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The Value of Seasonal Energy Storage Technologies for the Integration of Wind and Solar Power

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Abstract

Energy storage at all timescales, including the seasonal scale, plays a pivotal role in enabling increased penetration levels of wind and solar photovoltaic energy sources in power systems. Grid-integrated seasonal energy storage can reshape seasonal fluctuations of variable and uncertain power generation by reducing energy curtailment, replacing peak generation capacity, and providing transmission benefits. Most current literature focuses on technology cost assessments and does not characterize the potential grid benefits of seasonal storage to capture the most cost-effective solutions. We propose a model-based approach for comprehensive techno-economic assessments of grid-integrated seasonal storage. The approach has two major advantages compared to those presented in the literature. First, we do not make assumptions about the operation of the storage device, including annual cycles, asset utilization or depth of discharge. Rather, a model is used to calculate optimal storage operation profiles. Second, the model-based approach accounts for avoided power system costs, which allows us to estimate the cost effectiveness of different types of storage devices. We assess the cost competitiveness of three specific storage technologies including pumped hydro, compressed air, and hydrogen seasonal storage and explore the conditions (cost, storage duration, and efficiency) that encourage cost competitiveness for seasonal storage technologies. This study considers the Western U.S. power system with 24% to 61% of variable renewable power sources on an annual energy basis (up to 83.5% of renewable energy including hydro, geothermal, and biomass power sources). Our results indicate that for the Western U.S. power system, pumped hydro and compressed air energy storage with 1 day of discharge duration are expected to be cost-competitive in the near future. In contrast, hydrogen storage with up to 1 week of discharge duration could be cost-effective in the near future if power and energy capacity capital costs are equal to or less than ~US$1,507 kW^{-1} and ~US$1.8 kWh^{-1} by 2025, respectively. However, based on projected power and energy capacity capital costs for 2050, hydrogen storage with up to 2 weeks of

discharge duration is expected to be cost-effective in future power systems. Moreover, storage systems with greater discharge duration could be cost-competitive in the near future if greater renewable penetration levels increase arbitrage or capacity value, significant energy capital cost reductions are achieved, or revenues from additional services and new markets—e.g., reliability and resiliency—are monetized.

The integration of high shares of variable renewable energy (VRE), such as wind and solar photovoltaic (PV) power, raises technical challenges that need to be solved to enable high renewable power systems. For example, VRE is weather dependent, and therefore the power generation is uncertain and exhibits variable diurnal and seasonal patterns. These properties cause more frequent and/or steeper net load—electricity demand minus VRE availability—fluctuations that require greater flexibility in the power system and can complicate grid operations. Energy storage devices can provide a variety of services to help support the integration of VRE, including better aligning the balance between supply and demand, supplementing transmission, and providing operating reserves[1,2]. Sub-hourly variation of VRE generation can largely be addressed by a variety of operational practices, such as better scheduling, but it can be also assisted by short-term storage devices with fast response rates and high power-to-energy ratios, e.g., high-power batteries and flywheels[3–5]. Diurnal shifts can be largely met with devices that have storage capacities of 4 to 8 hours, including certain batteries and pumped storage.

Beyond diurnal storage, research has found that very high penetrations of VRE could be facilitated by storage technologies with even longer duration (12+ hours) to help shift energy during multi-day periods of supply and demand imbalance [6,7]. Candidate technologies could include pumped hydro storage (PHS) and compressed air energy storage (CAES). Approaching 100% renewable power systems could require seasonal storage capacities of weeks or months, including hydrogen or other fuels[3,4,8]. Seasonal storage at the scale needed to make this transition has yet to be deployed at the large scale[8,9].

Significant research has been devoted to the techno-economic assessment of short-duration storage technologies focusing on market value assessments[10,11], many of which consider batteries[12–14]. However, there is a lack of understanding of the value of grid-integrated seasonal energy storage technologies and their impacts on power system operations.

Current seasonal storage studies have two major limitations. First, modeling seasonal storage has been based on the analysis of chronological time series of VRE generation and load without considering power system network constraints[15–17]. Including network constraints allows for a more realistic representation of the power system, the ability of seasonal storage to benefit from mitigating network congestion, which is particularly important on high renewable power systems, and more accurate characterization of storage operational parameters including cycles and depth of discharge. Including network constraints with the time series approach above can significantly increase computational requirements[18,19]. For short-duration storage this is mitigated by decomposing the problem into many smaller problems and running sequentially; however, for seasonal energy storage the model must consider the benefit of shifting energy across many months, thereby limiting the ability to decompose the problem temporally and again raising computational concerns. Second, the techno-economic assessment of seasonal storage has been limited to the cost estimation of storage technologies, i.e., without a corresponding profitability analysis[1,9,20], the estimation of operational seasonal storage requirements for VRE integration[3,15,16], or the optimal siting and/or sizing of a given seasonal storage technologie[21,22].

We propose a methodology for the comprehensive assessment of grid-integrated seasonal storage technologies. The proposed method uses a more detailed power system representation to better understand the type of storage asset needed on the power system (e.g., discharge durations, round-trip efficiencies) and the resulting operating parameters for that storage device (e.g., cycles, utilization, depth of discharge). while also overcoming computational limitations. We investigate the total system value—avoided production costs (operational value) and avoided capacity costs (capacity value) associated with the storage device—of PHS, CAES, and hydrogen seasonal storage technologies in the Western Interconnection of the United States; see Supplementary Fig. 1. The methodology assesses the cost effectiveness of seasonal storage technologies across different discharge durations and the conditions under which given storage devices are cost-competitive.

Modeling framework and techno-economic assessment

The most common approach for modeling seasonal storage is to use net load analysis[16,17,22]. Net load analysis is easy to implement and uses simplified assumptions regarding the behavior and control of the storage device, but there are some critical drawbacks to this approach. Most notably, power system network constraints are not considered, and the interactions of the seasonal storage device with other power system elements—e.g., generators, transmission, and other storage devices—are not captured. This could lead to an underestimation of VRE curtailment and/or storage needs because congestion-related VRE surpluses as well as start-up and ramping constraints of thermal generators are neglected[22]. Thus, to improve the assessment of seasonal energy storage, power system models with higher temporal and spatial granularity should be used[11,21,23].

Proposed modeling framework

This paper evaluates seasonal energy storage in four steps involving three types of decision-support models for each year analyzed, as described in Fig. 1. First, the ReEDS (Regional Energy Deployment System) model[24,25] is used for the capacity expansion planning problem. ReEDS determines the cost-optimal power generation, transmission, and short-term (up to 8 hours of discharge duration at rated power before its energy capacity is depleted[26]) storage capacity expansion. ReEDS is run for the entire U.S. power system from 2018–2050 based on technology cost projections, fuel costs, projected electricity demand, and reliability constraints. To look at high shares of VRE, an 80% national renewable portfolio standard (RPS) is assumed[27,28]. Second, the generation, short-term storage fleet, and transmission network from ReEDS are transferred to a production cost tool (PLEXOS[29]) to perform the chronological simulation of power system operations. In these initial simulations, PLEXOS is run without the seasonal storage device for the Western Interconnection power system in the years 2024, 2032, 2036, 2040, and 2050 (5 base cases). Next, a 2-GW storage device with characteristics described later is added to a single location, and a price-taker model, RODeO (Revenue Operation and Device Optimization)[30,31], is used to optimize the yearly operation of the seasonal storage device based on locational marginal prices (LMPs) from the PLEXOS output in the previous step and nodal net load constraints. The storage dispatch from RODeO is used to generate state-of-charge (SOC) targets for the end of each day. Finally, PLEXOS is run again including the optimized storage operation results from RODeO as constraints for the seasonal storage device; thus, PLEXOS optimizes the hourly operation of the storage device while following the seasonal dispatch shape defined by RODeO. In this way, RODeO establishes the seasonal storage dispatch, while PLEXOS optimizes unit commitment and dispatch in line with current markets (i.e., day-ahead with limited future knowledge). This method is able to effectively address computational limitations associated with the simultaneous optimization of power system operations for the entire year by allowing the problem to be discretized into days and run sequentially. Alternative approaches include expanding the optimization period within the production cost model, which can be computationally challenging, particularly when retaining the hourly resolution needed to capture intraday market opportunities.

After running PLEXOS with the seasonal storage device included, we collected information on production cost, electricity mix, LMPs, curtailment, and emissions. The following section provides additional details regarding the modeling tools and the implementation of the proposed framework.

