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The peaking potential of long-duration energy storage in the United States power system

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ABSTRACT

In this work, we investigated the peaking potential for storage with durations of 4 h up to durations of 168 h (1 week). The peaking potential for a given storage duration is the amount of storage that can be added to a power system before that storage can no longer serve the peak net demand period at full rated capacity. We found that for the United States, 168 h of storage would be sufficient to serve about 27 % of peak demand, or about 215 GW in the current system. However, more than one-half of this amount could be served by storage with 12 h or less of capacity. As deployment of wind and solar grows, the peaking potential increases significantly, and under decarbonization scenarios, approximately one-half of the peak demand could be served by storage of up to 168 h; but again, the majority of this storage could be with durations of up to 12 h. The potential is also driven by the mix of wind and solar, and by storage efficiency, with the deployment of solar having the largest impact for both storage peaking potential and the mix of durations.

1. Introduction

The significant decline in battery energy storage costs, along with growing deployment of variable renewable energy (VRE), has greatly increased interest in and deployments of new stationary storage. Much of the storage now being deployed in the United States is serving the peak summertime demand, which typically occurs during a roughly 4-hour window in late afternoon. Batteries with durations in the range of 2–6 h provide high capacity credit, meaning that they can reliably shave the peak, and therefore offer an increasingly cost-effective alternative to conventional fossil-fueled peaking capacity. Most of the new storage consists of lithium-ion batteries with durations of 4 h or less [1] and there are over 400 GW of storage proposed to be added to the U.S. electricity grid at the end of 2021 [2].

Substantial analytical evidence shows that a 4-hour duration can provide high capacity credit in today's summer-peaking system, and there are significant market opportunities for 4-hour storage [3–6]. This potential exists even absent decarbonization efforts. However, it is also well understood that as greater amounts of storage are deployed, its marginal capacity credit drops [7]. This occurs as storage creates flatter, wider net peak demand profiles, and may also shift the net demand peaks to winter. Complicating the analysis of energy storage as a source of peaking capacity is the significant variation in regional grid conditions, especially related to increased and varying mixes of VRE. In particular, solar photovoltaics (PV) narrows the peak demand period and increases opportunities for storage, particularly in summer-peaking systems [8,9]. Interest is considerable in longer-duration energy storage as a resource to help decarbonize the grid, and multiple studies identify significant contributions of storage of various durations in grids with large contributions of VRE [10–17].

Because capacity is a primary value stream for storage deployments [3,18], it is important to understand the possible transition to longer-duration storage as a source of dependable peaking capacity. Therefore, it is also important to understand how this substantial source of value will change under various scenarios of VRE and storage deployment.

The work we present here seeks to help address the gap in understanding the role of storage of various durations as a source of firm capacity. We examine durations from 4 h to 168 h (1 week) for different regions of the United States under current grid conditions, and under scenarios of grid evolution, including those with significant VRE under decarbonization scenarios. The analysis we perform is not an economic analysis, but an analysis of how much storage *could* contribute if it were to be built for addressing periods of peak demand. This framing can help lay the foundation for the economic analysis that will be needed to fully understand the role of longer-duration storage in a decarbonized power

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system.

2. Methods

The methods employed in this work are designed to evaluate the peaking potential of storage, meaning its ability to substitute for the traditional capacity resources used to ensure resource adequacy. We define the peaking potential as the power capacity of storage (with a given duration) that can reduce the peak net load with approximately full capacity credit.

This peaking potential is analogous to a technical potential for renewable energy technologies (e.g., [19]) in that it does not depend on the economic viability of a technology, only on its ability to serve load as stated. The method is technology agnostic in that it considers only the storage duration, defined as the number of hours that the storage can discharge at its rated power capacity, and the storage round-trip efficiency, which governs the ratio of charging to discharging. In this work, we assume that the charging power is always equal to the discharging power (i.e., if a device discharges at 100 MW it can also charge at 100 MW).

The peaking potential of storage is a function of a region's net-load shape. Because the net load is the load adjusted for wind, PV, and storage generation (including storage charging), all three of those elements impact the net load, and thereby impact the storage peaking potential.

To calculate net loads for both near- and long-term grid conditions, we use the Regional Energy Deployment System (ReEDS) model. ReEDS is a long-term capacity expansion model of the contiguous U.S. power system [20]. It takes a system-wide optimization approach to choose the generation, transmission, and storage resources that will minimize the total cost of building and operating the power system from present day through 2050. ReEDS includes wide-ranging power and storage generation technologies, including land-based wind, offshore wind, utility-scale PV, rooftop PV, concentrating solar power, geothermal, hydropower, pumped-hydropower storage, batteries (with durations of 2–10 h), traditional large-scale nuclear, nuclear small modular reactors, coal (with and without carbon capture), natural gas combined cycle (with and without carbon capture), natural gas combustion turbines, biopower (with and without carbon capture), landfill gas, and hydrogen combustion turbines. Transmission in the model is represented between the model's 134 balancing areas (shown in Fig. 1 below). The model also includes representations of current state and federal policies, such as state renewable portfolio standards, California's carbon dioxide (CO_2) requirements, the Regional Greenhouse Gas Initiative, and federal clean energy tax credits. Model inputs and assumptions are consistent with the 2021 Standard Scenarios [21], which use the National Renewable Energy Laboratory 2021 Annual Technology Baseline [22] for all technology cost and performance assumptions and the Annual Energy Outlook 2021 [4] for demand growth and fuel price projections.

We modeled grid conditions from 2022 to 2050 in 2-year increments using the 12 scenarios in ReEDS that are summarized in Table 1. The Reference scenario was modeled before passage of the Inflation Reduction Act [23] and is therefore likely conservative in terms of renewable deployment. A variety of nationwide CO_2 emission limits and PV and wind cost trajectories were used to generate various futures. The scenarios are not intended to be predictive, but rather to provide a range of conditions and generation mixes for evaluating the peaking potential for storage. Total capacity and annual generation plots for the scenarios are included in the Supplementary Information (see SI Fig. 12).

Planning reserve margins or other resource adequacy requirements are generally established at a regional (as opposed to national) level [24], and we evaluate the peaking potential for storage for 12 regions in the United States, as shown in Fig. 1. For regions that have an organized electricity market, these regions approximately follow the boundaries of those market regions. Other region boundaries are created based on a combination of North American Electric Reliability Corporation reliability regions, balancing area regions, and transmission planning regions (see the SI for definitions of regional name acronyms).

The PV and wind shares for these 12 regions across the 12 scenarios are summarized in SI Table 2. and SI Table 3.. In 2050, PV annual generation shares in each region range from 5 % to 87 %, and regional wind generation shares range from 0 % to 82 %.

We use 7 years (2007–2013) of historical hourly wind, solar, and load data to produce the regional net-load profiles. Prior work has shown that it is important to include multiple years of weather data when analyzing firm capacity or peaking capacity contributions [15,25–27]. By using 7 years of weather and load data, we can capture longer-term trends that might not appear in the data set for a single year.

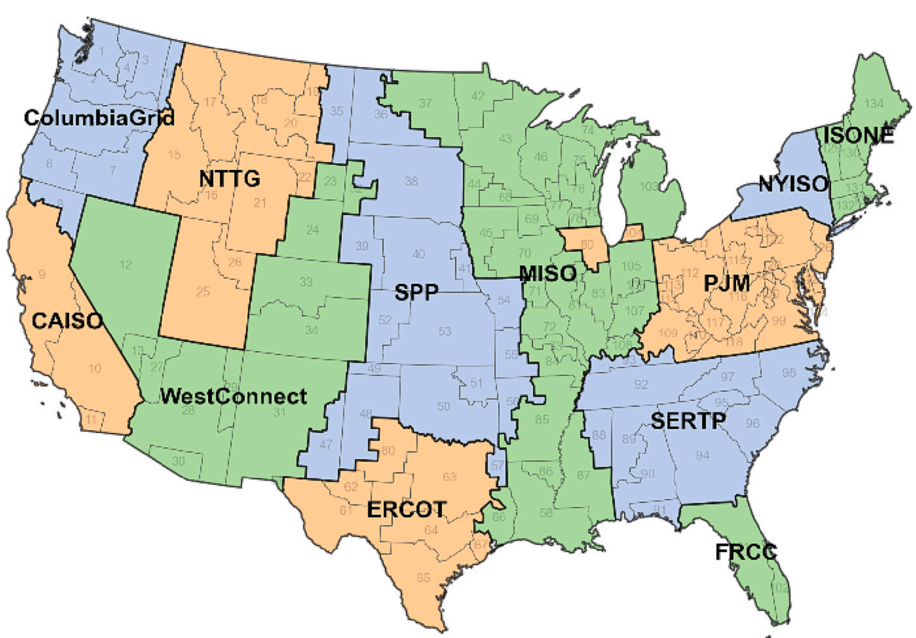

Fig. 1. Map showing the 12 regions used for determining peaking capacity potential. The underlying regions are the 134 ReEDS model regions used for determining the power system buildout. See SI for definitions of regional name acronyms.

