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# **Bill Savings vs. Backup Power:**

Evaluating operational tradeoffs for home solar+storage systems

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## **Report Organization**



## **Context and Motivation**

- □ Adoption of residential solar photovoltaic+energy storage systems (PVESS) is driven by both bill savings opportunities and customer demand for backup power
- □ Prior work by this team ([Gorman et al., 2022;](https://emp.lbl.gov/publications/evaluating-capabilities-behind-meter) [Gorman et al., 2023\)](https://emp.lbl.gov/publications/solarstorage-household-back-power) explored PVESS backup power capabilities during long-duration power interruptions (e.g., due to severe weather events), when customers are assumed to be able to anticipate the event and charge their batteries in advance
- <sup>◻</sup> In many cases, however, power interruptions are unpredictable (and often relatively short); for those types of events, a customer will typically set its battery to maintain some minimum capacity in reserve in case of an interruption, which reduces the capacity available for managing utility bills
- □ This study evaluates this operational tradeoff to help customers and installers configure backup reserve settings, and to inform decision-making more generally about the customer value of backup power services compared to utility bill savings
- □ This study utilizes Berkeley Lab's **[PRESTO](https://presto.lbl.gov/home)** tool to produce stochastic simulations of (predominantly short-duration) power interruption events, and builds on an earlier case-study demonstrating PVESS backup performance during short-duration interruptions (Baik [et al., 2023](https://emp.lbl.gov/publications/backup-power-performance-solar-plus))

## **Bill Savings vs. Backup Power Value**

## A *"back-of-the-envelope" comparison*

- <sup>◻</sup> BTM storage capacity can be used for bill savings or reserved for backup power to mitigate a potential future power outage
- The text boxes provide a simple back-of-theenvelope 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
- $\Box$  In this simple comparison, the marginal bill savings are larger than the reliability value
- ◻ But to rigorously compare the two requires consideration of outage timing and how that aligns with solar production and load, rate structure, and constraints on grid charging and discharging, among other factors

### **Marginal Reliability Value**

Assuming:

- \$5/kWh value of lost load
- 1.5 interruptions per year

### *Value of 1 kWh of storage capacity in reserve*

= 1 kWh \* \$5/kWh \* 1.5 interruptions = **\$7.5/year**

### **Marginal Bill Savings Value**

*(the opportunity cost of holding 1 kWh of storage in reserve)*

Assuming:

- Peak to off-peak pricing differential of \$0.05/kWh
- TOU prices apply only on weekdays

### *Value of using 1 kWh of storage for price arbitrage*

= 1 kWh \* \$0.05/kWh \* 260 weekdays = **\$13/year**

## **Study Overview**

**Objective:** Evaluate how the customer value of PVESS is impacted by the backup reserve setting, considering the trade-off between reliability value and utility bill savings

**Audience and Purpose:** Inform customer and installer decision-making when configuring PVESS systems, as well as product, business model, and policy design that consider the multiple potential value streams of BTM PVESS

**Approach:** Simulation-based analysis using modeled solar and end-use level load profiles, and stochastic simulation of power interruption events

### **Key Elements of Study Scope:**

- □ Single-family residential buildings across a diverse set of climates and geographies
- ◻ Standardized set of tariff structures and PVESS configurations across all locations
- ◻ Empirically based mix of short- and long-duration events
- ◻ Sensitivity cases around key assumptions

## **Key Caveats and Points of Clarification**

- ◻ Battery backup reserve settings can often be easily adjusted through an app, and some manufacturers offer features that increase the reserves when a storm is approaching
- □ This analysis assumes that the simulated power interruptions cannot be anticipated by the customer; we discuss in the conclusions how relaxing that assumption would impact the results
- □ This is not a cost-effectiveness analysis and does not consider storage costs; we can compare the sources of customer value evaluated in this study to typical storage costs as a point of reference
- ◻ The modeled power interruptions in each of the study locations are based on a 5-year historical period and are intended to capture a diversity of interruption patterns, but are not necessarily representative of long-term historical averages or expected future interruption patterns
- ◻ The study considers a standard set of tariff structures applied across all study locations; we do not analyze the actual tariff structures offered in each location, nor do we consider several other common tariff structures (discussed in the conclusions) less relevant for this particular analysis
- □ Analysis is based on current U.S. residential building stock, though load sensitivities are indicative of how changes to the building stock (e.g., increased electrification) could impact the results