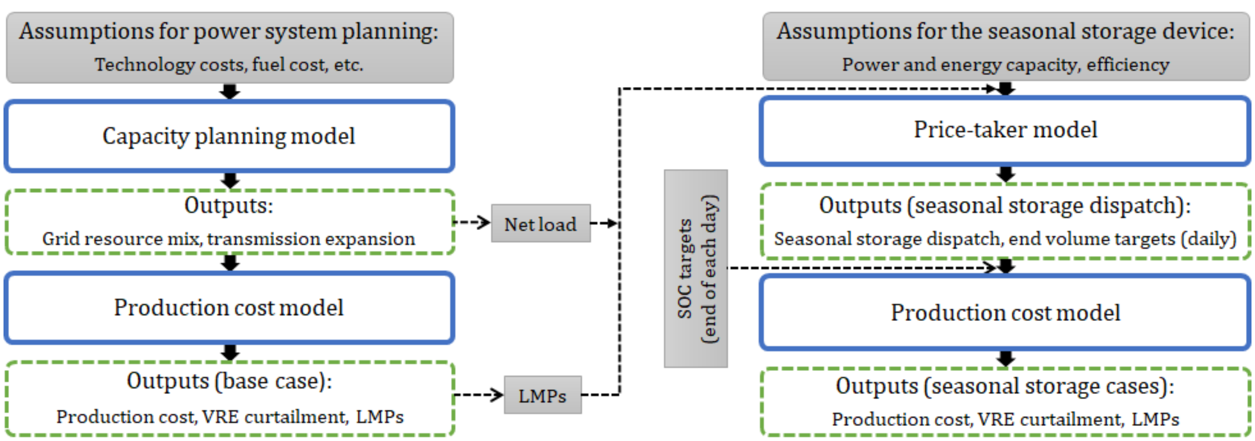

Fig. 1: Multi-model approach for the assessment of seasonal storage. Gray boxes denote input data (techno-economic assumptions) or information for the simulation and optimization of the power system or the storage device. Blue boxes denote power system or storage device simulation and optimization models, e.g., capacity planning model (ReEDS[24,25]), production cost model (PLEXOS[29]), and storage device price-taker model (RODeO [30,31]). Green dashed boxes denote outputs from power system or storage device simulation and optimization models.

Power system and seasonal storage modeling tools

Capacity expansion model

The power generation and transmission capacity planning model ReEDS, which uses high-fidelity modeling and high spatial resolution, is used to determine the optimal power generation and transmission as well as short-term storage fleet for the 2024–2050 U.S. electricity system (see Fig. 1 and Supplementary Fig. 1). In ReEDS, each season is modeled using a representative day of four chronological time slices[24,25]. The corresponding techno-economic assumptions—e.g., electricity demand growth, fossil fuel prices, technology cost, and existing fleet retirements—are provided in the RPS reports[27,28].

Production cost and Price-taker models

The production cost model PLEXOS is used to perform the annual simulation, i.e., the minimization of the total production cost, of the unit commitment and economic dispatch decisions for the 2024–2050 Western Interconnection power system configurations (with and without the seasonal storage device) based on the capacity deployment provided by ReEDS (see Supplementary Fig. 1). The unit commitment and economic dispatch problems are implemented as mixed-integer linear programming models using the direct current optimal power flow formulation in PLEXOS. For every scenario, the day-ahead electricity market for the corresponding calendar year is simulated with a 1-day optimization window with hourly resolution plus 1-day look-ahead with 4-hour resolution. The relative optimality gap was set to 0.05%. The price-taker model RODeO was run to determine the optimal seasonal dispatch for each seasonal storage case. The objective function is the maximization of the energy arbitrage revenue based on the LMPs time series from the PLEXOS runs of the corresponding base case. The net load data (net load for 2024–2050 Western Interconnection power system configurations at the Southern California Edison (SCE) zone) were used to define the operational constraints for the seasonal storage device in RODeO as follows: for every seasonal storage case analyzed, VRE hourly surplus, i.e., $S_h = \max\{0, -NetLoad_h\}$, where $NetLoad_h$ denotes the net load during hour h, was used as an upper bound constraint for charging the seasonal storage device. The net load is calculated considering must-run thermal power plants that are on the system at minimum stable generation levels. Thus, the storage device can charge only during hours with VRE surplus, and the maximum power rating is defined either by the maximum power capacity of the device or the magnitude of the VRE surplus, i.e., $P_h \leq \min\{Pcap, S_h\}$, where $Pcap$ denotes the power charging capacity of the storage unit. Similarly, conventional generation requirements, i.e., $CGR_h = \max\{0, NetLoad_h\}$, were used as an upper bound for the generation of the seasonal storage device. Thus, the maximum generation from the storage device is defined either by the maximum power generation capacity or the magnitude of the conventional generation requirements, i.e., $G_h \leq \min\{Gcap, CGR_h\}$, where $Gcap$ denotes the power generation capacity of the storage unit. In this study, the power charging capacity is equal to the power generation capacity, thus $Pcap = Gcap$.

Cost-benefit analysis

To better understand cost competitiveness of seasonal energy storage technologies, a benefit-to-cost ratio (BCR) analysis is performed.

Even though the levelized cost of energy (LCOE) or levelized cost of storage are widely used for the economic assessment of storage technologies[1,6,32], these metrics ignore the avoided costs—e.g., avoided energy costs, avoided capacity costs, or both—and therefore such metrics can provide an inadequate economic assessment and/or comparison between storage technologies[33,34]. Thus, we use the BCR[12,34] metric for the economic assessment of seasonal storage technologies based on modeling the whole power system to account for avoided costs as well as costs associated with the storage technologies. First, the capital recovery factor, CRF, is calculated based on the lifetime of each technology τ (years), and the discount rate, r (%), i.e., 7%, as expressed in equation (1).

$$CRF = \frac{r.(1+r)^{\tau}}{(1+r)^{\tau}-1} \qquad (1)$$

Then, the power capacity overnight construction cost, C_p (US\$ MW^{-1}), the power capacity of the storage device, $PCap$ (MW), the energy capacity overnight construction cost, C_e (US\$ MWh^{-1}), and the energy capacity, $ECap$ (MWh), of the storage device are used to estimate the total capital cost, TCC (US\$), as described in equation (2).

$$TCC = C_p.PCap + C_e.ECap \qquad (2)$$

The total capital cost, the capital recovery factor, and the interest rate are used to calculate the levelized annual cost, LAC (US\$), based on the analysis period, T (years), i.e., 20 years,—the time horizon for which the economic assessment is conducted[34]—as defined in equation (3).

$$LAC = CRF.TCC.\frac{(1+r)^{T}-1}{r.(1+r)^{T}} \qquad (3)$$

The total system value, TSV (US\$), is estimated based on the operational value, OV_t (US\$), and the capacity value, CV_t (US\$), of the storage device for each year t in the analysis period, as given in equation (4).

$$TSV = \sum_{t=1}^{T} \frac{OV_t + CV_t}{(1+r)^{t}} \qquad (4)$$

Then, the BCR metric is calculated using equation (5). Note that our BCR calculations are based on the operation value instead of the energy market value (energy arbitrage revenue), which is commonly used for the assessment of storage technologies; however, the energy market value approach is based on fixed electricity market prices and has some limitations, e.g., this approach ignores electricity market elasticity as well as the effects of increased penetration levels of VRE generation and system redispatch associated with the introduction of a storage device[35].

$$BCR = \frac{TSV}{LAC} \qquad (5)$$

Finally, the LCOE metric, defined as the ratio of the levelized annual cost to the total annual energy production, can be calculated using equation (6). The variable Gen_t represents the total power generation from the storage device during year t.

$$LCOE = \; LAC / \sum_{t=1}^{T} Gen_t \qquad (6)$$

Note that the formulation of the cost-benefit analysis as described does not include operation-and-maintenance (O&M) costs as well as revenue from ancillary services and avoided T&D costs; however, the O&M costs represent a marginal contribution to the LAC of seasonal storage technologies, e.g., hydrogen, CAES, and PHS[1]. Additionally, the calculation of revenues from ancillary services and avoided T&D costs involves significant uncertainties regarding future electricity markets. As a reference, under current power system configurations and electricity markets, ancillary services and avoided T&D costs could represent additional revenue streams on the order of energy and capacity values for energy storage technologies[10,35]. Average ancillary service values reported in the literature range from US$8 per kW-year to US$123 per kW-year, depending on the service[10]. Similarly, average avoided T&D costs range from US$72 per kW-year to US$124 per kW-year, depending on the service[10]. Thus, our BCR calculations are likely conservative.

The BCR analysis, including estimated capacity value, is performed for each seasonal storage technology and for each system configuration, e.g., power and energy storage capacity, based on 2025–2045 and 2050–2070 operation windows. The value of energy storage is calculated for 5 years (2024, 2032, 2036, 2040, and 2050), with each year representing a different renewable energy mix and therefore system configuration. For each configuration, we consider a case without seasonal storage (base case) and 15 seasonal storage cases. In each seasonal storage case, a single 2 GW of storage power capacity is added to the SCE zone, illustrated in Supplementary Fig. 1. This power capacity of the seasonal storage device represents approximately 1% of the peak load of the Western Interconnection power system in 2050, and it is sufficiently large to be discernible from the numerical optimization tolerance, given the scale of the power system[26]. Three different generic storage technologies were used (hydrogen, CAES, and PHS, which are commonly used in the literature [3,9,20]) with a combination of five storage discharge durations: 1 day (1d), 2 days (2d), 1 week (1w), 2 weeks (2w), and 1 month (1m). Thus, there are 16 scenarios for each of the five power system configurations, which corresponds to a total of 80 scenarios analyzed. For a given technology, the corresponding energy capacity, e.g., kWh, can be calculated based on the storage discharge duration, the power capacity, and the round-trip efficiency, e.g., 2 GW of storage power capacity with 1 day of discharge duration and 50% efficiency is equivalent to $24h * \frac{2GW}{\sqrt{0.5}}$ or 67.88 GWh of energy capacity, assuming all losses occur during charging and discharging and the same efficiency for charging and discharging (the assumptions used in this study). The corresponding economic assumptions for each generic technology are presented in Table 1, including efficiency, lifetime, and power and energy capacity capital costs for each technology.

