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The potential for battery energy storage to provide peaking capacity in the United States

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ABSTRACT

Providing peaking capacity could be a significant U.S. market for energy storage. Of particular focus are batteries with 4-h duration due to rules in several regions along with these batteries' potential to achieve life-cycle cost parity with combustion turbines compared to longer-duration batteries. However, whether 4-h energy storage can provide peak capacity depends largely on the shape of electricity demand. Under historical grid conditions, beyond about 28 GW nationally the ability of 4-h batteries to provide peak capacity begins to fall. We find that the addition of renewable generation can significantly increase storage's potential by changing the shape of net demand patterns; for example, beyond about 10% penetration of solar photovoltaics, the national practical potential for 4-h storage to provide peak capacity doubles. The impact of wind generation is less clear and likely requires more detailed study considering the exchange of wind power across multiple regions.

1. Introduction

The deployment of energy storage on the U.S. grid is potentially limited by a variety of factors—primarily costs, but also performance, material availability [1], and geographic constraints for technologies such as pumped hydro [2,3]. Other limits to grid energy storage deployment include limited market size for many of the key applications; for example, deployments of battery storage for high-value ancillary services such as frequency regulation [4,5] are limited to a few gigawatts (GW), given the inherent size of the market [6].

A key emerging market for stationary storage is the provision of peak capacity, as declining costs for battery storage have led to early deployments to serve peak energy demand [4]. Much of the storage being installed for peaking capacity has 4 h of capacity based on regional rules that allow these devices to receive full resource adequacy credit [7]. Yet the potential for storage with this or other durations is unclear, which has important implications for policies that support development of energy storage resources. Understanding the ability of shorter duration storage to provide peaking capacity is of growing importance as it greatly impacts the economic viability of these resources [8].

The potential for limited-duration storage to provide peak capacity is driven in part by its ability to reduce net demand, which is a function of the duration of energy storage and the shape of electricity demand patterns. But as more storage is deployed, the peaking events it serves become longer—so storage must serve a wider part of the demand curve. This reduces the batteries' ability to act as a peaking resource, and therefore decreases their value.

In this study, we explore the potential for utility-scale energy storage to provide peak capacity in the U.S. power grid. We identify the current market for peak capacity generation. We then evaluate the amount of U.S. peak capacity that could be served by storage with different durations, and we examine how this potentially changes with deployment of various combinations of solar photovoltaics (PV) and wind.

2. The concept of peaking capacity applied to energy storage

Peaking capacity represents generators that typically run during periods of high demand, which include simple-cycle gas turbines, gas and oil-fired steam plants, and reciprocating engines [9]. The fleet of conventional generators that provide most U.S. peak capacity today is aging, and future retirements will provide opportunities for substantial amounts of battery storage to enter this market.

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Out of the approximately 1,187 GW of U.S. generation capacity (as of the end of 2017), about 261 GW is fossil-fueled peaking capacity [10].[1] Assuming the existing generation fleet has the same retirement characteristics as the historic fleet, we would expect about 150 GW of peak capacity to retire over the next 20 years [11].[2] The fraction of this capacity that could potentially be replaced with storage of various durations is determined in part by the ability of storage to actually serve peak demand.

There is significant focus on the ability of battery storage to provide peaking capacity. Batteries (particularly lithium-ion based batteries) are increasingly cost-competitive compared to fossil-fueled peaking capacity, but their cost-competitiveness declines rapidly beyond about 4–8 h of duration [8]. This is because the energy component (the battery module) is a large fraction of the total system costs, and costs scale roughly linearly with energy capacity. So it is important to identify the ability of 4-h batteries to provide an alternative to conventional peaking capacity. While we focus on batteries due to their declining prices and recent deployments, this analysis is not restricted to battery technologies. Certain technologies, including pumped hydro storage plants and compressed air energy storage plants—typically with more than 8 h of capacity—are used as peaking capacity [4,12].

The ability of a generator to provide “firm” capacity is defined by its capacity credit, or the fraction of nameplate capacity that contributes to reliably meeting demand [13]. To achieve a very high capacity credit, a storage device must have sufficient duration (hours of discharge at full capacity) to carry it through the period of peak electricity demand. There have been relatively few estimates of the capacity credit of energy storage using formal methods [14,15]. Most U.S. studies examine only a fixed amount of storage [16–18], and only a few examine the impact of increasing storage deployment on storage capacity credit, which is needed to determine technical or market potential [19–23].

Overall, the previous literature is not comprehensive in terms of geographical scope, storage penetration level, or the impact of variable-generation wind and solar deployment. Greater assessment is increasingly important as different planning entities are considering or establishing rules for energy storage providing peaking capacity and resource adequacy. As an example, a California Public Utilities Commission (CPUC) rule for California’s investor-owned utilities states that storage with 4 h of continuous discharge capacity is eligible to meet resource adequacy requirements [24,25]. Other regions such as the New York Independent System Operator (NYISO) have introduced “4-h rule” for energy storage but are actively studying the duration requirements for to participate in provision of system capacity [26]. Overall, there is ongoing need for analysis and discussion of how much storage might be actually capable of meeting peak demand particularly under future conditions of increased renewable energy deployment.

