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Probabilistic resource adequacy assessment of ERCOT under high data center load growth and high renewable energy potential through 2050

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Keywords: resource adequacy, probabilistic reliability assessment, ERCOT, Monte Carlo simulation, capacity expansion modeling, large flexible loads, PLEXOS platform

Abstract

The Electric Reliability Council of Texas (ERCOT) faces mounting reliability challenges as electrification, large flexible loads (e.g. data centers, hydrogen, crypto, and industrial demand), and high renewable penetration reshape system dynamics. Traditional reserve margin–based planning is increasingly inadequate, as periods of highest risk are shifting to net peak hours and extended low-renewable events. To address these challenges, we developed a probabilistic resource adequacy (RA) framework using PLEXOS® to evaluate ERCOT's long-term RA outlook through 2050. We modeled baseline growth, high load growth from data centers and cryptocurrency, enhanced ancillary service requirements, and targeted transmission expansion, with sensitivities to technology costs, fuel prices, and policy uncertainty (e.g. Inflation Reduction Act repeal). We quantified reliability outcomes through probabilistic metrics, including loss of load expectation, loss of load probability, and expected unserved energy, to capture the marginal contribution of conventional, renewable, and storage resources. Our results show that rapid load growth, particularly from data centers, intensifies RA risks absent complementary transmission and resource expansion; however, transmission upgrades and enhanced ancillary services improve adequacy by mitigating congestion and stabilizing net load variability. We benchmarked our framework against the February 2021 Winter Storm Uri through hourly operational simulations, which validate the framework's capability to replicate observed stress conditions and unserved energy outcomes. These findings collectively underscore that ERCOT's future reliability hinges on coordinated planning across generation, transmission, and demand-side flexibility. This study provides a novel integration of long-term capacity expansion and probabilistic RA modeling, offering actionable insights for system operators, policymakers, and market stakeholders navigating ERCOT's transition to a high-renewable, high-load future.

1. Introduction

1.1. Background and motivations

Probabilistic resource adequacy (RA) assessment is becoming a critical component of modern power system planning with the accelerating integration of variable renewable energy (VRE) sources. With the growth in renewable penetration and electrification-driven load increases, reliability risks and operational vulnerabilities are continuously rising (Bellenbaum *et al* 2019, Busby *et al* 2021, Nyangon 2025). According to the North American Electric Reliability Corporation (NERC), weather-dependent factors have long shaped system performance (NERC 2026). For example, extreme temperatures dictate peak demand periods, winter cold snaps can constrain natural gas availability, ambient conditions impair gas turbine output and reliability, and seasonal hydro variations introduce uncertainty (Panteli *et al* 2017, Busby *et al* 2021, Nyangon 2024, Chen *et al* 2025). However, as grids increasingly depend on variable renewables such as wind and solar, the emphasis on stochastic weather modeling and adequacy evaluation is becoming far more essential. The consequences of degraded reliability are substantial. The Electric Reliability Council of Texas (ERCOT) experienced widespread rolling blackouts during Winter Storm Uri, affecting millions of residents across the state and visible from satellite imagery (Kwon *et al* 2020, Magness 2021, Pi *et al* 2022).

To better understand and address the aforementioned challenges, it is essential to clarify four core concepts. Probabilistic RA assessment varies widely depending on objectives and scope. (1) Although RA must be analyzed on an hourly basis in line with real-time operating conditions, it can be classified as long-term (influencing planning horizons spanning several years, i.e. 30–50 years) or short-term (affecting only seasonal or near-term operations). (2) It can be deterministic (relying on fixed reserve margin thresholds) or probabilistic (employing Monte Carlo simulations (Kwon *et al* 2020), PLEXOS-based modeling (Exemplar 2026), and similar techniques). (3) It can be expansion-oriented (using integrated optimization for future capacity decisions (Chen *et al* 2018)) or operational (focusing on unit commitment and economic dispatch (DOE 2025)). (4) It can be metric-driven (centered on loss-of-load indicators such as loss of load expectation (LOLE) and expected unserved energy (EUE) Kwon *et al* (2020), Matraeva *et al* (2022)) or stress-test-based, i.e. evaluating performance under extreme events (Chen *et al* 2025).

Consequently, the most appropriate RA assessment framework must be tailored to specific market structures, policy contexts, and application requirements, as investment signals and planning responsibilities differ fundamentally across market designs. This market-specific framing shapes methodological choices regarding temporal resolution, stochastic representation, and adequacy metrics.

High load growth and variable renewable penetration affect overall system reliability. Increasing electricity load demand driven largely by electrification and data centers combined with the growing share of VRE sources such as wind and solar, intensifies reliability risks through pronounced seasonal variability, forecast uncertainty, and correlated weather dependencies (Bennett *et al* 2021, Nyangon 2024, 2025). Sustained high load growth shifts dominant adequacy shortfalls toward winter periods, where cold weather simultaneously reduces thermal plant availability, constrains fuel supply, and lowers renewable output in many regions, thereby amplifying vulnerability for system operators (Nyangon and Akintunde 2024).

Addressing these challenges requires integrated capacity expansion modeling that co-optimizes long-term investment decisions with operational feasibility under uncertainty. This approach aligns closely with the core tenets of ERCOT's current market framework, preserving the integrity of existing arrangements, including the energy-only market design, ancillary services procurement, and established short-term dispatch protocols, without necessitating major regulatory changes or structural overhauls.

2. Literature review

In this study, we propose a RA assessment scheme that integrates capacity expansion modeling while evaluating high-load and renewable scenarios without overlooking extreme tail risks. Probabilistic methods have increasingly been applied to assess long-term RA in high-renewable power systems, particularly under the evolving operational complexity of the ERCOT grid. Traditional deterministic frameworks, based primarily on static reserve margins and peak load projections, have proven inadequate in capturing the stochastic interactions between VRE, demand uncertainty, and thermal unit contingencies (LaBarbara *et al* 2020, Sun *et al* 2022). Consequently, probabilistic approaches leveraging convolution-based analysis and Monte Carlo simulation have emerged as dominant paradigms for capturing uncertainty propagation across temporal and spatial scales. Sun *et al* (2022) demonstrated a comprehensive probabilistic modeling framework using production cost and reliability tools to evaluate RA in a future ERCOT system dominated by solar PV and hybrid storage. Their findings indicate that multi-stage probabilistic assessments significantly enhance the fidelity of adequacy estimation but increase computational demands by one to two orders of magnitude. Similarly, LaBarbara *et al* (2020) applied stochastic dispatch modeling to summer adequacy studies in ERCOT, revealing the sensitivity of system performance to correlated renewable outputs and thermal derating events. Extending this perspective, Chen *et al* (2025) emphasized the importance of evaluating adequacy under extreme weather conditions, including winter storms and heat waves. Collectively, prior studies highlight the need for flexible, operationally detailed probabilistic frameworks that incorporate unit commitment constraints, ramping limits, forecast uncertainty, and extreme-event stress testing.

Despite the advancement of probabilistic frameworks in international power systems research, (e.g. Bellenbaum *et al* (2019) for European systems), explicit application of traditional reliability indices–LOLE, loss of load probability (LOLP), EUE, and effective load carrying capability (ELCC)—within ERCOT-specific literature remains limited. While the NERC probabilistic assessments report reference values for ERCOT from 2026 to 2029 (EUE = 11.1–17.1 GWh; NEUE = 8.7–18.9 ppm; LOLH = 0.9–3.6 event-hours/year; PRM = 13.8%), few peer-reviewed studies directly integrate these metrics into model calibration or validation (DOE 2025, NERC 2026). Bellenbaum *et al* (2019) developed a quantile-regression-based Monte Carlo framework for calculating LOLP and LOLE across interconnected European systems, illustrating the role of correlated stochastic inputs and inter-regional exchanges in mitigating adequacy risk—an approach still nascent in ERCOT applications. Complementary research by Kwon *et al* (2020) introduced a market-based RA assessment model incorporating strategic behavior and investment decisions under high VRE penetration, highlighting the need for probabilistic constructs that account for endogenous market feedbacks. Collectively, these studies reveal that while probabilistic adequacy metrics are conceptually recognized in ERCOT's evolving RA discourse, their full integration into long-term planning and operational frameworks—particularly those reflecting hybrid resource dynamics and market interactions—remains a critical area for methodological expansion.

This paper builds on four interrelated areas: (1) probabilistic RA assessment; (2) long-term capacity expansion approaches; (3) extreme weather stress test analysis; (4) projected data center load growth.

2.1. Probabilistic RA assessment

With the increasing flexible loads and the growing volatility caused by the integration of VRE (Zhang *et al* 2020, Amin *et al* 2021, Nyangon 2024), RA issues are becoming increasingly severe in electricity networks (Mantegna *et al* 2025). The solutions primarily involve deterministic reserve margins and probabilistic Monte Carlo simulations. As mentioned before, deterministic methods include planning reserve margin targets, while probabilistic approaches employ Monte Carlo sampling of demand, wind, solar, and forced outages to compute LOLE, loss of load hour (LOLH), and EUE. However, these approaches do not consider the mutual influence between high load growth from data centers and renewable uncertainties. Short-term risks are triggered by extreme events such as equipment failures or severe weather. Long-term risks are caused by unreasonable capacity mix or load forecast defects.

Resource adequacy assessment is becoming an essential component of ERCOT's grid reliability framework with the accelerating integration of VRE and data-center-driven loads. With the growth in high load forecasts and renewable penetration, the complexity of adequacy evaluation and reserve planning is continuously increasing (LaBarbara *et al* 2020, DOE 2025). According to reports published by ERCOT, RA is assessed through a combination of Seasonal Assessment of Resource Adequacy (SARA) reports using reserve margins, probability-based modeling of weather scenarios, load forecasts, resource outages, and demand response, plus ELCC valuation for wind and solar resources. The Monthly Outlook for Resource Adequacy (MORA) employs probability-based modeling to estimate hourly risks of insufficient operating reserves during peak periods and is released two months in advance on the first Friday of each month. ERCOT also applies the operating reserve demand curve (ORDC) for scarcity pricing and enforces newly adopted reliability standards requiring loss-of-load events no more than once in ten years, with duration under 12 h and manageable magnitude (ERCOT 2023). Due to limitations in capturing tail events and long-term uncertainties, the system can operate more effectively with a practical long-term probabilistic RA assessment through integrated capacity expansion modeling and high-load scenario evaluation to decrease systemic risks in planning.

2.2. Long-term capacity expansion approaches

Long-term capacity expansion approaches for probabilistic RA assessment are commonly divided into optimization-based and simulation-based methods (Min *et al* 2018, Nyangon 2025). This division reflects not merely computational preference, but contrasting epistemological commitments regarding how uncertainty, reliability, and system evolution are represented. Optimization-based models typically determine an optimal generation mix by minimizing system costs subject to predefined technical, economic, and policy constraints under projected load growth. Reviews of high-renewable systems (Levin *et al* 2024) and VRE-dominated planning in ERCOT (Ghanbarzadeh *et al* 2025) illustrate how such models embed reliability requirements, often through reserve margin constraints, within deterministic formulations. Yet the mechanisms of deterministic versus probabilistic clearing materially alter reliability outcomes, particularly when flexible demand, correlated renewable variability, and stochastic outages are abstracted into static parameters. Because optimization methods frequently rely on point forecasts and stylized representations of variability, they risk overlooking stochastic feedbacks between operational stress and investment decisions, thereby creating latent planning gaps in RA. Although capacity expansion is practically driven by load forecasts, policy mandates, and technology cost trajectories, much of the literature continues to frame adequacy primarily through reserve margin metrics, limiting engagement with risk distributions and tail events (Makarov *et al* 2015, Schleifer *et al* 2023, Hussain *et al* 2024).

Simulation-based approaches, by contrast, configure portfolios through iterative scenario analysis that captures system costs, renewable generation shapes, and operational constraints across multiple futures (Eriksson and Gray 2017, Zhao *et al* 2021, Nyangon 2025). Rather than prescribing a single least-cost solution, these methods explore how portfolios perform under diverse realizations of demand and supply conditions. However, the omission of full Monte Carlo uncertainty in many applications can still produce unpredictable shortfalls (Ma *et al* 2022, Manfredi and Trinchero 2022, Deshpande *et al* 2024). Recent advances therefore advocate integrated frameworks that couple capacity expansion with production cost and siting models to enhance temporal and spatial granularity (Mongird and Rice 2024), alongside stochastic engines such as the PLEXOS® framework that explicitly model demand, wind, solar, and outage distributions. Scenario selection is increasingly guided by risk-based criteria, load growth beyond baseline forecasts and renewable penetration exceeding predefined thresholds, while emerging work argues for redefining scenarios around expected risk distributions and extreme patterns. As VRE penetration deepens, multi-year wind datasets can improve capacity value estimation (Milligan *et al* 2017), flexibility assessments span multiple timescales (Emmanuel *et al* 2020), and storage becomes central to adequacy (Ghanbarzadeh *et al* 2025). Nevertheless, uncertainty quantification in long-term forecasting remains nascent, particularly regarding climate extremes and distributed generation (Nyangon 2024, Aditya *et al* 2025), motivating probabilistic and artificial intelligence (AI)-enabled metamodeling approaches to reconcile computational tractability with reliability rigor (Priesmann *et al* 2024).

2.3. Extreme weather stress test analysis

Extreme weather stress testing reconfigures probabilistic RA assessment by embedding tail-risk dynamics within long-term system planning. Recent analyses of ERCOT demonstrate that meteorological severity coupled with correlated generator outages can precipitate reliability shortfalls under high-load conditions, as evidenced during Winter Storm Uri (LaBarbara *et al* 2020, DOE 2025, Nyangon 2025). Yet these studies largely stop at recommending enhanced weatherization or heightened attention to rare events, without articulating an integrated mitigation architecture. In practice, mitigation strategies cluster into distinct yet interdependent categories, such as generator weatherization, firm fuel supply contracts, forward capacity procurement, reference planning adjustments, and demand response programs, each of which intervenes in operational outcomes rather than emerging purely from market equilibria. Such interventions, while necessary, remain incomplete absent alignment with capacity expansion modeling and regulatory design that internalize extreme-event risk across planning horizons. The intensification of heatwaves, windstorms, and flooding further amplifies infrastructure vulnerability precisely during peak demand intervals, exposing structural weaknesses in conventional RA metrics (Ghosh and De 2022, Chen *et al* 2025). Stress-testing methodologies therefore integrate probabilistic risk assessment with systems-thinking approaches to capture cascading failures, recovery pathways, and cross-sectoral dependencies (Linkov *et al* 2022, Nyangon and Byrne 2023). In this recursive interplay between mitigation design and adequacy modeling, extreme weather stress testing emerges not merely as a diagnostic tool, but as a structuring mechanism for resilience-oriented capacity expansion in VRE systems.

2.4. Projected data center load growth

The rapid expansion of data centers, driven primarily by the transition to power-intensive generative AI and cloud computing, represents a generational shift in electricity demand. Globally, data centers already account for approximately 1.5%–3% of total electricity consumption, with projections indicating sustained compound annual growth through 2030 as AI model training and hyperscale cloud services intensify computational intensity (Chen *et al* 2023, Yuan *et al* 2023, IEA 2025). Within the United States, forecasts anticipate a tripling of data center capacity, with incremental annual demand increases reaching 150–250 TWh and raising the sector's share of national electricity consumption toward 7.5% by 2030. ERCOT has emerged as a focal geography in this transformation, benefiting from an energy-only market structure, favorable siting conditions, and proximity to both VRE resources and natural gas infrastructure. As of early 2026, more than 78 facilities are operational in Texas, with nearly 27 GW in the development pipeline, while large-load interconnection requests have surged to over 233 GW, representing a 300% year-over-year increase. Although ERCOT's adjusted 2030 peak forecast stands near 145 GW, raw interconnection requests imply potential peaks exceeding 200 GW under high-growth scenarios. Such projections materially alter seasonal risk profiles, amplify winter adequacy concerns, and introduce voltage, frequency ride-through, and sub-synchronous oscillation vulnerabilities that conventional planning

Table 1. Detailed comparison information of the existing and proposed approaches.

Approach / reference	Methodology & key uncertainties	Extreme events / Data center (DC) integration	Advantages & disadvantages
Deterministic (ERCOT 2025, 2026)	Fixed reserve margin. Captures peak load and basic outage rates.	No—assumes typical conditions.	+ Simple, low computation. – No chronology or tail events.
Probabilistic (Consulting 2025, NERC 2026)	Convolution and outage probability tables. Captures load uncertainty.	No explicit extreme-event replication.	+ Good for ELCC. – Lacks operational constraints (UC/ED).
Sun *et al* (2022)	Monte Carlo + chronological production cost simulation.	No explicit extreme events or DC growth.	+ High fidelity operational modeling. – Computationally intensive.
LaBarbara *et al* (2020)	Stochastic dispatch modeling. Correlated renewables/thermal derates.	Summer focus; no winter extremes or DC flexibility.	+ Identifies ERCOT risk drivers. – Limited to seasonal adequacy.
Chen *et al* (2025)	Regular hours and tail-event investment evaluation. Captures extreme weather events.	Yes (extreme events), but no DC flexibility.	+ Explicit tail-risk evaluation. – Not linked to long-term expansion.
This study	Integrated PLEXOS expansion + MC RA with Uri stress test.	**Yes**—Uri-scale winter events + high-load DC scenarios.	+ Full probabilistic simulation, DC integration, and policy alignment.

frameworks insufficiently capture (Conto *et al* 2025). These dynamics underscore the need to treat projected large-load growth not as an exogenous assumption, but as a structurally endogenous driver of capacity expansion, operational flexibility, and system reliability.

The magnitude and uncertainty of projected data center growth necessitate a corresponding evolution in ERCOT's RA paradigm, shifting from deterministic reserve margins toward probabilistic, system-wide reliability assessment. High VRE penetration, particularly wind and solar, compounds this need, given the uncertain and weather-dependent capacity value of variable generation (Min *et al* 2018, Kwon *et al* 2020, Nyangon and Byrne 2023). Probabilistic load flow modeling and stochastic Monte Carlo simulations therefore become essential for capturing correlated uncertainties across load trajectories, renewable output, forced outages, and extreme weather events (Abbasi and Mohammadi 2023). Yet many prior studies treat data center demand as a static forecast input rather than integrating it dynamically within long-term capacity expansion and operational adequacy simulations. This oversight risks mischaracterizing reliability outcomes, particularly where large, flexible loads interact with renewable intermittency and seasonal imbalance. As summarized in table 1, existing methods often separate expansion modeling from probabilistic adequacy assessment, limiting their ability to capture feedback effects between investment decisions and reliability risk. Our proposed framework addresses these shortcomings by embedding projected data center growth, renewable penetration, demand response aggregation, and extreme weather scenarios within an integrated probabilistic RA architecture. In doing so, we recognize that different capacity expansion pathways yield materially different reliability distributions when combined with concentrated large-load growth, thereby reframing adequacy as a recursive interaction between structural demand transformation and stochastic system performance (Huang *et al* 2020, Norris *et al* 2025).

