Effective Load Carrying Capability Study

Final Report

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PREPARED FOR

Electric Reliability Council of Texas ("ERCOT")

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TABLE OF CONTENTS

TABLE OF FIGURES

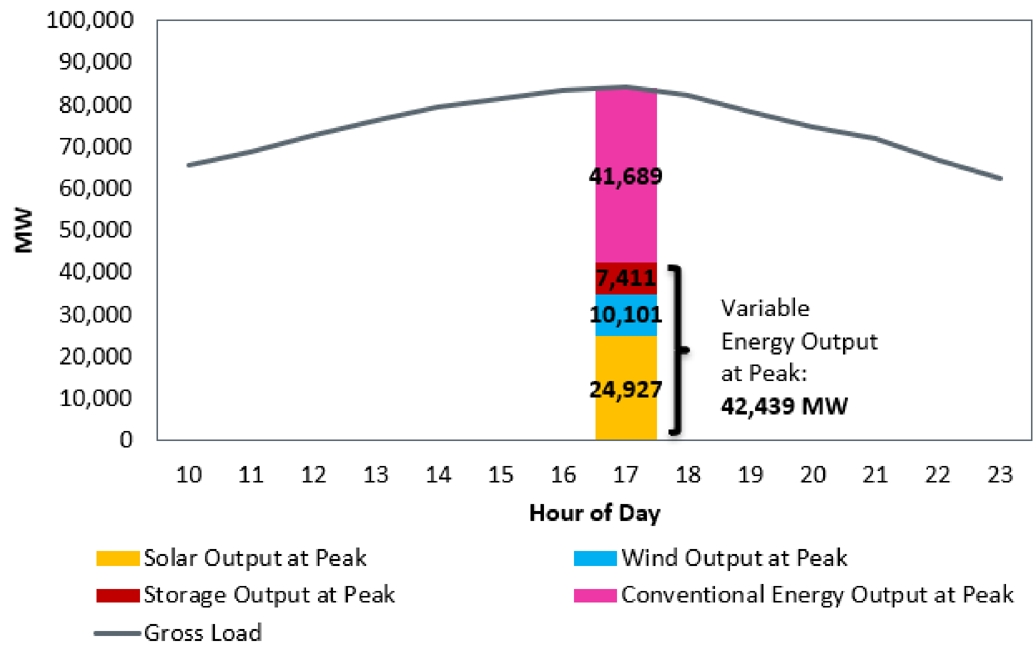
TABLE OF TABLES

EXECUTIVE SUMMARY

Planning for electric system reliability requires quantifying the impact of unique attributes of all resource classes and their associated interactions. Non-dispatchable resources such as wind and solar are contingent on weather conditions and storage resources are affected by energy limitations. Conventional generators can be affected by correlated outage risk and fuel limitations.

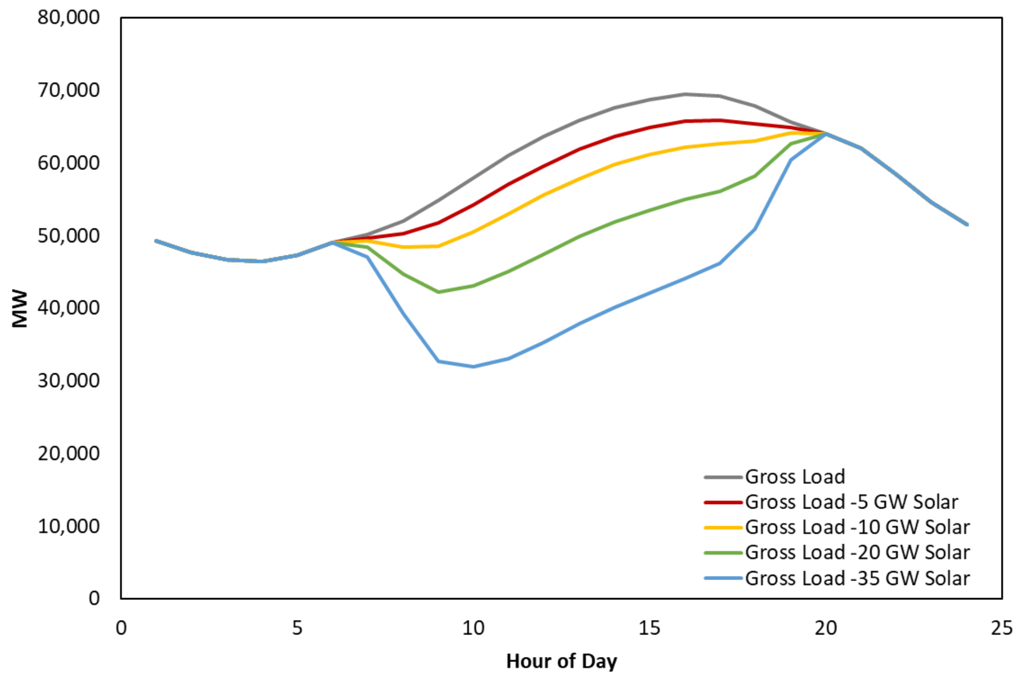
The reliability value of generators is not simply a function of their output during peak load or even peak net load conditions. Almost all electric systems are affected by temporal aspects related to energy limitations or the impact on performance of generator commitment patterns. These reliability issues are particularly important during the current period of rapid transition of the generation mix. Between 2016 and 2024, over 35 gigawatts (GW) of solar PV and 7 GW of battery are projected to be installed in the ERCOT system. During the projected 2024 gross load peak, the combination of wind, solar, and batteries could potentially serve over 42 GW of the total need as depicted in Figure ES1.

Figure ES1. Renewables Capacity Contribution at Gross Load Peak (2024)



This 42 GW of contribution to the gross load peak is not representative of the reliability value of the wind, solar, and battery fleet however. Figure ES2 indicates that the reliability need in 2024 is no longer during the gross load peak hour.

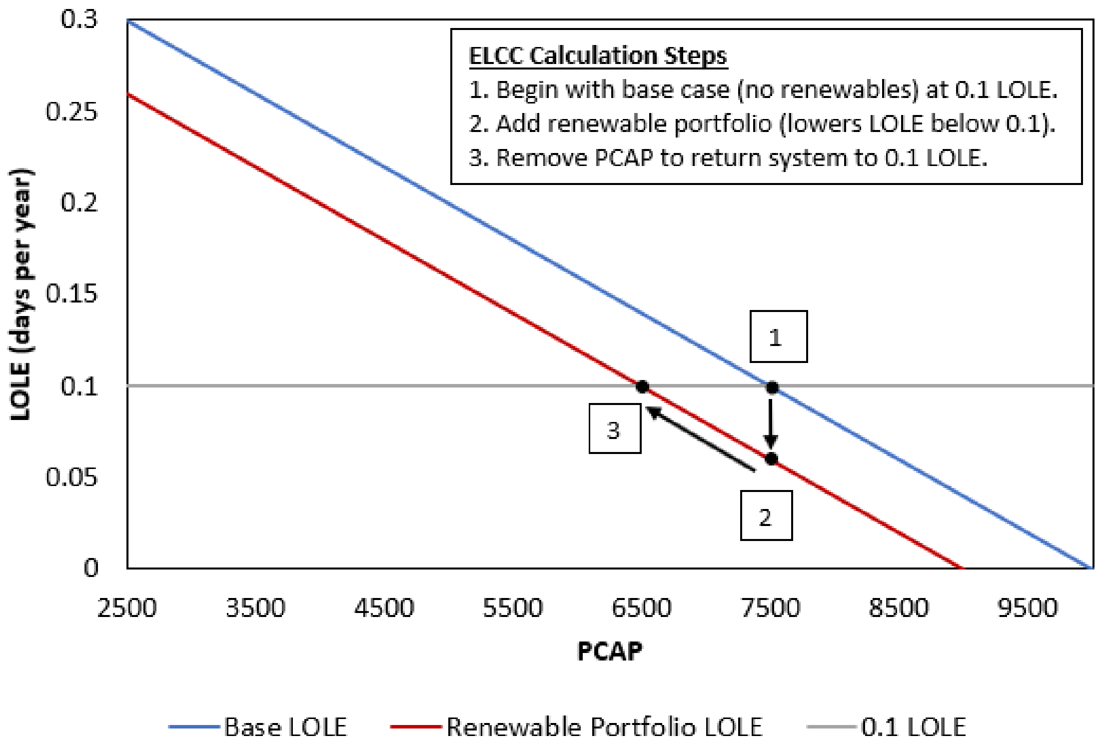
Figure ES2. Net Load Peak Shift Due to Solar PV Investment



Net load has shifted to late in the day due to the massive build-out in the solar PV fleet. Reserves are shortest during this period. With this in mind, how should the reliability value of each resource class be recognized? Reliability planning is a multi-faceted process requiring consideration of both total and incremental need. From this perspective, this study quantifies both the total contribution and marginal contribution of each resource class. The total contribution is quantified as an average Effective Load Carrying Capability (ELCC) and the marginal contribution as a marginal ELCC.

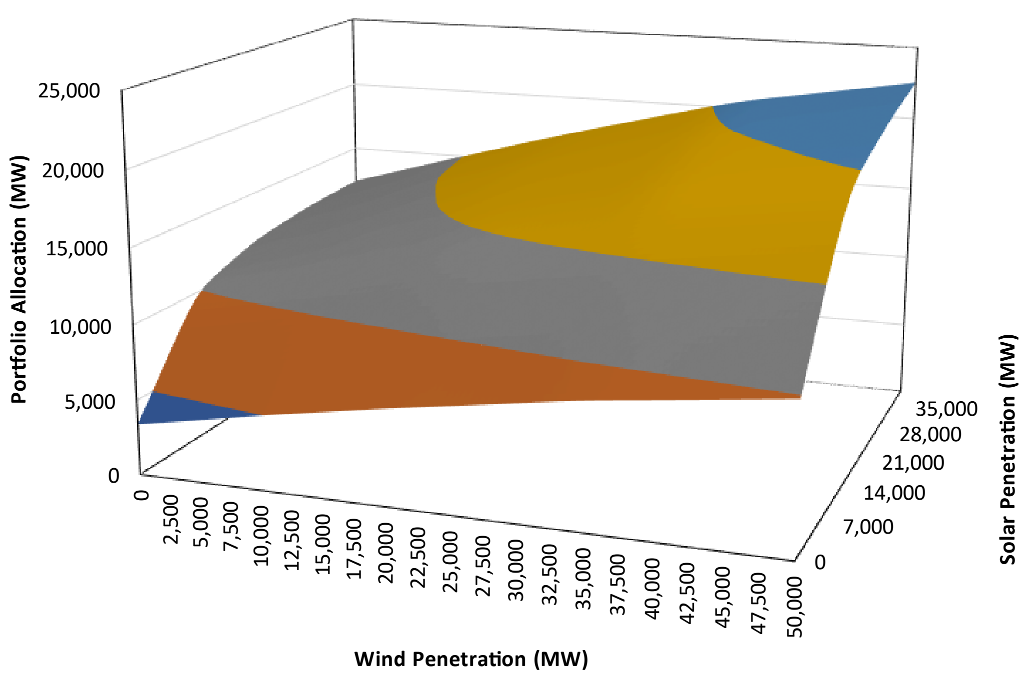
ELCCs are calculated via simulations of the ERCOT system using Astrapé Consulting's Strategic Energy and Risk Valuation Model (SERVM). Over 250 different portfolios were simulated with combinations of different resource penetration levels and technology attributes, and adjustments were made to load or capacity to keep reliability at the industry standard of 1 day in 10 years of Loss of Load Expectation (0.1 LOLE). The ratio of the resource adjustment required to meet 0.1 LOLE to the capacity of the variable energy portfolio determines the portfolio ELCC. This process is illustrated in Figure ES3.

Figure ES3. ELCC Methodology



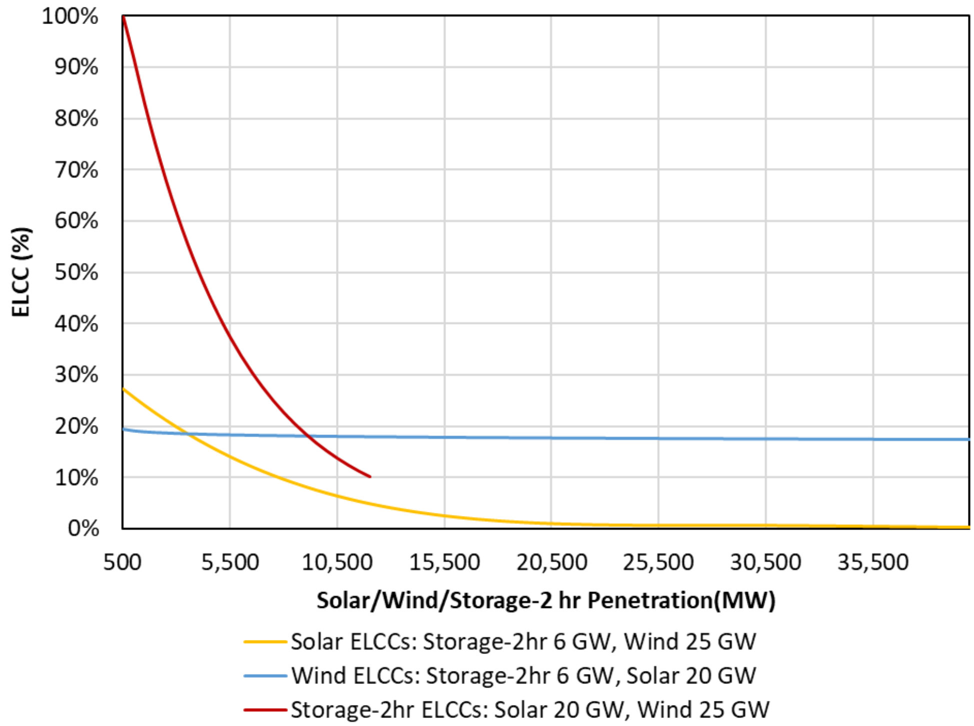
After calculating these portfolio ELCCs, we performed calculations to interpolate to any alternate portfolio. This process produced portfolio ELCC surfaces as shown in Figure ES4.

Figure ES4. Portfolio ELCC Surface (Wind, Solar, at 6 GW 2-Hour Storage)



Differential equations then provide the individual contributions by technology. The curve by technology identifies their marginal ELCCs as can be seen for the winter in Figure ES5.

Figure ES5. Winter Marginal ELCCs



In addition to distinguishing reliability value by technology, the location of resources and the specific configuration of each resources affect 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 West
  - Solar Non-West
- Storage Durations:
  - 2-hour
  - 4-hour
  - 8-hour

Once portfolio value and location or configuration values are calculated, a comprehensive analysis of the reliability value of future systems can be performed. To provide portfolio reliability information to stakeholders, ERCOT will integrate the results of this analysis into its resource adequacy assessment reports.

For the current Capacity, Demand, and Reserves (CDR) report, the values provided in Table ES1 are assigned to wind and solar using their "Peak Average Capacity Contributions," which is what ERCOT expects to be available on average during peak demand hours.[1]

Table ES1. Assigned CDR Peak Average Capacity Contribution[2]

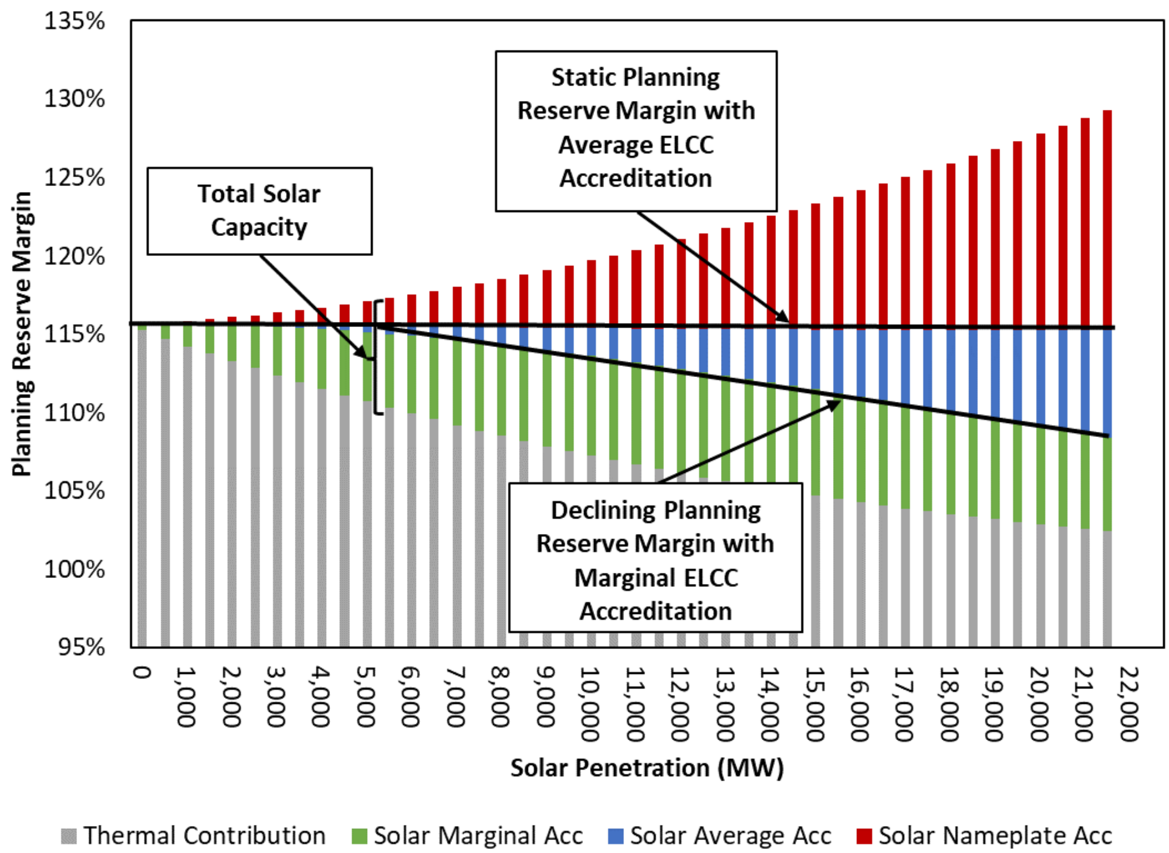
Technology	Summer Value (%)	Winter Value (%)
Solar	81	11
Wind-Coastal	57	46
Wind-Panhandle	30	34
Wind-Other	20	19
Storage	0	0

The capacity credit assigned to energy-limited resources in the CDR is based on output during the average of the top 20 gross load hours for multiple historical seasons (ten for wind; three for solar). While this method reasonable characterizes expected renewable energy production during gross peak load hours, it doesn't recognize that the net load may have shifted due to the renewable output. It thereby overstates the reliability contribution of these resources. Calculating the anticipated reserve margins with the Peak Average Capacity Contributions has correspondingly led to reserve margins which do not provide insight into the relative reliability value of the various portfolios.

