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The evolving energy and capacity values of utility-scale PV-plus-battery hybrid system architectures

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ABSTRACT

In this study, we explored how the value of hybrid systems comprising solar photovoltaics (PV) and lithium-ion battery storage could evolve over time. Using a price-taker model with hourly energy and capacity prices projected to 2050, we simulated the revenue-maximizing dispatch of three PV-plus-battery architectures, with fixed component sizing, in three locations. The architectures reflect different coupling types, which vary in terms of whether the PV and battery systems have separate inverters or a shared inverter and whether the battery can charge from the grid. We found that the highest-value architecture today varies largely based on PV penetration and the magnitude and timing of peak-price periods. As PV penetration increases over time—based on the evolution of the bulk power system—two trends emerge that indicate a convergence of the values of the systems studied. First, the energy values of the three architectures converge as an increasing fraction of energy from the coupled PV is used to charge the battery. Second, their capacity values converge to that of the battery as the capacity credit of stand-alone PV approaches zero. Of the systems studied, no single architecture has the highest year-one benefit-cost ratio in every region and year, and benefit-cost ratios of PV-plus-battery systems range from a 15% reduction to a 25% increase compared to separate PV and battery systems. Understanding the factors that influence the performance and economics of PV-plus-battery systems will help system planners and researchers evaluate the potential benefits of these hybrid resources to future power systems.

1. Introduction

Systems comprising solar photovoltaics (PV) coupled with lithium-ion battery storage, or PV-plus-battery hybrid systems, are of growing interest because of recent technology cost and performance improvements and state and federal policies [1]. It is estimated that approximately 40 utility-scale PV-plus-battery projects were installed on the bulk power system before 2020 [2], and over 25% of PV capacity in U.S. interconnection queues in 2020 was paired with battery systems [3]. It is expected that more than half of all battery capacity in U.S. interconnection queues will be paired with PV by 2023 [4], and interest in such systems is apparent internationally as well [5].

Two PV-plus-battery architectures are commonly discussed in the literature [6]: *AC-coupled* systems involve separate inverters for the PV and battery components, and *DC-coupled* systems involve a single shared inverter for both the PV and battery. We further divide the latter configuration into two subtypes: *loosely* coupled systems that use a bidirectional inverter that allows for charging from either the coupled PV or the grid, and *tightly* coupled systems that involve hardware (or controls) that disallow grid charging. PV-plus-battery hybrid system configurations are further characterized by component sizing via the PV inverter loading ratio (ILR), battery capacity, and battery duration.

Each aspect of PV-plus-battery configuration influences the plant's cost and value; therefore, the long-term deployment potential of PV-plus-battery systems could depend on which architecture is pursued. The goal of the present study is to inform the long-term deployment potential of PV-plus-battery systems by exploring (a) whether coupling PV and battery technologies results in improved net-economic performance of the joint system and (b) if so, which form of coupling provides the greatest net-economic benefits. Because answers to these questions could also vary both by location (which defines solar and wind resource, load patterns, and state-level policy drivers) and over time, we evaluate the cost and performance of different PV-plus-battery architectures across these dimensions.

Information on costs for PV-plus-battery systems in the literature is limited. Existing market data for operating and planned PV-plus-battery systems indicate that the power purchase agreement (PPA) price of a PV-plus-battery system is currently \$4/MWh–\$14/MWh higher than that of a comparable stand-alone PV system [3], but these values reflect the impact of the federal investment tax credit (ITC) and a range of assumptions regarding component sizing [7,8]. Bottom-up engineering models

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have also been developed to estimate costs related to engineering, procurement, and construction (EPC) and project development functions, typically with a fairly detailed treatment of balance-of-system (BOS) costs[1] [9–12]. Scenario analyses with such models indicate that coupling a battery with utility-scale PV could reduce total project costs relative to those of comparable separate PV and battery projects.

To quantify the *value* that can be realized by PV-plus-battery systems, previous analyses have often used price-taker modeling methods, which are ideal for exploring how value varies across multiple dimensions due to their computational efficiency. Price-taker analyses for stand-alone PV (e.g., in California [13], New York [14], Texas [15], and other locations across the United States [16]; in Ontario, Canada [17,18]; in locations in western Europe [19]), stand-alone storage (e.g., compressed air energy storage [20], pumped hydro storage [21], sodium sulfur batteries and flywheel energy storage [22], hydrogen storage [23]), and concentrating solar power with thermal energy storage (CSP-TES; e.g., in Spain [24] and various U.S. locations [25,26]) serve as helpful context for the valuation of PV-plus-battery systems. In particular, previous price-taker analyses of CSP-TES have shown that the value of solar-plus-storage technologies is fairly insensitive to the optimization window because most of the shifting of the solar generation is done within the day or among adjacent days [27–29]. Also, these previous analyses have shown that the assumption of perfect foresight tends to overvalue solar-plus-storage technologies, but it still provides a reasonable approximation of value because of the predictable diurnal pattern of energy prices and solar energy availability [3,27,30,28].

In addition to bulk power system applications (the focus of this work), there have been several analyses that explore PV-plus-battery systems in behind-the-meter (e.g., [31–33]) and microgrid (e.g., [34]) applications. This area of research primarily focuses on retail electricity rate savings to residential (e.g., in [35–38]), commercial (e.g., in [39–41]), and industrial (e.g., in [41]) customers as well as reliability benefits to the distribution network (e.g., in [42–44]). These analyses demonstrate that battery capital costs, retail rate structures, policy-related financial incentives and subsidies, and demand profiles are the primary drivers of distribution-connected PV-plus-battery system economics.

Price-taker studies involving utility-scale PV-plus-battery are also emerging, and they typically explore a small subset of the factors that influence plant design, operation, and value. Zhang et al. [45] found that accounting for price and PV generation uncertainty in the real-time operation of PV-plus-battery systems in PJM could increase revenue by reserving battery energy and power capacity in the day-ahead (DA) market to be able to respond to fluctuations in real-time (RT) prices and PV generation. Carriere et al. [46] compared control strategies for PV-plus-battery systems in DA and RT markets in France and found that using the battery to shift PV generation to higher-value hours provided greater value than using the battery only to compensate PV forecast errors. Małkowski et al. [47] compared simulations to experimental tests of PV-plus-battery systems for using the battery to balance RT PV generation to satisfy DA obligations in Poland and found that this application results in levelized costs that are up to three times higher than DA market prices. These studies, however, focused on the operation of coupled systems and did not consider differences in system architectures or charging the battery from the grid.

Denholm et al. [48] employed price-taker modeling to study AC- and DC-coupled PV-plus-battery systems with a fixed configuration in California, using historical hourly energy prices and simulated hourly energy prices for the year 2020. They found that coupled PV-plus-battery systems have higher benefit-cost ratios compared to separate systems, but their comparison of AC- and DC-coupled systems did not reflect the efficiency differences between these architectures.

[1] BOS costs include all costs not related to the PV or battery components (e.g., hardware, labor, permitting, overhead, customer acquisition, and construction).

DiOrio et al. [49] developed a heuristic dispatch model that incorporates more-detailed physical modeling of battery components, including nonlinear effects associated with, for example, voltage and current, heat transfer, and degradation. They used this model to dispatch AC- and DC-coupled systems in a single location against hourly PPA time-of-delivery factors and similarly found that coupled PV-plus-battery systems have higher benefit-cost ratios than separate systems. However, the focus of their analysis was on the value to the plant owner, not to the bulk power system, and they did not investigate how future technology cost declines could affect project economics.

Gorman et al. [3] used price-taker modeling with historical prices to explore how the value of PV-plus-battery systems in California and Texas vary based on the battery dispatch algorithm. They found that the day-ahead persistence algorithm, which provided a lower bound on value, could reduce the average market value of a PV-plus-battery system by up to ~10–20% relative to the perfect foresight algorithm, depending on location. They also demonstrated that coupling decreased the average market value relative to separate systems, but they considered only an AC-coupled system that was constrained to charge from the PV component only. Furthermore, they compared these market values to existing PPA prices instead of project costs and did not consider future values or costs.

Our work expands on these previous analyses by combining the capabilities of several existing electricity sector modeling tools with different temporal and geographic scales to explore the net-economic performance of PV-plus-battery systems over a wide geographic extent and into the future. Given fixed component sizing, we explore how energy and capacity values for PV-plus-battery systems vary (a) by region (as represented by three U.S. states: Texas, New York, and California) and (b) based on the nature of coupling. Moreover, our analysis quantifies the *future* value of PV-plus-battery systems based on simulated electricity prices—which include components of both energy and capacity value—that reflect evolving grid conditions projected through 2050 using a capacity expansion model. Finally, we evaluate and compare the net-economic performance of PV, battery, and PV-plus-battery systems across all years, locations, and architectures. The objective of this analysis is to provide insight about the motivations for coupling PV and battery systems and the factors that influence the operation and value of different coupling types as the bulk power system evolves.

2. Methods

The future value of PV-plus-battery systems depends on plant-specific factors and the power system onto which those plants are integrated. To the former point, the future costs of PV-plus-battery systems will depend on trajectories for PV panels, battery cells, and enabling power electronics and related BOS costs. To the latter point, the future generation mix will influence electricity price profiles and, in turn, the operational strategy (and value) of PV-plus-battery systems. Both the future costs and operational strategy will also depend on the nature of coupling, which defines the various energy pathways that are available in a hybrid configuration. To represent all of these factors, we leverage information from multiple tools that, when combined, generate information about the evolving generation mix, temporal information about future electricity prices, and estimates for the future costs and performance of PV and battery technologies.