Table 1
List of the 12 scenarios used in this work to produce net-load shapes. The CO_2 reduction target is relative to 2005. The PV and wind share as a percent of total generation in 2050 are the results from the model. The 100 % by 2050 scenarios also have an interim CO_2 reduction target of 95 % in 2035.

Scenario	PV cost projection	Wind cost projection	CO_2 reduction target	PV share in 2050	Wind share in 2050
Reference	Moderate	Moderate	None	22 %	21 %
Ref – 95 % by 2050	Moderate	Moderate	95 % by 2050	32 %	39 %
Ref – 100 % by 2050	Moderate	Moderate	100 % by 2050	35 %	35 %
Low PV Cost	Advanced	Moderate	None	25 %	15 %
Low PV Cost – 95 % by 2050	Advanced	Moderate	95 % by 2050	32 %	33 %
Low PV Cost – 100 % by 2050	Advanced	Moderate	100 % by 2050	35 %	28 %
Low Wind Cost	Moderate	Advanced	None	18 %	34 %
Low Wind Cost – 95 % by 2050	Moderate	Advanced	95 % by 2050	26 %	49 %
Low Wind Cost – 100 % by 2050	Moderate	Advanced	100 % by 2050	25 %	50 %
Low PV Cost + High Wind Cost	Advanced	Conservative	None	29 %	8 %
Low PV Cost + High Wind Cost – 95 % by 2050	Advanced	Conservative	95 % by 2050	43 %	20 %
Low PV Cost + High Wind Cost – 100 % by 2050	Advanced	Conservative	100 % by 2050	53 %	15 %

However, the historical data do not include the impacts of climate change on heating and cooling demand, or changes in wind or solar resources that might occur.

We calculate the peaking potential for storage with discrete hourly durations of 4, 12, 24, 72, and 168 h (1 week). These durations were selected to cover a reasonable set of duration of up to one week and are not intended to represent any specific type of long-duration storage technology. A 2160-hour (90-day) storage is discussed as a sensitivity. We also present select results that consider a continuous range of durations by evaluating the marginal storage duration required to reduce the peak.

To calculate the peaking potential for various durations of storage, we first create the hourly net-load profile for the 7-year time series assuming no storage in the system. The net load is the hourly load in a given year minus the contribution of VRE. Hourly load is assumed to be the same as the historical load, but adjusted by a load growth factor (i.e., the magnitude of load grows while the shape does not). The VRE generation is based on the buildout of wind and solar for the year being considered. This net load calculation is done for each of the 12 regions independently. We then follow the iterative approach described by Frazier et al. [28]. We first add 4-hour storage and dispatch it chronologically through the 7 years of net load until further additions of 4-hour storage can no longer reduce the net-load peak by the rated power capacity of the storage device. At this point, the added storage has flattened the load to the point where net-load peaks are longer than 4 h. The amount of capacity added up to this point (measured by the power of the storage) is the peaking capacity for that duration. For example, if after adding 500 MW of 4-hour battery storage the peak net demand period is 5 h long, then the peaking potential for 4-hour storage would be 500 MW.

We then iteratively add 12-hour storage until the 12-hour storage is no longer sufficient to cover the period of highest peak net demand, meaning that either the net load is longer than 12 h for at least one period over the 7-year period, or that the storage is not able to recharge sufficiently in between peak periods to serve a peak. We continue this process with the 24-, 72-, and 168-hour storage. This peaking potential is both sequential and cumulative in that we always start with the shortest-duration storage and progress to the longer durations. Importantly, this method assumes that the charging capacity equals the discharging capacity—which would be typically true for batteries, but might not be the case for other technologies, particularly those with largely decoupled charge-and-discharge cycles, such as hydrogen. We model storage with round-trip efficiencies of 85 %, 60 %, and 35 %, with higher efficiencies representing lithium-ion, the midrange representing long-duration flow batteries or thermal storage, and the lowest value representing hydrogen [29–31]. We focus primarily on results using the 60 % efficiency, and we assume that all durations of storage have the same round-trip efficiency in the base case analysis. No outages of storage or other resources are considered.

Also, per Frazier et al. [28], we implement a foresight penalty to help counterbalance our approach of using perfect foresight in the storage dispatch that can impact shorter-duration storage. This foresight penalty reserves 1 h to address uncertainty in the dispatch, so the peaking potential of 4-hour storage is determined by when the peak is wider than 3 h, the peaking potential of 12-hour storage is determined by when the peak is wider than 11 h, and so on.

The peaking potential is analogous to the amount of storage of a given duration that can be added at full capacity credit but does not replace alternative capacity credit calculations. Similar approximation methods for calculating a peaking potential or capacity credit of storage have been employed by Parks [32] and Mills and Rodriguez [33]. Other methods rely on Monte Carlo simulations to calculate an effective load-carrying capacity [34,35]. Work by Jorgenson et al. [36] has shown that the approximation methods can yield results similar to those of the Monte Carlo methods.

3. Results and discussion

We first consider the peaking capacity of energy storage under current (2022) grid conditions. We then examine results for future grid mixes that include greater amounts of VRE. We then present sensitivity cases to examine additional impacts on storage peaking potential.

3.1. Peaking capacity under current grid conditions

The ability of storage to provide firm capacity is driven largely by the shape of the net-load peak and how it changes with the addition of storage. Fig. 2 provides an example under current (estimated) grid conditions in the PJM region (see map in Fig. 1), using the worst-case conditions across 7 years of weather data. The top chart shows the impact of deploying storage with durations of 4, 12, and 24 h to the normal load shown in black during the 3-day period with the peak demand. The peak demand for the year of about 154 GW occurs on the afternoon of July 20. After the addition of about 2.6 GW of 4-hour storage (shown in orange), the peak has flattened and now has a length of 4 h. Any additional storage will need more than 4 h of capacity to further reduce the peak with 100 % capacity credit (especially considering our foresight penalty). The impact of 12-hour storage is shown in green and demonstrates a much larger opportunity to reduce the net demand peak by about 18 GW before the peak demand periods are 12 h long. While the limit to 4-hour storage is due to the increasing length of peak periods that result from storage, the limits to deployment of longer-duration storage are the reduced lengths of available charge periods. By the time peaks are longer than about 9 h, a storage device

