Energy storage resource adequacy contributions considering state of charge deviations

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Energy storage resource adequacy contributions considering state of charge deviations

Mark Noll†, Jonghwan Kwon‡, Todd Levin‡

***Abstract*—Resource adequacy (RA) studies commonly represent energy storage via economic dispatch, with the real-time state of charge (SOC) of storage units implicitly assumed to follow a predetermined schedule until scarcity conditions arise. This paper explores the implications of this assumption, by documenting how downward deviations in energy storage SOC in real-time operations affect reliability outcomes. Applying a probabilistic RA model to an ERCOT-like system with 5 GW of energy storage, we quantify the sensitivity of normalized expected unserved energy (NEUE) and marginal effective load carrying capability (ELCC) to SOC deviations across two-, four-, and eight-hour storage durations. We find that a downward SOC adjustment equal to 25% of maximum storage energy capacity increases system NEUE by a factor of 1.6–2.3 and reduces the marginal storage ELCC by 11–13 percentage points, both of which represent significant differences compared to reference cases. Metrics for shorter-duration storage technologies are most sensitive to SOC deviations on a relative basis, shaped by the nature of lost load within the specific test system. The results highlight the importance of accurately modeling energy storage operations when accrediting storage in RA modeling efforts to help ensure model outcomes are consistent with real-world operational behavior.**

***Index Terms*—Energy storage, resource adequacy, economic dispatch, effective load carrying capability, Monte Carlo simulation**

I. Introduction

Most modern electricity systems are designed to satisfy a resource adequacy (RA) standard intended to limit the magnitude and/or frequency of system-wide loss of load events, e.g., no more than one day of lost load every ten years. System RA is typically evaluated using a Monte Carlo–based model ("RA model") that generates a large number of scenarios for generator and transmission outages, wind and solar output, and/or electricity demand; these may in turn be driven by one or more shared factors such as ambient weather conditions. The RA model then simulates electricity system operations under each of these scenarios and aggregates the results to establish a set of RA metrics. Common system-level metrics include the loss of load expectation (LOLE), loss of load probability (LOLP), loss of load hours (LOLH), expected unserved energy (EUE), normalized expected unserved energy (NEUE), while the effective load carrying capability (ELCC) is often used for capacity accreditation for individual generators and demand-side technologies [1]. RA metrics have several important applications in real-world power system planning and operations, including to (1) determine the system-wide and regional planning reserve margin, (2) accredit resources that participate in capacity markets or other capacity-based RA constructs, and (3) inform integrated resource planning studies conducted by vertically integrated utilities. As RA metrics are determined in part or entirely by model simulations, differences in modeling assumptions and formulations can have significant implications for suppliers and consumers of electricity.[1]

At the same time, the rapid deployment of energy storage technologies has motivated efforts to revisit models and capacity accreditation methodologies to ensure that these technologies are appropriately represented [3]–[5]. Whereas initial approaches to representing storage relied on heuristics or other simplifying assumptions, a number of recent papers and real-world accreditation efforts have represented energy storage in RA models via economic dispatch [6]–[9]. While implementation details differ, this storage representation generally involves a two-stage process to (1) establish a charging and discharging schedule by solving a day-ahead economic dispatch problem (possibly with unit commitment) to minimize system costs over the next 24–48 hours, and then (2) model real-time operations in which final system conditions (e.g., generator outages, net load) are realized. In current literature and applications, energy storage units are generally assumed to maintain their day-ahead schedule in real-time operations except under extreme conditions, such as when storage discharge would be necessary to supply operating reserves or prevent lost load. In practice, however, there are a number of factors that might cause the state of charge (SOC) of an energy storage resource to deviate from its day-ahead schedule in real-time operations as explained in, e.g., [10]–[12]. Specific causes of these deviations include:

- Periods of high or low real-time prices, as well as uncertainty about future real-time prices, which may render it economically rational for storage resources to schedule real-time output that differs from their day-ahead schedules.
- Changes in SOC associated with storage providing operating reserves and other market products, as well as a more general inability of market operators to accurately track and/or forecast storage SOC.
- Limitations of real-time market-clearing software, including time lags between offer submission and market clearing and short look-ahead horizons (typically one

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[1]For instance, annual load payments in recent PJM Reliability Pricing Model Base Residual Auctions have increased from $2.2 billion for the 2024/2025 delivery year to $14.7–$16.4 billion for the 2025/2026 to 2027/2028 delivery years, in part due to changes to resource accreditation methodologies [2].

hour or less) which may limit the ability of storage units to manage SOC as desired.

In real-world applications, the desire to avoid premature depletion of storage fleet SOC prior to periods of system stress was a key factor in the decision of the California System Operator (CAISO) to introduce temporary "minimum state of charge constraints" in its real-time market-clearing software during the summers of 2021–2023 [13], [14]. While other North American system operators have not yet adopted similar policies in their real-time markets, similar measures may be considered in response to perceived reliability risks associated with energy storage, especially as storage capacity continues to grow.

To help inform this discussion, in this work we investigate how downward SOC deviations of different magnitudes affect the resource adequacy contributions of energy storage resources of different durations, as well as overall system reliability, as measured by marginal storage ELCC and system NEUE, across several different storage durations. For an ERCOT-like grid with 5 GW of energy storage, we find that introducing a decrease in SOC in real-time operations equal to 25% of maximum storage energy capacity results in 1.6–2.3× increases in system NEUE and absolute declines of marginal storage ELCCs by 11–13 percentage points, with the RA value of shorter-duration storage technologies affected the most. The high sensitivity of these metrics to SOC deviations, even with only a modest amount of battery storage, highlights the importance of aligning RA model assumptions with likely storage behavior based on analysis of historical performance or otherwise accounting for likely operational patterns.

The rest of the paper is organized as follows. Section II discusses the relevant related literature on storage representation in RA models. Section III describes the RA model and high-level methodology, while Section IV provides more details about the specific test system and scenarios analyzed as part of the case study. Section V presents results for the different scenarios, while Section VI discusses key conclusions and opportunities for future research.

II. Literature Review

The resource adequacy contribution of a given energy storage technology depends on a number of factors. These include the physical characteristics of the technology, e.g., duration, roundtrip efficiency, and installed capacity [15]–[19]; features of the broader electricity system, including load, renewable and thermal generation, and network topology [8], [20], [21]; and the assumed operational strategy of storage units [7], [8], [22]–[30], the focus of this work.

