Evaluating the Interactions Between Variable Renewable Energy and Diurnal Storage

Nathaniel Gates, Wesley Cole, A. Will Frazier, and Pieter Gagnon

National Renewable Energy Laboratory

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Abstract

Cost reductions and policy support have led to rapid deployment of solar photovoltaic (PV), wind, and diurnal storage technologies in the United States. This deployment is expected to continue. In this work, we enhance a national-scale capacity expansion model to evaluate the interactions between PV, wind, and diurnal storage and examine how they affect the U.S. power system evolution through 2050. Our least-cost optimization framework captures investments with greater fidelity by evaluating storage and variable renewable energy operations for all hours of the year. We identify significant synergies between diurnal storage and PV, and to a lesser extent, wind. Modeled power system scenarios that result in more PV always have higher storage deployment, and scenarios that result in more storage always have higher PV deployment. This synergy is largely due to the diurnal alignment of PV generation with 4-hour to 8-hour storage, and to the ability of PV to narrow system peaks and allow shorter-duration storage to serve as a peaking resource. Interactions between storage and wind, which does not exhibit the same diurnal generation pattern as PV, are less pronounced, though we do observe that longer-duration storage resources appear to provide greater value for wind.

Table of Contents

List of Figures

List of Tables

1 Introduction

Over the past decade, cost reductions and policy support have led to increased deployment of wind and solar photovoltaic (PV) systems in the United States (Barbose et al. 2016; Bolinger, Seel, and Robson 2019; Wiser and Bolinger 2019). Wind and PV are anticipated to continue to play an increasingly larger role in the power system (BNEF 2019; IEA 2019; EIA 2020a; Cole, Corcoran, et al. 2020). With that assumption, improved understanding of systems with higher penetrations of variable renewable energy (VRE) is important, particularly considering the system requirements associated with VRE integration (Denholm and Hand 2011).

Because the output from wind and PV generators is both variable and uncertain (Cole et al. 2017), the challenge of integrating VRE grows with their penetration. That relationship means the value of flexibility grows in a power system along with the penetration of VRE (Denholm and Hand 2011; McPherson and Tahseen 2018; Denholm et al. 2016). Grid flexibility can be achieved in many ways, including from demand-side resources such as heating or electric vehicles (Schuller, Flath, and Gottwalt 2015; Bloess, Schill, and Zerrahn 2018), transmission (Schaber et al. 2012), VRE participation in grid services (Loutan et al. 2017; P. L. Denholm, Sun, and Mai 2019), changes to system operation (Bird and Milligan 2012), and energy storage (Denholm and Hand 2011; McPherson and Tahseen 2018). With recent cost declines in diurnal storage (Nykvist and Nilsson 2015) that are projected to continue (Schmidt et al. 2019; Cole and Frazier 2020), diurnal storage has an increasing potential to become a key source of grid flexibility.

In this work we are particularly interested in the capturing the interaction of VRE and storage in models that represent interconnect-wide or multi-interconnect electricity systems. These models tend to be sufficiently large that the high-resolution chronological temporal resolution needed for storage is not possible within the traditional optimization framework. In the U.S., models such as the National Energy Modeling System (NEMS) (EIA 2020b) and the Integrated Planning Model (IPM) (EPA 2020) are regularly used for national-scale analyses such as the Annual Energy Outlook (EIA 2020a). These models have shown an increasingly large fraction of VRE and storage in their reference case projections over the past several years (Cole, Gates, and Mai 2021), which has increased the need to understand how VRE and storage might interact in these large-scale models.

We aim to improve understanding of how diurnal storage impacts large-scale power system evolution, particularly in futures with higher penetrations of VRE. We focus on the interaction of diurnal storage with wind and PV, and how these interactions differ from each other. Specifically, using a national-scale electric sector long-term planning model we evaluate how more deployment of wind, PV, or diurnal storage changes system build-out and operation through 2050. Prior work indicates that PV and storage can be synergistic (Denholm and Margolis 2016; Cole, Frew, et al. 2018; Frew et al. 2019; Mallapragada, Sepulveda, and Jenkins 2020), but the drivers of that relationship have not been fully investigated. Synergies with wind are less clear because much of the work exploring wind-storage benefits was done before the price declines of batteries were realized (Zhao et al. 2015).

Conducting this analysis at a national scale required enhancements to a national-scale capacity expansion model in order to capture the interactions of storage with wind and PV, as well as to more accurately capture the energy arbitrage value of storage (Davies et al. 2019; Brijs et al. 2019). For example, Mallapragada et al. (2020) find use representative regions with a high temporal resolution model to find that storage value changes based on the relative mix of wind and solar. We aim to extend that kind of modeling capability and analysis to a national-scale modeling platform. In the methods section, we describe how adjustments were made to allow for chronological, hourly representation of wind, PV, and diurnal storage within a national-scale model. We then discuss the scenario design used to examine the PV-wind-storage interactions, and finally we present results and discussion.

The novel contributions of this work are to 1) demonstrate a method to represent high resolution modeling of storage capabilities within a national-scale capacity expansion model and 2) analyze the relationship of wind and PV with new diurnal storage deployment.

2 Methods

2.1 Modeling Overview

To investigate the relationships between PV, wind, and diurnal storage, we added new capabilities to the Regional Energy Deployment System (ReEDS) model. ReEDS is a capacity expansion model that projects power system investment and operation through 2050 for the conterminous United States (Brown et al. 2020). It is a linear optimization model that uses a system-wide perspective to minimize total electricity sector system costs. The model is constrained to ensure physical limits, resource limits, and policy requirements are respected. The model includes 134 electricity supply-demand balancing areas and 356 wind resource regions, providing high spatial resolution that is important to adequately capture the behavior of PV, wind, and other resources (Krishnan and Cole 2016). Additionally, each balancing area and resource region has multiple technology and resource classes, which further improves the model fidelity. ReEDS models the following VRE and storage technologies: land-based and offshore wind, utility scale and residential rooftop PV, battery storage with durations of 2, 4, 6, 8, and 10 hours, and pumped-storage hydropower (PSH), which is assumed to have a duration of 12 hours.

Several aspects of ReEDS allow the interactions between wind, PV, and diurnal storage to be resolved. ReEDS includes high-resolution resource supply curves and resource profiles. These enable the model to represent regional variations between VRE resources, where these variations include differences in capital costs, grid capture connection costs, and production profiles which can influence an option's value to the grid. ReEDS also represents transmission, including allowing for new transmission investment along existing corridors. It captures challenges related to increasing penetrations of VRE, including VRE curtailment, declining capacity credit (where capacity credit is defined as the fraction of capacity that contributes to the planning reserve margin, i.e., "firm capacity") with increased VRE penetration, and the need to hold additional operating reserves as VRE penetration grows. And recently, detailed storage capacity credit calculations that use hourly data and respect chronology have been added to ReEDS (Frazier et al. 2020), and the data set for capacity credit calculations has been expanded from one to seven meteorological years (Cole, Greer, et al. 2020), increasing the capacity credit accuracy.

In this work, we extend these capabilities to better represent energy arbitrage and curtailment avoidance of storage. Historically, ReEDS has evaluated storage arbitrage at its native temporal resolution of 17 time-slices, where those time-slices are comprised of four chronological time periods representing an average day in each season plus a summer peak period. This resolution has limited ability to model the energy arbitrage value provided by storage as intra-time-slice price variability was not adequately captured. Additionally, the ability of storage to avoid curtailment was represented using a parameterization of independent production cost modeling scenarios. This work improves the model's ability to represent both energy arbitrage and curtailment avoidance of storage and adds an estimate of curtailment avoidance from new transmission.

To better capture energy arbitrage and curtailment avoidance values, we built a module that operates between each year solved by ReEDS. For example, after ReEDS solves for the 2022 build-out, we run the module to calculate parameters that will be used for the next year that is to be solved by ReEDS. The parameters need to be updated before each solve because they are sensitive to system conditions such as load shape, PV penetration, and wind penetration. The module first solves a simplified dispatch model for the 134 regions over one year, simultaneously optimizing generation, transmission, and storage behavior at an hourly time resolution. The dispatch model provides hourly energy prices, transmission flows, storage operation, and conventional generation operation for each region. The dispatch model outputs are adjusted to account for start costs and minimum generation levels to provide more realistic pricing and generation levels. The hourly prices are then used to calculate the arbitrage value for new storage resources. The transmission flows, storage operation, and generation values are used to calculate both the curtailment of VRE resources and the potential for new storage to avoid that curtailment. Both the arbitrage value and curtailment rates are then passed into the core ReEDS optimization to inform the next solve year. The module provides the hourly granularity and chronology that allows for better valuation of storage resources. Additional details about the module, which we call the ReEDS Augur, are provided in the appendix.

2.2 Scenario Design

The scenarios used in the work are summarized in Table 1. They were selected to cover a range of outcomes across the space of PV, wind, and storage deployment. We chose to use cost sensitivities to explore alternative future deployment rather than prescribe exogenous deployment levels in order to avoid interfering with fundamental economic competition captured within the model. However, because we also wished to examine scenarios with high penetrations of renewable energy (RE), we ran the nine scenarios in Table 1 twice: once as is and once with an 80% RE generation requirement by 2050. This RE requirement was ramped linearly from 20% in 2020 to 80% in 2050 and was applied at the national level. The RE requirement scenarios provide a perspective where the RE penetration level is fixed; therefore, storage will change the mix of RE but not the amount.

Table 1. Scenarios Used in this Work. Each of these nine scenarios was run twice: once as is and once with a requirement of 80% RE generation by 2050.

Scenarios are run as is and with an 80% RE requirement by 2050.		**VRE Cost Assumptions**		
		Low PV Cost	**Reference PV/Wind Cost**	**Low Wind Cost**
Storage Assumptions	**Low Battery Cost**	Low Battery Cost + Low PV Cost	Low Battery Cost	Low Battery Cost + Low Wind Cost
	Reference Battery Cost	Low PV Cost	Mid-case	Low Wind Cost
	No New Storage	No New Storage + Low PV Cost	No New Storage	No New Storage + Low Wind Cost

The scenarios include reference and low-cost sensitivities on PV, wind, and battery technologies. The No New Storage scenarios are artificial but provide a counterfactual to understanding system evolution when additional storage is not allowed to be part of that evolution. In these scenarios, all existing storage (including nearly 23 GW of PSH) is included, but no new storage is allowed.

The capital costs for storage, utility-scale PV, and land-based wind that are used for the scenarios in Table 1 are taken directly from the 2020 Annual Technology Baseline (NREL 2020) and are shown in Figure 1. The Low Wind Cost scenarios also have lower costs for offshore wind. Capital costs for all other resource types did not vary for any other technology type, including PSH. Financing costs are also taken from the 2020 Annual Technology Baseline and are kept constant across all scenarios.

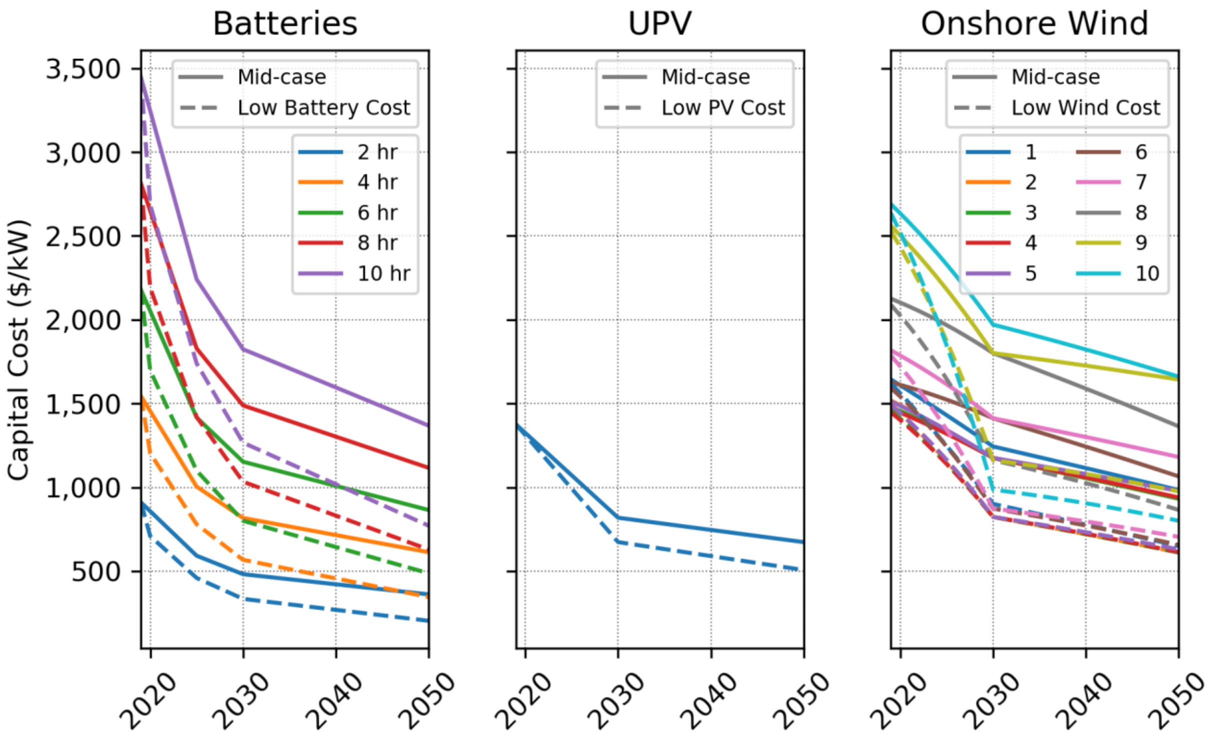

Figure 1. Capital costs for storage, utility-scale PV (UPV) and land-based wind used in these scenarios (NREL 2020). These values are adjusted within the model based on regional capital cost multipliers (Brown et al. 2020). The wind values show the 10 resource classes modeled. Values are in 2018$.

In addition to lower capital costs, the low-cost scenarios have lower fixed operation and maintenance costs. For PV and wind, the low-cost scenarios include performance improvements beyond those in the Mid-case. These performance improvements are represented within the model by capacity factor increases over time.

Other scenario assumptions are consistent with the default values used by the ReEDS model in the 2020 Standard Scenarios (Cole, Corcoran, et al. 2020) and are described in the ReEDS model documentation (Brown et al. 2020). The scenarios include state and federal policies that were in place as of June 30, 2020. Key assumptions, including fuel prices and demand growth, are provided in the appendix.

3 Results

3.1 Deployment Results

The Mid-case scenario results in a 2050 power system with 707 GW of PV, 284 GW of wind, and 215 GW of storage, with a fleet-wide average storage duration of 5.3 hours (see Figure 2). This scenario is used as the basis for comparison to understand the interactions of storage and VRE.

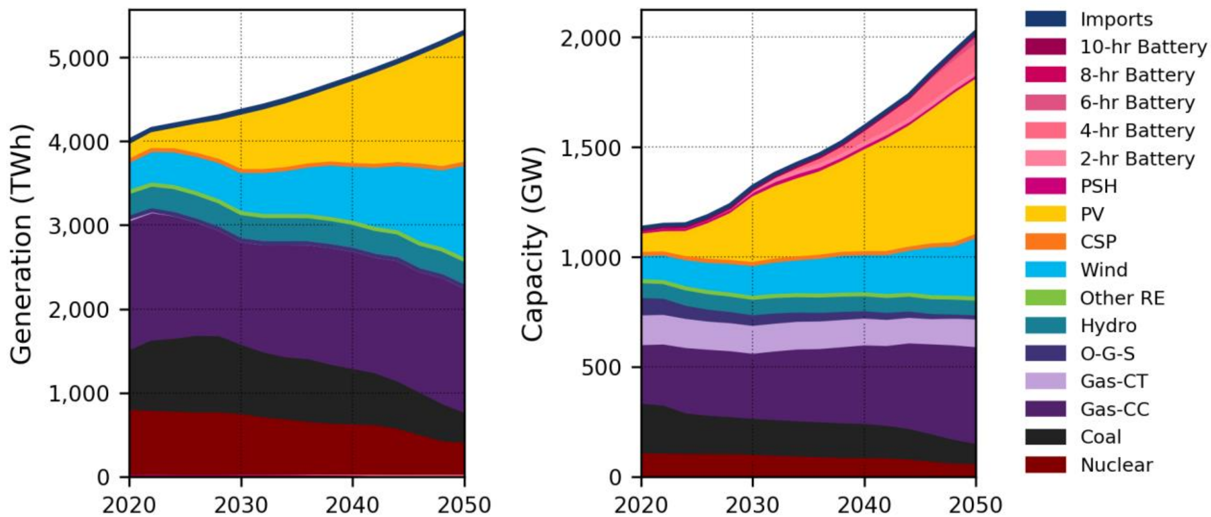

Figure 2. Generation (left) and capacity (right) by technology in the Mid-case scenario. PV includes UPV, distributed UPV, and distributed PV technologies. Wind includes land-based and offshore wind technologies. Other RE includes biopower, geothermal, and landfill gas technologies. CSP is concentrating solar power, O-G-S is oil and/or gas steam, Gas-CT is natural gas combustion turbine and Gas-CC is natural gas combined cycle generation technology.

Figure 3 shows the capacity difference relative to the Mid-case scenario across the scenarios with no RE requirement and highlights many important interactions between system build-out and storage. We consider those differences here by looking at Figure 3, first across the rows (groups of battery cost sensitivities) and then the columns (groups of PV/wind cost sensitivities).

Looking across the first two rows, storage deployment is always higher in the Low PV Cost scenarios than in the scenarios with reference or low wind cost. In other words, scenarios more favorable to PV deployment result in greater storage deployment for a given battery cost assumption, indicating a PV-storage synergy that we see repeated throughout our results and reported elsewhere in literature (Hartner and Permoser 2018; Denholm and Margolis 2016; Mallapragada, Sepulveda, and Jenkins 2020; Frazier et al. 2020). In the Low Wind Cost scenario with reference battery prices, storage actually decreases slightly relative to the reference case. Trade-offs with other forms of capacity are limited when only looking across the rows.

Looking down the columns, we find the same PV-storage synergy. Scenarios with lower battery costs (and therefore more battery deployment) have higher levels of PV capacity. This trend can be seen even in the low wind cost column, though the magnitude of the PV deployment change is smaller. These scenario results suggest there is a positive feedback loop between PV and storage deployment. PV capacity is higher in scenarios with more storage, and storage capacity is higher in scenarios with more PV.

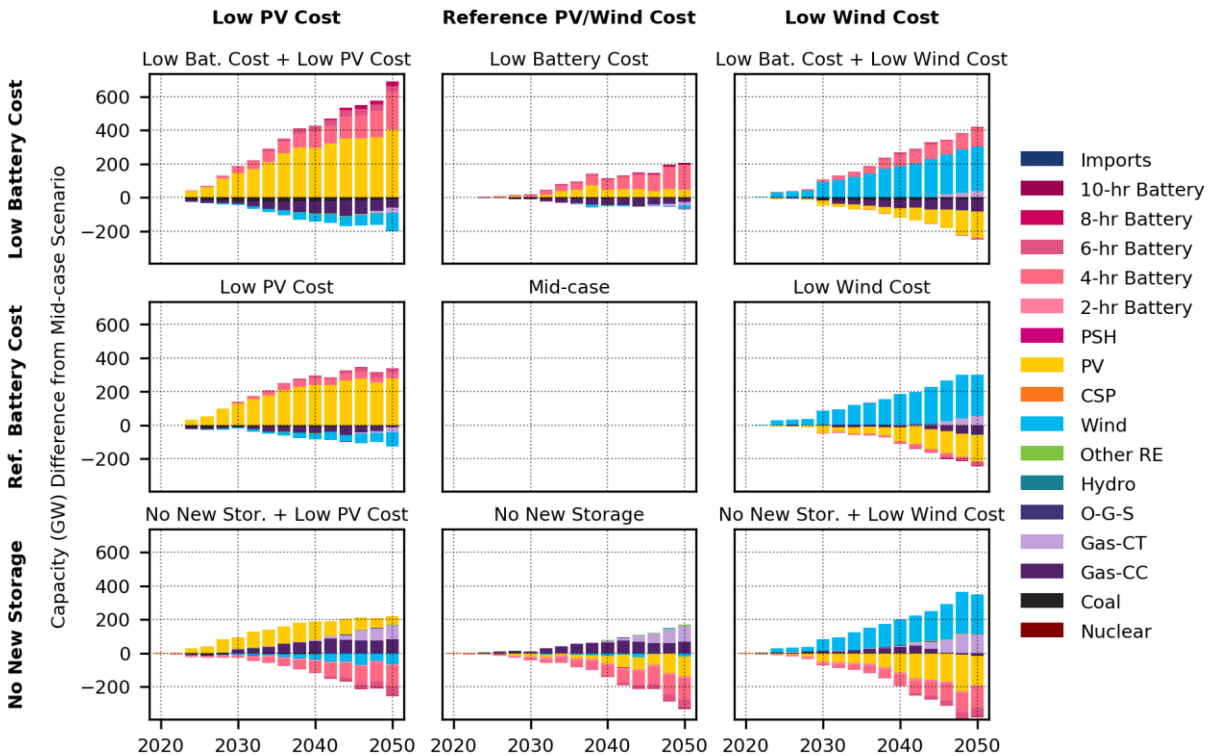

Figure 3. Capacity difference between the scenarios without an RE requirement and the Mid-case scenario. The scenario sensitivity groups are shown in bold as row and column titles.

We also see that storage deployment has a relatively moderate impact on natural gas technologies. Scenarios with less storage have more natural gas capacity, indicating a trade-off in how firm capacity is provided to the system (where firm capacity is defined as capacity that contributes to the planning reserve margin). This natural gas trade-off is less than one-to-one, such that more than 1 GW of storage is substituting for each gigawatt of natural gas capacity displaced in the alternative scenarios.

