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Research article

The impact of energy storage on the reliability of wind and solar power in New England

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A R T I C L E I N F O

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A B S T R A C T

In this study, the potential of wind and solar power to reliably meet the electricity demand of New England is evaluated, as well as the role of energy storage in improving the reliability of the region's renewable energy system. Using 44 years of hourly weather data from 1980 to 2023 obtained from the NASA MERRA-2 reanalysis product, the variability of these renewable resources and their impact on the region's electricity supply and demand is investigated. With varying mixes of wind and solar resources and sufficient resources capacity to generate electricity equal to annual demand, we find that a wind-dominant system can meet approximately 73% of the region's hourly electricity demand, whereas a solar-dominant system can only meet about 69%. However, incorporating 12 h of energy storage enhances the overall reliability of a wind-dominant system to 86%. In comparison, incorporating the same amount of energy storage in a solar-dominant system results in an overall reliability of approximately 87%. Ultimately, our analysis shows that achieving 100% reliability in meeting the annual electricity demand of New England requires addressing the mismatch between electricity demand and resource availability in terms of both location and time. This can be achieved through the integration of significant amounts of energy storage and/or wind and solar resources installations capable of generating electricity that exceeds peak demand by at least 3 times.

1. Introduction

In an effort of decarbonizing its energy infrastructure and combat climate change, each state within New England region has embarked on an ambitious path. This collective effort is marked by the establishment of new renewable energy targets and a progressive increase in each state's specific Renewable Portfolio Standard (RPS) [1–6]. These individual RPS policies reflect the commitment of each New England state to promote renewable energy generation, fostering a greener future and contributing to the region's overall efforts in mitigating climate change. Efforts, such as incorporation of distributed energy resources, adoption of electric or alternative energy vehicles, and energy-efficient methods to establish a modern and reliable electric grid powered by clean energy will require substantial changes to the grid's infrastructure and operation [7], which will impact the shape of the future electric grid. However, to achieve these goals, it is critical to understand the region's electricity production and consumption processes, and the renewable resource capacity availability within its borders.

New England comprises six states in the northeastern part of the United States: Connecticut (CT), Maine (ME), Massachusetts (MA), New Hampshire (NH), Rhode Island (RI), and Vermont (VT). The region operates under the Independent System Operator of New

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England (ISO-NE) [8], the regional transmission organization responsible for coordinating and managing the electric grid across New England. ISO-NE ensures the reliable supply of electricity throughout the region, and it has established operational zones based on the geographical locations of each of the New England's states (MA, CT, RI, VT, NH, ME). However, it's important to note that Massachusetts (MA), which contributes approximately 46% of the total electricity consumption within the region [9,10], differs from the other states as it is composed of three separate zones within ISO-NE: Northeast Massachusetts-Boston (NEMA-BOST), Southeast Massachusetts (SE-MASS), and Western/Central Massachusetts (WC-MASS) [8]. These zones play a significant role in coordinating and managing electricity within Massachusetts, contributing to the overall stability of the New England electric grid, as the state emerges as a key player in the region's electricity landscape.

As New England moves towards increasing wind and solar electricity generation, as they are the preferred resources for low-carbon electricity systems [11], the inter-annual variability and uncertainty of these resources will pose challenges to power system planning and operations, as it impacts the amount of capacity required to meet demand and reserve requirements, raising concerns about system reliability. Therefore, understanding and identifying how to overcome seasonal and weather-driven variability of such resources will be essential to meeting the region's decarbonization goals.

Notably, recent studies such as those by Mahdavi et al. [12] and Mahdavi et al. [13], Danso et al. [14], François et al. [15], and Harrison-Atlas et al. [16], offer valuable insights into addressing resource adequacy and reliability challenges associated with the integration of variable renewable electricity (VRE) technologies in electricity systems and the importance of flexibility measures. Using different approaches, including exploring electricity generation from biomass, wind, and solar power (Mahdavi et al. [12] and Mahdavi et al. [13]), assessing hydropower flexibility in West Africa for integrating solar and wind energy (Danso et al. [14]), identifying the influence of winter North Atlantic Oscillation on Climate-Related-Energy penetration in European regions (François et al. [15]), and analyzing the temporal complementarity of wind-PV hybrid systems across the United States (Harrison-Atlas et al. [16]), these studies enrich the understanding of renewable energy dynamics. Alongside with research like the ones by Heide et al. [17] and Weitemeyer et al. [18], that emphasizes the need for storage and balancing in fully renewable power systems, all these studies provide a broader context to the challenges New England might face.

Aligned with this, this research aims to examine the core limitations, challenges and barriers associated with the mismatch between the energy demand and supply that are preventing widespread electricity deployment from intermittent renewable energy sources in New England. The analysis herein calculates the mismatch between energy production and electricity consumption based on a given wind and solar capacity level and specified demand. To bridge the identified gap, a combination of either loading reduction or loading shifting, or the utilization of alternative forms of power that can be dispatched on demand such as from energy storage (like in pumped hydro storage or batteries) needs to be used. The potential of meeting New England's electricity demand exclusive through wind and solar power generation, supported by energy storage is analyzed in this study by employing a methodology used by Rinaldi et al. [19] and Tong et al. [20], ensuring alignment with stablished practices. The details of our approach are presented in the "Method of Approach" section of this paper, demonstrating a thoughtful adaptation of their methods to our study. We explore the details and challenges of variable renewable energy more thoroughly than models with multi-year steps allow. Here, we examine the basic limits of systems focused on wind and solar, regardless of cost. Our results do not focus on realistic power system details, instead, we look at how the variability of these renewable resources might affect the practicality of reliable systems, therefore, this remains relevant even as technology evolves.

While the research retains its foundational focus on New England, the ripples of its implications reverberate broadly. By focusing on the unique blend of renewables and grid challenges in New England, which serves as a microcosm of the broader global energy transition, we uncover insights that extend far beyond this region alone and can be transferable to similar regions worldwide, offering valuable guidance on managing high renewable energy penetration and variability. The parallels between New England and other regions facing comparable challenges underscore the universal relevance of our findings. Moreover, our research aligns with the overarching goals of sustainability and grid stability, making it pertinent to the global energy discourse. The alignment of our results with larger-scale studies underscores the robustness and generalizability of these conclusions.

2. Method of Approach

2.1. Solar and wind capacity factors

The capacity factors of wind and solar in this study are determined using 44 years, from 1980 to 2023, of historical hourly wind and solar resource data obtained from NASA's MERRA-2 reanalysis product [21,22]. The MERRA-2 has a global grid resolution of 0.5° latitude and 0.625° longitude and contains 361 × 576 grid cells as highlighted in Table 1 (see Section S1 for more details).

A generation profile for the New England region was created using a shapefile that defines the geographical boundaries of New England [23], ensuring accurate representation for both solar and wind resources. Then, solar and wind capacity factors were estimated with the same resolution as MERRA-2 for each grid cell in the region. The calculated factors reflect actual energy output in

Table 1
List of reanalysis datasets used in this study.

SOURCE	REANALYSIS DATASET	TIME RANGE	OUTPUT SPATIAL RESOLUTION	OUTPUT TEMPORAL RESOLUTION
MERRA-2	Solar - M2T1NXRAD_5.12.4	1980–2023	0.5° × 0.625°	Hourly
MERRA-2	Wind - M2T1NXSLV_5.12.4	1980–2023	0.5° × 0.625°	Hourly

contrast with the rated energy output of the system, which is computed as power capacity times a 1-h duration [11,20,24].

To obtain the solar capacity factor, the following three variables from MERRA-2 data are utilized: SWGDN – Surface incoming shortwave flux [W·m^{-2}]; SWTDN - Top-of-atmosphere incoming shortwave flux [W·m^{-2}]; and the T2M – 2-m air temperature [K]. Then the in-panel radiation is estimated by first determining the solar zenith and the solar incidence angles for each grid based on the location's latitude, longitude, and time [25–27]. An empirical piecewise model is utilized to differentiate the direct and diffuse solar radiation components by considering the clearness index, which is the both ratios of surface to top-of-atmosphere, and the local time [28]. It is also assumed a horizontal single-axis tracking system with solar panels tilt of 0° and a maximum tuning angle of 45° to improve the potential solar availability, as compared to flat plate solar panels. Even that rooftop solar installations are excluded from this analysis by the used of single-axis trackers, this model increases solar power potential generation and produces less variability. The effect of irradiance and the surrounding air temperature are both considered to calculate the solar power output originating from a specified panel [19,20,24], aligning with the description of Huld et al. [29], (see Section S2 for more details) and Pfenninger and Staffell [30] performance model.

