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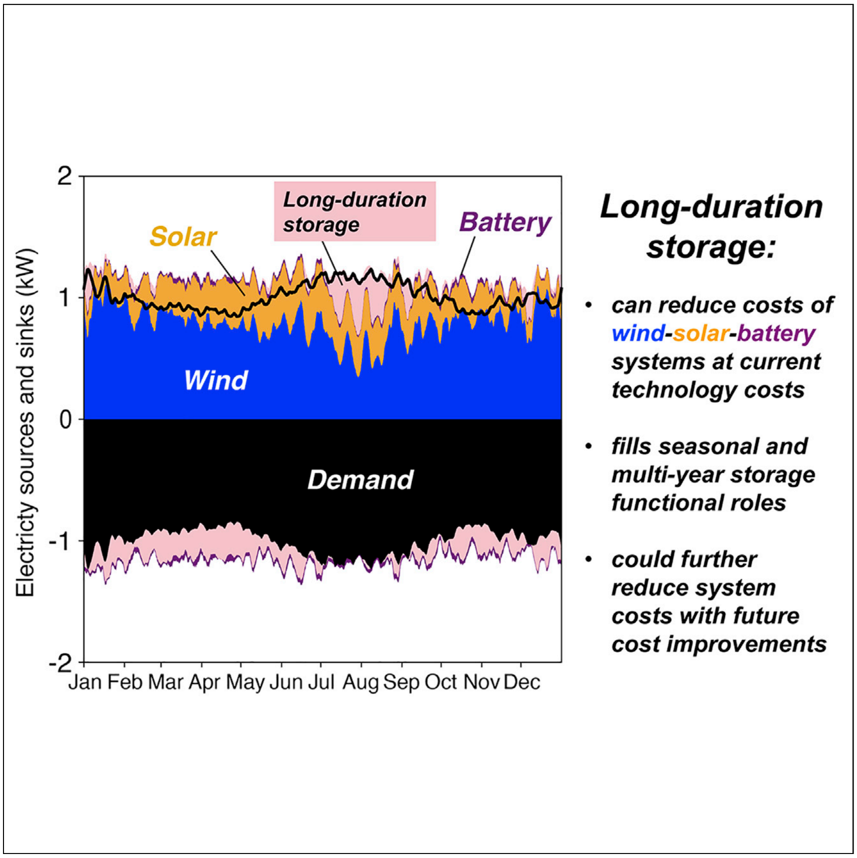
Role of Long-Duration Energy Storage in Variable Renewable Electricity Systems



Laws in several U.S. states mandate zero-carbon electricity systems based primarily on renewable technologies, such as wind and solar. Long-term, large-capacity energy storage, such as those that might be provided by power-to-gas-to-power systems, may improve reliability and affordability of systems based on variable non-dispatchable generation. Long-term storage can reduce costs of wind-solar-battery electricity systems at current technology costs by filling seasonal and multi-year storage functional roles. Innovation in long-term storage technology could further improve the affordability of reliable renewable electricity.

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HIGHLIGHTS

Long-duration storage (>10 h) reduces costs of wind-solar-battery systems

Long-term wind and solar dataset captures seasonal and multi-year storage roles

Dependence on long-duration storage increases with optimizations over more years

Long-duration storage cost reductions lower system costs 2× more than batteries

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Role of Long-Duration Energy Storage in Variable Renewable Electricity Systems

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SUMMARY

Reliable and affordable electricity systems based on variable energy sources, such as wind and solar may depend on the ability to store large quantities of low-cost energy over long timescales. Here, we use 39 years of hourly U.S. weather data, and a macro-scale energy model to evaluate capacities and dispatch in least cost, 100% reliable electricity systems with wind and solar generation supported by long-duration storage (LDS; 10 h or greater) and battery storage. We find that the introduction of LDS lowers total system costs relative to wind-solar-battery systems, and that system costs are twice as sensitive to reductions in LDS costs as to reductions in battery costs. In least-cost systems, batteries are used primarily for intra-day storage and LDS is used primarily for inter-season and multi-year storage. Moreover, dependence on LDS increases when the system is optimized over more years. LDS technologies could improve the affordability of renewable electricity.

Context & Scale

Laws in several U.S. states now require the adoption of zero-carbon electricity systems based primarily on renewable technologies, such as wind and solar. Long-term, large-capacity energy storage may ease reliability and affordability challenges of systems based on these naturally variable generation resources. Long-duration storage technologies (10 h or greater) have very different cost structures compared with Li-ion battery storage. Using a multi-decadal weather dataset, our results reveal that long-duration storage can fill unique roles, like seasonal and even multi-year storage, making it valuable to least-cost electricity systems. Indeed, we find that variable renewable power systems are much more sensitive to reductions in long-duration storage costs than to equal reductions in battery costs. Long-term modeling horizons, typically not used by utilities and regulators, are necessary to capture the role and value of long-term storage, informing technology investments and policy.

INTRODUCTION

U.S. states and territories such as California, Maine, New Mexico, Washington, Hawaii, and Puerto Rico have enacted legislation specifying that by 2040–2050 all electricity must be generated by renewable or zero-carbon sources.[1–6] Analogous policies are being contemplated, proposed, and/or enacted in other states, countries, and regions around the world.[7–11] An even larger group of states have some form of renewable energy requirement in place (e.g., renewable portfolio standards that specify the capacities of wind, solar, and energy storage to be deployed; Table S2).

However, reliable electricity systems based on variable energy sources, such as wind and solar, must accommodate the variability with, for example, energy storage or "firm" generators, such as hydroelectricity, nuclear, natural gas with carbon capture and storage (CCS), geothermal, and bioenergy. Indeed, a prominent study demonstrated that the addition of low- or zero-carbon "firm" generators lowers the overall costs of electricity systems with high fractions of variable renewable energy sources.[12] Geothermal energy and hydropower are severely constrained due to available sites suitable for expansion.[13] Moreover, state laws that specify that generation must come from zero-carbon resources legally preclude use of natural gas with or without CCS for generation (Table S2). Hourly averaged wind and solar resources within the contiguous U.S. (hereinafter "the U.S.") over the 39-year period from 1980-2018 (Figure S1) reveal gaps in the availability of these resources that often span consecutive days and in some cases weeks (especially for wind).[14] The combination of these longer-duration resource gaps and high reliability standards (e.g., >99.97%)[15] requires systems that rely solely on wind and solar generation to overbuild generation capacity and/or deploy prodigious amounts of energy storage.[13,14,16–19]

Batteries are increasingly the focus of large-scale energy-storage projects; they made up 88% of new additions to grid-scale storage globally in 2016.[20,21] Batteries can be readily deployed anywhere, have high (e.g., 90%) round-trip charge-discharge efficiencies, and their costs have steadily declined.[22,23] In general, storage can add value to variable renewable energy systems (VRE).[24] As storage capital costs decrease, more storage is deployed, and system costs fall. However, the economics of battery storage are strongly dependent on the use scenario.[25] As more storage gets deployed, the marginal value per kWh of storage falls.[26] In contrast to hourly backfilling of power or smoothing of the daily cycle, meeting multi-day or week-long gaps between supply and demand requires even larger quantities of storage capacity with much lower utilization rates.[14,26] The levelized cost of battery-related energy storage sufficient to fill longer-duration gaps in solar and wind generation thus remains high. Consequently, to achieve highly reliable wind and solar-only electricity systems, substantially ''overbuilding'' and distributing solar and wind capacity over large areas (perhaps facilitated by high voltage direct current, HVDC, transmission), may still be less costly than the required battery storage.[14,27]

Here we assess the potential of long-duration energy storage (LDS) technologies to enable reliable and cost-effective VRE-dominated electricity systems.[13,26,28] LDS technologies are characterized by high energy-to-power capacity ratios (e.g., the California Energy Commission, CEC, defines LDS as having at least 10 h of duration).[29] Unlike costs of conventional Li-ion batteries, LDS options are usually not limited by energy-capacity costs (x axis in Figure 1). Rather, power-capacity costs typically dominate total LDS costs (y axis in Figure 1). The energy capacity times the energy-related capital costs is a small fraction of the total cost. For a variety of storage technologies, we provide the total capital cost divided by the power and again by the usable energy capacity of typical systems characterized in the literature (Figure 1; Table S3 includes additional performance metrics). Some technologies for long-duration applications, such as power-to-gas-to-power (PGP), pumped hydro storage (PHS), and compressed air energy storage (CAES), have additional flexibility in that the power and energy capacities for a given project can be sized independently (Table S4 provides energy and power specific capital costs). For comparison, short-duration storage technologies dominated by energy-capacity costs include flywheels, capacitors, and Li-ion and lead-acid batteries. Separating power and energy costs is more difficult for batteries. Most redox flow batteries have storage durations of 1–4 h, excluding them from the LDS category by CEC standards.[30] Redox flow batteries with 8–10 h durations exist, but are rare.[31] Other battery chemistries typically match short-term applications, but Form Energy's pilot aqueous air battery system claims a 150 h duration at undisclosed costs.[32] All large-scale CAES designs demonstrated to date combust non-renewable natural gas,[33] and PHS is limited to certain geographical locations and has a high water footprint.[34] Technological options and viability of various LDS candidates including thermal energy storage (TES) are considered in more detail in the Discussion. Utility-scale PGP hydrogen energy-storage projects are currently expanding.[35–38] For these reasons, we choose current costs for renewable PGP (with hydrogen for energy storage and fuel cells and electrolyzers for power conversion) to represent our base case for renewable LDS technology. As Li-ion batteries are commonplace, we set them as the base case short-duration storage technology (stars in Figure 1; Table 1 base case costs). By varying the costs of the base case across a wide range, we aim to characterize the broader grid role of LDS, and to determine the relationship between such costs and the systemwide value of LDS in power systems based primarily on variable renewable energy.

Many economy-wide deep decarbonization (80% carbon-emissions free) strategies do not include an LDS pathway, including the U.S. White House's mid-century plan.[13,39–41]

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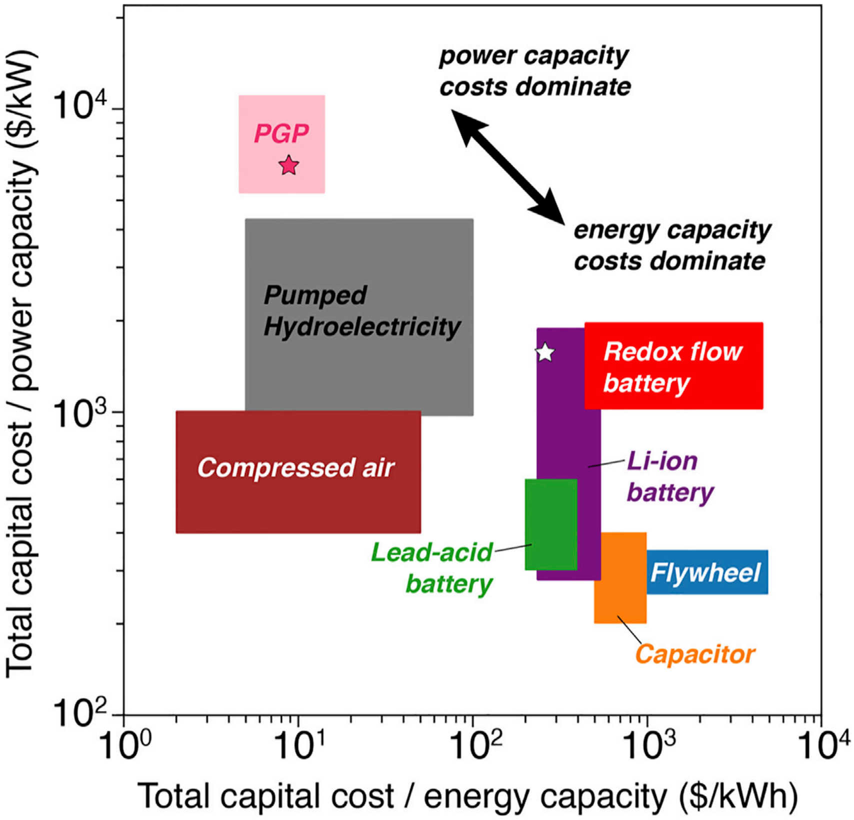

Figure 1. Long- and Short-Duration Energy Storage Technology Capital Costs by Capacities
Power-limited technologies are on the upper left, while energy-limited technologies are on the bottom right of the figure. The total capital cost by capacity for each storage technology is depicted with a box representing a range of values found in the literature (Tables S3 and S4). The height shows the range in capital costs divided by installed power capacities for typical systems and the width represents the range in capital costs divided by the usable energy storage capacities for typical systems. This figure does not show the impact of the different efficiencies and lifetimes for these storage options. The star in the Li-ion battery box (purple) is the base case cost for short-duration storage used in this analysis. The star in the PGP box (pink) reflects the base case cost for LDS divided by optimal power and energy capacities from the 2018 base case system. Base case cost and performance assumptions are in Table 1.

Generally, if low-cost dispatchable fossil fuels are included in the technology mix at about 20% or more of demand, LDS is minimized or not included.[26,42–46] Although there have been some assessments of LDS in deeply decarbonized economy-wide systems, many deploy LDS within specific predetermined assumed use cases or scenarios.[13,17,47] However, in an economy-wide deep decarbonization optimization for Europe, flexibility from LDS (PGP and TES) made a substantial contribution to the smoothing of variability from wind and solar and to the reduction of total system costs.[48] In modeled least-cost 100% CO_2 emissions-free energy systems, fully decarbonized electricity is generally used for heating, synthesis of hydrogen and natural gas, and many other energy services, sometimes with minimal deployment of long-term energy storage.[34,49,50]

State governmental agencies are specifically interested in studies focused on LDS interactions with zero-carbon and renewable electricity systems.[29] A data-driven optimization based on 5 years of European load and weather data and projected 2050 asset costs (without cost sensitivity studies) found that electricity system costs were reduced by 24% when LDS was included (as PGP with 10-fold lower power-capacity costs relative

Table 1. Base Case Costs and Assumptions

	PGP Storage	To PGP	From PGP	Battery Storage	To and from Battery	Wind	Solar
Assumptions from U.S. Energy Information Administration [96] except when otherwise noted							
Technology description	Underground salt cavern[a]	PEM electrolysis, plus compression[b]	Molten carbonate fuel cell, CHP	Li-ion battery	Li-ion battery	Wind turbines, onshore	Solar PV, single-axis tracking
Technology type	Storage (of H_2)	Conversion (produce H_2)	Conversion (consume H_2)	Storage	Conversion	Generation	Generation
Capacity (fixed) cost type	Energy capacity ($/kWh)	Power capacity ($/kW)	Power capacity ($/kW)	Energy capacity ($/kWh)	Power capacity ($/kW)	Power capacity ($/kW)	Power capacity ($/kW)
Capacity (fixed) cost	0.16[c,100]	1,058[69]	5,854[68]	261[25]	1,568[25]	1,657	2,105
Project life (yrs)	30[101]	12.5[69,101]	20[68]	10[102]	–	30	30
Discount rate	0.07	0.07	0.07	0.07	–	0.07	0.07
Capital recovery factor (%/yr)	8.06	12.26	9.44	14.24	–	8.06	8.06
Fixed O&M cost ($/yr)	0	0	0	0	–	47.47	22.02
Round-trip efficiency	49%[d,68,69]			90%[22]		–	–
Self-discharge rate	0.01% per year[103]	–	–	1% per month[104]	(6 h charging time)[25]	–	–
Annualized Capital Costs Paid Hourly							
Fixed cost	1.47×10^{-6} $/kWh/h	0.0148 $/kW/h	0.063 $/kW/h	0.004 $/kWh/h	–	0.021 $/kW/h	0.022 $/kW/h
Variable cost	0.000 $/kWh/h	0.000 $/kW/h	0.000 $/kW/h	0.000 $/kWh/h	–	0.000 $/kW/h	0.000 $/kW/h

Economic and technological assumptions regarding wind, solar, LDS, and batteries used for the base case simulation. The base case LDS technology is modeled as PGP with renewable hydrogen. See model formulation in Section S1 for more detail.

[a]See Section S5; Table S9 for more detail on underground H_2 storage costs.

[b]See Section S5; Table S10 for more detail on fixed costs and lifetimes of polymer electrolyte membrane (PEM) electrolyzers and compressors.

[c]This cost is equivalent to \$6.3/kg H_2. The higher heating value (HHV) is 39.4 kWh/kg H_2.

[d]PEM electrolyzers and molten carbonate fuel cells with combined heat and power (CHP) are both modeled as 70% efficient.

to current costs), when compared with a projected year 2050 scenario that involved only battery and PHS in conjunction with curtailed variable renewable generation.[51] Least-cost solutions for a modeled emissions-free, 99.9% reliable electricity system for the PJM (Pennsylvania, New Jersey, Maryland) load-balancing region, based on 4 years of load and weather data, contained substantially curtailed wind and solar generation relative to average load, and only 9–72 h of storage.[27] Considering simplified generator profiles (without load data) and 20 years of wind and solar resource availability in four U.S. states, a study estimates with step-wise fixed capacities that meeting baseload demand (shaped as a constant flat line) 100% of the time requires storage energy-capacity costs below \$20/kWh.[28] A European power model based on 30 years of VRE data excluded both short- and long-term storage, but found that single-year studies can yield results that deviate by as much as 9% from the long-term average.[52] In contrast to previous studies that involve predetermined use-models or neglect cost sensitivity studies, in our work, we use real resource and load data to assess what characteristics, in terms of power and energy costs, would be required for long-term storage technologies to make a substantive contribution to variable renewable electricity systems.