Table 1. Techno-economic assumptions for seasonal energy storage technologies[20,36,37]

Technology (round-trip efficiency, lifetime)	Year	Power capacity cost ($ kW^{-1})			Energy capacity cost ($ kWh^{-1})		
		Min	Ref.	Max	Min	Ref.	Max
Hydrogen	2025	1,507	3,013	4,520	1.8	3.7	5.5
(40%, 18 years)	2050	650	1,300	1,950	0.5	1.0	1.5
CAES	2025	434	817	984	9.1	34.9	80.8
(60%, 30 years)	2050	415	755	947	8.9	31.0	81.6
PHS	2025	573	1,156	1,819	17.4	50.3	101.8
(80%, 55 years)	2050	573	1,164	2,807	17.3	50.9	97.4

Ref. = reference cost values. The projected values—e.g., minimum (min), reference, and maximum (max)—for power and energy capacity capital costs for CAES and PHS were based on the average projected values from three references[20,36,37]. The reference value for power and energy capacity capital cost of hydrogen were based on a report from the International Energy Agency[37], while the corresponding min and max values were based on a -/+50% from the reference value. Note that the standard deviation of projected capital cost for hydrogen storage reported in the literature is ~50%[20]. CAES represents advanced system designs that do not burn gas. Moreover, the techno-economic assumptions presented in this table are not intended to represent any specific energy storage installation.

Integration of VRE and seasonal storage dispatch profiles

This section summarizes the results regarding the optimal short-term storage capacity deployment, power generation, and transmission capacity expansion for the 2024–2050 Western Interconnection power system provided by ReEDS. The results from the production cost simulations, which were implemented in PLEXOS, are summarized in Fig. 2. The optimal generation mix for each system configuration is shown in Fig. 2a. The share of wind and solar PV power in the generation mix increases from ~24% in 2024 to ~61% in 2050, whereas the share of natural gas and coal power generation decreases from ~44% in 2024 to ~11% in 2050. Additionally, in the 2024–2050 time frame, the share of hydropower and nuclear power decreases by 3%, as a result of assumed plant retirements. The deployment of VRE, which has zero marginal generation cost, is expected to reduce the total Western Interconnection production (operational) costs, chiefly fuel costs, by ~54% from 2024 to 2050, as observed in Fig. 2b. Moreover, despite the significant deployment of short-term storage capacity (from 6.1 GW in 2024 to 33.5 GW, or ~7.4% of the total installed generation capacity in 2050, as illustrated in Fig. 2c), VRE curtailment is projected to increase significantly as wind and solar PV are deployed in the Western Interconnection power system, as shown in Fig. 2d. Additionally, the deployment of PHS capacity in the Western Interconnection power system is consistent with some scenarios from the RPS study, which project the deployment of 15–35 GW of PHS in the United States between 2030 and 2050[27].

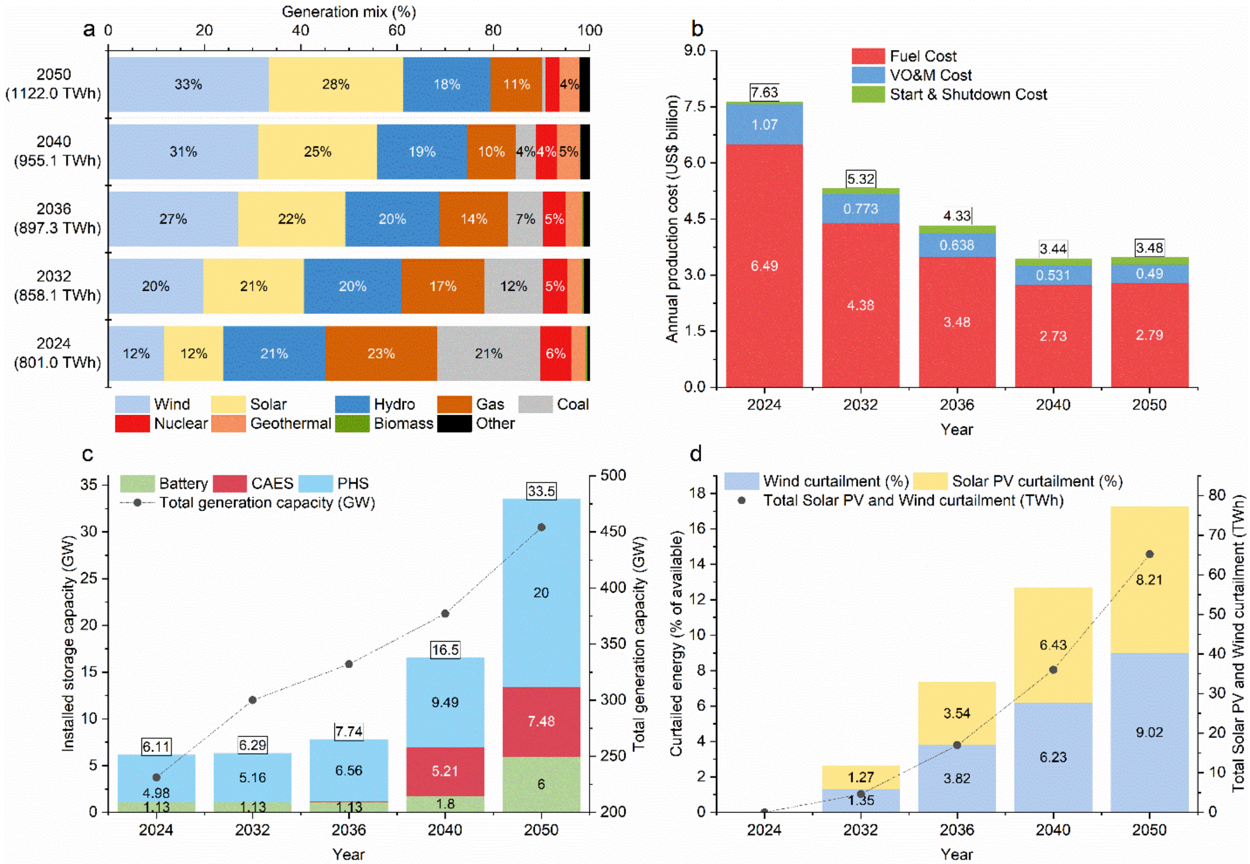

Fig. 2: Evolution of the Western Interconnection power system from 2024 to 2050 in the base cases. **a**, Generation mix for the corresponding year with the total electricity demand values in parenthesis. **b**, Breakdown of annual production cost. **c**, Short-term storage, e.g., up to 8 hours of duration, capacity deployment (left vertical axis), and total installed power generation capacity (right vertical axis). **d**, Curtailment of wind and solar PV in terms of percentage of available energy (left vertical axis) and total VRE curtailment in terms of TWh (right vertical axis).

To illustrate the opportunities for seasonal storage in the 2024–2050 Western Interconnection power system, the net load and the hourly LMPs time series for the SCE model zone are shown in Fig. 3. This zone was selected because it has a large electricity demand coupled with a significant deployment of VRE, substantial regional interconnection, and favorable policies for new and emerging technologies. Note that for this specific zone there are no must-run thermal power plants. As observed in Fig. 3a, the magnitude (GW) as well as the number of hours with negative net load, e.g., hours for which VRE generation is greater than the load, increase as the installed capacity of VRE increases. This is particularly true during spring and summer, given the seasonality of VRE (particularly solar PV). As an example, the number of hours with VRE surplus in the SCE zone increases from ~4% in 2024 to ~23% in 2050, whereas the number of hours with zero LMP increases from ~0% in 2024 to ~22% in 2050; see Fig. 3b. As a result, the hourly average LMPs decrease from US\$23.3 MWh^{-1} in 2024 to US\$18.0 MWh^{-1} in 2050 (Fig. 3b), and the temporal variability (expressed as standard deviation) of the LMPs increase from ~US\$3.2 MWh^{-1} in 2024 to ~US\$12.3 MWh^{-}

[1] in 2050. These findings are consistent with previous studies that show that the integration of VRE decreases average wholesale electricity prices while increasing the corresponding temporal variability[38–40].

