Evaluation of ELCC Methodology in the ISO-NE Footprint

Report for

Natural Resources Defense Council

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FOREWORD

This report was prepared by General Electric International, Inc. (GEII), acting through its Energy Consulting group, based in Schenectady, New York. Questions and any correspondence concerning this document should be referred to:

Eduardo Ibanez, Ph.D.

Technical Director
GE Energy Consulting
General Electric International, Inc.

One River Road, Building 40
Schenectady, New York 12345
Phone: (303) 475-9437
eduardo.ibanez1@ge.com

Legal Notices

Project Team

GE Energy Consulting

Eduardo Ibanez, Ph.D.

Mitch Bringolf

Natural Resources Defense Council (NRDC)

Bruce Ho

Thomas Rutigliano

Nick Pappas (NP Energy, consultant to NRDC)

Kevin Porter (Exeter Associates, Inc., consultant to NRDC)

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EXECUTIVE SUMMARY

Successfully decarbonizing New England's energy system on the timeline and scale called for by state policies and climate science will require rapid and transformational change of the region's power grid in the coming years. In addition to large-scale deployment of renewable energy resources, energy storage, energy efficiency, and demand response, electric loads are anticipated to expand considerably to meet increasing shares of transportation, heating, and industrial energy end uses. The Independent System Operator of New England (ISO-NE) can play a central role in facilitating a successful, reliable, and cost-effective transition to a decarbonized grid through its planning, operations, energy and ancillary services markets, and forward capacity market (FCM), but to do so all these systems will need to evolve to support an increasingly diverse and complex resource mix.

ISO-NE's ongoing efforts to reform Resource Capacity Accreditation (RCA) in its FCM is a critical workstream in preparing for this energy transition and the influx of new clean energy resources.[1] The RCA market reforms will have significant implications for both new resource development and existing resource retention, including through the proposed transition to the use of Effective Load Carrying Capability (ELCC), or a similar approach such as Marginal Reliability Impact (MRI), to evaluate resources' reliability contributions. The Natural Resources Defense Council (NRDC) contracted with General Electric Energy Consulting (GE Energy Consulting) to study the impacts of different methodological choices facing ISO-NE as it undertakes the RCA reform effort, with a specific focus on the application of an ELCC approach to the ISO-NE resource fleet. In this report, NRDC and GE present findings demonstrating the importance of carefully considering several key issues as part of the RCA reforms, including:

- What portfolio of resources is necessary to ensure reliability for ISO-NE while cost-effectively achieving each New England state's decarbonization mandates, and how will that portfolio evolve over time with the introduction of new clean energy resources?

- How should the FCM best assess and incorporate the use limitations of the conventional thermal generating fleet, including the risk of fuel supply shortages and operating challenges associated with more extreme weather caused by climate change?

- Should resources be valued based on their total reliability contributions (average ELCC) or on the reliability contribution of the marginal unit (marginal ELCC)?

- Can reliability be reasonably approximated with a single annual compliance regime, or is a seasonal regime more appropriate to address the distinct reliability needs of a dual-peaking system?

As illustrated throughout this report, each of these considerations can have significant implications for resource accreditation value, and, in turn, the economic incentives for the development and retention of different resources within the FCM. In addition to ensuring the FCM results in a reliable electric system for New England, program design must consider market efficiency, distributional equity and fairness across resources and ratepayer groups, market stability, and predictability. This report is intended to illustrate, through quantitative analysis, the need for ISO-NE, New England states, and the

[1] *See* ISO-NE, "Resource Capacity Accreditation in the Forward Capacity Market Key Project," https://www.iso-ne.com/committees/key-projects/resource-capacity-accreditation-in-the-fcm/.

region's stakeholders to carefully consider these important and in some cases potentially competing priorities in the careful design of the reformed capacity market.

Further, while the policy authority for clean energy development and resource planning in New England rests with the states, it is critical that ISO-NE's market be compatible and synergistic with the aggressive decarbonization targets adopted by the large majority of these states, which represent the large majority of the region's electrical load.[2] In addition to fairly compensating clean energy resources for their reliability contributions, it will be essential for the FCM to provide effective signals for state- and utility-level planning to identify, plan for, and ultimately capture reliability value as a key element of state clean energy portfolios. At the same time, ISO-NE's forward analysis of resource contributions must continuously and iteratively incorporate incoming generation driven by state clean energy policies.

Having clear, predictable capacity revenue streams is important to ensuring a diverse, reliable fleet of resources in the region, including both resources developed in accordance with or supported by state policies and resources that are financeable by market participants. In the case of clean energy, capacity payments could form a significant share of some resources' lifetime market value, particularly for storage and hybrid resources. Capacity valuation may also be a key differentiator between clean resource portfolio selections that focus only on least-cost Renewable Energy Credits (RECs) or on more diversified resource needs to meet New England ratepayers' co-optimized clean energy and reliability needs at least cost. Thus, reformation of the FCM through the RCA reform effort has the potential to determine the project viability of new resources for years to come, with many market and policy implications—including whether New England is able to achieve its decarbonization targets cost effectively—hinging on the finer details of a highly complex technical process. NRDC and GE offer this report to provide quantitative analysis and policy context to support a more robust and informed discussion of RCA reforms as ISO-NE, the New England states, market participants, and other stakeholders in the region deliberate this critical proceeding.

About the Study (Methodology)

The analysis reflected within this report is an attempt to explore the impacts of critical methodological design choices for ISO-NE's RCA reform, as ISO-NE seeks to implement an ELCC-type accreditation methodology for resources beginning in its 19th Forward Capacity Auction (FCA 19), to be held in February 2025 for capacity year June 1, 2028, to May 31, 2029. ISO-NE has proposed to use a variant of ELCC known as MRI, which is conceptually and quantitatively similar to the marginal ELCC accreditation approach discussed in this report. Understanding the implications of the transition to an ELCC/MRI-based capacity accreditation, including the methodological junctions to be confronted en route to a final market design proposal, is the core focus of this report.

The NRDC-GE study used the GE Multi-Area Reliability Simulation (GE MARS) software to forecast ELCC results for different resource categories under a range of different input assumptions and RCA design choices. The modelling software and data were intended to align with the software and data utilized by

[2] Five of the six New England states—Connecticut, Massachusetts, Maine, Rhode Island and Vermont—which collectively account for over 90% of the region's electric load have adopted economy-wide targets requiring reductions in GHG emissions of at least 80% by 2050. The Analysis Group, "Pathways Study, Evaluation of Pathways to a Future Grid," at 6, available at: https://nepool.com/wp-content/uploads/2022/05/NPC_20220426_Pathways_FULL_REPORT_FINAL_v2.pdf; ISO-NE, "2022 Annual Energy Forecast Itemization: ISONE Control Area and New England States," available at: https://www.iso-ne.com/static-assets/documents/2022/04/lf2022_itemized.xlsx.

ISO-NE, translated to forward-looking resource portfolios for 2028 and 2040. As further discussed in Section 2, the base cases for this study, shown in Table 1, included considerable expansion of clean energy resources, including over 13 gigawatts (GW) of utility-scale and distributed solar, over 6 GW of onshore and offshore wind, and 2 GW of battery storage by 2028, and higher levels of clean energy resources in 2040, consistent with the resource buildout in the April 2022 Pathways study[3] that ISO-NE commissioned to examine potential market approaches for achieving an 80% reduction in power sector GHG emissions below 1990 levels by 2040. Existing thermal resources were retained in the NRDC-GE model's base case years, except for 95 megawatts (MW) of coal resources, which were assumed to retire by 2040. Based on these assumptions, we estimate that the proposed carbon-free resources would be able to serve 61% of ISO-NE's annual load in 2028 and 90% in 2040.

Table ES-1. Base case capacity mix (MW)

Unit Type	2028	2040
Nuclear	3,356	3,356
Coal	95	0
CC Gas	12,388	12,388
ST Gas	1,337	1,337
GT Gas	1,855	1,855
Oil	4,430	4,430
Hydro	1,637	1,637
PSH	1,742	1,742
Other	1,241	1,241
Utility-scale solar	8,262	11,928
Distributed solar	4,943	7,500
Onshore wind	1,872	4,401
Offshore wind	4,700	16,014
Battery	2,000	12,953

Utilizing the 2028 and 2040 base cases, the study assessed the ELCC values of resource classes under a wide range of scenarios and input assumptions. The analysis included marginal ELCC—the capacity value of the next incremental unit of a specific resource type to be added to the system; average ELCC—the capacity value of all units of a specific resource type currently on the system; and portfolio ELCC—an average ELCC methodology which includes a positive or negative adjustment reflecting the synergistic or antagonistic effects, respectively, between resource classes.

Sensitivity analyses were further performed to understand the impacts of:

- **Gas Supply Limitations:** The impact of increasing or decreasing expected outages of gas resources during constrained fuel supply events;

[3] The Analysis Group, "Pathways Study, Evaluation of Pathways to a Future Grid," available at: https://nepool.com/wp-content/uploads/2022/05/NPC_20220426_Pathways_FULL_REPORT_FINAL_v2.pdf

- **Ambient Temperature Derates for Thermal:** The inclusion or exclusion of thermal derate events related to high temperatures;
- **Electrification:** The impact of higher loads driven by electrified transportation, heating, and industrial demand; and
- **Using LOLE vs. EUE as the ELCC Design Metric:** The impact of using Expectation of Unserved Energy (EUE), which measures reliability event magnitude, in lieu of Loss of Load Expectation (LOLE), which measures reliability event frequency.

The main goal of the study was to explore how capacity value calculations using the ELCC technique vary under a series of sensitivities. The study relied on the Pathways study and other existing datasets to create future portfolios in ISO-NE, but did not consider issues such as system costs, capital or operational costs by technology, revenue streams, or financial viability of existing or proposed resources.

Key Findings and Recommendations

The results of this quantitative study provide critical insights for ISO-NE, New England state policymakers, and the region's stakeholders for the design of the RCA reforms. Key findings and recommendations are summarized below.

Finding 1: Clean Energy Resources Provide Substantial Reliability Value.

The diverse portfolio of utility-scale solar PV, wind, and battery storage resources modelled in the study is capable of providing 5,388 megawatts (MW) of effective load carrying capability in 2028, which could enable significant retirements among the existing conventional fleet and represents 21% of ISO-NE's gross peak load. By 2040, the utility-scale solar PV, wind, and battery storage is capable of displacing 12,460 MW, equivalent to 44% of ISO-NE's gross peak load.

For reference, in terms of energy, the installed utility-scale PV and onshore and offshore wind capacity (all of which contribute to the calculated portfolio ELCC) would be able to meet 26% and 55% of ISO-NE's energy demand on an annual basis in 2028 and 2040, respectively. Including distributed solar PV, these values increase to 34% and 65% of energy in 2028 and 2040, respectively. Further expanding the analysis to include nuclear and hydro, we estimate that carbon-free resources would be able to serve 61% of ISO-NE's annual load in 2028 and 90% in 2040, under the study's base case assumptions.

The synergistic effects of the utility-scale solar PV, wind, and battery storage clean resource portfolio are also significant. Increasing penetrations of solar are synergistic with storage resources, which have a higher ELCC as the net peak period tightens to a narrower band of evening hours. Similarly, excess production from both solar and wind resources are more valuable during periods of high production if storage is present to shift that energy value to periods of demand.

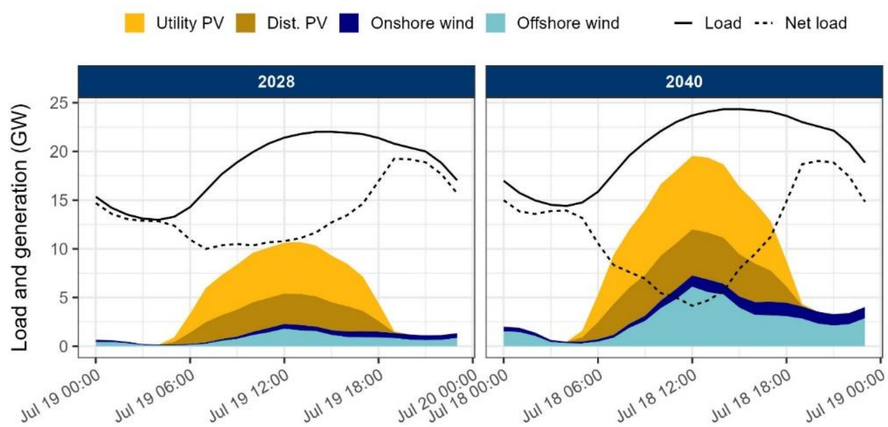

Figure ES-1. Load, net load, and renewable generation during the peak summer days

Appropriately compensating clean resources for their contributions to reliability will be critical to achieving a reliable, least cost, decarbonized grid and to ensuring that the growing levels of clean energy resources that are needed to achieve decarbonization are financeable. Providing proper reliability signals in markets will also help policymakers and utilities design synergistic clean energy policies and portfolios.

Recommendation 1: *Ensure the RCA market design appropriately reflects the reliability contributions of clean energy resources, including solar, wind, and storage, and the interactive effects between resources.*

Finding 2: Capturing Thermal Limitations Is Key to Ensuring Reliability and Equity.

Thermal resources, like all generating resources, have well-documented engineering limitations that impact their ability to support reliability. In ISO-NE, these include ambient derates driven by high temperatures, correlated outages driven by extreme weather events (both heat and cold), and pipeline supply risk during more severe and/or extended cold weather, such as polar vortex events. Capturing these resource limitations is critical for ensuring fidelity of the RCA reforms and the FCM as a whole. From a competitive equity standpoint, it is also necessary to ensure equivalent levels of scrutiny of the reliability characteristics of both the conventional thermal fleet and the emerging fleet of clean energy resources.

Historically, these thermal resource limitations have not been captured within the modelling framework of ISO-NE's FCM. This has resulted in overestimation of these resources' reliability contributions and underestimation of the LOLE resulting from the portfolio of resources selected in the FCM.

This study tested the impact of these limitations on ELCC, finding significant impacts, particularly from fuel supply issues as the system transitions to greater winter peaks. Fuel supply risk, which occurs in winter months, only impacts ELCC significantly when reliability is constrained in winter (for an annual portfolio analysis) but can become very significant for the marginal ELCC of gas resources when modelled as large events. Ambient temperature derates, while smaller in the range of magnitudes in the modelling, may also become more persistent and significant as climate change induces more heat events including more sustained overnight temperatures.

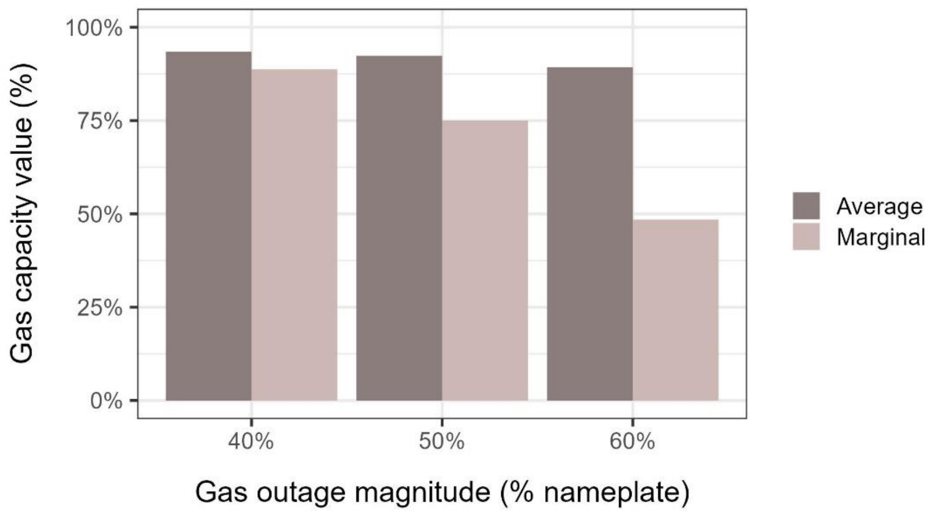

Figure ES-2. Gas unit average and marginal capacity value for gas 1-week outages in 2040

The magnitude and frequency of thermal resource limitations as a result of polar vortex events, heat waves, and other extreme weather are a key uncertainty for the ELCC analysis of gas resources. The analysis offered within this report is intended to be illustrative. The authors recommend additional analysis and more explicit representation of the gas system in the ISO-NE RCA reform development to understand the complex dynamics that may result during future such events, which may be both more severe due to climate change and unfold with different operational characteristics as demand changes due to greater electrification and with shifts in the region's power generation portfolio.

Recommendation 2: *Ensure the RCA market design and modelling assumptions reflect the realities of thermal limitations, including correlated outage risk due to fuel supply constraints and ambient derates.*

Finding 3: Average and Marginal Resource Accreditation Will Result in Different Incentives and Equity Outcomes.

A key design choice within ISO-NE's RCA reform effort is the selection of an *average* or *marginal* ELCC approach as the accreditation structure for resources, a design choice which will have significant implications for investment market signals for new resources, including clean energy resources, in the coming years. To better understand the impact of this design choice, this study quantified the values of average and marginal ELCCs for the 2028 and 2040 resource portfolios, finding significant differences in the valuation for both clean energy and conventional resources under the two accreditation schemes.

Average ELCC accredits resources at their proportional share of the total reliability contribution of their entire resource class (e.g., *all* solar resources), returning the full perfect capacity produced by a resource class back to that resource class, including a share of the portfolio effects (positive or negative) accrued across resource classes. Proponents of average ELCC accreditation argue that it more fairly allocates the full reliability value produced by resources back to those same resources in a manner that sums to the total reliability need, providing a durable and financeable investment signal. In the context of applying ELCC to emerging clean energy resources, average ELCC can be viewed as paying the clean energy fleet the same as the conventional generation it displaces in aggregate, rather than extrapolating value solely from an assessment of the marginal unit.

Marginal ELCC accredits resources based on the incremental reliability contribution of the next like resource (e.g., the *last* solar resource), returning to all resources the capacity value of the marginal resource. Proponents of marginal ELCC accreditation argue that it provides a more efficient investment signal for new resource investments, providing a fungible, substitutable product for capacity market clearing at the margin. However, marginal ELCCs are unlikely to sum to the total reliability need, requiring an adjustment to the firm capacity requirement to achieve an integrated portfolio meeting a desired reliability standard. In the context of applying ELCC to emerging clean energy resources, marginal ELCC can differ substantially as saturation and interactive effects shift the marginal value of resources at different penetration levels and in different portfolio mixes. Thermal resources with coincident outages and fuel supply risk can also experience notable declines in marginal value relative to average when real-world limitations are properly incorporated into the modelling.

While either accreditation approach can return a reliable resource portfolio if the market is cleared properly, the resulting market signals can be substantially different. This analysis attempted to quantify the difference between the average and marginal ELCC awards on a future system with a much higher penetration of clean energy resources, finding that the difference between the two frameworks resulted in a significant difference for the aggregate clean energy portfolio in both 2028 and 2040. Specifically, under a marginal accreditation scheme in 2028, 41% of the reliability contributions of the utility-scale solar, wind, and storage fleet are compensated to all customers as a demand adjustment rather than directly back to the contributing resources; 52% is returned to customers rather than contributing resources from the 2040 clean resource fleet.

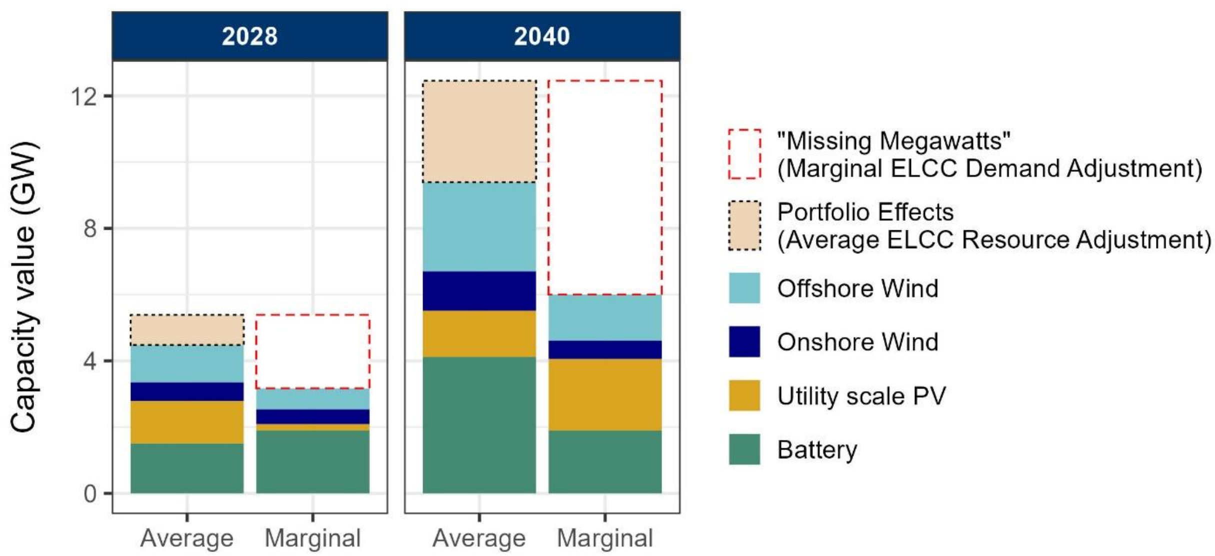

Figure ES-3. Clean Resource Fleet Valuation Under Marginal and Average ELCC Approaches

The authors wish to emphasize the importance of considering the trade-offs between marginal and average approaches, which will have considerable implications for resource development considering the magnitude of the gap between the two approaches in ISO-NE. In particular, the marginal approach could have significant equity and incentive impacts for resource developers, which are seeking stable long-term financing, as well as for utilities and states seeking to ensure the benefits of their clean energy investments are returned fairly to their ratepayers rather than socialized across all ISO-NE customer groups. To the extent a marginal accreditation approach undervalues the total reliability contributions of resources needed to decarbonize the grid, other compensation schemes beyond the FCM, either within ISO-NE's markets or outside of them, may be necessary to provide the "missing money" needed to finance these resources.

