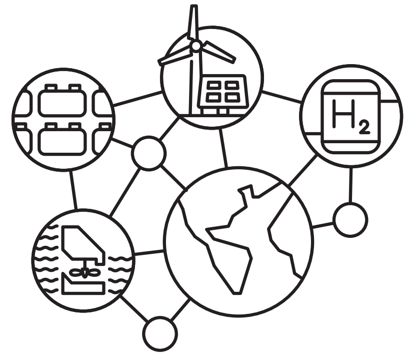
# Storage Futures Study

## Distributed Solar and Storage Outlook: Methodology and Scenarios


Ashreeta Prasanna, Kevin McCabe, Ben Sigrin, and Nate Blair




Storage Futures Study

# Distributed Solar and Storage Outlook: Methodology and Scenarios

Ashreeta Prasanna, Kevin McCabe, Ben Sigrin, and Nate Blair

**Suggested Citation:** Prasanna, Ashreeta, Kevin McCabe, Ben Sigrin, and Nate Blair. *Storage Futures Study: Distributed Solar and Storage Outlook: Methodology and Scenarios*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-7A40-79790. https://www.nrel.gov/docs/fy21osti/79790.pdf.

## NOTICE

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office, U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Wind Energy Technologies Office, U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Water Power Technologies Office and U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Office of Strategic Analysis. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.



*Front and back cover photos: iStock 936999506, iStock 1178922834, iStock 1202603676, iStock 1270012506.*

NREL prints on paper that contains recycled content.

# Preface

This report is one in a series of the National Renewable Energy Laboratory's Storage Futures Study (SFS) publications. The SFS is a multiyear research project that explores the role and impact of energy storage in the evolution and operation of the U.S. power sector. The SFS is designed to examine the potential impact of energy storage technology advancement on the deployment of utility-scale storage and the adoption of distributed storage, as well as the implications for future power system infrastructure investment and operations. The research findings and supporting data will be published as a series of reports, with each report being released on its completion. The following table lists the specific research topics planned for examination under the SFS and the associated publication formats.

This report, the fourth in the SFS series, provides a set of scenarios for cost-effectiveness and customer adoption for a range of scenarios that include future technology costs and valuation of backup power.

The SFS series provides data and analysis in support of the U.S. Department of Energy's Energy Storage Grand Challenge, a comprehensive program to accelerate the development, commercialization, and utilization of next-generation energy storage technologies and sustain American global leadership in energy storage. The Energy Storage Grand Challenge employs a use case framework to ensure storage technologies can cost-effectively meet specific needs, and incorporates a broad range of technologies in several categories: electrochemical, electromechanical, thermal, flexible generation, flexible buildings, and power electronics.

More information, any supporting data associated with this report, links to other reports in the series, and other information about the broader study are available at https://www.nrel.gov/analysis/storage-futures.html.

| Title | Description | Relation to This Report |
|---|---|---|
| *The Four Phases of Storage Deployment: A Framework for the Expanding Role of Storage in the U.S. Power System* | Explores the roles and opportunities for new, cost-competitive stationary energy storage with a conceptual framework based on four phases of current and potential future storage deployment, and presents a value proposition for energy storage that could result in cost-effective deployments reaching hundreds of gigawatts of installed capacity. | Provides broader context on the implications of the cost and performance characteristics for the U.S. grid and provides a grid-scale backdrop to the distributed storage conclusions of this report. |
| *Storage Futures Study: Storage Technology Modeling Input Data Report* | Reviews the current characteristics of a broad range of mechanical, thermal, and electrochemical storage technologies with application to the power sector. Provides current and future projections of cost, performance characteristics, and locational availability of specific commercial technologies already deployed, including lithium-ion battery systems and pumped storage hydropower. | Provides storage technology cost and performance assumptions that inform storage deployment and grid evolution scenarios presented in this report. |
| *Storage Futures Study: Economic Potential of Diurnal Storage in the U.S. Power Sector* | Assesses the economic potential for utility-scale diurnal storage and the effects that storage capacity additions could have on power system evolution and operations. | Analyzes utility-scale storage deployment and grid evolution scenarios as a complement to this report. |
| *Storage Futures Study: Distributed Solar and Storage Outlook: Methodology and Scenarios* | Assesses the customer adoption of distributed diurnal storage for several future scenarios and the implications for the deployment of distributed generation and power system evolution. | This report. |
| *Grid Operational Implications of Widespread Storage Deployment (forthcoming)* | Assesses the operation and associated value streams of energy storage for several power system evolution scenarios and explores the implications of seasonal storage on grid operations. | Considers the operational implications of storage deployment and grid evolution scenarios to test the four-phase framework and ReEDS results. |
| *Storage Futures Study: Executive Summary and Synthesis of Findings (forthcoming)* | Synthesizes and summarizes findings from the entire series and related analyses and reports, and identifies topics for further research. | Includes a discussion of all other aspects of the study and provides context for the results of this study. |

# Acknowledgments

We would like to acknowledge the contributions of the entire Storage Futures Study team, as well as our U.S. Department of Energy (DOE) Office of Energy Efficiency and Renewable Energy Strategic Analysis Team colleagues, as core contributors to this document. Those contributors include Paul Denholm, Wesley Cole, Will Frazier, Nate Blair, and Chad Augustine from the National Renewable Energy Laboratory (NREL) and Kara Podkaminer from DOE. We would like to thank Darice Guittet and Brian Mirletz and the broader System Advisor Model team for their help integrating PySAM modules within the NREL Distributed Generation Market Demand (dGen) model, and specifically Sam Koebrich for the use of his code to generate some of the figures.

We would also like to acknowledge the feedback and contributions of other NREL staff and the Technical Review Committee, including Doug Arent (NREL/Chair), Paul Albertus, Ines Azevedo, Ryan Wiser, Susan Babinec, Aaron Bloom, Chris Namovicz, Arvind Jaggi, Keith Parks, Kiran Kumaraswamy, Granger Morgan, Cara Marcy, Vincent Sprenkle, Oliver Schmidt, David Rosner, John Gavan, and Howard Gruenspecht for providing reviews and detailed comments.

# List of Acronyms

| | |
|---|---|
| BTM | behind-the-meter |
| DER | distributed energy resource |
| dGen | Distributed Generation Market Demand (dGen) model |
| EIA | U.S. Energy Information Administration |
| kW | kilowatt |
| kWh | kilowatt-hour |
| LBNL | Lawrence Berkeley National Laboratory |
| MW | megawatt |
| MWh | megawatt-hour |
| NPV | net present value |
| NREL | National Renewable Energy Laboratory |
| PV | photovoltaics |
| ReEDS | Regional Energy Deployment System |
| SAIDI | system average interruption duration index |
| SAIFI | system average interruption frequency index |
| SAM | System Advisor Model |
| SFS | Storage Futures Study |
| USD | U.S. dollars |

# Executive Summary

Declining battery storage costs and the growing emphasis on resiliency and grid services have led to heightened interest in pairing battery storage with distributed solar to provide value to customers and the distribution grid. The increasing deployment of distributed energy resources (DERs), including battery storage, is an important and emerging theme in modern power systems. DERs can contribute to grid flexibility, reduce grid power losses, and support demand-side management. Existing behind-the-meter battery capacity is estimated to be approximately 0.8 GW / 1.6 GWh in the United States at year-end 2020 (Wood Mackenzie and U.S. Energy Storage Association 2020). The market for small-scale battery systems is expected to increase dramatically, pushed by a desire for backup power and the deployment of distributed solar photovoltaics (PV). The recently approved Federal Energy Regulatory Commission (FERC) Order 2222 (FERC 2020) enables DERs to participate in regional wholesale capacity, energy, and ancillary service markets alongside traditional (utility-scale) generation. Order 2222 and new DER compensation mechanisms like the New York State Value of Distributed Energy Resources (VDER) (NYSERDA 2020b) are anticipated to unlock new market opportunities for DERs and thus lead to additional deployment of DER capacity.

Due to the nascent market status for distributed battery storage systems, there are relatively few published projections of distributed battery storage deployment. This work addresses that gap by characterizing the potential for behind-the-meter battery storage and identifying key drivers of adoption. This report describes the expanded capabilities of the Distributed Generation Market Demand (dGen) model to analyze the economics of distributed (behind-the-meter) PV paired with battery storage systems[1] and presents projections of adoption for the contiguous United States out to 2050 under a range of scenarios. These scenarios use technology cost and performance assumptions consistent with the National Renewable Energy Laboratory's 2020 Standard Scenarios paired with updated battery cost projections (Augustine and Blair 2021) and existing policies. Additional scenarios evaluate sensitivities to the value of backup power and DER compensation mechanisms, collectively characterizing the future potential for behind-the-meter storage and identifying key drivers of adoption.[2]

In order to calculate battery storage system and PV adoption, the dGen model first determines the technical, economic, and market potential:

- **Technical potential**: The maximum amount of technically feasible capacity of PV-only and PV + battery storage systems, with PV system size limited by customer's rooftop area and energy consumption, and battery capacity capped as a fraction of the optimal PV capacity at a specific site.
- **Economic potential**: A subset of technical potential, economic potential is estimated as the total capacity that has a positive return on investment or a positive net present value (NPV). Economic potential can also be interpreted as the total capacity of systems that are cost-effective in a specific year.

[1] Stand-alone battery storage systems are not considered in this analysis.
[2] Broader power sector and economywide decarbonization targets are not captured in this analysis, which would likely accelerate and increase the adoption of both distributed PV and battery storage systems.

- **Market potential**: The fraction of economic potential representing the customer's willingness to invest in a technology given a specified payback period.
- **Adoption**: Adopted[3] capacity is the capacity projected to be purchased by residential, commercial, and industrial building owners and installed at the customer premises in a behind-the-meter configuration. Adoption is based on applying a Bass diffusion function where the upper limit of adoption is set to the market potential.

A description of each level and the key assumptions and corresponding potential capacity for the Base Case scenario in 2050 is described in Figure ES-1.

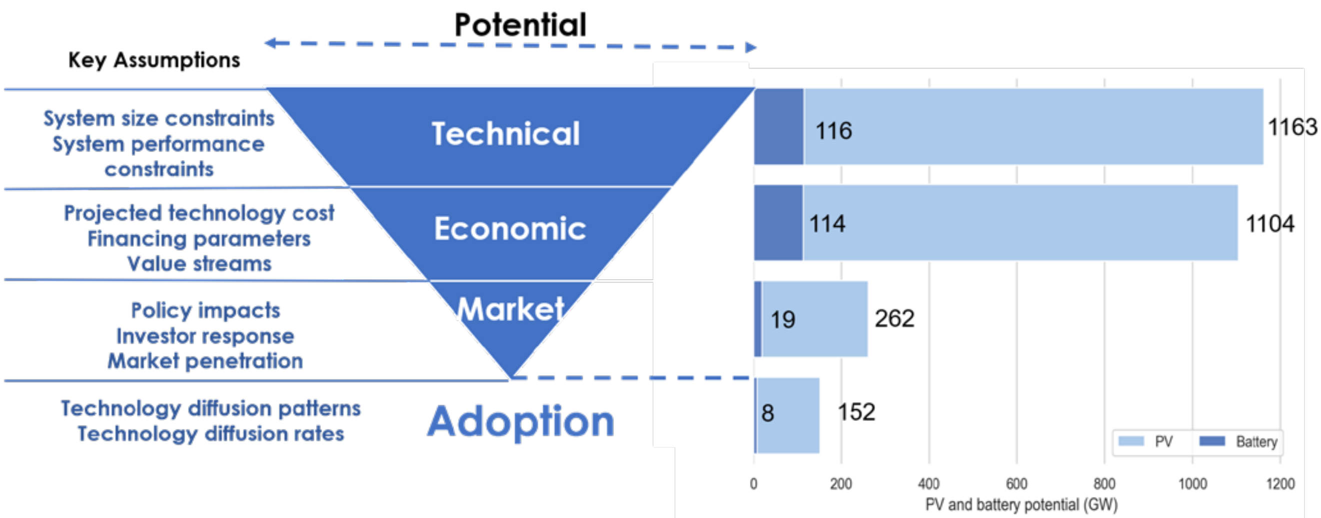



**Figure ES-1. Methodology to determine adoption/deployment of distributed storage systems and PV and battery potential (GW) for the Base Case scenario in 2050**

Adapted from Lopez et al. (2012)

Table ES-1 summarizes the economic potential alongside the projected cumulative battery and PV capacity deployed or adopted by 2050 for all scenarios evaluated.[4]

[3] The terms deployment and adoption are used interchangeably in this report.
[4] The cumulative PV capacity presented in Table ES-1 is the sum of PV capacity from PV-only and PV + battery storage systems.

Table ES-1. Distributed PV and Battery Economic Potential and Adoption for all Scenarios Through 2050

| Scenario Name | Scenario Description | Battery Economic Potential GW / GWh | Battery Projected Cumulative Adoption GW / GWh | PV Economic Potential (GW) | PV Projected Cumulative Adoption (GW) |
|---|---|---|---|---|---|
| Base Case | Moderate cost projections for both PV and battery storage systems; all other inputs are default values; the value of backup power is considered | 114 / 228 | 8 / 16 | 1,104 | 152 |
| Advanced Cost Batteries Scenario | Advanced (low) cost projections for batteries paired with moderate cost projections for PV | 147 / 294 | 11 / 22 | 1,114 | 160 |
| Advanced Cost PV Scenario | Advanced (low) cost projections for PV paired with moderate cost projections for batteries | 116 / 232 | 11 / 22 | 1,142 | 223 |
| Advanced Cost PV + Batteries Scenario | Advanced (low) cost projections for PV paired with advanced (low) cost projections for batteries | 147 / 294 | 16 / 32 | 1,143 | 234 |
| No Backup Value Scenario | Moderate cost projections for PV and batteries and no value of backup power | 85 / 170 | 5 / 10 | 1,100 | 146 |
| No Backup Value + Advanced Cost Batteries Scenario | Advanced (low) cost projections for batteries and no value of backup power | 116 / 232 | 7 / 14 | 1,110 | 150 |
| 2x Backup Value Scenario | Moderate cost projections for PV and batteries and double the value of backup power across all states and sectors | 138 / 276 | 11 / 22 | 1,060 | 139 |
| 2x Backup Value + Advanced Cost Batteries Scenario | Advanced (low) cost projections for batteries and double the value of backup power across all states and sectors | 245 / 490 | 17 / 34 | 1,085 | 151 |
| Net Metering Extensions Scenario | All states switch to net metering compensation from 2020 through 2050 | 111 / 222 | 8 / 16 | 1,080 | 209 |
| National Net Billing Scenario | All states switch to net billing compensation in 2020 through 2050 | 114 / 228 | 8 / 16 | 1,105 | 145 |

For all modeled scenarios, we find an economic potential for battery storage capacity ranging from 85 –245 GW / 170–490 GWh and cumulative adopted battery storage capacity in 2050 ranging from 5–17 GW / 10 –34 GWh. Although there is significant economic potential for behind-the-meter battery storage (more than 300 times the existing installed capacity), only a small fraction of this is adopted under our modeled scenarios. Selected insights from our analysis follow:

- **There is significant economic potential for distributed PV + battery storage systems under all modeled scenarios.** The Base Case economic potential for distributed battery storage coupled with PV is approximately 114 GW / 228 GWh, which is more than 90 times the 2020 capacity. In the scenarios investigated, the upper bound of economic potential for distributed battery storage coupled with PV is 245 GW / 490 GWh under the 2x Backup Value + Advanced Cost Batteries Scenario, and the lower bound is 85 GW / 170 GWh under the No Backup Value Scenario.

- **Despite the high economic potential, modest growth in distributed PV + battery storage adoption is projected under our modeled scenarios.** Under the Base Case, the projected deployment of distributed battery storage capacity is 8 GW / 16 GWh, 7% of the economic potential, with a range across scenarios from 5–17 GW / 10–34 GWh.

- **The substantial decrease from economic potential to adoption reflects a long payback period, and consequently a lower share of customers willing to invest.** The average payback periods of distributed PV + battery storage systems are fairly long: 11 years for the residential sector, 12 years for the commercial sector, and 8 years for the industrial sector in 2030.

- **At the national scale, the most important drivers of distributed co-adopted battery storage are a combination of advanced (low) future battery cost and a high value for backup power.** The highest adoption estimate for battery capacity is under the 2x Backup Value + Advanced Cost Batteries Scenario (+121% compared to the Base Case).

- **Combined cost reductions in both PV and battery storage technologies drive additional adoption compared to cost reductions in battery technology alone.** The Advanced Cost PV + Batteries Scenario, which considers a reduction in future costs for both PV and batteries, has higher battery deployment compared to the Base Case, increasing by 106%.

- **PV + battery systems have larger PV capacity compared to PV-only systems.** Average PV system size in PV + battery storage system configurations (8 kW for residential systems) is larger than in PV-only configurations (4 kW for residential systems). Battery storage thus increases the PV capacity. This is likely due to the ability of the battery to increase the economic value of PV.

- **Local conditions dictate adoption.** Differences in location-specific parameters across the United States also result in significant differences in the amount and rate at which distributed battery storage capacity is adopted in various states and counties.

- **Storage deployment is highly sensitive to the regional value of backup power.** The value of backup power used in this analysis has high regional variation across the United States. The sensitivity of storage deployment to the value of backup power is higher in specific states and sectors with higher value of backup power.

- **Retail tariffs that include high demand charges, time-of-use tariffs, and tiered tariffs encourage PV + battery storage adoption.** However, other factors such as climate, load profile, electricity price, and DER compensation mechanism, combined with retail tariffs, can minimize their impact. In the residential sector, fixed structure rates, the most common retail rate structure, do not incentivize battery storage.

With this first demonstration of the battery capabilities of the dGen model, the results presented in this report are primarily useful for scenario comparison to understand different drivers of deployment, but they have some limitations and are not intended as precise forecasts. The numerical precision reported in the results is intended to differentiate and allow comparison across scenarios where differences in values are small. As the market evolves and additional data are available, further calibration should be performed. In addition, the model does not consider emerging sources of revenue for PV + battery storage systems such as participation in wholesale markets, demand response programs, or grid services. Additional enhancements of dGen will be needed to explore such research questions. Finally, deployment of distributed storage may be affected by bulk power system evolution and front-of-the meter storage deployment. However, this analysis does not consider those interactions. Potential areas of further interest are projecting the adoption of community DERs and storage capacity and their impact on the distribution grid, exploration of the trade-offs between distributed and utility-scale storage, and the role of DERs in supporting the transition to a decarbonized economy.

In summary, economic potential for distributed battery storage is significant. The increasing customer adoption of PV + battery storage systems can bring about both benefits and challenges for electric utilities. Adoption projections of DER and battery storage at high spatial and temporal resolution, as presented in this report, can enable informed planning of technical infrastructure that can help planners capture the benefits and mitigate challenges to support the ongoing trend toward distributed electricity generation.

# Table of Contents

# List of Figures

# List of Tables

# 1 Introduction

Widespread deployment of storage systems is considered essential to enable reliable energy grids powered with a high percentage of renewables and to achieve grid decarbonization (NREL 2016; Stenclik, Denholm, and Chalamala 2017). Distributed storage systems can provide multiple grid services, including reducing demand, reducing peak consumption, arbitrage of energy from low to high periods of demand, and ancillary grid services. Additionally, distributed storage systems are particularly effective when paired with zero-marginal-cost renewable energy resources to provide bill savings to the customer. The declining cost of battery storage systems and the critical importance of balancing variable renewable energy production with load motivates an examination of the role of distributed battery storage in future power systems.

Like many other emerging energy technologies, battery storage systems are scalable and can be deployed in kilowatt to gigawatt scales and interconnected to the grid at multiple voltage levels. This report focuses on battery storage systems adopted by consumers along with photovoltaics (PV) for their homes and businesses to directly offset electricity consumption and for reliability services via behind-the-meter (BTM) configurations. Unlike utility-scale storage, BTM batteries directly engage with the retail power system at distribution-level voltages and produce more locational value to the power system per kilowatt (Burger et al. 2019); however, they also tend to be more expensive per kilowatt and thus require dedicated analysis to determine their cost-effectiveness.

Cost-effectiveness, or the ability to provide a positive return on investment, is often the most important factor motivating the adoption of distributed energy resources (DERs) and battery storage. Cost-effectiveness in this study is determined through a detailed cash flow analysis of PV and battery storage systems that considers system revenue calculated as the sum of three main value streams. The first is customer bill reduction by decreasing or shifting consumption to avoid high demand charges (i.e., higher electricity rate billed based on the highest instantaneous level of monthly power demand) and time-of-use charges (i.e., electricity rates with diurnal price variance). The second is the value of backup power in the case of planned or unplanned system outages. The third is revenue from selling excess generation from the PV system.

Due to the relative market novelty of distributed battery storage systems, there are comparatively few published projections of distributed battery storage adoption or deployment. Significant uncertainty surrounds cost-effectiveness, impacted by future battery storage system cost reductions and production improvements, evolution of retail electricity rates, and evolution of public policy to encourage technology innovation and/or grid decarbonization. These uncertainties motivate this report and the following research questions:

1. What is the outlook of distributed storage in the United States based on current tariffs, incentives, and expected R&D improvements?
2. What are the drivers that affect adoption?

To answer these research questions, the National Renewable Energy Laboratory's (NREL's) Distributed Generation Market Demand (dGen) model (Sigrin et al. 2016) was used to simulate the cost-effectiveness and subsequent customer adoption of PV and battery storage for residential, commercial, and industrial entities in the contiguous United States. As part of the

Storage Futures Study (SFS), the dGen model was modified to enable it to evaluate BTM battery storage in addition to the existing capabilities for distributed resources (e.g., solar PV, wind, and geothermal energy). New model development includes integrating the PySAM battery storage model, adding the value of backup power, and considering PV-only and PV + battery storage systems as candidate technologies for customer adoption. PySAM is a Python-based application programming interface to programmatically access the functions and models from NREL's System Advisor Model (SAM).[5] SAM is a detailed techno-economic system model that provides the ability to simulate PV, batteries, and other technologies considering detailed system performance and efficiency while linking these to a cash flow analysis. The specific methods and models used to determine the technical, economic, and market potential in dGen are described in Figure 1.

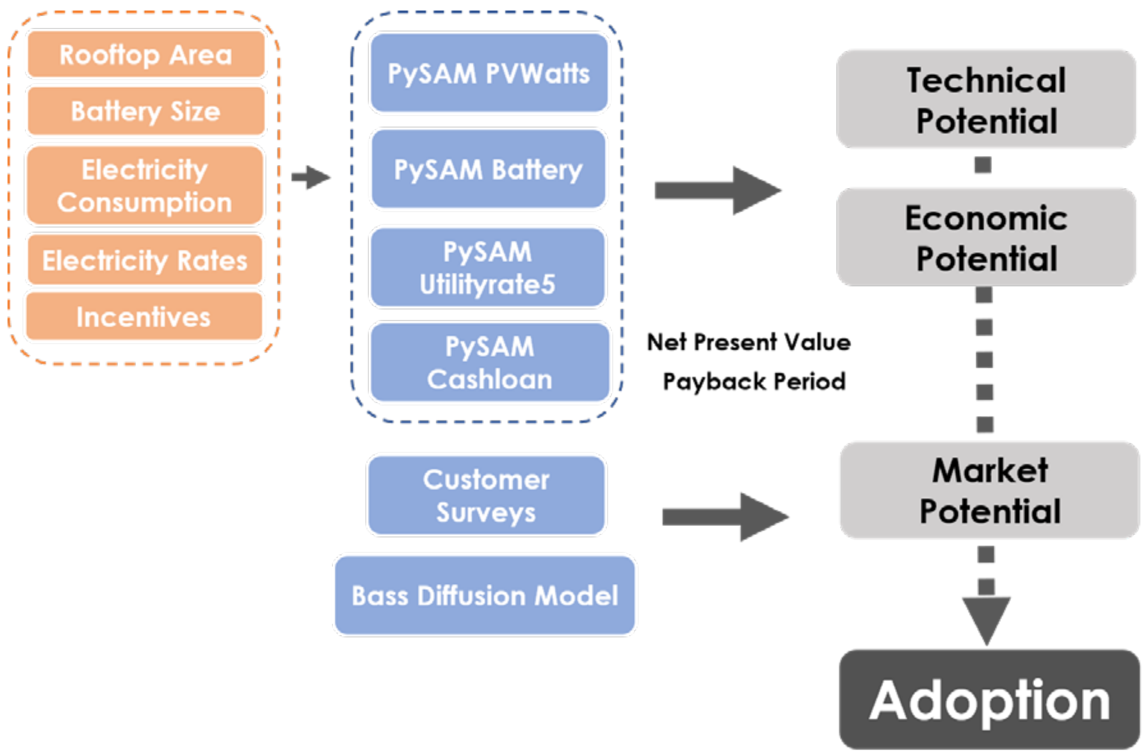



**Figure 1. Models and tools to determine adoption/deployment of PV and battery storage systems**

The remainder of the report is organized as follows. Section 2 describes the data used in dGen and development of the model. Section 3 describes our results, which include a range of scenario-based battery storage adoption projections and how these are distributed by sector and geography. Finally, in Section 4, we discuss the results and their implications.

