A Risk Informed Capacity Analysis Commitment Tool for Reliable Bulk Power System Operation

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***Abstract*—The New York Independent System Operator (NYISO) has introduced the Capacity Analysis Commitment Tool (CACT) to support real-time operational decisions when reliability risks emerge from unforeseen deviations between day-ahead (DA) schedules and real-time (RT) system conditions. However, CACT currently lacks quantitative metrics to assess short-term operational adequacy and guide operators in least cost risk mitigation strategies. To bridge these gaps, this paper proposes a risk-informed enhancement to CACT (Risk-CACT) that integrates probabilistic reliability assessment into real-time market operations. The framework evaluates unit commitment outcomes under stochastic uncertainty, generator outages, and transmission contingencies. When hourly Loss of Load Probability (LOLP) exceeds a pre-defined reliability threshold, Risk-CACT initiates a commitment scheduler and/or commitment shift that adjusts generator and energy storage schedules to reduce system operational risk. The approach is validated on a representative New York State (NYS) synthetic grid to evaluate its performance under 2024 and 2030 scenarios with increasing renewable penetration. Results demonstrate that Risk-CACT effectively quantifies and mitigates operational risk, enabling informed recommitment decisions and maintaining reliability in future high-renewable systems.**

Keywords—commitment scheduler, electricity market operations, operational resource adequacy, risk assessment and mitigation, uncertainty quantification.

I. Introduction

In the era of grid transition marked by increasing renewable integration and the retirement of firm thermal capacity, real-time operations have become more challenging than ever before. Currently, the NYISO employs a security-constrained unit commitment and economic dispatch (SCUC/SCED) framework for day-ahead (DA) and real-time (RT) market operations [1]. Although market algorithms produce optimal schedules under normal conditions, real-time deviations caused by outages, renewable variability, and network constraints frequently necessitate operators' actions. These actions, typically out-of-merit commitments and reserve deployments, rely heavily on operator judgment and lack quantitative reliability metrics to guide decisions under uncertainty.

To assist operators in managing unforeseen real-time deficiencies, the Capacity Analysis Commitment Tool (CACT) [2] was developed as a post-processing framework that schedules additional generation in a cost-effective and transparent manner. CACT interfaces with the unit commitment (UC) schedule as an out of market risk mitigation solution to address additional capacity needs in the real-time market. Its two modules, i.e., the commitment scheduler and commitment shift, enable targeted operational adjustments: the scheduler commits additional resources to meet incremental capacity requirements, while the shift redistributes generation across time to resolve localized constraints within load, reserve, and network limits while preserving overall economic efficiency. Despite being effective for deterministic post-analysis, CACT lacks probabilistic treatment of reliability risks arising from generator outages, load uncertainty, and renewable uncertainties that increasingly dominate system performance under high renewable penetration. This leads to negative consequences of either overcommitment with increased generation production cost or under-commitment with power grids exposed to unmitigated reliability risks.

To address these limitations, we develop a risk-informed CACT framework that integrates deterministic operational scheduling with stochastic reliability assessment to support real-time decision making. Within this framework, we introduce the Operational Resource Adequacy (OpRA) module and couple it with CACT's operational logic. OpRA models generator availability using Markov-based forced outage representations and captures load and renewable uncertainty through stochastic scenario generation. Using Monte Carlo simulation, OpRA evaluates both locational and system-wide shortfalls to estimate Loss of Load Probability (LOLP) and identify high-risk hours or zones. These probabilistic adequacy metrics are then used to guide CACT's commitment scheduling and redispatch decisions. When risk thresholds are exceeded, the integrated Risk–CACT framework reallocates commitments and dispatch to mitigate exposure while preserving cost efficiency. This approach transforms CACT from a post-processing tool into a risk-informed operational planning platform, enabling operators to proactively manage uncertainty with reliability metrics embedded directly in the scheduling logic.

The rest of the paper is organized as follows: Section II presents the CACT framework, outlining shortfall modeling and reliability evaluation through OpRA and the risk-informed LOLP-based commitment adjustment. Section III describes the NYS synthetic grid setup, scenario generation, and additional MW estimation at LOLP threshold under two study scenarios. Section IV concludes the paper with key findings and insights.

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II. METHODOLOGY

This section presents the proposed Risk-CACT framework, incorporating OpRA-based reliability evaluation and the design of a risk-informed commitment strategy in CACT.