# **Data and Methods**



## **Data and Methods Overview**

### *Each element described further in the following slides*

- □ 10 locations (counties) representing a diversity of climates and geographies
- <sup>◻</sup> Representative baseline load profiles for single-family homes from NREL ResStock: select median, high, and low consumption cases; 1-hour interval load data
- □ Stochastic power interruptions simulated using LBNL's **[PRESTO](https://presto.lbl.gov/home)** model
- <sup>◻</sup> Solar systems sized at 100% of annual consumption, up to available roof area
- <sup>◻</sup> Weather data from AMY 2018 used for both load and solar simulations
- <sup>◻</sup> Two-stage storage dispatch modeling to compare bill savings and reliability value across a range of battery reserve levels
	- □ Annual Dispatch Model simulates dispatch over every hour of the year in response to rate structure; estimates bill savings from storage and passes hourly battery state of charge (SoC) to the next model
	- □ Interruption-Event Dispatch Model simulates dispatch during stochastic power interruption events produced by PRESTO
- □ Sensitivity analyses for varying battery sizes, customer load levels, customer value of lost load (VoLL), rate levels, and reliability levels

## **Overview of Analysis Structure**

### **End-Use Load Profiles<sup>1</sup>**

- ❑ Simulated hourly profiles from NREL's ResStock
- ❑ Single-family residential buildings (median, low, high cases)

### **Solar Profiles<sup>1</sup>**

❑ Simulated using NREL's System Advisor Model (SAM)

### **Power Interruption Profiles<sup>1</sup>**

- ❑ Stochastically generated via LBNL's [PRESTO](https://presto.lbl.gov/home) model
- ❑ Use historical data from poweroutage.us to specify county-level SAIDI and SAIFI





## **Ten Locations Studied**



- Selected ten counties, each encompassing a metropolitan area (same locations analyzed in earlier [Gorman et al., 2023](https://emp.lbl.gov/publications/solarstorage-household-back-power) report)
- ◻ Locations span a diverse range of climates (hot, cold, and temperate) and solar insolation levels (sunny/cloudy and lower/higher latitude)
- ◻ Locations also capture important regional differences in current building stock conditions (e.g., high prevalence of electric-resistance based heating in the Southeast and Northwest)
- ◻ As described later, a uniform set of rate structures and related sensitivities are applied across all locations, rather than using rate structures or levels particular to each location

## **Building Load Simulations**

- ◻ Used publicly available profiles developed with NREL's [ResStock](https://www.nrel.gov/buildings/resstock.html) building simulation platform, which produces statistically representative distributions of building models by county
- ◻ Selected three representative building models corresponding to the median, 20<sup>th</sup> percentile (low-usage), and 80th percentile (high-usage) annual electricity consumption levels across all baseline building models in each study location
- ◻ Building loads vary across locations due to climate and regional end-use characteristics
- ◻ End-use characteristics also vary across modeled homes within individual regions (see slide 45 for additional building characteristics



## **PV System Sizing and Generation**

- □ PV system sizes stipulated based on annual energy consumption, subject to available roof area
	- Sizing varies across median, high-usage, and low-usage homes, given differences in annual consumption
	- Roof-area constraint never binds for the customer loads selected (see slide 46)
- ◻ Presumption is that PV systems are sized for reasons other than backup power (e.g., to minimize utility bills)
	- Consistent with current installation practices in most major markets ([EnergySage](https://www.energysage.com/data/#intel-16) 2023)
	- **PV systems sized for resilience purposes could** be larger ([Simpkins et al. 2016\)](https://doi.org/10.1109/ISGT.2016.7781237)
- ◻ Hourly PV generation simulated with NREL's System Advisor Model (SAM), assuming default values (e.g. for orientation, losses, DCto-AC ratio, etc.)