For wind capacity factor calculation, the raw wind speed data at the eastward and northward directions are required at 10 m and 50 m above the surface. These components are denoted by the variables U10 M and V10 M (representing the eastward and northward wind speeds at 10 m, respectively) and U50 M and V50 M (representing the eastward and northward wind speeds at 50 m, respectively). The raw wind speed data for these variables are obtained from the MERRA-2 repository. Subsequently, utilizing a power-law relationship, the raw wind speed data is interpolated to 100 m, which is the wind turbine hub height assumed in this study (Eqs. (1) and (2) below) [20]:

$$\alpha = \frac{log\left(U_{50,i}\right) - log\left(U_{10,i}\right)}{log(50) - log(10)} \tag{1}$$

$$U_{100,i} = U_{10,i} * \left(\frac{100}{10}\right)^{\alpha} \tag{2}$$

where the grid and alpha exponent for wind profile is represented by i and α respectively, and the wind speed at 10, 50, and 100 m are represented by U10, U50, and U100 sequentially.

Then Pythagorean theorem is used to find the wind speed magnitudes at each grid point (Eq. (3)):

$$wind\ speed = \sqrt{U^2 + V^2} \tag{3}$$

where the variable U represents the eastward wind component, and the variable V represents the northward wind component [22].

Subsequently, a piecewise function is applied as follows [11,31,32].

- Capacity factor (CF) is zero, when wind speed is below a cut-in speed (u_{ci}) of 3 m per second (m/s) or above the cut-out speed of 25 (m/s); and
- CF is calculated by the ratio u_{ci}^3/u_r^3 when wind speed is between the cut-in speed of 3 (m/s) and rated speed (u_r) of 12 (m/s); and
- CF = 1.0 when wind speed is between the rated speed of 12 (m/s) and the cut-out speed (u_{co}) of 25 (m/s).

The procedure descripted above produces wind and solar capacities for each hour and grid cell that matches the same resolution of the MERRA-2 data. Then from that, an hourly power generation profile, average weighted by area, is generated specifically from New England' wind and solar resources. The area-weighted averaging process ensures that the desired total wind and solar capacity is spatially average across the entire New England region.

Recognizing the limitations inherent in reanalysis models, which include significant geographical imbalances and the potential for overestimating or underestimating wind and solar output [33], it is crucial to acknowledge that the capacity factors derived from reanalysis data may differ from real-world systems. In this study, we refrain from relying solely on these reanalysis-derived capacity factors for all calculations. Instead, we utilize them to characterize the time and location-based properties of the resources, where their values have demonstrated strong agreement with empirical data [33]. Notably, the normalized capacity values presented herein are calculated using the generation values and the real-world capacity factors—specifically, 38% for wind (CFwind = 38%) and 25% for solar (CFsolar = 25%). These real-world capacity factors are derived from the National Renewable Energy Laboratory Annual Technology Baseline (ATB) for utility-scale solar photovoltaics and wind [34], taking into account various factors such as solar irradiance, wind speed classes, and technological advancements. It is also important to acknowledge that our decision to avoid exclusive reliance on reanalysis-derived capacity factors is not only driven by the known limitations of these models but also by the broader consideration of the potential impact of infra-hour wind speed variability on capacity factor calculations. Hourly data inherently introduces a limitation related to infra-hour wind speed variability, a factor that we recognize and consider in the justification for our approach.

2.2. Hourly electricity demand

New England energy consumption information, hourly electricity demand real time data, forecasted system demand, along with the percent of total electric energy generation by resource type are retrieved from the ISO-NE platform [9,10] and the EIA – U.S. Energy

Information Administration [35]. To construct a dataset reflecting New England's hourly electricity demand spanning 44 years (1980–2023), we employed a 9-year hour-by-hour average (2015–2023) to represent the hourly demand for a single year. This approach aimed to enhance the robustness of our analysis by looping this averaged demand over the 44-year period, effectively mitigating small variations in demand from year to year. Our investigation included a comparison of the 9-year average demand with each of the 9 years individual year demand data, revealing a modest difference ranging from 5.0% to −5.4%. This analysis underscores the justification for utilizing the 9-year average, demonstrating its ability to provide a more consistent dataset for trend analysis over an extended timeframe. By adopting this method, interannual variations primarily stem from weather-related events rather than changes in electricity demand, further strengthening the reliability of our results.

2.3. Resource analysis

The ratio of the total produced wind and solar electricity to the total electricity demand over the 44 years is defined as the generation value and expressed as a multiplier, such as "1x generation" if the electricity generated over the 44-year period is equal to electricity demanded over the same period (Eq. (4)).

$$GV = \frac{\sum_{t=1980}^{2023} E_{\text{wind}}(t) + E_{\text{solar}}(t)}{\sum_{t=1980}^{2023} D(t)} \tag{4}$$

where GV represents generation value, $E_{\text{wind}}(t)$ is the electricity generated by wind power at time t, $E_{\text{solar}}(t)$ represents the electricity generated by solar power at time t, and $D(t)$ is the hourly electric demand at time t. The summations are taken over the period from 1980 to 2023.

The installed wind and solar capacities represent the maximum amount of energy that can be generated from wind and solar resources, respectively, based on the size and capacity of the installed infrastructure. These capacities are determined during the planning and construction phase of a renewable energy project and are not influenced by hourly variations in resource availability. In this study, they are determined based on a predetermined resource combination, herein represented as the proportion of wind and solar generation (SF% solar and 100-SF% wind), the generation value, and the hourly resource data. Then the same hourly resource data, which accounts for factors like weather conditions and time of day, is used to compute the power generated from each resource on an hourly basis. Subsequently, the fraction of satisfied daily electricity demand over the 44-year span (1980–2023) is calculated as a function of this defined resource mix. The installed capacity for wind, solar, and storage are estimated using the following equations (5)–(7) respectively [20]:

$$Wind_{Cap,y} = (1 - \text{SF}) \ * \ \text{OB} \ * \ \text{Pwr\_avg}_y * \frac{\text{Hrs}_y}{\sum_{=y} \text{CF}_{wind}} \tag{5}$$

$$Solar_{Cap,y} = \text{SF} \ * \ \text{OB} \ * \ \text{Pwr\_avg}_y * \frac{\text{Hrs}_y}{\sum_{=y} \text{CF}_{solar}} \tag{6}$$

$$Storage_{Cap,y} = \ \text{Pwr\_avg}_y * \text{Batt}_s \tag{7}$$

where y represents the year and s represent the size. $Wind_{Cap}$, $Solar_{Cap}$, and $Storage_{Cap}$ represent respectively the installed capacities of wind, solar, and storage. SF is the fraction of energy generated from solar. OB is the capacity overbuilt. Pwr_avg is the average power demand. Hrs is the total hours in the year. CF_{Wind} is the wind capacity factor and CF_{Solar} is the solar capacity factor. Batt is the battery storage [20].

Furthermore, we define reliability herein, as the percentage of satisfied New England electricity demand, and is calculated as the ratio of the power generated by the system to the hourly electric demand over the period of 1980–2023 [11,19,20] (Eq. (8)):

$$R_t = \frac{P(t)}{D(t)} \text{ x } 100 \quad \text{for } t \in [1980, 2023] \tag{8}$$

where $P(t)$ is the power generated by the system at a specific time t, $D(t)$ is the hourly electric demand at time t, and R_t represents the reliability at a specific time t. Reliability calculation is performed for each hour t withing the time range from 1980 to 2023, and it is expressed as a percentage.

The concept of reliability in this context, refers to situations where demand is not met exclusively due to the absence of electricity allocation from power production facilities, as the assumption is made that there are no energy losses in the system or service interruptions.

A computational model that predicts and simulates future scenarios, outcomes, and behaviors of a system was created using Python programming language [36,37]. Utilizing the electricity demand, installed capacities, and the resource data as inputs, the simulation is run in a forward direction, starting from a present state, and simulating the future developments to monitor the generation of wind and solar power, the storage charge or discharge process, if existent, and the potential of the hourly electricity demand be met by wind, solar and energy storage. The model optimizes electricity systems without considering any policy, spatial variation, and capacity markets. (Fig. S2 depicts a flow diagram of the algorithm). If there is excess wind and solar generation, it is used to charge the energy storage to up to 100%, after which a curtailment is applied to the wind and solar generation. If the amount of wind and solar generation are not enough to meet demand, the storage will kick in and energy discharge will occur until storage is empty. It is important to highlight that due to the analyses be based on an hour-to-hour scenario, storage discharging is trigged based exclusively on the current system hour status. If the storage system has sufficient energy present, the difference between wind and solar generation and demand is completely met. A more uniform storage dispatching process can be achieved by incorporating better methods to accurately forecast future demand and wind and solar generation, thus reducing demand management and backup capacity requirements.