Here we comprehensively assess the roles and interactions of LDS and batteries for highly reliable wind-solar-storage electricity systems in the U.S. and several of its regional interconnects. Specifically, we use historical hourly averaged wind and solar resource data derived from a reanalysis weather dataset,[53] historical electricity demand data from all balancing authorities across the contiguous U.S.,[54] and a macro-scale energy model[55] to evaluate the relative merits and cost-effectiveness of LDS in conjunction with batteries for filling hourly, daily, weekly, seasonal, and inter-annual gaps in solar and wind generation in such systems, regions, and time periods. The large geographical areas and high temporal resolution require abstraction to make analyses tractable. Our model allows evaluation of system cost and performance, with 100% reliability as a strict constraint, over the U.S. during a multi-year time period (1980–2018), while maintaining a high temporal resolution (1 h). Insofar as comparisons can be made, our model is in qualitative agreement with more detailed multi-nodal electricity models.[14,41,51,56–58] Hourly data were necessary and sufficient to assess compliance with existing resource adequacy planning regulations that require meeting hourly averaged demand for all but (at most) 1 h in a decade.[15] Inter-annual weather variability substantially impacted generation costs in a European power system.[52] The multi-decadal weather record is necessary to obtain a statistically significant description of infrequent weather-related events and inter-annual variability that affects seasonal and multi-year storage requirements and moreover facilitates assessment of system reliability over the comparable lifetimes of capital assets on an electricity grid.

We consider a limiting best case that minimizes variability of wind and solar generation by assuming lossless transmission from generation to load over all of the U.S., providing a lower bound for the minimum amount of storage required. The macro-scale electricity model thus represents an agglomerated single generation source at a given time, connected without any loss at that same time to a single agglomerated load (i.e., the load-balancing region is the U.S.) We have also evaluated the robustness of our conclusions for smaller, regional geographic scales that confine both load balancing and resource availability to existing U.S. interconnect regions without assuming construction of new transmission. While it is important to explore a multitude of transition pathways due to various uncertainties in how these technologies will develop,[13] the current legal framework in a growing number of U.S. states requires the adoption of a renewables-dominated electricity system (Table S2). Therefore, we evaluate various possible end-states in a variety of asset cost scenarios that meet that requirement. Least-cost solutions were found for installed capacities and dispatch schedules (with perfect foresight and no assumed use-models) for wind and solar generation, battery storage, and LDS, subject to the constraint that hourly averaged demand must be met 100% of the time to comply with the existing regulatory framework for resource adequacy planning. A range of battery and LDS costs were considered, with cost and technical assumptions for the base case (PGP and Li-ion) presented in Table 1. Further details of our data sources and analytical approach are in the Methods. The base case exemplifies one LDS technology at current costs as a benchmark starting point. We then parameterize widely to determine the conditions and use cases under which long-term storage lowers system costs compared with curtailment and/or extensive deployment of short-term storage technologies.

RESULTS

Long-Duration Storage Meets Summertime Demand and Coexists with Batteries

Figure 2 presents dispatch curves of the least-cost systems for 2018, assuming current costs (Table 1). Electricity sources in Figure 2 include both the generation technologies (wind and solar) and discharge of storage technologies (batteries

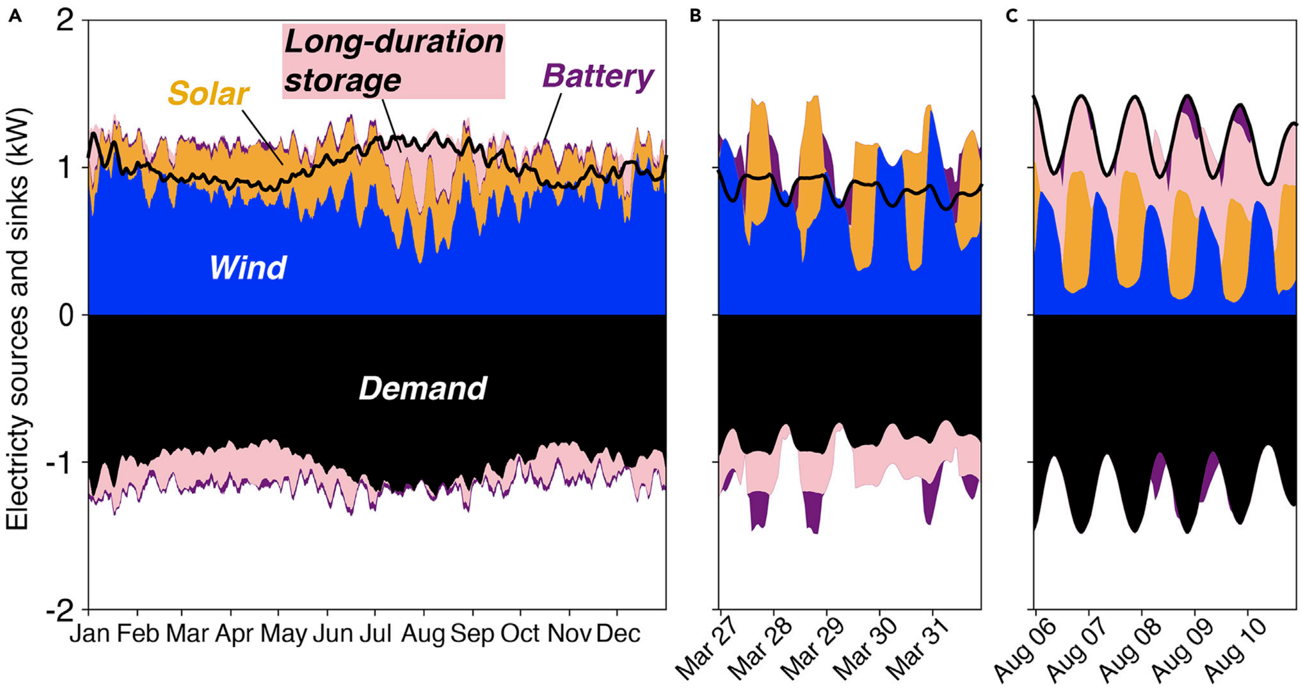

Figure 2. Base Case Dispatch Schedule

Electricity sources to the grid (positive values) and electricity sinks from the grid (negative values) are balanced at each hour of 2018.

(A) Annual results with 5-day averaging.

(B) 5-day period with maximum battery discharge (starting at 07:00PM CST).

(C) 5-day period with maximum LDS discharge (starting at 05:00PM CST).

The black area represents end-use demand (as does the black line). At each hour, generation from wind and solar plus dispatch from LDS and battery storage is balanced by end-use demand and charging of LDS and battery storage. LDS primarily provides inter-season storage whereas batteries provide intra-day storage.

and LDS) to the grid. Electricity sinks include both end-use demand and charging of storage technologies. Sources and sinks are balanced each hour (so that maximum positive values for any hour in Figure 2 mirror the most negative values in the corresponding hour). LDS (pink) and batteries (purple) are both present in the least-cost system.

The annual view of dispatch in this base case (Figure 2A, smoothed with a 5-day moving average) shows that when wind resources (blue) decrease during the summer months, the combined generation from wind and solar power are not sufficient to meet demand. A substantial amount of LDS (pink) is thus discharged to meet a substantial portion of demand during this low-resource period. In contrast to this large and seasonal discharge of LDS, batteries (purple) are routinely charged and discharged in small amounts throughout the year (Figure 2A). Curtailment is calculated in the model but not displayed in Figure 2. In the base case, wind and solar capacities are 2.5x and 1x average demand with average capacity factors of 0.36 and 0.27, respectively. VRE curtailment is on average 9% of VRE generation (i.e., 3% of VRE capacity).

Figures 2B and 2C show daily dispatch dynamics for the 5-day periods with the greatest battery and LDS discharge in March and August, respectively. In each case, solar peaks correspond to noon. In this base case least-cost system, energy is sometimes transferred between batteries and LDS. Figure 2B shows simultaneous discharging of batteries and charging of LDS in the afternoon on March 28th and 29th, and in the morning on March 28th and April 1st. Conversely, Figure 2C shows simultaneous discharging of LDS and

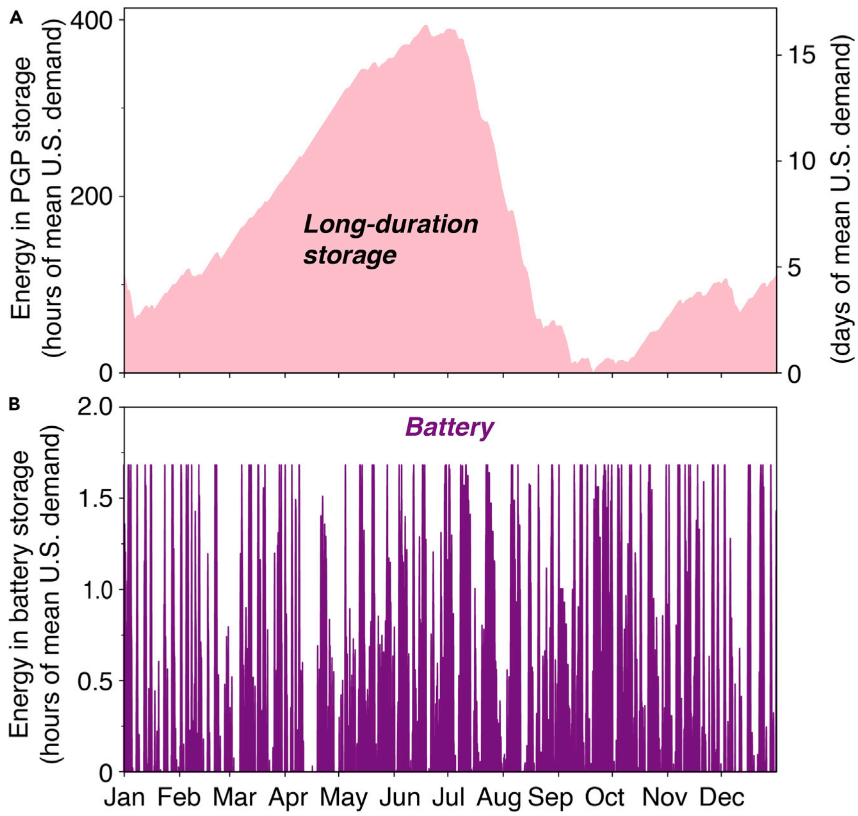

Figure 3. Energy Storage during 1 year (2018) in the Base Case

(A and B) (A) LDS energy storage (B) battery energy storage. The maximum amount of available energy to meet demand with LDS (394 h, or 16 days of mean U.S. demand) and batteries (1.7 h of mean U.S. demand) is equal to the optimized energy-storage capacity for these technologies. The large LDS capacity is used primarily for inter-season storage. In contrast, the relatively small battery capacity is used primarily for intra-day storage.

charging of batteries at night on August 8th and 9th. This phenomenon of inter-storage transfer is also observed in systems with only solar, LDS, and batteries (i.e., no wind; Figure S2), and wind, LDS, and batteries (i.e., no solar; Figure S3).

As discussed, LDS is used primarily to provide large amounts of inter-season energy storage, mostly discharging in summer. While solar is most abundant during the summer months, wind availability decreases in summer time.[59] Because least-cost optimizations of the base case include larger capacities of wind than solar, LDS is important for meeting summertime demand. Figure 3A highlights this behavior in the base case in 2018, showing that the amount of energy stored in LDS (as hydrogen fuel for PGP) increases during winter, spring, and fall, when renewable resources (especially wind) are abundant, and is drawn down in the summer, when combined resources are relatively scarce. LDS thus cycles only once a year and has an energy capacity equivalent to 394 h (16 days) of mean U.S. demand. In contrast, Figure 3B shows that batteries are used to frequently provide small amounts of stored energy, cycle approximately once per day, and are frequently charged to their full installed energy capacity equivalent to 1.7 h of mean U.S. demand.

Multiple-Year Simulations Reveal the Role of Inter-annual Storage

Longer time periods are more likely to include large-scale weather events like wind droughts that require large reserves of stored energy. To examine long-term

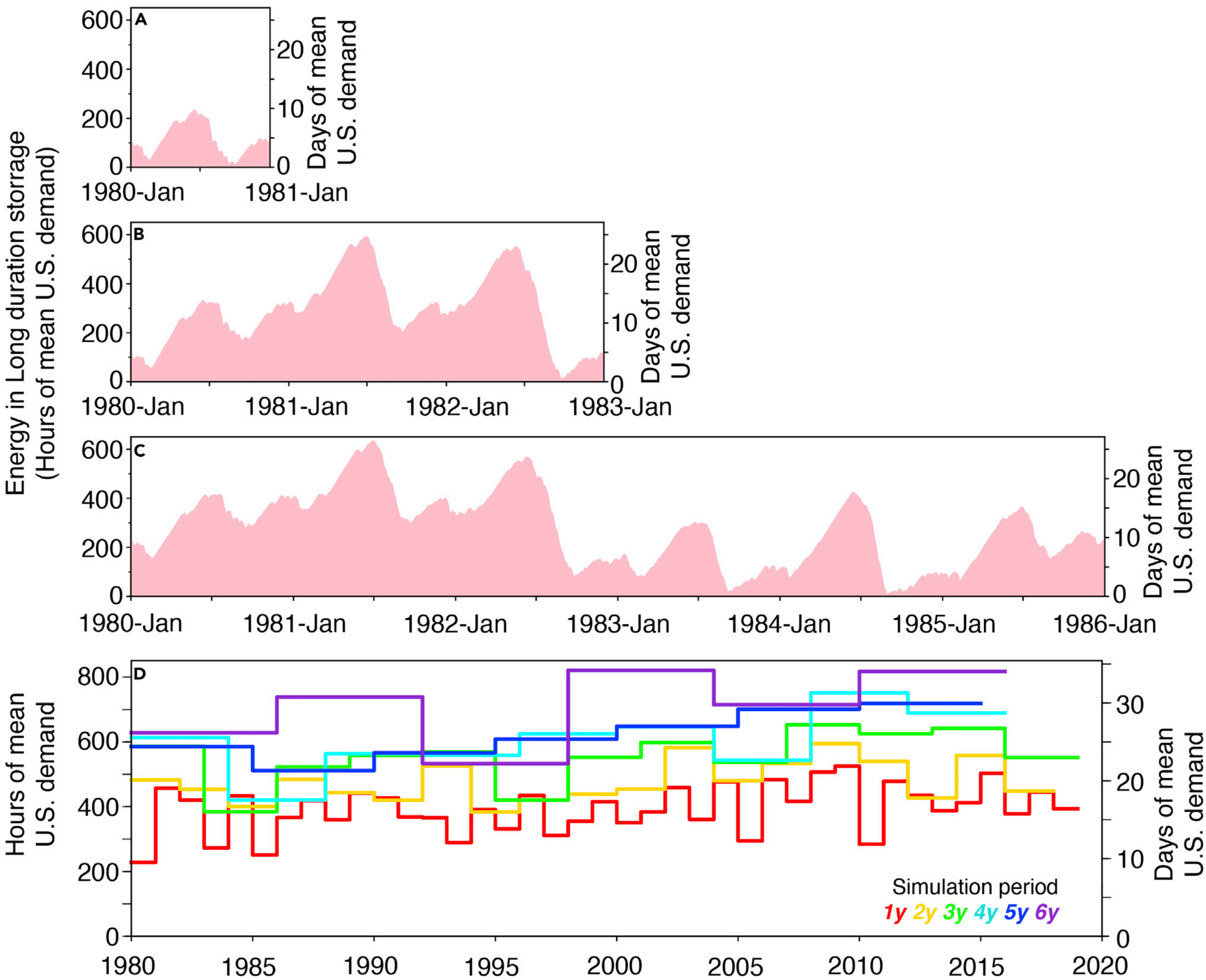

Figure 4. Effect of Simulation Length on Energy in Long-Duration Storage

(A–D) Energy in LDS over (A) 1 year (1980), (B) 3 years (1980–1982), and (C) 6 years (1980–1985). in (D) 1-, 2-, 3-, 4-, 5-, and 6-year simulations were performed across all 39 years of wind and solar data available (1980 to 2018). The horizontal sections of the lines represent the optimized LDS capacity for the periods simulated. Storage in the model is constrained to start and end with the same amount of energy. Dependence on LDS increases when the system is optimized over more years, as LDS is used for multi-year storage in addition to seasonal storage.

variations, simulations across the full 39 years of available wind and solar data (1980–2018) were modeled for 1-, 2-, 3-, 4-, 5- and 6-year periods, while still assuming current technology costs (Table 1; Figures 4 and 5). Indeed, longer simulation lengths typically resulted in larger deployed capacities of LDS to ensure system reliability during infrequent low-resource periods (Figure 4). Figure 4C highlights an example of multi-year storage dynamics in a 6-year simulation from 1980-1985, where substantial energy was in LDS during the first 3 years (1980–1982), and energy then was depleted during the second 3 years (1983–1985). Overall, the median energy capacity of LDS assets in the 6-year simulations was 85% greater than the median energy capacity of LDS assets in the 1-year simulations (Figure 5). These substantial differences highlight the need for assessment of system performance over multiple years to meet resource adequacy planning standards for a reliable electricity system.

