on the storage chemistry being deployed. Future research should test the sensitivity of our findings to a range of degradation models. Our analysis applies to LFP chemistries, which see limited additional degradation from storage cycling compared with an idling-only use case, but this degradation characteristic does not hold for all storage chemistries available in the market.

Only under a "perfect storm" of circumstances does raising the reserve setting increase total customer value (bill savings + reliability value). Within our analysis, that outcome occurs only where the customer resides in a location with inferior reliability (e.g., 10x their county average frequency), has exceptionally high VoLL (e.g., 10x our base-case), is on a net billing rate or on a TOU rate that allows grid discharging but not grid charging, and (depending on the location) the price arbitrage differential is relatively modest. Only where all of those conditions hold does raising the reserve level increase customer value.

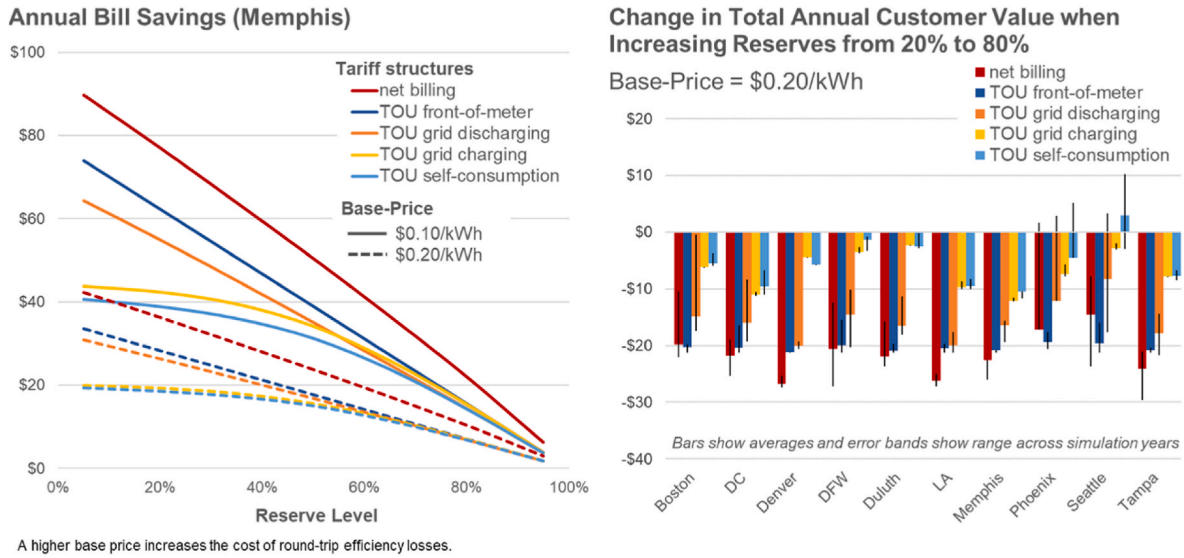

Fig. 10. Impact of higher base price on bill savings (left image y-axis, in dollars) and total customer value (right image y-axis, in dollars). All other assumptions from the base-case (10 kWh storage, median load profile, $5/kWh VoLL, $0.5/kWh price arbitrage differential).

While an exceptional outcome within our analysis, the fact that increasing reserves can sometimes increase customer value illustrates that specific circumstances matter and should be considered when making decisions about storage reserve settings.

Tariff policies and interconnection rules can significantly impact the setting of appropriate reserve levels. As noted above, the size of the pricing differential is important, with larger differentials further increasing the opportunity cost of holding capacity in reserve. In addition, we found that allowing grid charging largely obviates the need for caring about reserve levels, as the battery can be restored to full SoC using grid energy soon after its discharge cycle. Regulators focused on maximizing the grid value of customer-sited storage should consider allowing grid charging to ensure customers reduce the amount of storage kept in reserve and thus make available to provide grid services.

Importantly, this study does not consider all possible tariff structures—for example, net metering with constant rates, which is a common structure, but one in which storage provides no incremental bill savings value. Constant electricity rates, however, are common across the U.S. and in some of the locations we study (e.g., Memphis), emphasizing that our results are meant to highlight potential tradeoffs residential customers would face if tariff designs were updated to the more modern, time-varying, designs we consider. The study also does not consider demand response or virtual power plant (VPP)-type programs, where batteries can earn revenues from responding to discrete events. In practice, customers typically receive advance warning for those events, and would therefore be able to adjust their reserve setting prior to the event, in order to maximize their revenues, and then immediately restore their reserve setting to its normal value following the event. Finally, we do not consider tariffs that expose households to wholesale prices, given the relative scarcity of this residential tariff structure in the U.S. Nevertheless, such future work could consider such hypothetical cases to more accurately assess how reductions in overall system value are impacted when households hold storage in reserve.

Future work could leverage the framework developed in this study to create a full cost-effectiveness and/or cost-benefit evaluation, which would calculate bill savings values based on specific, rather than generic, tariff structures and electricity prices and combine such results with data on installation costs. Such work is important given the small average annual savings we calculate in this paper, which would lead to particularly long payback periods for storage systems. Similarly, our study focused on modeling the tradeoff that customers make when deciding what reserve setting is optimal, but did not investigate what customers have implemented today. Future work should consider a more empirical approach, which aims to understand what customers are choosing in practice and what drives those choices.

Furthermore, our study focused on individual residential customers, rather than considering electricity sharing with other community institutions via microgrid designs. This practice could have potential, especially when considering community service operations—such as hospitals, police and fire stations, and emergency shelters—as they have significantly higher value for secure electricity supply. Nevertheless, enabling such electricity sharing requires additional investments and institutional designs, which were out of scope for this paper. We also did not consider commercial or industrial customers, which may have more critical loads and therefore higher VoLLs than considered in the paper. Those customers have much more heterogeneous load profiles, and thus, it is much more challenging to create more generalizable results.

Technological advancements (e.g., dynamic reserve settings or predictive algorithms that anticipate possible interruptions) may also impact how customers make this tradeoff, and how much reliability value they receive. The analysis is predicated on unpredictable power interruptions. To the extent customers can anticipate interruptions and adjust their reserves dynamically, the value of maintaining higher default reserve levels will further diminish. The analytical framework developed here could be applied in the future to evaluate the benefits of such technological advancements.

Finally, it should be emphasized that this analysis focuses solely on usage decisions and does not address customer investment decisions or any tradeoffs between backup power and bill savings therein. Thus, while we show that customer bill savings dominate the tradeoff when setting the reserve level, reliability value may still be a critical part of the overall value equation for the customer investment decision, as several prior studies have shown.

CRediT authorship contribution statement

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

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors do not have any competing interests to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jup.2025.102035.

Data availability

Data will be made available on request.

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