Recommendation 3: *Thoroughly examine the policy and efficiency benefits and trade-offs between marginal and average RCA approaches, as well as potential hybrid approaches, before moving forward with a final structure.*

Finding 4: Balancing Annual Reliability on a Dual-Peaking System Is Highly Sensitive to Input Assumptions.

ISO-NE faces reliability risk in both summer and winter periods. While ISO-NE's gross peak currently occurs during the summer period, trends on both the demand and supply side may result in increasingly tight system margins in winter months in the coming years. As ISO-NE has warned in recent years, winter fuel supply risk for some thermal resources is a major concern and a driver of winter reliability events.

Understanding the likelihood, magnitude, and dynamics of reliability events in both seasons is critical to the accurate calibration of the RCA modelling which will underpin capacity market outcomes. As this study shows, small shifts in input variables for either season can have potentially outsized effects on the model outcomes. As an example, small adjustments to assumptions regarding winter outage risk due to fuel supply can rapidly shift observed loss of load events to winter months, which modifies critical hours and significantly changes the ELCC analytical outcomes. This is particularly true for marginal ELCC which solely observes reliability contributions on the margin. As shown in this study, projected marginal reliability contributions can shift rapidly when assumptions shift LOLE events between seasons.

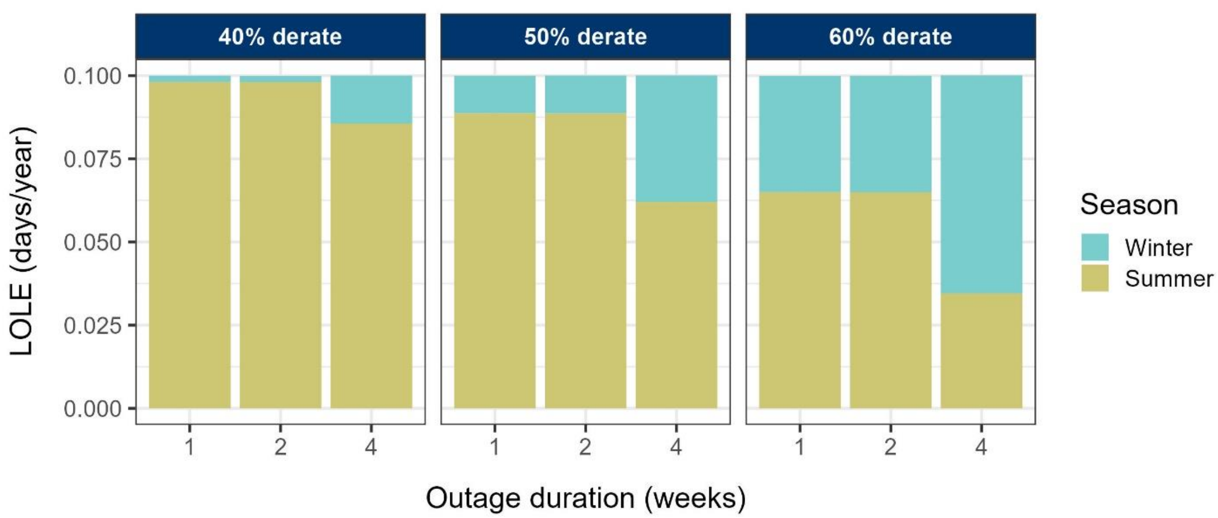

Figure ES-4. Distribution of daily LOLE by season across gas supply scenarios in 2040

The net effect is a high degree of sensitivity to input assumptions which are lumpy and unpredictable but which will need to be assumed (more than three years in advance under the current FCM) with a significant degree of confidence for model calibration. For instance, it is difficult to accurately predict how frequent and significant future polar vortex events will become with climate change, and also difficult to have perfect foresight into the dynamics of the gas system which will determine whether resources are available during these events. However, the model will require a pre-set structure for and distribution of these events to be operable.

One potential solution to this challenge could be to adopt a two-period capacity market, similar to the seasonal market design in PJM. A seasonal market design would allow more direct analysis and compensation for the divergent reliability risks across the two seasons and limit the risk of incorrectly weighting risks across seasons. The authors recommend additional analysis to better understand seasonal reliability risks in the near-, medium-, and longer-terms to better assess the merits of a seasonal capacity accreditation structure.

Recommendation 4: *Consider the trade-offs between an annual and seasonal FCM and RCA in the context of ISO-NE's near-term transition to a dual-peaking and, later, winter-peaking system.*

Finding 5: Other Considerations Such as the Choice of Reliability Metric and the Growing Impacts of Climate Change Also Must Be Considered in the RCA Design.

The selection of daily LOLE vs. EUE as the metric to drive ELCC calculations has an outsized effect on certain types of generating units. In this study, capacity values for solar PV and 4-hour battery storage changed significantly when comparing ELCC results between these two metrics (solar PV capacity value was higher with EUE and storage capacity value was lower). Similarly, when coupled with a dual-peaking system, as outlined in the previous finding, marginal capacity values using EUEI for thermal units with fuel supply issues can vary significantly (by up to 7% in this study).

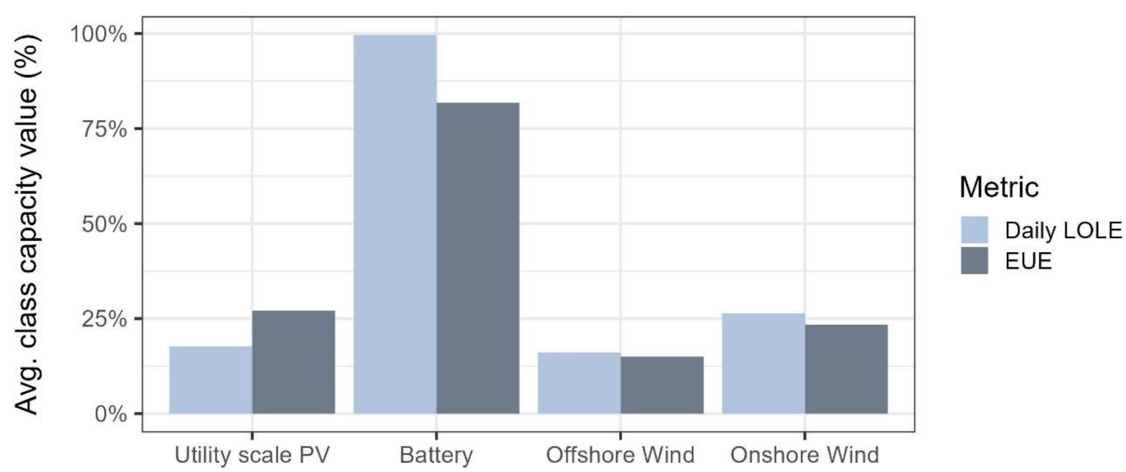

Figure ES-5. Average class capacity value using daily LOLE or EUE as metric in the ELCC process

Carefully choosing the metric to drive the results and appropriately translating the desired reliability goal into the target level for the reliability metric are critical. The implications of those decisions should be studied and understood because they can introduce significant variations in capacity accreditation results for some resources.

Further work is also necessary to anticipate how assumptions or certain system conditions may evolve over time. This study considered the implications on capacity accreditation of including higher levels of electrification, which affect hourly and seasonal trends for load shapes. Additional consideration may be necessary to understand the impacts of climate change, including on demand shapes, thermal outage rates, generation from renewable resources, frequency of extreme weather events (such as heat waves or winter storms), and the availability of neighboring areas to provide external capacity assistance.

Recommendation 5: *Consider the impacts and durability of other key RCA design features and assumptions, including choice of reliability metric (LOLE vs. EUE) and the impacts of climate change.*

Study Recommendations

- **Recommendation 1:** Ensure the RCA market design appropriately reflects the reliability contributions of clean energy resources, including solar, wind, and storage, and the interactive effects between resources.
- **Recommendation 2:** Ensure the RCA market design and modelling assumptions reflect the realities of thermal limitations, including correlated outage risk due to fuel supply constraints and ambient derates.
- **Recommendation 3:** Thoroughly examine the policy and efficiency benefits and trade-offs between marginal and average RCA approaches, as well as potential hybrid approaches, before moving forward with a final structure.
- **Recommendation 4:** Consider the trade-offs between an annual and seasonal FCM and RCA in the context of ISO-NE's near-term transition to a dual-peaking and, later, winter-peaking system.
- **Recommendation 5:** Consider the impacts and durability of other key RCA design features and assumptions, including choice of reliability metric (LOLE vs. EUE) and the impacts of climate change.

1 INTRODUCTION

The capacity of a system to reliably serve its load can be quantified through resource adequacy studies. Capacity value is the contribution of any resource in the system to meet reliability goals and maintain a reliable supply of power. As the energy mix evolves towards higher penetration of clean energy resources and other sources of risks are identified (such as likelihood of gas supply shortages or disruption), existing capacity valuation and capacity accreditation approaches must evolve to appropriately capture the contributions of different resources in ensuring electric grid reliability.

This report summarizes a collaborative effort of the Natural Resources Defense Council (NRDC) and GE Energy Consulting with the objective of identifying how different assumptions may affect the capacity valuation of resources in the ISO New England (ISO-NE) footprint in the medium and longer term. The goal is to inform the ongoing effort by ISO-NE and the New England Power Pool (NEPOOL) to review the capacity accreditation of resources in ISO-NE's Forward Capacity Market (FCM) auctions.

The analysis in this report was performed by modeling the ISO-NE footprint for two future years in the GE Multi-Area Reliability Simulation (GE MARS) software. The GE MARS model was used to calculate the capacity value of resources via the Effective Load Carrying Capability (ELCC) technique. The remainder of this section introduces the GE MARS model, the ELCC technique and some additional considerations.

1.1 GE Multi-Area Reliability Simulation (GE MARS) software

A loss of load expectation (LOLE) reliability evaluation was performed for different scenarios. The GE MARS model was used to calculate the daily LOLE, in days per year, for each case. The daily LOLE determines the numbers of days in which a loss of load (i.e., a power outage/disconnection) would be expected to occur on average across a large number of system conditions[4].

GE MARS is based on a sequential Monte Carlo simulation, which provides a detailed representation of the hourly loads, generating units, and interfaces between the interconnected areas. In the sequential Monte Carlo simulation, chronological system histories are developed by combining randomly generated operating histories of the generating units with the inter-area transfer limits and the hourly chronological loads. Consequently, the system can be modeled in great detail with accurate recognition of random events (e.g., equipment failures), as well as deterministic rules and policies, which govern system operation, without the simplifying or idealizing assumptions often required in analytical methods.

GE MARS uses state transition rates rather than state probabilities, to describe the random forced outages of thermal units. State probabilities give the probability of a unit being in a given capacity state at any particular time and can be used if one assumes that the unit's capacity state for a given hour is independent of its state at any other hour. In contrast, a sequential Monte Carlo simulation recognizes the fact that a unit's capacity state in a given hour is dependent on its state in previous hours and influences its state in future hours. It thus requires the additional information that is contained in the transition rate data.

[4] For a thorough description of how daily LOLE is calculated in reliability models, please refer to Stephen, Gord; Tindemans, Simon H.; Fazio, John; Dent, Chris; Figueroa Acevedo, Armando; Bagen, Bagen; et al. (2021): Clarifying the Interpretation and Use of the LOLE Resource Adequacy Metric. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.17054219.v2

For this analysis, the ISO-NE footprint was represented in an isolated fashion, i.e., no ties or assistance were represented between ISO-NE and external areas. The inclusion of neighboring regions would complicate the calculation because the LOLE of ISO-NE and external regions could have divergent trends as scenarios are modeled and distort the calculation of capacity value estimates. Nevertheless, the isolation of the ISO-NE footprint allows for the fast calculation of capacity value, with the implicit assumption that all resources in ISO-NE contribute to ISO-NE resource adequacy.

Additional discussion on how the GE MARS model for ISO-NE was constructed is summarized in section 2 of this report.

1.2 Capacity value methodology

This study follows the North American Electric Reliability Corporation's (NERC) Integration of Variable Generation Task Force (IVGTF) recommendation[5] to use a probabilistic-based method to calculate capacity value for time-varying output resources. For all resource types, the study team utilized the Expected Load Carrying Capability (ELCC) method to calculate the capacity value by pool, as follows[6]:

1. Beginning without the unit(s) of interest included, perfect capacity was added/removed to the ISO-NE system until the ISO-NE LOLE reached 0.1 days/year.
2. The unit(s) of interest was added to the ISO-NE system, which caused the LOLE metric to decrease (i.e., increased resource adequacy).
3. Perfect capacity was removed from the ISO-NE system until the resulting LOLE reached 0.1 days/year once again.
4. Capacity value of the unit(s) of interest was measured as the perfect capacity removed in step 3.

Thus, capacity value is the additional load that can be served while maintaining the same reliability level of 0.1 days/year. This level was set to 0.1 days/year because this is a de-facto standard in the industry and is the current reliability goal established for ISO-NE by the Northeast Power Coordinating Council (NPCC). Additional sensitivities were performed using expected unserved energy (EUE), which measures the number of megawatt hours (MWh) expected to be unserved in a year, as the reliability metric used to drive the ELCC calculations, instead of LOLE.

While both are probabilistic metrics that can be extracted from the same simulation, LOLE and EUE represent different quantities. LOLE represents the *frequency* of loss-of-load events, while EUE captures the expected *loss of energy* (a proxy for magnitude) of those events. Typically, these metrics are co-related to a certain degree[7], but the choice of metric may influence the results of ELCC-type calculations. For instance, the capacity value of thermal units without correlated outages tends to be unaffected by the selection of metrics, but energy-limited resources (such as storage or demand-

[5] NERC IVGTF report: https://www.nerc.com/comm/PC/Pages/Integration-of-Variable-Generation-Task-Force-(IVGTF)-2013.aspx

[6] Keane, A., Milligan, M., Dent, C.J., et al., "Capacity Value of Wind Power", IEEE Transactions on Power Systems, Vol. 26(2):564-572, 2011.

[7] Ibanez, E., and M. Milligan., "Comparing Resource Adequacy Metrics and Their Influence on Capacity Value." Available at: https://www.nrel.gov/docs/fy14osti/62847.pdf

response) could have variations in the results[8]. Another significant difference is that the daily LOLE metric has a specific threshold (0.1 days/year) that is widely accepted as a reliability target across North America. There is no equivalent standard level of reliability for EUE or similar energy-based metrics[9].

The calculation of capacity value with the ELCC methodology was performed for different combinations of study years and scenarios, as described in section 2. Additionally, the capacity value of various resources was assessed with different ELCC approaches:

- Marginal ELCC, where the capacity was measured for the addition of the next incremental resource added to the system (e.g., for the next incremental addition of wind)
- Average ELCC, where the capacity value of all resources of a similar type was measured (e.g., for all existing utility-scaled PV)
- Portfolio ELCC, where the capacity value of multiple resource types was measured at once (e.g., for the combination of wind, solar and storage)

Calculation of capacity values through the ELCC technique often involves an iterative process. Steps 2 and 3 described above usually involve a series of trial-and-error guesses until the system of interest has reached pre-determined convergence criteria. This can lead to long-lasting simulations, which is not desirable if many resource types or sensitivities need to be calculated. One way to improve the overall computational speed is to use a Marginal Reliability Improvement (MRI) technique. The MRI calculations are not iterative and require the following steps:

1. Start with the base model and record the LOLE (LOLE_i)
2. Add the incremental MWs of the representative unit to be measured and record the LOLE (LOLE_m)
3. Replace the incremental MWs of the representative unit with perfect capacity of the same size in the same location and record the LOLE (LOLE_p)

The capacity value is then calculated as the relative change of the system LOLE with the resource of interest, compared to the change in LOLE when adding perfect capacity, as such:

$$\mathrm{CV_i}=\frac{\mathrm{LOLE}_i - \mathrm{LOLE}_m}{\mathrm{LOLE}_i - \mathrm{LOLE}_p} = \frac{\Delta LOLE_{resource}}{\Delta LOLE_{perfect\ capacity}}$$

MRI calculations only require a finite amount of resource adequacy simulations and some of them are common when testing different resource types (for instance, steps 1 and 3 above would be shared by resources of the same nameplate capacity in the same simulations). MRI-based capacity values are

[8] W. Hall et al "Valuing Capacity for Resources with Energy Limitations," GE Energy Consulting, available at: https://www.nyiso.com/documents/20142/4358080/01082019%20Capacity%20Value%20of%20Resources%20with%20Energy%20Limitations_v2.pdf

[9] For the purposes of this study, the EUE target levels for 2028 and 2040 are set to the EUE observed in the Reference scenario, when daily LOLE for ISO-NE is equal to 0.1 days/year. This results in different EUE targets across both years.

generally considered to be a good approximation of ELCC results and are being considered as the technique to be used for these studies in several ISOs[10], including ISO-NE.

1.3 Annual versus seasonal capacity values

This section discusses another design choice when implementing capacity valuation of resources: the span of time considered by that calculation. Two distinct options are being consider by ISOs around the country, including ISO-NE: annual and seasonal capacity values.

Annual capacity values perform the calculations introduced in section 1.2 considering all the hours in the year at the same time. This is a measure of the contribution of the resource being studied to resource adequacy across the year, regardless of the timing of loss of load events.

Seasonal capacity values on the other hand limit the calculations to a portion of the year. Most commonly, summer and winter capacity values would be calculated by splitting a year in two separate halves and applying the calculations to the selected months. Under the example provided in Figure 1, the summer capacity value would only be influenced by the events and system conditions in the summer. This value would be representative of the contribution of the resource to meeting resource adequacy during the summer months. It is possible to slice the year into smaller increments (e.g., quarterly or monthly), but the separation of summer and winter is currently the dominant option being considered across the country.

Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Seasonal	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec

Figure 1. Example of scope of annual vs. seasonal calculations

Seasonal capacity values have the benefit of better separating the characteristics of resources and the system across summer and winter. For instance, some thermal resources have lower ratings in the summer due to higher ambient temperatures, some can be affected by fuel delivery issues in the winter (e.g., gas-powered generators during high-demand periods in the winter), and certain renewable resources have variable generation output (e.g., solar resources are impacted by lower irradiance in the winter). Additionally, many system conditions change between seasons: load patterns differ between summer and winter, seasonal peak forecasts can vary differently, emergency operating procedures may also change seasonally, etc. These changes can influence the timing of expected system outages and, ultimately, the capacity value of the different resources.

However, calculating seasonal capacity values does require the existence of measurable risk across both seasons. A system with expected outages in the summer would require additional corrections for the winter months until enough risk is found in the winter to allow for techniques like ELCC or MRI to be applied with sufficient accuracy.

In systems with risk only in the summer, the annual capacity value would be a preferrable approach, which would equal the capacity value for the summer season. This happens because, with all the risk

[10] E. Ibanez, M. Bringolf "Support for NYISO Capacity Accreditation Project" available at: https://www.nyiso.com/documents/20142/30276257/GE-Support%20for%20NYISO%20Capacity%20Accreditation%20Project_0428.pdf

located in the summer months, any winter modelling is irrelevant to the results. The same logic applies to winter-dominated systems, where the winter capacity value equals the annual value.

In systems with a measurable and significant[11] amount of risk in both seasons, the annual capacity value will be a blend of the summer and winter capacity values. As mentioned earlier, it will measure the contribution of the resource to the reliability of the system for the entire year. The exact combination of both values will depend on how the risk is divided amongst the two seasons and it is, therefore, sensitive to the input assumptions in the model. Under these conditions, when both seasons have risks of similar magnitude, there are valid arguments for using either annual or seasonal values.

Ultimately, the decision of using an annual or a seasonal approach is one of many steps in designing a robust process, along with the technique to be used (ELCC, MRI, other) or the choice of metric (e.g., daily LOLE vs. EUE).

[11] The risk, as measure by the chosen reliability metric, needs to be large enough so that the capacity value has an acceptable level of accuracy. The determination of the magnitude will depend on the choice of software, simulation conditions, modeling assumptions, etc.

2 METHODOLOGY

This section describes how the GE MARS model of ISO-NE was developed and simulated. It also includes the description of different sensitivities and the approach of testing different metrics.