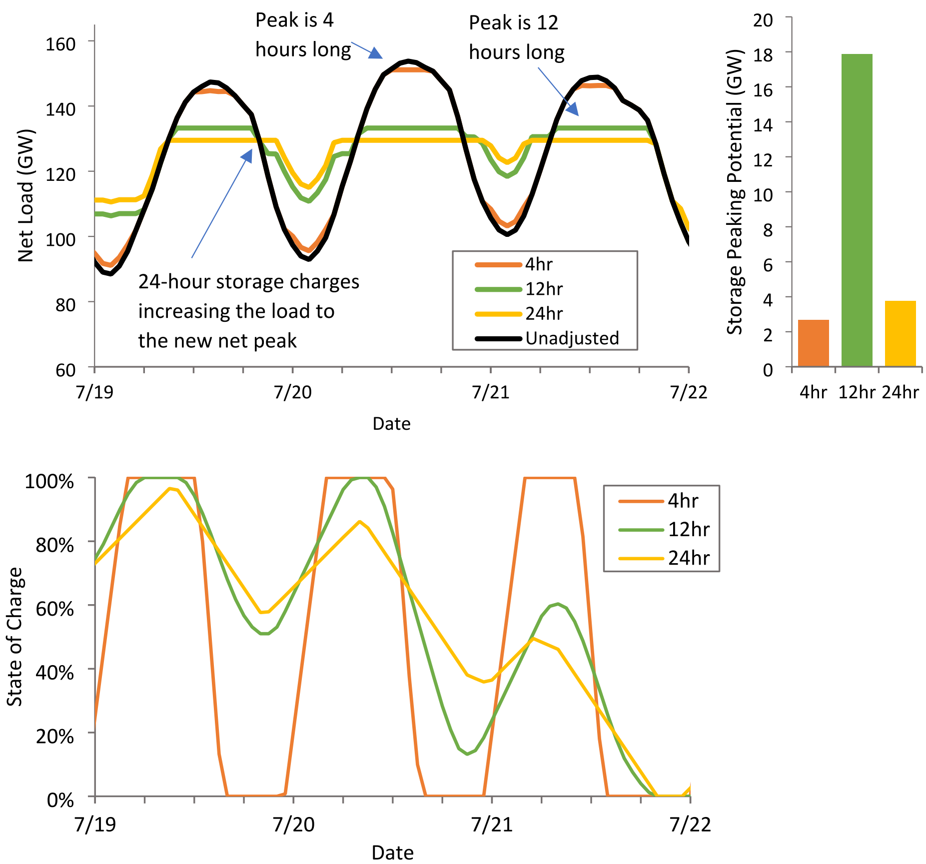

Fig. 2. The top chart shows the net load in the PJM region from July 19–22 using estimated 2022 grid conditions (but applying 2011 weather data) with 4-, 12-, and 24-hour storage. The unadjusted line shows the net load before any storage is dispatched, and the lines for each storage duration show the net load after that duration of storage has been added and dispatched. The bottom chart shows the corresponding states of charge for the storage devices. The bars on the right show the power capacity of storage at which the ability to reduce peak net demand falls below 100 %.

with a 60 % efficiency will be unable to completely recharge in the remaining 15 h in the day, so could not sustain multiple continual days of complete discharge-and-charge cycles (an 85 % efficient device could sustain an 11-hour-long peak on a continuous basis). As a result, after the addition of 12-hour storage, the significant limits to contribution from 24-hour storage due to an inability to recharge can be observed in the state-of-charge plot at the bottom. The 24-hour device begins the peak period on July 19 with a nearly full state of charge and discharges to about 60 % of capacity by the end of the peak period in the late evening. It is able to recover to about an 80 % state of charge before the second peak period on the 20th begins, and it then discharges until reaching approximately 40 % state of charge at about midnight. Because of the nearly flat load, there are only about 4 h between the net peak demand periods, and it can only recharge to about 50 % state of charge before the next long discharge period on July 21. This means the 24-hour device can add only about 3.5 GW of further peak reduction, compared to the much larger contribution of the 12-hour device, with the peaking potential of each duration shown in the plot to the right.

Note that in Fig. 2, peaks widen not only because of how storage discharges and clips the peak, but also because of how storage recharges and raises the off-peak demand, seen at the end of the day on July 19, which is indicated by the arrow. After the addition of a 24-hour device, the net peak event has become nearly flat from the morning of July 20 to the late evening of July 21, or for about 38 h, with only a 5-hour "off-peak" period in the early morning of July 21.

As a result of these kinds of long periods of flat net load, a significant limit to longer-duration storage may be the inability to recharge in the face of multiple, repeating peak demand periods occurring over several days. Longer-duration storage systems must rely on energy carried across one or more days to address these multiday peak demand periods, and the critical factor determining the contribution of long-duration storage becomes how many days in a row very high demand may be expected.

Fig. 3 shows the impact of deploying storage beyond 24 h of duration in the same region, but the image extends to the 19-day period of highest demand. For clarity, we only show the peak part of the unadjusted curve, and we combine the contributions of the 4-, 12-, and 24-hour storage to net load in the orange line (which is the same as what is represented in the top of Fig. 2). The 72-hour storage device (blue line) is able to reduce the net demand by a much greater amount compared to the 24-hour device, as it has sufficient energy to address the large 3-day peak period from July 19–21. The following days have much lower demand, and there is sufficient time during off-peak hours to recharge (with the 72-hour device essentially acting as a roughly 12-hour device during this period). Had the demand in the days following the 21st been similar to the previous days, the 72-hour device would have had a much lower potential contribution. After the addition of 72-hour storage, the load is nearly flat for 5 days, and there are very few opportunities for recharging, which limits the ability of 168-hour storage (red line) to make a very large contribution.

Significantly different patterns are observed in other regions, particularly those with winter peaks. Fig. 4 shows the results for the period of peak net load in FRCC, which contains most of the state of Florida (see the map in Fig. 1). Florida is often a summer-peaking system, but the highest peak over the 7-year data set occurs on the morning of January 10, using 2010 weather data during a period of extreme cold temperatures. Like other regions with a winter peak, this example shows a dual peak, with one short peak in the morning and one in the evening. This allows 4-hour storage to make a significant contribution, particularly as it can recharge in the middle of the day. The addition of 4-hour storage (orange line) reduces the peak net demand period on the morning of January 10 by over 9 GW before the peak demand period becomes longer than 4 h. However, in this example, the addition of 4-hour storage, combined with the relatively high demand during the overnight hours, results in a very flat load for nearly 48 h from the evening of January 8 to the morning of January 10. This flat load means

