# Modeling Methods for Capturing System Interactions of Combined Technologies: A Study of PV + Battery


Brady Cowiestoll, Jennie Jorgenson, and Matthew Irish

*National Renewable Energy Laboratory*



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

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

**Technical Report**
NREL/TP-5C00-79769
March 2022

# Modeling Methods for Capturing System Interactions of Combined Technologies: A Study of PV + Battery

Brady Cowiestoll, Jennie Jorgenson, and Matthew Irish

*National Renewable Energy Laboratory*

**Suggested Citation**
Cowiestoll, Brady, Jennie Jorgenson, and Matthew Irish. 2022. *Modeling Methods for Capturing System Interactions of Combined Technologies: A Study of PV + Battery*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5C00-79769. https://www.nrel.gov/docs/fy22osti/79769.pdf.

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

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

**Technical Report**
NREL/TP-5C00-79769
March 2022

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

## 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 the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.



*Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.*

# Acknowledgments

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. This work was supported by the U.S. Department of Energy (DOE) Office of Energy Efficiency and Renewable Energy (EERE) Solar Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government.

The authors would like to thank Paul Denholm of NREL for his guidance in shaping this work. We would also like to thank Trieu Mai, Dan Steinberg and Jaquelin Cochran of NREL for reviewing the final product.

# List of Acronyms

| | |
|---|---|
| BA | balancing authority |
| BIR | battery inverter ratio |
| CAMX | California-Mexico |
| CEM | capacity expansion modeling/model |
| CSP | concentrating solar power |
| dGen | Distributed Generation Market Demand model |
| DOE | U.S. Department of Energy |
| EERE | DOE Office of Energy Efficiency and Renewable Energy |
| h | hour |
| hrs | hours |
| MW | megawatts |
| NERC | North American Electric Reliability Corporation |
| NG-CT | Natural gas-combustion turbine |
| NREL | National Renewable Energy Laboratory |
| NWPP-CA | Northwest Power Pool-Canada |
| NWPP-US | Northwest Power Pool-United States |
| PV | photovoltaic |
| RE | renewable energy |
| REC | renewable energy certificate |
| RMPP | Rocky Mountain Power Pool |
| RMRG | Rocky Mountain Reserve Group |
| RPM | Resource Planning Model |
| RPS | renewable portfolio standard |
| SRSG | Southwest Reserve Sharing Group |
| VG | variable generation |
| VRE | variable renewable energy |
| WECC | Western Electricity Coordinating Council |

# Executive Summary

The costs of solar photovoltaics (PV) and batteries have been decreasing in recent years, leading to increasing installations of them—both independently sited and colocated solar PV and battery systems—and growing interest in how the technologies can interact with the electric grid at greater deployment levels. Given the increasing deployment of these technologies, it is important to understand the value and limitations of battery storage for the grid as well as potential value of colocating battery storage and PV, particularly within the realm of future system planning. However, representing the dynamic nature of these technologies to accurately capture their potential values is challenging within capacity expansion models (CEMs) given their typical formulation as a linear program. Interactions between variable renewable technologies, such as PV, and storage resources are nonlinear and thus novel approaches must be developed to robustly capture the interactive effects of these technologies.

This report presents methodological developments to represent more fully the value and limitations of combined (i.e., installed in the same model year and region) PV and battery installations (PV + battery) in CEMs using the Resource Planning Model (RPM), which co-optimizes capacity investments, transmission investments, and reduced-order dispatch in the Western Interconnection of North America through 2045. We use RPM to simulate the evolution of the generation and transmission system under two core scenarios—a baseline scenario and a high renewable deployment scenario—coupled with sensitivities assuming low and midline PV and battery cost projections. When incorporating PV + battery systems, it is important that CEMs adjust their methodology to accurately capture both the firm capacity combined technologies can provide and their ability to reduce expected curtailment. We find that without adjustments for the inherent nonlinearities, PV + battery systems are undervalued in linear CEMs. The interactions between these technologies have an increasing impact on CEM expansion decisions as solar deployment rises.

# Table of Contents

## List of Figures



## List of Tables

# Introduction

Battery costs have been declining rapidly in recent years and are expected to continue to decline, leading to indications of accelerating deployment of batteries (NREL 2020; Feldman and Margolis 2020). This, coupled with increasing deployment of variable generation (VG), has led to a growing interest in battery technologies being deployed to provide many grid services, in particular energy shifting and provision of operating reserve (EIA 2020). Importantly, the “duck curve” phenomenon has led to strong interest in simultaneous deployment of solar photovoltaic (PV) arrays with battery storage, enabling shifting of energy from midday to non-solar hours (Gorman et al. 2020; Denholm et al. 2015). The increased interest in coupled PV and battery systems (called here *PV + battery*) is apparent in recent installations as well as existing project pipelines (Wiser et al. 2020; Feldman and Margolis 2020). Given the U.S. trend toward increased levels of variable generation and the high renewable targets in some states (Barbose 2021), it is important to understand what role these hybrid systems could play and how they might compete with or complement other forms of renewable energy.

Employing directly coupled PV + battery hybrids can introduce capital cost efficiencies compared to independent systems through shared expenses such as common hardware and interconnection costs (Feldman et al. 2021; Cabral, Booth, and Peterson 2017). Configurations where the PV and battery components share an inverter (“DC-coupled”) can reduce round-trip efficiency losses when solar generation from the coupled PV is stored, reduce “clipping” by storing energy when PV generation exceeds the rating of the system’s inverter, and store PV generation that occurs during cloudy conditions at a voltage too low to be inverted (known as “low voltage harvesting”) (Eurek et al. 2021). While such direct coupling of the technologies is of interest, systems that experience the same grid conditions even if not directly coupled can also share many benefits. In this paper we call PV and battery systems that are installed electrically close to each other such that they experience the same grid conditions but are not necessarily directly tied *combined* systems. Such combined PV + battery systems can store PV energy that would otherwise be curtailed and can contribute more toward resource adequacy requirements than stand-alone PV systems, although the specific contribution depends on system configuration (Mills and Rodriguez 2020). The ultimate deployment of both coupled and combined PV + battery systems will be determined by the balance of future costs and the benefits associated with energy arbitrage, long-run capacity contributions, and operating reserve provision (Eurek et al. 2021; Cowiestoll 2019). In addition, policy considerations such as the federal investment tax credit, state renewable portfolio standards, and storage mandates can also drive PV + battery deployment.

Capacity expansion models (CEMs) are well-suited to analyze technology trade-offs (including PV and battery technologies) and the implications for future power systems. These models are used to simulate and explore power system evolution at a regional, national, or international scale, and they are frequently used for power system integrated resource planning and to inform policy decision making. Many CEMs exist with different purposes and structures (Eurek et al. 2016; Brown et al. 2020; Mai et al. 2013; Hargreaves et al. 2015; EIA 2019a; Bistline et al. 2020). CEMs typically operate as least-cost optimizations, choosing the suite of generation, storage, and transmission investments that meets projected electricity demand and all other constraints at least cost. CEMs require a variety of exogenously specified inputs, including future technology costs and fuel prices, future demand, and changes in policies. Additionally, and importantly for combined technologies such as PV + battery systems, these models are typically linear optimization models. Linear models have many strong advantages, including solve times and feasibility of solutions. However, there are inherent nonlinearities in the relationships between two incremental investments, such as the ability of newly built storage to reduce curtailment on newly built solar, within this framework. Therefore, model adjustments are required to capture potentially cost-competitive co-investments in compatible technologies, as they are unlikely to be adequately represented in a purely linear model. Inadequate representation of all costs associated with a technology, operational requirements, or the potential of beneficial interactions between technologies can lead to technology bias in CEM results. As PV + battery technology gains awareness from utilities and grid planners, understanding the model adjustments needed to accurately represent these and other combined technology interactions in CEMs is important.

In this report, we use a CEM developed at the National Renewable Energy Laboratory (NREL), the Resource Planning Model, to demonstrate a methodology to include PV + battery technologies as investment options for planning models. First, we provide an overview of the CEM, detail the PV + battery implementation, and discuss methods to address the nonlinearities discussed above. Then, we present sample results for the Western United States, which include four configurations of PV + battery systems as technology options. Finally, we discuss the various investment tradeoffs that can result.

# Model Overview

NREL's Resource Planning Model (RPM) is a CEM designed to investigate the evolution of a regional power system such as a utility service territory, state, or balancing authority (BA) area (Mai et al. 2013; Cochran et al. 2021). RPM co-optimizes new generation and transmission investments through 2045 in 5-year increments, beginning with existing infrastructure in 2020. Investment decisions for the type, amount, and location of new capacity are determined with a least-cost optimization that ensures the ability to meet load in all hours, considering capacity, energy, and ancillary service requirements. The least-cost algorithm minimizes overall system cost, including capital costs, fixed and variable operation and maintenance costs, and fuel costs, while adhering to state and national policies, regulations, and environmental constraints. RPM models hourly dispatch for a representative sample of days throughout a year. Each hourly step balances generation with load, maintains the required amount of reserve capacity, and remains within operational constraints for individual generators and transmission paths. This section gives a brief overview of the model's analytical approach and its use for the current analysis.[1]

The study reported here focuses on the RPM representation of the Western Interconnection of North America, which includes all or parts of 13 states in the western United States, two western provinces in Canada, and a small region of northern Mexico. This area encompasses 36 model

[1] Previous work provides additional details about RPM's modeling approach (E Hale, Stoll, and Mai 2016; Cowiestoll 2019; Cochran et al. 2021; Elaine Hale, Stoll, et al. 2021).