2.1 GE MARS model description

One of the goals in this study was to study how capacity value calculations would vary for different system conditions and how they could evolve over time. To this end, two study years were selected:

- 2028 was selected because it is expected to be one of the first capacity years that would be affected by the proposed changes to capacity accreditation process in ISO-NE.
- 2040 was selected to capture how longer trends (especially increasing amounts of renewable energy resources and storage) would affect the ELCC results, and because this year was modeled as part of the ISO-NE Pathways study, which looked at the future trajectory of the region's grid.[12]

GE Energy Consulting created a model of the ISO-NE footprint to perform the analysis in this study. The starting point was GE Energy Consulting's non-proprietary database, which is based on publicly available datasets from FERC, NERC, NPCC, and the ABB Velocity Suite. The resulting capacity mix is summarized in Table 1.

The list and characteristics for thermal, hydro and pumped storage hydro (PSH) units were extracted from the GE Energy Consulting database for both 2028 and 2040. The total installed capacity for those unit types was comparable to the values in the Pathways study. Thermal units were represented using a two-state model with an expected forced outage rate (EFOR) derived from the latest NERC Generating Availability Data System (GADS) report[13]. Additional assumptions for common-mode failure events for thermal units are presented in the next subsections.

The projected nameplate capacity for utility-scale and distributed solar, onshore and offshore wind, and batteries for 2040 were based on the Pathways study. For 2028, data on solar and onshore wind capacity were found in the GE database. Offshore wind and battery capacity quantities were increased from the GE database, to reflect recent results and trends from Forward Capacity Auctions (FCA) and projects in development.

Because resource adequacy results are greatly influenced by the few top riskiest hours of the year, it is common practice to simulate different load conditions. In this case, load, wind, and solar PV profiles were created for 6 historical weather years (2007 to 2012) for each area in the two footprints. Historical load profiles were gathered from ABB Velocity Suite and then adjusted to the area's forecasted peak and energy, consistent with the forecasted peaks in the production cost model. GE MARS was then allowed to randomly choose one of the weather years simulated for each of the 2,000 replication runs for each simulation. The same weather year was selected across hourly data for load, wind and solar.

[12] The Analysis Group, "Pathways Study, Evaluation of Pathways to a Future Grid," available at: https://nepool.com/wp-content/uploads/2022/05/NPC_20220426_Pathways_FULL_REPORT_FINAL_v2.pdf

[13] NERC "Generating Availability Data System: https://www.nerc.com/pa/RAPA/gads/Pages/GeneratingAvailabilityDataSystem-(GADS).aspx

Representative onshore/offshore wind and solar PV profiles were created for ISO-NE for the 6 weather years by averaging the profile for multiple locations within the area. Wind profiles were created using NREL's WIND Toolkit[14]. Solar profiles were created using NREL's National Solar Radiance Database (NSRDB)[15] and System Advisory Model (SAM)[16].

Table 1. Base case capacity mix (MW)

Unit Type	2028	2040
Nuclear	3,356	3,356
Coal	95	0
CC Gas	12,388	12,388
ST Gas	1,337	1,337
GT Gas	1,855	1,855
Oil	4,430	4,430
Hydro	1,637	1,637
PSH	1,742	1,742
Other	1,241	1,241
Utility-scale solar	8,262	11,928
Distributed solar	4,943	7,500
Onshore wind	1,872	4,401
Offshore wind	4,700	16,014
Battery	2,000	12,953

To create the wind profiles, simulated meteorological wind data was gathered from NREL's WIND Toolkit for several locations across the ISO-NE footprint. These data include hub height, wind speed, temperature, and pressure which are based on the latitude and longitude, and year of historical data. The wind data were then converted into an hourly generation profile using a generic power curve. GE Energy Consulting adjustments to the generation includes loss factors such as wake loss, density adjustment, random outages, and electrical losses.

To create the solar profiles, simulated irradiance data were gathered from NREL's NSRDB for different locations across ISO-NE. The irradiance data were then inputted into SAM to calculate an hourly generation profile using the assumed system configurations found in Table 2. The resulting wind and solar profiles were then scaled to match the installed capacity for each scenario year.

[14] National Renewable Energy Laboratory "Wind Integration National Dataset Toolkit": https://www.nrel.gov/grid/wind-toolkit.html

[15] National Renewable Energy Laboratory "National Solar Radiation Database": https://nsrdb.nrel.gov/

[16] National Renewable Energy Laboratory "System Advisory Model": https://sam.nrel.gov/

Table 2. System configuration used in SAM

Input	Value
DC/AC Ratio	1.3
System tilt	0°
Azimuth angle	180°
Inverter efficiency	96%
System losses	14.08%
Fixed or Tracking	1 Axis Tracking
Ground coverage ratio	0.4

For simplicity, it was assumed that all installed battery capacity has a storage duration of 4 hours (i.e., a 100 MW unit would be able to store 400 MWh).

While Table 1 presented the mix of resources in terms of capacity, Table 3 summarizes how much energy wind and solar resources represented in the two study years would produce. The energy is represented in terms of the percentage of gross system load that solar and wind resources could generate. In total, wind and solar resources provide energy sufficient to serve 33.6% and 65.2% of gross load in the modelled 2028 and 2040 scenarios, respectively.

Table 3. Potential energy from wind and solar as percentage of gross load

Unit Type	2028	2040
Utility-scale solar	12.1%	15.7%
Distributed solar	7.2%	9.9%
Onshore wind	4.4%	9.4%
Offshore wind	9.9%	30.2%

2.2 Gas supply risk

Traditionally, outages of thermal resources have been considered independent, typically measured through metrics such as expected forced outage rate (EFOR). However, there are system risks that can affect multiple units simultaneously. A well-documented example in ISO-NE is the risk of outages for gas units due to fuel supply uncertainty in the winter months. For instance, heading into winter 2021-2022, ISO-NE reported that 3,700 MW of gas generation were at risk of being unable to secure fuel and run during cold weather.[17] That represents approximately 40% of the 9.27 GW of gas only generation[18] in ISO-NE. The actual risk fluctuates day to day and on a given day may be higher than this level.[19]

The study team considered this a potential reliability risk and decided to explore its effect on the results. To this end, three different levels of gas outages were considered as sensitivities:

1. Loss of 40% of gas unit capacity (3,700 MW)
2. Loss of 50% of gas unit capacity (4,635 MW)
3. Loss of 60% of gas unit capacity (5,562 MW)

Along with the severity of the outage, we also considered the effect of having different outage durations. This was accomplished by derating the capacity for gas units for the amounts listed above for a window of time centered around the winter peak load for:[20]

- 1 week
- 2 weeks
- 4 weeks

For the base case conditions, the study team selected to derate gas capacity by 3,700 MW (40%) for 1 week around the winter peak. For certain scenarios we also considered a more severe scenario, with a gas capacity derate of 50% for 2 weeks around the winter peak. The impact of the other combinations of severity and duration are further presented as sensitivities.

2.3 Impact of ambient temperature

The study team examined the impact that high ambient temperatures can have on thermal unit performance and how those changes can affect the capacity valuation of thermal resources. This sensitivity is based on a paper by researchers at Carnegie Mellon University[21]. That paper presents the estimated variation of forced outage rates for different types of units as temperature increases.

Within the GE MARS framework, it is much easier to input how capacity changes with temperature, so the results in the paper were converted into capacity derates as a function of temperature, resulting in the trends presented in Table 4 and Figure 2. Under the worst conditions modeled (i.e., temperatures

[17] ISO-NE, "NEPOOL Participants Committee Report," November 3, 2021, slide 18, available at: https://www.iso-ne.com/static-assets/documents/2021/11/november-2021-coo-report.pdf.

[18] Gas-only units not including the LNG-fueled Mystic generating units. ISO-NE, 2022 CELT Report, available at: https://www.iso-ne.com/static-assets/documents/2022/04/2022_celt_report.xlsx.

[19] The 2021/22 NPCC Winter Assessment assumed "5,682 MW of gas-fired generation assumed unavailable due to the fuel supply constraint" for New England for the Severe assumptions in the probabilistic section of the study (Appendix VIII), available at: https://www.npcc.org/content/docs/public/library/reports/seasonal-assessment/2021/npcc-2021-2022-winter-assessment.pdf

[20] A similar approach was performed by NPCC in 2017: "NPCC Natural Gas Disruption Risk Assessment" available at: https://www.npcc.org/content/docs/public/library/publications/other/2017-npcc-natural-gas-disruption-risk-assessment-rev.pdf

[21] S. Murphy, F. Sowell, J. Apt, "A time-dependent model of generator failures and recoveries captures correlated events and quantifies temperature dependence" (2019) Applied Energy, Vol. 253, Available: https://doi.org/10.1016/j.apenergy.2019.113513

exceeding 35°C, or 95°F), the impact is a loss of just over 1,300 MW of thermal capacity out of 24.7 GW available, which represents a derate of 5.3%.

Table 4. Percentage capacity derates by technology and by temperature

	Ambient temperature (°C)				
Generator type	15	20	25	30	35
Combined cycle	0	0	0	0.83	3.93
Combustion turbine	0	0	0	1.21	3.78
Diesel	0	2.76	2.65	3.40	6.69
Hydro/PS	0	0	0	0.42	5.83
Nuclear	0	0	1.14	4.01	9.91
Steam turbine	0	0	0	1.97	4.54

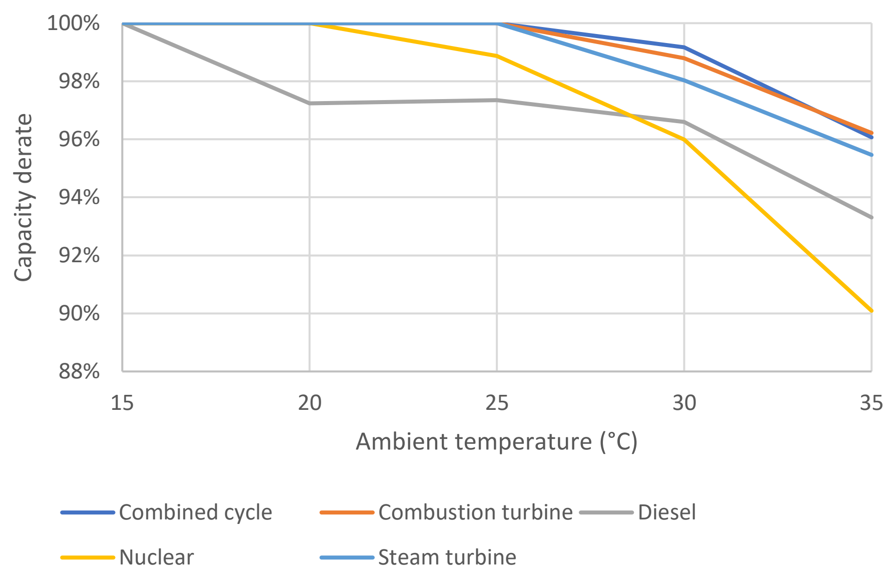

Figure 2. Capacity derates applied to thermal units in the GE MARS model

These derates were applied for each hour of the simulation for the units in the model. Temperature profiles for an average ISO-NE location were developed for each of the 6 weather years simulated.

The impact of ambient derates is included in the base case and its impact on the capacity value results is presented as a sensitivity.

2.4 Impact of higher levels of electrification

The study team considered one final sensitivity to capture how increased electrification levels, and their impacts on load shape, could affect the capacity valuation of resources. To perform the simulation, we modified the base shape of the load for ISO-NE to represent greater levels of electrification. We used data from the NREL Electrification Future Study (REF)[22] to develop the necessary load modifications.

Using public datasets from the REF study, we extracted the load shapes for the business as usual and high-electrification scenarios for the six New England states. From those data, we calculated the average weekly shape for each month of the year, on an hourly basis. The difference between those load shapes was then applied to our GE MARS dataset. The resulting load shapes for an average day per season are represented in Figure 3 and Figure 4 for the years 2028 and 2040, respectively.

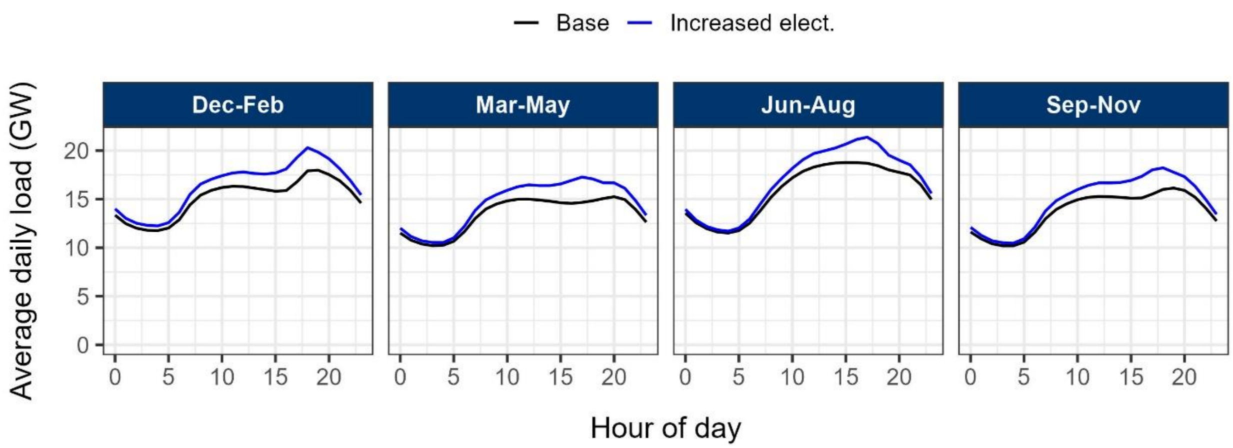

Figure 3. Average daily shapes for load for the higher electrification sensitivity (2028)

In 2028, the effect of increased electrification is most noticeable in the summer and winter months, and it primarily increases the load during the day. Across the year, the gross load increases by 8% and summer and winter load peaks increase by 13%. In 2040, the effect of increased electrification is much more pronounced, and it affects most hours of the year, although the largest increases in load still happen during daylight and early night hours, with the biggest impacts again in the summer and winter months. Energy demand increases by 26% in this year, and summer and winter peaks increase by 41% and 45%, respectively.

[22] T. Mai, et al. "Electrification Futures Study," National Renewable Energy Laboratory. Available: https://www.nrel.gov/analysis/electrification-futures.html

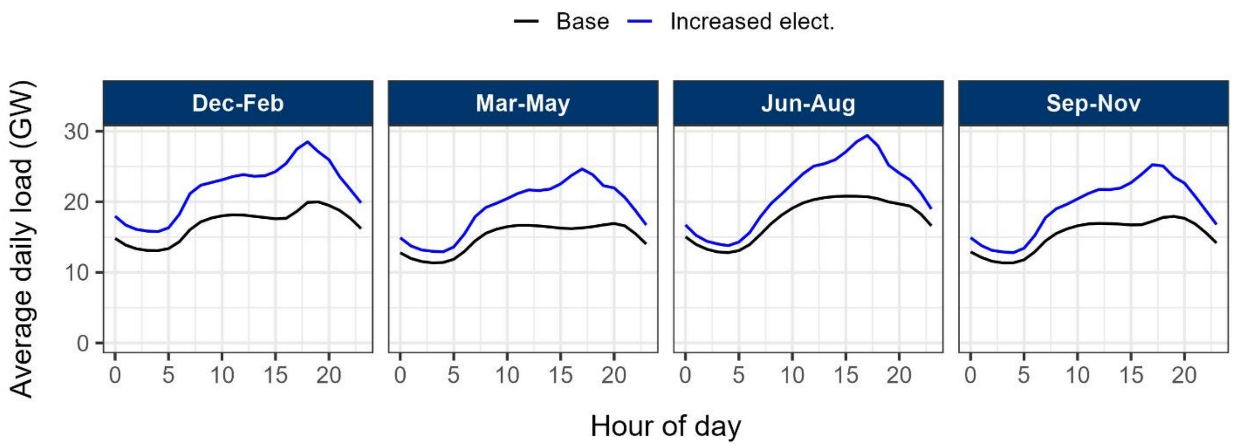

Figure 4. Average daily shapes for load for the higher electrification sensitivity (2040)

The impact of potential future higher levels of electrification is not considered in the base case, but it is considered as a sensitivity.

2.5 Base case summary

The base case in this study is comprised of the assumptions listed in section 2.1 with the addition of:

- Derate gas capacity by 3,700 MW (40%) for 1 week around the winter peak (section 2.2)
- Ambient derate for thermal units (section 2.3)
- No increased electrification impact on load shapes (section 2.4)

Figure 5 shows a summary of system conditions during the peak load days in 2028 and 2040. The graph represents the generation from wind and solar resources as colored stacked areas. Total gross load is represented as a black continuous line and, finally, net load (load minus renewable generation) is represented by a dashed black line. Net load is an important driver in the system as it represents the demand that will be met by non-renewable resources.

From the chart, we can see that the deployment of solar PV is significant in both study years. The load and net load shapes resemble different stages of what is commonly known as the "duck curve."[23] In essence, the presence of solar in the middle of the day decreases the amount of net load until sunset. Offshore wind also contributes to this effect, based on the charts. The effect is that during the peak days, the period of risk hours (high net load) becomes more concentrated and much narrower, in the hours surrounding sunset. In 2040, the additional presence of solar and offshore wind further reduces the net load, with a much flatter profile in the night hours.

[23] National Renewable Energy Laboratory "10 years of analyzing the duck curve", https://www.nrel.gov/news/program/2018/10-years-duck-curve.html

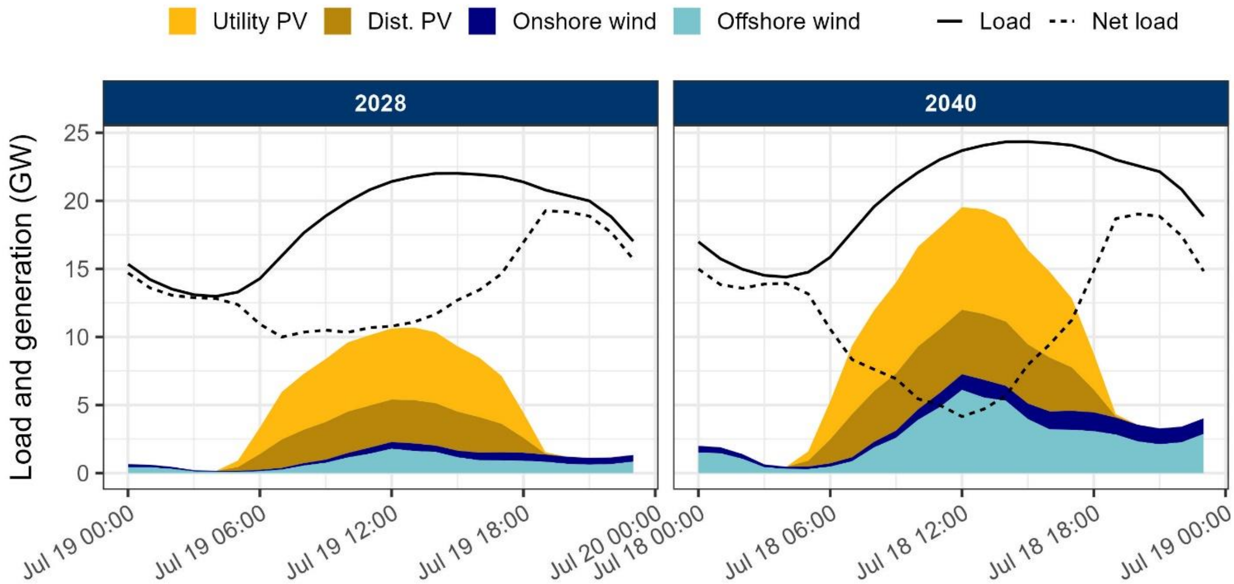

Figure 5. Load, net load, and renewable generation during the peak summer days

Similarly, Figure 6 represents the same data but plotted for an average day per season. The “duck curve” effect is visible across all seasons. In spring and fall, load levels are usually smaller, so net load values are much smaller. Interestingly, solar makes a smaller contribution in the winter, which is balanced by a larger amount of generation from onshore and offshore wind.

