Effective Load Carrying Capability Study

Final Report

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PREPARED FOR

Electric Reliability Council of Texas ("ERCOT")

PREPARED BY

Kevin Carden
Alex Dombrowsky
Aditya Nathan

Astrapé Consulting

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EXECUTIVE SUMMARY

Planning for reliability for structured capacity markets and vertically integrated utilities requires formal quantification of the reliability contribution of each resource class in order to ensure compliance with reliability standards. The reliability contribution of resource classes is generally expressed as its Effective Load Carrying Capability (ELCC). In energy-only markets such as ERCOT, while there is currently no capacity accreditation scheme, it is still important that market participants have insight into the reliability contribution of each resource class. ERCOT contracted with PowerGEM to perform an ELCC study to quantify the contribution of each resource class to Planning Reserve Margins (PRM) reported in ERCOT's Report on Capacity, Demand and Reserves in the ERCOT Region (CDR). The use of the ELCC approach has been codified in ERCOT's Nodal Protocols.[1]

ELCCs are generally calculated relative to the 1-day-in-10-years (0.1 LOLE) reliability standard used in most of North America. In 2024, ERCOT introduced a multi-pronged reliability standard. This standard requires compliance with the 0.1 LOLE metric but also puts limitations on the magnitude and duration of individual reliability events. The maximum modeled average hourly firm load shed is a parameter to be calculated and updated by December of each year based on guidance from Public Utility of Texas staff and Transmission Operations. The longest firm load shed event must be shorter than 12 hours. An exceedance threshold of one percent is applied to both the magnitude and duration criteria, meaning that no more than one percent of events can exceed the criteria thresholds.[2] The standard was not adopted until after the ELCC study completion. Therefore, for this study, SERVM was calibrated to 0.1 LOLE for the summer and winter seasons separately, but the seasonal LOLE will be explored for subsequent studies.

ELCCs are calculated via simulations of the islanded 2026 ERCOT system using PowerGEM's Strategic Energy and Risk Valuation Model (SERVM). The ELCC of a resource class is not a static value; it is contingent on the penetration of the resource class, underlying load characteristics, and interactions with other resource classes among other variables. To capture this dynamic, PowerGEM simulated dozens of portfolios with combinations of different resource penetration levels and technology attributes, and adjustments were made to load or capacity to keep reliability at the target. The ratio of the resource adjustment required to meet the reliability target to the capacity of the variable energy portfolio determines the portfolio ELCC. This process is illustrated in Figure ES1**Error! Reference source not found.**.

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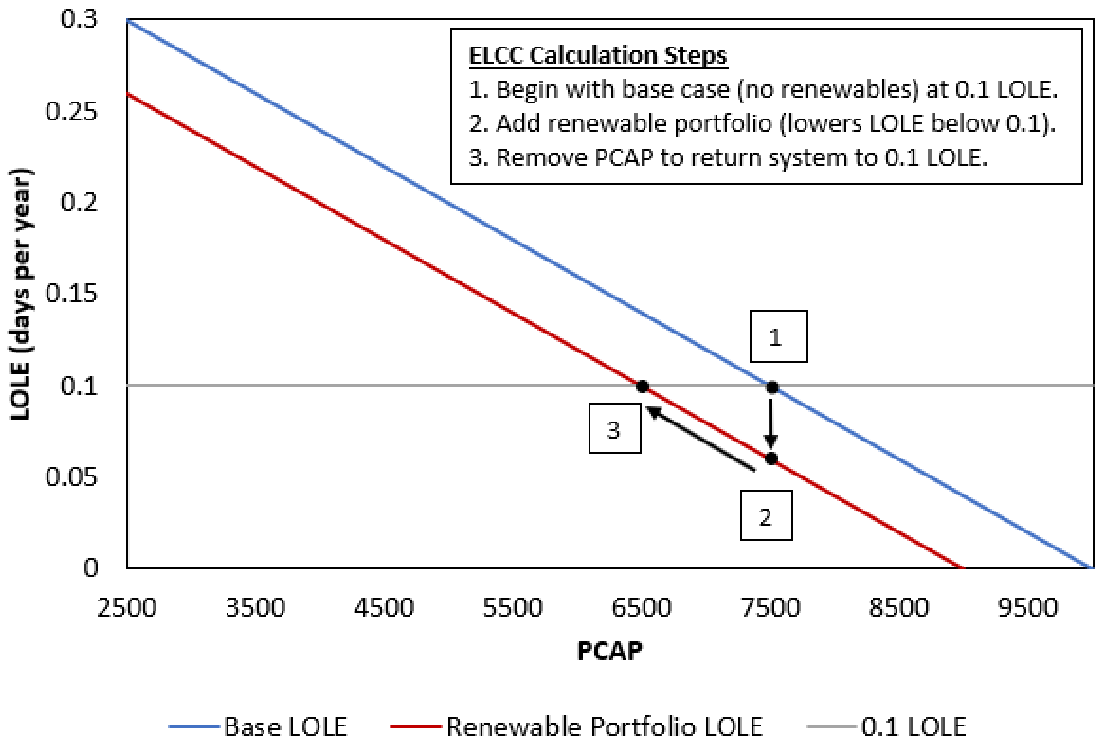
[1] See Protocol Sections 3.2.6.2 and 3.2.6.4, https://www.ercot.com/files/docs/2024/06/28/03-010125_Nodal.docx

[2] See the adopted standard: 54584_106_1426419.PDF

Figure ES1. ELCC Methodology



For the 2024 ELCC study, PowerGEM explored alternative methodologies to capture interactions between different durations of storage resources. Fully analyzing the possible ranges of ERCOT portfolios consisting of wind, solar, and 4 different duration batteries in SERVM would require a 6-dimensional matrix of hundreds of thousands of scenarios. Given the intractability of analyzing such a matrix, PowerGEM proposed constructing a tool to quantify the discrete contribution of any storage portfolio up to 30GW of capacity consisting of any mix of durations for any combination of wind and solar capacity, each up to 60 GW. This tool is built in Excel but is calibrated to SERVM simulations to ensure constraints such as charging limitations and cycle efficiency as well as beneficial attributes such as the ability to serve ancillary services factor into the ELCC quantification.

A challenge with ELCC calculations is whether resources are given credit for their average or their marginal contribution to reliability. The sum of average ELCC contributions for all resources in a system that is precisely compliant with the reliability requirement will be equal to:

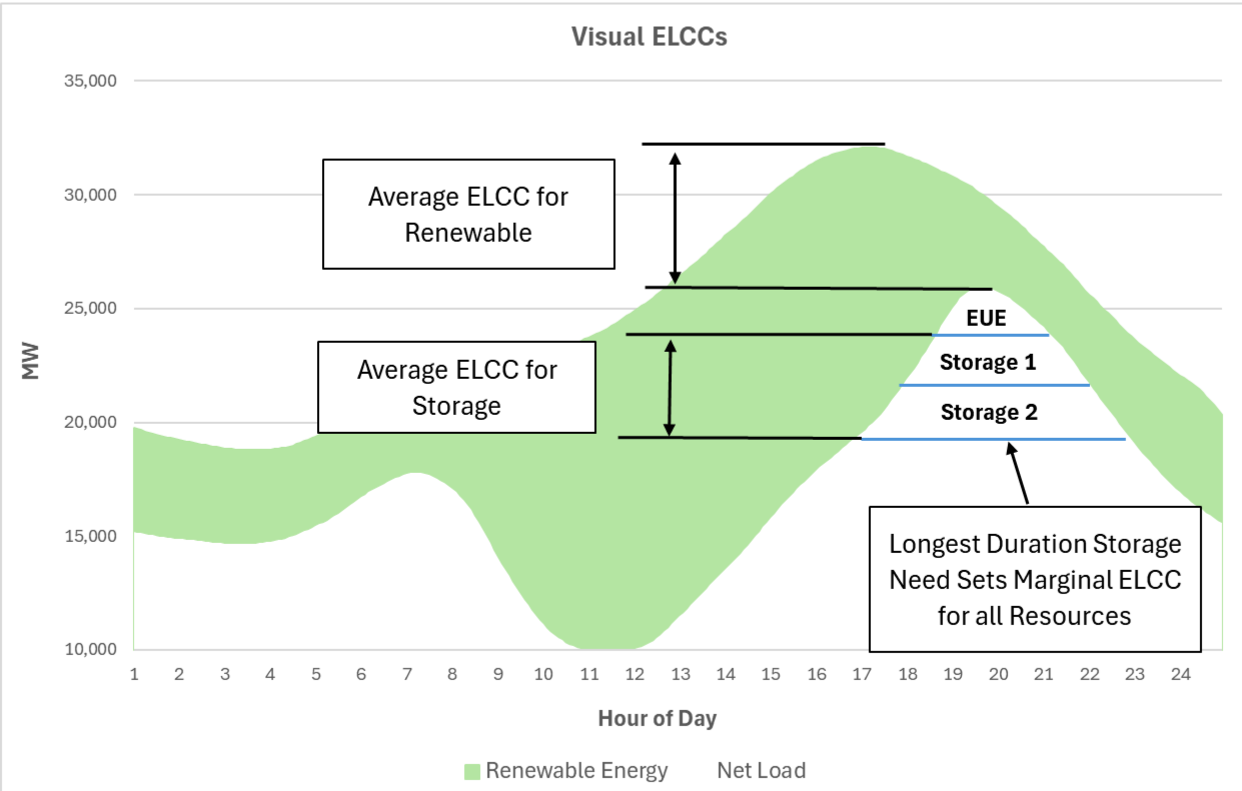
$$Reliability\ Requirement = Peak\ Load * (1 + Planning\ Reserve\ Margin).$$

This is generally informative for planners to determine how long or short a given system will be. The marginal ELCC for every resource class is valuable to determine the contribution of the next resource to the system. This is generally informative for planners to determine how long or short a given system will be.

The marginal ELCC for every resource class determines the reliability contribution of the next resource to the system (which is useful information for the market), as well as helps distinguish the difference in reliability value of incremental energy during the hours with highest risk of unserved energy versus other hours of the day, a new reporting requirement for the CDR.

The Figure ES2 illustration provides visual guidance on the application of average and marginal ELCCs. The sum of all the average ELCCs is a stacking of the reliability contribution of all classes of resources and shows the aggregate contribution relative to the peak load forecast.

Figure ES2. Visual ELCC Example



Output of resources during critical hours – defined as either Expected Unserved Energy (EUE) hours or hours where incremental energy would reduce EUE – approximates marginal ELCC.

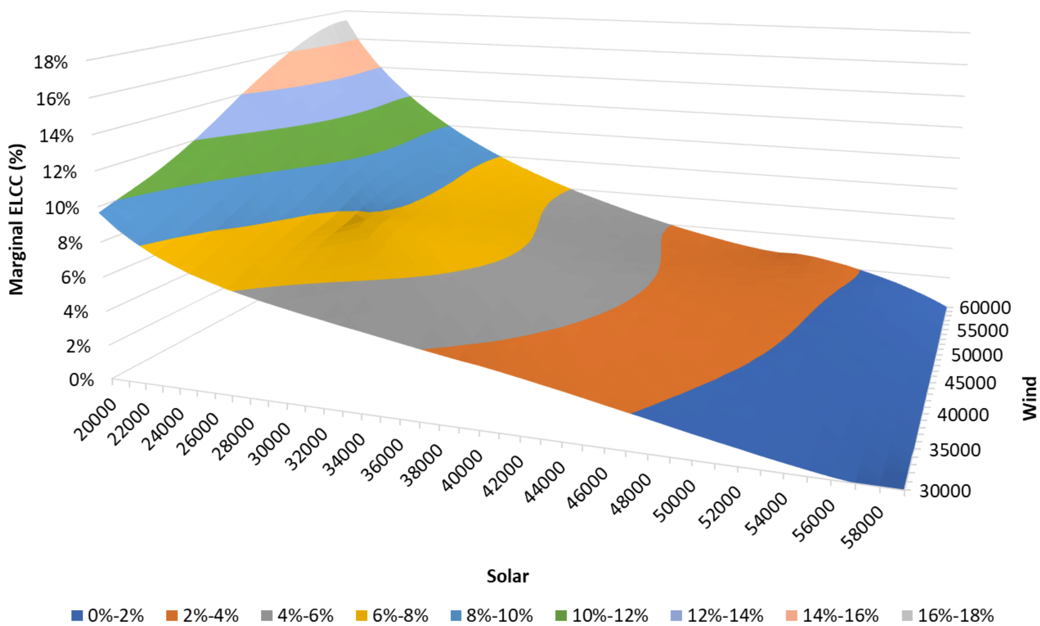
The approach used for this ELCC study was to match average ELCC to summer afternoon risk periods and marginal ELCC to summer evening risk periods. This is not a perfect mapping since ELCC recognizes that the contribution to reliability is not a snapshot of conditions in any specific hour, but rather the reduction in net load peak that occurs over several hours. With the 2025 solar penetration, it is expected that the solar output during the gross load peak has minimal contribution to reliability (since all reliability problems are expected to be concentrated in the evening) so neither the average ELCC nor the marginal ELCC recognizes the full output of solar during gross peak periods.

Winter average ELCCs are mapped to both morning and evening winter risk periods as the timing of the net load peaks are essentially identical to the gross load peaks.

ELCC RESULTS

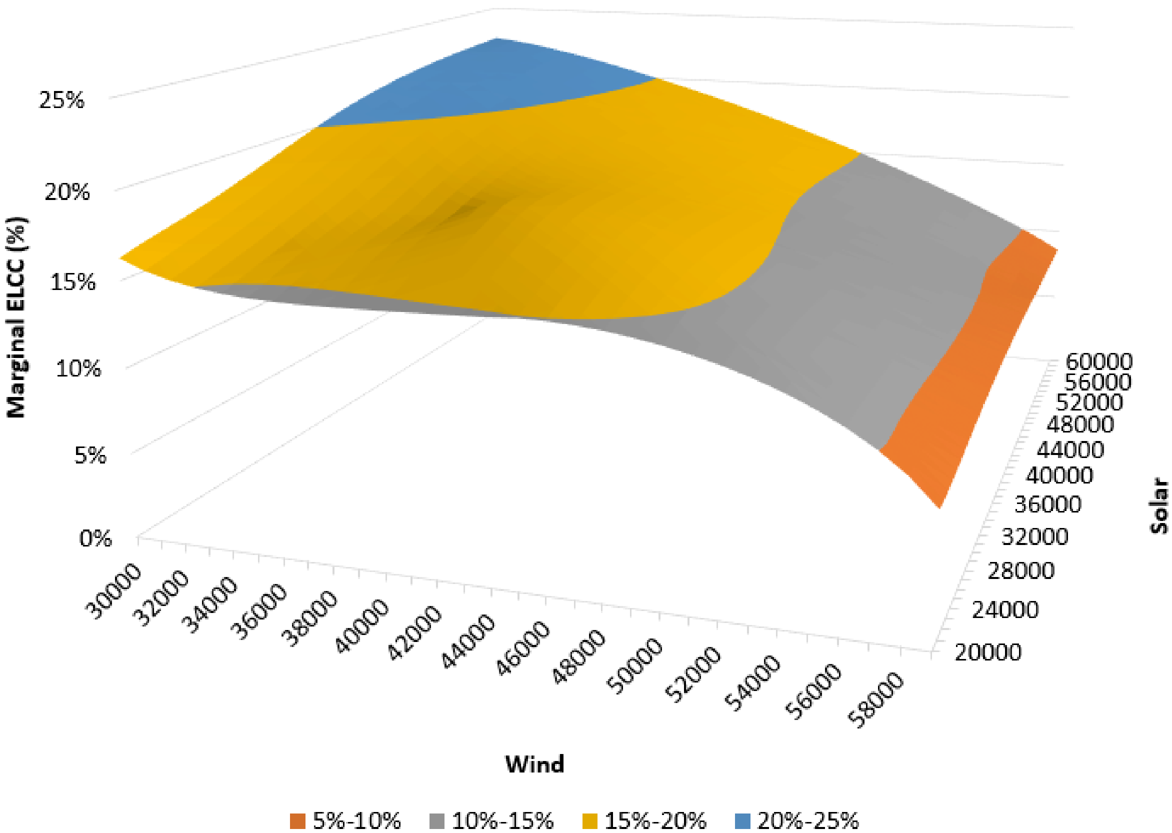
Given reliability need has historically been concentrated in summer afternoon hours, the reliability contribution of solar has been assumed to be quite high – the reliability credit for solar in past CDRs has been 74-100% between 2010-2024. The shift to winter reliability and the large additions of solar capacity have significantly lowered the projected contribution of marginal solar additions in the summer, as shown in Figure ES3. In the winter, solar output is minimal in very early morning hours and very late evening hours during reliability risk periods. As solar penetration grows, incremental solar capacity does not contribute significantly to reliability.