To ensure that the simulation results are not affected by the initial condition, the initial storage state is set to empty, when assuming storage availability, but at the end of the 44-year period, the end-storage state is maintained as the initial state of the next simulation loop. This technique is called loopback, and it enables the simulation to run forward from the beginning until there are no storage state changes detected as compared to the previous loop [8]. Various scenarios are simulated using different combinations of resource mixes, generation values, and storage capacities [11,20]. However, all of them assume perfect storage conditions with 100% efficiency and unlimited charge and discharge rates. A mathematical representation of the model formulation is provided below in Eqs. (9)–(17) [19]:

Capacity:

$$C^{g,s} \geq 0 \forall g, s \tag{9}$$

Dispatch:

$$0 \leq D_t^{g} \leq C^{g} f_t^{g} \quad \forall g, t \tag{10}$$

$$0 \leq D_t^{\text{to s}} \leq \frac{C^s}{\tau^s} \quad \forall s, t \tag{11}$$

$$0 \leq D_t^{\text{from s}} \leq \frac{C^s}{\tau^s} \quad \forall s, t \tag{12}$$

$$0 \leq S_t^{s} \leq C^{s} \quad \forall s, t \tag{13}$$

$$0 \leq D_t^{\text{from s}} \leq S_t^{s}(1-\delta) \quad \forall s, t \tag{14}$$

Storage energy balance:

$$S_1 = (1-\delta)S_T\ \Delta t + \eta^s D_T^{\text{to s}}\ \Delta t - D_T^{\text{from s}}\ \Delta t \quad \forall s \tag{15}$$

$$S_{t+1} = (1-\delta)S_t\ \Delta t + \eta^s D_t^{\text{to s}}\ \Delta t - D_t^{\text{from s}}\ \Delta t \quad \forall s, t \in 1, \cdots, (T-\ 1) \tag{16}$$

System energy balance:

$$\sum_g D_t^{g} \Delta t + D_t^{\text{from s}}\ \Delta t = M_t + D_t^{\text{to s}}\ \Delta t \quad \forall g, t \tag{17}$$

where superscript g indicates renewable generation technology (solar and wind), superscript s represents energy storage, and subscript t denotes time step - an hour in a year (beginning from 1 and finishing at T). The f_t variable is the wind and solar capacity factors, and variable M_t denotes New England electricity demand at time step t. Both variables are representing data in hourly basis. Constants δ, η^s, and τ represent energy stored loss rate, energy storage's round-trip efficiency, and storage charging duration, respectively. Decision variables consist of D_t^{g} (hourly deployed electricity from the generation technology assets at hour t), C^g (dispatched capacity of generation technology assets), $D_t^{\text{from s}}$ (discharged energy from the grid to energy storage) and $D_t^{\text{to s}}$ (charged energy from energy storage to the grid), and C^s (dispatched capacity of energy storage). The state variable S_t indicates energy stored in energy storage, and is also deduced by the optimization. The time step size (1 h in the model) is represented by Δt. All variables are non-negative. The system energy balances in Equations (9)–(17) by varying the generation and storage assets' decision variables, which are governed by fundamental physical constraints. Equation (9) represents generation and energy storage capacity constraints. Equation (10), based on historical capacity factors that are dependable on weather and chosen technology, constrains renewable energy generation. Equations (11) and (12) constrain the discharged energy and charged energy based on energy storage capacity and storage charging duration. Equations (13)–(16) define respectively the discharged and charge energy, and the stored energy in energy storage. Energy storage assumes steady-state operation in equation (15). Lastly, Equation (17) depicts the energy balance constraint for the whole renewable electricity system.

3. Results and discussion

3.1. Solar and wind resources variability

In order to gain a comprehensive understanding of the renewable energy potential in New England, it is essential to analyze both the solar and wind resources availability within the region. Understanding the magnitude and variability of solar radiation, influenced by climatic factors, is crucial for optimizing power system design, including incorporating storage capacity for reliability. Similarly, variations in wind resource and power production across locations and time scales [38] demand accurate measurements for effective development. Integrating this comprehensive understanding into planning ensures the optimal performance of renewable energy systems, addressing challenges and meeting the region's energy demands.

Fig. 1a and d depict the variations in solar and wind resource availability in New England throughout the year. Normalized based on a 44-year average from 1980 to 2023, the data visually represents daily median and range, highlighting seasonal patterns in both solar and wind resources.

Fig. 1b illustrates the hourly variability of solar resources specifically during summer days (June, July, and August), while Fig. 1c focuses on the hourly variability of solar resources during winter days (December, January, and February). Similarly, Fig. 1e highlights the hourly variability of wind resources on summer days, and Fig. 1f emphasizes the hourly variability of wind resources during winter days. Notably, solar resources experience significant fluctuations during morning and evening hours, underlining the impact of weather conditions and sun position changes on solar power generation. Despite greater hourly variability than solar, wind resources consistently contribute to energy production. Understanding the hourly, daily and seasonal variability in wind and solar resources is crucial for optimizing renewable energy system design.

3.2. Electricity demand and the co-variability of wind and solar resources

Fig. 2a depicts the area-weighted median power variability from wind (blue) and solar (green) resources in New England throughout an entire year, as well as a dataset of New England's hourly electricity demand (red bars). The data is each normalized by their respective 44-year average (1980–2023). It highlights that, at times, neither wind nor solar power can meet the electricity demand alone. Combining both resources improve system reliability and addresses the seasonal variability of each resource. However, the inherent variability of wind and solar still causes instances where the combination is insufficient. The large variability of the wind resource over various time scales, along with the contrasting seasonal patterns and amplitude of solar power compared to either, the electricity demand or wind resource, pose a major challenge for system reliability without energy storage. This requires the need for additional generation with high ramp rates to compensate.

Fig. 2b and c present a graphical representation of the hourly variability of electricity demand and wind and solar resources for summer and winter days. Electricity demand and wind resources both exhibit moderate-length daily cycles, while solar resources have longer daily cycles. However, if we look at the hourly variability, both solar resource and electricity demand are less variable than wind resource, as depicted in Fig. 2b and c. The importance of energy storage can also be inferred from these figures. The extreme daily cycle of solar resources can place significant reliability constraints on the power system, which could lead to the requirement of high ramp rates of additional generation during the early morning and late evening hours. Energy storage plays a critical role in mitigating these constraints by allowing for the smooth and stable integration of renewable energy sources into the power system.

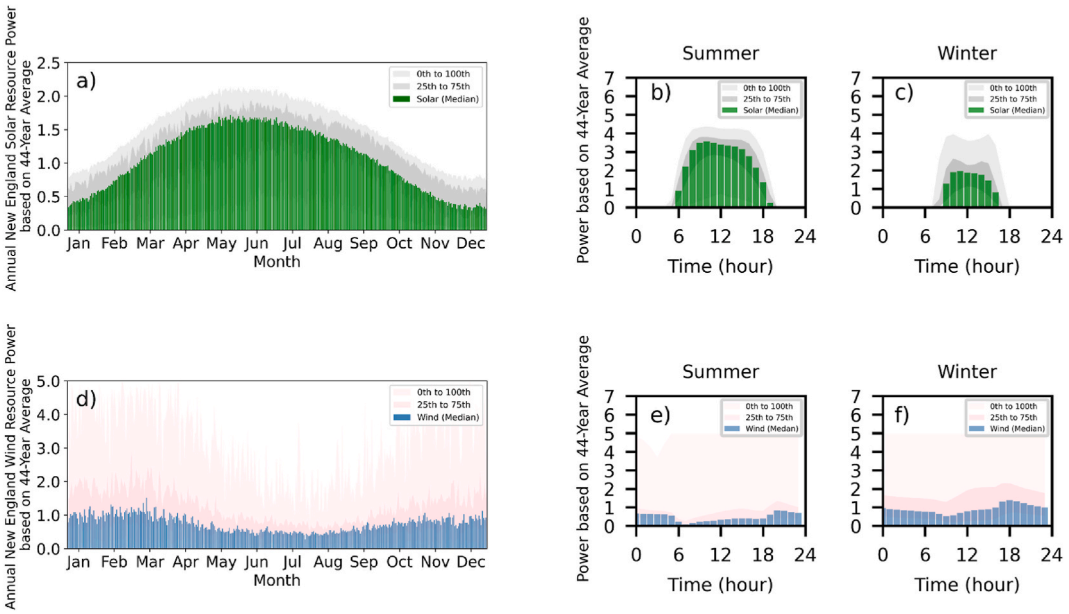

Fig. 1. New England's time-dependent solar and wind resources availability (1980–2023): Daily and seasonal variability of the solar (a) and wind (d) resources. Hourly variation during summer and winter days respectively for solar (b and c) and wind (e and f) resources. Median values are represented by bars, with darker shading indicating the middle 50% of observations and lighter shading covering the full range of observations. The solar and wind data are each normalized by their respective 44-year average.