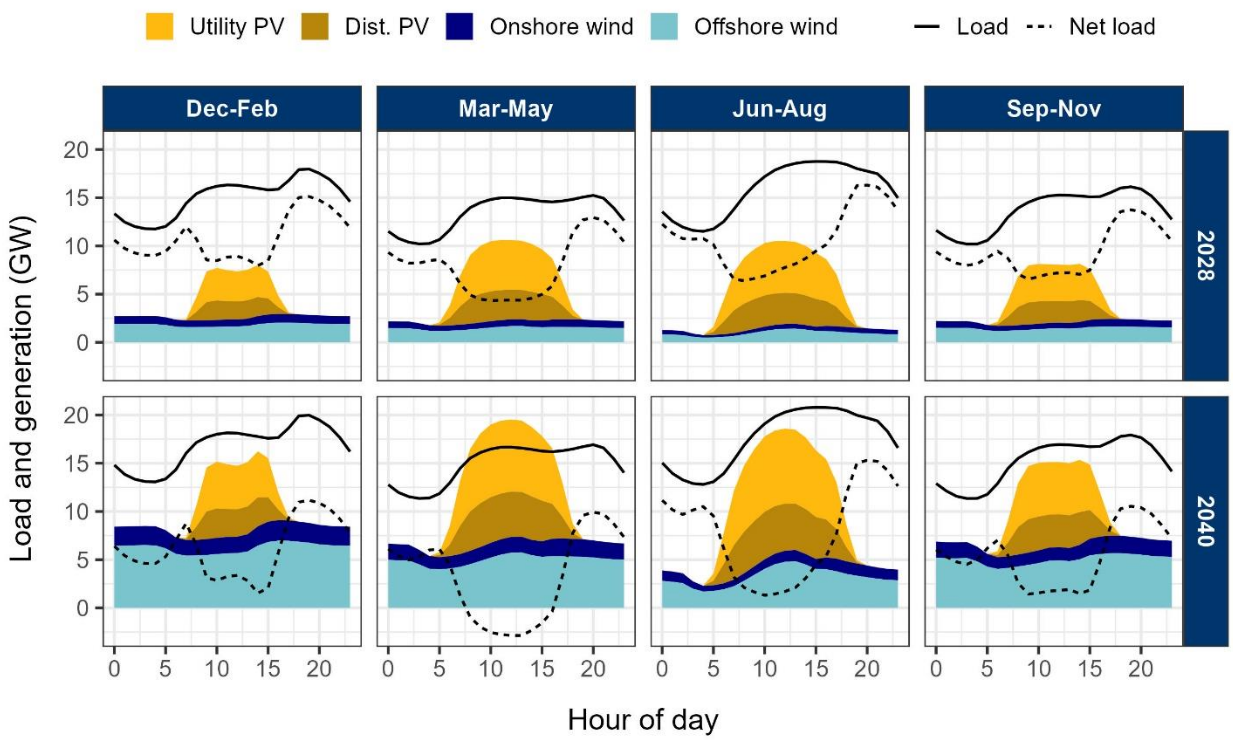

Figure 6. Load, net load, and renewable generation for an average day per season

For both study years the reference system was driven to a common level of daily LOLE of 0.1 days/year. The distribution of LOLE is slightly different, as shown in Figure 7. For 2028, the LOLE is primarily concentrated in July and August, with some additional events found in June and September. The distribution in 2040 is similar but starts showing some amount of LOLE in January. This represents a transition in the system, where winter margins are smaller, and ISO-NE experiences a mixture of summer and winter outages.

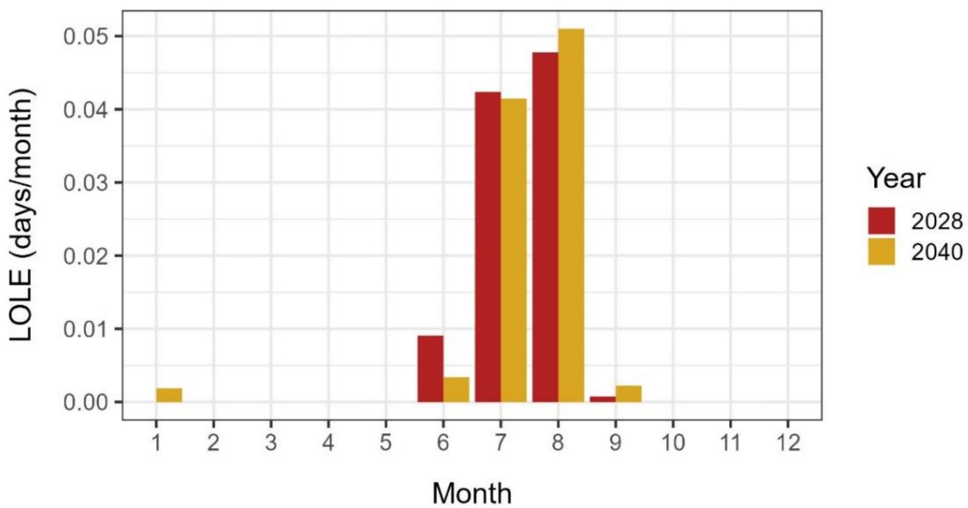

Figure 7. Loss of load expectation by month for both study year

Finally, Figure 8 shows how the system risk (as measured by hourly LOLE) is typically distributed across hours of the day. For 2028, the risk is concentrated in the hours immediately following sunrise, coincident with the hours of high net load in Figure 5. For 2040, the risk is more evenly distributed across all hours of the night, similar to how net load is much flatter across those same hours.

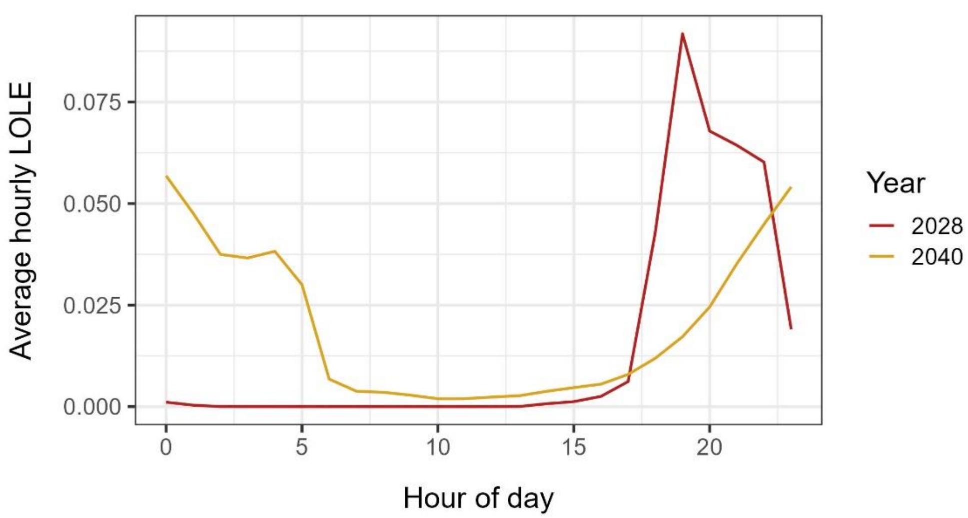

Figure 8. Distribution of hourly LOLE by hour of day

2.6 Choice of metric

Across the base case and sensitivities, the ELCC calculations were performed with two metrics: daily LOLE, and EUE. The two metrics were used to recognize that current reliability requirements in ISO-NE are determined in terms of daily LOLE, but ISO-NE has proposed using EUE in the capacity value process. The choice of metric can potentially have an impact on capacity value results because they greatly influence the timing and magnitude of outages.

To understand this behavior, it is useful to see the relationship of the two metrics across the different cases used to calculate the capacity value. For instance, to calculate the capacity value of battery storage we compare the reference case to a case without any battery storage on the system and drive both cases to criteria. To calculate the capacity value of solar we also include a case without any solar in the system. These examples are extracted from section 4.5.1; please refer to that section for additional discussion on these specific scenarios.

When those cases are driven to the same level of daily LOLE, there are variations in the amount of EUE, as seen in Figure 9. For the same level of daily LOLE, the case without storage will have a smaller EUE, while the case without solar will have a larger EUE. This happens because the cases without solar result in longer outages, spreading the risk over more hours in a day. The daily LOLE metric only accounts for whether an outage happened in a day, regardless of how many hours or how much energy was not served. When we remove battery storage the outages are shorter and more concentrated, compared to solar. Both effects can be seen in Figure 10.

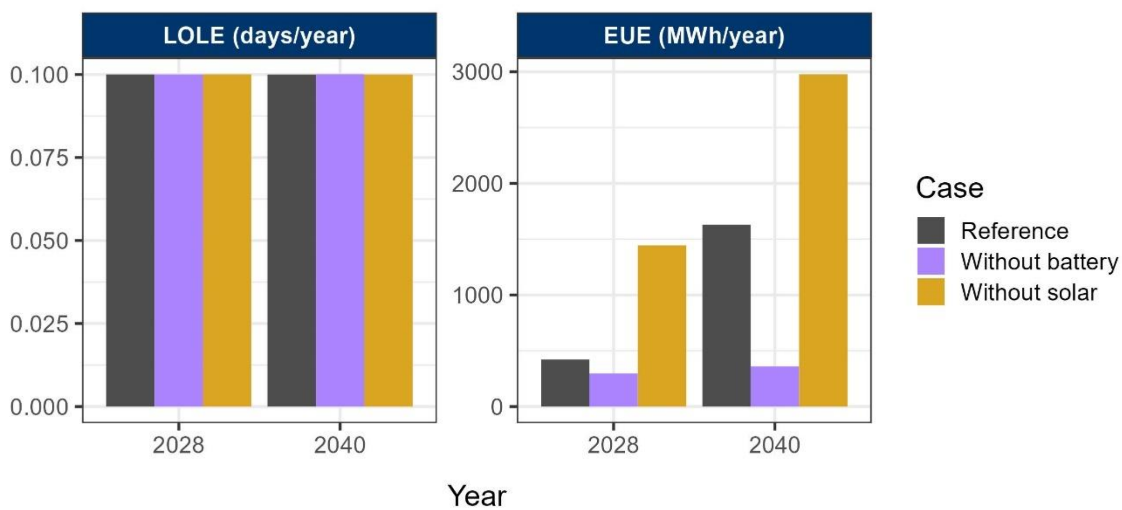

Figure 9. Daily LOLE and EUE for the different cases used to calculate class average ELCC

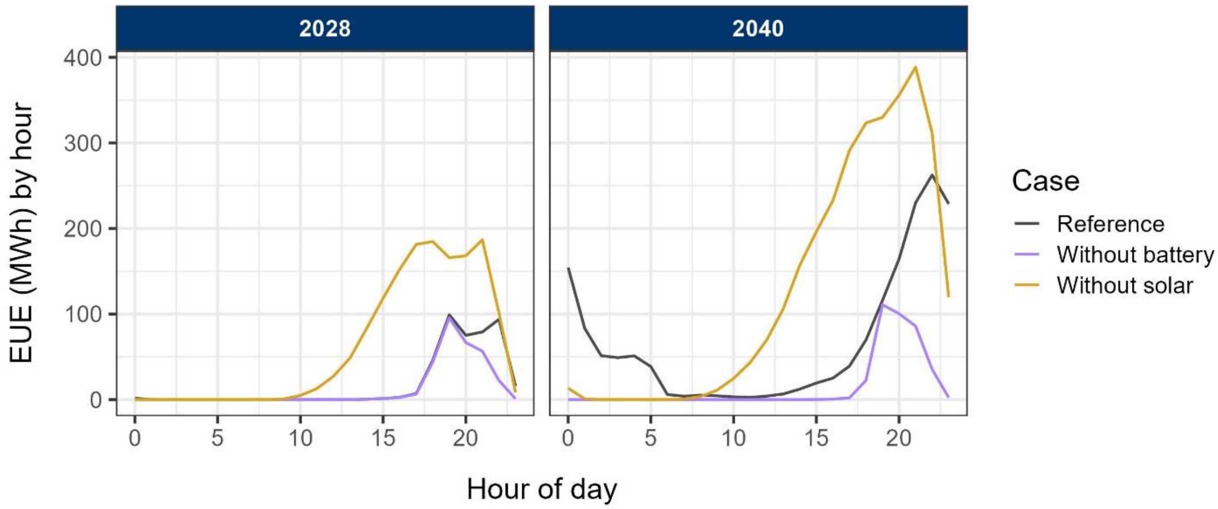

Figure 10. Distribution of EUE by hour of day for cases with the same daily LOLE

Figure 11 and Figure 12 show the same information, but for cases in which the EUE is the same across scenarios (2028 and 2040 are calculated independently). In both years, the outages translate in more days of risk in the case without battery and fewer in the case without solar.

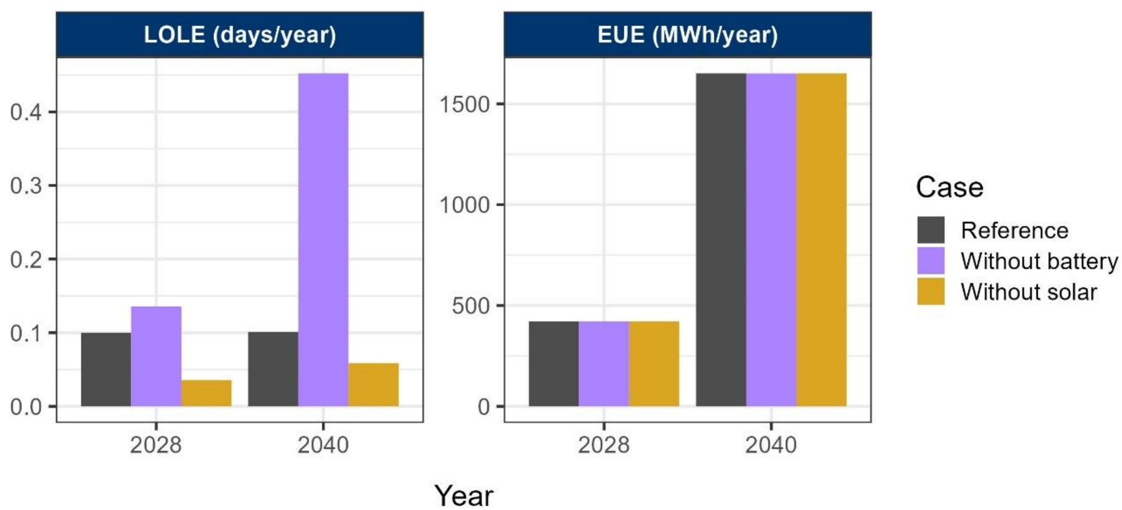

Figure 11. Daily LOLE and EUE for the different cases used to calculate class average ELCC

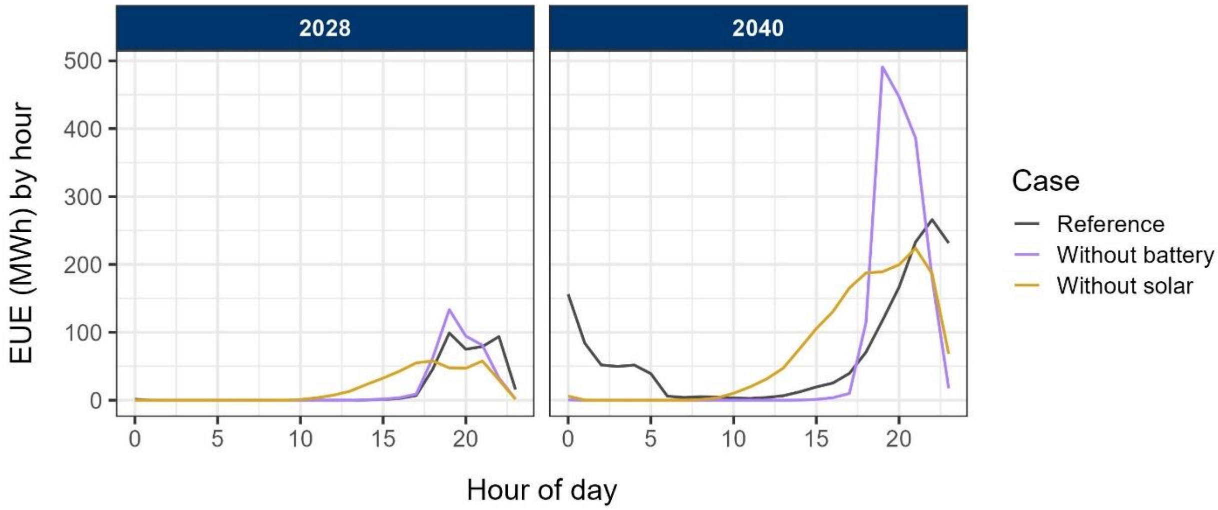

Figure 12. Distribution of EUE by hour of day for cases with the same daily EUE

When the nature of outages changes between the cases being compared, it affects how much capacity needs to be added to the system to match the initial daily LOLE or EUE. For instance, in 2040 the two cases "Without battery" differ by more than 1,800 MW. This change directly affects the capacity value calculated by the ELCC or MRI methodologies, up to 14% in the case of battery storage in 2040. The variations in outage behavior can also be present in cases with smaller perturbations, making marginal calculations also susceptible to the choice of metrics.

3 IMPACT ON THERMAL RESOURCES

This section summarizes how the different assumptions in the model impact the capacity valuation of thermal resources.

3.1 Impact of fuel supply constraints

First, we examine how the different assumptions on fuel supply constraints can affect the capacity value of existing thermal resources. As detailed in section 2.2, we consider gas supply constraints that derate the existing 9.27 GW of gas-only generation by 40%, 50% and 60%. That impact is considered for 1, 2, and 4 weeks around the winter load peak.

As the magnitude and duration of the gas constraints increase, we observe interesting trends in the distribution of LOLE across months, as shown in Figure 13. In 2040, as the severity of the events increases, the risk shifts from the summer to the winter months. For 1 and 2 weeks around the winter load peak, the winter events accumulate in January. With a duration of 4 weeks, we see a significant increase of LOLE in December as well and the system experiences a higher share of LOLE in the winter than in the summer, overall. This happens because, as we previously pointed out, the study year 2040 presents a system where the margins are much smaller in the winter. In 2028, the LOLE is overwhelmingly concentrated in the summer months, although there are traces of LOLE observed in winter months under the most severe conditions.

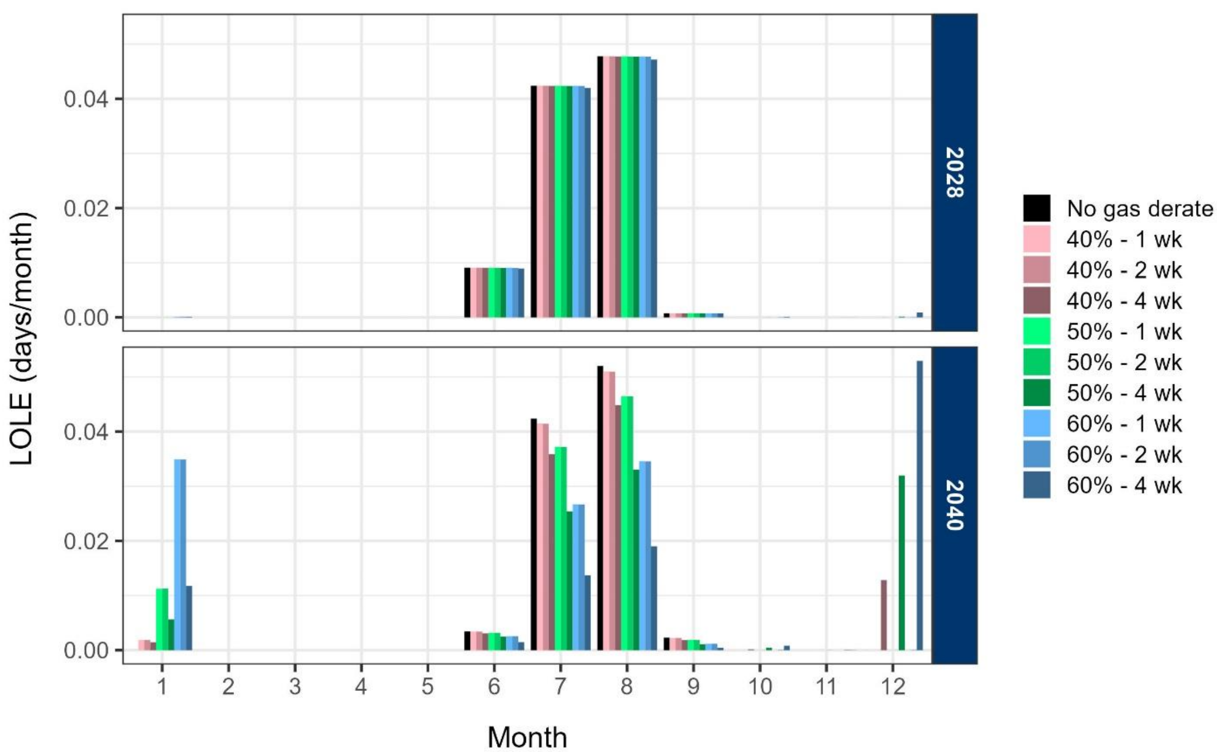

Figure 13. Distribution daily LOLE by month across all gas scenarios

This distribution of risk indicates that, in the short-to-medium term, the summer season is the main driver for resource adequacy needs in ISO-NE. The GE MARS model in this study was not benchmarked to match ISO-NE's internal model. However, recent reports by NPCC (which do utilize ISO-NE official data) do not show immediate concerns about winter reliability risk[24]. These probabilistic results contrast with recent public statements from ISO-NE, which highlight that gas supply is a significant source of risk and that reliably serving load would be challenging during a severe winter[25].

If the fuel security issue is such a large driver of reliability risk, that would suggest that the near-term modeling would resemble the most severe scenarios in the 2040 results in Figure 13. Further work may be necessary to reflect those limitations in the ISO-NE probabilistic model, by accurately reflecting the fuel disruption scenarios and carefully weighting the probability of a severe winter (versus mild or moderate winters, which are not considered to be problematic). That exercise will ensure that fuel security risks are appropriately represented. As discussed in section 1.3, the correct identification of the main risk drivers in the summer and in the winter can greatly influence the capacity valuation of resources that perform differently across seasons.