BAs, which are the primary regional units in RPM (Figure 1).[2] Embedded within this zonal structure, the model can create a "focus region," within which generation units, transmission lines, and loads are represented with much detail. While the modeling did include such a focus area, we here focus predominantly on a new methodology instead of specific regional projections so our results have been aggregated to either the interconnection level or to reliability regions defined by the North American Electric Reliability Corporation (NERC) (Figure 2).[3]

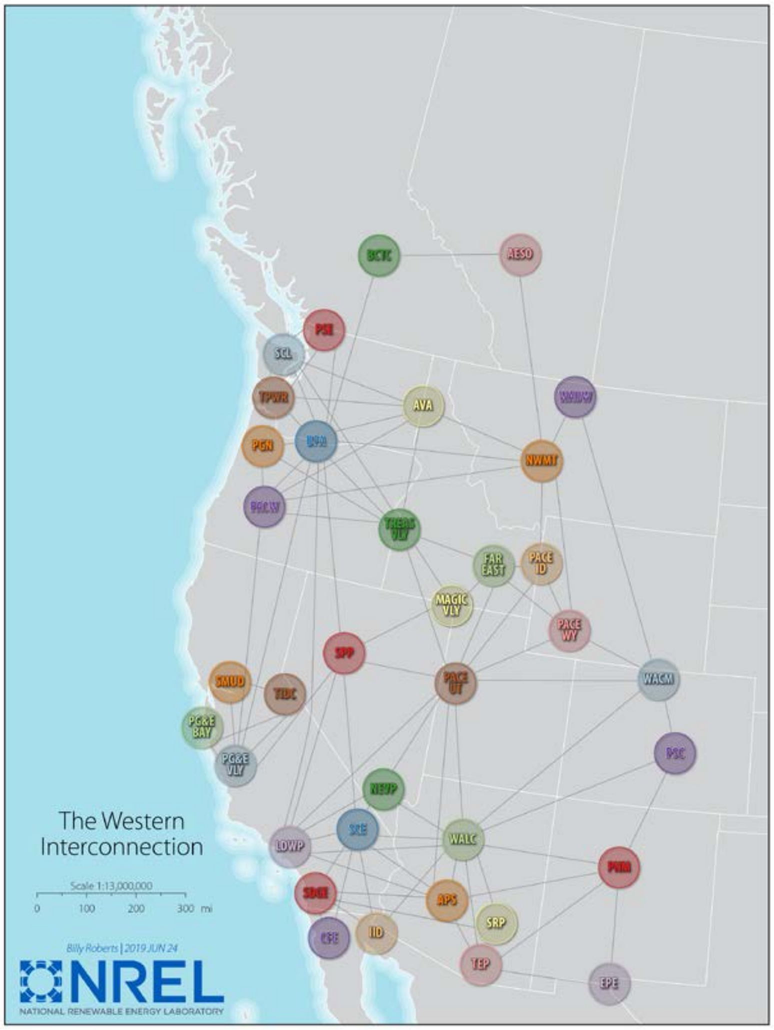


**Figure 1. Balancing authorities modeled in RPM in the Western Interconnection of North America**

---

[2] Modeled BAs are closely, although not perfectly, aligned with real BAs as designated in the data used in Phase 2 of the Western Wind and Solar Integration Study (Lew et al. 2013). Three of the smaller BAs—Public Utility District No. 2 of Grant County, Public Utility District No. 1 of Chelan County, and Public Utility District No. 1 of Douglas County, all in Washington state—have been combined with the Bonneville Power Administration.

[3] At the time of this work, we did not have sufficient data for solar in the Northwest Power Pool in Canada, so our results exclude that region, though it was included in our modeling.


**Figure 2. NERC subregions in the Western United States used for planning reserve regions in RPM (NERC 2015)**

CAMX: California-Mexico; NWPP-CA: Northwest Power Pool-Canada; NWPP-US: Northwest Power Pool-United States; RMRG: Rocky Mountain Reserve Group; SRSG: Southwest Reserve Sharing Group



RPM is highly spatially resolved to accurately capture renewable resources. The model includes 55 PV, 45 concentrating solar power (CSP), and 71 wind resource areas in its footprint. These areas describe the location-specific resource potential (developable area after accounting for various land use exclusions), performance (annual and hourly capacity factors), and grid interconnection distances (to substations, transmission nodes, or load nodes). Because the model takes a central planning approach to utility-scale generation build-out, customer-sited PV for each BA is added exogenously from the midline projections from the NREL-developed Distributed Generation Market Demand model, or dGen (Sigrin et al. 2016)[4].

RPM makes investment decisions based on assumptions about the evolution of power sector needs, requirements, and expected costs. Future load is calculated based on annual growth rates by BA from the Western Electricity Coordinating Council (WECC) 2024 Common Case (WECC 2014), which averages 1.2% per year across the footprint. Hourly demand, wind, and solar profiles are based on 2012 meteorology for all modeled future years. We include statewide renewable portfolio standards enacted as of May 2019, the federal renewable energy tax credits for solar and wind, California's storage mandate,[5] California's carbon cap and trade program, and existing demand response programs, but not local incentives for renewables or storage or any more recent clean energy targets. Projected cost data for new natural gas-fired, battery, geothermal, biomass, wind, and solar capacity are from NREL's 2019 Annual Technology Baseline central case (NREL 2019). Fuel prices are from the U.S. Energy Information Administration's Annual Energy Outlook 2019 Reference case (EIA 2019b).

As mentioned, RPM includes dispatch modeling to inform the economics of generation options when making investment decisions. It uses a reduced-form dispatch algorithm, modeling five 24-

---

[4] The dGen configurations used for this run have PV Rooftop increasing from 20 GW in 2020 to 30 GW in 2045

[5] Though the projects under development for this mandate have been procured, information regarding these projects was unavailable before this work was done. Therefore, we allow new storage (including PV + battery) investments to count toward this requirement.

hour dispatch periods (Low, Mid, High, Low VG, and Peak)[6] within each model year, representing the connections between periods to capture storage dispatch according to (Elaine Hale, Cowiestoll, et al. 2021). The consideration of chronological dispatch allows RPM to better capture the impact of variable resources and subsequent need for ramping, energy-shifting of batteries, and potential curtailment. Each hour of the dispatch period is weighted by how many hours in the year it represents for the purpose of accurate *annual* accounting. Furthermore, wind, solar, and load profiles are scaled so that annual quantities (e.g., annual energy production and consumption) are retained. Periods are connected to each other for the purpose of energy arbitrage with storage based on the amount of energy that could flow among them (Elaine Hale, Cowiestoll, et al. 2021). This approach balances the model so that it can capture seasonal, diurnal, and hourly variations in electricity supply and demand as well as longer-term annual values needed to inform investment decisions.

Within each dispatch period, RPM's energy balance equations ensure hourly supply and demand match for every node and zone. These equalities account for imports, exports, transmission losses, storage losses, and renewable curtailment. In addition, RPM endogenously co-optimizes energy and operating reserve. Operating reserve modeled include frequency regulation, spinning contingency reserve, and flexibility ramping reserve. We only model reserve in the "up" direction.[7] Reserve provision is restricted by generator-specific ramp rates and the timescale of the reserve products. Additionally, storage resources must have stored energy available to be able to provide reserve. As is common in production cost simulations, we model the need to hold reserve capacity available but do not model reserve deployment (e.g., contingency events) explicitly. We use a linear representation of generators, a DC optimal power flow transmission representation, and must-run coal[8] and nuclear plants. The model captures economic retirements by removing generators with capacity factors less than 10% for coal and nuclear facilities, 5% for combined cycle units, and 1% for combustion turbines. These retirement values were chosen to only retire plants that are very likely to be retired due to under-utilization, as we do not have all the plant-specific cost parameters to assess whether a plant is economic.

Additionally, between solve periods, RPM calculates several metrics to better capture parameters relevant to storage and variable renewable energy that cannot be represented within the five dispatch periods. These include the capacity credit of variable and storage technologies and all causes of curtailment. Capacity credit refers to the fraction of variable or storage resources

---

[6] For each dispatch period, the same 24 sequential hours are selected for wind, solar, and load profiles. For all but the Peak period, those 24 hours are the average of a full week to avoid putting undue weight on any particular day of the week. Using 24 hours for each of five dispatch periods yield 120 total dispatch hours modeled in this configuration of RPM. Previous work describes the methods used to select the days within a dispatch period, except for the Low VG period, which is selected as the period with the lowest expected coincident variable generation (Mai et al. 2015; Getman et al. 2015; Cochran et al. 2021).

[7] We model only up reserve for several reasons. First, simulations from production cost models frequently show much lower costs for down reserve; usually there is zero cost for providing these products. Additionally, a least-cost model will preferentially have more units at maximum capacity, such that down reserve constraints are typically nonbinding. And finally, our model does not in most cases have minimum generation levels, making it even more likely that down reserve would be nonbinding.

[8] We assume all large coal-fired units over 300 MW in the focus region and over 550 MW elsewhere are operating during all modeled hours because of a lack of integer unit commitment.

counted toward planning reserve margins.[9] Typically, CEMs count a fraction of variable and storage resources toward this reserve margin to represent that these technologies are not always available. RPM estimates the capacity credit of variable resources based on the reduction of the peak 100 net-load hours (Madaeni, Denholm, and Sioshansi 2012). Average curtailment in RPM is estimated through a regression populated by hundreds of production cost modeling runs to better capture the diverse drivers of curtailment, including the existing generator fleet and deployment levels of variable generation. *Marginal* curtailment for new resources is calculated for each individual variable technology in each resource region based on an assumption of a "minimum generation" level, below which further variable generation would be curtailed (E Hale, Stoll, and Mai 2016; Elaine Hale, Cowiestoll, et al. 2021). Importantly, we implement a piece-wise binning structure for curtailment (as well as capacity credit), whereby larger amounts of installed capacity within a single model year tends to receive a lower capacity credit and higher expected curtailment. Figure 3 shows how these calculations interact with the RPM optimization model to create the overall RPM algorithm.

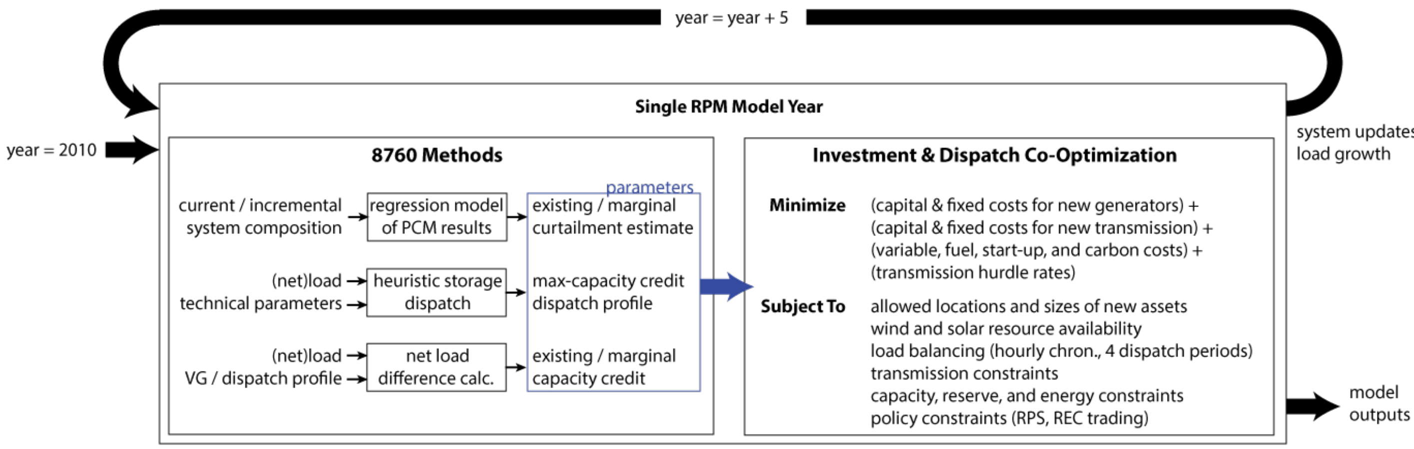


**Figure 3. Algorithmic structure of RPM**

REC: renewable energy certificate; VG: variable generation

# Methods for Representing Coupled PV and Batteries

## Modeling Background

Prior to this work, RPM included solar and storage investment options of two utility-scale PV technologies (fixed-tilt and single-axis tracking arrays), one general storage technology (lithium-ion batteries of various storage durations[10]) and concentrating solar power (CSP) with several configurations of solar multiple and storage duration. Utility-scale PV is generally characterized in RPM by an hourly generation profile, which varies by resource region; a decision to invest in

[9] Planning reserve margins are typically used as a computationally tractable way to measure the need for power systems to acquire excess capacity to ensure sufficiently high reliability. Though reliability is typically measured by more probabilistic methods, these are difficult to incorporate within CEMs.
[10] Existing pumped-storage hydropower is also included within RPM, but not allowed for new investment in this report. Storage durations are configurable by RPM run, and here included 0.5, 1, 2, 4 and 8-hour batteries.

