Solar and wind energy can help to decarbonize electricity production but require other technologies, such as energy storage, to reliably meet demand. We study systems combining intermittent renewables with storage and other technologies and compare their electricity costs to alternatives. We estimate that in high-resource regions, with optimal resource mixes, low storage energy capacity costs (<$20/kWh) are necessary for cost-competitive, reliable baseload electricity generation. However, when other technologies meet 5% of demand, costs can be halved, even with significantly more expensive storage.
SUMMARY
Deeply decarbonizing electricity production will likely require that low-carbon sources meet energy demand throughout days, years, and decades. Wind and solar energy are possible low-carbon options, but resource variability can limit their reliability. Storage can help address this challenge by shaping intermittent resources into desired output profiles. But can solar and wind energy with storage cost-competitively fulfill this role? How do diverse storage technologies compare? We address these questions by analyzing systems that combine wind and solar energy with storage to meet various demand profiles. We estimate that energy storage capacity costs below a roughly $20/kWh target would allow a wind-solar mix to provide cost-competitive baseload electricity in resource-abundant locations such as Texas and Arizona. Relaxing reliability constraints by allowing for a few percent of downtime hours raises storage cost targets considerably, but would require supplemental technologies. Finally, we discuss storage technologies that could reach the estimated cost targets.

INTRODUCTION
Wind and solar energy technologies are two options for generating low-carbon electricity, and the costs of these technologies have dropped in recent decades while their market shares have grown.1–3 In some prospective analyses, these costs continue to fall to levels where the levelized cost of wind and solar electricity drops below higher-carbon alternatives.4

However, to allow intermittent wind and solar generation to meet demand, back-up generation, energy storage, expanded transmission infrastructure, demand-side management, and energy curtailment may be required,5–11 affecting the total costs of supplying solar and wind electricity. These costs are important to account for, as are the costs incurred by operating any type of power plant intermittently.

Among different approaches to addressing renewables’ intermittency, energy storage has certain advantages. Storage can require agreement from fewer decision-makers than transmission infrastructure expansion and may be easier to implement. It may allow for greater quantities of electricity to be time-shifted when needed than demand-side management and could achieve greater carbon emissions reductions than using back-up generation such as natural gas turbines.

Yet despite declines in recent decades,12 energy storage costs remain relatively high. Even in Texas, for example, which has one of the highest wind capacity factors
in the U.S., a modeled wind plant providing baseload power was found to require large amounts of compressed air energy storage (CAES), raising its cost above other options such as a combined cycle natural gas plant. There are signs of substantial cost decline, however, with recent bids for combination renewables with storage plants in Colorado and Hawai’i reaching costs comparable to those of natural gas peaker plants.

Determining cost targets at which the storage of wind and solar energy becomes cost-competitive requires a consideration of storage use context. In past work, for example, cost targets have been determined for storage performing renewable energy arbitrage in today’s electricity supply system, i.e. charging from wind or solar when electricity prices are low for later resale when demand and prices are higher. In this work, we focus instead on a potential future supply system that is further dominated by renewables. This work’s novel contribution is to estimate the costs of using wind and solar energy with storage to reliably supply various output profiles, while investigating the features of storage technologies that would be most beneficial.

We consider output shapes for wind and solar power plants with storage that resemble those observed in current electricity supply systems because guaranteeing these output shapes may provide one option for low-risk and easy integration of renewables into the generation mix. In current systems, a combination of price signals and generation costs divides generation into different grid roles: baseload, intermediate, and peaker power plants. These grid roles are defined by the electricity demand and the relationship between fixed and variable costs for conventional power plant technologies. Technologies with lower variable and higher fixed costs typically operate as baseload plants, while generation sources with higher variable and lower fixed costs operate as peaker plants.

Our analysis accounts for inter- and intra-year variation in the solar and wind resources and covers several locations with different levels of resource availability. This work extends beyond studies using data on a single year or a typical year by using twenty years of wind and solar resource data to capture the variations that may occur over a lifetime of a power plant. Moreover, we consider the effect of combining wind and solar energy to take advantage of the complementarity in their resource availability over time.

We designed our study to reflect key differences among energy storage technologies in order to gain insight into the cost features of storage and therefore types of storage technologies that can be most beneficial. We solve for the cost-minimizing renewable power capacity and energy and power capacities of storage for a particular use context and for differences across storage technologies in the capital cost intensities of their power capacity (e.g., in $/kW) and energy capacity (e.g., in $/kWh). This work builds on a method developed earlier but modifies the modeling objective so as to meet specified electricity output profiles rather than to perform energy arbitrage for profit maximization.