[5] NREL System Advisor Model (https://sam.nrel.gov)

# 2 Methods and Data

As part of the Storage Futures Study, the dGen model was adapted to include the PySAM[6] detailed battery storage model and the corresponding PySAM *Cashloan* model. In addition, updated input data were used in simulations. Specific updates to input data are listed below and explained in the subsequent sections:

1. Current and future costs for solar-plus-storage systems.
2. The utility tariffs and incentives for DER and battery storage specific to states and sectors.
3. The value of backup power.
4. Historical battery storage adoption data.

## 2.1 Study Parameters

Each dGen analysis begins with sampling representative customers, or agents, for the designated study. To capture the variation in attributes driving DER adoption, dGen uses a statistical framework to represent the individual-level characteristics through a set of agents for every county in the United States. In this study, dGen simulates the 93,120 individual agents (i.e., 10 agents per county-sector for every county across the country) that are used to calculate technical and economic potential, which are then used to determine adoption estimates. Of these agents, 31,080 represent residential customers, 31,080 represent commercial sector customers, and 30,960 represent industrial customers. Each agent is assigned a unique location, system capacity (based on maximum rooftop area), and annual electricity consumption by sampling from a distribution of the same parameters. This allows for representation of both investment decisions made at the individual level and the variability in the population (Sigrin et al. 2016).

The model runs for 18 time steps, at 2-year intervals, from 2014 to 2050. For each simulated year, 8,760 hourly time steps are used to determine the main economic parameters such as bill savings and net present value. The first three simulation years (2014, 2016, and 2018) are considered historical years, and the adopted battery capacity in these years is set to values based on a review of historical adoption data (described in Section 2.7). Historical storage adoption is used as a starting point for future adoption; however, the Bass diffusion parameters for PV + battery storage have not been calibrated using these data. This is due to a lack of granularity and insufficient data points. Currently, only a few states have historical data on distributed PV + battery storage adoption. The Bass diffusion parameters in dGen have instead been calibrated for each state and sector using historical data of PV adoption; this data set in contract contains more than 10 years of historical data.

## 2.2 Costs

Data on distributed storage costs used in the dGen model are explained in detail in the *Storage Futures Study: Storage Technology Modeling Input Data Report* (Augustine and Blair 2021). That report includes current and projected future costs for all modeled storage technologies, including batteries, and the costs of battery storage systems used in dGen for the different sectors

[6] NREL-PySAM (https://nrel-pysam.readthedocs.io/en/master/)

and system sizes are obtained from that report. In Augustine and Blair (2021), a bottom-up cost model was used to generate current detailed costs for residential and commercial/industrial systems. Future cost projections were derived based on the percentage decreases found via a literature survey of anticipated utility-scale storage cost reductions (Cole et al. 2020) and applied to the residential and commercial cost starting points. It should be noted that the cost reductions for the battery pack were significantly greater than the cost reductions for other battery storage system (soft) costs. Figures 2 and 3 show the current cost breakdowns for the residential costs and the commercial/industrial costs. The residential cost breakdown has a higher fraction of non-hardware costs. For PV-only systems, the technology costs used in dGen come from NREL's 2020 Annual Technology Baseline data set (NREL 2020).

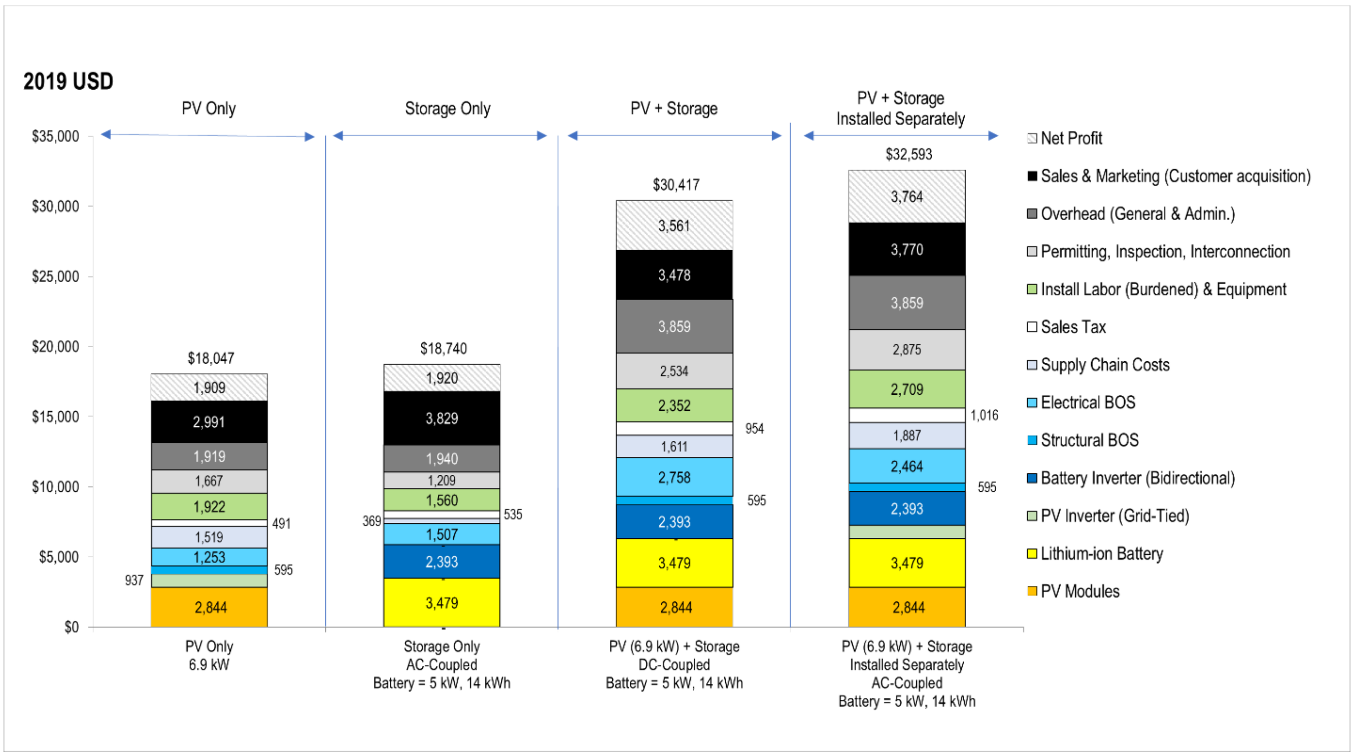



**Figure 2. Cost of residential PV stand-alone, battery storage stand-alone, and PV + battery storage systems estimated using NREL bottom-up models (Augustine and Blair 2021)**

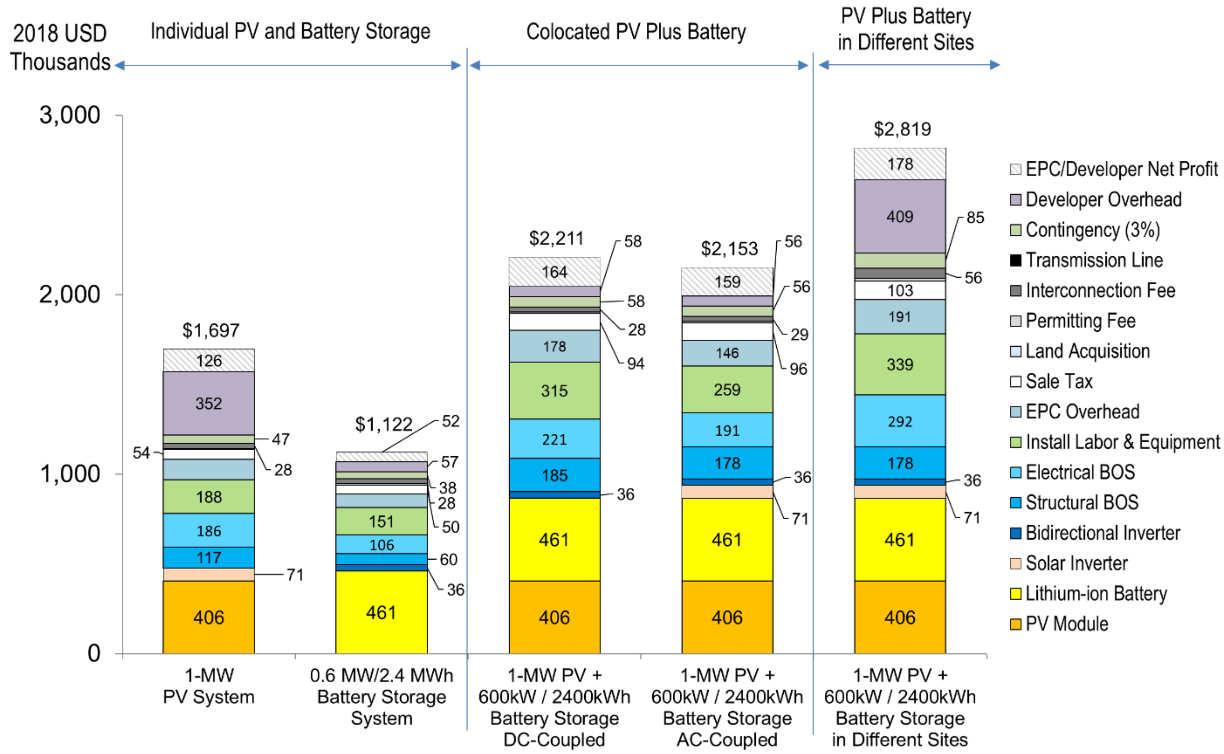



**Figure 3. Estimated costs of commercial and industrial stand-alone PV, battery storage stand-alone systems, and PV + battery storage systems using NREL bottom-up model (Augustine and Blair 2021)**

## 2.3 Load Profiles

The dGen model is an agent-based model in which each agent is a representative customer in a specific county and sector. Each customer (agent) is modeled using a normalized hourly electric consumption pattern based on EnergyPlus building energy use simulations for a typical meteorological year, and scaled based on the annual consumption of each agent (Sigrin et al. 2016). The profiles are assigned based on building type and location (based on weather station locations), with 17 load profiles for 17 building types at each location across the United States. The level of detail in the hourly consumption profiles, in combination with the retail electricity tariffs assigned to each customer, enable detailed PV generation and battery dispatch modeling.

## 2.4 Retail Electricity Rates and Incentives

To estimate the value of DER systems to agents, dGen calculates the projected electricity bills derived from location-specific retail electric rates. For this study, rate structures were updated based on recent data from the Utility Rate Database (OpenEI 2020), an open-source database of actual rate data for most U.S. electric utilities.

Incentives for PV and battery storage are also included in dGen and applied across a range of geographic scales, such as electric service territories, counties, states, and the entire country. PV incentives are obtained from the Database of State Incentives for Renewables & Efficiency (DSIRE) database (DSIRE 2020). Incentives for battery storage are identified for each state from utility websites, the Pacific Northwest National Laboratory's Energy Storage Policy Database

(PNNL 2020), and the DSIRE database (DSIRE 2020). States and utilities that provide incentives for battery storage are listed in Table 1, along with the specific incentive program considered in dGen.

The Federal Investment Tax Credit (ITC), a key incentive for spurring early adoption, is also considered in dGen. At the time this analysis was carried out, the investment tax credit was scheduled to expire without extension. Therefore, within dGen, we model the credit to expire in 2020 for residential systems and to decrease from 30% of installed cost to 10% for nonresidential systems in 2020. In December 2020, the investment tax credit was extended for another 2 years. However, because our model simulations were complete by then, our results do not consider this 2-year extension. We do not consider the omission of the 2-year extension to significantly impact our long-term projections. This is because the 2-year extension would only lead to improved economics in a single simulation year of dGen, and its impact would be minimal when compared to the subsequent 16 simulation years in the model. Renewable portfolio standards and storage-specific mandates are also not considered as part of our modeled scenarios because they need to be translated into economic incentives to be represented within dGen. Due to a lack of detailed information of how renewable portfolio standards and storage-specific mandates would provide economic incentives, they were not considered in this analysis.

**Table 1. Incentives for Battery Storage**

| State | Incentive Program | Reference/Website Source | Scope |
|---|---|---|---|
| Arizona | Salt River Project (SRP) Battery Storage Incentive | SRP (2021) | Up to $3,600 ($300 per kWh-DC) per customer; limited to 4,500 customers |
| California | Self-Generation Incentive Program | State of California (2021) | $1 billion through 2024 |
| Florida | JEA Battery Incentive Program | JEA (2021) | $4,000 rebate per home/business |
| Maryland | Maryland Energy Storage Income Tax Credit Program | Maryland Energy Administration (2020) | $750,000 in energy storage income tax credit certificates |
| Nevada | Net metering and energy storage device programs | NVEnergy (2021) | 50% of equipment costs or $3,000 |
| New York | NYSERDA's Retail Energy Storage Incentive | NYSERDA (2020a) | $4 million, with a target of 1,500 MW of energy storage by 2025 and 3,000 MW by 2030 |
| Oregon | Oregon Solar + Storage Rebate Program | Oregon Department of Energy (2020) | $2 million |

## 2.5 Wholesale Prices

Depending on the system configuration, resource characteristics, and agent-specific energy consumption patterns, imbalances in the temporal profiles of an agent's system generation and electricity consumption may result in hours in which generation exceeds consumption. The excess generation, when permitted to be exported to the electric grid, is valued based on state or utility policies that dictate the compensation mechanism available to BTM customers. Typical mechanisms include net metering, in which customers with grid-connected distributed generation receive full retail credit for energy that the customers produce but do not consume, and net billing, in which excess generation is valued at a predetermined sell rate (Zinaman et al. 2017).

In states and sectors where net billing is the prevailing policy, dGen uses wholesale electricity prices as the sell rate. These wholesale prices are resolved by year and region, and can also vary by scenario, depending on the grid makeup simulated by NREL's Regional Energy Deployment System (ReEDS) model. Wholesale electricity prices by year and ReEDS balancing area in the Standard Scenarios (Cohen et al. 2019) are used as inputs to the dGen model runs.

## 2.6 Value of Backup Power/Resiliency

An important consideration for customers when deciding whether to install battery storage is its ability to provide backup power. For example, the growth in wildfires in California has led more homeowners to consider having backup power. Also, the role battery storage can play in preventing events such as the Texas blackouts and the corresponding value of having backup power in such situations is an evolving area of analysis. Future climate scenarios imply more extreme weather and therefore an even larger desire—and thus value—for backup power.

To analyze if the ability to provide backup power drives adoption of battery storage, we include a new value stream in dGen financial calculations. This value stream is intended to reflect the monetized value provided by the battery storage system as a source of backup power to customers. We assign the value for backup power to equal a customer's willingness to pay to avoid service interruptions or outages. We consider this a reasonable assumption because PV + battery storage systems are commonly sold as backup power systems. Also, by using this proxy, we can use existing estimates of the value of service reliability for electricity customers in the United States.

A Lawrence Berkeley National Laboratory (LBNL) report on the value of service reliability (Sullivan, Schellenberg, and Blundell 2015) combines 34 data sets from surveys on interruption cost estimation or willingness to pay.[7] The LBNL report contains customer interruption costs per event by season, time of day, day of week, and geographical regions within the United States. We use that report as our main source of data and compare it with customer willingness-to-pay data from other studies to ensure consistency (Baik, Davis, and Morgan 2018; Baik et al. 2020; Baik, Morgan, and Davis 2018).

To assign the interruption costs provided in the LBNL report to customers in specific sectors and locations, we use the cost data in the LBNL report multiplied with the U.S. Energy Information Administration's (EIA's) EIA-861 data (EIA 2020). EIA-861 data include information on service reliability, expressed as follows:

[7] Although this reference is from 2015, it is the only analysis that provides U.S.-wide values for customer willingness to pay to avoid an outage. No other study has complied and standardized these values across all states and for all sectors.

- System average interruption frequency index (SAIFI),[8] which indicates how often the average customer experiences a sustained interruption (of over 5 minutes) over the reporting year.
- System average interruption duration index (SAIDI),[9] which indicates the total duration of interruption for the average customer over the reporting year.

The process by which the data provided in the LBNL report and EIA-861 are combined is described as follows:

1. The value (in USD) per event for each sector from the LBNL report is matched to the expected hours (SAIDI) from EIA-861.
2. The value of a single event is then multiplied by the number of expected events per year (SAIFI) to derive an annual value that a customer in a specific sector and state would pay to avoid an outage.[10,11]

Figure 4 provides the range of values used for backup power for each sector and state. In the figure, the value of backup power follows a similar pattern of regional differences for each sector; in other words, states that have high values of backup power in the industrial sector also have high values of backup power in the residential and commercial sectors, although the magnitude differs significantly across the sectors.

The states where customers have the highest values for backup power calculated using the method described here include North Carolina, Maine, West Virginia, Vermont, and New Hampshire.[12] These states have the highest number of service interruptions with longer average durations based on EIA-861 data. The average value of backup power ranges from $11,400 to $351,420 per year in the industrial sector; from $410 to $19,230 per year in the commercial sector; and from $3 to $70 in the residential sector. Although battery storage systems can only provide backup power for a few hours, in dGen, the full value of avoiding an outage is assigned to the value stream of the battery system. This assumption is made partly to simplify the calculation and is supported by the fact that a battery storage system paired with PV could likely provide power for more than 2 hours during daylight hours. Battery storage systems modeled within dGen have a power duration of 2 hours, an assumption based on the average battery duration reported in the U.S. Energy Storage Monitor (Wood Mackenzie and U.S. Energy Storage Association 2020). In the United States, only six states[13] have reported an average outage duration longer than 10 hours (EIA 2020).

[8] SAIFI is calculated for each year as the sum of the total number of customers that experienced an interruption of more than 5 minutes, divided by the total number of customers (EIA 2020).
[9] SAIDI is calculated for each year as the sum of all customers interrupted for more than 5 minutes times the number of minutes they experienced an interruption, divided by total number of customers (EIA 2020).
[10] Although there is variation in the value of backup power for each state and corresponding sector, all customers within the same state and sector are assigned the same average value of backup power.
[11] We process the EIA data set to derive the average number of expected events (SAIFI) and expected hours (SAIDI) for each event by state, because it only provides information by utility. For states that have multiple utilities, the average number of outages and duration of each outage is derived by taking the weighted average, with the number of customers served by the utility as the weighting factor.
[12] States are listed in order of magnitude of the value of backup power.
[13] Connecticut, Massachusetts, Maine, Vermont, West Virginia, and North Carolina.

The method used to calculate the value of backup power presented here has limitations. Average values might not reflect extreme cases in which longer or more frequent service disruptions occur. Also, the calculated estimates are based on historical data provided by utilities and do not reflect the recent rise of blackouts and extreme weather in the last several years. These data should be reviewed periodically to capture current trends. Future outages and extreme weather events might increase disruptions to service and thus result in higher costs and demand for backup power. In addition, future disruptions could increase in new areas that historically have not had frequent service disruptions. To address some of these limitations, we consider scenarios in which the value of backup power is doubled. We also consider a scenario with no value for backup power to analyze the sensitivity to this input. By including the value of backup power, we provide a first estimate to build and improve on in future analysis. Future work could update the value of backup power for current and future years, as well as consider additional sensitivities with 5 or 10 times the value of backup power.

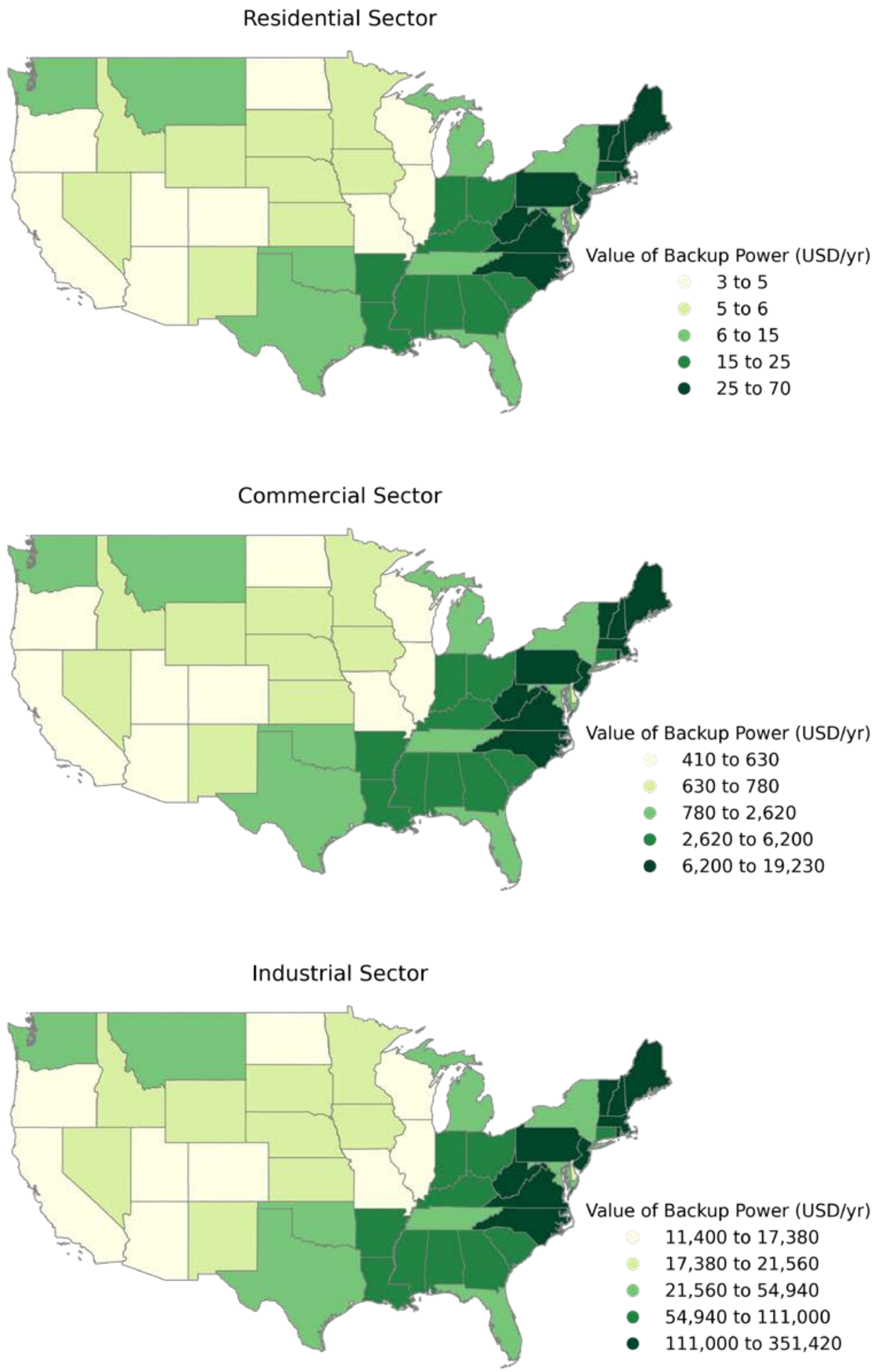



**Figure 4. Value of backup power (USD per year) by state and sector for the contiguous United States**

Color bins are set according to the quantile classification scheme (Rey and Anselin 2007)

## 2.7 Historical Storage Adoption

Data on historical battery storage adoption are based on the U.S. Energy Storage Monitor (Wood Mackenzie and U.S. Energy Storage Association 2020) and classified by state, sector, and year. Though the market for distributed PV systems has experienced decades of robust growth throughout the United States, BTM storage systems could still be considered a nascent technology. Thus, the lack of availability of granular historical storage adoption data precludes a more detailed calibration study to estimate the parameters that inform diffusion of the technology, as has been performed for other technologies in previous dGen studies (Dong and Sigrin 2019). Nonetheless, the known storage deployment still serves a purpose within the dGen framework by (1) providing an accurate value to initialize the amount of historical adoption in the model and (2) ensuring the amount of deployed storage capacity for the modeled years between 2014 and 2018 is constrained to the known totals (Figure 5). Based on the U.S. Energy Storage Monitor (Wood Mackenzie and U.S. Energy Storage Association 2020), we estimate that there is approximately 800 MW of BTM battery capacity installed across all sectors and states at year-end 2020.