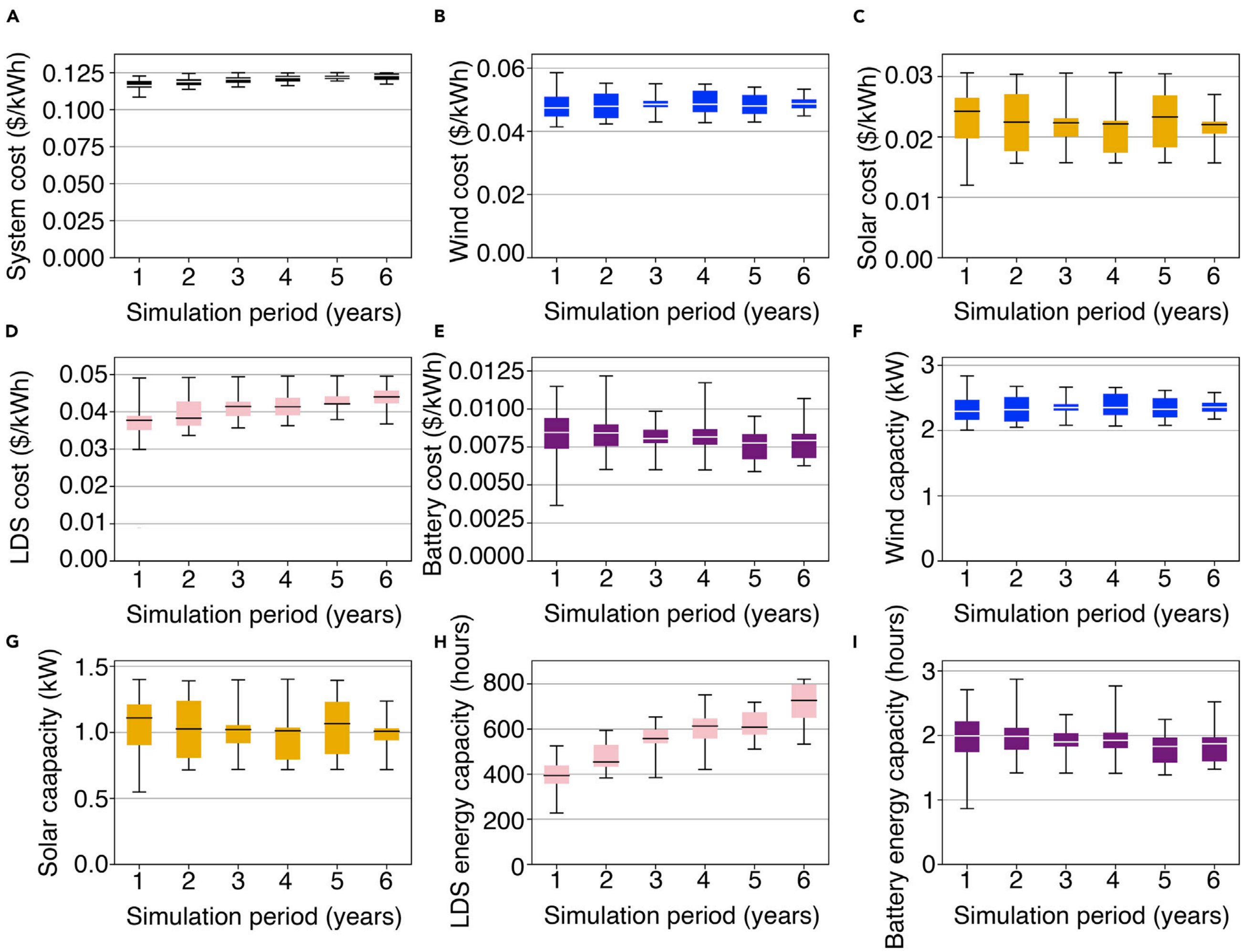

Figure 5. Distribution of Results for Various Simulation Lengths

Box and whisker plots show the distribution of total system cost, and individual technology capacities and contributions to system cost for various simulation lengths (1- to 6-year lengths). Whiskers represent the minimum and maximum of each dataset. With hourly resolution and many decision variables, the linear optimizer is computationally limited to 6-year simulation lengths for these systems. Power capacity is normalized such that 1 kW is mean U.S. demand and energy capacity is presented in hours of mean U.S. demand. Figures S5 and S6; Tables S5 and S6 provide supporting details and data for this figure. The impact of simulation length is strongest for LDS energy capacity where multi-year storage is a possibility. The median energy capacity of LDS deployed in the 6-year simulations was 85% greater than the median energy capacity of LDS deployed in the 1-year simulations.

When least-cost optimizations were performed for single years of weather data from 1980 to 2018, the resulting installed capacities of LDS, batteries, wind, and solar were 29%–68% higher in some years than in other years (Figure 5). Asset builds based on a single year are not robust (i.e., do not reliably meet demand) for other years (Figure S4A). Specified asset capacities from simulations of varying lengths were applied to other years of data to assess the system reliability in other years (Figure S4B). While longer modeling horizons more accurately predicted needs (Figure S4B), 4-year simulations are not necessarily enough to meet North American Reliability Corporation (NERC) resource adequacy planning standards.[15] Future analyses could explore how many simulation years are adequate to ensure that specified asset builds will meet regulatory resource adequacy standards over the lifetime of the capital asset stock on a typical grid.

Total system costs varied much less than the capacities of individual technologies (and their contributions to total system cost) (Figure 5). Total system costs were between $0.11/kWh and $0.12/kWh across the 39 years studied (Figure 5), as different capacities of technologies trade off to maintain similar total system costs across the 39 years. LDS and wind dominated least-cost systems; together they made up about 75% of total system costs in all years 1980–2018 for all simulation lengths (Figure 5).

System Sensitivities to Region, Technology Mix, and Cost

In addition to the base case results already presented, we also performed a series of sensitivity analyses, varying the geographical area, available technologies, and technology costs. For example, to accommodate existing transmission constraints, we evaluated systems in smaller geographical regions corresponding to three largely independent interconnections in the U.S.: The Western Interconnection, the Eastern Interconnection, and the Texas Interconnection (Figure S7). Because our demand data is limited to the U.S., we exclude the contributions to the interconnections from Canada and Mexico. Using 2018 data, 100% reliable least-cost wind-solar-LDS-battery systems for each of these regions entailed technology mixes similar to the entire contiguous U.S. system, with investments in wind and LDS constituting two-thirds or more of total system costs.

To understand the relative benefits of using LDS and batteries individually and in combination, we performed a series of simulations in which some of the base case technologies (i.e., wind, solar, batteries, and LDS) were not available to the model. As shown in Figure 6, regardless of the mix of variable renewable generation technologies, introduction of LDS at current costs reduced total system costs relative to a battery only case. Indeed, in all cases in which LDS and batteries were included, the least-cost system was produced by spending more money on LDS than on batteries. The lowest system cost ($0.12/kWh) corresponds to the wind-solar-LDS-battery base case, as compared with $0.04/kWh for current U.S. system-averaged generation costs.[60]

We also tested the sensitivity of system costs and configuration of the least-cost system to changes in storage costs for the wind-solar-LDS-battery base case using 2018 data. System costs are effectively only sensitive to reductions in LDS costs when compared with equivalent reductions in battery costs (Figure 7A). In Figure 7A, power-capacity (conversion) and energy-capacity (storage) costs of LDS are scaled by the same factor. Simulations in which power- and energy-capacity costs for LDS were varied independently are shown in Figures 7B and S8. We varied total cost for batteries, as separating power and energy costs is difficult for this technology. For LDS with PGP as the base case, total system costs are more sensitive to relative reductions in power-capacity costs (i.e., electrolyzer and fuel cell costs) than they are to reductions in energy-capacity costs (i.e., underground storage of hydrogen) (Figure 1 and S8). In contrast, for Li-ion batteries, energy-capacity costs dominate total costs (Figure 1). The PGP base case is compared with other LDS technologies including PHS and CAES in Figure 7B. The marked energy and power costs for both PHS and CAES represent annualized fixed costs for current technologies, where PHS and CAES are modeled with the same round-trip efficiency and self-discharge rate as PGP (costs in Table S4; lifetimes in Table S3). PGP at current costs is a competitive option for the LDS functional role while also meeting renewable requirements unlike current large-scale CAES demonstrations (Figure 7B); see the Discussion for further detail. Relative to other LDS technologies, PHS has high energy-capacity costs, which may limit its ability to compete in the LDS grid role.

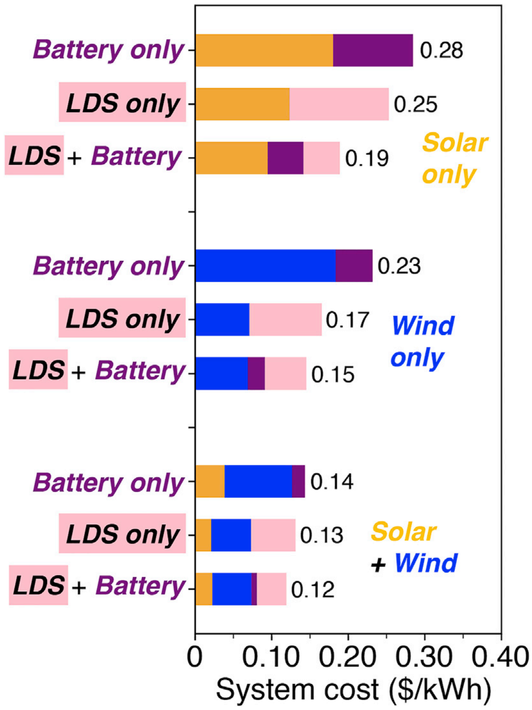

Figure 6. System Costs with Different Technology Combinations

In the top-most three bars, generation is obtained by solar only; in the middle three bars, by wind only; and in the bottom-most three bars generation is obtained by a combination of solar and wind. Within each group of three bars, the top-most bar represents a system with battery storage only, the middle bar represents a system with LDS storage only, and the bottom-most bar allows both storage technologies to be deployed. Stacked areas in each bar represent the cumulative contribution of each technology to total system cost over the optimization period (2018). The bottom-most bar represents the wind-solar-LDS-battery base case. Table S8 supports this figure. In all cases, introduction of LDS reduces overall system costs compared with a system with only batteries.

We explored the sensitivity of least-cost asset builds and dispatch schedules to changes in storage costs. A 4-fold reduction in LDS costs entirely eliminated batteries from the least-cost system (Figures S9B and S10B). Conversely, eliminating LDS from the least-cost system required a 100-fold reduction in battery costs (Figures S9D and S10D). LDS also disappeared from the least-cost system with a 2x increase in LDS costs relative to current costs, whereas batteries remained until there was a 3.5x increase in current battery costs (Figures S9A, S9C, S10A, and S10C). In the system where battery costs were reduced by a factor of 100, and LDS at current PGP costs is eliminated, batteries fill the seasonal storage functional role (Figure S11). In contrast, in the case where LDS costs are reduced by a factor of 4, and batteries at current costs are eliminated, LDS is not used for high-frequency, intra-day storage (Figure S11). Less costly LDS resulted in an increased fraction of wind generation, whereas less costly batteries resulted in an increased fraction of solar generation in the least-cost system, highlighting the different needs to smooth out the qualitatively distinct variabilities in wind and solar resources (Figure S10).

DISCUSSION

Our results demonstrate that electricity systems that use only wind and/or solar generation and storage to reliably meet electricity demand cost substantially less if LDS is included as a storage option (Figure 6). The benefits of LDS are quite robust across

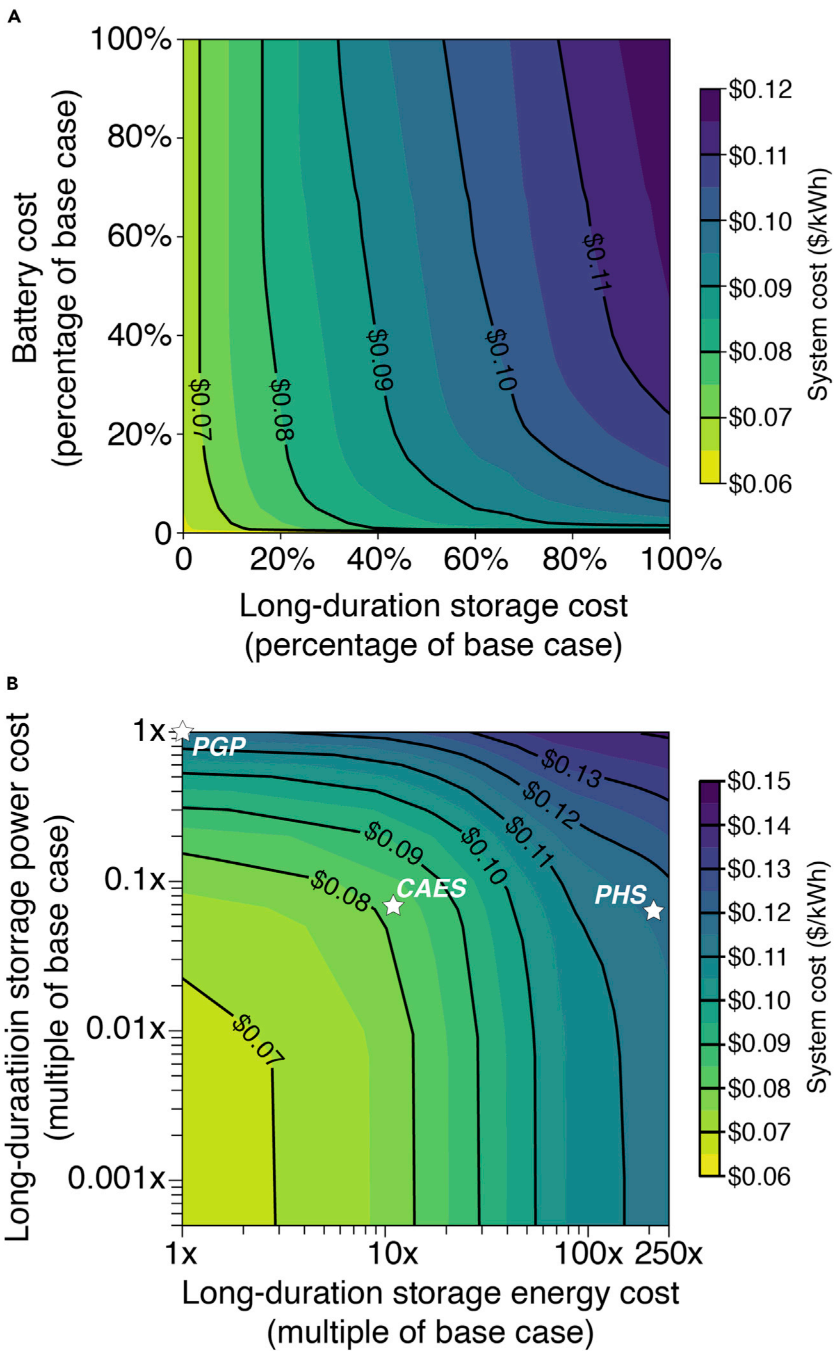

Figure 7. Sensitivity of System Cost to LDS and Battery Costs

(A) LDS and battery costs are independently reduced from base case assumptions (100% of base case costs) to free (0%), and total system costs for the optimization period (2018) are plotted as contour lines. Capacity and dispatch of each technology, including wind and solar, were optimized in response to each combination of LDS and storage costs. The system costs are much more sensitive to reductions in LDS costs than to reductions in battery costs.

(B) LDS power and energy costs are scaled independently by multiples of base case costs. The base case system cost, with current PGP costs, is displayed with a star at 1×. All system costs are generated using physical characteristics of PGP (round-trip efficiency, self-discharge rate), thus the CAES and PHS stars represent annualized fixed costs for these technologies and not system costs

Figure 7. *Continued*
(costs in Table S4; lifetimes in Table S3). Note: CAES power costs are based on a carbon-emitting design; see Discussion for further detail. For PGP and CAES technologies, system costs are more sensitive to reductions in power costs than they are to similar reductions in energy costs. Figures 1 and S8 provide additional detail.

single- and multi-year time periods, different spatial scales, and a wide range of modeled technology costs.

Implications of Changes in Energy Storage Costs

Because of uncertainty in future technology costs, it is essential to explore a wide spread of cost sensitivities when evaluating future electricity systems. Over a very wide range of battery costs, introduction of LDS leads to lower system costs—even at current PGP costs—provided that very high reliability (>99.97%) is a strict constraint on system design (Figure S9). For example, for a solar-battery only system at current costs, our model produces a system cost of \$0.28/kWh; adding LDS at current PGP costs decreases the system cost by 32% to \$0.19/kWh (Figure 6). Although still expensive when compared with current average U.S. electricity system costs of \$0.04/kWh,[60] LDS minimizes expensive short-term storage that would otherwise be needed to compensate for the diurnal cycle of sunlight, and reduces and the overbuilding of generation that would otherwise be needed to compensate for the seasonal variation in insolation. System costs decrease further when there is a mix of wind and solar generation (at current asset costs), as least-cost systems optimize to avoid overbuild of generation and short-term energy storage (Figure 6). These system cost comparisons suggest that least-cost, reliable, emissions-free electricity systems benefit from the inclusion of complementary technologies, and that asset capacities will vary based on which technologies are allowed in the system. Deployment of LDS provides an expanded suite of low-cost options for building reliable, zero-carbon electricity systems with a variety of wind and/or solar asset mixes.