Below, we review and discuss a subset of the broader RA literature that satisfies four criteria; these papers include those which (1) model energy storage operations in a time-sequential manner, which is especially important for energy-limited resources [3]–[5]; (2) use sequential Monte Carlo simulation with a large number of samples to calculate RA metrics, rather than analytical methods; (3) compare outcomes under two or more different energy storage operational strategies; and (4) represent electricity system operations using some form of economic dispatch. Other work has applied stochastic and/or approximate dynamic programming to simulate storage operations under uncertainty to derive RA metrics [24], [25], [28]; however, these methods have not been adopted in real-world use cases to the same extent that economic dispatch–based approaches (or simpler ones) have been.

Stephen et al. [9] compare RA model outcomes for several different energy storage operational strategies, including economic dispatch with imperfect foresight, reliability dispatch (in which storage discharges only to mitigate lost load and then recharges as soon as possible), and expectation dispatch (storage schedule is fixed in advance without ability to adjust to real-time conditions). The authors find that storage ELCC values are lower when storage is operated using economic dispatch, as opposed to reliability dispatch, and recommend the former as the most realistic energy storage representation considered in the paper. Awara et al. [31] analyze storage capacity credits under reliability dispatch as well as a price-taker revenue maximization model with perfect foresight for a modified version of the ERCOT grid. Both methods are found to yield high (>80%) capacity credits for four-hour duration storage, but shifting the original dispatch profile forward and backward by 1–2 hours reduces the capacity credit by 4–40 percentage points. Bhattarai et al. [32] find that key RA metrics for energy storage differ depending on whether storage is operated to minimize wind curtailment or to maximize energy price arbitrage under assumed perfect foresight. Leibowicz et al. [8] find large differences in system RA metrics result when different storage scheduling methods are applied, but do not assess implications for energy storage ELCC values. Dratsas et al. [7], [33] propose a "real-time redispatch" storage scheduling method, finding that this method produces storage ELCC values that fall in between those calculated by either a perfect foresight or a fixed shape operational strategy. Finally, the SERVM model described in, e.g., [6], which is widely used for industry RA analysis in North America, is also capable of scheduling energy storage via economic dispatch with real-time recourse, alongside other methods such as reliability dispatch. For a review of how RA assessment has evolved across several real-world jurisdictions, we refer the reader to [3].

Our review of the existing literature yields two key observations. First, many studies find that RA metrics are sensitive to the manner in which storage operations are represented. Second, the majority of these papers recommend an economic dispatch–based energy storage representation in which storage is scheduled over a 24–48-hour look-ahead horizon and then re-dispatched based on updated system conditions in real-time. However, to our knowledge, no paper to date has explored the sensitivity of any given method to SOC deviations of the type described in the previous section; rather, the focus has been on comparing methods to each other. We address this gap in the literature by quantifying the sensitivity of storage ELCC and system NEUE to fixed, real-time SOC deviations between the day-ahead schedule and real-time dispatch. As previously discussed, such deviations may be witnessed in real-world systems for a variety of reasons, but have not yet been explicitly modeled in the literature.

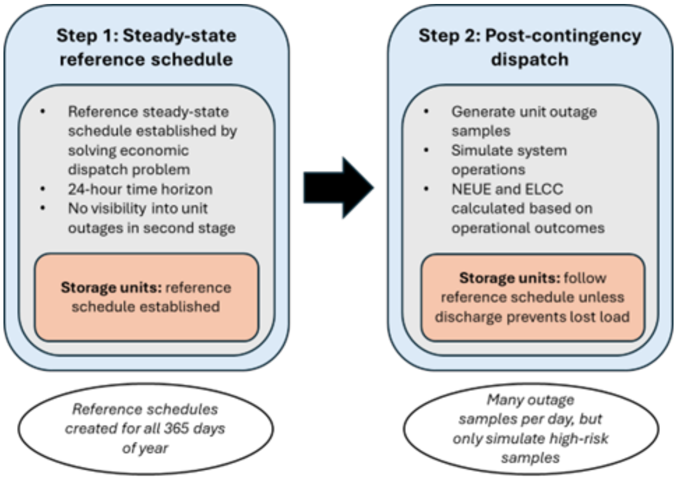

Fig. 1. Depiction of two-step RA model logic used in this paper.

III. Methodology

A. Probabilistic RA Model

We apply the probabilistic reliability assessment model described in [34] to calculate a set of key RA metrics. The model simulates system operations in two phases. First, for each day, an economic dispatch problem with a 24-hour optimization time horizon is solved to minimize the sum of costs associated with system operations and load shedding without foresight into generator outages. The solution to this optimization problem establishes a "steady-state" reference schedule for all generation and storage resources before any generator contingencies are experienced. Next, in a second "post-contingency dispatch" phase, we generate a large number of samples of power plant unit outages by applying a two-stage Markov model that captures temperature-dependent outage rates, similar to [35]. Once a unit outage or recovery occurs within a given sample, the system is re-dispatched to minimize the costs associated with generator dispatch and load shedding within that hour, without consideration of future hours; this is repeated sequentially for each hour that remains in the day. During post-contingency dispatch, all units that are not on outage are available to provide energy subject to ramp rate limitations, i.e., unit commitment constraints and startup costs are not considered. Operating reserves are also not explicitly modeled, as we assume all unit capacity is available to provide energy and mitigate load curtailment. Results from each sample of the post-contingency dispatch stage are aggregated and used to calculate probabilistic RA metrics. Computational performance is improved via parallelization made possible by the fact that each sample of unit outages in a given day is simulated independently. We also apply an efficient sample filtering method to only simulate post-contingency dispatch when there is a sufficiently high risk of lost load. The full mathematical formulation and a more detailed description of the model can be found in the Appendix.

B. Energy Storage Representations

The energy storage representation in the model is broadly similar to the economic dispatch strategy used in other RA models discussed in the literature review. In the first stage, storage resources are scheduled to minimize total system costs across each day's 24-hour horizon, with binary state variables included to prevent storage from simultaneously charging and discharging. We also include boundary constraints in this scheduling stage requiring the SOC of each energy storage resource in the final hour to return to its SOC in the first hour (assumed to be 75% for this analysis). Next, in the post-contingency dispatch phase, energy storage resources are constrained to follow their steady-state schedule until the hour in which storage discharge becomes necessary to reduce or altogether prevent lost load, in which case storage is eligible to discharge below its steady-state SOC. Under this strategy, stored energy is effectively treated as the final resource to be called upon before load shedding occurs. If a storage unit does discharge beyond its original schedule in post-contingency dispatch to help mitigate lost load, it is not eligible to recharge later in that day, nor is it required to return to its initial SOC in the final hour of the day.[2] Fig. 1 summarizes the overall RA model structure and the assumptions for storage operations within each stage, while the Appendix contains the exact set of constraints used to represent storage as described above.