These same trends are also seen in the scenarios with an RE requirement (see Appendix Figure 25), and when looking at generation instead of capacity (see Appendix Figure 26 and Appendix Figure 27). For results presented as generation penetration values over time, see Appendix Figure 28 and Appendix Figure 29.

To provide a clearer picture of the 2050 system build-out across each scenario, Table 2 summarizes the VRE, wind and PV penetration levels as a percent of generation. The VRE penetration levels range from 43% to 73%, the wind levels from 13% to 48%, and the PV levels from 20% to 56%.

Table 2. VRE, Wind and PV Penetration Levels by Percent Generation in 2050 Across the Suite of Scenarios

Scenarios with no RE Constraint			
VRE% (wind%/PV%)	**Low PV Cost**	**Ref PV/Wind Cost**	**Low Wind Cost**
Low Battery Cost	61% (13%/48%)	51% (20%/31%)	61% (40%/21%)
Ref Battery Cost	57% (15%/42%)	50% (22%/28%)	60% (38%/21%)
No New Storage	47% (16% (31%)	43% (19%/23%)	56% (36%/20%)
Scenarios with an 80% RE Constraint			
VRE% (wind%/PV%)	**Low PV Cost**	**Ref PV/Wind Cost**	**Low Wind Cost**
Low Battery Cost	73% (17%/56%)	73% (27%/46%)	73% (47%/26%)
Ref Battery Cost	73% (24%/49%)	72% (31%/42%)	73% (47%/26%)
No New Storage	70% (34%/36%)	70% (38%/32%)	72% (48%/24%)

3.2 Storage Utilization

Storage utilization varies across the 12 scenarios that allow new storage to be built. Figure 4 shows the 2050 storage utilization in average cycles per day across these 12 scenarios (for reference, Appendix Figure 30 shows the storage deployment by duration in each scenario in 2050). This storage utilization is the capacity factor (based on generation) of the storage device divided by its duration and then multiplied by 24 hours. Across all scenarios, storage devices nearly always cycle less than once per day, on average. In the scenarios with reference battery costs and no RE requirement, storage utilization increases with duration, with PSH as an outlier. PSH has lower utilization because in ReEDS it has a lower assumed round-trip efficiency than batteries (80% versus 85%), which means batteries will be used before PSH. Also, PSH has a longer duration, which means it can move considerable amounts of energy with fewer average cycles per day.

The longer-duration resources cost more than the shorter-duration resources.1 Unless they can be utilized more than the shorter-duration resources, it will be challenging for them to realize more value to justify the higher cost. The duration-utilization relationship is strongest with low wind costs, as higher wind penetrations lead to longer-duration curtailment events (Denholm and Mai 2019). The higher utilization can come from avoiding curtailment during these longer curtailment duration events or from serving peak demand when the peaks become wider (Denholm et al. 2020).

In the scenarios with reference battery costs and an 80% RE requirement, utilization is higher for nearly all durations than in the scenarios with no RE requirement. With the RE requirement in place, avoiding curtailment becomes more valuable, and storage utilization increases to prevent more curtailment. The increasing utilization with longer-duration storage is also very strong in the Low Wind Cost scenario with an 80% RE requirement.

[1] Relative to 2-hour storage, storage devices of 4-, 6-, 8- and 10-hour durations cost more by a factor of 1.7, 2.4, 3.1, and 3.8, respectively. See the 2020 Annual Technology Baseline (NREL 2020) for more details.

The low storage cost scenarios generally have lower utilization rates than the corresponding reference storage cost scenarios. With lower-cost storage, more storage is deployed, which spreads the storage utilization opportunity across a larger amount of storage. The same would be true of other grid resources—doubling the natural gas fleet would increase overall gas generation, but the fleet-wide utilization rate of natural gas would decrease. In addition, cheaper storage can be used less and still be worth building.

Perhaps most significantly, we see that in nearly every scenario and storage duration, storage utilization is higher in the Low PV Cost scenarios than in the Low Wind Cost scenarios. This relationship demonstrates one element of why the PV-storage synergy exists. The diurnal patterns of PV generation are well-aligned with the capabilities of 2-hour to 8-hour storage (Denholm and Mai 2019), which enables storage to be more effectively utilized when coupled with PV than with wind. Similarly, we see that in the Low Wind Cost scenarios, storage utilization tends to be higher for the longer durations than for the shorter durations (even more so compared to the Low PV Cost scenarios). This trend follows the evidence that wind curtailment events tend to be longer than PV curtailment events (Denholm and Mai 2019) and are therefore better suited for longer-duration storage.

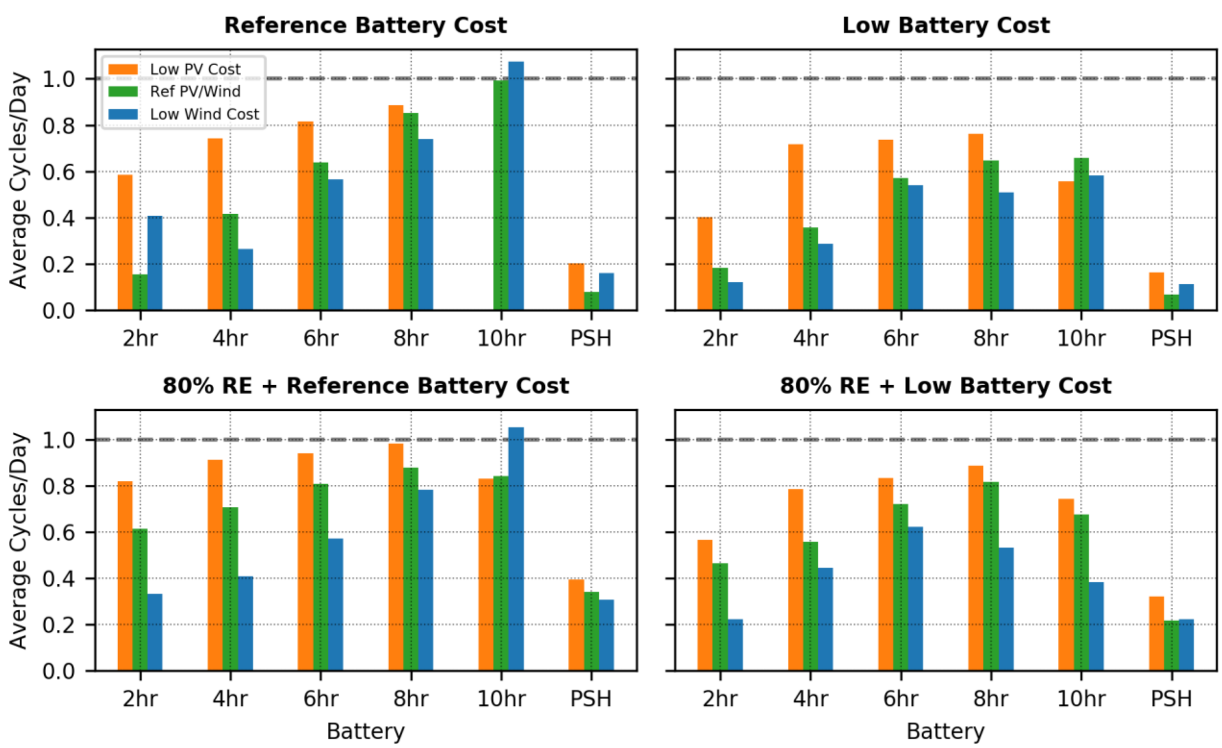

Figure 4. Storage utilization rates in annual average cycles per day in 2050 across the 12 scenarios that allow new storage. Utilization is shown by battery storage duration and for PSH. The Low PV Cost scenario does not deploy any 10-hr battery storage by 2050.

Examining the generation by time-slice (Figure 5), we see why storage utilization is higher in cases with high PV penetration. Across all three scenarios shown, storage charges during the day and discharges at night. The charging profile takes this shape because PV generation occurs exclusively during the day, whereas wind generation is spread more evenly across all periods.

Storage is being used to shift energy in time, and the higher the PV generation the more storage is used to shift PV-generated electricity from daytime hours to evening and overnight hours.

Together, storage and PV are able to displace Gas-CC generation in the Low PV Cost scenario. By contrast, in the Low Wind Cost scenario, the net Gas-CC generation remains similar to that of the Mid-case scenario, and wind generation displaces PV generation, leading to reduced storage utilization. These trends persist across each season, though they are most pronounced in the spring (which has the highest levels of curtailed energy) and the summer (which has the greatest solar resource). Increasing storage deployment by lowering the battery costs further enhances these trends (see Appendix Figure 31).

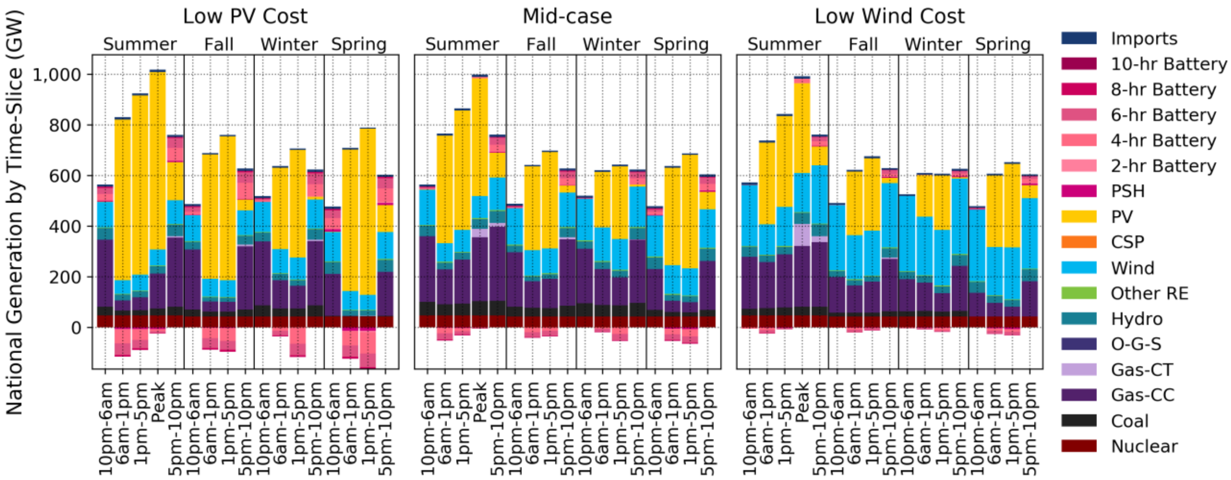

Figure 5. Generation by time-slice for the scenarios indicated. Negative storage generation indicates storage is charging. Time-slice times are in local time.

Hourly details, produced by the ReEDS Augur module, confirm these trends. Figure 6 shows hourly dispatch profiles in 2050 for the peak load, peak net load, and peak curtailment days (defined by the peak hour) across the same three scenarios examined in Figure 5. In the Low PV Cost scenario, storage charging is highest during the day, with discharging occurring primarily at night but also in the morning. The storage utilization is much less in the Mid-case scenario and especially the Low Wind cost scenario, with storage charging during the morning in both scenarios for the peak load and peak net load days. The ability of storage to avoid curtailment is highlighted in the peak curtailment days, with curtailment occurring mainly during the day in the Low PV Cost scenario and spread throughout the day in the Low Wind Cost Scenario. This highlights a trend in curtailment avoidance that will be explored later on, namely that energy storage of durations from 2-hours to 12-hours is better able to avoid curtailment caused by PV than by wind due to the difference in curtailment event duration. Finally, while the peak curtailment day occurs in the spring in all three scenarios, it is shifted earlier by nearly a month in the Low Wind Cost scenario.

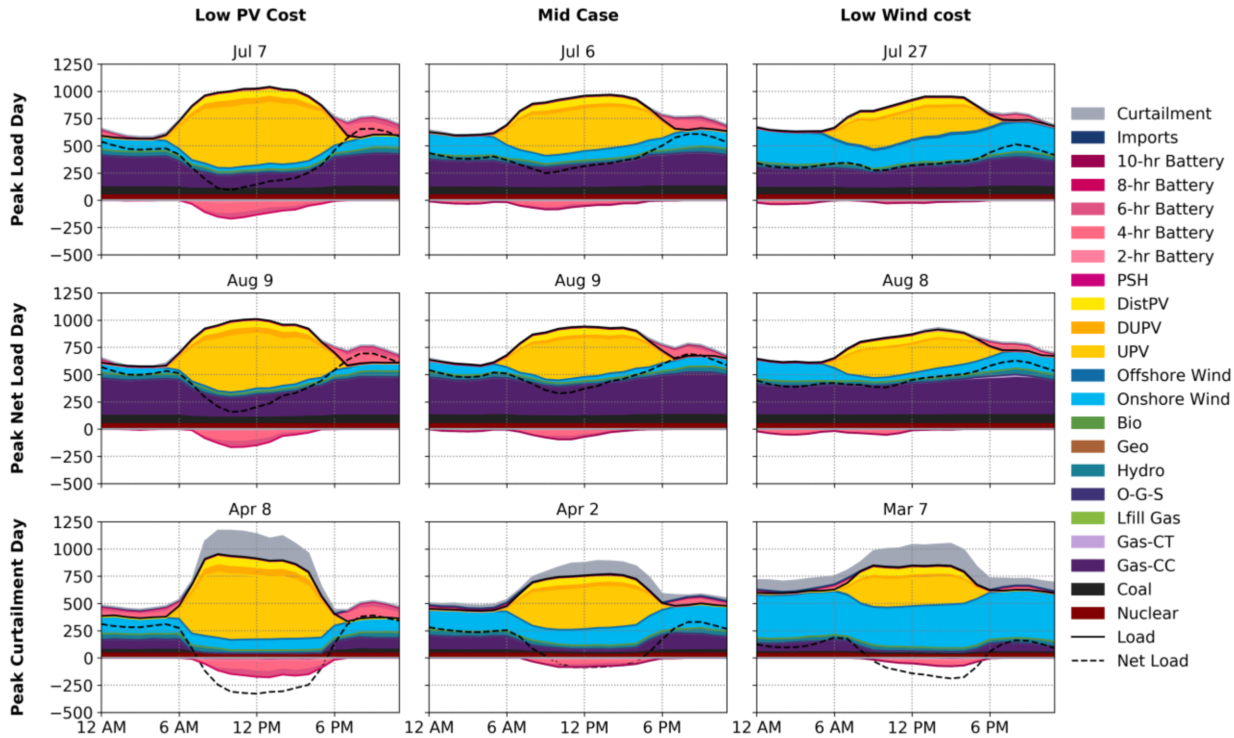

Figure 6. Dispatch results from the ReEDS Augur module for selected "peak" days in 2050 for the Low PV Cost, Mid-case, and Low Wind Cost scenarios. The technologies indicate generation, and the y-axis units are GW. Negative storage generation indicates storage is charging. Times are in Eastern Standard Time (EST).

3.3 Storage Revenue and Impact on Prices

We next consider economic summary metrics to better understand why the resulting capacity expansion decisions are made. Within our modeling framework, storage can provide capacity, energy, and operating reserve services to the national electric grid. Figure 7 shows the fraction of revenue that storage receives over time from each of these services by duration across the scenarios indicated. These revenues are computed from the storage generation and grid service prices, which prices will be shown later in the section.

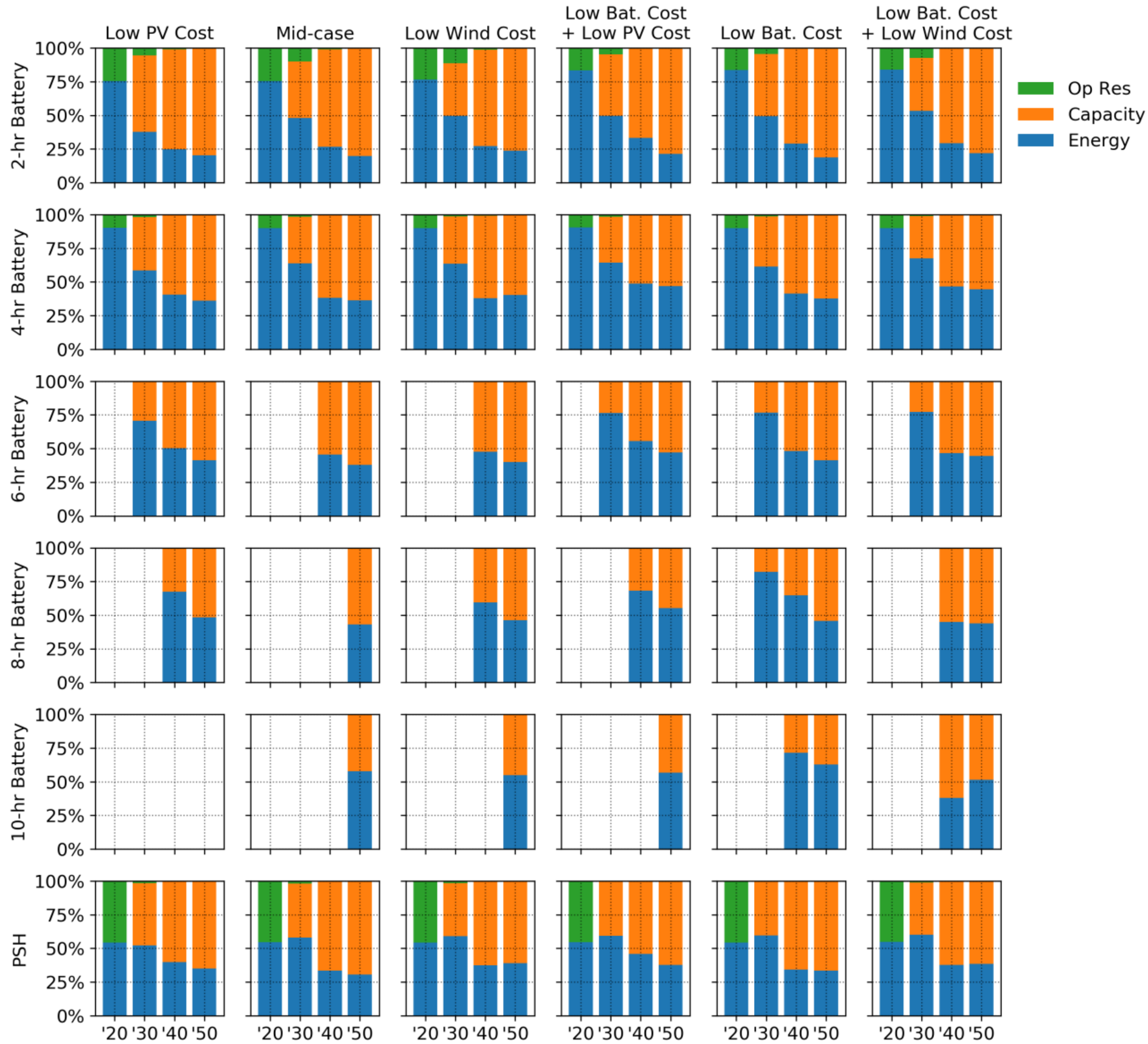

Figure 7. Fraction of storage revenue from providing operating reserves, capacity (resource adequacy for annual peak load), and energy services for the scenarios (columns) and storage durations (rows) indicated. Op Res is operating reserve. Missing revenue fractions indicate a given technology was not deployed in that year.

In 2020, capacity prices within the model are low because most regions have generation capacity that is greater than the planning reserve assumptions used in ReEDS (NERC 2018). The operating reserve fraction is highest in 2020 because the amount of storage is lower and the market for this service has not yet been saturated. The operating reserve provision is the smallest of the three value streams (Denholm, Sun, and Mai 2019); so over time, as storage deployment increases the operating reserve market becomes saturated and operating reserve prices fall. Additionally, the operating reserve provision is increasingly shared among a larger fleet of storage resources, so the relative value of providing the service is diminished.

As the storage fleet evolves over time, longer-duration storage is added, and a greater fraction of the storage value is derived from providing capacity. This shift reflects a greater need for firm capacity over time, which results in higher firm capacity prices in the model. Additionally, increased storage deployment suppresses on- and off-peak price differences, diminishing the value of energy arbitrage. Shorter-duration storage gets a greater fraction of its value from providing firm capacity in part because longer-duration storage has more energy potential. That additional energy capability is used to provide additional energy value, and it increases the share of revenue from energy services.

In the Low Battery Cost sensitivity scenarios, the share of revenue that storage gets from capacity decreases and the share from energy increases relative to the corresponding reference battery cost scenarios (see Appendix Figure 38–Figure 40 for a more granular comparison). This shift is driven by at least two factors: 1) increased storage deployment causes the capacity credit of storage to decline, making it more difficult to provide capacity services and 2) lower battery prices reduce firm capacity prices in the model, which lowers the revenue opportunity for providing capacity.

The first factor is demonstrated in Figure 8 for 4-hour storage (see Appendix Figure 32–Figure 35 for other durations). The average capacity credit of storage falls as penetration increases in all scenarios. The rate of decline depends on the amount of PV in the system, with the Low PV Cost scenarios seeing a slower decline and the Low Wind Cost scenarios seeing a more rapid decline (see Appendix Figure 28 and Appendix Figure 29 for a detailed breakdown of VRE penetration by technology across scenarios). This relationship means the exact same amount of storage receives higher capacity credit with low PV costs than it does with low wind costs, which supports the observed PV-storage synergy.

