

deep carbon reduction mandates (e.g. emissions cuts of greater than 50%). Rather than using a point estimate of future BES costs, we work parametrically, exploring how storage capital costs determine the grid-average cost and emissions intensity of electricity. Electricity storage can provide a variety of services such as frequency regulation to support integration of intermittent renewables, but here we limit our analysis to bulk (multi-hour) storage of electricity.

Our primary contribution is to assess the economics of BES as a function of its power- and energy-specific capital cost when it is used to achieve deep decarbonization of electricity supply. Applying a simple model enables us to parametrically evaluate the role of the capital cost which is the single most important determinants of the economic viability of BES. Previous work has examined the economics of specific BES technologies in comparison to gas turbines in low carbon grids.⁵⁻⁷ The rationale for focusing on gas as a rival for BES is low carbon emissions compared to coal, high operational flexibility, and low capital costs. Several studies have examined the competitiveness of a wide array of storage technologies at the grid level. These systems-level assessments use complex utility-grade models (e.g. incorporating security-constrained unit commitment) to take into account the specifics of the modeled grid and its reliability requirements. An example is the Pacific Northwest National Laboratory's (PNNL) report on the intra-hour balancing requirements to facilitate a 20% penetration level for wind.⁷ But existing literature does not cover the parametric "what if" question we address here: what are the price and performance parameters required for BES to play a significant role in enabling intermittent renewables to achieve deep emissions cuts in the electricity sector.

Our modeling approach allows us to estimate the economically optimal amount of bulk storage—both energy storage and peaking capacity. Estimating storage requirements is a complicated task. An important factor here is the cost of storage, which the literature often underestimates. Barnhart and Benson⁸ picked a storage scale equal to 4–12 hours of the average electricity demand in order to evaluate the energetic and material implications of large-scale deployment of storage systems. In a different study however, Pickard⁴ used a storage size roughly 5.5 times larger than the average daily primary energy demand, while neither of these authors justified their selection from an economic point of view. Denholm and Hand⁹ applied a dispatch model to the Electric Reliability Council of Texas (ERCOT) grid and concluded that wind and solar penetration levels as high as 80% while keeping the curtailment rates below 10% would require a combination of load shifting and storage of one day of demand. Similarly, Denholm and Hand's analysis is not based on any economic metrics such as cost of storage or even wind and solar plants themselves. Parametric modeling of the BES capital cost allows us to explore its impact on the overall cost of electricity supply and to assess the economically optimal deployment of BES over a wide range of estimates for the BES capital cost.

2. Data and methods

We use real world wind and load data to build our electricity system model. We optimize the size and dispatch order of the

generation fleet to minimize the cost of electricity supply under a range of BES costs and GHG emissions constraints. Our analysis is based on the following key simplifying assumptions. First, since our focus is on deep emissions reductions under which essentially all coal power plants have to retire (or have carbon capture and sequestration, CCS retrofits) and because deep reductions will likely not occur until the existing fleet nears the end of its economic life, we ignore the existing capacity and perform a green-field analysis. Second, transmission costs and constraints are ignored. Third, since we are studying BES, we use a temporal resolution of 15 minutes. We do not treat reliability and security constraints of the grid. Fourth, we ignore forecast errors in the load and wind profiles. Finally, we limit our time horizon to one year, ignoring inter-annual variations in load and wind. We examine the impact of these assumptions on our policy-relevant conclusions in the Conclusion section and Table S1 (ESI†).

2.1 Modeling energy storage

Variations in the engineering and economic parameters of BES technologies obviously affect their cost effectiveness in supporting renewables. No BES technology, except PHS has been deployed at large scale so far (PHS accounts for 99% of the existing 141 GW global electricity storage capacity.¹⁰ Limited experience and the emergence of new technologies make assessing the importance of BES in low emission grids difficult. As Table 1 illustrates, current literature uses widely different assumptions about the capital cost (CapEx) and efficiency of BES systems.

Hittinger *et al.*¹¹ as well as Sundararagavan and Baker¹² studied the significance of selected economic and technical parameters and concluded that CapEx was consistently the single most important parameter undermining the economic feasibility of electricity storage systems. We therefore, focus on CapEx as the main variable of BES throughout our analysis. We first draw general conclusions by treating BES as a black box with fixed technical characteristics but variable CapEx (see Table 2). This approach allows us to perform a systems level analysis to provide a first order estimate of the market share of BES in low carbon economies. We then study specific BES technologies in a wide range of CapEx estimates to assess their significance in lowering the cost of cutting carbon emissions.

We assume that the total CapEx of a BES facility is the sum of two components, one proportional to the peak power capacity and the other proportional to the stored energy capacity. We further assume that any combination of power and energy capacities is technically feasible. Power-specific capital cost (X_P) has units of \$ per kW, and the energy-specific capital cost (X_E) has units of \$ per kW h. In the case of PHS for example, X_P and X_E primarily represent the CapEx of turbomachinery and water reservoir, respectively.