PV incurs capital and fixed operation and maintenance costs proportional to nameplate capacity for both the PV plant and a transmission spur line to connect the facility to the transmission grid. RPM also evaluates prospective PV plants based on an annually computed capacity credit and expected curtailment rate, as discussed in the previous section. Storage technologies are categorized by the duration, or number of hours of storage included,[11] round-trip efficiency, and cost. Similarly to PV, the model dynamically estimates the annual capacity credit of storage and its ability to reduce curtailment of existing variable resources. Storage technologies are allowed to shift energy between periods, but in a limited manner subject to the chronology and duration of the dispatch periods, which ensures feasibility of the storage dispatch profile when expanded into a full 8,760-hour year (Elaine Hale, Cowiestoll, et al. 2021).

One challenge for these technology types, particularly at high deployment of renewables, is the inability for new storage investments and new utility-scale investments in variable renewable generation technologies to interact within the model. In particular, capturing the ability of new storage investments to reduce the curtailment of new solar facilities would require a nonlinear equation, which cannot be represented in RPM or other linear CEMs.[12] Equation 1 shows a simplified linear formulation of the curtailment constraint within RPM for just solar and storage resources, where $Curt_{tot}$ is the total curtailed generation on the system, $C$ represents the total capacity of either existing (*ex*) or new PV (*pv*) resources, along with any mitigation of curtailment from new storage (*st*) resources, and *curt* represents the precalculated curtailment impact rate per installed capacity from the methods shown in Figure 3 (page 6). The $C_{pv}$ and $C_{st}$ variables represent decisions within the model.

$$Curt_{tot} = C_{ex} * (curt_{ex} - C_{st} * curt_{st}) + C_{pv} * curt_{pv} \tag{1}$$

This equation is linear, but it does not capture the ability of new storage to impact curtailment from new PV. Mathematically, such an impact can be captured with an interaction term such as in Equation 2.

$$Curt_{tot} = C_{ex} * (curt_{ex} - C_{st} * curt_{st}) + C_{pv} * curt_{pv} - \boldsymbol{C_{pv} * C_{st} * curt_{st}} \tag{2}$$

The final (bolded) term in Equation 2 captures the ability of new storage to reduce curtailment of new PV capacity; however, because the multiplication of two variables ($C_{pv}$*$C_{st}$) makes this a nonlinear equation, it cannot be used within the linear optimization underlying RPM. However, excluding this interaction from the model would result in an overestimate of the curtailment from incremental PV by underestimating incremental storage's ability to reduce the curtailment, leading the optimization to undervalue both technologies as solar deployment rises. This interaction also applies to the capacity credit of a combined PV + battery systems, where a battery component can shift solar energy to more advantageous hours, improving the capacity credit of the solar resource. However, by representing this resource pair as a single technology,

[11] RPM can represent several storage classes, each defining a different configuration of energy capacity, round trip efficiency, and cost. The analysis reported here includes 4-hour and 8-hour battery configurations of lithium-ion technology.

[12] This is also the case for wind, but we focus on PV and battery hybrids in this report because of the increasing interest in coupling solar and storage for new utility-scale solar builds.

the nonlinearity can be wrapped into the calculation of $curt_{pv\text{-}st}$, a new parameter evaluated external to the optimization in the same manner as $curt_{pv}$ and $curt_{st}$, thereby avoiding the need for a nonlinear formulation within the optimization. It should be noted here that all *curt* terms are calculated in RPM according to a binning structure, where increased amounts of installed capacity will have increasing curtailment (for PV) or curtailment reduction (for storage). The above equations do not include these bins for simplicity sake in explaining the underlying dynamics.

As marginal solar curtailment rates increase with increasing deployment of PV, there is a strong argument for installing both PV and batteries simultaneously to enable the use of new solar energy in non-daylight hours rather than in the hours already experiencing overgeneration. It is therefore important to understand how to represent the interactions of these combined technologies in CEMs and how these interactions might change future investment decisions.

## Representation of PV + Battery Technology

Combined or coupled technologies could manifest on the grid by several mechanisms, including noncoupled installations that are electrically close to each other (i.e., combined), AC-coupled, loosely DC-coupled, and tightly DC-coupled configurations (Eurek et al. 2021). AC-coupled systems, where the resources do not share an inverter, represent a straightforward installation, but they do not include significant benefits in terms of equipment expenditures or system efficiency. DC-coupled systems share an inverter, and they enable charging either from only the PV system (tightly coupled) or from both the PV system at an improved efficiency but also from the grid (loosely coupled).

The range of cost impacts from these different installation mechanisms is uncertain (Eurek et al. 2021). Also, the ability to claim U.S. federal tax credits for the battery investment depends on the amount of charging from the PV system and the value of the federal investment tax credit declines over time.[13] For this work, we model a tightly DC-coupled configuration[14] of PV + battery systems, where the battery can only charge from the PV plant and is not allowed to charge directly from the grid. This represents a modeling choice and not an expectation of how coupled systems would operate in the future. We include a cost reduction of $0.1/kW over independent PV and battery systems, which is a simple approximation used to test the modeling methodologies and is not representative of expected cost reductions. More-representative costs of coupled systems can be found in Feldman et al. (2021).

Research has shown that as solar deployment increases, the system operation converges toward a tightly coupled system—that is, storage is typically dispatched to shift local PV generation even when allowed to grid-charge (Schleifer et al. 2021). This indicates that although this approach includes a reduced value for the coupled system, it remains a reasonable estimation and can be

[13] The U.S. federal investment tax credit applies to PV + battery installations in which the PV system provides at least 75% of the input for the battery annually for the first 5 years of operation. The federal investment tax credit can offset up to 30% of eligible PV and battery expenses for projects that start construction before 2020, and it steps down to 10% after 2025 (NC Clean Energy Technology Center 2020).

[14] The methodology described here can also be used to represent other coupling configurations.

expanded in future work. We assume batteries connected to PV systems have a round-trip efficiency of 88%,[15] which is slightly higher than that of stand-alone batteries in RPM (85%) because of the reduced inverter losses in this configurations (DiOrio, Denholm, and Hobbs 2020). The battery is assumed to be replaced once in the lifetime of the coupled facility, as the lifetime of batteries is shorter than typical PV facilities. We do not capture a potential value of DC-coupled PV + battery systems with undersized inverters—avoided inverter "clipping." The shared inverter for PV + battery systems allows PV generation that would otherwise be wasted (i.e., "clipped") by the inverter size to be sent directly to the battery. The magnitude of clipping losses depends on the location, but it is less than 3% for systems with inverter loading ratios of 1.3 (Eurek et al. 2021).

Though the mechanics within RPM represent a directly coupled technology, the most important aspects of this work apply also to systems that are not directly coupled but simply installed simultaneously in a manner that is better termed combined instead of directly coupled. Therefore, and because RPM does not fully represent all aspects of coupled technologies, we for the rest of the report refer to the RPM representation as a combined technology.

RPM represents the combined technology as a utility-scale single-axis tracking PV array and a battery, with an inverter loading ratio of 1.3, which is the ratio of the DC-rating of the PV panel capacity to the AC-rating of the inverter capacity. We consider four configurations of PV + battery systems for this analysis (Table 1). The configurations are characterized by (1) the battery inverter ratio (BIR), which is the rated power capacity of the battery relative to the PV installed AC capacity (i.e., the inverter capacity), and (2) the duration, or number of hours the battery could discharge at full power capacity. All battery constraints represented for stand-alone battery systems are similarly enforced for batteries combined with PV, with the exception that batteries in the combined system can only charge from the attached PV array.

**Table 1. Battery Configurations in the PV + Battery Technology Scenario**

| Class | Battery Inverter Ratio | Battery Duration | Round Trip Efficiency |
|---|---|---|---|
| C0 | 50% | 4 hours | 88% |
| C1 | 50% | 8 hours | 88% |
| C2 | 100% | 4 hours | 88% |
| C3 | 100% | 8 hours | 88% |

While most aspects of PV + battery technologies remain similar to their underlying components, an important aspect of the combined technology is how the capacity credit should be accounted for in the planning reserve margin within the CEM. The addition of a battery increases the dispatchability of the PV facility because some energy can be stored. However, the batteries are still energy-limited with no guarantee for full dispatchability during all peak hours, given our assumption that the battery only charges from the PV system and so may not be full during the peak period, as well as the possibility that the duration of the peak is longer than the battery

[15] There is a range of estimates for the round-trip efficiency of these systems. The Annual Technology Baseline, published after the modeling work was completed for this analysis, uses 87% (NREL 2021).

duration. To account for both factors, we modify the capacity credit calculation used for stand-alone storage (Frazier et al. 2020) to incorporate charging from a fixed source (PV) while also allowing the PV to directly generate if the top hours fall during times of solar output. The capacity credit is computed relative to the inverter size, such that systems with larger batteries will have a higher capacity credit than those with smaller batteries. This calculation is performed before each model solve year to inform investment decisions in that year based on the net load profiles.