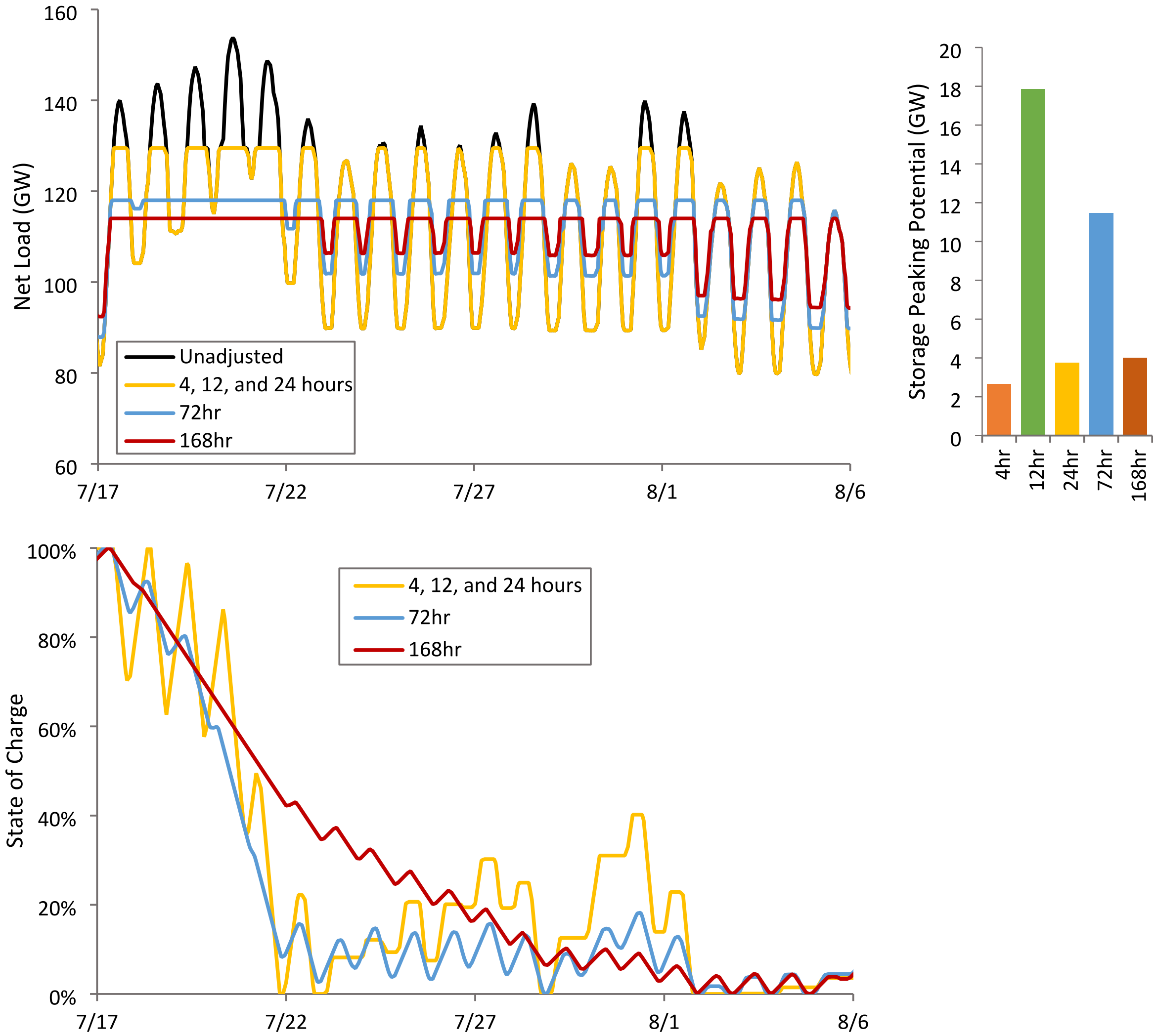

Fig. 3. Addition of 72- and 168-hour storage to the PJM simulation over the 19-day period that includes the highest total net demand, with the net load show in the top chart and the storage state of charge included in the bottom chart. The figure uses the net load after the addition of 4-, 12-, and 24-hour storage, as seen in Fig. 2. The bar chart in the top right shows the peaking potential of the various durations of storage.

that after the contribution of 4-hour storage, additional 12- and 24-hour storage can provide relatively little additional peaking capacity. Fig. 4 (bottom) shows a longer period and demonstrates the potential opportunity for longer-duration storage. Because this period of extreme cold only occurs for about 48 h, the storage with 72 h of capacity is able to carry over sufficient energy to dramatically lower the peak by about 20 GW, which is more than the shorter durations combined. However, after the addition of 72-hour storage, the net load becomes nearly flat for about 8 days, and the 168-hour storage (not shown in the hourly curve) is unable to make a meaningful contribution to further reducing the peak—which is somewhat similar to the impact previously observed in the PJM example.

These results demonstrate the dramatic change in net-load patterns and the role of carrying energy over multiple days, with the associated implications of foresight of the energy supply and demand patterns, days to weeks in advance. The impact of foresight on the ability of storage to serve as a peaking resource is not well understood, and is an important area of research, especially as longer duration technologies are brought to market. Inability to anticipate events will likely reduce the ability of storage technologies to displace traditional peaking capacity.

While variation is significant across the regions analyzed, there are some consistent themes, as illustrated in Fig. 5. The top chart shows the results for all regions, with the peaking capacity for each duration expressed as a fraction of annual peak demand. This allows for equitable comparison across regions of different sizes. The bottom chart shows the absolute values. The national total peaking potential is shown in the donut chart in each graph in the figure. In many U.S. regions in the current power system, the peak net-load period can be very narrow and a sizable portion of that load can be served by storage technologies with 4 h of duration. On average, about 4 % of total demand can be served by 4-hour storage, even with the 1-hour derate, which corresponds to about 33 GW of total capacity nationally. The combined contribution of durations up to 12 h is about 16 % of the peak, or about 130 GW. However, after the addition of 12-hour storage, the net load may be fairly flat for more than 1 day, which limits the contribution of 24-hour storage in many cases, following the examples shown previously.

Many regions also demonstrated peak periods that lasted only a few days; therefore, 72-hour storage could provide a larger contribution than 24-hour storage. After significant deployment of 72-hour storage, net loads become flat for many days in a row in several regions, which limits opportunities for 168-hour storage.

The overall potential of diurnal storage for peaking capacity in the current grid of about 130 GW is roughly 5 times the current capacity of diurnal storage in the United States (about 25 GW, largely in the form of pumped storage [4]). Storage technologies with durations of up to a 7-day capacity that have yet to be deployed at scale could add another

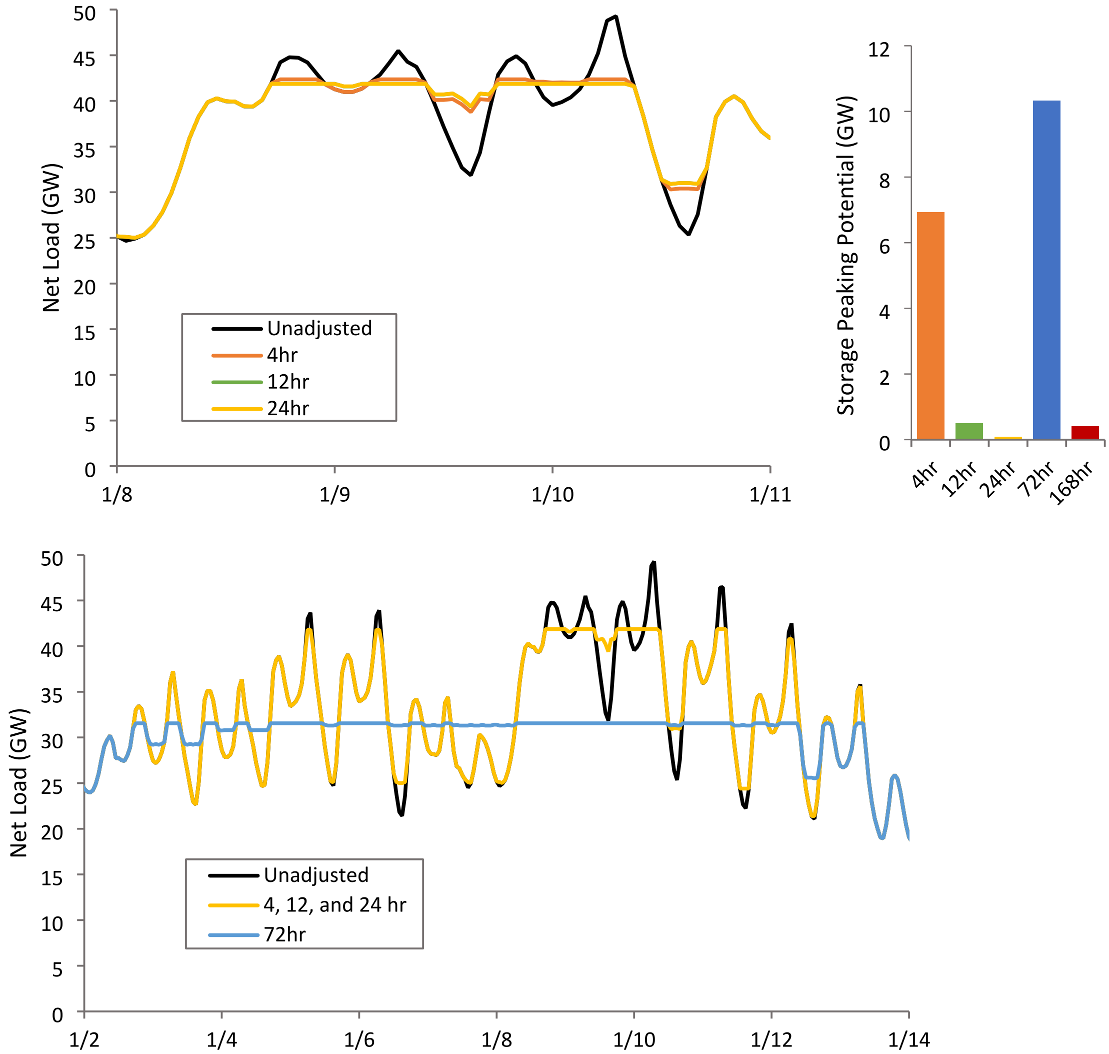

Fig. 4. Net-load profile for FRCC (Florida) in a simulated 2022 grid mix with 2010 weather conditions. The top chart shows the peak demand period with 4-, 12-, and 24-hour storage. The bottom chart shows a longer period and includes 72-hour storage. The peaking potential by duration is also shown in the top right.