A. Capacity Analysis Commitment Tool (CACT)

The CACT is a post–unit commitment corrective framework developed to assist NYISO control room operators in addressing real-time capacity deficiencies. CACT enables operators to manually schedule or reschedule resources to satisfy additional MW requirements during specific hours of a study period and to evaluate Supplemental Resource Evaluation (SRE) or Out-of-Merit (OOM) requests for system reliability. It identifies resources without a day-ahead schedule that can be newly committed in hours of need at minimal production cost, and resources with excess capacity that can be reallocated to constrained intervals to maintain system balance and reserve requirements.

The objective is to allocate additional dispatch to generating units not awarded DA commitments, which can be expressed as:

$$\begin{aligned} min\sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{D}}&\left(c_{1,i}\cdot\bar{g}_{i,t}+c_{0,i}\cdot\bar{u}_{i,t}+SU_{i,t}+Pe_{add}\cdot\bar{u}_{i,t}\right)\\ &+\sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}}\left(c_s^c\cdot\bar{P}_{s,t}^c-c_s^d\cdot\bar{P}_{s,t}^d\right) \end{aligned} \tag{1}$$

s.t. $\forall t\in\mathcal{T}$:

$$\sum_{i\in\mathcal{D}}\bar{g}_{i,t}+\sum_{s\in\mathcal{S}}\left(\bar{P}_{s,t}^d-\bar{P}_{s,t}^c\right)\geq S_{t|LOLP_{th}};\forall i\in\mathcal{D} \tag{2}$$

$$g_{i,t}=g_{i,t}^{DA}+\bar{g}_{i,t};\quad\forall i\in\mathcal{I} \tag{3}$$

$$u_{i,t}=u_{i,t}^{DA}+\bar{u}_{i,t};\quad\forall i\in\mathcal{I} \tag{4}$$

$$P_i^{min}\cdot u_{i,t}\leq g_{i,t}\leq P_i^{max}\cdot u_{i,t};\quad\forall i\in\mathcal{I} \tag{5}$$

$$u_{i,t}-u_{i,t-1}=X_{i,t}^{on}-X_{i,t}^{off};\quad\forall i\in\mathcal{I} \tag{6a}$$

$$X_{i,t}^{on}\geq u_{i,t}-u_{i,t-1};\quad\forall i\in\mathcal{I} \tag{6b}$$

$$X_{i,t}^{off}\geq u_{i,t-1}-u_{i,t};\quad\forall i\in\mathcal{I} \tag{6c}$$

$$X_{i,t}^{on}+X_{i,t}^{off}\leq 1;\quad\forall i\in\mathcal{I} \tag{6d}$$

$$SU_{i,t}=su_i\cdot\left(X_{i,t}^{on}-X_{i,t}^{on-DA}\right) \tag{6e}$$

$$(X_{i,t-1}^{up}-T_i^{up})\cdot(u_{i,t-1}-u_{i,t})\geq 0;\quad\forall i\in\mathcal{I} \tag{7a}$$

$$X_{i,t}^{up}-X_{i,t-1}^{up}\leq 1;\quad\forall i\in\mathcal{I} \tag{7b}$$

$$X_{i,t}^{up}\leq u_{i,t}\cdot M;\quad\forall i\in\mathcal{I} \tag{7c}$$

$$X_{i,t-1}^{up}-X_{i,t}^{up}\leq M\cdot\left(1-u_{i,t}\right)-1;\quad\forall i\in\mathcal{I} \tag{7d}$$

$$(X_{i,t-1}^{dn}-T_i^{dn})\cdot(u_{i,t}-u_{i,t-1})\geq 0;\quad\forall i\in\mathcal{I} \tag{7e}$$

$$X_{i,t}^{dn}-X_{i,t-1}^{dn}\leq 1;\quad\forall i\in\mathcal{I} \tag{7f}$$

$$X_{i,t}^{dn}\leq(1-u_{i,t})\cdot M;\quad\forall i\in\mathcal{I} \tag{7g}$$

$$X_{i,t-1}^{dn}-X_{i,t}^{dn}\leq M\cdot u_{i,t}-1;\quad\forall i\in\mathcal{I} \tag{7h}$$

$$\begin{aligned} g_{i,t}-g_{i,t-1}\leq RU_i\cdot u_{i,t-1}&+P_i^{min}\left(u_{i,t}-u_{i,t-1}\right)\\ &+P_i^{max}(1-u_{i,t-1});\quad\forall i\in\mathcal{I} \end{aligned} \tag{8a}$$

