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Planning reliable wind- and solar-based electricity systems

Tyler H. Ruggles [a,1,*], Edgar Virgüez [a,1,*], Natasha Reich [b], Jacqueline Dowling [a], Hannah Bloomfield [c], Enrico G.A. Antonini [a,d,e], Steven J. Davis [f], Nathan S. Lewis [b,g], Ken Caldeira [a,h,*]

[a] Department of Global Ecology, Carnegie Science, Stanford, CA, United States
[b] Division of Chemistry and Chemical Engineering, California Institute of Technology, Pasadena, CA, United States
[c] School of Engineering, Newcastle University, Newcastle, England, UK
[d] CMCC Foundation, Euro-Mediterranean Center on Climate Change, Lecce, Apulia, Italy
[e] RFF-CMM European Institute on Economics and the Environment, Milan, Lombardy, Italy
[f] Department of Earth System Science, Stanford University, Stanford, CA, United States
[g] Beckman Institute, California Institute of Technology, Pasadena, CA, United States
[h] Gates Ventures, Kirkland, WA, United States

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ABSTRACT

Resource adequacy, or ensuring that electricity supply reliably meets demand, is more challenging for wind- and solar-based electricity systems than fossil-fuel-based ones. Here, we investigate how the number of years of past weather data used in designing least-cost systems relying on wind, solar, and energy storage affects resource adequacy. We find that nearly 40 years of weather data are required to plan highly reliable systems (e.g., zero lost load over a decade). In comparison, this same adequacy could be attained with 15 years of weather data when additionally allowing traditional dispatchable generation to supply 5 % of electricity demand. We further observe that the marginal cost of improving resource adequacy increased as more years, and thus more weather variability, were considered for planning. Our results suggest that ensuring the reliability of wind- and solar-based systems will require using considerably more weather data in system planning than is the current practice. However, when considering the potential costs associated with unmet electricity demand, fewer planning years may suffice to balance costs against operational reliability.

1. Introduction

Electricity systems that rely predominantly on variable renewable resources will require different approaches to ensure acceptable reserve margins and resource adequacy (i.e., a median loss-of-load-expectation of zero [1]) than those used for systems that rely on firm, dispatchable generation. The historical approach to planning (i.e., identifying the required capacities necessary to reliably supply electricity) and regulatory approval for systems based on fossil fuel resources generally uses averaged demand and generation data to establish a safety or "reserve" margin of generating capacity [2].

With increasing generation from wind and solar resources, innovative system planners are pursuing methods to constitute new safety margins (e.g., flexible reserve margins) in their planning processes [3]. New planning processes are critical because these resources exhibit substantial variability on timescales that range from seconds to years, introducing new challenges [2,4,5]. Thus, a better representation of the spatiotemporal variability of wind and solar resources is required [6,7]. The reliability of wind- and solar-based electricity systems has been studied by characterizing extreme events that jeopardize the systems' ability to meet demand at all times. Some of these studies focus on the characterizations of events with low availability of wind or solar resources [8,9], weather patterns that pose high stress on the system [10,11], or the influence of regional geophysical resource variability on the necessary adjustments for wind and solar-based electricity systems to operate reliably [12–15]. Additionally, climate change may introduce further variability in the future than in the 20th century [16,17].

Given inter-annual variability of wind and solar resources [4,18,19] and occasional wind or solar "droughts" [6,9], the reliability of electricity systems based on such resources may be improved by

* Corresponding authors at: Carnegie Science, Stanford, CA, United States.
E-mail addresses: truggles@carnegiescience.edu (T.H. Ruggles), evirguez@carnegiescience.edu (E. Virgüez), kcaldeira@carnegiescience.edu (K. Caldeira).
[1] These authors contributed equally (equally contributing first authors).

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incorporating multiple years of weather data into models used for planning. Indeed, studies have shown that electricity systems that rely primarily on variable renewable generation, and are designed to be 100 % reliable based on a single year of resource and demand data, may have very different generation capacities and lower system costs when compared to systems designed to remain reliable over multiple years of varying weather [20–23]. Similarly, systems that are planned including weather years with extreme weather events will have higher costs compared to systems that are planned based on average weather years. The former systems may operate more reliably in years with other extreme events [20].

Studies have thus analyzed the operational characteristics necessary to firm an electricity system based on wind and solar resources (e.g., necessary energy storage requirements) [24], how to optimize the use of existing capacities (e.g., economic dispatch models) [24], and how to optimize capacity building over a defined period of time (e.g., capacity expansion models) [25,26]. However, previous work in the long-term system planning space, where capacity expansion models are applicable, has largely neglected an analysis of how resource adequacy improves as models are optimized over longer periods of time. Thus, the trade-off between increasing systems' cost and their improved reliability has not been quantified to our knowledge, nor have studies quantified the benefits of representing more weather years for systems with different technical characteristics.

Here, we assess the trade-offs among cost, asset capacities, and the resource adequacy of idealized solar- and wind-based electricity systems, as well as the incremental cost of increasing resource adequacy as a function of the number of years of weather data used in electricity system planning. We used the ERA5 dataset of historical weather data from 1979 to 2020 to derive wind and solar resource profiles at 4-hour time steps for each of 42 calendar years over the contiguous United States (hereafter referred to as the U.S.) [27]. We calculated plausible synthetic electricity demand profiles for each weather year [28], including diurnal patterns of non-heating and non-cooling loads and the influence of temperature variation on electrical heating and cooling. Next, we determined least-cost system configurations (i.e., planned systems) using a macro-scale energy model based on different numbers of years of weather data. The model identified the least-cost electricity system and the costs of building, operating, and maintaining system assets while it ensured that 100 % of demand was supplied in each time step of the planning years. The number of years of weather data used to plan the different least-cost systems was varied from 1 to 40 years. As a greater number of years of weather data were used to plan systems, more weather variability was considered. Lastly, we tested (i.e., operated systems) the resource adequacy of the designed systems over 10 randomly selected years of weather data not used for planning. This process allowed the assessment and comparison of the annual hours of lost load, asset capacities, and system costs for 114,600 operational years as a function of the number of years of weather data that were used to plan the electricity system.

We repeated this analysis for three illustrative electricity system scenarios representing different plausible electricity systems. First, we model a scenario with exclusively solar and wind power generation in conjunction with battery storage (*Solar+wind+battery*). This is the most limiting scenario because the only dispatchable, albeit highly energy-constrained, technology is battery storage. While future continent-scale energy systems will undoubtedly contain a wider array of generation and storage technologies, the *Solar+wind+battery* scenario illustrates a technology set that has been studied and currently exists in certain micro-grid and island regions where combustion fuels may be costly and difficult to acquire [29,30]. The second scenario uses solar and wind generation, battery storage, and dispatchable generation (DG) (modeled as natural gas-fired generation) constrained to meet no more than 5 % of the total energy demand (*Solar+wind+battery+DG*). This scenario illustrates a limiting low-carbon emission scenario with low capital cost, flexible, firm generation that can buffer the system from the most severe instances of weather variability. Flexible, dispatchable generation has been shown to substantially reduce electricity costs in systems heavily dependent on variable renewable generation [31]. Additionally, considering the useful lifetime of gas plants being built today, it is possible many regional to continental power systems will transition through a low-emission state with substantial solar and wind generation and constrained rates of natural gas dispatch [32]. The third scenario includes solar and wind generation, battery storage, and access to a hydrogen power-to-gas-to-power system to provide seasonal or long-duration energy storage (*Solar+wind+battery+H_2*). Long-duration energy storage (LDES) is considered a potential key technology in future net-zero emissions energy systems. LDES has been shown to increase the utilization of wind and solar assets while decreasing the cost of electricity in low- and zero-emission electricity systems, compared to systems without such technologies [33,34]. Inter-annual weather variability may affect systems containing LDES differently than systems with shorter duration energy storage, such as the *Solar+wind+battery* scenario. This is because LDES can operate on a seasonal cycle as opposed to daily weather cycles, which drive the behavior of shorter duration energy storage.