Stipulated PV System Size (kW<sub>pc</sub>)



## **Power Interruption Events**

- We simulate stochastic power interruption events for each location using Berkeley Lab's [PRESTO](https://presto.lbl.gov/home) model
- ◻ PRESTO uses historical county-level hourly power interruption data from [PowerOutage.US](https://poweroutage.us/) to stochastically simulate power interruption events that reflect the actual timing, duration, and frequency of interruptions over the empirical training period (roughly 2017-2021)
- We run 1,500 simulation years per location, though not all years have a power interruption
- ◻ In some locations (DFW, LA), average duration per event is quite long, due to long-duration events that occurred within our historical period (see slide 47)

### **Summary of Simulated Power Interruption Events for Study Locations**



## **Tariff Structures and Grid Charging/Discharging Rules**

### **We consider two common tariff structures that incentivize storage adoption:**  *(1) Net metering with time-of-use (TOU) rates* **and** *(2) Net billing with flat rates*

Under both structures, storage generates bill savings by arbitraging between high and low prices (for net billing: between import and export prices; for TOU: between peak\* and off-peak prices)

Storage dispatch is also impacted by grid charging and discharging constraints:

- <sup>◻</sup> Default is that storage charges only from surplus solar and discharges only to meet net-load
- <sup>◻</sup> TOU variants considered that allow grid charging and/or grid discharging (see table)

*Tariffs/variants not evaluated*: net metering with flat rates, net billing with TOU rates, virtual power plant (VPP) programs, storage charging from all solar generation (not just surplus) *\*TOU peak period is 3-7 pm weekdays*

### **Modeled tariff structures and grid charging/discharging constraints**



## **Annual Dispatch Model for Bill Savings**

- □ Model simulates storage dispatch in response to tariff structure, subject to specified reserve level
- □ Dispatches storage sequentially hour by hour, based only on conditions within that hour
	- For TOU, charges during off-peak periods and discharges during peak periods, subject to grid charging and discharging constraints
	- For net billing, charges from surplus solar and discharges to meet net load
	- In both cases, charges and discharge as soon and as quickly as possible, subject to loads, PV generation, reserve setting, battery power constraints\*, and round-trip efficiency\*
- ◻ Key outputs are battery state of charge (SoC) timeseries and annual utility bill
- ◻ *Bill savings from storage***:** Calculated as the difference in the utility bill relative to the corresponding PV-only case

*\* Assume 85% roundtrip efficiency and a 2-hour battery duration, which correspond roughly to typical current residential battery storage systems. See [Tracking the Sun](https://emp.lbl.gov/tracking-the-sun/).*

## **Interruption Event Dispatch Model**

- <sup>◻</sup> Only PV systems with battery storage can provide backup during power interruptions
- <sup>◻</sup> Battery SoC at the beginning of each interruption even is passed from the annual dispatch model (previous slide)
- <sup>◻</sup> Model dispatches storage in each hour sequentially, given PV production, battery SoC, and battery power constraints (see figure)
- <sup>◻</sup> System is configured for whole-home backup, in order to maximize the amount of backup load served
- <sup>◻</sup> If the PVESS cannot meet all loads in an hour, individual end-uses are dropped, starting with the lowest priority load, until remaining loads fully served

*\* Battery power constraint is based on the stipulated storage kWh sizing and assumed 2-hour duration. The battery power constraint is almost never binding in this analysis, though this analysis is conducted over hourly intervals and therefore does not consider sub-hourly load spikes.*

### **PVESS dispatch logic during power interruptions**







# **Results**



## **Results Organization**

### <sup>◻</sup> **Building Intuition: Stepping through the Memphis\* Base-Case**

- ◻ Bill savings from storage across reserve levels
- ◻ Reliability value across reserve levels
- $\Box$  Unpacking the reliability value results
- ◻ Total customer value of storage across reserve levels
- <sup>◻</sup> **Base-Case Results for All Locations**
- <sup>◻</sup> **Sensitivity Cases**

*\* The focus initially on Memphis is largely arbitrary, as the intent is to introduce the analytical framework and illustrate general relationships. That said, it was chosen for this purpose largely because most the key drivers (e.g., climate, interruption profile, etc.) are near the middle of the distribution among the different study locations. In any case, as we show later, results across all locations are fairly similar.*