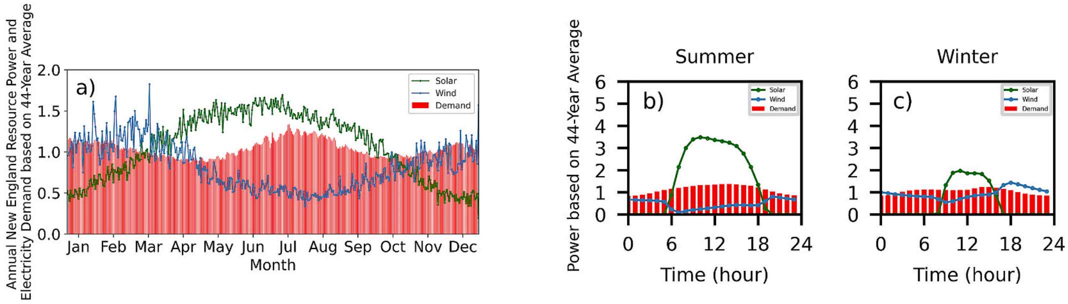

Fig. 2. New England's time-dependent electricity demand and solar and wind resources availability: The figure depicts the median power variability for electricity demand (red bars) and wind (blue) and solar (green) resources in a daily and seasonal basis (a) and in an hourly interval during summer (b) and winter (c) days. The solar, wind, and demand data are each normalized by their respective 44-year average. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

3.3. Energy generation and storage coupling

Fig. 3 depicts the correlations between the following three factors: the reliability of the power generated by wind and solar resources in terms of meeting the total annual electricity demand, the amount of electricity generated by assuming across New England region's resources aggregation, and the energy storage availability. A linear scale is applied to the vertical axes of the top row (Fig. 3a), and the graphs concentrate in showing the process of meeting up to 90% of the total annual electricity demand. In contrast, the bottom row (Fig. 3b) y-axes logarithmically demonstrate the ability to meet the subsequent 10%. It is worth noting that satisfying all but 0.1% or 0.01% of New England annual electricity demand equals to 8.76 h or 53 min of yearly outage respectively (365 days = 8760 h = 100%). The top x-axes depict the amount of installed wind and solar capacity (function of wind and solar capacity normalized by demand) and the bottom x-axes represent the amount of generation as a function of wind and solar generation divided by demand. In both rows (Fig. 3a and b), the shift from 100% wind to 100% solar in the generation mix occurs gradually from left to right, and in each plot, cases containing various amounts of energy storage capacity (0, 12, and 24 h, and 7, and 31 days of storage) are represented by the dotted lines. The solid green line represents the scenario where the total energy demand matches the total energy produced. The top row (Fig. 3a) shows an initially linear increase in the proportion of electricity demand satisfied by incorporating renewables with several wind and solar combinations. If the renewable power is increased by 5%, the generation also increases by approximately 5%, with relatively low sensitivity to electricity storage assumptions. On the other hand, the bottom row (Fig. 3b) highlights that when the

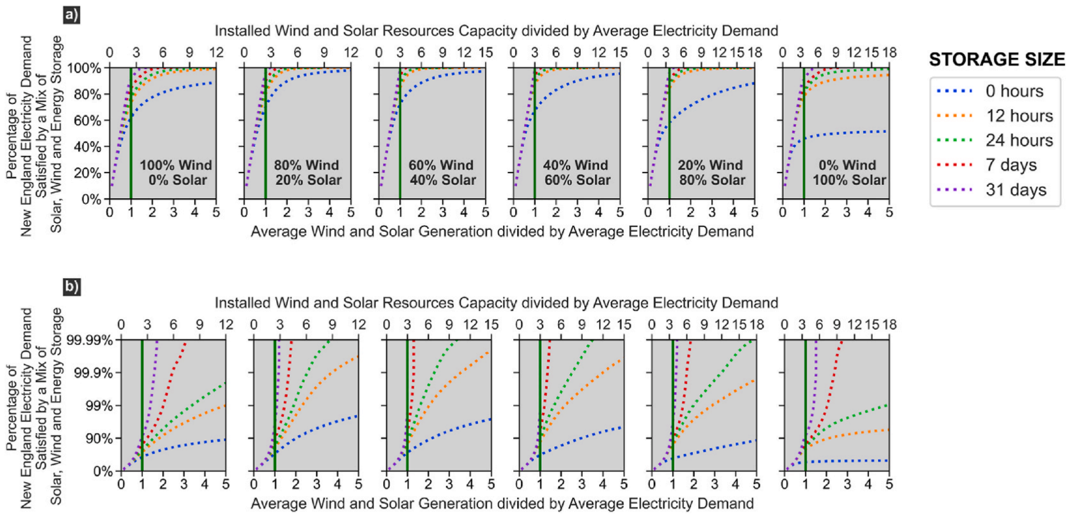

Fig. 3. Impact of energy storage capacity and generation on reliability in New England: The dotted lines represent the reliability (expressed as a percentage of demand met (y-axes) on both (a) linear (top row) and (b) logarithmic (bottom row) scales) of combinations of wind and solar resources consolidated across New England and shifting gradually from 100% wind (left panel) to 100% solar (right panel) as the available energy storage (dotted lines) increases along increases of the installed solar and wind generation capacities (function of solar and wind generation normalized by demand) (top x-axes) or quantities (bottom x-axes). Capacities of 0, 12, and 24 h, as well as 7, and 31 days of storage are represented by the different colors of the dotted lines. The vertical solid green line in each plot, represents the capacity at which the total energy demand and the total energy produced over the period of 44 years matches. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

proportion of electricity demand met surpasses 90% (for each renewable mix scenario), there is a sharp rise in the amount of electricity storage and/or generation needed.

As indicated by the point where the zero (0) hours of storage line intersects with the 1x generation (solid green line) in Fig. 3a, MERRA-2 reanalysis data shows that 62% of the New England's total annual electricity demand theoretically could be met by wind power alone, when considering wind resource consolidated across the region, 1.x generation, and no storage scenario. Meanwhile, under the same conditions (1.x generation without any energy storage), Fig. 3a shows that only 46% of the region's total hourly electricity demand could be satisfied by solar power generation (Table S1). The percentage amount increases to around 78% of hourly demand satisfied by solar power when 12 h of storage is introduced in the mix (Table S1). However, as depicted by the crowding of dotted lines in the 100% solar plot in Fig. 3a and S3, the reliability benefits significantly decrease with addition of storage that exceeds 12 h in a solar-only generation system. This poor system performance is mostly due to the extreme variation on the amount of solar radiation available during the course of the day, especially in the early mornings and evenings when the sun is not shining. Conversely, when it comes to wind resources, the reliability of the system only experiences a slight improvement when energy storage is integrated, and due to the weak daily circle and considerable variability nature of such resource, system benefits decrease even further when storage with above 4 h' worth of energy is considered, as seen in Fig. 3a and S3. To achieve high reliability from a system composed of wind power only, substantial amounts of overbuild or significant energy storage capacity, equivalent to multiple weeks' worth of energy, is required. That is the case regardless of whether the cumulative Statewide resources are considered or not.

The slope of each dotted line in Fig. 3a shows the required wind and solar incremental capacity that needs to be installed (>1.x generation) to cause a reliability boost. Additionally, as can be noted by the constant slopes to the left of the solid green line, which represents cases of under-generation, Fig. 3 highlights that as the amount of capacity installation rises (top x-axis), reliability (y-axis) increases uniformly. However, it's worth noting that the relationship between capacity installation and reliability is different for cases where a solar-dominant mix with less than 12 h of energy storage are considered (Fig. 3 and S3). In these cases, the benefits of increasing storage levels become less pronounced as reliability improves. Relatively, in cases situated to the right of the solid green line (greater than 1.x generation), where rising slopes can be observed, the benefits of increasing reliability by installing extra capacity, decreases. For example, it highlights that by adding 0.5x generation to a solar-dominated mix (80% solar/20% wind) with 1x generation (to a total of 1.5x) and no storage, increases the total annual electricity demand met from 58% to 66% (Table S2). In a wind-heavy mix (80% wind/20% solar) with 1x generation scenario, it shows that the addition of 0.5x generation (to a total of 1.5x) improves the overall 70% reliability up to 84% (Table S2). Adding 12 h of storage capacity to these same scenarios shows an extremely impact in the final results, increasing the reliability of the system up to approximately 94% and 93% respectively (Table S2).