$$\begin{aligned} g_{i,t-1}-g_{i,t}\leq RD_i\cdot u_{i,t}&+P_i^{min}\left(u_{i,t-1}-u_{i,t}\right)\\ &+P_i^{max}(1-u_{i,t});\quad\forall i\in\mathcal{I} \end{aligned} \tag{8b}$$

$$P_{s,t}^d=P_{s,t}^{d\_DA}+\bar{P}_{s,t}^d;\quad\forall s\in\mathcal{S} \tag{9a}$$

$$P_{s,t}^c=P_{s,t}^{c\_DA}+\bar{P}_{s,t}^c;\quad\forall s\in\mathcal{S} \tag{9b}$$

$$P_{s,t}^c\leq I_{s,t}^c\cdot C_s^{max};\quad\forall s\in\mathcal{S} \tag{9c}$$

$$P_{s,t}^d\leq I_{s,t}^d\cdot D_s^{max};\quad\forall s\in\mathcal{S} \tag{9d}$$

$$I_{s,t}^c+I_{s,t}^d\leq 1;\quad\forall s\in\mathcal{S} \tag{9e}$$

$$SOC_{s,t}=SOC_{s,t-1}+\eta_s^c\cdot P_{s,t}^c-P_{s,t}^d/\eta_s^d;\quad\forall s\in\mathcal{S} \tag{9f}$$

$$SOC_s^{min}\leq SOC_{s,t}\leq SOC_s^{max};\quad\forall s\in\mathcal{S} \tag{9g}$$

where $c_{1,i}$ and $c_{0,i}$ are marginal and no-load cost; $SU_{i,t}$ is startup cost of additional committed units; $u_{i,t}$ is the unit commitment; $g_{i,t}$ denotes scheduled generation within $\left[P_i^{min},P_i^{max}\right]$; $X_{i,t}^{on}/X_{i,t}^{off}$ are binary on/off status; $X_{i,t}^{up}/X_{i,t}^{dn}$ are up/down time variables with limit $[\mathrm{T_i^{up}},\mathrm{T_i^{dn}}]$; RU_i/RD_i are ramping up/down limits; su_i start-up cost for all generator i in $\mathcal{I}$; M is a large constant; Pe_{add} is penalty cost for additional generator; $S_{t|LOLP_{th}}$ is the additional requirement derived from the OpRA defined reliability threshold. For storage, c_s^c/c_s^d are charge/discharge costs, with power limit $[P_{s,t}^c,P_{s,t}^d]$ and rated capacity C_s^{max},D_s^{max}; $I_{s,t}^c,I_{s,t}^d$ are charge/discharge control; $SOC_{s,t}$ is state of charge within $[SOC_s^{min},SOC_s^{max}]$; η_s^c & η_s^d are the charge/discharge efficiencies for storage s in $\mathcal{S}$. Variables with superscript "DA" denote day-ahead schedules, while barred variables represent CACT corrective adjustments.

In commitment scheduler, we allow only dispatchable generators ($\mathcal{D}\subset\mathcal{I}$) not participating in DA schedule and storage to participate. Startup costs account for existing schedules, and a penalty cost discourages unnecessary commitment when no additional requirement exists. At time t, the additional requirements $S_{t|LOLP_{th}}$ can be satisfied through new commitment $\bar{g}_{i,t}$ and storage (2). Commitment scheduler must respect DA schedules (3)-(4) with generation capacity bound by (5). Startup/shutdown constraints are defined in (6a)-(6d), minimum up/down times in (7a)-(7h), ramping limits in (8a)-(8b), and storage charge/discharge adjustments in (9a)-(9b) with operational constraints in (9c)-(9g).

B. Operational Resource Adequacy (OpRA)

The OpRA tool enhances operator situational awareness by quantifying loss-of-load risk and supporting in-market and out-of-market reliability actions. In this study, OpRA is integrated with the CACT framework to identify and mitigate operational reliability risks in real time. The tool comprises submodules for simulating unplanned generator outages and modeling load and renewable uncertainty, forming a probabilistic foundation for risk-informed commitment and dispatch decisions.