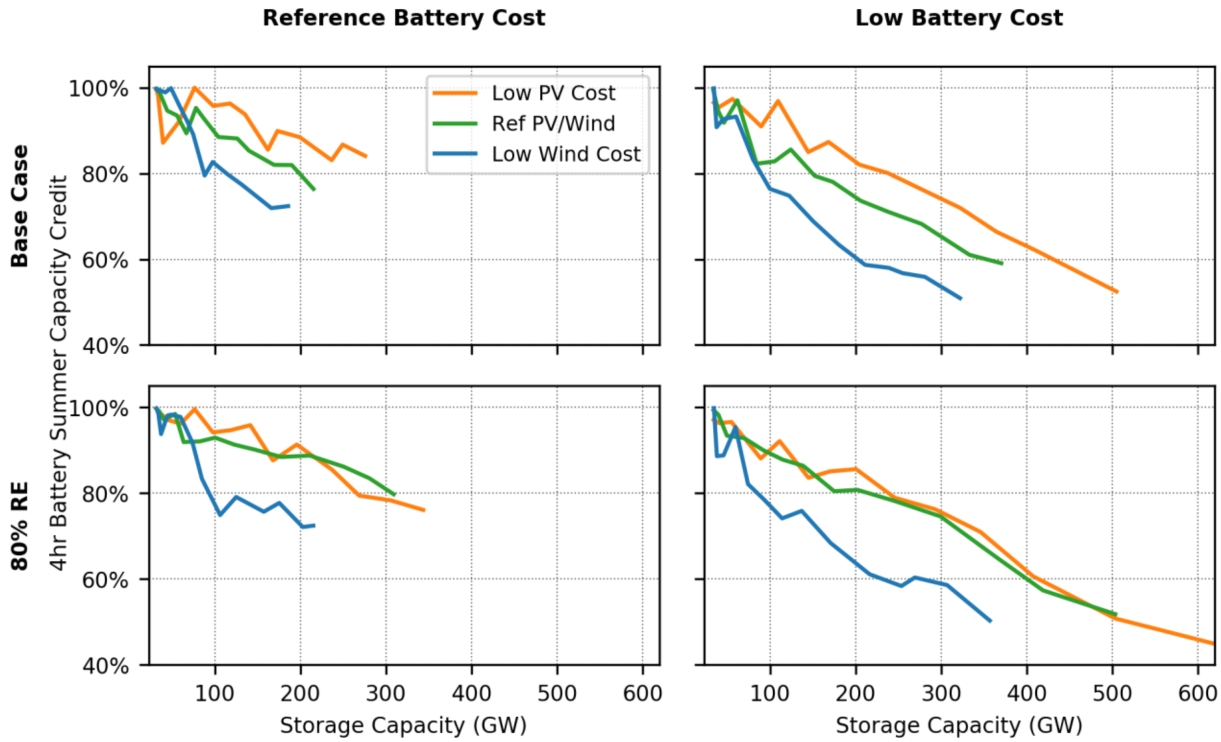

Figure 8. National average summer capacity credit of 4-hour storage as a function of total storage capacity

This factor is further explained by looking at the different ways the net load profiles develop over time in scenarios with high PV penetration compared with high wind penetration. Figure 9 shows the national average hourly net load profiles over time for a day in winter and a day in summer for the Low PV Cost, Mid-case, and Low Wind Cost scenarios. High PV penetration decreases the net load during the mid-day and increases it at every other time, leading to a narrowing of the evening peak and a larger difference between the evening peak and the mid-day valley. These conditions increase the value of diurnal storage. By comparison, high wind penetration decreases the net load throughout day. These conditions lead to a smaller difference between the mid-day valley and the evening peak net load and result in a smaller arbitrage opportunity for diurnal storage. The Mid-case scenario net load is a mix between the two, with a pronounced decrease during the mid-day and a minor increase at every other time in 2050.

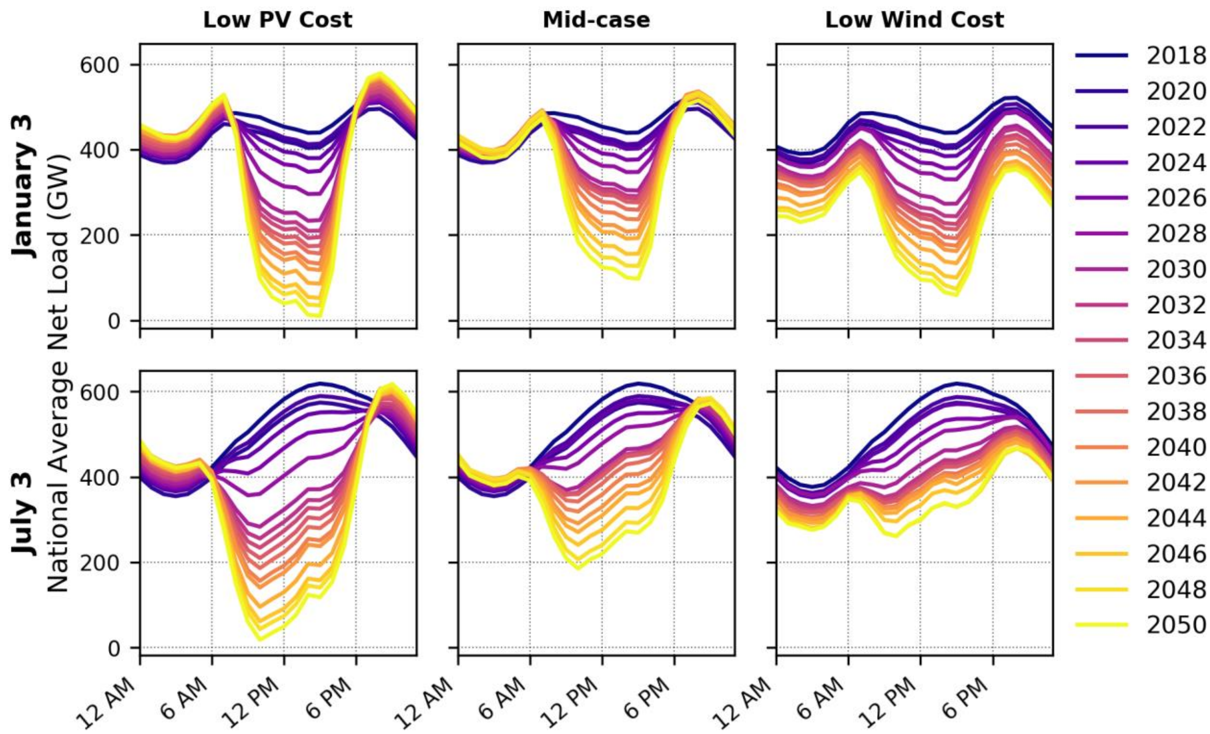

Figure 9. National average net load by year for a day in the winter and summer for the Low PV Cost, Mid-case, and Low Wind Cost scenarios. Times are in EST.

The second factor driving the capacity value of storage is illustrated in Figure 10, which shows the national average capacity price that generators receive for providing firm capacity within the model (this capacity price is the marginal value from the planning reserve margin constraint). Across every scenario, capacity prices are lower in scenarios that have higher storage deployment. Wind and PV deployment also affect the capacity prices. Scenarios with high PV deployment have lower capacity prices than the base case, whereas scenarios with high wind penetration have higher capacity prices. Additions of PV and storage both lead to lower capacity prices, so the lower PV and storage deployment in the high wind penetration scenarios lead to those higher capacity prices. This trend is starker in the 80% RE cases where wind and PV trade off with one another more directly.

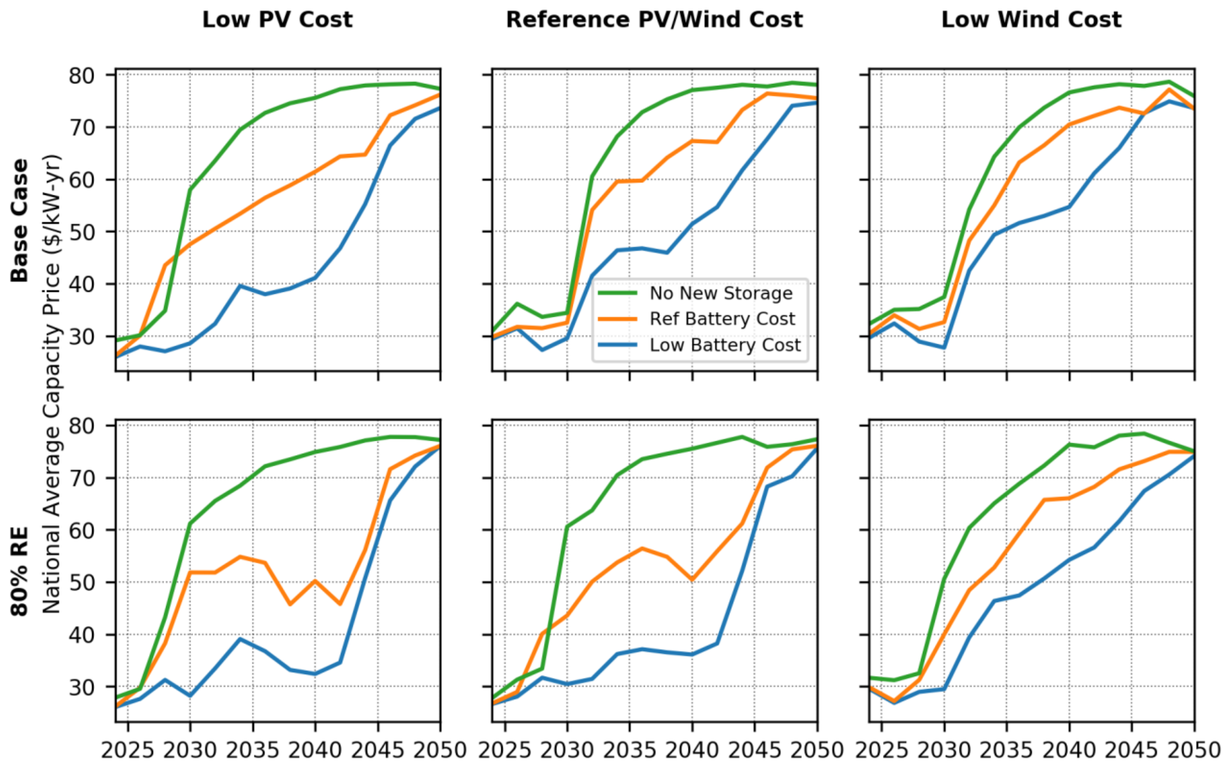

Figure 10. Modeled national average capacity price across the suite of scenarios

Figure 11 shows the impact of storage and VRE costs on modeled energy prices (this energy price is the marginal from the load balancing constraint). Not allowing new storage deployment results in higher energy prices relative to scenarios where storage deployment is allowed, with the greatest difference occurring in scenarios with higher levels of PV deployment. These higher energy prices result from less-efficient use of generators than would otherwise be the case if storage could shift energy in time. Though low battery costs lead to more battery deployment and a reduction of overall system costs, they have limited effect on energy prices; this is due in part to the lower overall storage utilization in the Low Battery Cost scenarios (refer to Figure 4) and because more storage cannot necessarily move a low-cost fossil unit from being the unit on the margin.

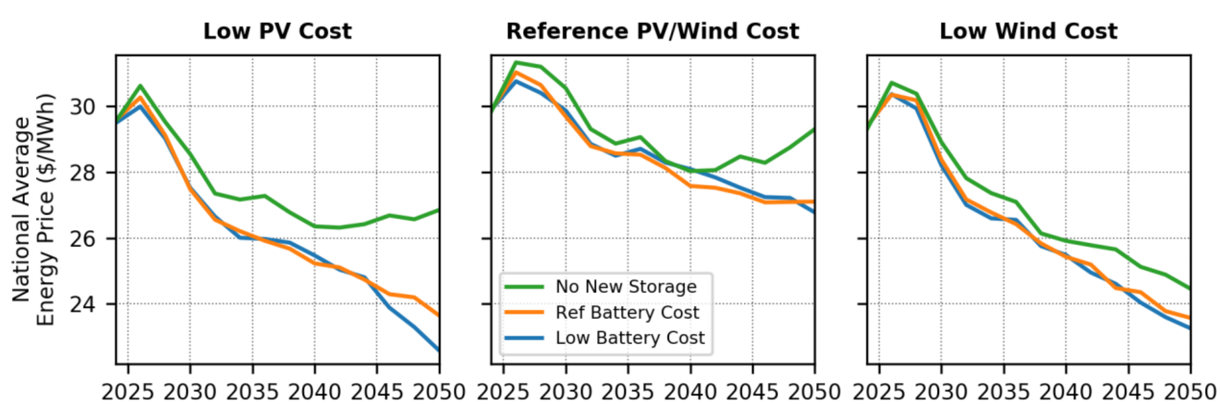

Figure 11: Modeled national average energy price across the base case scenarios.

Modeled operating reserve prices are highly affected by the presence of storage (see Figure 12). Scenarios that do not allow for new storage see flat or increasing operating reserve prices. This relationship is most pronounced in scenarios with the 80% RE requirement because the operating reserve requirement is larger in scenarios that have more VRE (Cole, Eurek, et al. 2018). The scenarios with low battery costs have operating reserve prices that are even lower than those with reference battery costs. The additional storage deployment further reduces operating reserve prices. This price suppression occurs because storage deployment motivated by capacity and energy services can also serve the much smaller market of operating reserves.

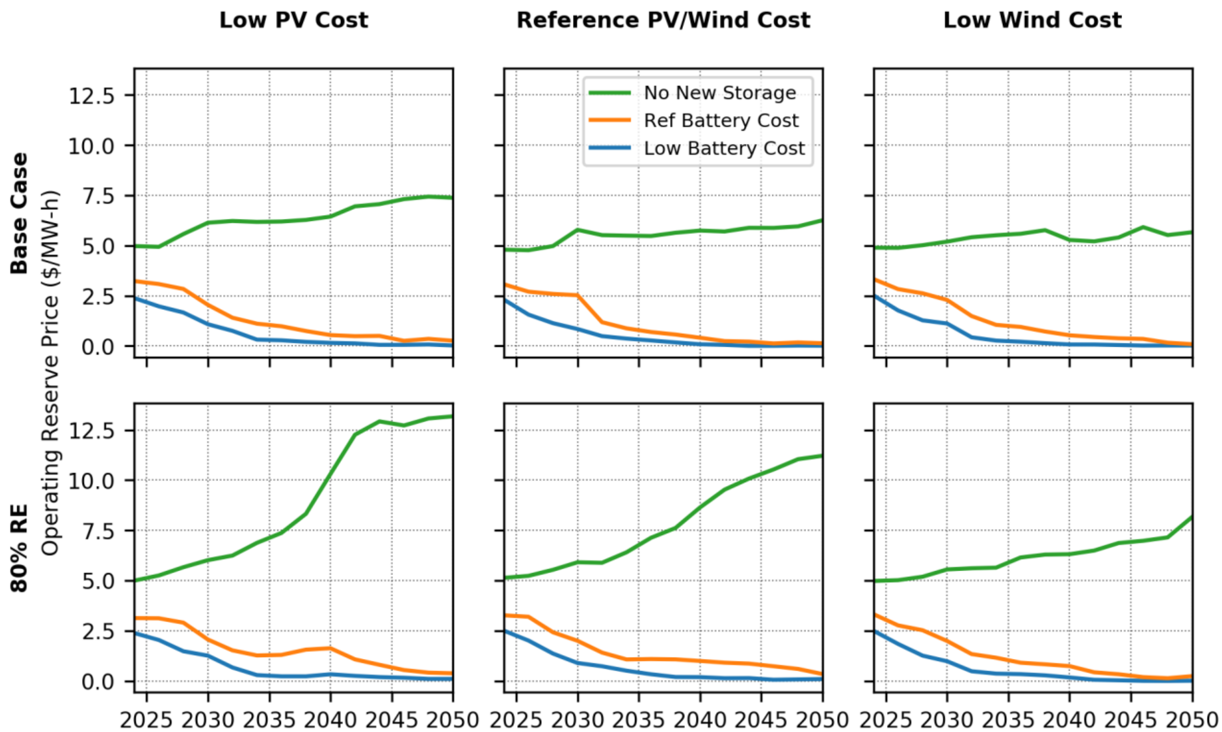

Figure 12. National average operating reserve prices across the suite of scenarios. These reserve prices are presented here as the sum of the prices for the three different reserve products represented in the model. For a breakdown of each reserve price see Appendix Figure 41-Figure 43.

3.4 Impacts of Storage on Curtailment and Transmission

Storage, VRE curtailment, and transmission are highly interrelated. Absent system changes, increased VRE will lead to increases in VRE curtailment (Denholm and Margolis 2007; Denholm and Hand 2011; Mills and Wiser 2013). Both storage and transmission are flexibility options that can reduce curtailment, and in that way they are substitutes for one another. However, the way they offset curtailment is different. Storage shifts energy in time, while transmission shifts energy in space. Additionally, storage is a source of firm capacity, while transmission generally can only facilitate the trading of firm capacity.

Figure 13 shows the curtailment rate in each scenario as a function of VRE penetration. Curtailment rates are higher in scenarios without new storage than in scenarios that allow new storage. For scenarios that allow new storage, curtailment rates are higher in the Low Wind Cost scenarios than in the Low PV Cost scenarios, even for the same VRE penetration level. This lower curtailment rate is because storage is better able to reduce PV curtailment than wind curtailment for the reasons discussed above. Curtailment never goes to zero because removing curtailment entirely is less cost-effective than allowing an optimal level of curtailment (O'Shaughnessy, Cruce, and Xu 2020).

In the scenarios with the 80% RE requirement, the relationship between storage and curtailment is especially strong. Absent the ability to build new storage, average curtailment rates are at or near 10% in 2050, which means marginal curtailment rates are much higher.

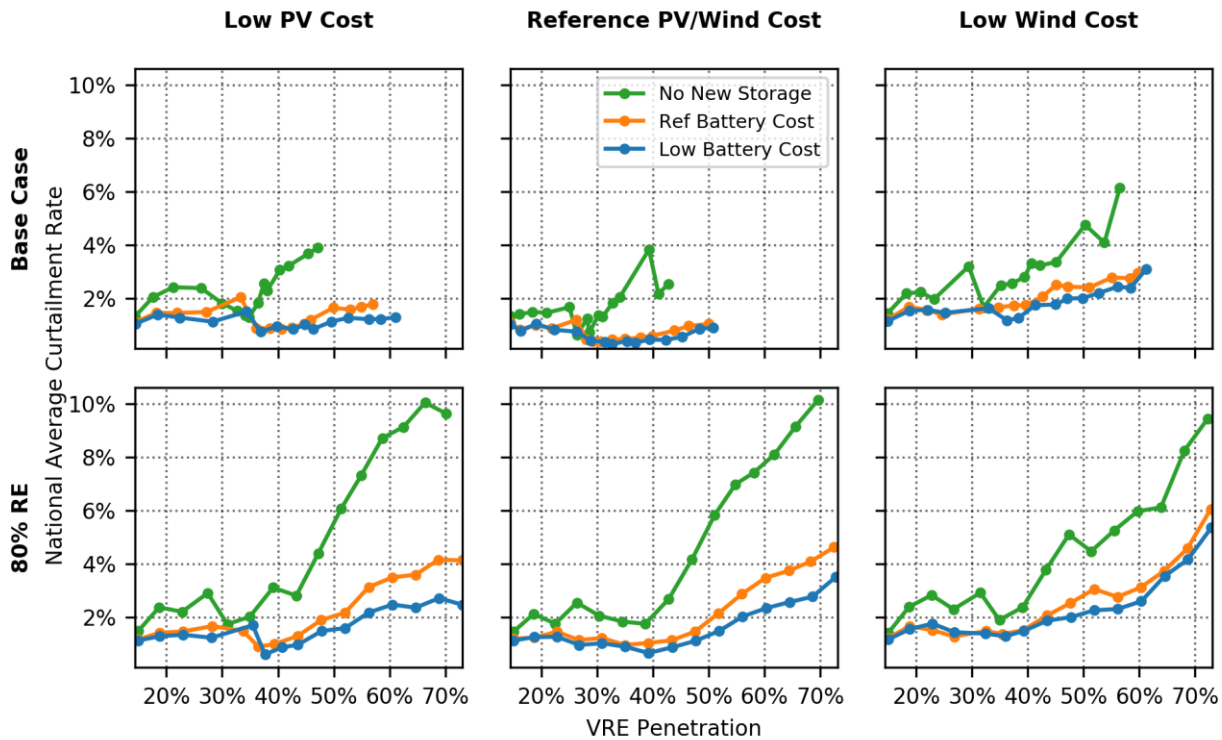

Figure 13. National average curtailment rate versus VRE penetration, where penetration is the fraction of total generation from VRE. For the same data plotted over time, see Appendix Figure 44.

Cumulative long-distance transmission capacity is shown in Figure 14. Storage reduces the need for transmission investments, particularly in the 80% RE scenarios. When storage is not available to provide flexibility and reduce curtailment, transmission builds are much higher. Scenarios with low-cost storage always have lower transmission builds than the other scenarios for a given VRE penetration.

Scenarios with low wind costs have higher transmission capacity relative to scenarios with reference wind or low PV costs, which is indicative of the synergy between wind and transmission (Jorgenson, Denholm, and Mai 2018). The effect of battery costs on transmission capacity is greater in the Low PV Cost scenarios than in the Low Wind Cost scenarios. This relationship suggests storage is particularly important in facilitating the economic use of PV, as without it, an outsized amount of transmission capacity is needed to attempt to provide the flexibility that would otherwise come from storage. By contrast, the absence of new storage has less effect on transmission investments in the Low Wind Cost scenarios.