2. Experimental procedures

The Experimental Procedures section describes the model, critical model inputs, and the steps in the study workflow, and is split into multiple sections. First, an overview of the model is presented in the ***Macro-scale energy model*** section, while a full mathematical formulation of the model is presented in the ***Model formulation*** section of the Supplementary Material. Second, the data used to define the inputs is described in the ***Model inputs*** section. Lastly, the ***Scenarios of input weather data*** section presents the methodology for selecting the specific sets of input data used for system planning.

2.1. Macro-scale energy model

A reduced-order, parsimonious, macro-scale energy model (MEM) was used to represent a continental-scale electricity system across the U. S. [33,35–38]. The model assumed lossless transmission from generation to load across the U.S., and hence had a single node with the U.S. as the load-balancing region. A least-cost optimization was performed using a linear program that solved for the installed capacities and dispatch of the system assets. At each 4-hour time step, energy was balanced in the model, with the electricity load supplied equal to the dispatched power plus the dispatched stored energy. Ramp rates were not constrained for any modeled technology.

2.2. Model inputs

The model was based on existing technologies and current cost estimates (Table 1). Calculation of the parameters in Table 1 can be found in the ***Model formulation*** section of the Supplementary Material (Table S1). The fixed capital investment for each system component represented the purchase cost and installation of each component, including all ancillary components and needs during installation such as instrumentation, piping, electrical, buildings, and service facilities [39]. The resulting fixed hourly cost included the fixed capital investment plus fixed annual operation and maintenance costs. Variable operation and maintenance costs and variable fuel costs were included as appropriate. Batteries were assumed to have a 1 % per month self-discharge rate and a 1:4 power-to-energy ratio. This ratio was based on market trends for Li-ion systems that have been paired with solar PV to reduce solar curtailment and better align power output with electricity system demand [40–42]. Proton exchange membrane (PEM) electrolyzers were used to convert electricity into hydrogen.

Wind and solar resources were represented by 4-hourly time series of capacity factors derived from the ERA5 weather reanalysis data [28].

Table 1
Techno-economic values for electricity technologies.

Economic parameter	Solar PV [43]	Wind [43]	Combined-cycle gas turbine [43]	Utility-scale battery storage [44]	Electrolysis facility [45]	Salt cavern H_2 storage [46,47]	Molten carbonate fuel cell [48,49]
Fixed capital cost $\left(\frac{\$}{KW_e}\right)$	1,300	1,300	950	370 $\left(\frac{\$}{yW_e}\right)$	1,100	0.21 $\left(\frac{\$}{kWHh_e}\right)$	5,000
Fixed O&M cost $\left(\frac{\$}{yrkW_e}\right)$	15	26	12	12	36	0.016 $\left(\frac{\$}{yrkWh_e}\right)$	43
Lifetime (yr)	25	25	30	10	7 stack, 40 BoP, 15 compressor	30	20
Heat rate $\left(\frac{Btu}{KWh}\right)$	-	-	6,370	-	-	-	-
Fixed hourly cost* $\left(\frac{\$}{hkW_e}\right)$	0.015	0.016	0.010	0.0074 $\left(\frac{\$}{hkWh_e}\right)$	0.021	3.7e-6 $\left(\frac{\$}{hkWh_{LKH}}\right)$	0.058
Relative efficiency	-	-	54 %	90 % round-trip	70 % (LHV)	0.01 % per year	70 %
Variable O&M cost $\left(\frac{\$}{kWh_e}\right)$	0	0	0.0019	0 (applied in fixed O&M)	0	0	0
Variable fuel cost** $\left(\frac{\$}{kWh_e}\right)$	-	-	0.019	-	-	-	-
Total variable cost*** $\left(\frac{\$}{kWh_e}\right)$	0	0	0.0210	0	0	0	0

* Calculations are based on our assumed discount rate of 7 %.
** The variable fuel cost for the combined-cycle plant is based on $3/MMBtu natural gas.
*** Calculations are based on the variable O&M and variable fuel cost.

Solar capacity factors were calculated using a horizontal single-axis tracking system with a tilt ranging from 0° to 45°. The solar panel power output was calculated based on the in-plane irradiance and module temperature [50]. Wind capacity factors were calculated based on a representative wind turbine with a 100 m hub height and a 1.6 MW nameplate capacity [51–53]. The turbines had a cut-in speed of 3 m s^{-1}, a maximum output at 12 m s^{-1}, and a cut-out speed of 25 m s^{-1}. Annual mean capacity factors were calculated for each ERA5 grid cell. Aggregate time series were then produced using an area-weighted average of the 25 % of these ERA5 cells that had the highest annual capacity factors. This aggregation smoothed the resource profiles by averaging over a quarter of the U.S. cells, thus producing a less variable profile while using the most productive regions. This historical weather dataset had a mean wind capacity factor (CF) of 29 % and solar CF of 26 %, which are comparable to the U.S. mean wind CF of 35 % and solar CF 25 % for installed projects [54]. Within our 42-year dataset, the variability in the mean of the annual capacity factors, calculated using relative standard deviation, for wind generation was 4.80 %, and 1.49 % for solar electricity generation (Fig. S5).

A synthetic demand profile was used to preserve any correlations between wind and solar availability and electricity load. The methods developed by Waite and Modi in their study of future peak electricity demands and load profiles were used to calculate plausible electricity demand across the U.S. [55]. Waite and Modi constructed a predictor of historical electricity demand as a function of temperature based on U.S. building stock information and U.S. Census American Community Survey Data 2010. Their predictors minimize the sum of squares between the predicted monthly electricity usage and actual 2010 monthly state-level electricity usage for each building class. A plausible hourly electricity load for a 2010-type building stock from years 1979 through 2020, concurrent with the wind and solar profiles, was calculated using this approach in conjunction with historical hourly ERA5 temperatures. The calculations were performed at the census tract level, then aggregated to obtain a total for the U.S.

2.3. Scenarios of input weather data

We first designed system builds by optimizing asset capacities and dispatch using different lengths of input weather data assembled by concatenating randomly sampled years from the 42-year dataset (P_{years} = 1, 2, 3, 4, 5, 7, 10, 15, 25, and 40). In this design phase, we constrained the model to meet electricity demand in each time step, resulting in 100 % resource adequacy. We then tested the performance and evaluated the resource adequacy of each designed system against 10-year-long input weather and demand data (operation years: $O_{years} = 10$) built by concatenating randomly sampled years from the years not used for planning. These tests used a dispatch-only mode in which the asset capacities were fixed. Thus, some systems could not supply all the demanded electricity, leading to lost load. These steps are illustrated in Fig. 1.