80 GW of peaking potential, combined to provide over 25 % of the nation's total peaking capacity. However, these values could also grow significantly, especially when considering the impact of new VRE on net-load patterns.

3.2. Changes with grid mix

As the grid evolves, the potential opportunities for storage of various durations will vary based on two factors. The first is the overall change in electricity demand due to electrification, population growth, and so on. The second is the impact of VRE on load shape, with examples provided in Fig. 6, illustrating net loads during the peak periods shown previously in PJM and FRCC, as well as the CAISO region of California (regions are shown in Fig. 1). The left set of plots shows the simulated 2022 cases. These are based on estimated loads and VRE contributions in 2022, assuming historical weather with the highest peak conditions across the 7 years of weather data. These plots show the significant impact of solar that has already been deployed in California, but a limited impact in the other regions. The righthand set of figures shows the results in 2050 from the Reference 95 % by 2050 scenario. In these examples, the normal load (orange line) has grown by 38 %, which would increase the potential for storage by the same amount compared to the 2022 scenario, assuming no change in load shape. However, the addition of VRE creates narrower peak net-load periods, particularly in the summer-peaking systems. In FRCC, the impact is to create a lower net peak period in the middle of the day. Lowering the net peak demand and creating a lower net peak period in the middle of day both will generally increase opportunities for storage of various durations.

Fig. 7 shows how the storage peaking potential changes in the Reference 95 % by 2050 scenario for these three regions (CAISO, FRCC, and PJM). For each location, the lefthand chart shows the growth in absolute potential as a result of both the assumed load growth and the change in net-load shape due to VRE deployment. To help show how the contribution from each duration changes, the righthand chart shows the fraction of the total peaking potential for each duration.

The results show significant growth in opportunities for storage across regions, but also with significant variations in both the total growth and growth by duration. Both CAISO and FRCC show a significant increase in opportunities over time, but PJM shows little growth opportunities in the near term (and the lowest relative growth of the regions analyzed). The opportunity for storage in PJM in the near term drops as PV clips the peak and creates a flatter summer-peak profile. This has been noted in previous analysis of other regions [25]. Overall, strongly summer-peaking systems, such as CAISO, tend to have the least dramatic shifts in duration mix, while winter-peaking systems, or systems that shift from summer to winter peaking with increased PV deployment, can have very volatile net-load shapes that create dramatic shifts in duration mix, as illustrated in the FRCC results in Fig. 6. Note

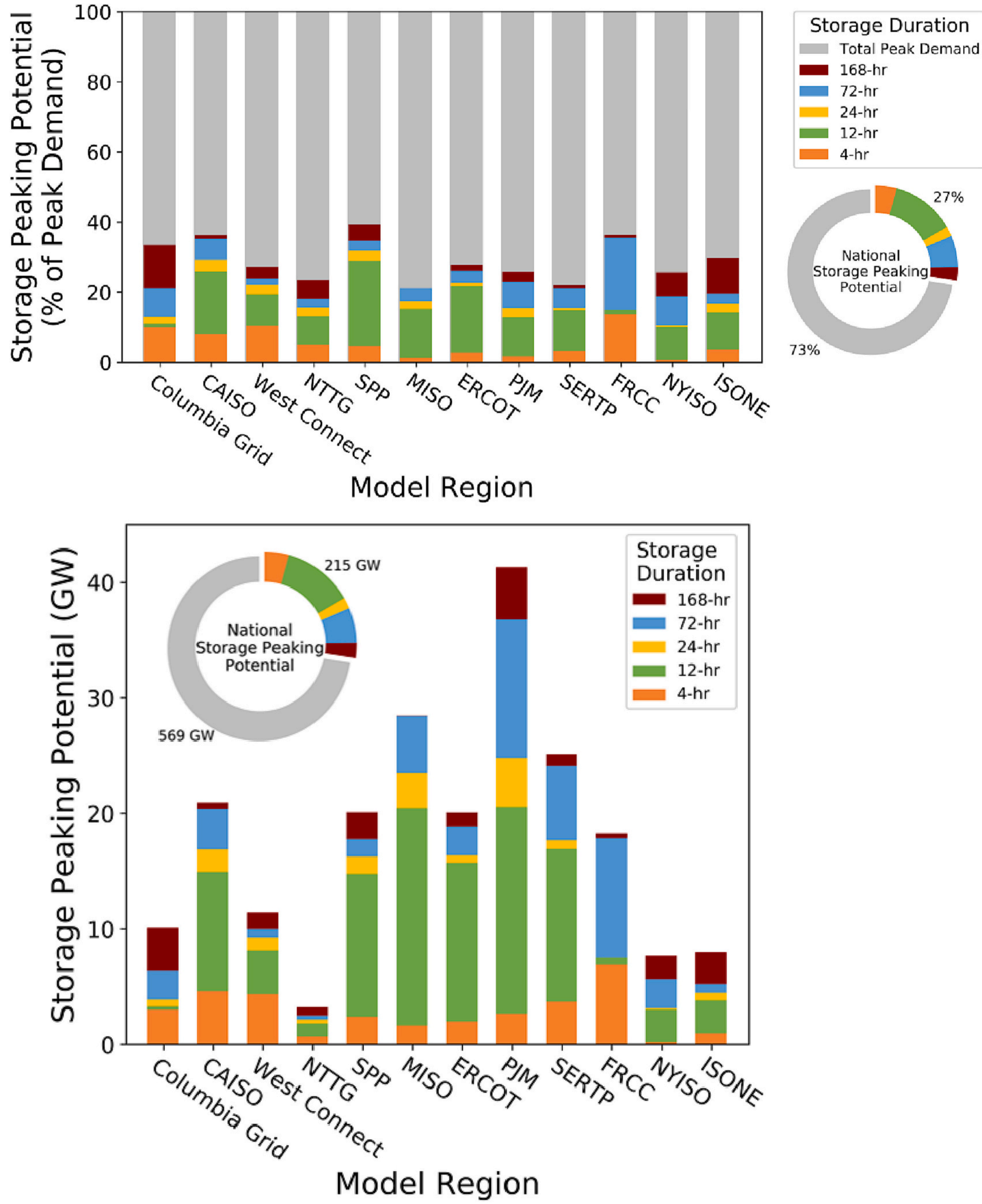

Fig. 5. Regional peaking potentials of energy storage on a relative (top) and absolute (bottom) basis using estimated 2022 conditions across 7 years of weather data. Regions are shown in Fig. 1.

that changes in storage peaking potential that result from the additional PV and wind generation are assigned to storage for this analysis, although the combined value of storage and VRE could be shared for other applications, such as determining market renumeration [37,38].

Fig. 8 provides the results for all regions aggregated to national totals for the Reference 95 % by 2050 scenario. Fig. 8 (left) shows that opportunities for all durations increase substantially, but the most significant growth opportunity occurs with 4-hour storage, driven largely by the narrowing of net-load peaks due to solar. The distribution by duration is shown on the right of the figure and demonstrates how the growth in 4-hour storage reduces the opportunities for 12-hour storage (on a percentage basis) moving from 2022 to 2050, although the total opportunity increases due to load growth.