## **Base-Case Assumptions and Sensitivities**



- (a) "Price arbitrage differential" refers to the price differential between peak and off-peak or between import and export prices. The base-case assumption is intentionally small, to focus initially on cases where the results are driven more strongly by reliability value.
- (b) "Base price" refers to either the off-peak period price (for TOU rates) or the export price (for flat net billing). A higher base price increases the cost of round-trip efficiency losses.
- (c) The base-case VoLL assumption is roughly equal to the average residential VoLL within the literature (see slide 53).
- (d) The base-case interruption frequency for each county is based on historical interruption data obtained from PowerOutage.US for 2017-2021.
- (e) The base-case battery size roughly corresponds to the most-typical battery size [observed within the market today,](https://emp.lbl.gov/tracking-the-sun) whereas the larger battery size in the sensitivity case may be more reflective of how a customer would size its battery for whole-home backup.
- (f) The base-case customer load profile is based on the ResStock building model with the median annual electricity consumption for the county, while the sensitivities are based on the building models with the 20<sup>th</sup> and 80<sup>th</sup> percentile annual electricity consumption levels.

**Reserve Level** and **State of Charge:** May be denominated in kWh terms or as a percentage of the battery's usable kWh capacity

**Net Load:** The difference between total (gross) customer load and PV generation

**Bill Savings:** Just the bill savings from storage, calculated as the difference between the utility bill for the PVESS and the corresponding PV-only case without storage

**Reliability Value:** The value of power interruptions mitigated by the PVESS, calculated as the product of the total energy served during each power interruption and the stipulated value of lost load

**Total Customer Value:** The sum of Bill Savings and Reliability Value

## **Illustrative Dispatch Profiles for Two Tariff Structures and Two Storage Reserve Levels**

- ◻ Under both rate structures, storage charges from surplus solar during morning hours and begins its discharge in the late afternoon after solar drops off
- ◻ The particular variant of TOU arbitrage shown here (with no grid discharge) discharges only partially, even with a low reserve setting, given the limited amount of load during the TOU peak period
- ◻ In contrast, net billing discharges all the way down to the reserve level, as long as there is load to serve
- □ Increasing the battery reserve levels reduces the depth of discharge



*Note: For ease of interpretation, battery charge and discharge are both shown as positive values, differentiated by their shading.*

# **Bill savings from storage decline with reserve levels**

At different rates depending on tariff structure

- $\Box$  Purpose of the chart is to illustrate how bill savings change with reserve level (rather than focusing on absolute bill savings amount)
- ◻ Steepest decline is for net billing and TOU front-of meter rates, where bill savings fall more-or-less linearly with reserve level
- <sup>◻</sup> For TOU cases *without* grid discharging (the bottom two lines), changes in bill savings are gradual up to about a 50% reserve level, as a substantial portion of battery capacity tends to sit idle anyway, as there isn't enough peakperiod net load to fully discharge the battery



## **Reliability value is fairly insensitive to reserve level**

At least for these base-case annual average values

This surprising result reflects several factors:

- 1. The simulated power interruptions are relatively infrequent and short, based on the specific historical period used
- 2. The initial SoC at the start of the interruption events is often quite high, even at low reserve levels, under certain tariffs
- 3. The net load for the battery to serve during power interruptions, after accounting for PV production, is often quite small

*The next set of slides illustrate points #2 and 3, while later results will examine scenarios where reliability value is more sensitive to reserve level*



## **The initial SoC may be high even if reserve levels are low** Depending on the timing of the interruption and tariff structure

- ◻ The initial SoC depends partly on the timing of interruption events and how they align with the daily charging/discharging cycle (slides 50-52)
- The initial SoC is also highly dependent on tariff rules related to grid charging/discharging
- $\Box$  For tariffs where battery discharges fully but charges only from solar (e.g., net billing), the initial SoC is sensitive to reserve level
- $\Box$  In contrast, if grid charging is allowed, then battery will be fully charged during most hours of the day; initial SoC insensitive to reserves
- ◻ Under the TOU self-consumption tariff, the initial SoC is less sensitive to reserve level due to shallower discharge during daily arbitrage