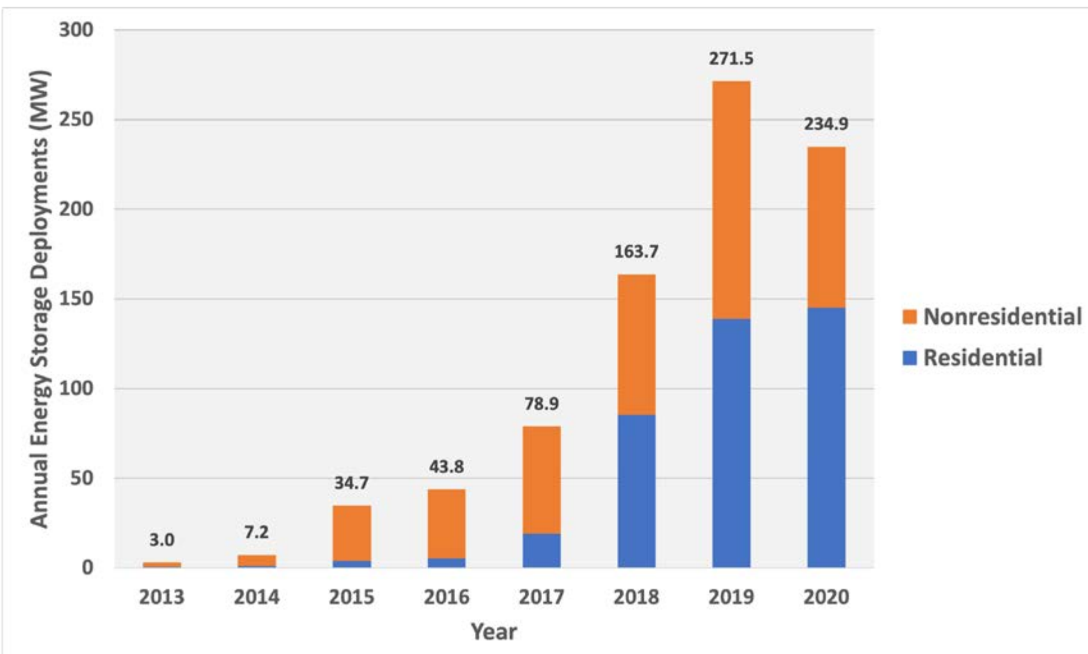



**Figure 5. Observed annual energy storage deployments (MW) in the residential and nonresidential sectors (Wood Mackenzie and U.S. Energy Storage Association 2020)**

## 2.8 PySAM Detailed Battery Model Integration

The major development work to enhance dGen implemented in this project was the integration of a detailed battery model and the corresponding financial model from SAM[14] for residential and nonresidential customers. This allows dGen to evaluate the technical and economic potential of PV-only and PV + battery storage systems. The dGen model uses the SAM calculation engine accessed via a Python wrapper, called PySAM (NREL 2019). In particular, the *Battery*,

[14] NREL System Advisor Model (https://sam.nrel.gov).

*Cashloan*, and *Utilityrate5* modules from PySAM were integrated into the dGen framework to enable more detailed analysis.

The PySAM detailed *Battery* module represents a significant step forward in dGen's ability to simulate BTM PV + battery storage systems. The detailed module allows the user to specify a wide variety of technical parameters, including battery chemistry type, current and capacity values, charge limits, degradation, and many others. Of particular importance for BTM battery storage systems is the battery dispatch strategy, which dictates the flow of energy between the PV system, battery, and grid. The detailed battery model includes strategies such as peak shaving (one-day look ahead and one-day look behind), price signal forecasting, and manual dispatch. Though each agent in dGen could ostensibly optimize the system configuration by evaluating all strategies, the scenarios completed for this report only select between the price signal forecast and peak shaving dispatch strategies to reduce runtime and computational requirements. A detailed explanation of these dispatch strategies is provided in Section 2.8.2.

Though the *Cashloan* and *Utilityrate5* modules share many of the internal calculations of the primary dGen implementation, integrating these PySAM modules enables more comprehensive financial and tariff-specific calculations and, ultimately, yield more detailed results that can provide greater insight into the system configuration as a whole (e.g., detailed cashflow arrays and various levelized cost outputs). PySAM also supports chaining of multiple unit modules—thus, simulated battery outputs feed directly into the *Cashloan* and *Utilityrate5* modules. This fully integrated approach streamlines the agent simulation process and ensures the calculations for each agent are internally consistent.

### 2.8.1 Selection of Optimal System Configurations

The identification of the optimal system and battery dispatch for each agent is based on calculating the net present value (NPV) for a range of system sizes for a combination of PV and battery systems with the corresponding dispatch options and selecting the system with the highest NPV. The NPV for each agent is calculated based on a cashflow analysis in which system revenue is the sum of savings as compared to consuming grid-sourced electricity (includes peak shaving), revenue from selling excess generation back to the electric grid, and the value of backup power. The NPVs for each system size and configuration is calculated using the PySAM *Cashloan* model. The highest (optimal) NPV is evaluated using the *minimize scalar* algorithm in the SciPy optimize Python package (Virtanen et al. 2020). For each agent, the following system configurations are passed into the optimization algorithm, along with the corresponding *Cashloan* function:

- PV + battery storage system using the peak shaving dispatch algorithm from PySAM
- PV + battery storage system using the price signals dispatch algorithm from PySAM
- PV-only system
- No PV or battery system (evaluated as part of the minimum bounds for each of the above cases).

In each evaluation, a PV system size is first selected, using zero as the lower limit and with the upper limit defined as either the size that offsets 100% of the agent's annual electricity consumption or the size that uses the full developable roof area (whichever is smaller). This is then coupled with the detailed battery storage model from PySAM and the battery system size is calculated using a PV-to-battery ratio, which is specified by sector (Feldman and Margolis 2018; DiOrio, Denholm, and Hobbs 2020; McCabe et al. 2020). The optimization algorithm then evaluates the NPVs of different combinations of PV and battery system sizes paired with the two options for battery dispatch. The battery dispatch algorithms are discussed in detail in Section 2.8.2. The optimization function terminates once the optimal (system with the highest NPV) is identified. To showcase some detailed examples, the evaluation of the optimization function for a selected agent is described in detail below.

Figure 6 shows the PV and battery system sizes evaluated for a commercial office (agent) in California. All battery storage systems have a power duration of 2 hours. In this figure, the upper two graphs show the optimization evaluations for PV + battery storage system with the respective dispatch algorithms, and the lower figure the PV-only system. In these figures, each evaluation is numbered on the x-axis, and the y-axis on the left shows the PV and battery system capacity. The y-axis on the right shows the NPV of the combined PV + battery storage system. The peak shaving and price signal figures present the successive evaluations in which the optimization function approaches an optimum by increasing PV and battery system sizes, leading to an increase in NPV. For this specific customer, the PV + battery storage system with the peak shaving dispatch algorithm results in the highest NPV.

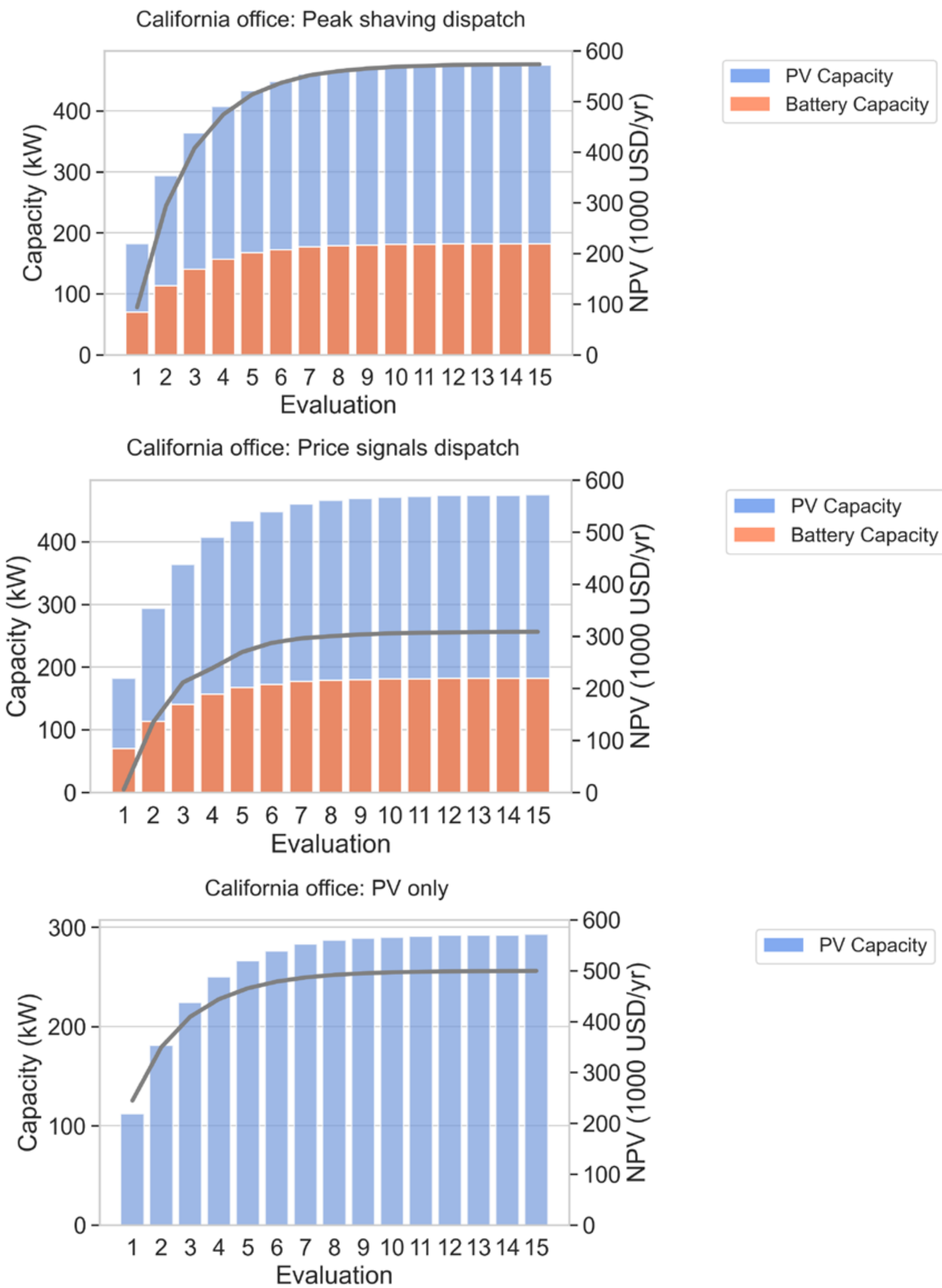



**Figure 6. PV and battery system sizes with evaluated NPV for an office building in California**

All battery storage systems have a power duration of 2 hours. The gey line shows the NPV.

### 2.8.2 Storage Dispatch

The battery dispatch strategy can have a large impact on the NPV of a system, especially when the retail tariffs applied have hourly or subhourly variation. In dGen, the PV and battery system sizes for each agent are optimized using two dispatch strategies available via the PySAM battery dispatch options. The dispatch strategies used are the peak shaving dispatch (DiOrio 2017) and the price signals dispatch (Mirletz and Guittet 2021). The peak shaving strategy has been developed to automatically perform peak shaving to reduce demand charges, without considering energy costs. The price signals dispatch algorithm combines forecasts of day-ahead load, generation, and the utility rates to dispatch the battery in the hours when retail rates are high. Both dispatch strategies aim to minimize costs to the customer by dispatching the battery to meet load (rather than store excess PV generation when prices are low and export it back to the grid when prices are high). However, there can be differences between the peak shaving dispatch and price signals dispatch in cases where the peak energy charges are not coincident with peak demand usage. Although the revenue from selling excess generation back to the electric grid is considered to be a value stream for the battery system, the battery dispatch options currently modeled within dGen are limited to those available within SAM. These dispatch options perform heuristic charge and discharge of the battery to minimize peaks or shift loads to avoid consumption during periods where rates are high, but they do not optimize for revenue from sale of excess PV (DiOrio 2017). Therefore, any additional value from selling excess PV generation to the grid is purely coincidental, and the battery storage systems modeled have a limited ability to improve the system economics by selling excess PV production when prices are high or storing it by charging when prices are low.

Differences between the two dispatch strategies are observed during several hours in Figure 7 and Figure 8. To illustrate this, the battery power provided to the load using the two different dispatch strategies are plotted for residential and commercial customers in California and Texas. For readability, a selected month of the year is presented. The peak shaving dispatch algorithm dispatches the battery to avoid higher demand charges, while price signals dispatch algorithm dispatches the battery during periods of higher prices. In the case of the residential customer in California (Figure 9), almost no difference between the peak shaving and price signals dispatch strategies is observed. This is likely due to the time-of-use pricing for this specific customer, where in both cases the battery discharges to reduce the evening peak in load.

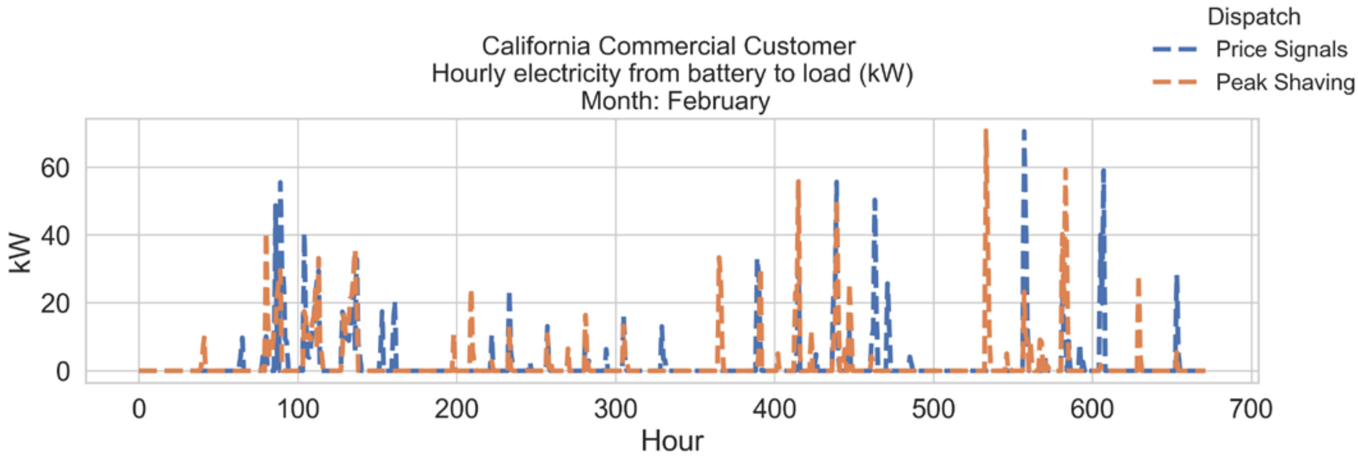



**Figure 7. Hourly battery power to load for an office building in California**

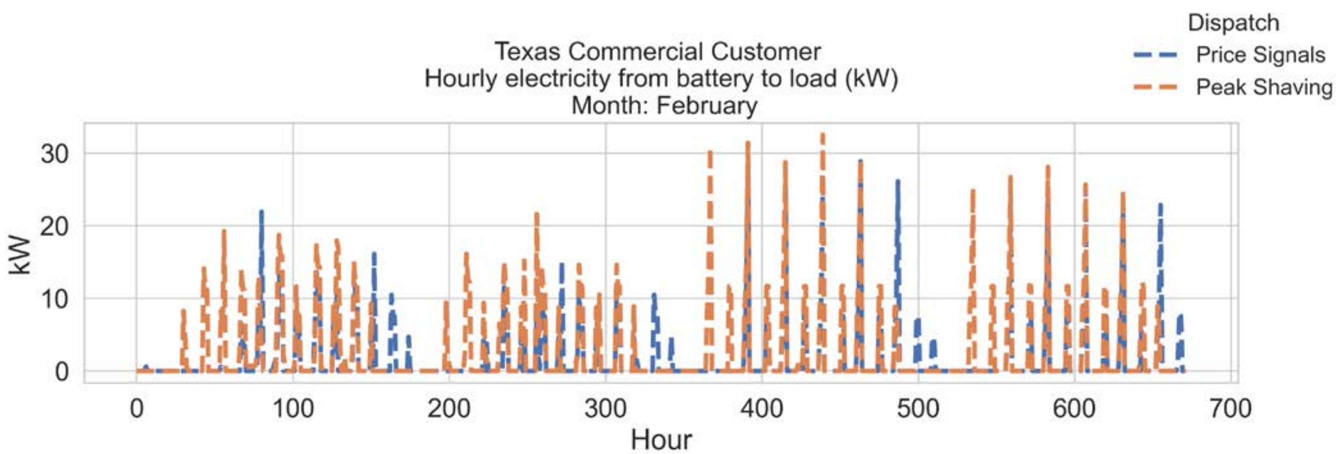



**Figure 8. Hourly battery power to load for an office building in Texas**

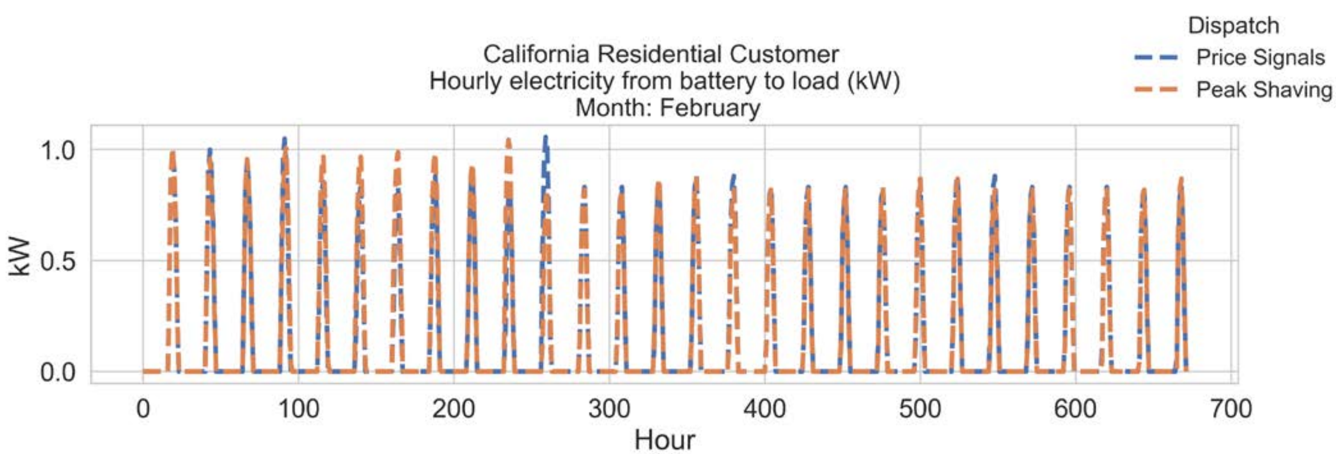



**Figure 9. Hourly battery power to load for a single-family house in California**

## 2.9 Scenario Analysis Framework

To evaluate the sensitivity of dGen results to costs, storage valuation, incentives, and compensation schemes, several scenarios are modeled in dGen. These scenarios result in upper and lower bounds of solar and storage adoption estimates. This section lists the subgroups of all the scenarios simulated in dGen for this study. The subgroups are organized according to the input parameters analyzed for sensitivity. Table 2 provides a summary of all modeled scenarios.

### *Base Case*

The Base Case is intended to provide a baseline for comparison with other scenarios. It considers moderate (or mid-range) cost projections for PV and battery storage systems, net billing or net-metering compensation schemes currently in place in each state, and the calculated value for backup power. All other incentives and rates inputs are default values that correspond to those described in Section 2.

### *Technology Cost Scenarios*

The three additional technology cost scenarios are:

- Advanced Cost Batteries Scenario, which has moderate PV cost projections (advanced costs result in the lowest projections for cost)
- Advanced Cost PV Scenario, which has moderate (middle) cost projections for batteries
- Advanced Cost PV + Batteries Scenario.

These scenarios aim to quantify the impact of variation in PV and battery storage cost. In the Advanced Cost Batteries Scenario, lower future costs for batteries defined in the model input data report (Augustine and Blair 2021) are paired with moderate cost PV systems (as defined in the 2020 Annual Technology Baseline). In the Advanced Cost PV Scenario, lower future costs for PV (as defined in the 2020 Annual Technology Baseline) are paired with moderate cost battery systems. Finally, in the Advanced Cost PV + Batteries Scenario, both PV and batteries have lower future costs.

### *Value of Backup Power Scenarios*

The four value of backup power scenarios are:

- No Backup Value Scenario
- 2x Backup Value Scenario
- No Backup Value + Advanced Cost Batteries Scenario
- 2x Backup Value + Advanced Cost Batteries Scenario.

These scenarios aim to quantify the impact of variation in the value of backup power. In the No Backup Value Scenario, the value of batteries providing backup power is not considered. In the 2x Backup Value Scenario, the value of backup power is doubled across all states and sectors. In the No Backup Value + Advanced Cost Batteries Scenario, less costly batteries and moderate cost PV are considered without backup power. This scenario is intended to test whether costs or the value of backup power have a larger influence on adoption. Finally, in the 2x Backup Value + Low Cost Batteries Scenario, both less expensive batteries and moderate cost PV are considered with double the value of backup power to give an estimate for the upper end of adoption.

### *DER Valuation Scenarios*

The two DER valuation scenarios are:

- Net Metering Extensions Scenario
- National Net Billing Scenario.

The DER valuation scenarios aim to quantify the impact of the type and value of compensation for DERs. Depending on the system configuration, resource characteristics, and customer-specific energy consumption patterns, DER systems sited at customer locations might produce energy in excess to the consumption. This excess generation, when permitted to be exported to the electric grid, is valued based on local policies that dictate the compensation mechanism available to BTM customers. We consider two scenarios—National Net Billing and Net Metering Extensions—that set the rate at which excess energy is sold back to the grid as wholesale and retail rates, respectively. In the National Net Billing Scenario, all states switch to net billing compensation in 2020, which continues through 2050. Net billing compensation entails that energy sold back to the grid is valued at a predetermined sell rate (Zinaman et al. 2017). In dGen, this sell rate is set to the annual average wholesale market price applicable in the region obtained from the ReEDS model. In the Net Metering Extensions Scenario, all 30 states that currently have net metering continue with net metering compensation until 2050, and the other 20 states switch to net metering compensation in 2020 and continue with it through 2050. Net metering occurs when energy sold back to the grid is valued at the applicable retail rate.

**Table 2. Description of All Modeled Scenarios**

| Scenario Group | Scenario Name | Scenario Description |
|---|---|---|
| Technology Cost Scenarios | Base Case | Moderate cost projections for both PV and battery storage systems; all other incentives and rates inputs are default values, and the value of backup power is considered. |
| | Advanced Cost Batteries Scenario | Advanced (low) cost projections for batteries paired with moderate cost projections for PV |
| | Advanced Cost PV Scenario | Advanced (low) cost projections for PV paired with moderate cost projections for batteries |
| | Advanced Cost PV + Batteries Scenario | Advanced (low) cost projections for PV paired with advanced (low) cost projections for batteries |
| Value of Backup Power Scenarios | No Backup Value Scenario | Moderate cost projections for PV and batteries and no value of backup power |
| | No Backup Value + Advanced Cost Batteries Scenario | Advanced (low) cost projections for batteries and no value of backup power |
| | 2x Backup Value Scenario | Moderate cost projections for PV and batteries and double the value of backup power across all states and sectors |
| | 2x Backup Value + Advanced Cost Batteries Scenario | Advanced (low) cost projections for batteries and double the value of backup power across all states and sectors. |
| DER Valuation Scenarios | Net Metering Extensions Scenario | All states switch to net metering compensation from 2020 through 2050. |
| | National Net Billing Scenario | All states switch to net billing compensation from 2020 through 2050. |

# 3 Results

In this section, we present economic potential and adoption projections for distributed PV + battery storage systems considering several scenarios. The scenarios enable us to examine the sensitivity of projected deployment to changes in single or multiple input parameters, and they are important to understand the key drivers of market growth. We present our results in the same methodological order as the simulations are carried out in dGen: Results on economic potential for distributed PV + battery storage systems are first presented, followed by adoption projections at different scales.

Adoption projections are first presented at a national scale, grouped into the three scenario groups: technology cost scenarios, value of backup power scenarios, and DER valuation scenarios (Section 2.9). Each scenario group includes the Base Case as a benchmark, and the sensitivity to different attributes nationwide is discussed. Following this, results by state, county, and sector for relevant scenarios are presented. Additional results for the adoption such as average PV and battery system size and percentage of co-adoption are also presented.