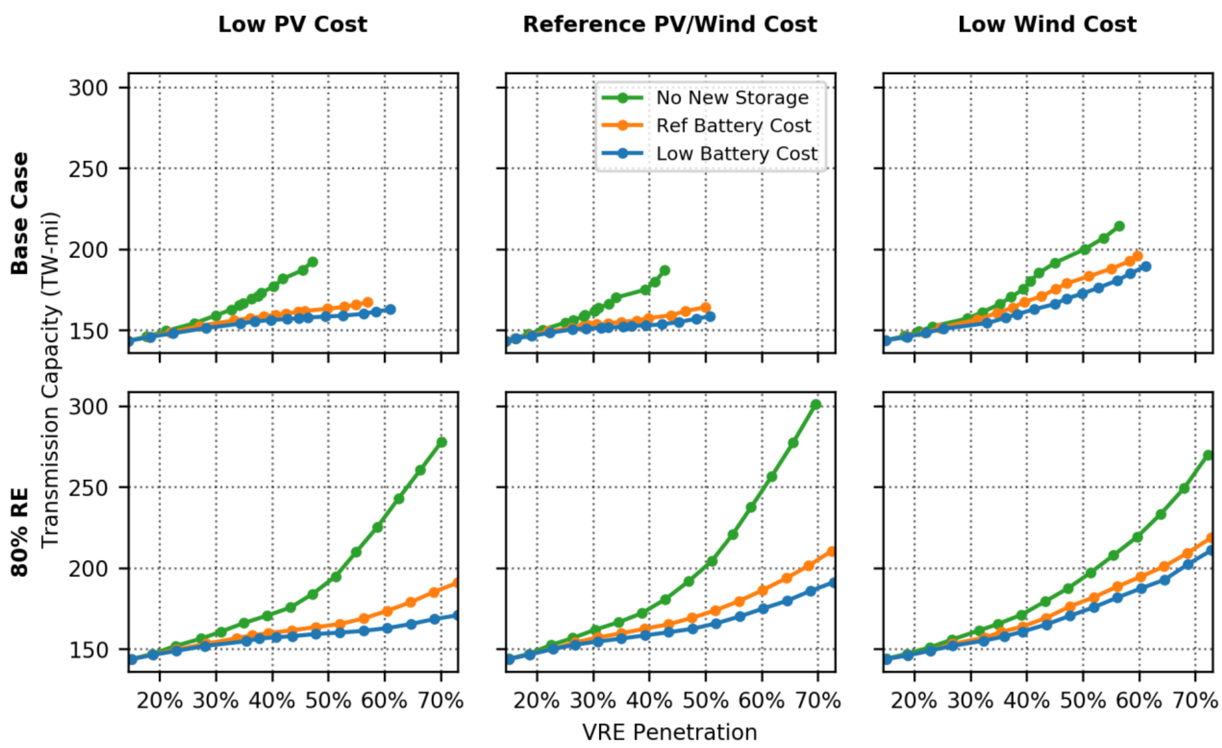

Figure 14. Cumulative long-distance transmission capacity versus VRE penetration, where penetration is the fraction of total generation from VRE. These values do not include spur lines built to connect wind and solar plants to the grid. For the same data plotted over time, see Appendix Figure 45.

3.5 Impact of Storage on Emissions

Annual power sector CO_2 emissions are shown in Figure 15. In the scenarios without an RE requirement, the scenarios that have more storage also have lower CO_2 emissions. The greatest difference occurs in the scenarios with low PV costs, reflecting once again the PV-storage synergy. The CO_2 emissions reduction generally follows the deployment results presented in Figure 3, where scenarios with more storage also have more PV. That additional PV offsets some fossil-fueled generation and leads to lower emissions. This CO_2 reduction effect results from the change in investments induced by storage, and not just the change in system operations (Bistline and Young 2020).

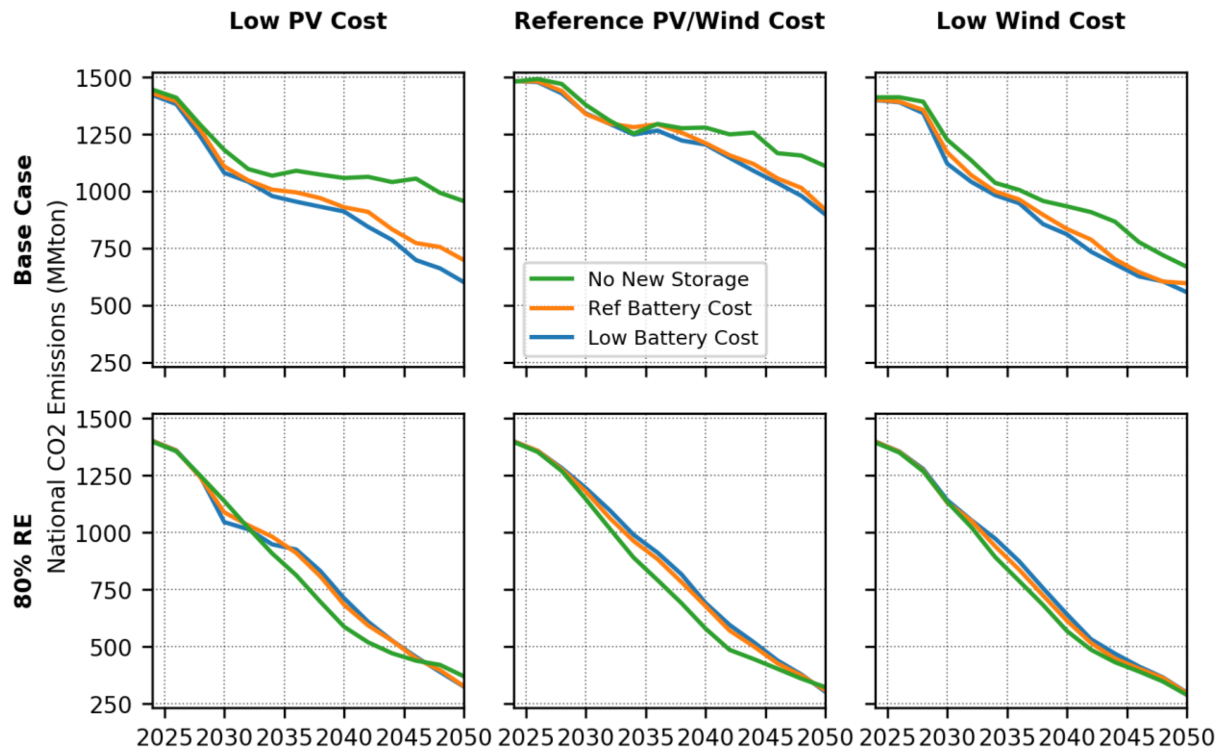

Figure 15. Annual CO_2 emissions across the suite of scenarios

The scenarios with an 80% RE requirement have the opposite result, though to a lower magnitude and mainly in the mid-term: scenarios without storage have the lowest annual emissions throughout most of the years and scenarios modeled. Because of the rapid growth in RE forced into the model by the 80% requirement, there is a high demand for flexibility to help integrate that RE. The model finds some flexibility by reducing reliance on coal-fired generators and increasing reliance on gas-fired generators. These gas-fired generators can ramp more effectively over the course of a day because of shorter start-up and shut-down times and different minimum generation levels. The flexibility of gas-fired generation thus reduces RE curtailment rates and leads to fewer emissions. Additionally, the scenarios without storage have more wind and less PV generation, which changes the regional mix of resources in a way that can lower emissions.

This emissions analysis includes combustion-only emissions and does not include the full life-cycle scope of generator manufacturing and decommissioning, fossil fuel extraction or transmission line construction, which may become more important with high deployments of PV or storage capacity. With that caveat in mind, more storage enables a lower-carbon grid.

4 Conclusion

In this work, we used a national-scale capacity expansion model to examine the interactions between PV, wind, and storage. We found significant interactions among these three technologies, with the strongest interactions occurring between PV and storage.

Scenarios that had more PV always had more storage, and scenarios with more storage always had more PV. This analysis did not demonstrate the causality of that relationship, but it provides clear evidence of the correlation and identifies contributing factors, such as PV narrowing the net load peaks and increasing the difference between low and high prices. Wind and PV also traded off with one another, as scenarios with more wind had less PV and vice-versa, though this trade-off was always less than one-to-one.

Storage utilization was highest in scenarios with more PV and in scenarios that required a higher amount of VRE generation. In scenarios with more wind generation, longer-duration storage resources were utilized more heavily than shorter-duration resources. In scenarios with low storage costs, overall storage utilization was lower because of a much larger build-out of storage.

Storage generally receives a larger fraction of value from providing firm capacity services than from providing energy, but both are important factors of total storage value across all scenarios and durations. Longer-duration storage resources tend to receive a larger fraction of their revenue from providing energy services (e.g., energy arbitrage) than shorter-duration resources. Operating reserve values tend to be small, as the market is saturated by the large amount of storage deployed. In the absence of new storage, modeled prices for firm capacity, energy, and operating reserves all increase relative to scenarios that allow new storage. In other words, storage can have a significant downward impact on operating reserve, energy, and capacity prices.

Storage serves to lower curtailment rates of both wind and solar resources but has a stronger impact on reducing PV curtailment than wind curtailment. Wind deployment appears to be more strongly correlated with transmission than PV deployment.

Finally, we see that storage leads to lower power sector CO_2 emissions, primarily by enabling higher penetrations of PV, and we note that life-cycle emissions from manufacturing additional PV are outside of the scope of this work.

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Appendix

This section includes a description of the ReEDS Augur module, Augur methodology validation efforts, and additional scenario results to supplement the body of the paper.

ReEDS Augur Module

ReEDS includes four types of diurnal storage technologies: batteries (with 2, 4, 6, 8, and 10 hours of duration), PSH (with 12 hours of duration), concentrating solar power (CSP) with thermal energy storage (with 10 and 14 hours of duration), and compressed air energy storage[2] (with 12 hours of duration). Longer duration storage technologies are not currently represented.

An important revenue source for diurnal storage is energy arbitrage, where storage charges when prices are low and discharges when prices are high. Arbitrage opportunities require fine time resolution to capture price deltas between high and low-price periods. Aggregating to time-slices, such as is done in ReEDS and other large-scale capacity expansion models, can "average out" these price deltas and underestimate the arbitrage opportunity for storage. Local arbitrage opportunities can also be lost by aggregating in space. To accurately capture the energy arbitrage value that storage can provide, storage must be modeled at a fine enough resolution in time and space to capture these dynamics. Aggregation can significantly undervalue energy storage arbitrage potential. However, modeling with high resolution in time and space can be computationally expensive. Ideally, the energy arbitrage value of storage would be computed by using an hourly production cost simulation alongside the investment decision. However, such an approach would make the ReEDS model intractable, even if some simplifications to the production cost formulation were applied. To balance the competing demands of both temporal and spatial resolution with solve time and accurately value energy storage arbitrage in the ReEDS model, the Augur module was developed. Though the Augur module is used to calculate parameter relevant for storage, VRE, and transmission, we primarily focus on how it supports improved storage modeling.

The Augur module is a new capability in ReEDS that is run in between ReEDS solve years. The module computes several nonlinear parameters that are then fed back into ReEDS as marginal linear values for the next solve year (see Figure 16). The primary purpose of Augur is to accurately compute these marginal values using chronological, hourly data of wind, PV, and load. Augur computes the following parameters:

- Storage energy arbitrage revenue
- Amount of storage by duration that can receive full capacity credit
- Marginal capacity credit of wind and PV
- Ability of storage to recover otherwise curtailed energy (differentiated by curtailment from existing generators versus from new generators)
- Curtailment from existing VRE generators
- Marginal curtailment rate of new VRE generators
- Firm capacity contribution of existing VRE generators

[2] Compressed air energy storage is modeled in ReEDS but was not considered in the scenario analysis presented in this work.

- Marginal capacity credit of new VRE generators
- Curtailment reduction potential of new transmission lines

These parameters require a finer time resolution than the ReEDS time-slices provide and are particularly important for accurately modeling storage and VRE deployment in capacity expansion. The ReEDS Augur module workflow is summarized in Figure 16.

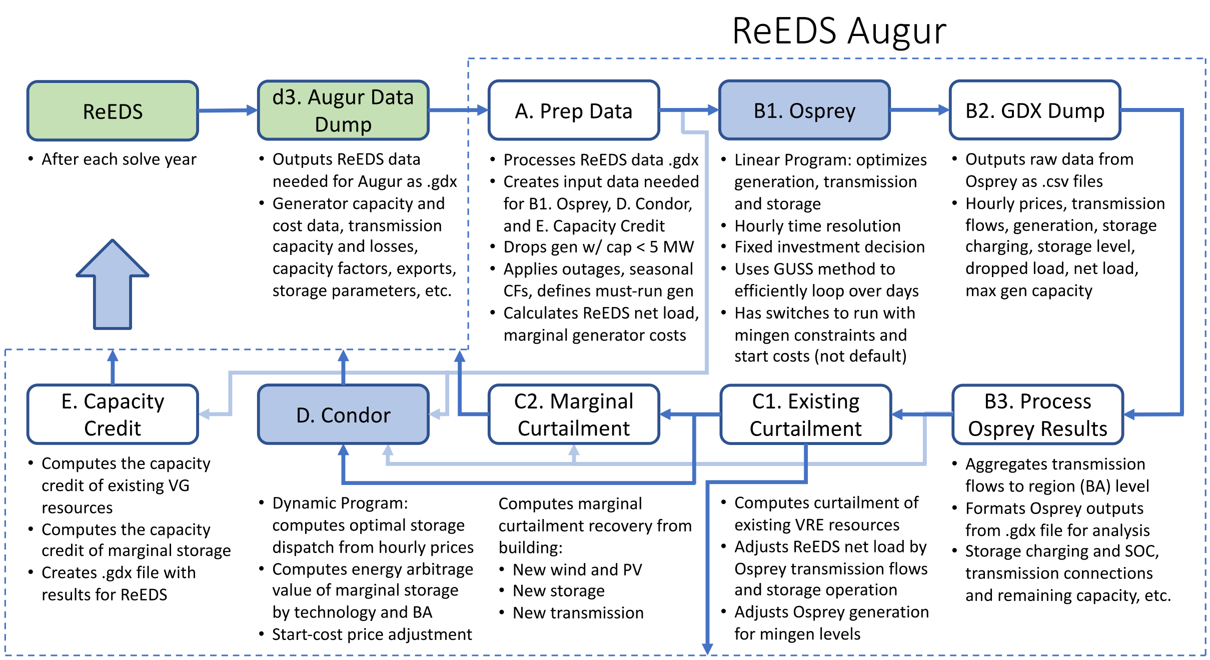

Figure 16. Summary workflow of the ReEDS Augur module. BA is balancing area, CF is capacity factor, GDX is GAMS (General Algebraic Modeling Language) Data eXchange, and SOC is state of charge. The names of the different elements of the flow chart correspond to the names of the scripts that are part of the ReEDS model. See https://www.nrel.gov/analysis/reeds/request-access.html to get access to the ReEDS repository.

A core piece of the ReEDS Augur module is a linear program we call Osprey that optimizes generation, transmission, and storage at the regional level across the entire United States at an hourly time resolution. This yields hourly prices by region which are then used in a dynamic program we call Condor to compute the energy arbitrage value of marginal storage. The storage deployment from Osprey is used to compute existing and marginal curtailment rates. The storage capacity credit contribution is computed from ReEDS results as previously described in (Frazier et al. 2020). The Augur results are aggregated to the time-slice level before being passed back to ReEDS, giving it the marginal values for the next solve year.

ReEDS Output Processing

After each ReEDS solve year, the relevant ReEDS outputs are prepared for Augur. In particular, the load growth for the following year is applied, and the generators scheduled for retirement in the next year are removed. Hourly net loads are computed for the entire year using resource profiles from the Renewable Energy Potential (reV) model (Maclaurin et al. 2019), and these are converted into EST so that energy trading among regions is not being distorted by differences in time zones. Generators with less than 5 MW of capacity are dropped and thus ignored in Augur. Generator operating costs are computed from ReEDS' fuel costs, heat rates, and variable operations and maintenance (VOM) costs. Exports to Canada are represented as additional load in regions where that occurs. These ReEDS outputs are then formatted and passed to Osprey.

Osprey Linear Program

Osprey is a linear program (LP) that optimizes generation, transmission flows, and storage operation across the 134 model regions at an hourly resolution. It does this quickly enough to run in between each ReEDS solve year without significant computational expense. This is accomplished because each day is solved independently, with storage generators being required to start and end at the same state of charge but being allowed to choose that state of charge. Furthermore, the following generator constraints are not enforced to reduce solve time: minimum generation levels, ramp rates, mean time between start-up and shut-down, start-up costs., and operating reserves. Despite these omissions, the transmission and generation behavior and the resulting hourly regional price profiles are sufficient to enable energy arbitrage values to be computed accurately (see Method Validation below). Additional adjustments to account for start-up costs and minimum generation levels are applied downstream in other Augur components.

To get accurate generation behavior while ignoring start-up costs and minimum generation levels, certain generators are treated as must-run generators and are given seasonal capacity factors according to their seasonal outage rates. These include nuclear, geothermal, and non-dispatchable hydropower. To simplify the optimization problem, the contribution of these must-run generators is removed from the net load profile and the adjusted net load profile is used in Osprey. For dispatchable hydro, the seasonal hydro energy budget is used to create a minimum daily generation requirement. Canadian imports are treated in the same way as dispatchable hydro.

Transmission losses are modeled using the same loss values as ReEDS (1% losses per 100 miles of transmission distance). Dropped load is allowed in order for the model to always be feasible. And in order to reduce degeneracy among transmission losses, storage losses, and VRE curtailment, we apply a small cost ($0.001/MWh) to storage discharging and to transmission flows.

To solve the Osprey linear program efficiently, the GAMS Gather-Update-Solve-Scatter (GUSS) method is used to loop through the days while keeping the optimization program in memory. The parameters for each day are updated, including the adjusted net load profile, the maximum generation capacity available, and the daily required dispatchable hydro generation. As mentioned previously, the storage generation is constrained to start and end at the same level, effectively giving the optimization a circular boundary condition where it views future days as being identical to the current day.[3] This method does not allow interday energy arbitrage and thus is currently unsuitable for long-duration storage.

[3] This assumption was tested under a wide range of scenarios, including scenarios with up to 100% renewable energy, and it was never found to result in meaningful differences with other options that solved for 48 hours but only implemented the first 24 hours.

Osprey Results

Osprey outputs include hourly prices, transmission flows, generation levels, storage charging, and storage levels, all by region and generator. The prices are taken as the marginal from the load balance constraint.

These results are processed for use in further analysis downstream. The transmission flows are aggregated to the region level, and the transmission-adjusted net load is computed by adjusting the regional net load for the regional transmission, with the must-run generators' contributions added back in.

The hourly prices that come out of Osprey are adjusted to account for generator start-up costs. For each hour, the number of transmission-connected regions[4] are computed using the NetworkX[5] Python package (Hagberg, Swart, and S Chult 2008). For each generator start, the start cost is applied by spreading it across the number of hours that the generator is on for a given day. Each generator's "bid price" is computed as its operating cost plus the amount needed to recover the start costs for that day. In each transmission-connected region and for each hour, the maximum generator bid price is computed, and the new price is the maximum of either the original Osprey price or the maximum generator bid price. Validation against PLEXOS production cost modeling results indicated that the start-costs are primarily responsible for the hourly price spikes, and removing start-costs from PLEXOS yielded price profiles that were very similar to those of Osprey. As the primary purpose of these prices is to compute the energy arbitrage value of storage using a price-taking dynamic program, spreading the start costs over the hours the generator was on compared to applying them all at once at the start will on average have a reasonably similar effect.

Existing Curtailment

With the generation profiles from Osprey, the curtailment from existing VRE resources can be computed. This method includes an adjustment for minimum generation levels that were ignored in the Osprey linear program. The curtailment of existing VRE resources is computed as follows:

- Generators that are on but below their minimum generation level are ramped up to that level.
- Generators that are on but above their minimum generation level are ramped down to that level.
- The adjusted generation level is computed by summing the generation for each region.
- Storage generation is added to the transmission-adjusted regional net load.

[4] A transmission-connected region is a set of balancing areas that do not have transmission congestion between them. These transmission-connected regions are necessary for handling degeneracy in estimating curtailment. For example, if region A and B are connected with a 100 MW transmission line, but using less than 100 MW of that line, they would be a transmission-connected region. If region A is curtailing VRE, then that means region B does not have the capability to accept that energy, otherwise the transmission line would be used to move the curtailed power to region B. This also means that if new VRE is added in region B (which has no curtailment), the new VRE would have to be curtailed because region B already has the opportunity to import free power from region A. Transmission-connected regions can be different in each our because the transmission lines that are congested can change each hour.

[5] https://networkx.org/

- Curtailment is computed by subtracting the transmission-and-storage-adjusted net load from the adjusted generation levels for each region.
- The curtailment is required to be less than or equal to the VRE generation in that region.

In recognition that some aggregated ReEDS generators are much larger than actual generators, the minimum generation level is computed differently for generators above 500 MW of capacity. For these large generators, the hourly minimum generation level is computed as a fraction of the generation. For all other generators, it is computed as a fraction of the generator capacity. For large generators in hours when the generation is below 500 MW, the minimum generation level is computed as a fraction of 500 MW instead of the generation. Figure 17 summarizes this minimum generation level adjustment method. The minimum generation fractions used are shown in Table 3, and come from the Western Electricity Coordinating Council Transmission Expansion Planning Policy Committee Database (WECC 2015).