The specific years of input data were selected using a bootstrapping resampling method where years were selected randomly with replacements from the 42-year data set (1979-2020). The case with the longest weather record ($P_{years} = 40$) typically sampled 25 to 28 distinct weather years (Fig. S7). There were always > 10 non-overlapping years available for inclusion in the O_{years}. The cases with the shortest weather record ($P_{years} < 10$) had almost always distinct years.

The random selection process that determined the years in each simulation allowed modeling many different possible systems for each scenario P_{years}, with the set of simulations that had the same P_{years} value designated as an ensemble. Ensembles of 500 systems were modeled for $P_{years} \leq 10$, ensembles of 150 systems were modeled for $P_{years} = 15$ and for $P_{years} = 25$, and ensembles of 20 systems were modeled for $P_{years} = 40$, for a total of 3,820 systems. Afterward, lost load tests were performed over $O_{years} = 10$ of weather data for each system resulting in testing over 114,600 operational years for all systems and all three scenarios.

3. Results & discussion

The Results & Discussion section describes the main results of the study and discusses their relevance in a global context. Characteristics of the planned systems are described in the ***System costs and capacities*** section, followed by an analysis of the lost load resulting from testing the planned systems in the ***Resource adequacy*** section. Next, the tradeoff between system costs and resource adequacy is analyzed in the ***Marginal***

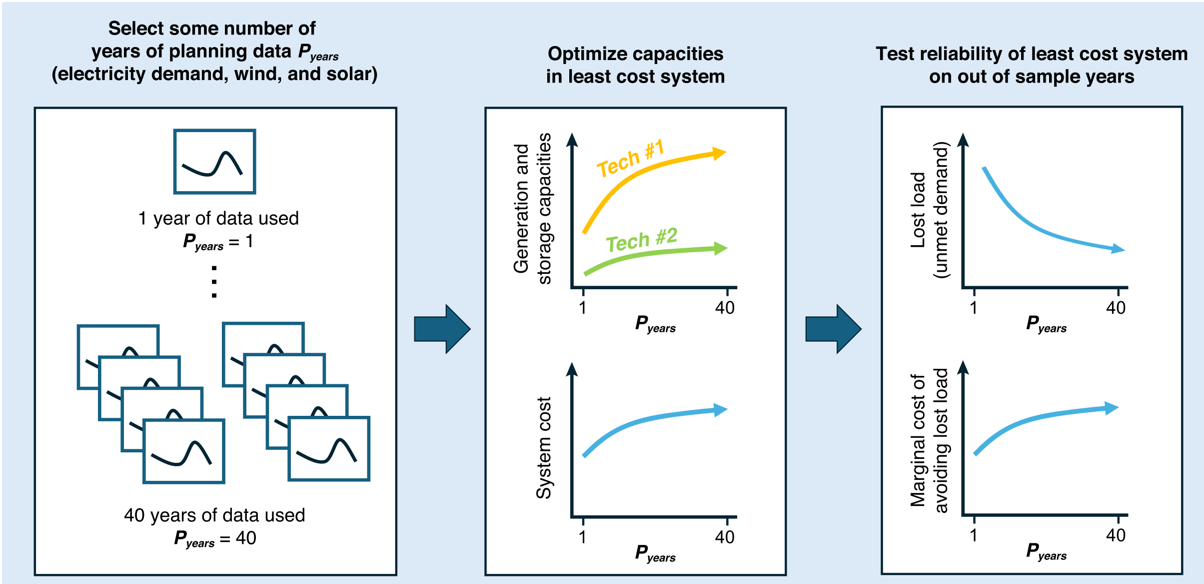

Fig. 1. Schematic analysis workflow. The analysis workflow is split into three steps. In the first step, data is selected for use as input data for the system planning model. Sets of input data are created of varying lengths, including random weather years from the 42 years of historical weather data. In the second step, the least-cost systems are planned using their input data and require zero lost load. The asset capacities and system costs are the main parameters of interest from the second step. In the final step, the planned systems are tested by operating each of them on 10 years of historical data that were specifically not used during the system planning process. Asset capacities are held fixed during this last step; thus, lost load results when planned systems are incapable of meeting 100 % of electricity demands.

costs of avoided lost load section. Finally, a detailed analysis of the specific years of data used for planning versus the years used for testing is presented in the ***Critical weather years*** section. This section is followed by a ***Discussion*** where all the results are interpreted.

3.1. System costs and capacities

Resource adequacy during the operating years improved as more years of weather data (P_{years}) were used to plan the system. But this increase in reliability came at the expense of an increase in the levelized cost of electricity (LCOE), regardless of the technologies available (Fig. 2a–c). Due to the lack of dispatchable generation, *Solar+wind+battery* systems were particularly sensitive to wind and solar variability, with an overall higher LCOE. They exhibited rapid increases in LCOE as P_{years} increased (Fig. 2a). In contrast, when dispatchable generation, modeled as natural gas-fired generation, was permitted to supply up to 5 % of electricity demand (Fig. 2b), the dispatchable generation was used during ~20 % of the hours. This dispatchable generation largely compensated for weather variability and limited the average increase in LCOE for reliable *Solar+wind+battery+DG* systems to just 3.0 % between P_{years}=1 and P_{years}=40 (Fig. 2b). Due to the availability of dispatchable stored hydrogen, the planned *Solar+wind+battery+H_2* systems were less costly than *Solar+wind+battery* systems, yet were more costly than the *Solar+wind+battery+DG* systems (Fig. 2c).

In least-cost idealized systems, the availability of dispatchable generation (e.g., natural gas) substantially reduced wind and solar capacities and decreased curtailment. For example, when systems were planned using one year of weather data (P_{years}=1), the average wind and solar generation capacities were 37 % and 43 % greater in *Solar+wind+battery* systems than in *Solar+wind+battery+DG* systems, respectively (Table 2). Meanwhile, 60 % of available wind and solar generation was curtailed, on average, in the *Solar+wind+battery* systems, as compared to 38 %, on average, in *Solar+wind+battery+DG* systems.

As P_{years} increased, capacities of different technologies did not increase uniformly. In *Solar+wind+battery* systems (Fig. 2d), average solar and battery capacities increased by 71 % and 110 % between P_{years}=1 and P_{years}=40, respectively, but wind capacities decreased by 18 %. For P_{years}=1, these systems had substantial variability in their planned asset capacities indicating that optimal system builds were strongly affected by the different weather years (Table 2). The observed increase in solar capacity and decrease in wind capacity is supported by Rinaldi et al. [36] who find severe, persistent wind droughts across the U.S. have historically occurred much more frequently than severe, persistent solar droughts. Thus, when planning over increasing numbers of years, there is a higher probability of sampling a year with a severe, persistent wind drought that necessitates expanding solar and battery capacities to make up for the wind generation shortfall. In addition to lower frequencies of severe, persistent resource droughts, the inter-annual variability of total solar availability is much lower than for wind (Fig. S5).

Solar+wind+battery+DG (Fig. 2e) systems exhibited relatively little change in the mean values of asset capacities as P_{years} increased, and show the system optimization is not greatly sensitive to the weather inputs. The exception to this insensitivity is that the dispatchable generation capacity increased by 39 % between P_{years}=1 and P_{years}=40 (with a corresponding decrease in utilization rate; Fig. 2e). The relative insensitivity of asset capacities for *Solar+wind+battery+DG* systems to P_{years} is further supported by the smaller spread in asset capacities for P_{years}=1 compared to the *Solar+wind+battery* systems (Table 2). In the *Solar+wind+battery+H_2* scenario, as P_{years} increased from 1 to 40 years, wind, solar, and electrolyzer capacities remained relatively constant (each changed by less than 15 %; Fig. 2f) due to the availability of dispatchable stored hydrogen. In contrast, the hydrogen storage and fuel cell capacities increased substantially, by 62 % and 45 %, respectively (Fig. 2f), which is consistent with studies showing that longer modeled time horizons increase the value of long-duration storage [13,15,33]. Additionally, battery capacity decreased by 41 % – representing the largest relative decrease in asset capacity among the systems evaluated.