2.5. Contribution and paper organization

The main contribution of this study is an integrated probabilistic RA assessment framework that addresses critical gaps in long-term power system planning under high load growth and VRE deployment. The framework combines three technical components within a unified PLEXOS-based modeling environment:

(1) Long-term capacity expansion optimization (2025–2050) with endogenous investment decisions under demand growth uncertainty, technology cost evolution, and policy scenarios, determining economically optimal generation portfolios while maintaining planning reserve margins.

(2) Monte Carlo probabilistic adequacy assessment employing stochastic sampling of operational uncertainties (demand variability, renewable generation, forced thermal outages) to quantify reliability

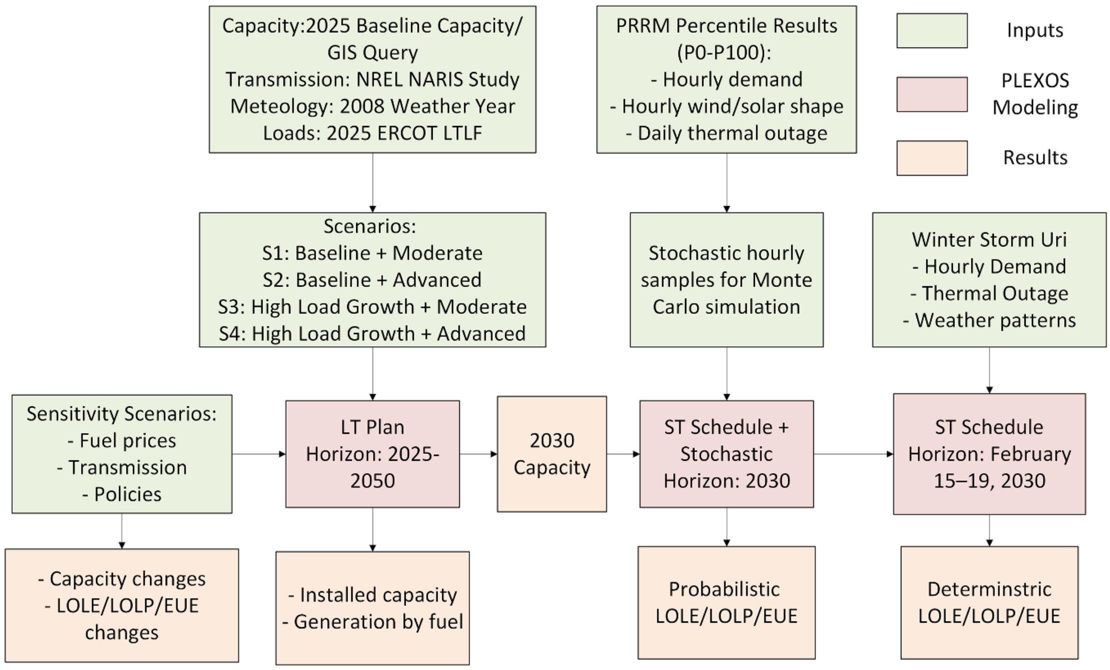

Figure 1. Study methodology flowchart showing LT expansion to Monte Carlo adequacy assessment and Uri simulation pathways.

metrics (LOLE, LOLH, EUE) that capture winter-dominant risks and temporal correlation effects not captured by deterministic planning.

(3) Extreme weather stress testing using Winter Storm Uri as a case study to evaluate system resilience under compound low-probability, high-consequence events that exceed the scope of traditional probabilistic methods.

The remainder of this paper is organized as follows. Section 3 describes the methodology applied in this study. Sections 3.1–3.3 present the capacity expansion framework, section 3.4 details the probabilistic RA assessment methodology, and section 3.5 introduces the extreme weather stress test design. Section 4 reports the results, including long-term capacity expansion outcomes across scenarios (section 4.1), sensitivity analysis under various future uncertainties (section 4.2), probabilistic adequacy risk assessment using Monte Carlo simulation (section 4.3), and deterministic RA evaluation under extreme weather conditions such as Winter Storm Uri (section 4.4). Section 5 discusses the key findings and their policy implications, and section 6 concludes the paper.

3. Methodology

3.1. Integrated modeling framework

This study employs a three-component analytical framework implemented in PLEXOS® (Exemplar 2026) to evaluate ERCOT RA under high load growth and renewable penetration scenarios. The framework integrates: (i) long-term capacity expansion optimization (2025–2050), (ii) probabilistic RA assessment via Monte Carlo simulation for the year 2030, and (iii) deterministic extreme-event backcasting of Winter Storm Uri operational performance. Figure 1 presents the methodological workflow linking these analytical components.

The long-term capacity expansion employs the PLEXOS Long-Term (LT) Module, which performs multi-period investment optimization with endogenous capacity decisions subject to Projected Assessment of System Adequacy (PASA) constraints. The model minimizes total system cost, comprising annualized capital expenditures, fixed and variable operations and maintenance (VO&M) costs, fuel costs, and emissions costs, while satisfying energy balance, minimum planning reserve margin, and operational feasibility constraints. The capacity expansion optimization is solved as a single-step perfect foresight problem over the full 2025–2050 planning horizon with annual investment decision stages. In each year, the model determines optimal capacity additions, retirements of existing assets, and operational dispatch decisions. This single-step approach co-optimizes investments, retirements, and operations across the entire horizon, ensuring that early-period decisions account for long-term system evolution, policy trajectories, and technology cost reductions. The perfect foresight assumption represents a cost-minimizing upper bound on system performance, as it eliminates forecast error and myopic decision-making that would occur under sequential planning approaches. To manage computational complexity while preserving temporal fidelity, we employ a representative period sampling strategy selecting six representative days per quarter and twelve time blocks per day, consistent with established capacity expansion modeling practices (Palmintier and Webster 2011, Poncelet *et al* 2016).

The long-term capacity expansion minimizes the net present value of total system costs over the 2025–2050 planning horizon, as formulated in equation (1):

$$\min \sum_{t\in\mathcal{T}} \frac{1}{(1+r)^{t-2025}} \left[\sum_{g} \left(C^{\text{cap}}_{g,t} x_{g,t} + C^{\text{FOM}}_{g,t} K_{g,t} \right) + \sum_{h}\sum_{g} C^{\text{oper}}_{g,h,t} P_{g,h,t} \right] \tag{1}$$

where $t \in \mathcal{T}$ represents planning years (2025–2050), g indexes generation technologies, h indexes representative time blocks, r is the weighted average cost of capital (WACC) (discount rate), $x_{g,t}$ is new capacity additions (MW), $K_{g,t}$ is total installed capacity (MW), $P_{g,h,t}$ is generation output (MW), $C^{\text{cap}}_{g,t}$ is overnight capital cost ($/kW), $C^{\text{FOM}}_{g,t}$ is fixed operations and maintenance cost ($/kW-yr), and $C^{\text{oper}}_{g,h,t}$ represents variable O&M and fuel costs ($/MWh). The optimization is subject to capacity accumulation, planning reserve margin, and generation limits. Complete formulations are provided in appendix A.

The probabilistic adequacy assessment takes optimized capacity portfolios from the LT expansion and subjects them to stochastic evaluation using the PLEXOS short-term (ST) module and stochastic module. The ST Module solves hourly unit commitment and economic dispatch using mixed-integer linear programming with full generator technical constraints (minimum/maximum output, ramp rates, minimum up/down times, start-up costs). The Stochastic Module generates $N = 50$ independent Monte Carlo realizations, each representing a complete operational year (8760 hourly timesteps), by sampling probability distributions of forced thermal outages, renewable generation variability, and demand uncertainty. The short-term unit commitment and economic dispatch minimizes hourly operational costs including startup costs and value-of-lost-load (VOLL) penalties for unserved energy (equation (2)):

$$\min \sum_{h=1}^{8760} \left[\sum_{g} \left(C^{\text{VOM}}_{g} + C^{\text{fuel}}_{g,h} H_{g,h} \right) P_{g,h} + C^{\text{start}}_{g} u^{\text{start}}_{g,h} + C^{\text{VOLL}} \cdot \text{USE}_h \right] \tag{2}$$

where h indexes hours (1–8760), $P_{g,h}$ is generator output (MW), C^{VOM}_{g} is variable O&M cost ($/MWh), $C^{\text{fuel}}_{g,h}$ is fuel cost ($/MMBtu), $H_{g,h}$ is heat rate (MMBtu/MWh), C^{start}_{g} is start-up cost ($/start), $u^{\text{start}}_{g,h}$ is a binary start-up decision variable (1 if unit starts, 0 otherwise), C^{VOLL} is value of lost load penalty ($/MWh), and USE_h is unserved energy (MW). The optimization is subject to energy balance with unserved energy, unit commitment constraints (minimum up and down times, ramping limits), and reserve requirements. Battery storage is modeled with state-of-charge dynamics, subject to energy capacity and power limits. Complete formulations with detailed notation are provided in appendix A.

3.2. System representation

3.2.1. Spatial and temporal resolution

The ERCOT system is modeled using eight weather zones as defined in ERCOT operational planning documents: Coast, East, Far West, North, North Central, South, South Central, and West (ERCOT 2026). This zonal aggregation balances computational tractability with sufficient spatial granularity to represent transmission constraints, locational resource deployment, and regional load patterns (Brown *et al* 2023). Inter-zonal power transfer capabilities are represented through Interface Transfer Limits (ITLs) derived via nodal-to-zonal aggregation methodology described in section 3.2.2.

Temporal resolution varies by modeling component. The LT expansion employs representative period sampling (6 days/quarter, 12 time blocks/day) totaling 288 representative timesteps per year, with a sample reduction algorithm. This algorithm replaces the full chronological series with a smaller yet statistically representative subset of periods. The reduction preserves key variability by aggregating similar or low-probability samples while maintaining fidelity to the original load and renewable generation distributions (Exemplar 2026). The probabilistic adequacy assessment and Uri simulation employ full chronological resolution at hourly timesteps (8760 h yr^{-1} and 144 h respectively).

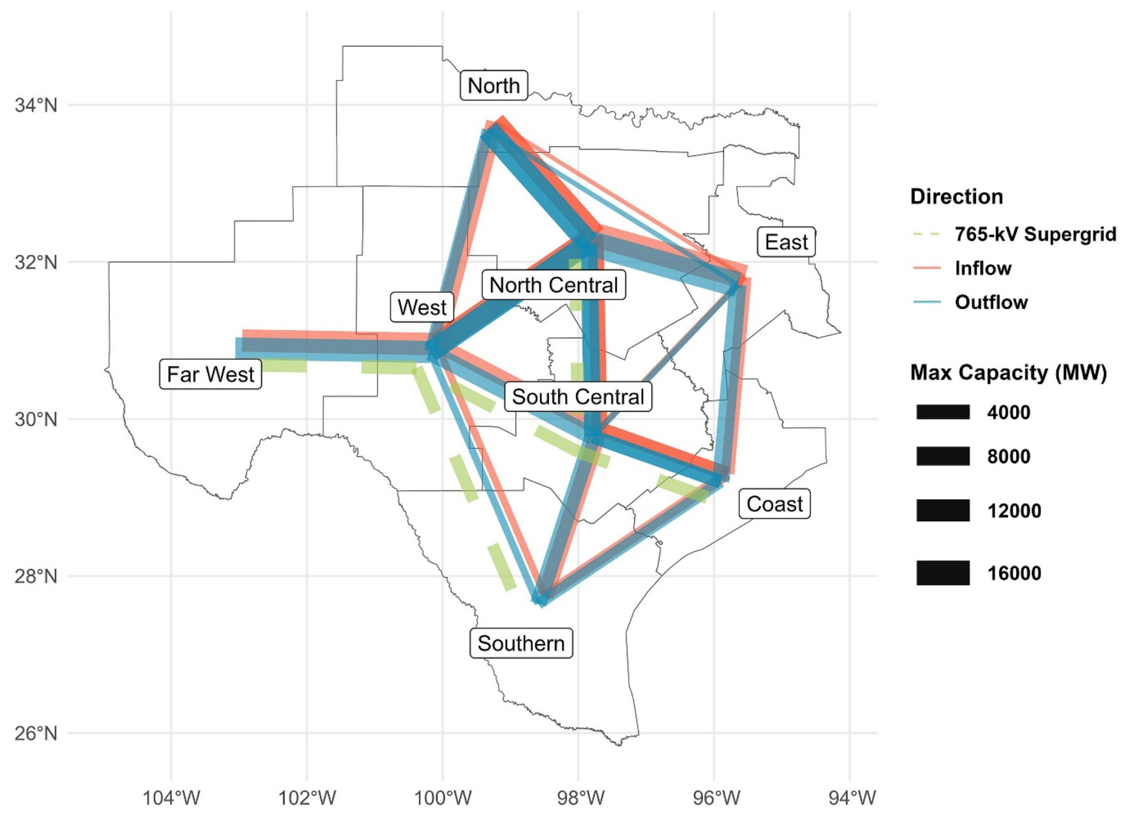

Figure 2. ERCOT zonal model with transmission interfaces.

3.2.2. Transmission network modeling

Inter-zonal transmission capacity or ITL is modeled using Interface Transfer Limits derived from detailed nodal network topology. Following the methodology established by the National Renewable Energy Laboratory's North American Renewable Integration Study (NARIS) and the Regional Energy Deployment System (ReEDS) Brinkman (2021), Ho *et al* (2021), Sergi *et al* (2024). Sergi *et al* (2024) employs linearized DC power flow approximation with Power Transfer Distribution Factor (PTDF) matrices to model the distribution of power injections across the ERCOT high-voltage transmission network comprising approximately 56 000 buses and 94 000 transmission elements sourced from FERC Form 715 submissions and NARIS base case data (Brown *et al* 2023, FERC 2026). For each inter-zonal interface, they calculate maximum feasible power transfer without violating thermal limits, voltage constraints, or stability margins. Given the physical asymmetry of transmission networks, forward and reverse transfer limits are calculated independently. They output the county-level ITLs in the NARIS report and in this study, we further aggregate them to zonal boundaries, as shown in figure 2.

The baseline transmission topology represents existing 345-kV infrastructure. In the sensitivity analysis, we model a future transmission expansion scenario reflecting ERCOT's Strategic Transmission Expansion Plan (STEP), which upgrades five critical corridors to 765-kV extra-high-voltage (EHV) configuration (ERCOT 2025a). The 765-kV circuits support approximately 3000 MW per circuit—derived from surge impedance loading of 2400MW plus thermal headroom—compared to 800–1200 MW for existing 345-kV infrastructure (ERCOT 2025b).

Upgraded corridors include Coast–South Central, North Central–South Central, South Central–West, West–Far West, and West–South interfaces, with capacity increases ranging from 600 MW to 3000 MW per corridor and the West Texas Export Limit expanding from 12.7 GW to 16.2 GW. The upgraded lines are shown as green dashed lines in figure 2.

3.2.3. Load characterization

Hourly system demand is represented using ERCOT LT load forecast (LTLF) data covering 2025–2044 with zonal disaggregation (ERCOT 2025c). To capture uncertainty in data center deployment and large flexible load growth, we employ two demand trajectories:

Base load scenario: Peak demand grows from 85 GW (2025) to 143 GW (2050) at 2.6% annual average growth rate (AAGR). Under this scenario, data center interconnection requests are reduced to 49.8% of contracted values based on historical completion rates, transmission service provider (TSP) officer-attested load additions are reduced to 55.4%, and all large load ramp schedules include 180-day commissioning delays.

High load scenario: Peak demand grows from 85 GW (2025) to 234 GW (2050) at 5.1% AAGR. This scenario incorporates all executed interconnection agreements without risk adjustments, representing maximum plausible load growth under aggressive data center deployment.

Overall, the Base scenario adds 10 GW of data center load by 2030, while the High scenario adds 35 GW. Projection extension from 2044 to 2050 employs zone-specific extrapolation of terminal growth trends. Detailed load construction methodology, including extrapolation procedures, zonal disaggregation, and historical validation, is provided in appendix B.

3.2.4. Generation fleet representation

Existing and committed inventory is compiled from U.S. Energy Information Administration (EIA) Form 860 annual data (EIA 2025), ERCOT Capacity, Demand, and Reserves (CDR) reports (ERCOT 2025), and ERCOT geographic information system (GIS) Report (ERCOT 2025). Resources retired prior to January 1, 2019 and settlement-only generators excluded from ERCOT CDR reports are omitted from the model. The existing generation fleet includes conventional steam coal (Coal), natural gas steam turbine, Natural gas–fired combined cycle (CCGT), natural gas–fired internal combustion turbine (OCGT), other natural gas, petroleum or oil, hydro, onshore wind turbine, solar photovoltaic (Solar PV), and battery storage units.

Generator capacities employ maximum nameplate ratings with seasonal adjustment factors (summer, winter, fall, spring) applied via monthly capacity files reflecting ambient temperature impacts on thermal unit performance and derate schedules. Private use network generators are modeled to preferentially serve on-site loads with excess capacity available to ERCOT markets. Planned resources advance to 'Financial Security and Notice to Proceed' status in ERCOT GIS or 'Under Construction' designation in EIA Form 860/860 M are included with projected in-service dates. Tables C1 and C2 summarize planned capacity additions and retirements for future years.

Thermal generator operating costs employ technology- and age-stratified parameters from Intertek's assessment of fossil generator flexibility impacts (Intertek 2023). Start-up costs and VO&M are assigned from 25th percentile, median, and 75th percentile cost distributions based on unit age relative to the installed fleet of equivalent technology type (Coal, CCGT, and OCGT).

Forced outage behavior is characterized using technology-specific equivalent forced outage rates from the Texas Reliability Entity's 2023 assessment (Texas Reliability Entity 2024), together with mean time to repair (MTTR) values from ERCOT's 2022 Reserve Margin Study (ERCOT 2023). Planned maintenance is modeled by converting annual outage schedules into equivalent hourly derate factors based on MTTR assumptions, thereby distributing outage impacts across the modeled years in the LT simulations (ERCOT 2023). The capacity credits of thermal generators are determined by integrating planned maintenance rates with forced outage rates.

Future generation expansion candidates encompass the full portfolio of commercial and near-commercial generation and storage technologies: CCGT, OCGT, enhanced geothermal systems (EGSs), small modular reactors (SMRs), onshore wind, offshore wind, utility-scale Solar PV (fixed-tilt and single-axis tracking), solar-plus-battery hybrid systems, and standalone lithium-ion battery energy storage systems with 1-h, 2-h, and 4-h duration configurations.

Techno-economic parameters are sourced from the National Renewable Energy Laboratory's 2025 Annual Technology Baseline, including overnight capital costs, fixed operations and maintenance (FOM), V&OM, WACC, and economic asset lifetimes (NREL 2024). We employ the ATB Moderate and Advanced technology cost trajectories to bound future cost uncertainty, with Moderate representing evolutionary cost improvements consistent with historical trends and Advanced representing accelerated cost reductions from technological breakthroughs and manufacturing scale economies. These cost trajectories apply uniformly to all expansion technologies: solar PV, onshore wind, offshore wind, battery storage (all durations), CCGT, OCGT and nuclear (large and SMR). The single exception is EGS: the ATB Advanced cost trajectory is replaced with updated estimates from Chen and Cohan (2026), which indicate substantially higher cost reduction potential based on recent pilot-scale testing and field demonstration results. The assumptions on future generator candidates are summarized in table C3.