The overall range of national peaking potentials across all scenarios is shown in Fig. 9. The top plot shows the total national potential for all durations combined for the 5 scenarios that largely capture the range of the results (the full range of scenarios are shown in SI Fig. 14). The light blue curve (labeled "No Change in Grid Mix") shows the growth in storage potential due only to load growth. This assumes no change in shape compared to 2022. While electrification of transportation and heating will likely produce differences in load shape, the overall impact requires further study, and holding the shape constant helps isolate the impact of VRE deployment. In the cases with different grid mixes, the total national storage potential in the near term drops a small amount due to the impact of PV shown previously in the PJM example. However, this is a short-term phenomenon, and ultimately the deployment of VRE has a much greater impact on the storage opportunity than load growth. The bottom plot in Fig. 9 shows the fraction of the total provided by

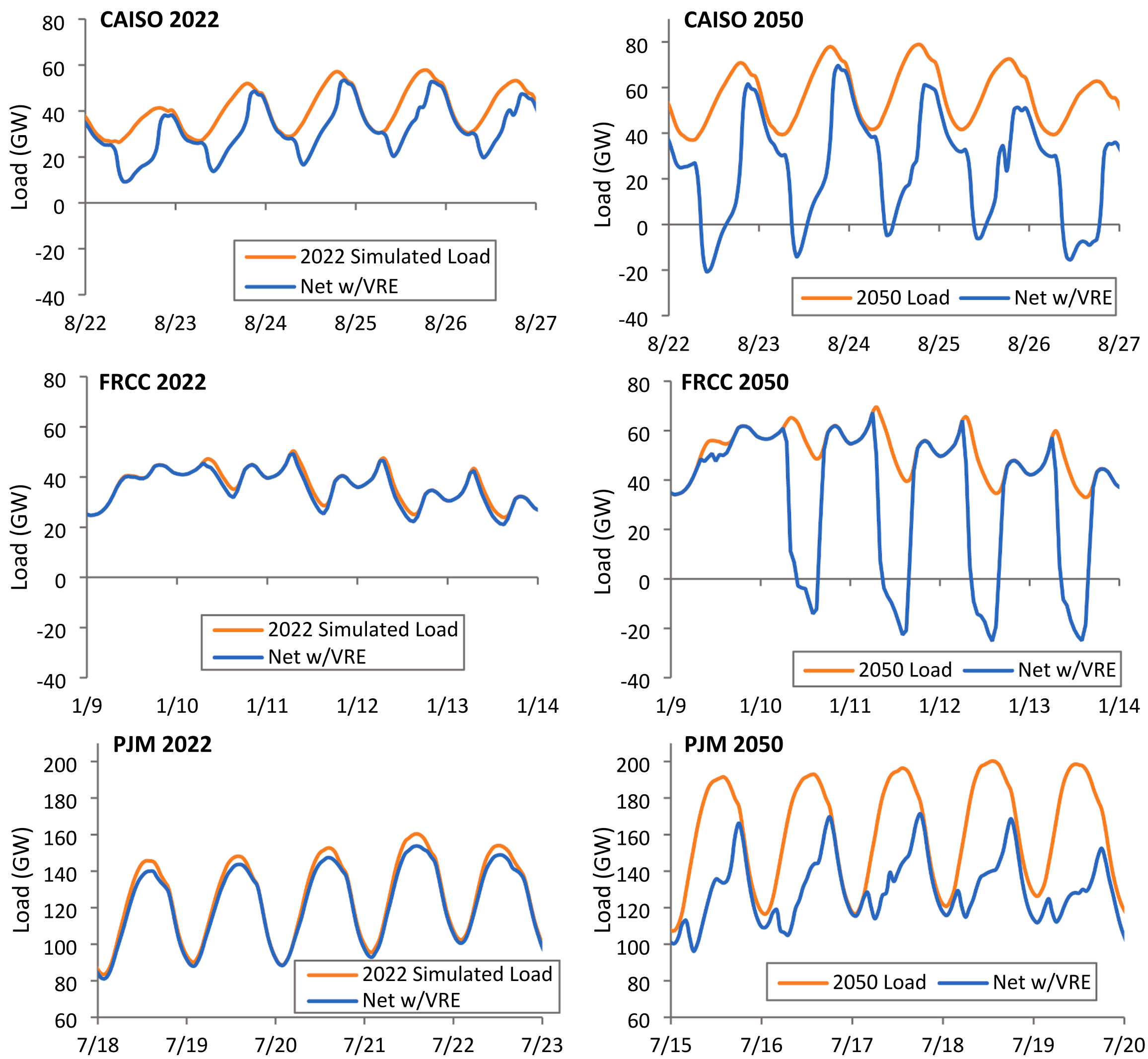

Fig. 6. Change in net-load shape with deployment of variable renewable energy during peak periods in 2022 (left) and 2050 (right) under the Reference 95 % by 2050 scenario for CAISO (top), FRCC (middle), and PJM (bottom). The CAISO and FRCC results show the same weather year in 2022 and 2050, but the PJM results use a different weather year to account for the shift in peak net load that occurs in PJM simulations.

diurnal storage (up to 12 h), with the remainder being the multiday (24- to 168-hour) capacity. In the current grid mix, about 60 % of the opportunity is for 4- to 12-hour storage, with this fraction decreasing somewhat over time. This decrease is largely impacted by the ultimate wind/solar mix, where higher solar shares tend to support the higher contribution from the shorter durations (and the highest overall contribution of storage of all durations).

The total storage peaking capacity opportunity of about 230 GW in 2022 grows to at least 370 GW in 2050 across the scenarios evaluated and is much higher in decarbonization scenarios. Overall, the greater variability in net load created by VRE allows storage to meet a greater fraction of the peak demand. A large limitation of storage in the 2022 scenarios is the creation of long periods of flat net loads, effectively eliminating the traditional off-peak period where spare thermal and other capacity can be used to recharge storage. Cases with large amounts of VRE create new periods of low net demand, exemplified by the "duck curve" allowing for recharging [8,9], and the greatest increase in peaking potential is associated with the highest PV deployment scenarios. Further illustrations of the relationships between VRE deployment and peaking potential are provided in the SI (see SI Fig. 15 and SI Fig. 16).

3.3. Sensitivity cases

We performed three sets of sensitivities across the scenarios. The first was to examine the impact of our choice of specific discrete durations. As an alternative, we analyzed the incremental duration required to achieve full capacity credit as a function of deployment. Fig. 10 provides an example, where the y-axis indicates the duration required to achieve full capacity credit and the x-axis shows the amount of storage capacity that can achieve this full capacity credit. The capacity is normalized in terms of annual peak demand. We show results for the FRCC, CAISO, and PJM regions for the 2022 grid mix (solid lines) and the 2050 grid mix from the Reference 95 % by 2050 scenario (dashed lines). Because load shapes remain constant, and storage is measured on a fractional basis, the only difference between 2022 and 2050 is the change in the generation mix and, therefore, the net-load shape. This allows for equitable comparison across regions of different sizes. Because this method of presentation eliminates the effect of load growth, it provides another indicator of the increased opportunities for storage that result from increased VRE deployment.

These results emphasize the highly nonlinear increase in duration requirements as a function of storage contribution to peak. These curves demonstrate how a vertical step often occurs around the 12-hour point (in five of the six curves). This supports the results that show a limited