RESULTS

Our results are presented in three sub-sections. We first discuss results on the least-cost combinations of wind, solar, and energy storage installations that meet simplified baseload, intermediate, and peaker power plant output shapes. We then estimate cost targets for energy storage that would enable these plants to reach cost-competitiveness with traditional electricity sources. Finally, we discuss...
Cost-Minimized Wind, Solar, and Storage Installations for Baseload, Intermediate, and Peaker Power Plants

Here we examine how wind and solar energy and storage can be used to provide baseload, intermediate, and peak power outputs for twenty years across four locations representing different combinations of high and low resource availability (Table 1): Arizona, Iowa, Massachusetts, and Texas. In each location, we solve for the cost-minimizing operation (Figure 1) and sizing of wind and solar energy generation along with storage while varying technology costs and the installed capacity of wind and solar power (Figure 2).

Various factors affect the levelized cost of shaped energy (LCOSE, in $/kWh), including the location, degree of solar and wind mixing, output shape, and technology costs. The costs of energy from optimized systems are summarized in Figure 3 for two different storage technology cost structures, with power and energy capacity costs of $1,000/kW and $20/kWh (Tech I) and $700/kW and $150/kWh (Tech II). For both technology cost structures, round-trip efficiencies are 75%, and projected wind and solar total costs of ownership are $1,500/kW and $1,000/kW, respectively (see Experimental Procedures). Examples of technologies with costs similar to Tech I are pumped hydroelectric storage (PHS), compressed air energy storage (CAES), and proposed flow battery technologies using highly abundant and low-cost elemental constituents. Examples of Tech II might include future Li-ion batteries after further cost reduction, and possibly other closed battery technologies, flywheels, and supercapacitors. Results for other solar and wind costs are also available (Figures S56–S61).

We find that across locations and output shapes the least-cost resource portfolio draws on a combination of wind and solar energy (Figure 2). Consistent with their energy resource profiles (Figures S70 and S71), systems in Arizona favor solar in the wind-solar mix, while those in Texas favor wind. In Iowa and Massachusetts, a relatively balanced mix is preferred. For Tech I, the least-cost portfolio LCOSE values are lowest in Arizona and Texas and highest in Iowa and Massachusetts across all output shapes, while in all locations the peaker and bipeaker output shapes are roughly 1.3 times more costly than the intermediate and baseload shapes (Table S1). For Tech II, Arizona has the lowest LCOSEs across output shapes, and Massachusetts the highest, while Iowa and Texas have nearly identical LCOSEs for all roles except bipeaker (Table S2). In addition, for Tech II, peaker and bipeaker output shapes are 1.2 times as costly to produce as baseload and intermediate shapes are. In comparison, energy from competing technologies (e.g. natural gas) can be almost twice as expensive for peaker plants than for baseload.

Technology costs also impact the cost-minimized system sizes and LCOSEs of wind and solar plants with storage. As expected, the LCOSE rises with the costs of storage (Figure 3) and wind and solar energy technologies (Figures S56–S61). The effects of

Table 1. Twenty-Year Average Capacity Factors for Wind and Solar Resources

<table>
<thead>
<tr>
<th>Location</th>
<th>Wind Capacity Factor</th>
<th>Solar Capacity Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arizona</td>
<td>38.1%</td>
<td>34.1%</td>
</tr>
<tr>
<td>Iowa</td>
<td>51.7%</td>
<td>25.5%</td>
</tr>
<tr>
<td>Massachusetts</td>
<td>39.8%</td>
<td>24.2%</td>
</tr>
<tr>
<td>Texas</td>
<td>61.2%</td>
<td>31.0%</td>
</tr>
</tbody>
</table>
varying the wind and solar costs on the cost-optimal mix are shown in Figures 2 and S56–S59, with wind or solar emphasized in the installed power capacity mix as the costs of each technology drops. As storage energy capacity costs rise, the installed capacity of wind or solar generation relative to both storage energy capacity and plant output power generally increases for cost-minimized systems (Figures 4 and S49–S51). This is because for higher storage energy capacity costs, it is less expensive to install more renewables generation than to increase storage capacity, even if this leads to the renewables plant generating energy that is in excess of the energy used as baseload, intermediate, bipeaker, or peaker output. Figure 4 shows the drop in the ratio of renewable power to output power as storage energy capacity costs fall for the case of a baseload solar energy system in Iowa, where the solar power capacity ranges from 7.1 to 17 times greater than the output power.