Since ELCC analysis is designed to normalize for reliability contribution across all resource classes, reliability planning should produce similar reliability metrics for two different portfolios that result in the same reserve margin. For instance, a portfolio with all conventional capacity that provides a 15% reserve margin should demonstrate the same LOLE as a portfolio with heavy renewable and storage penetration that also has a 15% reserve margin. A visual of a system's reserve margin as solar penetration increases is shown in Figure ES6. Average ELCC accreditation will keep a static reserve margin since all portfolios that keep the system at 0.1 LOLE are deemed to have the same capacity. Marginal accreditation will result in a declining reserve margin since resources only get credit for their contribution to the net load peak hours.

[1] https://www.ercot.com/files/docs/2021/08/18/June_1__2021_Nodal_Protocols.pdf
[2] https://www.ercot.com/files/docs/2022/05/16/CapacityDemandandReservesReport_May2022.xlsx

Figure ES6. Marginal Versus Average ELCC and Their Effect on the Planning Reserve Margin



Every class of non-dispatchable and energy-limited resource exhibits declining reliability value with penetration. This effect is driven by the shift in net load for non-dispatchable resources and the expansion of hours needed for energy limited resources. However, interactions among resource classes can be synergistic, delaying the decline in the ELCC of particular resources. For 2024 projected portfolios, incremental solar PV will provide significantly lower reliability value per installed MW than the average ELCC provided by these resources, while short duration batteries (2-hour) will supply more value on the margin than they do on average as seen in Table ES2. This information should factor into decisions for further expansion.

Table ES2. 2024 Marginal and Average ELCCs

Technology	Installed Capacity (MW)	Marginal ELCC (%)	Average ELCC (%)
Wind-C	5,900	21.80%	27.80%
Wind-O	29,233	14.90%	24.35%
Wind-P	4,903	21.80%	27.65%
Solar Non-West	20,856	3.50%	35.90%
Solar West	14,095	8.70%	42.15%
Storage 2-hour	7,620	79.94%	73.97%

ELCCs have not typically been quantified for thermal resources since they are dispatchable and theoretically do not have energy constraints. A common assumption is that the Equivalent Forced Outage Rate Demand (EFORd) is a reasonable proxy for the impact that these generators will have on the need for reserves. The only reduction in the reliability contribution of these resources would be due to unplanned outages. Accrediting capacity for thermal resources is typically done by quantifying the difference in nameplate or Installed Capacity (ICAP) and Unforced Capacity (UCAP). UCAP is generally calculated as a function of both its ICAP and its EFORd. The goal of this thermal ELCC analysis was to determine the impact of unit outages on the ability of traditional, EFOR-based units to serve load and to translate this impact into an ELCC equivalent for these resources. It is important to note that these ELCC scenarios did not take into consideration the potential impact to outages resulting from new plant weatherization standards enacted by the Texas Public Utility Commission.

The analysis performed was an initial examination of the impacts of outages on the ability of thermal resources to carry load. The results show that the ELCC of thermal resources is influenced by more than just the EFOR. The 1-EFORd accreditation on the right overstates the reliability of the thermal resources found by the ELCC simulations in the ELCC columns in Table ES3. The thermal ELCC results reflect a range of assumptions, mainly battery and renewable penetrations, cold weather outages, and fuel unavailability assumptions. Ultimately, more research into the expected cold-weather performance and fuel adequacy concerns will be necessary to determine which specific assumptions should drive both accreditation and resource adequacy assessments.

Table ES3. Thermal ELCC Results

Battery, Solar, and Wind Penetration	Thermal	Cold Weather	Fuel	Winter ELCC (%)	Summer ELCC (%)	Winter UCAP/ Winter CDR Rating (%)	Summer UCAP/ Summer CDR Rating (%)
0	2024	Base	None	89.6%	89.8%	94.6%	93.9%
0	2024	Base	Include Fuel	87.5%	89.8%	94.9%	93.9%
0	2024	2011	None	87.5%	89.8%	94.9%	93.9%
0	2024	2011	Include Fuel	83.5%	89.5%	95.0%	94.0%
0	2024	2011 and 2021	None	78.0%	89.6%	95.1%	94.0%
0	2024	2011 and 2021	Include Fuel	67.7%	89.6%	95.1%	94.0%
2024	2024	Base	None	89.9%	90.8%	96.1%	94.4%
2024	2024	Base	Include Fuel	87.9%	90.7%	96.3%	94.4%
2024	2024	2011	None	87.9%	90.7%	96.3%	94.4%
2024	2024	2011	Include Fuel	83.4%	90.7%	96.6%	94.4%
2024	2024	2011 and 2021	None	78.9%	90.8%	96.9%	94.4%
2024	2024	2011 and 2021	Include Fuel	69.3%	90.8%	97.1%	94.4%

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 42 weather years, 5 levels of economic load forecast,[3] and 20 draws of generating unit performance for a total of 4,200 iterations for each simulated case. Each individual iteration simulates 8,760 hours for the study year of 2024.

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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, a critical aspect of this modeling effort is the correct economic and operational characterization of emergency procedures. 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]

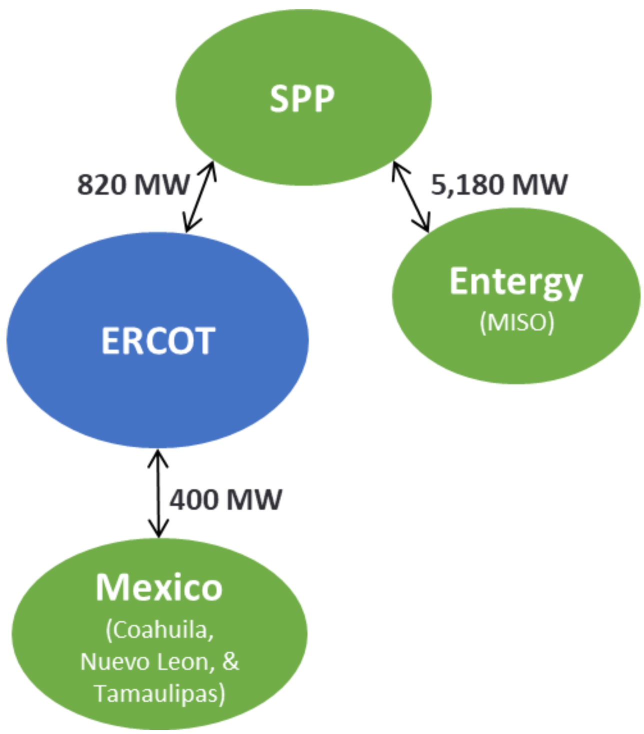
B. STUDY YEAR

The ELCC study analyzed the expected conditions and resources in 2024.

C. STUDY TOPOLOGY

For this study, the ERCOT region is assumed to have full deliverability of all generation within ERCOT. Neighboring electric systems - Entergy, SPP, and Mexico – were also modeled, as shown in Figure 1.

Figure 1. Study Topology



[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.

D. COMPONENTS OF SUPPLY AND DEMAND

Load and resource accounting for the 2024 system is based on ERCOT's conventions in the May 2022 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 2024 were included in the study and assumed to come online in January of the year, and any units coming only after June 2024 were excluded in the study to maintain a homogeneous resource mix for the study year. Firm peak load is reduced for incremental rooftop photovoltaic (PV) forecast, 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. Products with call limits, ERS and TDSP load management programs, were excluded from the base case simulations. 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 Capacity was 0.1 for the summer and winter seasons.

Table 1. Supply and Demand Summary for 2024 Study Year

	ERCOT System
Peak Load (MW)	**80,554**
Load Reduction (MW)	**2,823**
LRs serving RRS (MW)	1,591
10-Minute ERS (MW)	35
30-Minute ERS (MW)	890
TDSP Curtailment Programs (MW)	307
Supply	
Conventional Generation (MW)	67,560
Hydro (MW)	475
Wind (MW)*	40,035
Solar (MW)*	34,951
Storage (MW)*	7,620
PUNs (MW)	4,262
Capacity of DC Ties (MW)	1,220

Note: Energy Efficiency Programs are already removed from the modeled peak load and are not represented in the modeled load reduction programs (ERCOT Aggregate = 3,681 MW in 2024 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 2024. Astrapé simulated 42 weather years, from 1980

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

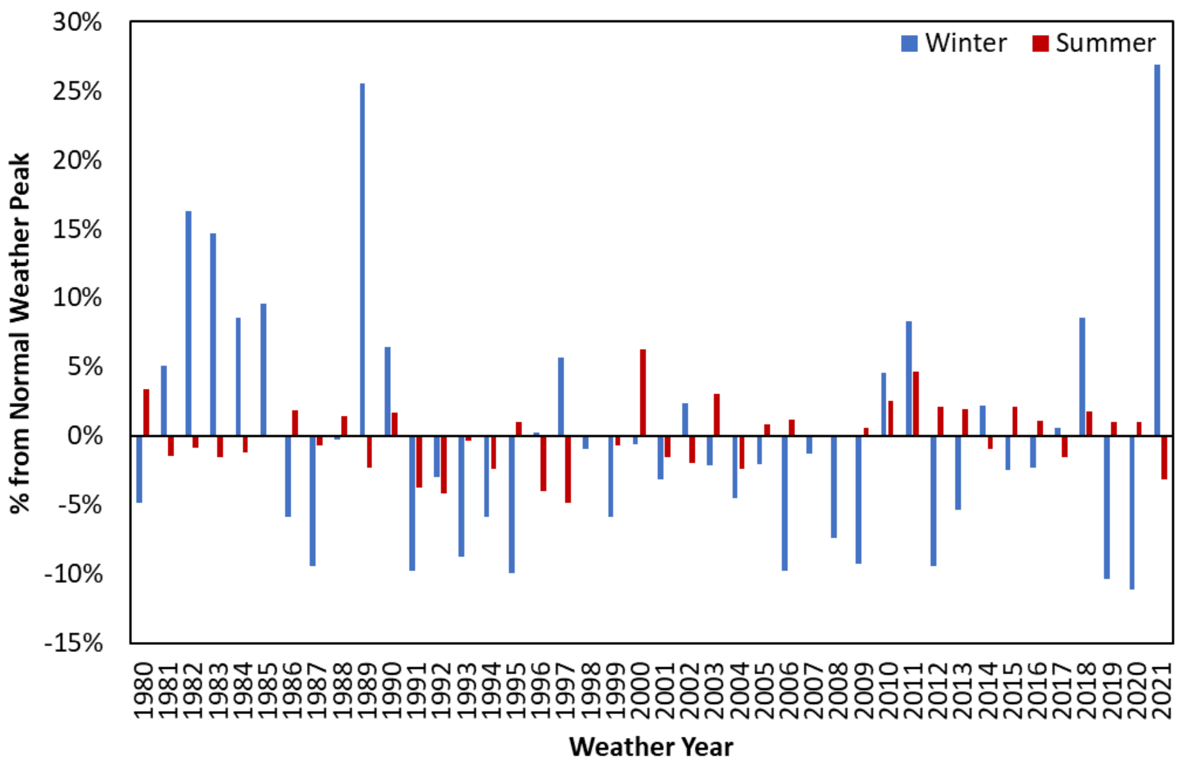
6 In general, the May 2022 CDR is the authoritative source, the following assumptions were used for including certain resource types: (1) switchable units – include as internal resources, with the units that are committed off-system excluded from our model. (2) unit additions/retirements – include or exclude starting in the CDR-specified year. (3) inactive planned – excluded from model

through 2021 (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]

E. DEMAND SHAPES AND WEATHER UNCERTAINTY MODELING

We represented weather uncertainty in the projected ERCOT 2024 peak load by modeling 42 load forecasts based on 42 historical weather patterns from 1980-2021.[8] Figure 2 shows the variability in summer and winter peak load across the 42 weather years simulated for this study. The most severe summer peak is 6.2% above the normal weather summer peak while the most severe winter peak is 26.9%% above the normal weather winter peak.

Figure 2. Seasonal Peak Load Variance by Weather Year



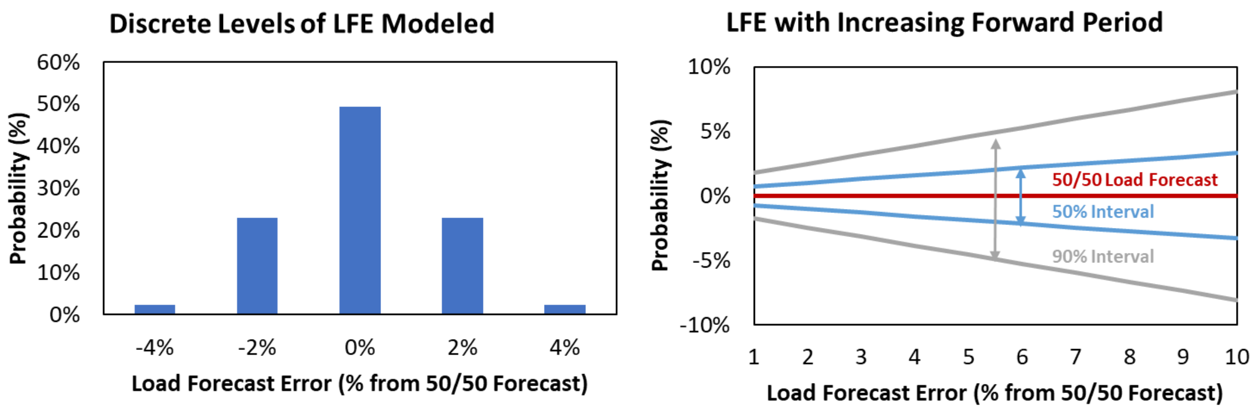
F. NON-WEATHER DEMAND FORECAST UNCERTAINTY AND FORWARD PERIOD

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 3, 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,

[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.
[8] Large Flexible Loads, as currently defined by ERCOT, are not accounted for in the SERVM modelling.

increasing by 0.66% with each additional forward year.[9] The distribution included no bias or asymmetry in non-weather LFEs. The left-hand chart of Figure 3 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.

Figure 3. Non-Weather Load Forecast Error



G. EXTERNAL REGION MODELING

The neighbors - Entergy, SPP, and Mexico - were updated to reflect 2024 load forecasts and resources. External regions' peak load and load shapes were independently developed based on publicly available peak load projections, historical hourly weather profiles, and historical hourly load data.

H. 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 2022 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

[9] 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.

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 2. Equivalent Forced Outage Rates by Asset Class summarizes fleet-wide and asset-class outage rates, including both partial and forced outages.

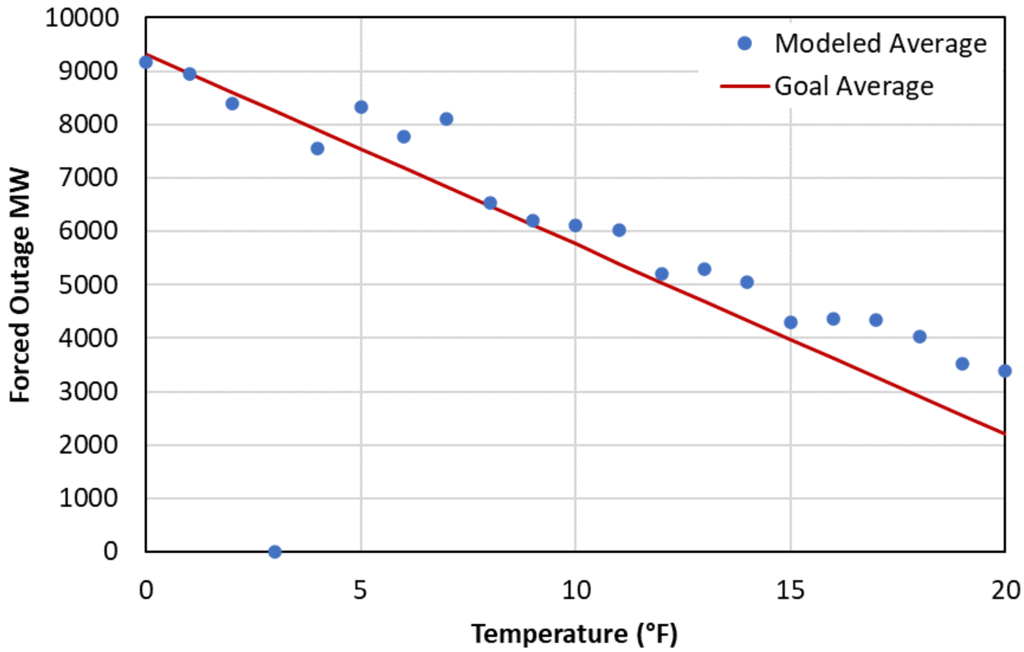
Table 2. Equivalent Forced Outage Rates by Asset Class

Unit Type	EFOR (%)
Gas	10.1
Biomass	4.9
Coal	10.2
Nuclear	0.3
Storage	5.0
Fleet Weighted Average	**8.92**

Additional forced outage probabilities were modeled for temperatures below 20°F, as shown in Figure 4. Forced outages from 2018-2021 as a function of temperature were analyzed while excluding winter storm Uri. A trend was added to the graph below 20 degrees and extrapolated to 0 degrees (Goal Average series below).[10] A linear probability was assigned with an hourly incremental forced outage probability of 1.07% at 0°F down to 0% at 20°F leading to an average of ~9,000 total MW being forced offline at 0°F. The impacts of the new weatherization requirements are not being considered in the temperature outage correlation modeling.