Forecast uncertainty for load, wind generation, and solar generation is modeled using historical forecast errors[3], defined as the difference between forecasted and actual values. For each category $r\in\{load,wind,solar\}$, the error term $\varepsilon_{r,t}$ error term derived from historical data as:

$$\varepsilon_{r,t}=X_{r,t}^{hf}-X_{r,t}^{ha}, \tag{10}$$

where $X_{r,t}^{hf}$ and $X_{r,t}^{ha}$ denote forecasted and actual values and for simplicity we assume $\varepsilon_{r,t}\sim\mathcal{N}(\mu_r,\sigma_r^2)$ follow a normal distribution with mean μ_r and standard deviation σ_r. For a future study year, forecast uncertainty is represented by sampling errors from, $\varepsilon_{r,t}^{(s)}\sim\mathcal{N}(\mu_r,\sigma_r^2)$, $s=1,\ldots,S$, and applying them to the future forecast $X_{r,t}^f$, to generate stochastic realizations,

$$X_{r,t}^{(s)}=X_{r,t}^f+\varepsilon_{r,t}^{(s)}. \tag{11}$$

These sampled trajectories (11) quantify load and renewable uncertainty, forming scenario inputs for adequacy evaluation.

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Probabilistic modeling of generator availability is essential for evaluating operational reliability under uncertainty. In this study, generator state transitions are modeled using a two-state Markov process defined by Mean Time to Failure/Repair (MTTF/MTTR). Probabilities are computed as $P_{fail,t} = 1 - e^{-\lambda_i}$ and $P_{repair,t} = 1 - e^{-\mu_i}$, where $\lambda_i = 1/MTTF_i$ and $\mu_i = 1/MTTR_i$ are the failure and repair rates. The generator status $A_{i,t}$ and availability $G_{avail,t}$ are then updated at each interval using a random draw $r_t \sim \mathcal{A}(0,1)$ defined in (12)-(13).

$$A_{i,t} = \begin{cases} 0, & if\ A_{i,t-1} = 1\ and\ r_t < P_{fail,t}, \\ 1, & if\ A_{i,t-1} = 0\ and\ r_t < P_{repair,t}, \\ A_{i,t-1}, & otherwise \end{cases} \tag{12}$$

$$G_{avail,t} = \sum\nolimits_i A_{i,t} \cdot g_{i,t} \tag{13}$$

The proposed Risk-CACT framework aims to provide grid operators in the control room with the situational awareness of potential generation capacity shortage. The scheduled transmission outages are considered in the security constrained unit commitment for market clearance and the same topology from the day-ahead market is used in the Risk-CACT tool to support real-time operation. The current implementation of Risk-CACT focuses on generator forced outages, with transmission security enforced through DC power flow and thermal limits. Extension to N-1 and N-1-1 transmission contingency analysis remains a direction for future research.

For each Monte Carlo scenario, system shortfall is computed as $S_t = L_t - G_{avail,t}$, with $S_t > 0$. The adequacy assessment considers both network-agnostic and network-constrained conditions. The non-networked approach may overestimate resource availability by ignoring transmission thermal limits and renewable curtailments, causing localized deficiencies even when total generation appears sufficient. By simulating $\mathcal{N}$ scenarios, LOLP at time t can be estimated as:

$$LOLP_t = P(S_t > 0) = \frac{1}{\mathcal{N}} \sum\nolimits_{n=1}^{\mathcal{N}} 1(S_t^n > 0), \tag{14}$$

where $1(\cdot)$ is the indicator function (1 if true, 0 otherwise).

C. Risk Informed CACT Modeling

The risk-informed CACT framework is developed using operational resource adequacy metrics from the OpRA tool.

1) Iterative LOLP-Convergence Approach: This baseline approach introduces probabilistic feedback from the OpRA module into the CACT correction loop. After the DA schedule is produced, the OpRA computes $LOLP_t$. If $LOLP_t$ exceed the predefined threshold α, the binary indicator Lu_t inform the CACT to commit additional capacity until the LOLP converges below the threshold. For $\forall t \in \mathcal{T}, \forall i \in \mathcal{D}, \forall s \in \mathcal{S}$:

$$\epsilon - M * (1 - Lu_t) \le LOLP_t - \alpha \le M * Lu_t, \tag{15a}$$

$$\gamma_t = \left(\sum\nolimits_{i \in \mathcal{D}} \left(u_{i,t}^{DA} * P_i^{max} \right) + \sum\nolimits_{s \in \mathcal{S}} P_{s,t}^{n\_DA} \right) * \rho, \tag{15b}$$