Figs. S8 through S11 compare asset capacities and system costs for systems initialized using 1-, 2-, 3-, and 4-hour time step resolution. These model results are remarkably insensitive to the tested differences in resolution, similar to the findings of Pfenninger [26] and Gonzato [56]. This insensitivity is because the weather events that most strongly

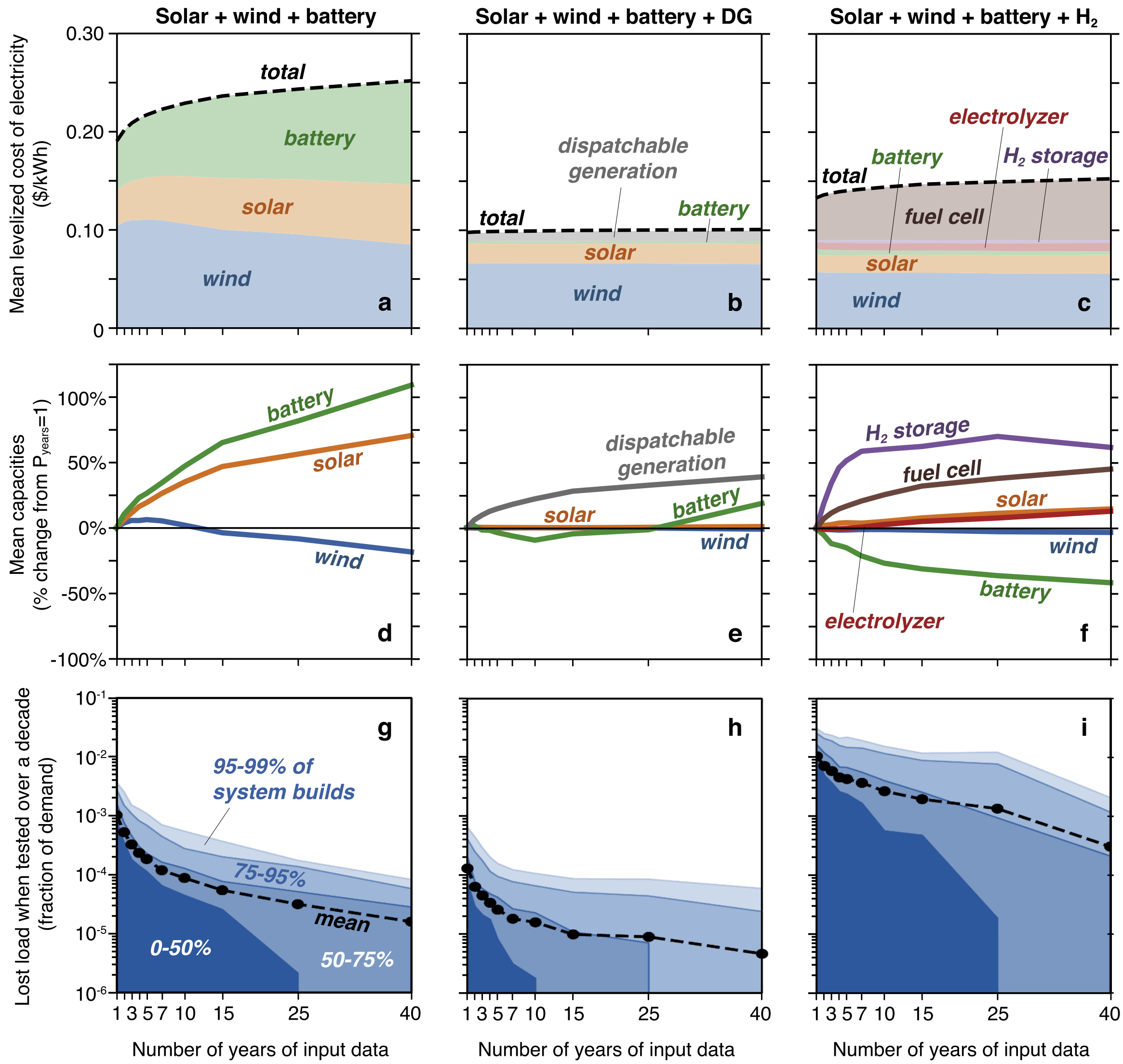

Fig. 2. System costs, capacities, and lost load. The top panels (a,b,c) show the mean levelized cost of electricity as the number of years used in system planning (P_{years}) increases. These panels reflect only the planned systems. Across all studied systems, as P_{years} increased, mean costs increased. The middle panels (d,e,f) show how the mean asset capacities changed as P_{years} increased. Across the three studied scenarios, as P_{years} increased, the planned systems increasingly favored different technologies, with some asset capacities increasing while others remained relatively unchanged or decreased. Plotted values are the mean values from the ensemble of planned least-cost systems. The bottom panels (g,h,i) show the lost load (unsupplied demand) from operational resource adequacy tests as the number of years of weather data used in system planning, P_{years}, increased. Each planned system was tested over ten randomly selected years of weather data not previously seen by the model for system operation ($O_{years} = 10$ years). Lost load decreased, and thus reliability increased, in each system as P_{years} increased. Including even a second year of weather data into system planning halved, on average, the amount of unsupplied demand during system operation tests.

influence system builds for the capacity expansion-type model used in this study are multi-hour or longer events as opposed to shorter-duration (hour length) fluctuations in resource availability or demand, which would be smoothed by 4-hour averaging.

3.2. Resource adequacy

Least-cost systems planned using a single year of weather data (P_{years}=1) frequently failed to meet electricity demand when operated over ten randomly-selected, out-of-sample years of weather data (Fig. 2). The lost load in operational years (O_{years}) was calculated as a percentage of mean demand (i.e., (total demand – total supplied demand)/total demand). This resulted in 0.082 % lost load for *Solar+wind+battery*, 0.0074 % for *Solar+wind+battery+DG*, and 1.00 % for the *Solar+wind+battery+H_2* scenarios (Fig. 2g–i). The black line represents the average lost load over each ensemble, while the color-shaded areas indicate the fraction of simulations corresponding to specific lost load levels. For example, the dark blue area represents the lost load for the half of the operational simulations with the least lost load per ensemble as we increase the number of years of input data.

Incorporation of a second year of weather data in system planning (incrementing from P_{years}=1 to P_{years}=2) decreased lost load in all systems by >50 %, with the largest decrease (61 %) observed for *Solar+wind+battery+DG* systems. Notably, 100 % resource adequacy was not obtained in half of the decade-long operational tests (O_{years}=10) until P_{years}=15 for the *Solar+wind+battery+DG* scenario, and until P_{years}=40 for the *Solar+wind+battery* and *Solar+wind+battery+H_2* scenarios. For reference, due to selecting years with replacement, the P_{years}=40 simulations were planned with at most 29 distinct years of weather data, leaving 13 or more out-of-sample years for operating each system (Fig. S7). In general, severe wind droughts with 24-hour average wind power output near 10 % of nameplate capacity were prevalent during the most extreme lost load events regardless of season. Moreover, these events were exacerbated during hotter months (April through October),

Table 2

Mean capacities and 5 percentile to 95 percentile spread values for systems built with one year of weather data by scenario. The "-" values indicate a technology was not included in the associated scenario. Percentile spread values are relative and are reported as percentages of the mean capacities.