Another consideration for the combined technology is that the marginal curtailment rate from PV + battery systems can be substantially different from stand-alone PV. For new investment options, we use a load duration curve methodology to calculate the marginal curtailment rates of each technology (E Hale, Stoll, and Mai 2016). This method uses the heuristic dispatch determined by the capacity value charging algorithm, which allows us to determine to what degree the battery can shift energy that would otherwise be curtailed in a given location.[16]

# Results

## Scenario Framework

Here, we create a scenario framework to evaluate the potential for PV + battery deployment under alternative market conditions as illustrated in Figure 4 (page 11). We consider two dimensions: renewable energy deployment and technology cost. We model both dimensions with and without PV + battery technology as a deployable option. The Baseline RE scenario includes all state-level renewable portfolio and clean energy standards and carbon caps as of May 2019; the High RE scenario increases the renewable energy targets to follow the results of NREL's *2017 Standard Scenarios Report* 80% RPS[17] scenario (Cole et al. 2017) by enacting the achieved state-level renewable energy fractions from that scenario and applying those as targets for this work. We also evaluate two technology costs projections for utility-scale PV and batteries: the low and mid cost projections from the 2019 Annual Technology Baseline (NREL 2019).[18]

These scenarios are not intended to predict future power sector evolution, but instead, are constructed to push the boundaries of power system evolution to better understand both the space under which these model improvements become most important and the impacts they may have. They represent a range of deployment of PV and all variable renewable sources (Figure 5), allowing us to analyze PV + battery considerations across a range of grid conditions.

[16] Given that the connection mechanism used in RPM only allows the battery to charge from the connected PV array, we do not account for the potential of PV + battery technology to reduce curtailment from other resources.

[17] RPS is renewable portfolio standard.

[18] All other technology costs in all scenarios follow the midline projections from the 2019 Annual Technology Baseline.

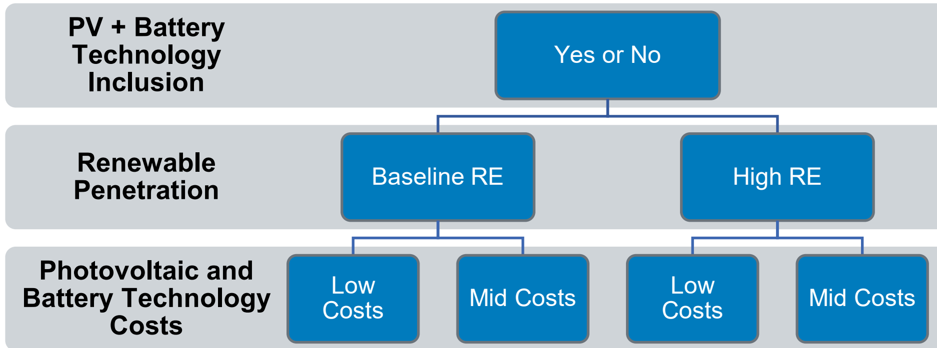


**Figure 4. Scenario framework for comparing including PV + battery technology in RPM**

RE: renewable energy

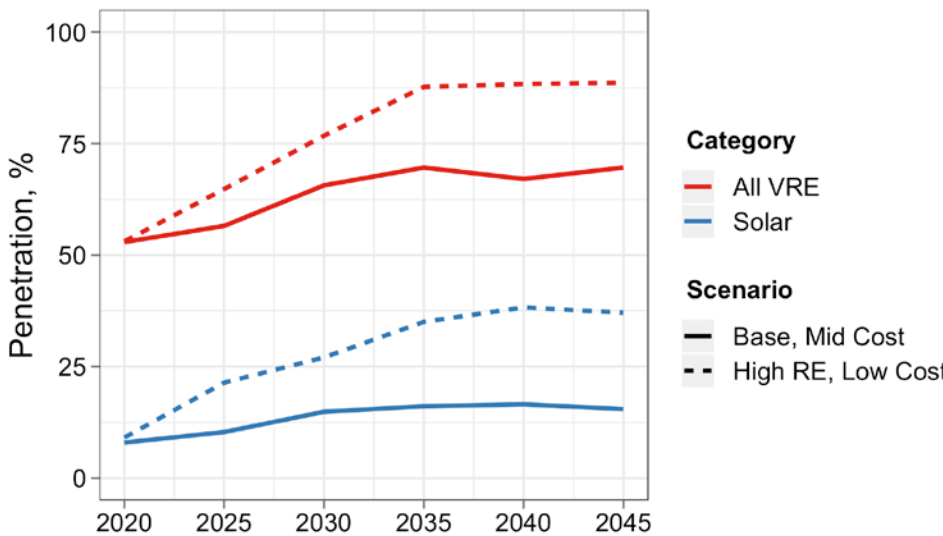


**Figure 5. Deployment of solar and all variable renewables (generation from technologies in each category as a percentage of total systemwide generation) for the two most extreme scenarios, showing the range of deployment analyzed in the scenarios**

VRE: variable renewable energy

## Capacity Credit

As future power systems move toward higher percentages of variable generation and storage resources, capturing the real contribution of variable and energy-constrained resources toward resource adequacy becomes increasingly important in CEMs, and in particular how coupled technologies might impact the capacity credit of each other (Cole et al. 2020; Zhou, Cole, and Frew 2018; Stephen, Hale, and Cowiestoll 2020).

The capacity credit computed for PV + battery configurations tends to fall between the capacity credits for battery storage and utility-scale solar. Figure 6 shows the capacity credit for PV + battery technology compared to other technologies for all regions across the footprint for the highest solar deployment scenario we analyzed: High RE, Low Cost. The interconnection-wide solar deployment in this scenario increases from 3% to 26% between 2020 and 2045 and shows strong regional variation. Though a wide range of capacity credit values is seen across regions and technologies, we note a consistent decline in the capacity credit of utility-scale PV as solar deployment increases, while the capacity credit of stand-alone storage increases because of the reduced peak length at increasing solar deployment. The combined PV + battery technology maintains a more consistent capacity credit across model solve years than stand-alone PV, demonstrating that the ability of PV + battery technology to dispatch during hours when high net load is captured within the CEM.

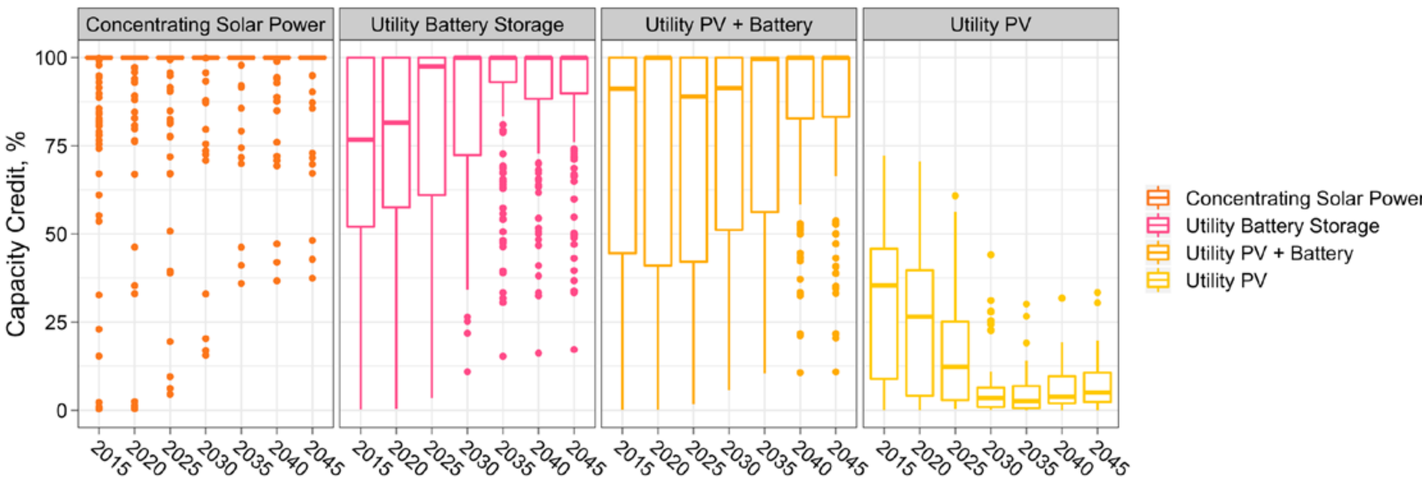


**Figure 6. Capacity credit of all technology configurations of utility-scale solar and storage options (not necessarily all installed) in the High RE, Low Cost scenario, aggregated across all configurations and all regions in the Western Interconnection**

Though significant regional variation exists, the capacity credit generally declines over time for stand-alone PV and generally increases over time for storage technologies.

Though deployment has a strong impact on the capacity credit of particularly solar energy technologies, many factors influence the capacity credit including installed storage capacity, load shape and relative mix of wind and solar, along with strong regional variation in these factors. Therefore, we have simply shown the trends over time as the power system evolves.

Even among the technologies shown in Figure 6, there is significant variation based on the storage configuration. Figure 7 shows the PV + battery and stand-alone battery capacity credit broken down by configuration, along with stand-alone PV for comparison. The configurations with 8-hr duration show consistently higher capacity credit across all years than the 4-hr duration. The configurations with 100% BIR maintain high capacity credit for coupled systems across all model years, as the larger battery size provides greater capability to shift energy to top load hours. The slight increase in capacity credit for stand-alone batteries across years is likely due to a decrease in the length of a typical peak event as solar deployment increases (Denholm et al. 2020).


**Figure 7. Capacity credit of PV + battery and stand-alone battery configurations across the entire Western Interconnection for the High RE, Low Cost scenario**

Though a larger battery component increases the capacity credit of PV + battery technology, the stark difference with stand-alone PV provides significant incentive for the model to install the coupled technology when firm capacity is required.

Figure 7 also shows the stark difference in capacity credit between PV without batteries and the configurations of PV + battery systems. While many factors influence the capacity credit of each technology, the influence of existing PV is of particular interest to this work, as it helps elucidate the space under which representing coupled technologies is most important. At lower PV deployment levels (i.e., the early modeled years), the difference between stand-alone PV and coupled PV + battery technology is not extreme, as seen for the NERC CAMX region in Figure 8, so there would be a smaller error associated with missing the interaction, similar to that described in Equation 2 (page 7). However, at higher deployment levels, the capacity credit of PV + battery technology more closely mirrors that of stand-alone battery storage while the capacity credit of stand-alone PV drops off and would lead to more significant error in the model. Failing to capture this important grid value for PV and battery interactions at higher deployment levels could lead to lower overall solar installations—as will be seen in subsequent sections.