Less costly LDS led to higher penetration of wind power generation in reliable, least-cost electricity systems, whereas less costly batteries led to higher penetration of solar power generation (Figures S9 and S10). Because wind resources can be low for periods of several weeks in the late summer, wind power penetration is facilitated by including an energy-storage technology that is capable of filling these extended gaps in which demand substantially exceeds generation. This characteristic occurs despite the relatively low PGP round-trip efficiency of 49%, which effectively increases costs associated with storing electricity for later dispatch (Table 1). In contrast, a major barrier to penetration of solar power is the ability to address diurnal variability. Electrochemical batteries are well-suited to this purpose due to their relatively low power conversion costs and high round-trip efficiencies. In the wind-solar-LDS-battery system, LDS and batteries coexist and fill complementary functional roles in the system (Figures 2 and 6). Including a wider range of technologies can lower system costs, but only if new technologies are less costly and physically similar to existing technologies, or physically different enough (in terms of cost structure, efficiency, lifetime, etc.) to complement existing technology by filling distinct functional roles.

Moreover, despite the recent focus on cost reductions and deployment of battery-based grid storage,[20,21] reducing LDS costs results in a lower system cost than the same proportional reduction in battery costs. By varying costs widely from the PGP and Li-ion base case, we capture the impact of LDS costs on renewable electricity costs. For example, a 10% reduction in LDS costs would reduce system costs by nearly twice as much as would a 10% reduction in battery costs (Figure 7A). In particular, it is the power-capacity costs (i.e., electrolyzer and fuel cell for PGP) that matter; the main expenditure on PGP is for conversion between electricity and hydrogen fuel as opposed to energy-capacity (i.e., storage) costs (Table 1; Figures 7B and S8). Furthermore, while other technologies like CAES and PHS could fill the LDS functional role, PGP is both renewable (unlike current CAES designs) and has no partial energy-cost limitations (unlike PHS).

The importance of LDS power-capacity costs explains why the least-cost system often transfers energy between LDS storage and battery storage (Figures 2, S2, and S3). Inter-storage transfer allows the electricity system to take advantage of the strongest characteristics of each technology. Due to high capital costs of conversion technologies associated with LDS, the use of a battery both during charging and discharging can reduce the amount of required LDS conversion capacity. Similarly, although batteries can dispatch electricity rapidly at low costs, their cost of energy storage is high. Therefore, costs can often be reduced if energy is stored in an LDS system and then slowly dispatched to a battery from which the energy can be rapidly dispatched when needed.

Technological Options for Long-Duration Storage

Although our base case reflects current cost and performance metrics of renewable PGP (Table 1), we explore LDS more generally by model runs, which vary these costs over a wide range of technology options. The results of this exercise suggest the potential for other LDS technologies with costs structures similar to PGP (Figure 1).

Large capacities of PHS exist worldwide, including 23 GW in the U.S., where it accounts for 95% of all utility-scale energy storage.[61,62] DOE's hydropower vision estimates that 36 GW of new PHS capacity is possible in the U.S. by 2050, but recent growth rates point to more modest PHS increases—perhaps 0.5 GW of new capacity by 2050.[63] Key constraints include limited geographical locations and effects on the magnitude and timing of downstream water flows. It is usually used for storage times of less than 1 week.[34] The costs of PHS projects are highly site and project specific;[64] depending on the local topography, the same dam might store very different quantities of water depending on the shape and depth of its reservoir, necessitating caution when extrapolating PHS costs. Furthermore, most PHS in the U.S. was built in the 1970s.[62] Such a mature technology is less likely to experience large future cost reductions due to learning curves and economies of scale.

CAES technology uses electricity to compress, cool, and store air underground, followed by subsequent air expansion through a series of turbo-expanders producing electric power on demand. There are two large-scale CAES plants in operation worldwide: a 290 MW plant in Huntorf, Germany, and a 110 MW plant in McIntosh, Alabama, USA.[65] Both store compressed air in salt caverns. Future CAES projects could use renewable electricity for the initial compression and cooling step without technological issues.[33] However, the Huntorf and McIntosh CAES plants both require supplemental heat when discharging and powering the grid. In both cases, the compressed air is pre-heated by burning natural gas before expansion.[65] There are conceptual adiabatic designs that pre-heat the expanding air with the stored heat of compression to avoid CO_2 emissions, but there have been no large-scale demonstrations of this approach.[33] Thus, regardless of the source of charging electricity, current CAES designs are inconsistent with goals of zero-carbon emissions and 100% renewable energy. Nonetheless, we include costs of current CAES designs in Figures 1 and 7 for comparison. Options for eliminating fossil CO_2 emissions from CAES (e.g., combusting fuel produced from a carbon neutral process or capturing and sequestering CO_2 from the exhaust) would increase the presented costs.

Utility-scale PGP projects are expanding at current costs.[35–38] PGP is an energy-storage technology in which electricity is converted into fuel (e.g., hydrogen via electrolysis), followed by a subsequent conversion of the fuel back into electricity either thermally (combustion turbines) or electrochemically (fuel cells).[34,66,67] In the future, substantial reductions in PGP power-capacity costs, and thus system costs, could be obtained if the costs of stationary fuel cells and electrolyzers were to decrease (Figure S8, current base case costs in Table 1). Current fixed costs of fuel cell and electrolyzer systems are about \$6,000/kW and \$1,100/kW, respectively (Table 1; with corroborating references).[25,68–70] PGP power-capacity costs could also be reduced by the development and deployment of new gas turbines that operate with 100% H_2 and have costs of about \$1,000/kW, comparable to conventional gas turbines that operate on CH_4.[71–73] It is also possible to perform methanation using electrolytic H_2 and concentrated CO_2 with relatively little energy input,[74–77] producing methane that could be stored as natural gas is routinely stored today, and later combusted in a turbine upon demand, with the CO_2 captured, concentrated, and recycled to form a closed loop. This alternative PGP process would replace the fuel cell or H_2-powered turbine[78] with a conventional methane-powered turbine, and allow geographically distributed, conventional methane gas storage, but would incur costs associated with the capture, concentration, and purification of CO_2 from flue gas as well as conversion costs associated with methanation.

TES systems provide a range of services from temporally shifting heating and cooling loads in buildings and industry to smoothing the power delivered to the grid from concentrating solar power (CSP) plants.[79] TES systems store energy as either sensible heat, latent heat, or via thermochemical reactions. Because we focus on an electricity system only model in this paper, we neglect TES systems that do not provide electric power. Unlike other energy-storage technologies that convert electric power into stored energy and back to electric power, TES systems almost exclusively store heat from a direct heat source such as CSP.[80] While coupled CSP-TES systems may play a role in a future zero-emissions electricity system, simultaneous power generation and energy storage by heat input complicates comparisons with other LDS technologies.

Model Architecture Changes

In addition to costs, below we consider the implications of model architecture changes, such as region size, electricity demand, the availability of other technologies, and temporal range and resolution.

Wind and solar resources are less variable when aggregated over larger areas.[14] Hence, confining the load-balancing region to individual states or independent system operator (ISO) regions generally requires more short-term and long-duration energy-storage capacity than the values obtained herein for the U.S. (Figure S7). Regardless of resource aggregation size, the addition of LDS leads to reductions in overall system costs because LDS storage is not limited by energy-capacity costs but rather the cost of power capacity (e.g., of electrolyzers and fuel cells for PGP; Figure S8B). This suggests that the system benefits of LDS that we find would occur in smaller regions, and that such benefits would be even more sensitive to changes in the cost of power capacity, than they would be to in the larger interconnects, or the entire contiguous U.S. Modeling additional transmission constraints would likely result in systems with higher required LDS capacities than our base case.[43] Lossless transmission thus represents a best-case scenario and a lower bound for storage capacity reliability requirements.

Along the U.S. eastern coast, offshore wind has higher capacity factors than land-based wind, and may reduce overall renewable electricity costs by competing with land-based wind and solar generation.[27,81] However, both land-based and offshore wind power technologies in the Eastern Interconnect have concurrent seasonal lows in the summer time.[59,81] LDS is expected to benefit electricity systems based on both land-based and offshore wind generation by filling seasonal resource gaps.

In most regions, the expansion of variable renewables into fossil fuel-based electricity systems can continue unabated for many years, but LDS may become increasingly valuable with lower fractions of natural gas. Indeed, LDS competes with natural gas in a 95% carbon-free electricity system, with system costs at \$0.09/kWh (Figure S12). With lossless transmission, the introduction of natural gas to the technology mix at 10% of demand minimizes or eliminates the need for storage (Figure S12). In some locations like Germany, LDS may be considered prior to 80% integration of renewables if there are transmission constraints.[42,82]

Here we constrain our analysis to the electricity sector to specifically explore scenarios relevant to states that have adopted, or are considering adopting, 100% renewable power laws. Other energy system models have explored the use of electricity for heating, fuels, chemical feed-stocks, and battery storage in electric vehicle fleets.[48] Although using electricity to satisfy the U.S. heating demand might substantially increase winter loads, it would not eliminate the need for LDS to compensate for inter-annual variability of solar and wind resources or reduced resource availability during different seasons or weather-related, multiple-day episodes in the electricity sector. Similarly, we would not expect our conclusions regarding the cost-effectiveness of adding LDS to wind-solar-battery electricity systems to be affected by whether deployed batteries are stationary or in battery electric vehicles; as discussed, changes in system costs are not very sensitive to changes in battery costs (Figure 7).

While the introduction of low- or zero-carbon "firm" generators, such as nuclear energy or natural gas with CCS would minimize or eliminate the need for storage technologies,[12,13] these technologies are generally excluded or limited either by regulation or mandate from future electricity systems in many regions (Table S2; Figures S13 and S14). Regardless of the actual level of penetration, compensating for the variability of wind and solar will be required, and utilization of firm generators for this purpose will involve: use of firm generation technologies at low capacity factors, increasing costs, curtailment of VRE, or deployment of short-term and long-term grid storage technologies, with the trade space between the latter two options the focus of the work described herein.

The use of weather data from different years produces considerable differences in the capacities of technologies deployed in least-cost systems (up to 213% higher for one year compared with another for battery energy capacity), but due to offsetting changes in deployed capacities of different technologies, total system costs are not very sensitive to inter-annual differences in weather (Figure 5). The use of hourly time resolution explicitly assumes that load balancing and grid stabilization on more rapid timescales will be obtained using other, currently available technologies. Our approach notably allows quantification of the duration and energy required to obtain reliability from a system that relies exclusively on wind and solar generation resources, along with energy-storage technologies, over a timescale comparable to the lifetime of capital assets on an electricity grid. Although we assume that the notional electricity system is built instantaneously and do not account for cost reductions associated with increases in deployment, the conclusions are robust over a wide range of storage technology costs.

Conclusions

Our results indicate that introducing LDS technology reduces system costs of reliable electricity systems consisting of solely wind and solar electricity generation and battery storage. Examples of technologies that can provide long-duration energy storage include PGP, compressed air, and pumped hydro. Due to its low energy-storage capacity costs, LDS provides seasonal and multi-year storage, substantially reducing the capacities of wind and solar generation that otherwise must be built to obtain high reliability over multi-year time periods. Indeed, we find that dependence on LDS increases when the system is optimized over more years. This is important because most grid planning tools used by utilities and regulators do not involve multi-year modeling horizons, and consequently may underestimate the value of LDS. Batteries are useful for hourly and daily storage because of their relatively low power-capacity costs, but do not provide cost-effective seasonal storage due to their high energy-storage capacity costs. Battery storage currently receives the vast majority of attention, investment, incentives, and mandates designed to promote zero-carbon grid storage technologies. However, relative to current costs, reductions in LDS costs would reduce system costs in a reliable wind and solar electricity system to a much greater extent than would equivalent reductions in battery costs. These results suggest that large-scale deployment of LDS and cost improvements in such technologies may greatly reduce the cost of future variable renewable electricity systems.

EXPERIMENTAL PROCEDURES

Resource Availability

Lead Contact

Further information and requests for resources and materials should be directed to and will be fulfilled by the Lead Contact, Jacqueline A. Dowling jdowling@caltech.edu.

Materials Availability

This study did not generate new unique materials.

Data and Code Availability

The macro energy model (MEM) uses historical wind and solar input data with hourly resolution over the contiguous U.S. for a 39-year period (1980–2018) and hourly demand data for mid-2015 through mid-2019 from the U.S. Energy Information Administration (EIA) where mean demand was 457 GW (Figure S1).[83] In the interest of transparency, the model code, input data, and analytical results are publicly available on GitHub at https://github.com/carnegie/SEM_public/tree/Dowling_et_al_2020.

Wind and Solar Capacity Factors

The hourly based wind and solar capacity factors used in this study are estimated using the Modern-Era Retrospective analysis for Research and Application, Version 2 (MERRA-2) reanalysis satellite weather data, which has a horizontal resolution of 0.5° by latitude and 0.625° by longitude.[53]

For solar capacity factors, we first calculate the solar zenith angle and incidence angle based on the location and local hour,[84,85] and then estimate the in-panel radiation.[86] We also separate the direct and diffuse solar components using an empirical piecewise model that takes into account both ratios of surface to top-of-atmosphere solar radiation (the clearness index) and the local time.[87] To improve the potential solar availability, we assume a horizontal single-axis tracking system with a tilt of solar panel to be 0° and a maximum tuning angle of 45°. Power output from a given panel is calculated using a performance model, which considers both the surrounding temperature and the effect of irradiance.[88,89]

For wind capacity factors, the raw wind speed data is first interpolated to 100 m by assuming a power law, based on wind speed at 10 and 50 m. The wind capacity factor calculation employed a piecewise function consisting of four parts: (1) below a cut-in speed (u_{ci}) of 3 m s^{-1} the capacity factor is zero, (2) between a cut-in speed of 3 m s^{-1} and rated speed (u_r) of 12 m s^{-1} the capacity factor is u_{ci}^3/u_r^3, (3) between a rated speed of 12 m s and cut-out speed (u_{co}) of 25 m s^{-1} the capacity factor is set to 1, and (4) above a cut-out speed of 25 m s^{-1} the capacity factor is zero.[14,90]

The solar and wind capacities are first estimated for each grid cell in the U.S., with the same resolution as in MERRA-2. We then selected grid cells over land where the annual mean capacity factor is larger than 26% for both solar and wind. We chose this threshold such that our resulting average capacity factors over the 39-year time frame were comparable to the reported capacity factors for utility scale generation of wind and solar in the U.S.[91] This threshold includes about one-quarter and one-half of the total possible grid cells for solar and wind, respectively. The continental or interconnect scale resource data are then calculated as the average of these grid cells with grid area as weights.

EIA Demand Imputation

The EIA began collecting hourly electricity demand information from all balancing authorities (BAs) across the contiguous U.S. in July 2015. The collection process is based on form EIA-930 where values are calculated by each reporting BA individually.[92,93] The original EIA data were queried from their open data database on September 10, 2019 via an application programming interface.[94] These data are the most temporally granular publicly available demand data that covers all of the contiguous United States. However, there are substantial quantities of missing and outlier values in the data. A data cleaning method was developed to remove outliers and replace missing and outlier values in order to create complete, usable data records.[54]

2.2% of the demand data were missing in the EIA's database. Additionally, some reported quantities are non-physical negative values or are extreme outliers. We developed an anomalous value screening process to flag the most extreme outliers for imputation. The screening algorithms are designed to respect the time series structure of the data and use excessive deviations as a reason to flag a value.

We used a multiple imputation by chained equations (MICE) technique for imputation.[95] Each missing or anomalous demand value is predicted using a linear regression on the demand during that same hour for each other BA. This method leverages correlations to help fill in some 1,000 h or longer consecutive data gaps. Other predictors in the linear regression include the leading and lagging demand values surrounding the hour being predicted (to encourage time series continuity) and the site's average demand for that day of the year and hour of day.

The performance of the MICE technique was measured by intentionally marking good data as missing, imputing said data, and comparing these imputations against the true values. This comparison was performed via assessing the mean absolute percentage error (MAPE). The mean MAPE value across all the BAs was 3.5%. The imputation method exhibited only a small bias of 0.33% measured as the mean bias across all BAs. The cleaned data are publicly available.[83]

Cost and Technological Assumptions

System costs in our model include fixed costs and variable costs. Variable costs were assumed to be zero for all technologies (wind, solar, PGP, and Li-ion batteries), thus our system cost is primarily based on discounted fixed costs. Table 1 presents these costs as well as power- and energy-capacity costs for PGP and batteries that were used in the base case. Wind and solar costs used for the base case were obtained from the U.S. EIA's 2018 Annual Energy Outlook.[96] Wind and solar capacity factors for the contiguous U.S. were calculated from the MERRA-2 reanalysis dataset as described above. Wind and solar capital costs are lower in the U.S. EIA's more recent 2020 Annual Energy Outlook and other references.[97–99] We choose to retain the higher values to align our cost assumptions with previous analyses for easier comparison of results. This choice will not substantially alter any of the technical conclusions reached in this paper about the utility of LDS but may slightly overestimate resulting system costs.

Capacity costs (fixed costs), lifetimes, and efficiencies for PGP storage technologies were evaluated from the H2A model data compiled by the National Renewable Energy Laboratory (NREL).[68,69,100,101] Battery storage capacity costs, efficiencies, and lifetimes were estimated from Lazard, a financial advisory and asset management firm.[102] The cost, energy capacity, and lifetime for Li-ion battery storage are based on usable energy capacity not nameplate capacity.[102] Specific values for battery storage characteristics were taken from Davis et al., and Pellow et al. and were within the ranges provided by Lazard.[22,25] We assumed a 100% operational uptime for batteries and PGP systems, so results should be scaled proportionately in either the cost or the installed asset capacity to include a buffer against scheduled outages. In sensitivity studies, capacity costs for batteries and PGP (power and energy) were scaled from 1×10^{-8} to 250, with 1 corresponding to Table 1 costs, and least-cost optimization was solved for each set of cost assumptions. For discussion of other storage costs besides PGP and batteries included in Figures 1 and 7, refer to Section S2.2.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.joule.2020.07.007.