Sizing renewables to have greater power capacity than the output shape power is a cost-reducing measure that is used in almost all of the cost-minimized systems

Figure 1. Storage System Operation
Twenty-year average storage operation for cost-minimizing systems for all locations, grid roles, and resources. The black line shows the output shape to be met while the dotted lines show storage charge and discharge operation when paired with solar (red) or wind (blue) resources. Power from both renewable generation and storage discharge combine to meet the output shape. Figures S2–S9 show additional detail, including the distribution of hourly storage behavior over the twenty-year period. The results in this figure are for cost-minimizing systems with generation costs of $1,500/kW for wind and $1,000/kW for solar and storage costs of $1,000/kW for power capacity and $20/kWh for energy capacity. These systems have an equivalent availability factor (EAF) of 100%, meaning that the output shape is met during 100% of the hours simulated. A similar plot for storage power and energy capacity costs of $700/kW and $150/kWh, respectively, is also available (Figure S1).
across the locations considered, and particularly for baseload and intermediate output shapes. This oversizing of renewables is typically reduced for an optimal wind-solar mix as compared to wind- or solar-only systems (Figure S51 versus Figures S49 and S50). The systems with lower storage power and energy capacities and higher renewables capacities generate greater amounts of excess energy (Figures S52–S54). In our model, this excess energy is curtailed and not assigned any economic value. However, we acknowledge that such value might be created in the future, thereby effectively lowering the cost of electricity.

The variability in resource availability over the twenty-year period also influences system characteristics and therefore the total plant cost. The impact of resource variability on the storage energy level is shown in the periods of deep discharge (Figure 5). The inter-year variability is particularly important in determining required system sizes and therefore costs, and this observation demonstrates the importance of studying system performance and energy cost using data over time spans longer than a year or two.

We find that allowing for periods of unmet demand relative to the desired output shape during infrequent but significant resource shortages can substantially reduce the costs of supplying electricity in baseload, intermediate, bipeaker, and peaker output shapes. A useful metric to quantify plant downtime is the equivalent availability factor (EAF): the

Figure 2. Electricity Cost Dependence on Wind-Solar Mix
Levelized cost of shaped electricity (LCOSE, $/kWh) for the four grid roles versus various combinations of wind and solar resources in Arizona, Iowa, Massachusetts, and Texas. Cost minima are marked with circles (+). The percent solar in the wind-solar mix is defined based on the installed power capacity of wind and solar generation (see Experimental Procedures). The results in this figure are for cost-minimizing systems with generation costs of $1,500/kW for wind and $1,000/kW for solar and storage costs of $1,000/kW for power capacity and $20/kWh for energy capacity (Tech I). These systems have an equivalent availability factor (EAF) of 100%. The results for Tech II ($700/kW, $150/kWh) are shown in Figure S10 while the impact of lowering the EAF to 99.9% is shown in Figures S11 (Tech I) and S12 (Tech II). Lowering the EAF to 99.9% in Texas causes a sizable change to the optimal wind-solar mix due to one large solar shortage event discussed in Experimental Procedures. Results for alternative generation costs are also available (Figures S56–S59).
The fraction of time during which the output shape is met over the time period considered (twenty years in this study). (See Experimental Procedures for the definition of EAF used here.) We present the effect of varying EAF from 100% to 80% in Figures 6 and 7. For both Tech I and Tech II this effect is greatest when wind or solar are used alone. Dropping the EAF from 100% to 95% for a wind or solar plant reduces the LCOSE by 33% on average when using Tech I and 55% when using Tech II. When the optimal mix of solar and wind are used, a reduction in EAF from 100% to 95% cuts the LCOSE by 25% on average for Tech I and 48% for Tech II.

In the case of a solar-only plant in Texas, dropping the EAF from 100% to 99.9% has a large impact on the LCOSE, as well as the optimal wind-solar mix, which for a Tech I system incorporates more solar for an EAF of 99.9% (Figure S11). Unmet demand hours for an EAF of 99.9% occur during a single large solar shortage event in Texas (Figure S20 versus Figure S28), whereas for an EAF of 100%, demand is met during this shortage event by increasing the storage duration significantly. This reported event in the Texas data highlights the importance of data validation (see Figure 3. Optimal Wind-Solar Mixes and Electricity Costs

Minimum levelized cost of shaped electricity (LCOSE, $/kWh) for the four grid roles (horizontal axis) and two different storage technologies (bar outline) in Arizona, Iowa, Massachusetts, and Texas. Bar color shading denotes the optimal resource mix as defined by the installed power capacities. To highlight the different sensitivities of the overall renewables and storage system cost to storage power and energy capacity costs, we selected two technologies with high/low cost combinations: Tech I (solid bar outline, $1,000/kW and $20/kWh) and Tech II (dotted bar outline, $700/kW and $150/kWh). Lower energy capacity costs yield lower LCOSE for all wind-solar mixes despite higher power capacity costs. The results in this figure are for cost-minimizing systems with generation costs of $1,500/kW for wind and $1,000/kW for solar and an equivalent availability factor (EAF) of 100%. Results for alternative generation costs are available in Figures S60 and S61.
Experimental Procedures) and careful study of rare events, which may not appear in every twenty-year period, when sizing systems for a particular EAF.

The periods of unmet demand associated with a reduction in EAF might be met by a combination of demand-side management (e.g. avoided demand) and supplemental generation (e.g. gas turbines). Alternatively, the resource shortages might be mitigated by spreading generation plants across a larger geographical area and expanding and improving the electricity transmission infrastructure. At a minimum, such systems could achieve costs comparable to those available in the best locations considered here, but only up to a limit imposed by resource constraints in the best locations. Understanding the potential for these mitigating technologies requires further study, but the results here suggest the significant impact they might have.