C. Energy Storage State of Charge Deviation Modeling

In the reference scenario, the SOC of each energy storage resource is assumed to exactly follow its steady-state schedule before additional storage output is needed to prevent lost load. We also consider several "deviation" scenarios in which the storage units' SOC is adjusted downward by a fixed amount prior to a loss-of-load event. The magnitude of the SOC deviation in each scenario is determined by a scalar β that lies between -1 and 0, multiplied by the maximum storage energy capacity, as shown in (1). Here, soc'_t is the revised SOC level including the downward deviation, which can never be less than zero; soc_t is the steady-state SOC level at time t; and SOC_i^+ is the maximum SOC of the resource.

$$\mathrm{soc}'_t = \max\left(\mathrm{soc}_t + \beta \cdot SOC_i^+, 0\right) \tag{1}$$

Finally, for comparison, we also include a fourth "fully charged" case, similar to the reliability dispatch strategy in other models, in which we set the SOC of energy storage to 100% in all hours in the reference scheduling stage. The three types of scenarios are illustrated in Fig. 2 for the reference case when $\beta = 0$ (black), a deviation scenario when $\beta = -0.125$ (red), and the fully charged scenario (green). We

[2]This restriction on charging within a day does not have a large effect on results because the vast majority of lost load is experienced within a single set of consecutive hours within a day, rather than across two different events. There are also practical reasons to expect storage charging to be limited between events, including the desire to avoid storage units charging from energy generated by other storage units, which would result in a net reduction in energy available to meet demand due to losses from charging and discharging inefficiencies.

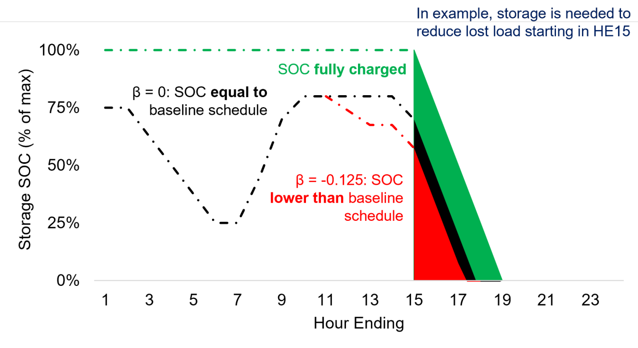

Fig. 2. Visual depiction of SOC trajectory for the reference scenario with $\beta = 0$ (black), a deviation scenario with $\beta = -0.125$ (red), and the fully charged scenario (green). The dotted lines represent the steady-state schedule prior to hour ending 15, when storage is first called upon to serve demand that would otherwise be curtailed. The shaded areas represent the amount of lost load the storage unit is able to mitigate in each case.

note that these scenarios are intended to provide an easy-to-interpret way to measure the effect of different SOC deviation magnitudes on key RA outcomes. The fixed-deviation design should be interpreted as a sensitivity experiment rather than a behavioral model, whose purpose is to isolate the reliability effect of SOC deviations. Though the chosen β values are not calibrated against historical data and/or modeling efforts that purport to simulate the likely magnitude and frequency of SOC deviations, they can inform the potential RA impact of such deviations to the extent that they are observed in real-world systems.

D. *Calculation of Normalized Unserved Energy (NEUE) and Marginal Effective Load Carrying Capability (ELCC)*

System NEUE for each scenario is calculated by summing the total amount of unserved energy across all samples and dividing this value by the total amount of electricity demand. Marginal ELCC is calculated using a standard iterative approach: we first determine the NEUE of a base system where 5 GW of four-hour storage operates under the reference case economic dispatch strategy ($\beta = 0$) in all scenarios. Next, we add a single 100 MW battery storage unit whose duration and operational assumptions depend on the specific dispatch scenario and storage duration being analyzed, as well as 100 MW of demand uniformly to each hour of the year. We then execute the RA model with the same set of unit outages as in the base system and calculate a new (higher) system NEUE. Added demand is iteratively adjusted until the resulting NEUE is within 0.05% of the base-system NEUE. When system NEUEs are sufficiently close, the marginal storage ELCC is then calculated as the unitless ratio of the final quantity of demand added in each hour to the 100-MW nameplate capacity of the added storage resource. Overall, the ELCC metric is intended to isolate the ability of a new storage resource operating under a given representation to support new load depending on its duration and assumed operational strategy. Mathematical formulas for both metrics are given in equations (2) and (3), where $ens_{t,s}$ is unserved energy in hour t and sample s, $D_{t,s}$ is demand in hour t and sample s (considering all samples, not just those with unserved energy), ΔD_{final} is the final uniform hourly demand increase that restores system NEUE to the base-case level, and $CAP^{\text{stor}} = 100$ MW is the nameplate capacity of the added marginal storage resource.

TABLE I
INSTALLED CAPACITY BY TECHNOLOGY TYPE FOR THE THREE SYSTEMS ANALYZED IN THE CASE STUDY.

Installed capacity (GW)	**5 GW, 2-hr duration**	**5 GW, 4-hr duration**	**5 GW, 8-hr duration**
Natural Gas CC	34.2	33.1	31.4
Natural Gas CT/ST	20.4	20.4	20.4
Nuclear	5.1	5.1	5.1
Onshore Wind	31.5	31.5	31.5
Solar PV	20.0	20.0	20.0
Battery storage (2-hour)	5.0	0.0	0.0
Battery storage (4-hour)	0.0	5.0	0.0
Battery storage (8-hour)	0.0	0.0	5.0
Total	116.3	115.1	113.4

$$\text{NEUE} = \frac{\sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} ens_{t,s}}{\sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} D_{t,s}} \tag{2}$$

$$\text{ELCC} = \frac{\Delta D_{\text{final}}}{CAP^{\text{stor}}} = \frac{\Delta D_{\text{final}}}{100} \tag{3}$$

IV. Case Study Description

We apply the RA model to a copperplate system derived from the topology and generation mix of the Electric Reliability Council of Texas (ERCOT) in 2021. We consider three different test systems; each contains 5 GW of energy storage with a different storage duration (two hours, four hours, and eight hours). Each system is constructed by removing existing hydro, coal, and battery storage units, increasing solar capacity to 20 GW, increasing peak demand by 10%, and adding 5 GW of battery storage with the relevant duration. Because the resulting systems exhibit different levels of lost load, we remove additional natural gas capacity in each case to create systems with a normalized expected unserved energy (NEUE) value of approximately 4 parts per million (ppm) when storage follows the reference economic dispatch case ($\beta = 0$).[3] The installed capacity of each technology type for each system is listed in Table I.