$$\left(\sum\nolimits_{i \in \mathcal{D}} \left(\bar{u}_{i,t} * P_i^{max} \right) + \sum\nolimits_{s \in \mathcal{S}} \bar{P}_{s,t}^{n} \right) \ge Lu_t * \gamma_t, \tag{15c}$$

where $P_{s,t}^{n\_DA} = P_{s,t}^{d\_DA} - P_{s,t}^{c\_DA}$ is the storage net discharge in DA; $\bar{P}_{s,t}^{n} = \bar{P}_{s,t}^{d} - \bar{P}_{s,t}^{c}$ is the storage adjustment in CACT; ρ defining the incremental commitment ratio can be designed per system configuration. M is a large constant ensuring numerical feasibility when $Lu_t = 0$, and ϵ is a small tolerance to prevent equality ambiguity. When $Lu_t = 1$, (15c) enforces additional commitment capacity γ_t at time t. The process iterates with OpRA re-evaluation after each CACT adjustment until all hourly $\mathrm{LOLP_t}$ values satisfy the reliability threshold α. Despite its flexibility under varying grid conditions, this approach requires costly iterations, and convergence depends on the step size γ_t, which may cause commitment overshoot.

2) Quantile Based Single Step Optimization: The Risk-CACT framework integrates probabilistic adequacy metrics from the OpRA module into the unit commitment correction process. The LOLP quantifies the likelihood of capacity deficiency as defined in (14). Risk-CACT's objective is to maintain this reliability metric below an acceptable threshold $LOLP_t \le \alpha$. If the calculated LOLP exceeds the threshold, additional generation is committed to reduce shortfall risk. The required incremental capacity is determined as the $(1 - \alpha)$ quantile or directly from the Complementary Cumulative Distribution Function (CCDF) of S_t^n distribution:

$$S_{t|LOLP_{th}} = Q_{1-\alpha}(S_t) = \inf\{x: CCDF_{S_t}(x) \le \alpha\}, \tag{16}$$

$$CCDF_{S_t}(x) = P(S_t > x) = 1 - F_{S_t}(x), \tag{17}$$

where $CCDF_{S_t}(x)$ represents the probability that the system shortfall exceeds a given magnitude x. In other words, it is the smallest shortfall level whose exceedance probability drops below the target LOLP threshold α.

III. Case Study

This study evaluates the Risk-CACT framework on a representative New York synthetic grid model. Two peak summer cases, i.e., 2024 and 2030 (with higher renewable penetration), are analyzed to assess the impact of renewable uncertainty on operational adequacy. For each case we generate 10,000 scenarios per hour. Results demonstrate how Risk-CACT mitigates shortfall risk within reliability thresholds. The following sections outline the grid setup, scenario generation, threshold calibration, and case results.

A. Synthetic Grid Description

The synthetic New York grid model used in this study is built upon publicly available transmission and generation datasets, comprising over 1,500 buses and 2,400 transmission lines. Each branch includes series reactance and emergency flow ratings (A, B,C), for DC power flow analysis. The network topology, and the spatial distribution of line thermal utilization under the proposed network-constrained assessment is shown in Fig. 1. Of the lines modeled, 12 exceed 90%, and 37 exceed 75% utilization of their normal rating. The most congested corridors are the Millwood to Dunwoodie interface (H–I) and Central East interface (E–F-G), serve the downstate load centers, while upstate regions operate below 50% utilization. Relaxing downstream constraints would increase flow capacity and enable greater renewable penetration from generation-rich upstate regions. This spatial heterogeneity confirms that the DC power flow formulation captures localized transmission bottlenecks that non-networked methods would overlook.

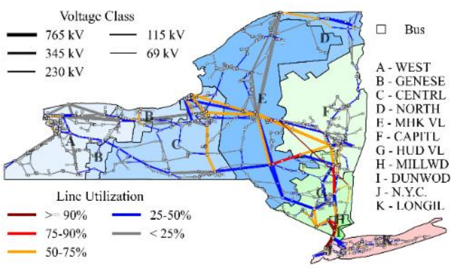

Fig. 1. New York State transmission system. Line color indicates thermal utilization; line width denotes voltage class.