[10] The extrapolated value at 0°F was not as extreme as the 2011 outages (14.7 GW, inclusive of forced outages from PUNs units as well, forced offline when system temperatures were roughly 14°F). Modeling this way reflected improvement from both 2011 and 2021 but also reflected an increased risk from what has been modeled in previous studies. https://www.ferc.gov/sites/default/files/2020-05/ReportontheSouthwestColdWeatherEventfromFebruary2011Report.pdf

Figure 4. Cold Weather Forced Outage Modeling[11]



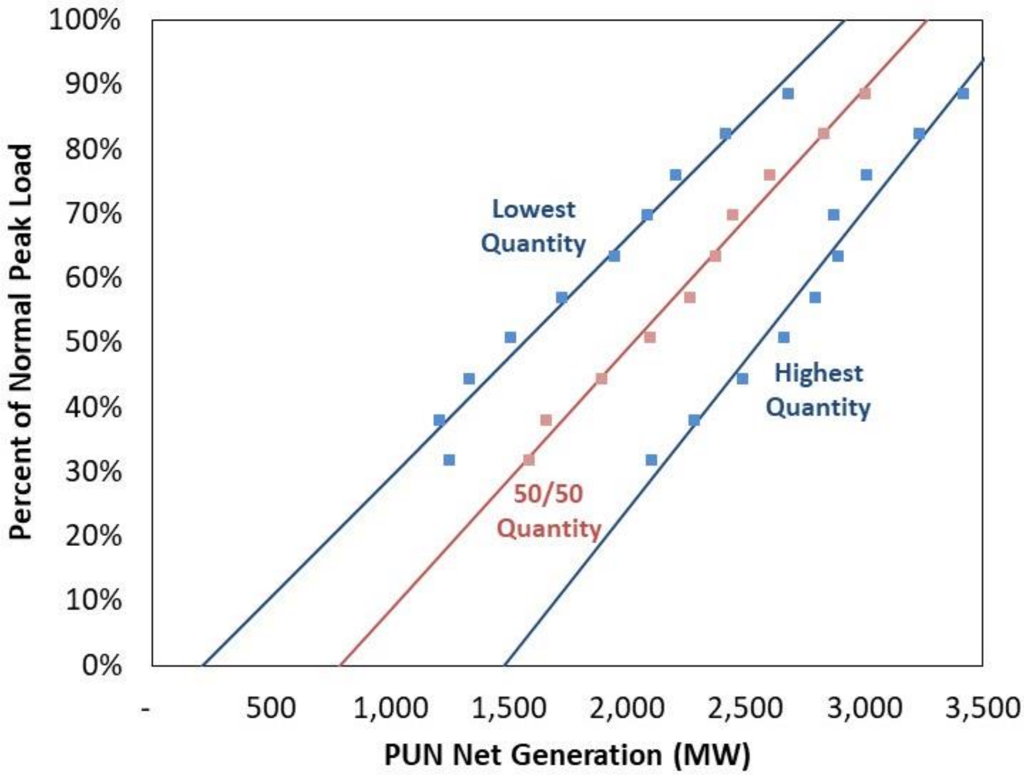
2. PRIVATE USE NETWORKS

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 5. 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.[12] 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 with load at or above 88% of normal peak load, PUN output produces at least 2,419 MW of net generation with an average of 3,002 MW.

[11] There were no temperature points between 3-4°F in the average temperature profile used in the SERVM simulations.

[12] Hourly net PUN output data by zone gathered from ERCOT.

Figure 5. PUN Net Generation



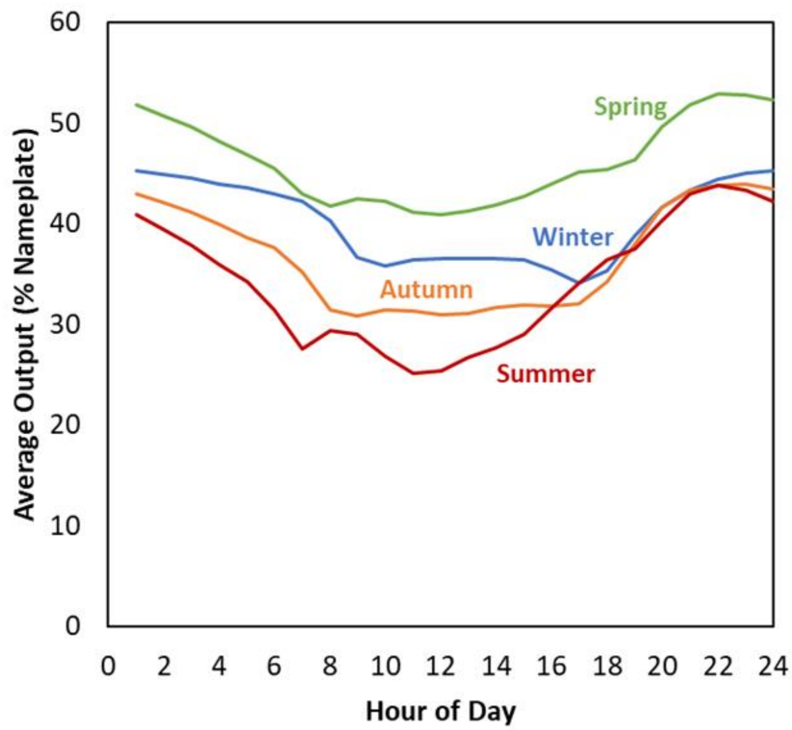
3. INTERMITTENT WIND AND SOLAR

We modeled a total quantity of intermittent wind and solar photovoltaic resources that reflects what ERCOT reported in the May 2022 CDR Report. An aggregate wind and solar profile 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 42 years of synthesized hourly wind shapes for each location of individual units across the system wind shapes over 1980 to 2021, as provided by ERCOT staff.[13] Figure 6 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 39.3%.

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

Figure 6. Average Wind Output by Month 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 county-specific synthesized output profiles over years 1980 to 2021.[14] In aggregate, solar resources had a capacity factor of 26.0% across all years.

STUDY APPROACH

A. ELCC SURFACE

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 calculated 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:

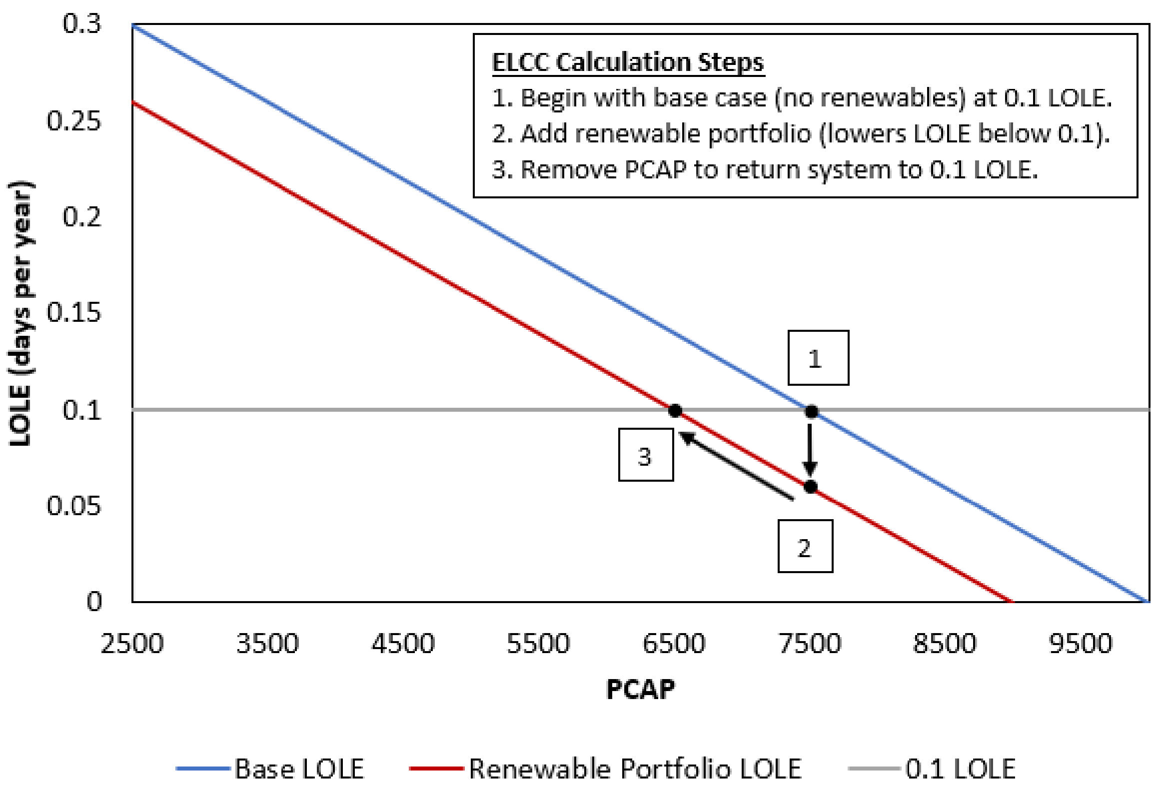
1. The first step in the portfolio ELCC analysis was to calibrate the base case to a 0.1 LOLE target in both the summer and winter seasons. The study year chosen was 2024 and involved removing all

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

the variable energy resources from ERCOT and adding perfect capacity – capacity with no outages or ramping limitations – until the summer and winter reliability risk is at 0.1 LOLE individually.

2. Starting with the base case at 0.1 LOLE above, solar, wind, and storage capacity was then added up to 40, 50, and 12 GW respectively at different storage durations, which improved the LOLE. Perfect capacity was then removed until the reliability risk in the summer and winter reduces 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 7, below represents the ELCC calculation process.

Figure 7. ELCC Methodology



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

- Solar capacity (MW): 0 - 40 GW
- Wind capacity (MW): 0 - 50 GW
- Energy Storage (2-, 4-, and 8-hour) (MW): 0 - 12 GW

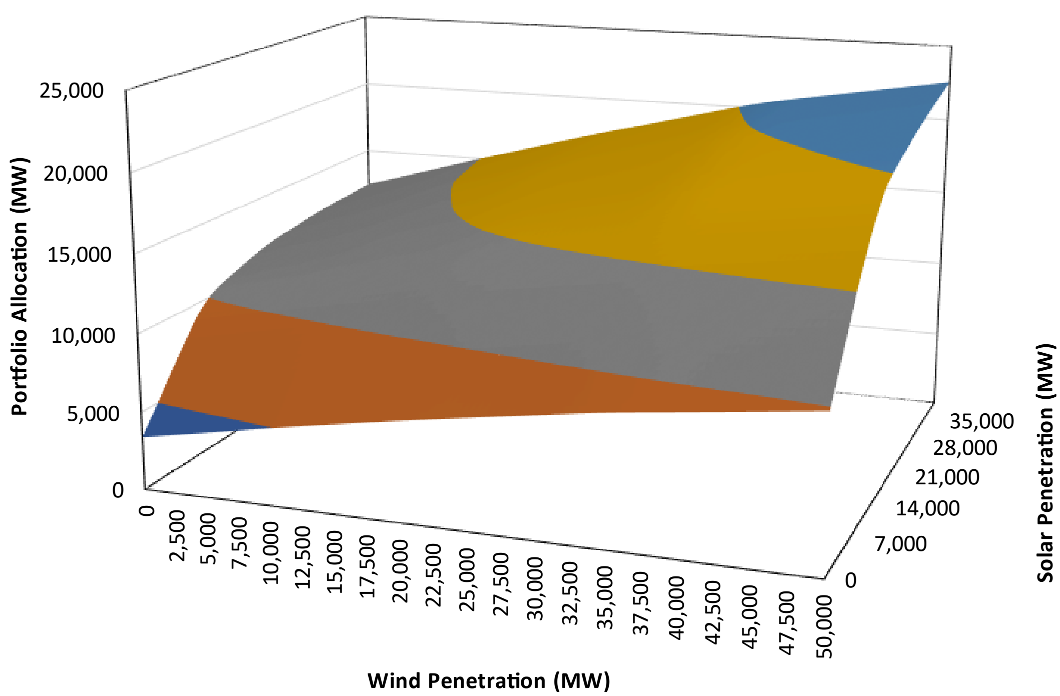
For example, Table 3 represents the matrix of all portfolios modeled in SERVM for 2-hour battery penetration of 4 GW.

Table 3. Summer Portfolio Capacity Contribution; Storage 2-Hour 4 GW

Solar/Wind	0	35000	40035	50000
0	3,687	7,187	7,589	8,934
5000	7,148	12,200	12,704	13,800
10000	10,272	15,765	16,319	16,923
15000	11,115	17,868	18,472	19,647
20000	11,927	18,579	19,122	20,433
30000	12,244	19,775	20,422	21,769
34951	12,393	20,270	21,004	22,379
40000	12,472	20,508	21,256	22,647

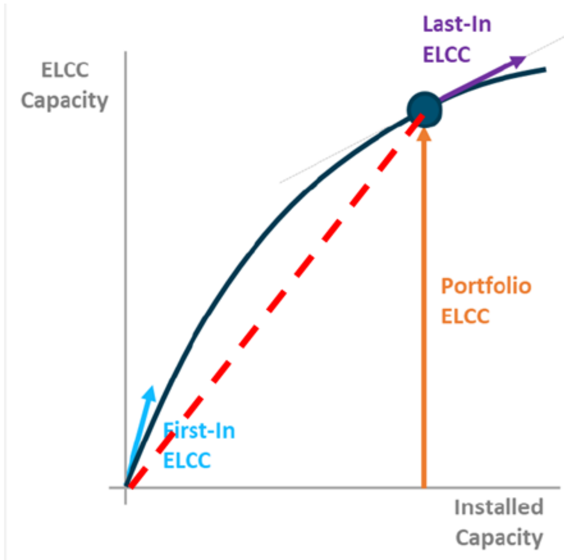
Similarly, ELCC matrices were built for no storage, 8 GW 2-hr storage, and 12 GW 2-hr storage in summer and winter. These small matrices were then interpolated at step-sizes of 500 MW each for the solar, wind, and storage dimensions to get 3-dimensional ELCC surfaces with monotonical decreasing first order derivatives. This interpolation was performed using a bivariate spline and performing triangular smoothing iteratively. Figure 8 represents one such dense surface for the summer with storage (2-hour, 4 GW).

Figure 8. ELCC Surface (4 GW, 2-Hour Storage)



Similar surfaces were constructed for different 2-hour storage penetrations between 0 – 12 GW at step-sizes of 500 MW. Starting from these surfaces, ELCCs were calculated for the individual resource classes that make up the portfolio at different investment levels. The delta method by E3 is well known and can be used to allocate portfolio ELCC to individual class resources.[15] As shown in Figure 9, the delta method relies on three measured ELCC values:

Figure 9. Delta Method

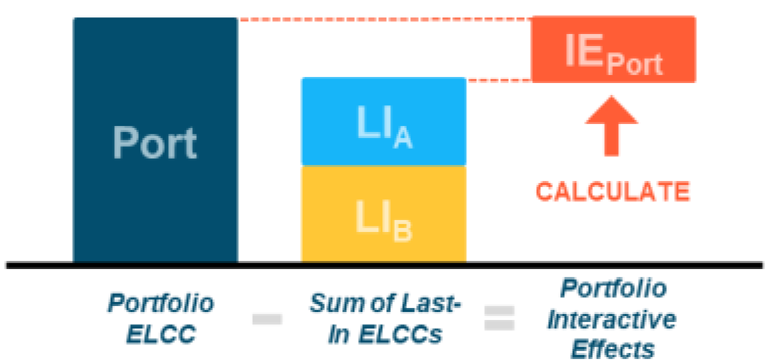


- **Portfolio ELCC**: total ELCC for a combination of intermittent and energy-limited resources
- **First-In ELCC**: represents the marginal ELCC of each individual resource in a portfolio with no other intermittent or energy limited resources
- **Last-In ELCC**: the marginal ELCC value of each individual resource when taken in the context of the full portfolio

The steps of the delta method are as follows:

1. **Calculate Portfolio Interactive Effects**: Calculated as the difference between the portfolio ELCC and the sum of the Last-In ELCCs for all individual resources as shown in Figure 10.

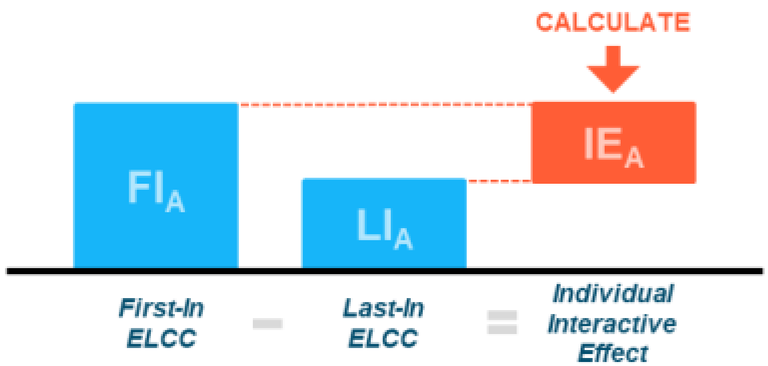
Figure 10. Portfolio Interactive Effects



[15] https://www.ethree.com/wp-content/uploads/2020/08/E3-Practical-Application-of-ELCC.pdf

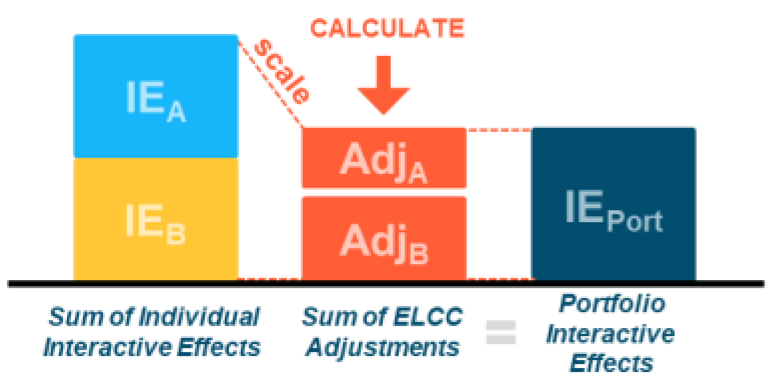
2. **Calculate Individual Interactive Effects**: Calculated as the difference between the First-In ELCC and the Last-In ELCC for each individual resource as shown in Figure 11.

Figure 11. Individual Interactive Effects



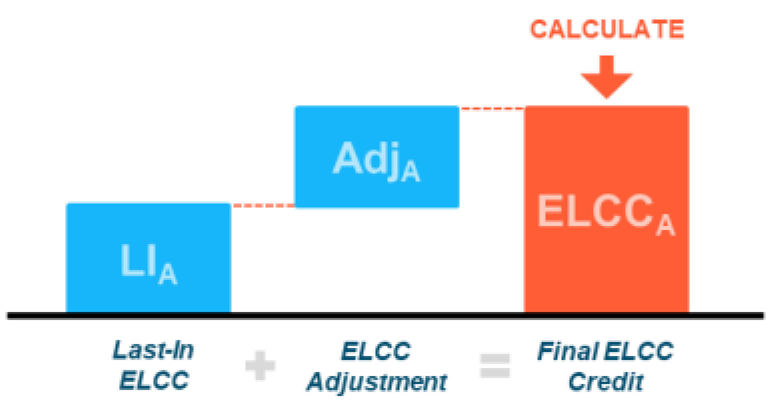
3. **Calculate Individual ELCC Adjustments**: Calculated by scaling all individual interactive effects to match the portfolio interactive effects as shown in Figure 12.