Cost and Performance Targets to Reach Cost-Competitiveness
Storage technology costs are the most significant impediment to the widespread adoption of stationary energy storage, though other performance factors are also important. At what storage costs do wind and solar energy systems with storage become cost-competitive with other generation technologies for reliably producing the output shapes studied here? Here we discuss cost targets for storage at which renewables-storage plants become competitive with other generation technologies. Figures 8, 9, and 10 compare the LCOE of combination renewables and storage plants with the estimated levelized cost of electricity (LCOE) of other generation technologies.
The LCOSE shows a higher sensitivity to storage energy capacity costs than to storage power capacity costs, as shown by the slopes of the iso-LCOSE lines. The percent reduction in LCOSE is generally less for a 50% reduction in storage power capacity costs than for a 50% reduction in storage energy capacity costs for the storage cost ranges shown in Figures 8, 9, and 10. The lowest LCOSEs for the use contexts examined here can be reached when using storage technologies with energy capacity costs at the lower end of the range considered, even when this is accompanied by a power capacity cost near the upper end of the range, where the range was chosen to cover current and potential future storage technologies. This finding is a result of the ratio of system energy to power capacity in the optimally sized storage systems for these use contexts, which corresponds to storage durations of about 6–180 hours (Figures S43–S45) and favors storage technologies with lower energy capacity costs relative to power capacity costs. Additional characteristics of cost-minimizing systems, including storage system power and energy capacities, the ratio of installed renewable power to system output power, and excess energy, are similarly presented in the Supplemental Information (Figures S37–S54).

We find that solar and wind energy plants with storage can be competitive with conventional generation technologies if storage energy capacity costs fall sufficiently...
(Figures 8, 9, and 10). A cost-optimal wind-solar mix with storage reaches cost-competitiveness with a nuclear fission plant providing baseload electricity at a cost of $0.075/kWh at an energy storage capacity cost of $10-20/kWh. To reach cost-competitiveness with a peaker natural gas plant at $0.077/kWh, energy storage capacity costs must instead fall below $5/kWh. To provide baseload, intermediate, bipeaker, and peaker electricity at $0.10/kWh with an optimal wind-solar mix, energy storage capacity costs must reach approximately $30–70/kWh, $30–90/kWh, $10–30/kWh, and $10–30/kWh, respectively. The Massachusetts and Iowa cost targets consistently fall at the lower end of the storage energy capacity cost target ranges, while those for Arizona and Texas are at the higher end. These cost comparisons all assume storage power capacity costs of $1,000/kW (the same as Tech I), a location- and technology-cost–specific optimal wind-solar mix, and output shapes defined in the Experimental Procedures. We note that the cost comparisons presented here do not account for external costs, including the costs of health and climate impacts, which can substantially increase the estimates of fossil-fuel based LCOEs given in Figures 8, 9, and 10.

When the EAF is relaxed, wind-solar systems with energy storage can reach competitiveness at higher storage costs. For example, allowing a system relying on an optimal wind-solar mix to fail to meet the specified output shape during 5% of hours (an EAF of 95%) enables it to reach cost-competitiveness with a nuclear baseload plant (electricity cost of $0.075/kWh) at storage capacity costs of $700/kW and $150/kWh (costs of Tech II) in Arizona and Texas, and nearly reach competitiveness in Iowa (Table S2). This EAF falls within the range estimated for current power plants in operation (see Experimental Procedures). However, we note that further research...
is needed to estimate the costs of supplying electricity during these failure hours if relying on a wind- and solar-dominated energy supply.

These results point to a number of different scenarios for achieving cost-competitive, reliable outputs from renewable energy systems using storage. These scenarios trade off storage technology innovation and cost reduction against a focus on complementary technologies such as demand-side management, supplemental generation, and transmission infrastructure expansion, alongside an optimal and location-specific diversification across wind and solar energy.

Evaluation of Candidate Storage Technologies
To meet the cost targets estimated in this paper, storage technologies should be able to achieve ultra-low energy capacity costs. Several mechanical and chemical storage systems may be suitable for achieving these target costs. Mechanical energy storage technologies, such as PHS and CAES, tend to have low energy capacity costs where suitable topography or underground caverns are available, with storage energy capacity costs estimated at under $20/kWh for some cases. PHS in particular has been proven to work for large-scale installations over many decades. However, both technologies also have geographical constraints due to the uneven availability of the required aboveground and underground features, which may inhibit further deployment. Moreover, while mechanical storage is scalable to large sizes, its energy density is considerably lower than electrochemical storage, and thus aboveground systems have larger spatial footprints. Electrochemical energy storage technologies face different limitations, including higher energy capacity costs compared to PHS and CAES, which are exacerbated by degradation over time.