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AUTHOR CONTRIBUTIONS

N.S.L. and K.C. conceived this study. J.A.D., K.C., and N.S.L. designed the analyses with contributions from K.Z.R., T.H.R., M.Y., and F.T. K.C., F.T., M.Y., and J.A.D. developed and tested the version of the model used in this study. K.Z.R. assisted with literature review, T.H.R. compiled various technology costs, and S.J.D. improved the figures and main text. J.A.D. performed the analyses and wrote the manuscript with interactive feedback from N.S.L., K.C., K.Z.R., T.H.R., S.J.D., M.Y., and F.T. All authors edited the manuscript and provided helpful discussions.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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Supplemental Information

Role of Long-Duration Energy Storage in Variable Renewable Electricity Systems

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1. Model formulation

1.1. Nomenclature

Symbol	Unit	Description
g	kW	Generation technology (wind, solar)
v	kW	Energy conversion (electrolyzer, fuel cell)
s	kWh	Energy storage (PGP storage, battery storage)
$froms$	kW	Discharge from energy storage
tos	kW	Charge to energy storage
t	h	Time step, starting from 1 and ending at T
c_{capital}	\$/kW for generation or conversion \$/kWh for storage	(Overnight) capital cost
c_{fixed}	\$/kW/h for generation or conversion \$/kWh/h for storage	Fixed cost
$c_{\text{fixed O\&M}}$	\$/kW/yr	Fixed operating and maintenance (O&M) cost
c_{var}	\$/kWh	Variable cost
f	-	Capacity factor (generation technology)
h	h/year	Average number of hours per year
i	-	Discount rate
n	yrs	Project life
Δt	h	Time step size, i.e., 1 hour in the model
C	kW for generation or conversion kWh for storage	Capacity
D_t	kW	Dispatch at time step t
M_t	kWh	Demand at time step t
S_t	kWh	Energy remaining in storage at time step t
γ	1/yr	Capital recovery factor
δ	1/h	Storage decay rate, or energy loss per hour expressed as fraction of energy in storage
η	-	Storage charging efficiency
τ	h	Storage charging duration

Table S1: Model nomenclature

1.2. Cost calculations

Fixed cost of generation and conversion technologies (wind, solar, electrolyzer, fuel cell):

$$c_{fixed}^{g,v} = \frac{\gamma c_{capital}^{g,v} + c_{\text{fixed O\&M}}^{g,v}}{h}$$

Fixed cost of energy storage (PGP storage, battery storage):

$$c^s_{fixed} = \frac{\gamma c^s_{capital}}{h}$$

Capital recovery factor:

$$\gamma = \frac{i(1+i)^n}{(1+i)^n - 1}$$

1.3. Constraints

Capacity:

$$0 \leq C^{g,v,s} \qquad \forall g, v, s$$

Dispatch:

$$\begin{aligned}
0 \leq & D^g_t \leq C^g f^g && \forall g, t \\
0 \leq & D^v_t \leq C^v && \forall v, t \\
0 \leq & D^{\text{to s}}_t \leq \frac{C^s}{\tau^s} && \forall s, t \\
0 \leq & D^{textfroms}_t \leq \frac{C^s}{\tau^s} && \forall s, t \\
0 \leq & S^s_t \leq C^s && \forall s, t \\
0 \leq & D^{\text{from s}_t} \leq S^s_t(1-\delta^s) && \forall s, t
\end{aligned}$$

Storage energy balance:

$$\begin{aligned}
S_1 &= (1-\delta^s) S_t \Delta t + \eta^s D^{\text{to s}}_T \Delta t - D^{\text{from s}}_T \Delta t && \forall s \\
S_{t+1} &= (1-\delta^s) S_t \Delta t + \eta^s D^{\text{to s}}_t \Delta t - D^{\text{from s}}_t \Delta t && \forall s, t \in 1, ..., (T-1)
\end{aligned}$$

System energy balance:

$$\sum_g D^g_t \Delta t + D^{\text{from s}}_t \Delta t = M_t + D^{\text{to so}}_t \Delta t \qquad \forall g, t$$

1.4. Objective function

$$\text{minimize(system cost)}$$

$$\text{system cost} =$$

$$\sum_g c^g_{\text{fixed}} C^g + \sum_g \left(\frac{\sum_t c^g_{\text{var}} D^g_t}{T}\right) + \sum_v c^v_{\text{fixed}} C^v +$$
$$\sum_s c^s_{\text{fixed}} C^s + \frac{\sum_t c^{\text{to s}}_{\text{var}} D^s_t}{T} + \frac{\sum_t c^{\text{from s}}_{\text{var}} D^s_t}{T}$$

2. Supplemental experimental procedures

2.1. Model limitations

The linear model considers scenarios with perfect foresight, perfectly efficient markets, and no transmission losses. Despite these simplifications, key findings of our study are in accord with and build on a similar European electricity system that included transmission modeling.[1] Simulations for the West, East, and Texas Interconnects further show the robustness of our results (Figure S7). The system was confined solely to the electricity sector and did not consider conversion of electricity into fuel to serve other sectors such as transportation or heating. We did not include carbon capture with natural gas because the regulatory and legislative environment considered is confined to zero-carbon and renewable electricity sources (Table S2). We evaluate the system over an hourly timescale. Other technologies, including perhaps batteries, are assumed to provide short term (minutes to hours) smoothing of power variability. Additionally, although we include a project lifetime and self-discharge rate for batteries, we do not track battery deterioration due to cycling. Previous studies of electricity systems for the U.S. with high variable renewable penetration depend on future projections, consider shorter time periods, do not satisfy hourly demand with the statutorily required resource availability, and/or use highly complex models.[2]

2.2. Storage technology costs

In Table S3 we list cost and performance metrics for a variety of energy storage technologies. This table builds off of the compiled information in Luo et al.[3] for the more mature technologies: pumped hydropower, compressed air energy storage, flywheels, capacitors, and lead-acid batteries; original works are cited in the table itself. More rapidly developing technologies, such as Li-ion batteries, redox flow batteries, and PGP cite more recent literature including references[4,5] and those listed for the base case in Table 1. For some storage technologies (pumped hydropower, compressed air, redox flow, and PGP) the power and energy capacities for a given project can be sized independently. For these technologies, and all of the others, we provide the total capital cost divided by the power and again by the energy capacity of typical systems characterized in the literature in Figure 1. In these cases, the flexibility of independently sizing power and energy capacities for a given project for the LDS candidates is not shown in this table. The values depicted in Figure 1 are shown in Table S3.

The increased flexibility of the four LDS technologies: pumped hydropower storage (PHS), compressed air energy storage (CAES), redox flow batteries (potentially because of the ability to separate power and energy capacities), and PGP is shown in Table S3 where capital costs are split into power-related capital costs and energy-related capital costs. The costs of PHS projects are highly site and project specific;[6] depending on the local geology, a dam capable of storing one quantity of water in one valley, could potentially store a very different quantity in another valley necessitating caution when extrapolating PHS costs. The conversion of pressurized air to power in a CAES systems relies on multiple stages of air expansion with some involving gas turbines.[7] This makes CAES inconsistent with with the zero carbon emissions and 100% RE goal of this analysis. Despite this, we include CAES in Table S4. We emphasize that either gas produced from a carbon neutral process would be needed for the turbine or carbon capture and storage of the CO_2 from the exhaust. Either option would increase the presented CAES costs.

3. Supplementary figures and tables

State	Max renewable requirement	Electricity sector end-state
Virginia[8]	100% RE by 2050[a]	100% RE-only by 2050[a]
Maine[9]	80% RE by 2030	100% RE-only by 2045
Hawaii[10]	100% RE by 2050	100% RE-only by 2045
New Mexico[11]	80% RE by 2040	Zero-carbon by 2045
New York[12]	70% RE by 2030	Zero-carbon by 2040[b]
California[13]	60% RE by 2030	Zero-carbon by 2045
Nevada[14]	50% RE by 2030	Zero-carbon by 2045[c]
Washington[15]	only zero-carbon requirements	Zero-carbon by 2045
Puerto Rico[16]	100% RE by 2050	100% RE-only by 2050
Washington D.C.[17]	100% RE by 2032	100% RE-only by 2032

Table S2: **100% clean power state laws: renewable vs. zero-carbon requirements.** Several states and jurisdictions have mandated the adoption of 100% clean electricity systems by 2030-2050. The term 'zero-carbon' is broader than renewable energy (RE), as it generally includes technologies like nuclear and large-scale hydropower, for example, that are not strictly renewable by policy definition in most state Renewable Portfolio Standards (RPS). RE technologies include wind, solar, batteries, renewable hydrogen, and others. Natural gas with CCS is currently not eligible as a "zero-carbon resource" for meeting clean energy mandates in states like California (although the CEC is actively discussing their eligibility for this purpose.)[18] Natural gas with CCS may be permitted in net "zero-emissions" electricity systems in states like New York. Most states with 100% clean power laws have mandated the adoption of primarily RE technologies prior to zero-carbon or RE-only electricity system end-states. RPS are also used to specify the capacities of certain RE technologies such as wind, solar, and energy storage to be deployed. Iowa was the first state to establish an RPS and since then, more than half of states have established RE targets.[19] While most state RE targets are between 10% and 45%, 14 states—California, Colorado, Hawaii, Maine, Maryland, Massachusetts, Nevada, New Mexico, New Jersey, New York, Oregon, Vermont, Virginia, Washington, as well as Washington, D.C., Puerto Rico, and the Virgin Islands—have requirements of 50% or greater.[19]
[a]Virginia's RE targets apply to 'Phase I' and 'Phase II' investor-owned utilities.
[b]New York's goal involves reducing 100% of the electricity sector's greenhouse gas emissions by 2040 as compared to 1990 levels.
[c]Nevada's 50% RE by 2030 target is binding; its 100% zero-carbon by 2050 target is non-binding.

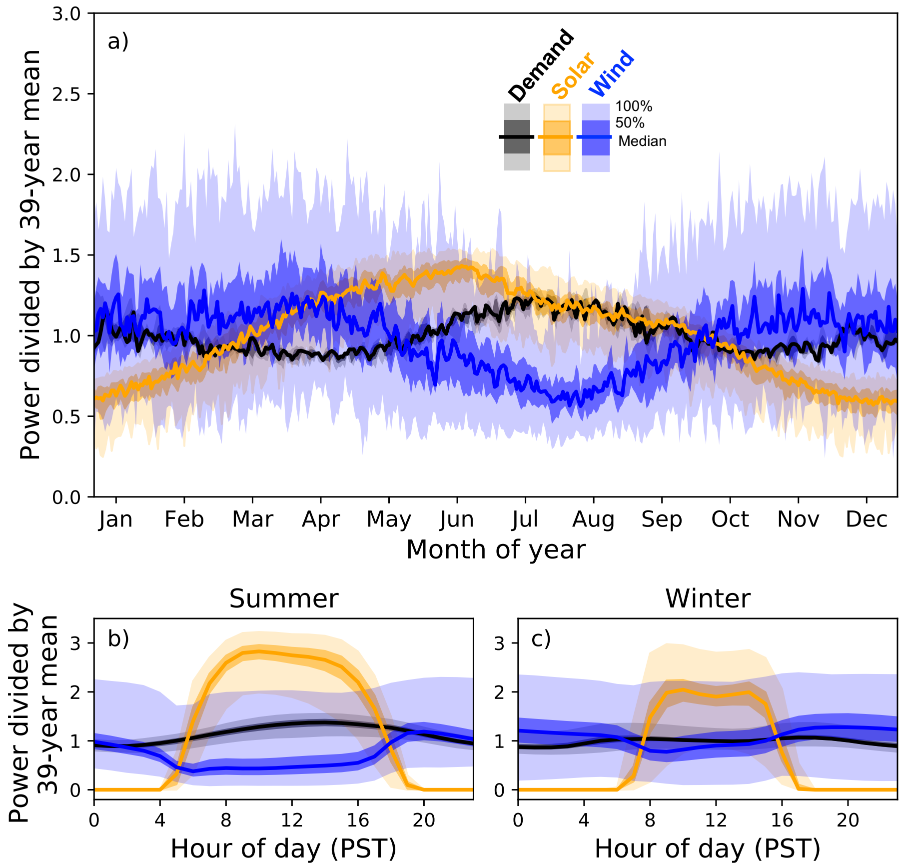


Figure S1: **Resource and demand variability.** The temporal variability of wind (blue) and solar (yellow) supply and electricity (black) demand over the contiguous United States from 1980-2018. Variability is shown over a) daily averaged, seasonal, b) hourly summer (June, July, and August), and c) hourly winter (December, January, February) timescales. The dark lines represent the median value, the darker shading represents the 25^{th} to 75^{th} percentile of data, and the lighter shading represents the 0^{th} to 100^{th} percentile of data. All data is normalized to its respective 39 year mean. See methods section on wind and solar capacity factors for more details. Data used in our analysis is displayed here. The plotting code is adapted.[20]

storage technology	total capital cost ($/kW)	total capital cost ($/kWh)	typical energy/ power	typical round-trip efficiency RTE (%)	typical lifetime (years)
flywheel	250-350 [7]	1,000-5,000 [7]	$\ll$1 [7,21]	~90–95 [7]	~15 [7]
capacitor	200-400 [7]	500-1,000 [7]	$\ll$1–1 [7]	~60-70 [7]	~5 [7]
lead–acid	300-600 [7]	200-400 [7]	<1-10 [7,22]	70-80, [7] 63-90, [22] 75–80 [23]	5-15 [7]
Li-ion	280-513, 488-980, 898-1,874 [24]	295-540,[e] 257-517,[e] 237-494[e] [24]	1, 2, 4 [24]	86-90 [24]	10 [24]
redox flow[a] (vanadium)	1,027-1,155, 1,788-1,956 [5]	4,106-4,620, 447-489 [5]	0.25, 4 [5]	70-78, 76-79 [5]	20 [5]
pumped hydropower[a]	2,500-4,300, [25] 2,000-4,000, [21] 975 [26]	5-100, [7] 97.5 [26]	1-24+, [7] 6-10, [25] 10, [21] 10 [26]	70-85, [7] 70-80 [21]	40-60, [7] 50[f]
compressed air[a]	400-800, [7] 800-1,000, [21] 650 [26]	2-50, [7] 16 [26]	1-24, [7] 40 [26]	42, [7] 45-60 [21]	20-40, [7] 30[f]
power-to-gas-to-power[a]	6,500-6,600,[b] 5,300-11,000[c]	5.6-8.8,[b] 4.6-14[c]	740-1,200[b]	electrolyzer 70,[d] fuel cell 70,[d] RTE 49[d]	electrolyzer 12.5,[d] cavern 30,[d] fuel cell 20[d]

Table S3: Technical characteristics of energy storage technologies with cost values reported as total capital costs divided by typical power and energy capacities.
[a]Technologies with more easily separated power and energy capacities and costs; values for the split costs for these technologies are include in Table S4.
[b]Characteristics for the specific PGP system used in this analysis and optimized using one year of 2018 demand and resource data and again with 6 years of 2013-2018 data.
[c]These values consider the two scenarios in the [b] note and the original uncertainty in fuel cell capital costs of 4,600-10,000$/kW instead of using the base case value of 5,854 $/kW. The PGP systems were not re-optimized based on the low and high fuel cell values.
[d]References in Table 1.
[e]Values originally reported based on nameplate energy storage, converted to usable energy by dividing by sqrt(0.9), where 90% is approximately the round-trip efficiency.
[f]Exact values used in Figure 7b.

storage technology	power-related capital cost ($/kW)	energy-related capital cost ($/kWh)
redox flow (vanadium)	941-1,143 [5]	196-356 [5]
pumped hydropower	600,[c, 26] 1,200 [27]	37.5,[c, 26] 75 [27]
compressed air	580,[c, 26] 595 (€/kW),[a, 28] 700 [27]	1.75,[c, 26] 2 (€/kWh),[28] 5 [27]
power-to-gas-to-power	6,380[b]	0.16

Table S4: Technical characteristics of candidate long duration energy storage technologies. Costs are split into power-related capital costs and energy-related capital costs.

[a]Based on 356.4 $/kW for the properly sized turbine and compressor plus 238.8 $/kW$_{turbine}$ for "other investment costs."[28]

[b]Based on 1,058 $/kW electrolyzer and 5,854 $/kW fuel cell costs (Table 1) and a 1:2 electrolyzer-to-fuel cell capacity ratio (results of the 2018 base case).

[c]Exact values used in Figure 7b. All storage variable costs are modeled as zero $/kWh.