The resulting impacts of the outages considered in this study are summarized in terms of total MW (Table 5), and in percentage terms relative to the 9.27 GW of gas-only resources in the region (Table 6). In 2028, the capacity value reduction is negligible, consistent with the lack of observed LOLE in the winter under the assumed conditions. The 2040 penalties are modest for the smaller outages and moderate for the most severe cases. A larger and/or longer outage leads to higher loss of capacity value, peaking at 10.4% for the more severe case.

Because this study calculated a single annual capacity value for each resource type, the effect of winter gas outages on this capacity value is implicitly weighted by the ratio of summer and winter LOLE. As the winter LOLE becomes more dominant, the penalty on the annual capacity value is more pronounced. Calculating seasonal accreditation for these resources was beyond the scope of this study, but such an approach would more clearly separate the effect of these assumptions without the implicit blending of the annual approach.

Table 5. Reduction of thermal capacity value due to fuel impacts (MW)

		Duration of gas derate		
Year	Gas derate magnitude	1 week	2 weeks	4 weeks
2028	40%	0.0	0.0	1.4
	50%	0.1	1.4	1.8
	60%	1.1	1.8	14.0
2040	40%	20.9	21.3	155.6
	50%	122.2	123.0	448.5
	60%	408.4	409.1	965.1

[24] For instance, in the NPCC 2021/22 Winter Reliability Assessment, Appendix VII (available at https://www.npcc.org/content/docs/public/library/reports/seasonal-assessment/2021/npcc-2021-2022-winter-assessment.pdf) or the NPCC 2021 Long Range Adequacy Overview (available at https://www.npcc.org/content/docs/public/library/resource-adequacy/2021/2021-11-30-npcc-long-range-adequacy-overview.pdf)

[25] Please refer to ISO-NE's presentation slides from FERC's New England Winter Gas-Electric Forum in Sep. 8, 2022 (available at https://www.iso-ne.com/static-assets/documents/2022/09/ne_gas_electric_forum_presentations.pdf) or ISO-NE's 2021/22 Winter Outlook (available at: https://www.iso-ne.com/static-assets/documents/2021/12/2021-22-winter-outlook.pdf)

Table 6. Reduction of thermal capacity value due to fuel impacts (% of gas nameplate)

		Duration of gas derate		
Year	Gas derate magnitude	1 week	2 weeks	4 weeks
2028	40%	0.0%	0.0%	0.0%
	50%	0.0%	0.0%	0.0%
	60%	0.0%	0.0%	0.2%
2040	40%	0.2%	0.2%	1.7%
	50%	1.3%	1.3%	4.8%
	60%	4.4%	4.4%	10.4%

Similar calculations were performed using EUE as the driving metric for the ELCC calculations, instead of using daily LOLE as the driving metric. Table 7 shows that the EUE results are comparable to the LOLE in Table 5 for 2028. The results in 2040 generally follow the same order of magnitude but can vary for some of the cases because reliability in 2040 is driven in part by the ability to supply energy, not just capacity (because of the large presence of storage).

Table 7. Reduction of thermal capacity value due to fuel impacts (MW), using EUE

		Duration of gas derate		
Year	Gas derate magnitude	1 week	2 weeks	4 weeks
2028	40%	0.0	0.0	0.0
	50%	0.0	0.0	2.0
	60%	2.0	2.2	6.5
2040	40%	7.5	7.6	133.5
	50%	60.3	60.6	437.0
	60%	267.6	269.2	988.7

Next, we examined the capacity value penalty of including fuel supply issues for a new combined cycle (CC) unit. A 200-MW unit was added to the system, and we measured the difference in its capacity value with and without fuel supply issues. We assumed that, during an outage event, the available gas supply in the system was utilized by existing gas plants units, so the 200-MW unit did not receive any fuel during the outage. The results are summarized in MW (Table 8), and a percentage of its capacity (Table 9).

Table 8. Reduction of capacity value for a marginal CC unit due to fuel impacts (MW)

		Duration of gas derate		
Year	Gas derate magnitude	1 week	2 weeks	4 weeks
2028	40%	0.0	0.0	-1.3
	50%	0.1	-1.1	0.4
	60%	1.4	1.3	5.8
2040	40%	9.9	9.3	43.8
	50%	37.4	37.2	94.8
	60%	90.4	90.9	138.5

Table 9. Reduction of capacity value for a marginal CC unit due to fuel impacts (% of nameplate)

		Duration of gas derate		
Year	Gas derate magnitude	1 week	2 weeks	4 weeks
2028	40%	0.0%	0.0%	-0.6%
	50%	0.1%	-0.5%	0.2%
	60%	0.7%	0.6%	2.9%
2040	40%	4.9%	4.7%	21.9%
	50%	18.7%	18.6%	47.4%
	60%	45.2%	45.5%	69.2%

As was the case with the existing thermal fleet, the impact of the gas derates in 2028 is negligible because the model finds that system risk is predominantly in the summer. However, in 2040 we see much higher derates for the incremental unit. Those derates can exceed 40% of nameplate for the most severe scenarios. As previously stated, these are derates of the annual capacity value, weighted between summer and winter. A seasonal assessment would lead to no change in the capacity value of thermal units in the summer and a greater penalty in the winter months, due to the presence of gas shortages in that season.

Table 10 shows the same results as in Table 8 for a similar case that uses EUE as the driving metric. The results are very similar in 2028 but in 2040 they can diverge by up to 7% of capacity.

Table 10. Reduction of capacity value for a marginal CC unit due to fuel impacts (MW), using EUE

		Duration of gas derate		
Year	Gas derate magnitude	1 week	2 weeks	4 weeks
2028	40%	0.0	0.0	0.0
	50%	0.0	0.0	-1.1
	60%	-1.2	-1.1	1.6
2040	40%	6.0	5.9	46.6
	50%	27.7	27.4	101.7
	60%	76.0	76.6	146.4

Table 11 compares the marginal capacity value for a gas CC unit for the year 2040. The differences range from 3 to 14 MW. To better understand why the choice of metric can have such a significant impact on the results, we will focus on the cases where the magnitude of gas derate is 60%.

Table 11. Reduction of capacity value for a marginal CC unit due to fuel impacts (MW) for 2040

		Duration of gas derate		
Metric	Gas derate magnitude	1 week	2 weeks	4 weeks
LOLE	40%	9.9	9.3	43.8
	50%	37.4	37.2	94.8
	60%	90.4	90.9	138.5
EUE	40%	6.0	5.9	46.6
	50%	27.7	27.4	101.7
	60%	76.0	76.6	146.4
Difference	40%	-3.9	-3.4	2.8
	50%	-9.7	-9.8	6.9
	60%	-14.4	-14.3	7.9

To calculate the marginal capacity value of a gas CC unit, we compare two cases "at criteria": a case without the unit and a case with the unit. Figure 14 compares the daily LOLE across these cases. The "LOLE" simulations all share the same daily LOLE, which is set at 0.1 days/year. The "EUE" cases all have the same annual EUE, but the resulting daily LOLE varies. In the case with no gas derate, the difference is minimal. In the cases with outages of 1 or 2 weeks, we observe the daily LOLE rising in the cases where "EUE" is the target.

For these cases, the EUE is the same, but the cases with the marginal gas CC unit have a higher daily LOLE. In order to match the daily LOLE in those cases to their respective Reference cases, we would need to add an additional 14 MW of firm capacity. This would mean reducing the capacity value of the marginal gas CC unit, which is the difference shown in Table 11.

For the case with outages lasting 4 hours, we observe the opposite situation. The "EUE" case has a lower daily LOLE in the case with the marginal unit, compared to the Reference. This results in a higher capacity value when using LOLE, as compared to EUE.

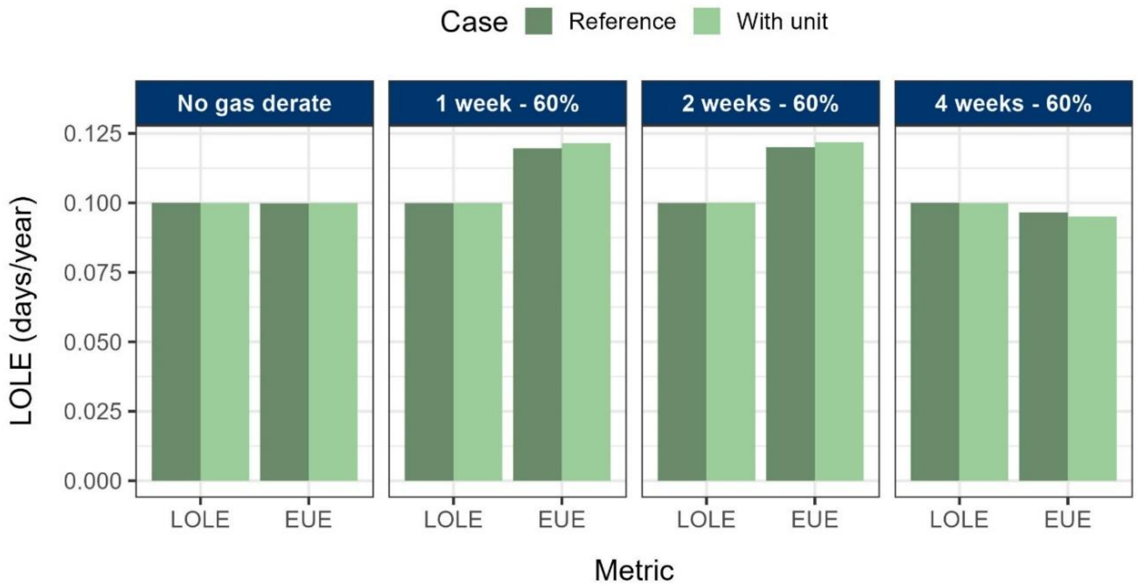

Figure 14. Daily LOLE results for marginal gas CC units, for different gas derates

Figure 15 shows the daily LOLE values in Figure 14, but disaggregating the annual data across months. The bottom portion of that figure shows the differences between the cases with the marginal unit and the reference. The case with no gas derate has nearly identical distribution of LOLE, which is concentrated in the summer months.

The cases with outages lasting 1 and 2 weeks shift LOLE from summer to January, as we previously saw in Figure 13. However, the case with the marginal unit accelerates that change. In particular, in the cases where the EUE is matched, the LOLE in January grows even more, leading to an overall increase in daily LOLE across the year. In contrast, the cases with 4-week outages shift the summer risk into the month of December. In this case, the "EUE" scenarios have an overall smaller value of daily LOLE.

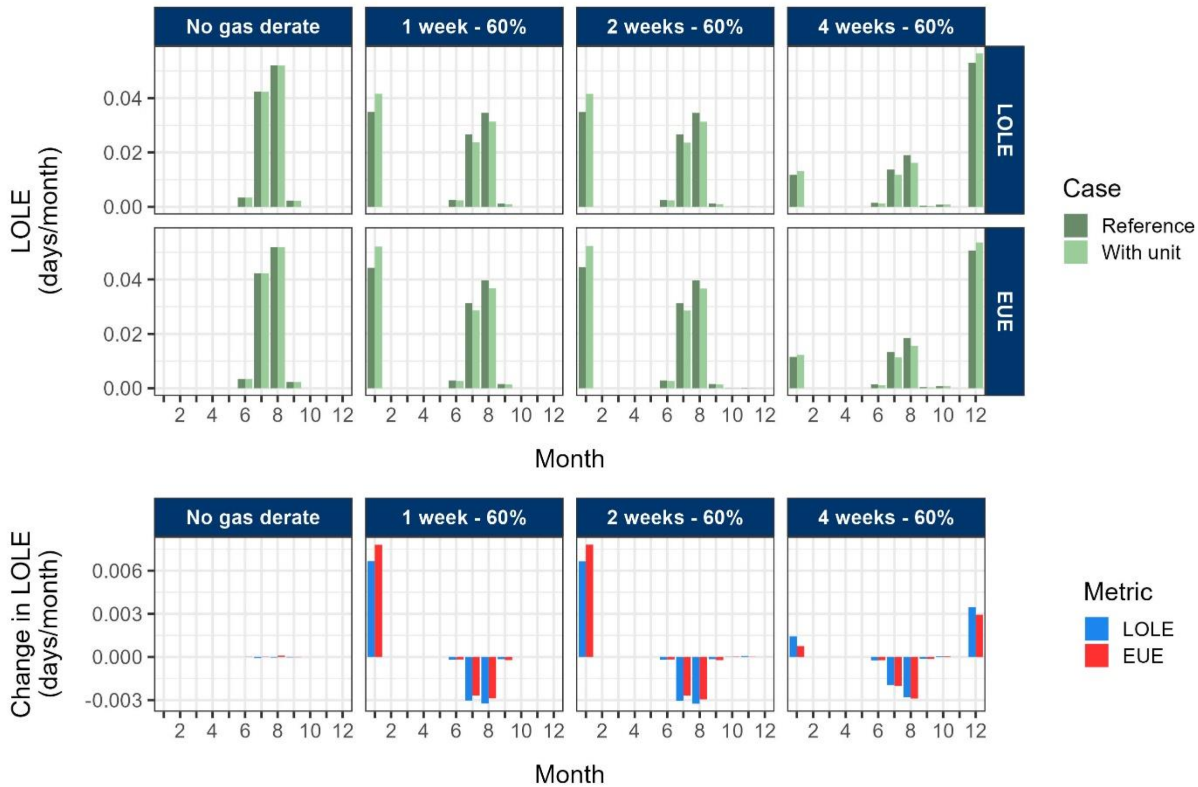

Figure 15. Monthly comparison of daily LOLE for marginal gas CC units, for different gas derates

Table 12 summarizes the resulting average and marginal capacity values for a gas CC unit in the year 2040, across the different levels of fuel impact. It combines the results presented in Table 6 and Table 9. The same data is represented in Figure 16 and shows that marginal values are consistently smaller than the average counterparts and that, in certain situations, marginal values can be as low as a third of the average value.

Table 12. Average and marginal gas CC capacity value due to fuel impacts (%) in 2040

		Duration of gas derate		
ELCC	Gas derate magnitude	1 week	2 weeks	4 weeks
Average	40%	93.5%	93.5%	92.0%
	50%	92.4%	92.4%	88.9%
	60%	89.3%	89.3%	83.3%
Marginal	40%	88.7%	89.0%	71.8%
	50%	75.0%	75.0%	46.3%
	60%	48.5%	48.2%	24.4%

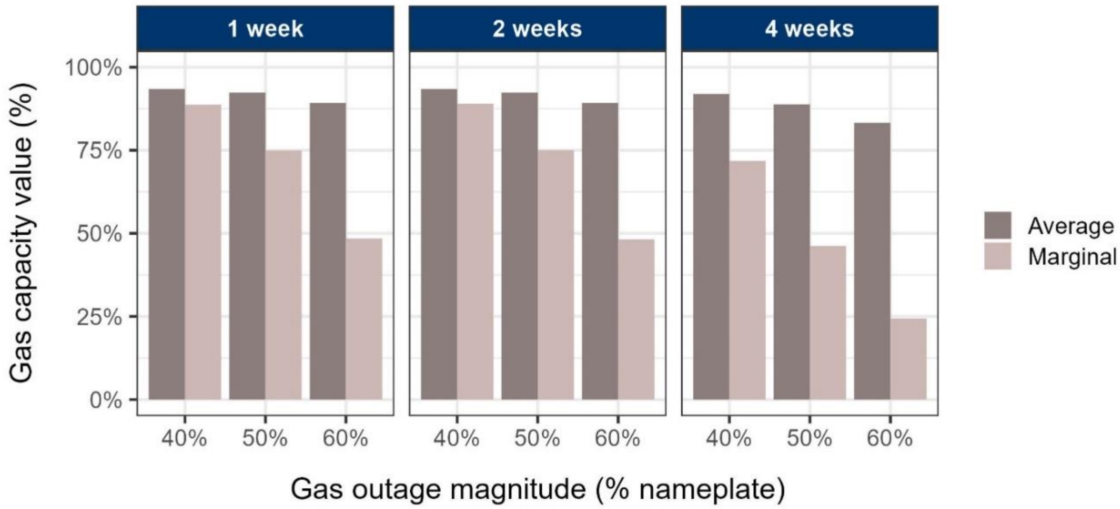

Figure 16. Gas CC capacity value for average and marginal results

3.2 Impact of ambient temperature derates

Section 2.3 summarizes the assumptions on how ambient temperature affects the capacity of thermal resources in our GE MARS model. The total maximum impact of those assumptions is estimated to be 1,300 MW. Once the cases were simulated and analyzed, we estimate that the portfolio effect on thermal units is small, around 120 MW (Table 13). This result is consistent across different assumptions for fuel supply and when using EUE as the driving metric (Table 14). These results represent the reduction in the thermal portfolio ELCC due only to the consideration of ambient temperature derates. The ambient-temperature penalties are calculated for different levels of gas outages: no outages, base conditions (40% derate for 1 week) and severe conditions (50% derate for 2 weeks).

Table 13. Impact of ambient temperature derates for all thermal units (MW)

Year	No gas outage	1 week, 40% derate	2 week, 60% derate
2028	119.7	119.7	118.3
2040	127.2	123.4	57.5

Table 14. Impact of ambient temperature derates for all thermal units (MW), using EUE

Year	No gas outage	1 week, 40% derate	2 week, 60% derate
2028	129.6	129.6	130.8
2040	132.9	128.4	78.5

The impact is relatively small because the risk hours in both 2028 and 2040 happen at night and are not found in high-temperature hours. Figure 17 shows the hourly load, net load and wind and solar generation (previously presented in Figure 5). At the bottom of Figure 17 we include the typical temperature ranges observed for ISO-NE in July and August. Because of the presence of solar (and offshore wind to a smaller degree), the critical hours of higher net load happen in the nighttime when temperatures are much lower and the ambient temperature derates (introduced in Table 4) are negligible.

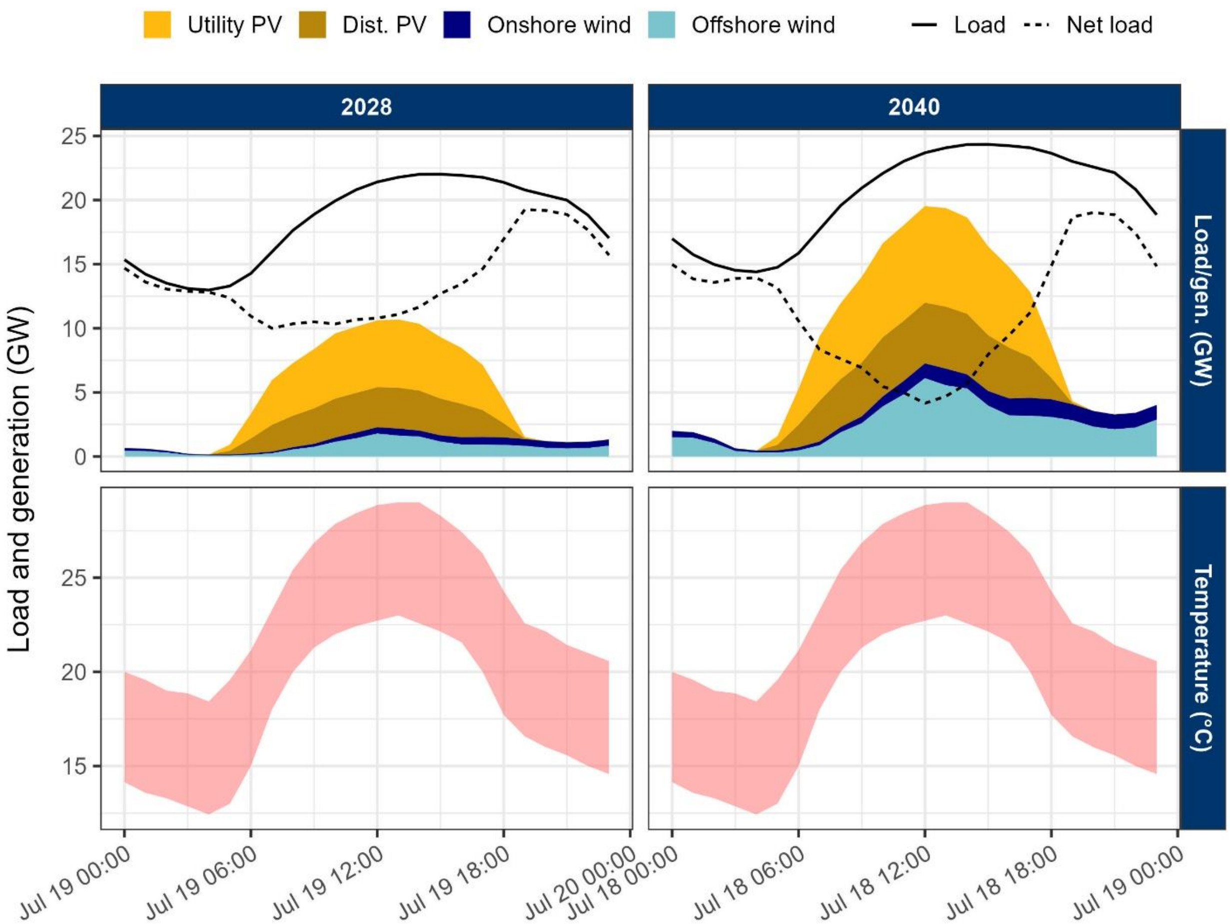

Figure 17. Load, net load, and renewable generation for the peak day, along with typical summer temperature ranges

We also measured the impact of the ambient temperature derate on a marginal combined cycle (CC) unit and a marginal diesel unit, both with a capacity of 200 MW. The resulting effect yields a derate of the units (Table 15 and Table 16) that are typically half of the maximum derate assumed in the inputs (as summarized in section 2.3).