**Average Initial SoC at Interruption-Start (Memphis)** 

## **Net load during power interruptions is often small** Suggesting that there isn't much load for the initial battery SoC to serve

- ◻ The simulated power interruptions for Memphis include short and long-duration events, with an average of ~6 hrs/event (see slide 14), and are evenly distributed throughout the year and by time of day (see slides 50-52)
- ◻ Across all simulated power interruptions, total customer load averages 11 kWh per event
- ◻ Most of that load is met by PV, leaving roughly 3 kWh, on average, to be covered by the initial SoC on the battery
- $\Box$  In addition to filling any net energy deficit with its initial SoC, the battery also supports backup power provision by balancing solar and load over the course of the event, and by bridging any gap for interruptions beginning pre-dawn



*Load Distribution across Interruptions (Memphis)*

## **Total customer value is maximized with low reserves** Under the specific set of base-case conditions assumed here

- ◻ Total customer value declines monotonically with increasing reserves, largely mirroring the corresponding drop in bill savings
- <sup>◻</sup> As such, total customer value is greatest when reserves are kept as low as allowed by the battery manufacturer
- □ Under TOU rates without grid discharging (the bottom two lines), total customer value is fairly flat up to  $~140-50\%$  reserves
- ◻ The remainder of the results explore the consistency of these basic findings across other locations and conditions



### <sup>◻</sup> **Building Intuition: Stepping through the Memphis Base-Case**

### <sup>◻</sup> **Base-Case Results for All Locations**

- □ Focus primarily on the two "bookend" tariff structures: net billing and TOU self-consumption
- □ Show how average annual bill savings, reliability value, and total customer value vary with reserve level
- ◻ Show range in annual total customer value across stochastic simulation years
- ◻ Spoiler alert(!): All locations show the same basic trends
- <sup>◻</sup> **Sensitivity Cases**

## **All locations exhibit similar bill savings trends**

### Slopes and levels differ by location, but all have the same basic shape

- ◻ For the TOU self-consumption tariff, bill savings taper gradually at low reserve levels, as daily cycling depth is constrained by grid charging/discharging limits
- ◻ Under net billing, grid discharging constraint is less binding (as battery can discharge through the night), leading to a more linear trajectory across locations
- <sup>◻</sup> Under both tariffs, grid charging/discharging constraints are more or less binding depending on solar and load levels and profiles, hence the observed spreads across locations
- ◻ But regardless, all locations exhibit the same basic trend under each rate design

#### **Annual Bill Savings**



## **Reliability value is generally insensitive to reserves**

### Albeit with typically a slightly more pronounced slope for net billing

- ◻ For the TOU self-consumption rate, the reliability value is effectively flat across all locations, reflecting the same set of factors mentioned in the Memphis example:
	- **EXEDENT Initial SoC is relatively high, regardless of reserve** level, due to limited depth of discharge during daily arbitrage cycle
	- For many locations, a significant share of simulation years have no interruption
	- The net load required to be served by the initial battery SoC is typically quite low (see slide 54)
- $\Box$  For the net billing structure, the trend has more discernible curvature due to the deeper daily discharge cycles

### **Annual Average Reliability Value**



## **Total customer value across is maximized at low reserves across all locations, even if only marginally so**

- ◻ 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 is therefore maximized by maintaining low reserves (subject to any battery manufacturer limits)
- ◻ The decline under the TOU self-consumption tariff is quite modest compared to net billing, given the much smaller drop in bill savings
- ◻ These results reflect average values across all years, given average reliability levels for each location and typical residential customer VoLL

#### **Average Annual Total Customer Value**



## **Alternative Figure Format for Remaining Results**

- $\nabla$  Figure on the right reduces the line chart on the left to the single value plotted by the bar segment: the *change* in customer value with an increase in reserves from 20% to 80%
- <sup>◻</sup> In this case, the value is *negative,* indicating that total value *declines* with higher reserves
- ◻ Error bands show the range in value change across stochastic simulation years



