Revisiting Capacity Market Fundamentals

Ke Xin Zuo*[1], Joshua C. Macey†[2], and Jacob Mays‡[3]

[1]Operations Research and Information Engineering, Cornell University, Ithaca, NY 14853
[2]Yale Law School, New Haven, CT 06511
[3]Civil and Environmental Engineering, Cornell University, Ithaca, NY 14853

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Abstract

Many liberalized electricity markets use capacity mechanisms to ensure that sufficient resources will be available in advance of operations. Recent events have called into question the ability of capacity mechanisms to provide sufficient incentives for reliability. A core challenge is that penalties for non-performance on capacity obligations are lower than what theory would suggest is economically efficient, giving suppliers an incentive to overstate their contributions to reliability. System operators can mitigate the effect of weak incentives by conducting accreditation studies that limit the size of the capacity obligation taken on by suppliers. However, the technical and administrative complexity of these accreditation studies has contributed to ongoing challenges for reliability and efficiency. This paper reviews fundamental elements of capacity market design, enabling a description of current inefficiencies as well as an identification of several assumptions stressed by the transition to variable and fuel-constrained resources. In light of these challenges, the clearest path of reform is to reduce reliance on accreditation studies, instead working to restore economic incentives through larger non-performance penalties. Given the financial risk this implies for suppliers, accreditation studies would nevertheless remain important in order assess credit risk and prevent the use of bankruptcy as a hedge.

1 Introduction

In systems that rely on private investment in electricity generation, the resource adequacy problem is addressed through market mechanisms that create an incentive for investors to build a portfolio of assets capable of delivering an appropriate level of reliability. A fundamental issue in this context is the significant volatility of electricity prices, driven by the high value of reliable power combined with our limited ability to shift consumption. Providing full-strength incentives for investors would entail that system operators allow prices to reach levels commensurate with this extraordinary value. Allowing such prices to reach end-use consumers is typically a political impossibility given the critical importance of electricity and the difficulty of differentiating in real time between genuine scarcity and the exercise of market power. Moreover, as witnessed in the catastrophic generation shortfalls experienced in Texas in February 2021, even a credible political commitment to full-strength spot prices in an "energy-only" market design is not sufficient to ensuring resource adequacy given risk aversion and barriers to contracting (Mays et al., 2022). In light of these challenges, regulators in most market areas have introduced a resource adequacy mechanism (e.g., a capacity market) that mandates contracts between loads and generators (Joskow and Tirole, 2007; Cramton et al., 2013; Borenstein et al., 2023).

*kz277@cornell.edu
†joshua.macey@yale.edu
‡jacobmays@cornell.edu

But recent events, most notably the approximately 57,000 MW of unplanned outages PJM experienced during Winter Storm Elliott, suggest that this model is not working as intended (PJM Interconnection, 2023). In response to the perception that capacity markets are not working, some regulators and market participants have begun to question whether they are capable of meeting resource adequacy needs. For example, Commissioner Mark Christie has written that "it is past time to reconsider whether [capacity] constructs, certainly those in the large, multi-state RTOs, are still capable of performing the important duties expected of them" (Christie, 2023).

In this paper, we discuss some of the reasons that existing resource adequacy mechanisms do not deliver on their theoretical promise. From an economic perspective, the core issue is that penalties for non-performance are weaker than what theory suggests they should be. The experiences of PJM and ISO-New England (ISO-NE), discussed in Aagaard and Kleit (2022), highlight the difficulty of implementing theoretically efficient payment structures. In PJM, the 2014 polar vortex exposed significant weaknesses in the capacity market design. During this event, PJM experienced a 22% forced outage rate, amounting to 40,000 MW of forced outages, with approximately half of these outages coming from gas-fired plants (PJM Interconnection, 2014). Non-performance charges for that period totaled just $38.9 million, which was only 0.6% of total capacity revenues (Federal Energy Regulatory Commission, 2015). This low penalty rate meant that even poorly performing resources could expect to pay only minimal penalties, placing most of the risk of under-performance on load. Similarly, ISO-NE faced its own challenges with resource performance. Prior to reforms, ISO-NE had provided capacity payments of $674 million to a set of resources that had provided on average only 17% of their Capacity Supply Obligations (Federal Energy Regulatory Commission, 2014). In response to these issues, both PJM and ISO-NE implemented significant reforms in 2014 to strengthen non-performance charges and improve the accreditation process. These reforms included measuring capacity performance during a narrower set of critical hours, increasing non-performance charges, and limiting exemptions to non-performance charges. However, these reforms faced several limitations. The potential for high non-performance penalties increased the risk of generator defaults. Concerns over generator credit risk were borne out in Winter Storm Elliott, with suppliers warning that "Non-Performance Charges penalties" could "drive generators into default, suspension or termination from the market, and potential bankruptcies" (Coalition of PJM Capacity Resources, 2023). Anticipating this challenge, both markets implemented stop-loss limits and other provisions that dilute the strength of the non-performance charges. As such, despite being significantly stronger than those used historically or in other U.S. markets, the current penalties in PJM and ISO-NE are still well below what would be suggested by theory.

Given these challenges, a second focus of reform efforts has been on improving capacity accreditation methods. By limiting the size of the capacity obligation taken on by suppliers, accurate accreditation can complement financial incentives and enable system operators to ensure system reliability despite constraints on non-delivery penalties. With increasing penetration of variable renewable resources and more frequent extreme weather events, the complexity of capacity accreditation has grown. When the grid was largely composed of dispatchable generators, resources were derated based on an equivalent forced outage rate (EFORd), which measures the expected generator availability across all hours for which there is demand on the unit. This approach is ill-suited for variable renewable energy (VRE) and battery-based energy storage, for which there is demand in almost all hours of the year (Wang et al., 2022; Schlag et al., 2020; Parks, 2019). Using EFORd also overestimates the reliability contributions of thermal resources by drawing from too large a sample of performance hours. If system stress were driven purely by high demand, this too-large sample could still give a reasonable estimate of the conditional expectation of resource performance in scarcity hours. In situations where system stress is driven by supply outages, however, it leads to too-high estimates of resource availability in the most severe stress events (Murphy et al., 2019, 2020; Dison et al., 2022). This overestimation is particularly important when plant outages are correlated. During Winter Storm Elliot, for example, the outage rate for gas generators reached 38% (Bryson et al., 2023), much higher than the EFORd in use at the time. A potential improvement on EFORd is to assess generator performance over a set of deterministic performance assessment hours (PAHs). Commonly, these PAHs are set to align with peak load but can also reflect historical hours in which load-shedding or tight operating conditions occurs. For instance, SPP currently accredits wind and solar resources by calculating the 60th percentile capacity value using the top three percent of historical monthly peak load hours (Federal Energy Regulatory Commission, 2022) while MISO accredits solar over RA hours corresponding to historically tight margin conditions (Stenclik, 2023; Midcontinent Independent System Operator (MISO), 2023). However, these designated PAHs are almost certainly not the hours in which shortages will occur in the future: since instances of severe system stress are rare by design, the set of PAHs used is often much larger than the set of likely scarcity hours. Further, accreditation over historical peak load hours can fail to capture the shift to dual or winter peaking systems (Keskar et al., 2023) and neglects the growing divergence between peak gross load and peak net load.

The above approaches to accreditation have been shown to cause significant economic inefficiency compared to an optimal benchmark consistent with marginal effective load-carrying capability (ELCC) (Bothwell and Hobbs, 2017). First coined by Garver (1966), the ELCC of a generator measures its expected performance during scarcity hours. While a significant conceptual improvement over past methodologies, ELCC has been plagued by inconsistency both in terminology and in implementation. Broadly speaking, ELCC is calculated by comparing system reliability with and without the resource in question. Per the definitions in Schlag et al. (2020) and Stenclik (2023), the system is calibrated to a reliability standard (typically 1-day-in-10 year LOLE) and measures the increase in system load that can be accommodated by the added resource while maintaining the same reliability level. Different methods using the name "ELCC" can lead to significantly different accreditation values (Amelin, 2009), with a key distinction made in recent industry reforms being the difference between average and marginal ELCC (PJM Resource Adequacy Planning Dept., 2024). Average ELCC considers the contribution of the entire fleet of a particular resource type, while marginal ELCC evaluates the incremental reliability contribution of a small additional amount of a resource. Average ELCC tends to overvalue resources when there is already a significant amount of that resource type in the system.

The goals of this paper are to clarify several debates in the design of resource adequacy mechanisms and to chart a direction for their reform. At a high level, our diagnosis suggests two potential routes to addressing the reliability threats currently facing capacity markets. The first would pair stronger prices with stronger performance bond or credit requirements for suppliers, with amounts corresponding to their non-performance risk. The second, more administrative approach would be through refined accreditation methods. Our central argument is that, given the significant roadblocks to determination and adoption of efficient accreditation values, the first of these routes is more promising. The main complication with this approach is the financial risk it implies for suppliers of capacity. Beyond the higher risk premia that would likely result from stronger penalties (Shu and Mays, 2023), this approach could stifle competition and lead to market power concerns if only a few companies are able to post the collateral required. Accreditation in this context would remain useful in ensuring that suppliers have credible physical backing for their financial positions. The paper begins with a general overview of the theory behind resource adequacy, accreditation, and the translation of adequacy metrics into market mechanisms. Section 2 clarifies terminology surrounding RA and Section 3 establishes the theoretical basis for marginal ELCC. Also in Section 3, we present a basic numerical example mimicking the situation in PJM, showing the consequences of alternative accreditation strategies and reliability targets. With this framework established, Section 4 discusses several issues that complicate accreditation studies, calling into question the ability of systems relying on them to guarantee reliability and efficiency. Section 5 highlights the implications that different market design choices have for financial risk of both suppliers and load-serving entities, and Section 6 concludes.

2 Defining Resource Adequacy

Resource adequacy (RA) refers to the ability of a portfolio of resources to limit involuntary loss of load in the system to a level deemed acceptable by regulators. For semantic clarity, we first distinguish three separate concepts related to RA: the **RA metric**, the **risk measure**, and the **reliability standard**. The RA metric refers to how individual shortage events are measured and aggregated within a given assessment period, usually one year of simulated operations. The risk measure refers to how this metric, computed across many simulated years, is converted into a single value. Lastly, the reliability standard refers to the target value against which the calculated risk measure is compared.

To formalize these concepts, let $\mathcal{H}$ denote the set of all hours in a year (assumed to be constant across years), $\mathcal{D}$ the set of all days, and Ω the set of all possible year-long scenarios for the system under study, assumed to be finite. We construct a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ where $\mathcal{F}$ represents the σ-algebra of events on Ω and $\mathbb{P}$ is a probability measure defined on $\mathcal{F}$ satisfying standard measure-theoretic properties. Let $X : \Omega \to \mathbb{R}$ be a random variable representing our RA metric for any given scenario.

For each generator g in the set of resources $\mathcal{G}$, let $x_g \in \mathbb{R}_+$ represent its installed capacity. There is no storage, and the generation resources are assumed to have no intertemporal operating constraints. We define $A_g : \mathcal{H} \times \Omega \to [0, 1]$ as a stochastic process representing the generator's availability, where $A_{g\tau\omega}$ denotes its realization in hour τ of scenario ω. The total available capacity $\hat{x}$, firm load D, and unserved load L are stochastic processes on $\mathcal{H} \times \Omega \to \mathbb{R}_+$, with realizations $\hat{x}_{\tau\omega} = \sum_{g \in \mathcal{G}} (x_g A_{g\tau\omega})$ and $L_{\tau\omega} = \max\{D_{\tau\omega} - \hat{x}_{\tau\omega}, 0\}$. Below, we illustrate how common RA metrics aggregate unserved load across time. Foreshadowing the complications that come with inclusion of storage and intertemporal operating constraints in RA frameworks, we note that these calculations rely entirely on physical availability and not on operational decisions made within each scenario.

- **Loss of Load Hours (LOLH)** measures the total number of hours in which shortfall occurs:

$$LOLH(\omega) = \sum_{\tau \in \mathcal{H}} \mathbb{1}\{L_{\tau\omega} > 0\}.$$

- **Loss of Load Events (LOLE)** is the total number of days in which there is at least one hour of lost load where $\mathcal{H}_d$ is the set of hours in day d:

$$LOLE(\omega) = \sum_{d \in \mathcal{D}} \mathbb{1}\{\max_{\tau \in \mathcal{H}_d} L_{\tau\omega} > 0\}.$$

- **Unserved Energy (UE)** is the total magnitude of shortfall:

$$UE(\omega) = \sum_{\tau \in \mathcal{H}} L_{\tau\omega}.$$

Given a RA metric that quantifies the degree of shortfall risk in a single realization ω, the risk measure can be formally defined as a functional ρ that maps from the space of random variables defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ to $\mathbb{R}$, transforming the RA metric to a single real number for comparison against the reliability standard. Two commonly used risk measures, both of which are coherent in the sense of Artzner et al. (1999) and thus have favorable properties for inclusion in an optimization problem like the one formulated in the next section, are expected value and CVaR. The former takes a probability-weighted mean of the RA metric across all scenarios, and the latter evaluates the shortfall in the worst-case scenarios beyond a specified threshold level. These risk measures are defined below with respect to a general RA metric X:

- **Expected Value (EV):** The expected value risk measure is defined as

$$\rho_{EV}(X) = \mathbb{E}[X] = \frac{1}{|\Omega|} \sum_{\omega \in \Omega} X(\omega),$$

  where the second equality holds if the set of scenarios is finite and equally probable.