Technology	Capacity unit	*Solar+wind+battery*	*Solar+wind+battery+DG*	*Solar+wind+battery+H₂*
Solar	% mean demand	$240^{+90\%}_{-40\%}$	$140^{+14\%}_{-11\%}$	$110^{+28\%}_{-32\%}$
Wind	% mean demand	$650^{+40\%}_{-45\%}$	$410^{+12\%}_{-7\%}$	$350^{+11\%}_{-13\%}$
Battery	Useful energy as hours of mean demand	$6.9^{+86\%}_{-49\%}$	$0.3^{+65\%}_{-53\%}$	$0.9^{+96\%}_{-72\%}$
Natural gas generation	% mean demand	-	$75^{+19\%}_{-15\%}$	-
Electrolyzer	% mean demand for input power	-	-	$20^{+23\%}_{-17\%}$
H_2 storage	Useful energy as hours of mean demand	-	-	$490^{+30\%}_{-29\%}$
Fuel cell	% mean demand for output power	-	-	$70^{+24\%}_{-22\%}$

which were additionally characterized by high solar output coincident with elevated cooling demand (Fig. S13).

3.3. Marginal costs of avoided lost load

Fig. 3 summarizes the relationships among lost load, system costs (LCOE), and the number of years of weather data used to plan the idealized least-cost electricity systems. As expected, across all scenarios, lost load decreased and costs increased as P_{years} increased (Fig. 3a and Fig. 3b). However, the benefits of such improved resource adequacy can be expensive, as shown by the increase in marginal cost of avoided lost load (i.e., the increase in LCOE divided by the reduction in lost load as P_{years} increases) when more years of weather data were used in planning the *Solar+wind+battery* and *Solar+wind+battery+DG* scenarios. Resource adequacy targets for U.S. power systems are typically characterized by reliability thresholds that often do not incorporate a value of lost load into their processes. However, the modeling approach used herein required zero lost load in the planning years, and assumed a value of lost load of \$10/kWh (a representative value found in many capacity expansion-type energy system models [57]) during operational tests. Under this approach, increasing P_{years} beyond 1 for the *Solar+wind+battery* and beyond 2 for the *Solar+wind+battery+DG* scenarios yielded a marginal cost of lost load avoided that exceeded the value of lost load. Additionally, the marginal cost of lost load asymptoted after P_{years}>10 years for the systems without H_2. In contrast, for the *Solar+wind+battery+H_2* systems, the marginal cost of avoided lost load was less than \$10/kWh, even when P_{years}=40, and showed the value of adding more years of weather data when planning least-cost *Solar+wind+battery+H_2* systems.

3.4. Critical weather years

In addition to testing least-cost systems operated during 10 randomly-selected out-of-sample weather years (operational years O_{years}=10; Fig. 2g–i), high- and low-resource availability years were identified that resulted in higher/lower resource adequacy when operating the planned electricity systems. Weather years 1989, 1996, and

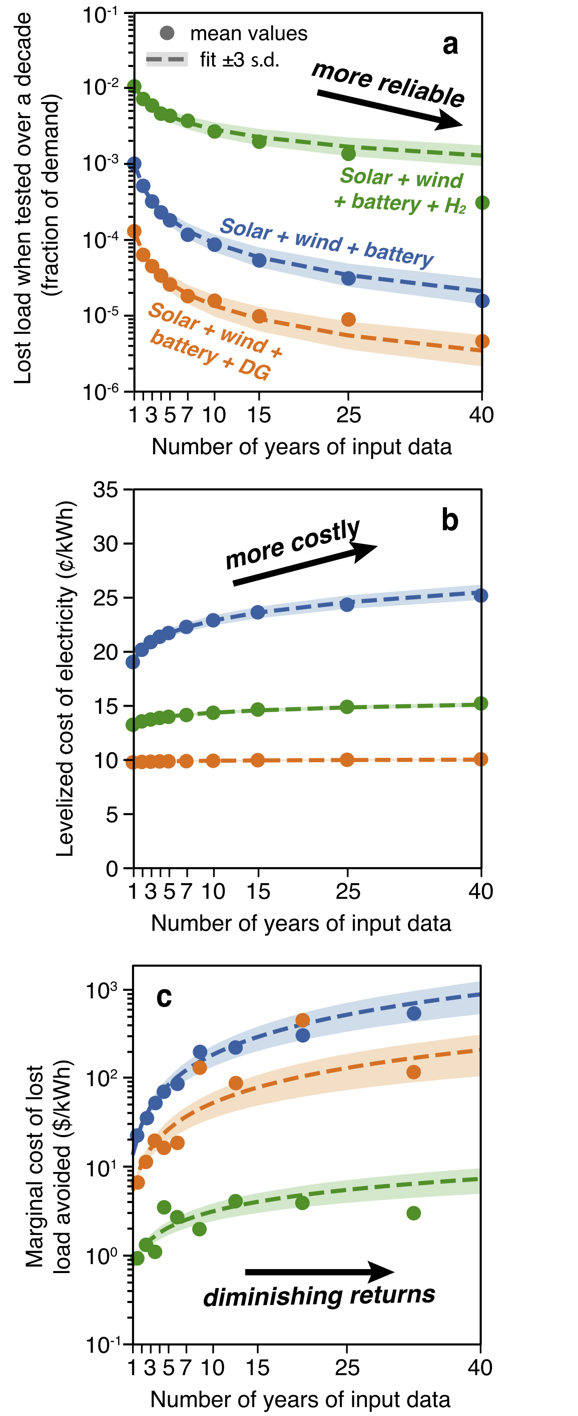

Fig. 3. Marginal cost of lost load avoided. A power law function was fit to a) the lost load during system operation for each studied scenario and b) the system levelized cost of electricity (LCOE) from the original planned systems. In these two panels, the mean value for each P_{years} value is shown along with the fit ± 3 sigma uncertainty. Panel c) shows the marginal cost of reducing lost load by adding more planning years (increasing P_{years}). The increase in LCOE is divided by the reduction in lost load as P_{years} increased. The expected function is the derivative of the LCOE fit divided by the derivative of the lost load fit, both derivatives taken with respect to P_{years}. The observed values were calculated based on the mean LCOE in conjunction with lost load values shown in a). Panel c) shows that for all modeled scenarios it becomes increasingly costly to avoid lost load as P_{years} increases, and that the marginal cost of lost load avoided can be substantially different for systems relying on different technologies.