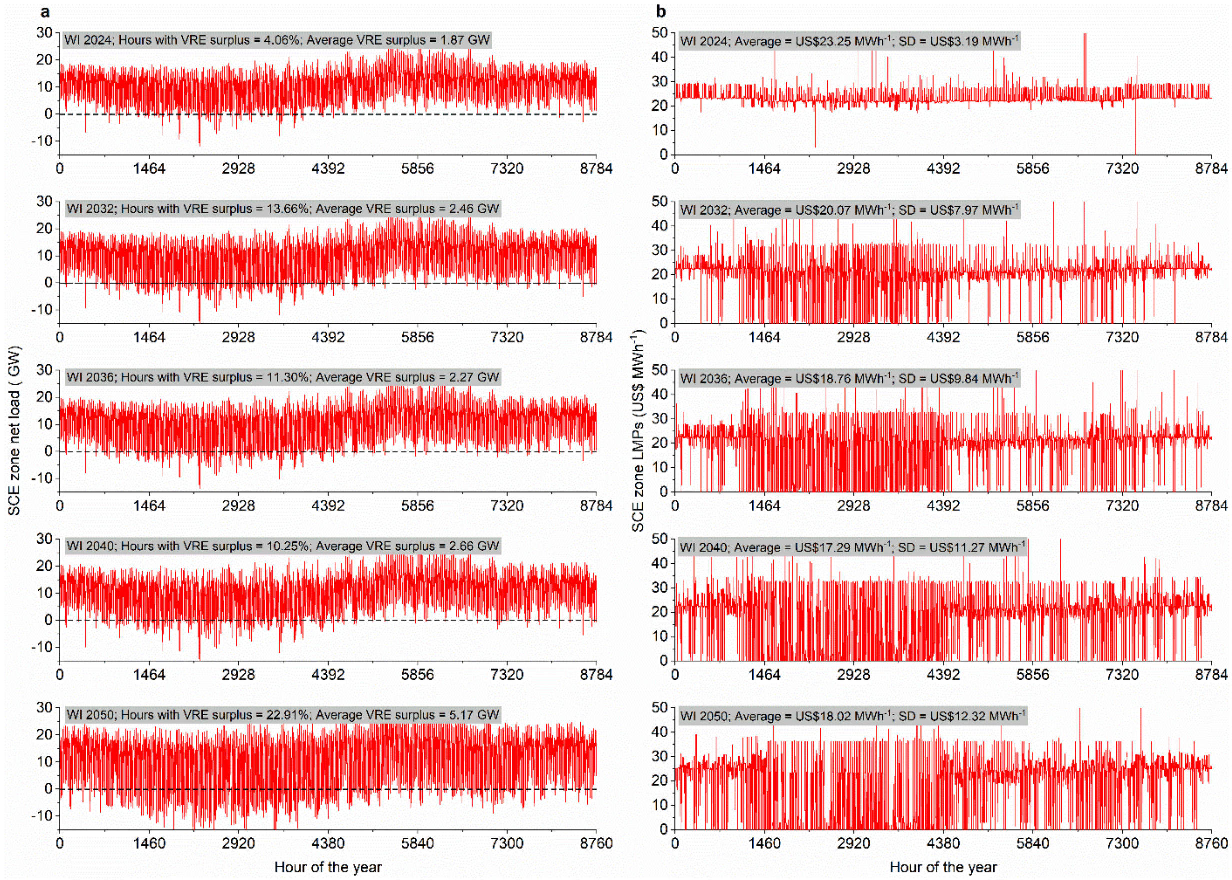

Fig. 3: Hourly net load and LMPs in the SCE zone from 2024 to 2050 without seasonal storage. **a**, Net load (GW). **b**, Hourly LMPs (US$ MWh^{-1}). The yearly average and standard deviation (SD) of the LMPs are included in the box on the top of each LMP time series. WI = Western Interconnection.

Based on the net load and LMP data illustrated in Fig. 3, the seasonal dispatch of the storage device was optimized using RODeO. As an illustration, the normalized SOC for each technology and storage duration in the 2050 Western Interconnection power system is summarized in Fig. 4. The normalization was based on the maximum SOC from the seasonal dispatch provided by RODeO. It is observed that, given its limited energy capacity, the shapes of the dispatch curves for 1d and 2d storage durations have more intra-seasonal fluctuations than the corresponding dispatch curves for 1w, 2w, and 1m storage durations. In contrast, given the higher storage energy capacity, dispatch curves for storage durations of 1w or greater show more synchronized operation with the seasonality of VRE. Moreover, it was observed that regardless of the technology (or efficiency), 1m of storage is underused, e.g., the maximum SOC from the seasonal dispatch provided by RODeO was always lower than the energy capacity of the storage device.

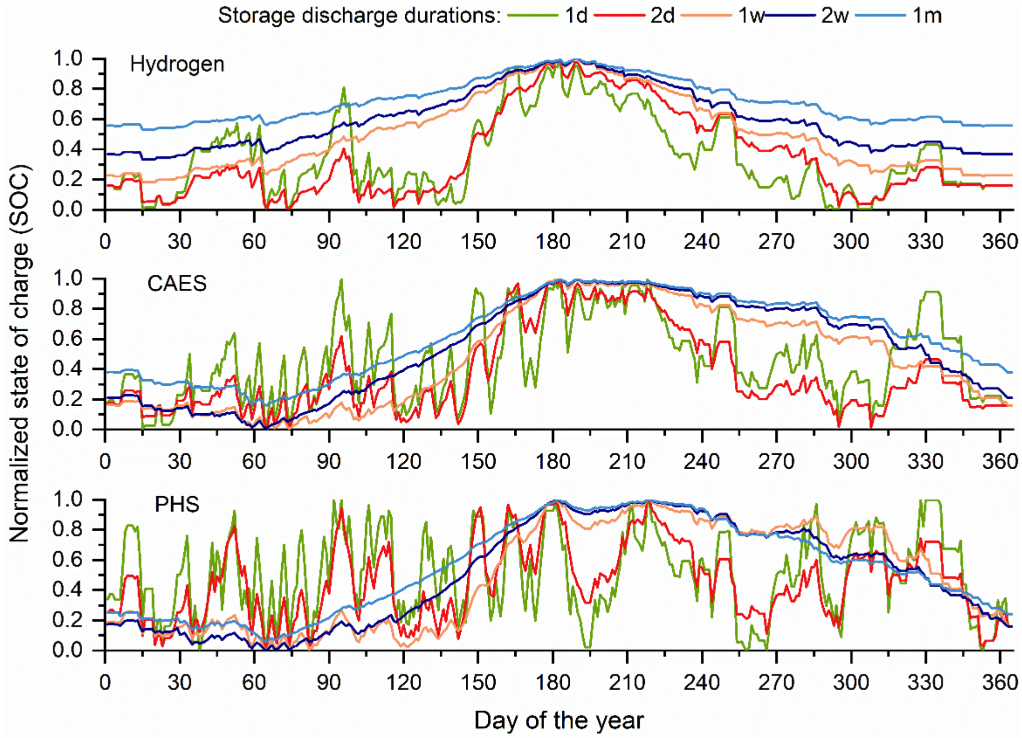

Fig. 4: Normalized SOC for the 2050 power system configuration. The energy capacity (maximum SOC) was used to normalize the SOC at the end of each day. The average optimal daily dispatch for each season is provided in Supplementary Fig. 2.

The integration of the seasonal storage device produces significantly different results than the base cases. First, the curtailment of VRE is reduced, not only in the region where the storage device was located (SCE zone) but also in neighboring regions. For instance, for the 2050 power system configuration and depending on the device efficiency and discharge duration, the seasonal storage device reduces wind and solar PV curtailment in California (which includes the SCE zone) between 7.4%–14.7% and 9.8%–15.5%, respectively (reduction of 0.6%–2.3% and 6.1%–7.9% for wind and solar PV curtailment in the Western Interconnection, respectively). This additional stored energy displaces fossil-fueled generation and reduces CO_2 emissions by 0.5%–1.8%. Additionally, the average SCE zone LMPs consistently increase, whereas the corresponding standard deviation decreases; see Supplementary Fig. 3.