3. Methods

Traditionally, the ability of a resource to provide reliable capacity is reflected in its capacity credit or effective load-carrying capability (ELCC) [13]. The standard method of calculating the ELCC of a generator is to add a generator to a base system, and then iteratively add load until the total system reliability (typically measured by loss of load expectation) is the same as the system before the new generator. ELCC approaches rely on a well-defined power system mix, with known capacities and outage probabilities for each generator in each system analyzed, and also considering retirements and additions. Calculating the ELCC of storage depends on either using exogenously determined storage dispatch (e.g., against historic market clearing prices) or integrating storage dispatch into the model. Full ELCC simulations (which are iterative in nature) can be computationally intensive when considering a large number of scenarios, especially when adding an endogenous storage dispatch.

NYISO, the PJM Interconnection, and other regions are actively evaluating storage duration requirements [7], and establishing detailed technically and financially binding rules for energy storage related to resource adequacy will require a rigorous ELCC analysis for each location.

In practice, the results of ELCC calculations typically depend on only a relatively few hours of the year—dominated by a few days of peak demand [27]. These are hot weekday afternoons for much of the United States, but may also include very cold days, particularly in regions that depend heavily on electric heating. This has led to the adoption of the “capacity factor” approximation approach, which focuses on generator availability during the hours of peak demand [28,29]. For example, previous analysis has demonstrated that under historical conditions, examination of solar and wind output during the highest net load hours of the year would provide an accurate assessment of capacity credit [27].

To estimate a regional and national potential for energy storage under a large range of variable generation (VG) penetrations, storage capacity, and durations, we use an approximation technique similar to the capacity factor approximation. Our approach determines how much storage (both power and energy) is needed to reduce net peak demand similar to approaches used by Refs. [29,30]. This is also similar to evaluating energy storage’s contribution to the planning reserve margin, which is typically assessed at the annual peak demand period [31]. As such, we refer to this approximation as the “peak demand reduction credit” (PDRC).

For each of the regions evaluated, we simulated a total of 300 storage power capacities (sized from 0 to 30% of the annual peak in 0.1% increments). For each storage power capacity, we determined the amount of storage energy required (hours of energy capacity) to reduce the annual peak demand by the storage power capacity. In cases where we add wind and solar (discussed in Section 5), the net peak demand (demand minus the contribution from wind and solar) is used. The process is illustrated in Fig. 1a for an example in the Florida Reliability Coordinating Council (FRCC) with a 2,000 MW storage device in a four-day period from June 19–23 using 2011 load data. In this example, we are attempting to reduce the annual peak demand of 41,626 MW by 2,000 MW. This means our target net peak demand (or demand met by the balance of the system) is 39,626 MW. The model steps through the hourly load data, discharging storage if load is greater than the targeted net peak demand, and charging if the load is less than the targeted peak demand, resulting in the net load curve shown in orange.

The charge/discharge energy is tracked as a cumulative variable, including an 80% roundtrip (AC) efficiency – this is shown in the lower curve (blue) in Fig. 1a. For simplicity, we did not optimize the timing of charging, but ensure that charging does increase the net peak demand. A more optimal charging pattern is illustrated later in Fig. 2. After stepping through a full year of data, the maximum value of the cumulative variable is identified, which is the amount of energy capacity that is required to achieve the desired peak

[1] The total number of internal-combustion, simple-cycle, or steam turbines fired by liquid or gas fossil fuels from the 2017 Energy Information Administration (EIA) Form 860 database, excluding combined heat and power plants, and non-grid-connected generators.

[2] Based on 60 GW of peaking plants that have been shut down since 1980 in EIA Form 860 with average age of 44 years, which also matches the near-term projected average retirement age of peaking plants from Ref. [11].