Figure 7. Electricity Cost Dependence on Equivalent Availability Factor for Tech II
Levelized cost of shaped electricity (LCOE, $/kWh) plotted against equivalent availability factor (EAF) for baseload and peaker roles using only wind (A, D), only solar (B, E), or an optimal wind-solar mix (C, F) across four locations and Tech II energy storage. Reducing EAF lowers system LCOE. LCOE data for Tech II are shown in Table S2. Corresponding system characteristics such as storage power, storage duration, storage size, and installed renewable power are shown in Figures S29–S36 and the data are presented in Tables S3–S10. For solar-only systems in Texas, lowering the EAF from 100% to 99.9% has a large impact on LCOE due to a solar shortage event described in Experimental Procedures.
and the need for technology replacement. However, while every electrochemical technology degrades with use, those with exceptionally low energy capacity costs may allow a full replacement of the component chemicals with acceptable cost impact.

The ability to install an electrochemical storage system in many locations is one of the technology’s greatest advantages as compared to PHS and CAES. But what is the potential for cost decline? A recent bottom-up analysis compares the chemical cost of battery storage, defined as the cost of energy-storing compounds normalized by their stored energy, for 40 technologies developed over the past 60 years. The chemical cost represents an approximate cost floor for each battery technology, barring cost reductions in the materials’ extraction and refining processes or reductions in material requirements (i.e. the materials intensities). To this minimum, the costs of additional materials, manufacturing, and other processes and requirements must be added to arrive at a system cost. Taking Li-ion batteries as an example and using current materials prices and materials intensities, the aforementioned analysis estimates that there are several distinct chemistries for which the range of chemical costs is $35–$100/kWh. Under some assumptions, these batteries could meet the energy capacity cost targets needed to provide electricity that is cost-competitive with traditional sources, particularly for systems that are located in resource-rich locations, use near-optimal renewable resource mixes, and have relaxed EAF requirements.
Electrochemical batteries with energy capacity costs lower than those of Li-ion may also be possible, with several proposed aqueous electrochemical options having estimated chemical costs below $10/kWh. However, a low chemical cost does not always translate into low system cost. For example, high temperature sodium-sulfur batteries have a $1–$2/kWh chemical cost but a system level energy capacity cost exceeding $500/kWh. Ambient temperature batteries that use highly abundant, inexpensive chemical components in a low-cost architecture may achieve lower costs. Moreover, the long storage durations required, as well as the need to tune energy and power in order to optimize LCOSE in different locations and with different resources, may make a flow battery architecture beneficial, with its significant economies of scale and modularity in energy and power capacities. As with PHS and CAES and unlike Li-ion batteries, flow batteries have independently scalable energy and power performance characteristics. Their energy capacity is determined by the sizing of the energy-storing medium, whether mechanical or chemical, and their power capacity by the sizing of the power generator, whether a turbine or an electrochemical stack. Nevertheless, not all flow battery chemistries have low energy cost. For example, for the most widely studied variant, vanadium redox flow batteries, energy capacity costs have been estimated at $100/kWh. However, with continued development flow battery costs may decrease. Li et al. recently described a low energy capacity cost battery with energy capacity costs projected to be in the range of $10–$20/kWh. While differences exist in the methods used for projecting costs and assigning cost components to energy- and power-capacity categories, we note that, for many of the locations and grid roles...
We highlight only a few options here, but other energy storage candidates such as hydrogen, synthetic methane, and ammonia \cite{37,38} could be analyzed similarly. The approach and results presented here can be used to assess many current or proposed storage technologies.

**DISCUSSION**

Scenarios in which renewable resources grow to meet a majority of society’s energy needs require finding ways to make a fluctuating renewable energy supply reliably meet demand. Shaping renewables output to match the traditional grid roles of baseload, intermediate, and peaker plants is one possible solution. Here we ask how much energy storage is needed, and how much technological innovation and cost reduction might be required to cost-effectively enable this outcome.

We find that achieving ultra-low storage energy capacity costs is one path for renewables plus storage to cost-competitively fill this role. The cost targets for storage depend on the location and output shapes, since these cost-minimizing systems require different storage sizes. For baseload plants, for example, we estimate that...
storage energy capacity costs would need to fall to roughly $10-20/kWh to reach cost-competitiveness with a nuclear fission plant, assuming a storage power capacity cost of $1,000/kW, if wind and solar are used together in an optimal mix. The lower end of the storage capacity cost range applies in Massachusetts and Iowa and the higher end applies in Texas and Arizona.