- **Conditional Value-at-Risk (CVaR):** For a given confidence level $\alpha \in (0,1)$, the CVaR risk measure is defined as

$$\rho_{\text{CVaR}_\alpha}(X) = \inf_{t \in \mathbb{R}} \left\{ t + \frac{1}{1-\alpha} \mathbb{E}\left[\max\left\{X - t, 0\right\}\right] \right\}.$$

  In the case of a finite, equally probable set of scenarios, CVaR can be calculated as

$$\rho_{CVaR_\alpha}(X) = \frac{1}{|\Omega|(1-\alpha)} \sum_{\omega \in \Omega} \max\{X(\omega) - VaR_\alpha(X), 0\},$$

  where $VaR_\alpha(X)$ is the α-quantile of the distribution of X, i.e., the smallest value x such that $P(X \leq x) \geq \alpha$.

In light of the above definitions, a **reliability standard** is a constraint on the maximum acceptable level of system-wide shortfall risk, as measured by a chosen risk measure applied to a specific RA metric. For example, consider the traditional "one day in 10 years" reliability standard, which can be expressed using the expected value risk measure applied to the LOLE metric:

$$\rho_{EV}(LOLE) \leq 0.1.$$

This constraint requires that the expected number of days with loss of load events (LOLE) should not exceed 0.1 days per year, which is equivalent to one day in 10 years. More generally, a reliability standard can be defined as

$$\rho(X) \leq R,$$

where R is the maximum acceptable level of risk. By setting a reliability standard, regulators and system planners seek to ensure that the system is designed and operated to maintain an adequate level of reliability, as assessed by the chosen RA metric and risk measure. The choice of RA metric and risk measure should reflect the specific reliability concerns and priorities of regulators, stakeholders, and the system operator, while the reliability standard should be based on consideration of the costs and benefits of maintaining different levels of reliability. The next sections will elucidate several considerations in constructing this standard and its relationship with capacity accreditation.

3 Accreditation Theory and Practice

In a balancing area consisting of many utilities and private investors, the resource adequacy challenge is to construct a framework in which the overall portfolio of resources will achieve a shared reliability standard. In liberalized markets, this framework typically includes a resource adequacy product and associated payment for contributions to reliability. Even in systems composed of multiple vertically integrated entities, operators must assess the contributions made by each participant to ensure that the collective reliability target is achieved. This section develops a principled approach to accreditation by integrating the above definition of resource adequacy into a generalized capacity expansion framework.

3.1 Reliability Constrained Generation Expansion

Building on the prior RA framework, we introduce an extensive form stochastic program describing a simplified generation expansion planning problem (GEP). The formulation excludes binary unit commitment variables, power flow laws, and intertemporal physical constraints, each of which poses additional challenges for accreditation methodology to be discussed in Section 4. Let $\mathcal{T}$ represent the hours in our planning horizon, $\mathcal{L}$ the set of demand segments, and consider the probability space $(\Omega, \mathcal{F}, \mathbb{P})$ defined previously, with scenario probabilities $\Pr(\omega)$ representing realizations of the measure $\mathbb{P}$. We formulate the social planning problem (SP) as follows:

$$
\begin{aligned}
\text{(SP)} \quad \text{Maximize} \quad & -\textstyle\sum_{g\in\mathcal{G}} C_g^{INV} x_g + \sum_{\omega\in\Omega} \Pr(\omega) \left(\sum_{l\in\mathcal{L}} \sum_{\tau\in\mathcal{T}} B_l d_{l\tau\omega} - \sum_{g\in\mathcal{G}} \sum_{\tau\in\mathcal{T}} C_{g\tau\omega}^{OP} p_{g\tau\omega} \right) \\
\text{s.t.} \quad & \\
& \forall \tau\in\mathcal{T}, \omega\in\Omega: \quad \textstyle\sum_{l\in\mathcal{L}} d_{l\tau\omega} = \sum_{g\in\mathcal{G}} p_{g\tau\omega} \quad [\lambda_{\tau\omega}] \quad \text{(Energy Balance)} \\
& \forall l\in\mathcal{L}, \tau\in\mathcal{T}, \omega\in\Omega: \quad d_{l\tau\omega} \le D_{l\tau\omega} \quad [\mu_{l\tau\omega}] \quad \text{(Demand Limits)} \\
& \forall g\in\mathcal{G}, \tau\in\mathcal{T}, \omega\in\Omega: \quad p_{g\tau\omega} \le A_{g\tau\omega} x_g \quad [\theta_{g\tau\omega}] \quad \text{(Generation Limits)} \\
& \textstyle\sum_{\omega\in\Omega} \Pr(\omega) \sum_{\tau\in\mathcal{T}} (D_{0\tau\omega} - d_{0\tau\omega}) \le \text{EUE}^{max} \quad [\delta] \quad \text{(Reliability Constraint)} \\
& \forall l\in\mathcal{L}, \tau\in\mathcal{T}, \omega\in\Omega, g\in\mathcal{G}: \quad d_{l\tau\omega}, p_{g\tau\omega}, x_g \ge 0 \quad [0] \quad \text{(Non-negativity)}
\end{aligned}
$$

The objective maximizes expected surplus across scenarios $\omega \in \Omega$ given probabilities $\Pr(\omega)$, with uncertainty in generator availability $A_{g\tau\omega}$, demand levels $D_{l\tau\omega}$, and marginal production costs $C_{g\tau\omega}^{OP}$. In a market setting, the choice of expected value in the objective corresponds to an assumption of complete markets in risk and the presence of at least one risk-neutral agent in the market (Ferris and Philpott, 2022). Each scenario spans a year-long planning horizon, with 8760 hours indexed by $t \in \mathcal{T}$. The decision variables include the capacity mix $x = (x_g)_{g\in\mathcal{G}}$ with annualized investment costs C_g^{INV}, generation levels $p_{g\tau\omega}$, and demand served $d_{l\tau\omega}$ in each segment $l \in \mathcal{L}$ with corresponding value B_l. We designate $l = 0$ as fixed demand with B_0 representing the value of lost load (VoLL), while other segments represent flexible demand. Apart from standard energy balance, demand limit, generation limit, and non-negativity constraints, we constrain the expected unmet fixed demand to be below EUE^{MAX}.

The relevant Karush-Kahn-Tucker (KKT) conditions, which are derived in Appendix A, allow a description of theoretically efficient prices in the market. From the complementary slackness on the demand limit constraint, we derive the expression for $\lambda_{\tau\omega}$ (the marginal value of meeting demand) during scarcity hours:

$$\lambda_{\tau\omega} = \Pr(\omega) \times (B_0 + \delta) \quad \text{if} \quad D_{0\tau\omega} - d_{0\tau\omega} > 0 \tag{1}$$

For ease of notation, we write the price of electricity as $\pi_{\tau\omega} = \frac{\lambda_{\tau\omega}}{\Pr(\omega)}$ where we normalize the dual value by the weight of the scenario ω in the objective. In any hour with unserved firm load, the scarcity price is $B_0 + \delta$. As such, if the reliability constraint is binding and $\delta > 0$, then the implied price in these hours is greater than the assumed VoLL. We call the implied price $B_0 + \delta$ the **implied VoLL**. Here, the dual multiplier of the reliability constraint δ is an "adder" that provides revenue sufficiency for the system to meet its RA requirement. From the KKT conditions in Appendix A, it is straightforward to see that we can write an equivalent formulation of our social optimization problem by removing the reliability constraint and instead substituting B_0 with $B_0 + \delta$ in the objective. The idea that a tighter reliability standard directly induces a higher endogenous scarcity price is important, as it forms the basis for the economic interpretation of ELCC.

In the context of the previous section, we note that the reliability standard is set relative to the expected value of unserved energy (EUE), which is continuous rather than a binary "loss of load"-type metric. This choice yields an intuitive, economically-aligned derivation of optimal accreditation values, explaining why it has become a de facto standard for accreditation even in systems nominally using the "1-in-10" LOLE standard. We address the implications of using alternative RA metrics and risk measures in Appendix B.

3.1.1 Deriving an Idealized Capacity Payment

As per standard duality arguments, a generator produces at its maximum available capacity whenever the price is above the variable cost of production; otherwise, it is off or marginal:

$$0 \leq (A_{g\tau\omega} \times x_g - p_{g\tau\omega}) \perp \pi_{\tau\omega} - C^{OP}_{g\tau\omega} \geq 0. \tag{2}$$

The long-run equilibrium conditions for capacity investment under perfect competition, with each technology making zero net profit in expectation, can be written as follows:

$$0 \leq x_g \perp \frac{\partial L}{\partial x_g} \geq 0 \quad \forall g \in \mathcal{G} \tag{3}$$

$$\Rightarrow 0 \leq x_g \perp -C^{INV}_g + \sum_{\omega \in \Omega} \sum_{\tau \in \mathcal{T}} \theta_{g\tau\omega} \times A_{g\tau\omega} \geq 0 \tag{4}$$

$$\Rightarrow 0 \leq x_g \perp \sum_{\omega \in \Omega} \sum_{\tau \in \mathcal{T}} \Pr(\omega) \left[A_{g\tau\omega}(\pi_\tau - C^{OP}_{g\tau\omega}) \mathbb{1}\{\pi_\tau - C^{OP}_{g\tau\omega} > 0\} \right] - C^{INV}_g \geq 0. \tag{5}$$

Note that the term from which we subtract the investment cost in Eq. (5) corresponds to the expected per-unit annual operating profit of generator g. Given prices π^* corresponding to the optimal dual values in the solution to (SP), the resulting ideal operating profits η in each year-long scenario are given by:

$$\eta^{IDEAL}_{g\omega} = \sum_{\tau \in \mathcal{T}} A_{g\tau\omega}(\pi^*_{\tau\omega} - C^{OP}_{g\tau\omega}) \mathbb{1}\{\pi^*_{\tau\omega} - C^{OP}_{g\tau\omega} > 0\}. \tag{6}$$

Under a suboptimal remuneration policy where price suppression occurs, restoring a socially optimal capacity mix x^* requires compensating generators for missing revenue. A clear example of how such suppression can arise is apparent from problem (SP): since spot markets do not include a constraint corresponding to long-run reliability targets, there is no way for the reliability adder δ to be incorporated in the spot price. More generally, spot price formation depends on algorithmic decisions made in real-time operations, such that the prices arising in real-world systems can differ from the idealized analysis Mays (2024). Without detailing the mechanism by which spot price formation occurs, an idealized capacity payment to a generator operating at 100% availability would be the total revenue difference between the price π^* that it receives in the socially-optimal case and the price $\hat{\pi}$ that it receives in practice:

$$CAP^{100} = \sum_{\omega \in \Omega} \sum_{\tau \in \mathcal{T}} \Pr(\omega) \left[(\pi^*_{\tau\omega} - \hat{\pi}_{\tau\omega}) \mathbb{1}\{(\pi^*_{\tau\omega} - \hat{\pi}_{\tau\omega}) > 0\} \right] \tag{7}$$

Here, we will assume that price suppression only occurs when both π^* and $\hat{\pi}$ are greater than the variable costs of any generator so that under both remuneration policies, generators are "on" at the same time. To allocate the capacity payment to different technologies, we discount the above based on the generator's availability during times of price suppression:

$$CAP^{IDEAL}_g = \sum_{\omega \in \Omega} \sum_{\tau \in \mathcal{T}} \Pr(\omega) \left[A_{g\tau\omega} (\pi^*_{\tau\omega} - \hat{\pi}_{\tau\omega}) \mathbb{1}\{(\pi^*_{\tau\omega} - \hat{\pi}_{\tau\omega}) > 0\} \right]. \tag{8}$$

3.2 Economic Accreditation

As previously shown, generation resources in a system with a binding reliability constraint need to be paid prices higher than the assumed VoLL during scarcity conditions. To determine in an economic sense the degree to which each generator contributes to reliability, we can compare the idealized capacity payment received by each technology to the payment that would be made to a unit of perfect capacity. This aligns with the standard notion of accreditation as a means to determine the equivalent firm capacity value of each resource. Taking the ratio of Eq. (8) over Eq. (7) results in an economic definition of ELCC, which can be interpreted as expected availability weighted by the degree of price-suppression at each time:

$$ELCC^{IDEAL}_g = \frac{\sum_{\omega \in \Omega} \sum_{\tau \in \mathcal{T}} \Pr(\omega) \left[A_{g\tau\omega} (\pi^*_{\tau\omega} - \hat{\pi}_{\tau\omega}) \mathbb{1}\{(\pi^*_{\tau\omega} - \hat{\pi}_{\tau\omega}) > 0\} \right]}{\sum_{\omega \in \Omega} \sum_{\tau \in \mathcal{T}} \Pr(\omega) \left[(\pi^*_{\tau\omega} - \hat{\pi}_{\tau\omega}) \mathbb{1}\{(\pi^*_{\tau\omega} - \hat{\pi}_{\tau\omega}) > 0\} \right]} \tag{9}$$

This ELCC calculation essentially determines probabilistic PAHs that are a function of the socially-optimal capacity mix, such that the assessment of generator performance is restricted to when price suppression occurs. Note that in the objective of (SP), we fix the value of inelastic demand at B_0, setting an administrative VoLL that functions as a price cap in the spot market. If prices are capped at this value, the system needs to compensate generators for missing revenues up to the level of the optimal implied VoLL $B^*_0 = B_0 + \delta$. In a simplified setting in which spot prices are suppressed only in instances of unmet demand, and at each time the magnitude of suppression is the uniform difference δ between B^*_0 and B_0, the optimal ELCC values given by Eq. (9) can simply be expressed as the expected generator availability over all shortfall hours, where the expectation is taken over all time-scenario pairs:

$$ELCC^{IDEAL}_g = \mathbb{E}[A_g | D_0 - d_0 > 0] \tag{10}$$

The expression in Eq. (10) corresponds to the conditional expectation of resource availability during scarcity hours, commonly treated as a shorthand description of accreditation value. However, given the potential misuse of this shorthand, it is worth specifying that Eqs. (9) and (10) are only equivalent when price suppression is uniform and occurs only during shortfall hours. In practice, given non-convexity, uncertainty, and other pricing challenges, this assumption is not satisfied in practice Mays (2024). The consequences of relaxing this assumption for capacity accreditation are the subject of ongoing work. The numerical example in this paper omits these price formation complications outside of scarcity, making the simplified expression in Eq. (10) a reasonable approximation.