Consistent with the methodology described in Section III, each system features four different cases:

- A no-deviation case where $\beta = 0$, in which the SOC of storage follows the reference schedule except when additional storage generation is needed to reduce lost load.
- A deviation case where $\beta = -0.125$, corresponding to a decrease in SOC equivalent to 0.25 hours of output at maximum capacity (1.25 GWh) for two-hour storage

[3] In the results below, this reference NEUE corresponds to a loss of load expectation (LOLE) of between 0.07 and 0.17 for the reference ($\beta = 0$) cases, similar in magnitude to the 0.1 LOLE reliability standard in place in U.S. jurisdictions. For reference, the long-term reliability standard of the Australian National Electricity Market, the only jurisdiction to our knowledge that relies on NEUE for its resource adequacy standard, is 20 ppm [36].

units, 0.5 hours of output (2.5 GWh) for four-hour storage units, and 1 hour of output (5 GWh) for eight-hour storage units.

- A deviation case where $\beta = -0.25$, corresponding to a decrease in SOC equivalent to 0.5 hours of output at maximum capacity (2.5 GWh) for two-hour storage units, 1 hour of output (5 GWh) for four-hour storage units, and 2 hours of output (10 GWh) for eight-hour storage units.
- A fully charged case, representing an upper bound on the resource adequacy contribution of storage.

All battery storage in each system is modeled as a single unit with 5 GW capacity, assuming 88% round-trip efficiency and a $10/MWh variable operations cost to reflect degradation. We consider a single weather year, which establishes hourly renewable outputs and temperature profiles used to determine temperature-dependent outage rates for each generation unit. All 365 days in the year are modeled in single-day increments with 1,000 generator outage samples generated per day. We also apply a sample filtering method to restrict the simulation of system operations to only those samples in which demand exceeds available power supply, excluding storage units, in at least one hour after contingencies are realized; the remaining samples are assumed to experience no unserved energy. That is, system operations are only simulated for the samples that meet the criteria in (4), where D_t is system demand in period t, $T_{i,t}$ is the capacity availability of thermal resource i at time t, and $R_{j,t}$ is the potential output of renewable resource j at time t. Storage resources are assumed not to experience outages, although such outages can be introduced in future work.

$$\max_{t=1,\ldots,24} \left(D_t - \sum_i T_{i,t} - \sum_j R_{j,t} \right) > 0 \quad (4)$$

All cases are run in parallel on the Argonne Laboratory Computing Resource Center Improv cluster, which has 128 cores and 256 GB of memory per node. To facilitate consistent comparison across storage dispatch assumptions, all scenarios for a given test system use the same resource outage samples. Outage samples differ across test systems because of differences in the underlying generation fleets.

V. Results

A. System NEUE

The system NEUE values resulting from each combination of storage duration and dispatch assumptions are summarized in Table II, with the parentheses displaying the ratio of each dispatch scenario's NEUE to that of that system's reference case. Recall that each system's reference case ($\beta = 0$) was designed to have approximately the same NEUE of 4 parts per million. The distribution of unserved energy by month and hour of day is shown in Fig. 3, with the size of each bubble corresponding to the quantity of unserved energy within the month-hour time period. As expected, the deviation cases ($\beta = -0.125$ and $\beta = -0.25$) have higher NEUE values compared to the reference cases because the amount of stored

TABLE II
System NEUE (parts per million) for different test systems (columns) and storage dispatch scenarios (rows).

Dispatch scenario	5 GW, 2-hr duration	5 GW, 4-hr duration	5 GW, 8-hr duration
$\beta = 0$ (Economic Dispatch w/ No Deviation)	4.5	4.3	3.8
$\beta = -0.125$ (Economic Dispatch w/ -12.5% SOC Deviation)	6.9 (1.5x)	6.0 (1.4x)	4.8 (1.2x)
$\beta = -0.25$ (Economic Dispatch w/ -25% SOC Deviation)	10.5 (2.3x)	8.3 (1.9x)	6.3 (1.6x)
Fully charged (SOC = 100%)	3.3 (0.7x)	2.9 (0.7x)	2.5 (0.7x)

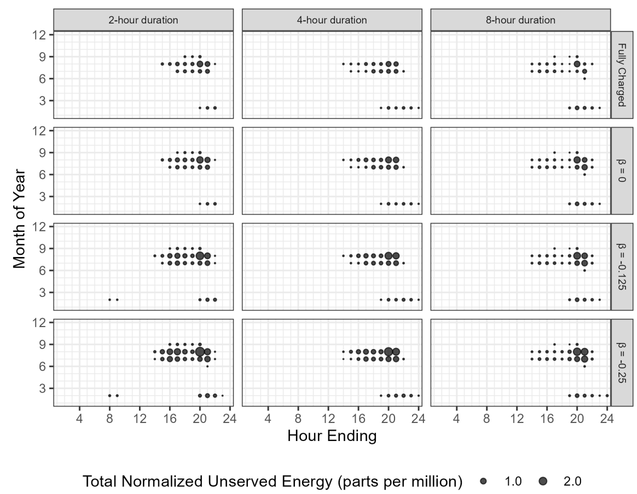

Fig. 3. Distribution of normalized unserved energy (ppm) by month and hour for different test systems and storage dispatch scenarios.

energy available to mitigate lost load is reduced, while the fully charged cases have less total lost load. The magnitude of the difference is significant; for a system with only 5 GW of four-hour storage, the $\beta = -0.25$ case, corresponding to a decrease in SOC of one hour's worth of maximum output, results in a near doubling of annual unserved energy.[4] Moreover, because the NEUE value averages unserved energy from across the entire year, the effect on any single outage event may be much larger. The largest daily quantity of normalized unserved energy in the four-hour case was approximately 300 ppm (or 98,000 MWh) for $\beta = 0$ and 665 ppm (or 218,000 MWh) for $\beta = -0.25$.