## **The same trends hold even under worse-than-average interruption years** (with one modest exception)

- ◻ Under worse-than-average interruption years, reliability value will tend to be higher, and potentially also more sensitive to reserve level
- Yet even in those years, total customer value declines with increasing reserves, as the added reliability value still does not offset the loss in bill savings
- $\Box$  This is illustrated by the error bands in the figure, which show the change in customer value across the 1,500 stochastic simulation years
- The sole exception is for the TOU selfconsumption tariff in Seattle, where total customer value in some years may be modestly higher if reserves are increased

### **Change in Total Annual Customer Value when Increasing Reserves from 20% to 80%**

Bars show averages and error bands show range across simulation years



## **Results Organization**

- <sup>◻</sup> **Building Intuition: Stepping through the Memphis Base-Case**
- <sup>◻</sup> **Base-Case Results for All Locations**

### <sup>◻</sup> **Sensitivity Cases**

- ◻ Increasing SAIFI and VoLL
- ◻ Increasing pricing differential
- $\Box$  Increasing the battery size
- ◻ See appendix for additional sensitivities (building load and base-price)

## **Total customer value increases with reserve level, if VoLL and interruption frequency are sufficiently high**

Here we apply progressively higher interruption frequency (SAIFI) and VoLL assumptions to the Memphis net-billing 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 average total customer value increases with higher reserves
- In contrast, under TOU structures where the SoC typically remains high regardless of reserve level (e.g., TOU self-consumption), the gain in customer value is small or negative, even with aggressive VoLL and SAIDI values

### **Change in Total Annual Customer Value when** Increasing Reserves from 20% to 80% (Memphis)



## **Results for other locations are similar, though in some cases considerably more pronounced**

### **Focusing here on net billing\*:**

- <sup>◻</sup> Doubling the SAIFI and VoLL does not materially change the results from the basecase in any of the study locations
- ◻ However, at 10x SAIFI and VoLL levels, total customer value increases with reserve level in almost all locations
- In some locations, the swing is substantial, partly reflecting the base-case interruption profiles (e.g., Phoenix has relatively frequent interruptions, while DFW has relatively long duration interruptions)

*\*Sensitivities for other tariff structures are provided in the appendix, slides 58-62*

### **Change in Total Annual Customer Value when** Increasing Reserves from 20% to 80% (net billing)



## **Larger price differentials can shift the economics back towards lower reserve levels, though not everywhere**

- ◻ The trends on the previous slide assume a modest differential between import and export prices (just \$0.05/kWh)
- Raising the differential between import and export prices increases the opportunity cost of holding additional battery capacity in reserve
- In half of the study locations, a price differential of \$0.20/kWh increases the opportunity cost enough to offset the reliability benefits of maintaining high reserves, even under high SAIFI and VoLL assumptions
- $\Box$  In the other locations, where reliability value is more sensitive to reserve levels, customer value is still greatest with high reserves

#### **Change in Total Annual Customer Value when** Increasing Reserves from 20% to 80%

Net billing with 10x SAIFI & 10x VoLL



## **Larger batteries can tilt the customer-economics toward either lower or higher reserves, depending on the tariff**

- $\Box$  Increasing the battery size has different implications, depending on tariff structure (see slide 55 for illustration)
	- For net billing and TOU rates that allow grid charging, larger batteries amplifies the sensitivity of bill savings to reserve level
	- For TOU rates that don't allow grid charging, it dampens the sensitivity, as much of the additional capacity goes under-utilized during daily arbitrage cycling
- $\Box$  In the latter case, this reduces the opportunity cost of holding higher reserves, though in most locations, total customer value still declines with reserve level