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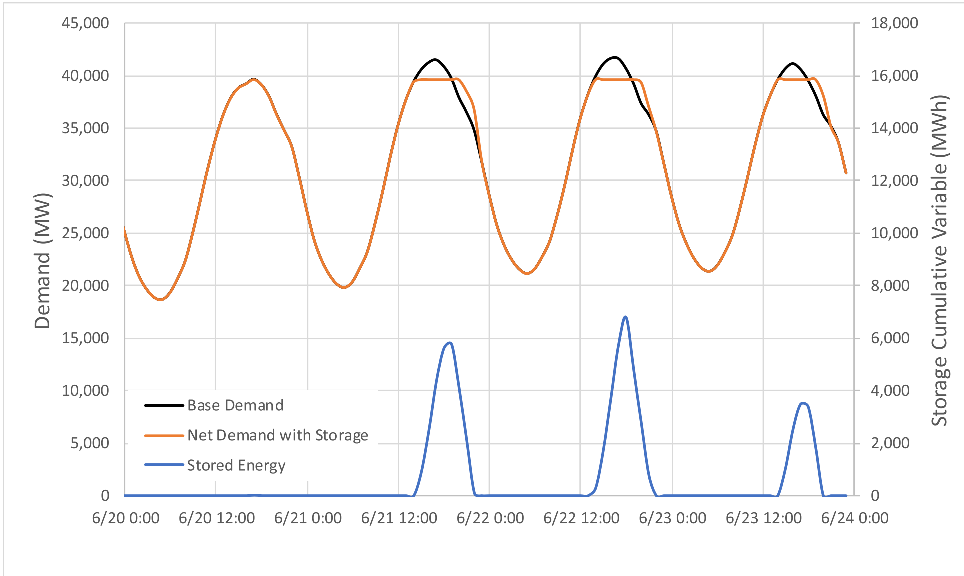
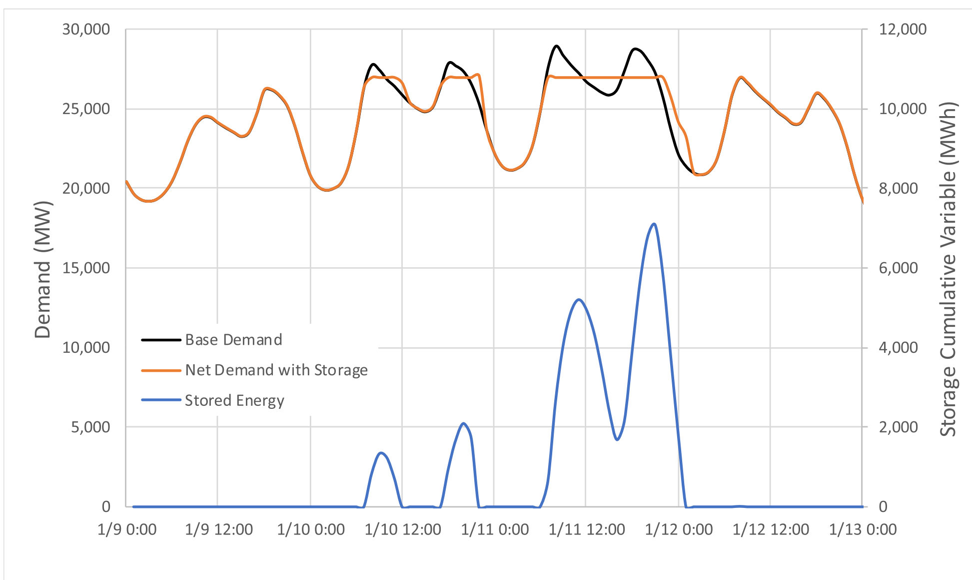


a) FRCC



b) NWPP-NW

Fig. 1. Method of estimating hours of storage needed to reduce peak demand by the power capacity of the storage device.

reduction for the given net load profile.

This cumulative variable tells of how many hours of storage are needed to reduce the peak demand by the full power capacity of the storage device, equal to a PDRC of 100%. In the FRCC example, the 2000 MW storage device requires about 6,800 MWh of energy capacity (or about 3.4 h). This means that a 2000 MW device with 4 h should have a PDRC of 100% (because 4 h is > the 3.4-h requirement).

Our simulations also ensure that the charging does not exceed the storage power capacity, or result in peak net demand that exceeds the target value. This later issue can be significant in cases with large amount of storage, or in regions with relatively flat load profiles. For example, Fig. 1b, shows a case for the Northwest Power Pool, also using 2011 data and with a target reduction of 2,000 MW. This region is winter peaking, with a double peak (morning and evening). Because there is not enough drop in demand in the middle of the day, the battery cannot fully recharge, resulting in a very long mid-day peak.

As we increase the power capacity, we reach the point at which more than 4 h are required, and the PDRC of a 4-h device begins to drop, often rapidly.

We should note that this method assumes perfect foresight and no forced outages of the storage unit. Imperfect forecasts could require a small amount of additional storage energy capacity to mitigate errors in the timing of discharge. This amount should be relatively small based on trends in forecasting of load and solar [32,33].