Figure 12. Individual ELCC Adjustments



4. **Calculate ELCC Accreditation:** Add individual resource ELCC adjustments to Last-In ELCC for each individual resource to get final ELCC credit as seen in Figure 13.

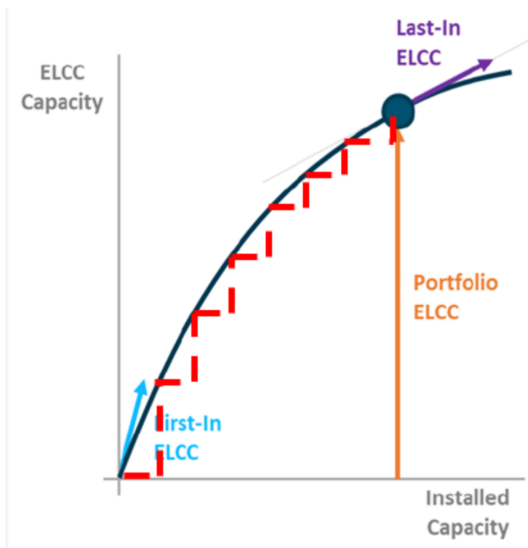
Figure 13. Final ELCC Accreditation



The delta method scales linearly between the first-in and last-in ELCC values as can be seen by the red dashed line in Figure 9. For high penetrations with a variety of different resource classes, this method can result in irregular accreditation for resource classes.

To combat this issue in this work, a modification was made to the delta method which involves integrating between the first-in and last-in ELCC values and is thus called the "integration method". The integration method integrates along the curve of the portfolio ELCC, from the first-ins to the portfolio installed capacity. Thus, the integration method performs consecutive calculations along the portfolio ELCC as shown in Figure 14.

Figure 14. Integration Method



The integration method breaks the linear scaling between the first-in and last-in ELCC values more accurately to the actual portfolio ELCC curve by capturing the non-linear nature of the ELCC curve as the installed capacity rises for different resource classes.

The flow chart for the integration method can be seen in Figure 15. The integration method relies on the development of the portfolio allocation dense surfaces. In equation (1), $\boldsymbol{A}$ represents the reliability contribution associated with installed capacities of renewable resources which is looked up on the dense surfaces.

$$\boldsymbol{A} = \boldsymbol{f}(\boldsymbol{IC_1}, \boldsymbol{IC_2}, \boldsymbol{IC_3}) \quad (1)$$

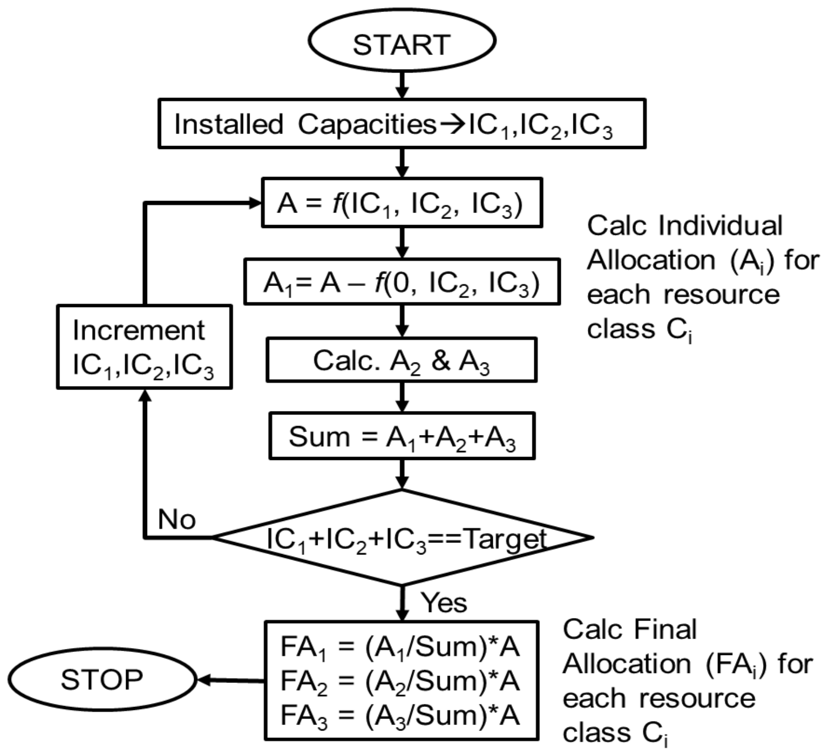
$$\boldsymbol{A_1} = \boldsymbol{A} - \boldsymbol{f}(\boldsymbol{0}, \boldsymbol{IC_2}, \boldsymbol{IC_3}) \quad (2)$$

In equation (2), $f(0, IC_2, IC_3)$ represents the capacity contribution/allocation considering only resource classes 2 & 3. Thus, subtracting this term from $\boldsymbol{A}$ calculated in equation (1) we get the capacity contribution/allocation of resource class 1 individually. Similarly, we can calculate $\boldsymbol{A_2}$ and $\boldsymbol{A_3}$, by setting the other two resource classes to 0. The total individual allocation can then be summed up for all resource classes and a running total can be tracked as the portfolio installed capacity is incremented up to the target value. Upon hitting the target value, the final allocation $\boldsymbol{FA_i}$ for the resource class $\boldsymbol{i}$ can be calculated as shown in equation (3).

$$\boldsymbol{FA_i} = \left(\frac{\boldsymbol{A_i}}{\boldsymbol{Sum}}\right) * \boldsymbol{A} \tag{3}$$

Here, $\boldsymbol{Sum}$ is the sum of the individual allocations for all resource classes across all iterations. $\boldsymbol{A}$ is the portfolio allocation at the final iteration and $\boldsymbol{A_i}$ is the individual allocation for resource class $\boldsymbol{i}$ in the final iteration.

Figure 15. Integration Method Steps



B. THERMAL ELCC APPROACH

The resource adequacy contribution of renewables and storage resources has been explored robustly over the recent decades through ELCC studies, but the accreditation of conventional thermal generators has not been explored as thoroughly. A common assumption is that the Equivalent Forced Outage Rate Demand (EFORd) is a reasonable proxy for the impact that these generators will have on the need for reserves. A system with homogeneous resources with EFORd of 10% would presumably need to carry reserves of 10% to compensate for that level of performance. However, that is only true if the system has perfect outage characteristics of 10% of the fleet offline in all hours of need. Random forced outages will lead to some hours having many more megawatts offline and some hours with less. Reserves of 10% would not protect reliability in hours with more outages. Generally reserve margin studies account for this, but the impact does not get assessed to the thermal fleet directly; it gets socialized by load on the demand side. Other performance effects of conventional units including correlated outages due to weather (as described below), fuel unavailability, or common equipment failures are often not considered at all.[16]

ELCCs have not typically been quantified for thermal resources since they are dispatchable and theoretically do not have energy constraints. The only reduction in the reliability contribution of these resources would be due to unplanned outages. Accrediting capacity for thermal resources is typically done by quantifying the difference in nameplate or Installed Capacity (ICAP) and Unforced Capacity (UCAP). UCAP is generally calculated as a function of both its ICAP and its EFORd as follows in equation (4).

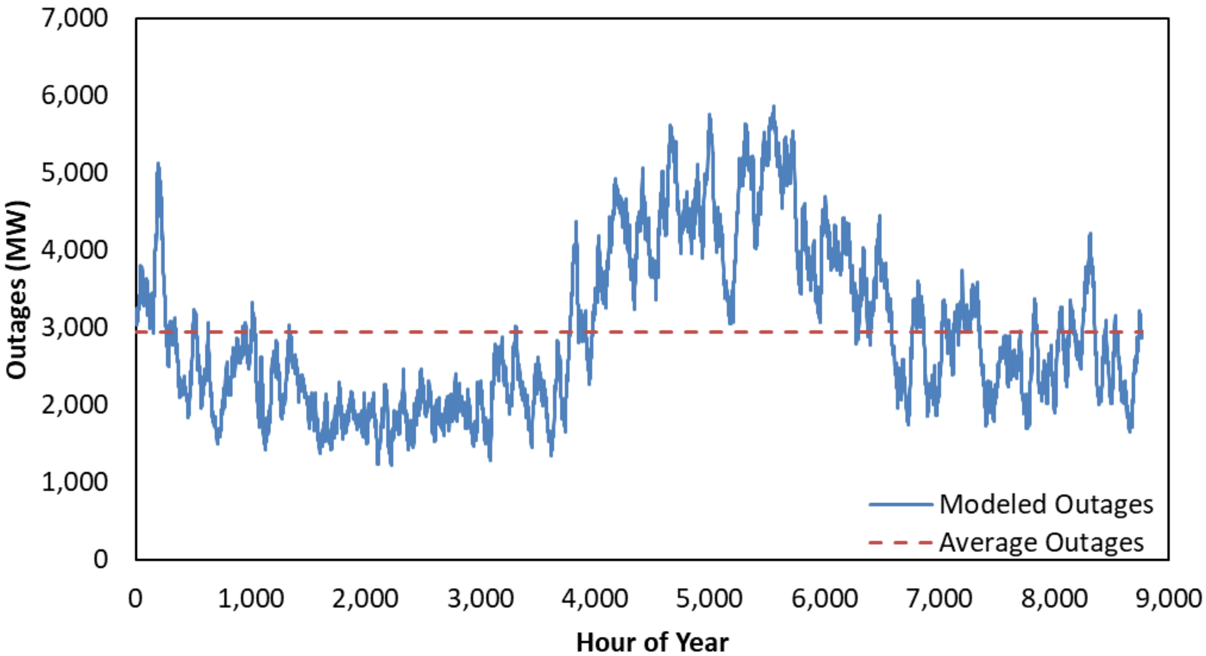
$$\boldsymbol{UCAP = ICAP * (1 - EFORd)} \tag{4}$$

However, the development of EFORd and its application in traditional resource adequacy modeling, even when applied as part of a UCAP formulation, is not sufficient to identify the true load carrying capability of such resources. While EFORd is an appropriate calculation for the determination of the expectations of a particular unit's availability when considered on an independent basis, its application in traditional resource adequacy modeling does not take into consideration of the distribution of system outages or the potential correlations in outages across a generation fleet that may impact the overall ability of the fleet to serve load.

A key component of reliability planning is accounting for generator performance uncertainty. Instinctively, a system with a 5% forced outage rate would need to carry about 5% more capacity to account for those outages. This would only work if a system always has exactly 5% of its generators on outages. However, in reality, the variability of ERCOT thermal unit outages means that some hours can have as little as 1,200 MW on outage while others can have up to 5,900 MW while the average is roughly around 3,000 MW. An example of hourly outages from a simulation are provided in Figure 16.

[16] Common equipment failures refer to the possibility that multiple generators can go offline simultaneously due to environmental controls, transmission line outages, step-up transformer failures, etc.

Figure 16. Average Outages Versus Modeled Outages Example



Outages correlated to severe weather events are also modeled. As cold temperatures become more extreme, the combination of increased demand on the resources and the effects of temperature on the equipment itself creates a higher overall risk of failure, as seen in 2011 and 2021 events. Astrapé incorporated the incremental hourly forced outage rates as a function of temperature when temperatures are below 20°F.

In addition to outage correlations with temperature, additional outages during extreme cold weather events due to the availability of fuel are also likely. While there is significant uncertainty to the impact that natural gas availability might have on reliability, internal ERCOT analysis performed after Winter Storm Uri identified 5,000 MW of outages that occurred due to a lack of fuel. This assumption was used for incremental outages due to fuel constraints in the most extreme winter conditions.

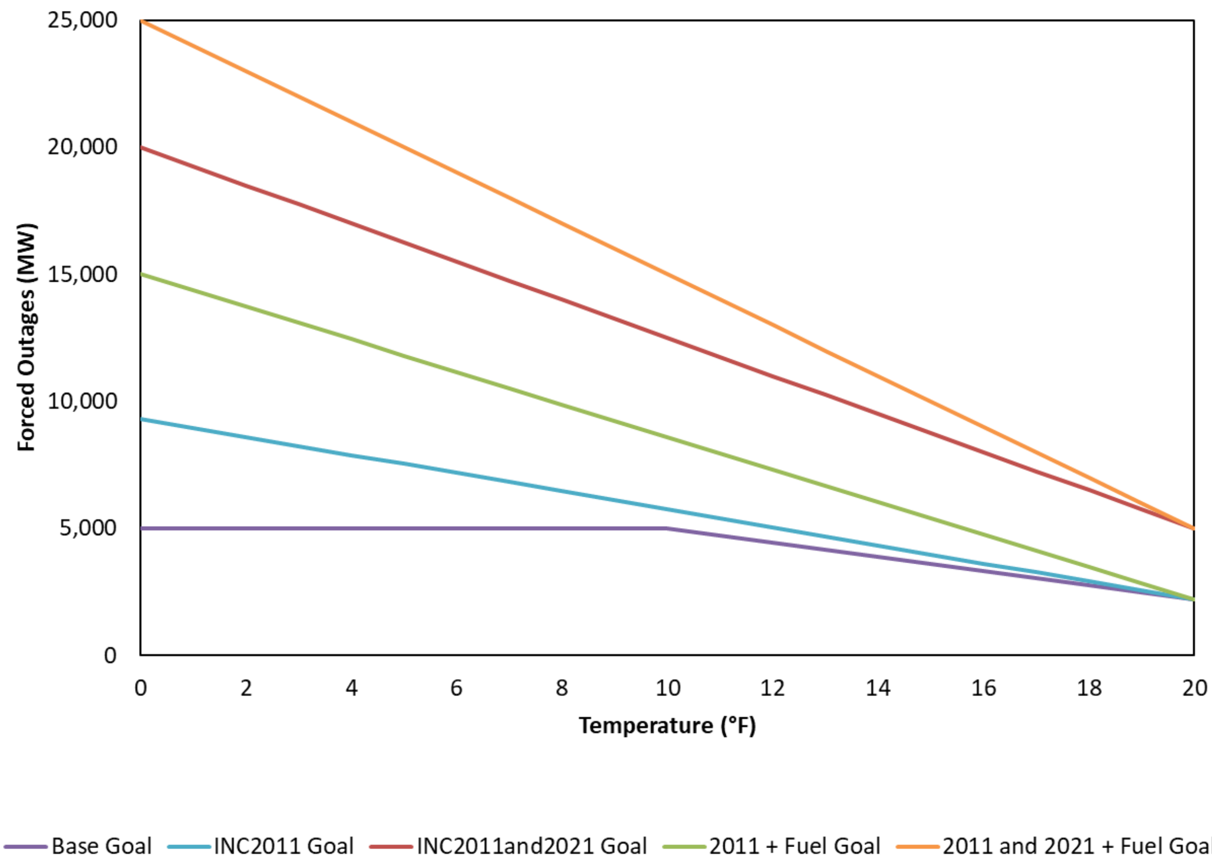
The goal of this analysis was to determine the impact of unit outages on the ability of traditional, EFOR-based units to serve load and to translate this impact into an ELCC equivalent for these resources. To calculate this impact, Astrapé started with base cases that were calibrated to a winter and summer LOLE of 0.1 days/year. Astrapé examined the ELCCs of the thermal fleet under the various renewable and energy-limited penetrations, cold weather thermal outage assumptions, and fuel availability assumptions defined in Table 4. It is important to note that these ELCC scenarios did not take into consideration the potential impact to outages resulting from new plant weatherization standards enacted by the Texas Public Utility Commission.

Table 4. Thermal ELCC Study Matrix

<table>
<tr><th>ELCC Scenario</th><th>Battery Penetration (GW)</th><th>Solar Penetration (GW)</th><th>Wind Penetration (GW)</th><th>Thermal Penetration (GW)</th><th>Cold Weather Outage Assumption</th><th>Fuel Availability Assumption</th></tr>
<tr><td>1</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td>0</td><td rowspan="3">Exclude 2021</td><td rowspan="9">Exclude 2021</td></tr>
<tr><td>2</td><td rowspan="2">2024 Portfolio</td></tr>
<tr><td>3</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>4</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td>0</td><td rowspan="3">Exclude 2011 and 2021</td></tr>
<tr><td>5</td><td rowspan="2">2024 Portfolio</td></tr>
<tr><td>6</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>7</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td>0</td><td rowspan="3">Include 2011 and 2021</td></tr>
<tr><td>8</td><td rowspan="2">2024 Portfolio</td></tr>
<tr><td>9</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>10</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td>0</td><td rowspan="3">Exclude 2021</td><td rowspan="9">Include 2021</td></tr>
<tr><td>11</td><td rowspan="2">2024 Portfolio</td></tr>
<tr><td>12</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>13</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td>0</td><td rowspan="3">Exclude 2011 and 2021</td></tr>
<tr><td>14</td><td rowspan="2">2024 Portfolio</td></tr>
<tr><td>15</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>16</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td rowspan="2">2024 Portfolio</td><td>0</td><td rowspan="3">Include 2011 and 2021</td></tr>
<tr><td>17</td><td rowspan="2">2024 Portfolio</td></tr>
<tr><td>18</td><td>0</td><td>0</td><td>0</td></tr>
</table>

A visual representation of the forced outages as a function of temperature for each fuel and outage combination is shown in Figure 17.