Fig. 1 presents the workflow developed for this study. First, we projected hourly prices by (1) optimizing generation and transmission buildout through 2050 using a capacity expansion model, and (2) optimizing the hourly operations of the resulting bulk power system using a production cost (or unit commitment and dispatch) model. These two steps provided the simulated hourly price and net load data used to create combined energy and capacity prices for future years. In addition, hourly PV generation profiles were obtained from a tool that uses location-specific weather and solar resource data to simulate PV system operation. The resulting hourly price and generation profiles

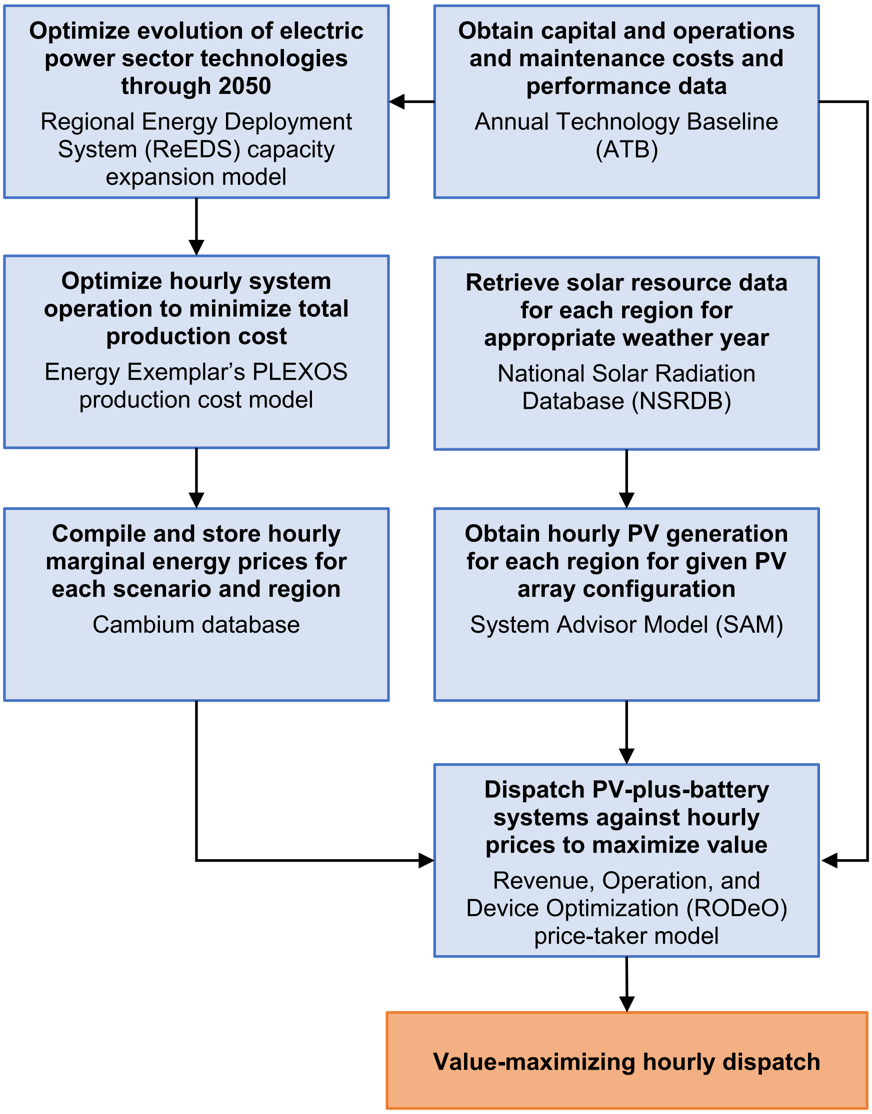

Fig. 1. Summary of the workflow developed for this analysis and the individual tools used at each step.

were used as inputs to a price-taker model to determine an individual plant's revenue-maximizing dispatch—accounting for configuration-specific energy pathways and efficiencies—which ultimately determines the plant's total value to the bulk power system.

Fig. 1 also shows the particular tools used in this analysis. While several of these tools are currently specific to the contiguous United States, the workflow can be applied to any location, and different tools can be substituted into the workflow. The following sections provide further detail about how this workflow was applied in the current analysis, including input data that were derived from tools upstream of our analysis (Section 2.1), details of our price-taker modeling setup (Section 2.2), and the specific PV-plus-battery configurations we explored (Section 2.3).

2.1. Input assumptions derived from upstream tools and analysis

The Regional Energy Deployment System (ReEDS) model is a capacity expansion model that simulates the least-cost generation and transmission build-out of the contiguous United States in every even year through 2050 [50]. For the scenarios used in this study, the cost assumptions that informed the build-out were derived from capital and O&M costs for all modeled technologies from the 2019 Annual Technology Baseline (ATB) [51]. In particular, the underlying ReEDS results that informed this analysis were based on price data from the Low RE Cost scenario, which assumes low-cost trajectories of capital, O&M, and financing costs for utility-scale and distributed PV, CSP, geothermal, and land-based and offshore wind technologies [52]. We used the Low RE Cost scenario to evaluate how the value of PV-plus-battery systems could evolve with large increases in renewable energy penetration.

ReEDS results for the states that comprise our three study regions—as represented by Texas, New York, and California—are shown in Fig. 2, which provides context for the results of the analysis. For example, renewable energy technologies' share of total capacity and generation is similar in each region by 2050 (despite starting at different levels in 2020). The resulting impacts on energy prices and peak net loads are shown in the Supplemental Information. Details about the evolution of the electricity sector in these three regions in the Low RE Cost scenario can be found in the 2019 Standard Scenarios report [52] and website [53].

Because our goal was to project the value of PV-plus-battery systems over time, the systems needed to be dispatched against electricity price profiles that evolve as the bulk power system in which they operate evolves. Therefore, outputs from ReEDS were used as inputs to the PLEXOS production cost model [54], which optimizes the hourly operation of the bulk power system and outputs hourly price data for every modeled year. These hourly prices (along with other operational data) were processed and stored in the Cambium database [55], which

Fig. 2. Capacity fraction (top) and generation fraction (bottom) of battery, PV, wind, and CSP in each region.

includes day-ahead energy prices (in 2018 U.S. dollars) for all even-numbered years from 2020 to 2050 for each of the 134 balancing areas represented in the 2019 version of ReEDS [56].

Our approach dispatches each PV-plus-battery system to capture both energy and capacity value by using price signals that include hourly capacity prices added to the hourly energy prices from Cambium. Resource adequacy metrics like capacity credit are typically assessed in terms of hourly loss of load probabilities, which represent the risk that generation will be insufficient to meet demand [57]. While the vast majority of hours in a year have little or no risk, there are higher-risk hours that typically coincide with the highest net loads [57]. Therefore, by incorporating capacity prices during hours with highest net loads as a proxy for high risk, our methodology maximizes capacity value by maximizing power output during high-risk hours (i.e., by minimizing the resulting net load during these hours, similar to the methodology developed in [58]).

To develop hourly capacity prices, we developed projections for the annualized cost, in \$/MW-year, of a natural gas combustion turbine (NGCT) [51] as an approximation for the avoided cost of new capacity, which is a typical approach for system planners [59].[2] Then, we distributed these annual capacity costs, weighted according to net load, over the top 3% of highest-net-load hours (Fig. 3); i.e., the capacity price for a given hour (in this subset of hours) is equal to the annual capacity cost multiplied by the ratio of that hour's net load to the sum of the net loads in the top 3% of highest-net-load hours. We chose 3% because the median capacity factor of peaker plants in the United States is 3% [64], and about half of U.S. peaking capacity had a capacity factor of 5% or less in 2019 [65]. While the capacity credit of PV-plus-battery systems is sensitive to the inclusion of hourly capacity prices in the dispatch price signals, there is minimal difference in capacity credit when the capacity costs are distributed over 1% or 5% as opposed to 3%. Additionally, the inclusion of hourly capacity prices minimally affects energy value (see Supplemental Information). An important element captured by this method is that the hours with capacity prices change over the years as the net load profile is affected by changing VRE and storage deployment.

These hourly prices reflect the assumptions that additional capacity is needed in the system and that NGCT capacity would be the lowest-cost, allowable capacity to meet system needs. These assumptions might not be true as the electricity sector and policy environment change. Not all regions need new capacity (e.g., PJM [66]), and four-hour battery capital costs are anticipated to be lower than NGCT capital costs in the next ten years [52]. Battery and PV-plus-battery systems are already

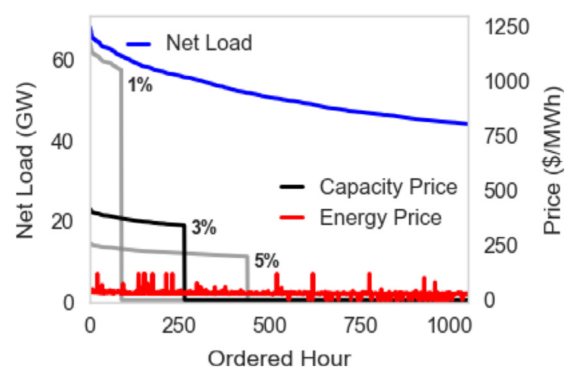

Fig. 3. Example net load duration curve (blue) for a subset of hours in a year and its translation into hourly capacity prices (black), with energy prices (red) and alternate distributions of capacity prices (gray) shown for comparison; the area under each of the 1%, 3%, and 5% curves is the same and is equal to the yearly capacity value.