3.3 Numerical Example

Since solving a capacity expansion model using all scenarios $\omega \in \Omega$ would be impractical, for the numerical examples we shift to a sample problem with S scenarios and denote the resulting model (SPS). While we avoid introducing additional notation to make the distinction explicit, it should be understood that ELCC and other outputs from model (SPS) will be estimates. We return the topic of sampling error in Section 4.1.1, here focusing instead on the different competitive equilibria that would be expected to arise under various market configurations. In the example, we construct a stylized instance of the PJM market with three representative generation technologies: wind turbines, combined cycle gas turbines (CCGTs), and nuclear generators. The nominal load, surface temperature, and wind-speed are derived from seven years of baseline historical data in the PJM region from 2007–2013. Table 1 provides a summary of key parameters for each technology. Note that for simplicity, operating costs are fixed. To simulate potential correlated, weather-dependent thermal outages for the CCGT and nuclear resources, failures are sampled from a non-homogenous Markov chain, constructed using techniques outlined in Murphy et al. (2019). For each historical year, five distinct CCGT and nuclear availability profiles are drawn, resulting in 35 year-long scenarios that are assumed to occur with equal likelihood. Wind availability and fixed load are directly derived from values in the historical weather year corresponding to each scenario. In the context of this paper, availability refers to the percent of the total installed capacity of a given resource type that is available. To model thermal outages, we split the total installed capacity x_g of each technology across N identical units with size x_g/N. For an individual thermal plant, a generator at time τ in scenario s is either 100% available or derated with 0% availability. Each of the N generators in a fleet is assumed to have identical characteristics, with the total resource-level availability $A_{g\tau s}$ given by the average of N binary values. With this in mind, the number of generators of each resource type N serves as a proxy for the degree of inter-fleet correlation, with $N = 1$ implying perfect correlation. In the following experiments, we first explore the effects of these correlation assumptions in an unrestricted system and subsequently assess the impact of binding EUE targets. In this subsection, all market equilibria implicitly assume "full-strength" prices, i.e., that embed the δ price adder discussed earlier. The administrative VoLL is set to \$10,000/MWh, twice as high as the \$5,000/MWh value currently used in ERCOT. Additionally, up to 10GW of flexible demand can be served, partitioned into five 2GW segments with linearly declining value.

Metric	Generation Technologies		
	NUC	CCGT	WIND
Investment Cost (C_g^{INV})	350,000	70,000	120,000
Operating Cost (C_g^{OP})	10	50	0
Availability ($A_{g\tau s}$)	Simulated	Simulated	Historical

Table 1: Model parameters for three representative types of generation (costs are per MW of installed capacity and per MWh of production/consumption)

3.3.1 Generator Correlation and the Seasonality of Risk

First, Table 2 presents results for a benchmark system in which the reliability constraint is fully relaxed under various values of N. Comparing the equilibria that arise, it is evident that the degree of inter-fleet correlation significantly impacts the optimal resource mix and the system's reliability. As the number of generators decreases, the risk of correlated thermal failures increases, resulting in higher shortfall risk across all selected RA metrics (EUE, LOLH, LOLE) and necessitating more installed capacity across all resource types. Using $N = 5$ as worst-case benchmark for the objective function value (i.e. the system-wide financial surplus, with lost load penalized at the administrative VoLL of \$10,000/MWh), we see that correlated failures introduce significant financial loss. At $N = 5$ generators, the total EUE is 0.009% of fixed demand; at $N = 100$ generators this number falls to 0.002%, approximating the target established in the Australian National Electricity Market (Australian Energy Market Operator (AEMO), 2022). In all cases, LOLE is well above the traditional target of 0.1. At the same time, LOLH is well below the estimate of 30 PAHs per year used by PJM to calculate non-performance charges in its capacity market (Ming, 2022). To take a closer look at when unmet demand occurs throughout the year, Figure 1 compares the distribution of unserved energy (shown as an average across scenarios) over time for a system with high and low inter-fleet correlation. When correlation is very mild, scarcity events occur primarily in the summer when gross demand peaks. However, if thermal outages are highly correlated, widespread gas failures in the winter significantly shift the system's risk seasonality.

Generators	NUC	CCGT	WIND	Δ Surplus (\$B/yr)	EUE	LOLH	LOLE
5	78.19	90.99	13.64	Benchmark	92.72	11.34	7.69
10	75.94	86.20	13.01	1.00	48.64	8.20	4.46
20	75.61	83.64	11.24	1.40	33.54	6.86	2.89
50	75.93	82.41	9.80	1.60	25.83	6.54	2.17
100	74.82	80.42	10.77	1.90	21.66	6.11	1.83

Table 2: RA Metrics for varying levels of generators at administrative VoLL = \$10,000/MWh (no reliability constraint)

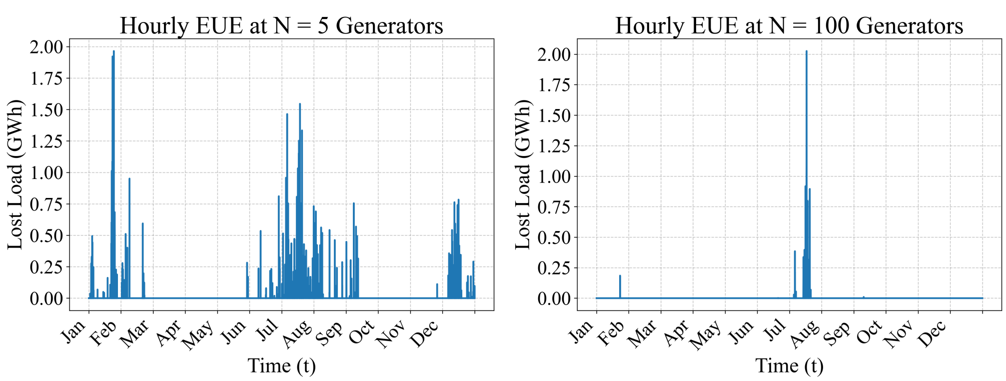

Figure 1: Expected lost load over time at high ($N = 5$) and low ($N = 100$) inter-fleet correlation

3.3.2 Reliability Targets and Implied Prices

Assuming a system with a high degree of inter-fleet correlation ($N = 5$), we now examine the impact of varying EUE-based reliability standards on system performance and resource composition. Table 3 presents key evaluation metrics for different target EUEs, while Figure 2 illustrates the temporal distribution of shortages. As the reliability standard becomes stricter, we observe a substantial increase in the implied VoLL, rising from \$55,921/MWh at a standard of 25 GWh/yr to \$529,198/MWh at 5 GWh/yr. As such, the example confirms that enforcing tight reliability standards, especially in a system with significant risk of correlated outages, implies prices substantially higher than typical estimates of VoLL (cf. Zhao et al. (2018); Murphy et al. (2020)). This increase is accompanied by increased capacity investments across all generation types. The system's risk profile also undergoes a shift, with winter accounting for ∼77% of EUE at 5 MWh/yr EUE compared to ∼44% in the unconstrained case.

EUE (GWh/yr)	Implied VoLL ($/MWh)	NUC	CCGT	WIND	Δ Surplus ($B/yr)	LOLH	LOLE
5.0	529,198	94.27	114.64	22.94	-4.00	0.49	0.49
10.0	202,560	86.46	114.96	23.09	-2.40	1.09	0.97
15.0	120,860	84.89	111.91	16.57	-1.60	1.57	1.37
20.0	79,154	82.78	109.62	16.46	-1.20	2.23	1.83
25.0	55,921	81.64	107.35	16.01	-0.90	2.86	2.29

Table 3: RA Metrics under Varying Levels of EUE Reliability Standard (GWh/yr) given high inter-fleet correlation

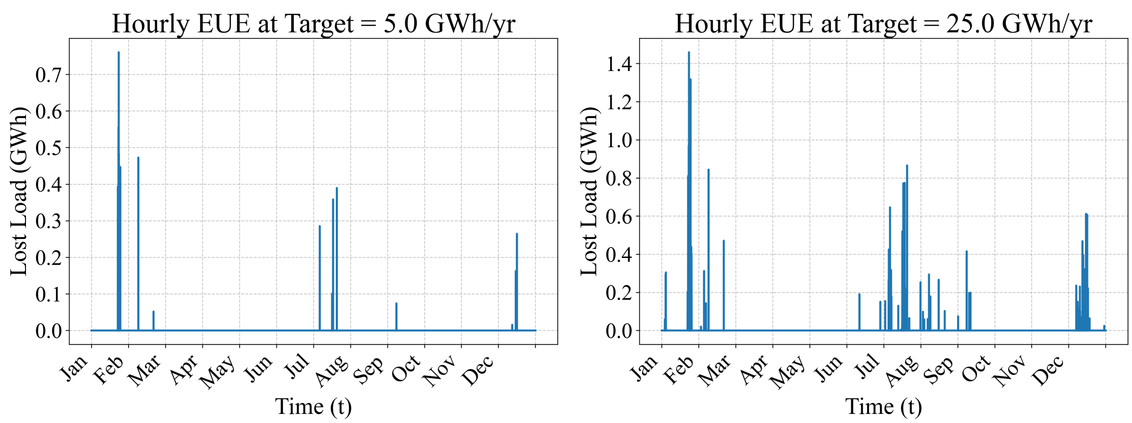

Figure 2: Expected lost load over time for tight vs moderate reliability standard given high inter-fleet correlation.

3.4 Commoditization and Reserve Formulation

The numerical results in Table 3 highlight the practical difficulty of achieving strict reliability targets in an energy-only market, as it can entail that prices be allowed to go well above the level acceptable to stakeholders. The primary alternative in practice has been to cap prices in the energy market, replacing the resulting "missing money" through a separate resource adequacy product. This subsection shows that ELCC values derived from the equilibrium capacity mix at a target EUE level can, in principle, be used in this setting to restore a socially optimal equilibrium under a system with a price cap. ELCC values determine the ability of resources in the system to provide the resource adequacy product, in effect acting as an "exchange rate" between different resource types.

In the following reserve-constrained formulation (RES), we mandate that the ELCC-derated sum of installed capacities be at least the expected demand served during designated shortfall hours. We note the contrast between this specification and the traditional definition of a planning reserve margin (PRM) relative to expected peak demand. Instead, achieving the reliability target at least cost requires that the margin requirement be based on the same "endogenous PAHs" used in the calculation of the economic ELCC values, i.e., when $D_{0\tau s} - d^*_{0\tau s} > 0$, where (*) signals that a value optimally solves (SPS). Assuming that there is at least one hour with shortfall, we formulate the reserve-constrained model as follows:

$$
\begin{aligned}
\text{(RES)} \quad \text{Maximize} \quad & -\sum_{g\in\mathcal{G}} C_g^{INV} x_g + \sum_{s\in\mathcal{S}} \Pr(s) \left(\sum_{l\in\mathcal{L}} \sum_{\tau\in\mathcal{T}} B_l d_{l\tau s} - \sum_{g\in\mathcal{G}} \sum_{\tau\in\mathcal{T}} C_{g\tau s}^{OP} p_{g\tau s} \right) \\
\text{s.t.} \quad & \\
& \forall \tau\in\mathcal{T}, s\in\mathcal{S}: \quad \sum_{l\in\mathcal{L}} d_{l\tau s} = \sum_{g\in\mathcal{G}} p_{g\tau s} \quad [\lambda_{\tau s}] \quad \text{(Energy Balance)} \\
& \forall l\in\mathcal{L}, \tau\in\mathcal{T}, s\in\mathcal{S}: \quad d_{l\tau s} \le D_{l\tau s} \quad [\mu_{l\tau s}] \quad \text{(Demand Limits)} \\
& \forall g\in\mathcal{G}, \tau\in\mathcal{T}, s\in\mathcal{S}: \quad p_{g\tau s} \le A_{g\tau s} x_g \quad [\theta_{g\tau s}] \quad \text{(Generation Limits)} \\
& \sum_{g\in\mathcal{G}} \text{ELCC}_g \times x_g \ge \mathbb{E}\left[d_0^* \mid D_0 - d_0^* > 0\right] \quad [\gamma] \quad \text{(Reserve Margin)} \\
& \forall l\in\mathcal{L}, \tau\in\mathcal{T}, s\in\mathcal{S}, g\in\mathcal{G}: \quad d_{l\tau s}, p_{g\tau s}, x_g \ge 0. \quad [0] \quad \text{(Non-negativity)}
\end{aligned}
$$

Below, we demonstrate that an appropriately calibrated reserve margin requirement, coupled with efficient accreditation, restores optimal levels of capacity investment in a market with a capped VoLL $B_0 < B_0^*$. Assuming the optimal solution x^* to (SPS) is known, we first establish that this mix is also feasible for (RES) in Lemma 1, the proof of which is given in Appendix C.

Lemma 1. Suppose x^* is an optimal solution to (SPS), that shortfall occurs in at least one modeled hour (i.e., there exists at least one (τ, s) pair where $D_{0\tau s} - d_{0\tau s}^* > 0$), and that ELCC is defined as expected availability during shortfall as in Eq. (10). Then x^* is feasible for (RES).

In the statement of Lemma 1, each generator's ELCC is assumed to reflect its expected availability during scarcity. As a result, it is straightforward to see that the reserve margin constraint is satisfied with equality under x^* - this is detailed in Appendix C. Building on this feasibility result, we can establish optimality under stronger conditions. The following theorem, with proof also in Appendix C, formalizes this relationship:

Theorem 1. Suppose x^* is an optimal solution to (SPS), that shortfall occurs in at least one modeled hour (i.e., there exists at least one (τ, s) pair where $D_{0\tau s} - d_{0\tau s}^* > 0$), that price suppression only occurs during scarcity hours (i.e., $\pi_{\tau s}^* - \hat{\pi}_{\tau s} > 0$ if and only if $D_{0\tau s} - d_{0\tau s}^* > 0$), and that price suppression is uniform in magnitude (i.e., there exists $\delta > 0$ such that $\pi_{\tau s}^* - \hat{\pi}_{\tau s} = \delta$ whenever $D_{0\tau s} - d_{0\tau s}^* > 0$). Then x^* is an optimal solution to (RES).