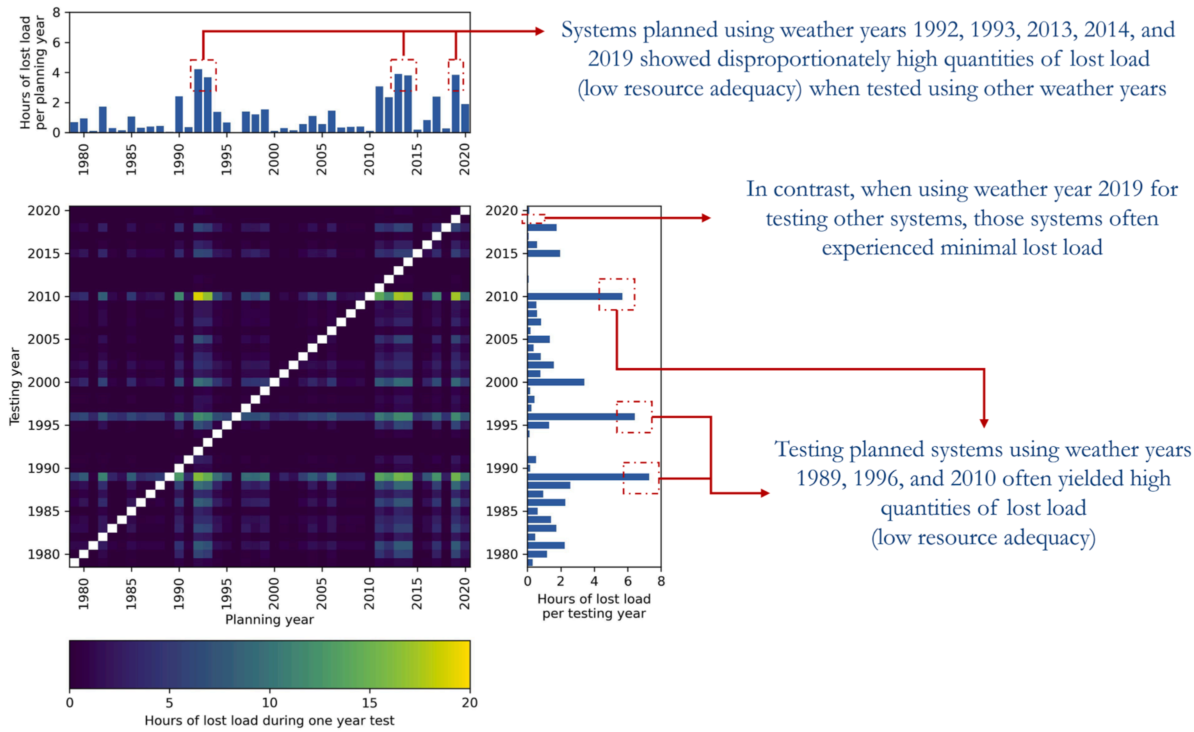

Fig. 4. Lost load by planning and operational year. Lost load is shown for *Solar+wind+battery+DG* systems planned based on a single year of input data, with resource adequacy evaluated during operation over a single year ($O_{years} = 1$). The planning year is shown along the x-axis, and the operational year along the y-axis, with the coloring corresponding to the lost load from each specific planning and operating combination. The resource adequacy of the modeled systems was not assessed for the year that was used for planning, because the lost load in that year is zero by construction. Consequently, the diagonal, in which the planning year is equivalent to the operational year, is blank. The histogram to the right (above) shows the mean lost load for each row (column) in the matrix. A few outlier years: 1989, 1996, and 2010, resulted in substantial lost load when planned systems were operated in those years.

2010 (Fig. 4) proved particularly challenging to meet electricity demand when used in single-year operational tests (O_{years}=1); *Solar+wind+battery+DG* systems that were planned using single-year weather records (P_{years}=1) were often unable to meet 100 % of demand when operated using 1989, 1996, and 2010 (other scenarios are shown in Fig. S2). These years had cold winter days that increased electric heating loads and persistent wind lulls, constituting conditions that have been shown to substantially influence the system capacities required to meet resource adequacy [58]. These years also exhibited large climate-related disruptions in resource supply, as represented by the multivariate ENSO index [59]. In contrast, 1992, 1993, 2013, 2014, and 2019 represented weather years that were less useful inputs for planning reliable *Solar+wind+battery+DG* systems (Fig. 4). Specifically, least-cost systems planned using one of these years often yielded substantial lost load compared to when they were planned using other weather years. Additionally, when these five years were used for the operational tests, they often yielded only small quantities of lost load regardless of which year the system used for planning, giving a false impression of high resource adequacy during the asset lifetimes.

Consequently, planning that used weather data from years with low wind and solar resources led to the systems with the highest resource adequacy when operating with other years (Fig. 5 and Table S2). For example, when 1996 was used as the planning year, the least-cost system contained 1.1 kW of dispatchable generation capacity for each kW of mean demand, representing 3.7 standard deviations above the mean dispatchable generation capacity of 0.75 kW per kW of mean demand. The system planned using 1996 was clearly an outlier, and moreover, substantial lost load was produced when 1996 was used as the operational year for systems planned using other weather years.

4. Discussion

The resource adequacy of wind- and solar-based electricity systems in operating years increased substantially as more years of weather data were used to plan the systems. Approximately 15 years of weather data in the planning period were required to obtain 100 % resource adequacy in half of the ten-year-long operational tests (O_{years}=10) in *Solar+wind+battery+DG* systems. In contrast, without dispatchable generation (which was modeled as natural gas-fired generation), 40 years of input weather data were required in the planning period to obtain systems that exhibited comparable levels of resource adequacy during operational years. This behavior may explain the recent failures of electricity systems during winter storms in 2022 (e.g., Winter Storm Elliot affecting the Central and Eastern US), given that seasonal resource adequacy assessments are routinely based on a limited number of weather years or as few as one typical meteorological year.

Optimizing a system on more years of data will inherently reduce lost load when tested on other weather years, but optimizing complex systems on many years of data can, in some cases, be prohibitively challenging. Further, as additional years are added to the planning process, the cost of the resulting system increases along with system reliability. One possible metric for judging "how many years is enough?" is the question "Beyond which input weather data length does the expected cost of increasing system reliability exceed the value of the increased reliability?" We illustrate this concept within the framework of this study, which required zero lost load during the planning years, by adopting a hypothetical $10/kWh for the value of lost load. For the *Solar+wind+battery* systems, a single year was sufficient to meet this threshold. These wind, solar, and battery systems are already relatively costly because the generation and storage assets must be overbuilt relative to the other scenarios to handle the variability of wind and solar resources without dispatchable generation (Table 2). This overbuild