Fig. 3b demonstrates that to satisfy the remaining 10% of the region's total annual electricity consumption utilizing wind and solar resources only, a combination of significant level of storage capacities and amounts lot greater than 1.x generation are required. This is despite of the use of any specific wind and solar resource combination, even when taking into account the combined wind and solar resources available across the entire region. Moreover, the practicality of utilizing wind and solar resources mix combined with energy storage to satisfy as much as 99.99% of the region's total annual electricity demand is also illustrated on Fig. 3b. It is worth noting that the North American Electricity Reliability Corporation (NERC) reliability standard requires that the LOLE (Loss of Load Expectation) for any balancing authority in North America should not exceed 0.1 day per year, which translates to a reliability percentage of around 99.97% [39]. As an example, for comparison, a system containing 12 h of storage coupled with resources combination of either 70% wind and 30% solar or 30% wind and 70% solar, requires amounts of generation 2.5.x [Table S4] and 3.x [Table S5] respectively to satisfy at least 99.97% of the total annual electricity demand of New England. This is equivalent to an amount of approximately 2.45 h of blackout per year. For these same mixes' composition, a reduction to 1.5x of overbuild generation [Table S2], in both cases, can be achieved by increasing the amount of energy storage to 7 days-worth of capacity. For other scenarios, refer to the Supplemental Information (Fig. S3, Tables S1–S7).

It is important to keep in mind that even when renewable sources, such as wind and solar, provide an average of 90% of electricity on an annual basis, there are still periods when their output is minimal. To prevent blackouts, the size of the backup dispatchable electricity service must be nearly as large as the total electricity system. Despite ideal conditions, wind, solar, and energy storage alone are not yet capable of fully replacing conventional sources of energy and meeting all electricity demand due to their variability and unpredictability. Complementary technologies or strategies may be necessary to ensure a reliable and resilient electricity supply. However, if sufficient energy storage or load-shifting capacity, capable of meeting total demand for several weeks, can be achieved, the combination of wind and solar energy has the potential to meet all electricity needs. This aligns with findings from numerous established studies, such as Jacobson et al. [40,41], Clack et al. [42,43], and Breyer et al. [44–46]. In final analysis, storage is essential for ensuring reliable electricity supply in a wind/solar mix system that relies heavily on solar generation. It can meet 90% of the total annual electricity demand, but after smoothing the daily cycle with 12 h of storage capacity based on the mean demand, further addition of storage results in a substantial decrease in its marginal benefit. Conversely, the variability of wind resources can be further reduced effectively by incorporating small amounts of energy storage that is equivalent to less than 4 h of average demand as seen in Fig. S3. In either scenario, fulfilling the final 10% of the total annual electricity demand using only wind and solar generation involves a significant increase in the amount of storage and/or installed capacity. It is worth noting that as reliability increases, the marginal return from additional capacity required to increase reliability decreases exponentially, leading to a substantial reduction in the general marginal benefit of this extra reliability enhancement.

3.4. Discussion

The shift towards a zero-carbon electricity system, relying primarily on wind power and solar photovoltaics, is challenged by the daily and seasonal variability of these renewable energy sources. This variability can result in a mismatch between energy demand and supply. To overcome this, storing large amounts of low-cost energy over long periods is crucial for reliable and affordable electricity systems. Considering this, in pursuing a diversified energy resources profile, New England recognizes that even with a high penetration of renewables, without utility-scale storage, it could potentially not achieve its goal of a clean electric grid [47–54], and thus that energy storage would be a key component of its portfolio. Therefore, the region is promoting the deployment of energy storage to improve the efficiency, cost-competitiveness, and stability of its electric grid while facilitating the transition to renewable energy sources [47–54]. With growing energy storage capacity, it has the potential to transform electricity generation and consumption, benefiting its ratepayers [47–54].

Without storage, maintaining grid balance requires electricity to be produced, delivered, and consumed nearly instantaneously [55, 56], requiring grid infrastructure to be sized to handle the yearly maximum consumption peak, despite significant fluctuations in consumer electricity demand both daily and seasonally as shown in Fig. 4, leading to inefficiencies and high costs for ratepayers [48]. Moreover, as the amount of intermittent renewable generation increases, the challenge of maintaining grid balance also increases [48, 57,58]. Energy storage technologies can manage the variable output of renewables and increase grid reliability and resiliency [48].

However, it is essential to understand how important economics and costs are in this context. Whatever is chosen to integrate into the electricity grid, to make it less carbon intensive and more efficient, must be done in a way that does not result in a massive increase in costs [59]. Factors such as application, project scope, and size can influence and differentiate the prices of energy storage technologies. If the capacity costs of energy storage fall sufficiently, wind and solar energy plants combined with storage can become feasible and competitive with traditional generation technologies [60], which could help reduce carbon emissions from the electricity sector.

One example of increasingly cost-competitive energy storage projects is battery energy storage. It offers a viable alternative to constructing new power lines for mitigating grid congestion. As battery costs continue to decline, these projects are becoming more attractive. For instance, by 2030, a 42% cost drop is expected to a 4-h duration lithium-ion battery system, bringing its current $386 per kWh cost to $225 per kilowatt-hour, while the costs of grid remain flat or rise [61]. In another case, the suggested cost would be even more attractive, around $149 per kWh by 2050 [62]. Nevertheless, the economic viability of energy storage, in the context where it is in competition with the alternative of expanding variable renewable energy capacity to address gaps between electricity demand and generation in both the short and long term, relies heavily on how often, how much, and for how long storage assets are used.

Regardless, a diversified energy portfolio is essential to New England in archiving the region's goal of creating a clean, affordable, resilient energy future, and energy storage it is an important component of it [48–54]. More specifically, long-duration storage technologies (10 h or more), as analysis shows that storage capacities of at least up to half a day are necessary to reliably meet the region's electricity demand with renewable resources, primarily wind and solar. The analysis indicates that the first 90% of the region's annual electricity demand can be met by overcoming the daily solar cycle and the hourly and daily wind variability but satisfying the remaining 10% will require overcoming the variability of the wind and solar seasonal cycles and addressing energy deficits during extended weather events that shut down renewable production for multiple days.

The analysis found that approximately 99% system reliability could be achieved by assuming extremely high energy storage levels

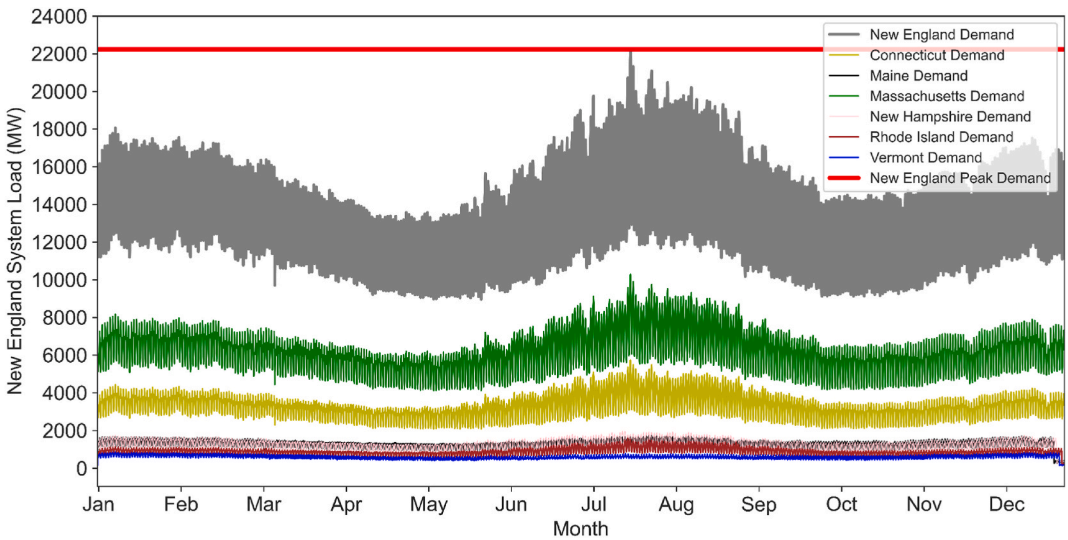

Fig. 4. New England's electricity load and peak demand, and the regions' individual states' load: A visual representation of the fluctuating energy consumption patterns over time for each of the states that form the New England region and the combined New England demand under the Independent System Operator of New England (ISO-NE).

(31 days) when no additional generation (1.x generation) was considered. Adding extra generation to the system reduced the amount of required storage, but a substantial amount of energy storage, equivalent to weeks' worth of electricity, was still needed to reach system reliability of 100%. At present prices, a battery storage system of this magnitude available to purchase today might not be a cost-effective solution. To add some context, the total capital investment for storage totaling 12 h of New England mean electricity demand, an approximately amount of 162.74 GWh, at prices of $263 per kWh for pumped storage hydro (PSH) [63] and $385 per kWh for Vanadium redox flow battery (RFB) [63], both being a 100 MW, 10-h installed system for example, would be $42.79 billion and $62.65 billion, respectively. It is worth noting that for a 24-h PSH system, the total installed cost is reduced to $143/kWh. Additionally, total system costs for these types of energy storages are more responsive to changes in power-capacity costs compared to changes in energy-capacity costs [24].