The model is calibrated for 2024, using generation and demand data from the NYISO Gold Book [4]. The 2030 configuration reflects increased renewable penetration, additional storage, and transmission reinforcements per the NYISO Comprehensive Reliability Plan (2021–2030) and CARIS (2020), achieving CLCPA targets of 70% renewable electricity and 6 GW storage. External interconnections are modeled as internal generators to preserve system closure. Since actual ISO network models are restricted under Critical Energy/Electric Infrastructure Information (CEII) regulations, this study employs a synthetic representation calibrated to these publicly available sources, and the methodology and results from the scenarios selected by the industry partners are representative of the New York power grid.

B. Scenario Generation and Uncertainty Modeling

Hourly system demand is based on NYISO historical data (2021–2023) and 2030 long-term forecasts [4]. Forecast uncertainty for load is modeled following (10)–(11), where the hourly forecast error, $\epsilon_t \sim \mathcal{N}(\mu_L, \sigma_L^2)$ is estimated from historical forecast–actual deviations, exhibiting 3-7% temporal deviation as shown in Fig.2.

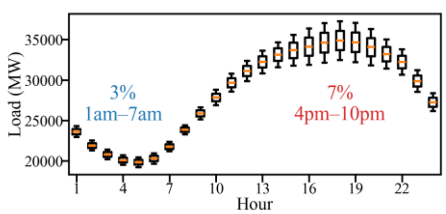

Fig. 2. Forecasted load with uncertainty band.

Offshore wind observations are obtained from NYSERDA's metocean buoys [5] and RU-WRF forecast ensembles [6] while onshore wind data are sourced from local airport weather stations and converted to power using NYISO's wind speed–power curve. Solar generation is modeled with NREL's PVWatts Calculator [7]. Forecast errors for all resources are derived from historical deviations and applied through Monte Carlo sampling, with future-year capacities scaled to reflect projected renewable expansion as shown in Fig. 3.

Renewable resources are modeled as stochastic, non-dispatchable generation and treated as curtailable within the day-ahead SCUC. Additional curtailment may occur in real-time operations as system conditions evolve. Generation commitment and dispatch are determined through security-constrained optimization consistent with NYISO market practices. Capacity adequacy risk is evaluated by jointly modeling renewable forecast uncertainty, stochastic generator forced outages, and network constraints through Monte Carlo simulation, allowing tail-risk events to be captured in the LOLP assessment. Although the peak load day does not necessarily correspond to the worst-case capacity risk due to renewable variability, it represents a high-stress operating condition and is selected, consistent with NYISO practice, to validate the real-time situational awareness and mitigation performance of the proposed Risk-CACT framework.

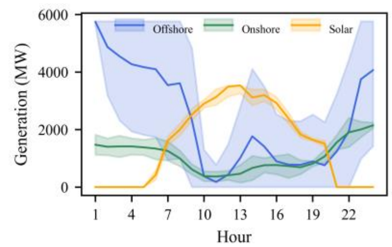

Fig. 3. Forecasted renewable generation profile with uncertainty band.

C. Reliability Threshold and CACT Modeling Criterion

The North American Electric Reliability Corporation (NERC) defines long-term reliability as maintaining a Loss of Load Expectation (LOLE) of 1 day in 10 years (0.1 day/year), while no formal standard exists for day to day operational risks. In this study, for demonstration, we calibrate an hourly LOLP threshold 0.0274% consistent with the NERC criterion.

TABLE 1. SENSITIVITY OF LOLP-CONVERGENCE ITERATIONS TO STEP SIZE

Step Size (γ_t)	2024 peak LOLP (0.21%)		2030 peak LOLP (2.05%)	
	Iterations	Δ MW	Iterations	Δ MW
10 MW	17	8.02	114	5.80
15 MW	11	3.02	76	5.80
20 MW	9	18.02	57	5.80
50 MW	4	38.02	23	15.80

Iterative approach for LOLP convergence depends on step size per CACT run. Smaller step sizes yield smoother convergence but require more iterations, whereas larger steps accelerate convergence risking over-commitment as shown in Table 1. For instance, prior to CACT correction, the 2024 and 2030 peak-hour LOLP values were 0.21% and 2.05%, respectively. Using a 10 MW step size required 17 and 114 iterations to reach the LOLP threshold, resulting in 8.02 MW and 5.80 MW excess commitment (Δ MW). Each CACT iteration requires ~3 minutes, making convergence computationally intensive, but it enables transparent and adaptive reliability-driven capacity adjustment.