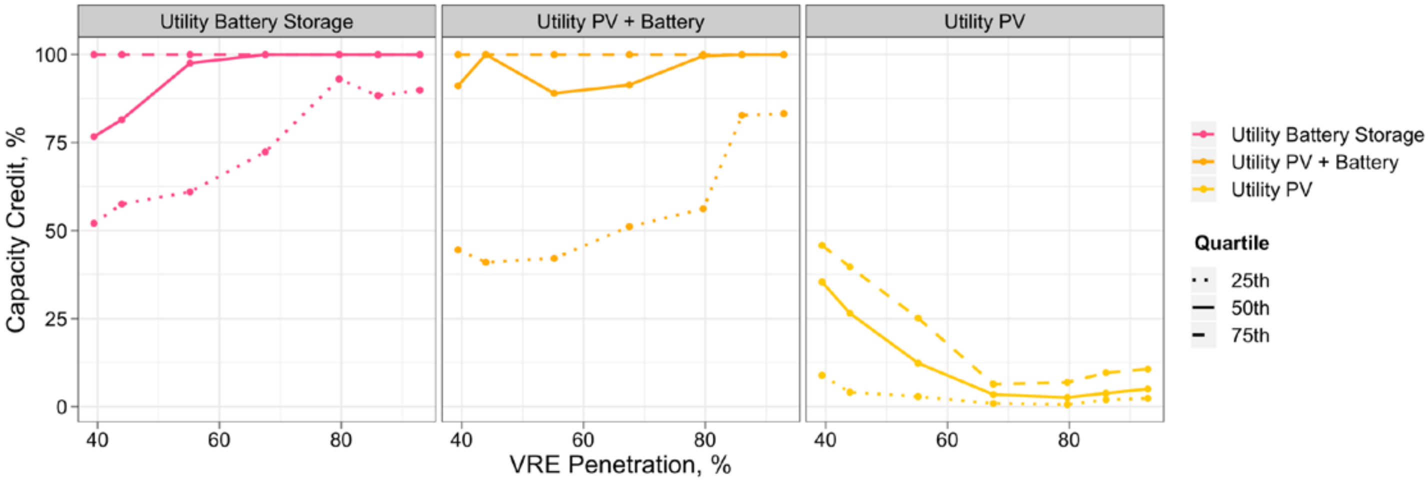


**Figure 8. Capacity credit for all U.S. NERC regions in the High RE, Low Cost scenario, relative to the variable renewable deployment**

Though utility PV capacity credit declines quickly with increasing deployment, the Utility PV + Battery capacity credit of this scenario increases with VG deployment, similar to Utility Battery Storage.

These results should not be taken as representative values for capacity credit of these technologies; rather, they are specific to the scenario analyzed. Many factors influence the capacity credit calculation and, therefore, the calculation is specific to the grid considerations and other assets within that system.

## Operational Value

Interactions between newly installed PV and battery systems provide two key aspects of improved operational value that are important to capture within CEMs: potential reduction of curtailment and energy shifting. The influence of curtailment is a potentially strong driver of technology investment that may be missed in CEMs if interactions between these technologies are not represented. CEMs that fail to capture the direct interaction of solar and battery installations in the same year may overestimate curtailment from the PV resource, leading to reduced investments in PV. For instance, Figure 9 shows the annual curtailment rate of PV + battery technology compared to stand-alone PV for 2020 through 2045. The marginal curtailment rate for PV + battery technology remains well below that of stand-alone PV throughout the solve years, and it becomes even more evident as deployment, and expected curtailment rates of stand-alone PV, increase. The introduction of batteries installed simultaneously with the PV systems greatly reduces the expected curtailment compared to stand-alone PV and all but eliminates expected curtailment with the largest battery sizes analyzed, as shown in Figure 9. Even 4-hour PV + battery technologies can significantly reduce curtailment relative to stand-alone PV, indicating a strong value of representing this combined technology and its potential grid value in CEMs.

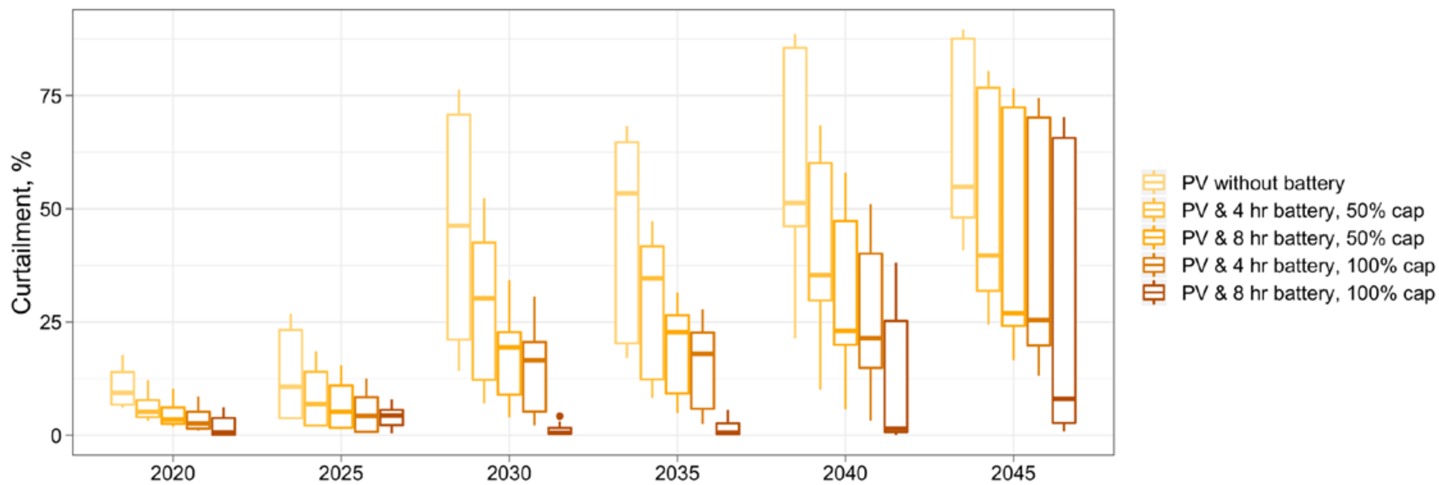


**Figure 9. Curtailment of PV + battery technology configurations across the Western Interconnection for the High RE, Low Cost scenario**

Battery configurations are defined based on the number of hours of storage and the BIR—the size of the battery relative to the PV array (e.g., "50% cap" indicates the battery capacity is 50% of the nameplate PV capacity).

We also wanted to understand how the model uses coupled technologies and whether the CEM can identify the value of the coupled system resulting from shifting of the solar resource. Figure 10 shows the hourly usage of the PV + battery plants by configuration across the RPM footprint for the High RE, Low Cost scenario in 2045 over the five modeled representative days. It illustrates when energy is used directly from the PV facility, when charging occurs, and when the battery discharges to provide energy to the grid. Strong differences can be seen in the dispatch profiles between PV + battery configurations, further indicating their different use cases and the ability of an appropriately configured CEM to identify the values of different configurations. The shortest duration batteries provide very little arbitrage opportunity and are typically used only in morning and evening ramping periods for an hour at a time. As the storage duration and battery size increases, more of the solar energy tends to be stored and used later, with the 8-hour configurations representing the extreme, where in most periods nearly all solar energy is put into the battery and used during the morning and evening shortly before and after typical solar production hours. Capturing this ability to shift energy and the restrictions on how much energy can be stored in the battery is an important aspect of representing the combined technology, and in particular in identifying the configurations that may be valuable to the grid under various circumstances. As the grid evolves, needs may change, with different configurations becoming competitive at different times for different systems.

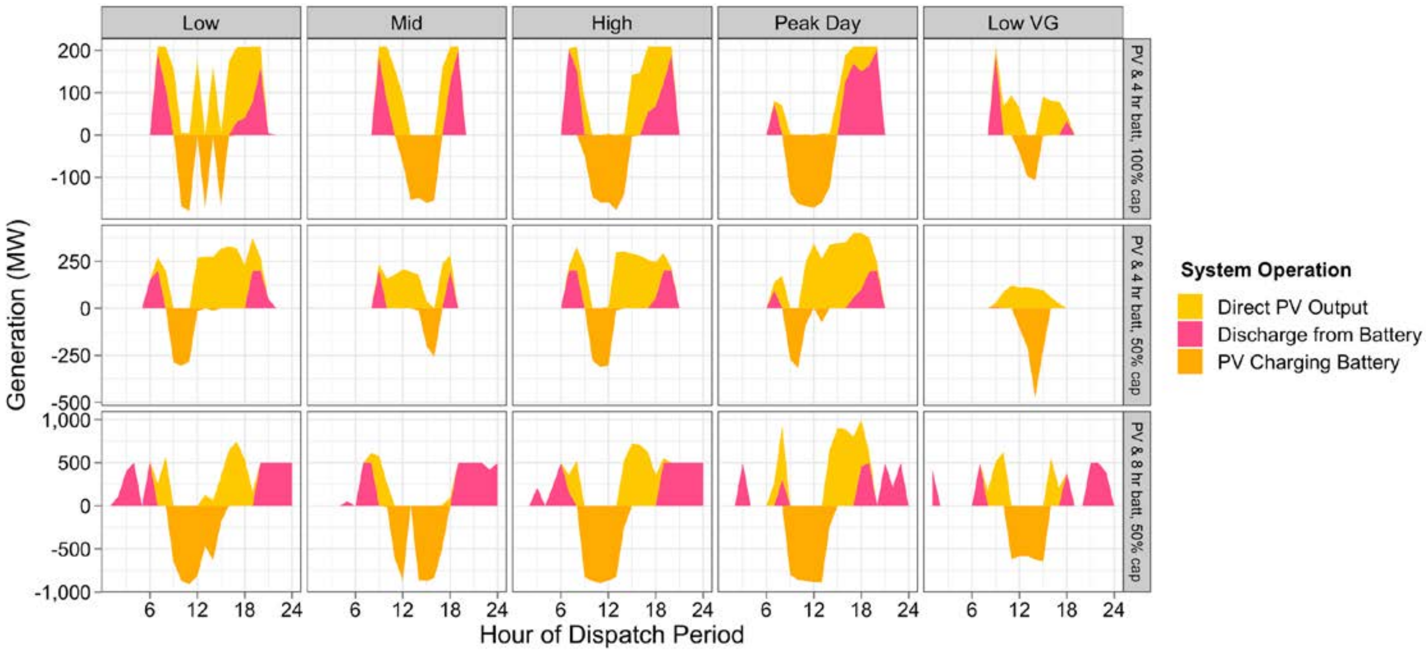


**Figure 10. Hourly PV + battery dispatch by configuration from the High RE, Low Cost scenario 2045**

## Impact of PV + Batteries on CEM Investments

To understand the trade-offs associated with PV + battery deployment, we analyze four scenarios with varying renewable energy targets and solar and storage cost projections (Figure 4, page 11) that result in a range of investment decisions of both solar and storage technologies. Figure 11 shows the total installed capacities by technology category for each scenario and year across the modeled footprint *without* PV + battery technology as an investment option. As expected, the High RE scenarios install significantly more wind and solar than the Baseline RE scenarios. Additionally, the Low Cost scenarios result in a substantial increase in installed solar capacity compared to the mid-line solar and storage cost projections used in the Mid Cost scenarios. In these cases, the model does not see the benefits of interactions between incremental PV and batteries, and most scenarios show low deployment of stand-alone utility-scale battery storage. The one exception is the combination of Low Cost technologies and High RE, which illustrates synergies between solar deployment and storage under favorable cost assumptions and otherwise limited representation of the value storage might bring in other scenarios.