[2] Our projections assume a discount rate of 5.5% and a financing term length of 20 years. Several independent system operators (ISOs), including PJM [60], Midcontinent ISO [61], ISO New England, and New York ISO [62] use an amortization period of 20 years for estimating the cost of new entry based on NGCTs. California ISO estimates the cost of new merchant generation with low-, mid-, and high-cost scenarios with financing periods of 20, 10, and 7 years, respectively [63].

beginning to replace new-build NG peaking capacity in places like California [67], Arizona [68], and Texas [69], and NYISO included battery storage for the first time in their 2020 Capacity Demand Curve report as a potential peaking technology because of state clean energy goals [70]. Furthermore, there has been increasing concern about gas generation assets becoming stranded before their economic lifetime [71, 72], especially as more places adopt clean and renewable energy standards and targets [73]. Finally, anticipated reliability concerns can be alleviated by demand-side management or new transmission [74]. The question of how resource adequacy assessment metrics and techniques must change with the evolving bulk power system is an active area of research [75].

Finally, the National Solar Radiation Database (NSRDB) provides hourly weather data that are used by the System Advisor Model (SAM) to produce hourly PV generation profiles [76]. We obtained PV production profiles for each region[3] from SAM's PVWatts model [76]. The profiles are based on a single-axis tracking PV array with a tilt of zero degrees, which is typical of most new PV systems [77,78]. Default values in SAM were assumed for the remaining parameters. To be consistent with the simulated prices from Cambium, we used the 2012 weather year for the PV generation profiles.

2.2. Price-taker analysis

Of the primary tools presented in Fig. 1, RODeO [79] played the main role in determining the value of PV-plus-battery hybrid systems in this analysis. RODeO is a price-taker, mixed integer linear program that optimizes a plant's hourly dispatch behavior to maximize the net revenue for the plant owner. Further details of RODeO, including the mathematical formulation, can be found in the Supplemental Information as well as in [23,80]. RODeO's low computational complexity—and, therefore, fast run time—allowed us to analyze a wide range of scenarios, spanning multiple hybrid system configurations, regions, and years. Because RODeO is a price-taker tool, we assumed each stand-alone and hybrid system is small enough relative to the total system that it does not change the marginal electricity prices [25]. For this analysis, we used an 8760-hour optimization window with perfect foresight of hourly weather and prices[4] [23]. We did not include ITC-related cost reductions associated with battery operation in the optimization objective, although we do account for them in the final cost results; so, while the model provides the value-maximizing dispatch, it does not provide the dispatch that maximizes the benefit-cost ratio.

To compare the PV-plus-battery hybrid systems to each other and to separate systems, we accounted for two value streams. First, the net energy value is the energy revenue minus the costs incurred by charging the battery from the grid, calculated by multiplying the hourly dispatch with the time-synchronous energy prices. Second, the capacity value is based on the approximate capacity credit,[5] which we estimated for each hybrid system using the capacity factor approximation during the 10 hours with the highest net load. The same number of hours is used for all variable renewable energy (VRE) technologies in ReEDS [50] and has been shown to provide a good approximation of stand-alone PV [82] and CSP-TES [83] capacity credit. Deriving the capacity *value*, then, requires multiplying our capacity credit approximation for the PV-plus-battery system by the annualized cost of NGCT capacity (previously described).

These value streams are not directly comparable with the revenue that might be earned by an independent developer in a wholesale market. Instead, they reflect avoided costs of energy and capacity, or the value that PV-plus-battery could provide as part of a least-cost planning process (e.g., by displacing fuel consumption, reducing variable O&M costs, and avoiding deployment of additional capacity). Previous research has shown that price-taker modeling of a solar-plus-storage technology provides a good approximation of the production cost reduction that would be seen by implementing the solar-plus-storage technology in a production cost model [25].

We did not include the value of ancillary services in this analysis because, historically, ancillary services markets and their associated values are typically small relative to energy and capacity markets [84–87], and they can be difficult to model and predict [88]. The assumption required by price-taker modeling that the system being modeled is small enough to not affect marginal prices likely does not hold for ancillary services markets, in which 77-MW or 137-MW systems like the ones in this analysis could be price-makers [89]. Furthermore, we wanted to consistently compare the value of PV-plus-battery systems among different areas by not including varying markets and participation rules and to avoid making assumptions regarding future ancillary services markets [65].

Our summary metric is the year-one benefit-cost ratio (BCR). The numerator of the BCR includes the capacity and net energy values during the first year of operation, and the denominator is the annual cost of the PV-plus-battery system (referred to as the annual capacity cost in this paper), which includes annualized capital costs and year-one fixed O&M costs. Like ReEDS, we assume that a project that comes online in a given year operates for that entire year and has costs equal to that year's costs in the Annual Technology Baseline (i.e., the build year is the first year of operation). We chose to present the year-one BCR to avoid projecting total annual value beyond 2050 for systems built after 2020 (given the assumed 30-year lifetime) and because we did not account for PV degradation in the RODeO simulations. Furthermore, our goal was to analyze how the value of these systems to the bulk power system might evolve relative to costs, not to analyze possible investment scenarios or decisions. However, for comparison, we also calculated the lifetime BCR, with the methodology and additional discussion in the Supplemental Information. The overall trends of the lifetime BCR and year-one BCR are the same, but the lifetime BCR is very sensitive to discount rate.

2.3. Configuration details and costs

The configurations we explore are shown in Fig. 4. These diagrams are simplified versions of the DC-coupled and centralized AC-coupled systems described in [6]. Each system comprises 100 MW_{DC} of PV capacity and 60 MW_{AC} of battery capacity, which is consistent with the system studied in [90]. The battery is sized so that it can discharge at its full capacity for four hours, uninterrupted, accounting for conversion losses and state-of-charge constraints. The unidirectional inverter (AC-coupled systems) and shared inverter (DC-coupled systems) are sized to maintain the same ILR of 1.3 and have an efficiency of 98%. Battery roundtrip efficiencies, including inverter losses, for each system (Table 1) are based on previous analysis of PV-plus-battery systems using the System Advisor Model (SAM) [49]. AC-coupled systems have lower battery roundtrip efficiency when charged from the PV because of the extra conversions performed by the PV and bidirectional inverters, compared to the DC-coupled system's DC-DC converter. Details about the PV-plus-battery systems and how their design and operation affect values and costs are shown in Table 1. For comparison, we also include results for PV and battery systems that are not co-located, hereafter referred to as separate systems or stand-alone systems; these systems operate independently of one another (i.e., are optimally dispatched separately) and do not benefit from shared capital or operations and maintenance (O&M) costs.

[3] The specific locations are based on the centroids of the ReEDS balancing areas: Big Spring, Texas; Los Angeles, California; and Albany, New York [50].

[4] According to [81], production cost models "cannot completely simulate market environments because they typically do not capture self-scheduling, bilateral contracts, scarcity pricing, bidding strategies, and other factors that can alter system dispatch from the 'least-cost' dispatch produced by a model." Therefore, the price inputs we used will not reflect the volatility in prices, particularly negative prices, seen in real markets. Consequently, the energy storage component is likely undervalued.

[5] Capacity credit is the portion of nameplate capacity that can be relied on to contribute to firm capacity (i.e., the capacity that counts toward the planning reserve margin).

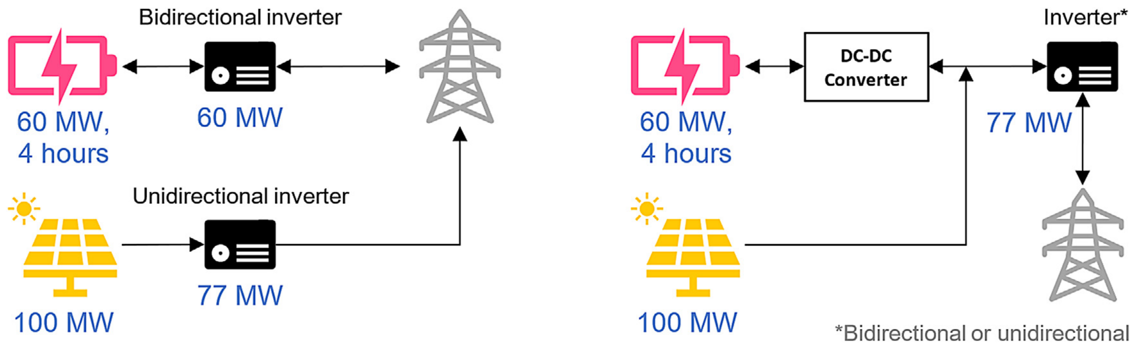

Fig. 4. AC-coupled systems (left), in which the battery and PV have separate inverters, and DC-coupled systems (right), in which the battery and PV share an inverter.

Table 1
Assumptions for each configuration explored in this study.

	AC-Coupled	DC-Coupled (Loose)	DC-Coupled (Tight)
Total power output capacity	137 MW	77 MW	77 MW
Battery energy source	Grid or PV	Grid or PV	PV only
Battery roundtrip efficiency	85% (grid charging) 86% (PV charging)	85% (grid charging) 87% (PV charging)	87% (PV charging)
Changes in energy value relative to separate systems	None, because of separate inverters	Limited by shared inverter Can capture energy that would otherwise be clipped by the inverter Higher roundtrip efficiency when storing PV energy	Same as loosely DC-coupled *Plus,* cannot arbitrage grid energy (i.e., buy low and sell high)
Changes in capacity value relative to separate systems	None, because of separate inverters	Limited by shared inverter	Limited by shared inverter Cannot charge battery from grid in preparation for potential capacity shortfalls
Changes in project costs relative to separate systems	Reduced costs because of shared land, permitting, site preparation and staging, switchgear, transformer, and monitors, controls, and communication systems [90]	Reduced costs due to same factors as AC-coupled, *plus* shared bidirectional inverter and lower interconnection costs [90] Increased costs because of distributed battery racks requiring more fire suppression and thermal energy management systems; increased labor costs (less experience with DC-coupled systems) [90,91]	
ITC eligibility	Full eligibility for PV components Eligibility for battery components scales with fraction of energy charged from PV, which must be at least 75%; otherwise, 0% for battery components		Full eligibility for all components

Table 2
Changes to capital and O&M costs from the PV Benchmark and ATB.