Table 15. Impact of ambient temperature derates for marginal units (MW)

Unit	Year	No gas outage	1 week, 40% derate	2 week, 60% derate
Gas CC	2028	2.6	2.6	1.7
	2040	0.6	0.2	11.2
Diesel	2028	5.8	5.9	6.3
	2040	3.7	1.4	3.2

Table 16. Impact of ambient temperature derates for marginal units (% of nameplate)

Unit	Year	No gas outage	1 week, 40% derate	2 week, 60% derate
Gas CC	2028	2.9%	2.9%	3.1%
	2040	1.9%	0.7%	1.6%
Diesel	2028	1.3%	1.3%	0.9%
	2040	0.3%	0.1%	5.6%

3.3 Impact of higher electrification

The inclusion of additional load due to higher levels of electrification changes the pattern for load, as discussed in section 2.4. As a result, the patterns for the hours of risk change and influence the capacity valuation of resources. Figure 18 presents the average daily shapes for load for the base and higher electrification cases and includes the corresponding shapes for net load. The changes are most noticeable in the summer (with a higher net load peak in the evening) and in the winter (with a higher double net load peak in the morning and evening).

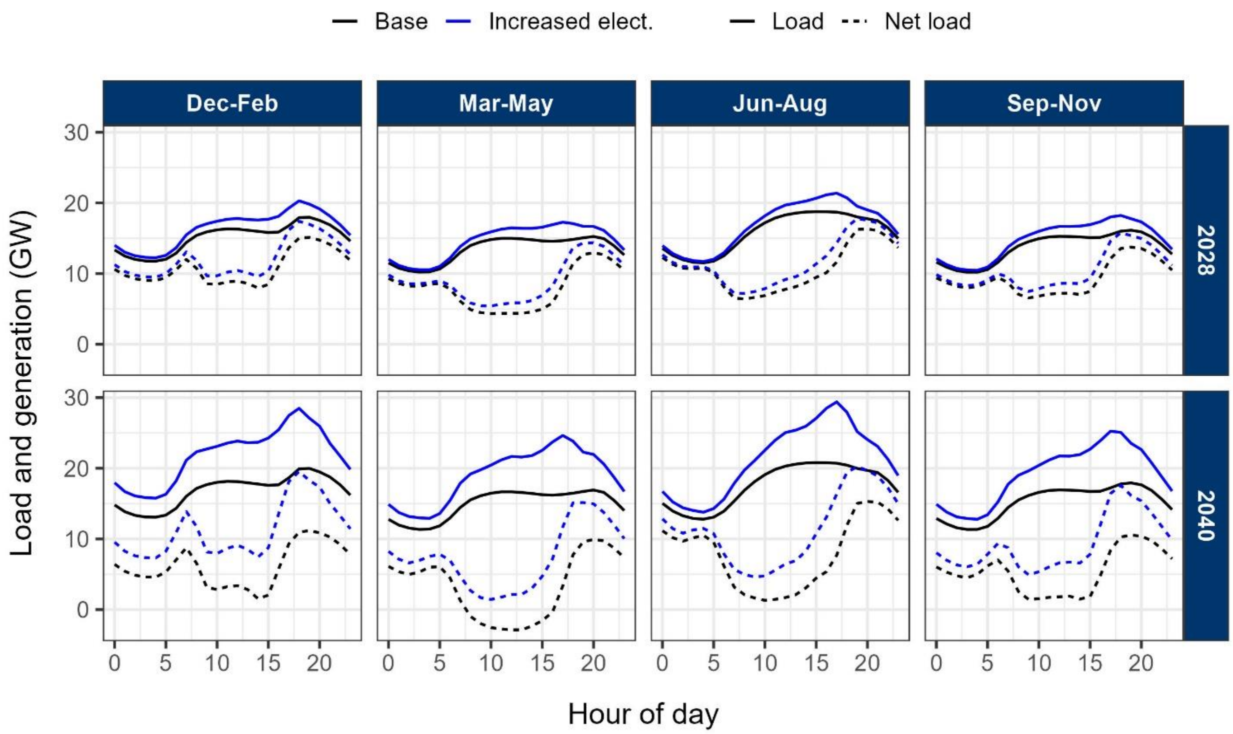

Figure 18. Load and net load for the base and higher electrification cases by seasons

The changes in load shapes influence how LOLE is distributed across the entire year. Figure 19 shows that with higher electrification, LOLE shifts slightly in 2028, mostly from July to August. However, in 2040 there is a shift of risk from the summer (July and August) to January, making winter events and conditions bigger drivers of annual reliability.

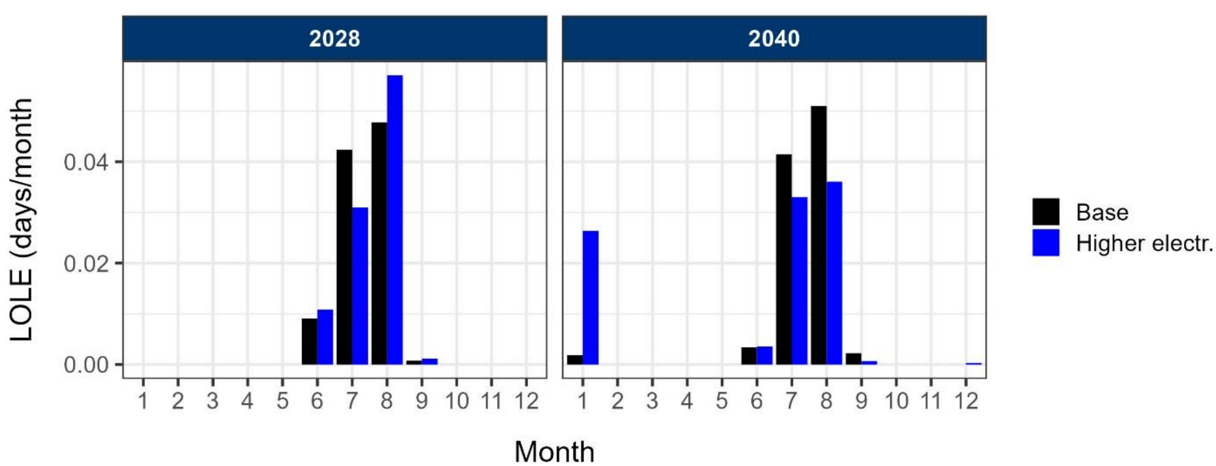

Figure 19. Distribution of daily LOLE by month for the electrification scenarios

The timing of the outages is also interesting. In 2028 we observe that higher electrification leads to risk happening earlier in the day, according to Figure 20. However, in 2040 the risk shifts, and a new period of LOLE risk occurs in the overnight hours in the winter as well as the summer.

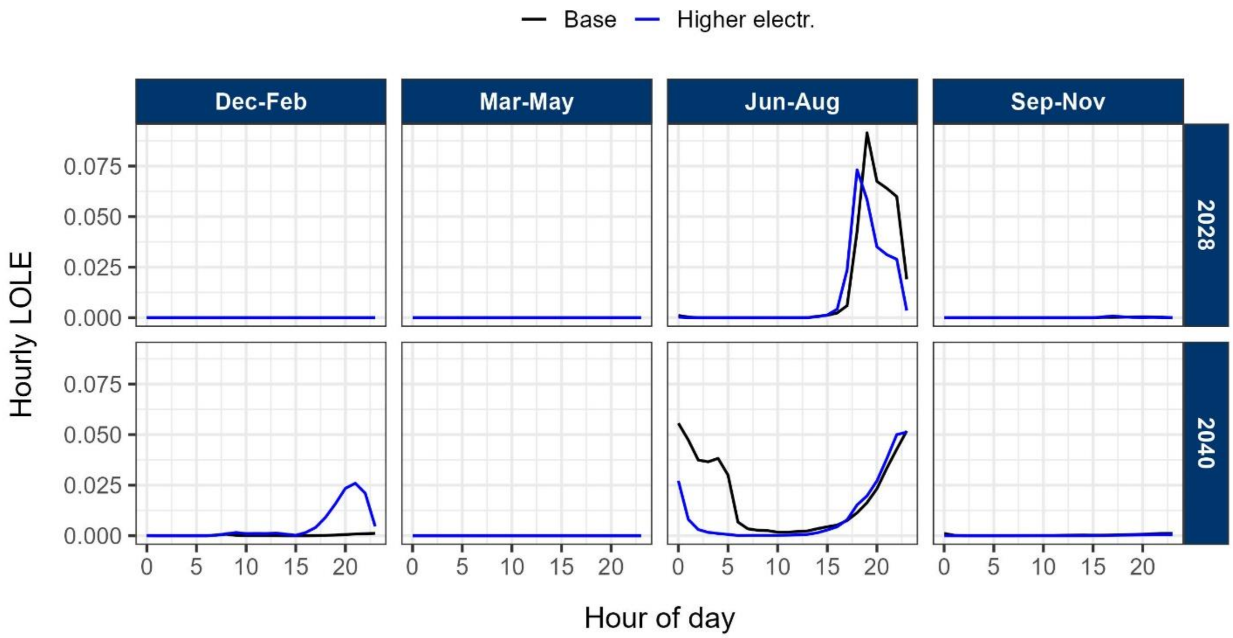

Figure 20. Distribution of LOLE by hour of the day and season for the electrification scenarios

We measured the capacity value of the marginal combined cycle (CC) and diesel units with and without the additional electrification load. This was done for the base case assumptions. The results using LOLE (Table 17), and EUE (Table 18) as the driving metrics are very similar. The impact on the calculated results is small for most cases. The exception is gas combined cycle units for the year 2040, which see a drop of between 26% and 34% of their capacity value. This is a consequence of outages and risk accumulating in the winter months. It is during those months that the assumption of fuel disruption becomes significant, and the result is a sharp decrease of marginal capacity value of this unit. As was the case with the fuel shortage sensitivities, it could be beneficial to calculate the impacts of higher electrification on seasonal accreditation factors.

Table 17. Impact of electrification for marginal units (MW)

Unit	Year	Capacity value (MW) Without electrification	Capacity value (MW) With electrification	Difference
Gas CC	2028	187.8	189.3	-1.5
	2040	177.4	123.9	53.5
Diesel	2028	177.1	180.7	-3.6
	2040	182.0	183.0	-1.1

Table 18. Impact of electrification for marginal units (MW), using EUE

Unit	Year	Capacity value (MW) Without electrification	Capacity value (MW) With electrification	Difference
Gas CC	2028	188.9	189.1	-0.2
	2040	183.7	115.0	68.6
Diesel	2028	179.1	179.7	-0.6
	2040	180.6	184.8	-4.1

4 IMPACT ON WIND, SOLAR, AND BATTERY STORAGE

This section examines several issues surrounding the calculation of capacity value through the ELCC method, such as the comparison of average by class and portfolio estimates and how the different assumptions in the model affect ELCC calculations.

There are different ways to calculate the capacity value of resources using ELCC methodologies, which do not always yield the same results. For instance, to calculate the contribution of renewable and battery storage resources to the system, we can consider:

- Portfolio capacity value: calculated by removing these resources at the same time and estimating their combined capacity value.
- Class average capacity value: calculated by removing each class (solar PV, battery, offshore wind, onshore wind) one at a time and measuring its impact on reliability through an ELCC calculation.
- Marginal capacity value: as discussed below in section 4.4[26].

4.1 Portfolio ELCC

First, we calculate the portfolio ELCC of combined wind, solar, and battery storage resources in both study years and present it in Table 19. This represents the firm contribution of these resources to resource adequacy, during times of need. In 2028 this represents 21% of the gross peak load (25,793 MW), while in 2040 it represents up to 44% of the gross peak load (28,448 MW). For reference, the installed utility-scale PV and onshore and offshore wind capacity (all of which contribute to the calculated portfolio ELCC) would be able to provide 26% and 55% of energy on an annual basis in 2028 and 2040, respectively. Adding distributed PV, nuclear and hydro resources, we estimate that the carbon-free resources in the ISO-NE footprint would be able to serve 61% of annual gross load in 2028 and 90% of load in 2040.

Table 19. Portfolio ELCC for wind, solar and battery storage combined

	MW	
	2028	2040
Portfolio	5,388	12,460

Table 20 presents how the portfolio ELCC results vary when the calculations use EUE as the metric of choice, instead of daily LOLE. Section 4.3.1 details this effect for each resource type individually, but the main takeaway is that capacity values drop for battery storage when using EUE, while solar capacity values increase.

[26] Additional discussion, including methods to bridge the differences between portfolio, class average and marginal ELCC, is available in N. Schlag, et al. "Capacity and Reliability Planning in the Era of Decarbonization: Practical Application of Effective Load Carrying Capability in Resource Adequacy," Energy and Environmental Economics, Inc., Aug. 2020, https://www.ethree.com/elcc-resource-adequacy/

In 2028, there is more installed solar, so the net effect on the portfolio is an increase of ELCC of 442 MW. In 2040, there is similar amount of battery storage and solar capacity, but the decrease in the capacity value of batteries drives the portfolio ELCC to be smaller by 950 MW.

Table 20. Portfolio ELCC for wind, solar and battery storage combined depending on choice of metric

	MW	
Metric	2028	2040
Daily LOLE	5,388	12,460
EUE	5,830	11,510

The effect of thermal ambient derates on the portfolio ELCC of wind, solar and battery storage is summarized in Table 21. In 2028, the changes are not substantial because those assumptions don't really affect the timing of outages (section 3.1 showed how risk remains concentrated in the summer). In 2040, the gas supply derate assumptions shift some of the risk into the winter months (as seen in Figure 13). This reduces the effective contribution of the portfolio, particularly solar because of the lower irradiance experienced in the winter.

Table 21. Portfolio ELCC for wind, solar and battery storage combined, by gas supply scenario

	MW	
Gas supply derate	2028	2040
40% derate, 1 week	5,388	12,460
60% derate, 2 weeks	5,386	12,072

Table 22 summarizes the effect of including thermal ambient derates on the portfolio ELCC of wind, solar and battery storage. The result in both years is a small increase (of around 200 MW in both years), when the derate is included in the model. As shown in Figure 17, solar output is highly correlated to high ambient temperatures, and these resources make up for the loss of that contribution from thermal units.

Table 22. Portfolio ELCC for wind, solar and battery storage combined, by ambient temperature scenario

	MW	
Thermal ambient temperature derate	2028	2040
Yes	5,388	12,460
No	5,182	12,257

4.2 Average by class vs. portfolio ELCC

We performed class average ELCC calculations, in addition to the portfolio results presented in the previous section. The average class ELCC calculations can be used to represent the contribution of a single resource type to resource adequacy. There are two distinct ways of calculating average class capacity values, as illustrated in Figure 21:

- “First in” average class capacity value is calculated when the resource is the first one added in the capacity stack, e.g., removing all wind, solar and battery storage and then calculating the ELCC for solar with the other resources absent. The result is the average capacity value of each class without presence of the others in the system
- “Last in” average class capacity values are calculated by considering the resources in a class as the last being added to the capacity stack

This section presents the results for both options and examines how the combination of average class values compares to the portfolio ELCC.

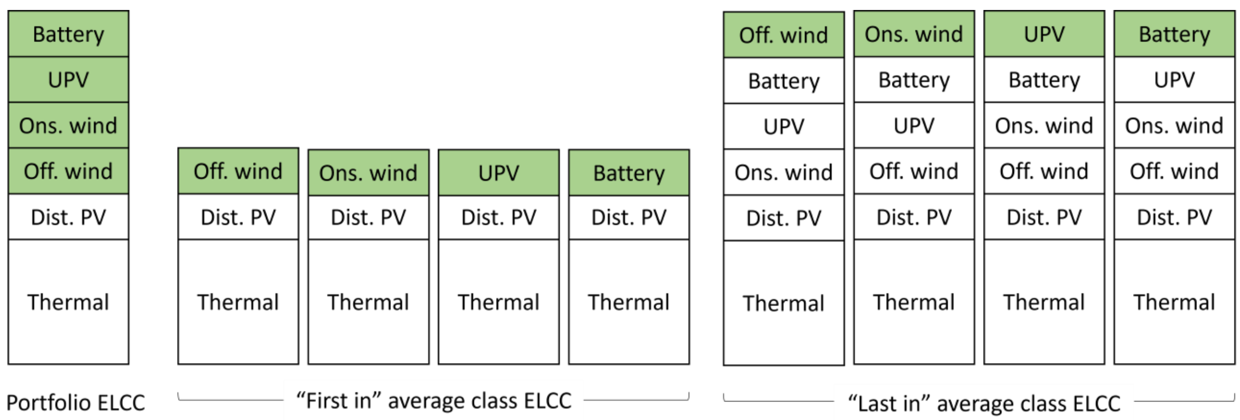

Figure 21. Portfolio vs “first in” or “last in” average class ELCC

The results for “first in” class average values are summarized in Table 23. These values capture the independent contribution of each of the four classes (utility-scales PV, batteries, offshore wind, and onshore wind). The sum of the class averages is lower than the portfolio ELCC presented in the previous section. This occurs because of the synergistic relationship of these resource classes. For instance, the amount of solar PV in these scenarios is sufficient to shorten the net load peak hours and create shorter duration of risk hours. When storage is deployed on top of this amount of solar it is much more effective because more events can be covered by the 4-hour battery limitation. Furthermore, storage can utilize the excess solar generation in the middle of the day to address critical hours around and after sunset. When the ELCC method considers both resources simultaneously, these synergies are capture and, thus, the portfolio ELCC leads to a larger capacity value that the sum of the individual components[27].

In 2028, the difference between the portfolio ELCC and the sum of class averages is small, at 136 MW (a 3% difference). However, in 2040 the difference is 2,182 MW, which represents an 18% difference.

[27] Further discussion, including methods to bridge the gap between portfolio and class averages can be found in in N. Schlag, et al. “Capacity and Reliability Planning in the Era of Decarbonization: Practical Application of Effective Load Carrying Capability in Resource Adequacy,” Energy and Environmental Economics, Inc., Aug. 2020, https://www.ethree.com/elcc-resource-adequacy/

Table 23. "First in" class average and portfolio ELCC

	MW		% Nameplate	
	2028	2040	2028	2040
Utility scale PV	2,050	2,277	15.5%	11.7%
Battery	1,508	4,117	75.4%	31.8%
Offshore Wind	1,124	2,695	23.9%	16.8%
Onshore Wind	570	1,190	30.4%	27.0%
Sum class averages	5,252	10,278		
Portfolio	5,388	12,460		

Alternatively, we can calculate the "last in" average capacity values for these classes, which are reported in Table 24. In this case the sum of class averages exceeds the portfolio ELCC values because the synergies between resources classes and embedded in each of the class averages and, thus, are double counted when they are added together. This is also reflected in the higher average capacity values, when compared to the values reported in Table 23. The biggest differences are found for battery storage (particularly in 2040) and utility-scale PV in 2040.

Table 24. "Last in" class average and portfolio ELCC

	MW		% Nameplate	
	2028	2040	2028	2040
Utility scale PV	2,340	4,925	17.7%	27.1%
Battery	1,991	7,245	99.6%	81.8%
Offshore Wind	755	1,897	16.1%	15.0%
Onshore Wind	494	563	26.4%	23.4%
Sum class averages	5,580	14,630		
Portfolio	5,388	12,460		

4.3 Impact of assumptions on class average ELCC

Below, we discuss how different assumptions and decisions related to using LOLE vs. EUE as the reliability metric, gas outages, ambient temperatures, and electrification affected capacity values for solar, wind, and battery storage resources in the analysis. This section includes only "last in" class average values.

4.3.1 Impact of LOLE vs. EUE

We first examine how the selection of LOLE or EUE as the reliability metric in the ELCC calculations affects the capacity value by class average. Table 25 summarizes capacity values as a percentage of installed nameplate capacity when using LOLE vs. EUE. The selection of the reliability metric does not affect wind resources to a substantial amount. However, EUE tends to increase the capacity value of solar PV and decrease it for battery storage, as compared to LOLE.

Table 25. Capacity value (%) by class average for daily LOLE and EUE

	2028		2040	
	Daily LOLE	EUE	Daily LOLE	EUE
Utility scale PV	17.7%	27.1%	25.4%	28.7%
Battery	99.6%	81.8%	55.9%	41.8%
Offshore Wind	16.1%	15.0%	11.8%	13.1%
Onshore Wind	26.4%	23.4%	12.8%	13.0%

To understand this behavior, it is useful to see the relationship of the two metrics across the different cases used to calculate the capacity value. For instance, to calculate the capacity value of battery storage we compare the reference case to a case without any battery storage on the system and drive both cases to criteria. To calculate the capacity value of solar we also include a case without any solar in the system.