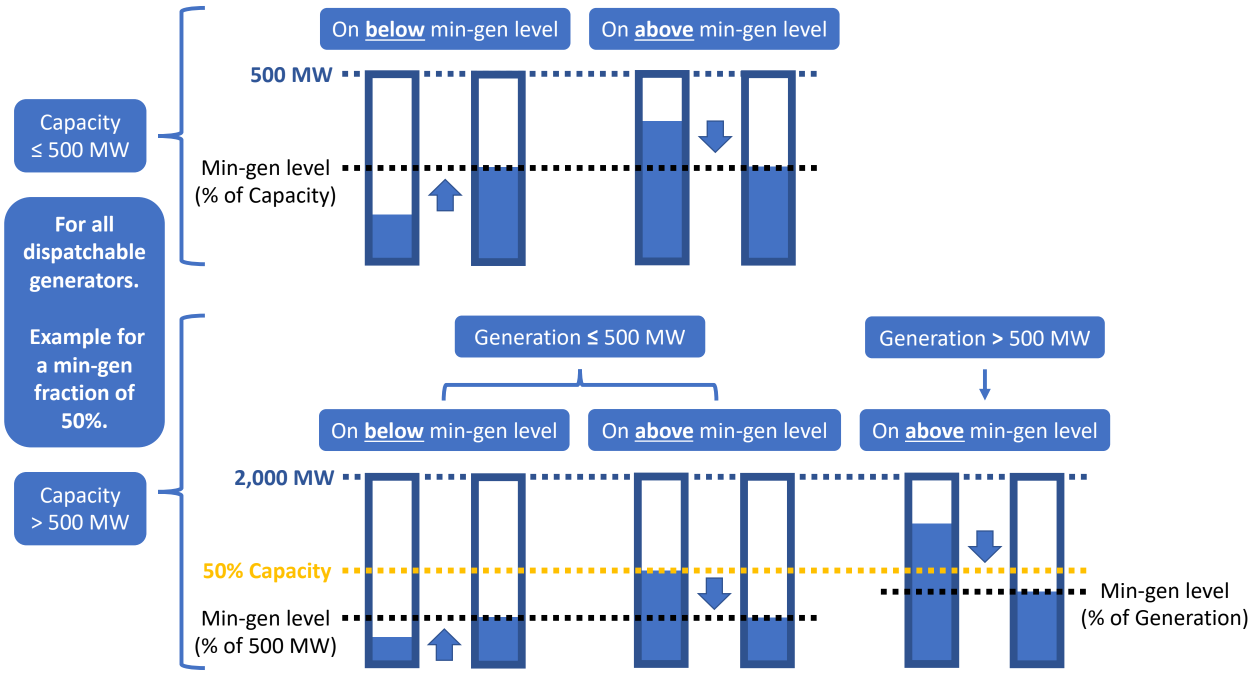

Figure 17. Summary of hourly minimum generation (min-gen) level adjustment used to compute existing curtailment. Example shown for a generator with a 50% min-gen fraction.

Table 3. Generator Properties Used in Augur. Systems with carbon capture and sequestration (CCS) use the same values as the corresponding non-CCS systems.

Technology Type	Start Cost ($/MW)	Minimum Generation Level (fraction of capacity)
Biopower	5.3	0.3
Coal	155.8	0.4
CSP	0	0.2
Gas-CC	83.7	0.55
Gas-CT	33.9	0.45
Geothermal	0	0.5
Landfill-gas	5.3	0.3
Nuclear	116.6	1
Oil/gas steam	33.9	0.45

Marginal Curtailment

Several different marginal curtailment parameters are computed from the Osprey results and the existing curtailment calculation. The regional net load adjusted for transmission and storage is further adjusted so that negative values represent hourly curtailment. The marginal PV and wind curtailment are computed by adding 1,000 MW of PV and wind capacity in each region and for each resource class. The marginal curtailment rate is computed as the fraction of this additional energy that cannot be used by the system, measured by subtracting the added generation from the adjusted net load profile and re-computing curtailment. These 1,000-MW marginal additions are done separately for each region and resource class.

The marginal storage curtailment recovery potential is computed using the same adjusted net load profiles from Osprey. One hundred megawatts of storage are added in each region to calculate the curtailment that can be reduced in that region via new storage. This is done separately for each storage duration. Cross terms are also calculated by adding both new storage and new wind or PV to each region to calculate the curtailment from new wind or PV that can be recovered by new storage.

Transmission is considered during these calculations by evaluating whether new wind or PV generation can be shared with other regions. For example, if a neighboring region has a net load of 1,000 MW in a given hour, and the transmission line to that region has 1,000 MW of unused capacity, up to 1,000 MW of PV or wind generation can be shared with that region during that hour.

Marginal curtailment reduction rates are also computed for transmission by adding 1,000 MW of new transmission between regions and determining the curtailment impacts from that new transmission.

Condor Dynamic Program

The storage energy arbitrage value is computed by Condor, a price taker model that finds the optimal storage dispatch given hourly energy prices and an amount and a duration of storage. It works by discretizing the storage dispatch problem and dividing it into independent subproblems of identical form, solving them all exhaustively and recursively using backward induction and then constructing the optimal storage dispatch given a starting condition. It uses the regional prices from Osprey that have been adjusted for start costs and dispatches storage of each duration separately to find the maximum possible revenue. It runs at an hourly resolution for the entire year, making decisions in each hour that respect constraints on energy capacity and power. Since Condor uses perfect foresight, the storage capacity of each storage resource is reduced by one hour in order to make the values more realistic. This is consistent with estimates that forecast accuracy accounts for roughly 20% of the energy value of storage (Dunbar et al. 2014). In order to avoid double-counting the energy arbitrage benefits of storage that was charged on otherwise curtailed energy and the curtailment recovery itself, the energy value of storage is reduced by the fraction of hours in each transmission-connected region that storage was charged when there was curtailment.

A central assumption of Condor is that prices are fixed. This assumption allows the decoupling of the balancing areas and storage devices when calculating arbitrage potential, because storage in one region is not allowed to influence prices for storage devices in other regions, and neither is storage within a region allowed to influence prices within that region. This price-taking approximation will become less accurate when storage deployment is very large in a given solve year. For large amounts of storage our approach will tend to over-estimate the energy arbitrage value, as it does not capture the smoothing effect of the storage deployment on prices. Capturing this more accurately would be computationally expensive. Future work is needed in this area to better understand the importance of this approximation.

Discretization is a requirement of dynamic programming, which suffers from the curse of dimensionality, and finer discretization increases the solve time exponentially. We performed tests on the results sensitivity to the discretization strategy and selected values accordingly. The storage energy levels are discretized in a manner that fixes the distance between each level, such that smaller duration storage has fewer discrete levels and larger duration storage has more. This causes the dynamic program to treat storage durations equally, instead of under-valuing longer duration storage relative to shorter duration storage (which would occur using a fixed number of discrete levels). In this work, the number of discrete energy levels for 2-hr duration storage is 15, which means that 4-hr duration storage has 30, on up to 12-hr duration storage (PSH) which has 90.

Figure 18 shows a sample week-long dispatch from Condor for a 4-hr battery for a region in the winter. Storage arbitrages between periods of low price and high price with perfect foresight subject to charge and discharge constraints. The effect is a smoother net load profile. The total storage level is 600 MWh due to the perfect foresight adjustment one-hour subtraction from the 4-hr duration 200 MW battery. The expenditure savings are computed as the cumulative difference between the cost to charge the battery and the revenue from discharging the battery at each hour. The storage efficiency penalty is applied to the storage charging, and the rate of charge doesn't quite reach 200 MW because of this.

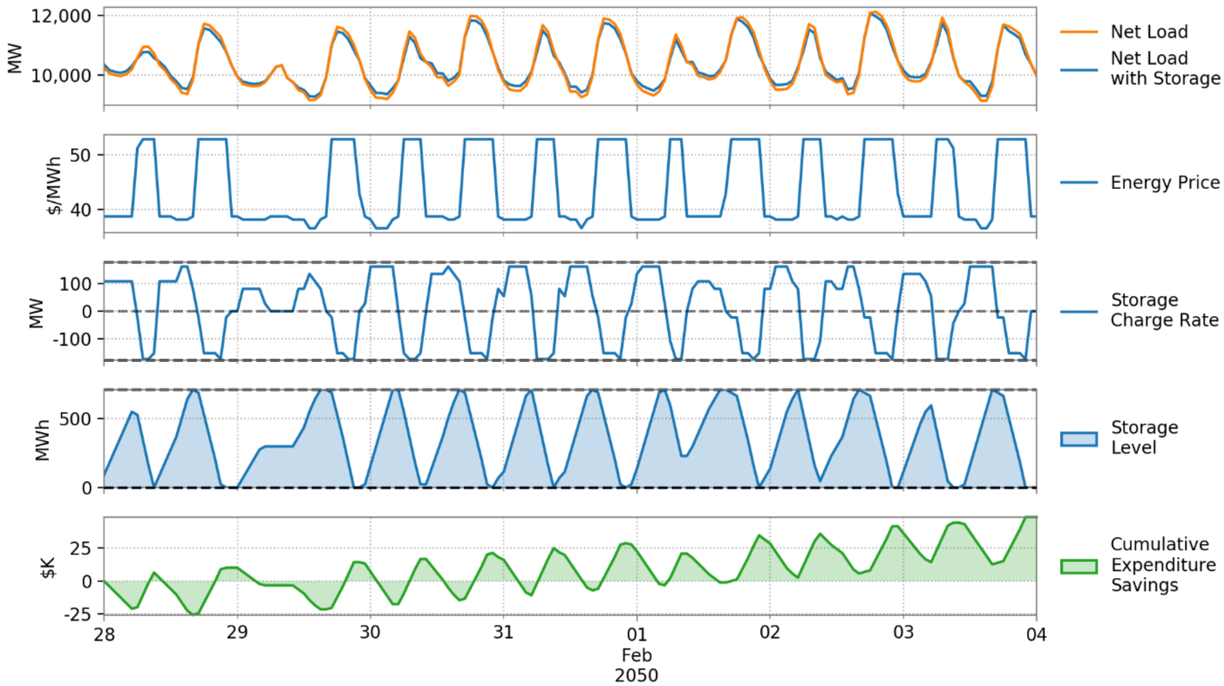

Figure 18. Condor dynamic program dispatch results for a 4-hr battery in a region during the winter

To decrease solution time, Augur defaults to running Condor for 4-hour and 8-hour duration battery storage and then uses linear interpolation to compute the energy arbitrage revenue for the other storage durations for each region (with PSH modeled as 12-hour duration storage). This is done with the revenues normalized by duration, which makes the linear interpolation a reasonable approximation. The storage arbitrage revenue is exact for 4-hour and 8-hour duration storage, and in general slightly underestimates the value of 2-hr, 10-hr and 12-hr storage and overestimates the value of 6-hr storage. Using interpolation appreciably reduces the Condor solve time and is suitable for general ReEDS analysis. For storage-focused analysis, Condor can be run for each storage duration individually, which is the setting used for the results in this work.

Capacity Credit

Storage and VRE capacity credit calculations are folded into Augur, and computed using the methods described Frazier et al. (2020) and Brown et al. (2020), respectively. The capacity credit calculation now uses 7 years of load and weather data to determine the firm capacity of existing VRE resources, which it does for each capacity credit region.

Method Evaluation

To assess the performance of the ReEDS Augur module, we compared Augur outputs with those from equivalent systems in the PLEXOS production cost model (Energy Exemplar 2019; Frew et al. 2019). Figure 19 shows the comparison of energy prices before the start costs were applied for the p64 model region in Texas in 2050. Prices follow the trends seen in PLEXOS except for the price spikes. These PLEXOS price spikes are a result of unit starts within the model, which we verified by removing start costs in PLEXOS.

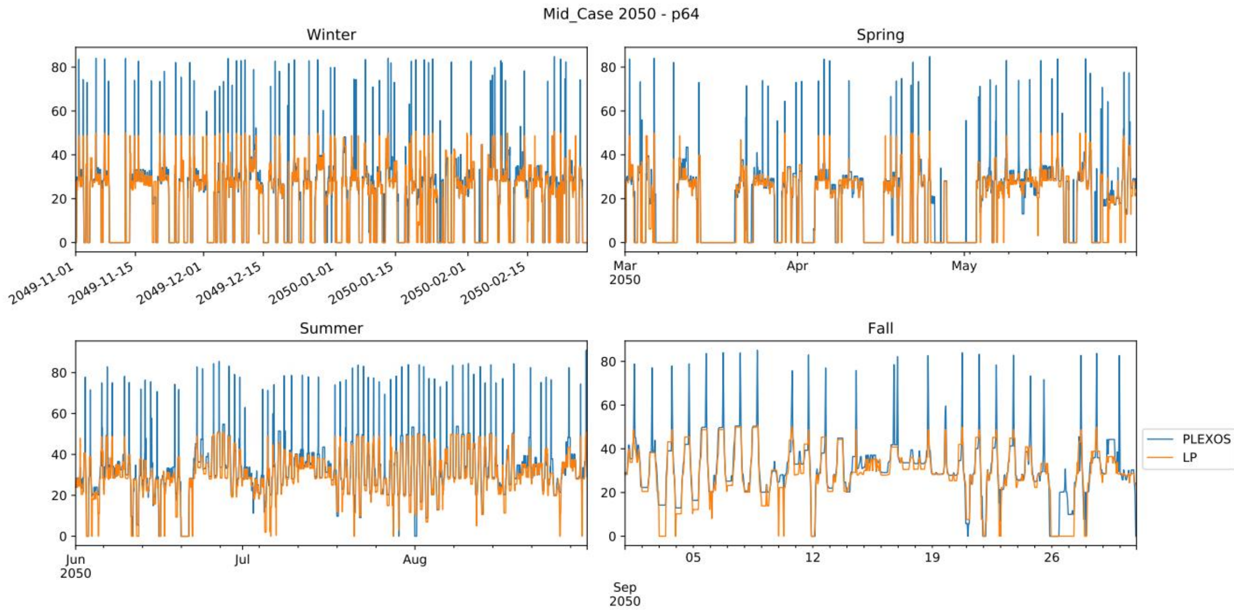

Figure 19. Energy prices from the Osprey LP (before start costs were applied) and from PLEXOS for the p64 region in Texas in 2050. The LP results can follow the PLEXOS results with high accuracy.

To validate the energy value of storage calculation, we ran the Condor dynamic program with both Augur and PLEXOS hourly prices for each region and compared the total storage revenue. With the start cost adjustment made to the Osprey prices, the values matched fairly well across multiple years and scenarios. Figure 20 shows the impact of adding start costs to the Osprey prices. Before adding start costs, the storage arbitrage value was much lower because of the missing price spikes. After including start costs, the arbitrage value matched much better with the arbitrage value seen in PLEXOS. And the storage revenue from Augur matched PLEXOS far better than the storage revenue from ReEDS in the prior model version.

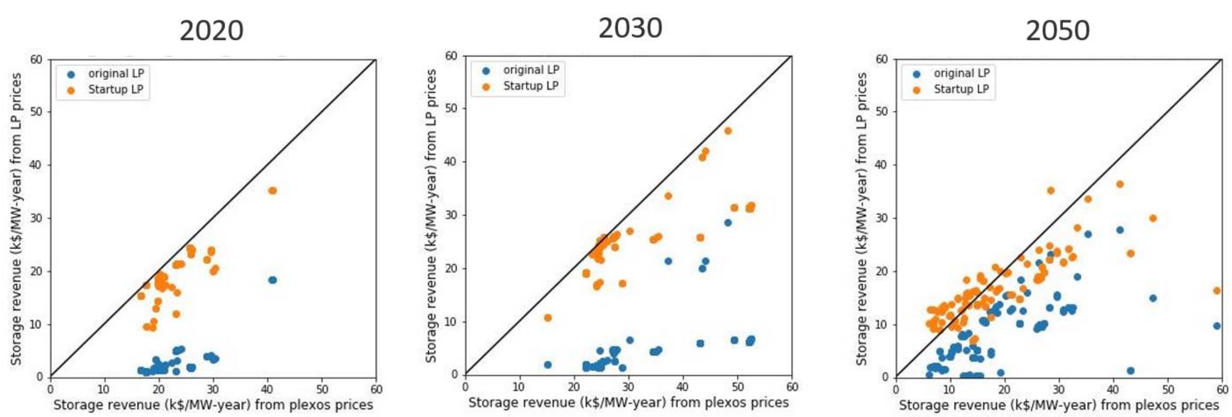

Figure 20. Annual storage arbitrage revenue from Osprey LP versus from PLEXOS. The blue dots show the values before start costs were applied to the Osprey LP outputs and the yellow dots are after. Each dot is one of the 134 regions in the ReEDS model.

To assess the curtailment calculation, we compared the Augur curtailment values with the values from PLEXOS and the former method used in ReEDS. Because there is degeneracy in the optimization problem between deciding whether to curtail energy or incur storage losses, we compared the sum of curtailment and storage losses. We did this at the season and Regional Transmission Organization (RTO) level to reduce the spatial effect of the degeneracy. Figure 21 shows the results of this comparison. The curtailment from Augur is better able to match the curtailment seen in PLEXOS. For reference, the former method used in ReEDS relied on convolutions of VRE and load distributions (Short et al. 2011).

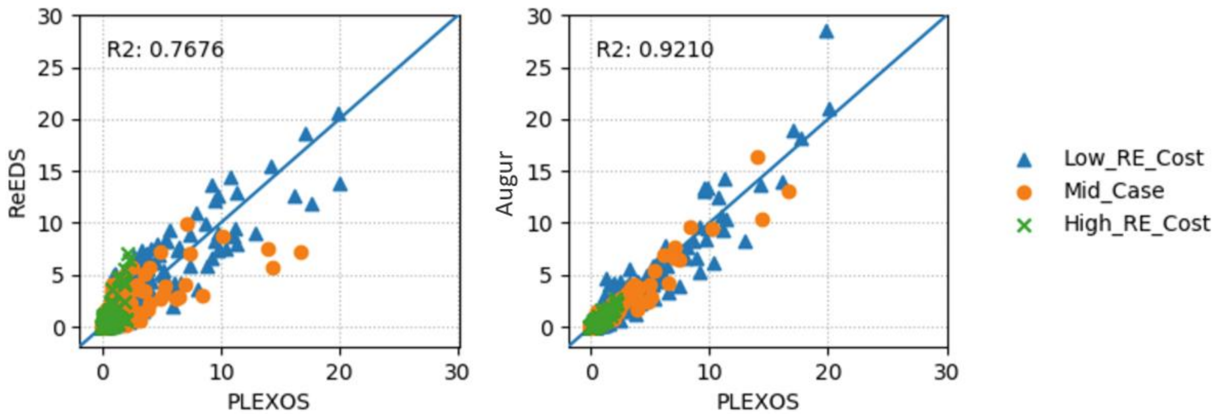

Figure 21. Curtailment (in TWh) in the former version of ReEDS (left) and using Augur (right) versus PLEXOS for scenarios spanning low and high RE costs. The Augur curtailment results better match the PLEXOS curtailment. Values represent the sum of curtailment and storage losses aggregated by season and RTO.

In addition to validation efforts comparing Augur prices, storage energy value and curtailment with PLEXOS, we are able to use Augur results to reproduce some of the findings of Denholm and Mai (Denholm and Mai 2019) who show that both the length of curtailment events and the number of large curtailment events increase in scenarios with high wind penetration. Figure 22 shows the distribution of curtailment event duration and length across nine scenarios. In every case, the Low Wind Cost scenarios have both longer duration and larger curtailment events than both the Reference PV/wind Cost and the Low PV Cost scenarios. Since our results come from a national analysis with different VRE penetration levels and the Denholm and Mai results come from analysis on an ERCOT system with fixed VRE penetration levels and no storage, the absolute distributions are different, but the trends across scenarios are the same. Because their results have no storage, the closest analogue is the No New Storage scenarios, which clearly show the trend of longer duration and larger curtailment events occurring in scenarios with high wind penetration. We observe the opposite trend in scenarios with high PV penetration (and hence low wind penetration). Both trends become more pronounced in scenarios with low battery costs.

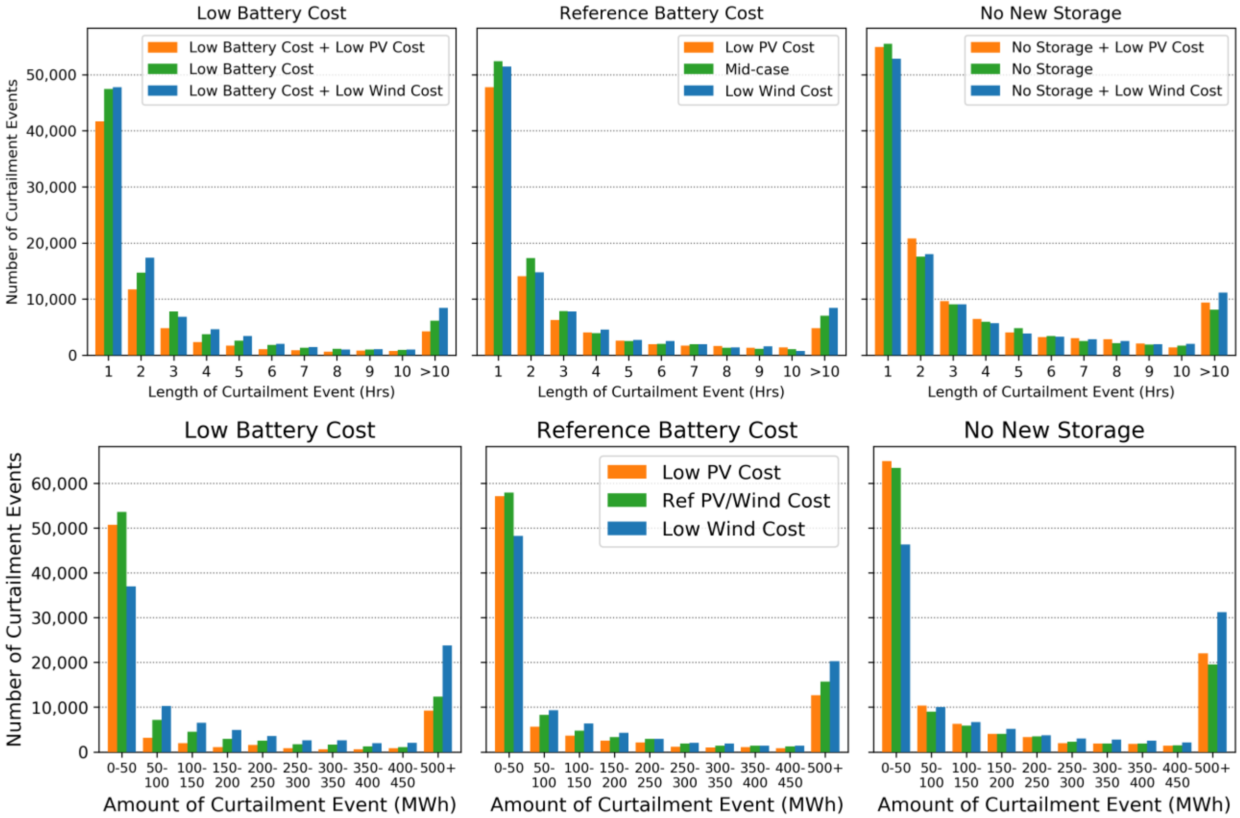

Figure 22. Distributions of duration (top row) and energy (bottom row) of curtailment events in 2050 across the nine scenarios without an RE constraint

Additional Model Inputs

Capital costs are taken from the 2020 Annual Technology Baseline (NREL 2020). The reference costs are from the projections labeled "moderate" and the low costs are from the projections labeled "advanced." Figure 18 shows the fuel price input assumptions, and Figure 19 shows the demand growth assumptions.