Cost Category	Changes
PV costs	O&M costs for PV systems include the annualized replacement cost of the inverter [92]. For DC-coupled systems, we removed the portion of O&M costs associated with the PV inverter replacement and instead used the annualized replacement cost of the shared inverter.
Battery costs	We incorporated the replacement of the entire battery pack after 15 years by finding the present value and then annualizing it over the 30-year life. We assumed the bidirectional inverter was adapted from PV inverter architecture, with a price of \$0.08/W_{AC} in 2019 [5]. We then projected this cost according to the ATB four-hour storage trajectory, but we did not allow the bidirectional inverter to have less than a 10% premium over unidirectional inverters [5,91]. We incorporated replacement costs for the bidirectional inverter similarly to those of the battery pack.
Interconnection costs	Interconnection costs for AC- and DC-coupled systems were assumed to be the same as in [90]. We scaled interconnection costs according to total output capacity at the point of interconnection, so the AC-coupled system's interconnection cost was based on a total of 137 MW, whereas the DC-coupled system's interconnection cost was based on a total of 77 MW.

We derived our cost assumptions by adapting and updating capital costs for stand-alone and hybrid systems from the 2018 U.S. Solar Photovoltaic System Benchmark [90,92], with the main changes shown in Table 2. We annualized capital costs over the system's 30-year lifetime, including replacement costs for the battery pack and inverter, assuming a discount rate of 5.5% [51]. We used PV O&M costs from the 2019 ATB and battery O&M costs from the PV Benchmark.[6] To be consistent with the Low RE Cost scenario assumptions, all PV-related capital and O&M costs were projected to 2050 based on the ATB low-cost utility-scale PV trajectory, and all battery-related capital and O&M costs were projected based on the ATB mid-cost four-hour storage trajectory. All costs are in 2018 U.S. dollars.

The annual capacity cost trajectories for separate PV and battery systems, AC- and DC-coupled systems, and NGCTs are shown in Fig. 5. For AC- and DC-coupled systems that happen to operate in a way that enables the battery's ITC eligibility, the shaded areas show the ranges of possible costs, depending on the fraction of battery energy that comes from the PV. Those ranges narrow significantly after the ITC steps down to 10% in 2025, reducing the incentive to charge completely (instead of just mostly) from PV to less than \$100,000 per year.

Tightly DC-coupled systems will always have the lowest capacity cost (the loosely dashed blue line) because the battery will always have full ITC eligibility. Annual capacity costs for AC-coupled (dash-dotted lines) and loosely DC-coupled (dashed lines) systems depend on how much the

[6] All O&M costs for both PV and battery systems are fixed, so variable O&M costs are zero. We implemented artificial variable O&M costs in the price-taker simulations for Texas to prevent the battery from cycling twice a day, but we did not include these costs in the post-processing step. See the Supplemental Information for the values used in each year.

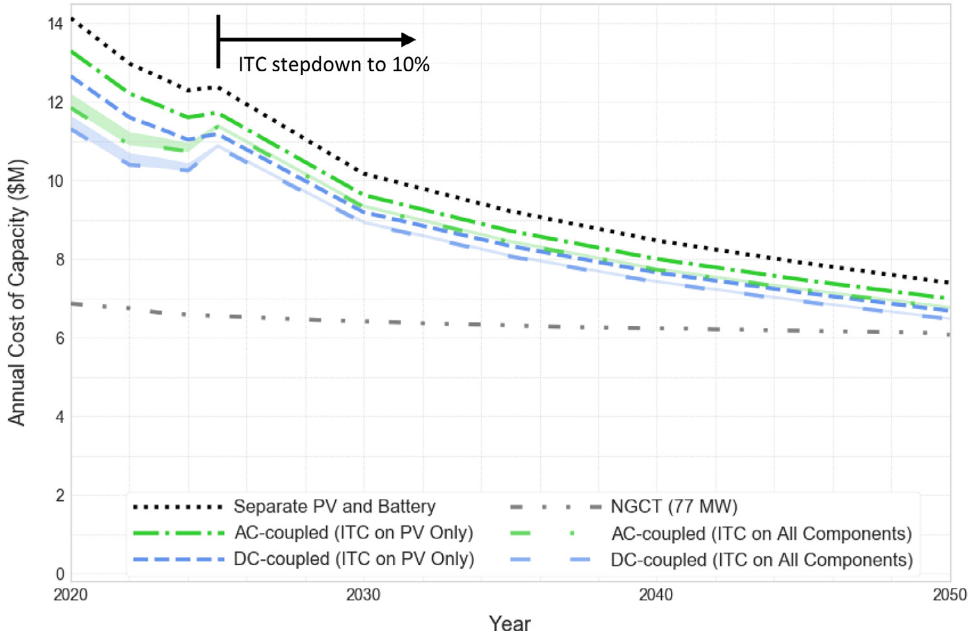

Fig. 5. Annual capacity cost trajectories, in millions of dollars, for the AC- and DC-coupled systems shown in Fig. 4 (100 MW_{DC} PV and 60 MW_{AC}, four-hour battery) and NGCTs.[7]

battery is charged from the grid, which dictates ITC eligibility and value for the battery component; therefore, these costs depend on the battery operation as determined by RODeO. The incentive to charge mostly from the coupled PV drops dramatically in 2025 as the cost savings associated with charging the battery at least 75% from the PV decline from about $600,000 to $250,000 and then continue falling over time. Eventually, most of the cost savings are associated with shared BOS costs (i.e., by AC-coupling), following by shared inverter and reduced interconnection costs (i.e., by DC-coupling). For this reason, and because our analysis focuses on long-term value, we did not include ITC considerations in the optimization objective. Insights from our results are largely independent of the ITC and are, therefore, relevant for locations without such incentive.

3. Results and discussion

In this section, we provide context for the BCRs of PV-plus-battery hybrid systems by first presenting the energy value, capacity value, and total value of stand-alone and hybrid systems.

3.1. Energy value

Fig. 6 shows the annual energy revenues, energy costs, and net energy values for 2020, 2030, and 2050.[8] In 2020, the coupling type that provides the highest value varies by location: AC-coupling has higher net energy value than DC-coupling in Texas, AC- and loose DC-coupling have similar net energy value in New York, and all three coupling types have similar net value in California. However, by 2050, all three coupling types have almost the same net energy value in each area (i.e., energy value is largely independent of coupling).

To understand why the different PV-plus-battery systems converge in value over time, we provide three sets of dispatch plots for a typical summer day: one set in Texas in 2020, when AC-coupled systems have higher energy value than DC-coupled systems (Fig. 7); one set in New York in 2030, when AC- and loosely DC-coupled systems have similar energy values that are higher than tightly DC-coupled systems (Fig. 8); and one set in California in 2050, when all three PV-plus-battery systems have similar energy values (Fig. 9). The typical dispatch behavior of separate systems is shown in the top left panel, and the typical dispatch behaviors of PV-plus-battery systems are shown in the remaining panels. Marginal energy prices are shown on the right axis.

With the low PV penetration in Texas in 2020, the hours with high demand and high prices coincide with solar generation, while wind generation and low demand suppress prices in the middle of the night. Therefore, the AC-coupled system operates like separate PV and battery systems: all PV generation is sent directly to the grid, and the battery charges during the low-priced, nighttime hours to discharge during medium- and high-priced, morning and afternoon hours. Both DC-coupled systems lose value because the shared inverter limits the power output during high-priced hours. The tightly DC-coupled system loses even more value by charging the battery from PV generation during medium-priced hours instead of sending it to the grid, and its limited arbitrage opportunity results in low battery use (i.e., the battery's value is limited by its inability to charge from the grid, especially in the presence of wind generation). A smaller battery could provide similar value at lower cost in this tightly coupled case.

In New York in 2030, the low-priced hours extend to slightly later in the morning than in Texas, and the price peak is later in the evening when there is no solar resource. The shared bidirectional inverter of the DC-coupled systems no longer limits the power output during the high-priced hours because it is the battery capacity that constrains how much power can be dispatched. The AC-coupled system and the separate systems now operate similarly to the loosely DC-coupled system: the battery is charged during the night and morning from both grid and PV energy, the PV generation during the late morning and afternoon is sent directly to the grid, and the battery discharges fully in the evening after the sun sets. The tightly DC-coupled system still loses value by charging from its own PV energy in the late morning instead of sending it to the grid.

In every year in this analysis, California has sufficient PV penetration to suppress the value of additional PV, so the dispatch behavior of all three PV-plus-battery systems is consistent from 2020 to 2050. More of each system's PV energy is used to charge the battery instead of going directly to the grid, and less of the battery's energy is charged from the grid. The AC-coupled system and both DC-coupled systems operate similarly: the battery charges from low-value PV energy in the morning and discharges during the evening. The separate PV and battery systems also

[7] The ITC has been extended in the time since this analysis was performed.
[8] See Supplemental Information for all years.