3.2.5. Renewable generation profiles

Wind generation profiles employ output time series from the National Renewable Energy Laboratory's Wind Integration National Dataset (WIND) Toolkit (Draxl *et al* 2015), which provides meteorologically consistent hourly generation estimates at 2-km spatial resolution covering 2007–2014 meteorological conditions. Candidate wind projects are assigned representative profiles based on geographic proximity to WIND Toolkit resource assessment points, with averaging across geographically similar clusters to produce representative capacity factor time series (Draxl *et al* 2015). For consistency with ERCOT load forecast meteorological assumptions, we employ 2008 as the reference weather year.

Solar photovoltaic generation profiles are synthesized using the National Renewable Energy Laboratory's System Advisor Model Blair *et al* (2018) with default configuration parameters modified only for inverter loss specifications and tracking mode (fixed-tilt, single-axis tracking, or dual-axis tracking). Identical methodology applies to existing solar generators and expansion candidates, ensuring temporal consistency between solar generation and load across all simulated conditions.

3.2.6. Fuel price projections

Natural gas prices employ hub-specific forward price curves for five delivery points: Henry Hub (Louisiana), Houston Ship Channel, Agua Dulce (South Texas), Texas-Oklahoma border, and Waha Hub (Permian Basin). Historical prices derive from Natural Gas Intelligence index data through 2024 (NGI 2025), with forward projections synthesized from Energy Exemplar proprietary forecasts calibrated to New York Mercantile Exchange (NYMEX) futures markets and fundamental supply-demand modeling (Exemplar 2026).

Fuel oil prices combine historical data from EIA Short-Term Energy Outlook and Annual Energy Outlook publications (EIA 2026a) with NYMEX and Intercontinental Exchange (ICE) forward market curves for refined petroleum products. Coal prices employ EIA-923 reported plant-level costs for the West South Central census region through December 2023 (EIA 2026b), with post-2023 prices derived from Powder River Basin forward markets and held constant beyond 2025 given limited coal capacity in ERCOT's projected generation mix.

3.2.7. Ancillary service requirements

ERCOT operational reserve requirements are explicitly modeled following the 2024 Day-Ahead Ancillary Services Plan (ERCOT 2024), including:

- Regulation up and regulation down reserves for automatic generation control
- Responsive reserve service for primary frequency response
- Non-spinning reserve service (Non-Spin) for 30-min contingency response
- ERCOT Contingency Reserve Service, introduced June 2023 to address uncertainty from increased renewable penetration (ERCOT 2023)

Generator and storage resource eligibility for ancillary service provision is determined by technology-specific operational characteristics including ramp rates, minimum stable generation levels, and start-up times. Minimum system inertia constraints employ technology-specific inertia constants from ERCOT's cost-benefit analysis of future ancillary services (ERCOT 2022).

A minimum planning reserve margin of 13.75% is imposed as a constraint in the capacity expansion optimization, consistent with ERCOT's target reserve margin (ERCOT 2023). However, ERCOT does not have a formal mechanism to enforce compliance with this target. In contrast, many other North American regions maintain reserve margins at or above their targets by requiring load-serving entities to procure sufficient capacity to meet reliability obligations (NERC 2026).

In the PLEXOS model, the annual planning peak load and projected firm capacity are used to enforce this minimum reserve margin on a yearly basis, ensuring that installed firm capacity exceeds peak demand by at least the specified margin in each planning year. Firm capacity credit values for renewable resources are set conservatively at 10% for both solar PV and onshore wind in the baseline scenarios which are consistent with ERCOT's approach to crediting intermittent resources in multi-year planning horizons (ERCOT 2025). The value reflects long-term planning prudence given capacity factor variability and correlation effects at high penetration. Thermal resources including CCGT, OCGT, and nuclear receive 95% firm capacity credit accounting for forced outage rates, while battery storage receives capacity credit based on duration ranging from 50% for 1 h systems to 80% for 4-hour systems.

We also evaluate sensitivity to this requirement through alternative scenarios with modified reserve margin targets (section 3.3), including a high firm capacity credit scenario (S5) that tests the adequacy implications of assigning historically observed upper-bound capacity credits to renewables (76% for solar, 28% for wind).

3.3. Scenario definition and sensitivity analysis

3.3.1. Core scenarios

The analysis employs a 2×2 factorial design crossing two demand trajectories (**Base load**, **High load**) with two technology cost pathways (**Moderate**, **Advanced**), producing four core scenarios:

- **Base load + Moderate technology costs**: Serves as the baseline scenario.
- **Base load + Advanced technology costs**: Evaluates standard demand with accelerated technology improvements.
- **High load + moderate technology costs**: Assesses high growth under standard cost projections.
- **High load + Advanced technology costs**: Explores the combination of high demand and rapid technological advancement.

This structure isolates the independent and interactive effects of load growth uncertainty and technology cost evolution on optimal capacity expansion pathways and system reliability outcomes.

3.3.2. Sensitivity scenarios

We conduct eight single-factor sensitivity analyses using **Base load + Advanced** technology costs as the reference case (table D1). Each sensitivity modifies a single parameter set while holding all other inputs constant, enabling attribution of capacity expansion changes to specific uncertainties:

S1. 765-kV transmission expansion. Models implementation of ERCOT's STEP with five inter-zonal corridor upgrades (Coast–South Central, North Central–South Central, South Central–West, West–Far West, West–South) increasing interface transfer limits by 600–3000 MW. Transmission capacity enhancements are assumed operational from 2026 onward. Tests whether enhanced transmission can defer or displace generation capacity through congestion relief and improved renewable resource access.

S2. Inflation reduction act (IRA) repeal. Eliminates all production tax credits (PTCs) and investment tax credits (ITCs) associated with the Inflation Reduction Act, including wind PTC, solar ITC, and enhanced credits for geothermal and storage technologies. Tax credits are removed across the entire 2025–2050 planning horizon. Quantifies policy dependency of renewable and emerging technology deployment.

S3(a)-(d). Natural gas price variations (±25%, ±50%). Applies uniform percentage adjustments to baseline natural gas price trajectories: 25% reduction, 50% reduction, 25% increase, and 50% increase. Price adjustments are applied consistently across all years from 2025–2050. These bounds span historical price volatility and represent sustained low-price scenarios (abundant shale gas production, weak demand) or high-price scenarios (supply constraints, increased LNG exports, implicit carbon pricing).

S4. 95% Carbon emissions reduction. Imposes a system-wide CO_2 emissions constraint requiring at least 95% of generation should come from emission-free resources, such as nuclear, wind, solar or geothermal. The constraint is enforced as a 2050 endpoint target; the perfect-foresight optimization determines the least-cost pathway to achieve this terminal goal. This scenario tests feasibility of deep decarbonization pathways consistent with net-zero economy-wide targets and identifying required technology mix transformations.

S5. High firm capacity of renewables. This scenario assumes higher firm capacity contributions for wind and solar resources. The baseline scenarios throughout this study apply conservative firm capacity values of 10% for both solar and wind (ERCOT 2025).

In contrast, this sensitivity scenario assigns solar 76% firm capacity value and wind 28%, representing the upper end of historical ranges observed in ERCOT CDR assessments from 2010–2024, where solar has ranged between 74%–100% and wind has remained near 30% (Consulting 2025). These capacity credit values are applied uniformly across the entire 2025–2050 planning horizon. The purpose of this scenario is to investigate the adequacy implications of capacity credit specification as renewable penetration increases, demonstrating that overestimating firm capacity contributions can lead to systematic under-building of generation resources and subsequent reliability shortfalls.

S6. Hourly capacity reserve margin. Rather than enforcing a planning reserve margin only at annual peak load, this scenario applies a 13.75% capacity reserve requirement to all sampled hours. This constraint is enforced in every simulated hour across all years from 2025–2050. By extending the constraint beyond traditional peak periods, the model ensures adequacy during both gross load peaks and net load peaks, which become increasingly important in systems with high renewable penetration and pronounced ramping dynamics.

For each sensitivity scenario, installed capacity by technology type is evaluated at milestone years 2030, 2040, and 2050 to assess differences in portfolio evolution. In addition, each scenario is subjected to ST scheduling using a selected stochastic sample that produces the highest LOLH in the baseline case, instead of running all samples. This approach maintains a consistent stressed operating condition across scenarios, enabling direct comparison of their relative impacts on RA while reducing computational burden.

3.4. Probabilistic RA assessment

3.4.1. Monte Carlo simulation framework

Probabilistic adequacy is evaluated through Monte Carlo simulation of 2030 system operations using capacity portfolios from the long-term expansion optimization. We generate $N = 50$ independent realizations, each representing one complete operational year (8760 hourly timesteps) with full chronological sequencing. For each realization, hourly unit commitment and economic dispatch are solved subject to operational constraints, reserve requirements, and system energy balance, with installed capacity and transmission topology fixed at 2030 projected levels. The sample size of 50 realizations provides sufficient statistical precision for central tendency metrics (e.g. LOLE, EUE) while acknowledging limitations in characterizing low-probability tail events.

The following subsections detail the uncertainty characterization (section 3.4.2), sampling and simulation methodology (section 3.4.3), and reliability metrics computed from simulation results (section 3.4.4).

3.4.2. Uncertainty characterization

All stochastic inputs derive from ERCOT's 2025 MORA (ERCOT 2026) , which provides monthly probabilistic representations developed from ERCOT's Probabilistic Reserve Risk Model. For each month, the MORA dataset reports percentile distributions (0th through 100th percentile, 10-percentile increments) for three primary uncertainty sources: demand uncertainty (hourly), renewable generation uncertainty (hourly), and thermal generation outages (monthly) ERCOT (2026).

The MORA distributions reflect 2025 system conditions and are scaled to 2030 levels while preserving probabilistic structure. Hourly demand percentiles are scaled using monthly peak load growth factors between 2025 and 2030. Renewable generation percentiles are converted from absolute MW to normalized capacity prior to application, allowing direct scaling with 2030 installed renewable capacity. Thermal outage MW values are converted to outage rates and applied proportionally to the 2030 thermal fleet composition.

3.4.3. Sampling and simulation methodology

For each Monte Carlo realization, we sample random percentiles from the MORA distributions to construct a unique system state trajectory. Percentile sampling employs independent uniform random draws for demand, wind generation, solar generation, and thermal outages at each temporal resolution (hourly for demand and renewables, daily for thermal outages). To preserve intra-day consistency, hourly demand and renewable profiles are sampled at the daily level. For example, selecting the 30th percentile of a solar availability distribution applies that percentile uniformly across all 24 h of the day, representing a persistently low-output solar day rather than hour-to-hour fluctuations.

Unit commitment and economic dispatch are solved hourly using mixed-integer linear programming with standard operational constraints: generator minimum/maximum output limits, minimum up/down time constraints, ramp rate limits, start-up and shut-down trajectories, must-run requirements, and ancillary service provision. Battery energy storage optimization includes state-of-charge tracking, charging/discharging efficiency, and auxiliary load representation. Transmission constraints enforce zonal interface transfer limits in each direction.

When available generation and reserves are insufficient to serve load and satisfy reserve requirements, the model invokes involuntary load shedding with associated VOLL penalty. We then identify adequacy shortfalls and enables direct calculation of unserved energy metrics, as elaborated in section 3.4.4.

3.4.4. Reliability metrics

For each Monte Carlo realization, we record the occurrence, magnitude, and duration of load shedding events. Aggregating across all realizations yields empirical distributions from which we compute standard probabilistic reliability metrics. The list of shared notation used across all metrics is defined, following by metrics including LOLH, LOLE, EUE, and LOLP (equations (3)–(6)).

Common Notation:

- N: Total number of Monte Carlo realizations ($N = 50$)
- i: Index for individual realization ($i = 1, 2, \ldots, N$)
- t: Index for time step (hour)
- T: Total time steps in the simulation horizon ($T = 8{,}760$ hours/year)
- $\mathrm{USE}_{i,t}$: Unserved energy (MW) in realization i at hour t
- H_i: Total number of hours with $\mathrm{USE}_{i,t} > 0$ in realization i
- $1(\cdot)$: Indicator function, equal to 1 if the condition is true and 0 otherwise

Using this notation, we define the following reliability metrics:

LOLH: Expected number of hours per year experiencing unserved energy, calculated as:

$$\mathrm{LOLH} = \frac{1}{N}\sum_{i=1}^{N} H_i. \tag{3}$$

LOLE: LOLE represents the expected number of days per year in which at least one hour of unserved energy occurs. The NERC reference reliability target of one day in ten years corresponds to an expected LOLE of 0.1 days per year, or equivalently 2.4 h per year (Rickerson 2023). In this study, LOLE is calculated by averaging the total number of loss-of-load hours across all Monte Carlo realizations and converting hours to days:

$$\mathrm{LOLE} = \frac{1}{N}\sum_{i=1}^{N} H_i/24. \tag{4}$$

EUE: Expected annual unserved energy in MWh. EUE offers better insights into the magnitude and duration of shortages, which makes it important with high renewable, battery, and demand-response penetration. The Energy Systems Integration Group (ESIG) suggests 1000 MWh yr^{-1} as a potential EUE target to complement traditional standards (PJM 2023, Stenclik 2024). The metric is calculated as:

$$\mathrm{EUE} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{8760} \mathrm{USE}_{i,t}. \tag{5}$$

LOLP: Probability of experiencing at least one hour of unserved energy in a given year, calculated as:

$$\mathrm{LOLP} = \frac{1}{N}\sum_{i=1}^{N} 1\left(H_i > 0\right). \tag{6}$$

Additionally, we report frequency distributions of unserved energy by month, hour-of-day, and magnitude to characterize temporal patterns and identify critical operating conditions contributing to adequacy risk.

3.5. Extreme weather stress test: winter storm Uri

3.5.1. Event characterization

Winter Storm Uri (14–19 February,) subjected ERCOT to unprecedented cold weather conditions resulting in widespread generator outages, demand surge, and approximately 1000 GWh of involuntary load shedding (Magness 2021). The event provides an empirical basis for evaluating system resilience under extreme conditions combining meteorological severity, infrastructure vulnerability, and operational stress.

We simulate 2030 ERCOT performance during a Winter Storm Uri-equivalent event using historical meteorological conditions and generator availability patterns applied to future capacity portfolios. This counterfactual analysis tests whether planned capacity expansion provides sufficient resilience against extreme weather or whether additional measures are required. This analysis uses 2021 meteorological conditions during February 14–19 exclusively for Uri simulation, while all other analyses in this study employ 2008 weather as the representative normal year.

3.5.2. Simulation methodology

Temporal scope: 14–19 February, 2021 (144 h) solved with hourly unit commitment and economic dispatch resolution. ERCOT has published hypothetical load profiles that remove the effects of emergency load shedding, thereby approximating the true underlying demand during Winter Storm Uri (ERCOT 2021a). These profiles indicate peak demand approximately 1.33 times higher than the 2021 Winter SARA forecast, reflecting the combined impacts of extreme cold weather and suppressed demand during curtailment (ERCOT 2021). In this study, the same 1.33× multiplier is applied to projected 2030 winter peak load to construct Uri-equivalent demand profiles.

Historical hourly wind and solar generation profiles from 14–19 February, 2021 are applied directly to existing renewable generators (ERCOT 2024). For new wind and solar capacity added by 2030, weather-zone–averaged capacity factors are derived from the historical profiles and applied to projected installed capacity by zone and technology. Thermal generator availability is represented by applying historical hourly forced outage rates observed during Winter Storm Uri as exogenous availability derates to the 2030 thermal fleet (ERCOT 2021a).

3.5.3. Counterfactual scenario design

To decompose the relative contributions of demand surge versus supply disruption to system inadequacy, we evaluate four counterfactual scenarios:

- **Full Uri:** Historical demand multiplier (1.33×) and historical outage rates (base case)
- **No demand spike:** Normal 2030 winter peak demand with historical Uri outage rates
- **No high outage:** Historical demand multiplier with normal forced outage rates
- **Normal 2030 Winter:** Normal 2030 conditions without ultra high loads and high outages (control case)

Full Uri (Scenario 1) represents the complete extreme event conditions and serves as the reference case for quantifying Uri impacts. Scenarios 2 and 3 are counterfactuals that isolate individual stress factors (demand surge or supply disruption) by removing one component while holding the other constant. Normal 2030 Winter (Scenario 4) represents typical winter operating conditions without extreme weather and serves as the control case.

This 2 × 2 factorial structure enables attribution of unserved energy to demand stress, supply disruption, and interaction effects. Scenario 4 provides controlling-purpose confirmation that the 2030 capacity portfolio maintains adequacy under normal winter conditions.

For each scenario, we quantify total unserved energy (GWh), peak unserved energy (MW), number of hours with load shedding, and temporal distribution of adequacy events. Comparative analysis across scenarios identifies primary drivers of extreme weather vulnerability and informs resilience planning strategies. To enable comparison with the probabilistic adequacy metrics (section 3.4.4), we calculate an annualized equivalent LOLE by scaling observed Uri unserved energy hours to an annual risk metric by extending 168 h to 8760 h.

4. Results

4.1. Long-term capacity expansion outcomes

Figure 3 presents the evolution of total installed capacity from 2026 through 2050 across the four core scenarios. Starting from 184 GW in 2025, total system capacity grows to 391–593 GW by 2050 depending on load trajectory and technology cost assumptions. Under base load conditions, installed capacity reaches 391 GW (Moderate costs) and 422 GW (Advanced costs), representing 85% and 100% increases respectively. High Load scenarios require substantially greater capacity expansion, 488 GW and 593 GW under Moderate and Advanced cost scenarios, which are equivalent to 1.65- and 2.22-times of 2025 capacity.