We explore the balance between X_P and X_E in determining the economics of BES and as a means to guide R&D in prioritizing its cost reduction targets. This strategy also helps in assessing the economically optimal ratio of power to energy capacity over a wide range of X_P and X_E . This optimal ratio has implications for the technical feasibility of large-scale adoption of some BES technologies, such as availability of minerals and



Table 1 Economic and technical characteristics of selected BES technologies. Values in bold represent the authors' best estimates and are used in Fig. 1

BES technology	X_P (\$ per kW)	X_E (\$ per kW h)	Efficiency (%)
Pumped hydroelectric storage (PHS)	2300, ⁷ 1500–2000, ¹³ 1200, ¹⁴ 600–2000, ^a ¹⁵	10, ⁷ 100–200, ¹³ 75, ¹⁴ 0–20, ¹⁵ 12 (plus \$2 per kW h for BOP), ¹² 10–100	70–85, ^{10,15,16} 80, ¹² 85, ¹⁴ 50–85, ¹⁷ 75–80
Underground diabatic compressed air energy storage (CAES)	1500–2300, ⁷ 2000, ¹² 1500–2000 ^b 655, ³ 850–1140, ⁷ 740–830, ¹³ 700, ¹⁴ 425–480, ¹⁵ 750–1200, ^c ⁸ 835, ^d ¹⁹ 450 (plus \$160 per kW for BOP), ¹² 850–1200 ^f 800–900, ¹³ 517, ¹⁵ 835, ¹⁹ 850–1200 ^f	7, ³ 3, ⁷ 5, ¹⁴ 3–10 (+\$50 per kW h for balance of plant equipment, BOP), ¹⁵ 5–25, ^e ¹⁸ 1–2, ¹³ 20, ¹⁹ 10, ¹² 5–25	4.2 and 0.8, ³ 4.2 and 0.75, ¹⁸ 4.2 and 0.67, ⁶ 0.7–0.8 (values present heat rate in GJ per MW h and work ratio) 0.7–0.8 and 4.2^h (heat rate in GJ per MW h and work ratio) 77, ³ 50–75, ²⁰ 55–70
Aboveground diabatic CAES (AD-CAES)	920, ⁱ ³ 1100–1700	200–240, ¹³ 50 (+\$40 per kW h for BOP), ¹⁵ 220–260, ^g ¹⁹ 200–250 8, ³ 10–50^j	77, ³ 50–75, ²⁰ 55–70
Underground adiabatic CAES (A-CAES)	450 (+\$100 per kW for BOP), ¹² 420–660, ¹³ 400, ⁱ ⁴ 200–580, ¹⁵ 450–650 3000 (+\$100 per kW for BOP), ¹² 350, ¹⁴ 260–810, ⁱ ⁵ 350–800 2000 (+\$100 per kW for BOP), ¹² 400, ¹⁴ 640–1500, ⁱ ⁵ 500–1500 3200 (+\$100 per kW for BOP), ¹² 942–1280, ⁷ 400, ⁱ ⁴ 1250–1800, ¹⁵ 1000–1500	200–400, ¹² 330–480, ¹³ 175–250 (+\$50 per kW h for BOP), ¹⁵ 330, ¹⁴ 300–450 534, ¹² 350, ¹⁴ 245 (+\$40 per kW h for BOP), ¹⁵ 250–400 400, ⁱ ² 200–400, ¹⁵ 200–400 630, ¹² 600, ¹⁴ 175–1000, ¹⁵ 173–257, ⁷ 200–600	65–85, ¹⁰ 75, ¹² 75–120, 75–90,¹⁵ 85–90,¹⁹ 75–90, ²¹ 60–95, ²² 70–90, ²³ 75–86,¹⁵ 75–90 75–85, ^{10,15} 85, ¹² 75, ^{14,21} 75–80, ^{19,24} 75–90, ²³ 75–85
Lead acid battery (PB-A)			75, ^{12,15,22,23} 70, ¹⁴ 65–70, ¹⁹ 60–65,^{21,24} 60–75
Sodium sulfur battery (NaS)			65–85, ¹⁰ 80, ¹² 70–85, ¹⁵ 65–75, ¹⁹ 65, ¹⁴ 75, ⁷ 75–78,²⁴ 65–70, ²¹ 85, ²² 65–80
Zinc bromine battery (ZnBr)			
Vanadium redox battery (VRB)			

^a In our opinion, storage costs reported by this source are too optimistic. ^b BOP: balance of the plant equipment. ^c We calculated this range based on the estimates for two different CAES facilities (1.35 MW with 8 and 20 hours of storage). ^d Values are based on cost estimates for two different CAES facilities (1.35 MW with 8 and 20 hours of storage). ^e Lower and upper bounds represent depleted gas reservoirs and domal salt caverns. ^f We assume that underground and aboveground CAES have similar specific power capital costs. ^g We estimated the energy-specific cost (X_E) of aboveground CAES based on the total costs cited for underground and aboveground CAES, assuming comparable values for their power-specific CapEx (X_E). ^h We assumed underground and aboveground CAES have comparable thermodynamic performance. ⁱ We adjusted the limited-publicly available cost estimates for A-CAES based on their and our estimates for diabatic CAES. ^j Energy density of cavern of A-CAES is roughly half of CAES. We therefore, doubled our estimates for CAES to calculate energy-specific cost (X_E) of A-CAES.

chemicals for electrodes (power capacity) and electrolytes (energy capacity) of flow batteries.