## 3.1 Economic Potential

Economic potential is essential in determining the amount of adoption, as it represents the upper bound for the subsequent filter of market potential and adoption in dGen. Economic potential is defined as the total capacity in a given year that could return a positive NPV.[15] A discounted cash flow analysis determines the profitability (e.g., the payback period, NPV, and monthly electricity bill savings) over the system's lifetime. This approach assumes the DER value is created through the sum of three value streams: (1) value created by reducing the electricity or fuel bills the agent would have paid had they not adopted, (2) value of backup power,[16] and (3) revenue from selling excess PV generation.[17]

In Figure 10, the total battery capacity in the United States estimated to have a positive NPV (economic potential) is shown for the Base Case, with the colored range representing the upper and lower estimates from other scenarios. The economic potential for battery storage systems co-adopted with PV is approximately 114 GW in the Base Case. Figure 11 shows the difference in the economic potential for battery storage capacity under all scenarios compared to the Base Case. Figure 11 highlights that the value of backup power along with battery cost are by far the most important drivers for improving the economic attractiveness of PV + battery storage systems; the 2x Backup Value + Advanced Cost Batteries Scenario has the highest economic potential for battery storage, with 245 GW of battery capacity.[18] The economic potential for battery capacity is almost the same as in the Base Case and Advanced Cost PV Scenario; however, the economic potential for PV capacity is higher in the Advanced Cost PV Scenario.

[15] The discount rate (real terms) used is 1.8%, based on the NREL Annual Technology Baseline (NREL 2020).

[16] The value of backup power is based on the scenario; for example, the 2x Backup Value considers two times the value of backup power calculated for the agent in the Base Case, whereas No Backup Value considers a zero value of backup power.

[17] The revenue from selling excess PV generation is also based on the scenario; for example, in the National Net Billing Scenario, the sell rate of excess generation is the wholesale electricity price, and in the Net Metering Extensions, the sell rate is the retail electricity rate. The Base Case considers a mix of both net metering and net billing compensation for the agent, based on the state it is located in and the sector it represents.

[18] The PV + Batteries Only Scenario is a specific sensitivity described in the subsequent paragraph.

Similarly, the Net Metering Extensions Scenario also shows a lower difference in economic potential for battery storage systems, but a higher economic potential for PV-only systems.

The economic potential presented in Figure 10 considers PV-only systems and PV + battery storage systems as possible system options. To quantify decision-making between these two system options, NPV is used as a decision variable and the system with the highest NPV is the selected technology. In practice, customers might select PV + battery storage systems based on other reasons or preferences, as long as they have a positive NPV. For several customers in dGen, both PV-only and PV + battery storage systems have a positive NPV. However, despite having a positive NPV, PV + battery storage systems might not be the selected technology because of the selection process where systems with the highest NPV are adopted. The economic potential of battery storage systems is therefore higher when PV + battery storage systems are the only available system configuration (excluding PV-only systems). The economic potential of battery storage systems when PV + battery storage is the only available system configuration is presented as the last row in Figure 11, labeled as "PV + Batteries Only." As seen in the figure, this scenario results in even higher economic potential for battery capacity with 325 GW under the Base Case.[19] Although PV-only systems are more cost-effective compared to PV + battery storage systems for a significant proportion of customers, the adoption of distributed battery capacity could be higher than the results presented in this report if customers select systems due to factors other than economics.

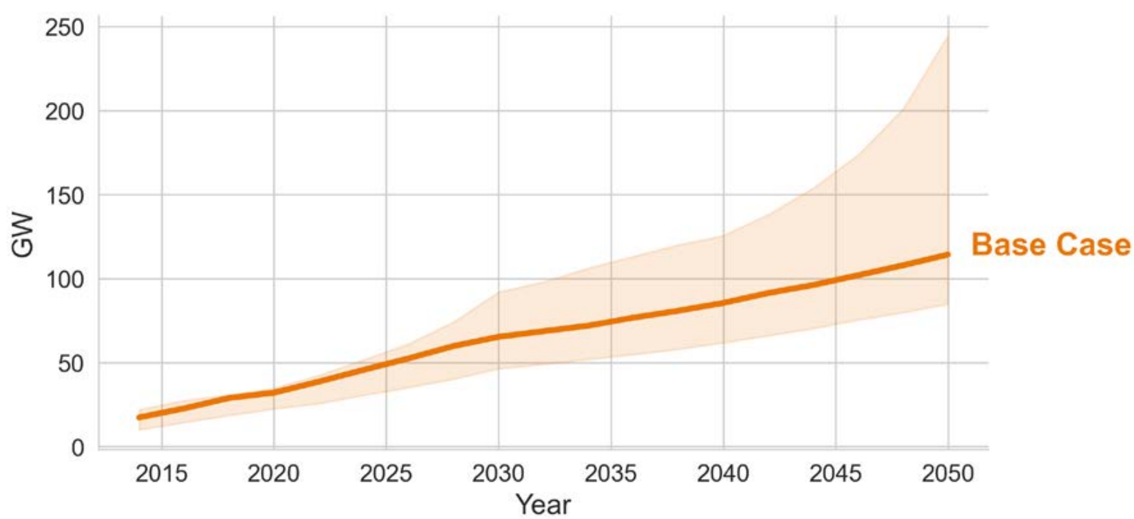



**Figure 10. Economic potential for battery storage by year**

Upper and lower bounds (in orange) represent the upper and lower estimates from all scenarios

[19] Figure 11 shows the differences in economic potential from the Base Case (i.e., 114 GW subtracted from 325 GW = 211 GW).

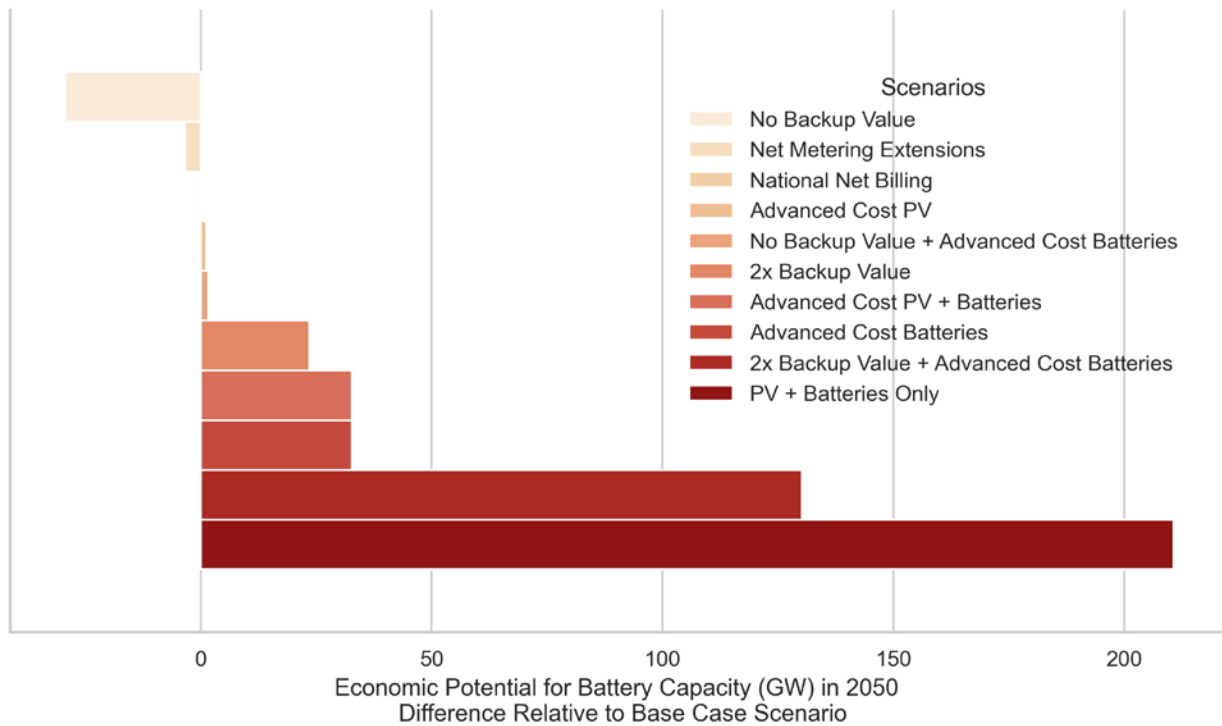



**Figure 11. Impact of sensitivity cases on 2050 economic potential**

Estimating market potential is the next step in modeling adoption. Market potential estimates build from the economic potential by identifying market penetration given a specified payback period (Figure 12). The economic potential, market potential, and estimates of adopted battery capacity in 2050 for all scenarios are presented in Table 3. In Table 3, although certain scenarios have the same economic potential for batteries, the economic potential for PV might differ. For example, the Advanced Cost PV + Batteries Scenario has the same economic potential for battery storage capacity as the Advanced Cost Batteries Scenario; however, it has higher economic potential for PV capacity (economic potential of PV capacity is not reported in Table 3).

**Table 3. Economic Potential, Market Potential, and Adopted Battery Storage Capacity by 2050**[20]

| Scenario | Economic Potential (GW) | Market Potential (GW) | Adopted Battery Capacity (GW) |
|---|---|---|---|
| No Backup Value Scenario | 85 | 12 | 5 |
| No Backup Value + Advanced Cost Batteries Scenario | 116 | 18 | 7 |
| National Net Billing Scenario | 114 | 19 | 8 |
| Base Case | 114 | 19 | 8 |
| Net Metering Extensions Scenario | 111 | 20 | 8 |
| Advanced Cost PV Scenario | 116 | 24 | 11 |
| 2x Backup Value Scenario | 138 | 26 | 11 |
| Advanced Cost Batteries Scenario | 147 | 27 | 11 |
| Advanced Cost PV + Batteries Scenario | 147 | 35 | 16 |
| 2x Backup Value + Advanced Cost Batteries Scenario | 245 | 58 | 17 |

## 3.2 Payback Period

Adoption of DER technologies is based on first identifying technical potential, economic potential, and market potential, and subsequently modeling diffusion of the technology by applying the Bass diffusion model. The payback period is used to determine the market potential, or the maximum market share for a specific customer segment. Therefore, the modest amount of adoption in comparison to the economic potential is due to the length of payback periods and their translation to maximum market potential, which is the upper limit of adoption. The relation between payback periods and maximum market share, which is a parameter used to model technology diffusion, is presented in Figure 12. As shown in the figure, payback periods of 10–15 years in the residential sector translate to below 20% of the maximum market share (or maximum market potential), whereas payback periods of 5–10 years in the commercial and industrial sector translate to below 20% of the maximum market share.

The average payback periods for the different sectors in the Base Case are presented in Figure 13. The average payback periods of distributed PV + battery storage systems are fairly long:[21] 11 years for the residential sector, 12 years for the commercial sector, and 8 years for the industrial sector in 2030. Therefore, the high economic potential (114 GW) translates to fairly modest market potential (19 GW), and finally 8 GW of adopted battery storage capacity by 2050. To evaluate the impact of lower technology cost on average payback periods, the average payback periods for all sectors under the Advanced Cost PV + Batteries Scenario is presented in Figure 14. As seen in the figure, the average payback periods decrease to 9 years for the residential sector, 10 years for the commercial sector, and 6 years for the industrial sector by 2030 under this scenario, resulting in higher adoption under the Advanced Cost PV + Batteries Scenario.

[20] This table only reports the economic potential, market potential, and adopted capacity of battery storage systems. However, all scenarios consider PV + battery storage systems installed as a combined system, and therefore the full economic potential in each scenario is the sum of PV and battery storage capacity.
[21] For comparison, the average payback period of adopted PV-only systems is less than 5 years for the residential sector.

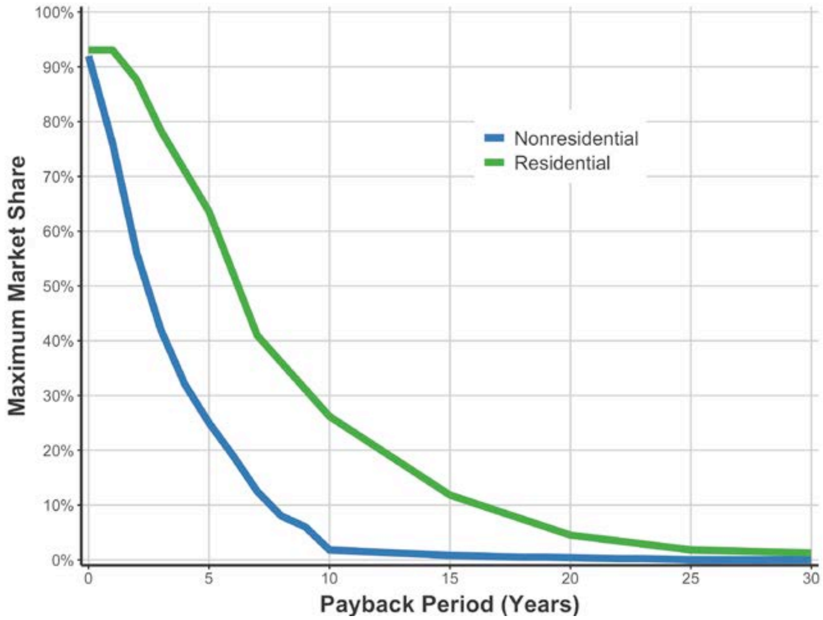



**Figure** 12**. Relation between maximum market share and payback period (Dong and Sigrin 2019)**

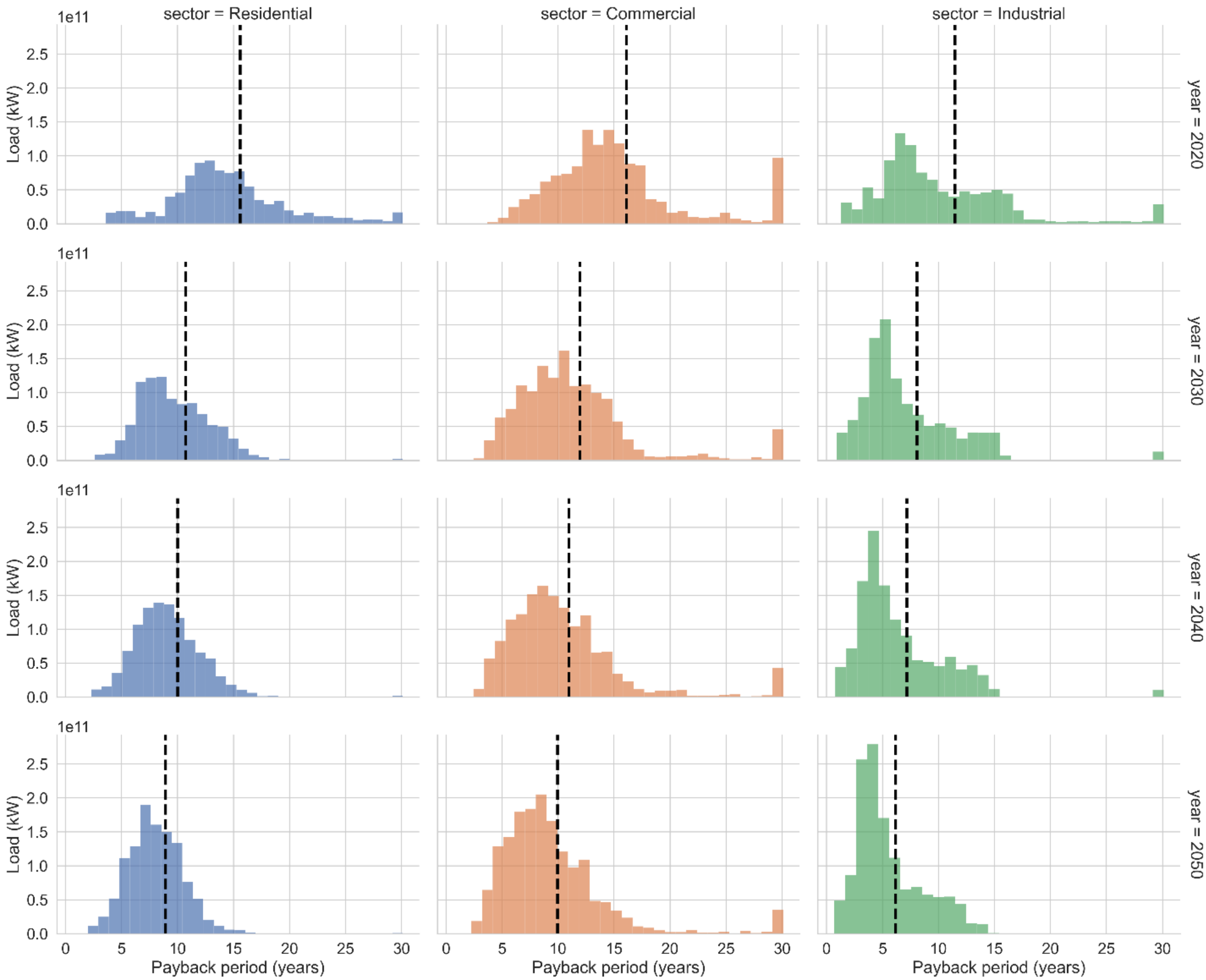



**Figure 13. Average payback periods for PV + battery storage systems for all sectors under the Base Case**

The black dashed line represents the average payback period

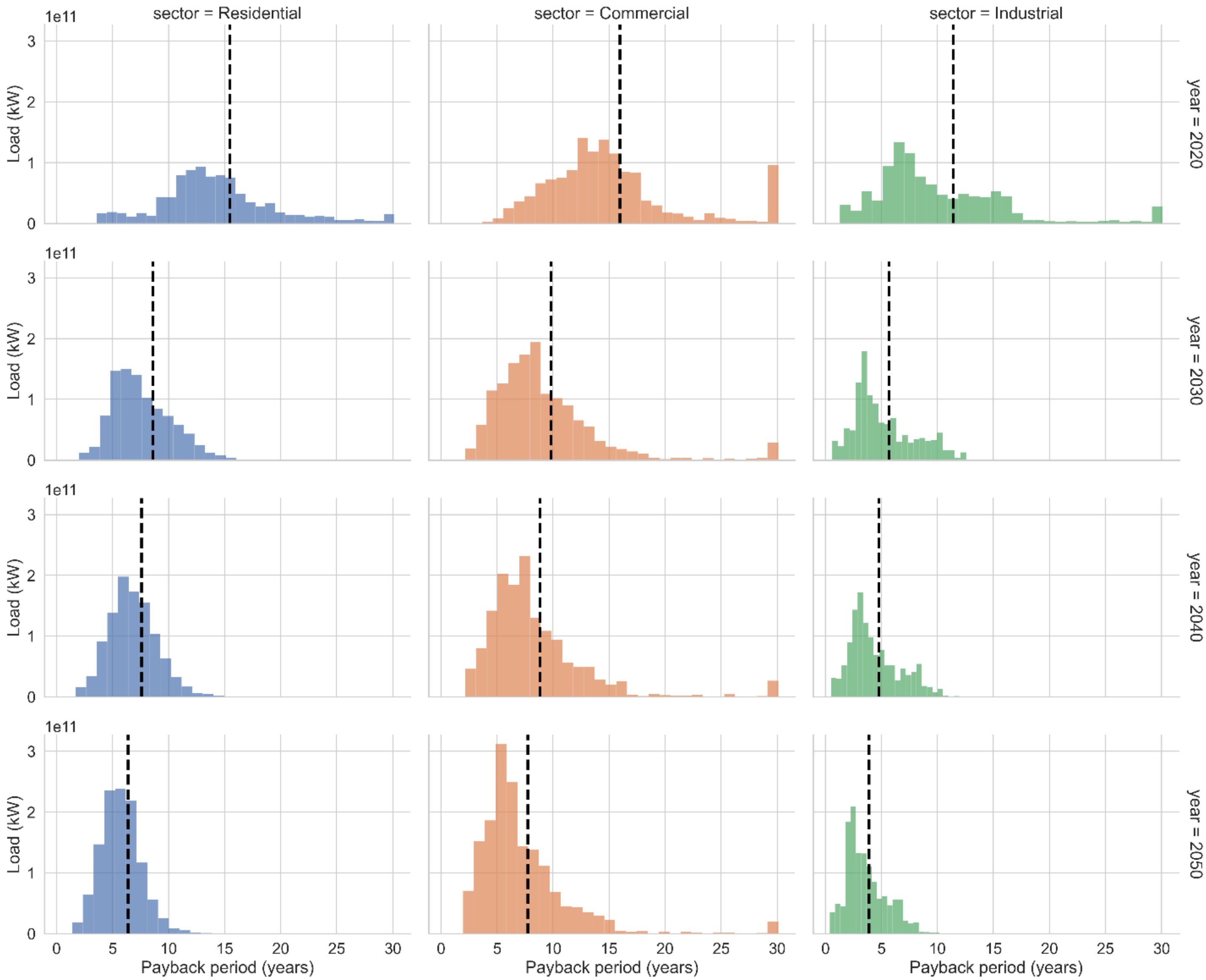



**Figure 14. Average payback periods for PV + battery storage systems for all sectors under the Advanced Cost PV + Batteries Scenario**

The black dashed line represents the average payback period

## 3.3 PV and Battery Adoption Estimates

Technology diffusion for each customer type is calculated by combining the economic attractiveness of potential adoption with insights from the diffusion of innovations framework popularized by Bass (1969) and Rogers (2003). According to this framework, the rate of diffusion is initially slow and then accelerates as additional customers consider a new technology. Therefore, the projected capacity deployments presented in the following paragraph build on the economic potential and market potential presented in the previous sections. These are based on historical data, which are still minimal for distributed batteries compared to distributed PV, for example, which has many more years of adoption history. In this analysis, the Bass diffusion function coefficients have been set to be the same for PV and battery adoption.

Projected deployment of battery storage capacity in the Base Case is 8 GW, with the lower bound of 5 GW in the No Backup Value Scenario and the upper bound of 17 GW in the 2x Backup Value + Advanced Cost Batteries Scenario (Figure 15). Projected deployment of PV capacity in the Base Case is 152 GW (Figure 16), with a lower bound of 139 GW in the 2x Backup Value Scenario and an upper bound of 234 GW in the Advanced Cost PV + Batteries Scenario. Note that PV capacity includes PV-only as well as PV + battery storage systems. Interestingly, PV adoption is more sensitive to modeled technology costs and DER valuation, and battery adoption is more sensitive to modeled value of backup power and technology cost. Higher variation in adoption estimates for battery capacity across scenarios is observed starting in 2025, whereas for rooftop PV, variation is observed after 2030.

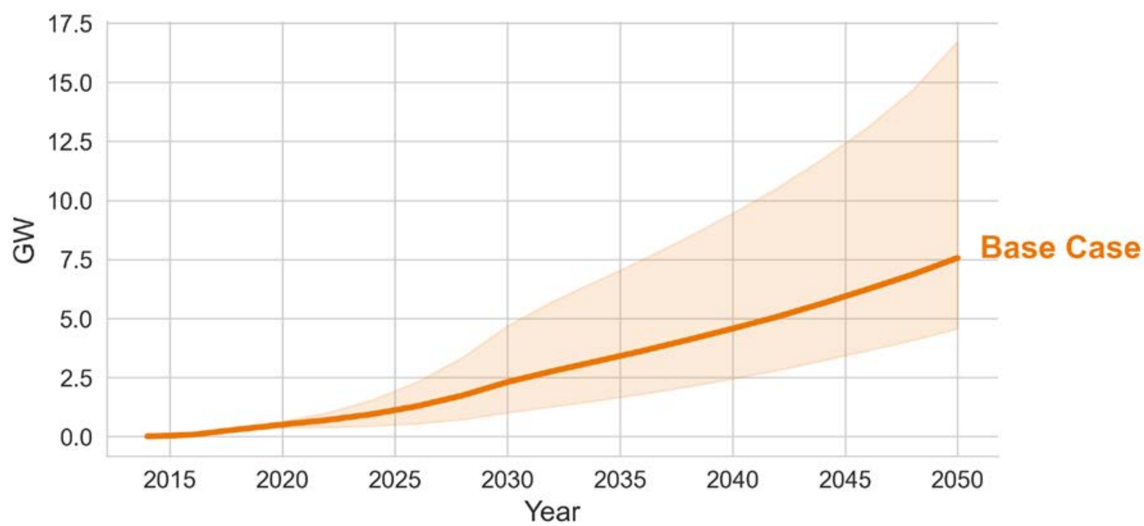



**Figure 15. Cumulative battery deployment by year for all scenarios**

Upper and lower bounds (in orange) represent the upper and lower estimates from all scenarios

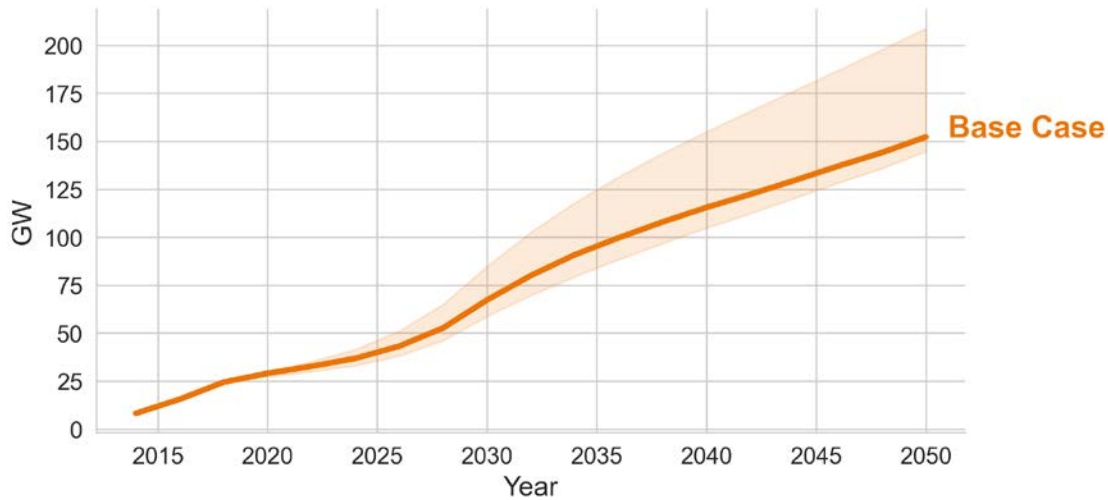



**Figure 16. Cumulative PV deployment by year for all scenarios**

Upper and lower bounds (in orange) represent the upper and lower estimates from all scenarios

### 3.3.1 Technology Cost Scenarios

In Figure 17, the technology cost scenarios are presented with the adoption estimates for each technology cost scenario by year. In the Base Case, 8 GW / 16 GWh of battery storage capacity and 152.2 GW of rooftop PV capacity could be deployed by 2050. The Advanced Cost PV + Batteries Scenario results in almost double the battery capacity by 2050: 15.6 GW of battery storage and 234 GW of PV. Table 4 includes the adopted capacity of PV and batteries for all technology cost scenarios. The Advanced Cost PV + Batteries Scenario, which considers a reduction in future costs of both PV and batteries, has higher battery deployment (+106%) than the Advanced Cost PV Scenario (+40%) and the Advanced Cost Batteries Scenario (+47%) compared to the Base Case. These results indicate that cost reductions in both technologies and the value added by the combined system drive additional adoption compared to independently installed technologies. The Advanced Cost PV Scenario and the Advanced Cost Batteries Scenario have similar cumulative battery storage capacity (11 GW), which indicates reduction in the cost of PV is favorable for both battery and PV adoption.