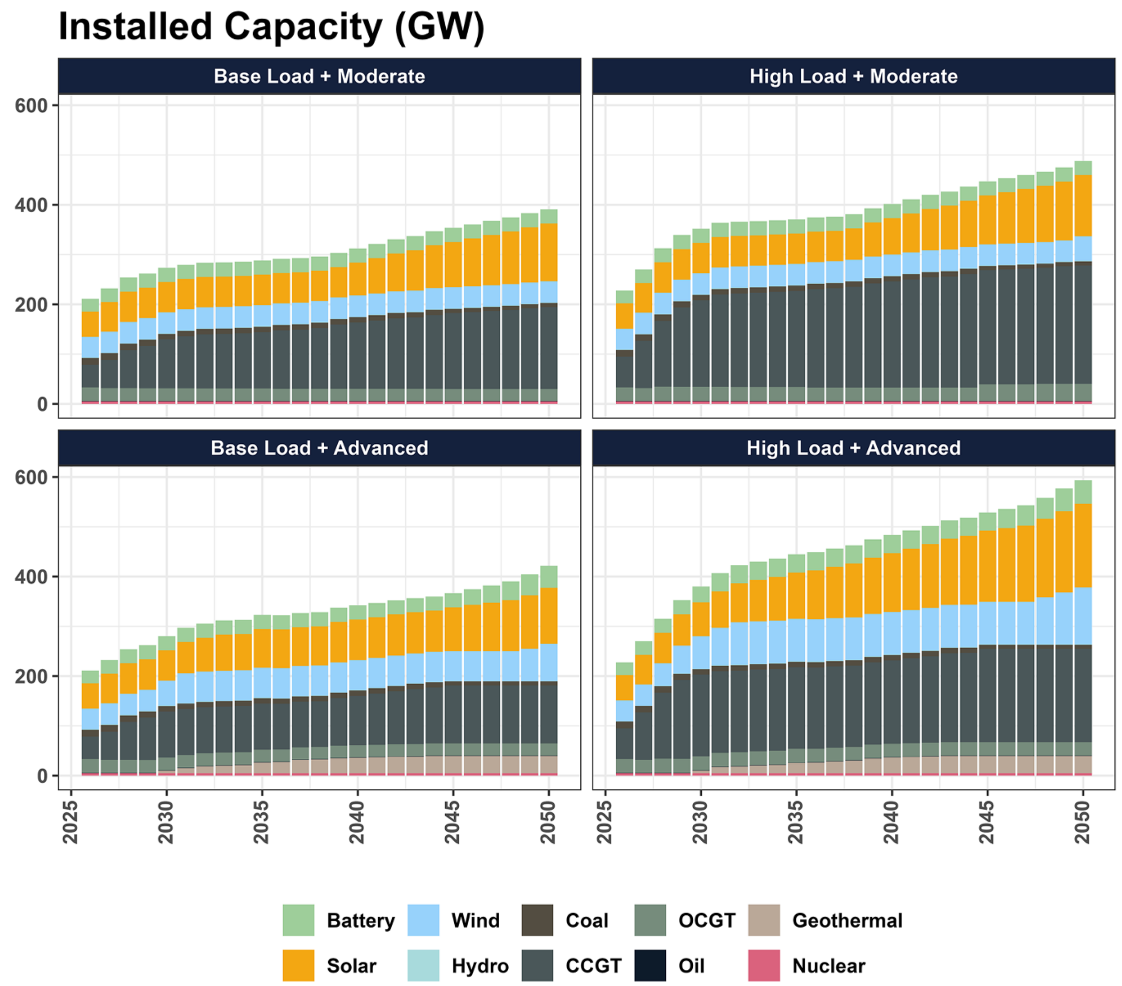

Figure 3. Total installed capacity (GW) from 2026 to 2050.

Technology composition differs markedly across cost scenarios. Under Moderate technology costs, CCGT dominate expansion, accounting for 122 GW (67%) of new capacity in the Base Load scenario and 196 GW in the High Load scenario by 2050 (table 2 and figure 4). Solar photovoltaic systems provide secondary capacity contributions of 55–62 GW, while wind, open-cycle gas turbines, and storage remain marginal. This technology mix reflects CCGT's superior capacity credit (0.85–0.90) and cost-competitiveness in energy-only markets despite exposure to natural gas price volatility and emissions constraints.

Advanced technology costs fundamentally transform the optimal expansion pathway. EGS emerge as economically competitive, contributing 34.5 GW across both load scenarios by 2050. CCGT deployment moderates substantially to 74 GW (base load) and 145 GW (high load) as declining renewable and storage costs shift the economic equilibrium. Renewable capacity expands dramatically: solar grows to 51–107 GW, wind to 32–72 GW, and battery energy storage to 16–19 GW by 2050. The High Load Advanced scenario exhibits the most diversified portfolio, with no single technology exceeding 145 GW or 25% of total capacity, reflecting the complementary energy and capacity value of different generation types under high renewable penetration.

Battery storage deployment remains minimal (0–3 GW) despite substantial solar and wind growth, reflecting cost economics and market structure. CCGT provides flexibility at lower annualized cost than 4-h batteries under Moderate assumptions: \$1300–\$1400/kW with 8760 potential hours versus \$1600/kW limited to 365 cycles annually. The planning reserve margin constraint does not inherently favor storage, as thermal resources satisfy adequacy requirements more cost-effectively. Additionally, ancillary service revenues that benefit batteries in actual ERCOT markets are not fully captured in long-term capacity expansion modeling. Under the 95% CO_2 reduction scenario, battery deployment increases to 19 GW, since storage becomes economic when carbon constraints eliminate low-cost thermal alternatives.

Renewable penetration (solar + wind generation as percentage of total energy) varies significantly across scenarios and remains moderate under baseline assumptions: Base+Moderate achieves 22% (2030)

Table 2. Installed baseline and new capacity additions (GW) across the core scenarios in 2025, 2030, 2040, and 2050.

Scenario	Year	CCGT	Other Gas	Solar	Wind	Battery	Coal	Nuclear	EGS
2025 Existing Baseline		35.2	22.6	35.8	40.6	15.6	13.7	5.3	0.0
Base load + Moderate	2030	54.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	2040	91.1	0.0	5.0	0.0	0.0	0.0	0.0	0.0
	2050	122.2	0.0	55.0	0.0	0.0	0.0	0.0	0.0
High load + Moderate	2030	130.4	2.8	0.0	0.0	0.0	0.0	0.0	0.0
	2040	170.6	2.8	12.1	0.0	0.0	0.0	0.0	0.0
	2050	195.6	10.2	62.1	6.6	0.0	0.0	0.0	0.0
Base load + Advanced	2030	48.9	0.0	0.0	7.5	0.0	0.0	0.0	5.0
	2040	57.0	0.0	20.5	17.5	0.0	0.0	0.0	30.8
	2050	74.2	0.0	51.2	32.1	16.0	0.0	0.0	34.5
High load + Advanced	2030	120.4	2.5	7.1	22.7	3.4	0.0	0.0	5.0
	2040	125.1	2.5	57.1	42.7	8.2	0.0	0.0	31.5
	2050	145.2	2.5	107.1	71.7	18.9	0.0	0.0	34.5

Notes: The 2025 baseline row reports installed capacity from the ERCOT December 2025 Capacity, Demand, and Reserves report for operational units. The Other Gas column aggregates non-CC gas units (gas steam, combustion turbine, and internal combustion) to preserve consistency with the available CDR technology breakout. Hydro, biomass, diesel, and DC tie resources are omitted because they are unchanged across the core expansion scenarios and are not represented as candidate expansion technologies in table 2.

increasing to 28% (2050), while Base+Advanced reaches 28% (2030) to 45% (2050). The 95% CO_2 reduction sensitivity scenario achieves 82% penetration by 2050, showing that high renewable penetration requires explicit carbon policy rather than emerging from cost optimization alone. The current energy-only market structure in ERCOT, absent state clean energy mandates or carbon pricing, produces CCGT-dominated portfolios even with IRA incentives, as firm capacity economics favor natural gas generation under current policy frameworks.

Temporal investment patterns (figure 4) show concentrated capacity additions during 2026–2035, driven by near-term load growth. High Load scenarios exhibit peak annual additions of 15–20 GW in the early 2030 s, moderating to 8–12 GW thereafter. Base Load scenarios maintain steadier investment rates of 6–10 GW annually through 2035, declining to 4–6 GW in subsequent years. This temporal concentration reflects the 10.6%–20.2% AAGR projected for 2025–2030 compared to 1.6%–2.1% for 2030–2040, indicating that the bulk of transformational capacity expansion occurs within the immediate planning horizon.

Annual generation patterns (figure 5) reflect the operational dispatch of expanded capacity portfolios. CCGT generation dominates across all scenarios, growing from 400 TWh (2026) to 950 TWh (2050) in the base load moderate case and reaching 1650 TWh under High Load Moderate conditions. This represents 65%–70% of total annual generation, with CCGT serving baseload and intermediate load. Solar generation increases from 60 TWh to 280–350 TWh by 2050 across scenarios. In Advanced cost scenarios, EGS provides 200–250 TWh annually by 2050, offering firm low-carbon baseload generation with capacity factors of 0.80–0.85. Wind generation contribution remains below 100 TWh in Moderate scenarios due to limited deployment but reaches 150–200 TWh in Advanced scenarios. Nuclear generation remains stable at 40–50 TWh annually across all scenarios.

4.2. Sensitivity analysis of technology costs, fuel prices, and policy scenarios

We evaluate capacity expansion robustness through eight sensitivity scenarios using Base Load + Advanced as the reference case. Figure 6 presents installed capacity differences at 2030, 2040, and 2050 milestones. Results demonstrate high sensitivity to natural gas prices and carbon policy, moderate sensitivity to IRA continuation, and minimal sensitivity to transmission expansion.

Transmission expansion: The 765-kV upgrade scenario produces negligible capacity impacts (<3 GW net difference across all years). By 2030, enhanced transmission enables 2.4 GW reduction in wind

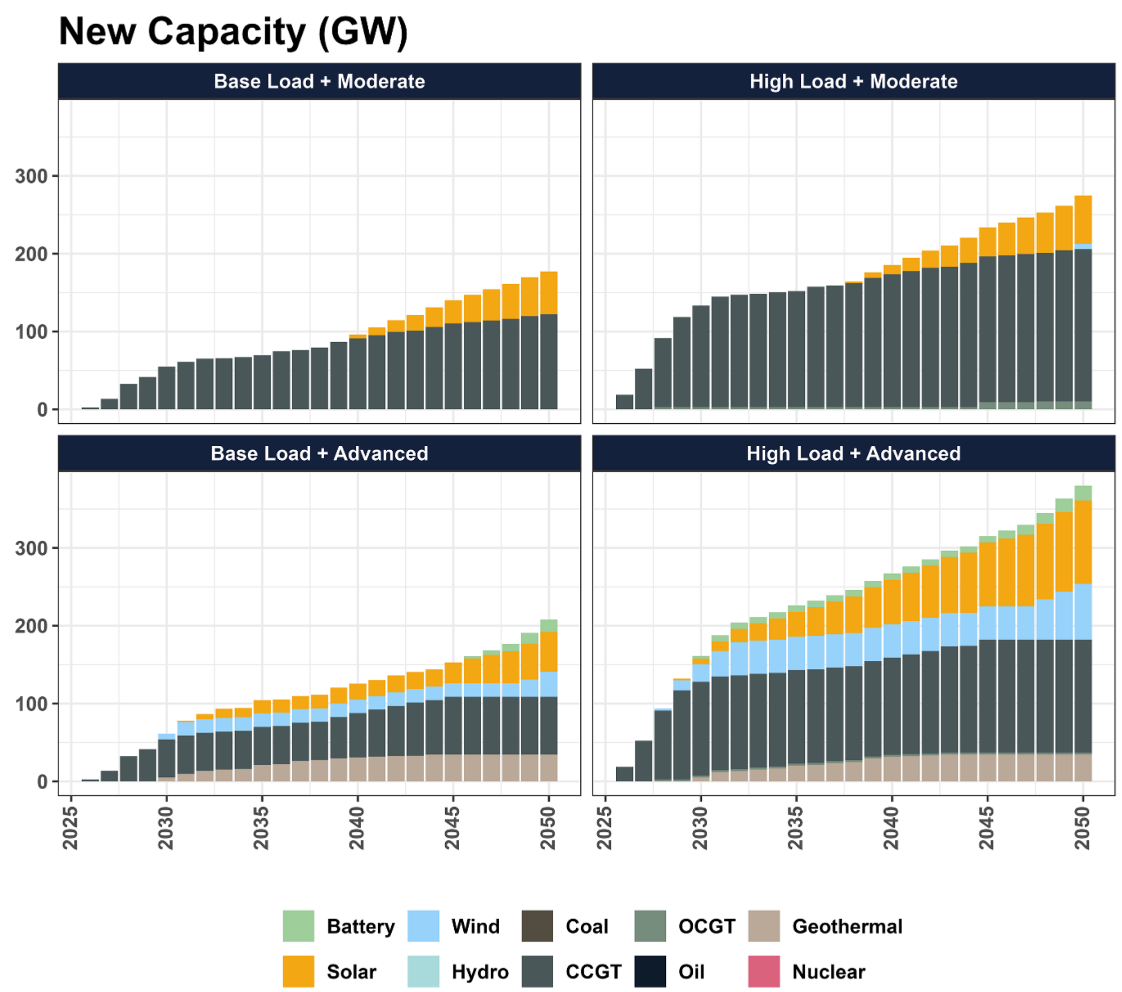

Figure 4. Newly installed capacity (GW) from 2026 to 2050.

capacity offset by 0.2 GW CCGT addition. By 2050, net capacity difference approaches zero, indicating transmission expansion value derives primarily from operational efficiency and congestion cost reduction rather than capacity deferral. This finding reflects concentrated load growth in urban centers where generation can be sited proximate to demand, reducing long-distance transmission dependence.

Inflation Reduction Act repeal: Eliminating federal production and ITCs reduces wind deployment by 7.5 GW (2030) and 12.1 GW (2050) and eliminates economic competitiveness of EGS entirely. CCGT partially substitutes for displaced renewables. Solar deployment shows resilience to IRA repeal with minimal capacity differences (<2 GW), suggesting solar economics are driven primarily by underlying technology cost trajectories rather than tax incentives over the study horizon.

Natural gas price variations: Fuel cost uncertainty produces strongly asymmetric capacity responses. A 50% price reduction displaces 32 GW of wind and 51 GW of solar by 2050 while adding 35 GW of CCGT. Conversely, 50% higher gas prices stimulate 57 GW of additional solar, 39 GW of wind, and 7.5 GW of battery storage by 2030, reducing CCGT by 11 GW. Low gas price scenarios (e.g. abundant shale production, weak demand) pose greater risk to clean energy deployment than high price scenarios provide acceleration.

95% carbon reduction: Imposing emissions declining linearly to 5% of 2030 baseline by 2050 produces dramatic portfolio transformation. The constraint mandates 59 GW of nuclear capacity, i.e. SMRs, by 2050, representing the first scenario where nuclear achieves economic deployment. Additional investments include wind (+56 GW), battery storage (+19 GW), and CCGT reductions (–29 GW). Solar deployment decreases by 12 GW relative to baseline despite aggressive decarbonization, as the optimizer substitutes wind for solar. This substitution reflects the higher annual capacity factor of wind over solar (ERCOT 2025), making each GW of wind more cost-effective for meeting the carbon constraint. Additionally, ERCOT winter peak reliability requirements favor wind, which maintains output during cold weather, over solar, which has near-zero nighttime generation. In addition, nuclear emergence reflects the constraint requiring firm low-carbon generation beyond EGS economic potential, forcing

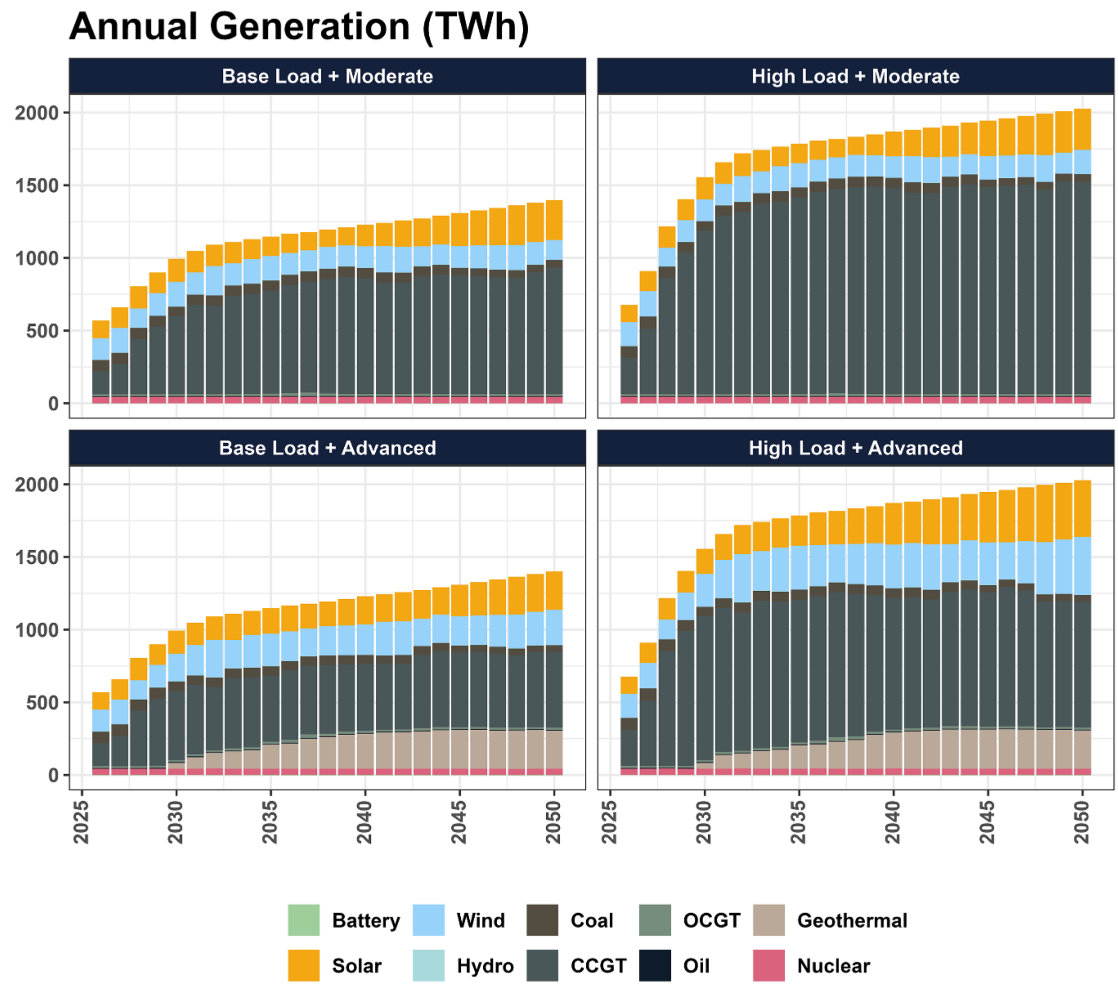

Figure 5. Annual generation (TWh) from 2026 to 2050.

deployment despite capital cost premiums. Overall, this scenario demonstrates that deep decarbonization targets consistent with net-zero emissions require either: (i) substantial nuclear or other firm low-carbon technology cost reductions, (ii) explicit carbon pricing or regulatory mandates, or (iii) acceptance that market-driven capacity expansion cannot achieve stringent climate targets without policy intervention.

4.3. Probabilistic RA assessment

Monte Carlo simulation of 2030 system operations across N = 50 independent realizations quantifies adequacy performance under stochastic demand, renewable generation, and thermal outage conditions. Table 3 summarizes reliability metrics for Moderate and Advanced technology scenarios.