Figure 17. Cold Weather Forced Outage and Fuel Availability Assumptions as a Function of Temperature



RESULTS

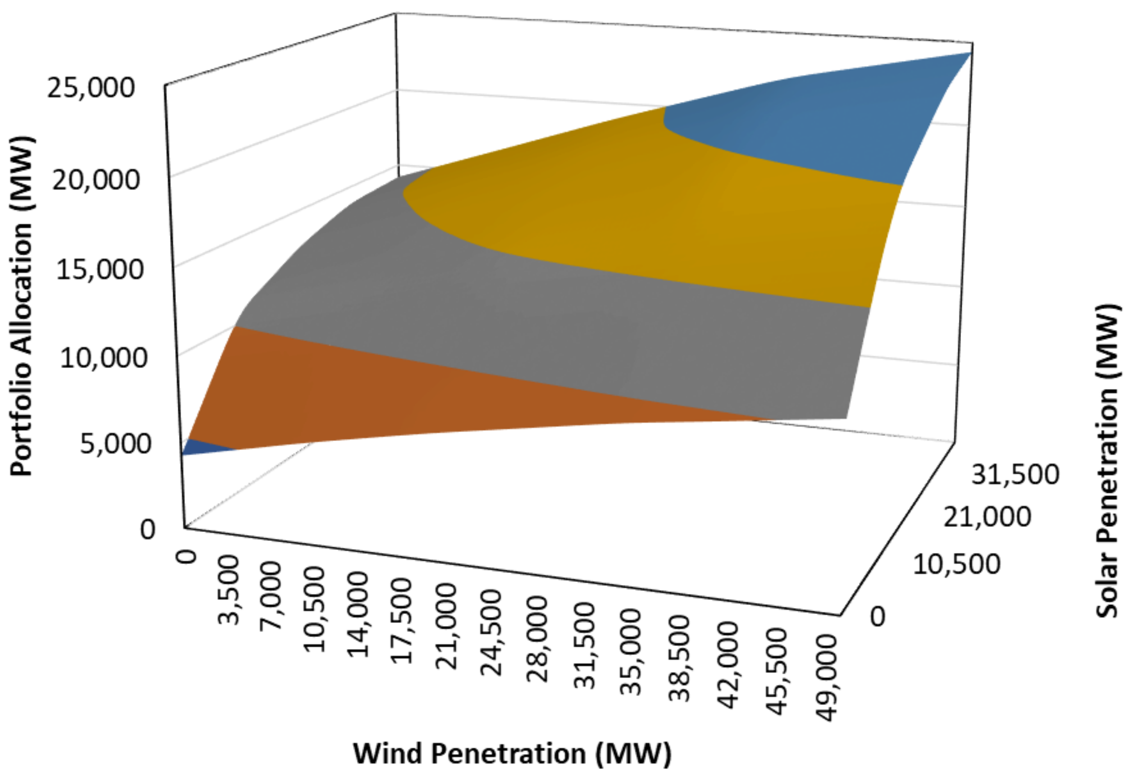
A. MODEL SETUP

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.

B. SUMMER MARGINAL ELCCS

Figure 18 depicts the capacity contribution surface for the summer for a 6 GW penetration of 2-hour storage. Similar surfaces were constructed for 2-hour storage levels between 0-12 GW at step sizes of 500 MW. The integration method (discussed in the previous section) was then applied to allocate capacity contributions to the individual resource classes and technology subclasses.

Figure 18. Summer Capacity Contribution Surface (2-Hour Storage, 6 GW)



The first order derivatives (marginal ELCCs) for these surfaces with respect to solar and wind can be seen in Figure 19, Figure 20, Figure 21, and Figure 22. Figure 19 has solar penetration varying with wind penetration held constant at 25 GW for different capacities of 2-hour storage. The first 5-10 GW of solar penetration flattens the net load shape creating an antagonistic reliability value relationship with storage. As solar penetration rises above this level, solar marginal ELCCs are higher for higher storage penetration. Figure 20, shows how solar marginal ELCCs vary for different wind penetrations. Solar exhibits a consistent but small synergistic reliability value relationship with wind penetration.

Figure 19. Summer Solar Marginal ELCC (Varying Storage Penetration, Fixed Wind Penetration)

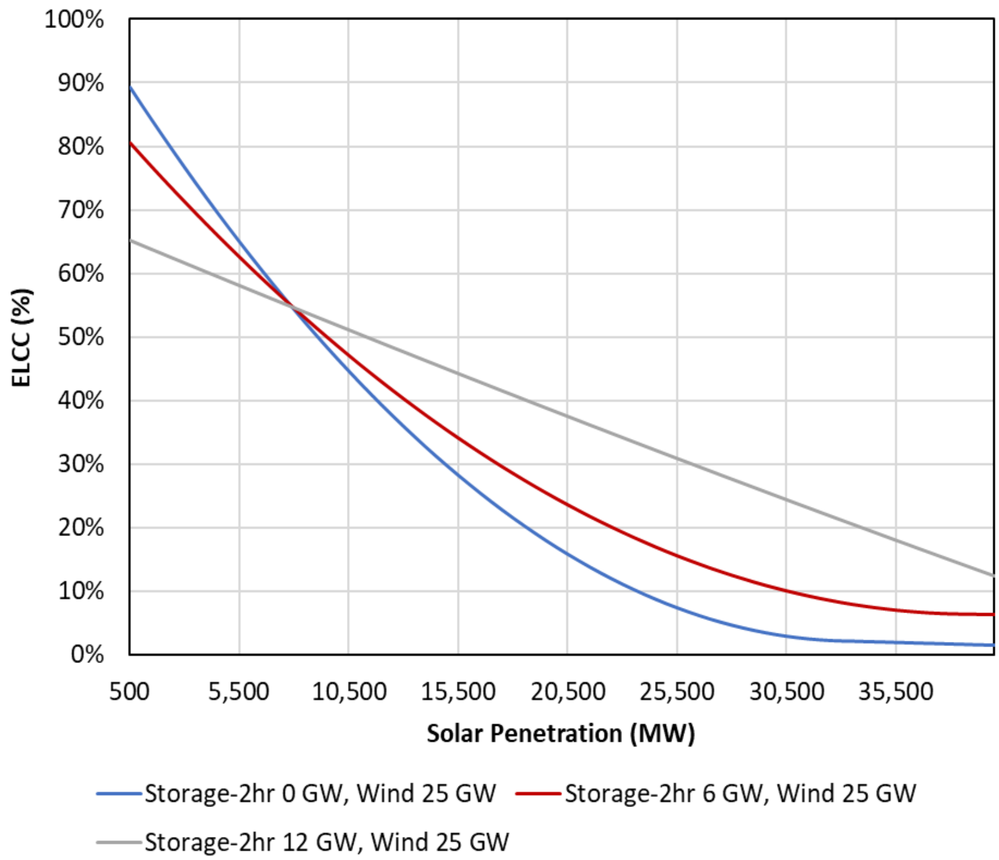


Figure 20. Summer Solar Marginal ELCC (Fixed Storage Penetration, Varying Wind Penetration)

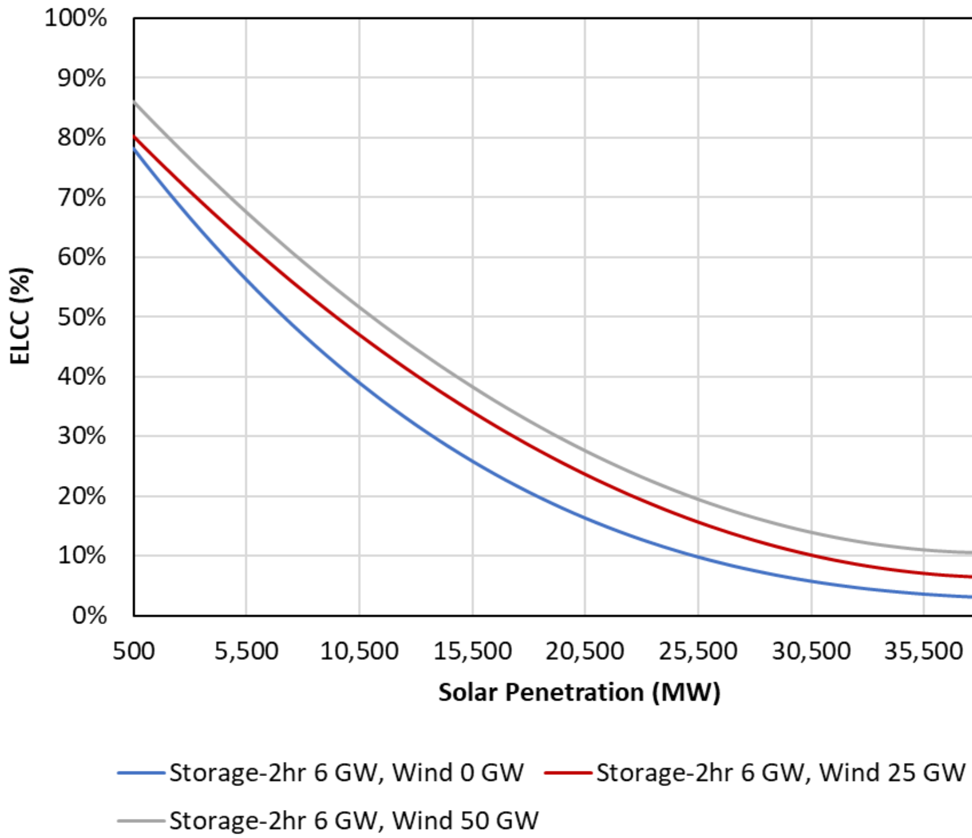


Figure 21 and Figure 22 show the wind marginal ELCCs for different solar and storage penetrations, one resource held constant while the other varies. Figure 21 shows wind marginal ELCCs with respect to wind penetration for different storage penetrations as solar penetration is held constant at 20 GW. Wind and 2-hour storage have minimal interactive effects, with a modest antagonistic effect at low 2-hour storage penetrations.

Figure 21. Summer Wind Marginal ELCC (Varying Storage Penetration, Fixed Solar Penetration)

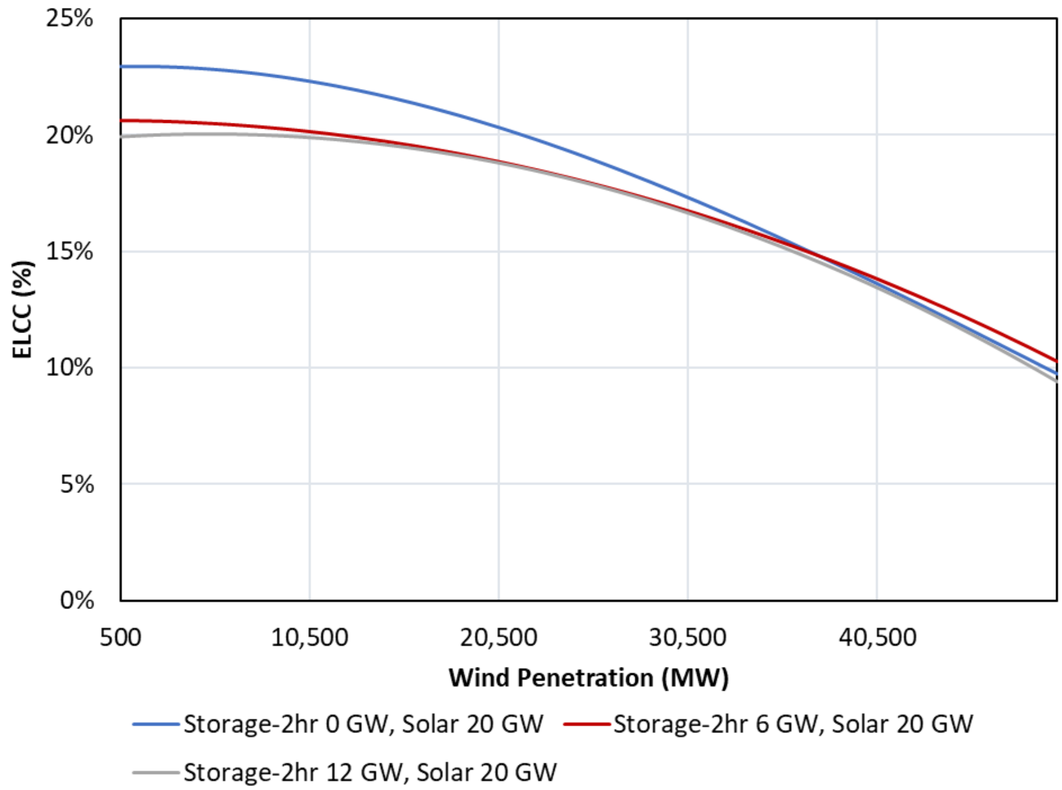


Figure 22. Summer Wind Marginal ELCC (Fixed Storage Penetration, Varying Solar Penetration)

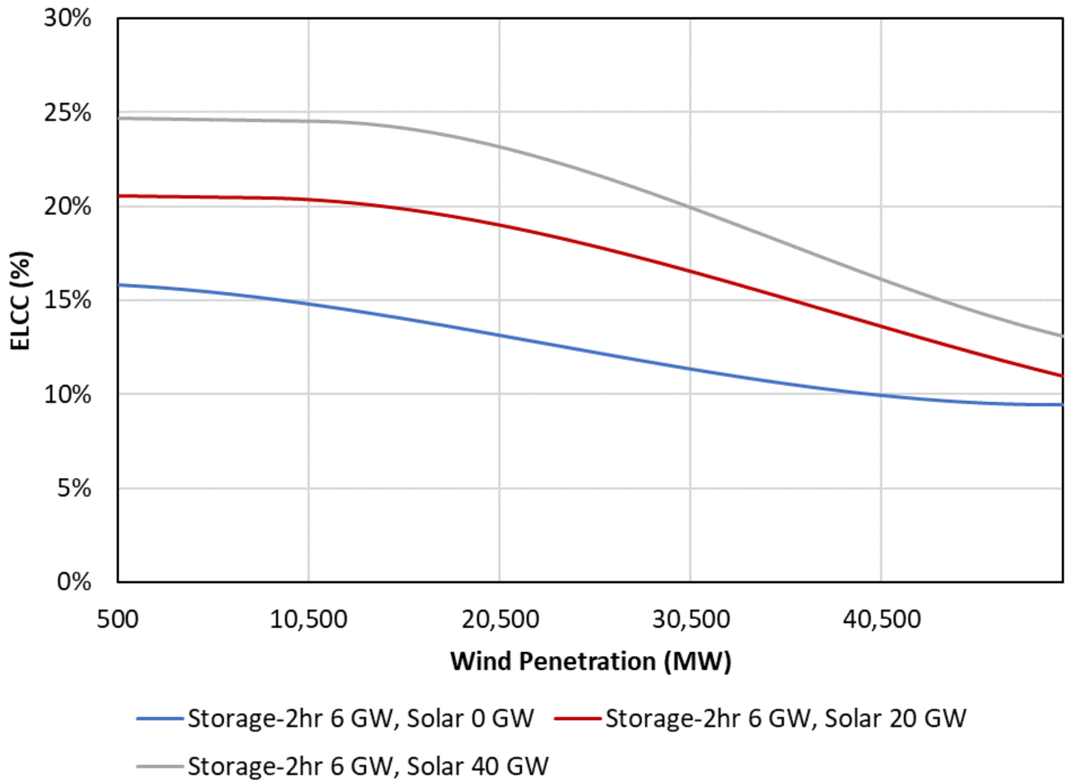


Figure 22 depicts summer wind marginal ELCCs as a function of wind penetration, with 2-hour storage penetration held constant at 6 GW for different solar penetration levels. The figure depicts the consistent synergy between wind and solar and echoes the result from Figure 20. Figure 23 and Figure 24 depict 2-hour storage marginal ELCC as a function of storage penetration with different wind and solar penetration levels. In Figure 23 solar is held constant at 20 GW and shows that there are minimal interactive effects between 2-hour storage and wind penetration, with modest antagonistic effects as were seen in Figure 21.

Figure 23. Summer 2-Hour Storage Marginal ELCC (Varying Wind Penetration, Fixed Solar Penetration)

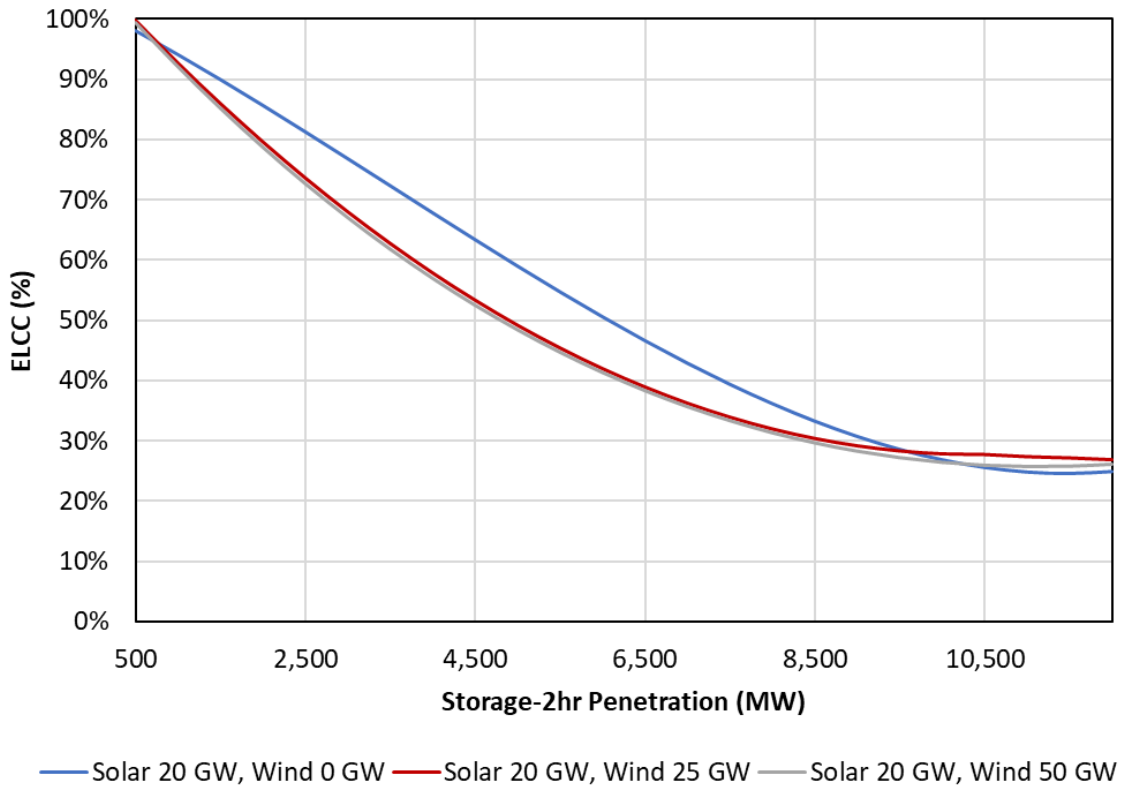


Figure 24. Summer 2-Hour Storage Marginal ELCC (Fixed Wind Penetration, Varying Solar Penetration)

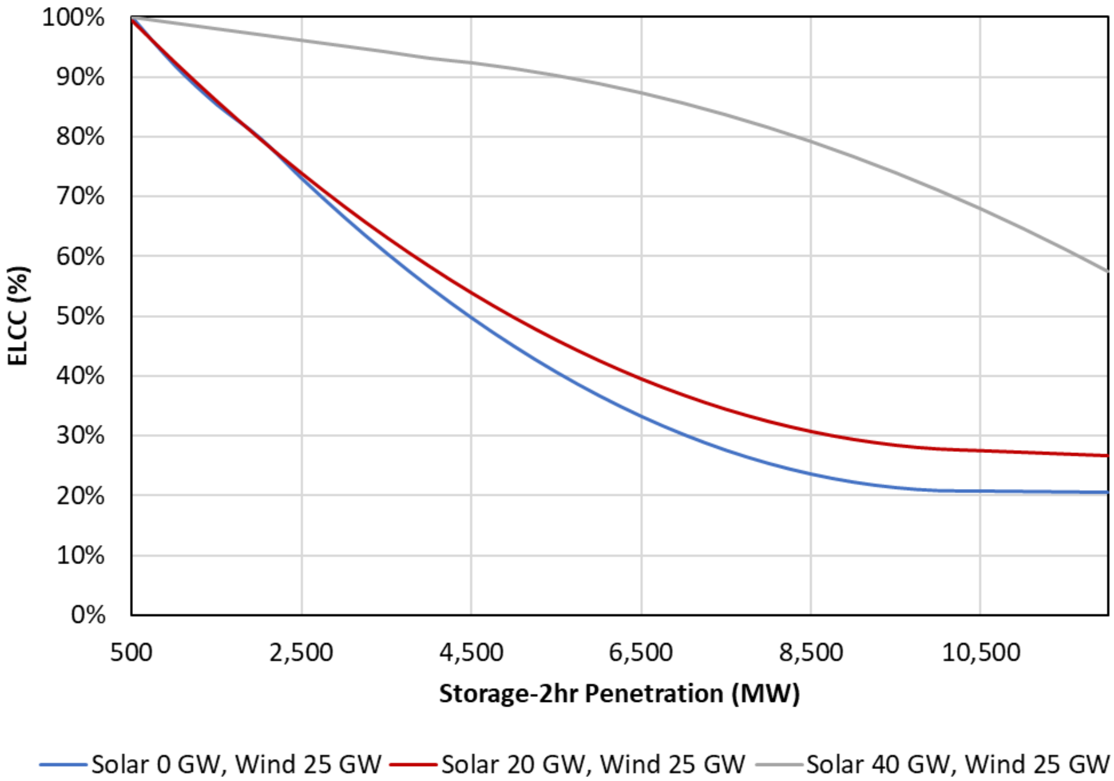


Figure 24 shows the significant synergy between solar and 2-hour storage. As the solar penetration goes above 20 GW, the net load shape has a narrow peak as can be seen in Figure 25 which benefits short-duration storage.