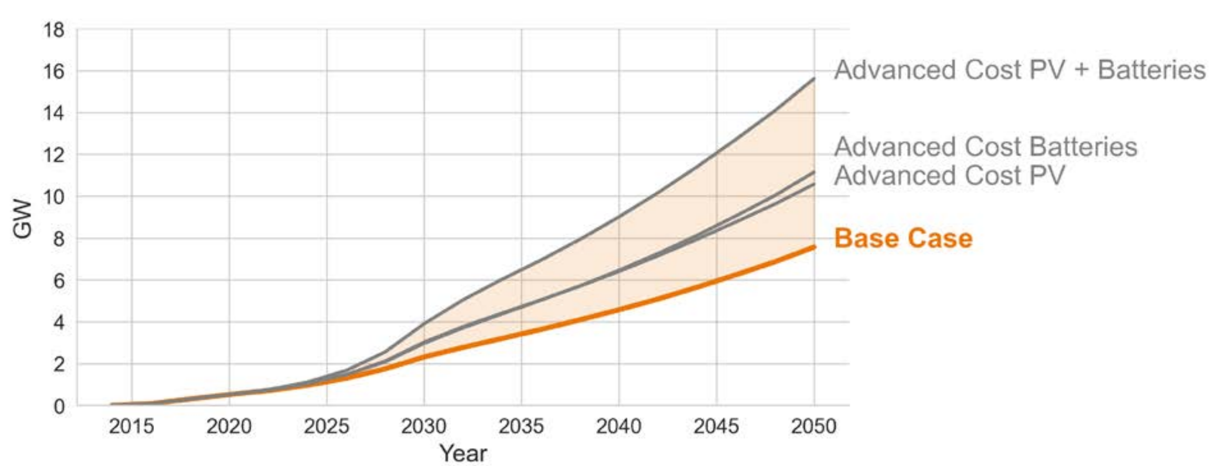



**Figure 17. Cumulative battery deployment by year for the technology cost scenarios**

**Table 4. Cumulative Adopted PV and Battery Storage Capacity by 2050 for the Technology Cost Scenarios**

| Scenario | Cumulative Battery (GW) | Cumulative Battery (GWh) | Cumulative PV (GW) |
|---|---|---|---|
| Advanced Cost PV + Batteries Scenario | 16 | 31 | 234 |
| Advanced Cost Batteries Scenario | 11 | 22 | 160 |
| Advanced Cost PV Scenario | 11 | 21 | 223 |
| Base Case | 8 | 15 | 152 |

### *3.3.2 Value of Backup Power Scenarios*

In Figure 18, the values of backup power scenarios are presented with the adoption estimates for each scenario by year. Table 5 shows the adopted capacity of PV and batteries for the value of backup power scenarios. The No Backup Value Scenario has the lowest battery adoption, with 5 GW of battery capacity (which is lower than the Base Case), whereas the highest adoption is in the 2x Backup Value + Advanced Cost Batteries with 17 GW of battery capacity.

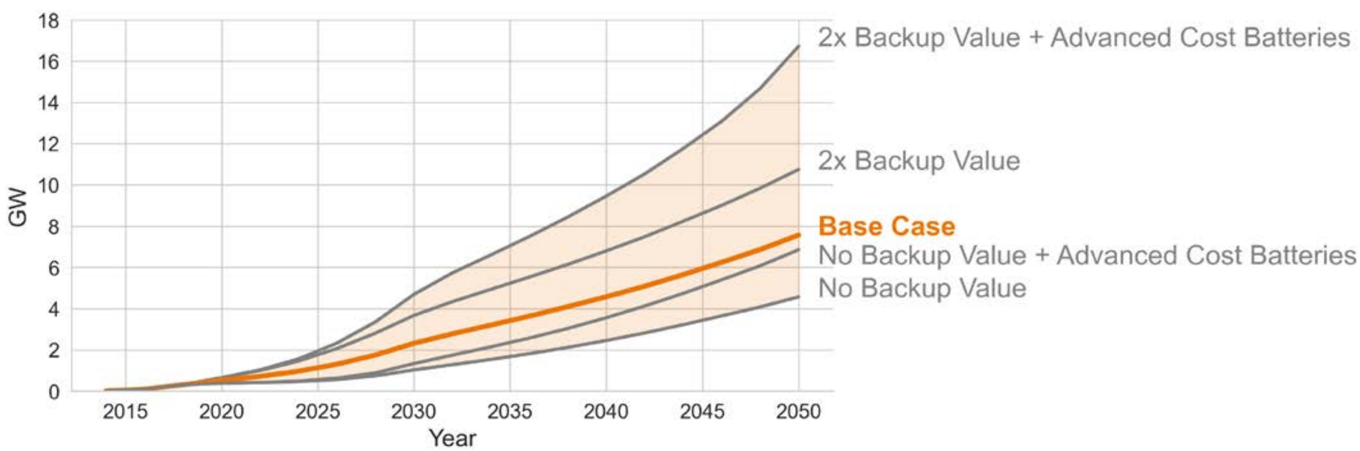



**Figure 18. Cumulative battery deployment by year for the value of backup power scenarios**

Including a monetary value for backup power increases battery adoption significantly. In the Base Case, where the value of backup power is included, the estimated battery capacity (8 GW) is almost double the capacity of the No Backup Value Scenario (5 GW). Decreasing the battery costs and doubling the monetary value for backup power both drive additional battery adoption. The 2x Backup Value + Advanced Cost Batteries Scenario results in the highest battery adoption estimate of 17 GW, which is higher than the Advanced Cost PV + Batteries Scenario (16 GW).

**Table 5. Cumulative Adopted PV and Battery Storage Capacity by 2050 for the Value of Backup Power Scenarios**

| Scenario | Cumulative Battery (GW) | Cumulative Battery (GWh) | Cumulative PV (GW) |
|---|---|---|---|
| 2x Backup Value + Advanced Cost Batteries Scenario | 16.7 | 34 | 151 |
| 2x Backup Value Scenario | 10.7 | 22 | 139 |
| Base Case | 7.6 | 15 | 152 |
| No Backup Value + Advanced Cost Batteries Scenario | 6.9 | 14 | 150 |
| No Backup Value Scenario | 4.6 | 9 | 146 |

### 3.3.3 DER Valuation Scenarios

In Figure 19, the DER valuation scenarios are presented with adoption estimates for each scenario by year, including the adopted capacity of batteries under all DER valuation scenarios. Our results show that DER valuation scenarios have a greater impact on the amount of PV adoption compared to battery adoption. Though PV adoption is higher in the Net Metering Extensions Scenario (209 GW) compared to the National Net Billing Scenario (145 GW) and Base Case (152 GW) (Figure 20), the cumulative battery capacity varies less across these scenarios (Table 6).

A possible explanation for almost no difference in the battery storage capacity under the Base Case and National Net Billing Scenario at a national scale is the model limitation of only considering two battery dispatch options. SAM is used to model the battery dispatch options, and the available automated dispatch options in SAM only include minimizing peaks or shifting loads to avoid high rates. However, to benefit from variation in wholesale prices, it would also be important to consider the wholesale price of electricity (selling price of excess PV generation in the National Net Billing Scenario) in the optimization algorithm, which determines battery dispatch.[22] Despite this limitation, an important result is that the PV capacity is lower under the National Net Billing Scenario (−4.9% compared to the Base Case), and this is likely due to adoption of PV + battery storage systems in preference to PV-only systems in this scenario when compared to the Base Case. Therefore, although we can see some of the benefits of battery storage in improving economics of the combined system under the National Net Billing Scenario, additional research is needed to explore how optimal battery dispatch combined with DER valuation and complex retail rates might increase the cost-effectiveness of battery storage when analyzed at a state or city scale. Section 3.4.2 provides additional insight on differences between states that have specific retail tariffs and DER valuation.

[22] The wholesale prices used in the model are resolved by year and region and can also vary by scenario. The lack of hourly resolution in wholesale prices also impacts the ability of the battery storage system to derive higher value in critical periods.

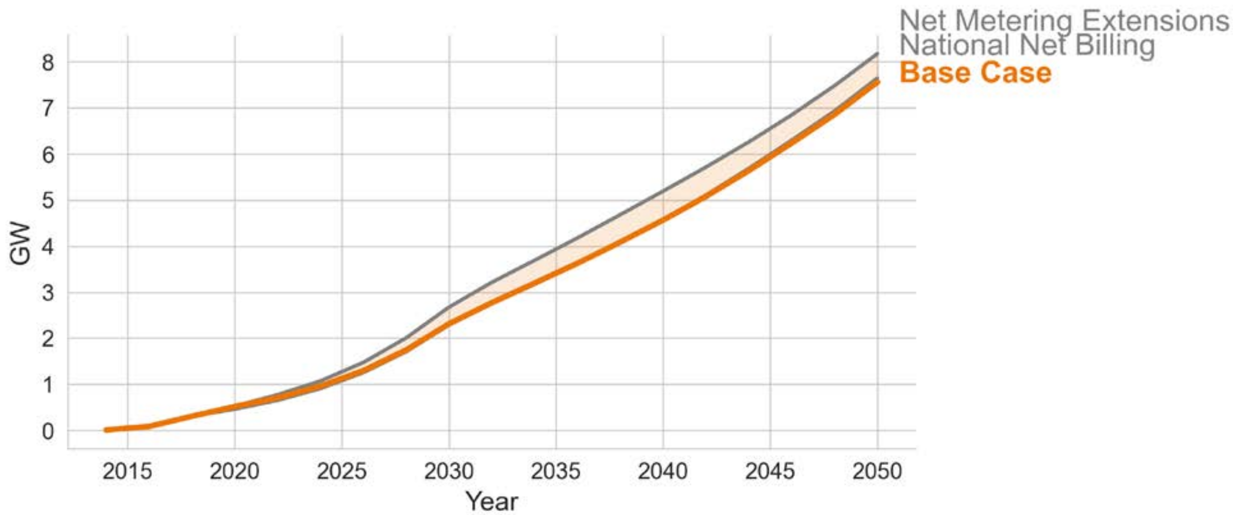



**Figure 19. Cumulative battery deployment by year for the DER valuation scenarios**

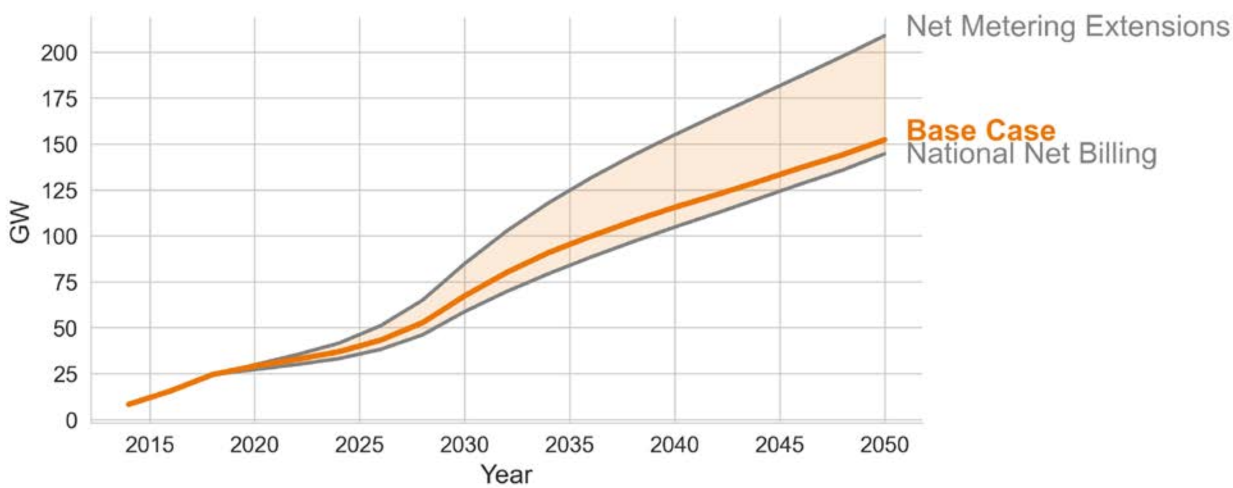



**Figure 20. Cumulative PV deployment by year for the DER valuation scenarios**

**Table 6. Cumulative Adopted PV and Battery Storage Capacity in 2050 for the DER Valuation Scenarios**

| Scenario | Cumulative Battery (GW) | Cumulative Battery (GWh) | Cumulative PV (GW) |
|---|---|---|---|
| Base Case | 8 | 16 | 152 |
| National Net Billing Scenario | 8 | 16 | 145 |
| Net Metering Extensions Scenario | 8 | 16 | 209 |

## 3.4 State- and County-Level Results

The adoption by state in the Base Case is presented in Figure 21. States with high battery adoption are shown in red, and states with lower battery adoption are shown in yellow. In the Base Case, several factors influence battery adoption, with the most important being retail electricity tariffs, the value of backup power, incentives, and historical adoption. Table 7 shows the states ranked by projected battery capacity in 2050 under the Base Case. Table 7 includes the load for each state and the battery capacity as a ratio of the total state load in the last column. This ratio can be used as an indicator to differentiate the impact of larger states and populations on battery capacity. States that have a high battery-to-load ratio (above 7) include Alabama, Arkansas, New Hampshire, Virginia, Louisiana, West Virginia, and California. Alabama is modeled with net billing compensation, a higher wholesale electricity price, and a tiered retail tariff for residential customers. This results in favorable economics for battery storage across all sectors because the battery storage system derives value for all three value streams: value from offsetting energy consumption, value from selling excess generation back to the electric grid, and the value of backup power. In Alabama, the residential sector has the highest projected battery capacity, followed by the commercial and industrial sectors. The tiered retail tariff in the residential sector is an important driver for the high battery adoption in this state.

Arkansas, New Hampshire, and California all are modeled with net metering until 2020 and then net billing from 2020–2050 (due to the expiration of net metering after 2020) in the Base Case. In Arkansas and New Hampshire, the high battery adoption is driven by favorable economics for the commercial and industrial sectors, which have high average retail tariffs (because of demand charges), higher average wholesale electricity prices, and higher backup power values. In California, the commercial and residential sectors have the highest projected battery adoption (also shown in Figure 24), and this is also because of high average retail tariffs (due to demand charges in the commercial sector and time-of-use tariffs in the residential sector) and incentives. Therefore, for states that have high projected battery storage capacity, multiple value streams drive adoption.

Increased adoption of battery storage systems in specific states or regions has implications for the utility servicing the region. This is because an increase in adoption of PV + battery storage systems can have an impact on utility revenue and the distribution grid managed by the utility. Young, Bruce, and MacGill (2019) find that the reduction in business revenue from households with PV almost doubles when they add battery storage, regardless of whether flat, time-of-use, or demand-based tariffs are applied. Pimm, Cockerill, and Taylor (2018) find that when operating to maximize savings from the time-of-use tariff, batteries could cause increases in peak demand at low-voltage substations if many batteries in the area commence charging at the start of the overnight off-peak price band. Therefore tariff design will play an important role in mitigating negative impacts of charging/discharging patterns. One method to implicitly coordinate dispatch of distributed storage systems sited at customer premises is through tariffs that are locationally specific, such as the Value of Distributed Energy Resources (VDER) or the Value Stack in New York (NYSERDA 2020b). Given the implications on electric distribution grids and utilities, it is clear that tariff design for PV + battery storage systems is a research topic that will require additional dedicated analysis.

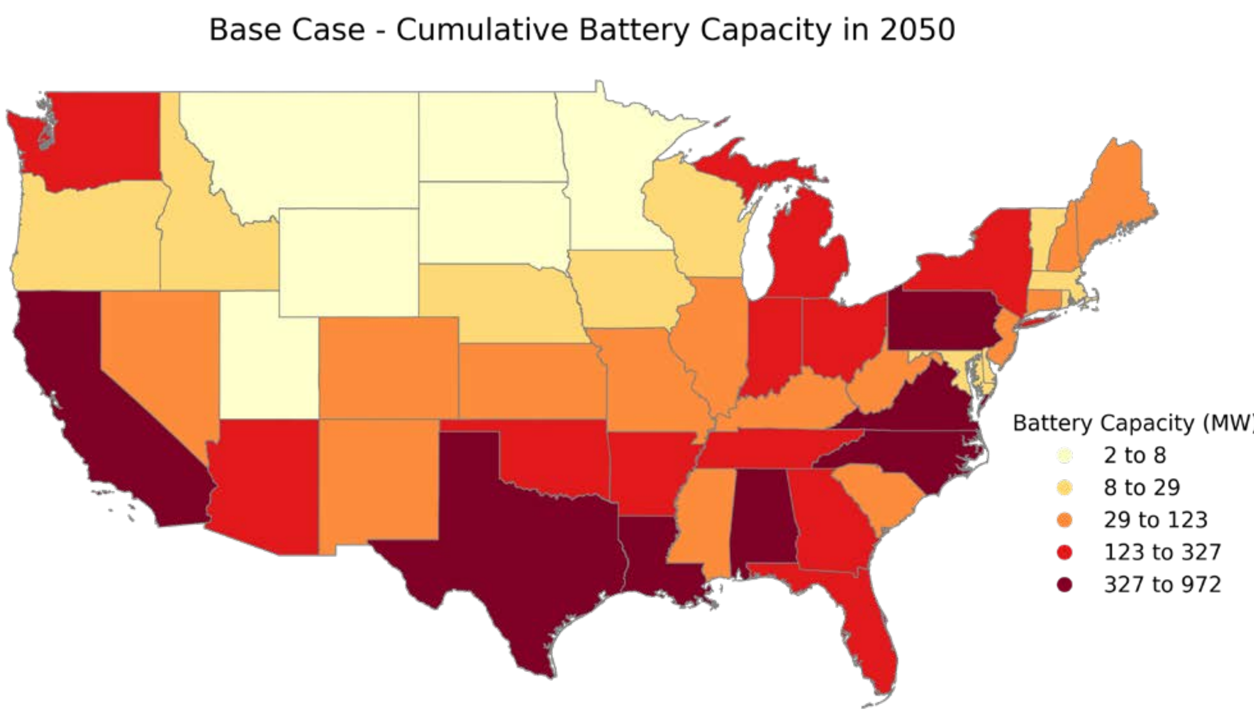



**Figure 21. Cumulative battery deployment by state for the Base Case in 2050**

Color bins are set according to the Jenks-Caspall classification scheme (Rey and Anselin 2007)

**Table 7. States in Order of Highest Projected Battery Capacity in 2050**

| State | Battery Capacity (MW) | Battery Energy (MWh) | State Annual Load (TWh) | Battery Energy-to-Load Ratio (MWh/TWh) |
|---|---|---|---|---|
| California | 972 | 1,992 | 283 | 7.04 |
| Texas | 866 | 1,733 | 453 | 3.82 |
| Alabama | 530 | 1,060 | 104 | 10.18 |
| Virginia | 495 | 989 | 122 | 8.14 |
| North Carolina | 433 | 865 | 147 | 5.88 |
| Louisiana | 408 | 815 | 105 | 7.75 |
| Pennsylvania | 371 | 741 | 153 | 4.85 |
| Ohio | 327 | 654 | 165 | 3.97 |
| Arkansas | 282 | 563 | 58 | 9.69 |
| Tennessee | 263 | 525 | 111 | 4.73 |
| Arizona | 234 | 470 | 93 | 5.05 |
| Florida | 213 | 427 | 235 | 1.82 |
| Washington | 209 | 418 | 109 | 3.85 |
| Indiana | 208 | 416 | 116 | 3.58 |
| Georgia | 183 | 366 | 152 | 2.41 |

| | | | | |
|---|---|---|---|---|
| New York | 182 | 367 | 120 | 3.07 |
| Oklahoma | 175 | 350 | 73 | 4.82 |
| Michigan | 137 | 275 | 112 | 2.46 |
| West Virginia | 123 | 245 | 34 | 7.28 |
| Kentucky | 114 | 227 | 106 | 2.15 |
| Illinois | 105 | 209 | 149 | 1.40 |
| New Jersey | 90 | 177 | 73 | 2.42 |
| Missouri | 81 | 163 | 89 | 1.84 |
| New Hampshire | 53 | 107 | 11 | 9.45 |
| New Mexico | 46 | 92 | 30 | 3.02 |
| Colorado | 44 | 88 | 69 | 1.28 |
| Kansas | 42 | 84 | 45 | 1.89 |
| Connecticut | 41 | 82 | 30 | 2.78 |
| Mississippi | 38 | 77 | 59 | 1.31 |
| Maine | 38 | 76 | 12 | 6.28 |
| South Carolina | 35 | 70 | 94 | 0.74 |
| Nevada | 31 | 63 | 41 | 1.52 |
| Delaware | 29 | 58 | 12 | 4.98 |
| Maryland | 24 | 48 | 61 | 0.79 |
| Massachusetts | 19 | 38 | 55 | 0.70 |
| Nebraska | 16 | 33 | 32 | 1.02 |
| Vermont | 15 | 31 | 6 | 5.28 |
| Oregon | 14 | 29 | 54 | 0.53 |
| Idaho | 14 | 29 | 28 | 1.01 |
| Wisconsin | 14 | 28 | 73 | 0.38 |
| Iowa | 14 | 28 | 51 | 0.54 |
| Rhode Island | 11 | 22 | 8 | 2.89 |
| Wyoming | 8 | 17 | 24 | 0.70 |
| Minnesota | 7 | 14 | 76 | 0.18 |
| Montana | 3 | 7 | 16 | 0.41 |
| South Dakota | 2 | 5 | 13 | 0.38 |
| Utah | 2 | 4 | 35 | 0.11 |
| North Dakota | 2 | 4 | 15 | 0.25 |
| District of Columbia | 2 | 3 | 11 | 0.29 |

### 3.4.1 Value of Backup Power Scenarios

To analyze how the value of backup power impacts the amount of battery adoption at the state level, sensitivity of cumulative battery capacity to the value for backup power is shown for all modeled states in Figure 22. In this figure, the battery capacity in the No Backup Value Scenario and the 2x Backup Value Scenario are presented relative to the Base Case in 2050. The relation between the value for backup power and battery adoption is not linear; a higher value of backup power could result in a nonlinear increase in adopted battery capacity. For example, in California, removing the value of backup power results in a 10-MW decrease in battery capacity, but doubling the value of backup power leads to a 189-MW increase in battery capacity (Figure 22). Sensitivity to the value of backup power can vary significantly across states, and the underlying reason is the difference in the value of backup power across states and sectors. In states along the East Coast, where the number and duration of service disruptions are high and the value of backup power is correspondingly high, the battery adoption results in these states are more sensitive to a variation in backup power (doubling or removal of the value). For example, North Carolina, which has the highest average value of backup power in the Base Case, has the largest sensitivity to this input, observed in Figure 22.