Our analysis is performed for 18 U S. regions that are based on

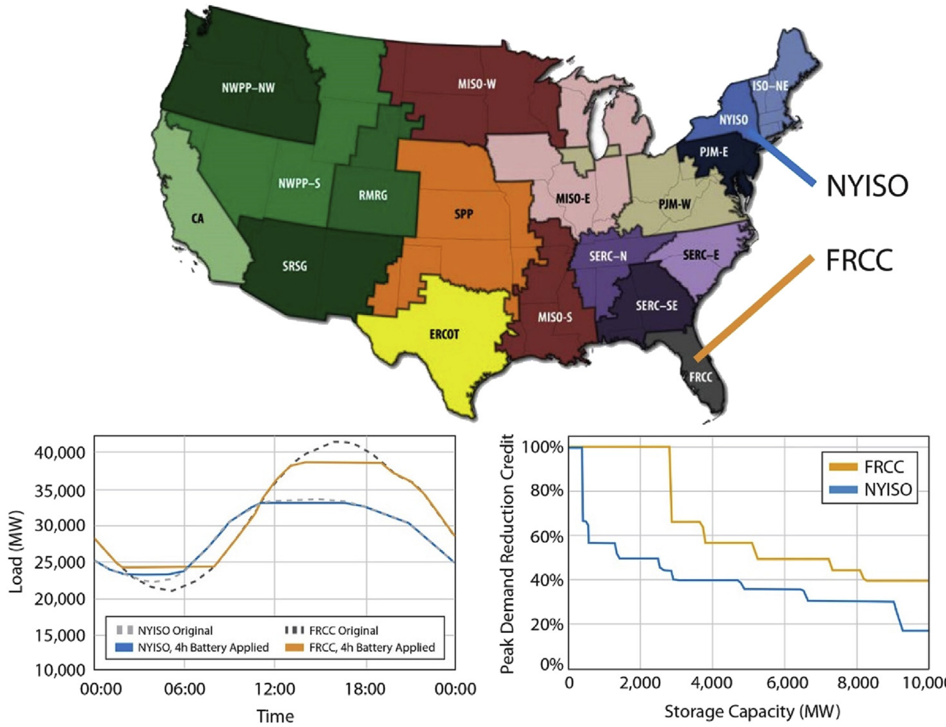


Fig. 2. Map of the regions used in this work. The peak demand reduction of 4-h energy storage in Florida and New York in 2011 is shown, along with the peak demand reduction credit for both regions as a function of deployed storage capacity.

the North American Electric Reliability Corporation (NERC) “Assessment Areas” shown in Fig. 2 [31]. Because of the size of Midcontinent Independent System Operator (MISO) and PJM, these were divided into smaller regions [west and east] to evaluate the impact of different demand patterns. We also divided the Northwest Power Pool [NWPP] into two regions to capture the impact of winter-peaking loads in the Pacific Northwest.

In addition to the regions evaluated, Fig. 2 also provides an example of the PDRC 4-h threshold for two regions: the Florida Reliability Coordinating Council (FRCC) and NYISO. The hourly load profiles (lower left) show the day of highest load for each region in 2011 including the impact of simulated storage. The profiles show the point at which 4-h storage can no longer reduce the net peak demand by the power capacity of the storage plant (meaning the PDRC of 4-h storage has fallen below 100%).

In Florida about 2,850 MW of 4-h storage can be deployed with a PDRC of 100% using 2011 data. Assuming perfect foresight of electricity demand, this suggests that 4-h storage could effectively contribute 2,850 MW of capacity toward the system planning reserve margin. In NYISO, only about 440 MW of 4-h storage can be deployed with full PDRC, despite NYISO having a peak that is only about 20% lower in this year. The reason can be seen in the left subplot of Fig. 1: the width of the peak demand in NYISO is much wider than that of FRCC.

These threshold values do not mean that the 4-h storage device can no longer provide any useable system capacity; rather, they mean that each MW of storage power capacity can no longer reduce the peak demand by 1 MW, implying a declining PDRC. The right curve in Fig. 1 illustrates the PDRC for both locations as a function of penetration for a 4-h storage device.

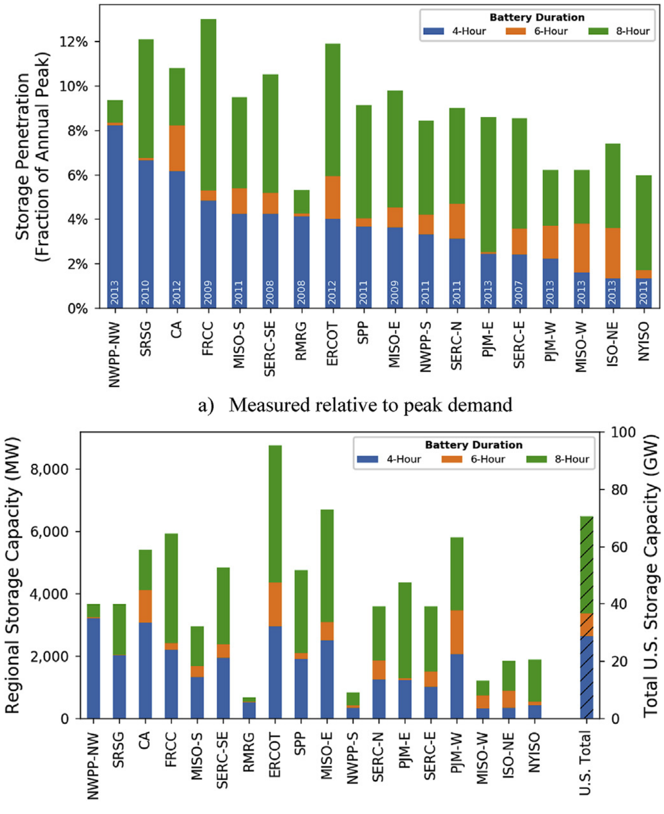
At the threshold value where the PDRC of 4-h storage falls below 100%, the width of the net load peak actually exceeds 4 h; this is because the entire peak event does not require the full power of the storage capacity, so energy can be rationed out during the shoulder hours to have the device ride through a longer peak. In the Florida example, this point is reached at 2,850 MW of storage, where the peak demand period has widened to 6 h. This creates a discontinuity in the PRDC for any additional 4-h storage beyond that point. To reduce the peak demand further, any additional 4-h storage must discharge at less than full rating for 6 h, which produces an effective PDRC of 4/6 or about 67%. Further 4-h storage beyond that would earn steadily less PDRC, as peaks get wider and peak days shift. The NYISO case shows an even more rapid drop to the point where the incremental PDRC falls below 50% after total installations of about 2,570 MW. Discontinuities in the data result from using discrete hourly load patterns, and using subhourly time intervals would smooth the curves. Use of subhourly data would not change the PRDC results assuming reported data represents hourly average power (energy), but could change the results if reporting instantaneous power, as discussed in Ref. [34].