In Appendix C, the KKT conditions for (RES) are derived and proven to be satisfied by the following set of dual variables:

$$
\begin{aligned}
\gamma &= (B_0^* - B_0) N_S \\
\lambda_{\tau s} &= \lambda_{\tau s}^* - (B_0^* - B_0) \text{ if } D_{0\tau s} - d_{0\tau s}^* > 0 \\
\lambda_{\tau s} &= \lambda_{\tau s}^* \text{ otherwise} \\
\mu_{l\tau s} &= \Pr(s) \times B_l - \lambda_{\tau s} \\
\theta_{g\tau s} &= \theta_{g\tau s}^* - \frac{\gamma \Pr(s)}{N_S} \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\}.
\end{aligned}
$$

Note that $N_S = \sum_{t\in T} \sum_{s\in\mathcal{S}} \Pr(s) \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\}$ is the optimal expected annual shortfall hours (i.e. the expected LOLH). Solving (RES) with x^*, the ideal capacity payment to a unit of perfect capacity corresponds exactly to the optimal dual value of the margin constraint γ^*. This value is given in Eq. (11) below and is analogous to the economic capacity payment CAP^{100} in Section 3.1.1.

$$
\gamma^* = \sum_{\tau\in\mathcal{T}} \sum_{s\in\mathcal{S}} \Pr(s)(B_0^* - B_0) \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\} \tag{11}
$$

Thus, the proposed economic ELCC, in combination with an appropriately calibrated margin requirement, can efficiently restore resource-adequate levels of capacity investment via optimal pricing of reserves. However, achieving near-optimal results from a PRM approach in practice requires a great deal of attention to the means of accreditation. Extending our numerical example to solve for a reserve-constrained equilibrium using (RES), the following results will examine the consequences of a miscalibrated margin requirement.

3.5 Correlated Failures and Mis-accreditation

In Section 3.3, we first evaluated the competitive equilibrium for varying levels of inter-fleet correlation without a reliability requirement and then did the same for a highly correlated system with increasingly stringent EUE targets. From solving (SPS) for each market setting, we proceed to calculate the corresponding economic ELCCs and compare them with two cases of inefficient accreditation. In the first suboptimal case, all resources are accredited by their expected availability over annual PAHs. As per past PJM practices (Ming, 2022), we use the top thirty hours of peak net load for thermal generators and the top 200 hours of gross load for wind. In the second case, only wind is accredited using PAHs, and thermal generators are derated by their EFORd (as has traditionally been the case across multiple RTOs). To inform the construction of an optimal margin constraint in (RES), we also compute the ideal level of resources, given by the expected demand served, or equivalently, the expected maximum available capacity during shortfall hours. Tables 4 and 5 present the empirical capacity credits and the optimal reserve requirements for the unconstrained and EUE-constrained configurations respectively. Across both sets of results, EFORd and PAH consistently overestimate the capacity value of thermal resources, particularly for Combined Cycle Gas Turbine (CCGT) units. Conversely, these methodologies mostly underestimate the capacity value of wind resources across all scenarios. While EFORd is completely invariant to the reliability of the system, the PAH approach assumes a direct connection between system stress and peak net or gross load. Our experiments highlight instances where the latter assumption is largely erroneous.

Taking a closer look at Table 4, as correlated thermal outages become the primary driver of load-shedding, the economic ELCC values and ideal reserve levels reflect the shift in risk seasonality towards winter months. However, the alternative accreditation values fail to follow suit, with the gap between the PAH-based ELCC and the efficient valuations widening with increased correlation. As can be seen by the decline in the minimum required effective capacity, shortfall risk becomes increasingly decoupled with load peaks. On the flip side, if there is little to no correlation, then unserved demand coincides almost directly with peak summer demand, which means wind would have a lower valuation than what is implied by the PAH approach. A more pronounced misalignment occurs when an upper limit on EUE is enforced in a highly-correlated system. As we have seen, the risk seasonality shifts even further into the winter under more stringent reliability targets. In Table 5 the economic ELCC values suggest that with a stricter reliability target, shortfalls in the test system are predominantly caused by widespread gas outages during cold temperatures with relatively lower risk of nuclear outages and stronger wind production. At an EUE of 5 GWh/yr, the PAH accreditation for CCGT exceeds the efficient value by more than three-fold, while the credited value of wind is less than half of what is optimal. Such prominent divergence in accreditation values challenges the notion that a PAH-based derating over a sufficiently narrow set of hours is a suitable estimate of a resource's marginal reliability contribution.

3.6 Implications of Mis-accreditation for Procurement

Recall that the reserve constraint as constructed in (RES) restores optimality in a price-capped market if both the ELCC and the margin requirement are optimal. If instead the system operator used the described

N	Min. Effective Capacity	NUC			CCGT			WIND	
		ELCC*	PAH	EFORd	ELCC*	PAH	EFORd	ELCC*	PAH
5	120.08	85.27%	86.27%	97.11%	56.43%	73.09%	94.21%	17.15%	10.51%
10	134.01	90.14%	93.91%	97.11%	74.11%	86.32%	94.22%	13.73%	10.51%
20	142.89	92.46%	92.94%	94.19%	84.48%	90.67%	94.19%	10.77%	10.51%
50	147.16	94.15%	94.96%	97.10%	89.51%	92.50%	94.19%	9.10%	10.51%
100	148.91	94.59%	95.51%	97.10%	96.09%	97.54%	97.62%	8.13%	10.51%

Table 4: Capacity credit values for varying levels of inter-fleet correlation, with entries marked as green if they exceed the economic accreditation (ELCC*) and red otherwise.

Max EUE	Min. Effective Capacity	NUC			CCGT			WIND	
		ELCC*	PAH	EFORd	ELCC*	PAH	EFORd	ELCC*	PAH
5	112.65	85.27%	91.71%	97.11%	24.26%	79.68%	94.21%	24.60%	10.51%
10	111.85	83.87%	91.50%	97.11%	29.99%	78.72%	94.21%	24.42%	10.51%
15	114.09	84.32%	91.41%	97.11%	35.06%	78.36%	94.21%	22.74%	10.51%
20	115.97	84.10%	88.99%	97.11%	38.97%	81.94%	94.21%	22.02%	10.51%
25	116.98	84.06%	89.68%	97.11%	42.01%	79.90%	94.21%	21.38%	10.51%

Table 5: Capacity credit values for varying EUE targets in a highly correlated system ($N = 5$), with entries marked as green if they exceed the economic accreditation (ELCC*) and red otherwise.

sub-optimal accreditation methods to derate each resource, what would be the financial and reliability impacts? For the same highly-correlated system with $N = 5$ generators, we solve (RES) to determine the reserve-constrained equilibrium resource mix and relevant evaluation metrics for both variants of inefficient accreditation. Since PAH and EFORd over-value the contributions of thermal generators, an added margin (defined as a percentage of the efficient reserve level in the first row of Table 4) may be applied to meet EUE targets. Table 6 empirically demonstrates the implications of PAH-based accreditation for increasing margin requirements. The price cap is set at \$2,000/MWh and rows are sorted in order of decreasing EUE, with the socially optimal equilibria highlighted for comparison. Foreseeably, without mandating additional procurement on top of the effective reserve level, the margin constraint is non-binding. If the goal is to restore an unconstrained social optima with an EUE of ∼92 GWh/yr, an appropriate margin should be set at 10-15% for the PAH method and 35-40% for the EFORd method. At this relaxed EUE target, the sub-optimality of alternative accreditations is not apparent and differences in the capacity mix are relatively minor. However, as we approach a stricter reliability requirement, the superiority of the economic ELCC becomes more apparent. For a target of 25 GWh/yr EUE, a ∼30% margin would be needed in the PAH case with at least a \$400M/yr loss in financial surplus compared to optimal values. When the target is raised to 10 GWh/yr EUE, the corresponding margin for the PAH approach would need to exceed 70%, resulting in \$3.3B/yr in financial loss and a ∼65% overbuild of CCGTs. Such distortion of the resource mix is likely to be exacerbated if thermal resources are accredited using EFORd. Evidently, it becomes increasingly costly and inefficient to counter poor accreditation with over-procurement as the reliability standard tightens. As per Table 6, the EUE improvement declines as the margin increases, such that it is impractical to achieve a 5 GWh/yr EUE target through PAH accreditation.

4 Accreditation Challenges

In the stylized analysis of Section 3, we are able to restore a socially optimal resource mix using economic accreditation values and an optimal margin requirement. This result, however, relies on several assumptions

Margin	NUC	CCGT	WIND	Δ Surplus ($B)	EUE	LOLH	LOLE
None	74.93	78.72	15.17	-1.20	303.32	32.46	17.57
5%	75.61	81.67	14.01	-0.70	233.59	26.09	14.97
10%	76.55	89.07	12.06	-0.10	129.17	15.37	9.94
*	78.19	90.99	13.64	Benchmark	92.72	11.34	7.69
15%	76.93	96.99	11.10	-0.10	76.57	8.83	6.37
20%	76.96	105.25	10.70	-0.40	50.08	5.71	4.43
25%	76.96	113.53	10.39	-0.80	34.58	3.71	2.86
30%	76.88	121.87	10.34	-1.30	26.05	2.57	2.03
*	81.64	107.35	16.01	-0.90	25.00	2.86	2.29
35%	76.79	130.21	10.33	-1.80	21.17	1.89	1.57
*	82.78	109.62	16.46	-1.20	20.00	2.23	1.83
40%	76.71	138.54	10.31	-2.10	17.74	1.60	1.34
45%	76.66	146.84	10.23	-2.90	15.46	1.17	0.97
*	84.89	111.91	16.57	-1.60	15.00	1.57	1.37
50%	76.63	155.12	10.20	-3.50	13.96	0.97	0.86
55%	76.58	163.42	10.19	-4.00	12.77	0.86	0.74
60%	76.56	171.68	10.14	-4.60	11.75	0.77	0.71
65%	76.56	179.92	10.07	-5.10	10.92	0.71	0.66
70%	76.57	188.16	9.99	-5.70	10.15	0.66	0.60
*	86.46	114.96	23.09	-2.40	10.00	1.09	0.97
*	94.27	114.64	22.94	-4.00	5.00	0.49	0.49

Table 6: RA Metrics for PAH Accreditation with Varying Margins (5 Generators)

and modeling simplifications. Even with these simplifications, implementation of improved accreditation methods could bring significant benefits relative to the status quo. However, several issues are likely to affect the ability of systems to deliver a targeted level of reliability within the accreditation framework described in Section 3. This section describes these challenges, several of which have become more consequential with rapid growth of wind, solar, storage, and other new technologies.

4.1 Computational Challenges

It is widely understood that incorporating variable and energy-limited resources entails additional modeling complexity, e.g., to address intertemporal operating constraints and flexibility needs (Stenclik, 2023). In some cases, it may be relatively straightforward to address this additional complexity through software improvements and increased computing resources. In other cases, the challenge may be more epistemic than computational. For example, many systems are currently debating how to determine fair accreditation values for aggregations of distributed energy resources. Here we focus on two challenges related to computing high-quality ELCC estimates.

4.1.1 Scenario Construction and Sampling

In Section 3.3.1, we showed that assumptions about the correlation between generators within a resource class significantly impacted the equilibrium resource mix and system reliability metrics. This finding is particularly relevant given recent winter storms that revealed how historical underestimation of weather-dependent outage risks and other potential sources of correlation resulted in over-accreditation, leaving the grid vulnerable to widespread failures.

More generally, any RA framework that relies on accurate accreditation is sensitive to how supply and demand uncertainties are represented in the analysis. Ideally, input modeling should reflect a range of possible future system conditions and consider the potential impacts of climate change on both demand patterns and resource availability. This requires comprehensive analysis of factors affecting resource capability during system stress events. Physical infrastructure constraints present one set of challenges: for thermal resources, particularly natural gas plants, fuel insecurity during extreme weather can have prolonged and wide-reaching reliability impacts. However, modeling fuel availability requires assessing risks associated with gas production and transport during extreme cold snaps, the details of which are typically excluded from electricity system models. Technological evolution introduces another layer of complexity: for storage resources, long-term degradation effects and rapid improvement in battery technologies complicate the valuation of their reliability contribution. The inclusion of aggregated distributed energy resources in accreditation adds further challenges, since the specific elements and locations within an aggregation may not be known far in advance.

Introducing greater detail into the representation of system uncertainty increases the computational intensity of assessing reliability in a large number of scenarios. As such, there is an inherent trade-off between model fidelity and tractability, introducing a significant risk of sampling error, particularly in capturing rare but consequential shortage events that are critical to resource adequacy assessments. Techniques such as importance sampling or moment-matching methods could potentially improve the representation of tail events without excessive computational overhead but require careful calibration to avoid introducing bias. Another approach might involve two-stage modeling, where a larger set of scenarios is used to identify critical periods, followed by more detailed analysis of these periods. Ultimately, the challenge lies in balancing the need for computational efficiency with the imperative to accurately represent the full spectrum of possible system conditions, particularly those that stress the system and reveal the true reliability contribution of different resources. The impact of sampling error highlights the importance of sensitivity analyses and the potential need for adaptive scenario selection techniques to ensure robust ELCC estimates.