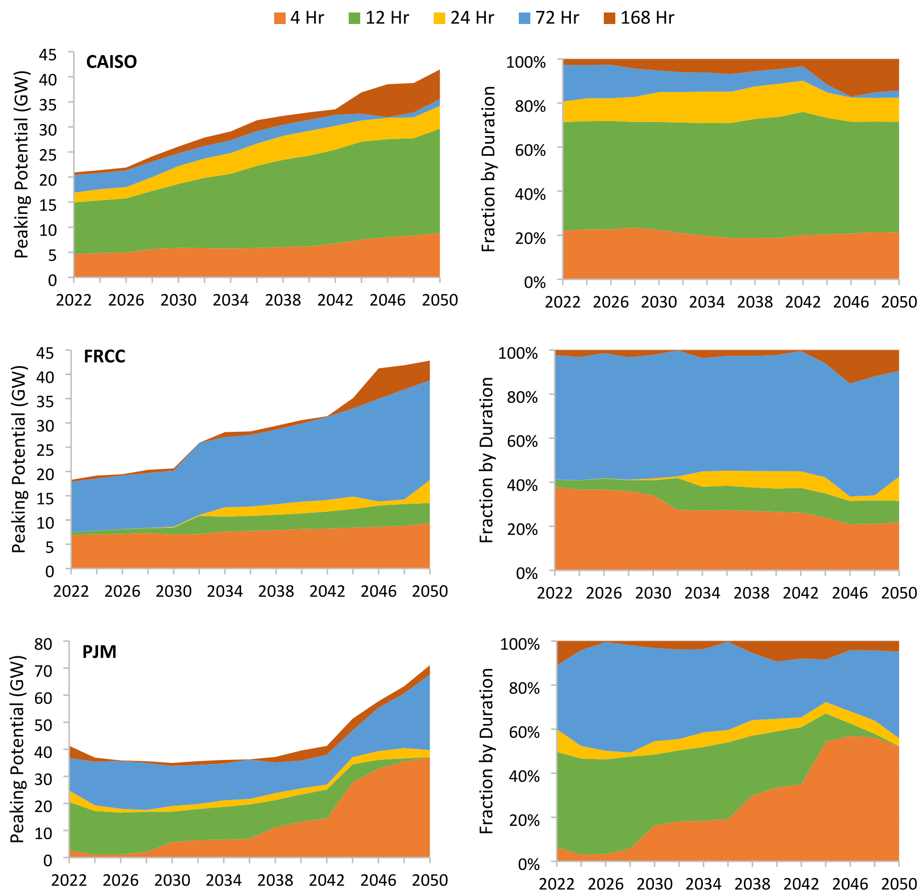

Fig. 7. Increase in peaking potential by duration over time in the Reference 95 % by 2050 scenario for CAISO (top), FRCC (middle), and PJM (bottom). The left charts show the absolute peaking potential and the right charts show the distribution of the total by duration.

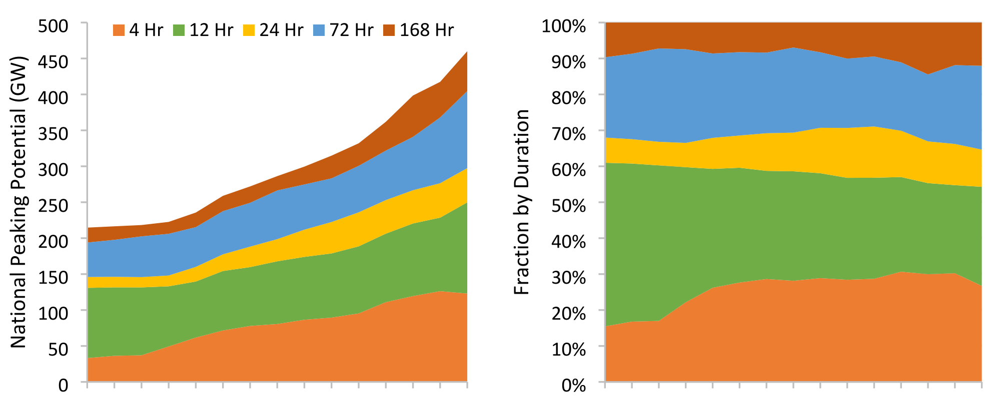

Fig. 8. National peaking capacity potential over time in the Reference 95 % by 2050 scenario (left). The share by duration is shown in the righthand plot.

(but non-zero) contribution of durations in the 24-hour range, demonstrating the "saturation" of diurnal storage and the shift to multiday peaking periods. However, these results also demonstrate that there may be opportunities for intermediate durations. For example, several regions show a plateau in the range of roughly 48 h, and properly scheduled 48-hour storage could serve much of the capacity that we serve with 72-hour storage. Similar plots for other regions and scenarios are shown in SI Fig. SI Fig. 16 and illustrate how these curves can vary across regions and renewable energy resource mixes.

The second sensitivity considered (Fig. 11) shows how the national storage peaking potential changes with different levels of assumed round-trip efficiency. The left set of bars shows the 2022 results, so the middle bar is identical to the ring chart in Fig. 5 (bottom). The other two sets show results for 2040 and 2050 in the Reference 95 % by 2050 case. Other periods and scenarios show similar trends. The 4-hour storage is nearly unaffected by the efficiency because 4-hour storage is very rarely limited by its ability to charge before an event. The 4-hour duration also means that even at 35 % round-trip efficiency, it can still function as a diurnal storage device with a full charge-discharge cycle of 15.4 h. The 12-hour storage is the most significantly impacted because changes in efficiency greatly impact its ability to recharge on the diurnal timescale, as noted earlier, and with 35 % efficiency, 12-hour storage can only serve about a 6-hour peak on a continual basis. Alternatively, 72-hour storage actually increases in peaking potential with lower efficiency

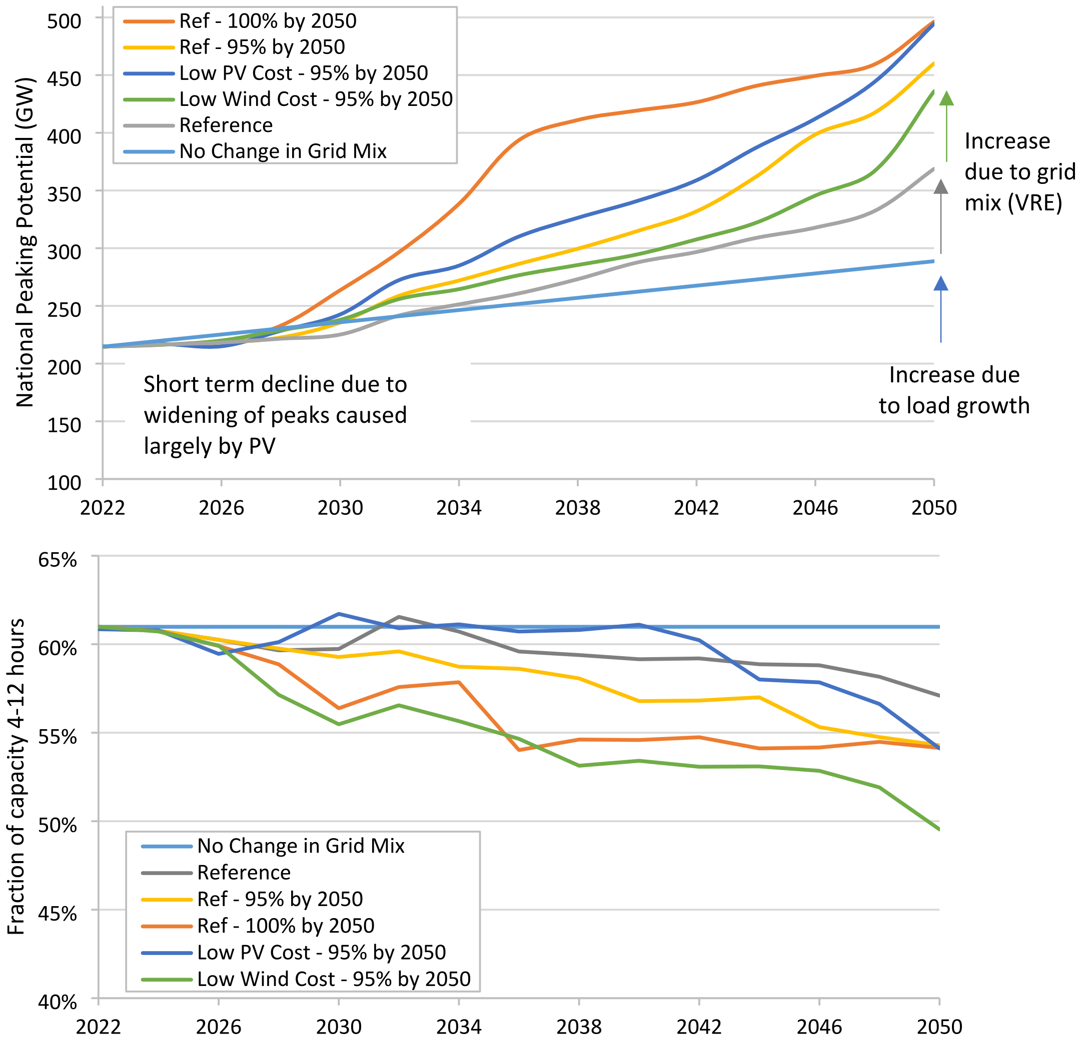

Fig. 9. National peaking potential for combined durations of 4–168 h (top) across the scenarios evaluated. The bottom chart shows the fraction of this potential provided by 4–12 h, which is more than 50 % across almost all combinations of scenarios and years.