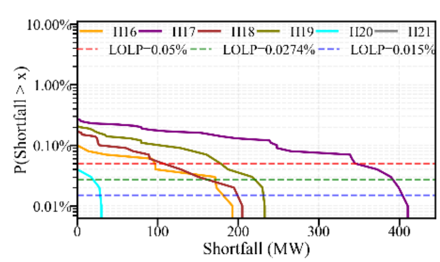

Fig. 4. Complementary CDF of system shortfall across high-risk hours.

To mitigate the computational burden, a quantile-based method is proposed to determine additional commitment requirements directly from the shortfall distribution (Section II.C). Given the day-ahead commitment, the OpRA module computes hourly LOLP and associated shortfall distributions. The CCDF of system shortfall during peak hours presents in Fig. 4 , where the intersection of each hourly CCDF curve with a specified LOLP threshold identifies the incremental capacity must be committed within the CACT framework to meet reliability criteria. This approach requires only a single CACT execution: OpRA evaluates 10k scenarios in ~ 1 minute, followed by one CACT run (< 3 minutes), resulting in a total runtime under 5 minutes. Fig. 4 further illustrates sensitivity to reliability thresholds (LOLP = 0.015%, 0.0274%, and 0.05%), showing that more stringent thresholds lead to higher additional commitment requirements (e.g., at hour H17, from approximately 373 MW to 399 MW to 411 MW). This analysis enables operators to quantify the trade-off between reliability targets and capacity commitment requirements, supporting informed decision-making under varying risk tolerances.

D. Case Results and Discussion

Committed generation profile for Year 2024 and 2030 scenarios before and after the CACT adjustment are illustrated in Fig.5. In 2024, only minor additional commitment is required during peak hours due to lower renewable share. Conversely, the 2030 system exhibits higher total commitment driven by greater load demand and renewable penetration, which increases variability in net load and forecast uncertainty.

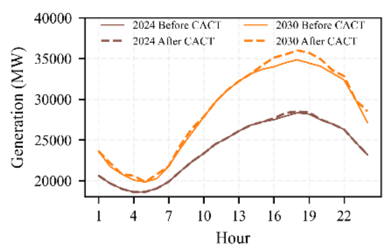

Fig. 5. Committed generation before and after CACT adjustment.

The corresponding LOLP across operating hours is illustrated in Fig.6. Without CACT correction, both systems exceed the reliability threshold (0.0274%) during peak periods (H17–H20) with the 2030 case reaching up to 2%, compared to 0.25% in 2024, even after accounting for a 30-minute contingency reserve. The elevated and extended LOLP during off-peak hours in 2030 reflects the impact of renewable intermittency on dispatch reliability. Implementation of Risk-CACT mitigates this risk by committing additional thermal and storage resources, restoring LOLP below the defined threshold while maintaining operational efficiency.

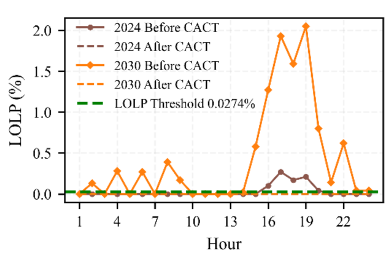

Fig. 6. Reliability assessment before and after CACT adjustment.

Emerging market initiatives are investigating uncertainty reserves to address forecast variability beyond static contingency margins. For the New York Control Area, [8] estimates that 2030 offshore wind variability could require procuring about 918 MW of hourly reserves. While such products enhance flexibility, they face challenges in validating reserve sizing through quantitative reliability assessments. The proposed Risk- CACT complements these efforts by quantitatively linking commitment actions to reliability outcomes, enabling coordinated, risk-based operations.

IV. CONCLUSION

This paper presents a Risk-CACT that embeds probabilistic risk assessment into post-commitment scheduling. The proposed Risk-CACT framework couples deterministic operational logic with stochastic reliability modeling through the OpRA module, enabling grid operators to make economically efficient and reliability-aware decisions in real time. By quantifying the loss of load risk across thousands of simulated system conditions, the framework identifies high-risk operating hours and informs adaptive commitment adjustments that directly mitigate reliability risk . The results demonstrate that the Risk-CACT effectively bridges the gap between deterministic market scheduling and probabilistic operational reliability, providing a computationally tractable framework suitable for integration into existing NYISO operational practices for reliable grid operations amid increasing renewable penetration and uncertainty.

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