Figure 25. Net Load Shape with Increasing Solar Penetration

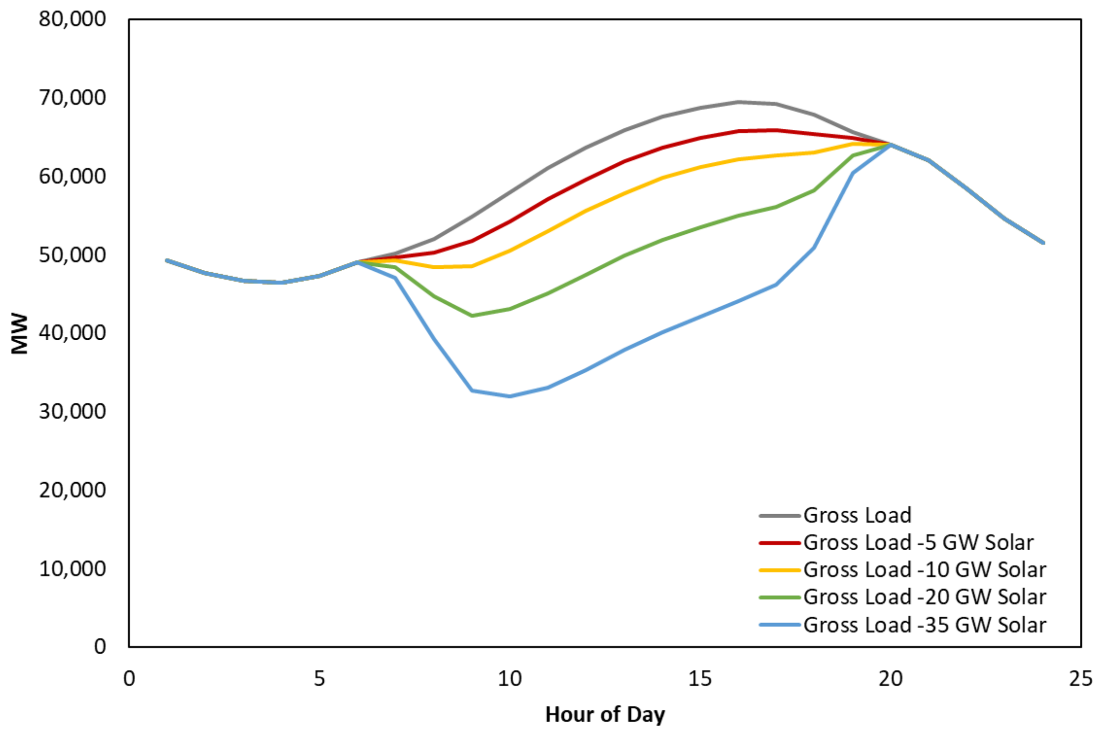
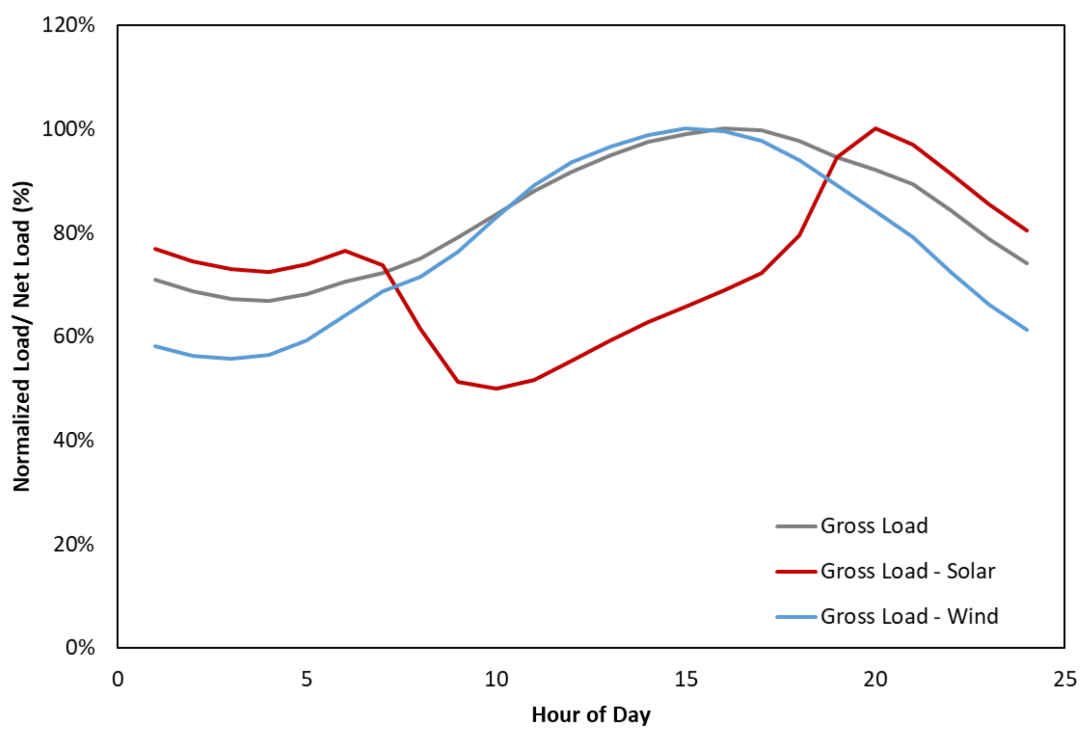
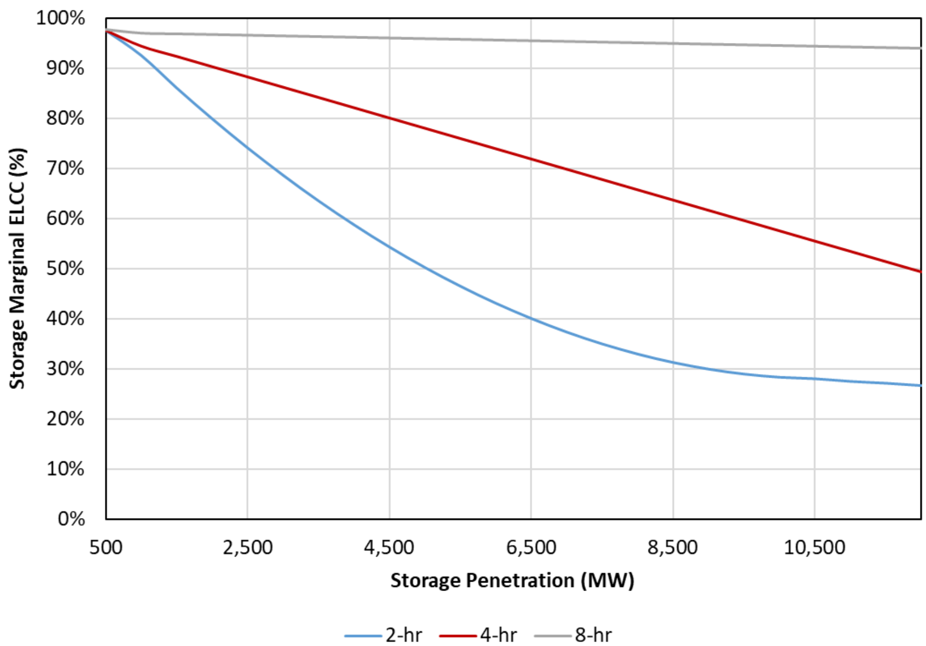


Figure 26. Normalized Net Load Shape Comparison



Summer marginal ELCC curves of different duration storage resources are depicted in Figure 27. Increased storage duration makes the decline in marginal ELCC less significant. Eight-hour storage showed only a minimal decline in the marginal ELCCs up to 12 GW of penetration. For this analysis all storage on the system was assumed to be of a certain duration (2-hour, 4-hour, or 8-hour).

Figure 27. Summer Storage Marginal ELCCs by Duration (Solar 20 GW and Wind 25 GW)



C. SUMMER AVERAGE ELCCS

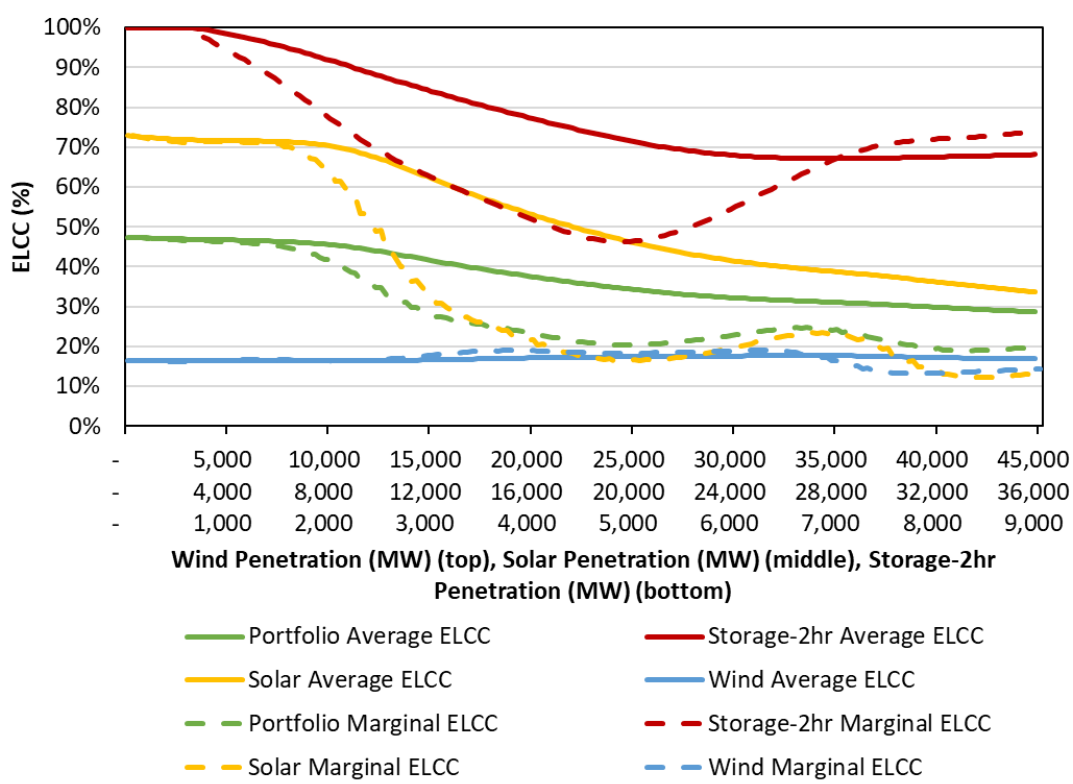
Applying the integration method on a discrete portfolio produces average and marginal ELCC curves for the wind, solar, and batteries included in that portfolio. As this report has demonstrated, the reliability contribution of any variable energy technology is contingent on the underlying penetration of all variable energy technologies, so calculating the average ELCC is sensitive to the order in which resources are added. The integration method assumes no vintaging of resources, so all resources are added in proportion to their final penetration. The marginal ELCC is calculated for a block of storage, a block of solar, a block of wind, and the sum of all three blocks. The marginal ELCCs by technology are allocated to add up to the portfolio ELCC. This continues until the total portfolio has been analyzed. The specific portfolio analyzed, and technology step sizes are shown in Table 5. Similar analysis using the same step sizes was performed for 4 and 8-hour duration storage.

Table 5. Integration Method Parameters

Resource Class	Increments (MW)	Total Penetration (MW)
Storage	50	9,000
Solar	200	36,000
Wind	250	45,000
Portfolio	500	90,000

The solid curves in Figure 28 represent the average ELCC values as the penetration rises, while the dashed curves represent the marginal ELCCs. The average ELCCs show a declining trend as the penetrations rise, except for 2-hour storage and wind. In the case of storage this is due to the interactive effects that 2-hour storage shares with solar. The 2-hour storage average ELCCs first fall as the first 20 GW of solar capacity flattens the net-load shape. After 20 GW, the solar penetration makes the net load shape produce a narrow peak, which benefits short-duration storage. In the case of wind, Solar investments shift the net load peak into the evening which provides the wind with added benefit.

Figure 28. Summer Resource Level ELCCs (Solar, Wind, and 2-Hour Storage)



The integration method produces similar results when replacing 2-hour storage with longer duration storage as seen in Figure 29 and Figure 30. As the solar penetration rises to 20 GW, the net-load peak is shifted later into the day and longer duration storage is better able to serve this peak than the shorter duration storage. Hence, the decline in the marginal ELCCs in the 4-hour storage case is less pronounced than in the 2-hour storage case, and the 8-hour case sees an even smaller decline. Solar marginal ELCCs are initially numerically close to the average ELCCs, but as the rising solar penetration shifts the net load peak to the early hours of the day or the late evening, the solar marginal ELCC starts declining rapidly. Wind marginal ELCCs see a synergistic relationship as the solar pushes the net load peak later into the day, but for higher wind penetrations they decrease.

Figure 29. Summer Resource Level ELCCs (Solar, Wind, and 4-Hour Storage)

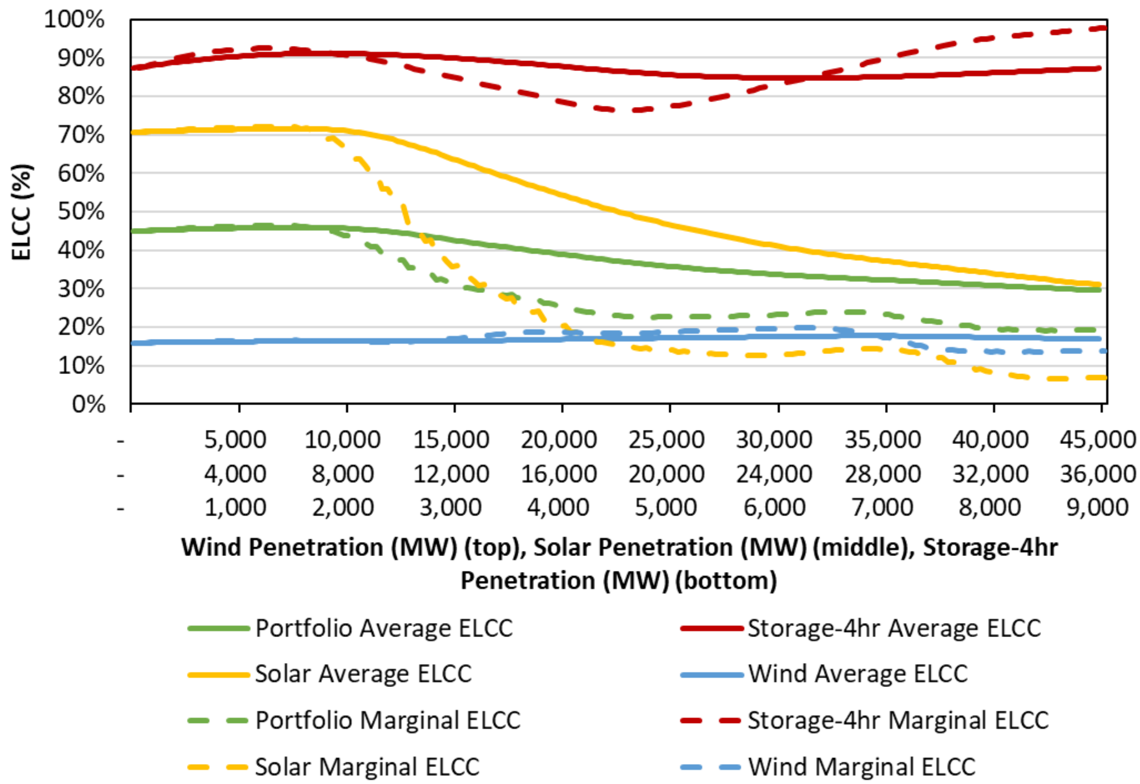
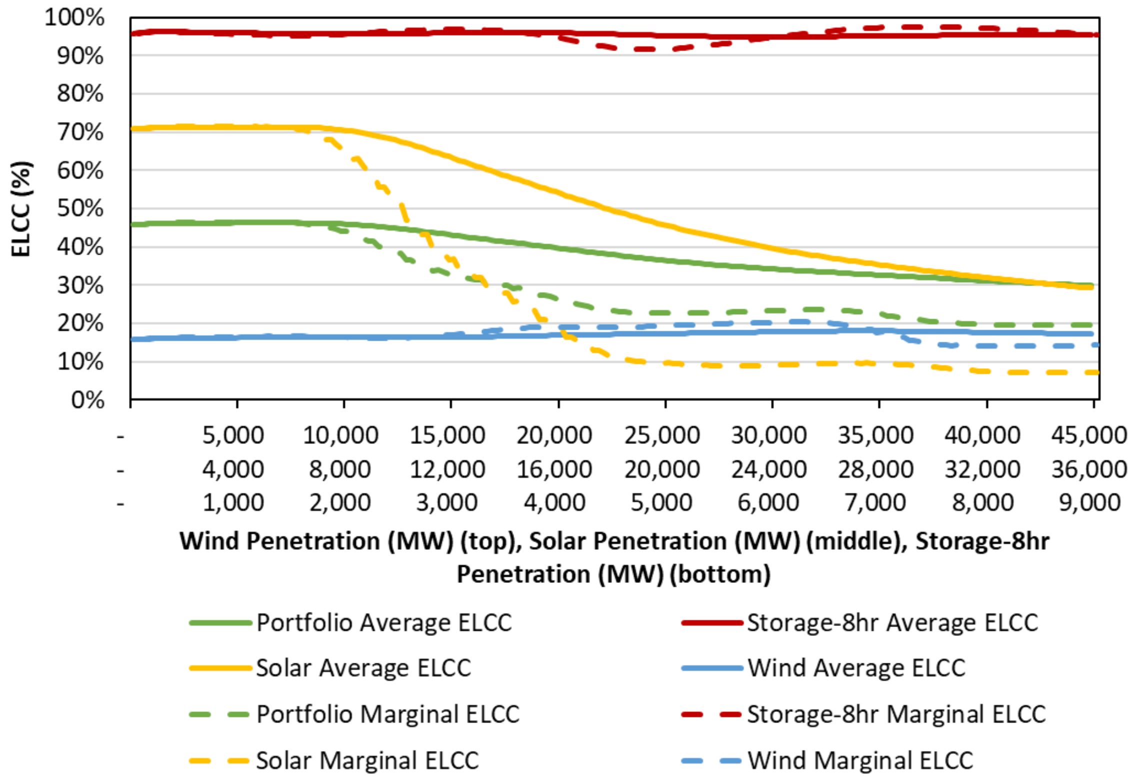