Some technologies offer lower energy capacity costs, such as PHS and CAES, but their application is geographically limited in scale. Various studies have cited the potential for significant cost declines in currently available electrochemical storage technologies, such as Li-ion batteries, but it remains unclear whether the cost targets described here are achievable. Whether materials resource constraints will limit deployment at terawatt-hour scale also remains an open question for these and other electrochemical technologies. Our analysis points to the importance of developing storage technologies that utilize abundant low-cost energy capacity components.

We also find that various approaches can be used to reduce the need for storage and thus relax the storage cost targets. For example, reducing the EAF from 100% to 95% cuts the LCOSE nearly in half when considering near-term cost projections for modern batteries (e.g. Tech II, see Table S2). We estimate that this 5% relaxation in EAF alongside optimally combining wind and solar would allow systems using Tech II to reach competitiveness with nuclear fission baseload electricity in high resource locations such as Arizona and Texas. However, this does not consider the cost of meeting the remaining 5% of demand through other means, such as demand-side management (avoided demand), or supplemental generation (e.g. fossil or other). The costs of these supplemental technologies should be assessed and considered. In addition, improved transmission infrastructure could be used to transport energy from locations with plentiful resources to those without, smoothing the variability in the renewable resource through the geographical dispersion of generation, though these effects require further analysis.

The costs of these supplemental technologies and of energy storage will determine their optimal combinations. Our results outline several potential scenarios for enabling the large-scale deployment of wind and solar energy to reliably meet electricity demand despite the fluctuating availability of these renewable energy resources.

**EXPERIMENTAL PROCEDURES**

**Wind and Solar Resource Data**

Hourly wind speeds at 100 m altitude and solar irradiance for a twenty-year period from 1997 – 2016 were obtained from AWS Truepower for locations in Arizona, Iowa, Massachusetts, and Texas. These locations were chosen to span a range of higher- and lower-resource locations (e.g. higher wind (TX, IA); higher solar (AZ, TX); lower wind (MA, AZ); lower solar (MA, IA)), based on their average solar irradiance and wind speeds (Table 1). Within each state, co-located wind and solar data sets falling between the state’s 70th and 80th percentile for resource availability were selected so that the results would be representative of a sizable area within each state with similar or better solar and wind resources. The data sets sampled do not exclude areas that are unlikely to be developed, such as protected areas, bodies of water, urban areas, and terrain features with unfavorable slopes. However, the selected sites are located away from bodies of water and urban areas.

Wind generation was calculated by selecting a high-performer among 16 on-shore turbine models tested, using turbine-specific power curves developed from...
published data using linear interpolation. The Vestas 112 was selected for all locations, and 100 m wind speeds were adjusted to the 94 m turbine hub height using the “logarithmic law” wind speed profile.

Solar generation was calculated using NREL’s solar simulator PVWatts within its System Advisor Model. Solar irradiance, surface pressure, and temperature were read directly from the aforementioned AWS TruePower data files (Weather Research and Forecasting (WRF) Model files). Wind speed at PV module height was estimated using the aforementioned data and the “logarithmic law”. Photovoltaic plants were based on the default options for crystalline silicon modules, single-axis tracking configuration tilted at local latitude with default azimuth (180 degree). The remaining simulation parameters are summarized in Table S12.

One reported solar shortage event in Texas causes a significant change in the optimal mix for systems with an EAF of 100%, as shown in Figure 2 versus Figure S11, and causes a considerable drop in LCOE when the EAF is relaxed from 100% to 99.9% (see Figures 6 and 7). This event was observed in the solar irradiance data between November 12 and 22, 2004. Other data sets also report a significant shortage, but with considerable solar irradiance on November 19, 2004. Further validation of this event and the fidelity and accuracy of all resource data should be pursued in future work and when sizing systems. To draw conclusions that are robust to these data uncertainties, we consider and present a range of values in the Supplemental Information for systems with EAFs of less than 100%, whose cost-minimizing characteristics likely depend on a larger number of shortage events and are therefore less affected by data uncertainty surrounding a single event.

Solar Energy, Wind Energy, and Energy Storage Technology Costs

The total cost of ownership for the wind plant was set to $1,500/kW, and the PV plant cost was set to $1,000/kW based on recent data and trends for utility-scale one-axis tracker systems. These costs are for near-term, future plants (entering into operation within a few years) and reflect the total cost of ownership, though in a simplified form where these costs are summed and treated as ‘overnight’ costs and then amortized when determining the cost of electricity (Equations 7, 8, and 9).

We assumed greater cost declines in solar energy than wind energy, as has been observed recently. We note that these costs are necessarily rough estimates given the significant uncertainty about future cost change (even in the near term), the limited data on costs in excess of installation costs (i.e. additional costs reflected in the total cost of ownership), and the variation in costs expected across locations. For this reason, we also varied the cost assumptions to investigate the impacts of other generation costs, with results available in Figures S56–S61. We examined a case with a wind plant cost of $1,000/kW and PV plant cost of $1,500/kW as well as a case where both wind and PV plant costs were $1,000/kW.