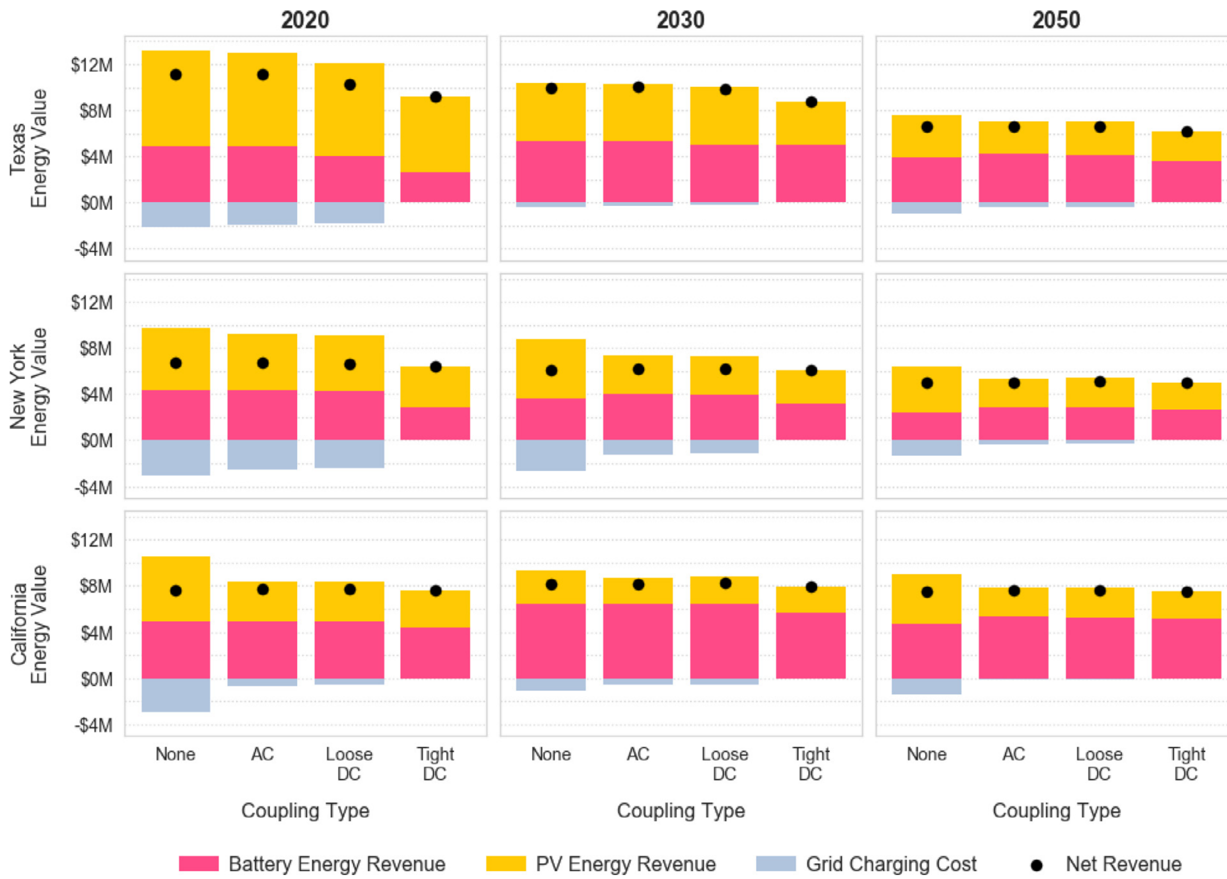

Fig. 6. Operation and energy value of separate (coupling type "None") and hybrid systems in 2020, 2030, and 2050.

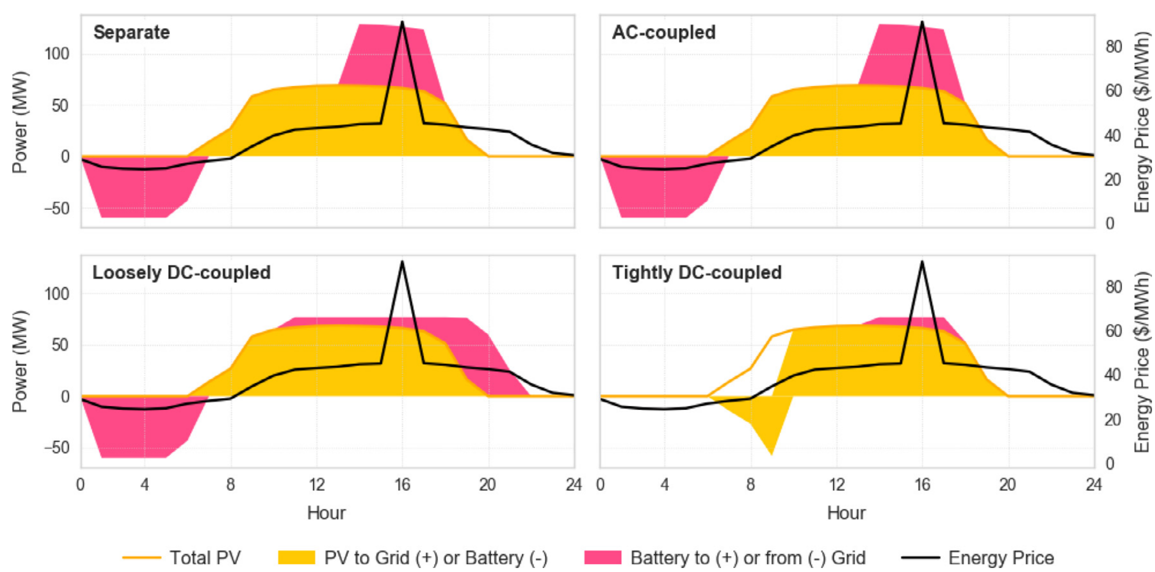

Fig. 7. Dispatch of separate and hybrid systems on a summer day in Texas in 2020.

have the same net dispatch behavior as the coupled systems. However, some low-value PV energy is forced to the grid because of the mismatch in PV capacity and battery capacity—the battery is undersized relative to the PV system. In scenarios with high PV penetration, an optimally sized system would likely have a larger battery capacity relative to the PV capacity.

By 2050, all three coupling types have almost the same net energy value in each area because the increased PV penetration and consequent suppression of daytime energy prices cause the PV-plus-battery systems to use a larger fraction of the PV energy to charge the battery (Fig. 10). Consequently, the AC-coupled system's PV inverter is used less, and the lost arbitrage value of the tightly DC-coupled system due to its inability to charge from the grid is reduced. The decline in net energy value over time results from increasing PV curtailment that the battery cannot capture because of capacity and energy limitations (Fig. 10).

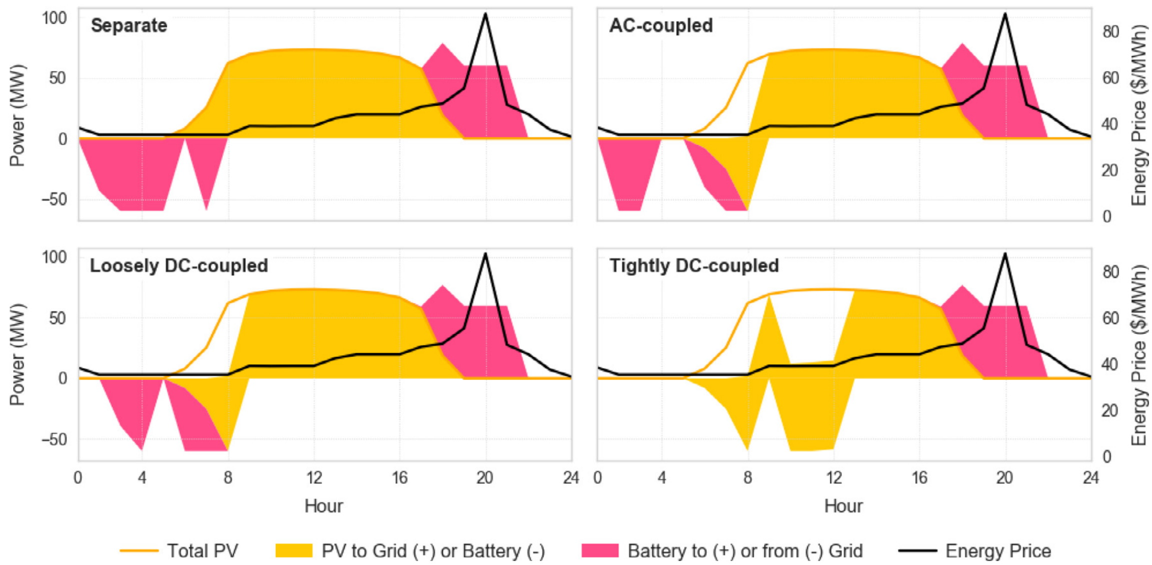

Fig. 8. Dispatch of separate and hybrid systems on a summer day in New York in 2030.

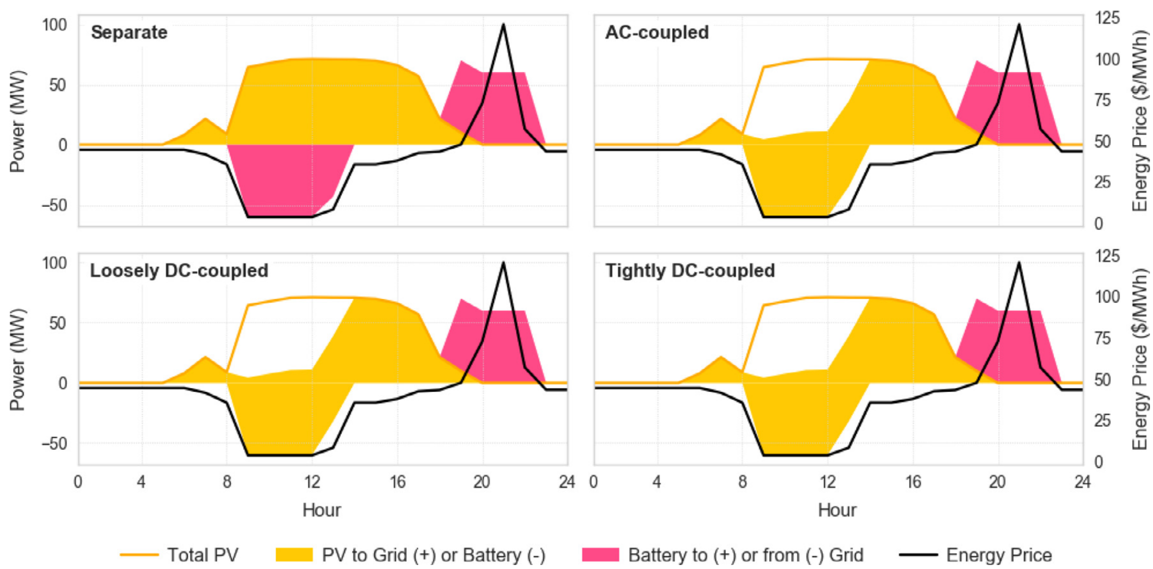

Fig. 9. Dispatch of separate and hybrid systems on a summer day in California in 2050.