The Moderate scenario exhibits LOLE of 0.18 events/year, exceeding the NERC reference standard of 0.1 events/year (one day in ten years). The 56% LOLP—indicating unserved energy occurrence in 28 of 50 realizations—demonstrates that adequacy risk is widespread across probable operating conditions rather than confined to rare statistical tail events. Total unserved energy across all realizations reaches 1132 GWh, yielding EUE of 22 646 MWh yr^{-1}, an order of magnitude above typical utility planning targets of 1000 MWh yr^{-1}. Peak unserved energy of 20 450 MW (occurring November 19 at 7 AM) represents 14% of projected 2030 peak load, indicating severe supply-demand imbalance during critical hours.

The Advanced scenario demonstrates material adequacy improvements. LOLE declines to 0.11 events/year, approaching the NERC standard; meanwhile, LOLP reduces to 44%, EUE decreases 38% to 13 973 MWh yr^{-1} and peak unserved energy reduces to 18 193 MW. These improvements reflect increased firm capacity from EGS, enhanced operational flexibility from battery storage, and higher renewable capacity providing energy diversity.

Temporal analysis (figure 7) reveals pronounced seasonal adequacy risk concentration across all 50 samples. Winter months (January, November, December) account for 179 h (82%) of unserved

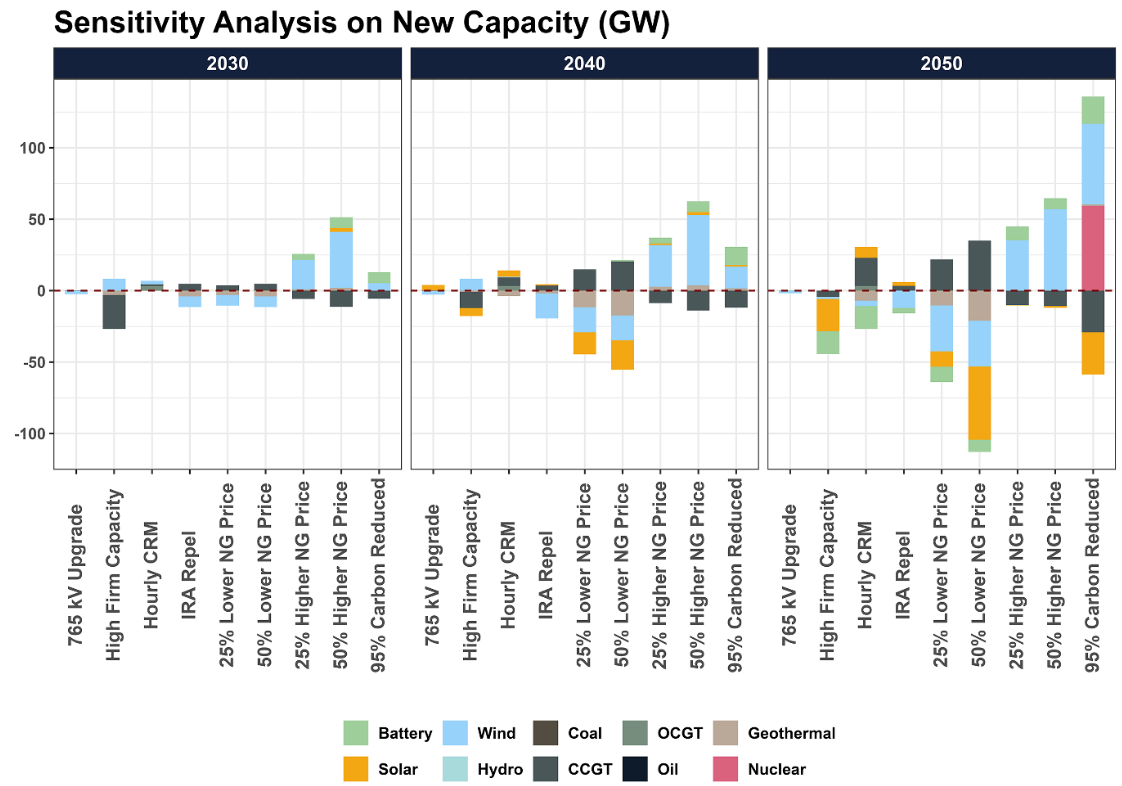

Figure 6. Sensitivity analysis on new capacity (GW).

Table 3. Probabilistic resource adequacy metrics for 2030 (Base Load).

Metric	Moderate	Advanced	Improve	References
LOLE (events/yr)	0.18	0.11	39%	0.1 (Rickerson 2023)
LOLH (h yr^{-1})	4.38	2.68	39%	2.4 (Rickerson 2023)
LOLP (risk)	56%	44%	21%	—
EUE (MWh yr^{-1})	22 646	13 973	38%	1000 (PJM 2023)
Peak USE (MW)	20 450	18 193	11%	—
P50 EUE (MWh yr^{-1})	8273	4673	44%	—
P90 EUE (MWh yr^{-1})	40 173	20 746	48%	—
Samples with USE	28/50	22/50	21%	—

energy events in the Moderate scenario and 112 h (84%) in the Advanced scenario, while January contributes the most. This winter-peaking adequacy risk contrasts sharply with ERCOT's historical summer-peaking pattern, reflecting the combination of: (i) heating electrification driving winter demand growth, (ii) reduced solar availability due to shorter days and lower irradiance, and (iii) cold-weather-induced thermal generator outages and fuel supply constraints. June exhibits moderate adequacy stress of 18–26 h of USE corresponding to early summer peaks before maximum solar production. Spring and fall show minimal adequacy risk.

Diurnal patterns indicate adequacy shortfalls concentrate during morning (5–7 AM) and evening (6–8 PM) net load peaks rather than absolute peak hours. In the Moderate cost scenario, Morning account for 71 unserved energy hours with average magnitude of 5450–6850 MW, driven by pre-sunrise load ramping before solar generation availability. Evening period exhibits 42 h averaging 5010–5590 MW as solar output declines concurrent with residential demand increases. During overnight hours, a total of 54 USE hours reflecting sustained thermal capacity shortfalls when economic dispatch minimizes online generation during low-load periods.

Correlation analysis (figure 8) between unserved energy and system drivers reveals weak statistical relationships. The low R^2 values indicate that adequacy failures result from complex multi-factor interactions rather than single-variable causation. High unserved energy events usually require coincident conditions from elevated demand, reduced renewable output, and thermal outages, which occur infrequently individually but produce severe consequences when combined.

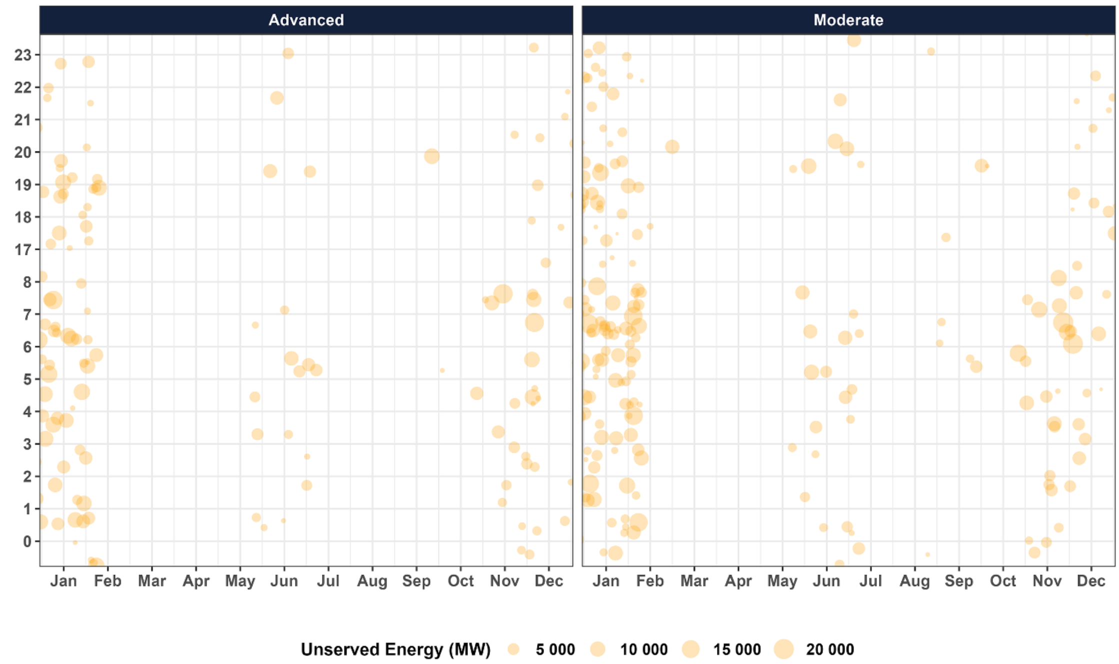

Figure 7. Temporal distribution of unserved energy across Monte Carlo realizations.

All these findings validate the necessity of probabilistic adequacy frameworks: deterministic planning based on peak load or reserve margins cannot capture the multi-dimensional stochastic risk space driving actual reliability outcomes. Improving adequacy requires addressing multiple dimensions simultaneously—firm capacity additions to manage thermal risk and operational flexibility to accommodate renewable variability and demand uncertainty—rather than single-factor interventions.

To evaluate how sensitivity capacity expansion pathways affect operational reliability, we conducted supplementary adequacy assessment for six sensitivity scenarios using the 2030 installed capacity portfolios from section 4.2. Rather than re-running all 50 realizations, we employ a representative stress scenario approach: Monte Carlo sample #8, which exhibited the highest unserved energy frequency in baseline analysis (20 h for Moderate scenario, 11 h for Advanced scenario).

Table 4 presents adequacy metrics across both core load scenarios and sensitivity scenarios. High Load scenarios demonstrate substantially degraded adequacy compared to Base Load: LOLH increases to 56 h yr^{-1} (5× higher) and annual EUE rises to 624 GWh (7× higher), with average unserved energy events reaching 11 143 MW. This degradation reveals that rapid data center-driven load growth outpaces even aggressive CCGT expansion, as gas-dominated portfolios concentrate risk during coincident thermal outages and peak demand periods. Low gas prices degrade adequacy as LOLH rises to 25 h and the annual EUE rises to 128 GWh. The gas-dominated portfolio (+35 GW CCGT, -83 GW renewables) reduces operational diversity and concentrates risk during coincident thermal outages and peak demand. Higher gas prices, on the other hand, improve reliability, reducing LOLH to 6 h and EUE by 60% as the scenario deploys +7.5 GW of battery storage and +2 GW of EGS.

Transmission expansion (765 kV) yields modest reliability gains despite minimal capacity changes, indicating value through congestion relief and geographic diversity rather than capacity quantity. The 95% CO_2 constraint replaces CCGT (–5.6 GW) with wind (+5.2 GW) and battery (+7.6 GW), which has minimum value to improve RA.

During the system planning, overestimation of the renewable capacity credit assumptions could lead to catastrophic adequacy degradation (LOLH reaching 723 h), showing that capacity credit assumptions are essential to prevent systematic underinvestment in firm capacity. Finally, the hourly capacity reserve margin approach strengthens reliability by enforcing minimum reserve requirements across all sampled hours rather than only during peak planning periods. This prevents economic dispatch from reducing online capacity below reserve thresholds during shoulder and overnight hours, thereby mitigating adequacy risk during net-load ramping conditions.

From the sensitivity analysis, we extract the build outs (table D2) from each scenario and run the ST scheduling using Monte Carlo sample 8, which were observed to have the most USE hours (20 h in Moderate and 11 h in Advanced). Low natural gas price (0.5 NG), upgraded transmission (765 kV), and

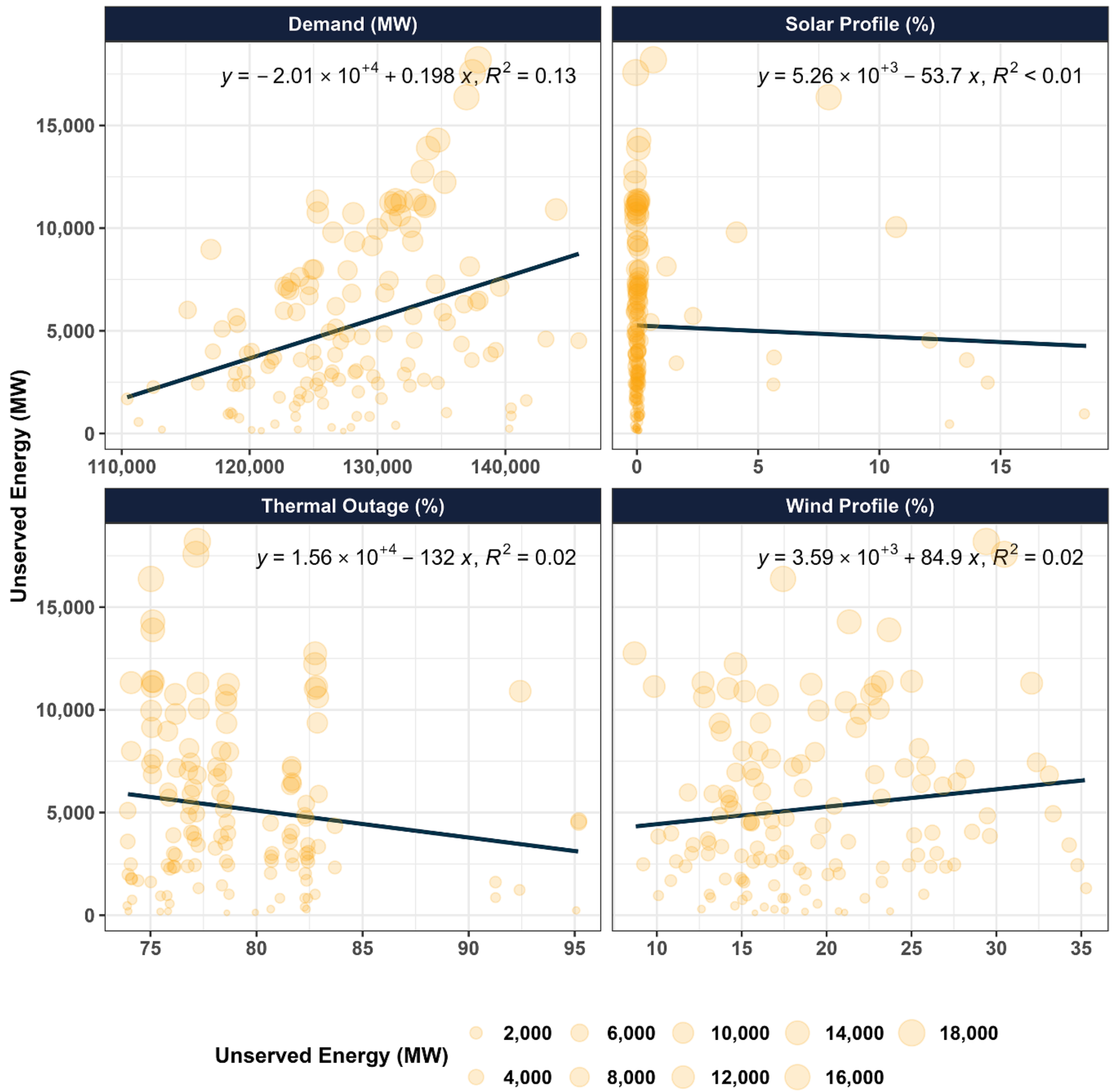

Figure 8. Correlation analysis of unserved energy drivers.

Table 4. Resource adequacy metrics for High Load and sensitivity scenarios (2030).

Scenario	LOLH (hrs yr^{-1})	EUE (MWh yr^{-1})	Avg USE (MW)
Reference Case	11	89 867	8170
High Load Case	56	623 989	11 143
Low NG Price (0.5x)	25	128 885	5155
High NG Price (1.5x)	6	38 373	6396
Transmission (765kV)	14	95 975	6855
95% Carbon Reduction	21	148 818	7087
High Firm Capacity Credit	723	5808 895	8034
Hourly Reserve Margin	6	39 233	6539

95% CO_2 removal (95 CO_2) would unnecessarily reduce or increase the LOLH. However, increasing natural gas price (1.5 NG) would significantly increase the RA as the LOLH reduced to 6 h per year, which is due to the addition of battery (7.5 GW) and EGS (2 GW). In the model setting, when we assumed a higher firm capacity from wind and solar and battery, the LOLH would significantly increase to 723 h, as less new firm capacity would be built (23.7 GW of CCGT and 3 GW of EGS). Thus, the system planner should be extremely careful when assigning firm capacity credit to renewable resources, since it could have a huge impact on RA.

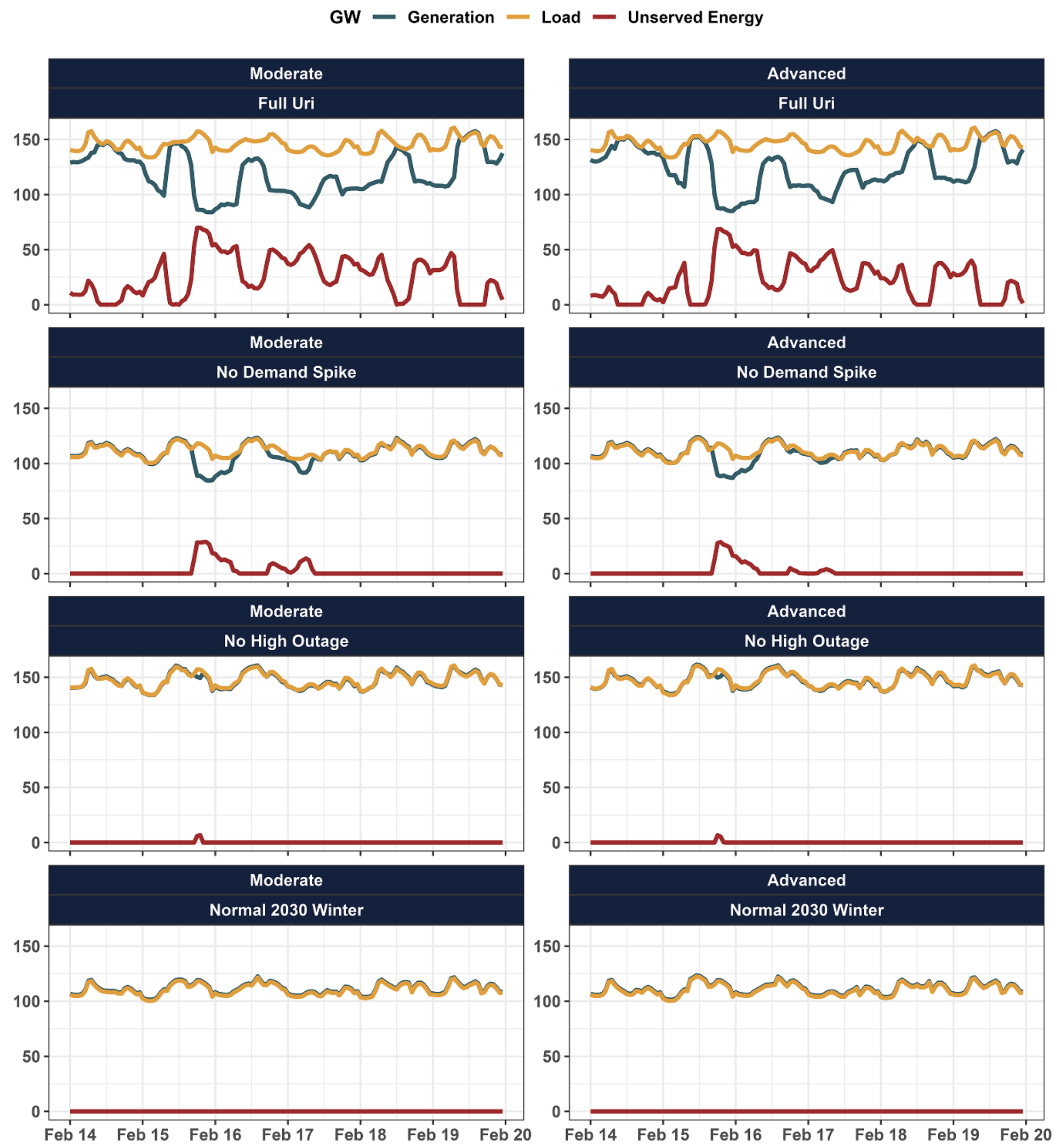

Figure 9. Hourly generation, load, and unserved energy during Winter Storm Uri simulation.