We map cost estimates for selected BES technologies on the X_E and X_P coordinate system in Fig. 1. The basis of our estimates is provided in Table 1. Two distinct regions are observed. Region 1 represents mechanical systems (PHS and CAES) distinguished with low energy capital cost (X_E) but very high values for power cost (X_P). Region 2 embraces electrochemical systems with intermediate values for X_E and X_P . We refer to BES systems situated in regions 1 and 2 as mechanical and electrochemical hereafter.

2.2 Load and wind data

Wind and load profiles are based on historical data from ERCOT in the United States between May 2012 and April 2013. Load is normalized to its peak and wind is normalized to installed capacity. We choose a temporal resolution of 15 minutes. Power spectrum analysis of wind farms indicates that the majority of high amplitude variations in their output occur at low frequencies (hourly and daily timescales),²⁵ so a 15 minute resolution over one full year captures requirements for bulk energy storage. Performing the analysis over one full year also enables assessing the need for long duration storage of electricity. The correlations between wind availability and electric load in our model are discussed in ESI†.

2.3 Electricity system model

We simultaneously optimize installed capacity and dispatch during operation of a generation fleet to meet the load at the minimum cost. We use a set of scenarios defined by a series of imposed constraints on the annual average GHG intensity of electricity ranging from 300 to 0 kgCO₂e per MW h (CO₂e equivalents are used to account for methane emissions, see ESI† for details). The power- and energy-specific CapEx of BES are varied to sample the two-dimensional (X_E and X_P) space within each emissions intensity scenario. The system-average leveled cost of electricity (LCOE, \$ per MW h) is minimized at each emissions intensity and at the sampled values of X_E and X_P . The LCOE includes fixed and variable operating and maintenance costs (FOM and VOM), fuel costs, and amortized CapEx. This optimization problem is solved in MATLAB using linear programming with the interior-points algorithm. It takes about 500 seconds on a 2012 vintage CPU for each of 320 sample points in the X_E and X_P plane. See ESI† for details of the mathematical model.

We assume that any combinations of simple and combined cycle gas turbines (SCGT and CCGT), wind farms, and BES can be utilized to meet the load. Our model also includes a generic generation source called dispatchable-zero-carbon, DZC. This category represents the (near) zero carbon but dispatchable technologies that are currently too costly but are likely to emerge as more cost effective in a carbon-constrained world. Examples can be gas turbines integrated with CCS, concentrated solar power (CSP) equipped with thermal storage, and nuclear power plants.

We vary X_E and X_P of BES in the range of 5–700 \$ per kW h and 100–2000 \$ per kW, respectively to cover 320 sample points. All BES technologies are assumed to have the same efficiency

Table 2 Technical and economic inputs of the model in the base case

Parameter	Value	Notes
CapEx of wind, SCGT, CCGT, DZC	2000, 800, 1100, and 9000 \$ per kW	Wind and gas turbine data are based on ref. 27–30.
FOM of wind, SCGT, CCGT, DZC	35, 10, 12, and 100 \$ per kW per year	FOM and VOM of DZC are based on nuclear and CSP ^{28,30}
VOM of wind, SCGT, CCGT, DZC	0, 10, 3, and 0 \$ per MW h	
Heat rate of SCGT, CCGT, and CAES	9.8, 6.7, and 4.2 GJ per MW h	
Work ratio of CAES	0.75	CAES data are based on Table 1
Storage efficiency	75%	An average based on Table 1
Price of gas	5 \$ per GJ	Based on lower heating value
Blended cost of capital	10%	Equivalent to a discount rate of ~8% for 20 years
X_P and X_E of BES	100–2000 \$ per kW and 5–700 \$ per kW h	Range used in simulation that cover 320 points in X_P , X_E space

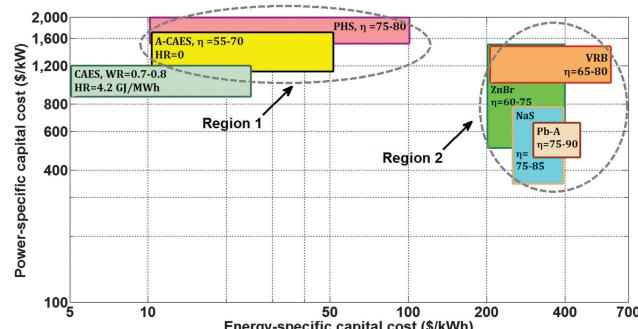


Fig. 1 Mapping of selected BES technologies on the X_E and X_P plane. Each box represents a BES technology and its location corresponds to the ranges shown in bold in Table 1 for X_E and X_P . Estimates for the storage efficiency (η), heat rate (HR), and work ratio (WR) are included. WR quantifies electricity used by the CAES plant per unit of electrical energy generated. Regions 1 and 2 represent mechanical and electrochemical technologies, respectively.

within a given scenario except for diabatic CAES which is modeled separately (because it consumes fuel during the discharging phase). Charge and discharge rates of BES are assumed to be equal.