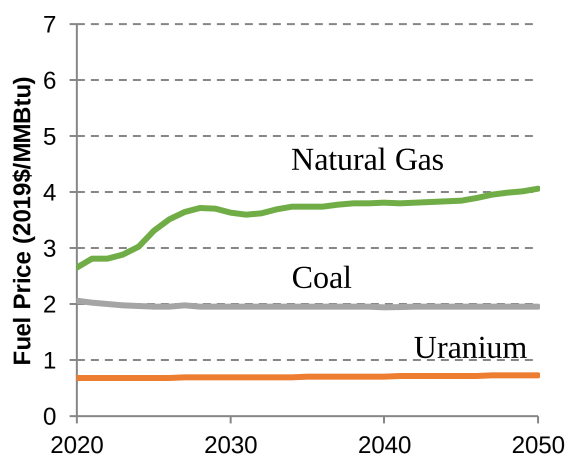

Figure 23. Fuel price inputs. Natural gas prices are elastic within the model. Coal and uranium prices are inelastic.

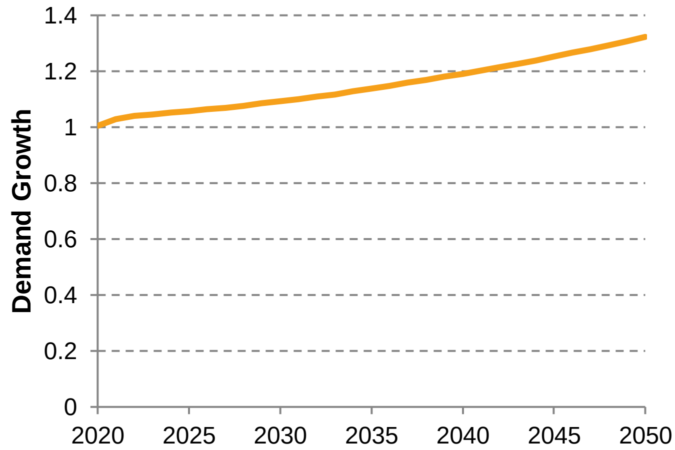

Figure 24. Demand growth trajectory

Additional Scenario Results

Figures 25–45 provide scenario results that supplement those in the body of the paper.

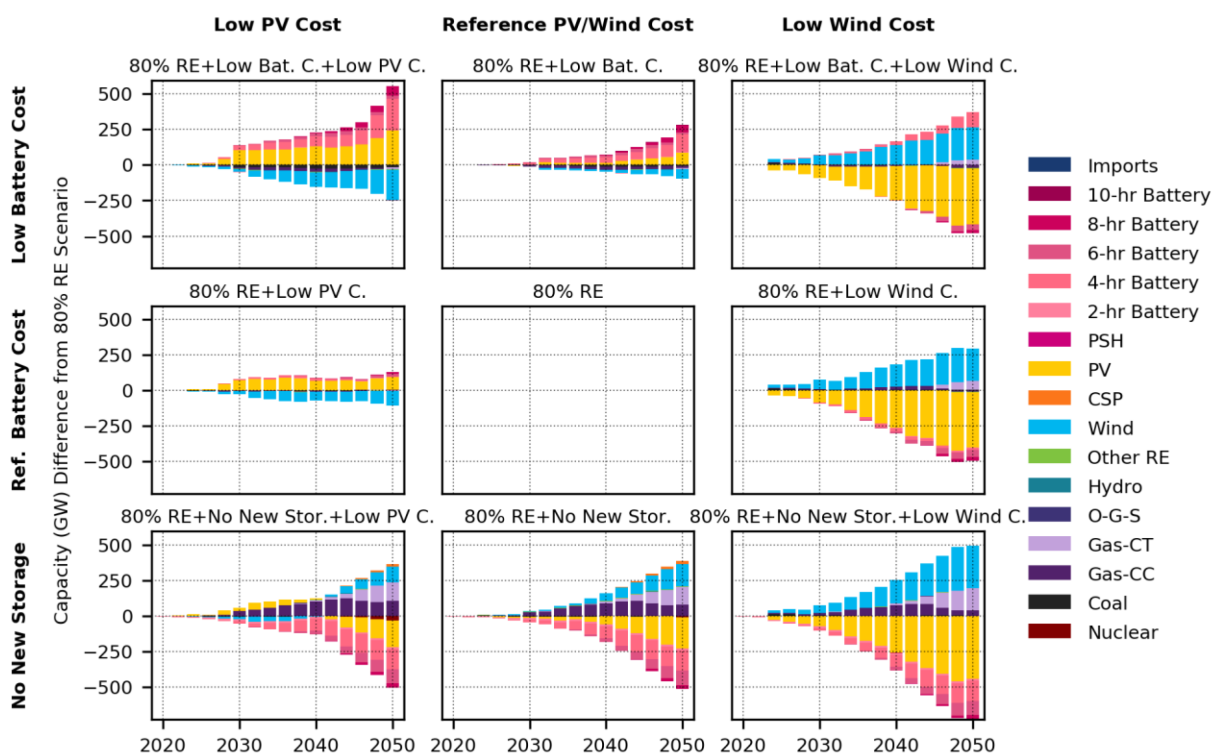

Figure 25. Capacity difference between the 80% RE scenarios and the 80% RE reference scenario

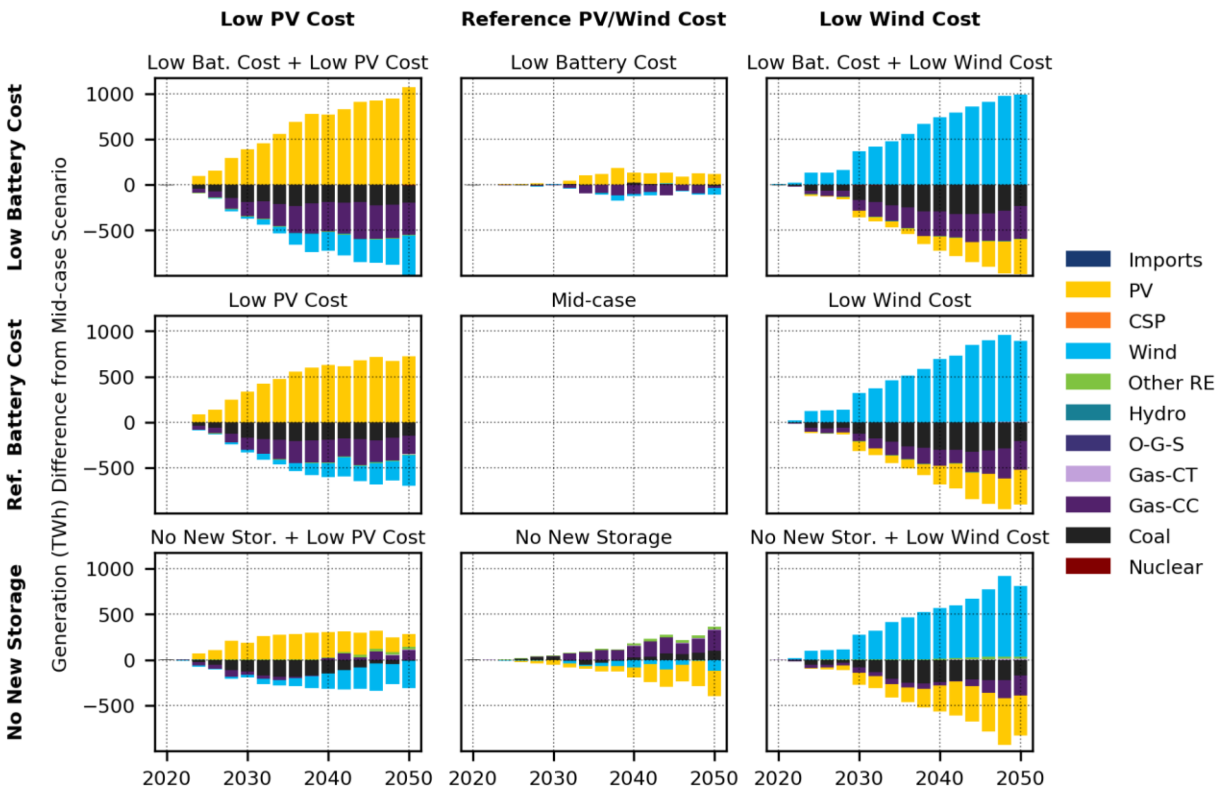

Figure 26. Generation difference from the Mid-case scenario across the scenarios without an RE constraint

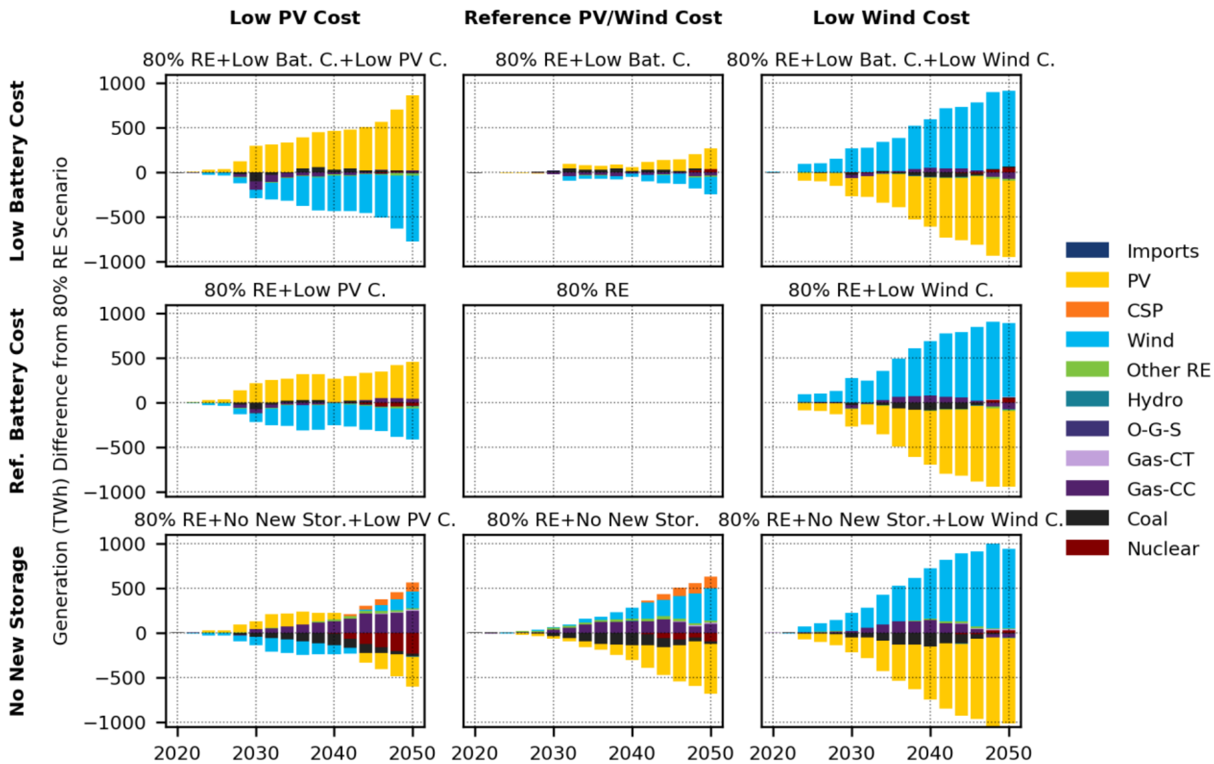

Figure 27. Generation difference from the 80% RE scenario across the scenarios with an 80% RE constraint

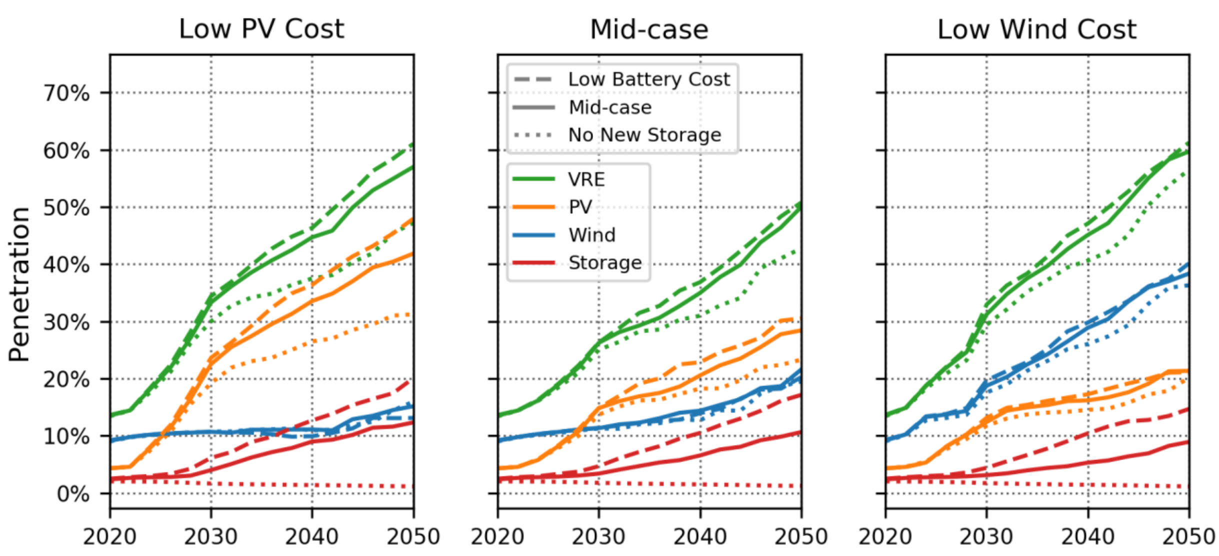

Figure 28. Penetration over time for VRE, PV, and wind (by generation) and storage (by capacity) for the base case scenarios

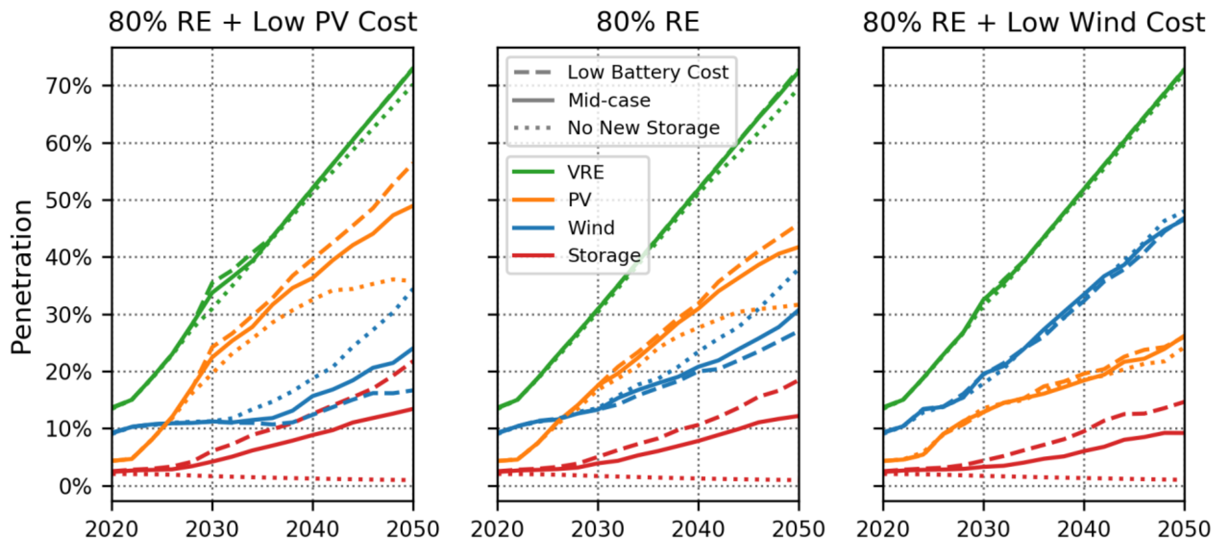

Figure 29. Penetration over time for VRE, PV, and wind (by generation) and storage (by capacity) for the scenarios with an 80% RE constraint

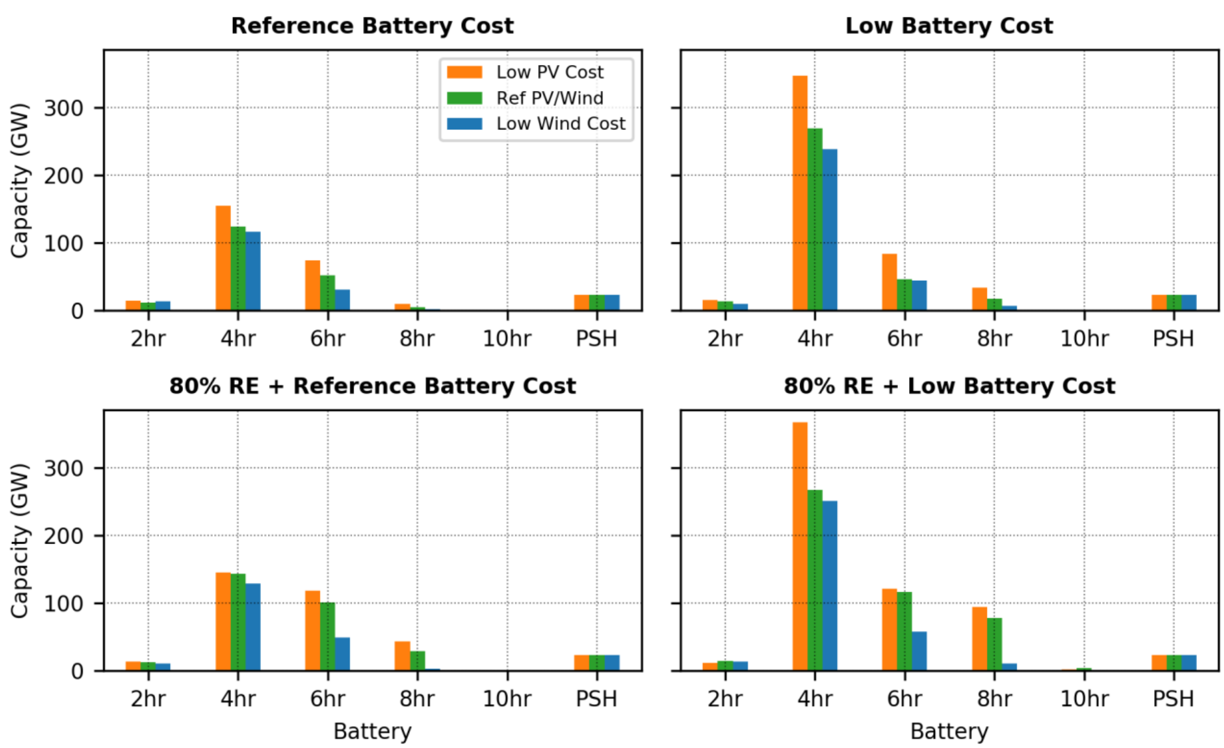

Figure 30. Storage deployment in 2050 across the 12 scenarios that allow new storage

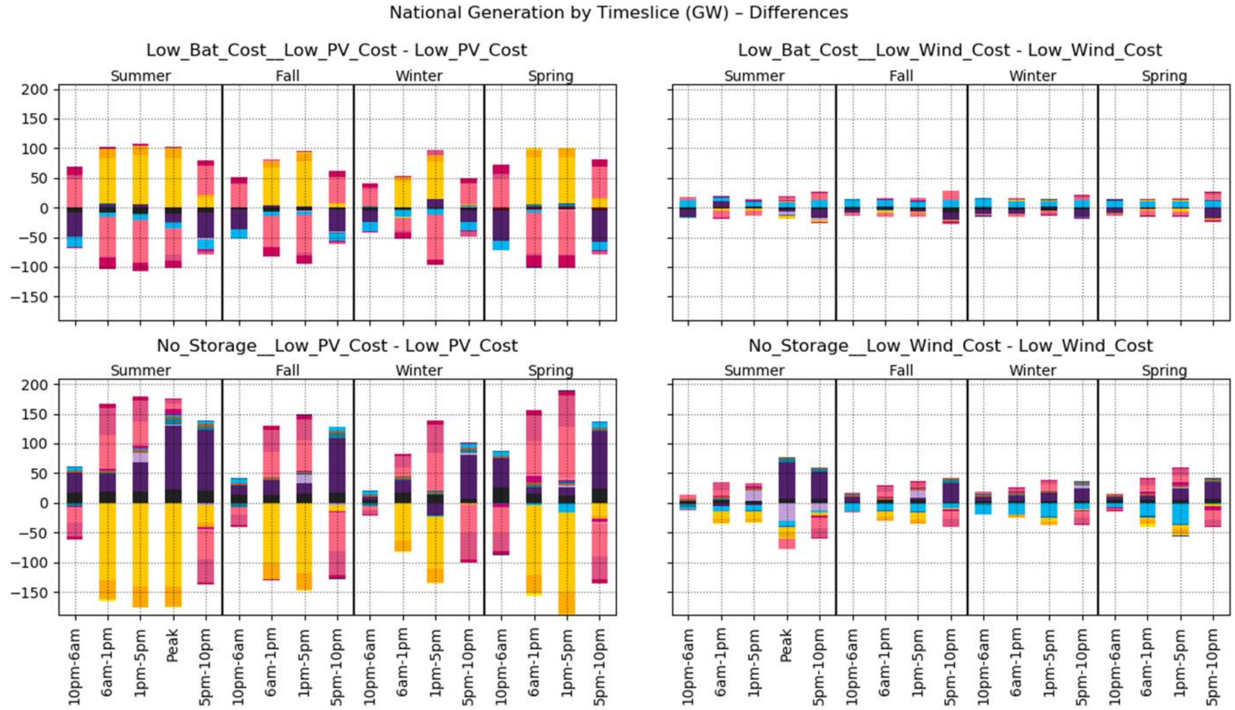

Figure 31. Differences in generation (GW) by time-slice in the Low PV Cost and Low Wind Cost scenarios for both increasing and decrease storage deployment