4.1.2 Dependence on the Resource Mix

In Section 3, accreditation values in (RES) are based on the optimal capacity mix found in (SPS). In order to enable planning, system operators attempt to announce resource accreditation values well in advance of the relevant operating period. For example, the PJM capacity market nominally occurs three years ahead of time. This gap implies that accreditation values will be based on an incorrect resource mix. When accreditation values based on this projected resource mix are used as an input into the capacity auction, a different equilibrium resulting in different accreditation values will arise, implying that the system might no longer meet its reliability target.

One potential response to this issue is to compress the timeline between accreditation and the performance interval, e.g., by moving the capacity market from a three-year-forward construct to a prompt-month construct. However, such a shift could weaken the effectiveness of capacity markets in terms of financial risk reduction and market power mitigation. A second potential response, proposed by the PJM Independent Market Monitor Monitoring Analytics, LLC (2023), is to formulate the capacity market along the lines of model (SPS) rather than model (RES), leading to endogenous determination of accreditation values within the auction. The major disadvantage of this approach is that computational limitations would severely limit the number of hours able to be included in the auction relative to the number typically included in accreditation studies.

4.2 Structural Challenges

While the previous category of challenges can be considered more narrowly technical and thus more straightforward to address with current capacity market frameworks, a second category is more fundamental in the sense that resolving them may not be possible without more significant market design changes.

4.2.1 Non-scarcity Missing Money

The idealized ELCC in Eq. (8) uses the difference between optimal prices π^* (from (SP)) and the suboptimal prices $\hat{\pi}$ formed in real-world markets. The logic of accreditation based on availability during scarcity relies on the assumption that price suppression will be most salient in these intervals. As discussed in Mays (2024), this assumption can be questioned due to price formation challenges arising from non-convexity, variability, and uncertainty. As a consequence, the conditions of Theorem 1 are not met in real-world markets and accreditation based on availability during scarcity intervals does not necessarily restore an optimal resource mix. While we leave a more complete discussion of this issue to future work, it is worth highlighting that the growth of storage could increasingly strain the assumption of no price suppression outside of scarcity intervals. Since storage offers into markets on the basis of opportunity costs, a suppressed price during load shedding will backpropagate into suppressed prices in all periods leading up to potential load shedding. As such, efficient accreditation would need to assess resource performance in a larger number of assessment hours.

4.2.2 Capacity Deliverability

RA studies typically include only a coarse representation of the transmission network, defining a small number of zones and assuming that resources are interchangeable within each zone. This simplification can lead to reliability challenges if operators are unable to resolve non-modeled transmission constraints that become binding in real-time operations. To address this issue, system operators in the U.S. conduct a series of studies to assess "deliverability" before certifying a resource as eligible to contribute to resource adequacy. By conducting these studies, and potentially requiring the construction of network upgrades identified in the studies, system operators hope to limit the risk arising from non-modeled constraints. While an accepted practice, it is not clear how transferable the results of deliverability studies are to RA studies, and the current process likely leads either to unforeseen reliability risks and/or inefficient investment in network upgrades. Further, the need to incorporate deliverability has been identified as a major barrier in efficient interconnection of new resources (Mays, 2023).

4.2.3 Operational Incentives

The contribution of generation resources in scarcity events is not only driven by exogenous factors, but also by operational decisions that depend on market rules. For example, the availability of a battery is not just a function of its mechanical status but also its state of charge, which depends on prior operating decisions. The optimal battery dispatch strategy may vary significantly based on system conditions, market structures, and the battery's participation in multiple service markets. As Zachary et al. (2022) and Gonzato et al. (2023) demonstrate, differing storage dispatch strategies can significantly impact LOLE without affecting system costs. A greedy dispatch policy has been proven to be EUE-minimizing (Zachary et al., 2021), providing a unique upper bound on storage's capacity credit that does not require foresight - an approach implemented in NREL's PRAS tool (Stephen, 2021). However, Stephen et al. (2022) shows that this upper bound can significantly exceed storage's actual reliability contribution when dispatch follows economic signals, particularly in cases of high supply variability and limited foresight. A similar issue applies to dual-fuel resources making fuel inventory decisions to prepare for potential natural gas supply interruptions. In the ISO-NE capacity market, for example, stop-loss provisions prevent generators from accruing more than approximately 1.5 hours worth of losses in a given month (ISO New England, 2022). As such, generators have less incentive to hold enough fuel to sustain operations through cold weather leading to high demand and supply disruptions that last several days or longer. Accurate accreditation in this context requires an assumption about the commercial strategies that will be taken by market participants given diluted economic incentives.

4.3 Administrative Challenges

An accreditation approach also requires that system operators update market rules and conduct accreditation studies quickly and accurately. It is not clear that RTOs, as they are currently structured, are capable or willing to do this. Despite the theoretical superiority of marginal ELCC, U.S. systems have been slow to adopt accreditation based on that approach. A 2022 jurisdictional survey by Newell et al. (2022) found significant misalignment in methodology across RTOs. Since the Brattle survey was published, the direction of reform has varied widely. While PJM has implemented marginal ELCC for all resource classes as of its 2025/2026 capacity auction (PJM Interconnection, 2024), the California Independent System Operator (CAISO) has reverted to an exceedance-based methodology (California Independent System Operator, 2024). Institutional inertia is particularly evident in the inconsistent treatment between renewable and conventional resources. For wind and solar resources, ISO-NE and NYISO have adopted a variant of the marginal approach called Marginal Reliability Improvement that is conceptually identical to marginal ELCC and should yield the same accreditation values (LeeVanSchaick and Coscia, 2021; Zhao, 2022), while SPP and MISO have retained average ELCC (Midcontinent Independent System Operator, 2022; Southwest Power Pool, 2022). However, the outdated methods for accrediting thermal resources outlined in Newell et al. (2022) remain largely unchanged. The fragmented landscape of capacity accreditation is a reflection of the fact that adoption of improved methods is not merely a technical question, but also requires stakeholder consensus within regulatory structures that can struggle to keep pace with technological and methodological changes.

Thus, even though there is relative consensus that marginal ELCC is the correct approach, disagreement about which method to apply and implementation delays may reflect administrative or governance challenges. Because RTOs use sector-weighted voting, they often require a supermajority to adopt major changes, and the changes that they do adopt often reflect the preferences of stakeholders that possess strong governance rights (Yoo and Blumsack, 2018). In addition, because many proposals are first developed in subcommittees but then have to be voted on by a larger stakeholder group, they have to pass through multiple veto points. In PJM, for example, ELCC reforms were first voted on by the Planning Committee, which met twenty-five times to discuss the reforms. The reforms then had to pass a Members Committee vote, at which point PJM submitted the reforms for FERC approval (Chmielewski, 2023). In other words, to improve accreditation methods, RTOs have to build consensus among stakeholders, some of whom might not benefit from resource adequacy reforms.

5 Financial Incentives, Risk Transfer, and Socialization

Given the challenges discussed in Section 4, this paper argues that the most promising direction of capacity market reform is to reduce reliance on accreditation by strengthening prices or penalties. The underlying economic issue necessitating a robust accreditation process is that the financial incentives provided to market participants are not consistent with their contributions to system reliability. With stronger financial incentives, manifesting as some combination of higher price caps (the assumed VoLL B_0 in the notation above) or stronger non-performance penalties (incorporating the effect of the price adder δ), suppliers would bear the financial consequences of a failure to deliver on contracts. In that idealized setting, market participants would not have an incentive to overstate the level of obligation they were capable of taking on.

Building on the numerical example in Section 3, this section describes the primary roadblock to such reform efforts, namely, the increased financial risk it implies for both buyers and sellers in the wholesale market. We describe the financial impact of three different market design configurations. The first is an **energy-only** design in which wholesale market prices are allowed to rise to the VoLL implied by the selected reliability standard. The second and third are archetypal forms of the installed capacity market design, **capacity payments** and **reliability options**. Capacity payments award generators with a lump-sum amount based on an estimate of their available capacity, as determined through an administrative process. In the modeled capacity payment, generators receive compensation based on their assumed performance across all modeled scarcity events, rather than for their actual performance during specific scarcity events. This approach provides a stable revenue stream that is largely decoupled from energy market outcomes, shifting performance risk from generators to consumers. With reliability options, on the other hand, generators receive a fixed premium in exchange for agreeing to pay back the difference between the market price and a pre-defined strike price during scarcity events. This structure effectively creates a price cap for consumers (up to their procured quantity) while maintaining suppliers' incentives to be available during high-price periods. In practice, most capacity mechanisms fall somewhere between these two ends of the spectrum, with energy prices and non-performance penalties creating a combined signal that falls short of the implied VoLL. Below, we present results from the example system demonstrating the financial implications of the three mechanisms for consumers and suppliers. In the case of the capacity payment, energy prices are capped at \$10,000/MWh; in the case of the reliability option, the same value is used as a strike price.

For purposes of these calculations, we assume that the market converges on the same socially optimal, risk-neutral equilibrium regardless of the profit distribution. With risk aversion and costs associated with hedging, the differences in risk socialization and allocation implied by the different designs could have significant real-world implications Shu and Mays (2023).

5.1 The Cost of Reliability for Consumers

To quantify the financial implications of these remuneration mechanisms for consumers, we analyze the distribution of electricity prices across the 35 modeled operating years under varying EUE standards. Table 7 presents these results for the set of sampled year-long scenarios, assuming the optimal resource mix given high inter-fleet correlation. As expected, the mean price increases with more stringent reliability targets across all three approaches, reflecting the added cost of improved reliability. Unhedged, energy-only prices are the most volatile, which becomes more pronounced as the implied VoLL rises. The increasing values of skew and kurtosis under this design indicate the salience of extreme price spikes as reliability requirements tighten. For instance, under the strictest EUE target of 5 MWh/yr, full-strength prices show a standard deviation of \$107.21/MWh, with the maximum annual price reaching \$523.30/MWh. By contrast, capacity payments demonstrate the lowest volatility and yield a more symmetrical, light-tailed cost distribution. For example, under the 5 MWh/yr EUE target, capacity payments have a standard deviation of only \$4.77/MWh. Since the lump sum capacity payment occurs in all years, it results in a relatively high minimum cost of electricity even in years where no shortages occur. Reliability options present an intermediate case, with much lower standard deviations than the energy-only design but leaving consumers exposed to high scarcity prices if they consume more than the volume of options procured.

Statistic	**Mean**	**Median**	**Std Dev**	**Min**	**Max**	**Skewness**	**Kurtosis**
EUE Target: 5 MWh/yr							
Energy Only	67.19	24.58	107.21	20.31	523.30	3.11	9.41
Capacity Payments	67.19	65.82	4.77	61.55	81.30	1.15	0.96
Reliability Options	67.19	62.94	13.15	58.67	130.84	3.57	14.09
EUE Target: 10 MWh/yr							
Energy Only	64.87	31.87	67.52	25.99	332.09	2.43	5.79
Capacity Payments	64.87	62.30	6.46	57.91	83.70	1.28	0.84
Reliability Options	64.87	61.36	10.06	55.77	97.21	1.64	2.03
EUE Target: 15 MWh/yr							
Energy Only	63.75	46.26	48.41	28.87	213.41	1.77	2.10
Capacity Payments	63.75	60.37	7.56	55.59	83.56	1.18	0.39
Reliability Options	63.75	59.04	9.78	53.69	87.70	1.03	-0.06
EUE Target: 20 MWh/yr							
Energy Only	63.02	43.66	43.60	31.04	186.88	1.62	1.43
Capacity Payments	63.02	59.75	8.68	54.10	84.44	1.20	0.32
Reliability Options	63.02	58.15	10.67	52.50	88.54	1.11	-0.01
EUE Target: 25 MWh/yr							
Energy Only	62.51	43.87	40.03	32.52	169.53	1.52	1.02
Capacity Payments	62.51	58.26	10.07	52.73	86.69	1.24	0.32
Reliability Options	62.51	56.82	11.82	51.29	89.65	1.16	0.07

Table 7: Price distribution statistics for the consumer cost of electricity ($/MWh) across modeled operating years under varying EUE reliability standards.

5.2 Financial Implications of Capacity Penalties and Payments

Turning to the generator perspective, Table 8 describes the distribution of operating profit (i.e., revenue minus operating cost) for different technologies at the generator level under a strict reliability standard (5 MWh/year EUE). Since each of the thermal generation types is modeled as 5 identical units, their operating profit distribution is across $35 \cdot 5 = 175$ modeled years. Given the assumption of risk neutrality, the expected operating profit in equilibrium equals the investment cost in 1 under each market design. However, the results reveal significant differences in operating profit profiles across generator types and remuneration mechanisms. In the energy-only design, all generator types experience high revenue volatility. The volatility is most pronounced for CCGTs, which experience a coefficient of variation of 3.43. During a year with low peak net load and no shortfalls, an individual CCGT could have zero operating profit. Capacity payments substantially reduce revenue volatility for all generator types, with minimum revenues quite close to annualized investment costs such that major financial losses are largely averted. By contrast, non-delivery penalties under a reliability options regime make it possible for individual generators to earn negative revenues in years with significant shortages, introducing significant concerns of bankruptcy and default.

The energy-only design preserves the market volatility necessary for efficient resource participation but leaves market participants more exposed to price spikes. Reliability options enable some risk sharing between buyers and sellers, but create significant non-performance risk for suppliers. Capacity payments mitigate price volatility for consumers and revenue instability for generators, effectively socializing some of the risk created by the fundamental volatility of electricity prices. As such, implementing this design preconditions

Statistic	Mean ($k)	Median ($k)	CV	Min ($k)	Max ($k)	Skewness	Kurtosis
NUC							
Energy Only	350.00	99.36	1.93	67.60	3351.41	3.19	9.56
Capacity Payments	350.00	339.68	0.10	307.93	452.32	1.11	0.64
Reliability Options	350.00	338.97	0.46	-288.81	914.78	-0.27	7.15
CCGT							
Energy Only	70.00	0.00	3.43	0.00	2098.34	4.83	30.48
Capacity Payments	70.00	68.38	0.07	68.38	108.18	4.48	25.36
Reliability Options	70.00	68.38	2.83	-587.19	1405.08	1.75	15.61
WIND							
Energy Only	120.00	46.96	2.03	41.36	1420.41	4.58	21.39
Capacity Payments	120.00	116.29	0.08	110.70	156.45	2.11	4.52
Reliability Options	120.00	116.11	1.27	-298.88	824.91	2.50	14.75

Table 8: Revenue distribution statistics by generator with EUE standard = 5 MWh/year, implied VoLL = $529,197.63 and administrative VoLL = $10,000. Note that all wind turbines in the fleet are assumed to have the same availability in each scenario.

the risk that market participants must manage through contracting, financial markets, or other means, at the expense of introducing problems of moral hazard.