We also observe that both the absolute and relative increases in NEUE differ by storage duration: for the two-hour system, the NEUE when $\beta = -0.25$ is 2.3 times higher than that of the reference case, whereas the NEUE for the four- and eight-hour cases are only 1.9 and 1.6 times higher than the reference cases. This is despite the fact that the two-hour storage technologies lose the least amount of total stored energy in any given SOC deviation scenario (i.e., the $\beta = -0.25$ scenario

[4]For this case, the system LOLE, which is another commonly used metric in RA analyses, also approximately doubled from 0.07 to 0.13.

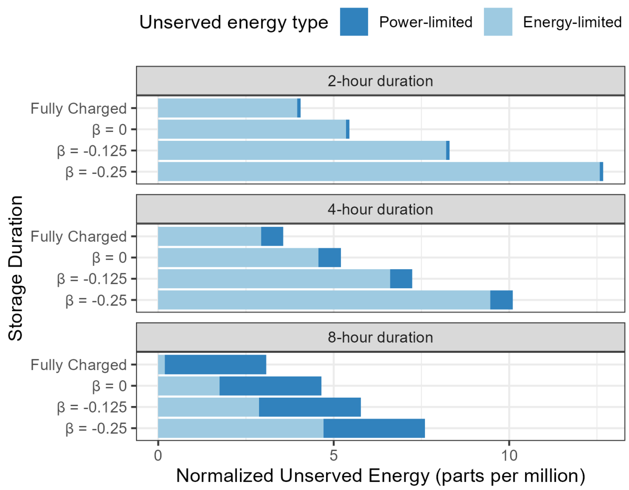

Fig. 4. Quantity of power-limited vs. energy-limited unserved energy for different test systems and storage dispatch scenarios.

results in 2.5 GWh of lost stored energy for two-hour storage vs. 5 and 10 GWh lost stored energy for four- and eight-hour storage).

This result is explained by the nature of modeled outage events. In our modeling framework, unserved energy was observed to be caused by one of two types of phenomena: power (or capacity) limits and energy limits. Unserved energy due to power limits arises from having insufficient available installed capacity to meet demand in an hour; for these cases, having an unlimited amount of stored energy would not prevent these shortfalls because the system is power-constrained. Energy-limited unserved energy, by contrast, occurs when storage could mitigate lost load if it had sufficient SOC, but cannot do so because SOC has been exhausted.[5] In Fig. 4, we plot the quantity of lost load by type for each scenario. In the two-hour storage reference case, the vast majority of lost load occurs as a result of energy limitations, meaning that further decreases in SOC translate nearly one-to-one to increases in unserved energy. The systems with four- and eight-hour duration storage have comparatively more power-limited unserved energy, which remains unaffected by SOC deviations; the result is that such deviations have a smaller total effect on unserved energy. Thus, holding overall system NEUE constant, systems that are dependent on shorter-duration storage are more sensitive to SOC deviations than those dependent on longer-duration storage, in which a higher share of loss-of-load events occur due to power limits. A corollary finding from Fig. 4 is that, for our ERCOT-like test system, a fully charged 8-hour battery is sufficient to mitigate almost all lost load caused by energy shortfalls. The above discussion highlights the importance of the nature of lost load in the base system when assessing the potential RA contribution of different energy-limited resources, a sensitivity of RA model outputs that has received relatively little attention in the literature thus far.

[5]Lost load could also in theory be caused by limited ramping capacity, but this was not observed in our results.

TABLE III
MARGINAL STORAGE ELCC (%) FOR DIFFERENT TEST SYSTEMS (COLUMNS) AND STORAGE DISPATCH SCENARIOS (ROWS).

Dispatch scenario	**5 GW, 2-hr duration**	**5 GW, 4-hr duration**	**5 GW, 8-hr duration**
$\beta = 0$ (Economic Dispatch w/ No Deviation)	18.0%	42.1%	85.0%
$\beta = -0.125$ (Economic Dispatch w/ -12.5% SOC Deviation)	11.6%	35.6%	78.5%
$\beta = -0.25$ (Economic Dispatch w/ -25% SOC Deviation)	6.6%	29.2%	71.8%
Fully charged (SOC = 100%)	22.0%	44.9%	91.7%

B. Storage Marginal ELCC

Next, Table III depicts the marginal storage ELCC values for each scenario. As expected, marginal ELCCs increase with duration: the reference case value is 18% for two-hour storage, 42% for four-hour storage, and 85% for eight-hour storage. Negative SOC deviations also cause declines in ELCCs, with the $\beta = -0.125$ scenarios resulting in 6–7 percentage point decreases and the $\beta = -0.25$ scenarios resulting in decreases of 11–13 percentage points depending on the storage duration. The absolute change is approximately the same across all durations, while the relative change is again largest for two-hour storage, a result of its low reference case ELCC.

Focusing on four-hour storage, the change in ELCC in the $\beta = -0.25$ scenario from 42% to 29% represents a 30% decrease in accredited capacity compared to the reference case, again, a significant change. A 100 MW, 4-hour battery storage resource that cleared the PJM 2027/2028 Reliability Pricing Model Base Residual Auction would receive a $333.44/MW-day payment for 50% of its installed capacity, based on system ELCC class ratings [2]. This is equivalent to roughly $6 million per year in income. A 13 percentage point decrease in capacity credit would therefore decrease capacity revenues by approximately $1.5 million per year, representing approximately 0.8% of the total installed cost of a 4-hour utility-scale lithium-ion battery system deployed in 2022, assuming an overnight installed cost of $482/kWh [37]. We note that due to saturation effects, the change in marginal ELCCs may be smaller for shorter-duration storage units at installed capacities greater than 5 GW. At the same time, the effect on NEUE—arguably, the more important RA metric from the system perspective—would be larger with a greater amount of storage capacity.

VI. CONCLUSION

This paper quantified how unanticipated downward deviations in energy storage units' SOC in real-time operations relative to a day-ahead schedule impact the system NEUE and marginal storage ELCC. Such deviations may occur in practice for a number of reasons including rational economic behavior on the part of storage units as well as limitations of current real-time market scheduling software and/or bidding processes. Simulations were run using a probabilistic resource adequacy model applied to three different ERCOT-like systems with 5 GW of two-, four-, and eight-hour energy storage and four different SOC deviation scenarios. Moderately sized decreases in SOC were found to have material effects on system NEUEs as well as marginal ELCCs for energy storage: across the three durations, reducing the available state of charge by 25% of maximum storage energy capacity increased the system NEUE by a factor of 1.6 to 2.3 and reduced marginal storage ELCCs by 11–13 percentage points. Furthermore, the relative sensitivity of both metrics to SOC deviations was highest for two-hour storage and lowest for eight-hour storage, emphasizing that the reliability contributions of longer-duration storage resources are more resilient against SOC deviations that may reflect less idealized operating conditions.