As indicated above, due to the current high cost of energy storage, the total system cost rises exponentially, if more than 90% of the region's annual electricity demand is satisfied by combining wind and solar power generation coupled with energy storage. Under the same system infrastructure scenario, achieving 100% reliability would require weeks' worth of energy storage capacity (Fig. 3). As an example, storage capacity equivalent to 31 days of New England average demand (~10,090 GWh) at the cost target of $100 per kWh [63–65] results in a capital expenditure of $1.009 Trillion approximately.

It is worth mentioning that our analysis was done by using a multi-decadal weather dataset (44 years of reanalysis data), and the results presented herein were in accordance with and restricted by the study's scope of highlighting the co-variability of electricity demand and wind and solar resources and their interaction with energy storage. We acknowledge significant limitation with our approach. To enhance generalization, we focus solely on the resource's constraints, omitting economic feasibility considerations. Moreover, we use area-weighted averages for solar and wind potential, neglecting the potential inclusion of areas with generation sitting restrictions. It's important to highlight that while this study employs a simple and straightforward methodology to assess the feasibility of meeting electricity demand through wind and solar power combined with energy storage, our approach produces results that are consistent and congruent with more complex and comprehensive models existent in the literature, including Jacobson et al. [40,41], Clack et al. [42,43], and Breyer et al. [44–46], particularly in evaluating the correlation between the percentage of met demand and the deployment of resources (i.e., energy storage capacity, wind, and solar power) [11,20]. Although these studies utilized more comprehensive yet less transparent models, our results highlight key distinctions. Clack et al. [42] study demonstrated an 80% reduction in emissions from the electric sector with wind and solar, even without storage, provided sufficient backup power from sources like generators or natural gas. Notably, our findings suggest that the presence of substantial energy storage is a primary factor differentiating these works. For instance, the difference in conclusions between the Clack et al. [42] study compared to Jacobson et al. [40] lies in the latter assuming the availability of large energy storage. Despite the nuances, all these studies converge on a crucial point, they all demonstrate that penetration of substantial amounts of wind and solar generated power is not only feasible but essential to create a comprehensive strategy that addresses renewable power grid energy transition. Furthermore, the model used in this study can be utilized to perform further simulations, where effects of different factors such as climate change, electric vehicles adoption, baseload generation availability, offshore wind resource, and others can be considered. For example, if wind and solar resources and/or electricity demand's spatial-temporal characteristics do not change, the normalized results obtained and depicted in Fig. 3 can be scaled to layouts with different net demand levels. If baseload generation be considered in the power generation mix, the results displayed in Fig. 3 would pertain specifically to the total net demand of baseload supply (the fraction of demand satisfied by wind and solar). System reliability is directly influenced by the correlation between the variability of baseload generation and the variability of wind and solar. The total system reliability increases if levels of cost-effective dispatchable baseload generation capacity availability increases, given that in both cases, the ratio of wind and solar capacity to net (total – baseload) demand met is constant.

Another consideration is climate change. Over the past decades, our understanding on how climate change impacts energy systems have increased significantly, but its effects across spatiotemporal are still not totally comprehended. Power systems' infrastructures can be affected by the changes on the weather conditions in which they operate [66]. Major climate variables such as increase air temperatures, increase or decrease in precipitation, sea level rise (increasing storms surges and flooding), increase in frequency of severe extreme events (high winds, floods, drought, typhoons, etc.) [67], and other, have directly impacts on energy demand and in the availability of wind and solar resources, consequently impacting system reliability. A detailed analysis with specific scenarios is required for further results.

Considerations of electric vehicle adoption is also pertinent to this study, as the adoption of electric vehicle in New England has been increasing consistently in the past few years. Take Massachusetts as an example, according to a recent poll, a slight majority of the State's drivers expects to own electric vehicle in the near future [68,69]. This willingness to embrace auto electrification goes directly in accordance with the state's decarbonization roadmap, which has goals such as 1 million zero-emission vehicles on the road by 2030 and by 2035 making all new cars sold in the state electric [70,71]. While the increase in electric vehicle sales is not expected to substantially increase the total electricity demand, the increased adoption of EVs can directly reshape the demand load curve [72,73]. For example, people charging their EVs at home when returning from work, increasing the peak load in the evenings. Once again, to fully understand the impact of the large-scale EVs adoption on the power system reliability, further simulations are needed.

Furthermore, recognizing the growing significance of offshore wind projects in New England, it is worth noting that offshore wind turbines offer higher output rates then onshore ones [74,75] and can directly affect the renewable system composition, thus affecting the total system reliability. Nevertheless, due to synchronized seasonal troughs of both onshore and offshore wind resources during summer, the use of storage still beneficial to the power system by offsetting these resource gaps.

All the factors mentioned above introduce challenges to accurately forecast future demand and natural resource consumption, however the results herein can be used by utilities, regulators, and decision-makers to develop strategies and to capture the role and value of long-term storage technology investments and policies.

4. Conclusions

In exploring the intricacies of New England's transition to 100% wind and solar power generation, our study aligns with significant advancements revealed in parallel investigations across diverse global energy scenarios. Drawing inspiration from the comprehensive evaluation of solar and wind power's reliability on a worldwide scale, our research corroborates the importance of analyzing spatial aggregation. Much like the observed improvements at continental levels globally, our findings underscore that aggregating New England's wind and solar resources is imperative for improving system reliability. Furthermore, insights from the examination of weather-driven fluctuations and seasonal variability inhered from wind and solar resources' impact on variable renewable energy guide our comparative analysis. Our study distinguishes itself by accentuating the multifaceted dynamics of New England's energy landscape, navigating the complex interplay of costs and the unique characteristics of the region. Unlike the generalized global models, our findings offer specific insights tailored to New England's intricacies, emphasizing the need for a strategic blend of technologies to ensure high reliability.

A substantial amount of supporting technologies, including energy storage, demand management, flexible generators, separate carbon-neutral, and others are required to reliably satisfied 100% of New England electricity demand in a wind and solar power generation only system scenario, even when entire region-scale wind and solar and resources aggregation is considered. Wind and power generation alone are not sufficient. Meeting 85% of New England electricity demand utilizing wind and solar resources, requires approximately 12 h' worth of energy storage (approximately 162.74 GWh). To satisfy the final 15% of demand, energy storage and/or excess wind and solar generating capacity amounts increase rapidly (7 days and 31 days' worth of energy storage in New England is approximately 2278 GWh and 10,090 GWh respectively).

Our emphasis on energy storage echoes the global sentiment expressed by numerous established studies, illuminating how these kinds of technologies play a pivotal role in achieving greater renewable power systems reliability, with subtle nuances based on regional land area, location, and geophysical resource. The need for competitive low-cost energy storage and/or electricity generation that can easily and efficiently be dispatched on demand are highlighted in the study. Further grounding our work is the recognition of long-duration energy storage (LDES) as a transformative element. Mirroring the acknowledgement of LDES's potential to significantly reduce system costs, we emphasize its role as a linchpin in New England's pursuit of reliable wind and solar electricity. Our insights align with the global discussion, emphasizing the underestimation of LDES value in typical grid planning tools and emphasizing the need for a diversified approach beyond the predominant focus on battery storage. Moving forward, the approach of choosing the right strategy to achieve high reliability and cost-effectiveness power systems will involve an evaluation of the availability and future costs of various technologies.

In summary, our research builds upon a foundation set by these global studies yet carves a distinctive niche by delving into the specifics of New England's energy landscape. By aligning our findings with these influential works, we underscore the universal relevance of our contributions while emphasizing the unique challenges and solutions that characterize New England's journey toward a renewable energy future.

Data availability

The electricity demand, solar, and wind capacity factors data generated for this study will be made available on request.

CRediT authorship contribution statement

Sergio Freeman: Writing – original draft, Visualization, Formal analysis, Data curation. **Ertan Agar:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors disclose potential competing interests as follows: Sergio Freeman acknowledges a financial relationship with National Grid plc through employment. The first author, Sergio Freeman, is currently employed by National Grid plc, and his PhD studies have been financially supported by the company.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e27652.