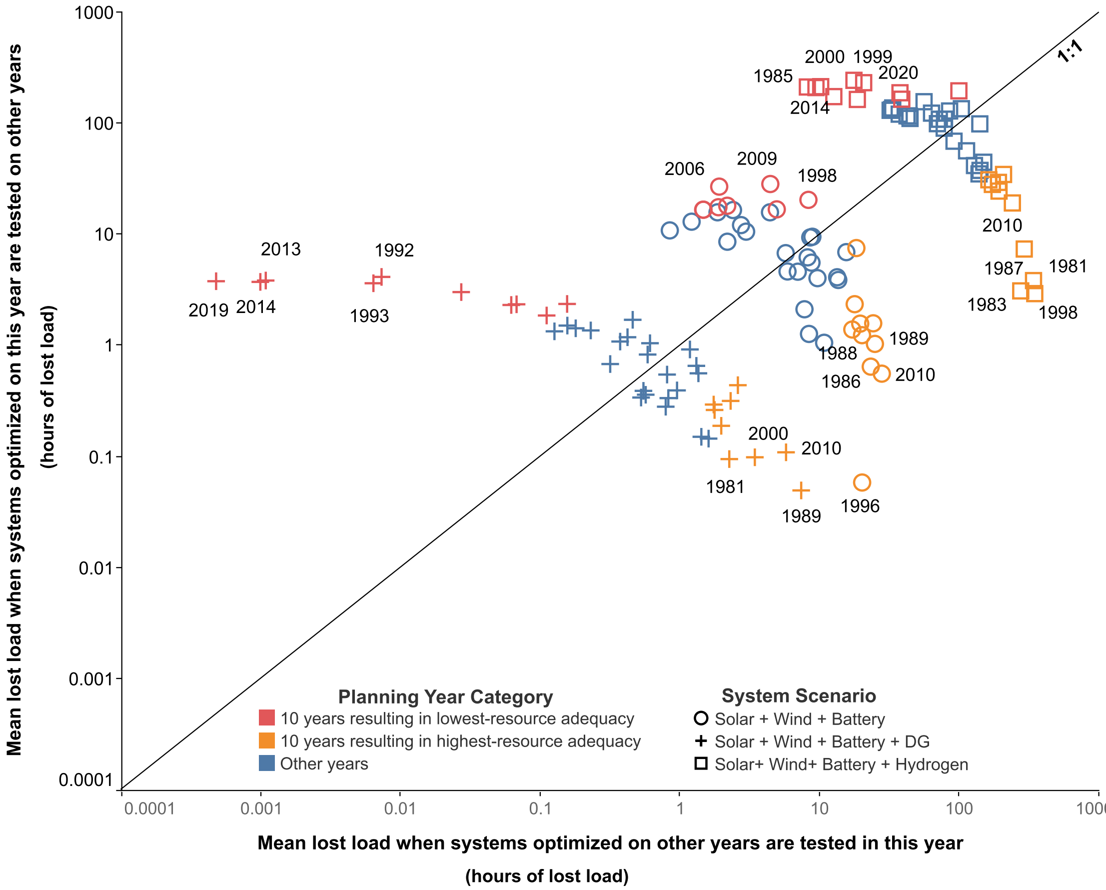

Fig. 5. Outlier planning and operational years. For each weather year, the mean lost load values are shown from the single-year planned systems and resource adequacy tests during operating years (values from the right and upper histograms in Fig. 4). A strong inverse relationship is evident for each scenario. The red markers represent the 10 high-resource years that yielded weaker planned systems, which experienced substantial lost load when operated with other years. Orange markers represent the 10 low-resource years that resulted in stronger planned systems, which experienced minimal lost load when operated using other weather years. Blue markers represent systems planned with all other years. The 2019 *Solar+wind+battery+DG* weather year is not depicted in the figure, because when used as a planning year the results of the mean lost load was 0.

makes it difficult to increase reliability at a cost of less than \$10/kWh of avoided lost load (Fig. 3c). For the *Solar+wind+battery+DG* systems, the lost load was already so low for $P_{years}=1$ that it was difficult to reduce that small value cost effectively. Thus, three years was sufficient to meet the \$10/kWh threshold. For the *Solar+wind+battery+H_2* systems, considering as many years as possible, up to and including the 40 years studied in this analysis, would continue to provide opportunities to avoid lost load at a cost that is lower than \$10/kWh.

When least-cost systems are planned to have 100 % resource adequacy, the *Solar+wind+battery+DG* scenario shows the substantial value derived from increasing the capacity of dispatchable generation, as opposed to increasing variable wind or solar generation (Fig. 2b). In this scenario, wind and solar generation are sized to provide the bulk of the power in these systems, whereas dispatchable generation is sized to compensate for weather variability and resource droughts (Fig. S12). While the study uses natural gas as a representation of firm, dispatchable generation, other dispatchable generation technologies could play a similar role. In the *Solar+wind+battery+H_2* scenario, the hydrogen conversion and storage assets increase in capacity the most. These results are in accord with other studies that have analyzed the challenges of relying on generation from wind and solar assets during peak electricity load periods [5,60]. Accordingly, the *Solar+wind+battery* scenario can be considered our most extreme limiting scenario because the only dispatchable, albeit highly energy constrained, technology is battery storage. It is unlikely that any large-scale power systems will be limited to these three technologies, but this technology set may be realized on smaller isolated grids. In contrast, the *Solar+wind+battery+DG* scenario can be considered a limiting low-carbon emission scenario with low capital cost, flexible, firm generation where the dispatchable generation buffers the system from the most severe instances of inter-annual variability.

The analysis herein reveals that the high- and low-resource years, as categorized in Fig. 5, differed for the three scenarios (Table S2). For example, batteries providing daily storage are well-matched to diurnal solar energy generation, whereas seasonal hydrogen energy storage is well-matched to buffering against seasonal lulls in wind power. Systems with substantial battery storage will be more sensitive to short-duration solar resource droughts than to wind resource droughts. In contrast, systems relying on hydrogen storage capacity may be more sensitive to longer-duration wind droughts than solar resource droughts. To obtain computational tractability, some capacity expansion models and studies attempt to include only the most appropriate selected time slices throughout the year, while others rely on representative days or time slices [61,62]. However, this study shows that it may be difficult to identify the most appropriate time slices based on the observed different sensitivities of systems with different technological compositions to weather events.

As P_{years} increases in the *Solar+wind+battery+H_2* scenario, the rapid increase in H_2 storage capacity shows the substantial value in H_2 storage as more years are modeled (Fig. 2f). This rapid rise is attributed to the modeled systems transferring stored H_2 between years. When a model is optimized over a single input year of weather data, no economic incentive is presented to store more H_2 than is used in that same year. In contrast, when a model is optimized over two input years, years with higher wind and solar capacity factors can produce excess H_2 for use as required in subsequent years. In practice, it is not possible to determine the exact amounts of H_2 produced and stored in one year that should be reserved for subsequent years. The benefits of larger H_2 storage capacity may consequently be overemphasized in the idealized model relative to real-world systems. Nevertheless, countries historically have established and used strategic fuel reserves, such as large-scale underground natural gas storage sites [63] and the Strategic Petroleum Reserve in the U.S. [64], to dampen the effects of extreme weather or price shocks in international trade. A Strategic Hydrogen Reserve that had a storage capacity larger than is needed for normal years of operations, but with spare capacity to handle years with high H_2 needs, could potentially serve such a role in the future.

In our scenarios, the *Solar+wind+battery+H₂* scenario had relatively low resource adequacy, with ~10 times greater lost load than the *Solar+wind+battery* scenario and ~100 times greater lost load than the *Solar+wind+battery+DG* scenario (Fig. 3). Some of this difference can be attributed to the modeling processes as well as the assumption of perfect foresight. A system planned using a single year of weather data will include 365 daily cycles of a battery system, allowing the battery storage capacity to be sized over days that have either high or low wind and/or solar generation. In contrast, if planned over a year of weather data, a system that includes hydrogen storage will experience only one seasonal cycle of that asset. The systems planned using the weather years that had high wind and solar availability exhibited high lost load when operated in other weather years, whereas systems planned using the weather years with low wind and solar availability performed well when operated in other weather years (Fig. S6). Hence, compared to least-cost capacity estimates, additional methods of determining the conversion and storage capacities of these seasonal technologies, including sampling many seasonal cycles, or including substantial reserve margins, would be beneficial to avoid under-sizing the capacities of these seasonally cycled assets.