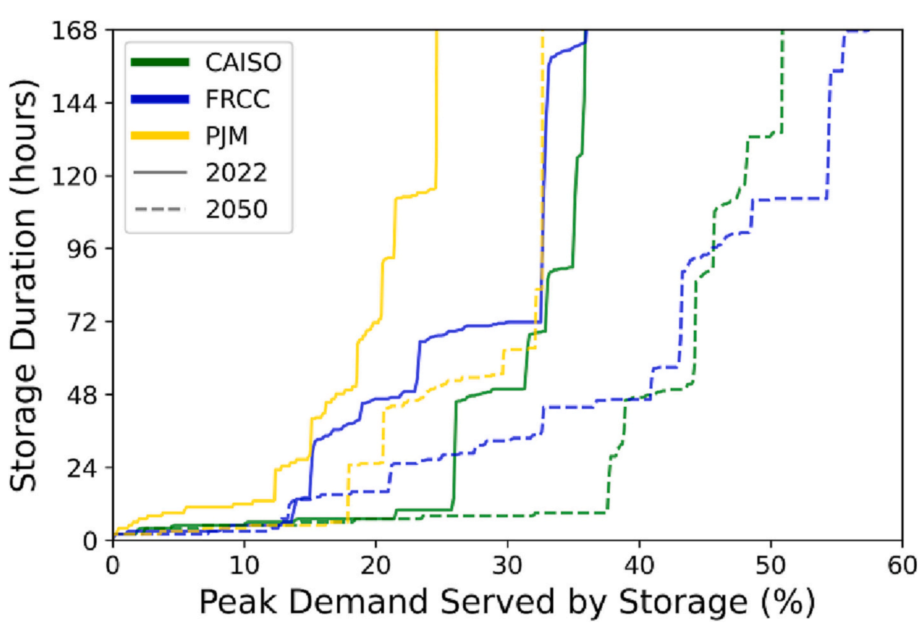

Fig. 10. Storage peaking potential as a function of continuous duration for three regions in 2022 and 2050 in the Reference 95 % by 2050 scenario. Plots for other regions and scenarios are provided in SI Fig. 16.

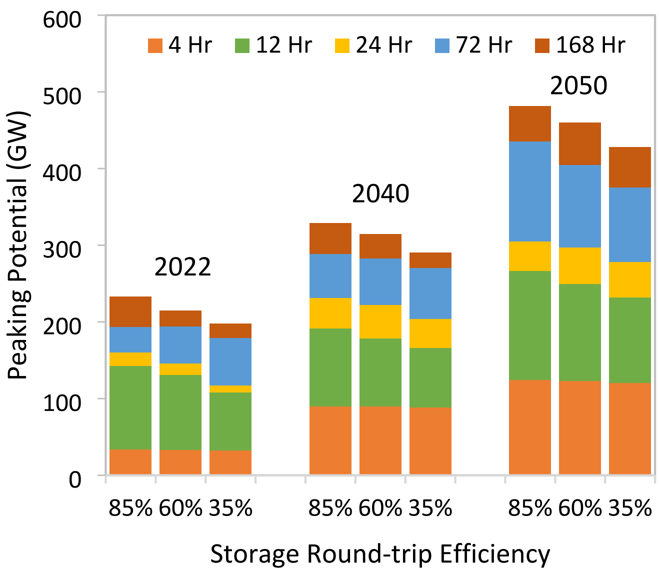

Fig. 11. National storage peaking potential for different levels of round-trip efficiency in the Reference 95 % by 2050 scenario for the years indicated.

because the lower potential from the 12- and 24-hour storage enables 72-hour storage to play a slightly larger role.

Finally, we also considered the potential contribution of a 2160-hour (seasonal) storage technology. We applied the same approach with this duration as previously, adding 2160 h after the shorter durations had been saturated. We found a significant potential for seasonal storage, and while we include the results in the SI, we do not include these results in the main scenarios for multiple reasons that may underestimate the actual potential for seasonal storage. A major issue is that seasonal storage devices are likely to be very different from other storage technologies in current use. We assume that all storage must be charged in the same region as it is discharged, which reflects how current electricity storage technologies are operated, since they are stationary, and both the charging and discharging components are in the same location. However, seasonal storage technologies may likely include the production of liquid or gaseous fuels like hydrogen, which can be transported. This decouples the location of charging from discharging. Furthermore, seasonal storage technologies such as hydrogen-fueled combustion turbines could be fueled by multiple resources, including biofuels, or even fossil fuels, as an emergency backup fuel in cases of extreme system stress. This means they are not necessarily tied to the availability of charging electricity, and could therefore discharge during additional periods. Furthermore, renewably generated fuels could be used for multiple applications beyond electricity storage, resulting in increased deployment of VRE intended for fuels production. This could further change net-load profiles, which was not considered in this modeling. There are other limitations of the modeling approach used, including the need to assume an initial state of charge of our multiyear simulations that sometimes limited the contribution of seasonal storage during the first few months of the simulation.

Because of these considerations, our results for seasonal storage are of limited use in estimating the peaking opportunities for seasonal storage.

4. Conclusions

Previous analysis has demonstrated significant potential for diurnal (up to about 12 h) storage to provide peaking capacity. There is also significant opportunity for longer durations of 24–168 h, particularly for durations that can address peak events that appear to often last in the range of 2–4 days. However, in the current grid, the storage peaking potential for these longer durations is typically smaller than for diurnal storage due to the saturating effect of shorter-duration storage.

The peaking potential is strongly dependent on both the mix of VRE generators deployed and on the net-load shape of the regions. While variation is significant across the regions, storage potential grows in all regions evaluated. In many scenarios of deep decarbonization, the national peaking potential for durations up to 168 h more than doubles compared to the current potential, with the majority of the increase associated with the impact of VRE. The growth in potential for durations longer than 12 h is greater than for 12 h or less; however, diurnal storage still exceeds more than 50 % of the total capacity in most scenarios evaluated.

The round-trip efficiency of storage is a secondary impact to peaking potential. It has almost no impact on the 4-hour peaking potential but can reduce the peaking potential of other durations by up to 25 %. This occurs because less-efficient storage systems require more energy to charge, which limits the ability of storage to sufficiently recharge before the next high-net-load period.

There are several limitations to this work to be addressed in future analysis. The most significant is the need to perform a comprehensive economic analysis of different durations. While provision of firm capacity is a key service, energy time shifting value also needs consideration, particularly with increased use of low variable-cost VRE resources. This work also did not consider the impact of changing load shapes, including the role of electric heating. Increased heating demand could increase both the magnitude and duration of winter peaks, and would have far less coincidence with solar output, which could reduce the ability of shorter-duration energy storage to meet the peak and shift the opportunities for longer durations.

This work also did not consider the change in storage peaking potential with increased VRE generation relative to the cost-optimal solutions provided by ReEDS. These results do quantify the potential for storage to provide peaking capacity within the context of VRE generation that was otherwise determined cost optimal. Storage and VRE could provide all peaking capacity for a given region if the capacities of VRE generation and storage are sufficiently overbuilt, but we chose to focus on cost-optimal generation mixes in the interest of practicality.

This work also highlights the importance of foresight in dispatching storage for peaking needs. We assumed perfect foresight, which led to multiday peaks. The ability to anticipate the weather and grid conditions that can lead to multiday peaking periods will be critical to gaining the greatest value from long duration storage technologies.

CRediT authorship contribution statement

Wesley Cole: Conceptualization, methodology, writing, visualization, supervision; Paul Denholm: methodology, writing, visualization; Vincent Carag: visualization, data curation; Will Frazier: Conceptualization, methodology, software.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.est.2023.106932.

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