The declining ability of 4-h energy storage to reduce peak demand would require utilities or developers to de-rate 4-h storage at the “threshold” value where the PDRC falls below 100% (potentially reducing capacity payments or other revenue associated with resource adequacy). This substantially decreases the economic value of 4-h storage—and the rapid decline in its PDRC implies a “practical” limit to its use as peaking capacity. As a result, continued economic use of storage as peaking capacity might require deployment of longer-duration storage. This could produce a trajectory in which 4-h storage is built first, until it reaches the point of diminishing capacity value at some point in the future, allowing developers to take advantage of declining battery prices [8,35] and then build longer-duration storage.

At each location we construct a “practical peaking potential” for energy storage of different durations using 7 years of data. Hourly load data for 2007–2013 was obtained from the Federal Energy Regulatory Commission’s Form 714 database [36] and ISO websites.[3] At each location, we add 4-h storage until the point at which the PDRC drops below 100%, establishing the threshold value for practical potential for storage of this duration. We then build 6-h storage and subsequently 8-h storage, finding the point at which the PDRC falls below 1 for each.

Once the threshold value is determined (MW of storage capacity), we normalize this value by dividing this value by the peak demand in that year. By normalizing the results, we can partially control for changes in demand that occur due to demographic and economic factors. This allows us to focus on the correlation between load shapes and storage across multiple weather years. For the base case (no wind or solar), across the 7 years of data, we selected the year that shows the lowest normalized threshold value, with the exception of one region. In all summer-peaking systems, the relationship between normalized threshold value and annual peak demand data shows either no relationship or a small negative correlation, indicating that storage does slightly worse in the years with highest demand, which would typically be the basis for the system planning reserve margin. In the NWPP-NW (a winter peaking region), storage actually performs better as a function of peak demand, so we chose an “average” year (2013) for that region. For the cases with added wind and solar in NWPP-NW we used the lowest value, as there is no clear trend, so we revert to the most conservative approach.

The lowest value of the seven years of data is then multiplied by the anticipated peak demand in 2020. This value is the practical potential for energy storage of a given duration. The 2020 peak demand in each region is derived from the [31] Long-Term Reliability Assessment.



a) Measured relative to peak demand

b) Measured by capacity (based on 2020 peak demand)

Fig. 3. Base case practical peaking potential for energy storage providing full peak demand reduction credit in 2020.

4. Results: base cases without the addition of wind and solar

Fig. 3 shows the results for each region. Fig. 3a measures the storage capacity relative to annual peak demand (i.e., the practical peaking potential in MW divided by the annual peak demand). This normalizes the results for the purposes of comparison among regions. The figure also shows which year was chosen, using the lowest value of the 7 years analyzed for all regions except for NWPP-NW, which uses 2013. Normalizing to annual peak also allows us to scale the storage to different annual peak demands for the purpose of evaluating the potential of storage in future years. Fig. 3b provides a total regional and national practical potential for incremental 4-, 6-, and 8-h capacity storage providing full PDRC in 2020. This represents our base case practical peaking potential, assuming no deployment of wind or solar.

Fig. 3a demonstrates the much greater ability of 4-h storage to reduce peak demand in strongly summer-peaking systems such as in California and the Southwest Reserve Sharing Group (SRSG) compared to regions that, while still summer peaking, have longer-duration peaks. The NWPP-NW also shows a relatively large potential for 4-h storage based on the shape of the winter peaks. The practical potential for 4-h storage at full PDRC is about 28 GW. This about four times greater than the entire regulating reserve requirement in the United States [6].

The step from 4 h to 6 h is relatively small (about 8 GW), because the first 4 h of storage typically widens the peak to about 6 h, leaving little room for 6-h storage. The 8-h step is much larger (about 34 GW), leading to a total potential for combined durations of about 70 GW. This is much lower than the total installed peaking capacity (261 GW) and less than half of the expected 20-year retirement number of 150 GW. However, these values do not account for the large increase in potential that results from the impact of renewable energy on net load shapes.