Cost competitiveness and targets for grid seasonal storage

As mentioned previously, two analysis periods were used: 2025–2045 and 2050–2070. The operational value, OV_t, was estimated based on the total avoided production cost, i.e., total production cost of the base case (without seasonal storage) minus the total production cost associated with the corresponding seasonal storage case. For instance, the Western Interconnection 2024 operational value for hydrogen seasonal storage with 1 day of duration is calculated as the difference between the total production cost of the Western Interconnection 2024 base case (without seasonal storage) and the total production cost of the Western Interconnection 2024 system with a hydrogen seasonal storage device with 1 day of discharge duration. This procedure was applied for each seasonal storage scenario and for the Western Interconnection 2024, 2032, 2036, 2040, and 2050 power system configurations. Then, linear interpolation or extrapolation was used to estimate the operational value for the remaining years in the 2025–2070 time frame (see Supplementary Fig. 4). A similar approach was used to estimate the total power generation from the storage device Gen_t for each year. Regarding the capacity value, two methods—i.e., a reliability-based method and a capacity factor-based approximation method—are commonly used to evaluate the capacity value of renewable power plants and storage devices[41–43]. Reliability-based methods use a large set of simulations to estimate the loss-of-load probability, which is used to calculate the effective load-carrying capability or the equivalent conventional power metric[42,43]. In contrast, capacity factor-based approximation methods are based on the capacity factor of the generator or storage device over a given subset of time periods, e.g., hours, during which the power system has a high probability of facing a shortage, e.g., periods or hours with the highest loads[42,43]. The reliability-based method can be computational expensive, whereas the capacity-factor-based method is more practical and can provide a reasonable approximation of the capacity value, e.g., based on the 10 highest load hours[41,42]. Thus, the capacity-factor-based method is used in this study to estimate the capacity value of seasonal storage. Note that while current practice is to estimate the capacity value based on just “peak load”, in future power systems with high shares of VRE it should be based on “peak net load” [35,44]. First, the capacity credit—the ability of the seasonal storage device to supply energy during periods of peak net load—was estimated based on the top 10 peak net load hours of the Western Interconnection 2024, 2032, 2036, 2040, and 2050 power system configurations. The period of peak load is normally less than 8 hours in duration[44]. To this end, the optimal storage dispatch provided by PLEXOS, which includes the SOC targets from RODeO, was compared with the top 10 peak net load hours to determine if the seasonal storage device is supplying energy during these hours. In general, e.g., for every seasonal storage scenario, it was observed that the seasonal storage device generates electricity at full capacity and/or has enough energy stored to generate at full capacity during the top 10 peak net load hours; see illustration in Supplementary Fig. 5. Thus, a 100% capacity credit is assumed for every seasonal storage device considered in this study. This assumption is consistent with previous studies that showed that storage devices with more than 10–12 hours of discharge duration can receive 100% capacity credit[43,44]. Note that this study contemplates storage devices with 1 day of storage discharge duration or greater. The next step is to determine the capacity cost—the cost of building a new peaking conventional thermal generator to supply electricity demand[33]—because the annual capacity value can be estimated by multiplying the power capacity (kW) by the capacity credit (% or fraction) and the avoided capacity cost of peaking generators (US$ per kW-year). Previous studies reported avoided capacity costs of US$190 per kW-year[33] and US$212 per kW-year[35] for the California Independent System Operator. In this study, the avoided capacity cost of peaking generators was assumed to be US$200 per kW-year.

Additionally, a lower value of US$150 per kW-year and an upper value of US$250 per kW-year were used to assess the sensitivity of the BCR metric to the capacity cost assumption.

Two metrics were used to evaluate the cost and the profitability of seasonal storage. First, the cost of seasonal storage was evaluated based on the levelized cost of energy (LCOE); see Fig. 5a. Based on the reference cost values reported in Table 1, for 2025, PHS is the cheapest technology for discharge durations lower than 16.9 days, whereas hydrogen storage is cheaper that CAES and PHS for discharge durations of 6.8 days (or more) and 16.9 days (or more), respectively. Moreover, for 2050, hydrogen storage is cheaper than CAES and PHS with 1.9 days (or more) and 3.1 days (or more) of discharge duration, respectively; however, the LCOE metric does not provide information regarding the cost competitiveness of each technology. Thus, the cost effectiveness, i.e., measured via the BCR metric, was used to evaluate the profitability of the seasonal storage technologies. The BCR metric considers not only the total cost, e.g., capital cost for power and energy capacity, but also the total system value, e.g., energy and capacity value, associated with the storage technologies. As defined previously, the BCR metric is the ratio between total system value—operational value plus capacity value—and the total capital cost of the storage device. The results regarding the operational value are summarized in Supplementary Fig 4, whereas the calculation of the capacity value was based on 100% capacity credit and US$200 per kW-year avoided capacity cost, as described previously in this section. The BCR results are summarized in Fig. 5b. For the 2025–2045 time frame and based on the reference cost values, only CAES and PHS with 1 day of discharge duration are cost-effective (BCR ≥1). Moreover, hydrogen storage with up to 1 week of discharge duration will be cost-competitive if power and energy capacity capital costs are equal to or less than ~US$1,507 kW^{-1} and ~US$1.83 kWh^{-1} by 2025, respectively. Thus, hydrogen seasonal storage is unlikely to be cost-effective in the near future unless significant capital cost improvements are achieved. For the 2050–2070 time frame, however, hydrogen seasonal storage with 1 day, 2 days, 1 week, or 2 weeks of discharge duration would be cost-competitive, whereas CAES and PHS are cost-competitive only for discharge durations of 1 day (CAES and PHS) or 2 days (CAES). In general, hydrogen seasonal storage is more cost-competitive than CAES and PHS for applications that require discharge durations of 2 days or more. This is primarily because of the energy capacity capital cost of hydrogen storage is lower than CAES and PHS; see Table 1 and Fig. 6. For example, for 2 days of discharge duration, the energy capacity capital cost share of the total capital cost for hydrogen storage is ~5.5%, whereas it is more than 70% for CAES and PHS, as illustrated in Fig. 6. This method for assessing the cost effectiveness of storage technologies represents a refinement of the LCOE analysis method presented earlier. For instance, the LCOE analysis shows hydrogen is preferred for discharge durations greater than 3.1 days, while the cost effectiveness calculations show not only a preference for hydrogen storage with a discharge duration of 2 days or more but also cost competitiveness for hydrogen storage discharge durations of up to 2 weeks.

Additionally, hydrogen is a flexible energy carrier that can be used in other sectors[45]—e.g., transportation, agricultural, industrial, and residential— which could provide additional revenue streams to hydrogen storage systems. Besides hydrogen, ammonia is a versatile energy carrier that can be used not only for seasonal storage but also for cross-sectoral applications, e.g., renewables to fertilizers and transportation fuels. Given the breadth of potential configurations and pathways for these energy carriers, we focus this study on electron-to-electron pathways with the recognition that exploration of alternative pathways is an area for future work. Moreover, our calculations do not include revenues from ancillary services and avoided transmission and distribution (T&D) costs. These revenue streams could be crucial for the cost effectiveness of seasonal storage. For example, hydrogen storage with 1 day, 2 days and 1 week of duration requires ~US$99.1 per kW-year , ~US$112.7 per kW-year, and ~US$181.7 per kW-year of revenue from additional services to be cost-competitive in the 2025–2045 time frame, respectively. Similarly, CAES and PHS with 2 days of duration requires ~US$19.9 per kW-year and ~US$50.7 per kW-year of additional revenue to be cost-effective in the 2050–2070 time frame, respectively. These required additional revenues appear feasible in current electricity markets, i.e., the reported average values of up to US$123 per kW-year and US$124 per kW-year for ancillary services and avoided T&D cost, respectively[10].