Figure ES3. Summer Evening Solar ELCCs



Wind resource reliability contributions are more stable, as shown in Figure ES4, but are also subject to further declines in ELCC with penetration as the risk of large area wind lulls have a larger impact on reliability.

Figure ES4. Summer Evening Wind ELCCs



Solar morning and afternoon winter ELCCs for penetrations expected by 2026 are less than 2%, and wind ELCCs in the winter are generally less than 32%.

Storage summer afternoon ELCCs indicate that 3 hours or longer duration is required to provide 91%+ ELCC over the next 5-year planning window. The summer evening storage ELCCs for storage with 5 hour or longer duration is required to provide 74%+ ELCC over the same planning window. Storage winter morning and evening ELCCs indicate that 5 hours or longer duration is required to provide 76%+ ELCC over the next 5-year planning window.

From an aggregate planning standpoint, significant solar and storage resources are being added over the next 5 years as shown in Figure ES5. However, the total reliability contribution of system resources is only rising modestly while load is projected to grow much faster. The composite system ELCC MW shown in Figure ES6 uses estimated values for the conventional fleet, so it does not provide precise indication of the reliability value of the portfolio, but it does highlight the potential gap between reliability capability of the system and the growing load forecast.

Figure ES5. Resource Portfolio Capacities

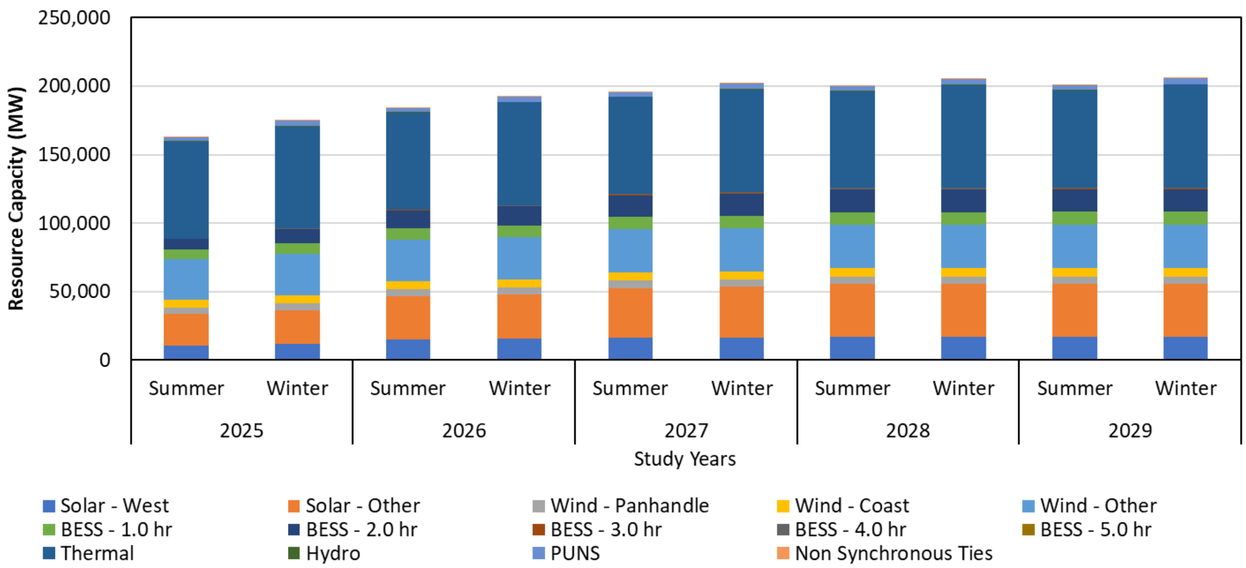
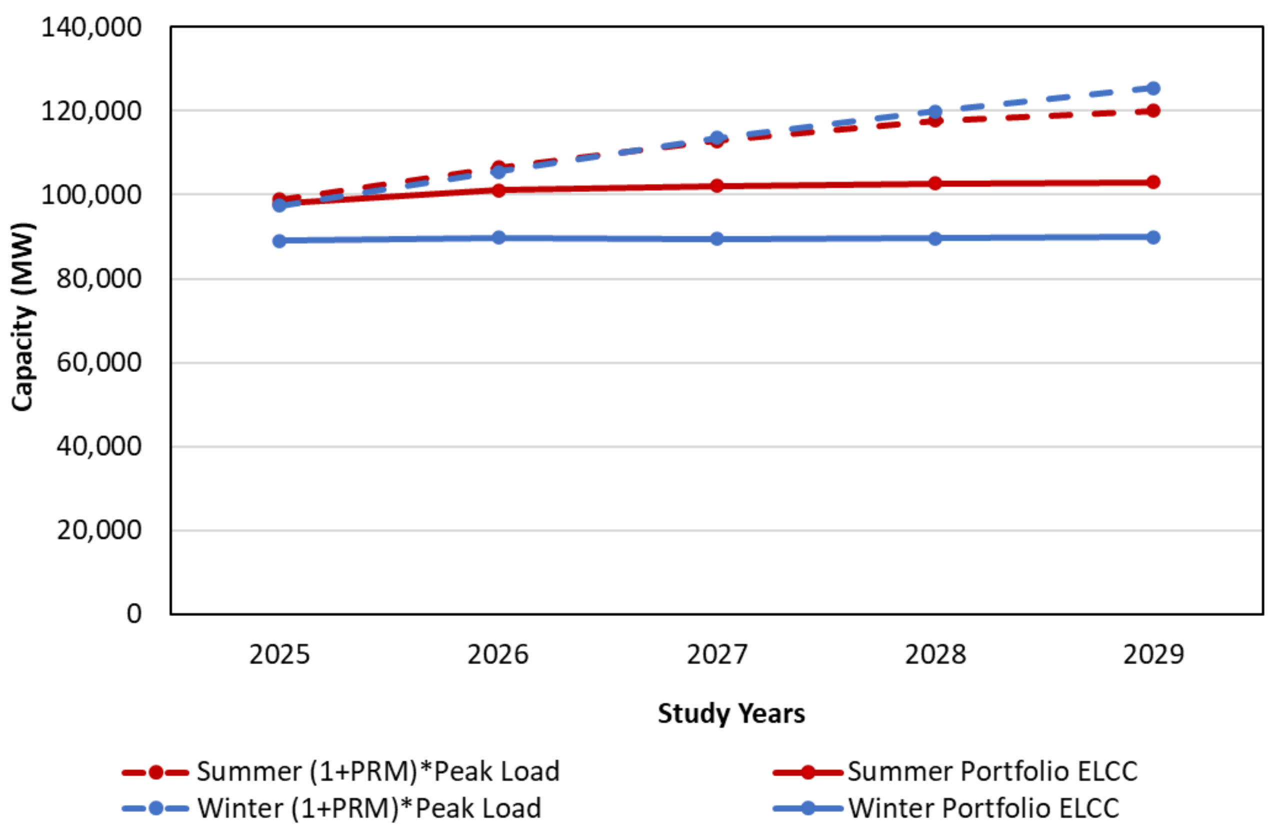


Figure ES6. Seasonal Portfolio ELCC Versus "1 + Planning Reserve Margin" Times Peak Load



In addition to distinguishing reliability value by technology, the location of resources affects reliability value. The following variables were also tested as part of this study:

- Wind Locations:
    - Wind Panhandle (Wind-P)
    - Wind Coastal (Wind-C)
    - Wind Other (Wind-O)
- Solar Locations:
    - Solar Other
    - Solar West
    - Solar Far West

Table ES1 and

Table ES2 provide a snapshot of the risk period ELCCs for 2025 projected penetrations of wind, solar, and storage capacity distinguished by location or duration respectively.

Marginal ELCCs of all resource classes exhibit the effects expected with large portfolios of energy-limited or non-dispatchable resources. As the penetration grows, the contribution of the next MW declines since the net load is being shifted to periods where solar or wind output is lower, or the duration need for the next MW of battery has grown since the initial batteries have already been deployed for the highest peak periods. The average ELCCs have also declined, but at a slower pace since average ELCC accounts for the higher contribution of the initial penetration.

Table ES1. 2025 Summer Risk Period ELCCs

Technology	Installed Capacity (MW)	Afternoon ELCC (%)	Evening ELCC (%)
Wind-C	5,678	30.83%	16.37%
Wind-O	29,796	15.68%	8.33%
Wind-P	4,669	33.58%	17.83%
Solar Other	22,922	27.21%	5.51%
Solar West	7,000	36.14%	7.32%
Solar Far West	3,653	36.14%	7.32%
Storage 1-hour	6,898	70.72%	13.71%
Storage 2-hour	7,651	93.29%	27.43%
Storage 3-hour	202	93.29%	41.14%
Storage 4-hour	247	93.29%	54.85%
Storage 5-hour	20	93.29%	68.15%

Table ES2. 2025 Winter Risk Period ELCCs

Technology	Installed Capacity (MW)	Morning ELCC (%)	Evening ELCC (%)
Wind-C	5,678	29.90%	29.90%
Wind-O	30,296	15.20%	15.20%
Wind-P	4,835	32.56%	32.56%
Solar Other	24,867	1.95%	1.95%
Solar West	7,934	2.59%	2.59%
Solar Far West	3,653	2.59%	2.59%
Storage 1-hour	7,847	25.46%	23.14%
Storage 2-hour	10,239	60.47%	56.15%
Storage 3-hour	202	86.08%	90.42%
Storage 4-hour	401	93.37%	93.37%
Storage 5-hour	20	93.37%	93.37%

KEY MODEL INPUTS AND PARAMETERS

A. MODELING FRAMEWORK

This study was performed using the Strategic Energy & Risk Valuation Model (SERVM). Like other reliability models, SERVM probabilistically evaluates the reliability implications of any given portfolio. It does so by simulating generation availability, load profiles, load uncertainty, inter-regional transmission availability, and other factors. SERVM ultimately generates standard reliability metrics such as loss-of-load expectation (LOLE), loss-of-load hours (LOLH), and expected unserved energy (EUE). Unlike other reliability modeling packages, however, SERVM simulates economic outcomes, including hourly generation dispatch, ancillary services, and price formation under both normal conditions and emergency operating procedures.

The multi-area economic and reliability simulations in SERVM include an hourly chronological economic dispatch that is subject to inter-regional transmission constraints. Each generation unit is modeled individually, characterized by its economic and physical characteristics. Planned outages are scheduled in off-peak seasons, consistent with standard practices, while unplanned outages and derates occur probabilistically using historical distributions of time between failures and time to repair. Load, hydro, wind, and solar conditions are modeled based on profiles consistent with individual historical weather years. Dispatch limitations and limitations on annual energy output are imposed on certain types of resources such as demand response, hydro generation, and seasonally mothballed units.

The model implements a week-ahead and then multi-hour-ahead unit commitment algorithm considering the outlook for weather and planned generation outages. In the operating day, the model runs an hourly economic dispatch of baseload, intermediate, and peaking resources, including an optimization of transmission-constrained inter-regional power flows to minimize total costs. During most hours, hourly prices reflect marginal production costs, with higher prices being realized when import constraints are binding. During emergency and other peaking conditions, SERVM simulates scarcity prices that exceed generators' marginal production costs.

To examine a full range of potential reliability outcomes, we implement a Monte Carlo analysis over a large number of scenarios with varying demand and supply conditions. Because reliability events occur only when system conditions reflect unusually high loads or limited supply, these simulations must capture wide distributions of possible weather, load growth, and generation performance scenarios. This study incorporates 44 weather years, 5 levels of economic load forecast,[3] and 25 draws of generating unit performance for a total of 5,500 iterations for each simulated case. Each individual iteration simulates 8,760 hours for the study year of 2026.

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[3] The five discrete levels of load forecast error we model are equal to 0%, +/−2%, and +/−4% above and below the ERCOT load forecast.

To properly capture the magnitude and impact of reliability conditions during extreme events, emergency operating procedures must be faithfully replicated. For this reason, SERVM simulates a range of emergency procedures, accounting for energy and call-hour limitations, dispatch prices, operating reserve depletion, dispatch of economic and emergency demand-response resources, and administrative scarcity pricing.[4]

B. STUDY YEAR AND TOPOLOGY

The ELCC study analyzed the expected conditions and resources in 2026. ERCOT was modeled as an island and all generation is assumed to be fully deliverable within the ERCOT region.

C. COMPONENTS OF SUPPLY AND DEMAND

Load and resource accounting for the 2026 system is based on ERCOT's conventions in the May 2024 Capacity, Demand and Reserves (CDR) Report, as summarized in Table 1.[5] The fleet summary developed by ERCOT staff for the CDR Report was the most recent data available when this study was developed.[6] Any units coming online before June 2026 were included in the study and assumed to come online in January of the year, and any units coming only after June 2026 were excluded in the study to maintain a homogeneous resource mix for the study year. Firm peak load is reduced for non-controllable load resources (LRs), 10-minute and 30-minute emergency response service (ERS), and Transmission/ Distribution Service Providers (TDSP) energy efficiency and load management. All wind, solar, and storage capacity was removed from the base case used for the ELCC surface development, and perfect combustion turbine capacity – capacity with no outages or ramping limitations – was added until the LOLE was 0.1 for the summer and winter seasons.

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[4] Similar to other reliability modeling exercises, our study is focused on resource adequacy as defined by having sufficient resources to meet peak summer load. As such, we have not attempted to model other types of outage or reliability issues such as transmission and distribution outages, common mode failures related to winter weather extremes, or any potential issues related to gas pipeline constraints or delivery problems.

[5] https://www.ercot.com/gridinfo/resource

[6] In general, the May 2024 CDR is the authoritative source, the following assumptions were used for including certain resource types: (1) switchable units – include as internal resources, with the units that are committed off-system excluded from our model. (2) unit additions/retirements – include or exclude starting in the CDR-specified year. (3) inactive planned – excluded from model.