When those cases are driven to the same level of daily LOLE, there are variations in the amount of EUE, as seen in Figure 22. For the same level of daily LOLE, the case without storage will have a smaller EUE, while the case without solar will have a larger EUE. This happens because the cases without solar result in longer outages, spreading the risk over more hours in a day. The daily LOLE metric only accounts for whether an outage happened in a day, regardless of how many hours or how much energy was not served. When we remove battery storage the outages are shorter and more concentrated, compared to solar. Both effects can be seen in Figure 23.

Under the ELCC methodology, the capacity value of a particular resource is calculated as the amount of perfect capacity that would need to be added to the system to counteract the removal of the resource in question, while maintaining the same level of reliability. Using LOLE instead of EUE (or vice versa) as the reliability metric in this calculation, however, can lead to different results. We can see this by looking at battery storage, for example. Using LOLE, the capacity value for battery storage of 99.6% for 2028 in Table 25 (1,991 MW) represents the amount of perfect capacity added to return the system to 0.1 days/year. However, if we try to match the starting EUE, the amount of perfect capacity needs to be corrected because adding the same level of perfect capacity that we calculated using LOLE (1,991 MW) would lead to a *smaller* EUE (i.e., an improved level of reliability rather than the same level) compared to the starting point (as seen in Figure 22).

Using EUE as the metric, we find that a smaller amount (354 MW in 2028, 1,829 MW in 2040) of perfect capacity needs to be added to the system to yield the same EUE as the reference case. That is, battery storage receives a higher capacity value when using LOLE instead of EUE. In the case of solar, the opposite is true: the amount of perfect capacity that must be added to the system in the "Without solar" case is *larger* when using EUE than it is when using LOLE to achieve the same level of reliability as in the Reference case (an additional 1,241 MW in 2028, and 660 MW in 2040). This results in a much higher estimate for solar capacity value when using EUE instead of LOLE.

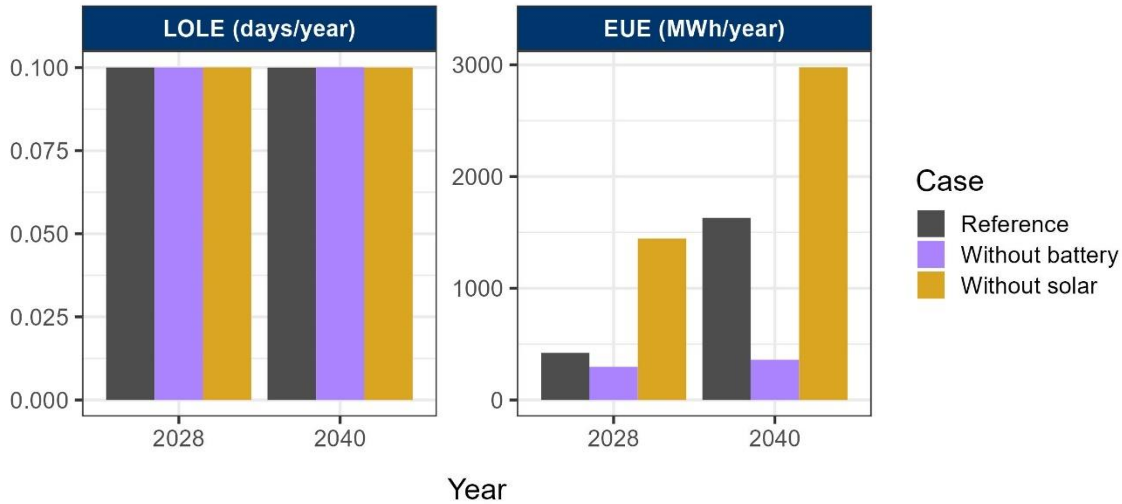

Figure 22. Daily LOLE for the different cases used to calculate class average ELCC

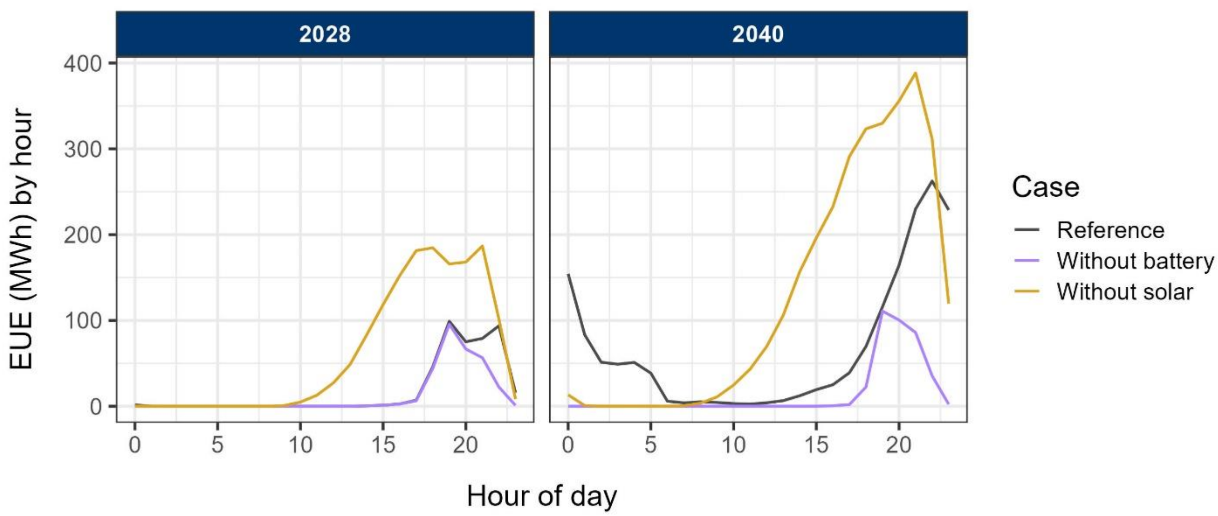

Figure 23. Distribution of EUE by hour of day for cases with the same daily LOLE

4.3.2 Effects of Gas Supply Limitations

Two main cases for fuel supply issues were simulated when measuring the capacity value of renewables: the base case (40% derate in gas capacity for a week around the winter peak), and a more severe outage (50% derate for 2 weeks around the winter peak). The effects on the class average for solar, wind, and battery storage is captured in Table 27. The effects of different levels of gas outages in 2028 were minuscule because, as discussed previously, the model primarily identified summer LOLE risk whereas gas supply assumptions relate to winter when the system was not short in the model. In 2040, as some of the modeled risk shifts to the winter, we observed some differences between gas scenarios' effects on the capacity value for offshore wind and utility-scale PV. Solar PV experienced the largest decrease in capacity value between the less and more severe gas outage scenarios. This is attributable to the fact that solar resources generate less during the winter, so greater wintertime LOLE risks (as a result of increased gas outages) also reduce the capacity value of these solar resources.

As stated earlier in the discussion of thermal resources (section 3.1), calculating annual capacity values for resources implicitly produces a weighted average of summer and winter performance that may mask some impacts during different times of the year. It would be interesting to also calculate seasonal capacity values for resources under different sensitivities to understand resources' different summer and winter capacity values and how these values may be impacted by different risks and future evolution of the grid.

Table 26. Capacity value (%) by class average for gas sensitivities

	2028		2040	
	40% 1-week	50% 2-weeks	40% 1-week	50% 2-weeks
Utility scale PV	17.7%	17.7%	25.4%	23.4%
Battery	99.6%	99.5%	55.9%	53.0%
Offshore Wind	16.1%	16.2%	11.8%	10.6%
Onshore Wind	26.4%	26.4%	12.8%	12.1%

4.3.3 Effects of Ambient Temperature Derates for Thermal

The inclusion or exclusion of ambient temperature derates did not influence the results of average capacity values for solar, wind, and battery storage resources in our modeling, as reflected in Table 27. As we previously discussed in section 3.2, the renewable capacity present in the system (particularly solar) pushes hours with risk later in the day, when ambient temperatures are lower and thus the impact of the temperature derates is limited during LOLE hours. Thus, inclusion of ambient temperature derates has only a small effect on the capacity value of renewables.

Table 27. Capacity value (%) by class average for ambient temperature sensitivity

	2028		2040	
	Base	No temp. derate	Base	No temp. derate
Utility scale PV	17.7%	16.8%	25.4%	25.0%
Battery	99.6%	99.4%	55.9%	56.0%
Offshore Wind	16.1%	16.0%	11.8%	11.8%
Onshore Wind	26.4%	26.0%	12.8%	12.9%

4.3.4 Effects of Electrification

Table 28 summarizes the impact of higher levels of electrification on the class average capacity values for solar, wind, and battery storage resources. There is a slight increase in the capacity values for solar and offshore wind in 2028 in the higher electrification sensitivity, because the change in load shapes in this sensitivity aligns better with the output of these resources in the summer months (see Figure 18).

In 2040, there is a significant increase in capacity value for battery storage resources. As seen in Figure 20 the Base case presents long periods of risk that usually span across most nighttime summer hours. Under higher electrification conditions, the hours of risk in the summer are cut in half and new risk hours emerge in the early hours of winter nights. So, overall, outages tend to be shorter and align better with the 4-hour energy limitation assumed for battery storage in this study, under higher electrification conditions.

Table 28. Capacity value (%) by class average for electrification sensitivity

	2028		2040	
	Base	Higher elect.	Base	Higher elect.
Utility scale PV	17.7%	20.1%	25.4%	26.6%
Battery	99.6%	100.0%	55.9%	73.0%
Offshore Wind	16.1%	18.2%	11.8%	11.1%
Onshore Wind	26.4%	26.9%	12.8%	13.8%

4.4 Marginal ELCC

This section presents marginal capacity values for solar, wind, and battery storage resources. Marginal values were measured by quantifying the capacity value provided by an incremental unit of 200 MW of each of utility-scale PV, onshore and offshore wind, and batteries. Each incremental until was added to the system independently and the capacity value was calculated using the ELCC technique.

Table 29 summarizes the marginal capacity value for renewables and also includes the class average results presented in previous sections, for reference. In 2028, the marginal capacity value of solar is very small, much smaller than the class average. This shows a sign of saturation. On the other hand, the battery marginal capacity value is very high under both marginal and average approaches. Both onshore and offshore wind have stable marginal and average capacity values.

In 2040, utility-scale PV has a higher marginal capacity value than in 2028, but still smaller than the class average. Battery storage capacity shows signs of saturation, with a relatively small marginal capacity value. Onshore wind's marginal capacity value is similar to the class average, but both values in 2040 are half of the values shown in 2028. Offshore wind also sees a reduction in marginal capacity value relative to 2028 and its marginal ELCC is smaller than the class average.

Table 29. Marginal and class average capacity value (%)

	Marginal ELCC		Class avg. ELCC	
	2028	2040	2028	2040
Utility scale PV	2.3%	18.2%	17.7%	25.4%
Battery	95.1%	14.6%	99.6%	55.9%
Offshore Wind	13.4%	8.7%	16.1%	11.8%
Onshore Wind	24.1%	12.5%	26.4%	12.8%

The most interesting interplay here happens again between solar and batteries. When looking purely from a resource adequacy perspective, in 2028, the system seems to experience saturation of solar. A relatively smaller deployment of battery storage in that year is able to take advantage of the excess solar capacity and shift that energy to meet the short net load peaks (Figure 18). In 2040, with much higher levels assumed for battery storage, the system is now saturated with batteries from a resource adequacy perspective. The hours of risk are spread more widely during the night in this scenario and make it more challenging for an incremental amount of new 4-hour battery storage to add to resource adequacy. However, with greater levels of battery storage on the system in 2040, an incremental addition of solar can take advantage of the existing battery storage and yield a higher marginal capacity value than it did in 2028.

This interplay between solar and battery storage capacity values is further examined in section 4.7.

4.5 Impact of assumptions on marginal ELCC

As with the discussion of thermal resources above, below we discuss how different assumptions and decisions in the accreditation methodology affect solar, wind, and battery storage capacity values.

4.5.1 Impact of LOLE vs. EUE

The selection of reliability metric to calculate marginal capacity value through ELCC has an impact on the results for utility-scale PV and batteries, as shown in Table 30. The changes for onshore and offshore wind are much smaller. The directionality of these changes (larger capacity values for solar and smaller for batteries when using EUE) is the same for marginal capacity values as they were for class averages. Please refer to section 4.3.1 for an explanation of how the shifts in risk drive these results.

Table 30. Marginal capacity value (%) by metric

	2028		2040	
	Daily LOLE	EUE	Daily LOLE	EUE
Utility scale PV	2.3%	5.9%	18.2%	20.1%
Battery	95.1%	70.2%	14.6%	9.6%
Offshore Wind	13.4%	12.1%	8.7%	9.7%
Onshore Wind	24.1%	21.7%	12.5%	11.8%

4.5.2 Effects of Gas Supply Limitations

Table 31 summarizes the marginal capacity value results for solar, wind, and battery storage under the two main cases for fuel availability. The base case assumes a 40% derate in gas capacity for a week, while the more severe case assumes a 50% derate for 2 weeks around the winter peak. The effect of changing the outage severity in 2028 is minimal, because the LOLE risk happens in the summer rather than during the winter when the gas outages are modeled.

In 2040 the effects are minimal for battery storage and onshore wind, but more noticeable for offshore wind and, especially, for utility-scale solar. With the increase in gas outage severity, increased reliability risks shift to the winter and the results start blending summer and winter values for capacity value (as was the case in similar cases previously presented). For solar PV, this translates into a net reduction of its annual capacity value because solar generation is significantly smaller in the winter when new LOLE risks are present. As with similar cases discussed above, it would be interesting to study the implications of using seasonal capacity value measures in these situations.

Table 31. Marginal capacity value (%) for gas sensitivities

	2028		2040	
	40% 1-week	50% 2-weeks	40% 1-week	50% 2-weeks
Utility scale PV	2.3%	1.8%	18.2%	11.7%
Battery	95.1%	94.8%	14.6%	13.2%
Offshore Wind	13.4%	13.2%	8.7%	7.0%
Onshore Wind	24.1%	23.8%	12.5%	13.1%

4.5.3 Effects of Ambient Temperature Derates for Thermal

Table 32 shows the marginal capacity value results for solar, wind, and battery storage resources are not influenced by the inclusion of ambient temperature derates for thermal resources. As previously noted, risk hours in the system happen for hours with lower temperatures in the summer so ambient temperature derates are not an important factor in the capacity value calculations for these resources.

Table 32. Marginal capacity value (%) for ambient temperature sensitivity

	2028		2040	
	Base	No temp. derate	Base	No temp. derate
Utility scale PV	2.3%	2.7%	18.2%	15.9%
Battery	95.1%	96.3%	14.6%	14.3%
Offshore Wind	13.4%	12.7%	8.7%	8.2%
Onshore Wind	24.1%	24.2%	12.5%	11.8%

4.5.4 Effects of Electrification

Higher electrification levels have a moderate impact on marginal capacity value of solar, wind, and battery storage resources. Battery resources benefit in the higher electrification scenario from more defined, shorted periods of risky hours (see Figure 20). Onshore and offshore wind capacity values only change marginally because of their lack of strong correlation to load. The changes for solar PV vary between the two study years. In 2028, the increased load in the middle of the day and the earlier timing of hours of risk, align better with hours of solar generation. However, the incremental marginal capacity value for solar in 2028 is still small because of the level of solar saturation. In 2040, some of the summer risk in the higher electrification scenario is shifted to the winter months, where solar generation is weaker. This causes the annual marginal capacity value of these resources to decrease.

Table 33. Marginal capacity value (%) for electrification sensitivity

	2028		2040	
	Base	Higher elect.	Base	Higher elect.
Utility scale PV	2.3%	7.0%	18.2%	14.6%
Battery	95.1%	99.6%	14.6%	20.1%
Offshore Wind	13.4%	14.9%	8.7%	7.1%
Onshore Wind	24.1%	25.3%	12.5%	12.1%

4.6 Capacity values for onshore and offshore wind

In the portfolio, class average, and marginal ELCC calculations presented above, offshore wind receives a noticeably lower capacity value than does onshore wind. This result is a product of saturation effects, rather than any inherent reliability advantage of onshore wind resources. As shown above in Table 2 in Section 2.1, the base cases in this study include over twice as many MWs of offshore wind as onshore wind in 2028 and over three times as many MWs of offshore wind than onshore wind in 2040.

Due to the much larger quantities of offshore wind assumed in these years, the incremental value (marginal ELCC) of adding additional offshore wind is lower than it is for onshore wind in the model. Under an average ELCC approach that represents the total reliability contribution of the class, the ELCC value of offshore wind does not decline as quickly as it does under marginal ELCC; however, saturation effects are still observed and the capacity values for offshore wind remain lower than for onshore wind due to the differences in class size.

4.7 Interactions between solar and storage

As shown above, of the resource types considered, solar and storage resources were most susceptible to experiencing saturation, which is the effect of having a reduction in average capacity factor when calculated as a ratio to installed capacity[28], in our modeling. In this section, we further consider how solar, and battery storage interact, finding that battery deployment can in part reduce solar saturation effects and vice versa. We considered these interactions by calculating capacity values for utility-scaled solar and battery storage installed at several different levels on the system for study year 2028. The amount of distributed PV, onshore and offshore wind were fixed in this modeling and equal to the values in the base case assumptions. We considered deployment of utility-scale PV between 0 GW and 12 GW and batteries at levels between 0 GW up to 13 GW, which roughly equals the total amounts deployed in the 2040 study year.

First, we examined how average and marginal ELCC evolve for solar PV as more solar capacity is added. Figure 24 shows these results across cases where battery storage was held constant at levels between 0 GW and 13 GW. An alternative representation of these data is presented in Figure 25. Without battery storage, solar capacity values, in both average and marginal calculations, start at a low level (around 10%) and continue decreasing with more deployment. The low starting point for utility-scale PV, even at low penetrations, is a result of saturation during these resources' highest performing hours due to

[28] When more solar or storage is added to the system, the absolute capacity value in MW will increase. However, when measuring as percentage of nameplate, capacity value growth slows down with respect to installed capacity.

the presence of distributed PV and offshore wind in the model. Adding battery storage, however, results in a significantly higher starting point for utility-scale PV's capacity value. In cases with 3 GW or more of battery storage, utility-scale PV starts with higher average and marginal capacity values of around 30%. Higher amounts of battery storage delay and reduce the saturation of solar capacity value, enabling these resources to contribute more to resource adequacy even as solar deployments increase.