Figure 30. Summer Resource Level ELCCs (Solar, Wind, and 8-Hour Storage)



D. WINTER RESULTS

Figure 31 depicts the winter capacity contribution surface for a 6 GW penetration of 2-hour storage. The variable energy portfolios analyzed have significantly lower reliability contributions in the winter as compared to the summer values at the same 2-hour storage penetration. The lower reliability contribution is driven by the timing and shape of reliability events. Winter reliability events are concentrated in the early morning hours when solar PV produces little energy. Winter peaks can also be persistently high reducing the reliability value of short duration storage. The marginal ELCCs for solar, wind and 2-hour storage can be seen in Figure 32.

Figure 31. Winter Capacity Contribution Surface (2-Hour Storage, 6 GW)

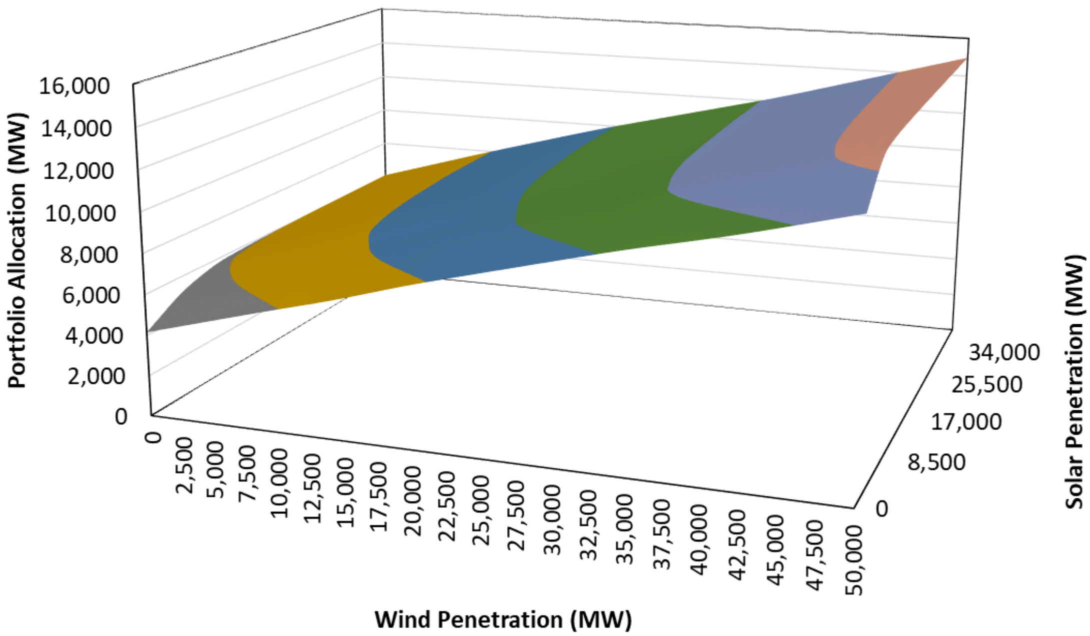
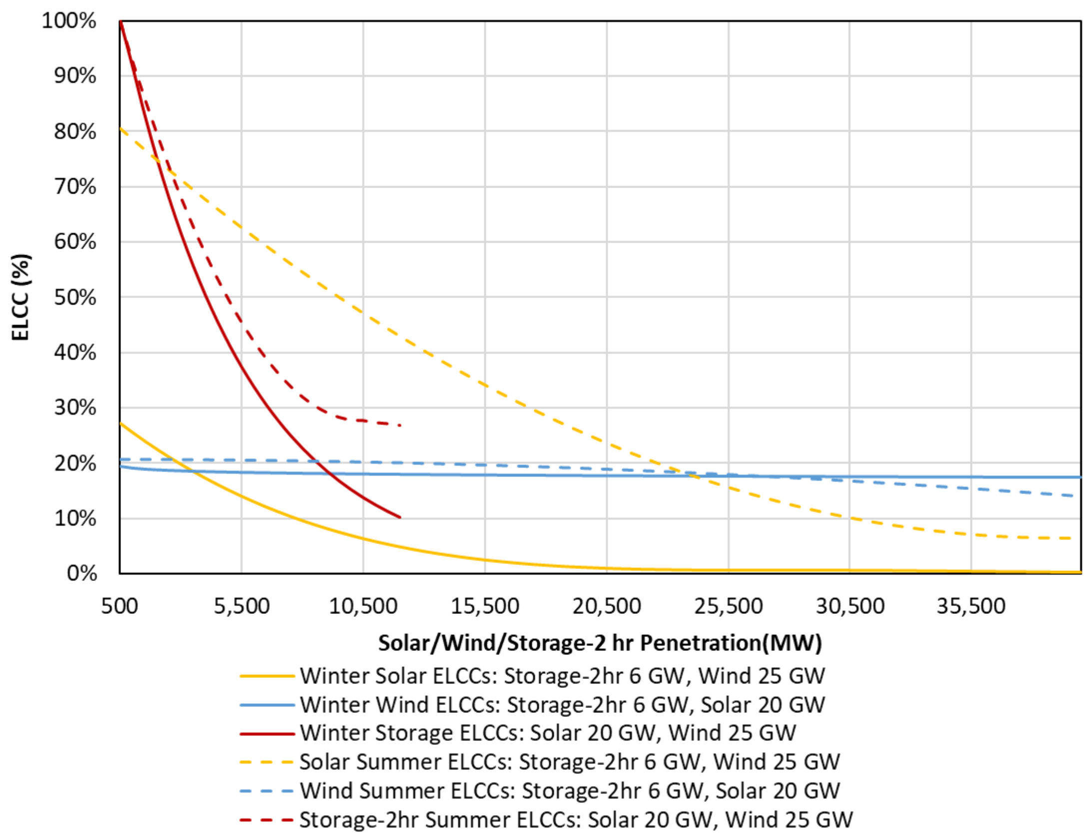


Figure 32. Winter vs Summer: Solar, Wind, and Storage (2-Hour) Marginal ELCCs



Wind marginal ELCCs in the winter see a small decline as wind penetration rises, as shown in Figure 32. The solar and storage (2-hour) marginal ELCCs in the winter see a quick decline as the penetration rises. The marginal ELCCs in the winter for solar are lower than in the summer due to fewer hours of sunlight and high loads during low solar output periods. The storage marginal ELCCs are also lower since the interactive effects between solar and storage are not as strong in the winter. Marginal ELCC curves for different storage durations in the winter are depicted in Figure 33. Storage marginal ELCCs in the winter depicted in Figure 33 decay faster and further than in the summer as depicted in Figure 27.

Figure 33. Winter Storage Marginal ELCCs by Duration (Solar 20 GW and Wind 25 GW)

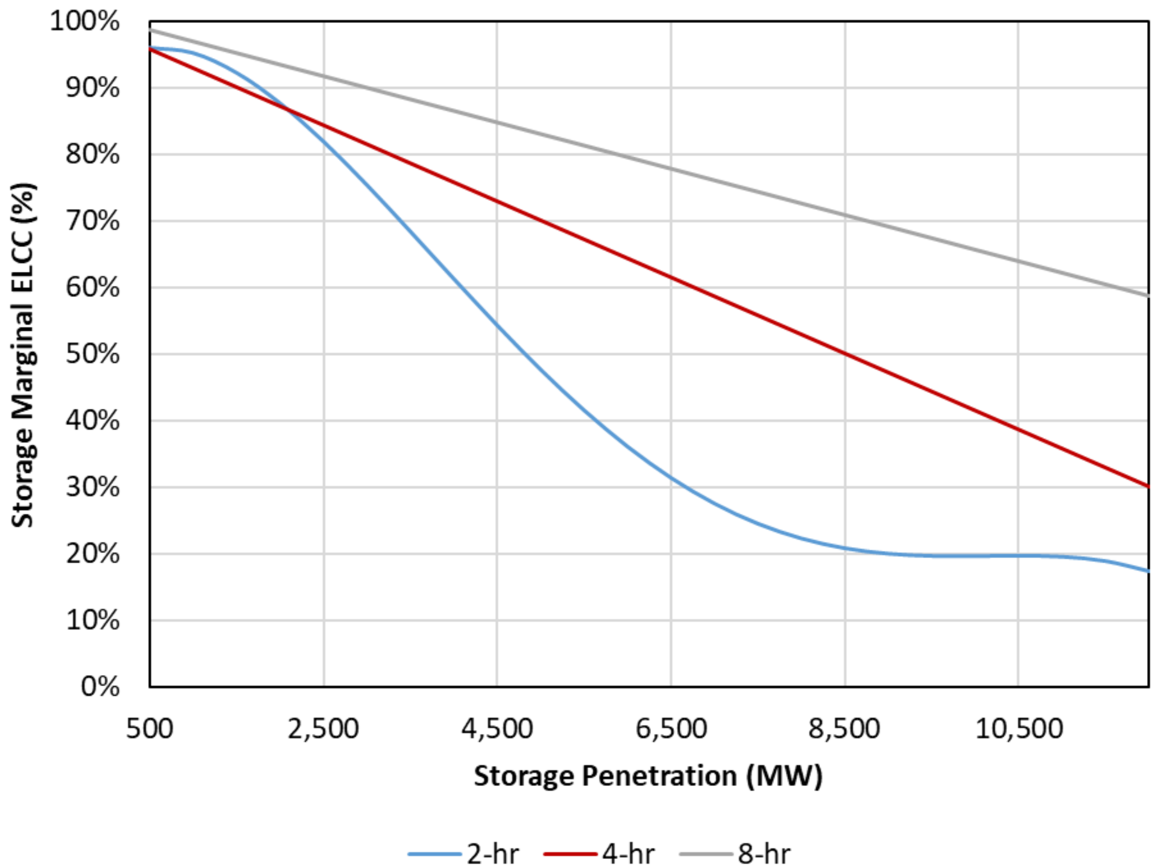
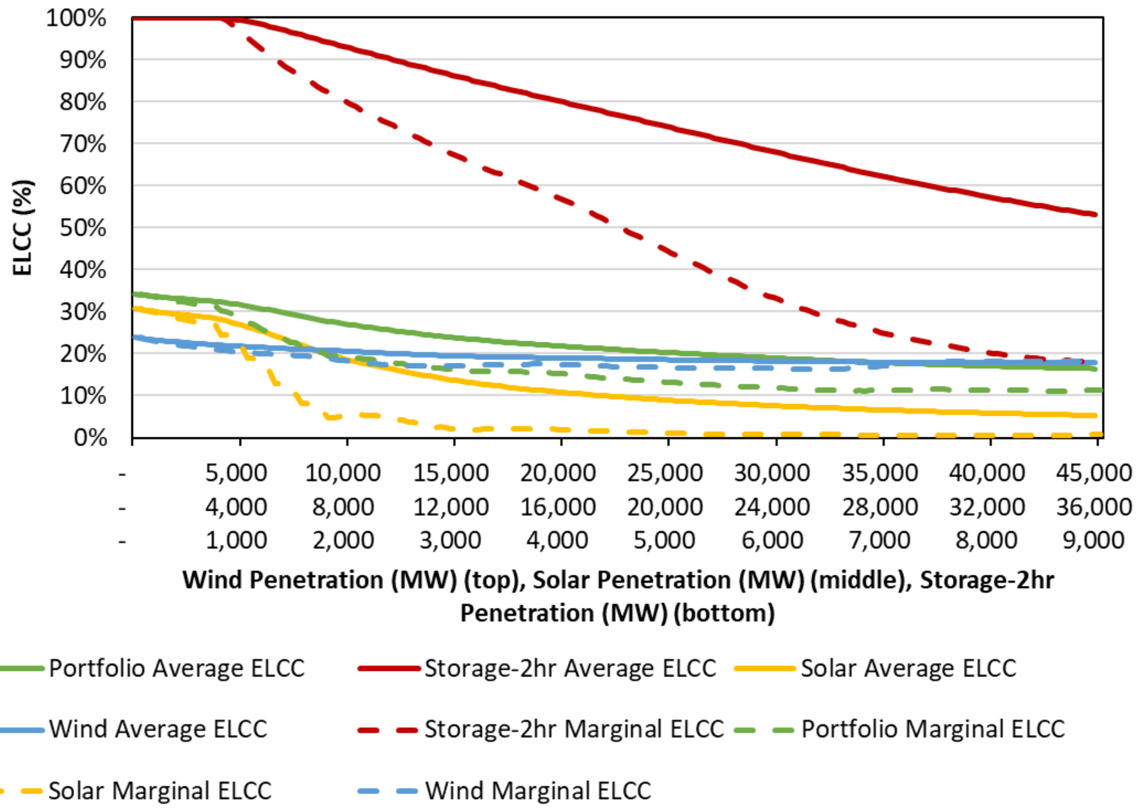


Figure 34. Winter Resource Level ELCCs Using the Integration Method (Solar, Wind, and 2-Hr Storage)



Applying the integration method on winter capacity contribution surfaces like the one depicted in Figure 31 result in the ELCC curves shown in Figure 34. The portfolio is incremented using the values in Table 5. In Figure 34 the solid curves represent the average ELCCs, and the dashed curves represent the marginal ELCCs. The solar and storage (2-hour) marginal ELCCs fall as the penetration rises as the net load peak is pushed later into the day. The winter wind ELCCs decline at a much slower rate as the wind penetration rises because the net load peak gets pushed to later in the day, which benefits the wind.

The integration method was applied with different storage duration levels and the results are depicted in Figure 35 and Figure 36. This analysis was performed on hypothetical storage portfolios where all the storage was set to 4-hour and 8-hour durations. The rate of decay for storage marginal ELCCs reduces as the duration increases as can be seen on comparing Figure 34, Figure 35, and Figure 36.

Figure 35. Winter Resource Level ELCCs Using the Integration Method (Solar, Wind, and 4-Hr Storage)

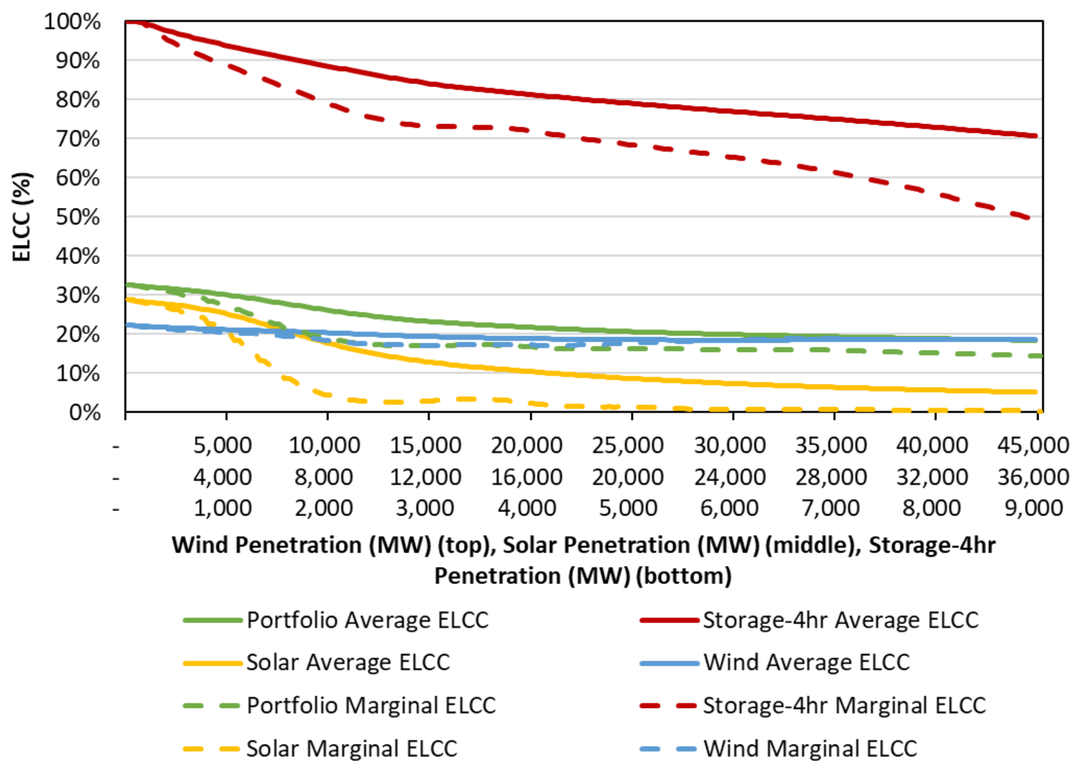
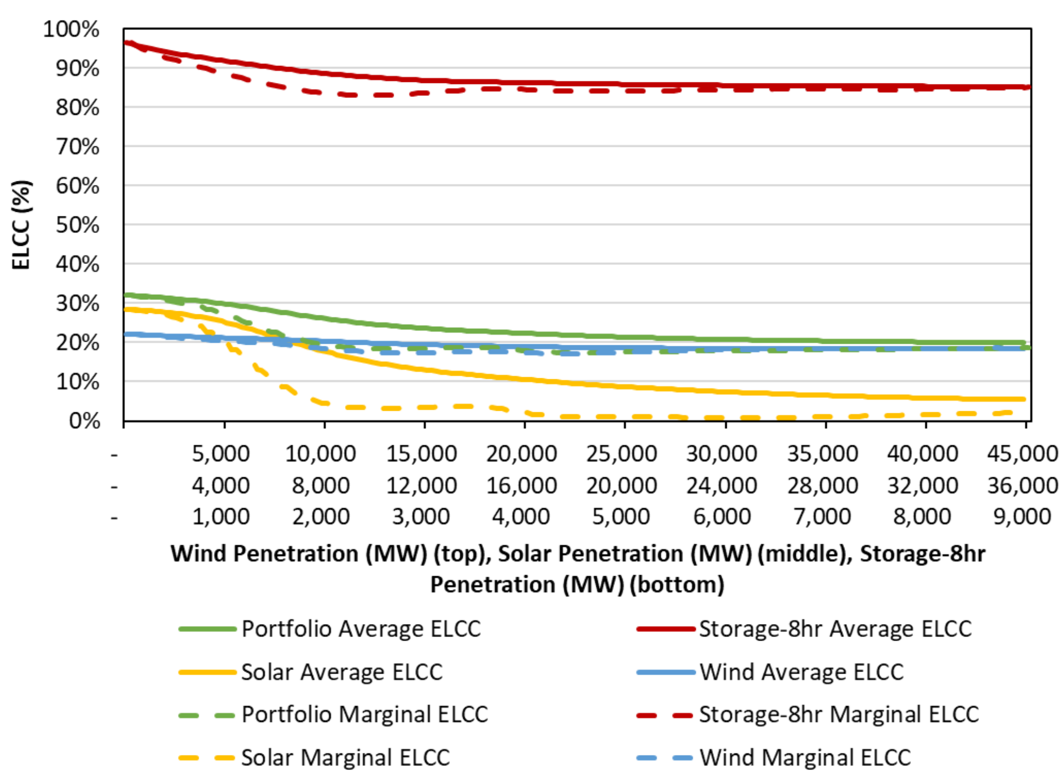