Table 1. Supply and Demand Summary for 2026 Study Year

	ERCOT System
Peak Load (MW)	**86,158**
Load Reduction (MW)	**2,622**
LRs serving RRS (MW)	1,115
LRs serving ECRS (MW)	250
10-Minute and 30-Minute ERS (MW)	885
TDSP Curtailment Programs (MW)	372
Supply	
Conventional Generation (MW)	67,079
Hydro (MW)	455
Wind (MW)*	41,642
Solar (MW)*	53,501
Storage (MW)*	23,243
PUNs (MW)	2,760

Note: Energy Efficiency Programs are already removed from the modeled peak load and are not represented in the modeled load reduction programs (ERCOT Aggregate = 3,497 MW in 2026 Study Year)
*Nameplate Capacity of Unit Category

On the demand side, this study started with ERCOT's zonal hourly load shapes under many possible weather patterns and peak load forecast for 2026. PowerGEM simulated 44 weather years, from 1980 through 2023 (with corresponding wind and solar conditions from the same years). When calculating expected values, an equal probability for each year's weather was assumed.[7]

D. DEMAND SHAPES AND WEATHER UNCERTAINTY MODELING

We represented weather uncertainty in the projected ERCOT 2026 peak load by modeling 44 load forecasts based on 44 historical weather patterns from 1980-2023. The calculated 50/50 loads for the 2026 study year is provided in Table 2. The 50/50 peak demand forecast includes load growth from large industrial loads including data centers and large flexible loads which have signed interconnection agreements with their Transmission Service Providers (TSPs). The impact of accounting for the TSP officer letter loads on ELCCs will be investigated during our 2025 studies.

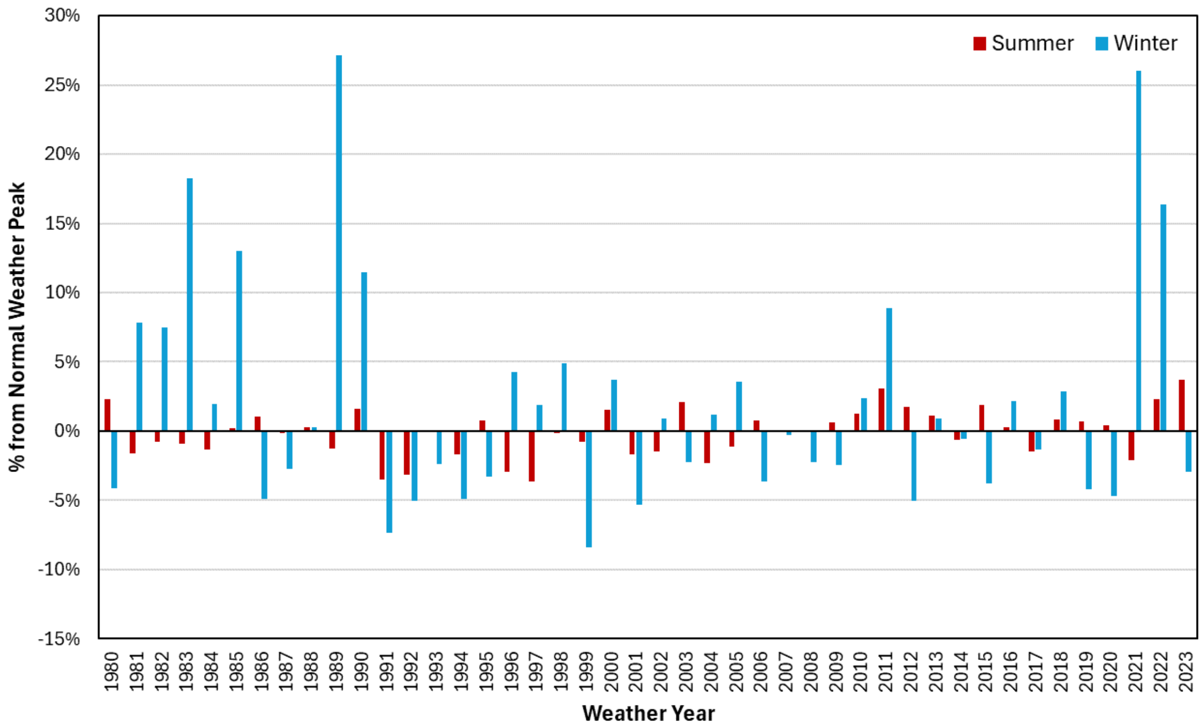
Table 2. Seasonal 50/50 Peak Before and After DC and LFL Additions

Scenario	Total Internal Demand (MW)	
	Winter	Summer
Before DC and LFL Additions	78,021	88,037
After DC and LFL Additions	86,051	99,550

[7] Applying equal probabilities is reasonable given that so many years can be taken to be fairly representative of the underlying distribution, assuming there is not a trend in the average weather or in the variability of weather.

Figure 1 shows the variability in summer and winter peak load across the 44 weather years simulated for this study. The most severe summer peak is 3.8% above the normal weather summer peak while the most severe winter peak is 24.7% above the normal weather winter peak.

Figure 1. Seasonal Peak Load Variance by Weather Year

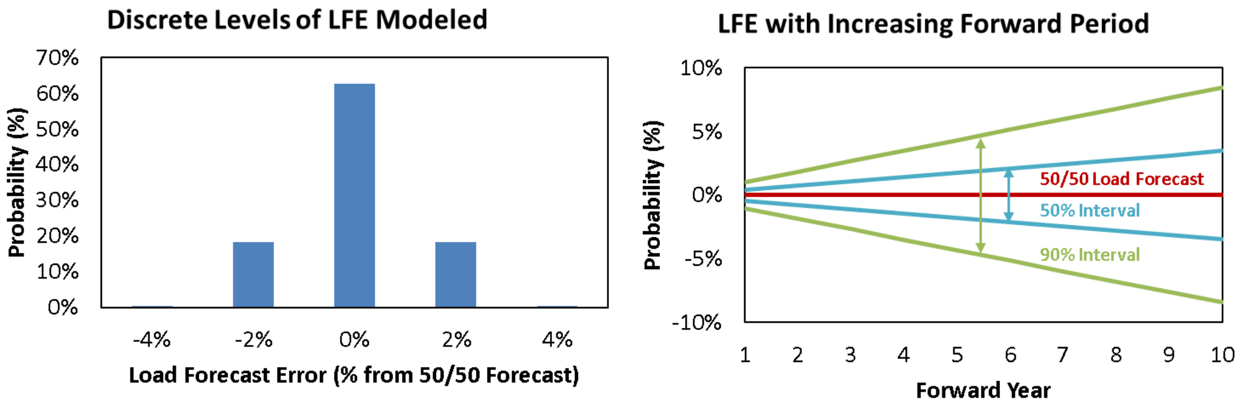


E. NON-WEATHER DEMAND FORECAST UNCERTAINTY AND FORWARD PERIOD

The load forecast errors were updated to reflect a 2-year ahead look that reflects that load may grow faster or slower than expected. As shown in the right chart of Figure 2, we assume that non-weather load forecast error (LFE) is normally distributed with a standard deviation of 0.43% on a 1-year forward basis, increasing by 0.66% with each additional forward year.[8] The distribution included no bias or asymmetry in non-weather LFEs. The left-hand chart of Figure 2 shows the five discrete levels of LFE we modeled, equal to 0%, +/−2%, and +/-4% above and below the forecast. The largest errors are the least likely, consistent with a normal distribution.

[8] This assumed LFE is a standard assumption that we developed in lieu of any ERCOT-specific analysis, which would require either a longer history of load forecasts in ERCOT or a new analysis developed out of ERCOT's peak load forecast, neither of which are currently available.

Figure 2. Non-Weather Load Forecast Error



F. GENERATION RESOURCES

The economic, availability, ancillary service capability, and dispatch characteristics of all generation units in the ERCOT fleet are modeled, using unit ratings and online status consistent with ERCOT's May 2024 CDR report.

1. CONVENTIONAL GENERATION OUTAGES

A major component of reliability analyses is modeling the availability of supply resources after considering maintenance and forced outages. We model forced and maintenance outages of conventional generation units stochastically. Partial and full forced outages occur probabilistically based on distributions accounting for time-to-fail, time-to-repair, startup failure rates, and partial outage derate percentages. Maintenance outages also occur stochastically, but SERVM accommodates maintenance outages with some flexibility to schedule maintenance during off-peak hours. Planned outages are differentiated from maintenance outages and are scheduled in advance of each hourly simulation. Consistent with market operations, the planned outages occur during low demand periods in the spring and fall, such that the highest coincident planned outages occur in the lowest load days. This outage modeling approach allows SERVM to recognize some system-wide scheduling flexibility while also capturing the potential for severe scarcity caused by a number of coincident unplanned outages.

We develop distributions of outage parameters for time-to-fail, time-to-repair, partial outage derate percentages, startup probabilities, and startup time-to-repair from historical Generation Availability Data System (GADS) data for individual units in ERCOT's fleet, supplemented by asset class average outage rates provided by ERCOT where unit-specific data were unavailable. Table 3. Equivalent Forced Outage Rates by Asset Class summarizes fleet-wide and asset-class outage rates, including both partial and forced outages.

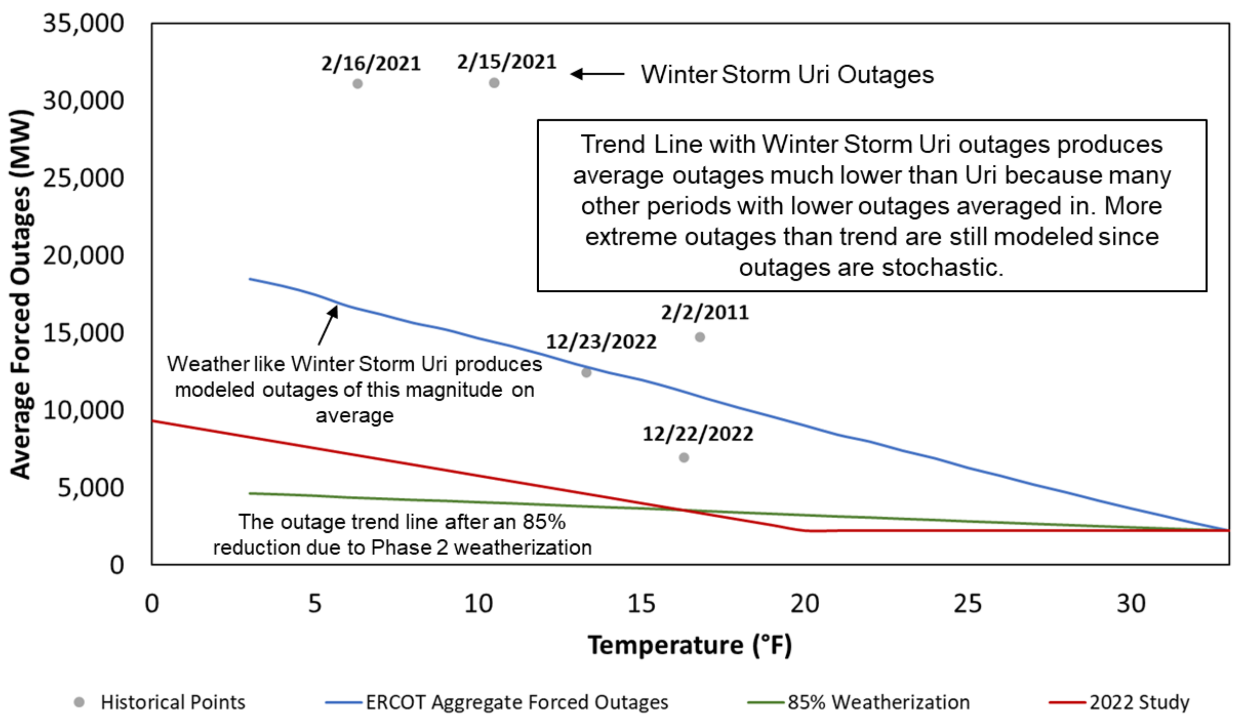
Table 3. Equivalent Forced Outage Rates by Asset Class

Unit Type	EFOR (%)
Gas	11.0
Biomass	2.4

Coal	27.9
Nuclear	2.1
Storage	5.0
Fleet Weighted Average	**11.4**

Additional forced outage probabilities were modeled for cold weather. Significant calibration work was performed to replicate outages observed in Winter Storms Uri and Elliott.[9] Based on forecasted improvement in cold weather performance by ERCOT, the incremental forced outage probability during extreme cold weather was reduced by 85% for the 2024 studies. The effect of this change is that during the coldest temperatures, the conventional fleet is expected to have a percentage on forced outage equal to its historical forced outage rate plus 15% of the incremental outages observed during the two most extreme winter events in history, as shown in Figure 3.

Figure 3. Cold Weather Forced Outage Modeling



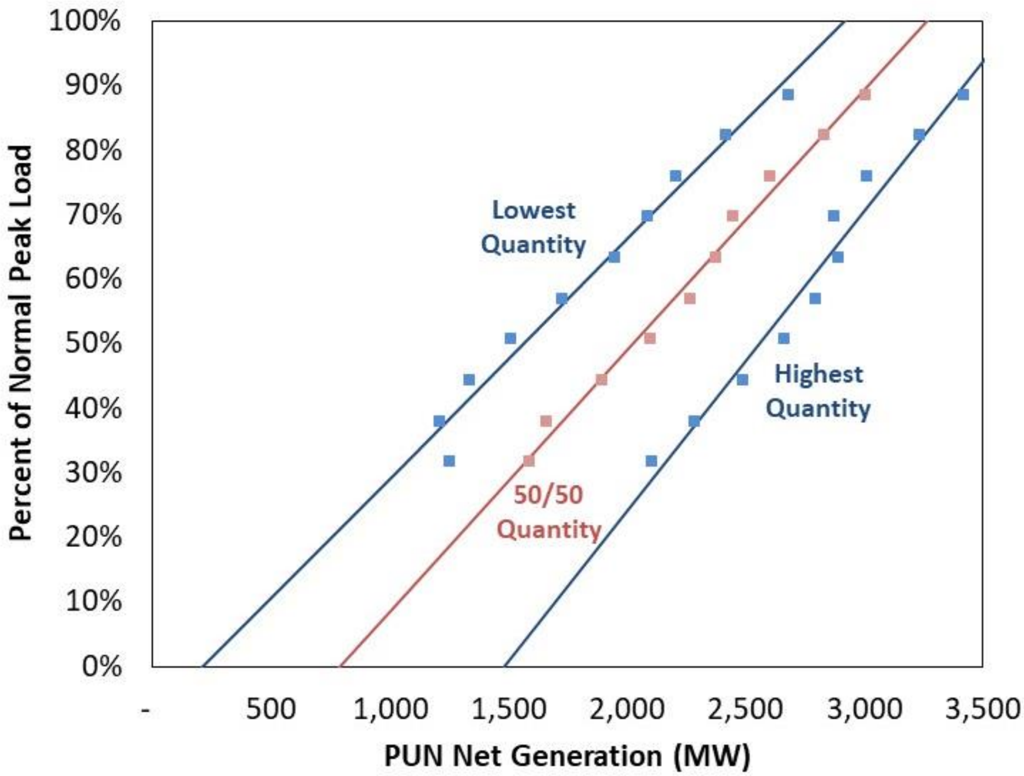
2. PRIVATE USE NETWORKS

We represent generation from Private Use Networks (PUNs) in ERCOT on a net generation basis, where the net output increases with the system portion of peak load consistent with historical data and as summarized in Figure 4. At any given load, the realized net PUN generation has a probabilistic quantity, with 10 different possible quantities of net generation within each of 10 different bands of system load.[10]

[9] More details on modeling weather events and associated thermal outage probabilities is available at https://www.ercot.com/files/docs/2023/08/23/4__Weather-based_Thermal_Outage_Modeling.pptx.
[10] Hourly net PUN output data by zone gathered from ERCOT.

Each of the 10 possible quantities has an equal 10% chance of materializing, although the figure reports only the lowest, median, and highest possible quantity. The probabilistic net PUN supply curve was developed based on aggregate hourly historical net output data within each range of peak load percentage. During scarcity conditions in the simulations with load at or above 88% of normal peak load, PUN output produces at least 2,306 MW of net generation with an average of 2,694 MW.