The experience of the PJM after Winter Storm Elliott illustrates this trade-off. Despite being relatively weak compared to the theoretical ideal, non-performance penalties were strong enough to cause several issues that highlight the complexities of practical implementation. The possibility of defaulting on capacity obligations dilutes the incentives that high non-performance penalties are intended to create. Furthermore, the process of defining excuses and retroactive replacement transactions introduces administrative complexity and subjective elements, leading to market uncertainty about penalty enforcement (Monitoring Analytics, LLC, 2023). These challenges led the PJM Market Monitor to propose eliminating non-performance penalties altogether, instead relying on ex-ante accreditation of capacity resources (Monitoring Analytics, LLC, 2023).

6 Conclusion

Recent events have called into question the ability of capacity markets to address resource adequacy challenges. This paper discusses several challenges that could prevent capacity mechanisms from achieving their intended aim of ensuring reliability and efficiency. The paper demonstrates how optimal accreditation values emerge naturally from price formation in idealized markets, while also highlighting the complex interactions between accreditation, financial risk, and market structure that must be managed in practice. The conceptual accreditation framework constructed in Sections 2 and 3 provides an economic basis for assessing resources' contributions to reliability, but more importantly, highlights the assumptions that must hold for this optimal accreditation to hold. In our stylized numerical example, "missing money" is merely the difference between an administrative price cap (the assumed VoLL) and the price implicit in resource adequacy targets (the implied VoLL). In this setting, both an idealized capacity mix and efficient marginal ELCC values—equal to resources' expected availability given shortfall—can be derived from a social optimization problem. However, this idealized framework is unlikely to translate directly to real-world markets, given the computational, structural, and administrative complications detailed in Section 4.

This paper argues that clearest direction of reform given these challenges is to reduce reliance on administrative valuations of resource reliability. Instead of being a central input into market outcomes, accreditation would serve as a backstop to stronger market prices and performance incentives. With that said, the analysis also highlights the primary challenge of a move toward stronger price signals. As demonstrated in Section 5, such reforms could significantly increase the financial risk faced by market participants. As such, reforms in this direction would require careful attention to credit risk, insurability, and the enforceability of penalties. Recognizing that some resource failures are inevitable in extreme weather events, an additional challenge is to differentiate between bad luck versus mismanagement in assessing penalties to avoid raising risk premia without materially improving reliability.

The analysis suggests two promising avenues for further research. First, each of the challenges described in Section 4 corresponds to an opportunity for theoretical and computational improvements that would reduce the consequences that mis-accreditation can have on reliability and efficiency. There is significant scope to extend the framework developed here to more realistic system representations with transmission constraints, ramping limitations, storage, and demand response. The framework established in this paper, which ties optimal accreditation values to the difference between ideal and realized prices, provides a foundation for these extensions. Second, the paper identifies a fundamental tension in the choices available to policymakers: either they can keep low non-performance penalties, in which case generators will not have sufficiently strong incentives, or they can increase non-performance penalties, in which case generators that are unable to pay the penalties will default on their obligations. Both options allow generators to avoid fully bearing the costs of a failure to deliver on capacity obligations. Accordingly, a key challenge in resource adequacy mechanisms is how to avoid moral hazard given the potential for under-penalization of non-performance. While it may be possible to address this challenge with stronger performance bond, insurance, or credit requirements, more work is needed to understand the different forms that such requirements could take. As power systems continue their transformation toward greater shares of variable and distributed resources, long-term resource adequacy will require mechanisms that facilitate effective risk sharing while preserving efficient investment signals—a challenge that extends well beyond the computational details of accreditation methods to fundamental questions about the organization of electricity markets.

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References

Aagaard, T. S. and A. N. Kleit (2022). *Electricity Capacity Markets.* Cambridge University Press.

Amelin, M. (2009). Comparison of capacity credit calculation methods for conventional power plants and wind power. *IEEE Transactions on Power Systems 24*(2), 685–691.

Artzner, P., F. Delbaen, J. Eber, and D. Heath (1999). Coherent measures of risk. *Mathematical Finance 9*(3), 203–228.

Australian Energy Market Operator (AEMO) (2022, June). 2022 wholesale electricity market electricity statement of opportunities. Available at `https://aemo.com.au/-/media/files/electricity/wem/planning_and_forecasting/esoo/2022/2022-wholesale-electricity-market-esoo.pdf`.

Borenstein, S., J. Bushnell, and E. Mansur (2023, December). The economics of electricity reliability. *Journal of Economic Perspectives 37*(4), 181–206.

Bothwell, C. and B. F. Hobbs (2017). Crediting wind and solar renewables in electricity capacity markets: The effects of alternative definitions upon market efficiency. *The Energy Journal 38*(SI1), 173–188.

Bryson, M., B. Chmielewski, D. Bielak, S. Kenney, and S. Bresler (2023, January). Winter storm elliott. Available at `https://pjm.com/-/media/committees-groups/committees/mic/2023/20230111/item-0x---winter-storm-elliott-overview.ashx;`.

California Independent System Operator (2024, January). Caiso ra processes and cpuc's slice of day: Resource adequacy modeling and program design working group. Technical report, California Independent System Operator. Available at `https://stakeholdercenter.caiso.com/InitiativeDocuments/White-Paper-ResourceAdequacyProcesses-CPUC-Slice-of-Day-Jan09-2024.pdf`.

Chmielewski, B. (2023, January). Capacity interconnection rights for elcc resources: Second read of solution package i. Available at `https://www.pjm.com/-/media/DotCom/committees-groups/committees/mrc/2023/20230125/item-01---1-cir-for-elcc-resources---presentation.ashx;`.

Christie, M. C. (2023). It's time to reconsider single-clearing price mechanisms in U.S. energy markets. *Energy Law Journal 44*(1), 1–30.

Coalition of PJM Capacity Resources (2023). Complaint of the coalition of PJM capacity resources. Available at `https://www.elibrary.ferc.gov`, Docket No. EL23-55-000.

Cramton, P., A. Ockenfels, and S. Stoft (2013). Capacity market fundamentals. *Economics of Energy & Environmental Policy 2*(2), 27–46.

Dent, C. J., N. Sanchez, A. Shevni, J. Q. Smith, A. L. Wilson, and X. Yu (2023). Resource adequacy and capacity procurement: Metrics and decision support analysis.

Dison, J., A. Dombrowsky, and K. Carden (2022, March). Accrediting resource adequacy value to thermal generation. Technical report, Astrapé Consulting. Available at `https://www.astrape.com/wp-content/uploads/2024/01/Accrediting-Resource-Adequacy-Value-to-Thermal-Generation-1.pdf`.

Federal Energy Regulatory Commission (2014, May). ISO New England Inc. 147 FERC ¶61,172.

Federal Energy Regulatory Commission (2015, June). Essential Power Rock Springs. 151 FERC ¶61,208.

Federal Energy Regulatory Commission (2022, August). Order accepting tariff revisions subject to condition.

Docket No. ER22-379-002. Available at https://www.spp.org/documents/67683/20220805_order%20-%20revisions%20to%20implement%20effective%20load%20carrying%20capability%20methodology_er22-379-002.pdf.

Ferris, M. and A. Philpott (2022). Dynamic risked equilibrium. *Operations Research 70*(3), 1933–1952.

Garver, L. L. (1966). Effective load carrying capability of generating units. *IEEE Transactions on Power Apparatus and Systems 85*(8), 910–919.

Gonzato, S., K. Bruninx, and E. Delarue (2023). The effect of short term storage operation on resource adequacy. *Sustainable Energy, Grids and Networks 34*, 101005.

ISO New England (2022, September). Performance of capacity resources and pay for performance. Available at https://www.iso-ne.com/static-assets/documents/2022/09/a03_mc_2022_09_13-14_performance_of_capacity_resources_memo_rev1.pdf.

Joskow, P. and J. Tirole (2007). Reliability and competitive electricity markets. *The RAND Journal of Economics 38*(1), 60–84.

Keskar, A., C. Galik, and J. X. Johnson (2023). Planning for winter peaking power systems in the united states. *Energy Policy 173*, 113376.

LeeVanSchaick, P. and J. Coscia (2021, August). Capacity accreditation: Conceptual framework and design principles. Presented by NYISO Market Monitoring Unit, Potomac Economics. Available at https://www.nyiso.com/documents/20142/23645207/20210730%20Potomac%20-%20Capacity%20Accreditation%20-%20Conceptual%20Framework-7-30-2021.pdf.

Mays, J. (2023). Generator interconnection, network expansion, and energy transition. *IEEE Transactions on Energy Markets, Policy and Regulation 1*(4), 410–419.

Mays, J. (2024). Sequential pricing of electricity. *Energy Economics 137*, 107790.

Mays, J., M. T. Craig, L. Kiesling, J. C. Macey, B. Shaffer, and H. Shu (2022). Private risk and social resilience in liberalized electricity markets. *Joule 6*(2), 369–380.

Midcontinent Independent System Operator (2022). Planning year 2022–2023 wind and solar capacity credit. Available at https://cdn.misoenergy.org/2022%20Wind%20and%20Solar%20Capacity%20Credit%20Report618340.pdf.

Midcontinent Independent System Operator (MISO) (2023, May). Resource accreditation white paper version 1.0 - draft. Available at https://cdn.misoenergy.org/MISO%20Draft%20Resource%20Accreditation%20Design%20White%20Paper628865.pdf.

Ming, Z. (2022, April). Pjm capacity market reforms. PJM Resource Adequacy Senior Task Force (RASTF). Available at https://www.pjm.com/-/media/committees-groups/task-forces/rastf/2022/20220411/item-2---e3-perspectives-on-capacity-market-reform.ashx.

Monitoring Analytics, LLC (2023, June). Capacity market design proposal: Sustainable capacity market (scm). Available at https://www.monitoringanalytics.com/reports/Presentations/2023/IMM_RASTF_CIFP_Capacity_Market_Design_Proposal_20230613.pdf.

Murphy, S., L. Lavin, and J. Apt (2020). Resource adequacy implications of temperature-dependent electric generator availability. *Applied Energy 262*, 114424.

Murphy, S., F. Sowell, and J. Apt (2019). A time-dependent model of generator failures and recoveries captures correlated events and quantifies temperature dependence. *Applied Energy 253*, 113513.

Newell, S. A., K. Spees, and J. Higham (2022, June). Capacity resource accreditation for new england's clean energy transition: Report 1: Foundations of resource accreditation. Technical report, The Brattle Group.

Parks, K. (2019). Declining capacity credit for energy storage and demand response with increased penetration. *IEEE Transactions on Power Systems 34*(6), 4542–4546.

PJM Interconnection (2014, May). Analysis of operational events and market impacts during the January 2014 cold weather events. Available at `https://www.hydro.org/wp-content/uploads/2017/08/PJM-January-2014-report.pdf`.

PJM Interconnection (2023, March). Winter storm elliott frequently asked questions. Available at `https://www.pjm.com/-/media/markets-ops/winter-storm-elliott/faq-winter-storm-elliott.ashx`.

PJM Interconnection (2024, July). 2025/2026 base residual auction report. Technical report, PJM Interconnection.

PJM Resource Adequacy Planning Dept. (2024, June). *PJM Manual 21A: Determination of Accredited UCAP Using Effective Load Carrying Capability Analysis* (5 ed.). PJM Interconnection. Available at `https://www.pjm.com/-/media/documents/manuals/m21a-redline.ashx`.

Schlag, N., A. Olson, I. Krad, V. Bhavaraju, R. Brown, N. Khendry, J. Kwok, J. Levine, J. Man, G. Martinez, S. Scheer, S. Swaminathan, S. Takasugi, D. Voorhees, and Z. Zhou (2020). Capacity and reliability planning in the era of decarbonization: Practical application of effective load carrying capability in resource adequacy. Technical report, Energy and Environmental Economics (E3), San Francisco, CA, USA.

Shu, H. and J. Mays (2023). Beyond capacity: Contractual form in electricity reliability obligations. *Energy Economics 126*, 106943.

Southwest Power Pool (2022). 2022 ELCC wind and solar study report. Available at `https://www.spp.org/documents/68289/2022%20spp%20elcc%20study%20wind%20and%20solar%20report.pdf`.

Stenclik, D. (2023). Ensuring efficient reliability: New design principles for capacity accreditation. Technical report, Energy Systems Integration Group, Reston, VA. Available at `https://www.esig.energy/new-design-principles-for-capacity-accreditation`.

Stephen, G. (2021). Probabilistic resource adequacy suite (pras) v0. 6 model documentation. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States).

Stephen, G., T. Joswig-Jones, S. Awara, and D. Kirschen (2022). Impact of Storage Dispatch Assumptions on Resource Adequacy and Capacity Credit. In *2022 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, pp. 1–6.

Wang, S., N. Zheng, C. D. Bothwell, Q. Xu, S. Kasina, and B. F. Hobbs (2022). Crediting variable renewable energy and energy storage in capacity markets: Effects of unit commitment and storage operation. *IEEE Transactions on Power Systems 37*(1), 617–627.

Yoo, K. and S. Blumsack (2018). Can capacity markets be designed by democracy? *Journal of Regulatory Economics 53*(2), 127–151.