The DC-coupled systems' ability to capture clipped energy has a negligible impact on energy value. In each region, total DC PV generation is 2.0–2.2% lower than total AC PV generation. However, most of that difference is a result of the PV inverter loss of 2.0%, which cannot be captured by the battery, and any PV generation that is actually in excess of the inverter capacity (not a result of inverter losses), goes through a battery with roundtrip efficiency of less than 90%. Therefore, the clipped energy that can actually be captured by the battery is significantly less than 2%. When all three PV-plus-battery systems operate similarly, the DC-coupled systems' ability to avoid clipping and higher battery roundtrip efficiency increase the net energy value by about 0.5% or less compared to AC-coupled systems (see Supplemental Information). However, the ILR for the configurations we analyzed is designed to lower inverter costs with minimal clipping for standalone PV systems. DC-coupled systems with higher ILRs would see greater benefit from avoided clipping.

In summary, AC-coupled systems and separate PV and battery systems provide more benefit to the power system than DC-coupled systems when it is valuable to discharge the battery when PV generation is high, and AC-coupled and loosely DC-coupled systems provide more benefit than tightly DC-coupled systems when the battery can provide more value by charging when there is no PV generation (e.g., to capture nighttime wind generation for morning peak net loads). Ultimately, with high PV penetration, the coupling type used for a PV-plus-battery system *with an ILR of 1.3* plays a minor role in in the system's net energy value. The fact that the PV-plus-battery systems will eventually converge in value is independent of region—it happens because higher PV penetration decreases marginal PV value. But the timing of the convergence does depend on the region because PV deployment over time depends on economic factors, particularly solar resource and policy drivers.

3.2. Capacity value

As shown in Fig. 11, as the capacity credit of stand-alone PV approaches zero with increasing PV penetration, the firm capacity of a PV-plus-battery system approaches that of the battery. In other words, the battery alone contributes to the PV-plus-battery system's firm capacity based on its ability to discharge during peak net load

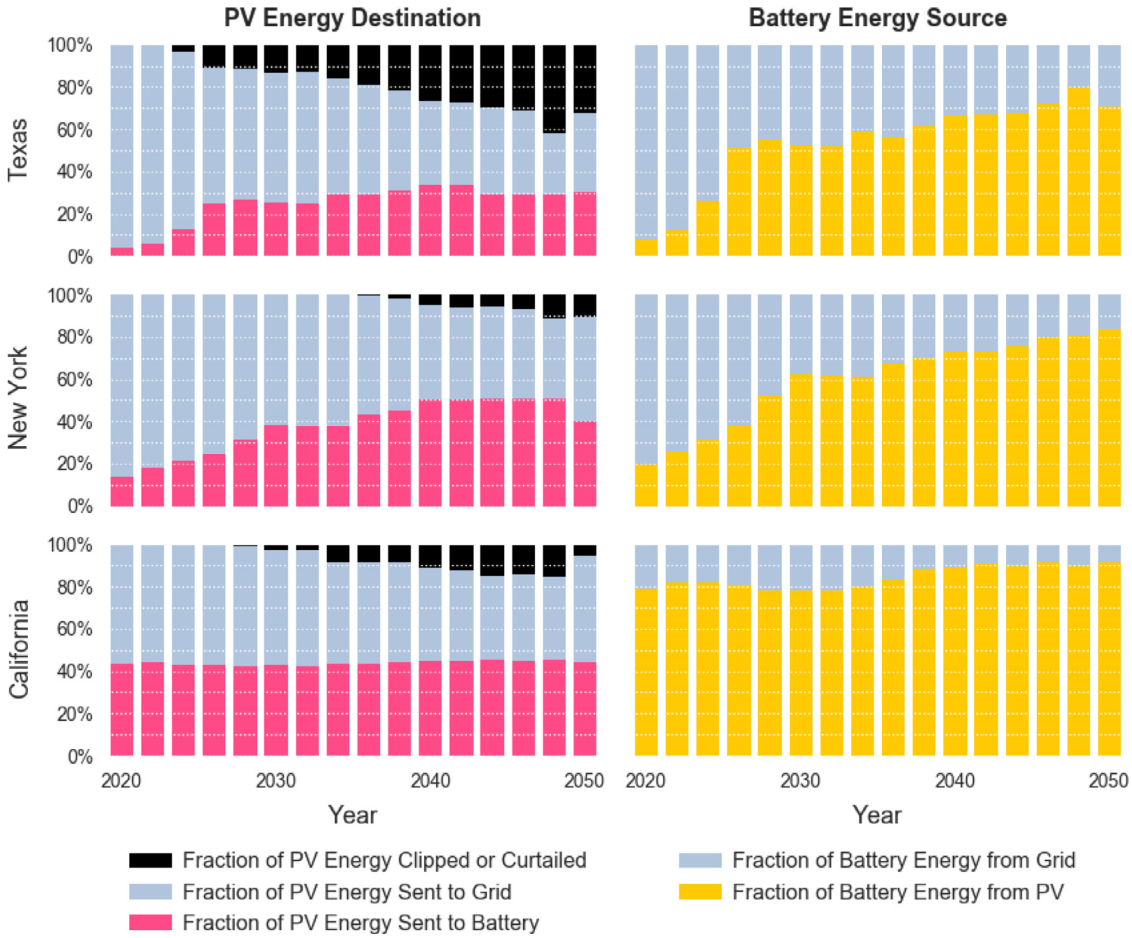

Fig. 10. Fraction of PV generation sold directly to the grid (left) and fraction of battery's energy from the PV array (right) for loosely DC-coupled systems.

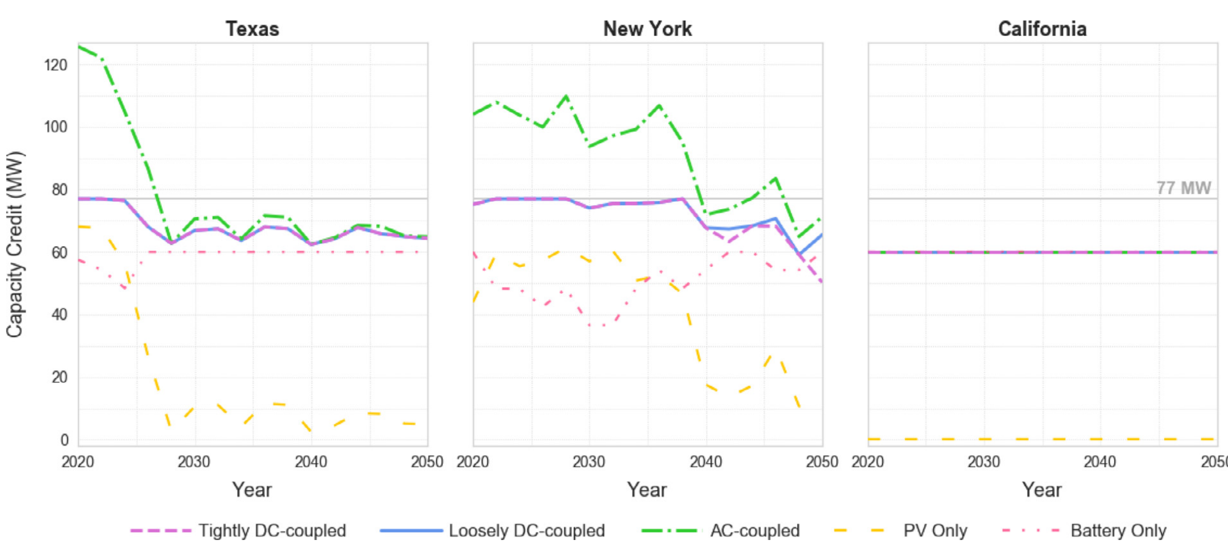

Fig. 11. Capacity credit of each hybrid system.

hours, regardless of whether the energy used to charge it comes from the grid or the attached PV array. In California, PV-plus-battery systems and standalone battery systems have the same capacity credit for all modeled years because additional PV consistently has a capacity credit of zero. However, the battery's inability to charge from the grid in the tightly DC-coupled system can prevent it from charging in preparation for low-solar hours with high net loads, reducing the PV-plus-battery system's total capacity value (e.g., New York in 2050).