We draw three major conclusions from this work. First, the demonstrated sensitivity of RA metrics to different energy storage SOC values highlights the importance of capturing realistic storage behavior in resource adequacy modeling efforts, especially as energy storage and other energy-limited resources continue to grow and potentially replace traditional thermal generation units. Modeling assumptions should be validated against real-world data to the extent possible, though this may be challenging in practice for a number of reasons, including the relative paucity of historical scarcity events and unique conditions associated with each event; heterogeneity in storage units' operational behaviors; and difficulty in even obtaining energy storage SOC and other operational data from grid operators and unit owners. In this work, we considered a range of potential deviation values as embodied by the β parameter; future work that aims to quantify the actual magnitude of such deviations observed in historical events would help to better contextualize this paper's results and the potential impacts observed on real-world electricity systems.

Second, our results emphasize the sensitivity of any given RA modeling exercise to error, including the makeup of the base system used to calculate NEUE and marginal ELCC values. This implies that there may be benefits to adopting policies that can incorporate historical outcomes as well as actual performance into capacity accreditation and compensation policies, in addition to RA model outputs. Many jurisdictions already combine historical availability during periods of system stress for thermal units with modeling outputs; similar approaches may be useful to consider for storage and other energy-limited resources. For instance, the Midcontinent Independent System Operator (MISO) recently received federal approval to combine probabilistic model-based accreditation with historical performance for all resources in future capacity auctions [38].

Finally, the sensitivity of lost load to SOC depletion suggests that grid operators should be cognizant of the reliability risks associated with energy storage units prematurely depleting stored energy (or failing to recharge) ahead of high-risk periods. It remains an open question whether market-based rules can be structured in a manner that fully aligns energy storage behavior with desired system outcomes. Certain aspects of market design, including sufficiently high energy and operating reserve offer caps and/or strict performance requirements on firm capacity suppliers represent two examples of market reforms that may limit incentives for such undesired SOC deviations [39]. If status quo market rules result in energy storage operational outcomes that are perceived to be misaligned with system reliability needs, it seems likely that system operators will come to rely more heavily on out-of-market actions to maintain operational reliability. Storage unit offer and dispatch patterns should be monitored to assess whether the behavior of the storage fleet aligns with system reliability needs, particularly on high-risk days.

Future work that would address the above knowledge gaps includes assessing systems with greater reliance on energy storage; modeling storage units as profit-aware units in RA modeling efforts; and explicitly analyzing historical storage operational outcomes during periods of system stress to help system planners and grid operators be aware of behaviors that may differ from operational patterns assumed in RA models.

VII. AI Usage Disclosure

AI was used to assist with post-processing model outputs into figures and tables used in this paper.

VIII. Acknowledgements

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Appendix A
Mathematical Formulation of the Probabilistic Resource Adequacy Model

A. Notation

Sets and indices:

$i \in I$	Generator or storage resource.
$t \in H$	Hourly time period.
$c \in C$	Risk scenario or post-contingency event.
$\Psi_{ES} \subseteq I$	Set of energy storage generators.
$\Psi_{VRE} \subseteq I$	Set of variable renewable energy generators.

Parameters:

ϵ_i^C	Energy storage charging efficiency for resource i.
ϵ_i^D	Energy storage discharging efficiency for resource i.
C_{cit}	Outage status of generator i in event c and period t; equal to 1 if available and 0 if unavailable.
CAP_i	Power capacity of generator or storage resource i.
$\overline{CHG}_{it}$	Steady-state energy storage charging schedule for resource i in period t.
D_t	Power demand in period t.
$\overline{G}_{it}$	Steady-state generator dispatch setpoint for generator i in period t.
MC_i	Marginal variable cost of generator i.
R_i^H	Hourly ramp capability of generator i.
S_{it}	Generation availability of generator i in period t.
SOC_i^+	Maximum state of charge of storage resource i.
$\overline{SOC}_{it}$	Steady-state energy storage state-of-charge for resource i in period t.

soc_{i1}	State of charge of storage resource i in hour 1, assumed to be 75 percent in the paper in all cases.
$VOLL$	Value of lost load.

Variables (all ≥ 0):

chg_{it}	Storage charging of resource i in period t.
c_{it}^{STO}	Storage status indicator for resource i in period t; binary variable.
$curt_{it}$	Curtailed variable renewable generation from resource i in period t.
d_{it}^{up}, d_{it}^{dn}	Generator redispatch up and down for generator i in period t.
ens_t	Unserved energy, also known as lost load, in period t.
g_{it}	Power output of generator or storage resource i in period t.
soc_{it}	State of charge of storage resource i in period t.

B. Steady-State System Scheduling

The first-stage steady-state scheduling problem is formulated below. The objective is to minimize the costs of generation and lost load over the course of each day. Equations (6)–(16) represent the usual constraints associated with economic dispatch in a copperplate system with generator and storage units. In particular, (6) represents the system balance constraint, (7)–(8) represent hourly generation output constraints, (9)–(10) represent ramping constraints, and (11)–(16) govern the relationship between storage generation, charging, and state-of-charge. Finally, all variables have non-negativity constraints which are omitted for brevity. The full formulation is given as:

$$\min \quad \sum_{i,t} MC_i g_{it} + \sum_t VOLL \cdot ens_t. \tag{5}$$

Subject to:

$$\sum_i g_{it} \quad - \sum_{i \in \Psi_{ES}} chg_{it} + ens_t - D_t = 0, \quad \forall t. \tag{6}$$

$$0 \leq g_{it} \leq CAP_i, \quad \forall i, t. \tag{7}$$

$$g_{it} + curt_{it} = S_{it} CAP_i, \quad \forall i \in \Psi_{VRE}. \tag{8}$$

$$g_{it} - g_{i,t-1} \leq CAP_i R_i^H, \quad \forall i, t. \tag{9}$$

$$g_{i,t-1} - g_{it} \leq CAP_i R_i^H, \quad \forall i, t. \tag{10}$$

$$0 \leq g_{it} \leq c_{it}^{STO} CAP_i, \quad \forall i \in \Psi_{ES}, t. \tag{11}$$

$$0 \leq chg_{it} \leq \left(1 - c_{it}^{STO}\right) CAP_i, \quad \forall i \in \Psi_{ES}, t. \tag{12}$$

$$c_{it}^{STO} \in \{0, 1\}, \quad \forall i \in \Psi_{ES}, t. \tag{13}$$

$$0 \leq soc_{it} \leq SOC_i^+, \quad \forall i \in \Psi_{ES}, t. \tag{14}$$

$$soc_{it} - soc_{i,t-1} - \epsilon_i^C chg_{it} + \frac{1}{\epsilon_i^D} g_{it} = 0, \quad \forall i \in \Psi_{ES}, t. \tag{15}$$

$$soc_{i,t=T} - soc_{i1} + \epsilon_i^C chg_{i1} - \frac{1}{\epsilon_i^D} g_{i1} = 0, \quad \forall i \in \Psi_{ES}. \tag{16}$$