Figure 4. PUN Net Generation



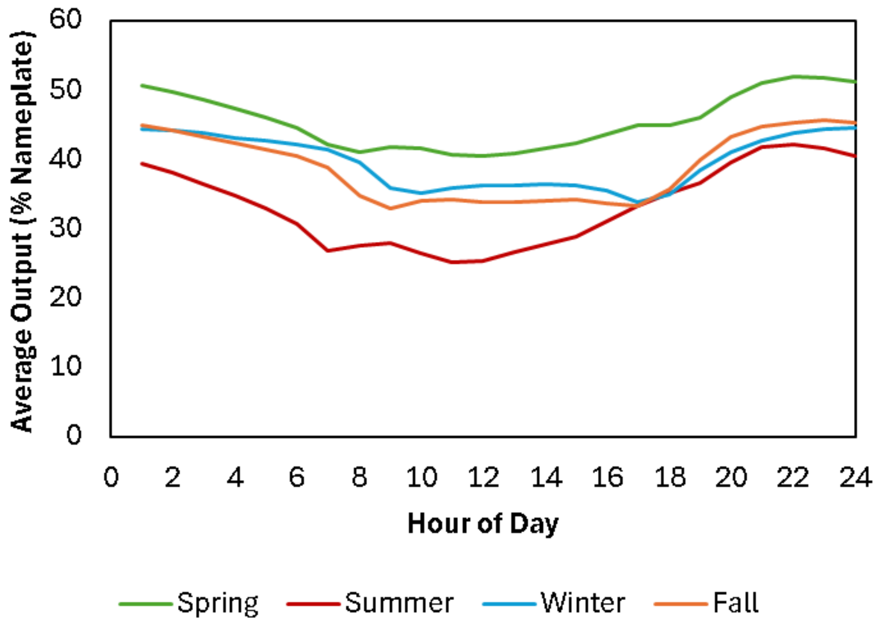
3. INTERMITTENT WIND AND SOLAR

We modeled a total quantity of intermittent wind and solar photovoltaic resources that reflects what ERCOT reported in the May 2024 CDR Report. Aggregate wind and solar profiles were created that used the same profile breakdown as the base case and then were used for simulations along the surface. Technology specific profiles were created by aggregating the appropriate profiles from the base case to obtain one average profile for each technology.

We developed our system-wide hourly wind profiles by aggregating 44 years of synthesized hourly wind shapes for each location of individual units across the system wind shapes over 1980 to 2023, as provided by ERCOT staff.[11] Figure 5 plots the average wind output by season and time of day, showing the highest output overnight and in spring months with the lowest output in mid-day and in summer months. The overall capacity factor for wind resources was 38.9%.

[11] ERCOT obtained the original wind profiles from UL (formerly AWS Truepower).

Figure 5. Average Wind Output by Season and Time of Day



We similarly model hourly solar PV output based on hourly output profiles that are specific to each weather year, as aggregated from unit level or county-specific synthesized output profiles over years 1980 to 2023.[12] In aggregate, solar resources had a capacity factor of 26.5% across all years.

ELCC SURFACE STUDY APPROACH

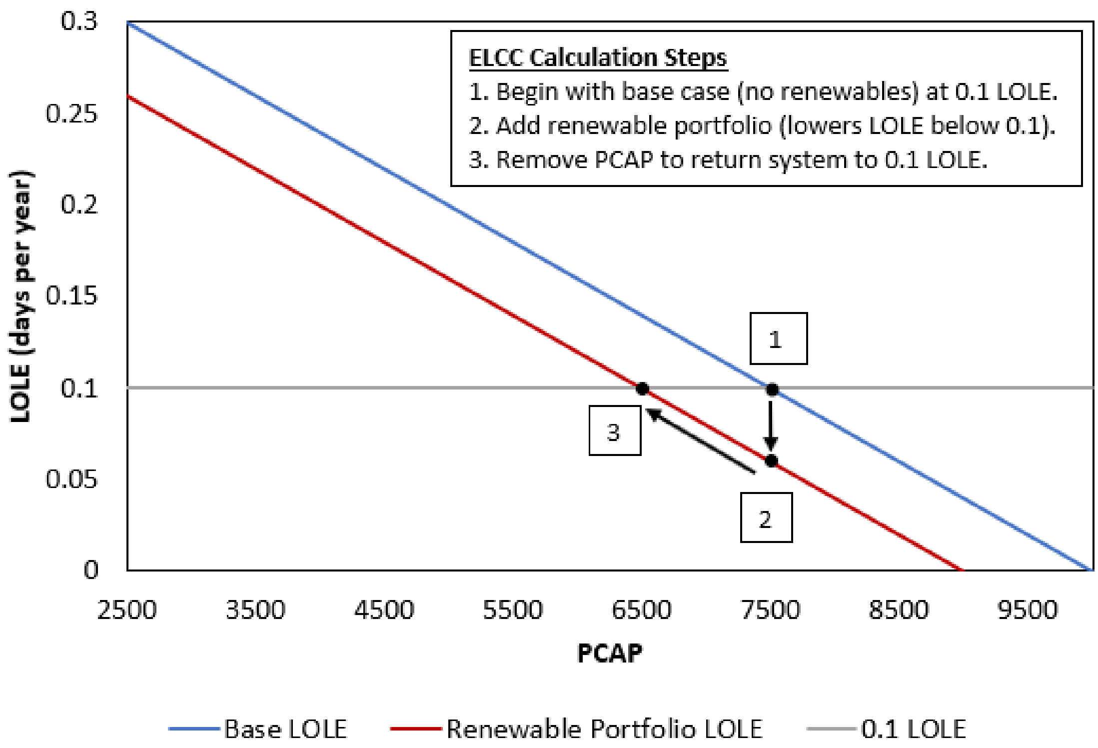
This study focuses on calculating the ELCC of renewable and energy storage portfolios. The ELCC of a variable energy resource is the capacity value (expressed in MW) associated with the resource's reliability contribution to the system. The ELCC can also be measured as a percentage of the calculated capacity value relative to the nameplate capacity value of the resource. The process used in this study consists of the following steps:

1. The first step in the portfolio ELCC analysis was to calibrate the base case to a 0.1 LOLE target in both the summer and winter. The study year chosen was 2026 and involved removing all the variable energy resources from ERCOT and some conventional generation and adding perfect capacity – capacity with no outages or ramping limitations – until the summer and winter reliability risk is at 0.1 LOLE individually.

[12] Individual county and site-specific output profiles for 1980-2021 were provided by ERCOT, obtained through UL (formerly AWS Truepower).

2. Starting with the base case at 0.1 LOLE above, solar and wind capacity of 60 GW each was added to the system, which improved the LOLE. Perfect capacity was removed until the reliability risk in the summer and winter was reduced to 0.1 LOLE. The MW value of perfect capacity removed was equal to the average ELCC of the added variable energy resource portfolio. Figure 6, below, represents the ELCC calculation process.

Figure 6. ELCC Methodology



The ELCC scenarios analyzed can be summarized as a combination of the following capacity vectors:

- Solar capacity (MW): 0 - 60 GW
- Wind capacity (MW): 0 - 60 GW

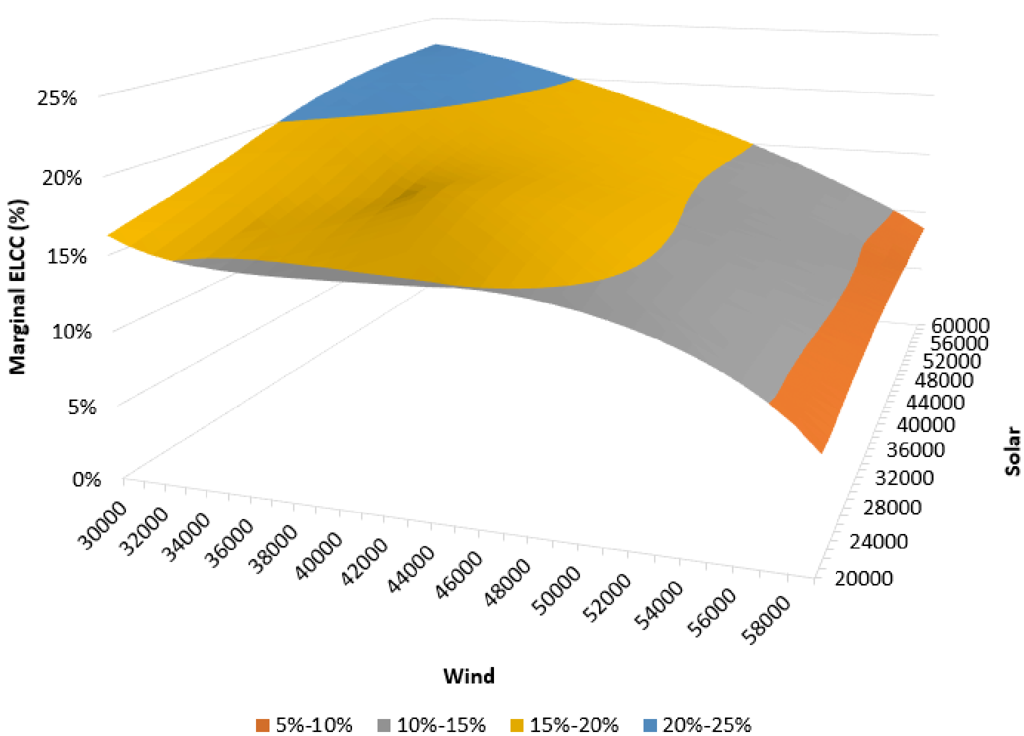
For example, Table 4 represents the matrix of all portfolios modeled in SERVM for a solar-wind surface.

Table 4. Summer Portfolio Capacity Contribution

		Wind MW						
		30,000	35,000	40,000	45,000	50,000	55,000	60,000
Solar MW	20,000	13,695	14,465	15,195	15,932	16,671	17,341	17,832
	25,000	14,108	14,931	15,733	16,554	17,359	18,065	18,564
	30,000	14,414	15,296	16,142	17,025	17,859	18,567	19,073
	35,000	14,664	15,611	16,518	17,328	18,239	18,935	19,445
	40,000	14,865	15,871	16,821	17,719	18,532	19,213	19,722
	45,000	15,021	16,067	17,047	17,952	18,755	19,236	19,924
	50,000	15,123	16,197	17,200	18,115	18,918	19,578	20,073
	55,000	15,170	16,265	17,287	18,214	19,023	19,691	20,193
	60,000	15,171	16,282	17,315	18,247	19,058	19,730	20,223

The ELCC matrices were constructed for varying wind and solar generation levels without storage in the system. These compact matrices were interpolated at step-sizes of 1,000 MW for both wind and solar dimensions to generate a wind-solar surface with monotonically decreasing first-order derivatives. The interpolation process utilized a bivariate spline approach, incorporating iterative triangular smoothing to refine the surface. Figure 7 represents a dense matrix between solar and wind in the summer. The goal of creating a 2-dimensional matrix of non-dispatchable resources (wind and solar) is to generate ELCCs for unlimited combinations of storage portfolios.

Figure 7. Summer Evening Wind ELCCs

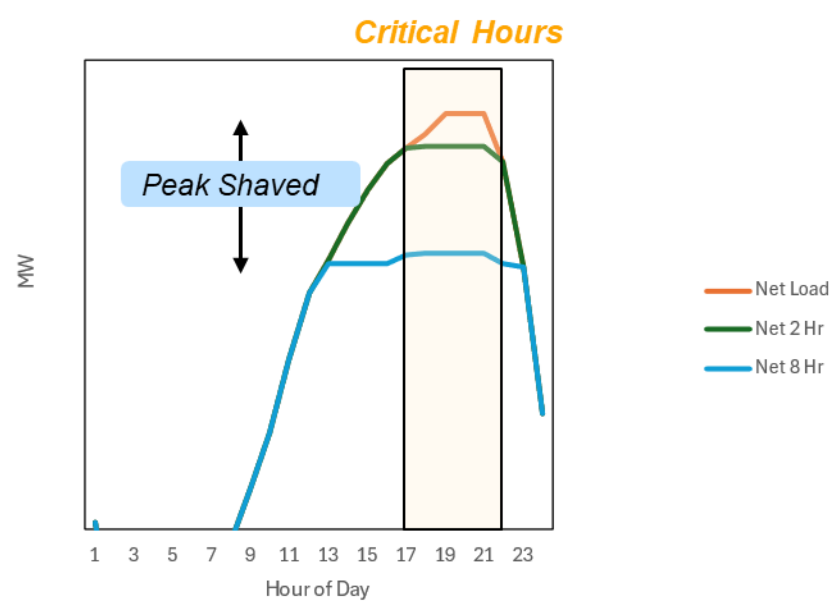


A similar surface was also constructed for Winter. These seasonal two-dimensional surfaces are then leveraged using an out-of-model approach to establish storage values for each portfolio. This out-of-model event-based approach helps to calculate the reliable storage capacity value for any combination of storage duration (X GW of 2-Hr Battery, Y GW of 4-Hr Battery, Z GW of 8-Hr Battery, etc.).

Steps for the Out-of-Model Event-Based Approach:

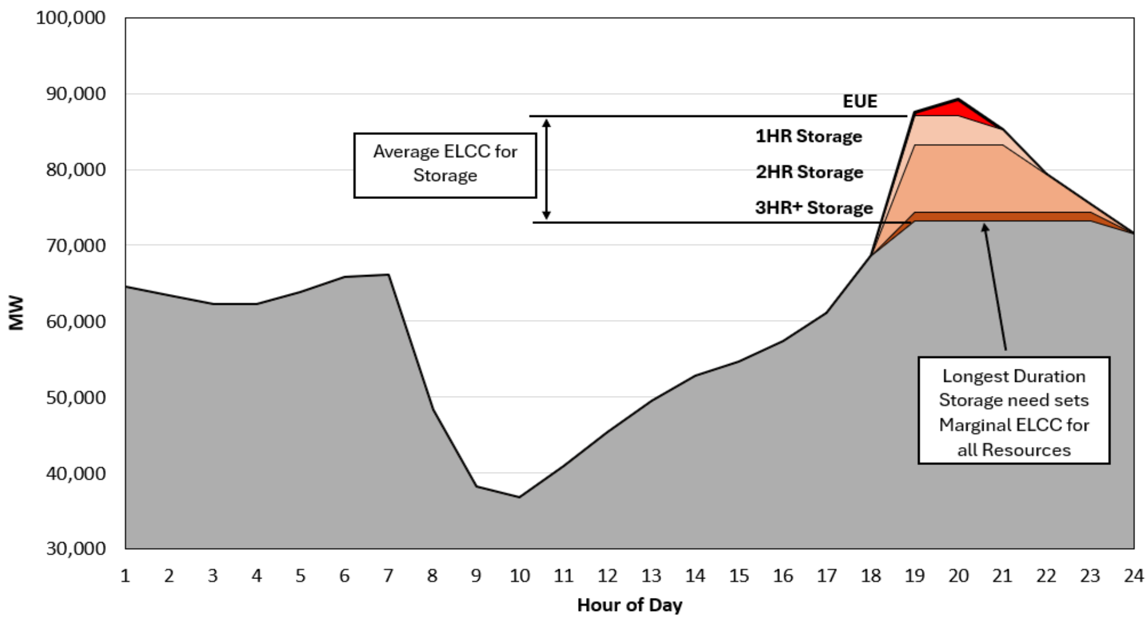
1. **LOLE Event Identification:**
   a. SERVM identifies numerous Loss of Load Expectation (LOLE) events at 0.1 LOLE for various Solar and Wind penetrations.
   b. This step determines all the Loss of Load days at different Solar-Wind penetration levels.
2. **Redistribution of Loss of Load Events via the Out-of-Model Tool:**
   a. The out-of-model tool redistributes Loss of Load (LoL) events to optimize using different storage technologies.
   b. This redistribution is guided by energy equity principles, ensuring a fair and effective allocation of energy resources.
   c. The tool evaluates storage technologies' capacity to meet energy demands during peak loss of load periods, prioritizing resource allocation to minimize unserved energy most equitably and efficiently.
3. **Storage Peak Shaving Capability:**
   a. For each day experiencing Expected Unserved Energy (EUE), the tool calculates the peak shaving capability of each storage technology, as shown in Figure 8.
   b. This step ensures storage systems effectively mitigate unserved energy by reducing peak demand.