The oscillations in New York for stand-alone PV and AC-coupled systems demonstrate the importance of considering all the factors that influence how the entire bulk power system might evolve. For example, renewable and clean energy policies simulated in this scenario result in a large increase in PV capacity in 2040 [52], driving the capacity credit

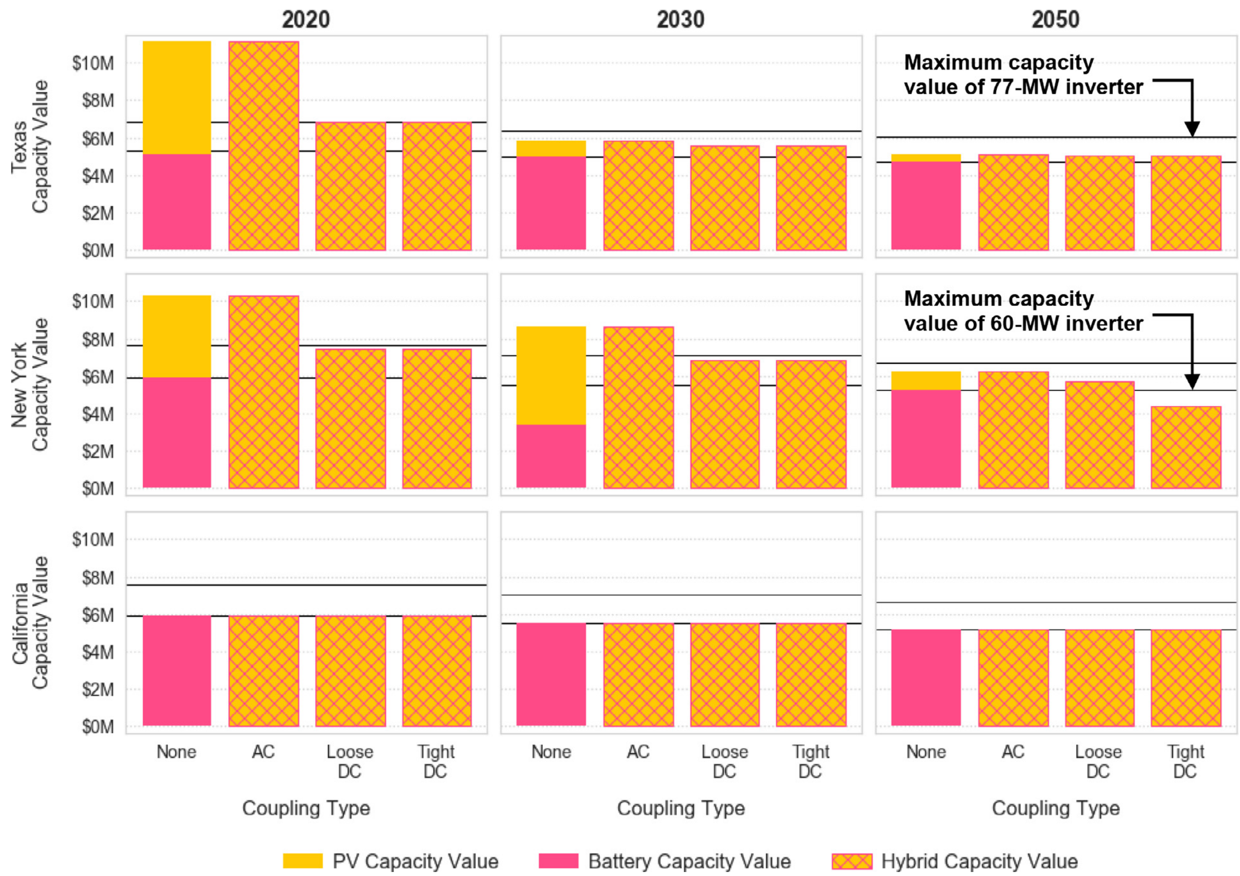

Fig. 12. Capacity value of separate (coupling type "None") and hybrid systems, compared to maximum possible capacity values for stand-alone PV or shared bidirectional inverter (77 MW, top line) and stand-alone battery inverter (60 MW, bottom line).

of PV down. Then, demand growth, with negligible accompanying capacity growth, causes the capacity credit to rebound slightly after 2042. Finally, the retirement of 1 GW of nuclear capacity prompts deployment of 3 GW of PV capacity in 2048, driving PV capacity credit back down.

Fig. 12 shows how the capacity credit translates to the capacity value of stand-alone and hybrid systems for the years 2020, 2030, and 2050. The horizontal black lines indicate the maximum capacity value of the DC-coupled systems (77 MW, upper line) and the battery (60 MW, lower line). Because the capacity value is based on the avoided cost of new capacity, the maximum possible capacity value of a PV-plus-battery system decreases over time as the cost of new NGCT capacity decreases, but the effect on capacity value is smaller than that of the falling capacity credit.

Using the capacity factor approximation to estimate capacity credit results in the PV-plus-battery systems having firm capacity equal to the sum of the firm capacities of separate PV and battery systems. However, the shared bidirectional inverter of the DC-coupled systems limits their firm capacity to 77 MW, even if the separate systems have more total firm capacity. In Texas in 2020, for example, the DC-coupled systems' capacity value is about $4 million lower than that of the AC-coupled or separate systems because of the difference in total power output capacity.

The capacity value trend over time follows the energy value trend in that the suboptimal design of certain components limits value compared to separate systems. In early years, the shared bidirectional inverter reduces the capacity value of DC-coupled systems compared to separate and AC-coupled systems. In later years, the undersized battery limits the firm capacity of PV-plus-battery systems to a maximum of 60 MW despite the total output capacity of 137 MW for the AC-coupled system and 77 MW for the DC-coupled systems. As PV penetration increases and suppresses the capacity value of stand-alone PV systems, the optimal PV-plus-battery system configuration will have a larger battery capacity relative to the PV array capacity.

3.3. Total value

Considering Figs. 6 and 12 together, the total value of each PV-plus-battery system decreases over time, which is consistent with the finding in [48] that PV-plus-battery system value declines with increasing PV penetration. However, at least some of the decline in total value is a result of suboptimal component sizing, particularly of the battery power capacity and duration, and not limitations inherent to coupling. In particular, a comparison of Fig. 11 and Fig. 13 shows that the largest fluctuations in normalized value coincide with the large fluctuations in capacity credit, which are driven largely by the total output capacity difference between separate or AC-coupled systems and DC-coupled systems. Smaller fluctuations are a result of changing energy value, as shown in California, where the capacity credit of each system remains constant from 2020 to 2050. These results point to the need for optimal PV-plus-battery system design that accounts for evolving economic and bulk power system conditions.

The decline in capacity value is not as large as the decline in energy value, so capacity value contributes an increasing portion of the total value over time. Consequently, the method of determining capacity value—both the capacity credit approximation and the translation of firm capacity to dollar value—becomes more important. Our results of the high capacity credit of four-hour storage are consistent with the literature in almost every year, given the high PV penetration [84]. However, each area sees a dramatic increase in storage deployment in 2050 that could reduce the accuracy of our approximation.

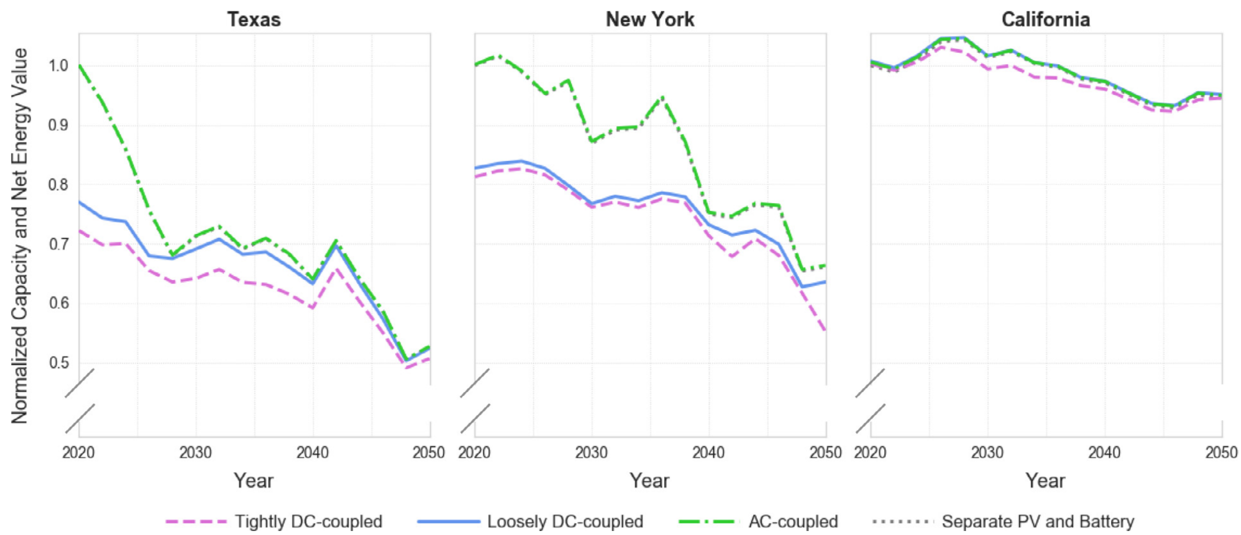

Fig. 13. Combined capacity value and net energy value of hybrid systems, normalized relative to the 2020 combined capacity value and net energy value of separate systems.

According to [93], the capacity factor during the 10 hours with the highest net load provides a good approximation of capacity credit because PV capacity credit is "highly sensitive to the most critical hours of the year, due to strong correlation between loads and generation. Adding more hours to the calculation reduces the approximated capacity value, biasing the result" [93]. As PV penetration increases, the correlation between PV generation and net load decreases, so the 10 highest-net-load hours might not provide the best estimate. More research is needed to understand how the accuracy of the capacity factor approximation changes with increased PV and battery penetration.

Additionally, our translation of capacity credit to capacity value requires assumptions about which technology is being avoided and the appropriate amortization period for new capacity of that technology. We assumed NGCT capacity was avoided and the amortization period was 20 years, which is consistent with several ISOs in the United States, including PJM [60], Midcontinent ISO [61], ISO New England, and New York ISO [62]. When we assume a higher cost of avoided capacity, we find increased capacity value for each PV-plus-battery system (see Supplemental Information). The value increase is greater for AC-coupled systems—at lower PV penetration levels—because of their higher capacity credit.