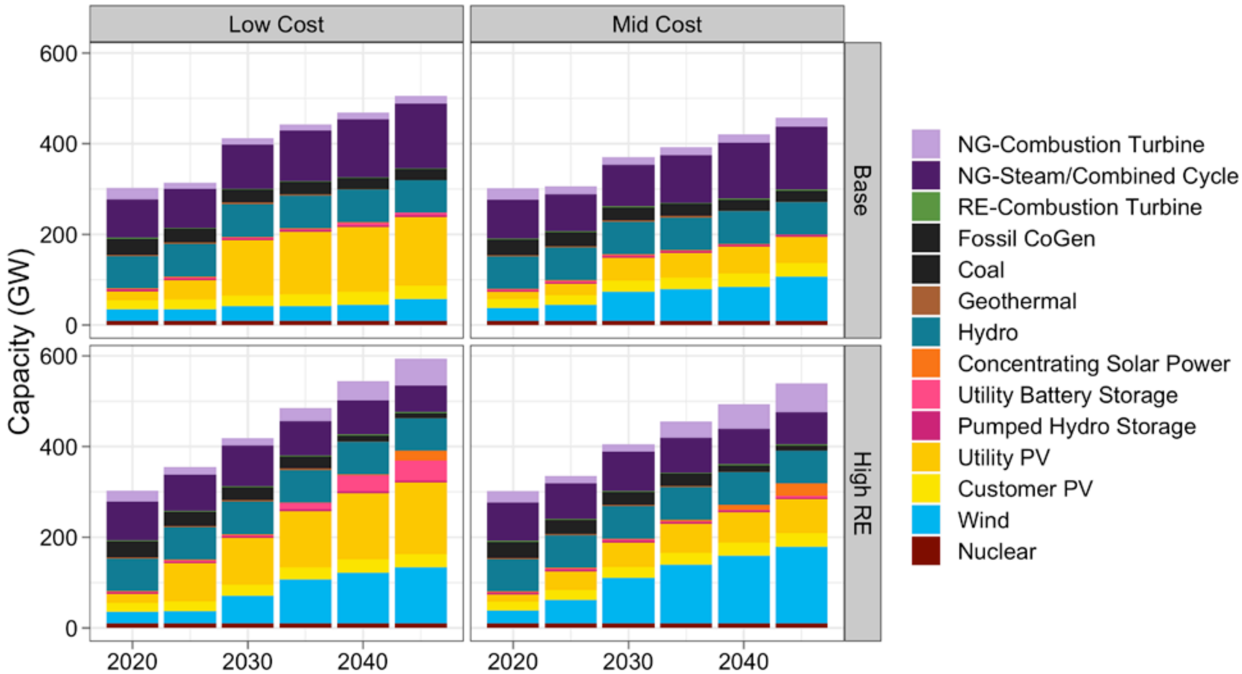


**Figure 11. Installed capacity across WECC in scenarios without PV + battery**

When PV + battery technology is enabled as an investment option, some of the installed solar is replaced instead by the new coupled technology type, as well as offsetting some investments in gas technologies. Figure 12 shows the changes in capacity investments for two key scenarios—Base, Mid Cost and High RE, Low Cost—when PV + battery becomes a technology option. A change in the positive y-direction indicates increased deployment, where negative y-values indicate decreased deployment. Note the dramatic difference in scale for the two scenarios, which illustrates much higher PV + battery deployment under the High RE, Low Cost scenario. At low deployment of solar as in the Base Mid Cost scenario, the PV + battery technology generally directly displaces stand-alone PV and batteries roughly at a one-to-one replacement rate. However, at higher levels of deployment, representing the integration of the combined technology increases the deployment of solar as the model recognizes the improved capacity credit and curtailment value of the new technology option. This is a key impact of the improved methodology modeled here. While solar deployment in the Base, Mid Cost scenario does not change when PV + battery technology is enabled in the model, staying at 15% in both cases, the deployment in the High RE, Low Cost scenario increases from 32% to 37% in 2045[19] when PV + battery technology is enabled. This demonstrates how improved representation of the combined impacts of new PV and batteries becomes increasingly important at higher solar levels of deployment.

---

[19] The NERC NWPP-CA region includes the Canadian portion of WECC, was excluded from the deployment calculation because the building of new solar was disallowed in this region because of poor data.

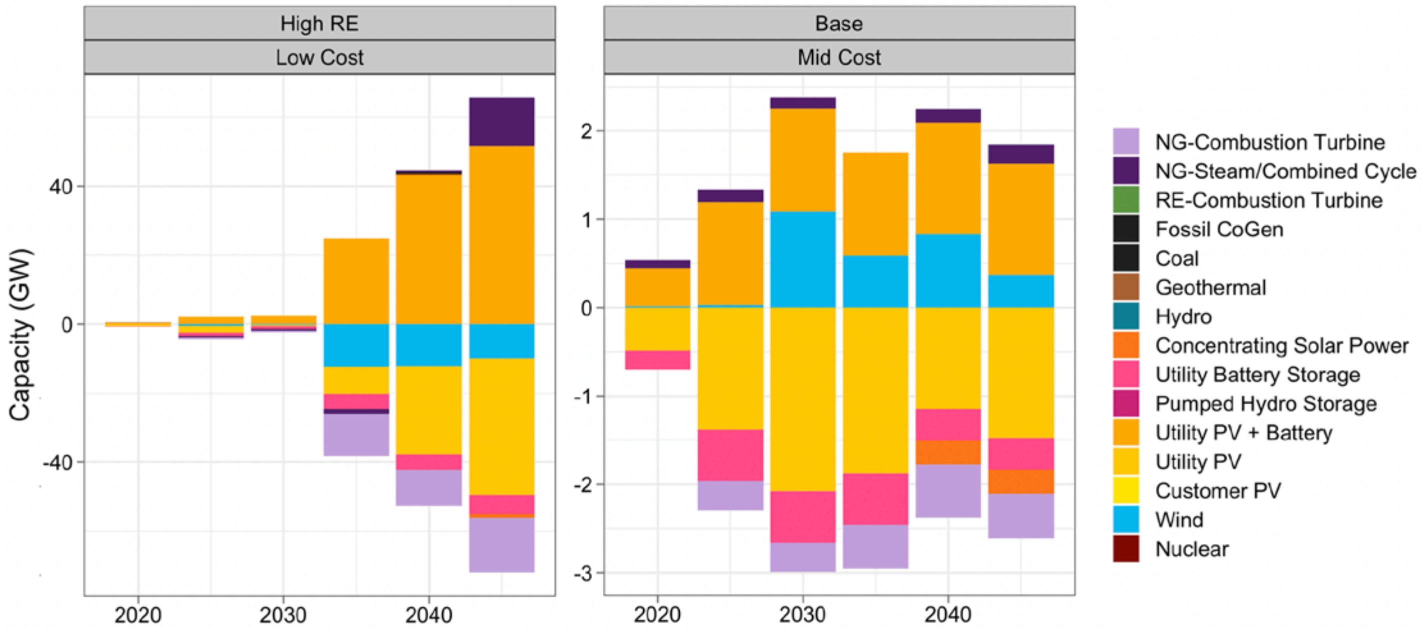


**Figure 12. Changes in installed capacity with the addition of PV + battery as a technology option**

Note the different scales for the subplots. The combined PV + battery technology tends to displace stand-alone installations of utility-scale PV and batteries; however, in the scenario with higher levels of solar deployment, the overall effect is increased installation of solar PV.

The capacities in the figure represent the inverter capacity of the coupled system; the total installed capacity of the system includes the battery capacity as well as the PV capacity, and it would be larger than is shown here. For example, a 100-megawatt (MW) PV + battery system with a BIR of 50% would consist of a 100-MW PV facility and a 50-MW battery.

The introduction of the PV + battery technology impacts the deployment of other technologies as well, in particular NG-combustion turbines, which are often built for firm capacity and see a reduction in deployment in all scenarios.[20] The related small increase in deployment of NG-steam/combined cycle capacity indicates an increased need for energy provision, which these units can provide at lower cost as a result of increased efficiency, over flexibility and firm capacity.

Figure 13 illustrates the configuration of PV + battery installations aggregated to NERC region for each scenario. We disaggregate the results by location as the regionality helps illustrate some of the value of PV + battery, as individual regions have varying solar resource, policy requirements, and load shapes. The Mid Cost scenarios build the smallest amount of PV + battery technology and also the shortest duration configurations, building only 4-hour storage with 50% BIR to minimize battery costs. The Low Cost scenarios build predominantly 8-hour with 50% BIR with a small amount of 4-hour storage, including 100% BIR. The dramatic

[20] Natural gas-combustion turbine (NG-CT) technology is the lowest-cost generator on a per-megawatt basis, and so is typically installed within RPM to meet the planning reserve margin. More accurately representing the capacity credit of the coupled technology reduces the need for capacity on the system and therefore the amount of NG-CT built.

difference between the Low- and Mid Cost scenarios shows that much of the deployment (and choice of configuration) is determined by initial cost. With lower PV and battery costs, the model deploys additional 8-hour batteries because of their ability to shift additional energy, thereby further reducing curtailment. Note that no scenarios deploy the 8-hour battery with 100% BIR in this work; however, further work might determine locations and grid conditions under which these longer duration battery options could be optimal.