References

[1] Connecticut Renewable Energy Portfolio Standard. Retrieved from https://portal.ct.gov/PURA/RPS/Renewable-Portfolio-Standards-Overview. Last accessed on January 20, 2024.
[2] Maine Renewable Energy Portfolio Standard. Retrieved from https://www.maine.gov/energy/initiatives/renewable-energy/renewable-portfolio-standards. Last accessed on January 20, 2024.
[3] Massachusetts Renewable Energy Portfolio Standard. Retrieved from https://www.mass.gov/renewable-energy-portfolio-standard. Last accessed on January 20, 2024.
[4] New Hampshire Renewable Energy Portfolio Standard. Retrieved from https://www.energy.nh.gov/renewable-energy/renewable-portfolio-standard. Last accessed on January 20, 2024.
[5] Rhode Island Renewable Energy Standard. Retrieved from https://ripuc.ri.gov/utility-information/electric/rhode-island-renewable-energy-standard-ri-res-program. Last accessed on January 20, 2024.
[6] Vermont Renewable Energy Standard. Retrieved from https://puc.vermont.gov/electric/renewable-energy-standard. Last accessed on January 20, 2024.
[7] M. Mcpherson, D. Harvey, B. Karney, System design and operation for integrating variable renewable energy resources through a comprehensive characterization framework, Renew. Ener. 113 (2017), https://doi.org/10.1016/j.renene.2017.06.071.
[8] ISO New England Maps and Diagrams. Retrieved from https://www.iso-ne.com/about/key-stats/maps-and-diagrams/#load-zones. Last accessed on January 20, 2024.
[9] Massachusetts Department of Energy Resources, Renewable and Alternative Energy Division, Solar Information & Programs. Retrieved from https://www.mass.gov/orgs/renewable-and-alternative-energy-division. Last accessed on January 20, 2024.
[10] ISO New England – Energy, Load, and Demand Reports. Retrieved from https://www.iso-ne.com/isoexpress/web/reports/load-and-demand/-/tree/zone-info. Last accessed on January 20, 2024.
[11] M.R. Shaner, S.J. Davis, N.S. Lewis, K. Caldeira, Geophysical constraints on the reliability of solar and wind power in the United States, Energy Environ. Sci. 11 (4) (2018) 914–925.
[12] M. Mahdavi, F. Jurado, K. Schmitt and M. Chamana, "Electricity generation from cow manure compared to wind and photovoltaic electric power considering load uncertainty and renewable generation variability," in IEEE Transactions on Industry Applications, doi: 10.1109/TIA.2023.333045. Retrieved from https://doi.org/10.1109/TIA.2023.3330457. Last accessed on January 20, 2024.
[13] M. Mahdavi, A. Awaafo, F. Jurado, D. Vera, R.A. Verdú Ramos, Wind, solar and biogas power generation in water-stressed areas of Morocco considering water and biomass availability constraints and carbon emission limits, Energy 282 (2023) 128756, https://doi.org/10.1016/j.energy.2023.128756.
[14] D.K. Danso, B. François, B. Hingray, A. Diedhiou, Assessing hydropower flexibility for integrating solar and wind energy in West Africa using dynamic programming and sensitivity analysis. Illustration with the Akosombo reservoir, Ghana, J. Clean. Prod. 287 (2021) 125559, https://doi.org/10.1016/j.jclepro.2020.125559.
[15] B. François, Influence of winter North-atlantic oscillation on climate-related-energy penetration in europe, Renew. Energy 99 (2016) 602–613, https://doi.org/10.1016/j.renene.2016.07.010.
[16] D. Harrison-Atlas, C. Murphy, A. Schleifer, N. Grue, Temporal complementarity and value of wind-PV hybrid systems across the United States, Renew. Energy 201 (2022) 111–123, https://doi.org/10.1016/j.renene.2022.10.060.
[17] D. Heide, M. Greiner, L. von Bremen, C. Hoffmann, Reduced storage and balancing needs in a fully renewable European power system with excess wind and solar power generation, Renew. Energy 36 (2011) 2515–2523, https://doi.org/10.1016/j.renene.2011.02.009.
[18] S. Weitemeyer, D. Kleinhans, L. Wienholt, T. Vogt, C. Agert, A European perspective: potential of grid and storage for balancing renewable power systems, Energy Technol 4 (2015) 114–122, https://doi.org/10.1002/ente.201500255.
[19] K.Z. Rinaldi, J.A. Dowling, T.H. Ruggles, K. Caldeira, N.S. Lewis, Wind and solar resource droughts in California highlight the benefits of long-term storage and integration with the western interconnect, Environ. Sci. Technol. 55 (9) (2021) 6214–6226, https://doi.org/10.1021/acs.est.0c07848.
[20] D. Tong, D.J. Farnham, L. Duan, et al., Geophysical constraints on the reliability of solar and wind power worldwide, Nat. Commun. 12 (2021) 6146, https://doi.org/10.1038/s41467-021-26355-z.
[21] R. Gelaro, et al., The modern-era retrospective analysis for research and applications, version 2 (MERRA-2), J. Clim. 30 (2017) 5419–5454, https://doi.org/10.1175/JCLI-D-16-0758.1.
[22] Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2). Retrieved from https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/. Last accessed on January 20, 2024.
[23] RegionMask. Countries/States (NaturalEarth). Create masks of geographical regions. Retrieved from https://regionmask.readthedocs.io/en/v0.11.0/index.html. Last access on January 20, 2024.
[24] J.A. Dowling, K.Z. Rinaldi, T.H. Ruggles, et al., Role of long-duration energy storage in variable renewable electricity systems, Joule (2020), https://doi.org/10.1016/j.joule.2020.07.007.
[25] J.E. Braun, J.C. Mitchell, Solar geometry for fixed and tracking surfaces, Sol. Energy 31 (1983) 439–444, https://doi.org/10.1016/0038-092X(83)90046-4.
[26] Meeus J.H., Astronomical Algorithms, Willmann-Bell, Incorporated, 1991. Retrieved from https://www.agopax.it/Libri_astronomia/pdf/Astronomical%20Algorithms.pdf. (Last accessed on 20 January 2024).
[27] R. Perez, P. Ineichen, R. Seals, J. Michalsky, R. Stewart, Modeling daylight availability and irradiance components from direct and global irradiance, Sol. Energy 44 (1990) 271–289, https://doi.org/10.1016/0038-092X(90)90055-H.
[28] D.T. Reindl, W.A. Beckman, J.A. Duffie, Diffuse fraction correlations, Sol. Energy 45 (1990) 1–7, https://doi.org/10.1016/0038-092X(90)90060-P.
[29] T. Huld, R. Gottschalg, H.G. Beyer, M. Topič, Mapping the performance of PV modules, effects of module type and data averaging, Sol. Energy 84 (2010) 324–338, https://doi.org/10.1016/j.solener.2009.12.002.
[30] S. Pfenninger, I. Staffell, Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data, Energy 114 (2016) 1251–1265, https://doi.org/10.1016/j.energy.2016.08.060.
[31] P.E. Bett, H.E. Thornton, The climatological relationships between wind and solar energy supply in Britain, Renew. Energy 87 (2016) 96–110, https://doi.org/10.1016/j.renene.2015.10.006.
[32] S. Rose, J. Apt, Quantifying sources of uncertainty in reanalysis derived wind speed, Renew. Energy 94 (2016) 157–165, https://doi.org/10.1016/j.renene.2016.03.028.
[33] I. Staffell, S. Pfenninger, Using bias-corrected reanalysis to simulate current and future wind power output, Energy 114 (2016) 1224–1239, https://doi.org/10.1016/j.energy.2016.08.068.
[34] National Renewable Energy Laboratory (NREL), Annual Technology Baseline (ATB) Cost and Performance Data for Electricity Generation Technologies [Capacity factor] 202210.25984/1871952, 2022. Retrieved from, https://atb.nrel.gov/electricity/2022/index. (Accessed 20 January 2024).
[35] U.S. Energy Information Administration, Massachusetts Profile Data, Reserves, 2023. Retrieved from https://www.eia.gov/state/?sid=MA. (Last accessed on 20 January 2024).
[36] van Rossum G., Python tutorial, Technical Report CS-R9526, Centrum voor Wiskunde en Informatica (CWI), Amsterdam, Python Software Foundation. Python Language Reference, May 1995 version 3.8. Retrieved from http://www.python.org. (Last accessed on 20 January 2024).
[37] Macro Energy Model (MEM). Retrieved from https://github.com/ClabEnergyProject/MEM (2019). Last accessed on January 20, 2024.
[38] A. Kumler, et al., Inter-annual variability of wind and solar electricity generation and capacity values in Texas, Environ. Res. Lett. 14 (2019) 044032.
[39] North American Electricity Reliability Corporation (NERC), Reliability Standards for the Bulk Electric Systems of North America, 2023 Standard BAL-502-RF-03. Retrieved from https://www.nerc.com/pa/Stand/Reliability%20Standards%20Complete%20Set/RSCompleteSet.pdf. (Last accessed on 20 January 2024).
[40] M.Z. Jacobson, M.A. Delucchi, M.A. Cameron, B.A. Frew, Low-cost solution to the grid reliability problem with 100% penetration of intermittent wind, water, and solar for all purposes, Proc. Natl. Acad. Sci. U.S.A. 112 (49) (2015) 15060–15065, https://doi.org/10.1073/pnas.1510028112.