Figure 8. Storage ELCC Quantification



4. **ELCC Calculation:**
    a. The average Effective Load Carrying Capability (ELCC) is calculated based on the peak shaving contribution of each storage duration class, as shown in Figure 9.[13]
    b. The marginal ELCC is determined by evaluating the average output of storage during storage-constrained periods, reflecting the incremental value of additional storage capacity.

Figure 9. Average and Marginal ELCC Calculation



5. **Seasonal Weighting of Net Load Reduction and Marginal ELCC Values:**
    a. The reductions in net load peak and marginal ELCC values are weighted to produce seasonal summer and winter ELCC estimates.
    b. This weighting is based on case probabilities derived from the stochastic model in SERVM, which considers variations in resource availability, demand patterns, and other uncertainties.

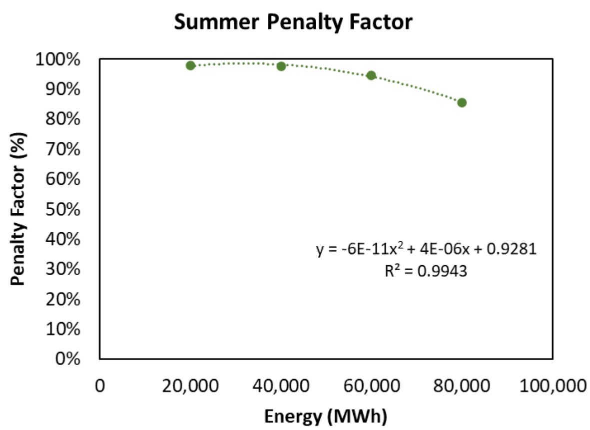
The results from the interpolated solar-wind surface, combined with the storage dispatch tool, are used to generate outputs for any specific solar-wind and storage profile. The solar and wind portfolio ELCC is derived from the interpolated surface, while marginal contributions are integrated to quantify the specific impact of solar and wind at various penetration levels. These contributions are then allocated based on location, such as Solar-West and Solar-Non-West.

[13] As discussed in the executive summary, average and marginal ELCC were mapped to risk periods based on closest alignment.

To ensure alignment with SERVM results, penalty factors were calibrated and applied to the ELCC values obtained from the Excel storage dispatch model, as shown in

Figure 10. These penalty factors account for both additional benefits, such as ancillary service contributions and interactions with other resources, and constraints, including starting state of charge (SOC) and outage impacts on other resources. This calibration process ensures a more accurate reflection of system dynamics and resource limitations.

Figure 10. Seasonal Penalty Factors



A final adjustment was made for forced outage risk on the batteries. Given variable and uncertain performance risk on batteries, we assumed a 5% impact on ELCC for batteries for all results published. As more performance data for batteries becomes available, future ELCC studies can more robustly measure the impact of outage risk on reliability contribution.

RESULTS

SERVM was calibrated seasonally to 0.1 LOLE for the summer and winter seasons separately. As the renewable portfolio penetration was increased, perfect capacity was removed from the system to calibrate it back to 0.1 seasonal LOLE.

Given reliability need has historically been concentrated in summer afternoon hours, the reliability contribution of solar has been assumed to be quite high – the reliability credit for solar in past CDRs has been 74-100% between 2010-2024. The shift to winter reliability and the large additions of solar capacity have significantly lowered the projected contribution of marginal solar additions in the evenings in summer, as shown in Figure 11. Solar output is minimal in the winter in very early morning hours and very late evening hours where reliability risk occurs. As solar penetration continues to grow, incremental solar capacity does not contribute much to reliability.

Figure 11. Summer Evening Solar ELCCs

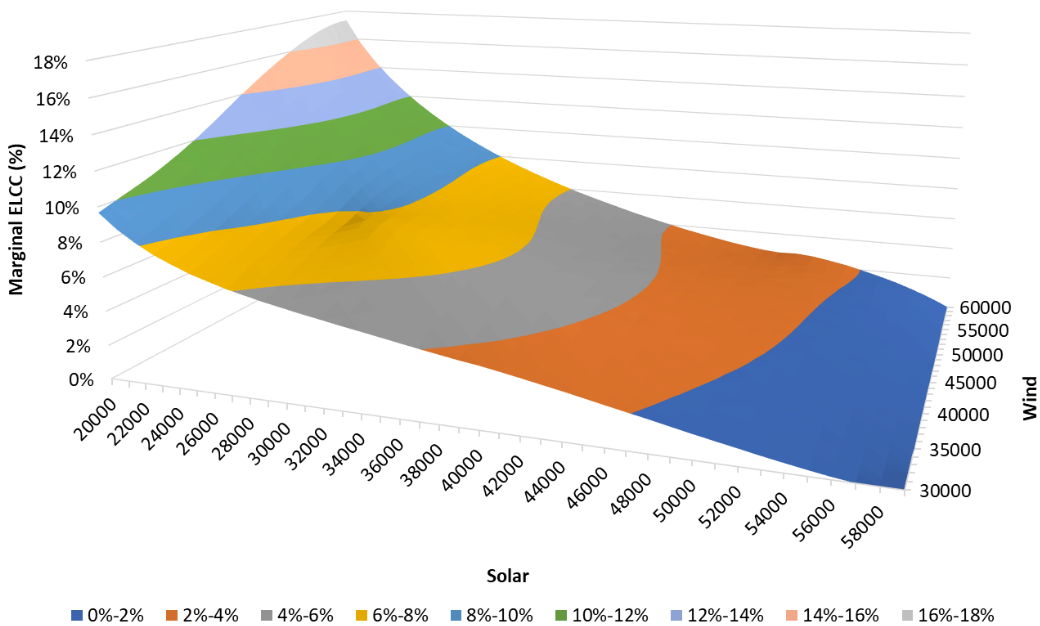
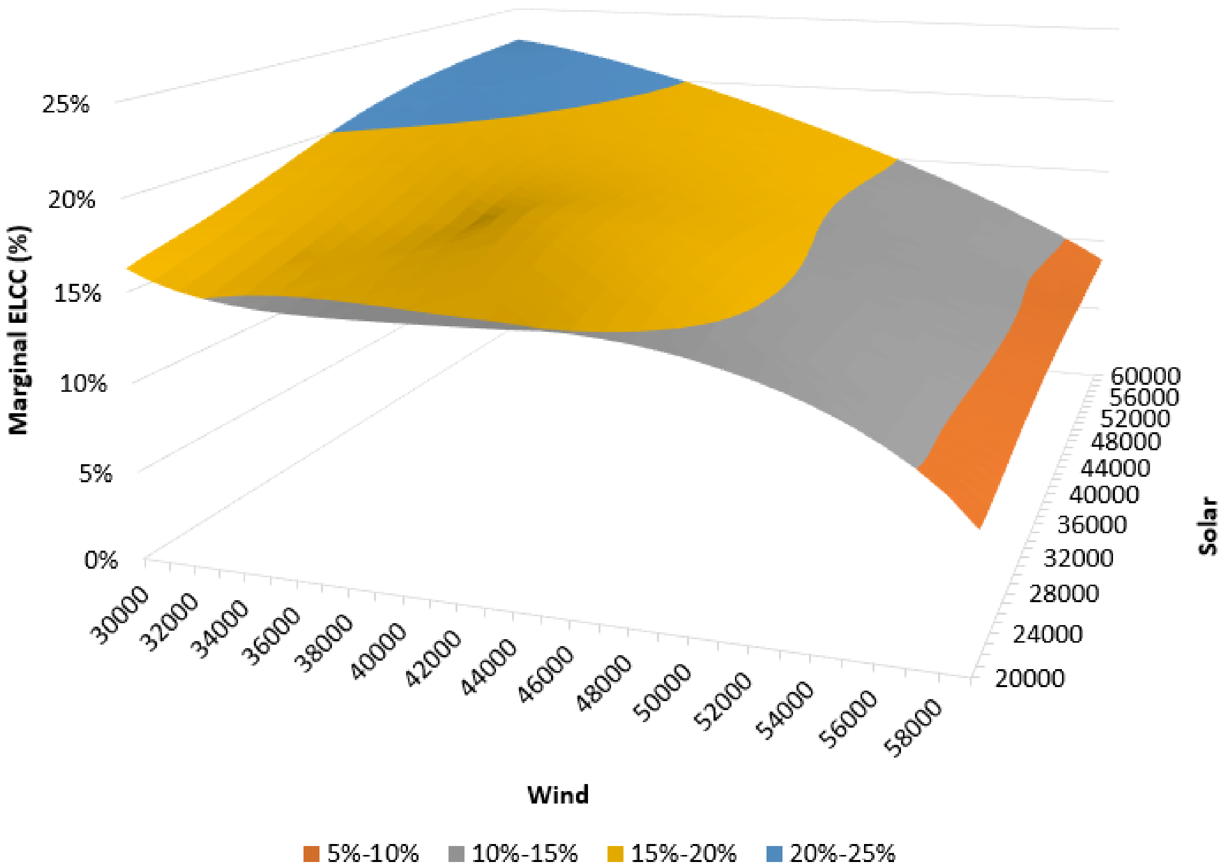


Figure 12 shows summer wind resource reliability contributions are more stable but are also subject to further declines in evening ELCCs with penetration as the risk of large area wind lulls have a larger impact on reliability.

Figure 12. Summer Evening Wind ELCCs



The resource class ELCC results mentioned above were also decomposed into technology or location specific ELCCs. Renewable profiles for each zone were created by calculating a weighted average of all the county level profiles for the zone or technology being analyzed. A 1-GW marginal unit was added at 2025 penetrations to calculate the following ELCCs:

- Wind-C
- Wind-O
- Wind-P
- Solar Other
- Solar West
- Solar Far West

Table 5 and

Technology	Installed Capacity (MW)	Afternoon ELCC (%)	Evening ELCC (%)
Wind-C	5,678	30.83%	16.37%
Wind-O	29,796	15.68%	8.33%
Wind-P	4,669	33.58%	17.83%

Solar Other	22,922	27.21%	5.51%
Solar West	7,000	36.14%	7.32%
Solar Far West	3,653	36.14%	7.32%
Storage 1-hour	6,898	70.72%	13.71%
Storage 2-hour	7,651	93.29%	27.43%
Storage 3-hour	202	93.29%	41.14%
Storage 4-hour	247	93.29%	54.85%
Storage 5-hour	20	93.29%	68.15%

Table 6 provide the summer and winter risk period ELCC results for each of the technology and location specific tests that were performed at the 2025 penetrations. These tables also show the results for 1-to-5 hour duration storage resources.

Table 5. 2025 Summer Risk Period ELCCs for Technology or Location Specific Results

Technology	Installed Capacity (MW)	Afternoon ELCC (%)	Evening ELCC (%)
Wind-C	5,678	30.83%	16.37%
Wind-O	29,796	15.68%	8.33%
Wind-P	4,669	33.58%	17.83%
Solar Other	22,922	27.21%	5.51%
Solar West	7,000	36.14%	7.32%
Solar Far West	3,653	36.14%	7.32%
Storage 1-hour	6,898	70.72%	13.71%
Storage 2-hour	7,651	93.29%	27.43%
Storage 3-hour	202	93.29%	41.14%
Storage 4-hour	247	93.29%	54.85%
Storage 5-hour	20	93.29%	68.15%

Table 6. 2025 Winter Risk Period ELCCs for Technology or Location Specific Results

Technology	Installed Capacity (MW)	Morning ELCC (%)	Evening ELCC (%)
Wind-C	5,678	29.90%	29.90%
Wind-O	30,296	15.20%	15.20%
Wind-P	4,835	32.56%	32.56%
Solar Other	24,867	1.95%	1.95%
Solar West	7,934	2.59%	2.59%
Solar Far West	3,653	2.59%	2.59%
Storage 1-hour	7,847	25.46%	23.14%

Storage 2-hour	10,239	60.47%	56.15%
Storage 3-hour	202	86.08%	90.42%
Storage 4-hour	401	93.37%	93.37%
Storage 5-hour	20	93.37%	93.37%

The results from the interpolated solar-wind surface, combined with the storage dispatch tool, were used to generate outputs for the forecasted solar, wind, and storage penetrations for the next 5 years. Figure 13 and Figure 14 provide the summer solar and wind risk period ELCCs overtime for each technology. The projected contribution of solar resources is expected to continue to decline over the next 5 years as we shift to winter reliability risk and continue to add large amounts of solar capacity to the system. Summer wind ELCCs and penetrations are more stable compared to solar.