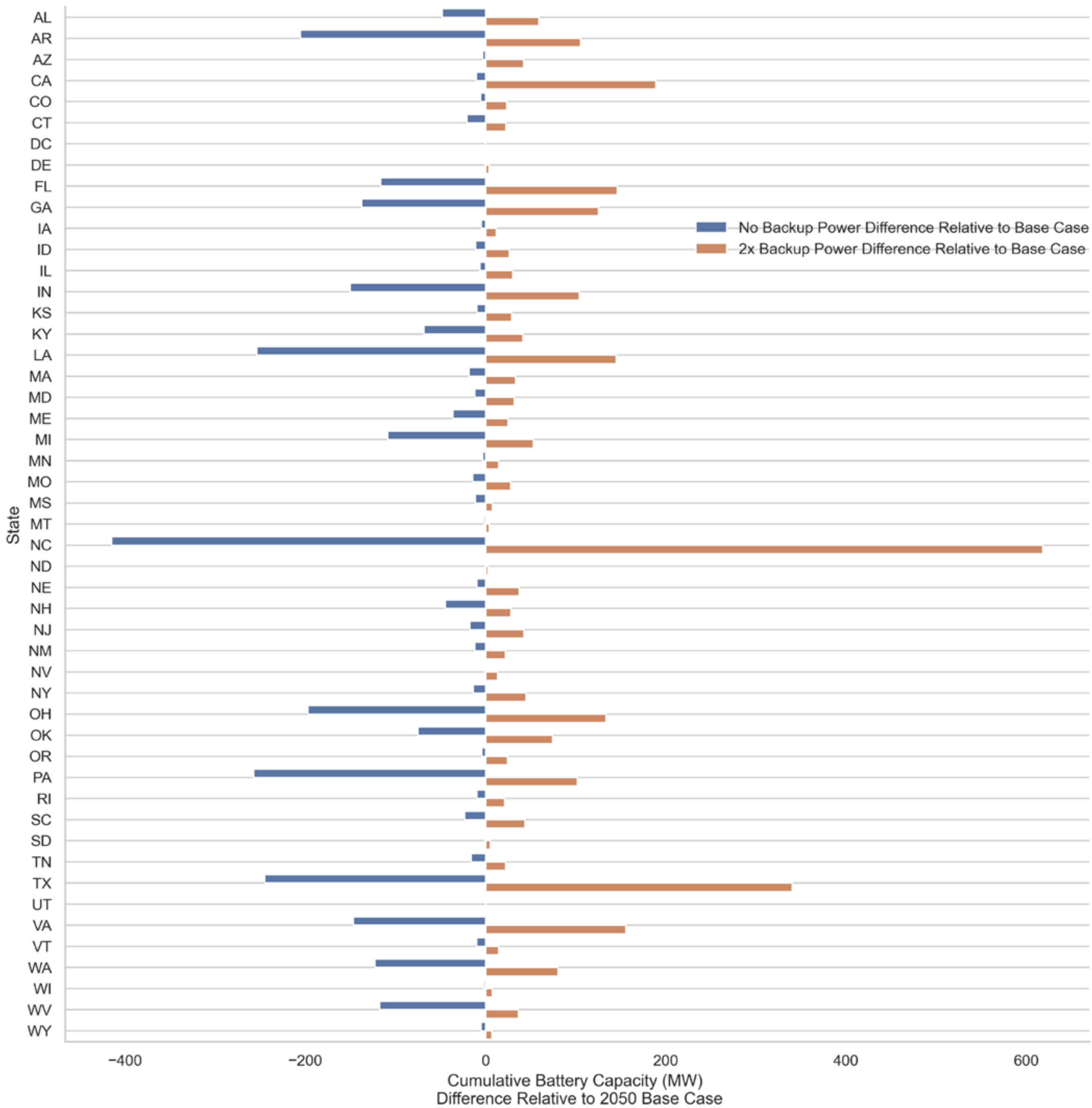



**Figure 22. Sensitivity to backup power by state: differences in battery capacity**

### 3.4.2 DER Valuation Scenarios

To aid analysis of how the DER valuation impacts the amount of battery adoption at the state level, sensitivity of battery capacity to DER valuation is presented for all modeled states in Figure 23. In this figure, the projected battery capacity for all states in the Net Metering Extensions Scenario and the National Net Billing Scenario are shown relative to the Base Case in 2050.

The differences in Figure 23 across states are informative to understand drivers of battery storage adoption; however, understanding the reasons for differences in sensitivity to DER compensation is not straightforward. The Base Case includes several states that have a switch from net metering to net billing that is due to the expiration of the net metering compensation schemes. In the National Net Metering Scenario, growth in battery storage capacity is mainly due to the increase in PV capacity and co-adoption of battery storage systems. Net metering drives PV adoption, and in many cases co-adopted battery storage systems are also cost-effective. In Alabama, battery adoption is mainly driven by the residential sector, which has the highest projected PV and battery capacity. California and Pennsylvania have the largest difference under the National Net Billing Scenario compared to the Base Case in 2050. In both these states, the growth in battery capacity is in the commercial and industrial sectors, where the larger battery storage systems can take advantage of compensation from net billing, in addition to other value streams to improve economics. Conversely, in Texas, reduction in battery capacity is mainly in the industrial sector because of a lower average wholesale electricity price. In Arizona, reduction in battery capacity is mainly in the residential sector, which has net metering compensation in the Base Case and therefore less favorable economics when DER valuation switches to net billing.

Figure 24 shows the differences in battery adoption across sectors for the Base Case, the National Net Billing Scenario, and the Net Metering Scenario for California.[23] This figure highlights how DER valuation impacts different sectors; adoption in the residential sector depends greatly on the net metering as a value stream, whereas the commercial sector continues to derive value from peak shaving and net billing compensation and can take advantage of multiple value streams because of a larger average system size.

[23] California is selected as an example because it has the highest (modeled) battery adoption in the United States.

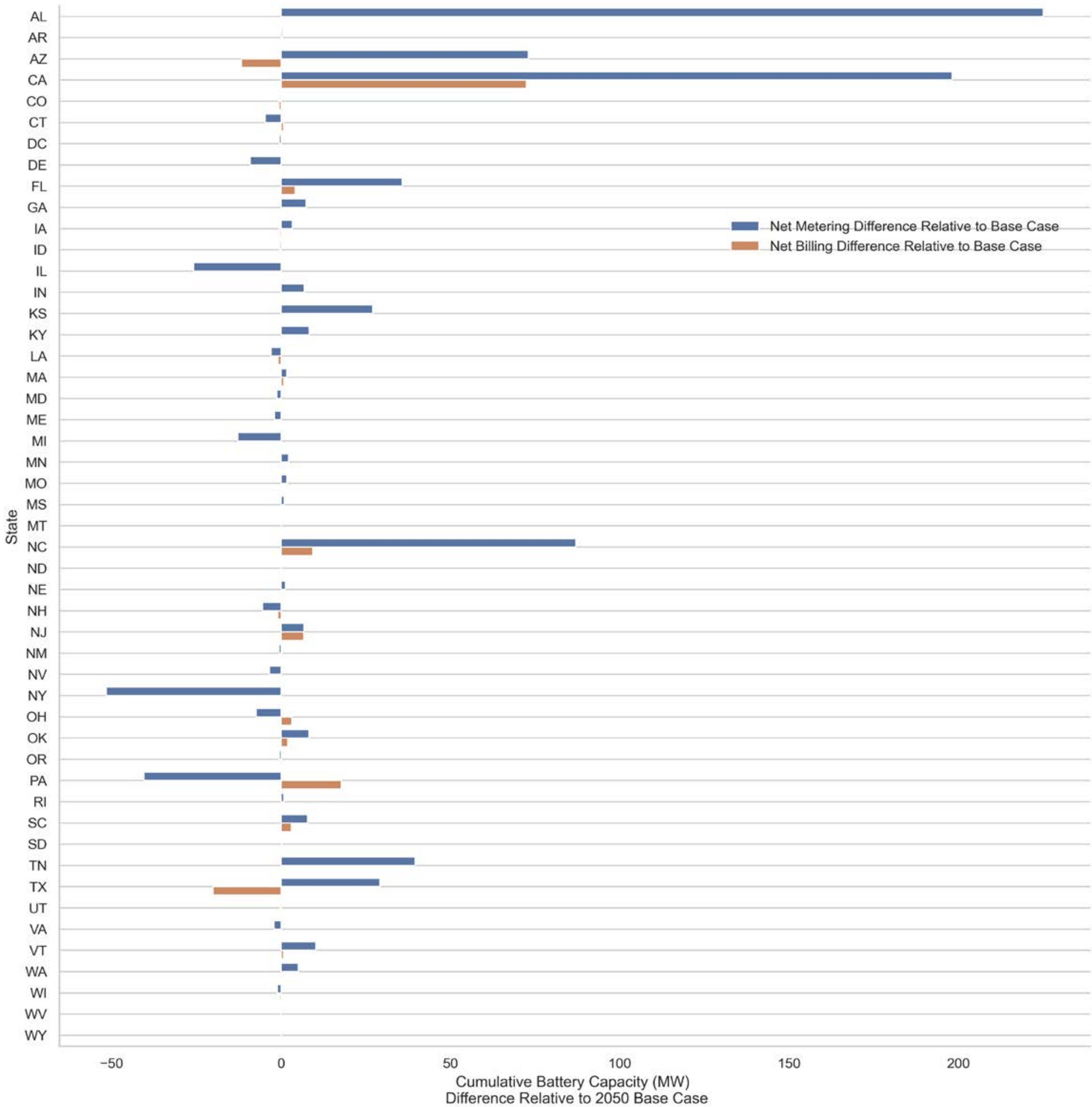



**Figure 23. Sensitivity to DER valuation by state: differences in battery capacity**

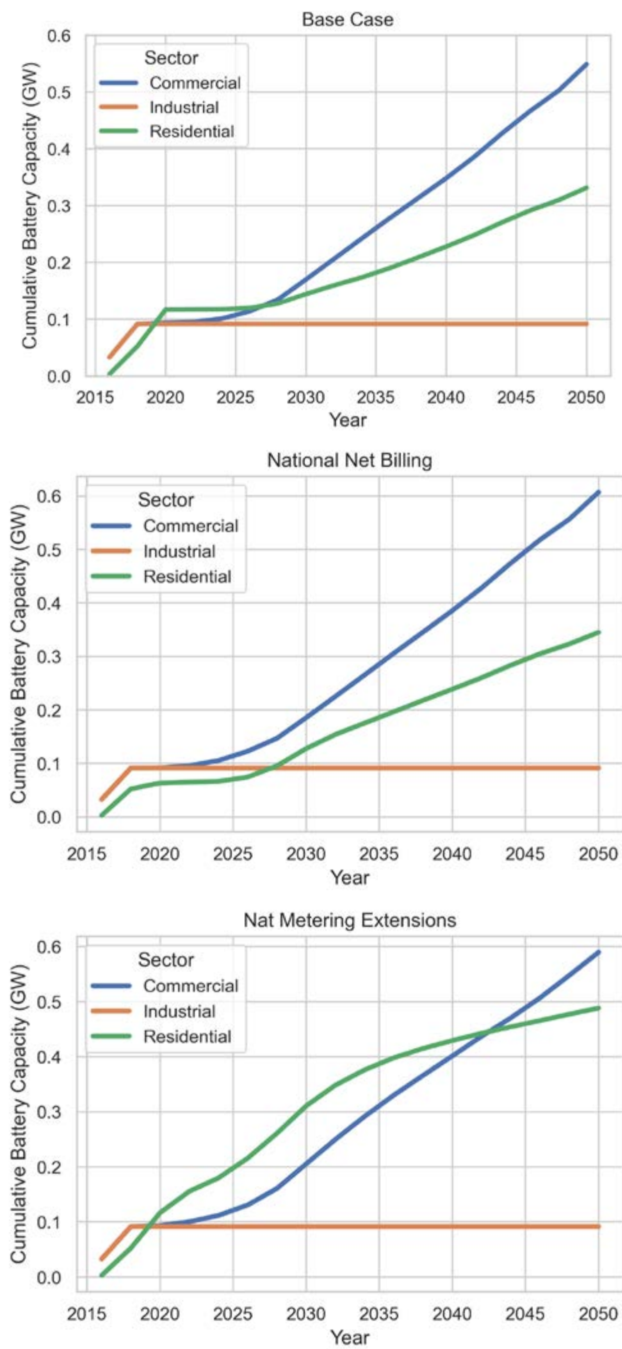



**Figure 24. Adoption trajectories for California under the Base Case, National Net Billing Scenario, and Net Metering Extensions Scenario**

The cumulative battery adoption in the years prior to 2020 are set in the model to values from historical data (Section 2.7). There is a sharp transition in the curves in 2018 accounted for by the switch from (actual) historical data to model results

## 3.5 County-Level Results

The adoption of battery storage by county in the Base Case is presented in Figure 25. Counties with high battery adoption are shown in red, and counties with lower battery adoption are shown in yellow. To further understand the cost-effectiveness of battery storage by region, the average NPV for PV + battery storage systems in each county under the Base Case for the year 2025 is shown in Figure 26. In dGen, the economic attractiveness of a system is evaluated based on the lifetime costs and revenue, where the revenue is the sum of savings compared to consuming grid-sourced electricity, revenue from selling excess generation back to the electric grid, and the value of backup power. Figure 26 highlights that as early as 2030, PV + battery storage systems are cost-effective (positive NPV) in many counties across the contiguous United States. In this figure, the total Base Case estimated battery capacity that is cost-effective by 2030 is 164 GW / 329 GWh.

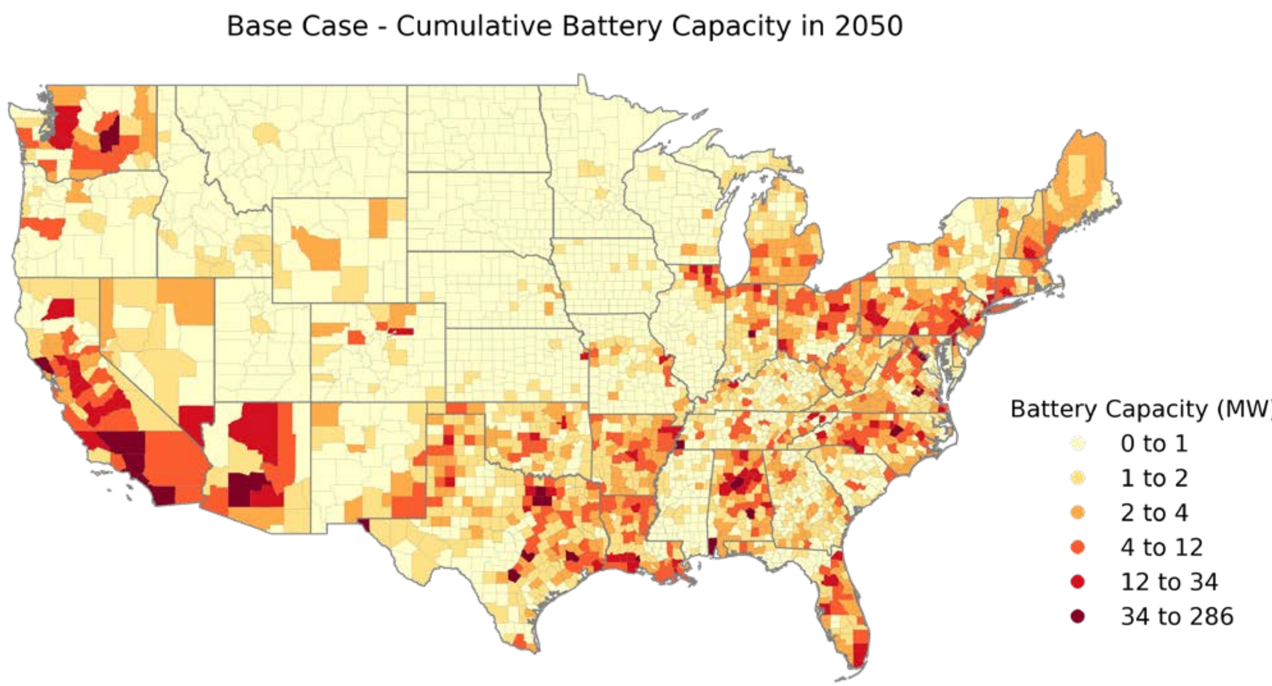
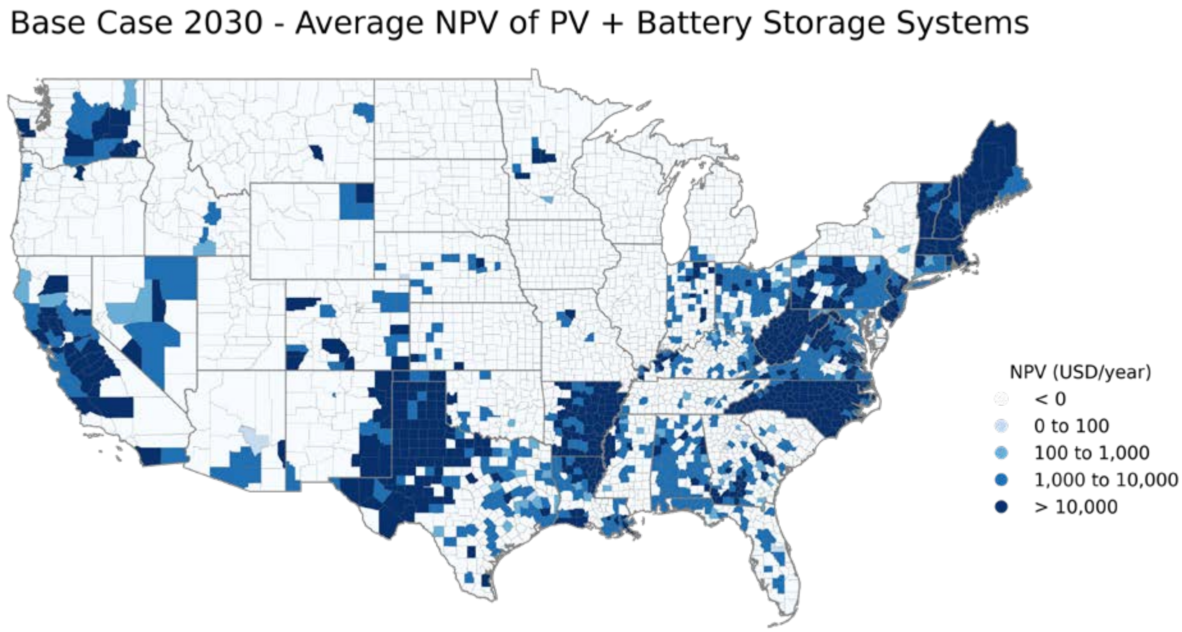



**Figure 25. Cumulative battery deployment by county for the Base Case in 2050**

Color bins are set according to the Jenks-Caspall classification scheme (Rey and Anselin 2007)



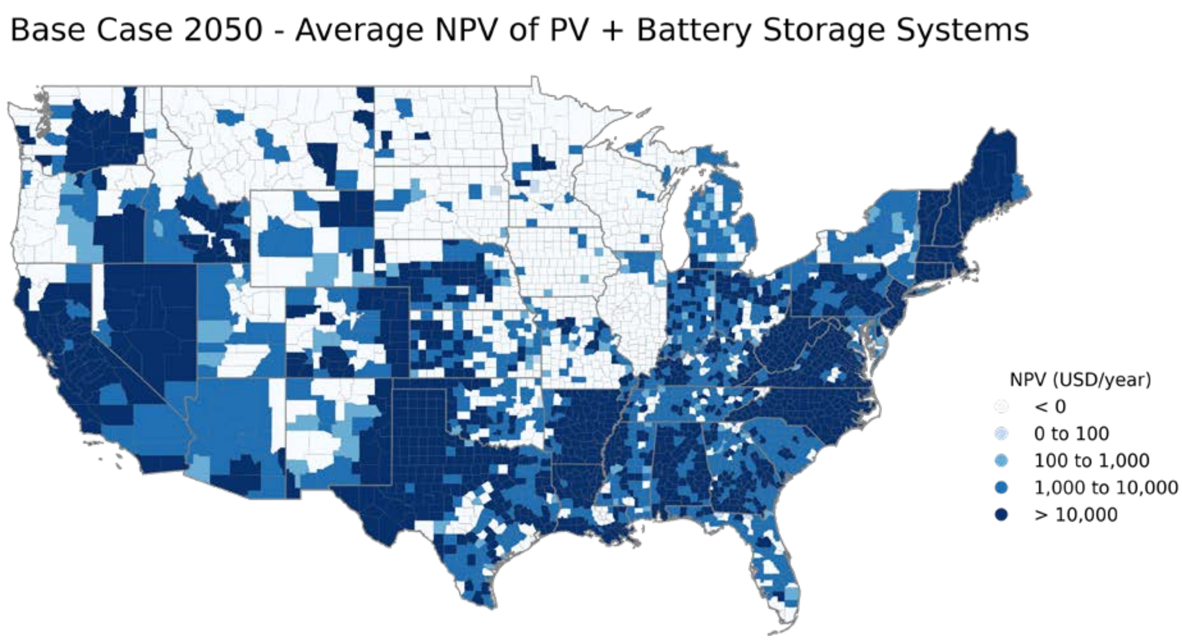




**Figure 26. Average NPV of PV + battery storage systems for each county in 2030 and 2050**

Although this figure shows the average NPV for PV + battery storage systems, these might not be the selected system with the highest NPV (PV-only systems are the alternative option)

## 3.6 Sector-Level Results

Building on the results shown in the previous sections, the battery adoption by sector is shown in Figure 27. In the Base Case, cumulative battery capacity is highest in the commercial sector, followed closely by the industrial sector, with the residential sector having the smallest adoption. Conversely, the residential sector has the most adopters, followed by the industrial and commercial sectors (Figure 28). Therefore, the higher cumulative battery capacity is explained by differences in system sizes across the sectors.

The impact of different scenarios on battery adoption by sector is shown in Figure 29, which presents differences in battery capacity relative to the Base Case for the nine modeled scenarios across the three sectors. In the residential sector, the 2x Backup Value + Advanced Cost Batteries Scenario results in the highest battery adoption, and most of the other scenarios have higher battery adoption than the Base Case (the No Backup Value Scenario and National Net Billing Scenario are the exceptions; the difference between the Base Case is not visible in Figure 29). This indicates that in the residential sector, adoption is mainly driven by a reduction in technology costs. In the commercial sector, the Advanced Cost PV + Batteries Scenario results in the highest battery capacity relative to the Base Case, even higher than the 2x Backup Value + Advanced Cost Batteries Scenario. In the commercial sector, peak shaving makes PV + battery storage systems economically viable; therefore, cost reductions in both PV and batteries drive higher battery adoption. In the industrial sector, the value of backup power plays a big role in driving battery adoption, and a significant decrease in battery capacity is observed in the No Backup Value Scenario. Conversely, battery capacity increases in the 2x Backup Value Scenario as well as the 2x Backup Value + Advanced Cost Batteries Scenario. Therefore, though technology costs are important, the value of backup power is also an important driver of adoption in this sector.