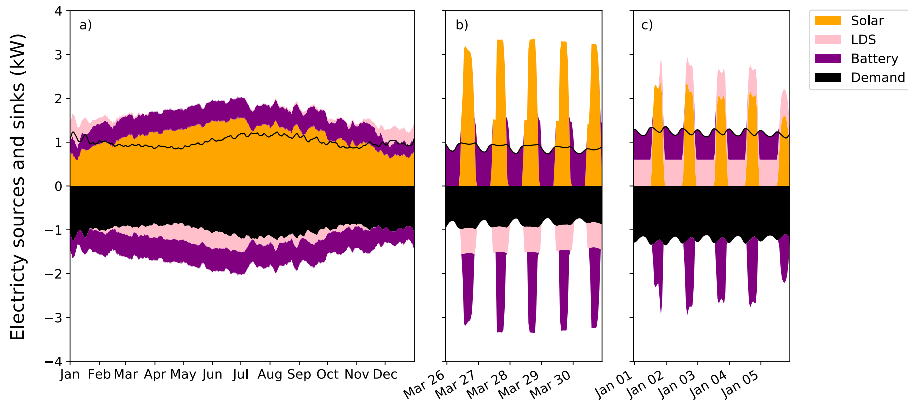


Figure S2: **Dispatch curves: solar, LDS, batteries.** a) Annual view of the solar only generation case for 2018. Batteries were charged and discharged on the daily cycle. LDS was charged during daily solar peaks and was used in wintertime during the seasonal low. b) 5-day period of maximum battery dispatch (starting at 08:00PM CST). Batteries were discharged, and LDS was simultaneously charged each day. c) 5-day period of maximum LDS dispatch (starting at 06:00PM CST). At peak daytime, excess solar and dispatched LDS were used to charge batteries. LDS and batteries met demand at night.

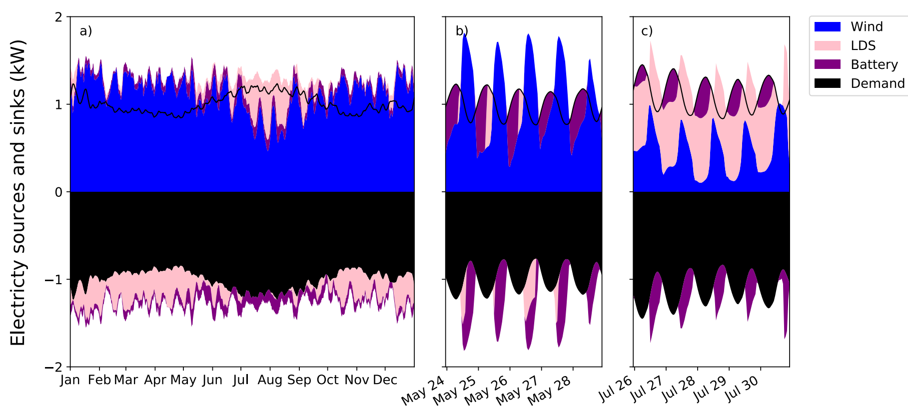
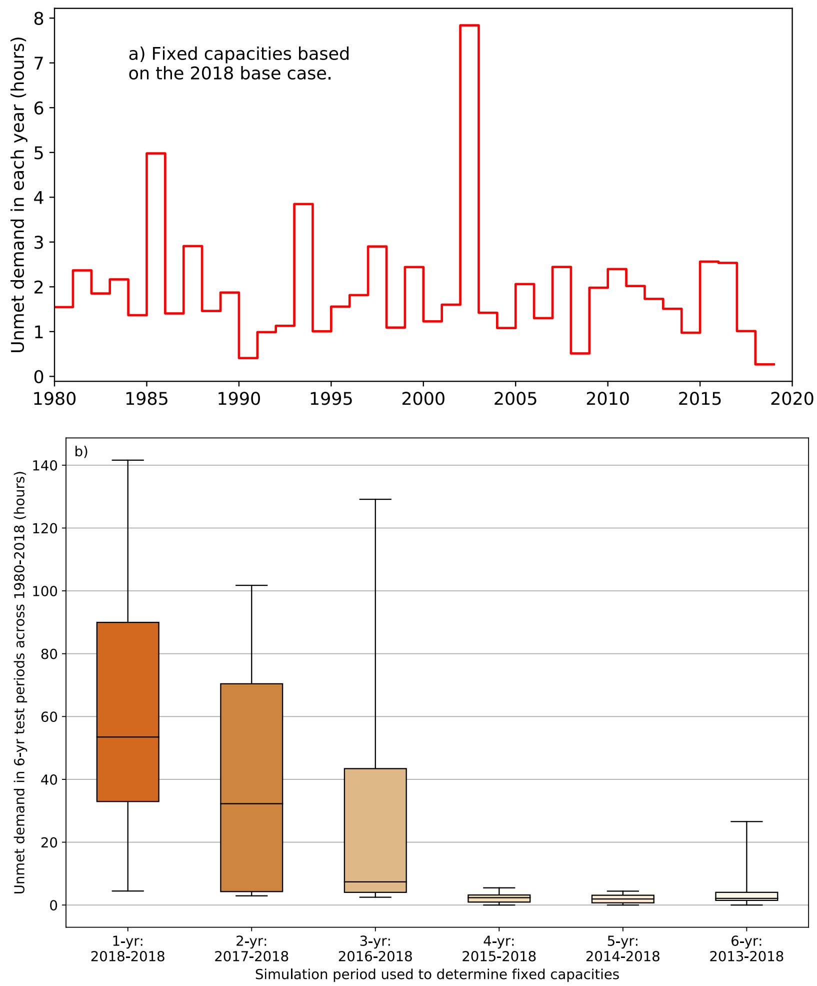


Figure S3: **Dispatch curves: wind, LDS, batteries.** a) Annual view of the wind only generation case for 2018. LDS was discharged primarily in the summer when the wind resource is least abundant. b) 5-day period of maximum battery electricity source (starting at 07:00AM CST). Batteries and LDS capture nighttime wind resource peaks. Both LDS and batteries meet demand during the day. c) 5-day period of maximum LDS electricity source (starting at 11:00AM CST). Simultaneous LDS discharge and battery charge occurred each night.



Fixed capacity	Solar (1 = mean U.S. demand)	Wind (1 = mean U.S. demand)	Battery (h of mean U.S. demand)	LDS (h of mean U.S. demand)	Conversion to LDS (1 = mean U.S. demand)	Conversion from LDS (1 = mean U.S. demand)
1-yr: 2018-2018	1.0296	2.4814	1.6841	393	0.2706	0.5335
2-yr: 2017-2018	1.0077	2.4382	1.6074	477	0.2846	0.5678
3-yr: 2016-2018	1.0546	2.3634	1.8687	551	0.2696	0.5718
4-yr: 2015-2018	0.9400	2.4262	1.6987	723	0.3179	0.6062
5-yr: 2014-2018	1.0293	2.3307	1.9466	745	0.3211	0.5933
6-yr: 2013-2018	1.0329	2.3211	1.9599	699	0.3143	0.5954

Figure S4: **Fixed capacities based on asset builds from various simulations.** The cost of unmet demand was set to \$10/kWh. a) Hours of unmet demand in each year over the 39 year period when specifying capacities based on results from the 2018 base case. Asset builds based on a single year are not always robust for other years. b) Fixed capacities based on 1-, 2-, 3-, 4-, 5-, and 6-yr asset builds from the 2010s (capacities shown in the table where mean demand over the full data set was 457 GW). Unmet demand met (hours) based on these capacities is shown for 6-year test periods across the data set 1980-2018 (7 data points per box). While longer horizon modeling more accurately predicts needs, four-year simulations are not necessarily enough to meet NERC reliability standards.[29] More detailed studies are needed to determine how many simulation years are enough.

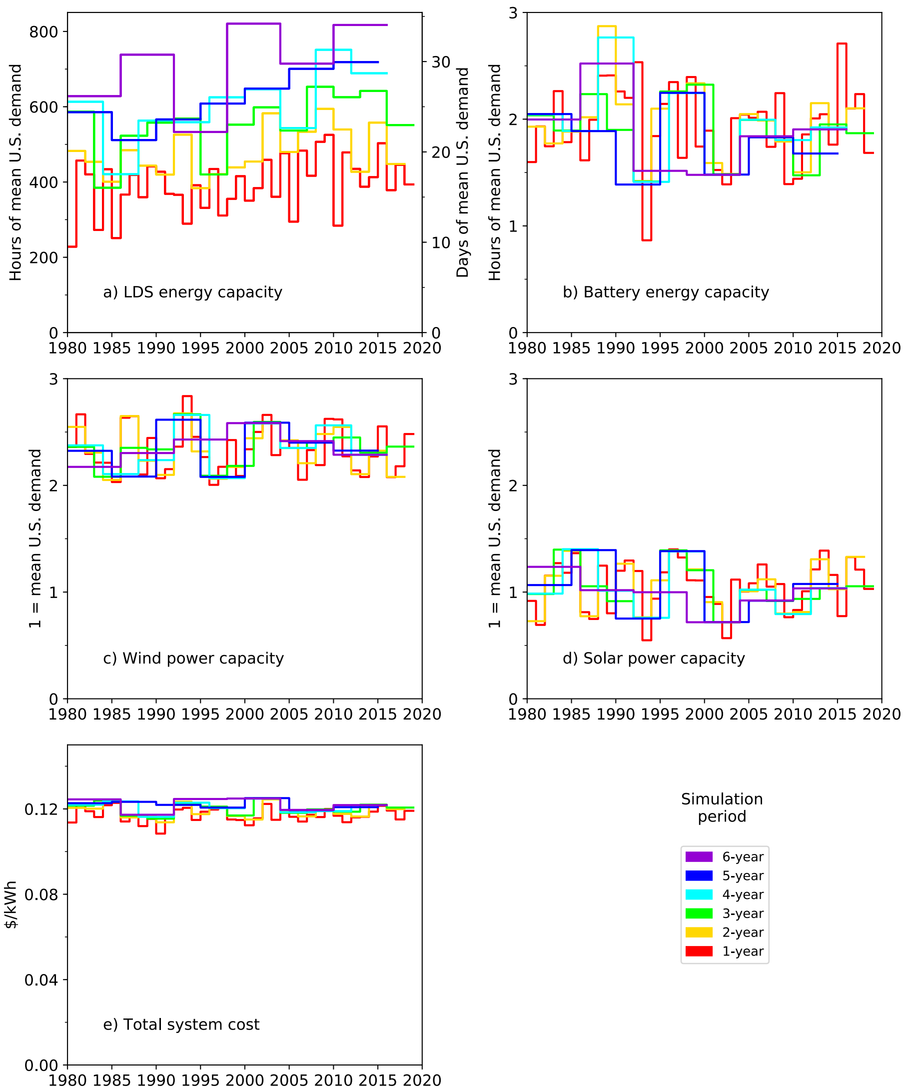


Figure S5: **Multiple year simulations: capacities.** 1-, 2-, 3-, 4-, 5-, and 6-year simulations were performed across all 39 years of wind and solar data available (1980 to 2018) for the contiguous U.S. The horizontal sections of the lines represent the optimized capacity for the periods simulated. Presented here are results for a) LDS energy capacity, b) battery energy capacity, c) wind power capacity, d) solar power capacity e) total system costs. In least-cost systems, longer simulation lengths resulted in larger installed storage capacities for LDS. System costs were ∼0.12 $/kWh for all simulation lengths.

Simulation length (across 39 years, 1980-2018)	**Data type**	**Total system cost ($/kWh)**	**LDS energy capacity (hours of mean U.S. demand)**	**Battery energy capacity (hours of mean U.S. demand)**	**Wind power capacity (1 kW = mean U.S. demand)**	**Solar power capacity (1 kW = mean U.S. demand)**
1-yr periods (start years: 1980, 1981, 1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2018)	max	0.123	525.28	2.71	2.84	1.4
	Q3	0.119	438.12	2.22	2.47	1.21
	median	0.116	393.53	1.99	2.3	1.11
	Q1	0.115	357.45	1.74	2.16	0.9
	min	0.108	228.1	0.86	2.0	0.55
	spread	13.0 %	130.0 %	213.0 %	41.0 %	155.0 %
2-yr periods (start years: 1980, 1982, 1984, 1986, 1988, 1990, 1992, 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016)	max	0.124	594.35	2.87	2.68	1.39
	Q3	0.121	529.7	2.12	2.51	1.24
	median	0.119	454.44	1.99	2.32	1.03
	Q1	0.117	433.0	1.78	2.14	0.81
	min	0.114	383.73	1.42	2.05	0.72
	spread	9.0 %	55.0 %	102.0 %	30.0 %	94.0 %
3-yr periods (start years: 1980, 1983, 1986, 1989, 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, 2016)	max	0.125	653.02	2.32	2.67	1.4
	Q3	0.122	598.4	2.04	2.4	1.05
	median	0.121	557.8	1.9	2.35	1.02
	Q1	0.118	536.79	1.83	2.31	0.92
	min	0.115	384.76	1.42	2.08	0.72
	spread	8.0 %	70.0 %	64.0 %	28.0 %	94.0 %
4-yr periods (start years: 1980, 1984, 1988, 1992, 1996, 2000, 2004, 2008, 2012, 2016)	max	0.125	751.28	2.77	2.66	1.4
	Q3	0.123	646.51	2.04	2.56	1.04
	median	0.122	613.24	1.92	2.35	1.01
	Q1	0.119	558.93	1.8	2.24	0.79
	min	0.116	420.82	1.41	2.07	0.72
	spread	7.0 %	79.0 %	96.0 %	29.0 %	95.0 %
5-yr periods (start years: 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2015)	max	0.125	718.57	2.25	2.62	1.39
	Q3	0.123	674.43	1.97	2.49	1.23
	median	0.122	608.48	1.83	2.33	1.07
	Q1	0.121	575.92	1.58	2.2	0.84
	min	0.119	511.4	1.39	2.08	0.72
	spread	5.0 %	41.0 %	62.0 %	26.0 %	94.0 %
6-yr periods (start years: 1980, 1986, 1992, 1998, 2004, 2010, 2016)	max	0.125	820.78	2.52	2.58	1.24
	Q3	0.125	797.47	1.97	2.43	1.03
	median	0.123	726.43	1.87	2.36	1.01
	Q1	0.12	649.74	1.6	2.29	0.94
	min	0.117	532.92	1.48	2.17	0.72
	spread	6.0 %	54.0 %	71.0 %	19.0 %	72.0 %

Table S5: **Distribution of capacities for various simulation lengths.** This data table supports Figure S5 and 5. Spread is defined as the relative difference between the max and the min: (max-min)/min × 100. The maximum is "spread" % greater than the minimum.

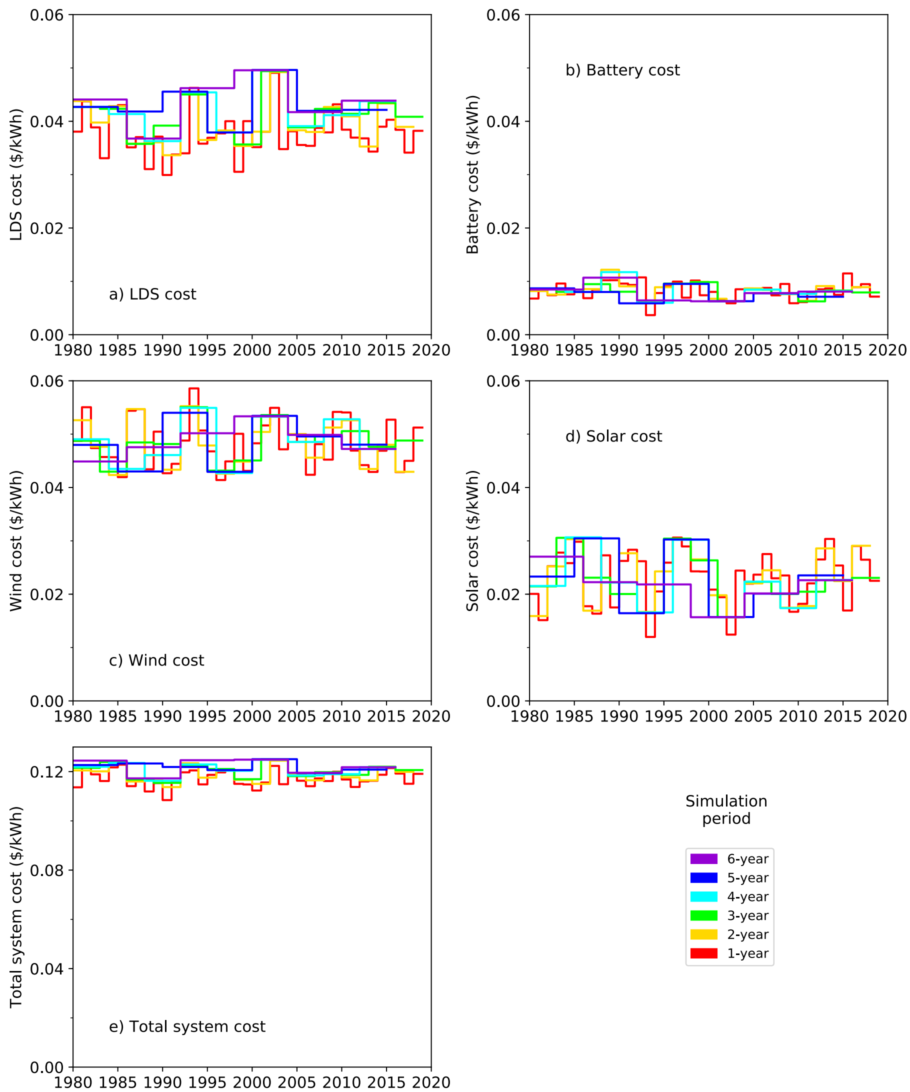
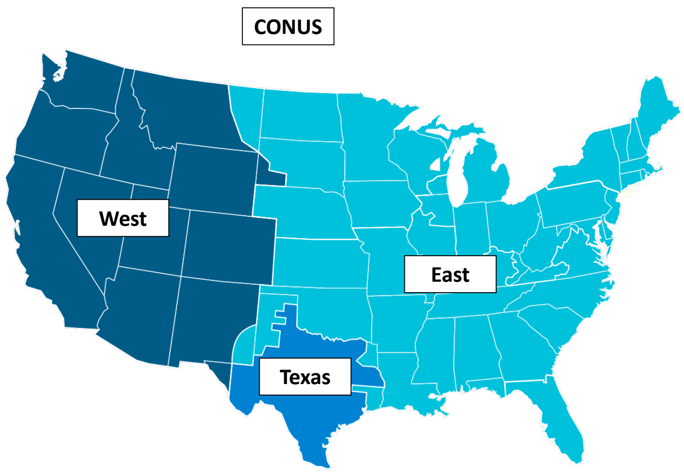


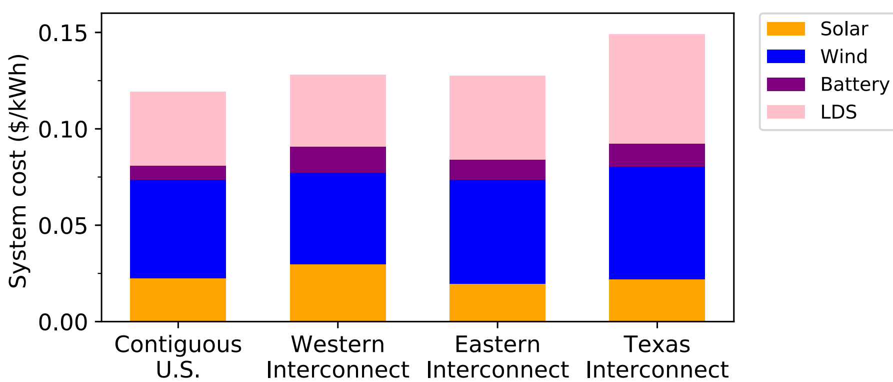
Figure S6: **Multiple year simulations: costs.** 1-, 2-, 3-, 4-, 5-, and 6-year simulations were performed across all 39 years of wind and solar data available (1980 to 2018) for the contiguous U.S. The horizontal sections of the lines represent the optimized investment in each technology for the periods simulated. Presented here are results for a) LDS cost, b) battery cost, c) wind cost, d) solar cost e) total system costs. LDS and wind technologies dominate system investments in all simulations periods across 1980-2018.