### **Change in Total Annual Customer Value when Increasing Reserves from 20% to 80%**

#### TOU self-consumption tariff







# **Summary and Conclusions**



## **Key Take-Aways**

- □ Across all locations, reliability value is (surprisingly) insensitive to reserve level
- <sup>◻</sup> As a result, the opportunity cost of holding storage capacity in reserve, in terms of foregone bill saving, tends to outweigh any gains in reliability value from mitigated power interruptions
- <sup>◻</sup> This is true both on average, across all 1500 years in our stochastic simulation of power interruptions for each location, and typically also in years with relatively severe interruptions
- <sup>◻</sup> This finding is also robust across tariff structures and across most of the sensitivities considered, including those related to rate level, customer load level, and storage sizing
- □ There are a limited set of circumstances within the set of conditions we analyzed where raising the reserve setting increases total customer value (bill savings + reliability value):
	- Customer resides in a location with exceptionally poor reliability (e.g., 10x their county average)
	- *And* customer has exceptionally high VoLL (e.g., 10x our base-case)
	- And customer 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 on that rate is relatively modest

## **Conclusions**

- □ Bill savings and reliability value are both important parts of the overall value equation for a customer investing in PVESS
- □ Bill savings tend to be more sensitive to the reserve level setting, and therefore in most circumstances justify maintaining as low a reserve setting as allowed
- □ The specific circumstances of any individual customer matter, and should be considered when making decisions about reserve level settings, but the results of this study can help to identify which factors are most critical for customers and installers to consider
- □ Tariff/interconnection rules also impact how customers make tradeoffs between bill savings and reliability value; for example, allowing grid charging largely obviates the need for customers to make that tradeoff, boosting the reliability value customers receive
- <sup>◻</sup> 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

## **Study Limitations and Implications**

- 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.
- <sup>◻</sup> The study should not be used directly for cost-effectiveness evaluation, as the bill savings values are based on generic tariff structures and illustrative electricity prices, intended purely to show how bill savings are impacted by reserve levels
- □ The study does not consider net metering with flat rates (despite its prevalence), as battery storage has no bill savings value under that rate structure, though it may provide reliability value
- □ The study also does not consider VPP-type programs where batteries can earn revenues from responding to demand response events, as customers would almost surely adjust their reserve levels around those discrete events to maximize their participation incentives
- □ The VoLL levels considered in this study are most representative of short-duration events; residential VoLL estimates for long-duration events are usually lower, which would further dampen the reliability value of maintaining higher reserves





# **Appendix**



## **Appendix Contents**



## **Key Characteristics of Modeled Homes in Our Analysis**



## **PV System Sizing and Roof Area Constraints**

- <sup>◻</sup> PV system sized to meet each customer's annual consumption, subject to available roof area
- <sup>◻</sup> Simplified roof constraint imposed by assuming that only 70% of total roof area available for PV
	- **IF In reality, this percentage may be smaller for** some homes due to shading, poor roof-plane orientations, obstructions, etc. (though those homes are also less likely to install PV)
- <sup>◻</sup> As shown in the figure, the roof area constraint never binds for any of our selected buildings (i.e., the PV panels never take up even 70% of the modeled home's roof area).
- <sup>◻</sup> Our median buildings tend to cover 20-50% of the roof area of the homes modeled



## **Power Interruption Events**

- ◻ Our simulations represent the probabilistic nature of stochastic interruptions
- The figures on the right display the distributions of individual power interruption simulated
- ◻ Some locations have higher probabilities of longer-duration interruptions (e.g., DFW and LA)
- These come out of our training data, which had particularly infrequent but high impact events in some locations (e.g. Winter Storm Uri impacting DFW, Public Safety Power Shutoff events impacting LA)



## **Basic PRESTO Interruption Statistics**



## **Basic PRESTO Interruption Statistics (cont.)**



# **Timing of Interruption Events**

By month and hour of day

The heatmap shows the average annual interruption hours across the hours of the day in each month

![](_page_50_Figure_3.jpeg)

per simulation year 0.00 0.25 0.50 0.75 1.00

## **Timing of Interruption Events**  Seasonal Distributions

- ◻ Consistent with the heatmaps on the previous slide, Boston and DC experience more outages during the spring, Phoenix experiences more outages in the summer, and Denver, DFW, and Seattle experience more outages during the winter
- ◻ Increasing the SAIDI and SAIFI of the regions by 10x results in a higher frequency of outages, leading to a flatter distribution and increasing the likelihood of outages being drawn from other months with moderately high SAIDI and SAIFI values

![](_page_51_Figure_3.jpeg)

**Reliability Case**

## **Timing of Interruption Events**  Daily Distributions

- PRESTO determines the starting hour of each interruption based on historical interruption patterns in each location
- $\Box$  In most locations, the distribution of outages is fairly evenly distributed across periods of the day
- ◻ Increasing the SAIDI and SAIFI of the regions by 10x results in a higher frequency of outages, which serves to further balance the distribution across hour periods.