C. Post-Contingency Dispatch

The second-stage dispatch problem formulation is presented below for a fixed post-contingency event c. Though we keep the t subscripts on variables for consistency with previous equations, note that the problem is solved on an hourly basis for each hour t of each post-contingency event and considering only the present time interval (rather than the entire day), a change that is reflected in the constraint definitions. The objective (17) minimizes the sum of the costs of generator re-dispatch, as measured by the redispatch variables d_{it}^{up} and d_{it}^{dn}, as well as lost load costs. The marginal cost of storage output (MC_i) is also increased in this stage to exceed that of other generators; combined with the additional constraints below, this helps to ensure that storage is the last resource dispatched to mitigate lost load. Moving to the constraints, (18) represents the system balance constraint for hour t. Equation (19) defines the relationship between generator steady-state dispatch and re-dispatch quantities. Constraints (20)–(24) limit output and charging based on available unit capacity for conventional, storage, and renewable units. Equations (25)–(28) enforce hour-to-hour ramping limits. Additional storage unit operations are encoded in equations (29)–(32); many of these depend on the newly introduced time t^0, defined as the first hour in which storage is required to discharge additional energy to mitigate lost load such that the energy storage state of charge decreases below its steady-state value. Equation (29) enforces the maximum energy storage state of charge, analogous to equation (14) in the steady-state problem. Equation (30) requires that storage units follow their steady-state charging schedule before the time t^0 is reached, then set charging to zero afterwards. Similarly, constraint (31) sets storage incremental charging and discharging to zero until time t^0 is reached; thereafter, storage discharge is only constrained by its maximum power output and availability as embodied in constraint (21). Finally, constraint (32) enforces the state-of-charge balance inclusive of the deviation scenarios described in equation (1) of the main text of the paper; in particular, the β parameter, which adjusts the storage SOC, is applied only in the hour in which time t^0 is reached.

$$\min \quad \sum_i MC_i \left(d_{it}^{up} + d_{it}^{dn}\right) + VOLL \cdot ens_t. \tag{17}$$

Subject to:

$$\sum_i g_{it} - \sum_{i \in \Psi_{ES}} chg_{it} + ens_t - D_t = 0. \tag{18}$$

$$g_{it} = \overline{G}_{it} + d_{it}^{up} - d_{it}^{dn}, \quad \forall i. \tag{19}$$

$$0 \leq g_{it} \leq C_{cit}\, CAP_i, \quad \forall i \notin \Psi_{ES}. \tag{20}$$

$$0 \leq g_{it} \leq C_{cit}\, CAP_i\, c_{it}^{STO}, \quad \forall i \in \Psi_{ES}. \tag{21}$$

$$0 \leq chg_{it} \leq C_{cit}\, CAP_i \,\left(1 - c_{it}^{STO}\right), \quad \forall i \in \Psi_{ES}. \tag{22}$$

$$c_{it}^{STO} \in \{0, 1\}, \quad \forall i \in \Psi_{ES}. \tag{23}$$

$$g_{it} + curt_{it} = C_{cit}\, S_{it}\, CAP_i, \quad \forall i \in \Psi_{VRE}. \tag{24}$$

$$d_{it}^{up} \leq CAP_i R_i^H, \quad \forall i. \tag{25}$$

$$d_{it}^{dn} \leq CAP_i R_i^H, \quad \forall i. \tag{26}$$

$$g_{it} - g_{i,t-1} \leq CAP_i R_i^H, \quad \forall i. \tag{27}$$

$$g_{i,t-1} - g_{it} \leq CAP_i R_i^H, \quad \forall i. \tag{28}$$

$$0 \leq soc_{it} \leq SOC_i^+, \quad \forall i \in \Psi_{ES}. \tag{29}$$

$$chg_{it} = \begin{cases} \overline{CHG}_{it}, & t < t^0, \\ 0, & t \geq t^0, \end{cases} \quad \forall i \in \Psi_{ES}. \tag{30}$$

$$g_{it} = \overline{G}_{it},\ d_{it}^{up} = d_{it}^{dn} = 0, \quad \forall i \in \Psi_{ES},\ t < t^0. \tag{31}$$

$$soc_{it} = \begin{cases} soc_{i,t-1} + \epsilon_i^C chg_{it} - \frac{1}{\epsilon_i^D} g_{it}, & t \neq t^0, \\ \max\Big(0,\ soc_{i,t-1} + \epsilon_i^C chg_{it} & \\ \quad - \frac{1}{\epsilon_i^D} g_{it} + \beta \cdot SOC_i^+\Big), & t = t^0, \end{cases} \quad \forall i \in \Psi_{ES}. \tag{32}$$

I. Review #259A

A. Paper summary

The paper studies the impact of state-of-charge deviations in storage units on system reliability for storage devices of different sizes. The metrics considered are the normalized expected unserved energy and the marginal effective load-carrying capability. Studies are carried out on an adapted ERCOT system.