5. Results: the potential for storage to provide peaking capacity changes with PV and wind

A number of analyses have demonstrated that PV can change the net load shape and potentially increase energy storage’s capacity credit or reduce the storage duration needed for full capacity credit [37–39]. Fewer analyses have looked at the effect of wind or the combination of wind and solar.

To quantify the impact of wind and solar on the practical potential of storage to provide peaking capacity, we repeat our simulations for all data sets with the addition of PV (up to 35% on an annual basis for all regions) and wind (also up to 35%).

Wind and solar sites were selected using the Regional Energy Deployment System (ReEDS) capacity expansion model. ReEDS is a national-scale model that minimizes the total system cost as it selects generation and transmission technologies to meet system requirements [40]. The specified penetration levels were implemented in ReEDS as model constraints at the state level, such that

[3] Because the boundaries of several regions in the Eastern Interconnection changed between 2007 and 2013 (mainly MISO, Southwest Power Pool [SPP], and Southeastern Electric Reliability Council [SERC]), some loads in older years were shifted to correspond to current boundaries. Because the System Advisor Model (the tool used to generate PV data) does not allow for years with more than 365 days, the last day of the year (12/31) was removed from the 2008 and 2012 load data, and those days were spot checked to ensure they would not impact the results.

each state had to meet the required annual penetration of wind and PV. This requirement can be met from in-state generators or from bundled trading of wind and PV from nearby states. Because of our focus on peaking capacity, only resources within the NERC assessment area were considered to contribute to capacity requirements. For regions with insufficient wind resources (FRCC, ISO-New England [ISO-NE], CA, and SERC), generation profiles for surrounding regions were used.

For PV, we assumed an approximately equal mix (on an energy basis) of fixed installations and single-axis tracking installations. Once the quantities of wind and PV were established in each of the 356 ReEDS regions, hourly generation profiles for 2007–2013 were generated using the reV model [52] with resource data from the National Solar Resource Database (NSRDB) [41] and the WIND Toolkit [42].

Existing wind and utility-scale solar were not considered for the zero-renewables cases. Some behind-the-meter (BTM) PV existed in the later years and is represented within the load data. This means that the zero PV cases actually have a small amount of BTM PV in some locations. Because most of the BTM PV has been installed in the last few years (after 2013), the overall impact should be relatively small. In our cases with renewables, the cases first used simulated profiles from existing locations and capacities, and then added new locations as selected by ReEDS. We used simulated weather data (rather than measured wind and PV generator profiles) for all cases for consistency; this is because relatively few wind and solar projects were installed before 2007, and we did not have access to 7 years of actual measured generator output from most of those projects.

Fig. 4 provides results for five regions that show some of the relationships we observed between VG deployment and the ability of 4-h storage to reduce peak demand. The results for all 18 regions are provided in the Supplemental Material. The amount of 4-h storage capacity with full PDRC is shown as a function of PV penetration, while the various wind penetrations are shown as different points at each PV penetration level. As before, our study uses the most conservative (i.e., lowest) value for all summer-peaking regions, including for NWPP-NW, which is winter peaking. The NYISO case (also seen in FRCC and ISO-NE) shows a fairly strong relationship between PV penetration and storage capacity with full PDRC, with modest impact of wind. The SRSG case (also seen in the CA curve) is similar in shape to the NYISO curve, but shows a drop in PDRC with penetrations of PV in the range of 5%–10%. This drop results from PV clipping the peak and widening the net load pattern, but it only occurs at relatively low penetration until the net load peak is shifted to later in the afternoon [29]. All other cases except NWPP-NW show increase in PDRC as a function of PV penetration, but with greater variability as a function of wind, or with discontinuities. Some locations also show a drop in PDRC at low PV penetration, similar to the SRSG case. In addition, the benefits of PV in some regions saturate, sometimes due to a seasonal shift in net peak demand from summer to winter. In locations where there is significant variability in PDRC as a function of wind, there are few consistent patterns across all regions. The MISO-E region shows most points above the zero-wind case, where wind acts to further narrow the peak, thereby increasing PDRC. However, there are other cases, such as SPP, where adding wind tends to decrease PDRC. In these cases, wind is flattening load and providing capacity credit, similar to the impact of PV at low penetration. Finally, the NWPP-NW case shows a very limited benefit from PV, due to the winter peak and limited solar output on this day, and it is the only case we found in which wind can negate the impact of PV on changing the net load shape and enabling greater amounts of 4-h storage.

The results in Fig. 4 show that significant changes in net load and corresponding impact on storage potential can occur at relatively low penetrations of PV (5%–10%), implying a near-term impact for regions with aggressive PV deployment goals. Some regions such as California have already deployed sufficient PV to demonstrate increased potential for 4-h storage. For example, California is projected to exceed 15% PV penetration by 2020 [29], implying a greater than 1,000 MW increase in potential for 4-h storage compared to the zero-solar case. Early storage deployments could be a key element to further reducing costs—and point to the continued need to assess the actual regional duration requirements in an evolving grid.