We consider four scenarios for emissions intensity of the grid; business as usual (BAU) and caps of 300, 150, and 0 kgCO₂e per MW h. Note that these values, even BAU (this scenario leads to an emissions intensity of ~448 kgCO₂e per MW h) represent sharp emissions reductions compared to the existing grids, mainly because coal is not included in our model. For instance, the average carbon intensity of the entire USA grid and the global average in 2010 were 503 and 536 kgCO₂ per MW h.²⁶

Table 2 summarizes various inputs of our model. Roundtrip efficiency of storage is set at 75%, an average value based on BES technologies in Table 1. The price of gas is fixed at \$5 per GJ (sensitivity analysis is provided in the ESI†). Operational considerations such as minimum up and down times, ramp rates, and part-load performance are not included in the model. We use a GHG intensity of 66 kgCO₂e per GJ (low heating value)⁶ for gas to account for upstream emissions in addition to combustion emissions, which leads to a GHG intensity of 647 and 442 kgCO₂e per MW h for the modeled SCGT and CCGT plants.

Our cost estimates for gas turbines and wind farms are based on values reported by the US Department of Energy (DoE),²⁷ US Energy Information Administration (EIA),²⁸ National Renewable Energy Laboratory (NREL),²⁹ and Lazard Ltd.³⁰ We use a value of \$9000 per kW for DZC. Each specific DZC technology will

face some geographical constraints (e.g. CSP requires high solar irradiance or CCS needs a suitable geologic formation). DZC, however, represents the least capital-intensive, dispatchable technology—whether CSP, nuclear, CCS, biomass or geothermal—that can be utilized in a given location. Our judgment is that 9000 \$ per kW is mostly likely an overestimate of this best-case DZC cost (see ESI† for our rationale and the sensitivity analysis on DZC cost).

Finally, our analysis treats the electricity grid in isolation from the other parts of the economy, most importantly transportation sector. It is reasonable to envision both a low-carbon power and transportation sector under economy-wide GHG emissions constraints in future. Storage of electricity in the form of low-carbon fuels to power the transportation and electricity generation fleet is a scenario that our analysis does not cover. Storage of electricity as a fuel (*i.e.* electrofuels and hydrogen) is more technically and economically likely than storage of electricity itself over long time scales (e.g. seasonal battery storage). Other low-carbon fuels (*e.g.* biofuels) can also fuel the power sector, which is not considered in our model.

3. Results and discussions

3.1 Cost of electricity

In our BAU scenario, wind and DZC are not economically viable and gas turbines and storage supply the electric load. CCGT dominates the electricity supply because of the high operating and fuel costs of SCGT compared to CCGT (see Table 2). Even without an emissions constraint, cheap BES reduces the need for peaking plants (SCGT) by increasing utilization of CCGT and thus lowering the cost of electricity. Emissions intensity, however, is insensitive to the storage cost because BES supplies at most 3% of the annual load. CCGT supplies almost all (>97%) of total electricity. Note that the 15 minute resolution may slightly overestimate the share of CCGT as it understates the advantage SCGT should get from its faster ramp rate.

Our central research question is how the capital cost of storage impacts the overall cost of electricity supply under tight carbon constraints. Fig. 2 illustrates LCOE at various emission caps over a wide range of X_E and X_P . The most general result is that energy capital cost (X_E) has a stronger influence on LCOE than does power cost (X_P) under all emission scenarios. Comparing Fig. 1 and 2, we can see that the existing mechanical BES systems are more likely to cost effectively curb emissions



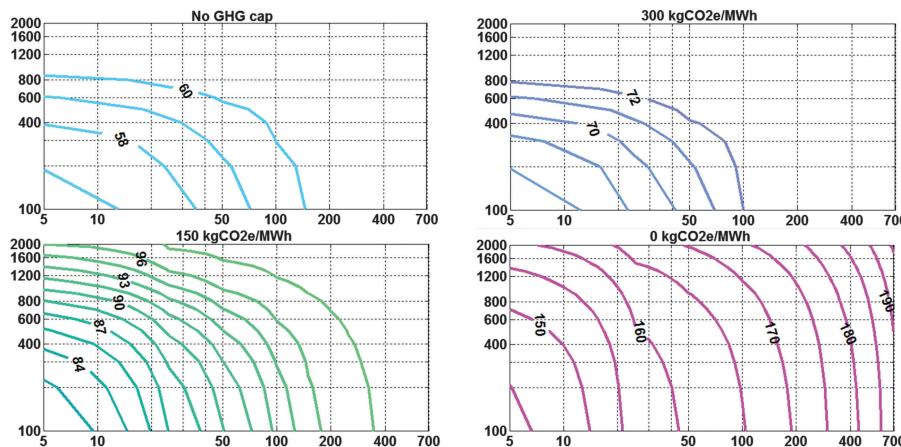


Fig. 2 Impact of X_E and X_P and emissions constraints on LCOE. Horizontal and vertical axes show X_E (\$ per kW h) and X_P (\$ per kW), respectively. Values on the graphs present LCOE (\$ per MW h). Subfigures from top left in counter clockwise order correspond to BAU (no emissions constraint), and caps of 300, 150, and 0 kgCO₂e per MW h. In all the contour plots, 320 discrete sample points are simulated to cover the range of 5–700 and 100–2000 for X_E and X_P . Contour spacing is constant in each plot; therefore, absence of contour lines in an area indicates no changes larger than the contour spacing. Also note that sharp changes are an artifact of the contouring algorithm.

due to their significantly lower X_E compared to electrochemical technologies, despite higher X_P of the mechanical systems.