Zachary, S., S. H. Tindemans, M. P. Evans, J. R. Cruise, and D. Angeli (2021). Scheduling of energy storage. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 379*(2202), 20190435.

Zachary, S., A. Wilson, and C. Dent (2022). The Integration of Variable Generation and Storage into Electricity Capacity Markets. *The Energy Journal 43*(4), 231–250.

Zhao, F. (2022, July). Resource capacity accreditation in the forward capacity market. Available at `https://www.iso-ne.com/static-assets/documents/2022/07/a02a_mc_2022_07_12-14_rca_iso_presentation_conceptual_design.pptx`.

Zhao, F., T. Zheng, and E. Litvinov (2018). Constructing demand curves in forward capacity market. *IEEE Transactions on Power Systems 33*(1), 525–535.

Appendices

Appendix A Optimality Conditions (EUE-constrained GEP)

The Lagrangian and relevant Karush-Kahn-Tucker (KKT) conditions for model (SP) can be written as follows:

$$
\begin{aligned}
L(x,p,d,\lambda,\theta,\mu,\rho) = &- \sum_{g\in\mathcal{G}} C_g^{INV} x_g + \sum_{\omega\in\Omega} \Pr(\omega) \left(\sum_{l\in\mathcal{L}} \sum_{\tau\in\mathcal{T}} B_l d_{l\tau\omega} - \sum_{g\in\mathcal{G}} \sum_{\tau\in\mathcal{T}} C_{g\tau\omega}^{OP} p_{g\tau\omega} \right) \\
&+ \sum_{\omega\in\Omega} \sum_{\tau\in\mathcal{T}} \lambda_{\tau\omega} \left(\sum_{g\in\mathcal{G}} p_{g\tau\omega} - \sum_{l\in\mathcal{L}} d_{l\tau\omega} \right) \\
&+ \sum_{g\in\mathcal{G}} \sum_{\omega\in\Omega} \sum_{\tau\in\mathcal{T}} \theta_{g\tau\omega} (A_{g\tau\omega} x_g - p_{g\tau\omega}) \\
&+ \sum_{l\in\mathcal{L}} \sum_{\omega\in\Omega} \sum_{\tau\in\mathcal{T}} \mu_{l\tau\omega} (D_{l\tau\omega} - d_{l\tau\omega}) \\
&+ \rho \left(\text{EUE}^{max} - \sum_{\omega\in\Omega} \Pr(\omega) \sum_{\tau\in\mathcal{T}} (D_{0\tau\omega} - d_{0\tau\omega}) \right).
\end{aligned}
$$

FOC with respect to x_g (capacity):

$$\frac{\partial L}{\partial x_g} = -C_g^{INV} + \sum_{\omega\in\Omega} \sum_{\tau\in\mathcal{T}} \theta_{g\tau\omega} \times A_{g\tau\omega} = 0 \tag{1}$$

$$\Rightarrow C_g^{INV} = \sum_{\omega\in\Omega} \sum_{\tau\in\mathcal{T}} \theta_{g\tau\omega} \times A_{g\tau\omega}. \tag{2}$$

FOC with respect to $p_{g\tau\omega}$ (generation):

$$\frac{\partial L}{\partial p_{g\tau\omega}} = -\Pr(\omega) \times C_{g\tau\omega}^{OP} + \lambda_{\tau\omega} - \theta_{g\tau\omega} = 0 \tag{3}$$

$$\Rightarrow \theta_{g\tau\omega} = \lambda_{\tau\omega} - \Pr(\omega) \times C_{g\tau\omega}^{OP}. \tag{4}$$

FOC with respect to $d_{0\tau\omega}$ (fixed demand served):

$$\frac{\partial L}{\partial d_{0\tau\omega}} = \Pr(\omega) \times B_0 - \lambda_{\tau\omega} - \mu_{0\tau\omega} + \rho \times \Pr(\omega) = 0 \tag{5}$$

$$\Rightarrow \mu_{0\tau\omega} = \Pr(\omega) \times (B_0 + \rho) - \lambda_{\tau\omega}. \tag{6}$$

FOC with respect to $d_{l\tau\omega}, l \neq 0$:

$$\frac{\partial L}{\partial d_{l\tau\omega}} = \Pr(\omega) \times B_l - \lambda_{\tau\omega} - \mu_{;\tau\omega} = 0 \tag{7}$$

$$\Rightarrow \mu_{l\tau\omega} = \Pr(\omega) \times B_l - \lambda_{\tau\omega}. \tag{8}$$

Complementary slackness conditions:

$$0 \leq (A_{g\tau\omega} \times x_g - p_{g\tau\omega}) \perp \theta_{g\tau\omega} \geq 0 \tag{9}$$

$$0 \leq (D_{l\tau\omega} - d_{l\tau\omega}) \perp \mu_{l\tau\omega} \geq 0 \tag{10}$$

$$0 \leq \rho \perp \mathrm{EUE}^{max} - \sum_{\omega\in\Omega} \Pr(\omega) \sum_{\tau\in\mathcal{T}} (D_{0\tau\omega} - d_{0\tau\omega}) \geq 0. \tag{11}$$

From Eqs. (3), (10), and (11), we see that the dual multiplier on the reliability standard ρ is added to B_0 during scarcity hours, and that it is only non-zero when the EUE constraint is binding. Additionally, Eqs. (1), (3), and (9) are used in the construction of the long-run equilibrium condition in section 3.1.

Appendix B Implications of Alternative Reliability Metrics

In Section 3, we presented a general economic accreditation using an EUE-based reliability target. Under restrictive assumptions, the resulting ELCC corresponds to the intuitive notion of accreditation as the expected availability in any hour with shortfall. If the social planner assumed an alternative RA metric, enforcing a reliability constraint would induce a different set of optimal prices π^*, leading to alternative computations of the economic ELCC. To elucidate the relationship between the RA metric and accreditation, we analyze the implications of using metrics like Loss of Load Expectation (LOLE), Loss of Load Hours (LOLH), and Conditional Value at Risk of Unserved Energy (CVaR(UE)).

B.1 Limitations of LOLE and LOLH

LOLE and LOLH are binary metrics that count the number of periods (typically days for LOLE and hours for LOLH) in which any amount of load is unserved. While these metrics are widely used in industry, they create problems in the context of capacity accreditation. Intuitively, any difference in available firm capacity during an hour with unmet demand should have a measurable impact on system reliability, as it mitigates the extent of load-shedding. However, this is not true under an LOLE/LOLH reliability standard. A model will only attribute reliability value to a resource under LOLE/LOLH if it can completely eliminate a shortfall, not reduce its size. To formalize this observation, let $\Delta C_{\tau\omega}$ be a small increase in available capacity in hour τ of scenario ω, and let $I_{\tau\omega}$ be an indicator function for a loss of load event. If $\Delta C_{\tau\omega} < D_{\tau\omega} - d_{\tau\omega}$, where $D_{\tau\omega}$ is the fixed demand and $d_{\tau\omega}$ is the served demand, then the value of $I_{\tau\omega}$ will not change with the increased capacity. Under LOLE/LOLH, an hour with 1 MWh of lost load would be treated the same as an hour with 1000 MWh of lost load, despite the significant difference in unserved energy.

In the context of model (SP), substituting a binary metric for EUE would imply an MILP with a constraint on $\sum_{\omega\in\Omega}\sum_{\tau\in T} \Pr(\omega) I_{\tau\omega}$. By deriving optimal dual values from a linearized form with fixed $I_{\tau\omega}$, it would be possible to define an economic ELCC along the lines of Section 3. However, in this formulation, an even smaller number of hours would have a non-zero marginal value of reliability. These are hours in which demand is perfectly equal to the available firm capacity in the system and a marginal change in supply would change the value of $I_{\tau\omega}$, i.e., $\sum_{g\in\mathcal{G}} A_{g,\tau\omega} x_g = D_{\tau\omega}$. Not only is completely omitting shortfall hours from consideration counterintuitive, an ELCC calculated over such a small set of events would be highly prone to sampling error and extremely sensitive to input assumptions. Likely for this reason, even systems that nominally plan to an LOLE target nevertheless base accreditation on a larger set of hours than would be strictly implied by LOLE.

Debates about which RA metric is most appropriate to use often invoke ex post evaluations of historical scarcity events to highlight the implications of the different options. More relevant for accreditation, however, are the forward-looking simulation studies performed by market operators. In Figure 3, we observe that LOLH and LOLE closely track EUE across varying levels of correlation in our example system, and that both metrics increase almost linearly as the EUE standard relaxes. To the extent such a tight correlation holds, even if LOLE or LOLH is the preferred target, the best approach from a modeling perspective could be to use EUE and modulate the target until the desired LOLE or LOLH is achieved. This approach could yield more easily interpretable and less error-prone accreditation values.

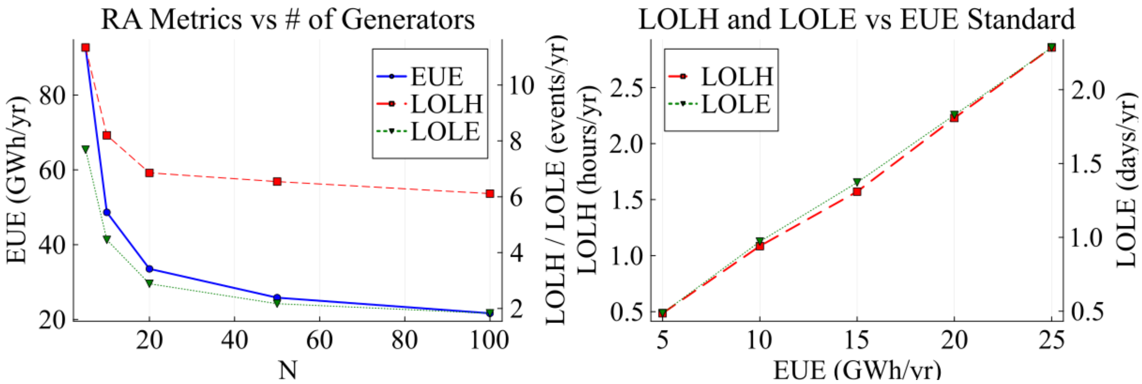

Figure 3: Behaviour of RA Metrics at varying levels of inter-fleet correlation (left) and behaviour of LOLE/LOLH at varying EUE standards (right).

B.2 Applying an Averse Risk Measure

What if instead of a different RA metric, the social planner applies an alternative risk measure across scenarios? Conditional Value at Risk of Unserved Energy (CVaR(UE)) is a risk-averse measure focusing on the expected value of the worst outcomes. If (SP) is modified such that the reliability constraint limits CVaR(UE) instead of EUE, the reliability adder ρ_ω will only have a non-zero value within the α-tail:

$$\rho_\omega = \begin{cases} \rho^* & \text{if } UE(\omega) \geq \mathrm{VaR}_\alpha(UE) \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

Where ρ^* is the optimal reliability adder in the CVaR-constrained problem and $\mathrm{VaR}_\alpha(UE)$ is the Value at Risk at confidence level α. As only tail scenarios have an impact on the assessed shortfall risk, the ELCC for generator g under CVaR(UE) becomes:

$$ELCC_g^{\mathrm{CVaR}} = \frac{\mathbb{E}\left[\sum_{\tau\in\mathcal{T}} A_{g\tau\omega}\mathbb{1}\{D_{0\tau\omega} - d_{0\tau\omega} > 0\} \mid UE(\omega) \geq \mathrm{VaR}_\alpha(UE)\right]}{\mathbb{E}\left[\sum_{\tau\in\mathcal{T}} \mathbb{1}\{D_{0\tau\omega} - d_{0\tau\omega} > 0\} \mid UE(\omega) \geq \mathrm{VaR}_\alpha(UE)\right]} \tag{13}$$

In this formulation, we are essentially taking the expected availability given shortfall over a risk-adjusted probability measure $\mathbb{Q}$ with scenario-specific probabilities $\mathrm{Pr}'(\omega)$:

$$\mathrm{Pr}'(\omega) = \begin{cases} \frac{\mathrm{Pr}(\omega)}{1-\alpha} & \text{if } UE(\omega) \geq \mathrm{VaR}_\alpha(UE) \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

To restore the risk-averse equilibrium under a CVaR reliability standard, the margin requirement in (RES) would also need to be calibrated using risk-adjusted weights as follows:

$$\sum_{g\in\mathcal{G}} \mathrm{ELCC}_g^{\mathrm{CVaR}} \times x_g \geq \mathbb{E}_{\mathbb{Q}}\left[d_0^* \mid D_0 - d_0^* > 0\right] \quad [\gamma_{RA}]. \tag{15}$$

The equivalent risk-neutral capacity payment in any year is given below, with γ_{RA}^* being the optimal dual value of the modified reserve margin constraint in Eq. (15):

$$CAP_g^{\text{CVaR}} = ELCC_g^{\text{CVaR}} \cdot \gamma_{RA}^* \cdot (1-\alpha) \tag{16}$$

While this formulation provides a theoretically sound extension of our economic ELCC framework to incorporate risk aversion, its implementation faces both theoretical and practical challenges. As discussed in Dent et al. (2023), extreme events appear rarely in historical records, providing very few samples for estimating $\text{VaR}_\alpha(UE)$. Moreover, the changing resource mix alters which weather conditions would stress the system, so identifying the periods in which future extreme events are likely to occur is difficult. For capacity products that include non-performance penalties, there is no practical way to determine in real time that the current year lies in the α-tail, making penalty assessment problematic. The narrower the confidence interval selected for CVaR calculation, the fewer hours contribute to ELCC evaluation—analogous to the sampling challenges identified with LOLE and LOLH. Following Dent et al. (2023), we conclude that while risk-averse extensions to the economic ELCC framework are theoretically appealing, the derived accreditation values may be inherently speculative, particularly in renewable-heavy systems.