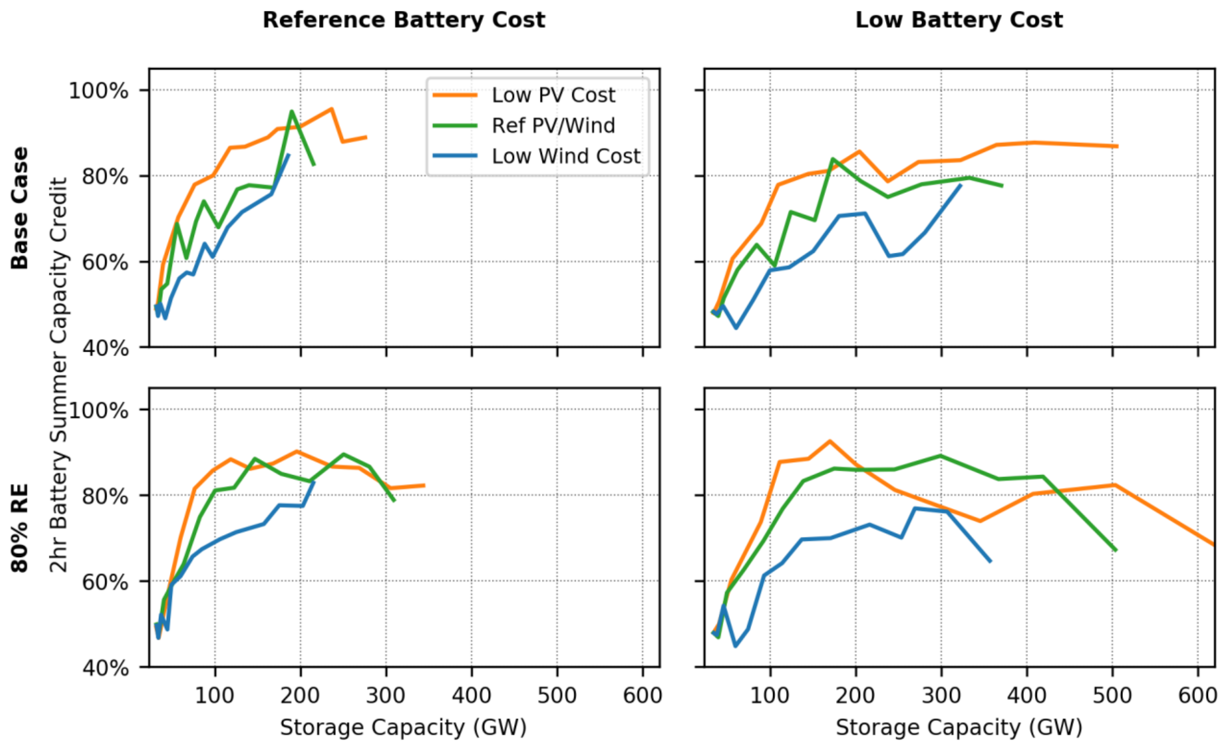

Figure 32. National average capacity credit in the summer for 2-hour battery storage as a function of total storage capacity deployed. Two-hour storage capacity credit begins low because many of the storage mandates in early years are satisfied by the model using 2-hour storage, and 2-hour storage often has a low capacity credit in those regions. Capacity credit grows as economic builds of 2-hour storage occur in regions with a higher capacity credit.

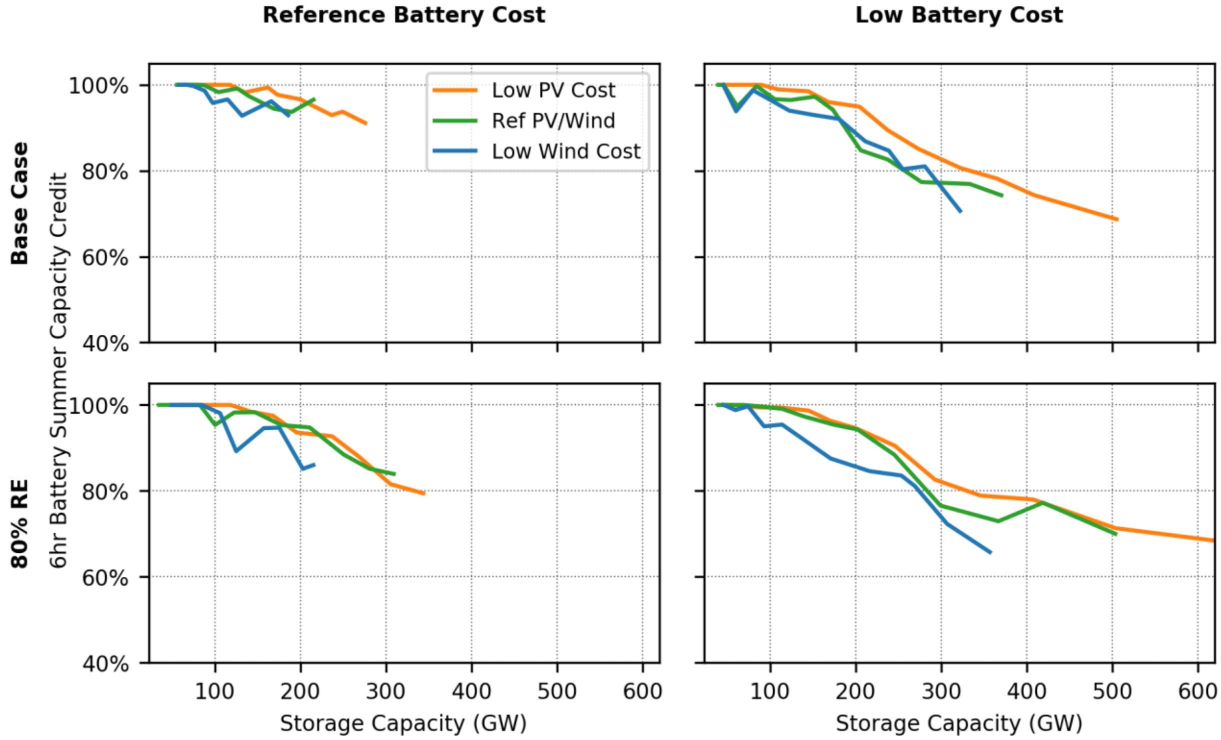

Figure 33. National average capacity credit in the summer for 6-hour battery storage as a function of total storage capacity deployed

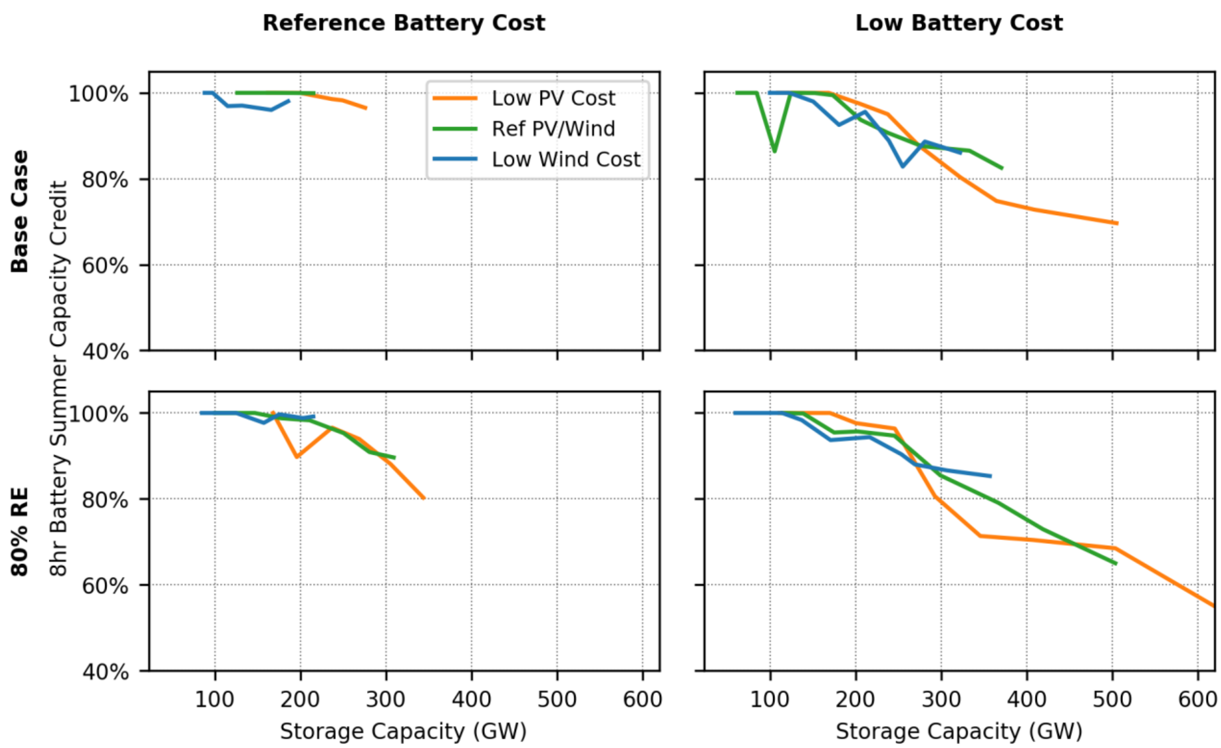

Figure 34. National average capacity credit in the summer for 8-hour battery storage as a function of total storage capacity deployed

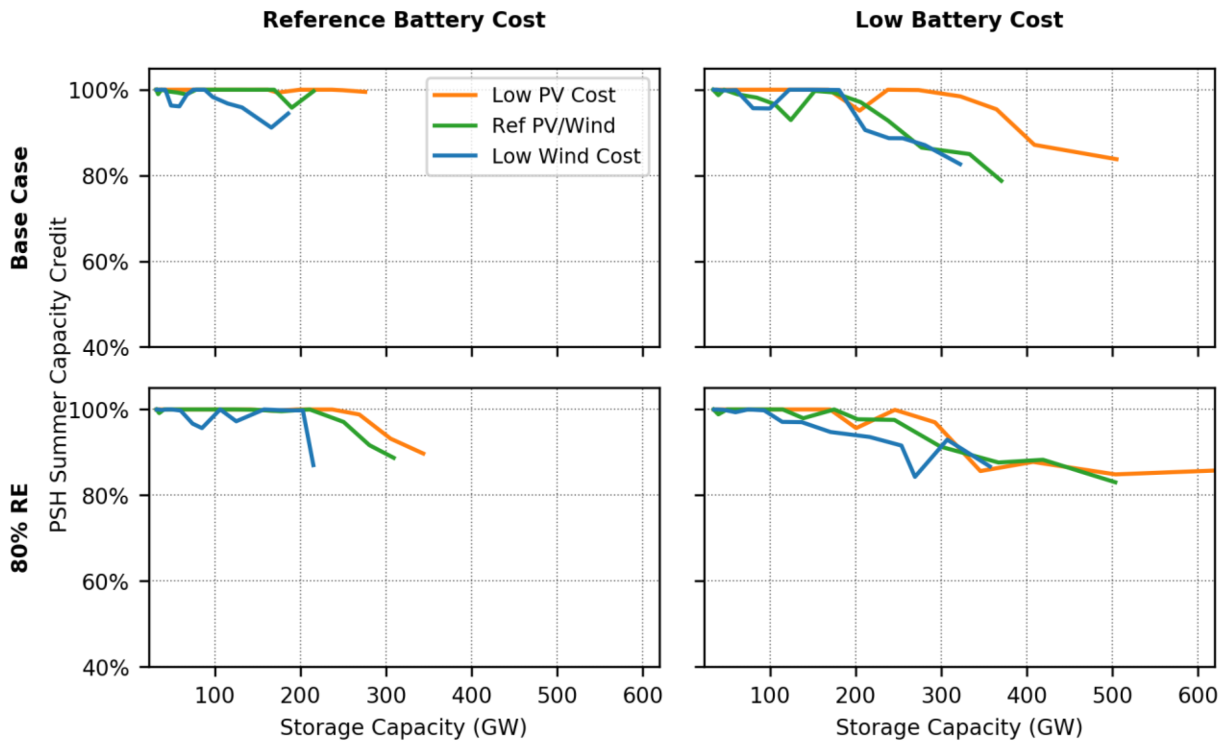

Figure 35. National average capacity credit in the summer for PSH as a function of total storage capacity deployed

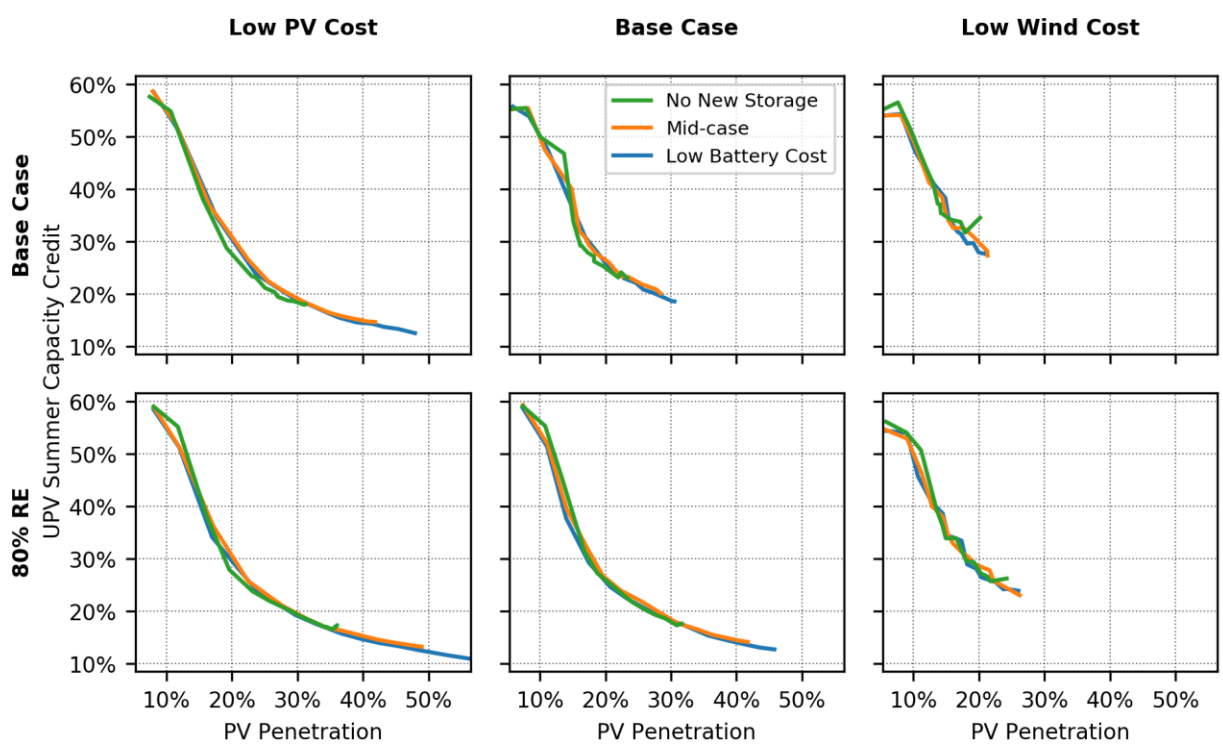

Figure 36. National average utility-scale PV (UPV) summer capacity credit as a function of total PV penetration

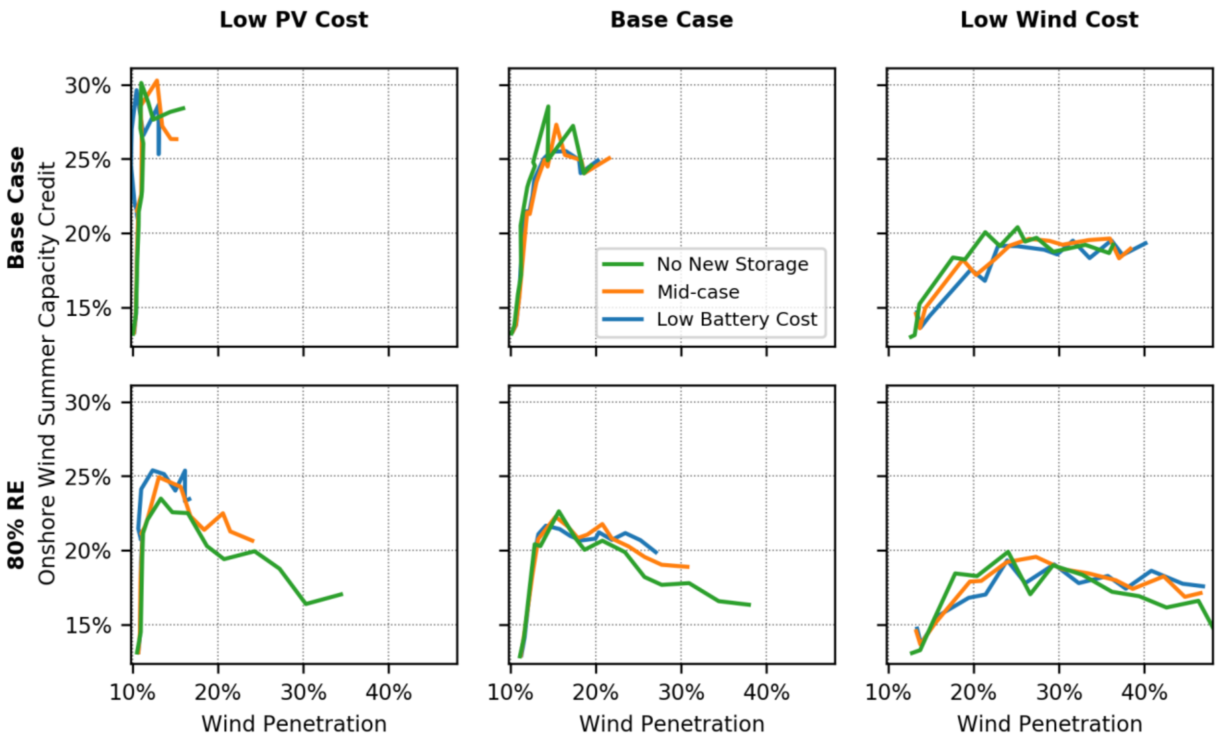

Figure 37. National average summer capacity credit for land-based wind as a function of wind penetration