[41] C.L. Archer, M.Z. Jacobson, Geographical and seasonal variability of the global "practical'' wind resources, Appl. Geogr. 45 (2013) 119–130.
[42] C.T.M. Clack, et al., Evaluation of a proposal for reliable low-cost grid power with 100% wind, water, and solar, Proc. Natl. Acad. Sci. U.S.A. 114 (2017) 6722–6727.
[43] A. MacDonald, C. Clack, A. Alexander, et al., Future cost-competitive electricity systems and their impact on US CO2 emissions, Nat. Clim. Change 6 (2016) 526–531, https://doi.org/10.1038/nclimate2921.
[44] M. Barasa, D. Bogdanov, A.S. Oyewo, C. Breyer, A cost optimal resolution for Sub-Saharan Africa powered by 100% renewables in 2030, Renew. Sustain. Energy Rev. 92 (2018) 440–457.
[45] A. Toktarova, L. Gruber, M. Hlusiak, D. Bogdanov, C. Breyer, Long term load projection in high resolution for all countries globally, Int. J. Elec. Power 111 (2019) 160–181.
[46] Guido Plebmann, Matthias Erdmann, Markus Hlusiak, Christian Breyer, Global energy storage demand for a 100% renewable electricity supply, Ener. Proced. 46 (2014) 22–31. Retrieved from, https://doi.org/10.1016/j.egypro.2014.01.154. (Accessed 20 January 2024).
[47] The State of Grid Energy Storage in Massachusetts – December 2019. Retrieved from https://www.uml.edu/docs/complete-the%20state%20of%20grid%20energy%20storage%20in%20massachusetts-final_tcm18-321989.pdf. Last accessed on January 20, 2024.
[48] State of Charge – Massachusetts Energy Storage Initiative Study. Retrieved from https://www.mass.gov/doc/state-of-charge-executive-summary/download. Last accessed on January 20, 2024.
[49] 2023 Annual Energy Report – A summary of progress made toward the goals of Vermont's Comprehensive Energy Plan. Retrieved from https://legislature.vermont.gov/assets/Legislative-Reports/2023-Vermont-Annual-Energy-Report.pdf. Last accessed on January 20, 2024.
[50] Rhode Island State Energy Profile. Retrieved from https://database.aceee.org/state/rhode-island. Last accessed on January 20, 2024.
[51] Rhode Island: Pathway to 2030. Retrieved from https://2030.acadiacenter.org/wp-content/uploads/2018/02/Acadia-Center_EnergyVision2030_RI-Target-Summary_20180130.pdf. Last accessed on January 20, 2024.
[52] Connecticut Public Utilities Regulatory Authority, CLEAN & RENEWABLE ENERGY REPORT, 2022. Retrieved from https://portal.ct.gov/-/media/PURA/2022-Clean-Renewable-Energy-Report.pdf. (Last accessed on 20 January 2024).
[53] MAINE GOVERNOR'S ENERGY OFFICE, ANNUAL REPORT, 2022. Retrieved from https://legislature.maine.gov/doc/9459. (Last accessed on 20 January 2024).
[54] 2022 New Hampshire Annual Energy Report. Retrieved from https://www.das.nh.gov/EnergyManagement/Documents/AnnualEnergyReport2022.pdf. Last accessed on January 20, 2024.
[55] M. Noussan, Performance based approach for electricity generation in smart grids, Appl. Energy 220 (2018) 231–241, https://doi.org/10.1016/j.apenergy.2018.03.092.
[56] Parikh Jyoti, Panda Rajiv, Agrawal Vinod, Smooth Operations: Power System Overcomes Covid-19 Challenges to Ensure Seamless Supply, 2020. Retrieved from https://www.researchgate.net/publication/347535557_Smooth_Operations_Power_system_overcomes_Covid-19_challenges_to_ensure_seamless_supply. (Last accessed on 20 January 2024).
[57] Taneja J., Growth in renewable generation and its effect on demand-side management, IEEE International Conference on Smart Grid Communications (SmartGridComm), Venice, Italy, 2014, pp. 614–619, doi: 10.1109/SmartGridComm.2014.7007715.
[58] S. Impram, S.V. Nese, B. Oral, Challenges of renewable energy penetration on power system flexibility: a survey, Ener. Strat. Rev. 31 (2020) 100539, https://doi.org/10.1016/j.esr.2020.100539.
[59] International Monetary Fund, World economic outlook, october 2022: countering the cost-of-living crisis, Chapter 3: Near-Term Macroeconomic Impact of Decarbonization Policies (2022). Retrieved from https://www.imf.org/en/Publications/WEO/Issues/2022/10/11/world-economic-outlook-october-2022. (Last accessed on 20 January 2024).
[60] J. Ziegler, et al., Storage requirements and costs of shaping renewable energy toward grid decarbonization, Joule 3 (2019) 2134–2153, https://doi.org/10.1016/j.joule.2019.06.012.
[61] Even High Battery Prices Can't Chill the Hot Energy Storage Sector. Retrieved from https://www.bloomberg.com/news/articles/2023-01-12/even-high-battery-prices-can-t-chill-the-hot-energy-storage-sector. Last accessed on January 20, 2024.
[62] National Renewable Energy Laboratory (NREL), Cost Projections for Utility-Scale Battery Storage: 2021 Update (2021). Retrieved from https://www.nrel.gov/docs/fy21osti/79236.pdf. (Last accessed on 20 January 2024).
[63] Viswanathan V., Mongird K., Franks R., Baxter R., Grid Energy Storage Technology Cost and Performance Assessment, Pacific Northwest National Laboratory, Richland, WA, USA, 2022 2022. Retrieved from https://www.pnnl.gov/sites/default/files/media/file/ESGC%20Cost%20Performance%20Report%202022%20PNNL-33283.pdf. (Last accessed on 20 January 2024).
[64] U.S. Energy Information Administration, Levelized Costs of New Generation Resources in the Annual Energy Outlook 2022, 2022. Retrieved from https://www.eia.gov/outlooks/aeo/pdf/electricity_generation.pdf. (Last accessed on 20 January 2024).
[65] Lazard L., Lazard's Levelized Cost of Storage Analysis. Lazard, 2022, pp. 1–24. Retrieved from https://www.lazard.com/media/42dnsswd/lazards-levelized-cost-of-storage-version-70-vf.pdf. (Last accessed on 20 January 2024).
[66] S.G. Yalew, M.T.H. van Vliet, D.E.H.J. Gernaat, et al., Impacts of climate change on energy systems in global and regional scenarios, Nat. Energy 5 (2020) 794–802, https://doi.org/10.1038/s41560-020-0664-z.
[67] Burillo D., Effects of climate change in electric power infrastructures, in: Okedu K.E. (Ed.), Power System Stability, 2018, pp. 1–10 IntechOpen (Last accessed on 20 January 2024), doi:10.5772/intechopen.82146.
[68] POLL: U.S. VOTERS SUPPORT FULL TRANSITION TO ELECTRIC CARS BY 2030. COLTURA. Retrieved from https://www.coltura.org/do-voters-support-100-evs-by-2030/. Last accessed on January 20, 2024.
[69] Poll: Majority of Massachusetts drivers expect to own electric vehicle soon, November 16 Energy News Network, 2021. Retrieved from https://energynews.us/2021/11/16/poll-majority-of-massachusetts-drivers-expect-to-own-electric-vehicle-soon/. (Last accessed on 20 January 2024).
[70] MASSACHUSETTS 2050 DECARBONIZATION ROADMAP. Retrieved from https://www.mass.gov/doc/ma-2050-decarbonization-roadmap/download. Last accessed on January 20, 2024.
[71] Massachusetts Clean Energy and Climate Plan for 2025 and 2030. Retrieved from https://www.mass.gov/doc/interim-clean-energy-and-climate-plan-for-2030-december-30-2020/download. Last accessed on January 20, 2024.
[72] Molina Bastida, Paula, Hurtado-Pérez, Elías, Pérez-Navarro A., Alfonso-Solar David, Light electric vehicle charging strategy for low impact on the grid, Environ. Sci. Pollut. Control Ser. 24 (2021). Retrieved from https://link.springer.com/article/10.1007/s11356-020-08901-2. (Last accessed on 20 January 2024), doi: 10.1007/s11356-020-08901-2.
[73] Global EV Outlook, Securing Supplies for an Electric Future, 2022. Retrieved from https://iea.blob.core.windows.net/assets/ad8fb04c-4f75-42fc-973a-6e54c8a4449a/GlobalElectricVehicleOutlook2022.pdf. (Last accessed on 20 January 2024).
[74] A. Díaz-Motta, F. Díaz-González, M. Villa-Arrieta, Energy sustainability assessment of offshore wind-powered ammonia, J. Clean. Prod. 420 (2023) 138419.
[75] B. Desalegn, D. Gebeyehu, B. Tamrat, T. Tadiwose, A. Lata, Onshore versus offshore wind power trends and recent study practices in modeling of wind turbines' life-cycle impact assessments, Clean. Eng. Technol. 17 (2023) 100691, https://doi.org/10.1016/j.clet.2023.100691.