Ranges of storage power capacity costs ($0–$2,000/kWh) and energy capacity costs ($0–$300/kWh) were used as simulation inputs, in order to cover a variety of cost combinations for current and potential future technologies. Storage round-trip efficiency was assumed to be 75% for the base case simulations but was varied from 55% to 95%, with results available in the Supplemental Information (Figures S62–S69).

The model assumes that any combination of energy and power capacities is allowed if it meets the constraints of the modeled use case. For truly modular technologies,
increasing power capacities requires one set of components, whereas increasing energy capacity requires another set of components. The assumption of modularity is more appropriate for some technologies (e.g., PHS, CAES, and flow batteries) and less for others (e.g., Li-ion batteries). However, for batteries that are less modular, the overall costs tend to be dominated by the energy capacity costs components, partly as a result of how the cost estimates have been constructed, with shared cost components being assigned to the energy capacity costs. For the use case considered here, the optimal energy capacity to power capacity ratios are high enough that treating these non-modular technologies as modular, while assigning most battery cost components to energy capacity rather than power capacity, yields a reasonable least-cost estimate for storage costs.

**Output Shapes and Equivalent Availability Factors**

Four output shapes were considered (Figure 11). The baseload plant provides a constant output for every hour of the twenty-year period, with a capacity factor of one. The intermediate shape is designed around the hours during which residential, commercial, and industrial loads operate, providing output from 08:00–22:00 daily. The peaker output covers the high demand period of 12:00–18:00. Finally, a fourth shape, the bipeaker, was defined to cover the hours from 08:00–11:00 and 18:00–22:00. This shape is designed to mitigate a side-effect of increasing reliance on solar energy resources, colloquially known as the “duck curve”, by generating during the hours before and after sunset. For each day, the number of in-demand hours are: 24 for baseload, 14 for intermediate, 7 for bipeaker, and 6 for peaker.

We also define an equivalent availability factor (EAF) as the fraction of in-demand time over twenty years during which the system is able to meet the output shape.
Partial delivery of the output power for a given hour is considered downtime and is counted toward hours when the system is not able to provide output. Among IEEE standard definitions, the EAF is most comparable to one minus the equivalent demand forced outage rate (1–EFOR_d) but the EAF would be lower than 1−EFOR_d for the same plant operation because the EAF does not count partial delivery. Historical estimates of 1−EFOR_d for competing technologies are 89.7%, 92.0%, and 97.3% for natural gas, coal, and nuclear plants, respectively. The highest EAF considered in our analysis is 100%, but we note that some maintenance downtime is likely for any power plant in operation. In the case of renewables, it may be possible to plan for maintenance during hours of low resource availability or off-demand hours (for outputs other than baseload). Some unexpected maintenance during in-demand hours may still be required, and we do not model the effects of this. Thus our modeled 100% EAF plants should be interpreted as achieving an EAF that is close to but likely slightly less than 100% in actual operation, assuming that the historical resource data on which sizing is based is representative (e.g. capturing key features of resource fluctuations) of future resource availability during plant operation. These effects require further study.

Storage Operation Simulation and LCOSE Minimization

Cost optimization of wind and solar resources with storage to meet a defined output shape was performed in two steps. For each wind-solar mix and output shape pair, all combinations of storage power capacity, $E_{max}$, and duration, $h$, and combined solar and wind power capacity, $P_{renewable} = P_{solar} + P_{wind}$, were simulated to produce a shaped output over the test period. For each time step, $\Delta_t$, renewable electricity generation, $x_g,t$, is obtained by combining solar and wind electricity generation, $x_{s,t}$ and $x_{w,t}$. We define $\tilde{x}_s,t = x_{s,t}/(P_{solar}\Delta_t)$ and $\tilde{x}_{w,t} = x_{w,t}/(P_{wind}\Delta_t)$, and $f_s = P_{solar}/P_{renewable}$. The electricity output, $x_{d,t}$, is defined by one of the output shapes considered in Figure 10 with an output power $P_{output}$. The state of charge, $x_{soc,t}$, is defined by the fraction of stored energy over the storage energy capacity. At the beginning of the twenty-year period, the state of charge is set to 1 (storage is full). At the end of the last time step, it is set to 0 (storage is empty). We define a roundtrip efficiency for energy storage, $\eta$, which is applied on charging. A binary availability variable, $x_{a,t}$, is then determined at each time step, $t = 1, ..., T$.