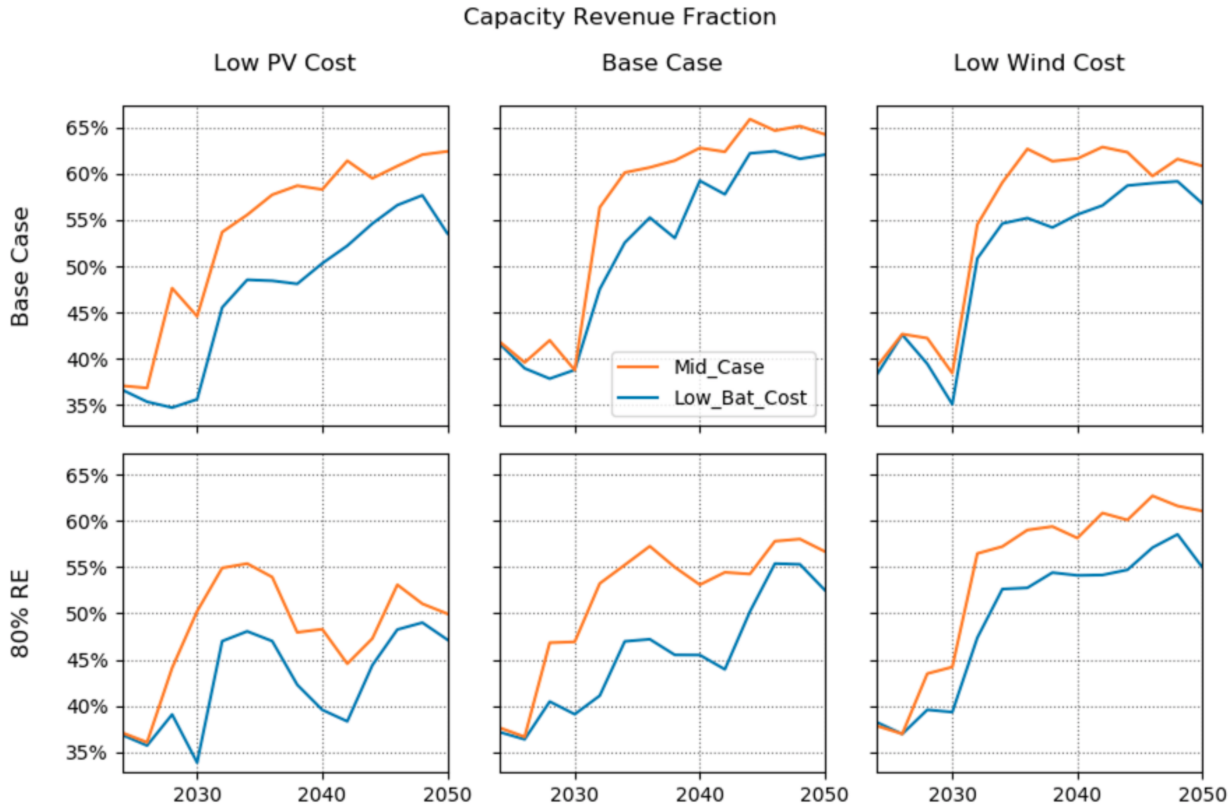

Figure 38. Fraction of storage revenue from providing capacity services

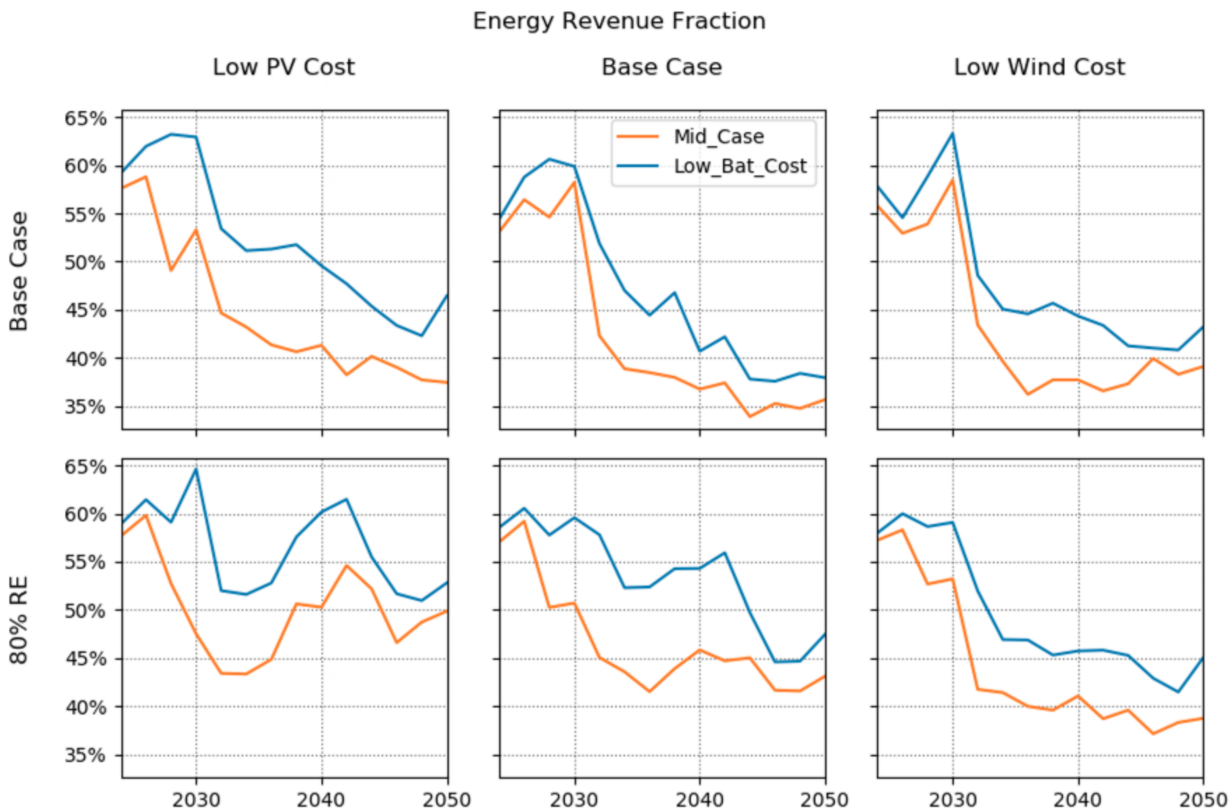

Figure 39. Fraction of storage revenue from providing energy services

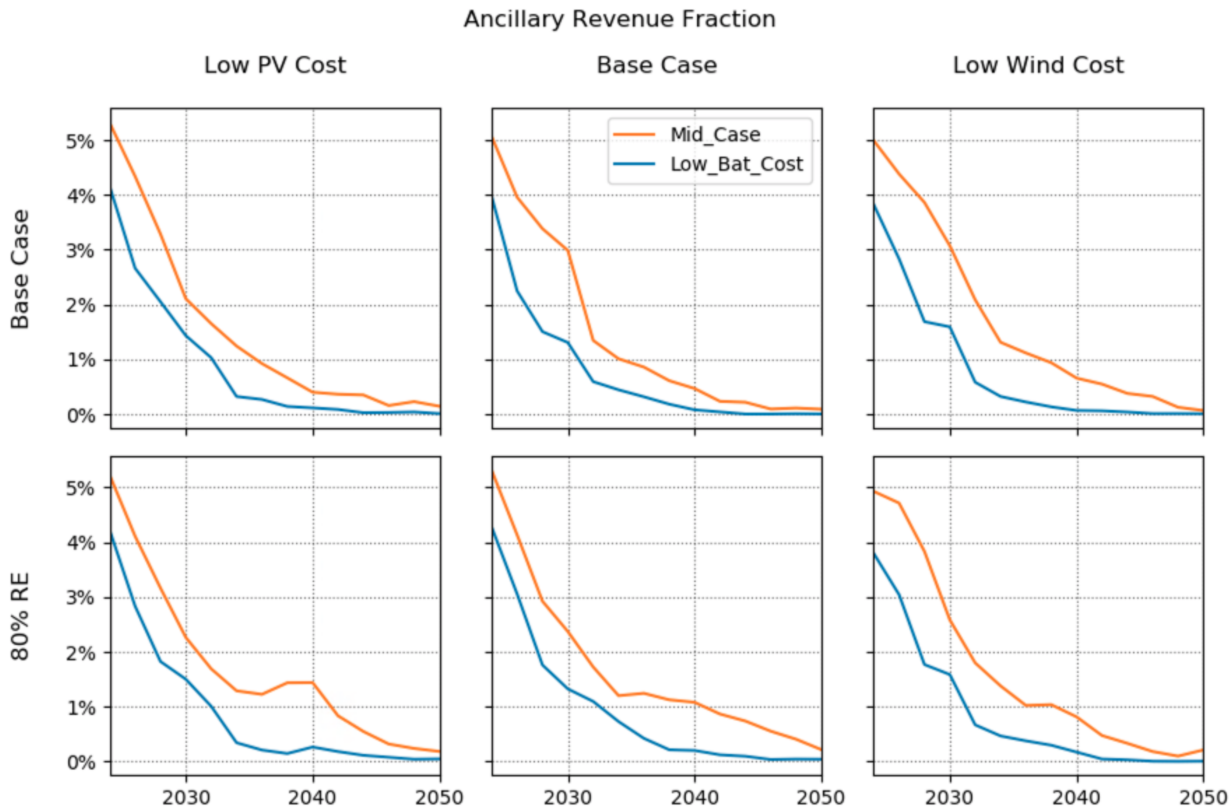

Figure 40. Fraction of storage revenue from providing operating reserves

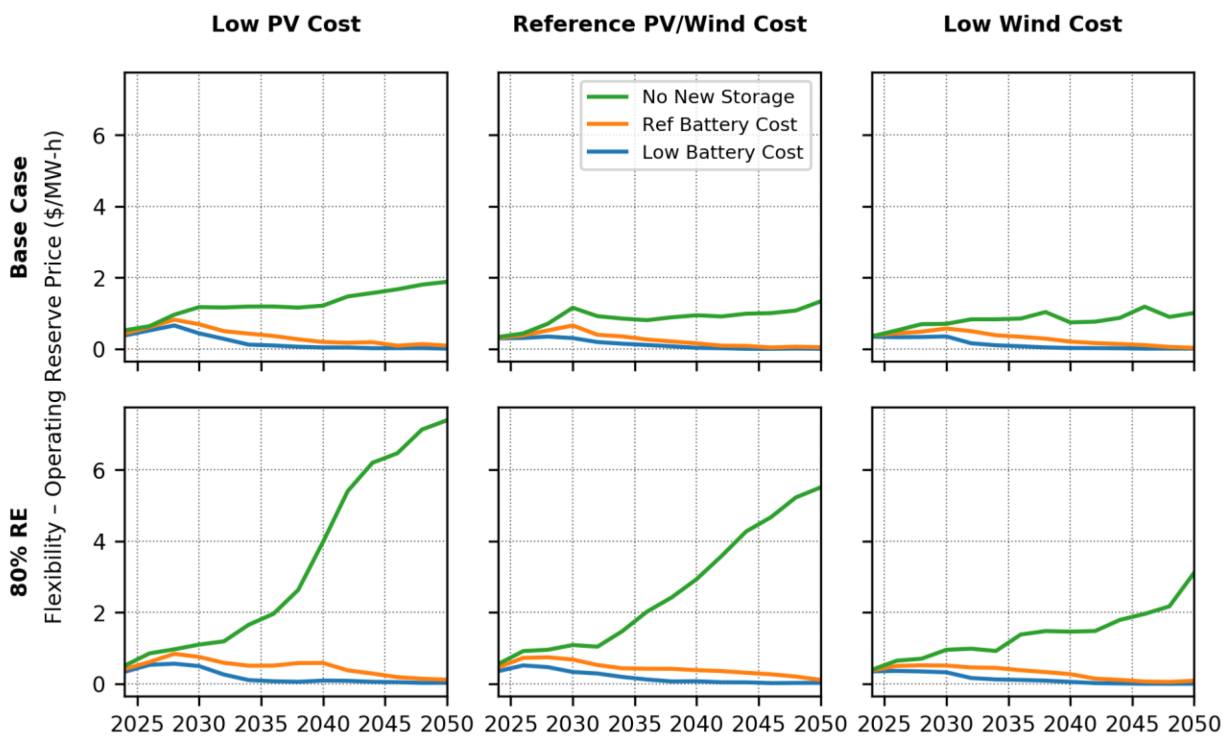

Figure 41. Modeled national average price for providing the flexibility operating reserve

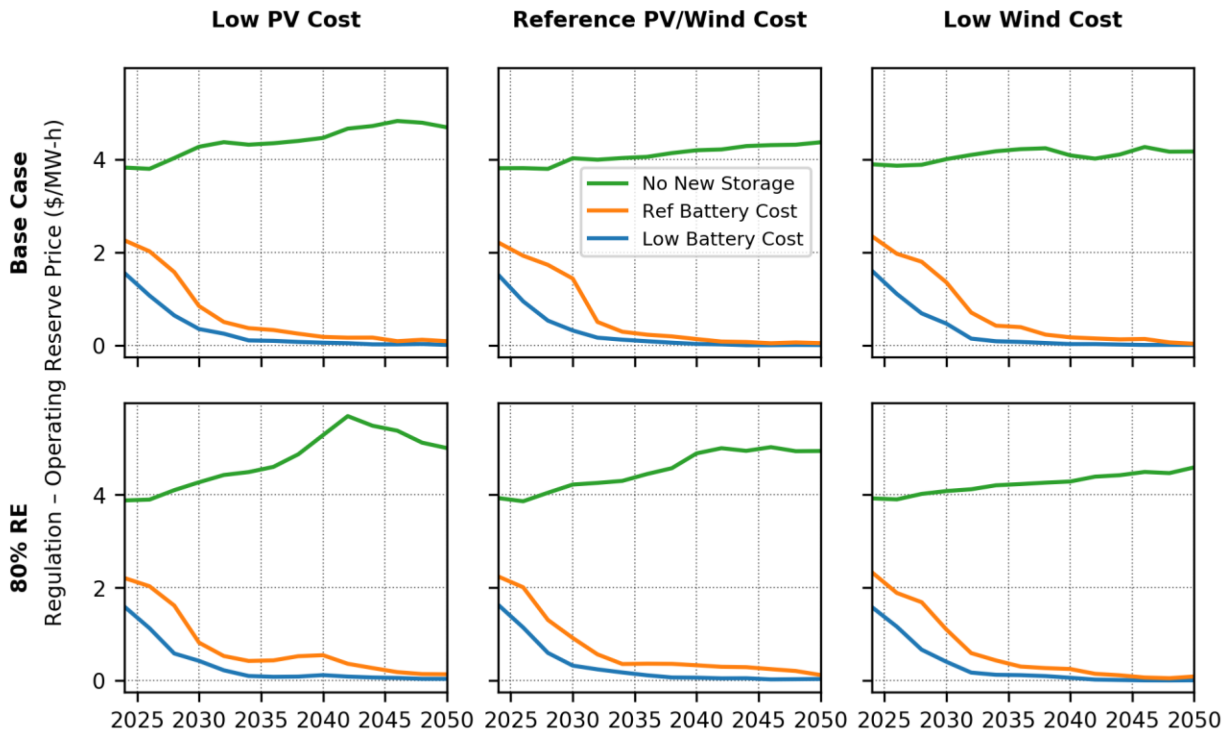

Figure 42. Modeled national average price for providing the regulation operating reserve

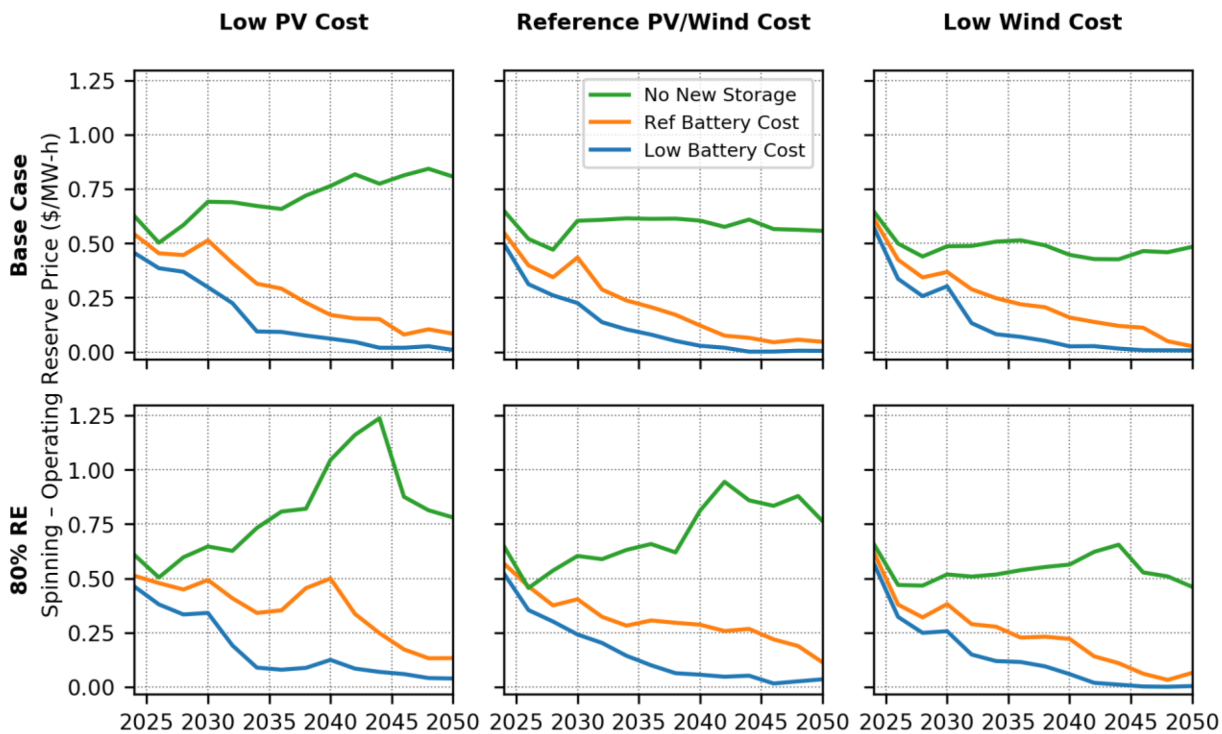

Figure 43. Modeled national average price for providing the spinning operating reserve

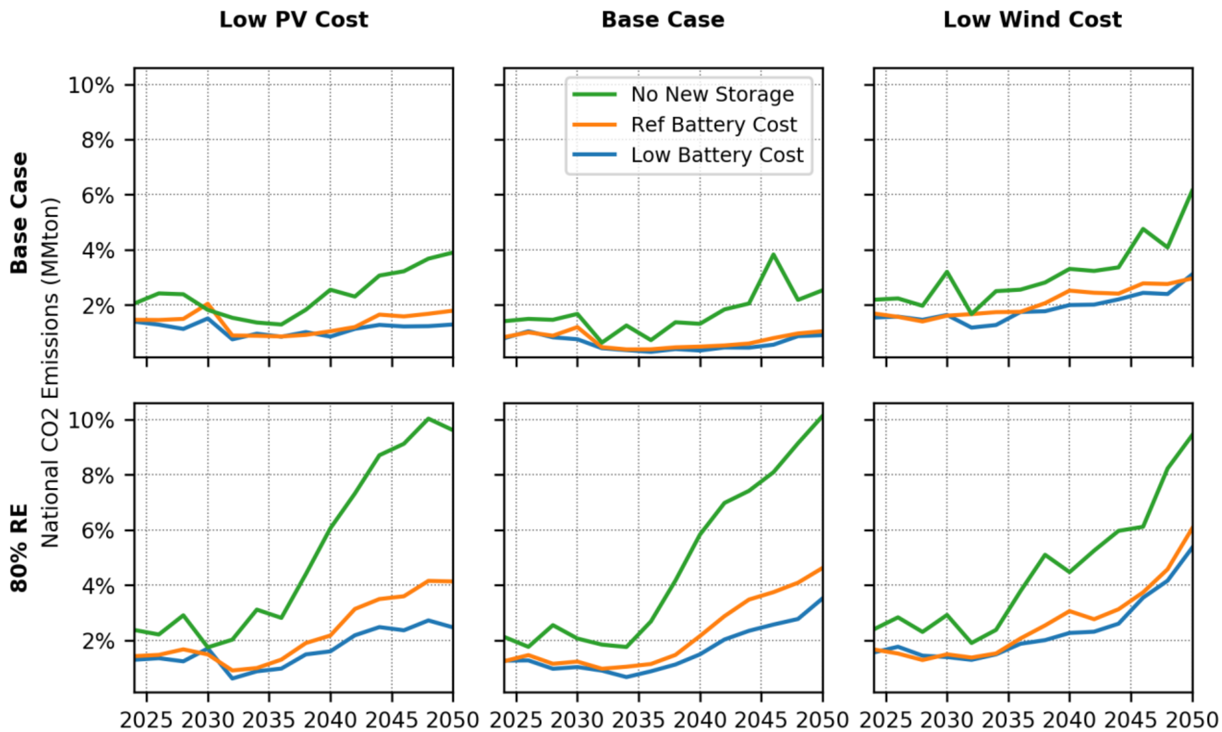

Figure 44. National average curtailment rate across the suite of scenarios

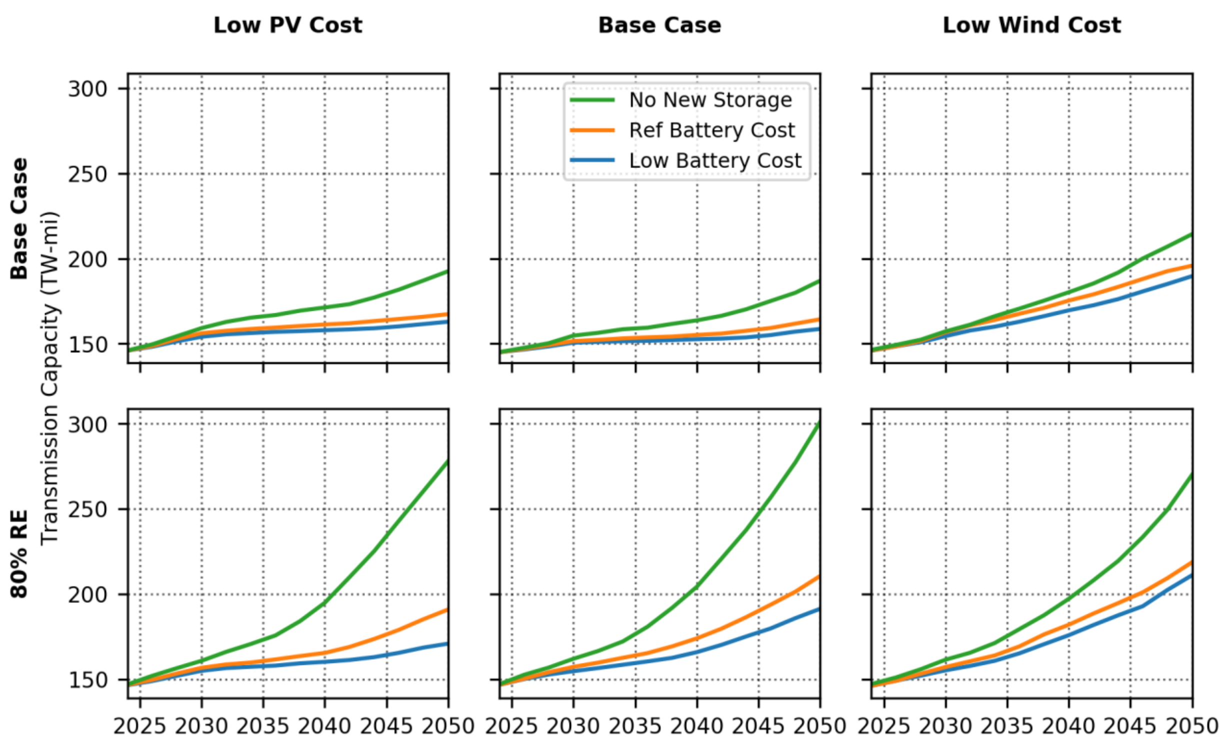

Figure 45. Transmission capacity in TW-mi across the suite of scenarios