Simulation length (across 39 years, 1980-2018)	**Data type**	**Total system cost ($/kWh)**	**LDS cost ($/kWh)**	**Battery cost ($/kWh)**	**Wind cost ($/kWh)**	**Solar cost ($/kWh)**
1-yr periods (start years: 1980, 1981, 1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2018)	max	0.123	0.049	0.011	0.059	0.031
	Q3	0.119	0.039	0.009	0.051	0.026
	median	0.116	0.038	0.008	0.047	0.024
	Q1	0.115	0.035	0.007	0.045	0.02
	min	0.108	0.03	0.004	0.041	0.012
	spread	12.0 %	64.0 %	213.0 %	41.0 %	155.0 %
2-yr periods (start years: 1980, 1982, 1984, 1986, 1988, 1990, 1992, 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016)	max	0.124	0.049	0.012	0.055	0.03
	Q3	0.121	0.043	0.009	0.052	0.027
	median	0.119	0.038	0.008	0.048	0.022
	Q1	0.117	0.036	0.008	0.044	0.018
	min	0.114	0.034	0.006	0.042	0.016
	spread	9.0 %	46.0 %	102.0 %	30.0 %	94.0 %
3-yr periods (start years: 1980, 1983, 1986, 1989, 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, 2016)	max	0.125	0.049	0.01	0.055	0.031
	Q3	0.122	0.043	0.009	0.05	0.023
	median	0.121	0.041	0.008	0.049	0.022
	Q1	0.118	0.039	0.008	0.048	0.02
	min	0.115	0.036	0.006	0.043	0.016
	spread	8.0 %	39.0 %	64.0 %	28.0 %	94.0 %
4-yr periods (start years: 1980, 1984, 1988, 1992, 1996, 2000, 2004, 2008, 2012, 2016)	max	0.125	0.05	0.012	0.055	0.031
	Q3	0.123	0.044	0.009	0.053	0.023
	median	0.122	0.041	0.008	0.049	0.022
	Q1	0.119	0.039	0.008	0.046	0.017
	min	0.116	0.036	0.006	0.043	0.016
	spread	7.0 %	37.0 %	96.0 %	29.0 %	95.0 %
5-yr periods (start years: 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2015)	max	0.125	0.05	0.01	0.054	0.03
	Q3	0.123	0.044	0.008	0.052	0.027
	median	0.122	0.042	0.008	0.048	0.023
	Q1	0.121	0.042	0.007	0.045	0.018
	min	0.119	0.038	0.006	0.043	0.016
	spread	5.0 %	31.0 %	62.0 %	26.0 %	94.0 %
6-yr periods (start years: 1980, 1986, 1992, 1998, 2004, 2010, 2016)	max	0.125	0.05	0.011	0.053	0.027
	Q3	0.125	0.046	0.008	0.05	0.023
	median	0.123	0.044	0.008	0.049	0.022
	Q1	0.12	0.042	0.007	0.047	0.021
	min	0.117	0.037	0.006	0.045	0.016
	spread	6.0 %	35.0 %	71.0 %	19.0 %	72.0 %

Table S6: **Distribution of costs for various simulation lengths.** This data table supports Figure S6 and Figure 5. Spread is defined as the relative difference between the max and the min: (max-min)/min $\times$ 100. The maximum is "spread" % greater than the minimum.



(a) Contiguous U.S. and its three interconnects



(b) System costs of the contiguous U.S. its three interconnects

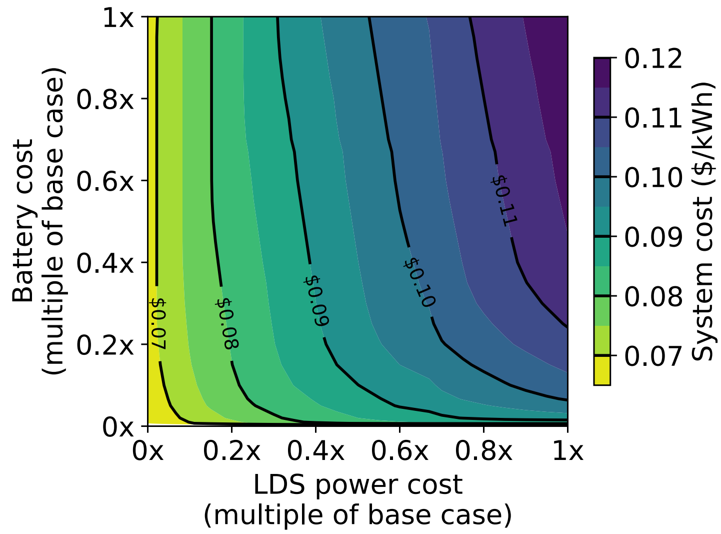
Figure S7: **System costs of different geographical regions.** System costs for the contiguous U.S. are compared to costs for systems confined to three largely independent interconnects: West, East, and Texas. Stacked areas in each bar represent the cumulative contribution of each technology to total system cost over the optimization period (2018). For each interconnect, the least-cost system includes substantial LDS and wind investment (66%, 76%, and 77% of total system cost for West, East, and Texas, respectively). The increased variability of wind and solar in small regions (such as Texas) requires compensation with more storage from both LDS and batteries. The map of the interconnects is adapted.[30] Table S7 supports this figure.

Region	**Wind**	**Solar**	**LDS**	**Battery**	**Total system cost ($/kWh)**
Contiguous U.S.	0.05	0.02	0.04	0.01	0.12
Western Interconnect	0.05	0.03	0.04	0.01	0.13
Eastern Interconnect	0.05	0.02	0.04	0.01	0.13
Texas Interconnect	0.06	0.02	0.06	0.01	0.15

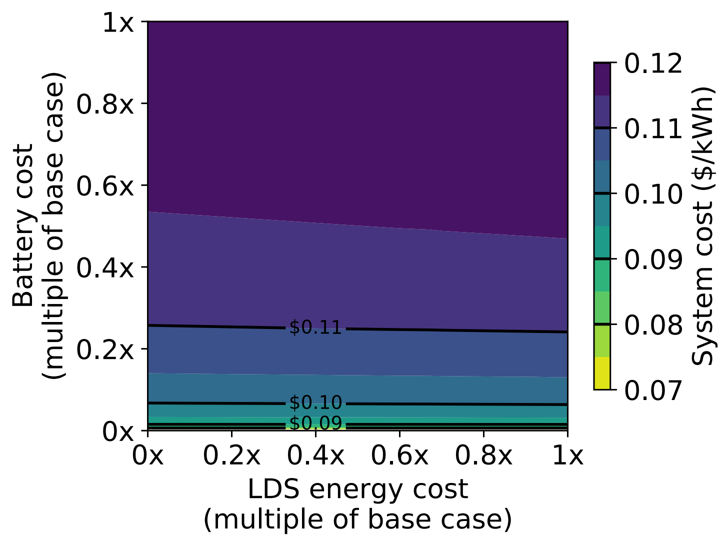
Table S7: **System costs of different geographical regions.** This data table supports Figure S7. Costs in $/kWh represent each technology's contribution to the total system cost. Costs for LDS include both power-related and energy-related costs. While rounded results are displayed in the table, exact values were used for secondary calculations.

Technology mix	**Wind**	**Solar**	**LDS**	**Battery**	**Total system cost ($/kWh)**
solar-battery	-	0.18	-	0.10	0.28
solar-LDS	-	0.12	0.13	-	0.25
solar-LDS-battery	-	0.09	0.05	0.05	0.19
wind-battery	0.18	-	-	0.05	0.23
wind-LDS	0.07	-	0.09	-	0.17
wind-LDS-battery	0.07	-	0.05	0.02	0.15
solar-wind-battery	0.09	0.04	-	0.02	0.14
solar-wind-LDS	0.05	0.02	0.06	-	0.13
solar-wind-LDS-battery	0.05	0.02	0.04	0.01	0.12

Table S8: **System costs with different technology combinations.** This data table supports Figure 6. Costs in $/kWh represent each technology's contribution to the total system cost. Costs for LDS include both power-related and energy-related costs. While rounded results are displayed in the table, exact values were used for secondary calculations.



(a) LDS power-capacity cost and battery total cost reductions



(b) LDS energy-capacity cost and battery total cost reductions

Figure S8: **Limiting factors of LDS and batteries.** Battery costs are varied as a total capacity cost while LDS energy capacity and power capacity costs are varied independently. a) Power-capacity and b) energy-capacity costs were reduced from base case assumptions (1x) to free (0x), and total system costs were plotted as contour lines ($/kWh). Each data point was a new simulation in which capacity and dispatch of each technology, including wind and solar generation, were reoptimized in response to each value of the conversion and storage costs. For batteries, we varied the total costs and maintained a 6 hour charging duration. Total electricity system costs in a least-cost system decreased substantially with reductions in LDS conversion costs and, to a lesser extent, battery storage costs. This behavior occurs because the use of LDS in the least-cost system is limited by power capacity, whereas the use of batteries is limited by their energy capacity.

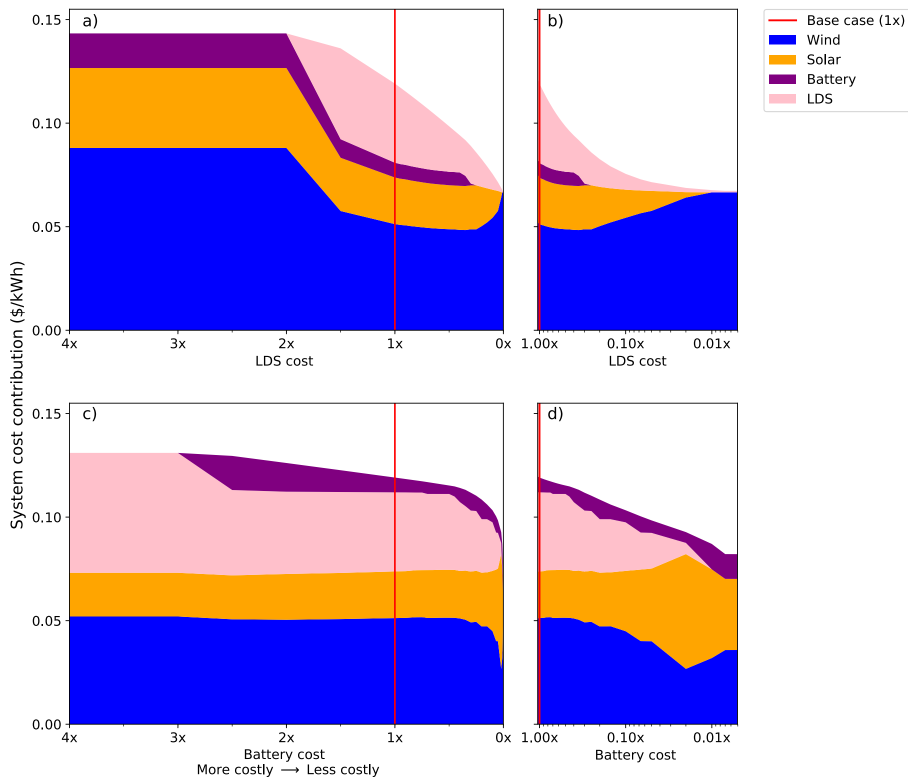


Figure S9: **System cost contributions vs. LDS and battery costs.** a, b) LDS and c, d) battery costs were varied from four times (4x) more costly than base case assumptions (1x) to free (0x). The contributions of each technology to the system cost for year 2018 are presented. Linear scale plots (a, c) showed that eliminating LDS from a least-cost electricity system required a ∼2x increase in costs relative to current costs, and batteries required a ∼3.5x increase in costs. The log scale plot of LDS cost reduction (b) showed that a ∼4-fold decrease in LDS costs (0.25x) eliminated batteries and reduced solar generation cost contribution. The log scale plot of battery cost reduction (d), showed that a ∼100-fold (0.01x) decrease in battery costs led to elimination of LDS and reduced cost contribution associated with wind generation.

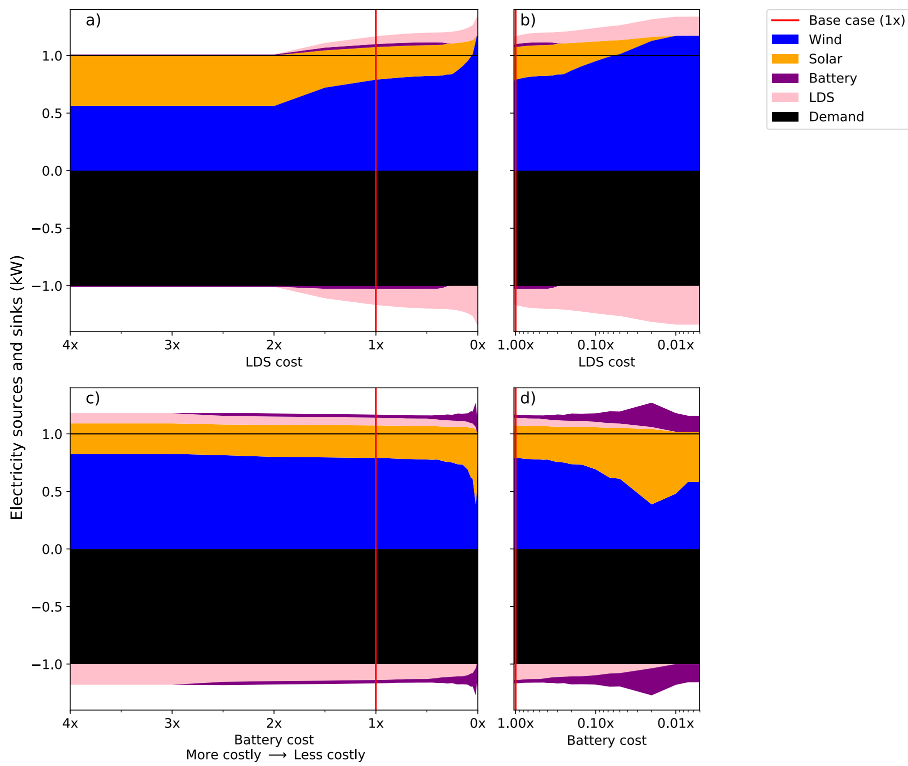
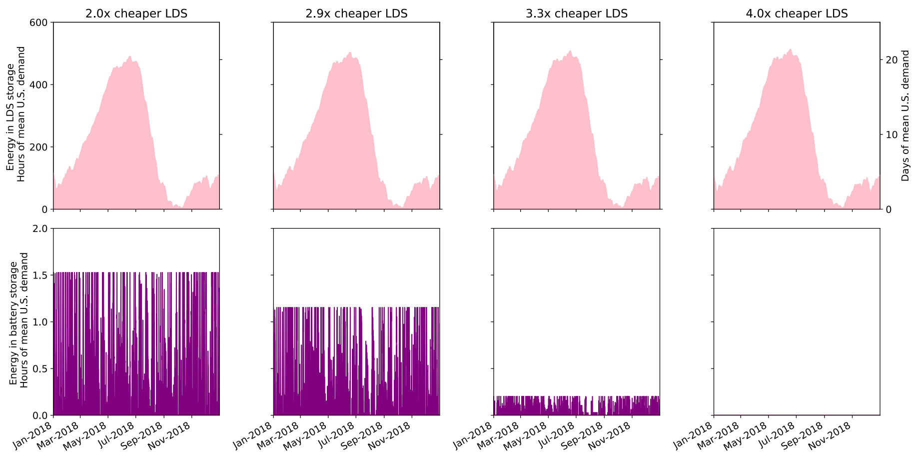
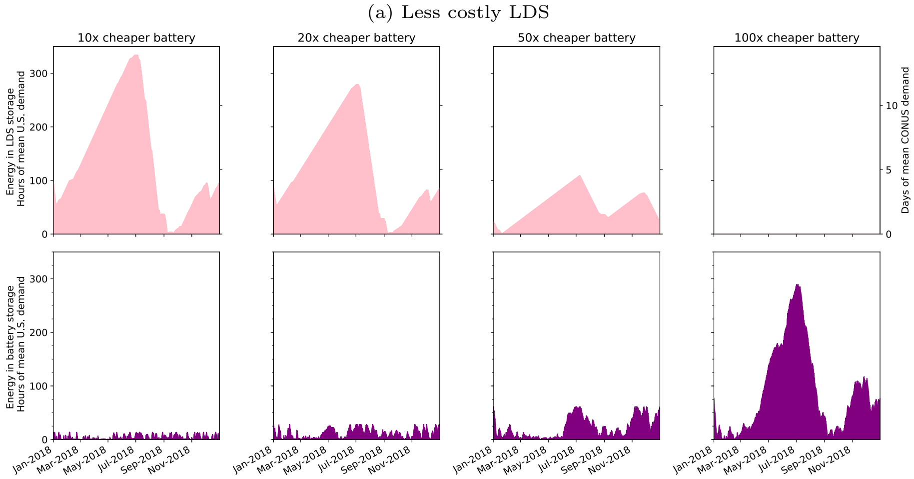


Figure S10: **Dispatched electricity as a function of LDS and battery costs.** a, b) LDS and c, d) battery costs were varied from four times (4x) more costly than base case assumptions (1x) to free (0x). Shares of electricity dispatched by each technology are shown on the y-axis. Total shares of electricity sources to the grid and those of electricity sinks from the grid are balanced for any hour in each simulation. The 49% round-trip efficiency of LDS is visually depicted in a, b) because the average power used for charging LDS was much larger than that obtained in discharging. This behavior can be compared to c, d) in which the 90% round-trip efficiency for batteries is evident. Cost contribution plots (Figure S9) in combination with power dispatch plots (Figure S10) allow determination of whether LDS's contribution to total system cost decreased because less LDS capacity was built or because LDS costs decreased.