The seasonal and inter-annual variability of wind and solar resources underscores the need to analyze many years of data in system planning, to capture low- and high-production years as well as a variety of severe weather events. Least-cost, parsimonious models of power systems that do not add additional reserve generation or storage capacity require decades of weather data in system planning to achieve high resource adequacy in future out-of-sample years of weather data. However, the data presented herein indicate that extending the planning period from a single year to even 2 or 3 years of input weather data can yield substantial improvements in resource adequacy over the operational lifetime of the system.

There are multiple limitations to the presented study that could impact the specific results, but would be unlikely to impact the general observed trends and takeaway messages from the study. In this work, a parsimonious model represented future deeply decarbonized electricity systems based on substantial wind and solar power generation. The model identified the least-cost electricity system based on a greenfield assumption of no preexisting generation infrastructure. To enable the computational tractability of our analysis, we used a single node representation and removed constraints associated with power and gas transmission. These simplifications allowed the planning of a least-cost system, while considering up to forty years of input wind, solar, and demand data. Representing smaller geographic regions would increase the variability in the input time series, likely leading to an increase in resource drought events [36]. Some of the effects of extreme weather were excluded from our model due to the omission of power and gas transmission networks that could be damaged or obstructed in events similar to Winter Storm Uri [65]. However, the failures of transmission and distribution networks for power systems are not typically assessed within the context of resource adequacy.

The modeling approach used herein constrained the lost load to zero during system planning. An alternative approach, outside of the scope of this study, is to pre-define a value of lost load (VoLL) for the planning systems, allowing the optimization model to determine the least-cost configuration and operations given a specific VoLL. One of the challenges with this methodology is that the VoLL – or the value of reliable, uninterruptible electricity service – varies based on the end-user. This value ranges from inflexible, highly valuable lifesaving loads in hospitals [66] to price-sensitive flexible industrial loads that participate in demand response programs [67]. Despite this, the North American Electric Reliability Corporation (NERC) have set strict resource adequacy requirements for North American power systems of 0.1 loss of load events per year [68] that do not directly incorporate the value or cost of those loss of load events. In alignment with the goal of planning systems that exceed NERC requirements, we decided to constrain the lost load to zero during system planning. This is instead of performing multiple simulations with multiple types of load ranging from firm to semi-flexible to very flexible all with different VoLL values in the planning process that could reasonably describe the range of VoLL values observed by end-users.

It is unlikely that large-scale electricity systems will be limited to the technologies studied in the three presented scenarios: wind, solar, and dispatchable generation, short-duration battery storage, and power-to-H_2-to-power energy storage. In the U.S., low- or zero-carbon emission nuclear and conventional hydroelectric generation had capacities of roughly 95 and 80 GW, or 21 % and 17 % of mean U.S. demand in 2022, respectively [54]. While these two technologies will certainly contribute to future systems in the U.S., their generation capacities have remained relatively stable for the last 30 years in the U.S. This suggests substantial expansion of these technologies may be politically difficult or geographically improbable. Thus, their combined capacities will likely not approach that of the dispatchable generation modeled in the *Solar+wind+battery+DG* scenario.

The incorporation of existing baseload nuclear generation into the model would effectively increase the variability of the net (residual) load (i.e., load minus nuclear power), and would thus amplify the effects of inter-annual variability exacerbating the general findings of this study. Conventional hydroelectric generation has its own seasonal and inter-annual variability. A recent study that included hydroelectric generation in California showed the seasonal variability in hydroelectric generation actually led to increased power-to-H_2-to-power usage, when compared to a system that excluded a representation of hydroelectric generation [36]. Further study of these two and other technologies should be considered in more detailed studies in the future.

Future energy systems may also experience weather conditions and variability that are not well-represented in the 42 historical weather years used in this study. Studies show that the effects of climate change in the coming decades will often be subleading compared to climate and weather variability [69]. Despite this, climatological reanalysis data shows upward trends in frequency and severity of wind and solar droughts [17]. Additionally, the effects of multi-year climatological events, such as El Niño and La Niña events, are represented in the weather data used herein. However, in our work, the sequence of years of weather data used for system planning was usually not in chronological order because of their random selection. This lack of continuous years potentially led to an underestimation of the effects of multi-year climatological drivers, and consequently potentially underestimated the value of increasing P_{years} during system planning. Future studies could consider augmenting historical weather data with synthetic data designed to represent historical and possible future climates. Such augmentation could be valuable for representing infrequent weather events and differing climate trajectories.

5. Conclusion

Daily, seasonal, and inter-annual weather variability pose challenges for planning electricity systems that rely heavily on wind and solar power, compared to systems relying heavily on fossil fuel or other dispatchable generation technologies. This paper illustrates how electricity systems planned using different weather data in the planning process differ in cost and generation and energy storage asset capacities, as well as in their ability to meet resource adequacy targets. Systems planned with more years of data cost more and, generally, have increased asset capacities. Additionally, the systems' performance and ability to reliably supply electricity demand is substantially improved by progressing from planning that uses one year, to planning that uses two years of weather data, with the lost load decreasing by >50 % for all three scenarios in operational tests. Despite this rapid reduction, we find that for the scenarios that exclude dispatchable generation, nearly 40 years of weather data are required when planning systems intended to achieve zero lost load when operated over 10 years in 50 % of operational test simulations. In comparison, this same adequacy was achieved when planning with 15 years of weather data when allowing a traditional dispatchable generation to supply 5 % of electricity demand.

Electricity systems are often forced to achieve high resource adequacy through regulatory requirements. However, we find that the marginal cost for these highly reliable systems may not be justified based on the economic cost of unsupplied electricity, i.e., the value of lost load. For example, the considerable reduction in lost load when progressing from one to two planning years (>50 %) is substantial but is accompanied by an increase in system costs. Specifically, the reductions in lost load experienced in the systems planned under the *Solar+wind+battery* scenario were outweighed by the substantial cost increase when incorporating a second weather year when planning. In contrast, planning that uses more years of input data provided cost-effective reductions in lost load for the *Solar+wind+battery+H_2* scenario up through the use of 40 years of weather data.

Lastly, we show that when specific weather years are used in the planning process, the planned systems have substantially higher resource adequacy than planning with other years of data. When used to test the operations of other planned systems, these same years often yield high quantities of lost load. In instances where multi-year weather records cannot be used in specific long-term planning models, it could be possible to intentionally select planning years that yield more robust systems.

Our results suggest that ensuring the reliability of wind- and solar-based systems will require using considerably more weather data in system planning than is the current practice. However, when considering the potential costs associated with unmet electricity demand, fewer planning years may suffice to balance costs against operational reliability.

Data and code availability

All model code, input data, and analysis results are publicly available and documented at: https://github.com/Carnegie/MEM_public/tree/Ruggles_et_al_2024.

CRediT authorship contribution statement

Tyler H. Ruggles: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Edgar Virgüez:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Natasha Reich:** Writing – review & editing, Visualization, Methodology, Formal analysis. **Jacqueline Dowling:** Writing – review & editing, Visualization, Methodology. **Hannah Bloomfield:** Writing – review & editing, Methodology. **Enrico G.A. Antonini:** Writing – review & editing. **Steven J. Davis:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Conceptualization. **Nathan S. Lewis:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Ken Caldeira:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

A link to the model code and data files used in this study are included in the "Data and code availability" section of this manuscript.

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TR is currently a Senior Analytics and Modeling Engineer at Powertech USA, Inc. TR produced most of his contributions to this work while he was affiliated full time to Carnegie Science.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.adapen.2024.100185.

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