3.4. Benefit-cost ratio

Fig. 14 shows the evolution of the BCRs of stand-alone PV and battery systems through 2050 (top row) and the change in BCR for each PV-plus-battery system relative to the combined BCRs of separate systems (bottom row). Combining PV and battery systems (dotted black line), with no cost savings, results in an averaging of the BCRs of stand-alone systems, which reduces its volatility relative to stand-alone systems. BCRs, like the normalized values in Fig. 13, are very sensitive to changes in capacity credit.

The BCRs of the PV-plus-battery systems generally follow the same trends as the BCRs of the combined separate PV and battery systems because coupling the systems—without changing component sizes—does not increase total value. Therefore, any increase in the BCR of a PV-plus-battery system over combined separate systems in a given year is driven primarily by reductions in annual capacity costs resulting from shared equipment, materials, labor, and infrastructure as well as the ITC's applicability to the battery. These cost reductions are greatest for tightly DC-coupled systems because of the battery's full ITC eligibility and, before the ITC stepdown, are large enough to give tightly DC-coupled systems higher BCRs than loosely DC-coupled systems. On the other hand, a decrease in the BCR of a PV-plus-battery system relative to combined separate systems is a result of lost value resulting from the operational constraints associated with a shared inverter. Furthermore, increases in BCRs over time are driven entirely by the declining annual capacity costs shown in Fig. 5.

Of the PV-plus-battery systems we studied, no coupling type has the highest BCR in every region, especially in the near term. AC-coupled systems have higher BCRs than DC-coupled systems when the added value achieved by having separate inverters is greater than the increase in cost associated with the additional inverter. DC-coupled systems have higher BCRs than AC-coupled systems when stand-alone PV has little or no capacity value and low energy value because the shared inverter reduces costs without limiting value. In the long term, because the PV-plus-battery systems in this analysis converge to the same dispatch behavior and value as PV penetration increases, the most cost-effective PV-plus-battery system is likely the one with the lowest cost.

Since the net-economic performance of PV-plus-battery systems relative to each other and to separate systems is more dependent on costs than on performance differences (i.e., higher efficiency and clipped energy capture, which had minimal effect in this analysis), it is important to understand the range of factors that contribute to uncertainty in cost estimates. Transmission interconnection costs can be highly variable, and long wait times can result in large opportunity costs resulting from delayed operation [94]. A higher cost per interconnection capacity in this analysis would have a greater effect on AC-coupled systems because of their higher total power rating, improving the relative cost-effectiveness of DC-coupled systems. Similarly, prohibiting grid charging of the battery could lower interconnection costs by avoiding extensive load interconnection studies that might be required if grid charging is allowed [94], which would improve the cost-effectiveness of tightly coupled systems compared to loosely coupled systems. In the California ISO, batteries can be added to generators behind the point of interconnection through a simpler modification process that can allow battery operation a year or more earlier compared to a stand-alone battery system that would have to go through the full interconnection process [95].

Another uncertain cost is that of the bidirectional inverter. We chose a cost of \$0.08/W (in 2019) based on the estimate in [5] for a simple bidirectional inverter adapted from PV inverter architectures, but the same reference notes that bidirectional inverter costs can be as high as \$0.30/W for "premium, custom-built products from top-tier manufacturers." A higher bidirectional inverter cost in this analysis would

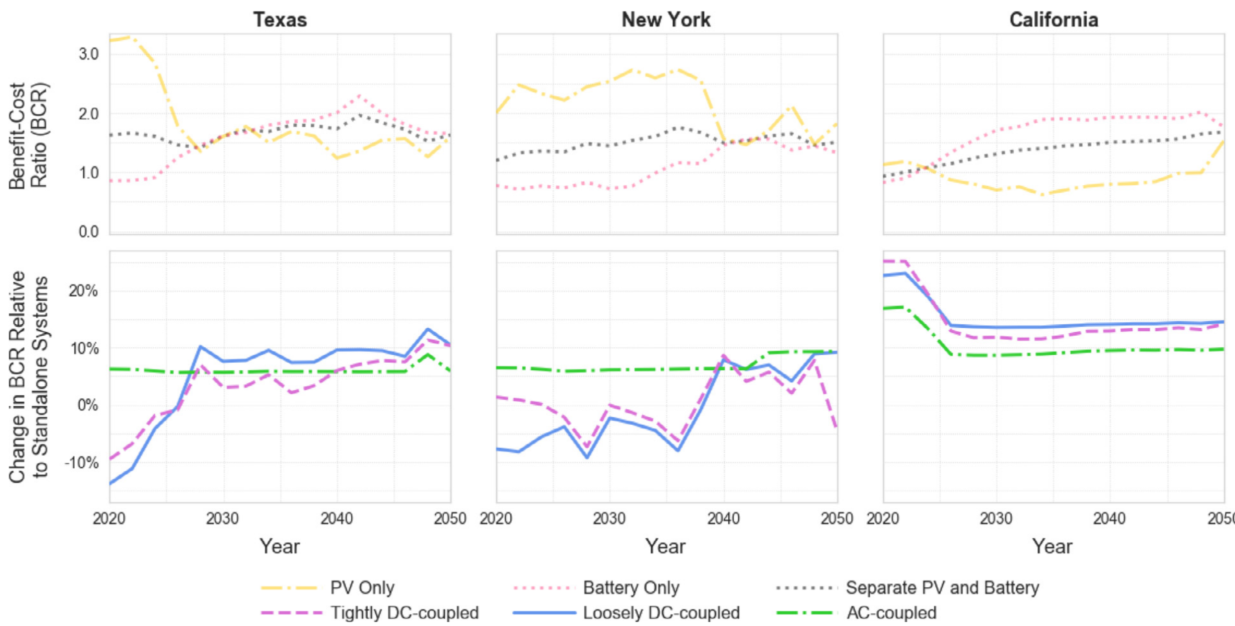

Fig. 14. BCRs of separate PV and battery systems (top) and changes in hybrid system BCRs relative to combined separate systems (bottom).

have a greater effect on the DC-coupled systems, which have a 77-MW bidirectional inverter, while AC-coupled systems have a 60-MW bidirectional inverter. Furthermore, we assumed that the tightly DC-coupled systems have a bidirectional inverter because the restrictions on how much energy the battery must charge from the PV for ITC eligibility last for only five years (compared to inverter lifetimes of 10–20 years [96]). A higher premium on bidirectional inverter costs might make it more cost-effective to invest in a PV inverter initially and wait for bidirectional inverter costs to fall before replacing the inverter.

Finally, it is important to note that the values and, therefore, BCRs reported in this analysis do not reflect that PV-plus-battery system capacity that is being added now and will continue being added to the bulk power system will affect the operation and value of new PV-plus-battery systems. Based on previous analyses of stand-alone PV (e.g., [97,98]) and stand-alone storage (e.g., [99,100]) systems, it is reasonable to assume that existing PV-plus-battery system capacity will reduce the marginal value of new PV-plus-battery system capacity. Furthermore, while this analysis compares different PV-plus-battery systems to each other and to separate systems, it does not address how these systems will compete with other generation technologies or how other generators' roles might change in response to increased PV-plus-battery system deployment (e.g., the analysis done in [65]). For these types of questions, other modeling tools, such as production cost or capacity expansion models, are required.

4. Conclusion

In this analysis, we used a price-taker dispatch optimization to determine how the energy and capacity values of PV-plus-battery hybrid system architectures evolve over time in areas with varying levels of solar resource and penetration of variable renewable energy and battery technologies. Increases in PV, wind, and battery penetration shift the magnitude and timing of marginal energy prices and peak net loads, so the marginal value of additional PV and battery capacity is very sensitive to grid conditions.

The PV-plus-battery system with the highest benefit-cost ratio differs by region, depending on solar resource and how electricity price patterns and magnitudes are affected by grid conditions. Generally, AC-coupled systems can provide more benefit if it is valuable to discharge the battery simultaneously with PV generation, and loosely coupled systems can provide more benefit if the battery provides higher value by charging during hours with no PV generation. However, as PV penetration increases, the PV-plus-battery systems converge in value: their capacity value converges to the battery's capacity value, and their energy value converges toward that of tightly DC-coupled systems. This convergence in value happens because a growing fraction of the coupled PV energy is sent to the battery instead of the grid.

However, hybridizing PV and battery systems—without optimizing component sizing—does not offer more energy or capacity value than separate PV and battery systems and can reduce value if the systems are not appropriately configured. The primary benefit of coupling is the reduction in annual costs because of shared equipment, materials, labor, and infrastructure.

Additional analysis could reveal greater insights into PV-plus-battery hybrid system design and value. For example, our analysis did not consider the impact of battery size or inverter loading ratio, which could change the value proposition for DC-coupled systems. Furthermore, we did not evaluate how assumptions or constraints for the battery dispatch algorithm affect value. For questions regarding how PV-plus-battery system deployment might affect the marginal value of new PV-plus-battery systems or how these systems will compete with and affect the operations of other generators, particularly natural gas combustion turbine and/or combined cycle generators, production cost modeling, capacity expansion modeling, or other types of equilibrium modeling tools are necessary. As the role of PV-plus-battery hybrid systems in the bulk power system continues to grow, it will be increasingly important to understand the impact of design parameters on economic performance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Datasets related to this article can be found at https://cambium.nrel.gov/ [55], https://atb.nrel.gov/electricity/2019/data.html [101], and https://openei.org/apps/reeds/ [53], hosted at the National Renewable Energy Laboratory.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.adapen.2021.100015.

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