(a) Less costly LDS



(b) Less costly batteries

Figure S11: **Cost-driven functional role dynamics.** This set of figures show energy stored in LDS and batteries at various costs. The top two rows of panels show that when LDS costs decrease at a factor of 4x, batteries disappear in the least-cost system. Despite lower LDS costs, LDS maintained its inter-season functional role, whereas batteries maintained their intra-day functional role. The bottom two rows of panels show that when battery cost is 100x cheaper, it is used more for inter-season storage than for purely intra-day storage, with the maximum energy stored in batteries reaching ~300 h of mean contiguous U.S. demand.

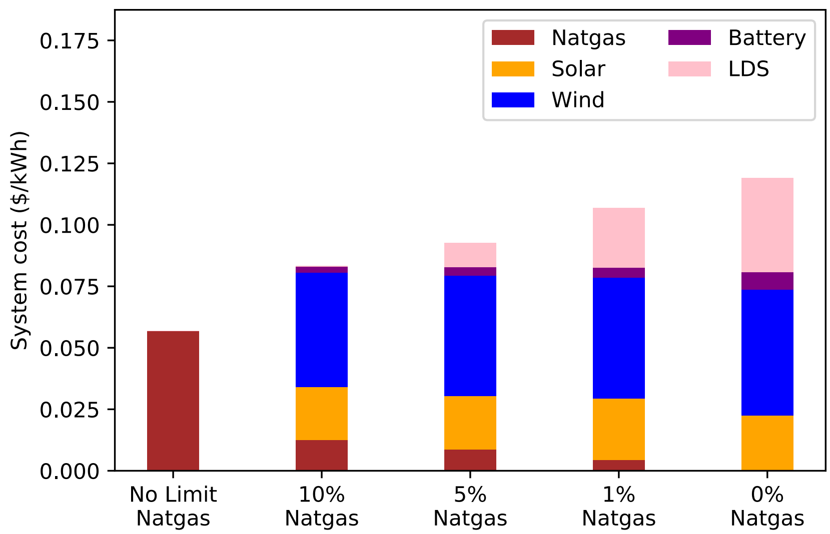


Figure S12: **Natural gas: System costs approaching a 100% decarbonized system.** A number of studies have shown that decarbonizing the electricity system becomes increasingly costly the close to 100% carbon-neutral the system is. We briefly explore these questions by allowing natural gas generators in our model but limit their annual dispatch to a fraction of total demand. We model 1) a system with current cost assumptions for natural gas with no limits on dispatch, 2) the same system with natural gas dispatch limited to 10% of annual demand, 3) natural gas limited to serving 5%, then 4) natural gas limited to 1% of demand. A reference bar is added that is the baseline no natural gas case modeled in the rest of this analysis. Stacked areas in each bar represent the cumulative contribution of each technology to total system cost over the optimization period (2018). Introduction of natural gas to the technology mix at 10% of demand minimizes or eliminates the need for storage. The system costs are: 1) 0.057 $/kWh, 2) 0.083 $/kWh, 3) 0.093 $/kWh, 4) 0.107 $/kWh, and 0.119 $/kWh for the reference case. Technical and economic inputs for natural gas are in Table S11.

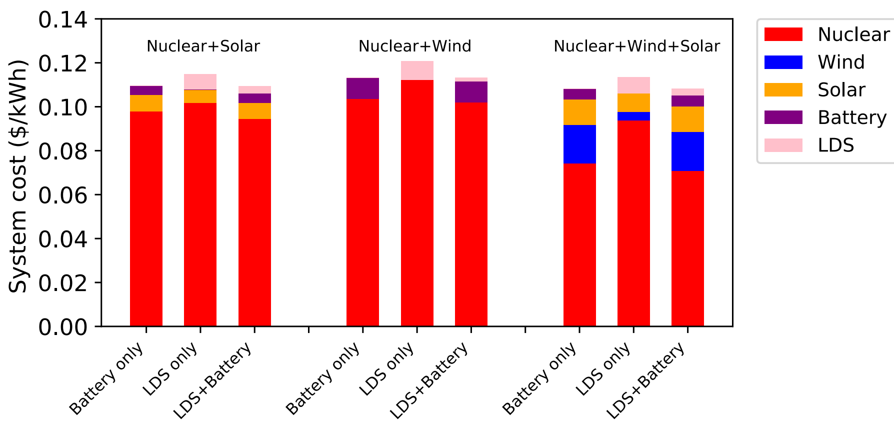


Figure S13: **Nuclear: System costs for different technology combinations.** In the left-most three bars, generation is provided only by solar energy and nuclear; in the middle three bars, by only wind energy and nuclear; and, in the right-most three bars, by a combination of solar, wind and nuclear resources. Within each grouping of three bars, the left-most bar represents a system with only LDS storage, the middle bar represents a system with only battery storage, and the right-most bar allows both storage technologies to compete. Stacked areas in each bar represent the cumulative contribution of each technology to total system cost over the optimization period (2018). Introduction of nuclear to the technology mix minimizes, but does not eliminate, the need for storage. Technical and economic inputs for nuclear are in Table S11.

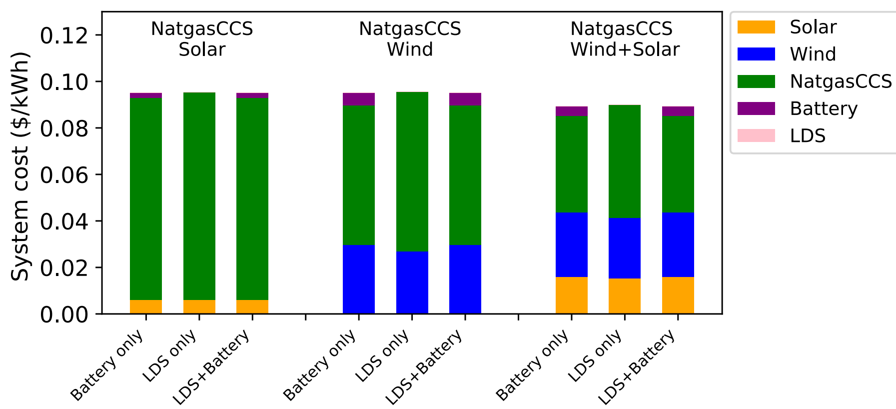


Figure S14: **Natural gas with carbon capture and storage (natgas CCS): System costs for different technology combinations.** In the left-most three bars, generation is provided only by solar energy and natgas CCS; in the middle three bars, by only wind energy and natgas CCS; and, in the right-most three bars, by a combination of solar, wind and natgas CCS resources. Within each grouping of three bars, the left-most bar represents a system with only LDS storage, the middle bar represents a system with only battery storage, and the right-most bar allows both storage technologies to compete. Stacked areas in each bar represent the cumulative contribution of each technology to total system cost over the optimization period (2018). Introduction of natgas CCS to the technology mix minimizes or eliminates the need for storage (especially LDS). Technical and economic inputs for natgas CCS are in Table S11.

4. Supplementary cost information

4.1. Base case long-duration storage technology: Power-to-Gas-to-Power (PGP) with renewable hydrogen

4.1.1. PGP underground storage

	Salt cavern (base case)	**Reference and comments**
Fixed capital cost ($)	7,434,940	Capital cost plus land costs for just the cavern (not compressor) H2A tab "Gaseous H_2 Geologic Storage" cell C217
Size (usable kg H2)	1,159,831	Default value in H2A model tab "Gaseous H_2 Geologic Storage" cell B103
Size (Energy rating, kWh)	45,697,341.40	Calculated here using the higher heating value (H2): 39.4 kWh/kg. From Hydrogen Delivery Scenario Model (HDSAM) V 3.1.
Fixed cost ($/kWh for storage)	0.16	Hydrogen Delivery Scenario Model (HDSAM) V 3.1. Note: Steward et al NREL report, (Table 3) quotes 0.16 $/kWh for dry mined salt caverns.
Lifetime (yrs)	30	Hydrogen Delivery Scenario Model (HDSAM) V 3.1.

Table S9: **Economic and technical assumptions for underground hydrogen storage.** Models and reports referenced.[31,32] This table supports Table 1. Figure 7b and Figure S8b show that results are not very sensitive to PGP energy capacity costs.

4.1.2. PGP electrolyzer + compressor combined fixed cost

Because electrolyzers and compressors are both power-rated conversion devices involved in the H_2 production step of PGP, we combined their fixed costs into one input variable for the model. To combine the fixed costs of electrolyzer and compressor devices, we determined the ratio of their system efficiencies as shown below.

Electrolyzer
Electrolyzer system efficiency = 67 kWh/kg[33]

Compressor
Design Flow to Each Compressor = 57,991 (kg/day)
Motor Rating per Compressor = 1,487 kW
Reference,[31] tab "Gaseous H_2 Geologic Storage", cell B138 and B145
Electricity required to compress 57,991 kg of H_2:
(1,487 kW) x 24 (h/day) = 35,688 kWh
Compressor system efficiency:
(35,688 kWh) / (57,991 kg H_2) = 0.6154 kWh/kg H_2

Electrolyzer / Compressor Ratio
Ratio of power consumption:
(67 kWh/kg) / (0.6154 kWh/kg) = 109
The electrolyzer consumes 109 times more power than the compressor for a given kg of H_2 that goes through the system. Thus, to combine the electrolyzer and compressor costs and put them into the units of the electrolyzer, we divide the fixed cost of the compressor by 109.

Combined fixed cost ($/kW for conversion)
Costs for electrolyzers and compressors in $/kW are in Table S10.
(1,045 $/kW) + (1392.2 $/kW)/109 = 1,058 $/kW
The combined electrolyzer + compressor fixed cost is represented as the H_2 production conversion cost in Table 1.

	Electrolyzer (PEM)	**Reference and comments**	**Compressor (Isentropic reciprocating)**	**Reference and comments**
Fixed capital cost ($)	118,258,606	Capital costs including O&M costs like labor PEM spreadsheet, tab "Capital costs", cell F36	2,070,236	H2A spreadsheet tab "Gaseous H_2 Geologic Storage" cell C182
Size (Power rating, kW)	113,125	Capital costs including O&M costs like labor PEM spreadsheet, tab "Capital costs", cell C41	1,487	H2A spreadsheet tab "Gaseous H_2 Geologic Storage" cell B182
Fixed cost ($/kW for conversion)	1,045 input into the electrolyzer[1]	Current Central Hydrogen Production from Grid PEM Electrolysis V3 2018	1392.2 used to compress[a]	Hydrogen Delivery Scenario Model (HDSAM) V 3.1
Lifetime (yrs)	10	Schmit, 2017[34]	15	H2A spreadsheet tab "Gaseous H_2 Geologic Storage" cell B160
Efficiency	70%	Current Central Hydrogen Production from Grid PEM Electrolysis V3 2018 tab "Process Flow" cell G12	100%	Assume no hydrogen leaks during compression.

Table S10: **Economic and technical assumptions for electrolyzers and compressors.** Models referenced include.[31,35] This table supports Table 1. Electrolyzer and compressor lifetime detail is available at the following link: `https://docs.google.com/spreadsheets/d/1nmrfp_s-C8Pqtqgyp3kgou2Pi8OtcXTFXiO-qWCvx9Q/edit?usp=sharing`.

[a]See electrolyzer + compressor combined fixed cost calculation. The electrolyzer consumes 109 times more power than the compressor for a given kg of H_2 that goes through the system. Thus, to combine the electrolyzer and compressor costs and put them into the units of the electrolyzer, we divide the fixed cost of the compressor by 109.

4.2. Firm generator technology costs

	Natural gas	**Natural gas with CCS**	**Nuclear**
Technology description	Conventional gas/ oil combined cycle	Advanced combined cycle with carbon capture and storage	Advanced nuclear
Total overnight capital cost [$/W]	982	2175	5946
Fuel cost [$/MMBtu]	3	3	-
Fuel cost [mills/kWh]	-	-	7.45
nth-of-a-kind heat rate [Btu/kWh]	6350	7494	10460
Fixed O&M cost [$/kW/yr]	11.11	33.75	101.28
Variable O&M cost [$/MWh]	3.54	7.20	2.32
Project life [yrs]	20	20	40
Calculated levelized costs			
Fixed cost [$/kWh]	0.012	0.027	0.065
Variable cost [$/kWh]	0.039	0.056	0.007

Table S11: **Economic and technical assumptions for natural gas, natural gas with CCS, and nuclear.** References included.[36–38] This table supports Figure S12, Figure S13, and Figure S14. An example calculation of fixed and variable costs for natural gas with CCS is in Table S12. Note: For nuclear we include only fuel costs as (in units of per kWh electricity not per kWh thermal) as variable costs and add all other non-fuel costs to the fixed cost.

4.2.1. Example calculation: natural gas with CCS fixed and variable cost

Variable cost calculation of natural gas with carbon capture and storage (NatgasCCS). This calculation supports Figure S14, Table S11, and Table S12.

Efficiency

Heat rate = 7493 (Btu/kWh)[36]
Heat content of electricity = 3412.14 (Btu/kWh)[39]
Efficiency: (1/7493) x 3412.14 = 0.4554

Fuel Cost

Fuel cost = 3 ($/MMBtu-thermal)[38]
Fuel cost = 0 (mills/kWh-electric)[38]
Heat content of electricity = 0.293 (MWh/MMBtu)[39]
Efficiency = 0.4554
Fuel cost ($/kWh-electric): (3/0.293/1000)/0.4554 + 0/1000 = 0.0225

Variable cost

Fuel cost ($/kWh-electric) = 0.0225
Efficiency = 0.4554
Variable O&M cost($/MWh) = 7.2[36]
Variable cost: (0.0225/ 0.4554) + (7.2/1000) = 0.0566

NatgasCCS: Fixed cost calculations	**Value**	**Reference and comments**
Capital cost ($/kW)	2175	EIA, AEO2018, Electricity Market Module, Table 2
Assumed lifetime (yrs)	20	EIA, AEO2018, Commercial Demand Module, Table 3
Capital recovery factor (% per year)	9.44%	Calculated with a discount rate of 0.07
Fixed O&M cost ($/kW-yr)	33.75	EIA, AEO2018, Electricity Market Module, Table 2
Fixed cost ($/kW-yr)	239.05	(capital cost * capital recovery factor) + fixed O&M cost
Fixed cost ($/kWh)	0.02727	Divide the cell above by hours in a year

NatgasCCS: Variable cost calculations	**Value**	**Reference and comments**
Fuel cost ($/MMBtu -thermal)	3	EIA, EPA2016, Table 7.20
Fuel cost (mills/kWh -electric)	0	EIA, EPA2016, Table 7.20
Heat rate (Btu/kWh)	7493	EIA, AEO2018, Electricity Market Module, Table 2
Efficiency	0.4554	Calculated here
Fuel cost ($/kWh -electric)	0.0225	Calculated here
Variable O&M cost ($/MWh)	7.2000	EIA, AEO2018, Electricity Market Module, Table 2
Variable cost ($/kWh)	0.0566	Calculated here

Table S12: **Economic and technical assumptions for natural gas with carbon capture and storage (NatgasCCS).** References included.[36–38] This table supports Figure S14 and Table S11.

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