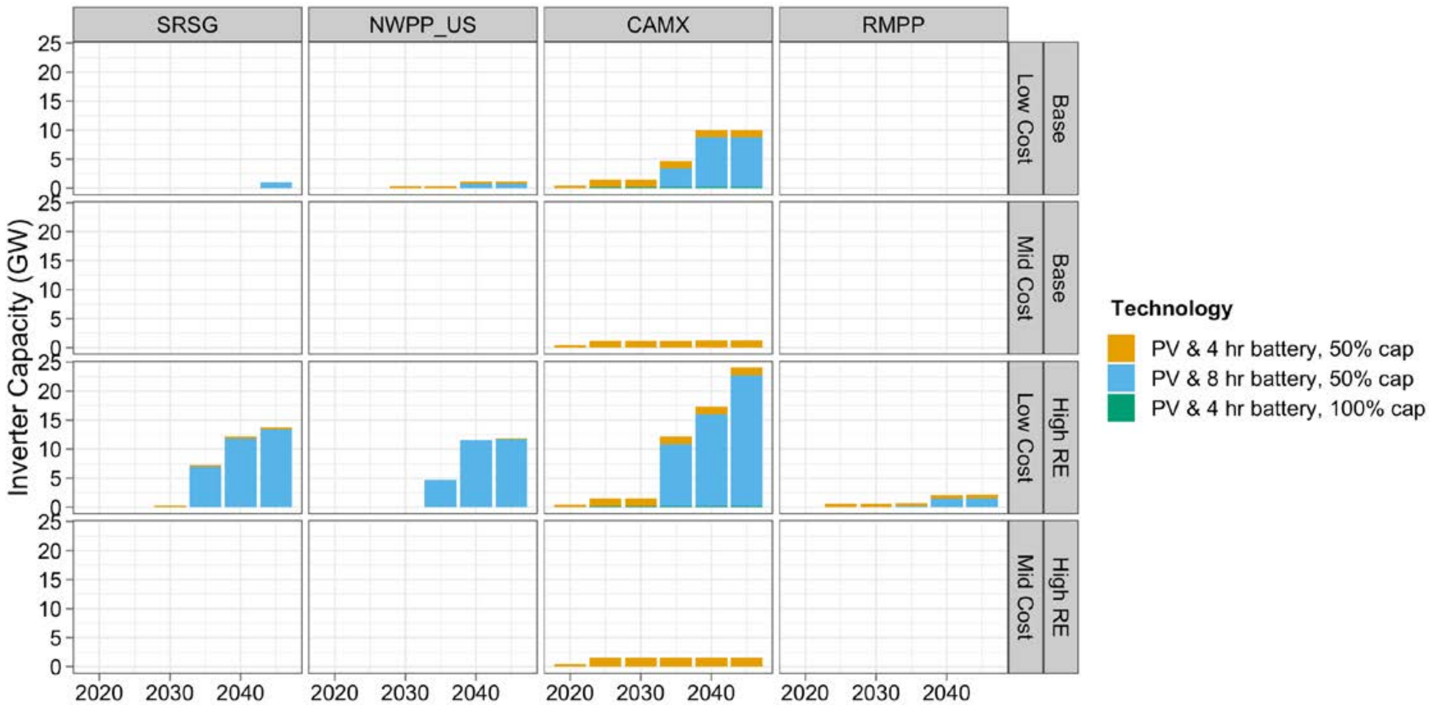


**Figure 13. PV + battery configurations installed by scenario and NERC region**

RMPP: Rocky Mountain Power Pool

A final important aspect of this analysis is determining why each configuration may be beneficial to the model. In the investment optimization of CEMs, a technology must provide enough value to the system across all constraints in the model to offset the costs of installing and using that technology. We measure the marginal values on RPM's optimization constraints to identify which constraints provided the most value to each technology being installed. These are termed "value streams" for each technology investment, and they offset the costs associated with the technology being installed. Figure 14 quantifies these value streams, of which the most common include providing energy to meet load, capacity value from contributing to the planning reserve margin based on the capacity credit of the resource, and value stream from contributing to renewable portfolio standards—both specific renewable or clean energy standards or the California storage mandate for storage technologies. For example, in the Base RE, Mid Cost scenario, only a single PV + battery technology was installed (4-hour battery with 50% BIR) in a single NERC region, CAMX, with a substantial amount of its value stream coming from the California storage mandate. However, the High RE, Low Cost scenario shows value streams of increased capacity, and installations of PV + battery systems without the storage mandate.

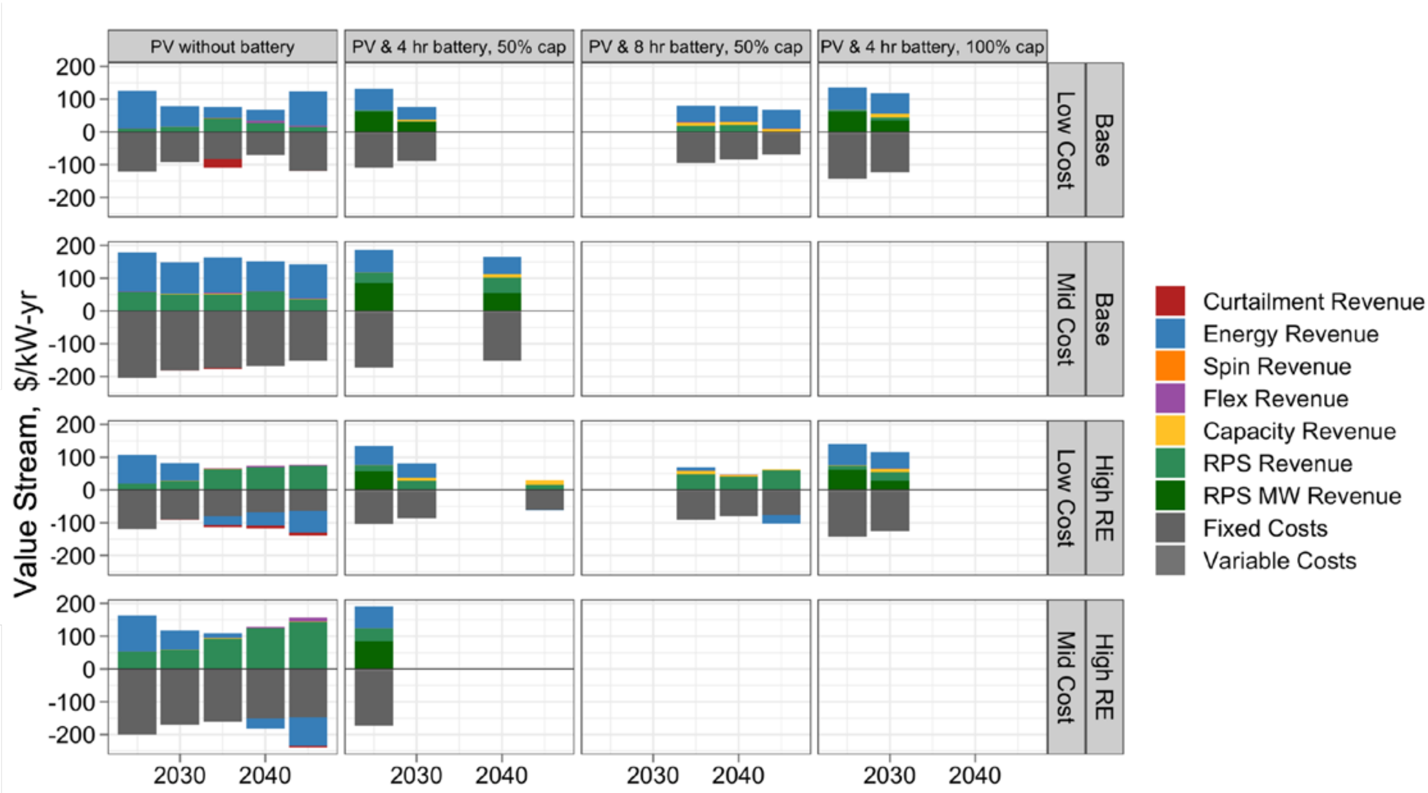


**Figure 14. Value streams for PV + battery technologies compared to stand-alone PV for all scenarios, aggregated for all regions**

Not all value streams are captured in the figure.

RPS MW refers to requirements for a specified amount of a technology based on installed capacity, rather than percentage as is typically done for RPS requirements. This is usually for a technology-specific carve-out.

Figure 14 demonstrates that energy value stream and RPS requirements (including storage) dominate much of the value stream for all technologies; however, the stand-alone PV incurs a negative energy value in addition to a negative curtailment value because of the inability of PV to shift its energy output and therefore dispatch during negatively priced energy hours. The PV + battery technologies can avoid this in nearly all cases. The PV + battery technologies also able to capture a small amount of capacity value because of the higher capacity credit these technologies receive.

The ability of the CEM to identify and account for the values of installing PV and batteries simultaneously becomes increasingly important for scenarios that drive higher the deployment levels of variable renewables, PV in particular. This interaction was not previously captured because of the linear representation of the independent technologies in the CEM. A coupled system might be installed for many reasons, including policy factors, operational values of improved charging efficiency and reliability concerns among others; however, in our model, the reduced cost and improved efficiency are drivers at lower deployment levels, as are the capacity credit and curtailment value at higher deployment levels.

# Conclusion

As PV and battery costs continue to decline and deployment of these technologies continues to increase, capturing the interactive effects of combined PV and battery systems in utility planning models becomes important. However, the costs and values of these effects are dynamic and inherently nonlinear, therefore making them difficult to accurately represent within typical linear program formulated CEMs. This report provides a framework for the types of adjustments needed to capture combined PV and battery systems in models like the Resource Planning Model. Such adjustments include incorporation of:

- A combined technology type (PV + battery) in the capacity credit calculation
- The ability of a combined technology to reduce curtailment
- The ability to operate the PV + battery systems more efficiently.

In this report, we present the impacts of these improvements to the model formulation, which result in increased overall PV deployment within the modeled system. We also present an evaluation of the value streams the combined PV + battery technology provides to the CEM. Though understanding the value of including combined technologies in CEMs is critical, our analysis only begins to understand the complexity of operating combined or coupled technologies within a model framework. Next steps include representing a variety of DC/AC ratios and the implications these might have for PV + battery investment and operation; allowing grid charging of the battery to represent loosely coupled systems; and better representing the cost and performance implications of truly coupling the two technologies.

# References


Barbose, Galen. 2021. "U.S. Renewables Portfolio Standards 2021 Status Update: Early Release." Berkeley, California: Lawrence Berkeley National Laboratory. https://eta-publications.lbl.gov/sites/default/files/rps_status_update-2021_early_release.pdf.

Bistline, John, Wesley Cole, Giovanni Damato, Joseph DeCarolis, Will Frazier, Vikram Linga, Cara Marcy, Chris Namovicz, Kara Podkaminer, and Ryan Sims. 2020. "Energy Storage in Long-Term System Models: A Review of Considerations, Best Practices, and Research Needs." *Progress in Energy* 2 (3): 032001.

Brown, Maxwell, Wesley Cole, Kelly Eurek, David Bielen, Ilya Chernyakhovskiy, Stuart Cohen, Jon Becker, et al. 2020. "Regional Energy Deployment System (ReEDS) Model Documentation: Version 2019." Golden, CO: National Renewable Energy Laboratory. https://doi.org/10.2172/1505935.