A second result is that inexpensive BES has a small impact on the LCOE in all scenarios except for the carbon free grid. LCOE differs only 6% (56.6 and 60.3 \$ per MW h) between the cheapest and most expensive BES system that we model in BAU. As expected, the impact of BES on LCOE rises when a tight cap of 150 kgCO₂e per MW h is imposed. But even then, BES cuts the costs by only 17% (81.2 *versus* 97.8 \$ per MW h) even though emissions are cut by 67% compared to BAU, an even deeper cut when compared with current emissions which include coal.

LCOE is more sensitive to storage cost when emissions are constrained to zero at which point there is a 27% difference between LCOE of the carbon free grid utilizing the cheapest BES system ($X_E = 5$ and $X_P = 100$, LCOE = \$143.9 per MW h) and the most expensive BES system ($X_E = 700$ and $X_P = 2000$, LCOE = \$195.9 per MW h).

The strong impact of storage cost on the LCOE in the completely decarbonized system is driven by the absence of gas turbines. Even under the low 150 kgCO₂e per MW h scenario, gas turbines (particularly CCGT) can cost-effectively manage the variability of wind, as explored in Section 3.2. Despite their higher fuel and operational cost, the relatively low CapEx of gas turbines allows them to out-compete BES in managing the variability of wind.

3.2 Storage cost and wind penetration

Since emission constraints and availability of affordable BES are often considered as requirements for large-scale adoption of intermittent renewables, we explore effect of these parameters on the economically optimum level of wind penetration in our model. Because our focus is on deep decarbonization targets, we discuss the results for the 150 kgCO₂e per MW h scenario (~33% of BAU emissions).

The distinct impact of mechanical and electrochemical BES technologies is evident in Fig. 3. While electricity cost is almost

the same (<5% difference), optimal size of the wind fleet using electrochemical BES is only 60% of the wind fleet using mechanical systems. This indicates that BES systems with low energy capital cost (X_E) facilitate higher penetration of wind energy. If electrochemical rather than mechanical BES systems are utilized, the optimal sizes of the SCGT and DZC fleet get larger to compensate for the smaller wind fleet. The optimal size of CCGT is almost insensitive to the storage cost (approximately 53% for both BES categories).

These results lead to the conclusion that the optimal wind capacity is very sensitive to the CapEx of BES, especially to its energy capacity cost (X_E). Therefore, mechanical BES systems (region 1 in Fig. 1) are better suited for large-scale integration of intermittent renewables, at their current costs.

While lower-cost storage increases wind's share of annual generation, it does little to change the overall electricity cost because it just shifts the balance between wind and DZC. This does not answer a related energy policy question: how important is bulk storage to manage high penetration of intermittent renewables? We explore this by removing DZC from the generation fleet—so intermittent renewables (wind in this case) are the only way to decarbonize—and then enforce a 150 kgCO₂e per MW h emissions cap. We then operationalize the “how important” question by comparing the optimal wind capacity to the capacities of BES and gas when we assume a generic mechanical BES system (energy and power costs of $X_E = \$30$ per kW h and $X_P = \$1500$ per kW). Under these assumptions, the optimal capacities of BES and gas are roughly 20% and 60% (respectively) of the capacity of wind. So one could say that BES is three times less important than gas in providing peaking power, under this tight emissions constraint and with current capital cost estimates. Under these conditions, about a third of annual load comes from gas, 6% from BES and the rest from wind. See Table S3 in ESI† for the extended results.

This result changes only as emissions are pushed towards zero. Then with zero or near-zero emissions and no use of DZC,

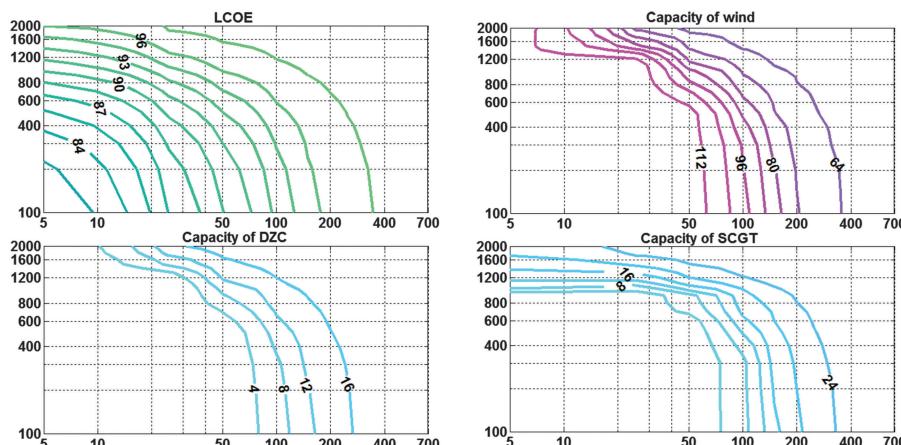


Fig. 3 Electricity system characteristics at an emissions cap of 150 kgCO₂e per MW h. Subfigures from top left illustrate LCOE, normalized wind capacity, DZC, and SCGT. All size values are percentage of peak electric load. Horizontal and vertical axes show X_E (\$ per kWh) and X_P (\$ per kW).

larger storage capacities will be needed to manage wind's intermittency as GT gets too polluting for such extremely low-carbon grids.