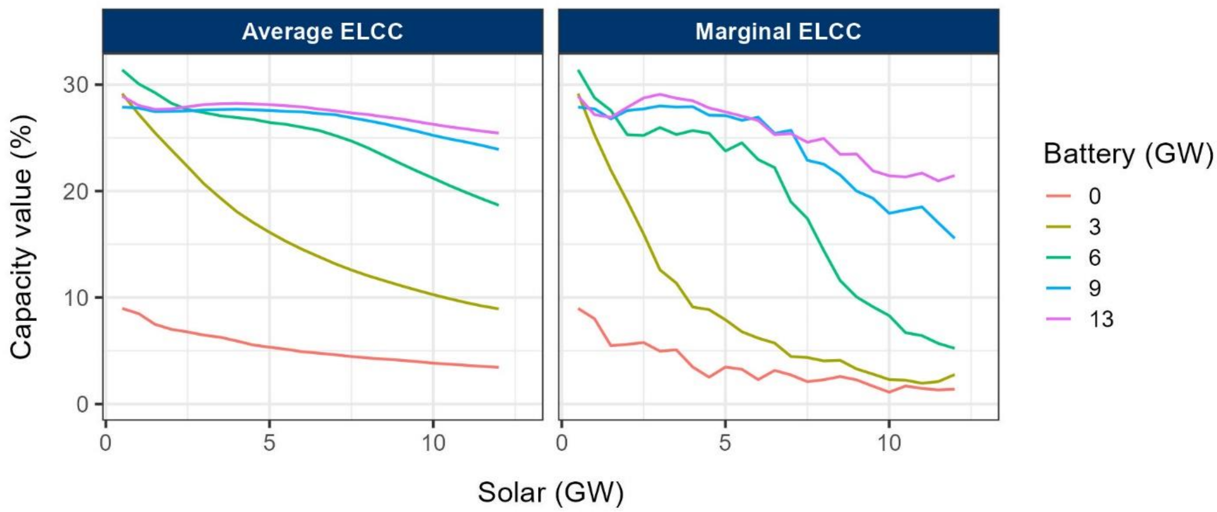

Figure 24. Average and marginal solar capacity value as a function of deployment, for different levels of battery storage

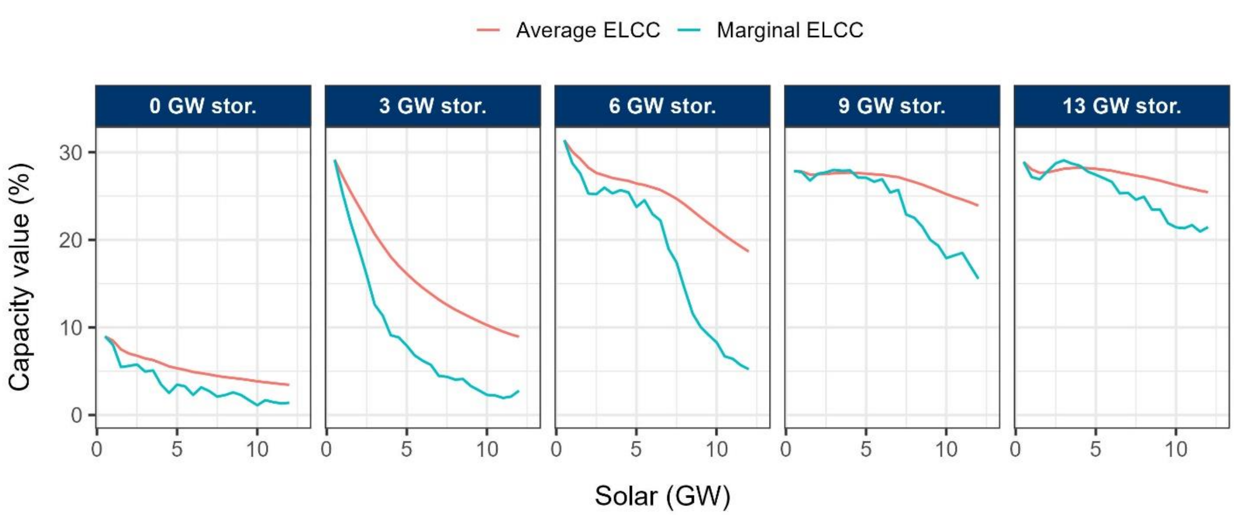

Figure 25. Comparison of trends for average and marginal solar capacity, for different levels of battery storage

A similar analysis can be performed for battery storage, by studying its average and marginal capacity value trends for different levels of solar deployment. This is represented in two different ways in Figure

26 and Figure 27. Across all levels of solar deployment, battery storage's capacity value starts very close to 100%. The marginal capacity value for battery storage then starts decreasing with higher levels of storage deployment. Battery storage's marginal capacity value decreases much more sharply than the average capacity value and is usually well below 50% of the average value. However, in both average and marginal calculations, higher levels of solar enable battery storage to maintain higher capacity values for longer at increasing penetration levels. As with the PV analysis above, this shows synergistic effects between battery storage and PV, with higher levels of one resource enabling greater capacity contributions from the other, and vice versa.

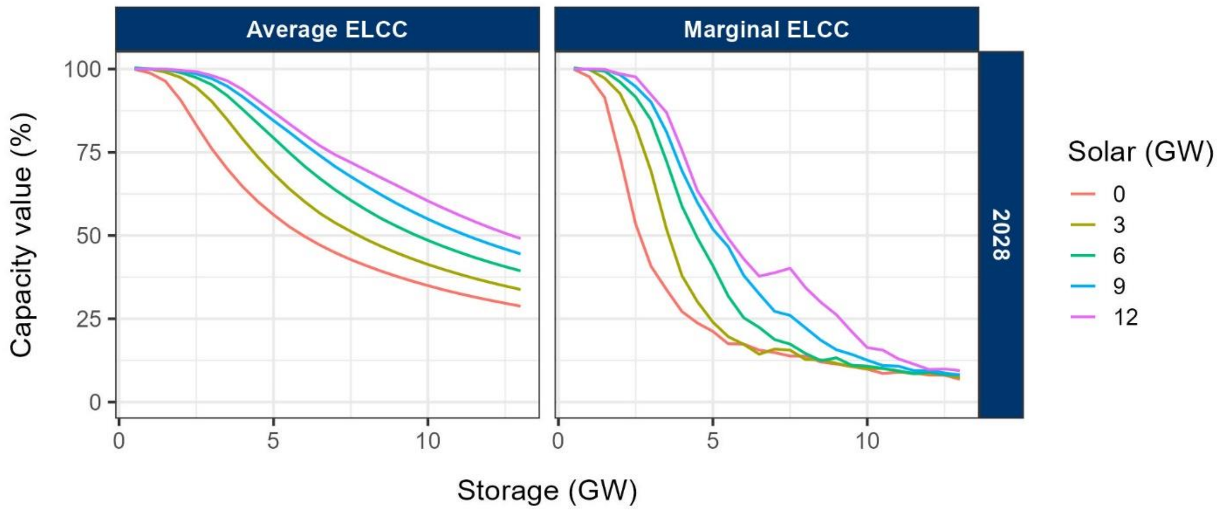

Figure 26. Average and marginal battery storage capacity value as a function of deployment, for different levels of solar

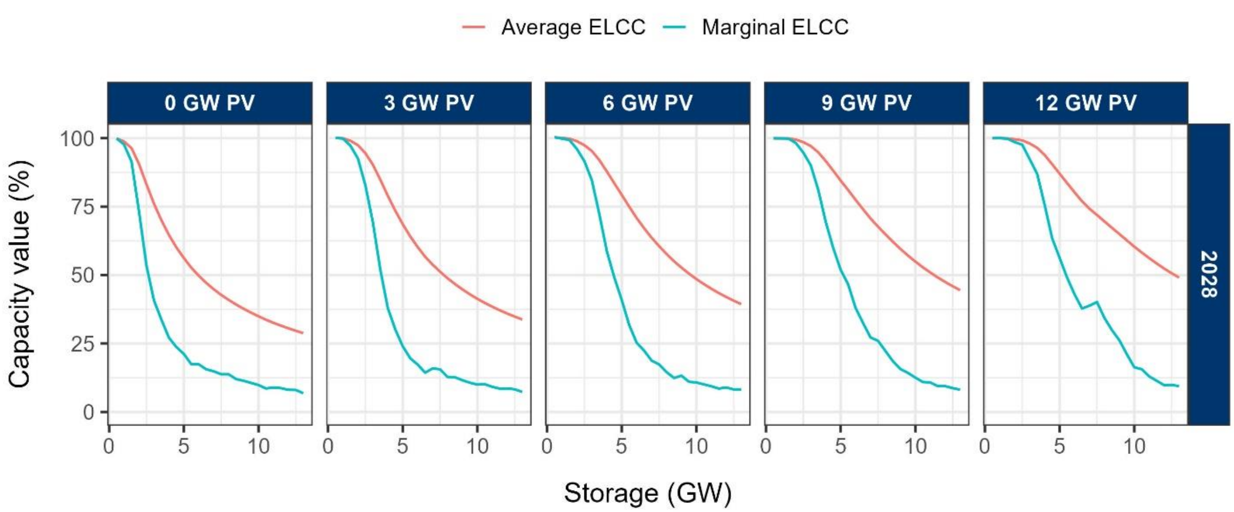

Figure 27 Comparison of trends for average and marginal battery storage capacity, for different levels of storage

The previous figures examined how the capacity value of solar changes with increased deployment, while the amount of battery storage is kept constant at different levels, and vice versa. However, those trends don't necessarily represent how the system is expected to develop, with an increasing mix of both being deployed simultaneously. To provide an example of how this could happen, Figure 28 shows the evolution of average solar capacity value as solar capacity increases. In this case, there are three trend lines, corresponding for different levels of battery deployment:

- "1:1" represents a deployment of 1 MW of battery storage for each MW of solar
- "2:1" represents a deployment of 1 MW of battery storage for every 2 MW of solar
- "1:0" represents no battery deployment

The figure shows how the simultaneous deployment of battery storage alongside solar gradually improves the class average capacity value for solar. The "1:1" trend curve endpoint on the left closely resembles the solar and battery storage deployment level in the 2040 study year.

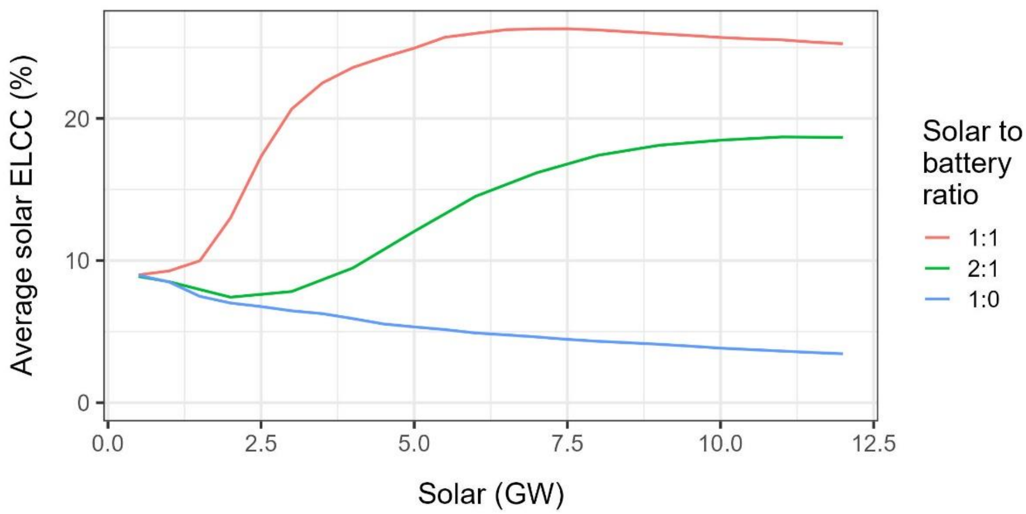

Figure 28. Average solar capacity value when deployed alongside battery storage with different ratios

5 SUMMARY

The results of the quantitative study provide critical insights for ISO-NE, stakeholders, and New England policymakers for the design of the Forward Capacity Market reform process. Key findings and recommendations are summarized below.

Finding 1: Clean Energy Resources Provide Substantial Reliability Value.

The diverse portfolio of utility-scale solar PV, wind, and battery storage resources modelled in the study is capable of providing 5,388 megawatts (MW) of effective load carrying capability in 2028, which could enable significant retirements among the existing conventional fleet and represents 21% of ISO-NE's gross peak load. By 2040, the utility-scale solar PV, wind, and battery storage is capable of displacing 12,460 MW, equivalent to 44% of ISO-NE's gross peak load.

For reference, in terms of energy, the installed utility-scale PV and onshore and offshore wind capacity (all of which contribute to the calculated portfolio ELCC) would be able to meet 26% and 55% of ISO-NE's energy demand on an annual basis in 2028 and 2040, respectively. Including distributed solar PV, these values increase to 34% and 65% of energy in 2028 and 2040, respectively. Further expanding the analysis to include nuclear and hydro, we estimate that carbon-free resources would be able to serve 61% of ISO-NE's annual load in 2028 and 90% in 2040, under the study's base case assumptions.

The synergistic effects of the utility-scale solar PV, wind, and battery storage clean resource portfolio are also significant. Increasing penetrations of solar are synergistic with storage resources, which have a higher ELCC as the net peak period tightens to a narrower band of evening hours. Similarly, excess production from both solar and wind resources are more valuable during periods of high production if storage is present to shift that energy value to periods of demand.

Appropriately compensating clean resources for their contributions to reliability will be critical to achieving a reliable, least cost, decarbonized grid and to ensuring that the growing levels of clean energy resources that are needed to achieve decarbonization are financeable. Providing proper reliability signals in markets will also help policymakers and utilities design synergistic clean energy policies and portfolios.

Recommendation 1: *Ensure the RCA market design appropriately reflects the reliability contributions of clean energy resources, including solar, wind, and storage, and the interactive effects between resources.*

Finding 2: Capturing Thermal Limitations Is Key to Ensuring Reliability and Equity.

Thermal resources, like all generating resources, have well-documented engineering limitations that impact their ability to support reliability. In ISO-NE, these include ambient derates driven by high temperatures, correlated outages driven by extreme weather events (both heat and cold), and pipeline supply risk during more severe and/or extended cold weather, such as polar vortex events. Capturing these resource limitations is critical for ensuring fidelity of the RCA reforms and the FCM as a whole. From a competitive equity standpoint, it is also necessary to ensure equivalent levels of scrutiny of the reliability characteristics of both the conventional thermal fleet and the emerging fleet of clean energy resources.

Historically, these thermal resource limitations have not been captured within the modelling framework of ISO-NE's FCM. This has resulted in overestimation of these resources' reliability contributions and underestimation of the LOLE resulting from the portfolio of resources selected in the FCM.

This study tested the impact of these limitations on ELCC, finding significant impacts, particularly from fuel supply issues as the system transitions to greater winter peaks. Fuel supply risk, which occurs in winter months, only impacts ELCC significantly when reliability is constrained in winter (for an annual portfolio analysis) but can become very significant for the marginal ELCC of gas resources when modelled as large events. Ambient temperature derates, while smaller in the range of magnitudes in the modelling, may also become more persistent and significant as climate change induces more heat events including more sustained overnight temperatures.

The magnitude and frequency of thermal resource limitations as a result of polar vortex events, heat waves, and other extreme weather are a key uncertainty for the ELCC analysis of gas resources. The analysis offered within this report is intended to be illustrative. The authors recommend additional analysis and more explicit representation of the gas system in the ISO-NE RCA reform development to understand the complex dynamics that may result during future such events, which may be both more severe due to climate change and unfold with different operational characteristics as demand changes due to greater electrification and with shifts in the region's power generation portfolio.

Recommendation 2: *Ensure the RCA market design and modelling assumptions reflect the realities of thermal limitations, including correlated outage risk due to fuel supply constraints and ambient derates.*

Finding 3: Average and Marginal Resource Accreditation Will Result in Different Incentives and Equity Outcomes.

A key design choice within ISO-NE's RCA reform effort is the selection of an *average* or *marginal* ELCC approach as the accreditation structure for resources, a design choice which will have significant implications for investment market signals for new resources, including clean energy resources, in the coming years. To better understand the impact of this design choice, this study quantified the values of average and marginal ELCCs for the 2028 and 2040 resource portfolios, finding significant differences in the valuation for both clean energy and conventional resources under the two accreditation schemes.

Average ELCC accredits resources at their proportional share of the total reliability contribution of their entire resource class (e.g., *all* solar resources), returning the full perfect capacity produced by a resource class back to that resource class, including a share of the portfolio effects (positive or negative) accrued across resource classes. Proponents of average ELCC accreditation argue that it more fairly allocates the full reliability value produced by resources back to those same resources in a manner that sums to the total reliability need, providing a durable and financeable investment signal. In the context of applying ELCC to emerging clean energy resources, average ELCC can be viewed as paying the clean energy fleet the same as the conventional generation it displaces in aggregate, rather than extrapolating value solely from an assessment of the marginal unit.

Marginal ELCC accredits resources based on the incremental reliability contribution of the next like resource (e.g., the *last* solar resource), returning to all resources the capacity value of the marginal resource. Proponents of marginal ELCC accreditation argue that it provides a more efficient investment signal for new resource investments, providing a fungible, substitutable product for capacity market clearing at the margin. However, marginal ELCCs are unlikely to sum to the total reliability need, requiring an adjustment to the firm capacity requirement to achieve an integrated portfolio meeting a desired reliability standard. In the context of applying ELCC to emerging clean energy resources, marginal ELCC can differ substantially as saturation and interactive effects shift the marginal value of resources at different penetration levels and in different portfolio mixes. Thermal resources with coincident outages and fuel supply risk can also experience notable declines in marginal value relative to average when real-world limitations are properly incorporated into the modelling.

While either accreditation approach can return a reliable resource portfolio if the market is cleared properly, the resulting market signals can be substantially different. This analysis attempted to quantify the difference between the average and marginal ELCC awards on a future system with a much higher penetration of clean energy resources, finding that the difference between the two frameworks resulted in a significant difference for the aggregate clean energy portfolio in both 2028 and 2040. Specifically, under a marginal accreditation scheme in 2028, 41% of the reliability contributions of the utility-scale solar, wind, and storage fleet are compensated to all customers as a demand adjustment rather than directly back to the contributing resources; 52% is returned to customers rather than contributing resources from the 2040 clean resource fleet.

The authors wish to emphasize the importance of considering the trade-offs between marginal and average approaches, which will have considerable implications for resource development considering the magnitude of the gap between the two approaches in ISO-NE. In particular, the marginal approach could have significant equity and incentive impacts for resource developers, which are seeking stable long-term financing, as well as for utilities and states seeking to ensure the benefits of their clean energy investments are returned fairly to their ratepayers rather than socialized across all ISO-NE customer groups. To the extent a marginal accreditation approach undervalues the total reliability contributions of resources needed to decarbonize the grid, other compensation schemes beyond the FCM, either within ISO-NE's markets or outside of them, may be necessary to provide the "missing money" needed to finance these resources.

Recommendation 3: *Thoroughly examine the policy and efficiency benefits and trade-offs between marginal and average RCA approaches, as well as potential hybrid approaches, before moving forward with a final structure.*

Finding 4: Balancing Annual Reliability on a Dual-Peaking System Is Highly Sensitive to Input Assumptions.

ISO-NE faces reliability risk in both summer and winter periods. While ISO-NE's gross peak currently occurs during the summer period, trends on both the demand and supply side may result in increasingly tight system margins in winter months in the coming years. As ISO-NE has warned in recent years, winter fuel supply risk for some thermal resources is a major concern and a driver of winter reliability events.

Understanding the likelihood, magnitude, and dynamics of reliability events in both seasons is critical to the accurate calibration of the RCA modelling which will underpin capacity market outcomes. As this study shows, small shifts in input variables for either season can have potentially outsized effects on the model outcomes. As an example, small adjustments to assumptions regarding winter outage risk due to fuel supply can rapidly shift observed loss of load events to winter months, which modifies critical hours and significantly changes the ELCC analytical outcomes. This is particularly true for marginal ELCC which solely observes reliability contributions on the margin. As shown in this study, projected marginal reliability contributions can shift rapidly when assumptions shift LOLE events between seasons.

The net effect is a high degree of sensitivity to input assumptions which are lumpy and unpredictable but which will need to be assumed (more than three years in advance under the current FCM) with a significant degree of confidence for model calibration. For instance, it is difficult to accurately predict how frequent and significant future polar vortex events will become with climate change, and also difficult to have perfect foresight into the dynamics of the gas system which will determine whether resources are available during these events. However, the model will require a pre-set structure for and distribution of these events to be operable.

One potential solution to this challenge could be to adopt a two-period capacity market, similar to the seasonal market design in PJM. A seasonal market design would allow more direct analysis and compensation for the divergent reliability risks across the two seasons and limit the risk of incorrectly weighting risks across seasons. The authors recommend additional analysis to better understand seasonal reliability risks in the near-, medium-, and longer-terms to better assess the merits of a seasonal capacity accreditation structure.

Recommendation 4: *Consider the trade-offs between an annual and seasonal FCM and RCA in the context of ISO-NE's near-term transition to a dual-peaking and, later, winter-peaking system.*

Finding 5: Other Considerations Such as the Choice of Reliability Metric and the Growing Impacts of Climate Change Also Must Be Considered in the RCA Design.

The selection of daily LOLE vs. EUE as the metric to drive ELCC calculations has an outsized effect on certain types of generating units. In this study, capacity values for solar PV and 4-hour battery storage changed significantly when comparing ELCC results between these two metrics (solar PV capacity value was higher with EUE and storage capacity value was lower). Similarly, when coupled with a dual-peaking system, as outlined in the previous finding, marginal capacity values using EUE for thermal units with fuel supply issues can vary significantly (by up to 7% in this study).

Carefully choosing the metric to drive the results and appropriately translating the desired reliability goal into the target level for the reliability metric are critical. The implications of those decisions should be studied and understood because they can introduce significant variations in capacity accreditation results for some resources.

Further work is also necessary to anticipate how assumptions or certain system conditions may evolve over time. This study considered the implications on capacity accreditation of including higher levels of electrification, which affect hourly and seasonal trends for load shapes. Additional consideration may be necessary to understand the impacts of climate change, including on demand shapes, thermal outage rates, generation from renewable resources, frequency of extreme weather events (such as heat waves or winter storms), and the availability of neighboring areas to provide external capacity assistance.

Recommendation 5: *Consider the impacts and durability of other key RCA design features and assumptions, including choice of reliability metric (LOLE vs. EUE) and the impacts of climate change.*

Study Recommendations

- **Recommendation 1:** Ensure the RCA market design appropriately reflects the reliability contributions of clean energy resources, including solar, wind, and storage, and the interactive effects between resources.
- **Recommendation 2:** Ensure the RCA market design and modelling assumptions reflect the realities of thermal limitations, including correlated outage risk due to fuel supply constraints and ambient derates.
- **Recommendation 3:** Thoroughly examine the policy and efficiency benefits and trade-offs between marginal and average RCA approaches, as well as potential hybrid approaches, before moving forward with a final structure.
- **Recommendation 4:** Consider the trade-offs between an annual and seasonal FCM and RCA in the context of ISO-NE's near-term transition to a dual-peaking and, later, winter-peaking system.
- **Recommendation 5:** Consider the impacts and durability of other key RCA design features and assumptions, including choice of reliability metric (LOLE vs. EUE) and the impacts of climate change.