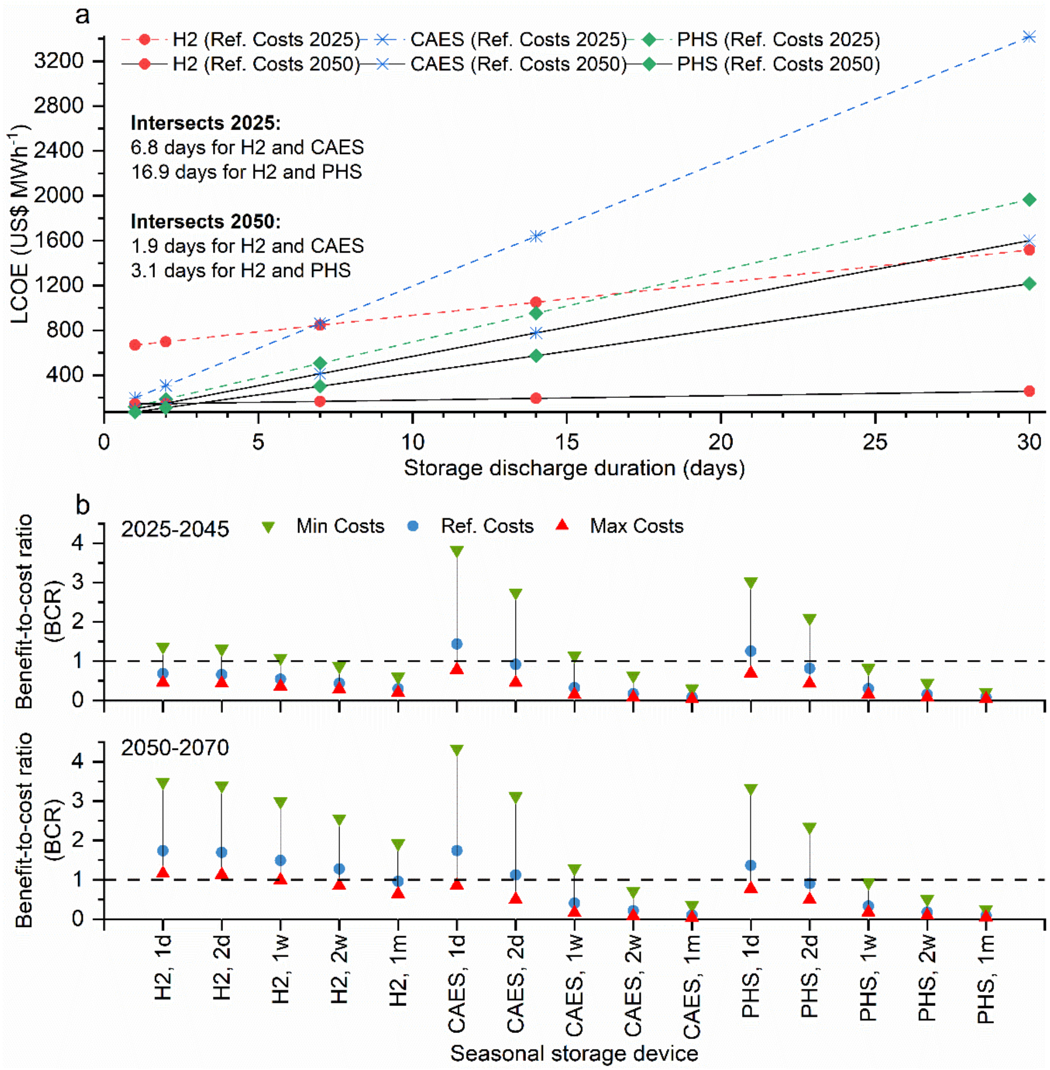

Fig. 5: Seasonal storage cost and profitability. **a**, LCOE for seasonal energy storage. **b**, Benefit-to-cost ratio for seasonal storage technologies. Time frames 2025–2045 (top panel) and 2050–2070 (bottom panel). H2 denotes hydrogen storage.

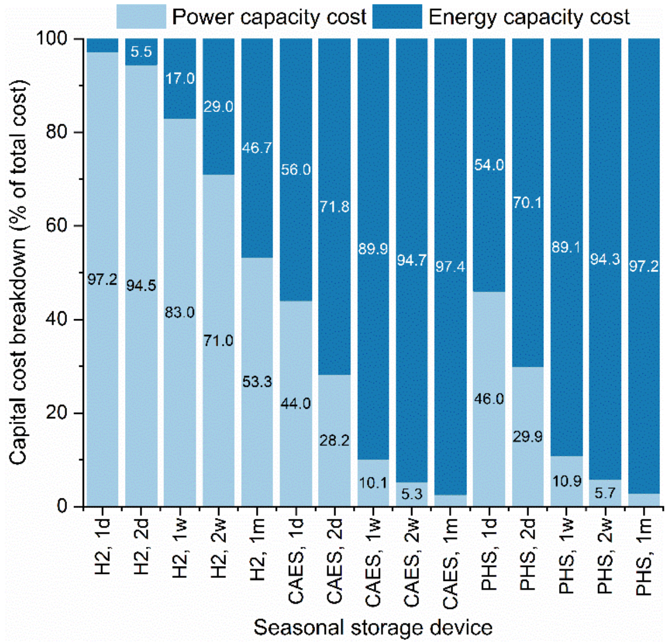

Fig. 6: Normalized capital cost breakdown for seasonal storage technologies under different discharge durations for the 2050-2070 operation windows. Similar results were observed for the 2025-2045 time frame. H2 denotes hydrogen storage.

Regarding the breakdown of the total system benefit, depending on the device efficiency and discharge duration, the share of operational value ranges from 6.6%–11.7% and 13.6%–24.0% for the 2025–2045 and 2050–2070 time frames, respectively. Thus, the value of a given seasonal storage device is driven mostly by its capacity value (essentially its ability to replace fossil-based peaking generators) rather than by operational value (load-shifting benefits), which is consistent with previous work[35]. As a reference, for the Western Interconnection power system in 2050, the estimate operational value ranges from US$29.1 per kW-year to US$54.2 per kW-year, depending on the storage device.

Because the capacity value is a major driver for seasonal storage value, a sensitivity analysis was performed to quantify the sensitivity of the BCR metric to the assumed avoided capacity cost of peaking generators; see Fig. 7. Although previous studies estimated the capacity value at approximately US$200 per kW-year in the Western Interconnection power system[33,35], as the VRE share on a power system increases, it is unclear how the impacts will affect the value and resulting market(s) for providing capacity. The sensitivity results show that for the 2025–2045 time frame, assumed avoided capacity cost could change the cost effectiveness of CAES and PHS devices with 2 days of discharge duration. For example, CAES and PHS with 2 days of duration are expected to be cost-competitive for avoided capacity cost at US$250 per kW-year but not for US$150 per kW-year. This is also true for CAES and PHS with 2 days of duration operating during the 2050–2070 time frame. Moreover, hydrogen storage is uneconomical for the 2025-2045 operation window and cost-effective with up to 2 weeks of discharge duration for the 2050-2070 time frame, regardless of the assumed capacity value. Additionally, hydrogen storage with 1 month of discharge duration is expected to be cost-competitive during the 2050-2070 time frame for avoided capacity cost at US$250 per kW-year but not for US$150 per kW-year.

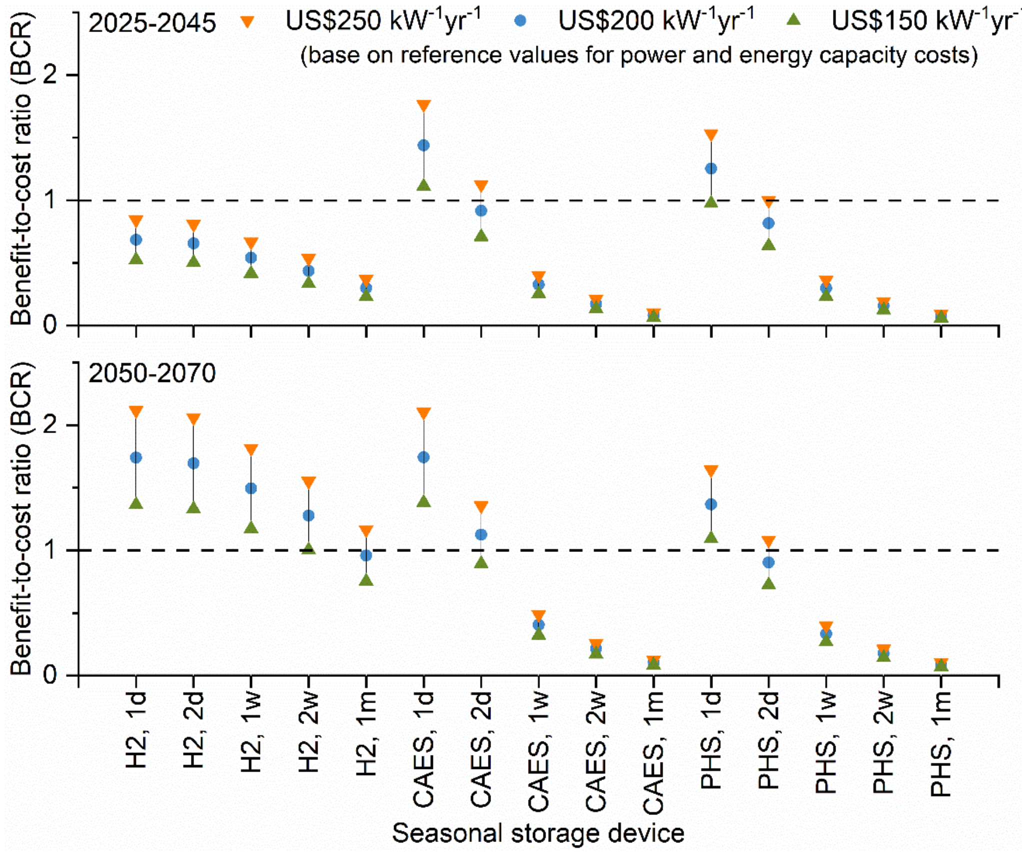

Fig. 7: Sensitivity of BCR metric to avoided capacity cost of peaking generators. Time frames 2025–2045 (top panel) and 2050–2070 (bottom panel). H2 denotes hydrogen storage. Additional sensitivities for the BCR metric—e.g., for min and max values of power and energy capacity capital costs—to the avoided capacity cost of peaking generators are provided in Supplementary Figs. 6 and 7.

In an effort to better understand the conditions that make seasonal storage cost-competitive, we explore the 2050 power- and energy-related cost targets at which seasonal storage becomes profitable with 1 day, 2 days, 1 week, 2 weeks, and 1 month of discharge durations. The analysis is based on generic storage technologies with 40%, 60%, and 80% round-trip efficiency and three possible lifetimes, i.e., 18 years, 30 years, and 50 years, for a total set of 9 generic storage technologies (combinations of 3 efficiencies and 3 lifetimes). Additionally, ranges of power- and energy-related costs were considered to capture the significant uncertainty in storage capital and operational costs. The results are summarized in Fig. 8, Fig. 9, and Fig. 10 for 18 year, 30 year, and 50 year lifetime, respectively.