3.3 Economically optimal deployment of storage

The amount of BES that is technically required for decarbonization with intermittent renewables is (somewhat) independent of the impact of storage on electricity costs. Based on the 150 kgCO₂e per MW h scenario, we can make the following comments on the economically efficient penetration level of BES. Refer to Fig. S4 in ESI[†] for graphical results.

The power capacity of BES remains below 30% and 10% of the peak load for the mechanical and electrochemical BES systems, respectively. Although mechanical technologies have higher X_P , their optimal power capacity is noticeably higher compared to electrochemical systems. This observation again highlights the significance of the energy-specific cost (X_E) in the overall economic viability of BES systems—a major disadvantage of the existing battery systems.

The optimal energy capacity of BES turns out to be small in general, even when we impose ~70% emission reductions compared to BAU. The mechanical storage fleet was sized to supply the average electric load for one full day on its own. This value sharply drops as the energy cost (X_E) increases while the power cost (X_P) simultaneously drops; *i.e.* moving to electrochemical systems. These relatively low energy capacities signal the unimportance of large-scale storage of electricity over long time horizons (*e.g.* seasonal storage) from an economic point of view. This is driven by the lower competitiveness of BES systems coupled with wind in comparison to low carbon and dispatchable generation facilities, like CCGT and DZC modeled here. Even when we consider the cheapest BES system simulated ($X_E = 5$ and $X_P = 100$, the lower left corner of Fig. 1), the BES fleet would be sized to store enough energy to meet the average load for ~40 hours. In other words, intermittent renewables (wind, as modeled here) can be used to decarbonize the electricity supply with a proportionally small requirement for BES since gas can provide much of the intermittency

management, even when the emissions intensity is cut to less than 30% of today's U.S. average. Substantial BES is required only when emissions are constrained to nearly zero and DZC is not allowed.

The BES share of the total supply of electricity is also small compared to the rest of the generation fleet. Approximately 6% of the demand is met by the electricity stored in mechanical BES systems (very sensitive to X_E) while this figure becomes marginal for battery technologies with their current capital costs. Even using the cheapest storage assumptions given above, the contribution of BES remains about 10%. The drop in the share of storage (and consequently the wind fleet) of the electricity supply at elevated storage costs is compensated by DZC.

3.4 Implications for specific BES technologies

Which BES technologies are closer to having an impact under carbon constraints and thus would merit a higher priority in R&D efforts directed at decarbonizing the electricity supply? We explore this question through a scenario in which energy- and power-specific costs of each BES technology are cut in half. As a measure of impact, we use share of the annual load supplied by BES (market share). Fig. 4 shows results for an emissions cap of 150 kgCO₂e per MW h while Fig. S5 (ESI[†]) shows a similar graph but for LCOE instead of market share.

None of the existing technologies gain noticeable market share, but when costs are halved PHS and A-CAES make larger gains in market share (7% and 9%, respectively) and make a corresponding impact in reducing the electricity cost (Fig. S5, ESI[†]). The simulated battery technologies remain prohibitively expensive even when their costs are halved compared to the current estimates.

We analyzed diabatic CAES separately since unlike all other BES technologies it has significant emissions. The CAES plant modeled here emits 277 kgCO₂ per MW h. We varied X_E and X_P of diabatic underground CAES in the range of 5–25 \$ per kWh and 850–1200 \$ per kW. Heat rate and work ratio of CAES are set at 4.2 GJ per MW h and 0.75. Aboveground CAES was not modeled due to its obvious weaker performance (caused by much higher



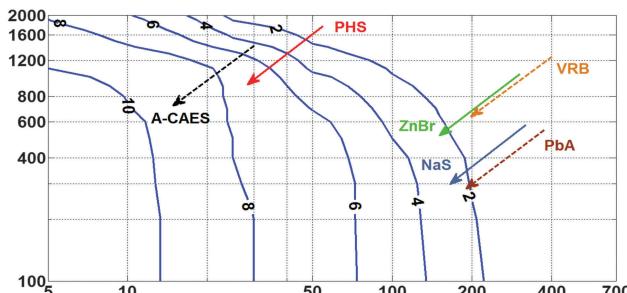


Fig. 4 Market share of BES (% of load supply) with a carbon cap of 150 kgCO₂e per MW h. Horizontal and vertical axes indicate X_E (\$ per kWh) and X_P (\$ per kW). Arrows start from the current cost estimates (average of the range shown for each technology in Fig. 1) and end at points with 50% reduction in both X_E and X_P .

energy-specific capital cost of >200 \$ per kWh. Availability of diabatic CAES made negligible differences in LCOE. The cheapest CAES system modeled ($X_E = 5$ \$ per kWh and $X_P = 850$ \$ per kW) could only store enough electricity to meet the average load for ~ 1 hour and its power capacity is 7% of the peak load. Despite having the lowest energy-specific cost (X_E) among all other BES systems, underground diabatic CAES is not a cost effective decarbonization tool. See ESI† for details on the CAES modeling.