Last but not least, if we enforce the minimum planning reserve margin to all hours, it also helps to increase the system RA (LOLH down to 6 h), since the scenario would provide finer temporal resolution when constraints on minimum planning reserve margin met the goal.

4.4. Winter storm Uri

In the last case study, we evaluate 2030 system resilience under Winter Storm Uri-equivalent conditions through deterministic simulation of February 14–20 operations. Four counterfactual scenarios decompose the relative contributions of demand surge and thermal outages to system inadequacy (figure 9 and table 5).

Full Uri conditions produce severe unserved energy: 3710 GWh over 127 h (Moderate) and 3176 GWh over 117 h (Advanced). Peak unserved energy exceeds 70 GW during morning hours of February 15–16, representing 47% of peak load. The annualized equivalent LOLE (297–322 hrs yr^{-1}) is 68–137× larger than Monte Carlo-based LOLE under normal operations (2.7–4.4 hrs yr^{-1} in table 3). The Advanced scenario achieves 14% reduction in total unserved energy and 8% reduction in event duration through increased firm capacity from EGS (5 GW maintains availability during cold weather) and battery storage providing operational flexibility. However, neither scenario achieves adequate capacity to fully serve load during the most extreme hours during the winter storm.

Table 5. Winter storm Uri simulation adequacy metrics: advanced vs moderate scenarios.

Counterfactual Scenario	Total USE (GWh)	USE	Avg USE (Hours)	Peak USE (MW)	Annualized LOLE (Hours/yr)
Advanced Technology					
Full Uri	3176	117	27 148	71 508	296.6
No Demand Spike	264	28	9428	30 997	71.0
No High Outage	12	3	4019	12 057	7.6
Moderate Technology					
Normal 2030 Winter	0	0	0	0	0.0
Full Uri	3710	127	29 216	74 148	321.9
No Demand Spike	360	30	12 014	36 041	76.0
No High Outage	13	2	6293	12 586	5.1
Normal 2030 Winter	0	0	0	0	0.0

No Demand Spike scenario (normal 2030 winter load + historical outages) reduces unserved energy by 90%–92%, showing that 2030 portfolios have resilience to withstand Uri-level thermal outages in isolation. The persistence of unserved energy (28–30 h) indicates that high forced outage rates affecting both thermal units (freeze-induced failures, fuel supply disruptions) and wind generation (icing, extreme cold) create adequacy shortfalls exceeding installed capacity margins. Advanced scenario superiority reflects EGS maintaining availability during cold weather unlike natural gas units vulnerable to fuel constraints.

No High Outage scenario (historical demand + normal outage rates) produces minimal unserved energy: 12.6 GWh/2 h (Moderate) and 12.1 GWh/3 h (Advanced). Near-complete adequacy demonstrates that 2030 portfolios can serve extreme winter peaks when generation availability remains normal. Residual shortfalls likely reflect transmission constraints or ramping limitations rather than fundamental capacity inadequacy.

Last but not the least, Normal 2030 Winter (control case) scenario exhibits zero unserved energy across all 144 h, confirming that 2030 capacity maintains full adequacy under typical winter operating conditions with substantial headroom.

5. Discussion

5.1. Capacity expansion trajectories and technology mix evolution

Long-term capacity expansion is driven primarily by load growth, technology cost trajectories, and policy stability. Under Moderate cost assumptions, CCGTs dominate additions, with 122–196 GW built by 2050, equivalent to 1.6–3.3× current CCGT capacity. This CCGT-dominated expansion reflects both economic fundamentals and Texas's unique policy framework. Economically, CCGT offers high capacity credits (95%), operational flexibility, and cost competitiveness ($1300–1400/kW capital cost) in energy-only markets. However, unlike California with SB 100 mandating 100% clean energy by 2045, New York with the Climate Leadership and Community Protection Act, or states with renewable portfolio standards, Texas has no state-level renewable portfolio standard, no binding carbon targets, and an energy-only market structure that rewards firm capacity without explicit mechanisms favoring low-carbon resources.

This policy-neutral environment drives cost optimization toward CCGT as the economically rational solution for meeting load growth and adequacy requirements. However, gas-centric portfolios increase exposure to fuel price volatility, cold-weather outages, and long-term decarbonization risks, as demonstrated in the 95% CO_2 reduction sensitivity scenario where nuclear and renewables displace CCGT capacity.

Advanced cost assumptions significantly alter expansion outcomes. Lower EGS capital costs enable 34.5 GW of deployment by 2050, providing firm, weather-resilient baseload generation. Concurrently, declining renewable and storage costs drive substantial increases in solar (+96%), wind (+123%), and long-duration storage, reshaping the optimal generation mix.

Capacity build-out is highly front-loaded due to rapid near-term load growth (10.6%–20.2% annually from 2025–2030). Most additions occur between 2026–2035, with annual builds of 15–20 GW under high-load scenarios. This unprecedented scale—120–180 GW over a decade—poses major challenges for supply chains (International Energy Agency 2023), interconnection processing (ERCOT 2025), and coordinated transmission development (ERCOT 2025a).

Sensitivity results indicate that natural gas price assumptions dominate technology mix outcomes. A 50% reduction in gas prices reduces wind by 32 GW and solar by 51 GW by 2050, while a 50% increase adds 57 GW of solar. This asymmetric response where low gas prices suppress renewables more than high prices encourage them poses risks to clean energy transition goals and suggests the need for policy support beyond cost declines. IRA repeal reduces wind by 12 GW and eliminates enhanced geothermal competitiveness, showing the importance of stable tax incentives to promote renewable plants. By contrast, a 765-kV transmission expansion has minimal capacity impact (<3 GW), indicating transmission primarily improves operational efficiency rather than capacity adequacy.

5.2. Adequacy risk assessment under transformational load growth

Probabilistic adequacy analysis shows persistent shortfalls by 2030 across Moderate and Advanced scenarios, greatly exceeding LOLE and EUE planning benchmarks (Billinton and Allan 1996). Adequacy risk has shifted decisively to winter, with scarcity hours exceeding summer events by 5–7×. This shift is driven by heating electrification, reduced winter solar output, and elevated cold-weather forced outages of gas generation (FERC and NERC 2021, EIA 2026). Risk also concentrates during morning and evening net-load ramps (15–20 GW h^{-1}), approaching system ramping limits. Weak correlations between unserved energy and individual drivers (maximum $R^2 = 0.13$) confirm that failures arise from rare, multi-factor stress events, reinforcing the value of probabilistic planning in high-renewable systems.

Backcasting Winter Storm Uri complements probabilistic adequacy frameworks optimized for typical conditions by highlighting their vulnerability to rare compound events that combine extreme demand with widespread supply disruptions. Under Uri-like conditions, unserved energy reaches 3176–3710 GWh, equivalent to 140–160 times annual EUE. Mitigating either demand spikes or elevated generator outages would eliminate 76%–98% of unserved hours.

The contrast between normal winter conditions with zero unserved energy and severe Uri-level shortfalls underscores a planning dilemma: systems optimized for expected conditions remain exposed to tail risks. Addressing this challenge requires layered resilience strategies combining market-driven capacity, strategic reserves, and demand-side flexibility.

5.3. Implications for ERCOT planning and policy

Current market structures may be insufficient to attract the level of capacity investment required under projected load growth. Elevated adequacy metrics, including LOLE and EUE, indicate that scarcity pricing alone may not deliver reliability consistent with traditional planning standards. Potential responses include strengthened scarcity pricing, forward capacity mechanisms, performance-based reliability obligations, or an explicit reassessment of acceptable risk levels during periods of rapid demand expansion.

The shift of adequacy risk from summer to winter requires immediate planning attention. Winter-specific adequacy assessments, enhanced winterization standards, fuel assurance for prolonged cold events, and seasonal capacity products that appropriately value winter availability are increasingly necessary. Beyond routine planning, extreme weather resilience demands additional measures. Uri backcasting suggests that resilience can be achieved through a combination of strategic reserves for rare events, large-scale interruptible load programs (on the order of 10–20 GW), materially higher reserve margins, or explicit acceptance of controlled reliability degradation supported by emergency response protocols.

Technology diversity materially improves resilience outcomes. The Advanced scenario demonstrates significant reductions in unserved energy through portfolios combining enhanced geothermal, storage, and renewables. Policies supporting diversification—such as sustained IRA incentives, targeted R&D, and streamlined interconnection—can strengthen reliability while advancing decarbonization.

Finally, integrating large flexible loads, particularly data centers, will require coordinated generation and transmission planning, streamlined interconnection, locational incentives, and potential load interruptibility requirements. Achieving deep decarbonization will similarly require policy interventions beyond cost declines, including clean energy standards, carbon pricing, or targeted nuclear support.

5.4. Study limitations and future research

This study estimates RA by translating future build-out profiles from the PLEXOS LT Plan into the ST Schedule. Despite enforcing minimum reserve margin requirements in the LT Plan, the ST simulations still exhibit substantial unserved energy. This outcome reflects structural differences between long-term planning and short-term operational modeling rather than a failure of the optimization.

The LT Plan relies on reduced chronology to manage computational complexity, representing load and generator availability with a limited number of time blocks. While sufficient for identifying aggregate capacity needs, this abstraction can mask critical intra-day dynamics. As a result, capacity portfolios that appear adequate in the LT Plan may fail to meet demand in the ST Schedule during specific hours, such as evening net-load peaks when solar output is unavailable and system flexibility is limited.

This issue is exacerbated under high renewable penetration, as variable resources are particularly sensitive to temporal resolution. Adequacy evaluated under aggregated blocks may therefore miss hour-specific shortfalls. Future work should explore increasing LT chronology resolution without excessive computational burden and iteratively feeding high-USE periods identified in ST simulations back into LT planning to better align long- and short-term adequacy outcomes.

In addition, the LT plan assumes perfect foresight regarding load growth, technology costs, and policy conditions. However, real-world investment decisions occur under uncertainty with potential for stranded assets or inadequate capacity if projections prove incorrect. For the new technology costs, currently we applied exogenous capex assumptions, but future studies should consider endogenous capex based on the installed capacity from previous solving steps.

In the Monte Carlo analysis, this study uses 50 realizations which provide reasonable statistical coverage for central adequacy metrics but may inadequately sample rare extreme events. This is the reason we include the case study applying the winter storm Uri condition. However, future work should consider employing larger sample sizes.

Last but not least, the RA analysis does not explicitly model demand response, interruptible load programs, or behavioral demand elasticity. Given the magnitude of projected adequacy shortfalls, demand-side flexibility may provide more cost-effective reliability enhancement than supply-side capacity additions. Future research should co-optimize supply and demand resources within integrated planning frameworks.

6. Conclusion

This study develops an integrated framework in PLEXOS for long-term capacity expansion and probabilistic RA assessment of ERCOT under rapid load growth and rising renewable penetration. By coupling long-term planning with Monte Carlo for reliability evaluation and extreme-event stress testing, the analysis captures both structural investment decisions and operational uncertainty. Accelerated data center growth drives unprecedented generation expansion requirements, while simultaneously shifting system vulnerability from traditional gross peak hours to net-load peak periods. Reliability risks increasingly arise when elevated demand coincides with higher-than-expected thermal outages, creating conditions under which blackouts become more likely.

The results demonstrate that ERCOT's future reliability cannot be secured through capacity expansion alone. Instead, system resilience depends on technology diversification, conservative and probabilistically grounded capacity credit assumptions, strengthened operational constraints, and coordinated planning across generation, transmission, and demand-side flexibility. Together, these elements are essential to managing adequacy risk in a high-load, high-renewable system undergoing structural transformation.

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Data availability statement

The data cannot be made publicly available upon publication because they contain commercially sensitive information. The data that support the findings of this study are available upon reasonable request from the authors.

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Appendix A. Complete optimization formulations

This appendix provides the complete mathematical formulations for the long-term capacity expansion and short-term unit commitment and economic dispatch optimization problems implemented in PLEXOS.

A.1. Long-term capacity expansion formulation

The capacity expansion model minimizes the net present value (NPV) of total system costs over the planning horizon $\mathcal{T} = \{2025, 2026, \ldots, 2050\}$:

$$\min \sum_{t\in\mathcal{T}} \frac{1}{(1+r)^{t-2025}} \left[\sum_{g\in\mathcal{G}} \left(C^{\text{cap}}_{g,t} x_{g,t} + C^{\text{FOM}}_{g,t} K_{g,t} \right) + \sum_{h\in\mathcal{H}} \sum_{g\in\mathcal{G}} \left(C^{\text{VOM}}_{g} + C^{\text{fuel}}_{g,h} \right) P_{g,h,t} \right]. \tag{7}$$

Decision variables:

- $x_{g,t}$: New capacity additions of technology g in year t (MW)
- $K_{g,t}$: Total installed capacity of technology g in year t (MW)
- $P_{g,h,t}$: Power generation from unit g in hour h of year t (MW)
- $R_{g,t}$: Capacity retirements of technology g in year t (MW)
- $P^{\text{chg}}_{s,h,t}, P^{\text{dis}}_{s,h,t}$: Battery storage charging/discharging (MW)
- $\text{SOC}_{s,h,t}$: Battery state of charge (MWh)

Parameters:

- $C^{\text{cap}}_{g,t}$: Overnight capital cost (\$/kW)
- $C^{\text{FOM}}_{g,t}$: Fixed operations and maintenance cost (\$/kW-yr)
- C^{VOM}_{g}: Variable operations and maintenance cost (\$/MWh)
- $C^{\text{fuel}}_{g,h}$: Fuel cost (\$/MWh)
- r: Weighted average cost of capital (discount rate)
- $D_{h,t}$: Electricity demand in hour h of year t (MW)
- FCC_g: Firm capacity credit of technology g (fraction)
- PRM: Planning reserve margin requirement (0.1375)
- $\text{AF}_{g,h,t}$: Availability factor for technology g (fraction)

Sets:

- $\mathcal{G}$: Set of generation technologies
- $\mathcal{S}$: Set of storage technologies
- $\mathcal{H}$: Set of representative hours (288 time blocks/year)
- $\mathcal{T}$: Planning horizon years

Subject to constraints:
Energy balance:

$$\sum_{g\in\mathcal{G}} P_{g,h,t} + \sum_{s\in\mathcal{S}} P^{\text{dis}}_{s,h,t} = D_{h,t} + \sum_{s\in\mathcal{S}} P^{\text{chg}}_{s,h,t} \quad \forall h\in\mathcal{H}, t\in\mathcal{T}. \tag{8}$$

Capacity accumulation:

$$K_{g,t} = K_{g,t-1} + x_{g,t} - R_{g,t} \quad \forall g\in\mathcal{G}, t\in\mathcal{T}. \tag{9}$$

Planning reserve margin:

$$\sum_{g\in\mathcal{G}} \text{FCC}_g \cdot K_{g,t} \geqslant (1+\text{PRM}) \cdot \max_{h\in\mathcal{H}} D_{h,t} \quad \forall t\in\mathcal{T}. \tag{10}$$

Generation capacity limits:

$$0 \leqslant P_{g,h,t} \leqslant \text{AF}_{g,h,t} \cdot K_{g,t} \quad \forall g\in\mathcal{G}, h\in\mathcal{H}, t\in\mathcal{T}. \tag{11}$$

Non-negativity:

$$x_{g,t} \geqslant 0, \quad R_{g,t} \geqslant 0 \quad \forall g\in\mathcal{G}, t\in\mathcal{T}. \tag{12}$$

Battery storage dynamics:

$$\text{SOC}_{s,h,t} = \text{SOC}_{s,h-1,t}(1-\sigma) + P^{\text{chg}}_{s,h,t}\eta^{\text{chg}} - \frac{P^{\text{dis}}_{s,h,t}}{\eta^{\text{dis}}} \quad \forall s\in\mathcal{S}, h\in\mathcal{H}, t\in\mathcal{T}. \tag{13}$$

State of charge limits:

$$0 \leqslant \text{SOC}_{s,h,t} \leqslant E^{\text{cap}}_s \quad \forall s\in\mathcal{S}, h\in\mathcal{H}, t\in\mathcal{T}. \tag{14}$$

Charging/discharging power limits:

$$0 \leqslant P^{\text{chg}}_{s,h,t} \leqslant P^{\text{chg,max}}_s, \quad 0 \leqslant P^{\text{dis}}_{s,h,t} \leqslant P^{\text{dis,max}}_s \quad \forall s\in\mathcal{S}, h\in\mathcal{H}, t\in\mathcal{T} \tag{15}$$

where σ is self-discharge rate, η^{chg} and η^{dis} are charge and discharge efficiencies, E^{cap}_s is energy capacity (MWh), and $P^{\text{chg,max}}_s$, $P^{\text{dis,max}}_s$ are maximum charge/discharge power (MW).

A.2. Short-term unit commitment and economic dispatch formulation

The short-term optimization is solved for each Monte Carlo realization i and each hour h over the full year (8760 hours), minimizing operational costs:

$$\min \sum_{h=1}^{8760} \left[\sum_{g\in\mathcal{G}} \left(C^{\text{VOM}}_g P_{g,h,i} + C^{\text{fuel}}_{g,h} H_{g,h} P_{g,h,i} + C^{\text{start}}_g u^{\text{start}}_{g,h,i} \right) + C^{\text{VOLL}} \cdot \text{USE}_{h,i} \right]. \tag{16}$$

Decision variables:

- $P_{g,h,i}$: Power output from generator g in hour h, realization i (MW)
- $u_{g,h,i}$: Binary commitment status (1 if online, 0 if offline)
- $u^{\text{start}}_{g,h,i}$: Binary start-up decision (1 if unit starts in hour h)
- $u^{\text{stop}}_{g,h,i}$: Binary shutdown decision (1 if unit stops in hour h)
- $\text{USE}_{h,i}$: Unserved energy in hour h, realization i (MW)
- $P^{\text{chg}}_{s,h,i}, P^{\text{dis}}_{s,h,i}$: Battery charging/discharging (MW)
- $\text{SOC}_{s,h,i}$: Battery state of charge (MWh).