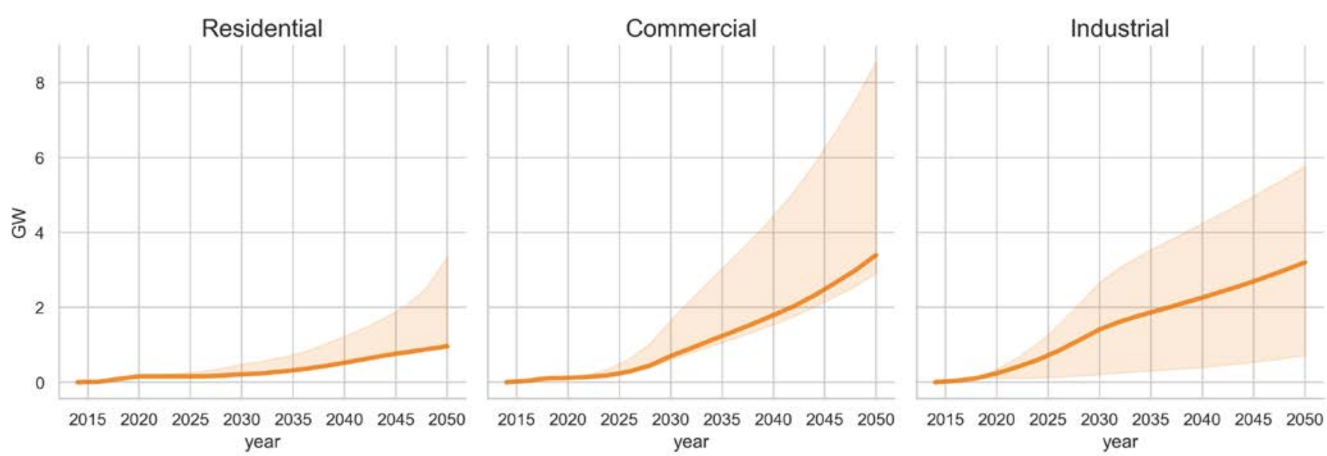



**Figure 27. Cumulative battery deployment by year and sector across all scenarios, with a line for the Base Case**

Upper and lower bounds (in orange) represent the upper and lower estimates from all scenarios

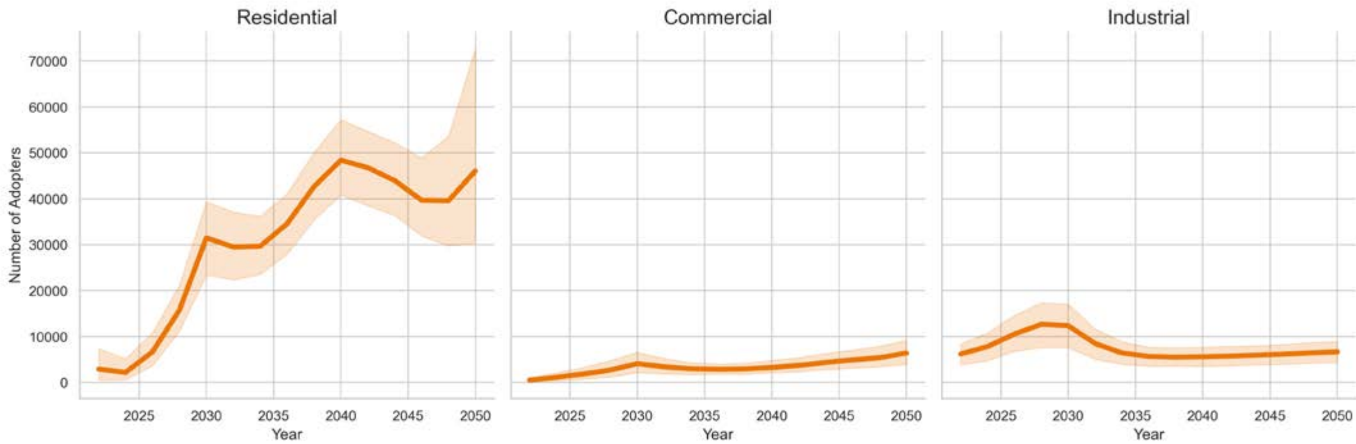



**Figure 28. Number of PV + battery storage adopters by year and sector in the Base Case**

Upper and lower bounds (in orange) represent the upper and lower estimates from all scenarios

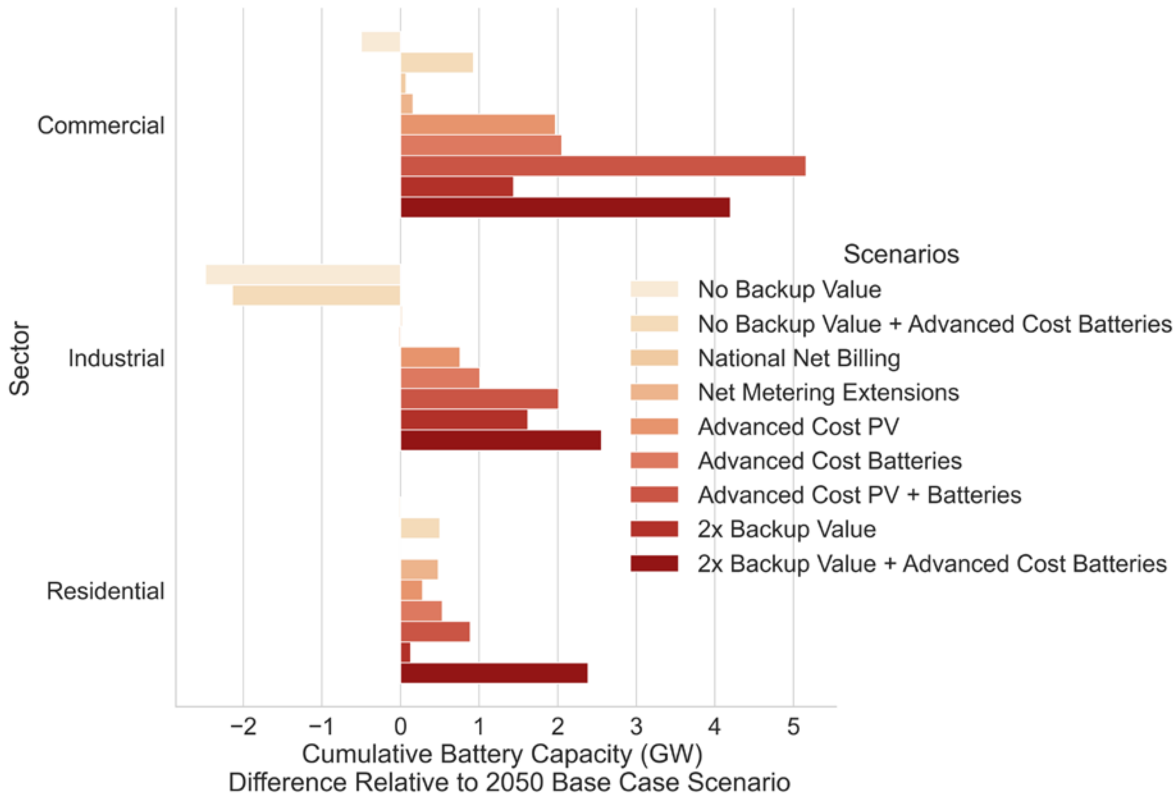



**Figure 29. Impact of sensitivities by sector and scenario on 2050 battery capacity**

## 3.7 Average System Size and Co-Adoption

Average PV system size in PV + battery storage systems (8 kW for residential systems) is larger than in PV-only systems (4 kW for residential systems) (Figure 30). Battery storage thus increases the PV capacity deployed (i.e., allows for a greater amount of DER on the system). This is likely due to the ability of the battery to increase the economic value of PV by storing excess PV generation, which is then exported to the grid at the DER compensation rate or used to offset consumption when electricity rates are high.

Average battery system sizes in the residential sector range from 2 kW / 4 kWh to 4 kW / 8 kWh and is shown by year in Figure 31. Both average battery system size and average rooftop PV size increase in the future, and this is likely due to decreasing PV and battery costs and higher retail electricity prices, which add to the system profitability. A similar result is observed by Hoppmann et al. (2014), who also find that the optimal size of both residential PV systems and battery storage increases significantly in the future.

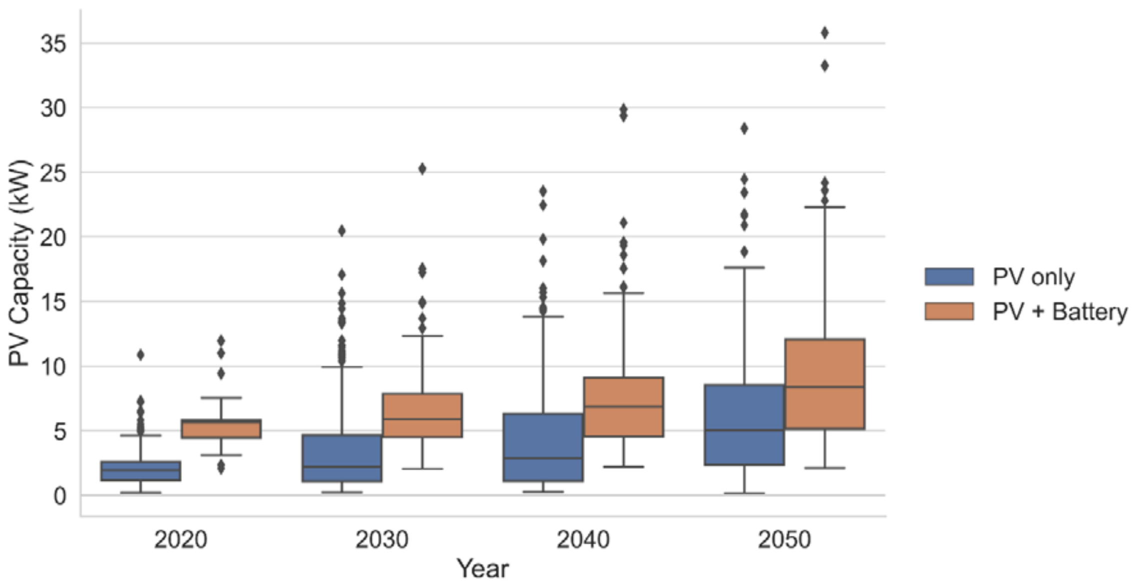



**Figure 30. PV system size for PV-only systems and PV + battery storage systems in the residential sector for the Base Case**

The figures represent a box plot where each box displays the five-number summary of a set of data. The five-number summary is the minimum, first quartile, median, third quartile, and maximum. In a box plot, we draw a box from the first quartile to the third quartile. A vertical line goes through the box at the median. The whiskers go from each quartile to the minimum or maximum. Dots or diamonds represent outliers.

In the commercial sector, the average PV capacity for PV + battery storage systems is almost 10 times larger than in the case with no battery. In the industrial sector, the average PV capacity for PV + battery storage systems is approximately five times larger than in the case with no battery. This is because peak shaving is an important revenue stream for PV + battery storage systems in these sectors. Battery storage systems in the commercial sector are, on average, larger than they are in the industrial sector, ranging from 150 kW to 200 kW / 300 kWh to 400 kWh, whereas in the industrial sector they range from 70 kW to 90 kW / 140 kWh to 180 kWh.

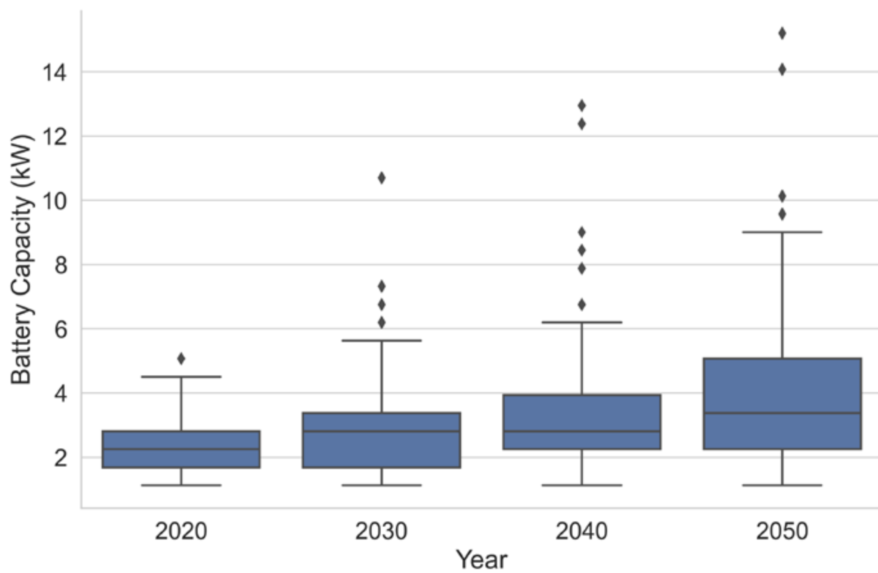



**Figure 31. Battery system size in the residential sector for the Base Case**

In the Base Case, co-adoption of battery storage systems ranges from 34% to 40% of total annual PV installations, depending on the year. The fraction of co-adopters is presented in Figure 32. This figure shows that a higher value of backup power (the Base Case compared to the No Backup Value Scenario) or lower technology cost (the Advanced Cost PV + Batteries compared to the Base Case) results in an increase in the number of adopters of PV + battery storage systems in comparison to adopters of PV-only systems.

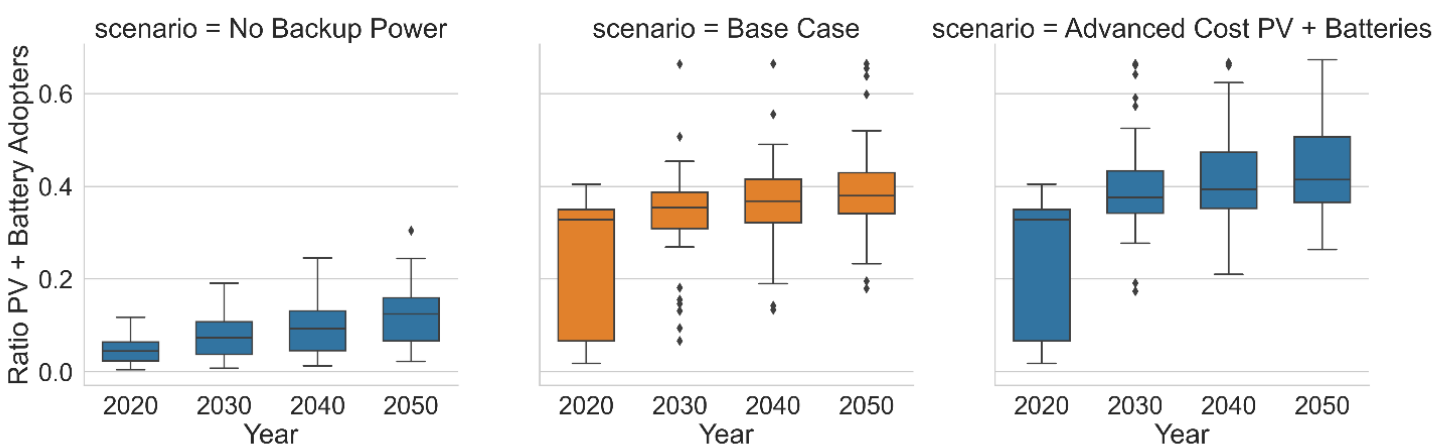



**Figure 32. Co-adoption of battery storage systems under selected scenarios**

## 3.8 Model Limitations and Caveats

Limitations to the results presented in this report are briefly discussed below:

1. Stand-alone battery storage systems are not evaluated in this analysis; only PV + battery storage systems and PV-only systems are modeled and evaluated.
2. Emerging sources of revenue for PV + battery storage systems such as participation in wholesale markets, demand response programs, or grid services are not considered in this analysis.
3. The method used to calculate the value of backup power presented has limitations. Average values might not reflect extreme cases where longer or more frequent service disruptions occur. Also, the calculated estimates are based on historical data provided by utilities—future outages and extreme weather events might increase disruptions to service and thus result in higher costs and demand for backup power.
4. The adoption rates are set by inputs called the Bass diffusion function coefficients. These are based on historical data, which are still minimal for distributed batteries compared to, for example, distributed PV, which has many more years of adoption history. In this analysis, the Bass diffusion function coefficients have been set to be the same for PV and battery adoption. Therefore, we might see a higher or lower than anticipated level of adoption of the economic potential if the model is calibrated to battery-specific data.
5. Significant electrification of the transportation or heating sectors and their impact on residential, commercial, and industrial load profiles are not considered in this analysis.
6. Sensitivities considering owning vs. leasing PV + battery storage systems are not included in this analysis. Sensitivities on financial parameters such as the discount rate are also not considered.
7. New DER valuation mechanisms such as the Value of Distributed Energy Resources (VDER) or the Value Stack (NYSERDA 2020b) are not considered.
8. The wholesale prices used in the model are resolved by year and region and can also vary by scenario. The lack of hourly resolution in wholesale prices impacts the ability of the battery storage system to derive higher value in critical periods when wholesale prices are high. Although dGen has the capability to use hourly wholesale prices as an input, the appropriate sources for these data (especially for future years) need to be determined.

# 4 Discussion, Conclusions, and Future Work

Using the NREL dGen model with new capabilities focused on distributed storage, we present one of the few available estimates for future distributed battery and PV adoption. This work is the result of significant development efforts to consider the most important revenue streams for battery storage. Despite certain limitations, which are discussed in Section 3.8, the model provides spatially rich results on battery adoption. Deployment drivers are locationally specific (e.g., specific rate structures, incentive programs, and value of backup power). Our results show that a combination of factors makes distributed PV + battery storage systems economically attractive and that the value streams considered in this study provide higher value for specific sectors.

Selected insights from our analysis are described below:

- **There is significant economic potential for distributed PV + battery storage systems under all modeled scenarios**. The Base Case economic potential for distributed battery storage coupled with PV is approximately 114 GW / 228 GWh, which is more than 90 times the 2020 capacity. In the scenarios investigated, the upper bound of economic potential for distributed battery storage coupled with PV is 245 GW / 490 GWh under the 2x Backup Value + Advanced Cost Batteries Scenario, and the lower bound is 85 GW / 170 GWh under the No Backup Value Scenario.

- **Despite the high economic potential, modest growth in distributed PV + battery storage is projected under our modeled scenarios:** Under the Base Case, the projected deployment of distributed battery storage capacity is 8 GW / 16 GWh, or 7% of the economic potential, with a range across scenarios from 5–17 GW / 10–34 GWh.

- **The substantial decrease from economic potential to adoption reflects a long payback period, and consequently a lower share of customers willing to invest.** The average payback periods of distributed PV + battery storage systems are fairly long:[24] 11 years for the residential sector, 12 years for the commercial sector, and 8 years for the industrial sector in 2030.

- **At the national scale, the most important drivers of distributed co-adopted battery storage are a combination of advanced (low) future battery cost and a high value for backup power.** The highest adoption estimate for battery capacity is under the 2x Backup Value + Advanced Cost Batteries Scenario (+121% compared to the Base Case).

- **Combined cost reductions in both PV and battery storage technologies drive additional adoption compared to cost reductions in battery technology alone.** The Advanced Cost PV + Batteries Scenario, which considers a reduction in future costs for both PV and batteries, has higher battery deployment compared to the Base Case, increasing by 106%. This deployment is greater than the deployment observed under cost reductions for each technology alone.

[24] For comparison, the average payback period of adopted PV-only systems is less than 5 years for the residential sector.

- **PV + battery systems have larger PV capacity compared to PV-only systems.** Average PV system size in PV + battery storage system configurations (8 kW for residential systems) is larger than in PV-only configurations (4 kW for residential systems). Battery storage thus increases the PV capacity. This is likely due to the ability of the battery to increase the economic value of PV.

- **Local conditions dictate adoption.** Differences in location-specific parameters across the United States also result in significant differences in the amount and rate at which distributed battery storage capacity is adopted in various states and counties.

- **Storage deployment is highly sensitive to the regional value of backup power.** The value of backup power used in this analysis has high regional variation across the United States.[25] The sensitivity of storage deployment to the value of backup power is higher in specific states and sectors with higher value of backup power.

- **Retail tariffs that include high demand charges (i.e., billing based on the highest instantaneous level of monthly power demand), time-of-use tariffs, and tiered tariffs are found to encourage PV + battery storage adoption.** However, other factors such as climate, load profile, electricity price, and DER compensation mechanism combined with retail tariffs can minimize their impact. In the residential sector, fixed structure rates, the most common retail rate structure, do not incentivize battery storage.

- **Percentage of battery co-adoption ranges from 34%–40% of total annual PV installations, depending on the year in the Base Case.** The percentage of battery co-adoption is sensitive to the value of backup power and technology cost; the percentage of battery co-adoption decreases to 7%–12% of total annual PV installations in the No Backup Value scenario and increases to 40%–45% of total annual PV installations in the Advanced Cost PV + Batteries scenario.

- **PV + battery systems have larger PV capacity compared to PV-only systems.** Average PV system size in PV + battery storage system configurations (8 kW for residential systems) is larger than in PV-only configurations (4 kW for residential systems) (Figure 30). Battery storage thus increases the PV capacity deployed (i.e., allows for a greater amount of DER on the system). This is likely due to the ability of the battery to increase the economic value of PV.

The process of developing and implementing the distributed storage (battery) technology within dGen revealed additional questions and research capabilities related to BTM battery storage adoption that would add to the insights reported here. Much of this future work stems from the list of caveats detailed in Section 3.8; the following is an initial list of potential future work activities:

[25] The value of backup power used in this analysis is calculated by combining EIA-861 data (EIA 2020) with value of service reliability estimates (Sullivan, Schellenberg, and Blundell 2015). Based on our calculation, certain states and sectors have a significantly higher average value of backup power, notably states along the East Coast and the industrial sector (Figure 4).

- Additional use cases for battery storage could be explored through additional dispatch mechanisms that are appropriate to optimize battery dispatch for multiple purposes (e.g., participation in wholesale markets, participation in demand response programs, or provision of grid services).
- Calibration is also important to improve the accuracy of our adoption projections; both surveys and actual data on battery deployment could be used to calibrate the model. Calibration is currently difficult because the number of market years and the size of the market are not as long or as large (for battery storage) as they are for distributed PV, for example. Calibration could continue to improve over the coming years.
- Testing of other methods to choose optimal system sizes is another area of research. Integrating the PySAM module (NREL 2019) within dGen with the REopt application programming interface[26] is one alternative to optimize system sizes.
- An option to evaluate stand-alone distributed battery storage systems—in addition to those tied to PV—would allow comparisons and evaluation of the hybrid system and stand-alone battery storage.
- Assessing the impact of significant electrification on the adoption of distributed storage is another significant area for future work.
    - Electrification could strongly impact the adoption of distributed storage. The growth and changing shape of local load could reduce the economic value of energy shifting from PV installations if load were to shift more to the daytime (or it could perhaps increase the value of load shifting if electric vehicle charging were to compound the peak effect in the evening).
    - Factors that could increase adoption include the move toward providing heating with electricity. This move could make backup power more valuable in cold climates during winter electricity outages.
    - Conversely, the growth of electric vehicle deployment and the potential for these vehicles to also provide backup power could significantly curtail the market for a separate stationary emergency backup power source.
- Finally, with high levels of utility-scale renewables, the overall system net load shape could change significantly to reflect the shift from fossil fuels to renewables. The system net load shape could then influence wholesale energy rates. Though utility rate values and configurations often trail the implementation of new grid generators, utility rate structures are anticipated to see significant changes by 2050. Those changes are not reflected in this work, but they could be analyzed with a stronger linkage to NREL's ReEDS and other models.

[26] "REopt Lite™ API (Version 1)," https://developer.nrel.gov/docs/energy-optimization/reopt-v1/

# References

Augustine, Chad and Nate Blair. 2021. *Storage Futures Study: Storage Technology Modeling Input Data Report*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5700-78694. https://www.nrel.gov/docs/fy21osti/78694.pdf.

Baik, Sunhee, Alexander L. Davis, and M. Granger Morgan. 2018. "Assessing the Cost of Large-Scale Power Outages to Residential Customers." *Risk Analysis* 38 (2): 283–96. https://doi.org/10.1111/risa.12842.

Baik, Sunhee, Alexander L. Davis, Jun Woo Park, Selin Sirinterlikci, and M. Granger Morgan. 2020. "Estimating What US Residential Customers Are Willing to Pay for Resilience to Large Electricity Outages of Long Duration." *Nature Energy* 5 (3): 250–58. https://doi.org/10.1038/s41560-020-0581-1.

Baik, Sunhee, M. Granger Morgan, and Alexander L. Davis. 2018. "Providing Limited Local Electric Service During a Major Grid Outage: A First Assessment Based on Customer Willingness to Pay." *Risk Analysis* 38 (2): 272–82. https://doi.org/10.1111/risa.12838.

Bass, Frank M. 1969. "A New Product Growth for Model Consumer Durables." *Management Science* 15 (5): 215–27. http://www.jstor.org/stable/2628128.

Burger, Scott P., Jesse D. Jenkins, Samuel C. Huntington, and Ignacio J. Pérez-Arriaga. 2019. "Why Distributed? A Critical Review of the Tradeoffs Between Centralized and Decentralized Resources." *IEEE Power & Energy Magazine* 17 (2): 16–24. https://doi.org/10.1109/MPE.2018.2885203.

Cohen, Stuart M., Jonathon Becker, David A. Bielen, Maxwell Brown, Wesley J. Cole, Kelly P. Eurek, Allister Frazier, et al. 2019. *Regional Energy Deployment System (ReEDS) Model Documentation: Version 2018*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-72023. https://doi.org/10.2172/1505935.

Cole, Wesley and A. Will Frazier. 2020. *Cost Projections for Utility-Scale Battery Storage: 2020 Update*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-75385. https://www.nrel.gov/docs/fy20osti/75385.pdf.

DiOrio, Nicholas. 2017. *An Overview of the Automated Dispatch Controller Algorithms in the System Advisor Model (SAM)*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-68614. https://www.nrel.gov/docs/fy18osti/68614.pdf.