![](_page_52_Figure_4.jpeg)

## **Value of Lost Load Literature and Assumptions**

- ◻ Customer interruption costs refer to the economic losses incurred by customers when they experience an interruption in electricity services. These costs are often normalized by the expected amount of unserved energy (measured in kWh) to estimate the monetary benefits of maintaining electricity supply during outages (i.e., VoLL)
- ◻ The figure on the right presents a summary of the VoLL estimates for residential customers across the U.S., as reviewed by [Gorman \(2022\) a](https://www.sciencedirect.com/science/article/pii/S1040619022001130)nd Baik [et al. \(2021\)](https://escholarship.org/content/qt92r6x0js/qt92r6x0js.pdf)
- ◻ The average lower bound of the VoLL estimates is \$4.91/kWh, while the upper bound averages \$11.70/kWh, though 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 and \$50/kWh

### 80 60  $VolL$  (\$2020/kWh)<br> $\stackrel{8}{\approx}$ 1990 2000 2010 1980 2020

#### **VoLL Estimates from the Literature**

![](_page_53_Figure_7.jpeg)

**Study Year** 

## **Average net load during power interruptions is relatively small in most study locations**

- ◻ One of the ways that storage supports backup power is through the initial SoC on the battery:
	- Bridges the gap until PV production begins, if the outage begins during non-daylight hours
	- Provides an additional source of energy to serve net load during the interruption
- ◻ Average load ranges from 4-80 kWh per interruption, across the study locations
- ◻ In most locations, a significant fraction of that load is met with energy produced by the PV system during the course of the interruption
- ◻ The remaining net load to be served by the initial SoC on the battery is <5 kWh in most locations, but higher in others—esp. DFW and LA, with high incidence of long-duration events

![](_page_54_Figure_7.jpeg)

**Average Customer Load per Interruption (kWh)** 

## **Increasing the battery size amplifies the sensitivity of bill savings to reserves on some rates, dampens it on others**

![](_page_55_Figure_1.jpeg)

## **The changes in bill savings and reliability value with reserves are not significantly affected by customer usage levels**

![](_page_56_Figure_1.jpeg)

## **At a higher base price\*, bill savings are less sensitive to reserves, but still outweigh the added reliability value**

### **Annual Bill Savings (Memphis)**

![](_page_57_Figure_2.jpeg)

### **Change in Total Annual Customer Value when** Increasing Reserves from 20% to 80%

![](_page_57_Figure_4.jpeg)

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (Boston)

![](_page_58_Figure_2.jpeg)

![](_page_58_Picture_46.jpeg)

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (DC)

![](_page_58_Figure_5.jpeg)

![](_page_58_Picture_47.jpeg)

 $-$ \$400

net billing

TOU front-of-

meter

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (Denver)

![](_page_59_Figure_2.jpeg)

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (DFW)

![](_page_59_Figure_4.jpeg)

![](_page_59_Picture_79.jpeg)

**59**

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (Duluth)

![](_page_60_Figure_2.jpeg)

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (LA)

![](_page_60_Figure_4.jpeg)

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (Memphis)

![](_page_61_Figure_2.jpeg)

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (Phoenix)

![](_page_61_Figure_4.jpeg)

charge

meter

discharge

consumption

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (Seattle)

![](_page_62_Figure_2.jpeg)

### **Change in Total Annual Customer-Value when** Increasing Reserves from 20% to 80% (Tampa)

![](_page_62_Figure_4.jpeg)

![](_page_62_Picture_62.jpeg)

![](_page_63_Picture_0.jpeg)

![](_page_63_Picture_1.jpeg)

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![](_page_63_Picture_10.jpeg)