Parameters:

- $H_{g,h}$: Heat rate of generator g in hour h (MMBtu/MWh)
- C^{start}_g: Start-up cost ($/start)
- C^{VOLL}: Value of lost load penalty ($/MWh, typically $9000)
- $P^{\min}_g, P^{\max}_g$: Minimum and maximum generation capacity (MW)
- $\text{FOR}_{g,h,i}$: Forced outage rate (stochastically sampled per realization)
- $T^{\text{up}}_g, T^{\text{down}}_g$: Minimum up/down time (hours)
- $R^{\text{up}}_g, R^{\text{down}}_g$: Ramp-up/down rate (MW h^{-1})
- $\text{RSV}^{\text{req}}_{h,i}$: Reserve requirement in hour h (MW)

Subject to constraints:
Energy balance with unserved energy:

$$\sum_{g\in\mathcal{G}} P_{g,h,i} + \sum_{s\in\mathcal{S}} P^{\text{dis}}_{s,h,i} + \text{USE}_{h,i} = D_{h,i} + \sum_{s\in\mathcal{S}} P^{\text{chg}}_{s,h,i} \quad \forall h. \tag{17}$$

Unit commitment logic:

$$P^{\min}_g u_{g,h,i} \leqslant P_{g,h,i} \leqslant P^{\max}_g u_{g,h,i} \left(1 - \text{FOR}_{g,h,i}\right) \quad \forall g \in \mathcal{G}, h. \tag{18}$$

Commitment state transition:

$$u_{g,h,i} - u_{g,h-1,i} = u^{\text{start}}_{g,h,i} - u^{\text{stop}}_{g,h,i} \quad \forall g \in \mathcal{G}, h. \tag{19}$$

Minimum up time:

$$\sum_{h'=h}^{\min\left(h+T^{\text{up}}_g-1,\,8760\right)} u_{g,h',i} \geqslant T^{\text{up}}_g \cdot u^{\text{start}}_{g,h,i} \quad \forall g \in \mathcal{G}, h. \tag{20}$$

Minimum down time:

$$\sum_{h'=h}^{\min\left(h+T^{\text{down}}_g-1,\,8760\right)} \left(1 - u_{g,h',i}\right) \geqslant T^{\text{down}}_g \cdot u^{\text{stop}}_{g,h,i} \quad \forall g \in \mathcal{G}, h. \tag{21}$$

Ramp-up limit:

$$P_{g,h,i} - P_{g,h-1,i} \leqslant R^{\text{up}}_g \cdot u_{g,h-1,i} + P^{\max}_g \cdot u^{\text{start}}_{g,h,i} \quad \forall g \in \mathcal{G}, h. \tag{22}$$

Ramp-down limit:

$$P_{g,h-1,i} - P_{g,h,i} \leqslant R^{\text{down}}_g \cdot u_{g,h,i} + P^{\max}_g \cdot u^{\text{stop}}_{g,h,i} \quad \forall g \in \mathcal{G}, h. \tag{23}$$

Reserve requirements:

$$\sum_{g\in\mathcal{G}}\left(P_g^{\max}u_{g,h,i}\left(1-\mathrm{FOR}_{g,h,i}\right)-P_{g,h,i}\right)\geqslant \mathrm{RSV}_{h,i}^{\mathrm{req}}\quad \forall h. \tag{24}$$

Battery storage constraints (identical to LT formulation):

$$\mathrm{SOC}_{s,h,i}=\mathrm{SOC}_{s,h-1,i}\left(1-\sigma\right)+P_{s,h,i}^{\mathrm{chg}}\eta^{\mathrm{chg}}-\frac{P_{s,h,i}^{\mathrm{dis}}}{\eta^{\mathrm{dis}}}\quad \forall s\in\mathcal{S},h \tag{25}$$

$$0\leqslant P_{s,h,i}^{\mathrm{chg}}\leqslant P_s^{\mathrm{chg,max}},\quad 0\leqslant P_{s,h,i}^{\mathrm{dis}}\leqslant P_s^{\mathrm{dis,max}}\quad \forall s\in\mathcal{S},h \tag{26}$$

$$\mathrm{SOC}_s^{\min}\leqslant \mathrm{SOC}_{s,h,i}\leqslant E_s^{\mathrm{cap}}\quad \forall s\in\mathcal{S},h. \tag{27}$$

Note on application: The same ST formulation is used for:

- **Monte Carlo simulations:** Parameters $D_{h,i}$, $\mathrm{FOR}_{g,h,i}$, and renewable availability are stochastically sampled from ERCOT MORA probability distributions for each realization $i=1,\ldots,50$.
- **Winter Storm Uri stress test:** Parameters are deterministically set to historical 14–19 February, 2021 conditions with elevated forced outage rates and demand multiplier.

Appendix B. Load forecast

Hourly system demand is represented using ERCOT LT Load Forecast (LTLF) data covering the period 2025–2044 with zonal disaggregation (ERCOT 2025c). To capture uncertainty in data center deployment and large flexible load growth, we employ two demand trajectories. Adjusted Load Forecast (Base scenario) reflects ERCOT's risk-adjusted projections incorporating historical realization rates for contracted large loads under the ERCOT LTLF report. Under this scenario, data center interconnection requests are reduced to 49.8% of contracted values based on historical completion rates, TSP officer-attested load additions are reduced to 55.4%, and all large load ramp schedules include 180-day commissioning delays (ERCOT 2025c). Alternatively, TSP-Provided Forecast (High scenario) incorporates all executed interconnection agreements, credible third-party forecasts, and TSP-attested loads without any risk adjustments; it represents maximum plausible load growth under aggressive data center deployment assumptions (ERCOT 2025c).

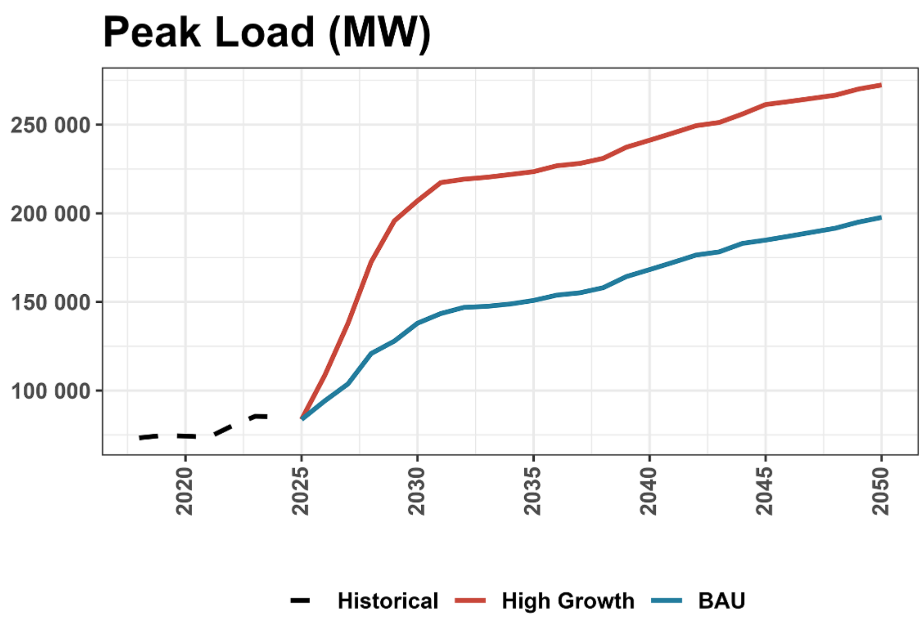

Figure B1. ERCOT-wide annual peak load comparing historical (2018–2024), the BAU scenario, and the High Growth scenario.

Projection extension to 2050 employs zone-specific extrapolation of 2025–2044 growth trajectories. Annual energy growth rates are calculated for each weather zone from the final five forecast years (2040–2044) and applied to subsequent years with linear tapering to zero by 2050, reflecting diminishing confidence in long-horizon projections. Hourly load shapes are preserved through normalized temporal weighting factors (month × weekday × hour) averaged over 2040–2044 and rescaled annually to match projected zonal energy totals, maintaining diurnal and seasonal load patterns.

From figure B1, the Base LTLF scenario exhibits AAGR of 10.6% for 2025–2030, substantially exceeding the historical 2.6% AAGR observed during 2018–2024. The High scenario projects 20.2% AAGR for the same period, unprecedented in ERCOT operational history. Growth moderates to 2.1%–1.6% AAGR for 2030–2040 as near-term data center deployment saturates, concentrating transformational load expansion within the immediate five-year planning horizon. Figure B2 shows the annual load in TWh by each weather zone.

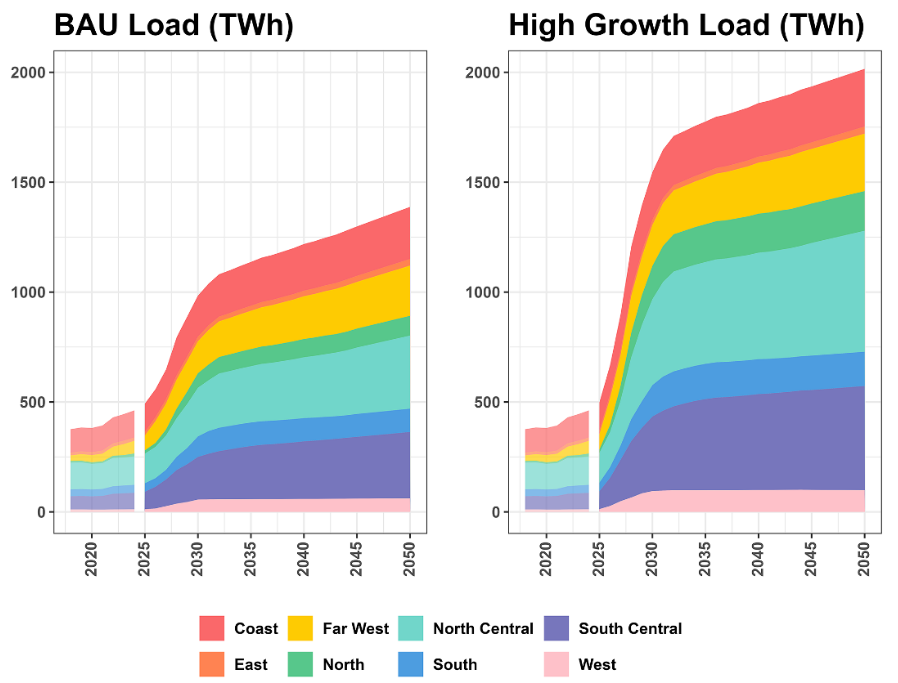

Figure B2. The annual load (TWh) by ERCOT weather zones.

Appendix C. Planned generators to build and retire

Table C1. Planned capacity in the ERCOT GIS query.

	2025	2026	2027	2028	Grand Total
Battery	3285	4628	1170	1200	10 283
Solar	3500	4500	3500	2500	14 000
Wind	0	0	0	0	0
CCGT	0	0	0	0	0
OCGT	0	0	0	0	0

Table C2. Planned retirement capacity by 5-year intervals (MW).

Tech.	2025–29	2030–34	2035–39	2040–44	2045–49	**Total**
CCGT	0	0	1393	0	0	1393
OCGT	2942	176	958	82	16	4174
Coal	1215	1660	0	2514	0	5389
Wind	75	0	0	0	0	75
Total	**4232**	**1836**	**2351**	**2596**	**16**	**11 031**

Table C3. Future technology costs by scenarios.

Technology	Year	CAPEX Adv. ($/kW)	CAPEX Mod. ($/kW)	FOM Adv. ($/kW-yr)	FOM Mod. ($/kW-yr)	WACC (%)
Battery 1hr	2030	556.2	1059.8	19.15	25.54	6.59
	2040	645.2	927.3	15.55	22.34	6.59
Battery 2hr	2030	665.8	1239.8	22.92	29.87	6.59
	2040	772.2	1084.8	18.61	26.14	6.59
Battery 4hr	2030	884.8	1599.7	30.46	38.55	6.59
	2040	1026.3	1399.8	24.73	33.73	6.59
CCGT	2030	1381.1	1403.3	30.7	31.8	5.36
	2040	1252.0	1292.5	27.1	29.0	5.36
EGS	2030	2099.1	12 726.4	121.68	188.83	5.15
	2040	1693.5	10 889.8	121.68	165.40	5.15
Nuclear	2030	6471.3	7616.4	126.0	175.0	5.65
	2040	3749.7	6314.4	126.0	175.0	5.65
Offshore Wind	2030	2241.4	4387.3	73.64	79.39	5.15
	2040	2744.8	3259.2	66.62	72.70	5.15
OCGT	2030	1270.5	1270.5	25.0	25.0	5.36
	2040	1172.5	1172.5	23.5	23.5	5.36
SMR	2030	6416.7	9650.0	118.0	136.0	5.65
	2040	2979.2	6373.8	118.0	136.0	5.65
Solar PV	2030	748.7	1193.5	16.64	17.99	4.38
	2040	642.8	824.5	12.30	14.26	4.79
Solar PV BESS	2030	1088.0	1855.7	45.86	54.64	4.64
	2040	1059.8	1399.5	39.24	48.24	4.94
Wind	2030	939.2	1408.0	26.31	29.26	5.19
	2040	1175.9	1261.4	21.35	27.26	5.36

Appendix D. Sensitivity analysis

Table D1. Sensitivity analysis scenarios modeled in the study.

Scenario	Modified inputs	Goal / Research Question
S1. 765-kV transmission	Five inter-zonal corridor upgrades (Coast–South Central, NC–SC, SC–West, West–Far West, West–South); ITL +600–3000 MW	Test if transmission can defer generation via congestion relief and improved renewable access
S2. IRA Repeal	Eliminate all PTC/ITC (wind, solar, geothermal, storage)	Quantify policy dependency of renewable deployment
S3a. Gas Price (−50%)	Baseline gas price -50%	Span historical volatility: low-price (abundant shale, weak demand) vs high-price (constraints, LNG exports) scenarios
S3b. Gas Price (−25%)	Baseline gas price −25%	(continued)
S3c. Gas Price (+25%)	Baseline gas price +25%	(continued)
S3d. Gas Price (+50%)	Baseline gas price +50%	(continued)
S4. 95% CO_2 Reduction	Constraint: ⩾95% emission-free generation	Test deep decarbonization feasibility; identify technology mix transformations
S5. High Firm Capacity	Solar: 76% firm capacity; Wind: 28% (ERCOT CDR historical values)	Investigate importance of updating firm capacity credits under high VRE penetration
S6. Hourly Reserve Margin	13.75% reserve requirement applied to all hours (not just peak)	Ensure adequacy during gross and net load peaks; capture ramping dynamics

Table D2. Sensitivity analysis on new capacity, comparing to the reference case (GW).

Year	SA Scenarios	Battery	Solar	Wind	CCGT	OCGT	EGS	Nuclear
2030	Base + Advanced	–	–	7.5	48.9	–	5.0	–
	765 kV Upgrade	–	–	−2.4	+0.2	–	–	–
	High Firm Capacity	–	–	+8.3	−23.7	–	–3.0	–
	Hourly CRM	–	–	+2.5	+1.1	+3.3	−0.1	–
	IRA Repeal	–	–	−7.5	+4.7	–	−4.0	–
	25% Lower Gas Price	–	–	−7.5	+3.7	–	−3.0	–
	50% Lower Gas Price	–	–	−7.5	+4.7	–	−4.0	–
	25% Higher Gas Price	+4.1	–	+20.6	−5.8	–	+1.0	–
	50% Higher Gas Price	+7.5	+2.6	+39.2	−11.2	–	+2.0	–
	95% Carbon Reduct.	+7.6	–	+5.2	–5.6	–	–	–
2040	Base + Advanced	–	20.5	17.5	57.0	–	30.8	–
	765 kV Upgrade	–	+3.7	−2.4	+0.3	–	−0.4	–
	High Firm Capacity	–	−5.5	+8.3	−11.4	–	−0.8	–
	Hourly CRM	–	+4.4	+0.5	+5.9	+3.3	−3.8	–
	IRA Repeal	–	+0.9	−17.5	+3.6	–	−1.9	–
	25% Lower Gas Price	–	−15.4	−17.5	+15.0	–	−11.7	–
	50% Lower Gas Price	+1.0	−20.5	−17.5	+20.5	–	−17.3	–
	25% Higher Gas Price	+4.1	+1.1	+29.1	−8.6	–	+2.8	–
	50% Higher Gas Price	+7.5	+2.0	+49.2	−13.8	–	+3.7	–
	95% Carbon Reduct.	+12.8	+1.0	+15.2	−11.9	–	+1.7	–
2050	Base + Advanced	16.0	51.2	32.1	74.2	–	34.5	–
	765 kV Upgrade	+0.3	−0.0	−1.8	−0.0	–	–	–
	High Firm Capacity	−16.0	−22.6	−1.5	−4.3	–	–	–
	Hourly CRM	−16.0	+7.7	−3.8	+19.7	+3.3	−7.0	–
	IRA Repeal	−3.8	+2.7	−12.1	+3.4	–	–	–
	25% Lower Gas Price	−10.7	−10.8	−32.1	+21.8	–	–10.4	–
	50% Lower Gas Price	−8.5	−51.2	−32.1	+35.0	–	–21.0	–
	25% Higher Gas Price	+9.9	−0.3	+35.2	−10.1	–	–	–
	50% Higher Gas Price	+7.7	−1.3	+57.1	−10.7	–	–	–
	95% Carbon Reduct.	+19.1	−29.5	+56.4	−29.1	–	+1.0	+59.3

Appendix E. Demand response from data centers

Data centers represent a unique demand-side resource for power system flexibility due to several technical characteristics distinguishing them from traditional electricity consumers. Computational workloads exhibit temporal flexibility through task scheduling, load balancing across geographic locations, and cooling system optimization. Unlike residential or commercial loads requiring immediate service delivery, many data center operations—including batch processing, machine learning model training, blockchain mining, and content rendering—can tolerate delays of minutes to hours without service degradation (Ghatikar *et al* 2012, Kim *et al* 2017).

To evaluate the reliability and economic value of flexible data center demand, we model demand response (DR) as a dispatchable resource with intertemporal energy balancing capability. During scarcity conditions—when locational marginal prices (LMPs) approach the ERCOT cap of \$5000 MWh^{-1}—data centers voluntarily curtail load, effectively providing capacity to serve inflexible demand. Curtailed energy is subsequently restored during low-price periods, allowing deferred computational tasks to be completed. Over the full simulation year, total curtailed energy must equal total restored energy.

In PLEXOS, flexible data center load is represented as a virtual generator in each weather zone with a maximum curtailment capability of 10 GW. Curtailment earns revenue at prevailing LMP (capped at \$5000 MWh^{-1}), while restoration incurs energy costs at the corresponding LMP. Net revenue reflects intertemporal price arbitrage and reliability value.

Using the Advanced technology 2030 scenario under Monte Carlo sample #8 (the most stressed baseline realization), enabling flexible data center DR eliminates all unserved energy, reducing LOLH from 11 hours to zero. Curtailment is concentrated in the previous unserved energy hours in January, February, and November, when adequacy risk is highest.