Cabral, Lis, Bill Booth, and Chris Peterson. 2017. "California Wholesale Electricity Prices Are Higher at the Beginning and End of the Day." Energy Information Association. https://www.eia.gov/todayinenergy/detail.php?id=32172#.

Cochran, Jaquelin, Paul Denholm, Meghan Mooney, Daniel Steinberg, Elaine Hale, Garvin Heath, Bryan Palmintier, et al. 2021. "The Los Angeles 100% Renewable Energy Study (LA100)." NREL/TP-6A20-79444. National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/1774871.

Cole, Wesley, Daniel Greer, Jonathan Ho, and Robert Margolis. 2020. "Considerations for Maintaining Resource Adequacy of Electricity Systems with High Penetrations of PV and Storage." *Applied Energy* 279 (December).

Cole, Wesley, Trieu Mai, James Richards, Paritosh Das, and Paul Donohoo-Vallett. 2017. "2017 Standard Scenarios Report: A U.S. Electricity Sector Outlook." Technical Report NREL/TP-6A20-68548. Golden, Colorado: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy18osti/68548.pdf.

Cowiestoll, Brady. 2019. "Contributions of Solar + Storage to Future Power Needs." Presented at the Energy Policy Research Conference, Boise, ID. https://www.nrel.gov/docs/fy20osti/74962.pdf.

Denholm, Paul, Jacob Nunemaker, Pieter Gagnon, and Wesley Cole. 2020. "The Potential for Battery Energy Storage to Provide Peaking Capacity in the United States." *Renewable Energy* 151 (May): 1269–77. https://doi.org/10.1016/j.renene.2019.11.117.

Denholm, Paul, Matthew O'Connell, Gregory Brinkman, and Jennie Jorgenson. 2015. "Overgeneration from Solar Energy in California: A Field Guide to the Duck Chart." NREL Technical Report NREL/TP-6A20-65023. Golden, CO: National Renewable Energy Laboratory. http://www.nrel.gov/docs/fy16osti/65023.pdf.

DiOrio, Nicholas, Paul Denholm, and William Hobbs. 2020. "A Model for Evaluating the Configuration and Dispatch of PV plus Battery Power Plants." *Applied Energy* 262: 1269–77. https://doi.org/j.apenergy.2019.114465.

EIA. 2019a. "The National Energy Modeling System: An Overview 2018." Washington, D.C.: Department of Energy. https://www.eia.gov/outlooks/aeo/nems/overview/pdf/0581(2018).pdf.

———. 2019b. “Annual Energy Outlook 2019 with Projections to 2050.” Washington, D.C.: U.S. Energy Information Association (EIA). https://www.eia.gov/outlooks/aeo/.

———. 2020. “Battery Storage in the United States: An Update on Market Trends.” Energy Information Administration (EIA). https://www.eia.gov/analysis/studies/electricity/batterystorage/pdf/battery_storage.pdf.

Eurek, Kelly, Wesley Cole, David Bielen, Nate Blair, Stuart Cohen, Bethany Frew, Jonathan Ho, Venkat Krishnan, Trieu Mai, and Benjamin Sigrin. 2016. “Regional Energy Deployment System (Reeds) Model Documentation: Version 2016.” Technical Report NREL/TP-6A20-67067. National Renewable Energy Lab.(NREL), Golden, CO (United States).

Eurek, Kelly, Caitlin Murphy, Wesley Cole, Will Frazier, Patrick Brown, and Anna Schleifer. 2021. “Representing DC-Coupled PV+Battery Hybrids in a Capacity Expansion Model.” Golden, CO: National Renewable Energy Laboratory.

Feldman, David, and Robert Margolis. 2020. “Q1/Q2 2020 Solar Industry Update.” Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy20osti/77772.pdf.

Feldman, David, Vignesh Ramasamy, Ran Fu, Ashwin Ramdas, Jal Desai, and Robert Margolis. 2021. “U.S. Solar Photovoltaic System and Energy Storage Cost Benchmark: Q1 2020.” NREL/TP-6A20-77324. Golden, CO: NREL.

Frazier, Will, Wesley Cole, Paul Denholm, Daniel Greer, and Pieter Gagnon. 2020. “Assessing the Potential of Battery Storage as a Peaking Capacity Resource in the United States.” *Applied Energy* 275. https://www.sciencedirect.com/science/article/pii/S0306261920308977?via%3Dihub.

Getman, Dan, Anthony Lopez, Trieu Mai, and Mark Dyson. 2015. “Methodology for Clustering High-Resolution Spatiotemporal Solar Resource Data.” NREL/TP-6A20-63148. Golden, CO: National Renewable Energy Laboratory.

Gorman, Will, Andrew Mills, Mark Bolinger, Ryan Wiser, Nikita Singhal, Erik Ela, and Eric O’Shaughnessy. 2020. “Motivations and Options for Deploying Hybrid Generator-plus-Battery Projects within the Bulk Power System.” *The Electricity Journal* 33 (5).

Hale, E, B. Stoll, and T. Mai. 2016. “Capturing the Impact of Storage and Other Flexible Technologies on Electric System Planning.” Technical Report NREL/TP-6A20-65726. Golden, CO: NREL. http://www.nrel.gov/docs/fy16osti/65726.pdf.

Hale, Elaine, Brady Cowiestoll, Jennie Jorgenson, Trieu Mai, and Dylan Hettinger. 2021. “Methods for Representing Flexible, Energy-Constrained Technologies in Utility Planning Tools.” NREL/TP-6A20-72120. Golden, CO: NREL (National Renewable Energy Laboratory (NREL).

Hale, Elaine, Brady Stoll, Jennie Jorgenson, Trieu Mai, and Dylan Hettinger. 2021. “Methods for Representing Flexible, Energy-Constrained Technologies in Utility Planning Models.” Technical Report, Forthcoming. Golden, Colorado: National Renewable Energy Laboratory.

Hargreaves, J., E.K. Hart, R. Jones, and A. Olson. 2015. “REFLEX: An Adapted Production Simulation Methodology for Flexible Capacity Planning.” *IEEE Transactions on Power Systems* 30 (3): 1306–15. https://doi.org/10.1109/TPWRS.2014.2351235.

Lew, D., G. Brinkman, E. Ibanez, A. Florita, M. Heaney, B. M. Hodge, M. Hummon, et al. 2013. "Western Wind and Solar Integration Study Phase 2." Technical Report NREL/TP-5500-55588. Golden, CO (United States): National Renewable Energy Laboratory (NREL). https://www.nrel.gov/docs/fy13osti/55588.pdf.

Madaeni, Seyed Hossein, Paul Denholm, and Ramteen Sioshansi. 2012. "Comparison of Capacity Value Methods for Photovoltaics in the Western United States." Technical Report NREL/TP-6A20-54704. National Renewable Energy Laboratory. http://www.nrel.gov/docs/fy12osti/54704.pdf.

Mai, T., C. Barrows, A. Lopez, E. Hale, M. Dyson, and K. Eurek. 2015. "Implications of Model Structure and Detail for Utility Planning: Scenario Case Studies Using the Resource Planning Model." Technical Report NREL/TP-6A20-63972. Golden, CO: National Renewable Energy Laboratory. http://www.nrel.gov/docs/fy15osti/63972.pdf.

Mai, T., E. Drury, K. Eurek, N. Bodington, A. Lopez, and A. Perry. 2013. "Resource Planning Model: An Integrated Resource Planning and Dispatch Tool for Regional Electric Systems." Technical Report NREL/TP-6A20-56723. Golden, Colorado: National Renewable Energy Laboratory. http://www.nrel.gov/docs/fy13osti/56723.pdf.

Mills, Andres, and Pia Rodriguez. 2020. "A Simple and Fast Algorithm for Estimating the Capacity Credit of Solar and Storage." *Energy* 210 (November). https://doi.org/10.1016/j.energy.2020.118587.

NC Clean Energy Technology Center. 2020. "Database of State Incentives for Renewables & Efficiency (DSIRE)." Database. 2020. http://www.dsireusa.org/.

NERC. 2015. "2015 Summer Reliability Assessment." North American Electric Reliability Corporation. http://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/2015_Summer_Reliability_Assessment.pdf.

NREL. 2018. "2018 Annual Technology Baseline." Golden, CO: National Renewable Energy Laboratory. https://atb.nrel.gov/electricity/2018/index.html.

———. 2019. "2019 Annual Technology Baseline." Golden, CO: National Renewable Energy Laboratory. https://atb.nrel.gov/electricity/2019/index.html.

———. 2020. "2020 Annual Technology Baseline." Golden, CO: National Renewable Energy Laboratory. https://atb.nrel.gov/.

———. 2021. "2021 Annual Technology Baseline." Golden, CO: National Renewable Energy Laboratory. https://atb.nrel.gov/.

Schleifer, Anna H., Caitlin A. Murphy, Wesley J. Cole, and Paul L. Denholm. 2021. "The Evolving Energy and Capacity Values of Utility-Scale PV-plus-Battery Hybrid System Architectures." *Advances in Applied Energy* 2 (May): 100015. https://doi.org/10.1016/j.adapen.2021.100015.

Sigrin, Ben, Michael Gleason, Robert Preus, Ian Baring-Gould, and Robert Margolis. 2016. "The Distributed Generation Market Demand Model (DGen): Documentation." Technical Report NREL/TP-6A20-65231. Golden, Colorado: National Renewable Energy Laboratory (NREL). http://www.nrel.gov/docs/fy16osti/65231.pdf.

Stephen, Gord, Elaine Hale, and Brady Cowiestoll. 2020. "Managing Solar Photovoltaic Integration in the Western United States: Resource Adequacy Considerations." Technical Report NREL/TP-6A20-72472. Planning for High Solar Photovoltaic Penetrations in the Western United States. Golden, CO: National Renewable Energy Laboratory.

WECC. 2014. "Release Notes for WECC 2024 Common Case, Version 1.1." Transmission Expansion Planning Department.

Wiser, Ryan, Mark Bolinger, Will Gorman, Joe Rand, Seongeun Jeong, Joachim Seel, Cody Warner, and Ben Paulos. 2020. "Hybrid Power Plants: Status of Installed and Proposed Projects." Berkeley, California: Lawrence Berkeley National Laboratory.

Zhou, Ella, Wesley Cole, and Bethany Frew. 2018. "Valuing Variable Renewable Energy for Peak Demand Requirements." *Energy* 165 (December): 499–511. https://doi.org/10.1016/j.energy.2018.09.009.