B. Comments for authors

- The topic of the paper and the contributions are well described and motivated and the topic relevant.
- Studies are carried out on a realistic test case, allowing for realistic quantitative assessments about the level of impact.
- The novelty of the paper lies mostly in the analysis as opposed to the methodology.
- The paper, however, is ambiguous in multiple places, e.g.
  - p.3: ”if a storage unit does discharge beyond its original schedule ...” => what is meant with ”beyond”?
  - p. 3: ”.. battery storage unit that differs depending on ...” => differs in what sense? Do you mean ”differs by”?
  - p. 4: the explanation at the beginning of this page on how the studies are carried out is not clear; => maybe a flowchart would be helpful; also ”different amount of electricity demand” => more or less and how much? and at the end: ”capacity of the resource” => do you mean the battery here? => overall, the description of the process is difficult to follow.
  - p. 4: ”battery storage with the relevant duration” => what do you mean with ”relevant”? And one sentence later: is it trial and error that you use to get to 4ppm, or is there a specific procedure?
  - p. 5: ”holding overall system NEUE constant” => what is meant with this or how do you achieve this?
  - p. 6: is the value of $333.44/MW directly taken from the mentioned market, or is some computation involved and what is meant with ”based on system ELCC class ratings”?
  - p. 6: right before the conclusion section: comparative statements are given such as ”smaller” and ”greater” but it is not entirely clear which situations are being compared, i.e. the ”than” is essentially missing
  - p. 6, Table III: it’s hard to understand what the percentages in this table actually mean; it might be useful to give the mathematical expression and also to give an intuitive explanation what 20% for example means

  hence, for better readability, it is crucial that the authors revise the paper and address ambiguities in the text; otherwise, the approach and some of the results are difficult to follow.
- The paper is mostly text with very few equations, which is convenient for reading, but it also hinders easier understanding. Please provide the metrics as mathematical expressions.
- in the text coal is mentioned, but in Table I, there is no coal; was it completely removed when adapting the system?
- constraint (2): this condition is fulfilled if the generation is greater than the load but in the text it is written ”for samples in which demand in any hour exceeds available power supply ...” => there seems to be a discrepancy; also, underneath ”min”, the index h is used but in the formula it is i; overall, it is not clear how this constraint is used
- it is stated on p. 5 that ”the effect on any single outage may be larger”; it would be interesting to not just get the ”averaged” results but also information on the outage that leads to the largest effect

C. Summarize your recommendation in one to two sentences

The topic of the paper is relevant, providing insights into the impact of SOC errors on specific metrics. In various places, the paper lacks clarity, as pointed out with examples in the detailed comments. It is crucial that the authors address these ambiguities in the final version.

— Gabriela Hug

II. Review #259B

A. Paper summary

The paper models and analyzes the impact of a mismatch between planned and actual battery storage state of charge on battery resource adequacy contribution. The central contribution of the paper is the development of a modeling approach to address this question, along with a case study based on an ERCOT-like system with 5 GW of battery storage.

B. Comments for authors

The paper addresses a timely topic and presents a credible method to answer the posed research question. The discussion of the power-limited and energy-limited outage types is interesting.

Comments:

1) A central weakness of the discussion, in the opinion of this reviewer, is the lack of discussion of how likely it is that SOC is lower by 12.5–25% in practice. As mentioned by the authors, for a 5 GW, 8-hour storage system this represents a significant amount of energy.
2) The significance of the sample filtering in (2) is not clear to this reviewer. Is this filtering pre- or post-contingency? In the latter case it is clear that this case would lead to unserved energy. Pre-contingency this is not so clear. Also, there seems to be a typo in the indices in (2).
3) If this reviewer understands correctly, the scenarios are computed on a daily 24-hour basis. What if the simulated outage occurs, say, at 11 pm and the day ends before the energy storage is depleted? Does the model capture this case?
4) An additional sensitivity analysis on the modeled return SOC (75%), the battery power (5 GW), or the RES share would have been interesting.

The authors are strongly encouraged to strive for more clarity in their methods for a final version of this paper. In the submitted version, instead of using mathematical formulations, some of the computations and metrics are awkwardly spelled out (e.g., beginning of Section III.D), creating ambiguity. Also, the referenced full model formulation is not very long and could be provided in the paper's appendix to make it more self-contained.

C. *Summarize your recommendation in one to two sentences*

I recommend acceptance. The paper asks a relevant research question and presents a solid method to assess it. The numerical results are insightful and have practical relevance.

— Anonymous reviewer

III. Review #259C

A. *Paper summary*

This paper investigates how downward deviations in energy storage state of charge (SOC) from a day-ahead economic dispatch schedule affect resource adequacy metrics.

Using a two-stage RA model applied to three ERCOT-like copperplate systems with 5 GW of two-, four-, and eight-hour battery storage, the authors parametrically reduce SOC via a scalar beta and measure changes to normalized expected unserved energy (NEUE) and marginal effective load carrying capability (ELCC).

From the numerical analysis, it shown that 25% SOC reduction increases NEUE by 1.6–2.3× and reduces marginal ELCC by 11–13 percentage points.

B. *Comments for authors*

Strengths:

- The paper addresses a timely and practically important question with direct relevance to ongoing capacity accreditation debates. The beta parameter provides a simple and easily interpretable framework for parameterizing SOC deviations.

Weaknesses:

- One significant concern is that the entire analysis relies on a single weather year. RA metrics are well-known to exhibit high inter-annual variability driven by weather-dependent load, renewable output, and temperature-dependent outage rates.
- The beta formulation (Eq. 1), while intuitive, is overly simplistic: it applies a fixed, uniform, deterministic scalar to all hours and all units simultaneously. Real-world SOC deviations are stochastic, time-varying, unit-specific, and endogenously driven by market incentives. Do real-world deviations tend to concentrate during high-risk hours? batteries would anticipate scarcity events that are quite profitable. The assumed beta values (-0.125, -0.25) are not calibrated against empirical data.
- The paper is not mathematically self-contained: the optimization formulations for both the day-ahead economic dispatch and post-contingency dispatch stages are deferred entirely to reference [34], a 2025 preprint.
- More clear description on the ELCC calculation (flow-chart?) would be appreciated for clarity.

C. *Summarize your recommendation in one to two sentences*

The paper poses a timely and practice-relevant research question and provides useful qualitative insights, but the quantitative results are not sufficiently validated due to reliance on a single weather year, an empirically un-calibrated deviation model.

— David Pozo

IV. Brief response to reviewers (optional)

No response

V. Brief summary of changes made to the final paper

The core methodological approach and numerical results remain unchanged between the initial submission and the final version of the paper. However, a number of revisions have been made to the manuscript. The first major revision is the addition of Appendix A to include the full mathematical formulation of the probabilistic resource adequacy model used for the analysis. Previously, the paper referenced another paper for the model description, which lacked detail on the storage representation. The specific representation of energy storage and other aspects of the model are described more clearly through these mathematical expressions. In addition, we have attempted to clarify other aspects of the methodology in Section III of the main text, including the sample filtering method and marginal ELCC calculation. Section V also includes several new results based on reviewer feedback. For instance, the new Figure 3 visualizes the seasonal distribution of lost load produced by the model to improve overall understanding and help alleviate one reviewer's potential concerns associated with a 24-hour daily time horizon, as the vast majority of lost load occurs well before the end of each day in all scenarios. Finally, minor textual changes for clarity have been made throughout.