Table E1 quantifies the economic performance of flexible data center DR through energy market arbitrage. Load restoration occurs during subsequent low-price periods, with optimal scheduling minimizing energy costs subject to the annual energy balance constraint. Total annual net revenue reaches approximately \$740 million, with the majority earned during winter stress periods, particularly November. These results demonstrate that large-scale flexible data center DR can provide substantial reliability enhancement while generating significant economic value, highlighting its potential role as a strategic adequacy resource in high-load ERCOT futures.

Table E1. Economic performance of flexible data center demand response (2030, \$ millions).

Month	Total Curt. (MW)	Total Rest. (MW)	Geographic Distribution (MW)	Curtail. Rev. (dollar; M)	Restor. Cost (dollar; M)
January	15 425	15 425	North: 8373; Far West: 6042; South Central: 860; West: 150	\$77.13	\$0.19
February	18 311	0	North: 12 805; Far West: 5507	\$91.56	—
March	0	18 311	North: 12 805; Far West: 5507	—	\$0.21
April–Aug.	0	0	No curtailment or restoration	—	—
September	21 827	21 827	North: 19 738; West: 1849; North Central: 240	\$109.13	\$0.45
October	0	0	No curtailment or restoration	—	—
November	93 020	93 020	North: 39 613; Far West: 27 146; South Central: 16 259; West: 6574; South: 3429	\$465.10	\$2.00
December	0	0	No curtailment or restoration	—	—
Annual Total	148 584	148 584	**North: 54%**; Far West: 26%; South Central: 12%; West: 6%; South: 2%	\$742.92	\$2.85

References

Abbasi A R and Mohammadi M 2023 Probabilistic load flow in distribution networks: an updated and comprehensive review with a new classification proposal *Electr. Power Syst. Res.* **222** 109497

Aditya T, Jaipuria S and Dadabada P K 2025 A review of methods for long-term electric load forecasting *J. Forecast.* **44** 1403–23

Amin M R, Negnevitsky M, Franklin E, Alam K S and Naderi S B 2021 Application of battery energy storage systems for primary frequency control in power systems with high renewable energy penetration *Energies* **14** 1379

Bellenbaum J, Böcker B, Kallabis T and Weber C 2019 Probabilistic methodology for adequacy assessment under uncertainty for a multi-region system (available at: https://papers.ssrn.com/abstract=4390364)

Bennett J A, Trevisan C N, DeCarolis J F, Ortiz-García C, Pérez-Lugo M, Etienne B T and Clarens A F 2021 Extending energy system modelling to include extreme weather risks and application to hurricane events in Puerto Rico *Nat. Energy* **6** 240–9

Billinton R and Allan R N 1996 *Reliability Evaluation of Power Systems* (Springer) (available at: https://link.springer.com/10.1007/978-1-4899-1860-4)

Blair N, DiOrio N, Freeman J, Gilman P, Janzou S, Neises T and Wagner M 2018 System advisor model (SAM) general description (version 2017.9.5) *Technical Report NREL/TP-6A20-70414* 1440404, MainId:13734 (available at: www.osti.gov/servlets/purl/1440404/)

Brinkman G *et al* 2021 The north american renewable integration study (NARIS): A U.S. perspective *Technical Report NREL/TP-6A20-79224* (National Renewable Energy Laboratory (NREL)) (available at: www.osti.gov/biblio/1804701)

Brown P R, Barrows C P, Wright J G, Brinkman G L, Dalvi S, Zhang J and Mai T 2023 A general method for estimating zonal transmission interface limits from nodal network data (arXiv:2308.03612v1)

Busby J W, Baker K, Bazilian M D, Gilbert A Q, Grubert E, Rai V, Rhodes J D, Shidore S, Smith C A and Webber M E 2021 Cascading risks: understanding the 2021 winter blackout in Texas *Energy Res. Soc. Sci.* **77** 102106

Chen C and Cohan D S 2026 Potential geothermal deployments for U.S. electricity and industrial heat *Energy Convers. Manage.* **348** 120711

Chen C, Hashimoto C M and Cohan D S 2025 Impacts of potential investments on electricity resource adequacy and emissions in Texas *Energy Strategy Rev.* **60** 101796

Chen X, Lv J, McElroy M B, Han X, Nielsen C P and Wen J 2018 Power system capacity expansion under higher penetration of renewables considering flexibility constraints and low carbon policies *IEEE Trans. Power Syst.* **33** 6240–53

Chen Y, Shi K, Chen M and Xu D 2023 Data center power supply systems: from grid edge to point-of-load *IEEE J. Emerg. Sel. Top. Power Electron.* **11** 2441–56

Consulting A 2025 Effective load carrying capability study (available at: www.ercot.com/files/docs/2025/02/12/2024ERCOT_ELCC_Study_Final_Report02112025.pdf)

Conto J, Cheng Y, Rose J and Schmall J 2025 Texas loads ride toward grid stability: voltage ride through of large power electronic loads *IEEE Power Energy Mag.* **23** 56–67

Deshpande S, Marx C and Kuleshov V 2024 Online calibrated and conformal prediction improves bayesian optimization (arXiv:2112.04620 [cs])

DOE 2025 Report on Evaluating U. S. grid reliability and security *Technical Report* U.S. Department of Energy (DOE)

Draxl C, Clifton A, Hodge B-M and McCaa J 2015 The wind integration national dataset (WIND) toolkit *Appl. Energy* **151** 355–66

EIA 2025 Annual electric power industry report, form eia-860 detailed data with previous form data (EIA-860A/860B) (available at: www.eia.gov/electricity/data/eia860/)

EIA 2026a Short-term energy outlook - U.S. energy information administration (EIA) (available at: www.eia.gov/outlooks/steo/)

EIA 2026b Form EIA-923 detailed data with previous form data (EIA-906/920) - U.S. energy information administration (EIA) (available at: www.eia.gov/electricity/data/eia923/index.php)

EIA 2026 Residential energy consumption survey (RECS) (available at: www.eia.gov/consumption/residential/data/2020/)

Emmanuel M, Doubleday K, Cakir B, Marković M and Hodge B-M 2020 A review of power system planning and operational models for flexibility assessment in high solar energy penetration scenarios *Sol. Energy* **210** 169–80

ERCOT 2021 Resource adequacy 2021b (available at: www.ercot.com/gridinfo/resource/2021)

ERCOT 2021a Available generation and estimated load without load shed data (available at: www.ercot.com/files/docs/2021/03/18/Available_Generation_and_Estimated_Load_without_Load_Shed_Data.xlsx)

ERCOT 2022 ERCOT interconnection inertia analysis (available at: https://view.officeapps.live.com/op/view.aspx?src)

ERCOT 2023 Commissioner memorandum 2023 (available at: www.ercot.com/files/docs/2023/03/08/PUCT_Commissioner Memo_52373_398_1272439.PDF)

ERCOT 2023 ERCOT adds new ancillary service to support grid reliability (available at: www.ercot.com/news/release/2023-06-12-ercot-adds-new)

ERCOT 2023 Resource adequacy 2022 (available at: www.ercot.com/gridinfo/resource/2022)

ERCOT 2024 ERCOT ancillary services study (available at: www.ercot.com/files/docs/2024/10/07/ERCOT-Ancillary-Services-Study-Final-White-Paper.pdf)

ERCOT 2024 Historic data - ERCOT wind profiles and solar PV profiles 1980–2023 (available at: https://ercot.servicenowservices.com/csp?id = kb_article_view&sysparm_article = KB0012237)

ERCOT 2025a ERCOT transmission planning: 345-kV and TX 765-kV strategic transmission expansion plan (STEP) (available at: www.ercot.com/files/docs/2025/01/28/ERCOT_Trending_Topic_345-kV_vs_765-kV_Transmission.pdf)

ERCOT 2025b 2024 regional transmission plan (RTP) 345-kV plan and texas 765-kV strategic transmission expansion plan comparison (available at: www.ercot.com/files/docs/2025/01/27/2024-regional-transmission-plan-rtp-345-kv-plan-and-texas-765-kv-strategic-transmission-expans.pdf)

ERCOT 2025c 2025 long-term load forecast reports (available at: www.ercot.com/gridinfo/load/forecast)

ERCOT 2025 ERCOT releases capacity, demand and reserves (CDR) report; planning reserves pressured as texas economy grows (available at: www.ercot.com/news/release/02132025-ercot-releases-capacity)

ERCOT 2025 GIS report (available at: www.ercot.com/mp/data-products/data-product-details?id = pg7-200-er)

ERCOT 2026 Maps (available at: www.ercot.com/news/mediakit/maps)

ERCOT 2026 Resource adequacy 2025 (available at: www.ercot.com/gridinfo/resource/2025)

Eriksson E L V and Gray E M 2017 Optimization and integration of hybrid renewable energy hydrogen fuel cell energy systems - a critical review *Appl. Energy* **202** 348–64

Exemplar E 2026 PLEXOS© energy modeling software (available at: www.energyexemplar.com/plexos)

FERC and NERC 2021 The February 2021 Cold Weather Outages in texas and the south central United States | FERC, NERC and regional entity staff report | federal energy regulatory commission (available at: https://ferc.gov/media/february-2021-cold-weather-outages-texas-and-south-central-united-states-ferc-nerc-and)

FERC 2026 Form No. 715 - annual transmission planning and evaluation report | federal energy regulatory commission (available at: www.ferc.gov/industries-data/electric/electric-industry-forms/form-no-715-annual-transmission-planning-and-evaluation-report)

Ghanbarzadeh T, Habibi D and Aziz A 2025 Addressing reliability challenges in generation capacity planning under high penetration of renewable energy resources and storage solutions: a review *Renew. Sustain. Energy Rev.* **212** 115461

Ghatikar G, Ganti V, Matson N and Piette M A 2012 Demand response opportunities and enabling technologies for data centers: findings from field studies *Technical Report* LBNL–5763E, 1174175 (available at: www.osti.gov/servlets/purl/1174175/)

Ghosh P and De M 2022 A comprehensive survey of distribution system resilience to extreme weather events: concept, assessment and enhancement strategies *Int. J. Ambient Energy* **43** 6671–93

Ho J *et al* 2021 Regional energy deployment system (ReEDS) model documentation: version 2020 *Renew. Energy* (https://doi.org/10.2172/1788425)

Huang P, Copertaro B, Zhang X, Shen J, Löfgren I, Rönnelid M, Fahlen J, Andersson D and Svanfeldt M 2020 A review of data centers as prosumers in district energy systems: renewable energy integration and waste heat reuse for district heating *Appl. Energy* **258** 114109

Hussain M S, Cho K and Park S-j 2024 Resource Adequacy and Integration of Renewables in Light of US, EU, and Pakistan's Evolving Power Sector *Energies* **17** 5051

IEA 2025 Energy and AI (available at: www.iea.org/reports/energy-and-ai)

International Energy Agency 2023 Electricity grids and secure energy transitions: enhancing the foundations of resilient, sustainable and affordable power systems (OECD) (available at: www.oecd.org/en/publications/electricity-grids-and-secure-energy-transitions_455dd4fb-en.html)

Intertek 2023 Power plant cycling cost and flexible generation (available at: www.intertek.com/power-generation/cost-of-cycling-analysis/)

J. Nyangon 2025 Smart grid strategies for tackling the duck curve: a qualitative assessment of digitalization, battery energy storage, and managed rebound effects benefits *Energies* **18** 3988

Kim K, Yang F, Zavala V M and Chien A A 2017 Data centers as dispatchable loads to harness stranded power *IEEE Trans. Sustain. Energy* **8** 208–18

Kwon J, Zhou Z, Levin T and Botterud A 2020 Resource adequacy in electricity markets with renewable energy *IEEE Trans. Power Syst.* **35** 773–81

LaBarbara K, Lin S, Logan C E and Brewer J H 2020 Summer resource adequacy in the ERCOT region *Technical Report DOE/NETL–2020/2603* (National Energy Technology Laboratory (NETL)) (available at: www.osti.gov/biblio/1631282)

Levin T, Blaisdell-Pijuan P L, Kwon J and Mann W N 2024 High temporal resolution generation expansion planning for the clean energy transition *Renew. Sustain. Energy Rev.* **5** 100072

Linkov I, Trump B D, Trump J, Pescaroli G, Hynes W, Mavrodieva A and Panda A 2022 Resilience stress testing for critical infrastructure *Int. J. Disaster Risk Reduct.* **82** 103323

Ma X, Zhang Z and Hua H 2022 Uncertainty quantization and reliability analysis for rotor/stator rub-impact using advanced Kriging surrogate model *J. Sound Vib.* **525** 116800

Magness B 2021 Review of February 2021 extreme cold weather event - ERCOT presentation *ERCOT Public* (available at: www.ercot.com/files/docs/2021/03/03/Texas_Legislature_Hearings_2-25-2021.pdf)

Makarov Y, Diao R, Etingov P, Hou Z, Huang Z, Meng D, Miller L, Samaan N, Sun Y, Vallem M, Vyakaranam B, Wang S, Wu D and Zhang Y 2015 Stochastic operations and planning PNNL–23680, 1179142, TE1103000 (available at: www.osti.gov/servlets/purl/1179142/)

Manfredi P and Trinchero R 2022 A probabilistic machine learning approach for the uncertainty quantification of electronic circuits based on gaussian process regression *IEEE Trans. Comput. Aided Des. Integr. Circuits Syst.* **41** 2638–51

Mantegna G, Huang Z, Van Caelenberg G, Frew B, Lynch M and O'Malley M 2025 Electric grid reliability in an era of unprecedented uncertainty: a review of advances in electric sector resource adequacy assessment and planning *Policy Regul. IEEE Trans. Energy Mark.* **4** 1–9

Matraeva L, Vasiutina E, Korolkova N, Maloletko A and Kaurova O 2022 Identifying rebound effects and formulating more sustainable energy efficiency policy: a global review and framework *Energy Res. Soc. Sci.* **85** 102402

Milligan M, Frew B, Ibanez E, Kiviluoma J, Holttinen H and Söder L 2017 Capacity value assessments of wind power *WIREs Energy Environ.* **6** e226

Min D, Ryu J-h and Choi D G 2018 A long-term capacity expansion planning model for an electric power system integrating large-size renewable energy technologies *Comput. Oper. Res.* **96** 244–55

Mongird K and Rice J 2024 An integrated and iterative multiscale modeling framework for robust capacity expansion planning *Curr. Sustain./Renew. Energy Rep.* **11** 77–84

NERC 2026 Long term reliability assessment *Technical Report* (North American Electric Reliability Corporation (NERC)) (available at: www.nerc.com/globalassets/our-work/assessments/nerc_ltra_2025.pdf)

NGI 2025 Natural gas price index data - FERC approved & ICE powered | NGI (available at: https://naturalgasintel.com/services/ngi-price-index-data)

Norris T H, Profeta T, Patino-Echeverri D and Cowie-Haskell A 2025 *Rethinking Load Growth: Assessing the Potential for Integration of Large Flexible Loads in US Power Systems, Text* (Nicholas Institute for Energy, Environment & Sustainability, Duke University) (available at: https://nicholasinstitute.duke.edu/publications/rethinking-load-growth)

NREL 2024 2024 electricity ATB technologies and data overview (available at: https://atb.nrel.gov/electricity/2024/index)

Nyangon J 2024 Climate-proofing critical energy infrastructure: smart grids, Artificial Intelligence and machine learning for power system resilience against extreme weather events *J. Infrastruct. Syst.* **30** 03124001

Nyangon J 2025 Physics informed neural networks for maritime energy systems and blue economy innovations *Mach. Learn.: Earth***1** 011002

Nyangon J and Akintunde R 2024 Principal component analysis of day-ahead electricity price forecasting in CAISO and its implications for highly integrated renewable energy markets *WIREs Energy Environ.* **13** e504

Nyangon J and Byrne J 2023 Estimating the impacts of natural gas power generation growth on solar electricity development: PJM's evolving resource mix and ramping capability *WIREs Energy Environ.* **12** e454

Palmintier B and Webster M 2011 Impact of unit commitment constraints on generation expansion planning with renewables, MIT web domain (available at: https://dspace.mit.edu/handle/1721.1/70116)

Panteli M, Pickering C, Wilkinson S, Dawson R and Mancarella P 2017 Power system resilience to extreme weather: fragility modeling, probabilistic impact assessment and adaptation measures *IEEE Trans. Power Syst.* **32** 3747–57

Pi Y, Ye X and Duffield N 2022 Rapid damage estimation of texas winter storm uri from social media using deep neural networks *Urban Sci.* **6** 62

PJM 2023 Proposed enhancements to PJM's capacity market rules - market seller offer cap, performance payment eligibility, and forward energy and ancillary service revenues (available at: www.pjm.com/-/media/DotCom/documents/ferc/filings/2023/20231013-er24-98-000.ashx)

Poncelet K, Delarue E, Six D, Duerinck J and D'haeseleer W 2016 Impact of the level of temporal and operational detail in energy-system planning models *Appl. Energy* **162** 631–43

Priesmann J, Münch J, Tillmanns M, Ridha E, Spiegel T, Reich M, Adam M, Nolting L and Praktiknjo A 2024 Artificial intelligence and design of experiments for resource adequacy assessment in power systems *Energy Strategy Rev.* **53** 101368

Rickerson W 2023 Item 7.1.1: reliability standard study preliminary results (available at: www.ercot.com/files/docs/2023/06/12/7-1-1-reliability-standard-study-preliminary-results.pdf)

Schleifer A, King A, Homer J and Levin T 2023 Assessing the resource adequacy and community impacts of an evolving grid: considerations for state regulators *Technical Report ANL–23/35, 2208815, 183578* (available at: www.osti.gov/servlets/purl/2208815/)

Sergi B, Brown P and Cole W 2024 Transmission interface limits for high-spatial resolution capacity expansion modeling *Booktitle2024 IEEE Power & Energy Society General Meeting (PESGM)* pp 1–5

Stenclik D 2024 New resource adequacy criteria for the energy transition: modernizing reliability requirements *Technical Report NREL/SR–6A40-89334, 2372882, MainId:90113* (available at: www.osti.gov/servlets/purl/2372882/)

Sun Y, Frew B, Dalvi S and Dhulipala S C 2022 Insights into methodologies and operational details of resource adequacy assessment: a case study with application to a broader flexibility framework *Appl. Energy* **328** 120191

Texas Reliability Entity 2024 2023 reliability performance and regional risk assessment (available at: www.texasre.org/Documents/About)

Yuan X, Liang Y, Hu X, Xu Y, Chen Y and Kosonen R 2023 Waste heat recoveries in data centers: a review *Renew. Sustain. Energy Rev.* **188** 113777

Zhang J, Guerra O J, Eichman J and Pellow M A 2020 Benefit analysis of long-duration energy storage in power systems with high renewable energy shares *Front. Energy Res.* **8** 1

Zhao J, Chen L, Wang Y and Liu Q 2021 A review of system modeling, assessment and operational optimization for integrated energy systems *Sci. China Inf. Sci.* **64** 191201