Regardless of the efficiency and the lifetime, a storage technology with a power-related cost of US$500 kW^{-1} would be cost-effective in the 2050-2070 time frame for discharge durations of 1 week, 2 weeks, and 1 month if energy-related cost is less than US\$6.9 kWh^{-1}, US\$3.5 kWh^{-1}, and US\$1.6 kWh^{-1} by 2050, respectively. For a power-related cost of US\$1000 kW^{-1}, the previous energy-related cost targets are US\$5.0 kWh^{-1}, US\$2.5 kWh^{-1}, and US\$1.2 kWh^{-1} for 1 week, 2 weeks, and 1 month of discharge duration, respectively. Moreover, for the same time frame and regardless of the efficiency and lifetime, a seasonal storage technology with energy-related cost at US\$1.0 kWh^{-1} by 2050 would be cost-competitive for 1 week, 2 weeks, and 1 month of discharge duration if power-related cost is less than US\$2074.0 kW^{-1}, US\$1808.5 kW^{-1}, and US\$1201.6 kW^{-1}, respectively. For energy-related cost at US\$2.0 kWh^{-1}, these power-related cost targets become more stringent, e.g., US\$1808.3 kW^{-1}, US\$1277.2 kW^{-1}, and US\$63.2 kW^{-1} for 1 week, 2 weeks, and 1 month of discharge duration, respectively. Note that the slope of the iso-BCR lines for 1 week, 2 weeks and 1 month of discharge duration indicates that the cost competitiveness of seasonal storage is mostly driven by the energy-related costs, while power-related costs, efficiency, and lifetime play a less important role. Therefore, efforts in research and development of seasonal storage technologies should focus on the design of storage devices with low energy-related costs.

Regarding the effects of lifetime on the cost effectiveness of seasonal storage, it is observed that for a storage technology with 1 week of discharge duration, 60% round-trip efficiency, and power-related cost of US\$1000 kW^{-1}, cost competitiveness is achieved if energy-related costs are less than US\$6.7 kWh^{-1}, US\$9.4 kWh^{-1}, and US\$10.9 kWh^{-1} by 2050 for 18 year, 30 year, and 50 year lifetime, respectively. Similarly, a storage technology with 1 week of discharge duration, 30 year lifetime, and power-related cost of US\$1000 kW^{-1} would be cost-effective if energy related costs are less than US\$7.1 kWh^{-1}, US\$9.4 kWh^{-1}, and US\$11.6 kWh^{-1} by 2050 for 40%, 60%, and 80% efficiency, respectively. This *ex ante* assessment of the economics of seasonal storage can help inform research and development decisions, policy makers, as well as industry investment.

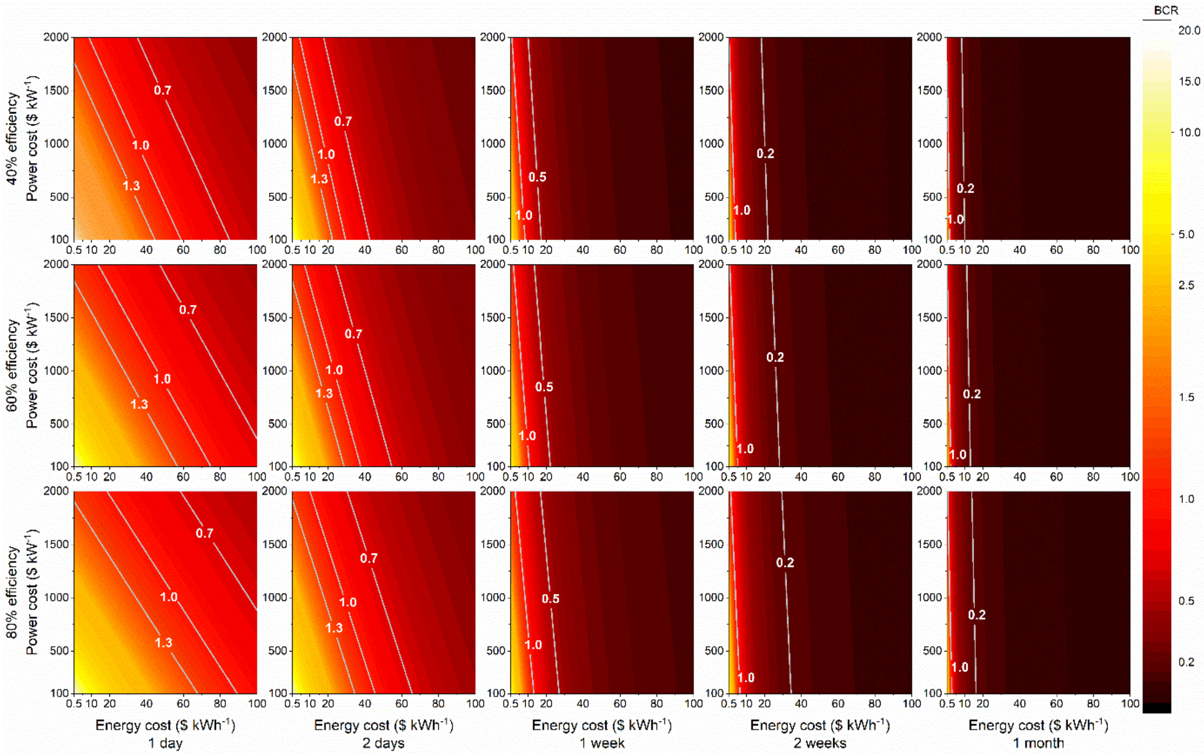

Fig. 8: Energy storage cost targets (2050) for technologies with 18 year lifetime, based on profitability in the 2050–2070 time frame. For every storage discharge duration—i.e., 1 day, 2 days, 1 week, 2 weeks, or 1 month—the area below the corresponding iso-BCR line BCR=1 represents the set of power and energy costs for which the corresponding seasonal storage technology is cost-effective.

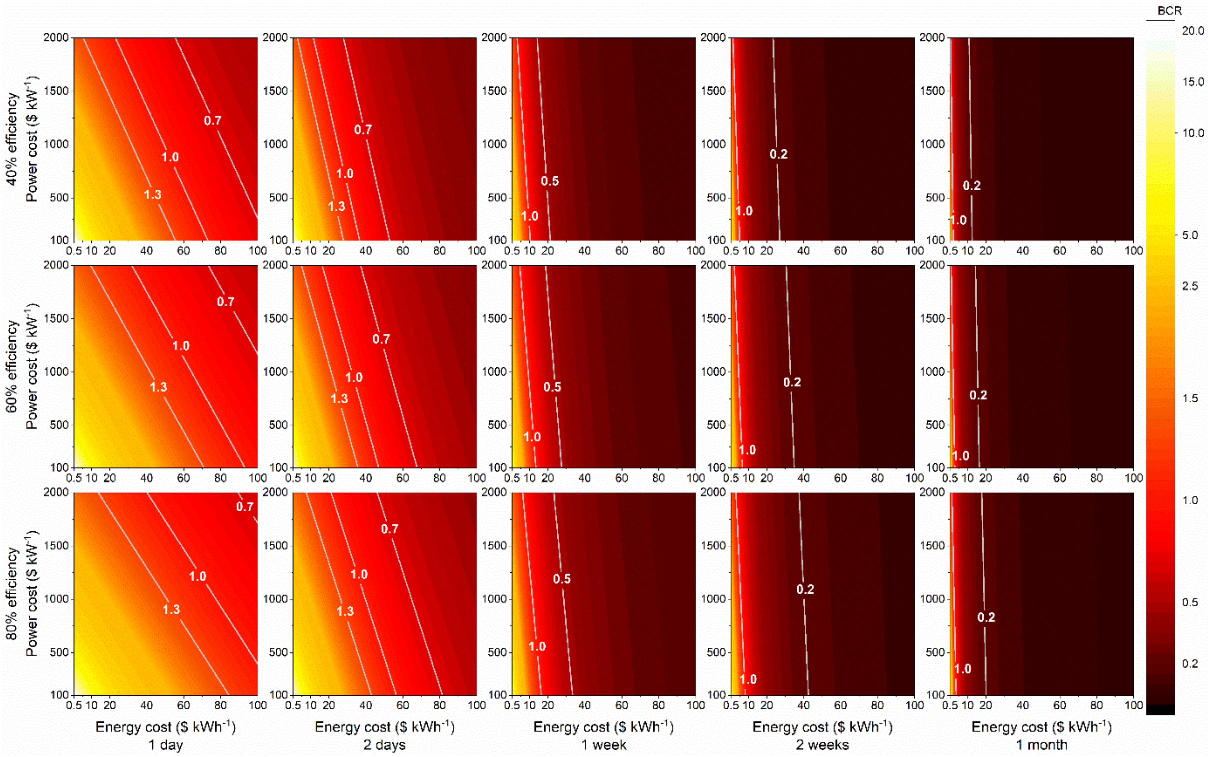

Fig. 9: Energy storage cost targets (2050) for technologies with 30 year lifetime, based on profitability in the 2050–2070 time frame. For every storage discharge duration—i.e., 1 day, 2 days, 1 week, 2 weeks, or 1 month—the area below the corresponding iso-BCR line BCR=1 represents the set of power and energy costs for which the corresponding seasonal storage technology is cost-effective.