Figure 13. Summer Solar Location Specific Afternoon and Evening ELCCs Over the Next 5 Years

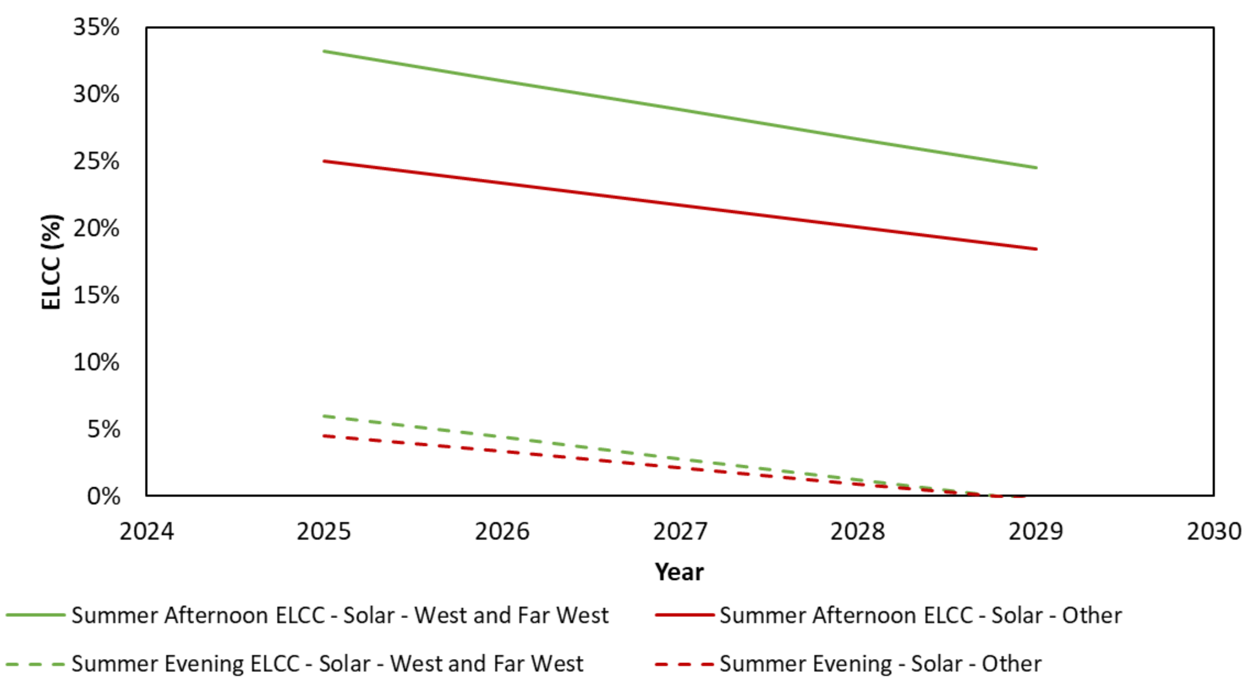


Figure 14. Summer Wind Location Specific ELCCs Over the Next 5 Years

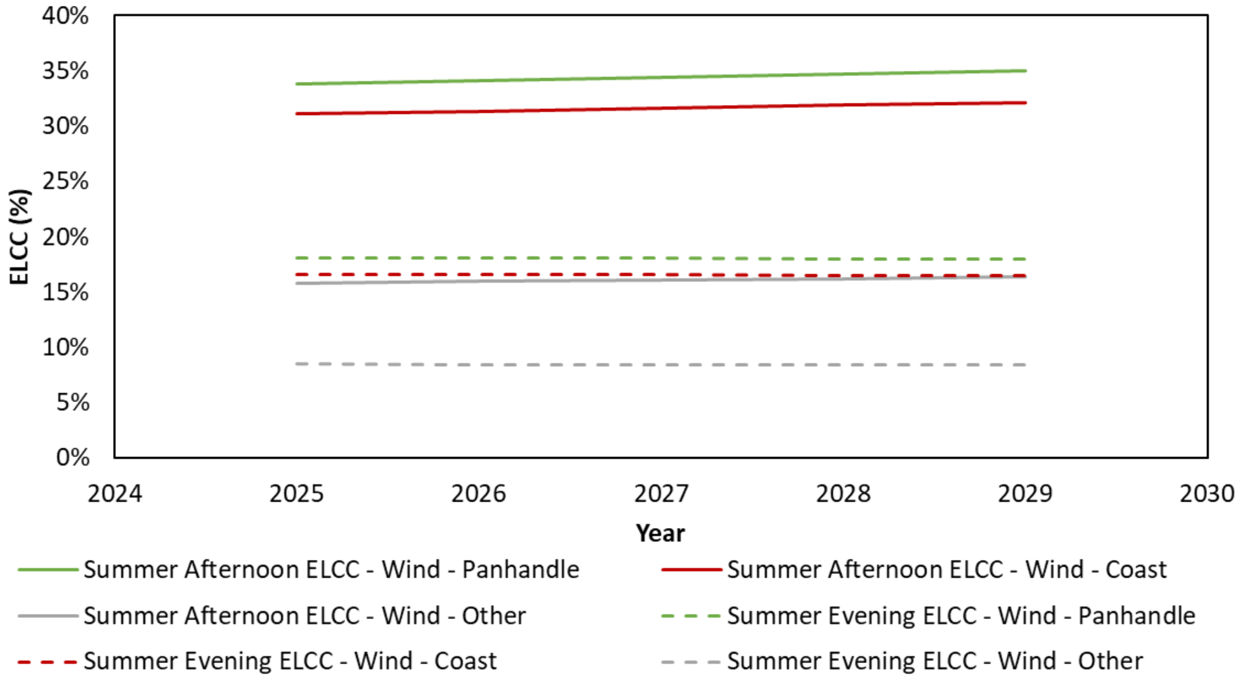


Figure 15 and Figure 16 provide the summer storage ELCCs for the next 5 years by duration. Summer afternoon storage ELCCs are expected to remain high over the next 5-year planning window while shorter duration resources contribution will continue to decline. Summer evening storage ELCCs indicate that 5 hours or longer duration is required to provide greater than 85% ELCCs over the next 5-year planning window.

Figure 15. Summer Storage Afternoon ELCCs of Varying Duration Over the Next 5 Years

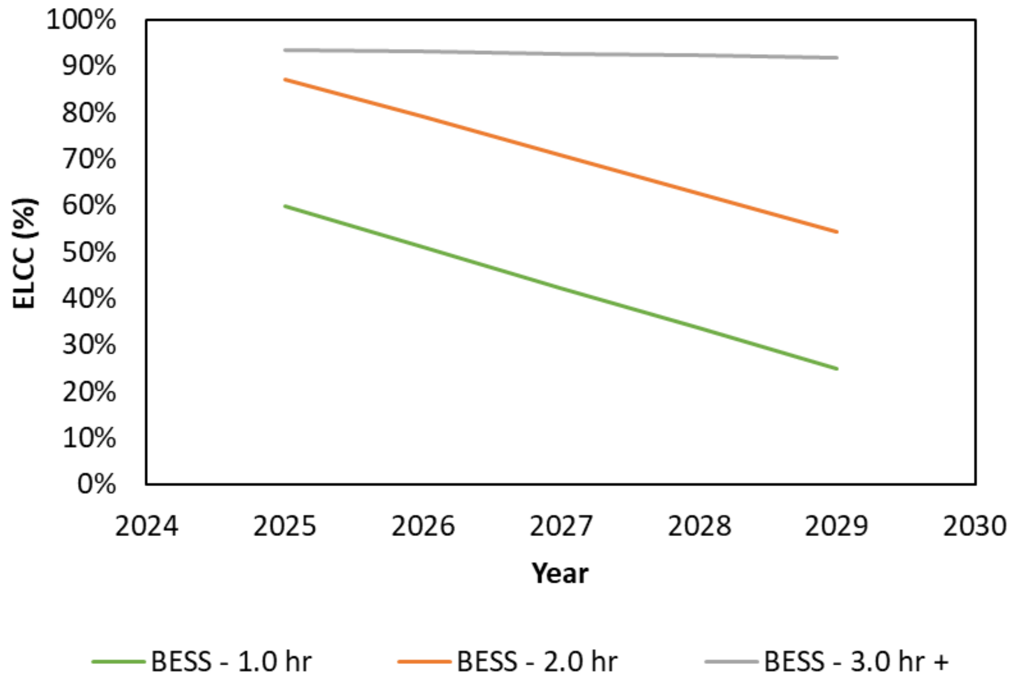


Figure 16. Summer Storage Evening ELCCs of Varying Duration Over the Next 5 Years

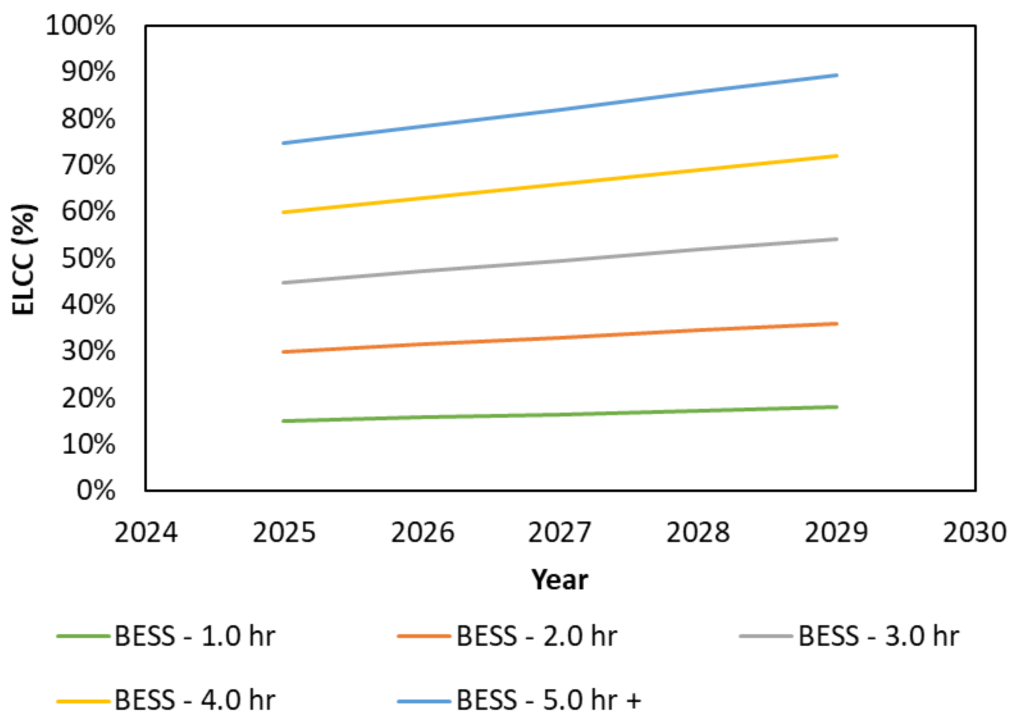


Figure 17 -Figure **20** provide the winter ELCCs for solar, wind, and storage, respectively. Winter morning and evening solar ELCCs over the next 5 years are low and continue to decline as penetration increases. Wind ELCCs stay relatively constant over the 5-year period with very slight declines in reliability

contribution. The winter morning and evening storage ELCCs all show a slow decline in reliability contribution across all durations.

Figure 17. Winter Solar Location Specific Morning and Evening ELCCs Over the Next 5 Years

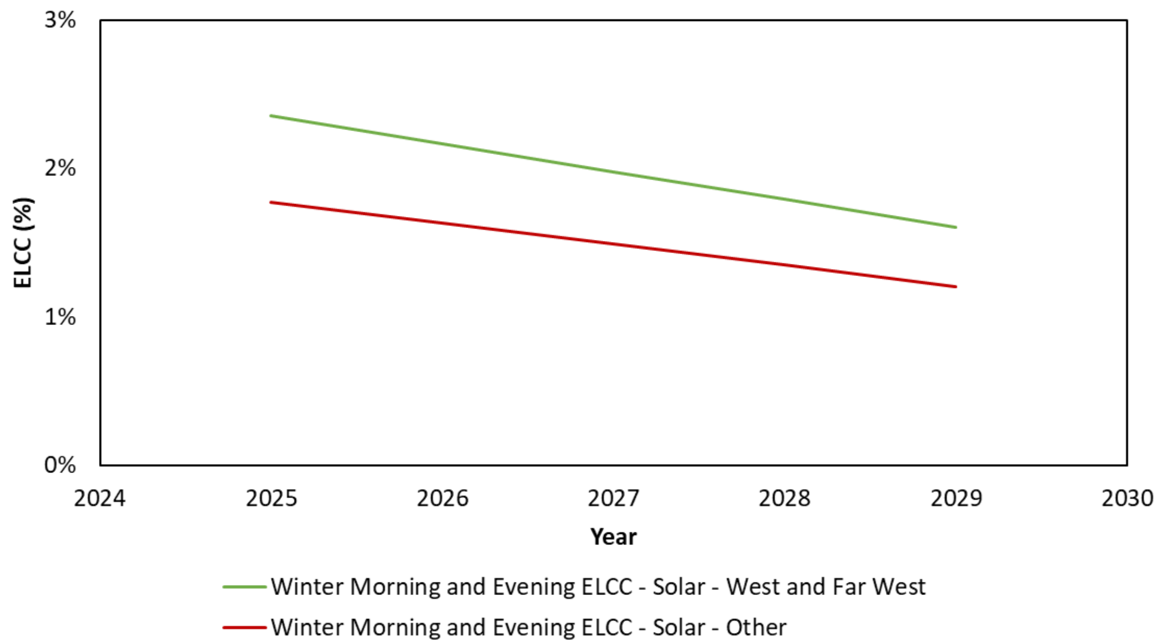


Figure 18. Winter Wind Location Specific Morning and Evening ELCCs Over the Next 5 Years

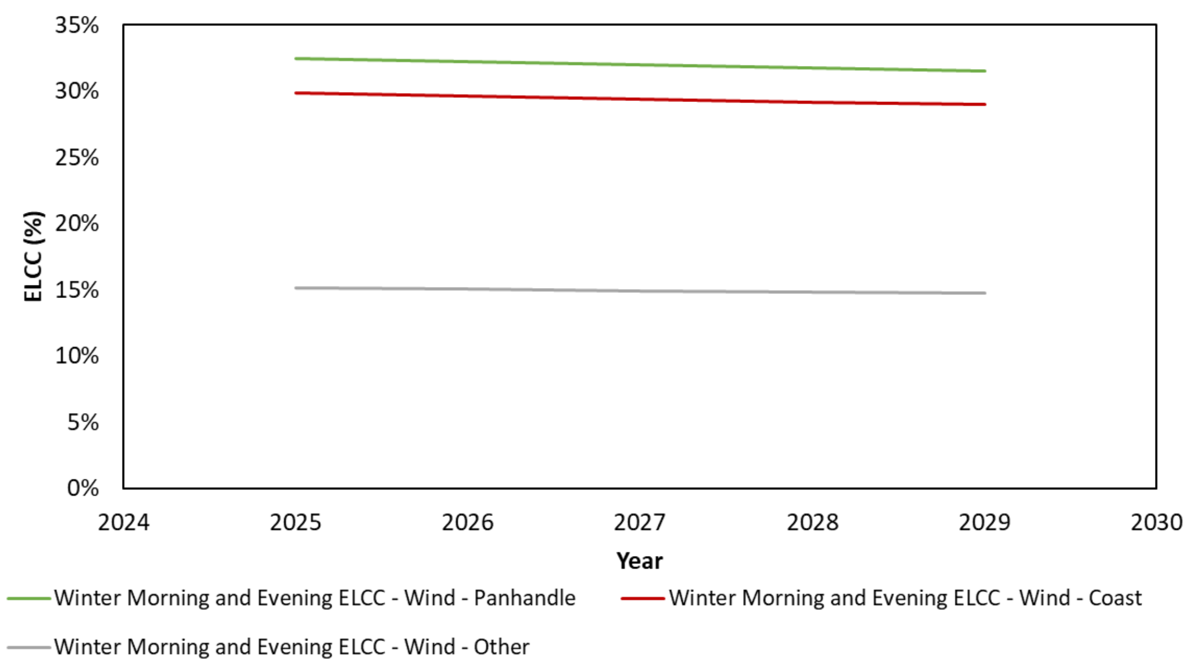


Figure 19. Storage Winter Morning ELCCs of Varying Duration Over the Next 5 Years