Appendix C Optimality of Reserve-constrained Form

C.1 Proof of Lemma 1

Proof. Given that x^* is optimal for (SPS), we know all primal feasibility conditions except the reserve margin constraint are guaranteed to be satisfied. To check feasibility, we begin by expanding both sides of the reserve margin constraint:

$$\sum_{g\in G} ELCC_g x_g \geq \mathbb{E}\left[d_0^* \mid D_0 - d_0^* > 0\right]$$

$$\sum_{g\in G} \frac{\mathbb{E}\left[A_g \mathbb{1}\left\{D_0 - d_0^* > 0\right\}\right]}{\Pr\left(D_0 - d_0^* > 0\right)} x_g \geq \frac{\mathbb{E}\left[d_0^* \cdot \mathbb{1}\left\{D_0 - d_0^* > 0\right\}\right]}{\Pr\left(D_0 - d_0^* > 0\right)}.$$

Since the probability of shortage $\Pr\left(D_0 - d_0^* > 0\right)$ is independent of g and assumed to be non-zero, the denominator on both sides of the expression cancel out and we can write the numerator in terms of the nominal probabilities $\Pr(s)$:

$$\sum_{t\in T} \frac{1}{|\mathcal{T}|} \sum_{s\in\mathcal{S}} \Pr(s) \sum_{g\in G} A_{g\tau s} x_g \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\} \geq \sum_{t\in T} \frac{1}{|\mathcal{T}|} \sum_{s\in\mathcal{S}} \Pr(s) d_{0\tau s}^* \cdot \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\}$$

Assuming x^*, if there is unmet demand in a time-scenario pair in (SPS), shortfall will also occur in (RES). By the complementary slackness condition on the generation limit constraint, which is identical to that in (SPS), we produce at max available capacity in shortfall hours since the scarcity price is assumed to be higher than any marginal cost of production:

$$\sum_{t\in T} \frac{1}{|\mathcal{T}|} \sum_{s\in\mathcal{S}} \Pr(s) \sum_{g\in G} p_{g\tau s} \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\} \geq \sum_{t\in T} \frac{1}{|\mathcal{T}|} \sum_{s\in\mathcal{S}} \Pr(s) d_{0\tau s}^* \cdot \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\}.$$

To further simplify the LHS, we know that no flexible demand will be met during scarcity hours so the total energy produced is equal to the fixed demand served in all shortfall hours by the energy balance constraint:

$$\sum_{t\in T}\frac{1}{|\mathcal{T}|}\sum_{s\in\mathcal{S}}\Pr(s)d_{0\tau s}\mathbb{1}\left\{D_{0\tau s}-d^*_{0\tau s}>0\right\}\geq\sum_{t\in T}\frac{1}{|\mathcal{T}|}\sum_{s\in\mathcal{S}}\Pr(s)d^*_{0\tau s}\mathbb{1}\left\{D_{0\tau s}-d^*_{0\tau s}>0\right\}.$$

We can then multiply both sides in the previous expression by $|\mathcal{T}|$ and then subtract both sides from the expected total demand during shortage hours $\sum_{t\in T}\sum_{s\in\mathcal{S}}\Pr(s)D_{0\tau s}\mathbb{1}\left\{D_{0\tau s}-d^*_{0\tau s}>0\right\}$:

$$\begin{aligned}&\sum_{t\in T}\sum_{s\in\mathcal{S}}\Pr(s)(D_{0\tau s}-d_{0\tau s})\mathbb{1}\left\{D_{0\tau s}-d^*_{0\tau s}>0\right\}\leq\sum_{t\in T}\sum_{s\in\mathcal{S}}\Pr(s)(D_{0\tau s}-d^*_{0\tau s})\mathbb{1}\left\{D_{0\tau s}-d^*_{0\tau s}>0\right\}\\&\sum_{t\in T}\sum_{s\in\mathcal{S}}\Pr(s)(D_{0\tau s}-d_{0\tau s})\mathbb{1}\left\{D_{0\tau s}-d^*_{0\tau s}>0\right\}\leq EUE^*\end{aligned}$$

Evidently, if we solve (RES) with x^*, this constraint is satisfied with equality. □

C.2 Proof of Theorem 1

Proof. For the proof, we construct a set of dual variables that, together with x^*, satisfy the optimality conditions for (RES). First, we derive the following Lagrangian and Karush-Kuhn-Tucker (KKT) conditions for (RES):

$$\begin{aligned}L(x,p,d,\lambda,\theta,\mu,\rho)=&-\sum_{g\in\mathcal{G}}C^{INV}_g x_g+\sum_{s\in\mathcal{S}}\Pr(s)\left(\sum_{l\in\mathcal{L}}\sum_{\tau\in\mathcal{T}}B_l d_{l\tau s}-\sum_{g\in\mathcal{G}}\sum_{\tau\in\mathcal{T}}C^{OP}_{g\tau s}p_{g\tau s}\right)\\&+\sum_{s\in\mathcal{S}}\sum_{\tau\in\mathcal{T}}\lambda_{\tau s}\left(\sum_{g\in\mathcal{G}}p_{g\tau s}-\sum_{l\in\mathcal{L}}d_{l\tau s}\right)\\&+\sum_{g\in\mathcal{G}}\sum_{s\in\mathcal{S}}\sum_{\tau\in\mathcal{T}}\theta_{g\tau s}(A_{g\tau s}x_g-p_{g\tau s})\\&+\sum_{l\in\mathcal{L}}\sum_{s\in\mathcal{S}}\sum_{\tau\in\mathcal{T}}\mu_{l\tau s}(D_{l\tau s}-d_{l\tau s})\\&+\gamma\left(\sum_{g\in\mathcal{G}}\mathrm{ELCC}_g\times x_g-\mathbb{E}\left[d^*_0\mid D_0-d^*_0>0\right]\right)\end{aligned}$$

FOC with respect to x_g (capacity):

$$\frac{\partial L}{\partial x_g}=-C^{INV}_g+\sum_{s\in\mathcal{S}}\sum_{\tau\in\mathcal{T}}\theta_{g\tau s}\times A_{g\tau s}+\gamma\times\mathrm{ELCC}_g=0 \tag{17}$$

$$\Rightarrow C^{INV}_g=\sum_{s\in\mathcal{S}}\sum_{\tau\in\mathcal{T}}\theta_{g\tau s}\times A_{g\tau s}+\gamma\times\mathrm{ELCC}_g \tag{18}$$

$$\Rightarrow C^{INV}_g=\sum_{s\in\mathcal{S}}\sum_{\tau\in\mathcal{T}}\theta_{g\tau s}\times A_{g\tau s}+\gamma\frac{\sum_{t\in T}\sum_{s\in\mathcal{S}}\Pr(s)A_{g\tau s}\mathbb{1}\left\{D_{0\tau s}-d^*_{0\tau s}>0\right\}}{\sum_{t\in T}\sum_{s\in\mathcal{S}}\Pr(s)\mathbb{1}\left\{D_{0\tau s}-d^*_{0\tau s}>0\right\}} \tag{19}$$

FOC with respect to $p_{g\tau s}$ (generation):

$$\frac{\partial L}{\partial p_{g\tau s}}=-\Pr(s)\times C^{OP}_{g\tau s}+\lambda_{\tau s}-\theta_{g\tau s}=0 \tag{20}$$

$$\Rightarrow \theta_{g\tau s} = \lambda_{\tau s} - \Pr(s) \times C_{g\tau s}^{OP} \tag{21}$$

FOC with respect to $d_{l\tau s}$ (demand served):

$$\frac{\partial L}{\partial d_{l\tau s}} = \Pr(s) \times B_l - \lambda_{\tau s} - \mu_{l\tau s} = 0 \tag{22}$$

$$\Rightarrow \mu_{l\tau s} = \Pr(s) \times B_l - \lambda_{\tau s} \tag{23}$$

Complementary slackness conditions:

$$0 \leq (A_{g\tau s} \times x_g - p_{g\tau s}) \perp \theta_{g\tau s} \geq 0 \tag{24}$$

$$0 \leq (D_{l\tau s} - d_{l\tau s}) \perp \mu_{l\tau s} \geq 0 \tag{25}$$

$$0 \leq \gamma \perp \sum_{g \in \mathcal{G}} \mathrm{ELCC}_g \times x_g - \mathbb{E}\left[d_0^* \mid D_0 - d_0^* > 0\right] \geq 0 \tag{26}$$

From Eq. (18), we can see that in place of a reliability adder in the prices, generators receive a lump-sum capacity payment γ derated by the ELCC in addition to the expected operating revenue. Let us denote the optimal expected annual shortfall hours as $N_S = \sum_{t \in T} \sum_{s \in \mathcal{S}} \Pr(s) \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\}$ and re-write Eq. (19) as the following:

$$\begin{aligned} C_g^{INV} &= \sum_{s \in \mathcal{S}} \sum_{\tau \in \mathcal{T}} \theta_{g\tau s} \times A_{g\tau s} + \gamma \frac{\sum_{t \in T} \sum_{s \in \mathcal{S}} \Pr(s) A_{g\tau s} \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\}}{N_S} \\ \Rightarrow C_g^{INV} &= \sum_{s \in \mathcal{S}} \sum_{\tau \in \mathcal{T}} \times A_{g\tau s} \left(\theta_{g\tau s} + \frac{\gamma \Pr(s)}{N_S} \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\} \right). \end{aligned}$$

Let us define dual variables θ' that include revenues from both the spot market and the reserve payment such that Eq. (19) takes the same form as the first-order optimality condition for x_g from (SPS):

$$\begin{aligned} \theta'_{g\tau s} &= \theta_{g\tau s} + \frac{\gamma \Pr(s)}{N_S} \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\} \\ \Rightarrow C_g^{INV} &= \sum_{s \in \mathcal{S}} \sum_{\tau \in \mathcal{T}} A_{g\tau s} \theta'_{g\tau s}. \end{aligned}$$

We know that the FOC w.r.t to x_g is satisfied by $\theta' = \theta^*$, and thus can identify a corresponding value of γ:

$$\frac{\gamma \Pr(s)}{N_S} \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\} = \theta_{g\tau s}^* - \theta_{g\tau s}.$$

Substituting Eq. (21) and the analogous expression in (SPS) into the above:

$$\begin{aligned} \frac{\gamma \Pr(s)}{N_S} \mathbb{1}\left\{D_{0\tau s} - d_{0\tau s}^* > 0\right\} &= (\lambda_{g\tau s}^* - \Pr(s) \times C_{g\tau s}^{OP}) - (\lambda_{g\tau s} - \Pr(s) \times C_{g\tau s}^{OP}). \\ &= \lambda_{g\tau s}^* - \lambda_{g\tau s}. \end{aligned}$$

Normalizing both sides w.r.t nominal scenario probabilities, the RHS gives us the difference in electricity prices between (RES) and (SPS):

$$\frac{\gamma}{N_S}\mathbb{1}\left\{D_{0\tau s} - d^*_{0\tau s} > 0\right\} = \pi^*_{g\tau s} - \pi_{g\tau s}.$$

Under the same capacity mix x^*, prices in (RES) and (SPS) only differ during shortfall. By Eqs. (23) and (26), $\pi_{g\tau s} = B_0$ when $D_{0\tau s} - d_{0\tau s} > 0$, which in this case is the same as when $D_{0\tau s} - d^*_{0\tau s} > 0$. Thus, we can derive an optimal γ for x^* as follows:

$$\begin{aligned}\frac{\gamma}{N_S}\mathbb{1}\left\{D_{0\tau s} - d^*_{0\tau s} > 0\right\} &= (B^*_0 - B_0)\mathbb{1}\left\{D_{0\tau s} - d^*_{0\tau s} > 0\right\} \\ \gamma &= (B^*_0 - B_0)N_S\end{aligned}$$

Per the above, it is straightforward to identify a set of dual variables that satisfy the stationarity conditions for (RES). We have already derived dual multipliers γ and θ that satisfy the FOC w.r.t x, and from θ, can directly compute λ and μ from Eqs. (21) and (23):

$$\begin{aligned}\gamma &= (B^*_0 - B_0)N_S \\ \lambda_{\tau s} &= \lambda^*_{\tau s} - (B^*_0 - B_0) \text{ if } D_{0\tau s} - d^*_{0\tau s} > 0 \\ \lambda_{\tau s} &= \lambda^*_{\tau s} \text{ otherwise} \\ \mu_{l\tau s} &= \Pr(s) \times B_l - \lambda_{\tau s} \\ \theta_{g\tau s} &= \theta^*_{g\tau s} - \frac{\gamma \Pr(s)}{N_S}\mathbb{1}\left\{D_{0\tau s} - d^*_{0\tau s} > 0\right\}.\end{aligned}$$

Finally, we verify that this set of dual variables, together with x^*, satisfy the remaining KKT conditions of the transformed reliability-constrained problem:

1. Primal feasibility: verified in Lemma 1.
2. Dual feasibility: We know that γ is non-negative and since it always holds that $\Pr(s) \times B_l \geq \lambda_{\tau s} \geq 0$, it is easily verifiable that all other proposed dual variables are non-negative, as required.
3. Complementary slackness:
   - Given $B_0 < B^*_0$, γ is positive and the reserve constraint is binding under x^*.
   - The complementary slackness condition on θ is identical to that in (SPS) and known to be satisfied by θ^* during non-shortfall hours. Since the capped VoLL is greater than all variable production costs, the condition is also satisfied during shortfall hours.
   - Given primal solution x^*, shortfall in (RES) coincides with shortfall in the solution to (SPS), thus the complementary slackness on μ holds.

Therefore, x^*, together with the proposed set of dual variables, satisfies all KKT conditions of the transformed reliability-constrained problem. Since the problem is convex, these KKT conditions are sufficient for optimality. Note that the uniqueness of the optimal solution to (RES) is not guaranteed. □