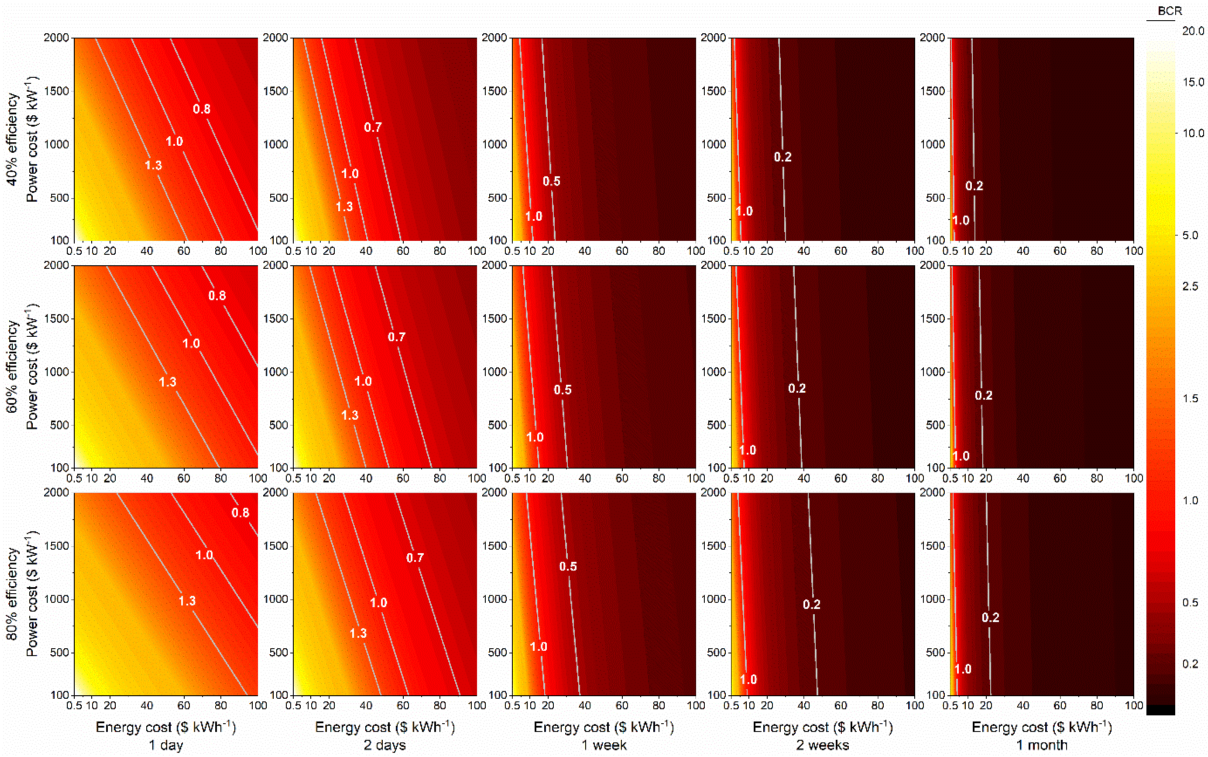

Fig. 10: Energy storage cost targets (2050) for technologies with 50 year lifetime, based on profitability in the 2050–2070 time frame. For every storage discharge duration—i.e., 1 day, 2 days, 1 week, 2 weeks, or 1 month—the area below the corresponding iso-BCR line BCR=1 represents the set of power and energy costs for which the corresponding seasonal storage technology is cost-effective.

Finally, the system operational value was compared to the storage plant energy market value. The energy market value or energy arbitrage revenue was estimated by multiplying the LMP time series and hourly dispatch profile (from PLEXOS) for each seasonal storage device. It was estimated that the energy market value captures only a fraction—e.g., from 52.3% to 84.5%, depending on the seasonal storage scenario and the year of operation—of the system operational value. As an illustration, the ratio between the plant energy market value and the system operational value for 2050 and for each seasonal storage device is shown in Fig. 11. For this specific year, the energy market value captures only a 67%-79.2% of the system operational value, depending on the seasonal storage scenario. This situation reflects the inability of energy markets to fully compensate storage devices for the operational benefits that they can provide to the system. This finding is consistent with previous work[46] and reiterates the importance of considering how to appropriately value storage and particularly long-duration storage, when developing market products.

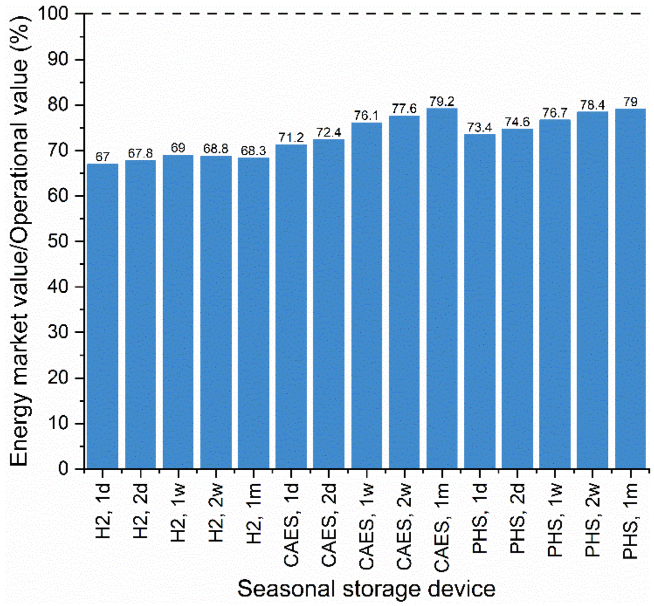

Fig. 11: Energy market value versus operational value for the Western Interconnection in 2050. H2 denotes hydrogen storage.

Conclusions

Although significant research efforts have been devoted to the techno-economic assessment of energy storage technologies, the understanding of the economics of seasonal energy storage and the corresponding impacts on power system operations has been largely overlooked. We developed a model-based approach for the comprehensive analysis of seasonal storage technologies in the context of the integration of high shares of wind and solar photovoltaic power sources in power systems. The approach was used to investigate the operational performance and cost-benefit comparison of three specific storage technologies (i.e., pumped hydro storage, compressed air energy storage, and hydrogen storage) as well as to develop a broader understanding of the cost, storage duration and efficiency conditions that encourage cost competitiveness for seasonal storage technologies. This investigation was performed for the Western Interconnection power system, considering the deployment of wind and solar power shares from 24% to 61% (on an annual energy basis). This approach has two major advantages. First, we do not have to make assumptions about the operation of the storage including cycles or depth of discharge. Instead, a model is used to calculate optimal storage operation profiles. Second, the approach accounts for avoided power system costs, which allows us to estimate the cost effectiveness of different types of storage devices.

Most literature for seasonal storage focuses on technology cost assessments and does not consider the potential grid benefits, which are important in establishing the cost effectiveness or profitability of installed storage plants. Strictly from a technology cost perspective, pumped hydro energy storage has the lowest cost for low discharge durations; however, as the installed discharge duration increases, hydrogen eventually becomes the lowest cost technology, due to the significantly lower energy storage capital costs compared to CAES and PHS. This occurs for discharge durations greater than 16.9 days in the 2025–2045 time frame and 3.1 days in 2050–2070 time frame. This behavior is consistent with findings in the literature, but this method does not answer the broader question of cost effectiveness for seasonal storage technologies.

Using a benefit-to-cost ratio method that considers operational and capacity value as benefits along with the assumed cost values, the most cost-effective storage systems have 1 day of discharge duration. Of the benefits considered, capacity value is the biggest driver. In the 2050–2070 time frame, the capacity value is around four times that of the operational value; in large part, this explains the preference for 1 day of discharge duration. In addition, though it is not the most cost-effective solution, a discharge duration of 2 days has a BCR greater than one for hydrogen and compressed air energy storage in 2050–2070. Moreover, for more than 2 days of discharge duration, the only cost-effective technology is hydrogen because of its lower cost for energy capacity.

Cost effectiveness for energy storage is sensitive to a variety of aspects including: (i) greater renewable energy share which could affect the arbitrage or capacity value; (ii) significant capital cost reductions, e.g., capital cost in 2025-2045 window falling below ~US\$1,000 kW^{-1} and ~US\$1.2 kWh^{-1} for power and energy capacity, respectively; or (iii) the ability of the storage device to monetize additional grid services or new markets, e.g., reliability and resiliency.

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