4. Conclusions

We draw two policy-relevant conclusions from this work. First, large-scale adoption of bulk electricity storage compared to variable renewables and gas turbines is neither technically required nor cost effective as a means to reduce carbon emissions even when variable renewables play a large role. In other words, intermittent renewables need not to wait for the availability of cheap bulk storage to become an effective tool for decarbonization. This conclusion breaks down only when emissions must be reduced by more than about 70% or when the cost of dispatchable-low-carbon power sources is very high (above \$9000 per kW with an emissions cap of 150 kgCO₂e per MW h at current BES cost estimates, see Fig. S2 and S3, ESI†). Second, at their current costs, adiabatic CAES and PHS show the most appealing prospects in lowering the decarbonization cost among other BES technologies due to their low energy-specific capital costs and despite their much higher power-specific capital costs.

The strength of our analysis, like any other, turns on its assumptions. Our most important simplifications include ignoring transmission, ignoring forecast errors of wind and load, and using a green-field model rather than one that allows dynamic adjustment of capacity over time. We have limited the simulation to 15 minute time intervals and have not modeled any reliability requirements (e.g. reserve margin). We have also used a fixed gas price of \$5 per GJ and a constant storage efficiency of 75%.

The following paragraphs tease out the quantitative conclusions that underpin each of the high-level claims, and explain why we think the policy-relevant conclusions are robust to our simplifying assumptions. Table S1 in ESI† provides a systematic

overview of all significant assumptions and their likely impact on the conclusions.

Our first conclusion is that availability of inexpensive BES has relatively small effects on the overall cost of electricity generation, unless extremely tight emission mandates are in place or dispatchable-low-carbon technologies are very expensive. Under an emissions cap of 150 kgCO₂e per MW h – a $\sim 70\%$ cut in emissions intensity compared to the current USA or world average – a reduction in storage costs by more than an order of magnitude (to $X_E = 5$ \$ per kWh and $X_P = 100$ \$ per kW from already optimistic values of $X_E = 25$ and $X_P = 1500$ from the mechanical BES category) cuts the cost of electricity generation by 16%. This is not a significant reduction when compared to the impact of cutting the capital cost of wind or DZC by 50%, which lowers electricity cost by 26% and 29%, respectively (see Table S6, ESI† for a complete list of cases and comparative costs and emissions). One should note that assessing the likelihood and the associated costs of cutting the capital cost of different technologies were not in the scope of our analysis. We analyzed only the effects of reducing the capital cost of BES, wind, and DZC on the cost of electricity supply.

The economically optimal deployment of bulk storage was a relatively small fraction of peak capacity, even when we imposed a tight emissions allowance of 150 kgCO₂e per MW h (see Fig. S4, ESI†). It is crucial to note that despite its smaller capacity compared to the wind and gas fleet in our model, the optimal capacity of BES is large compared to its current deployment-level. The current ratio of BES power capacity to peak load in the United States is below 3% (below 0.1% if PHS is excluded).³¹ Therefore, our results point to the need for a massive increase in capacity of BES, from the current value of 3% of the peak load to $\sim 10\%$ (for mechanical systems with their current costs, as shown in Fig. 3). More storage is needed, but storage capacity need not grow as fast as renewable, nor should lack of bulk storage limit the deployment of intertemporal low-carbon power. The ratio of the existing wind fleet to peak load is $\sim 8\%$ in the United States, for example, while the optimal value for the wind capacity using mechanical BES systems in Fig. 3 is $\sim 70\%$. In order to efficiently meet a carbon constraint (in this case 150 kgCO₂e per MW h) our model suggests that wind power needs to increase tenfold while the amount of storage need only triple.

The energy capacity of our optimally sized storage fleet sufficed to supply the average electric demand continuously for only 2 days with an emissions cap of 150 kgCO₂e per MW h, even with the cheapest storage cost system that we simulated ($X_E = 5$ \$ per kWh and $X_P = 100$ \$ per kW). Other than niche applications that are not captured in this analysis, it is therefore hard to justify the development of storage for significantly longer than a day. The optimal energy capacity of BES in the carbon-free grid also remained small (below one day of average load) when $X_E \geq \$25$ per kWh and $X_P \geq \$100$ per kW. Obviously if the cost of storage is significantly reduced compared to other decarbonization pathways and compared to its current values, BES would capture a larger market share.

In many respects, we use assumptions that are optimistic for BES and therefore we give an upper bound for its cost effectiveness.



The economically optimal size of the wind fleet would be lower in the real world once transmission requirements are taken into account (*i.e.* more capital-intensive wind farms). A smaller wind fleet would likely translate to a larger DZC fleet and hence, less variability in electricity supply. Therefore, the need for bulk storage and its impact on the overall cost of electricity would likely be lower than what we have presented here (see Table S1, ESI[†]). Imperfect forecasts of wind availability and electric load would also hurt the economics of wind and storage compared to dispatchable generators. Finally, increased geographical dispersion of wind farms in future low carbon grids can lower the variability in the aggregate wind generation and reduce the need for BES.