DiOrio, Nicholas, Paul Denholm, and William B. Hobbs. 2020. "A Model for Evaluating the Configuration and Dispatch of PV Plus Battery Power Plants." *Applied Energy* 262: 114465. https://doi.org/10.1016/j.apenergy.2019.114465.

Dong, Changgui and Benjamin Sigrin. 2019. "Using Willingness to Pay to Forecast the Adoption of Solar Photovoltaics: A 'Parameterization + Calibration' Approach." *Energy Policy* 129: 100–110. https://doi.org/10.1016/j.enpol.2019.02.017.

DSIRE. 2020. "Database of State Incentives for Renewables & Efficiency." https://www.dsireusa.org/.

Federal Energy Regulatory Commission (FERC). 2020. *Participation of Distributed Energy Resource Aggregations in Markets Operated by Regional Transmission Organizations and Independent System Operators*. Washington, D.C.: FERC. Order No. 2222. https://www.ferc.gov/sites/default/files/2020-09/E-1_0.pdf.

Feldman, David and Robert Margolis. 2018. "Q2/Q3 2018 Solar Industry Update." Golden, CO: National Renewable Energy Laboratory. NREL/PR-6A20-72810. https://www.nrel.gov/docs/fy19osti/72810.pdf.

Hoppmann, Joern, Jonas Volland, Tobias S. Schmidt, and Volker H. Hoffmann. 2014. "The Economic Viability of Battery Storage for Residential Solar Photovoltaic Systems - A Review and a Simulation Model." *Renewable and Sustainable Energy Reviews* 39: 1101–18. https://doi.org/10.1016/j.rser.2014.07.068.

JEA. 2021. "Solar Battery Incentive Program." https://www.jea.com/residential_customers/residential_rebates/solar_battery_incentive_program/.

Lopez, Anthony, Billy Roberts, Donna Heimiller, Nate Blair, and Gian Porro. 2012. *U.S. Renewable Energy Technical Potentials: A GIS-Based Analysis*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-51946. https://www.nrel.gov/docs/fy12osti/51946.pdf.

Maryland Energy Administration. 2020. "Maryland Energy Storage Income Tax Credit - Tax Year 2020." https://energy.maryland.gov/business/Pages/EnergyStorage.aspx.

McCabe, Kevin, Ashreeta Prasanna, Ben Sigrin, and Trevor Stanley. 2020. "Modeling Distributed Generation in California."

Mirletz, Brian and Darice Guittet. 2021. "Heuristic Dispatch Based on Price Signals for Behind-the-Meter PV-Battery Systems in SAM." In *IEEE 48th Photovoltaic Specialists Conference (PVSC)*, June 20–25, 2020.

National Renewable Energy Laboratory (NREL). 2016. "Energy Storage Possibilities for Expanding Electric Grid Flexibility." Golden, CO: National Renewable Energy Laboratory. NREL/BR-6A20-64764. http://www.nrel.gov/docs/fy16osti/64764.pdf.

———. 2019. "NREL-PySAM 2.2.0." https://nrel-pysam.readthedocs.io/en/master/.

———. 2020. "2020 Annual Technology Baseline." https://atb.nrel.gov/.

New York State Energy Research and Development Authority (NYSERDA). 2020a. "Retail Storage Incentives." https://www.nyserda.ny.gov/All-Programs/Programs/Energy-Storage/Developers-Contractors-and-Vendors/Retail-Incentive-Offer.

———. 2020b. "The Value Stack." https://www.nyserda.ny.gov/All Programs/Programs/NY Sun/Contractors/Value of Distributed Energy Resources.

NVEnergy. 2021. *Energy Storage Incentives: Program Handbook*. Las Vegas, NV: NVEnergy. https://www.nvenergy.com/publish/content/dam/nvenergy/brochures_arch/cleanenergy/handbooks/EnergyStorage-Handbook.pdf.

OpenEI. 2020. "Utility Rate Database." https://openei.org/wiki/Utility_Rate_Database.

Oregon Department of Energy. 2020. "Oregon Solar + Storage Rebate Program." https://www.oregon.gov/energy/Incentives/Pages/Solar-Storage-Rebate-Program.aspx.

Pacific Northwest National Laboratory (PNNL). 2020. "Energy Storage Policy Database." https://energystorage.pnnl.gov/regulatoryactivities.asp.

Pimm, Andrew J., Tim T. Cockerill, and Peter G. Taylor. 2018. "Time-of-Use and Time-of-Export Tariffs for Home Batteries: Effects on Low Voltage Distribution Networks." *Journal of Energy Storage* 18: 447–58. https://doi.org/10.1016/j.est.2018.06.008.

Rey, Sergio J. and Luc Anselin. 2007. "PySAL: A Python Library of Spatial Analytical Methods." *The Review of Regional Studies* 37 (1): 5–27. https://doi.org/10.52324/001c.8285.

Rogers, Everett M. 2003. *Diffusion of Innovations: 5th ed*. New York, NY: Free Press.

Sigrin, Benjamin, Michael Gleason, Robert Preus, Ian Baring-Gould, and Robert Margolis. 2016. *The Distributed Generation Market Demand Model (dGen): Documentation*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-65231. https://www.nrel.gov/docs/fy16osti/65231.pdf.

SRP. 2021. "Battery Storage Incentive." https://www.srpnet.com/electric/home/batterystorage/default.aspx.

State of California. 2021. "Self-Generation Incentive Program." https://www.selfgenca.com/.

Stenclik, Derek, Paul Denholm, and Babu Chalamala. 2017. "Maintaining Balance: The Increasing Role of Energy Storage for Renewable Integration." *IEEE Power and Energy Magazine* 15 (6): 31–39. https://doi.org/10.1109/MPE.2017.2729098.

Sullivan, Michael J., Josh Schellenberg, and Marshall Macdonald Blundell. 2015. *Updated Value of Service Reliability Estimates for Electric Utility Customers in the United States*. Berkeley, CA: Lawrence Berkeley National Laboratory. LBNL-6941E. https://doi.org/10.2172/1172643.

U.S. Energy Information Administration (EIA). 2020. "Annual Electric Power Industry Report, Form EIA-861 Detailed Data Files." https://www.eia.gov/electricity/data/eia861/.

Virtanen, Pauli, Ralf Gommers, Travis E. Oliphant, Matt Haberland, Tyler Reddy, David Cournapeau, Evgeni Burovski, et al. 2020. “SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python.” *Nature Methods* 17: 261–72. https://doi.org/10.1038/s41592-019-0686-2.

Wood Mackenzie and U.S. Energy Storage Association. 2020. *U.S. Energy Storage Monitor: Q2 2020 Full Report*. Edinburgh, UK: Wood Mackenzie.

Young, Sharon, Anna Bruce, and Iain MacGill. 2019. “Potential Impacts of Residential PV and Battery Storage on Australia’s Electricity Networks under Different Tariffs.” *Energy Policy* 128: 616–27. https://doi.org/10.1016/j.enpol.2019.01.005.

Zinaman, Owen, Alexandra Aznar, Carl Linvill, Naïm Darghouth, Timon Dubbeling, and Emanuele Bianco. 2017. “Grid-Connected Distributed Generation: Compensation Mechanism Basics.” Golden, CO: National Renewable Energy Laboratory. NREL/BR-6A20-68469. https://www.nrel.gov/docs/fy18osti/68469.pdf.

# Appendix. Backup Power Calculation

Table A-1 provides details on the value of backup power calculation. The SAIFI column lists the average customer interruptions by state, and the SAIDI column lists the average customer hours interrupted by state. Both these data sets are from EIA-861 (EIA 2020). The data in the "Interruption Cost/Event" column are from Lawrence Berkeley National Laboratory (Sullivan, Schellenberg, and Blundell 2015), where the corresponding monetary value according to SAIDI has been selected for the state and sector.

**Table A-1. Value of Backup Power (USD/year) by State and Sector for all U.S. States**

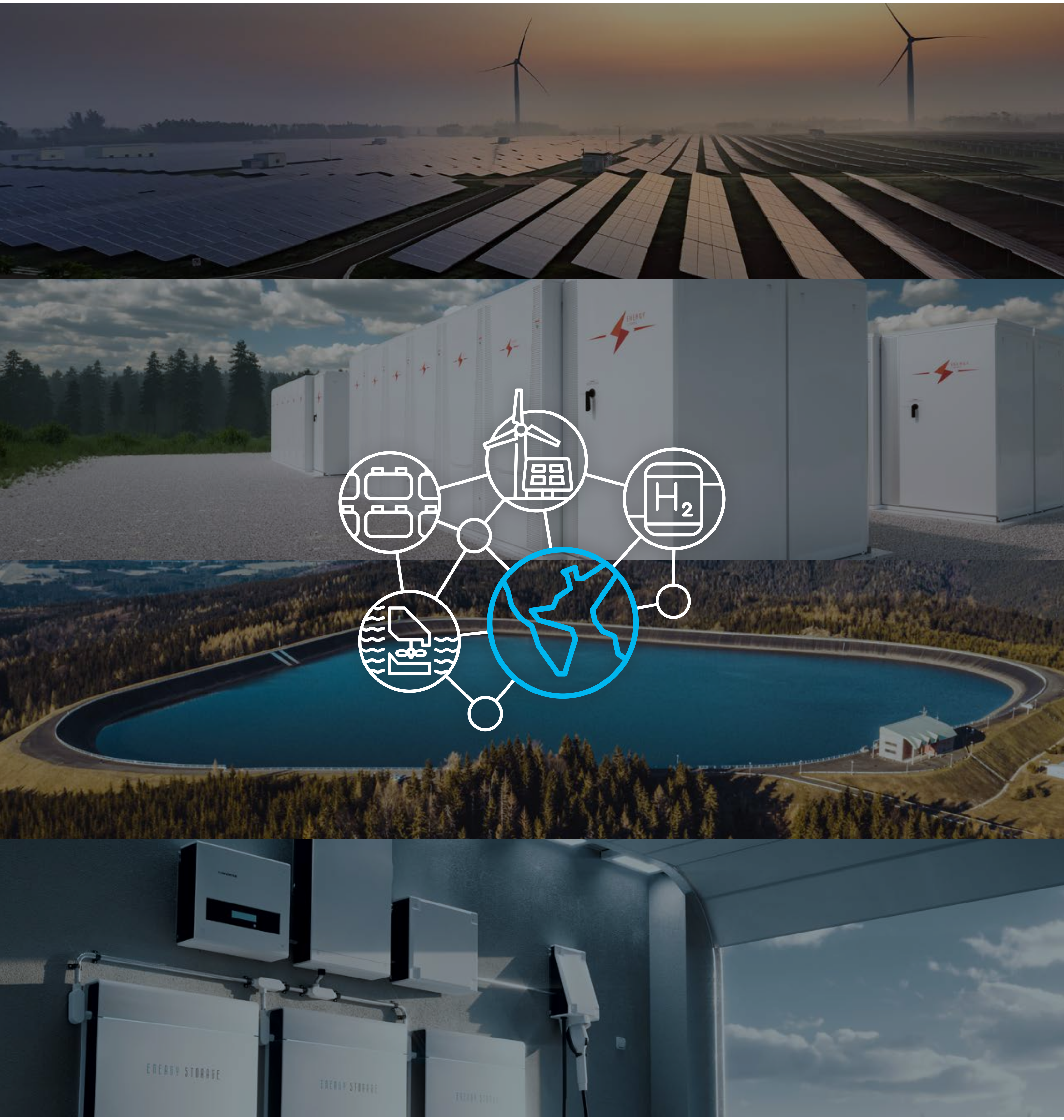
| State | SAIFI | SAIDI | Sector | Interruption Cost/Event (USD) | Value of Backup Power (USD) |
|---|---|---|---|---|---|
| Alaska | 3.1 | 5.6 | Industrial | 39,458 | 123,769 |
| Alaska | 3.1 | 5.6 | Commercial | 1,880 | 5,897 |
| Alaska | 3.1 | 5.6 | Residential | 10 | 30 |
| Alabama | 1.5 | 4.8 | Industrial | 39,458 | 57,996 |
| Alabama | 1.5 | 4.8 | Commercial | 1,880 | 2,763 |
| Alabama | 1.5 | 4.8 | Residential | 10 | 14 |
| Arkansas | 1.7 | 5.4 | Industrial | 39,458 | 68,059 |
| Arkansas | 1.7 | 5.4 | Commercial | 1,880 | 3,243 |
| Arkansas | 1.7 | 5.4 | Residential | 10 | 16 |
| Arizona | 0.9 | 1.9 | Industrial | 17,804 | 16,562 |
| Arizona | 0.9 | 1.9 | Commercial | 647 | 602 |
| Arizona | 0.9 | 1.9 | Residential | 5 | 5 |
| California | 1.0 | 3.3 | Industrial | 17,804 | 16,983 |
| California | 1.0 | 3.3 | Commercial | 647 | 617 |
| California | 1.0 | 3.3 | Residential | 5 | 5 |
| Colorado | 1.0 | 1.9 | Industrial | 17,804 | 17,079 |
| Colorado | 1.0 | 1.9 | Commercial | 647 | 621 |
| Colorado | 1.0 | 1.9 | Residential | 5 | 5 |
| Connecticut | 1.3 | 10.9 | Industrial | 84,083 | 105,498 |
| Connecticut | 1.3 | 10.9 | Commercial | 4,690 | 5,884 |
| Connecticut | 1.3 | 10.9 | Residential | 17 | 22 |
| District of Columbia | 0.6 | 1.8 | Industrial | 17,804 | 11,395 |
| District of Columbia | 0.6 | 1.8 | Commercial | 647 | 414 |
| District of Columbia | 0.6 | 1.8 | Residential | 5 | 3 |
| Delaware | 1.0 | 2.3 | Industrial | 17,804 | 18,373 |
| Delaware | 1.0 | 2.3 | Commercial | 647 | 668 |
| Delaware | 1.0 | 2.3 | Residential | 5 | 5 |

| | | | | | |
|---|---|---|---|---|---|
| Florida | 1.1 | 5.2 | Industrial | 39,458 | 44,620 |
| Florida | 1.1 | 5.2 | Commercial | 1,880 | 2,126 |
| Florida | 1.1 | 5.2 | Residential | 10 | 11 |
| Georgia | 1.5 | 6.2 | Industrial | 39,458 | 60,674 |
| Georgia | 1.5 | 6.2 | Commercial | 1,880 | 2,891 |
| Georgia | 1.5 | 6.2 | Residential | 10 | 15 |
| Hawaii | 2.0 | 3.2 | Industrial | 17,804 | 34,934 |
| Hawaii | 2.0 | 3.2 | Commercial | 647 | 1,270 |
| Hawaii | 2.0 | 3.2 | Residential | 5 | 10 |
| Idaho | 1.2 | 2.9 | Industrial | 17,804 | 20,926 |
| Idaho | 1.2 | 2.9 | Commercial | 647 | 760 |
| Idaho | 1.2 | 2.9 | Residential | 5 | 6 |
| Illinois | 0.9 | 2.4 | Industrial | 17,804 | 16,269 |
| Illinois | 0.9 | 2.4 | Commercial | 647 | 591 |
| Illinois | 0.9 | 2.4 | Residential | 5 | 5 |
| Indiana | 1.4 | 4.8 | Industrial | 39,458 | 56,816 |
| Indiana | 1.4 | 4.8 | Commercial | 1,880 | 2,707 |
| Indiana | 1.4 | 4.8 | Residential | 10 | 14 |
| Iowa | 1.0 | 2.1 | Industrial | 17,804 | 18,091 |
| Iowa | 1.0 | 2.1 | Commercial | 647 | 657 |
| Iowa | 1.0 | 2.1 | Residential | 5 | 5 |
| Kansas | 1.1 | 2.6 | Industrial | 17,804 | 19,249 |
| Kansas | 1.1 | 2.6 | Commercial | 647 | 700 |
| Kansas | 1.1 | 2.6 | Residential | 5 | 6 |
| Kentucky | 1.8 | 6.8 | Industrial | 39,458 | 70,435 |
| Kentucky | 1.8 | 6.8 | Commercial | 1,880 | 3,356 |
| Kentucky | 1.8 | 6.8 | Residential | 10 | 17 |
| Louisiana | 2.1 | 4.6 | Industrial | 39,458 | 82,622 |
| Louisiana | 2.1 | 4.6 | Commercial | 1,880 | 3,937 |
| Louisiana | 2.1 | 4.6 | Residential | 10 | 20 |
| Maine | 2.8 | 11.1 | Industrial | 84,083 | 235,522 |
| Maine | 2.8 | 11.1 | Commercial | 4,690 | 13,137 |
| Maine | 2.8 | 11.1 | Residential | 17 | 48 |
| Maryland | 1.3 | 5.6 | Industrial | 39,458 | 51,223 |
| Maryland | 1.3 | 5.6 | Commercial | 1,880 | 2,441 |
| Maryland | 1.3 | 5.6 | Residential | 10 | 12 |

| | | | | | |
|---|---|---|---|---|---|
| Massachusetts | 1.6 | 13.6 | Industrial | 84,083 | 130,522 |
| Massachusetts | 1.6 | 13.6 | Commercial | 4,690 | 7,280 |
| Massachusetts | 1.6 | 13.6 | Residential | 17 | 27 |
| Michigan | 1.4 | 7.4 | Industrial | 39,458 | 54,317 |
| Michigan | 1.4 | 7.4 | Commercial | 1,880 | 2,588 |
| Michigan | 1.4 | 7.4 | Residential | 10 | 13 |
| Minnesota | 1.0 | 2.1 | Industrial | 17,804 | 18,047 |
| Minnesota | 1.0 | 2.1 | Commercial | 647 | 656 |
| Minnesota | 1.0 | 2.1 | Residential | 5 | 5 |
| Mississippi | 1.5 | 4.5 | Industrial | 39,458 | 59,830 |
| Mississippi | 1.5 | 4.5 | Commercial | 1,880 | 2,851 |
| Mississippi | 1.5 | 4.5 | Residential | 10 | 14 |
| Missouri | 0.9 | 2.5 | Industrial | 17,804 | 16,807 |
| Missouri | 0.9 | 2.5 | Commercial | 647 | 611 |
| Missouri | 0.9 | 2.5 | Residential | 5 | 5 |
| Montana | 1.2 | 2.4 | Industrial | 17,804 | 21,744 |
| Montana | 1.2 | 2.4 | Commercial | 647 | 790 |
| Montana | 1.2 | 2.4 | Residential | 5 | 6 |
| Nebraska | 1.0 | 3.1 | Industrial | 17,804 | 18,302 |
| Nebraska | 1.0 | 3.1 | Commercial | 647 | 665 |
| Nebraska | 1.0 | 3.1 | Residential | 5 | 5 |
| Nevada | 1.0 | 2.1 | Industrial | 17,804 | 17,382 |
| Nevada | 1.0 | 2.1 | Commercial | 647 | 632 |
| Nevada | 1.0 | 2.1 | Residential | 5 | 5 |
| New Hampshire | 2.2 | 8.5 | Industrial | 84,083 | 182,495 |
| New Hampshire | 2.2 | 8.5 | Commercial | 4,690 | 10,179 |
| New Hampshire | 2.2 | 8.5 | Residential | 17 | 37 |
| New Jersey | 1.4 | 8.5 | Industrial | 84,083 | 119,266 |
| New Jersey | 1.4 | 8.5 | Commercial | 4,690 | 6,652 |
| New Jersey | 1.4 | 8.5 | Residential | 17 | 24 |
| New Mexico | 1.1 | 2.3 | Industrial | 17,804 | 19,506 |
| New Mexico | 1.1 | 2.3 | Commercial | 647 | 709 |
| New Mexico | 1.1 | 2.3 | Residential | 5 | 6 |
| New York | 1.0 | 6.8 | Industrial | 39,458 | 39,718 |
| New York | 1.0 | 6.8 | Commercial | 1,880 | 1,892 |
| New York | 1.0 | 6.8 | Residential | 10 | 10 |

| | | | | | |
|---|---|---|---|---|---|
| North Carolina | 2.1 | 29.4 | Industrial | 165,482 | 351,418 |
| North Carolina | 2.1 | 29.4 | Commercial | 9,055 | 19,229 |
| North Carolina | 2.1 | 29.4 | Residential | 32 | 69 |
| North Dakota | 0.9 | 1.6 | Industrial | 17,804 | 15,955 |
| North Dakota | 0.9 | 1.6 | Commercial | 647 | 580 |
| North Dakota | 0.9 | 1.6 | Residential | 5 | 5 |
| Ohio | 1.4 | 4.0 | Industrial | 39,458 | 55,089 |
| Ohio | 1.4 | 4.0 | Commercial | 1,880 | 2,625 |
| Ohio | 1.4 | 4.0 | Residential | 10 | 13 |
| Oklahoma | 1.3 | 2.9 | Industrial | 17,804 | 23,611 |
| Oklahoma | 1.3 | 2.9 | Commercial | 647 | 858 |
| Oklahoma | 1.3 | 2.9 | Residential | 5 | 7 |
| Oregon | 0.9 | 1.9 | Industrial | 17,804 | 16,099 |
| Oregon | 0.9 | 1.9 | Commercial | 647 | 585 |
| Oregon | 0.9 | 1.9 | Residential | 5 | 5 |
| Pennsylvania | 1.4 | 8.6 | Industrial | 84,083 | 120,382 |
| Pennsylvania | 1.4 | 8.6 | Commercial | 4,690 | 6,715 |
| Pennsylvania | 1.4 | 8.6 | Residential | 17 | 25 |
| Rhode Island | 1.6 | 9.9 | Industrial | 84,083 | 132,010 |
| Rhode Island | 1.6 | 9.9 | Commercial | 4,690 | 7,363 |
| Rhode Island | 1.6 | 9.9 | Residential | 17 | 27 |
| South Carolina | 1.6 | 7.8 | Industrial | 39,458 | 63,173 |
| South Carolina | 1.6 | 7.8 | Commercial | 1,880 | 3,010 |
| South Carolina | 1.6 | 7.8 | Residential | 10 | 15 |
| South Dakota | 1.0 | 1.5 | Industrial | 17,804 | 18,304 |
| South Dakota | 1.0 | 1.5 | Commercial | 647 | 665 |
| South Dakota | 1.0 | 1.5 | Residential | 5 | 5 |
| Tennessee | 1.8 | 3.3 | Industrial | 17,804 | 32,589 |
| Tennessee | 1.8 | 3.3 | Commercial | 647 | 1,184 |
| Tennessee | 1.8 | 3.3 | Residential | 5 | 9 |
| Texas | 1.3 | 2.8 | Industrial | 17,804 | 23,890 |
| Texas | 1.3 | 2.8 | Commercial | 647 | 868 |
| Texas | 1.3 | 2.8 | Residential | 5 | 7 |
| Utah | 1.0 | 2.1 | Industrial | 17,804 | 17,374 |
| Utah | 1.0 | 2.1 | Commercial | 647 | 631 |
| Utah | 1.0 | 2.1 | Residential | 5 | 5 |

| | | | | | |
|---|---|---|---|---|---|
| Vermont | 2.6 | 13.7 | Industrial | 84,083 | 220,197 |
| Vermont | 2.6 | 13.7 | Commercial | 4,690 | 12,282 |
| Vermont | 2.6 | 13.7 | Residential | 17 | 45 |
| Virginia | 1.8 | 8.5 | Industrial | 84,083 | 152,385 |
| Virginia | 1.8 | 8.5 | Commercial | 4,690 | 8,500 |
| Virginia | 1.8 | 8.5 | Residential | 17 | 31 |
| Washington | 1.2 | 4.5 | Industrial | 39,458 | 47,813 |
| Washington | 1.2 | 4.5 | Commercial | 1,880 | 2,278 |
| Washington | 1.2 | 4.5 | Residential | 10 | 12 |
| West Virginia | 2.6 | 12.3 | Industrial | 84,083 | 222,445 |
| West Virginia | 2.6 | 12.3 | Commercial | 4,690 | 12,408 |
| West Virginia | 2.6 | 12.3 | Residential | 17 | 46 |
| Wisconsin | 0.8 | 2.0 | Industrial | 17,804 | 14,354 |
| Wisconsin | 0.8 | 2.0 | Commercial | 647 | 522 |
| Wisconsin | 0.8 | 2.0 | Residential | 5 | 4 |
| Wyoming | 1.2 | 2.3 | Industrial | 17,804 | 21,517 |
| Wyoming | 1.2 | 2.3 | Commercial | 647 | 782 |
| Wyoming | 1.2 | 2.3 | Residential | 5 | 6 |



National Renewable Energy Laboratory
15013 Denver West Parkway, Golden, CO 80401
303-275-3000 • www.nrel.gov

*NREL prints on paper that contains recycled content.*

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency and Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

NREL/TP-7A40-79790 • July 2021