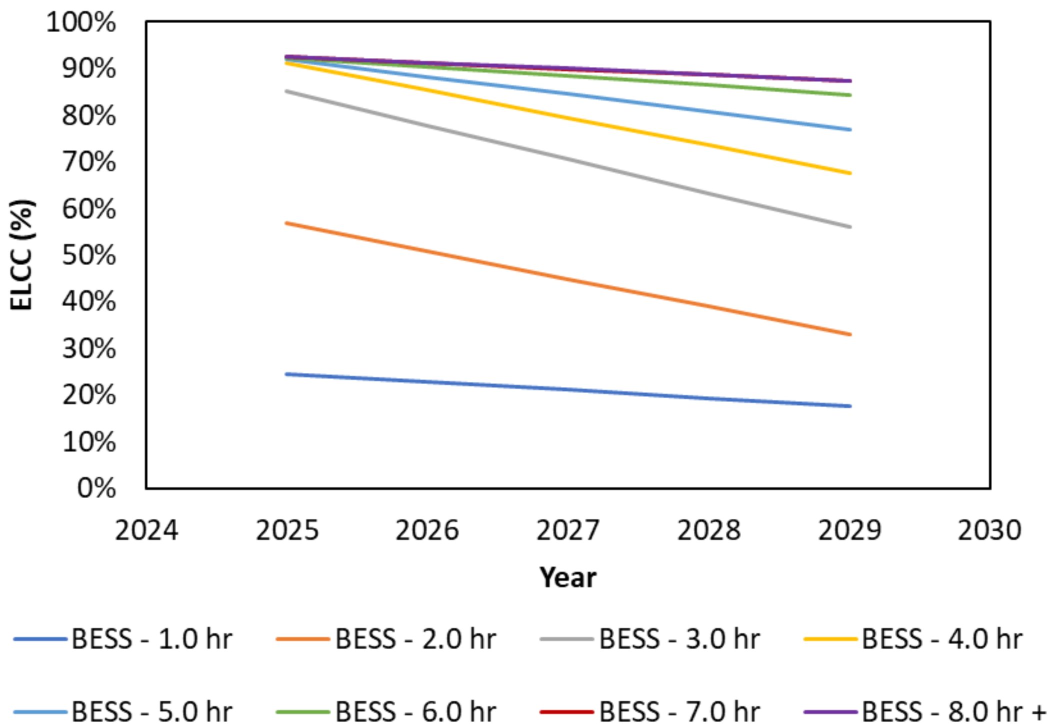
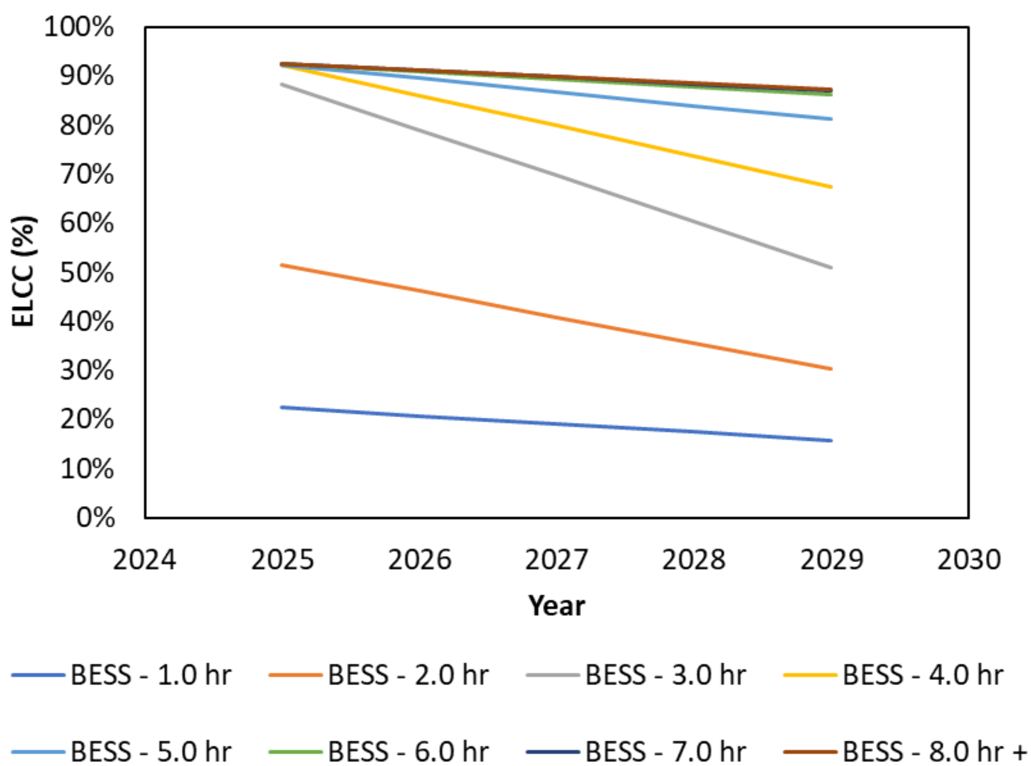


Figure 20. Storage Winter Evening ELCCs of Varying Duration Over the Next 5 Years



CONCLUSIONS AND NEXT STEPS

The out-of-model approach employed in this ELCC study marks an improvement over past studies because it allows for consideration of multiple storage durations. While the out-of-model approach for storage ELCC calculations does not consider constraints such as starting state of charge or ancillary service eligibility, results were calibrated with SERVM simulations to ensure these factors were considered in the final ELCC values.

The authors recognize the value of ELCC stability for all resource classes for signaling the reliability value of resources to those planning changes to the electric system. However, the reliability contribution of wind, solar, and storage are contingent not only on the penetration of each class, but on the composition of load in ERCOT and the performance characteristics of the conventional fleet. For example, electric heating loads, new large load responses to market price signals, or thermal generator winter performance could differ from current expectations and thereby significantly change the reliability contribution of the variable energy resource portfolio. Uncertainty in how these load and resource characteristics evolve in the future warrant monitoring of ELCC suitability for future forecast periods and their periodic re-estimation if needed.

APPENDIX

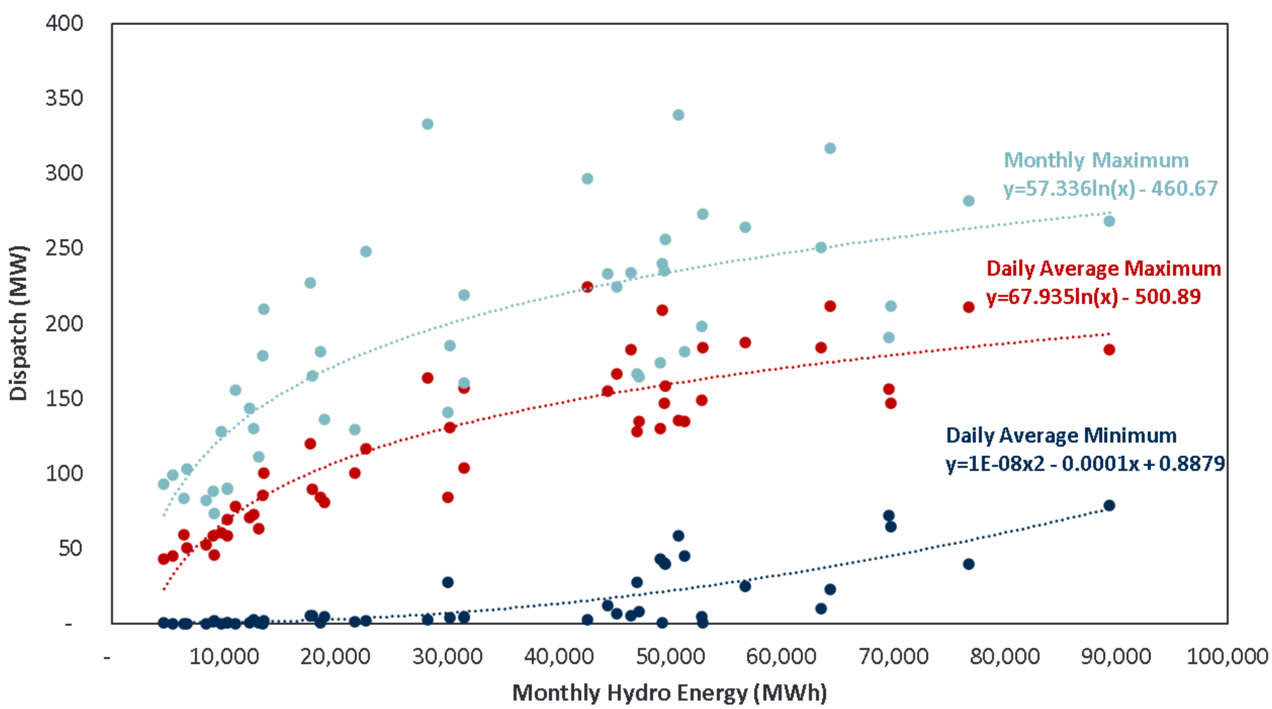
A. GENERATION RESOURCES

1. HYDROELECTRIC

We include 577 MW of hydroelectric resources, consistent with ERCOT's May 2024 CDR report. We characterize hydro resources using eight years of hourly data over 2020-2023 provided by ERCOT, and 44 years of monthly data over 1980-2023 from Form EIA-923.[14] For each month, SERVM uses four parameters for modeling hydro resources, as summarized in Figure A1: (1) monthly total energy output, (2) monthly maximum output, (3) daily maximum output, and (4) daily minimum output, as estimated from historical data.

When developing hydro output profiles, SERVM will first schedule output up to the monthly maximum output into the peak hours but will schedule some output across all hours based on historically observed output during off-peak periods up to the total monthly output. During emergencies, SERVM can schedule up to 49.25 MW in drought conditions and 116.15 MW for all other months.

Figure A1. Historical Hydro Energy Relationships



[14] https://www.eia.gov/electricity/data/eia923/

2. FUEL PRICES

We used the 2023 Annual Energy Outlook reference case fuel forecasts for the 2026 study year. The average fuel prices used in the study are presented in Table A1.

Table A1. ERCOT Fuel Forecasts

Coal Fuel Price ($/MMBtu)	Gas Fuel Price ($/MMBtu)	Diesel Fuel Price ($/MMBtu)
2.21	3.41	16.95

B. ANCILLARY SERVICE MODELING

Ancillary services are necessary to maintain the reliability of the ERCOT System. Ancillary services are procured to ensure sufficient resource capacity is online or able to be brought online in a timely manner to balance the variability that cannot be covered by the 5-minute energy market. The four types of Ancillary Services in ERCOT currently are: regulation up service, regulation down service, responsive reserve service, and non-spinning reserve service. ERCOT typically maintains a minimum of 3,000 - 4,000 MW of online upward reserves in order to protect reliability in the event of a disturbance or to provide the necessary flexibility to follow potentially volatile net load patterns. SERVM maintains these online upward reserves when adequate resources are available. When resource availability declines during simulations, emergency operating procedures are activated in SERVM to deploy reserves and call emergency resources such as demand response. Emergency operating procedures are discussed in more detail in Section C.

C. SCARCITY PRICING AND DEMAND RESPONSE MODELING

Several types of demand response participate directly or indirectly in ERCOT’s market, including Emergency Response Service (ERS), Load Resources, and Price Responsive Demand. These various resource types differ from each other in whether they are triggered by price-based or emergency actions, and restrictions on availability and call hours. Table A2 summarizes the resources, explaining how we modeled their characteristics and their assumed marginal costs when utilized, and how they were accounted for in the reserve margin.

Table A2. Summary of Demand Resource Characteristics and Modeling Approach

Resource Type	Quantity (MW)	Modeling Approach	Adjustments to ERCOT Load Shape	Reserve Margin Accounting
Energy Efficiency	3,497	Not explicitly modeled	None	Load reduction
Firm Fuel Supply Service	141	Triggered based on wind chill	None	None
Distribution Voltage Reduction	701	Emergency trigger before EEA Level 1	None	None
30-Minute ERS	875	Emergency trigger before EEA Level 1	None	Load reduction
10-Minute ERS	10	Emergency trigger before EEA Level 1	None	Load reduction
Load Management	372	Emergency trigger at EEA Level 1	None	Load reduction
Non-Controllable LRs	1,115	Economically dispatch for Responsive Reserve Service (most hours) or energy (few peak hours). Emergency deployment at EEA Level 2	None	Load reduction
Controllable LRs		Currently no controllable LRs modeled in ERCOT	*n/a*	*n/a*
4 CP Reductions	1,700	Not explicitly modeled	None	None; excluded from reported peak load
Price Responsive Demand	Variable	Not explicitly modeled	None	None; excluded from reported peak load

Sources and Notes:
Developed based on analyses of recent DR participation in each program and input and data from ERCOT staff.

1. EMERGENCY RESPONSE SERVICE

Emergency response service (ERS) includes two types of products, 10-minute and 30-minute (weather sensitive and non-weather sensitive) ERS, with the quantity of each product available changing by time of day and season as shown in Table A3. The quantity of each product by time of day and season is proportional to the quantities most recently procured over the four seasons of year 2023 and 2024, with the 2026 summer peak quantity assumptions provided by ERCOT.[15] Demand resources enrolled under ERS are dispatchable by ERCOT during emergencies but cannot be called outside their contracted hours and cannot be called for more than twenty-four hours total per season.

[15] For total ERS procurement quantities by product type and season, see https://www.ercot.com/mp/data-products/data-product-details?id=NP3-144-M

Table A3. Assumed ERS Quantities Available in 2026

Contract Period	Quantity			
	10-Min NWS *(MW)*	30-Min NWS *(MW)*	30-Min WS *(MW)*	Total *(MW)*
June - September				
TP1: Weekdays HE 6 AM - 9 AM	11.3	959.1	-	970.5
TP2: Weekdays HE 10 AM - 1 PM	11.6	958.9	-	970.5
TP3: Weekdays HE 2 PM - 4 PM	11.5	963.1	33.8	1,008.4
TP4: Weekdays HE 5 PM - 7 PM	10.4	842.2	32.5	885.0
TP5: Weekdays HE 8 PM - 10 PM	11.4	941.4	-	952.8
TP6: Weekend and Holidays HE 6 AM - 9 AM	11.4	895.7	-	907.1
TP7: Weekend and Holidays HE 4 PM - 9 PM	11.6	896.5	-	908.2
TP8: All Other Hours	11.5	907.3	-	918.7
October - November				
TP1: Weekdays HE 6 AM - 9 AM	15.8	713.1	-	729.0
TP2: Weekdays HE 10 AM - 1 PM	15.4	735.0	-	750.3
TP3: Weekdays HE 2 PM - 4 PM	15.5	743.7	6.9	766.1
TP4: Weekdays HE 5 PM - 7 PM	15.4	724.6	9.4	749.5
TP5: Weekdays HE 8 PM - 10 PM	15.7	701.2	1.0	717.9
TP6: Weekend and Holidays HE 6 AM - 9 AM	15.5	650.0	-	665.5
TP7: Weekend and Holidays HE 4 PM - 9 PM	16.2	654.3	-	670.6
TP8: All Other Hours	15.3	633.8	-	649.1
December - March				
TP1: Weekdays HE 6 AM - 9 AM	11.8	783.6	0.6	796.0
TP2: Weekdays HE 10 AM - 1 PM	11.9	790.6	-	802.4
TP3: Weekdays HE 2 PM - 4 PM	11.8	795.6	-	807.4
TP4: Weekdays HE 5 PM - 7 PM	11.7	802.5	0.6	814.8
TP5: Weekdays HE 8 PM - 10 PM	12.0	768.8	-	780.9
TP6: Weekend and Holidays HE 6 AM - 9 AM	12.2	737.5	-	749.6
TP7: Weekend and Holidays HE 4 PM - 9 PM	12.3	592.4	-	604.8
TP8: All Other Hours	12.3	740.5	-	752.8
April - May				
TP1: Weekdays HE 6 AM - 9 AM	14.4	810.7	-	825.1
TP2: Weekdays HE 10 AM - 1 PM	14.3	855.4	-	869.7
TP3: Weekdays HE 2 PM - 4 PM	14.0	855.7	-	869.7
TP4: Weekdays HE 5 PM - 7 PM	14.1	868.0	3.7	885.8
TP5: Weekdays HE 8 PM - 10 PM	14.2	804.4	-	818.6
TP6: Weekend and Holidays HE 6 AM - 9 AM	14.2	735.1	-	749.3
TP7: Weekend and Holidays HE 4 PM - 9 PM	14.3	727.0	-	741.3
TP8: All Other Hours	14.2	794.4	-	808.6

Sources and Notes:

Total available ERS MW for 2026 June-Sept. TP4 provided by ERCOT staff.

ERS 10-min and 30-min MW for other contract periods scaled proportionally to the study year quantities based on availability in 2023-2024.