Translating these results into a national practical potential requires choosing scenarios for PV and wind penetration at each location. These technologies are not currently deployed uniformly across the United States, so we sampled various combinations of wind and solar at each location, aggregated to the national level.

Fig. 5 shows the overall national practical potential for energy storage for about 20,000 combinations of VG penetration.[4] The x-axis provides the total amount of PV deployed nationally, and thus represents many combinations of PV deployment in each region. The lower bound of 2.3% represents the amount of PV deployed in 2018, with simulated PV deployed in historical locations [43]. At each PV penetration, we also evaluate a large number of wind penetrations. The y-axes represent the national practical potential for storage with full PDRC assuming 2020 peak demand projections (when deployed sequentially from 4 to 6–8 h). The curves show both a mean trendline and a band that captures 90% of the scenarios evaluated. The data shown intends to capture only the general relationship between variable generation deployment and storage potential, as the results include unlikely scenarios (e.g., concentrations of PV and wind in locations with poor resource, or cases in which wind-rich regions deploy mostly solar). Following regional results, there is a strong positive relationship between national practical potential for storage and PV deployment. Overall, the practical potential for 4-h storage appears to nearly double by the time PV achieves about a 10% national average penetration (compared to the 2018 PV case).

Curves showing the relationships between wind penetration and storage potential are provided in the Supplemental Material and demonstrate no observable trends. This implies that solar would be the main driver behind any change in the ability of storage to meet peak demand.

6. Conclusions and next steps

We demonstrate the opportunity for utility-scale storage to satisfy a substantial portion of U.S. peak capacity needs and thus expand beyond its current role in the relatively small ancillary services market. This analysis demonstrates roughly 28 GW of practical potential for 4-h storage providing peaking capacity, assuming current grid conditions and demand patterns. This deployment could help decrease storage costs—and storage deployed primarily to provide peaking capacity can provide additional benefits, such as a sink for low- or zero-value PV generation during non-peak periods. This in turn can enable greater PV deployment, which then increases the potential of 4-h storage. This effect can extend the practical potential for 4-h storage to 50 GW or beyond nationally (assuming PV provides 10% of the nation's electricity demand). Of course, there could be significant regional impacts, as the areas first to adopt 4-h storage could saturate their potential before full national deployment is reached. However, the

[4] Data are grouped into 20 equally spaced PV penetration bins for mean and percentile calculations, and lines were drawn from the center point of each bin.

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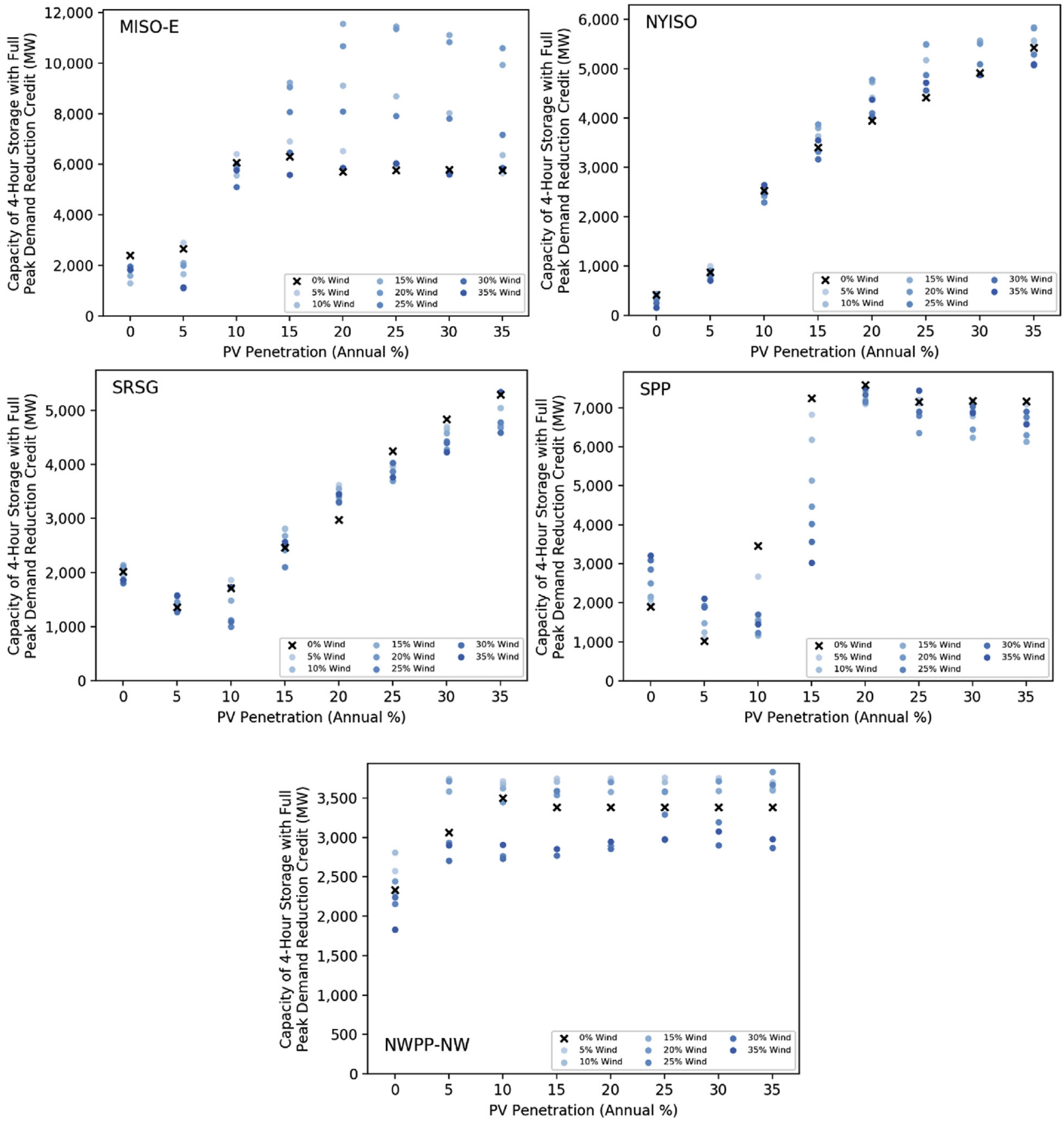