The price of natural gas in the future is obviously uncertain. Due to the strong performance of gas turbines in our results, especially CCGT, we assessed the effects of higher gas prices on the impacts that availability of cheap BES will have on the cost of electricity generation. Using higher gas prices mildly changes the aforementioned 16% drop in the cost of electricity with \$5 per GJ gas when the storage cost is reduced by more than an order of magnitude to $X_E = 5$ \$ per kW h and $X_P = 100$ \$ per kW (see Table S6, ESI[†]). The same order-of-magnitude drop in storage costs but now with 10 \$ per GJ gas, reduces the electricity cost by only 14%. This saving is again not significant when we compare it with the benefits of lowering the capital cost of wind itself or DZC. Halving the cost of wind and DZC at \$10 per GJ gas lowers the cost of electricity by 23% and 28%, respectively.

While electrochemical batteries are currently very far from being cost effective for bulk storage of electricity, they are or may be technically important and cost competitive in two other important applications in a low-carbon economy. First, they can be attractive tools for managing mismatch between supply and demand of electricity at finer temporal resolutions, which are not included in our study or ensuring reliability of the grid. These technologies have an economic advantage over other BES systems (*e.g.* PHS) and low carbon generators (*e.g.* DZC): they can be deployed in smaller scales and have higher operational flexibilities (*e.g.* higher ramp rates). Second, the electrochemical battery (and also hydrogen-based) technologies may play a central role in decarbonizing the transportation sector. Finally, note that each BES technology may well find a market niche (*e.g.* small islands with wind and diesel generation); here we examined only the large-scale electricity systems.

Our second high-level conclusion is that the economics of BES are primarily driven by its energy-specific capital cost. Therefore, mechanical storage technologies (characterized with low energy-specific X_E , but high power-specific X_P , capital costs) are currently more competitive compared to electrochemical systems (intermediate X_E and X_P). Even halving the capital costs of batteries makes marginal changes in the overall cost of electricity generation (see Fig. 4). Nevertheless, lowering the capital cost of mechanical systems, especially power-specific cost, drives a much steeper drop in decarbonization costs and it also boosts integration of wind and market share of storage. (Note that we have assessed the relative impacts of cutting the cost of various technologies on the cost of supplying low-carbon

electricity. We have not, however, studied the relative effects of R&D investment in reducing the capital cost of various technologies.) Therefore, developing BES technologies with low energy-specific capital costs (*e.g.* A-CAES) deserves a higher priority for bulk storage applications, unless the capital cost of systems with high power-specific costs (*e.g.* flow batteries) can be reduced much faster and more cheaply.

We acknowledge that siting of pumped-hydro and underground compressed air energy storage projects is geographically constrained in contrast to electrochemical systems. PHS requires two large water reservoirs with sufficient elevation difference and has a large land footprint. Underground storage of air needs a suitable geologic formation such as a salt dome. Our study did not include such restrictions.

We were surprised by the promise of underground adiabatic CAES in contrast to very poor performance of diabatic CAES. Despite having the lowest energy-specific capital cost (X_E) among all BES technologies we studied, gas combustion of diabatic CAES hurts its competitiveness under emissions constraints. The results point to the importance of developing storage technologies with low cost of energy capacity and low emissions and the more limited importance of roundtrip efficiency and power-specific cost of BES systems in lowering decarbonization costs.

Efficiency of electricity storage obviously varies with the type and design of the BES technology. We focused on the capital cost of storage systems as the dominant parameter impacting the economics of BES. Nevertheless, A-CAES has one of the lowest efficiencies among BES technologies; an average value of 63% compared to 75% for the generic BES system that we modeled (Table 1). In order to assess robustness of the results, we adjusted storage efficiency of the specific BES technologies in three scenarios: 75%, current estimates, and 10% improvement compared to the current values (see Table S8, ESI[†]). Even accounting for its low storage efficiency, A-CAES remains the most cost-effective technology.

Finally, note that that we simulated the generation fleet under an optimal GHG constraint. Non-economic choices may produce very different outcomes. A region that forgoes nuclear power or other large-scale DZC or restricts gas turbines beyond the carbon constraints simulated here will use more bulk storage.

Abbreviations

A-CAES	Underground adiabatic compressed air energy storage
AD-CAES	Aboveground diabatic compressed air energy storage
BAU	Business as usual scenario
BES	Bulk electricity storage
CAES	Compressed air energy storage (underground and diabatic)
CapEx	Capital cost
CCGT	Combined cycle gas turbine
CCS	Carbon capture and sequestration
CSP	Concentrated solar power



DZC	Dispatchable-zero-carbon generator
FOM	Fixed operating and maintenance cost
GHG	Greenhouse gas
GT	Gas turbine
LCOE	Levelized cost of electricity
NaS	Sodium sulfur battery
Pb-A	Lead-acid battery
PHS	Pumped hydroelectricity storage
SCGT	Simple cycle gas turbine
VOM	Variable operating and maintenance cost
VRB	Vanadium redox battery
X_E	Energy specific capital cost of BES
X_P	Power specific capital cost of BES
ZnBr	Zinc bromine battery

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