2. LOAD RESOURCES PROVIDING REAL-TIME RESERVES

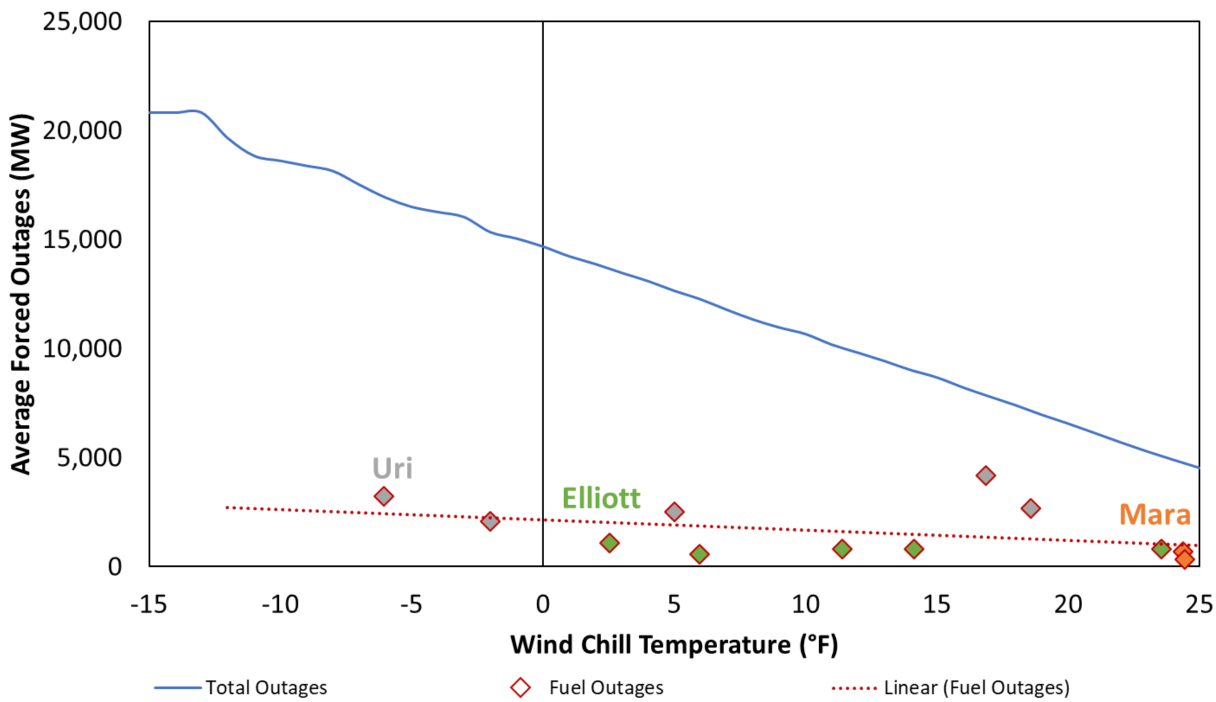
Consistent with ERCOT's published minimum Responsive Reserve Service (RRS) requirements, we modeled 1,115 MW of non-controllable load resources (LRs) that actively participate in the RRS market.[16] All 1,115 MW were modeled as responsive to Energy Emergency Alert, Level 2.

[16] Currently, 1,400 MW is the maximum quantity of non-controllable LRs that are allowed to sell responsive reserve service (RRS) and is the clearing quantity in the vast majority of hours.

3. FIRM FUEL SUPPLY SERVICE

The Firm Fuel Supply Service (FFSS) is an ERCOT service that was developed to address reliability during extreme cold weather conditions and is a firm-fuel product that provides additional grid reliability and resiliency during extreme cold weather. For this study, the selected approach estimated temperature-based decreases in fuel limitation outages for units providing FFSS. A fuel limitation outages trend line was constructed from historical outages, as shown in Figure A2, that assumes that about 4.5% of the fleet-wide outages were avoided by procuring FFSS. This assumption translates to a roughly 141 MW improvement in outages at 14 degrees and about 50 MW improvement in outages at 25 degrees. The outage improvement is represented within SERVM as a 141 MW perfect gas unit that provides a linear outage reduction improvement ranging from 50 to 141 MW as wind chill temperature decreases.

Figure A2. Firm Fuel Supply Service Historical Outage Analysis



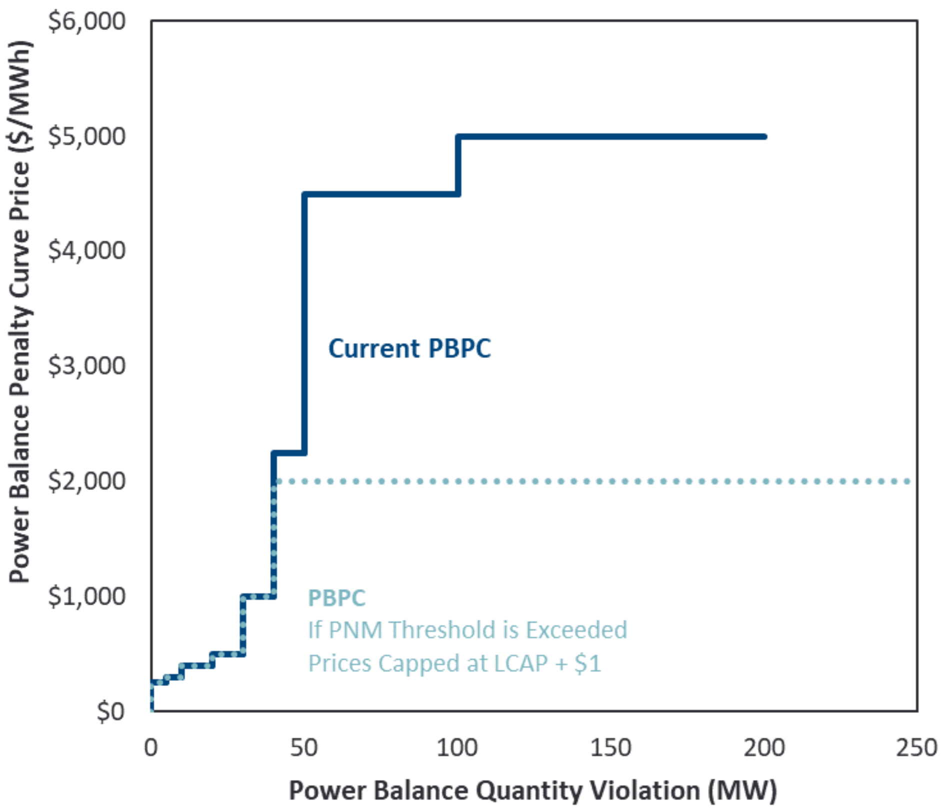
4. DISTRIBUTION VOLTAGE REDUCTION

Distribution Voltage Reduction (DVR) is a voluntary effort to reduce system demand, in response to a temporary decrease in available electricity supply, by systematically lowering the operating voltage on the distribution system. Voltage reduction is performed at ERCOT's instruction before an EEA Level 1 event is reached. This is modeled within SERVM as a 701 MW unit with no deployment limitations. The capacity amount is based on previous information requests that ERCOT sent to Transmission Operators regarding DVR program attributes and expected load reductions based on peak load scenarios.

5. POWER BALANCE PENALTY CURVE

The Power Balance Penalty Curve (PBPC) is an ECOT market mechanism that introduces administrative scarcity pricing during periods of supply scarcity. The PBPC is incorporated into the security constrained economic dispatch (SCED) software as a set of phantom generators at administratively specified price and quantity pairs, as summarized in the blue curve in Figure A3. Whenever PBPC is dispatched for energy, it reflects a scarcity of supply relative to demand in that time period that, if sustained for more than a moment, will materialize as a reduction in the quantity of regulating up capability. As the highest price, the PBPC will reach the system-wide offer cap (SWOC) which is set at the HCAP at the beginning of each calendar year, but which will drop to the LCAP if the PNM threshold is exceeded.

Figure A3. Power Balance Penalty Curve



Within SERVM, PBPC is modeled similarly as a phantom supply that may influence the realized price, and that will cause a reduction in available regulating reserves whenever called. However, only the first 200 MW of the curve at prices below the cap are modeled, and it is assumed that all price points on the PBPC will increase according to the schedule SWOC. It is also assumed that the prices in the PBPC are reflective of the marginal cost incurred by going short of each quantity of regulating reserves. Consistent with current market design, we assume that once the PNM threshold is exceeded, the maximum price in the PBPC will be set at the LCAP + $1/MWh or $2,001/MWh.[17] Note that even after the maximum PBPC price is reduced, ERCOT market prices may still rise to a maximum value of VOLL equal to $5,000/MWh during scarcity conditions because of the ORDC as explained in the following section.

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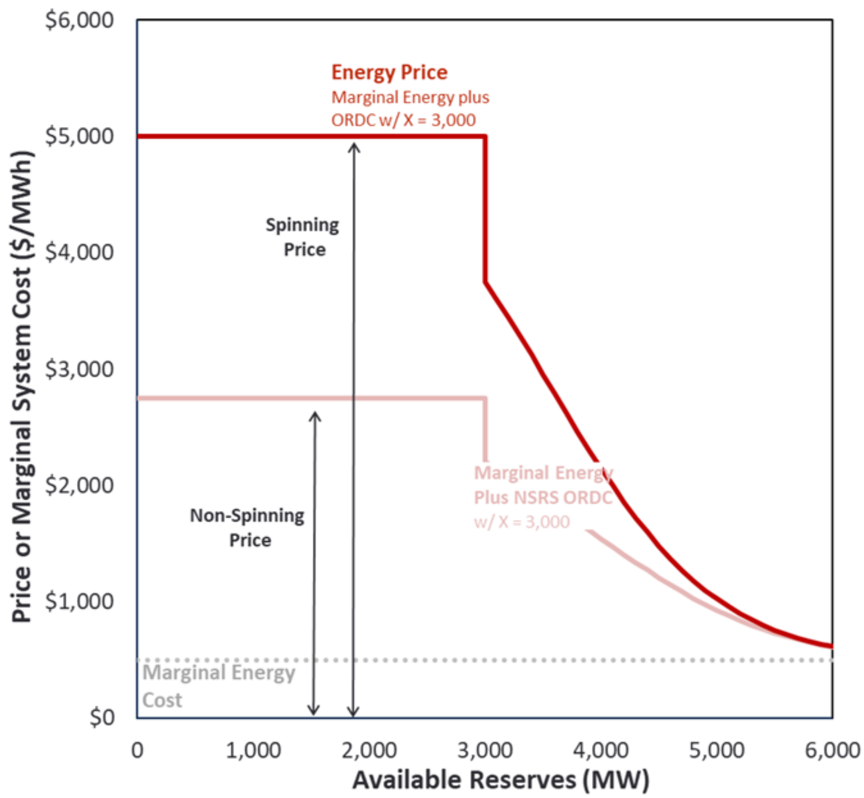
[17] https://www.ercot.com/files/docs/2021/12/14/037OBDRR_01_Power_Balance_Penalty_Updates_to_%20Align_with_PUCT_Approved_High_System_Wide_Offer_Ca.docx

6. OPERATING RESERVES DEMAND CURVE

The most important and influential administrative scarcity pricing mechanism in ERCOT is the ORDC that reflects the willingness to pay for spinning and non-spinning reserves in the real-time market. Figure A4 illustrates our approach to implementing ORDC in our modeling, which is similar to ERCOT's implementation, with some simplifications.

Figure A4. Operating Reserve Demand Curves



The ORDC curves were calculated based on a loss of load probability (LOLP) at each quantity of reserves remaining on the system, multiplied by the value of lost load (VOLL) caused by running short of operating reserves.[18] This curve reflects the incremental cost imposed by running short of reserves and is added to the marginal energy cost to estimate the total marginal system cost and price.

[18] Note that the lost load implied by this function and caused by operating reserve scarcity is additive to the lost load. This is because the LOLP considered in ERCOT's ORDC curve is caused by sub-hourly changes to supply and demand that can cause short-term scarcity and outages that are driven only by small quantities of operating reserves but are not caused by an overall resource adequacy scarcity, which is the type of scarcity we model elsewhere in this study. For simplicity and clarity, we refer to these reserve-related load-shedding events as "reserve scarcity costs" to distinguish them from the load shedding events caused by total supply scarcity. We do not independently review here ERCOT's approach to calculating LOLP, but instead take this function as an accurate representation of the impacts of running short of operating reserves.

The x-axis of the curve reflects the quantity of operating reserves available at a given time, where: (a) the spin ORDC includes all resources providing regulation up or RRS, suppliers that are online but dispatched below their maximum capacity, hydrosynchronous resources, non-controllable load resources, and 10-minute quickstart; and (b) the spin + non-spin ORDC include all resources contributing to the spin x-axis as well as any resources providing NSRS and all 30-minute quickstart units. Table A4 provides a summary of the resources in the model that were always available to contribute to the ORDC x-axis unless they were dispatched for energy. It should be noted that the realized ORDC x-axis during a given hour in the simulation can be higher (if other resources are committed but not outputting at their maximum capability) or lower (during peaking conditions when some of the below resources are dispatched for energy).

Table A4. Resources Always Contributing to ORDC X-Axis Unless Dispatched for Energy

Reserve Type	MW
Spin X-Axis	
Hydrosynchronous Resources	245
Non-Controllable Load Resources	1,115
Non-Spin X-Axis	
30-Minute Quickstart	5,058
Total Spin + Non-Spin	**6,894**

As in ERCOT's ORDC implementation, we calculated: (a) non-spin prices using the non-spin ORDC; (b) spin prices as the sum of the non-spin and spin ORDC; and (c) energy prices as the sum of the marginal energy production cost plus the non-spin and spin ORDC prices. However, as a simplification we did not scale the ORDC curves in proportion to VOLL minus marginal energy in each hour.[19] Instead, we treated the ORDC curves as fixed with a maximum total price adder of VOLL minus $500. This caused prices to rise to the cap of $5,000/MWh in scarcity conditions, because $500 is the cap placed on marginal energy prices in the model. Higher-cost demand-response resources were triggered in response to high ORDC prices and therefore prevented prices from going even higher but did not affect the "marginal energy component" of price-setting. We modeled the ORDC curves out to a maximum quantity of 8,000 MW where the reserve price adders were zero.

These ORDC curves create an economic incentive for units to be available as spinning or non-spinning reserve, which influences suppliers' unit commitment decisions. We therefore modeled unit commitment in two steps: (1) a week-ahead optimal unit commitment over the fleet, with the result determining which

[19] See ERCOT's implementation in http://lmpmarketdesign.com/papers/Back_Cast_of_Interim_Solution_B_Improve_Real_Time_Scarcity_Pricing_Whitepaper.pdf

long-lead and combined cycle resources will be committed;[20] and (2) an hourly economic dispatch that dispatches online baseload units, and can commit 10-minute and 30-minute quickstart units if needed to satisfy energy or ancillary service requirements.[21] Note that 10-minute quickstart units can earn spin payments from an offline position while 30-minute quickstart units can earn non-spin payments from an offline position. The model did not allow these resources to self-commit unless doing so resulted in greater energy and spin payments (net of variable and commitment costs) than would be available from an offline position. We used a similar logic to economically commit or de-commit units until the incentives provided by the ORDC were economically consistent with the quantity of resources turned on.

[20] Short-term resources are included in the week-ahead commitment algorithm, but their commitment schedule is not saved since it will be dynamically calculated in a shorter window. But using short-lead resources in the week-ahead commitment allows them to affect the commitment of long-lead resources.

[21] These week-ahead and day-ahead commitment algorithms minimize cost subject to meeting load as well as ERCOT's administratively determined regulation up, spinning reserve targets, and non-spin targets.