Fig. 4. Practical potential (GW) for 4-h energy storage with full peak demand reduction as a function of VG penetration by region in 2020.

general effect should provide additional potential for cost reductions to increase the competitiveness of 6- or 8-h storage.

The results show significant potential for energy storage to replace peaking capacity, and that this potential grows as a function of PV deployment. Our analysis (particularly Fig. 4) focuses on 4-h storage due both to current policy drivers [25] and the near-term cost competitiveness of 4-h batteries compared to those with longer duration. A key performance metric is the "breakeven" cost of batteries required to achieve life-cycle cost parity compared to traditional peaking resources. This breakeven cost is not a simple equivalence of capital costs due to a variety of factors, including the shorter lifetime of batteries and the greater operational flexibility of batteries compared to combustion turbines. The relative value of storage providing system flexibility (i.e., time-shifting of generation resources and avoided thermal plant starts) increases the value of batteries relative to combustion turbines and will vary by grid mix, fuel price, and storage size. Additional analysis is required to evaluate this breakeven cost as a function of deployment, considering the change in value as a function of PV deployment (which generally increases the value of storage) and the value of storage deployment (which decreases the value of storage). This will vary regionally as a function of these parameters plus the mix of other generation resources, with examples including [44,45]. These analyses can also consider that changes in emissions that result from storage operation [46,47]. Unlike traditional thermal generation, batteries used for peaking could also be sited on the distribution network, potentially providing additional value [48].

While we focus on battery storage, these results are more

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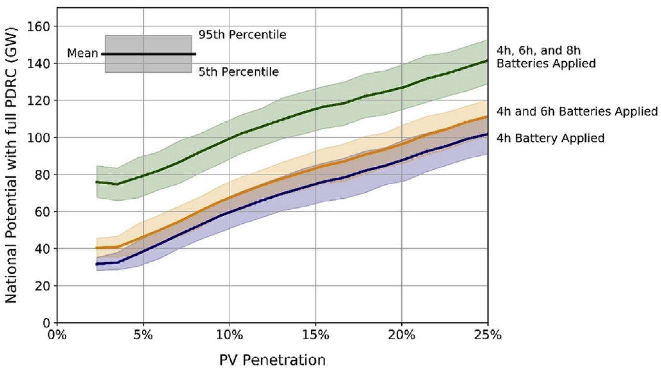

Fig. 5. National practical potential (GW) for 4-, 6-, and 8-h energy storage as a function of VG penetration.

generally applicable to storage with the same duration per unit of energy capacity. We performed sensitivity analysis on several cases with efficiencies ranging from 70% to 90%, which could represent a range of storage technologies. We found minimal impact on PDRC, particularly at relatively low penetration of storage. There may be a reduction in PDRC for technologies with lower round trip efficiency in scenarios with very large storage penetrations as storage begins to completely flatten the load (mostly commonly seen in cases with winter peaks, or where solar and storage shifts the net demand peak to the winter). In these cases, there may be insufficient time for storage technologies with lower efficiency to fully charge. This effect could be mitigated for technologies with low round trip efficiencies (such as hydrogen) but extremely long durations, as they allow for seasonal shifting of energy supply [8].

This preliminary analysis does not consider several elements that could affect the potential of storage to provide peaking capacity. Because this work relies on historical load patterns, it does not consider the possible impacts of changing electricity load patterns due to demographic shifts, climate [49], and electric vehicles [50] in the decadal time scales needed to achieve greatly increased PV penetration [51]. It also does not consider how additional transmission could enable larger regional sharing of wind and solar resources that could impact net profiles. Finally, while these results provide a basic indication of the overall potential for storage to provide peaking capacity, robust regional calculations using standardized effective load-carrying capability calculations will be needed to verify the results for any specific location.

CRediT author statement

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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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.renene.2019.11.117.

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