$$x_{g,t} = P_{renewable}\Delta_t(f_s\tilde{x}_s,t + (1 - f_s)\tilde{x}_{w,t})$$  \hspace{1cm} (Equation 1)

$$x_{d,t} = \begin{cases} P_{output}\Delta_t & \text{if output hours} \\ 0 & \text{otherwise} \end{cases} \hspace{1cm} (Equation 2)$$

$$x_{ch,t} = \begin{cases} \min(\eta(x_{g,t} - x_{d,t}), \eta E_{max}\Delta_t, (1 - x_{soc,t})\delta E_{max}) & \text{if } x_{g,t}>x_{d,t} \\ 0 & \text{otherwise} \end{cases} \hspace{1cm} (Equation 3)$$

$$x_{dch,t} = \begin{cases} \min(x_{g,t} - x_{d,t}, E_{max}\Delta_t, x_{soc,t}\delta E_{max}) & \text{if } x_{g,t}<x_{d,t} \\ 0 & \text{otherwise} \end{cases} \hspace{1cm} (Equation 4)$$

$$x_{soc,t} = \begin{cases} 1 & \text{if } t = 1 \\ x_{soc,t-1} + \frac{(x_{ch,t-1} - x_{dch,t-1})}{\delta E_{max}} & \text{otherwise} \end{cases}$$  \hspace{1cm} (Equation 5)
Our analysis uses a test period of twenty years, a time step ($\Delta t$) of 1 hr, 175,320 total time steps ($T$), and a round-trip efficiency ($h$) of 75% (in the base case). In the second step of the analysis, $E_{\text{max}}$, $h$, and $P_{\text{renewable}}$ are selected to minimize the LCOSE for each pair of storage power and energy capacity costs. The LCOSE expression considers electricity delivered in shaped output and corrected for by the the percentage of hours during which the system supplies sufficient power (i.e. does not fail). $H_d$ is the number of in-demand hours per day, as defined above: 24 for baseload, 14 for intermediate, 7 for bipeaker, and 6 for peaker. $C_s$, $C_w$, $C_p$, and $C_e$ are the total costs of ownership per unit solar power capacity, wind power capacity, storage power capacity, and storage energy capacity, respectively.

$$\text{Minimum LCOSE} = \min_{E_{\text{max}}, h, P_{\text{renewable}}} \left( \frac{\text{CRF} \times C_{\text{system}}}{P_{\text{output}} \Delta t \times \sum_{t=1}^{T} x_{s,t}} \right)$$

subject to,

$$\sum_{t=1}^{T} x_{s,t} \geq \frac{H_d}{24} \times T \times EAF. \quad (\text{Equation } 8)$$

The cost of ownership of the total system, $C_{\text{system}}$, can be expanded to:

$$C_{\text{system}} = P_{\text{renewable}} (f_s C_s + (1 - f_s) C_w) + E_{\text{max}} C_p^s + h E_{\text{max}} C_e^s. \quad (\text{Equation } 9)$$

The capital recovery factor applied here ($\text{CRF} = (r(1 + r)^n)/(1 + r)^n - 1)$) assumes an annual discount rate ($r$) of 5%, a twenty-year plant lifetime ($n$), and equal yearly payments.4,27,60,61 If two systems have identical LCOSE values, the minimization favors the energy storage system with the lower duration, even if it has a higher power capacity.

**LCOE from Competing Technologies**

The levelized cost of electricity (LCOE), in real 2017 US dollars, from other technologies was estimated to allow for a comparison to the modeled LCOSE. We use the same values for $H_d$ as we do in estimating LCOE for each of the output shapes, and the EAF for our base case LCOSE’s (100%). (This gives capacity factors ($H_d/24 \times EAF$) roughly comparable to those used to model the operation of baseload (85% – 90%) as well as peaker (30%) plants4,27 as well as the aforementioned 1–EFORj values.) We consider all output shapes for natural gas power plants, and only the intermediate and baseload output shapes for coal and nuclear plants, given their typical operation. We use the same CRF (and $r$ and $n$) as we do for the LCOSE calculations. Values for overnight construction costs (SC), fixed operations and maintenance (O&M) costs (OM$\text{fixed}$), variable O&M costs (OM$\text{var}$), and fuel costs (FC) were based on published estimates for near-term future plants entering into operation in 2022.27,62

$$\text{LCOE} = \left( \frac{\text{CRF} \times SC + OM_{\text{fixed}}}{H_d P_{\text{output}} \times 365 \times \text{EAF}} \right) + OM_{\text{var}} + FC \quad (\text{Equation } 10)$$

**SUPPLEMENTAL INFORMATION**

Supplemental Information can be found online at https://doi.org/10.1016/j.joule.2019.06.012.
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AUTHOR CONTRIBUTIONS

J.E.T. and M.S.Z. wrote the paper with contributions from J.M.M., G.D.P., J.S., M.F., and Y.M.C. J.E.T. led the research. M.S.Z., J.M.M., G.D.P., and J.S. wrote the code, ran the simulations, and visualized the results. J.E.T., M.S.Z., and J.S. analyzed the results. All authors contributed to the research concept and paper content.

DECLARATION OF INTERESTS

M.F. and Y.M.C. are co-founders of Form Energy, Inc. Y.M.C. is a co-founder of 24M Technologies, Inc.

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