Figure 36. Winter Resource Level ELCCs Using the Integration Method (Solar, Wind, and 8-Hr Storage)



D. TECHNOLOGY AND LOCATION SPECIFIC RESULTS

The resource class ELCC results mentioned in the previous sections 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 being analyzed. Table 6 represents the technology specific first-in and last-in ELCC at the 2024 penetration levels. First-in ELCCs represent the reliability value of the first tranche of the technology being analyzed assuming all other variable energy resources are held constant. The Last-in ELCC represents the reliability value of the last tranche respectively.

The portfolio average ELCCs reflect different trends than the trend observed in Table 6. While marginal wind ELCCs remain relatively static in the average ELCC build-up calculation, this locational specific analysis shows a marked decline in ELCCs. The wind ELCC remains relatively static across penetrations in an average ELCC calculation because of offsetting effects. Holding all external variables constant (as was done in Table 6), wind ELCC would decline because of correlated output. Keeping wind constant but increasing solar increases wind's value. Since the average ELCC captures the synergy between wind and solar as well as the declining reliability value of wind, the net effect is a relatively static ELCC.

Table 6. Technology/Location Specific First-In and Last-In ELCCs

	Technology	Summer ELCC (%)	Winter ELCC (%)	2024 Penetration (MW)
First In	Wind-C	33.8%	55.1%	[redacted]
	Wind-O	33.8%	23.4%	[redacted]
	Wind-P	33.5%	20.7%	[redacted]
	Solar Non-West	68.3%	24.6%	[redacted]
	Solar West	75.6%	20.7%	[redacted]
	Solar Tracking	72.3%	23.5%	[redacted]
	Solar DGPV	43.2%	17.2%	[redacted]
Last In	Wind-C	21.8%	49.1%	5,900
	Wind-O	14.9%	12.6%	29,233
	Wind-P	21.8%	13.9%	4,903
	Solar Non-West	3.5%	0.0%	20,856
	Solar West	8.7%	0.0%	14,095
	Solar Tracking	6.1%	0.0%	[redacted]
	Solar DGPV	2.3%	0.0%	[redacted]

The technology specific summer allocation was then decomposed from the resource classes as shown in Table 7 and Table 8.

Table 7. Summer Resource Class Capacity Contribution

Technology	Installed Capacity (MW) *[A]*	Summer Allocation (MW) *[B]*
Wind	40,036	6,705
Solar	34,951	11,597
Storage-2Hr	7,620	5,637

Table 8. Summer Technology/Location Specific Capacity Contribution

Technology	Installed Capacity (MW) *[C]*	First-In ELCCs (%) *[D]*	Last-In ELCCs (%) *[E]*	Average First & Last-In ELCCs (%) *[F]=([D]+[E])/2*	Standalone Average ELCC (MW) *[G]=[C]*[F]*	Summer Allocation (MW) *[H]*[17]	Summer Allocation (%) *[I]=([H]/[C])*
Wind-C	5,900	33.8%	21.80%	27.80%	1,640	1,087	18.43%
Wind-O	29,233	33.8%	14.90%	24.35%	7,118	4,719	16.14%
Wind-P	4,903	33.5%	21.80%	27.65%	1,356	899	18.33%
Solar Non-West	20,856	68.30%	3.50%	35.90%	7,487	6,466	31.00%
Solar West	14,095	75.60%	8.70%	42.15%	5,941	5,131	36.40%

Solar West gets a higher capacity contribution/ELCC due to it being able to provide capacity during the last hours of daylight which coincide with the net-load peak. Wind-C (coastal) and Wind-P (panhandle) perform better than Wind-O (other) due to the geographic spread of wind speeds in the summer months.

Similar results can be seen for the winter season in Table 9 and Table 10. Wind-C gets most of the capacity contribution due to the higher wind speeds along the coasts in the winter. Solar Non-West and Solar West last-in ELCCs are at 0% due to the diminished value of solar in the winter months.

Table 9. Winter Resource Class Capacity Contribution

Technology	Installed Capacity (MW) *[A]*	Winter Allocation (MW) *[B]*
Wind	40,036	7,641
Solar	34,951	2,579
Storage-2Hr	7,620	3,264

[17] $[H] = \frac{[G]_{wind\ or\ solar\ subclass}}{\Sigma[G]_{all\ wind\ or\ solar\ subclasses}} * [B]$

Table 10. Winter Technology/Location Specific Capacity Contribution

Technology	Installed Capacity (MW) *[C]*	First-In ELCCs (%) *[D]*	Last-In ELCCs (%) *[E]*	Average First & Last-In ELCCs (%) *[F]=([D]+[E])/2*	Standalone Average ELCC (MW) *[G]=[C]*[F]*	Winter Allocation (MW) *[H]*	Winter Allocation (%) *[I]=([H]/[C])*
Wind-C	5,900	55.10%	49.10%	51.55%	3,074	2,557	43.35%
Wind-O	29,233	23.40%	12.60%	10.00%	5,262	4,378	14.98%
Wind-P	4,903	20.70%	13.90%	8.80%	848	706	14.39%
Solar Non-West	20,856	24.60%	0.00%	12.30%	2,565	1,644	7.88%
Solar West	14,095	20.70%	0.00%	10.35%	1,459	935	6.63%

The results in Table 8 and Table 10 are summarized as seasonal capacity contributions (MW) in Figure 37 for solar technologies. The solar standalone and portfolio capacity contributions both decrease going from summer to winter.

Figure 37. Solar Technology Specific Seasonal Capacity Contribution

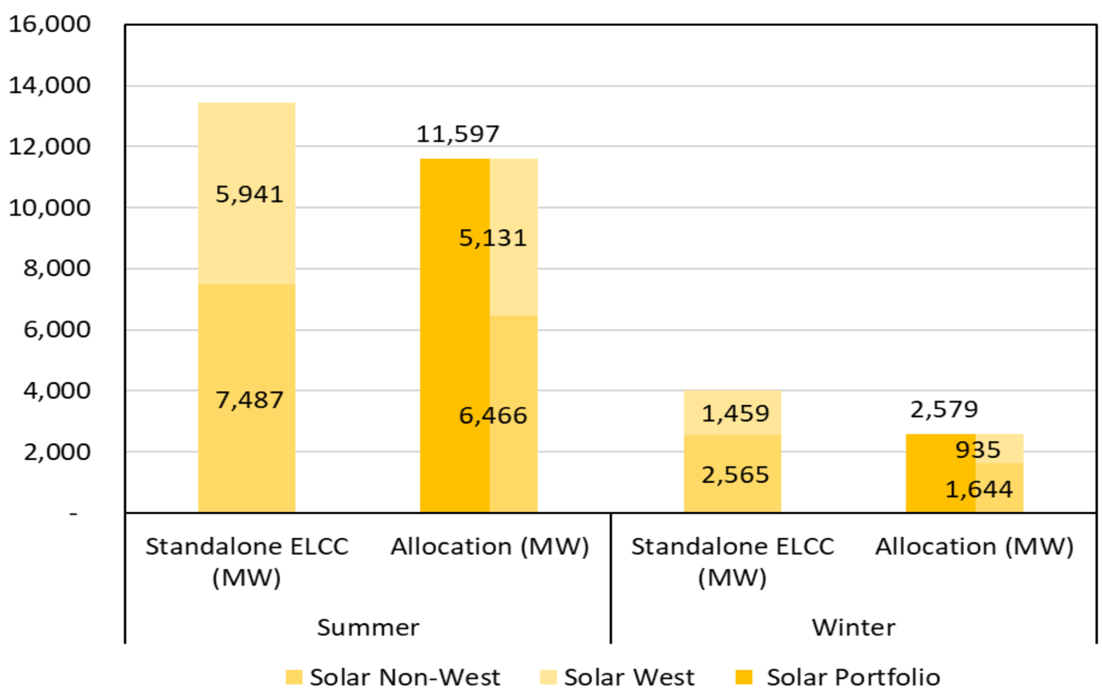


Figure 38. Wind Technology Specific Seasonal Capacity Contribution

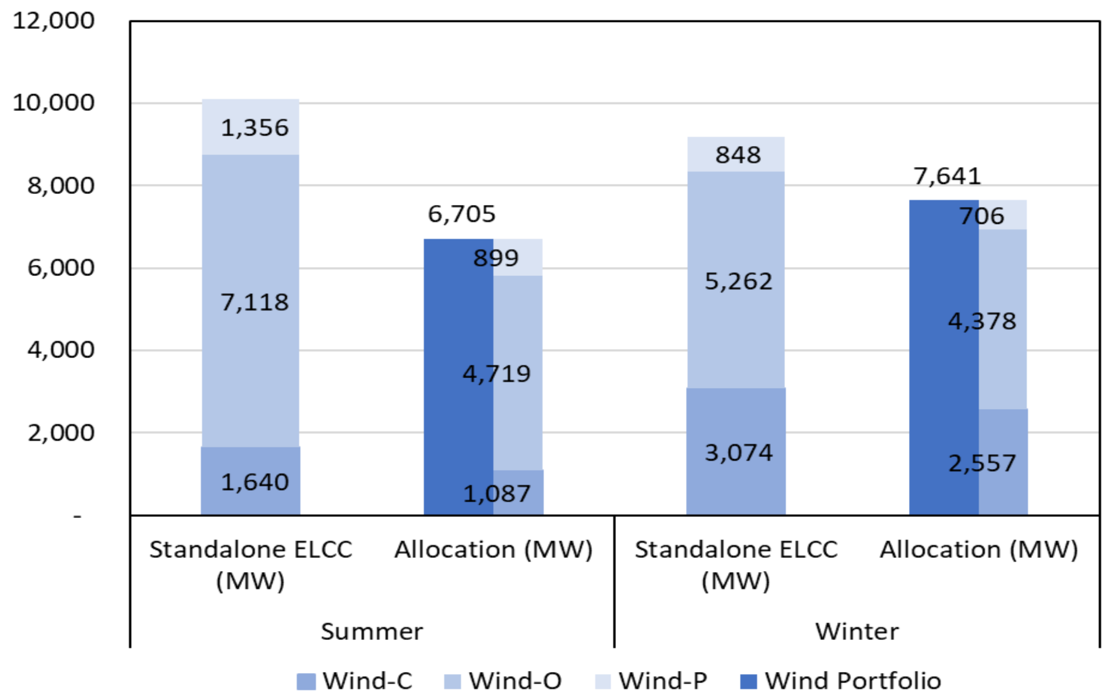


Figure 38 summarizes the seasonal capacity contributions (MW) of wind technologies. Wind technologies have an overall higher contribution in the winter as compared to the summer.

E. THERMAL ELCCS

The thermal ELCC results when no renewable or battery storage are present in the system are presented in Table 11. The analysis performed was an initial examination of the impacts of outages on the ability of thermal resources to carry load. The results show that the ELCC of thermal resources is influenced by more than just the EFOR. The 1-EFORd accreditation on the right overstates the reliability of the thermal resources found by the ELCC simulations in the left of the table. Depending on the cold weather assumption, the winter UCAP could overstate the actual reliability contribution of these resources compared to the ELCC result by anywhere from 5% to 17%. As noted earlier, the potential impacts of new weatherization standards are not accounted for in these results.

Table 11. Thermal ELCC Results – Effect of Cold Weather Assumptions with No Renewable or Storage Penetration

Battery, Solar, and Wind Penetration	Thermal	Cold Weather	Fuel	Winter ELCC (%)	Summer ELCC (%)	Winter UCAP/ Winter CDR Rating (%)	Summer UCAP/ Summer CDR Rating (%)
0	2024	Base	None	89.6%	89.8%	94.6%	93.9%
0	2024	2011	None	87.5%	89.8%	94.9%	93.9%
0	2024	2011 and 2021	None	78.0%	89.6%	95.1%	94.0%

When fuel availability restrictions are taken into account, the winter ELCC decreases even further, as shown in Table 12. For example, the last row of the table shows that by layering in fuel outages on top of the 2011 and 2021 cold weather assumptions, the ELCC of the thermal fleet can decrease another 10.3% down to 67.6%.

Table 12. Thermal ELCC Results – Effect of Fuel Availability with No Renewable or Storage Penetration

Battery, Solar, and Wind Penetration	Thermal	Cold Weather	Fuel	Winter ELCC (%)	Summer ELCC (%)	Winter UCAP/ Winter CDR Rating (%)	Summer UCAP/ Summer CDR Rating (%)
0	2024	Base	None	89.6%	89.8%	94.6%	93.9%
0	2024	Base	Include Fuel	87.5%	89.8%	94.9%	93.9%
0	2024	2011	None	87.5%	89.8%	94.9%	93.9%
0	2024	2011	Include Fuel	83.5%	89.5%	95.0%	94.0%
0	2024	2011 and 2021	None	78.0%	89.6%	95.1%	94.0%
0	2024	2011 and 2021	Include Fuel	67.7%	89.6%	95.1%	94.0%

As shown in Table 13, the winter thermal ELCCs increase with the addition of the 2024 wind, solar, and battery penetrations. For example, looking at the 2011 and 2021 cold weather outages with no additional fuel outages, the winter ELCCs raise from 78.0% to 78.9%.

Table 13. Thermal ELCC Results – Effect of 2024 Battery and Renewable Penetration on Thermal ELCC Results

Battery, Solar, and Wind Penetration	Thermal	Cold Weather	Fuel	Winter ELCC (%)	Summer ELCC (%)	Winter UCAP/ Winter CDR Rating (%)	Summer UCAP/ Summer CDR Rating (%)
0	2024	Base	None	89.6%	89.8%	94.6%	93.9%
0	2024	Base	Include Fuel	87.5%	89.8%	94.9%	93.9%
0	2024	2011	None	87.5%	89.8%	94.9%	93.9%
0	2024	2011	Include Fuel	83.5%	89.5%	95.0%	94.0%
0	2024	2011 and 2021	None	78.0%	89.6%	95.1%	94.0%
0	2024	2011 and 2021	Include Fuel	67.7%	89.6%	95.1%	94.0%
2024	2024	Base	None	89.9%	90.8%	96.1%	94.4%
2024	2024	Base	Include Fuel	87.9%	90.7%	96.3%	94.4%
2024	2024	2011	None	87.9%	90.7%	96.3%	94.4%
2024	2024	2011	Include Fuel	83.4%	90.7%	96.6%	94.4%
2024	2024	2011 and 2021	None	78.9%	90.8%	96.9%	94.4%
2024	2024	2011 and 2021	Include Fuel	69.3%	90.8%	97.1%	94.4%

A simple UCAP capacity accreditation does not accurately reflect the true reliability contribution of these resources.

The thermal ELCC results reflect a range of assumptions. Ultimately, more research into the expected cold-weather performance and fuel adequacy concerns will be necessary to determine which specific assumptions should drive both accreditation and resource adequacy assessments.

CONCLUSIONS AND NEXT STEPS

ELCC calculations are an important step in reliability planning. ELCCs provide insight into not only the reliability value of marginal technology decisions, but also the combined contributions of large variable energy resources to reliability. As ERCOT is in the midst of a significant transition to a portfolio with nearly 80 GW of variable energy resources, a robust picture of the reliability path during the transition is just as critical, if not more critical, than understanding the reliability characteristics of the system when the resource mix becomes more stable.

The ERCOT system with both summer and winter reliability risks require a sophisticated approach to monitoring the reliability value of all technology classes including wind, solar, energy storage, and conventional resources. ELCCs provide that framework and allow for equitable treatment of the reliability contributions of all resource classes. The impact of any type of dispatch constraint, limitation on the availability of energy, and correlations of output can be measured in total and on the margin with the ELCC method.

While the steps of implementing the ELCC method in ERCOT have not been finalized, it will likely entail both informational and accreditation elements. Incorporating ELCCs into informational processes such as the Capacity, Demand, and Reserves report will signal to the market the average and incremental value of each resource class and inform stakeholders on expected reliability conditions in the short term. Using marginal or average ELCCs in combination with various performance measurement mechanisms will affect resource accreditation and ensure that proper incentives are provided to generation resources to be available in critical reliability periods.

APPENDIX

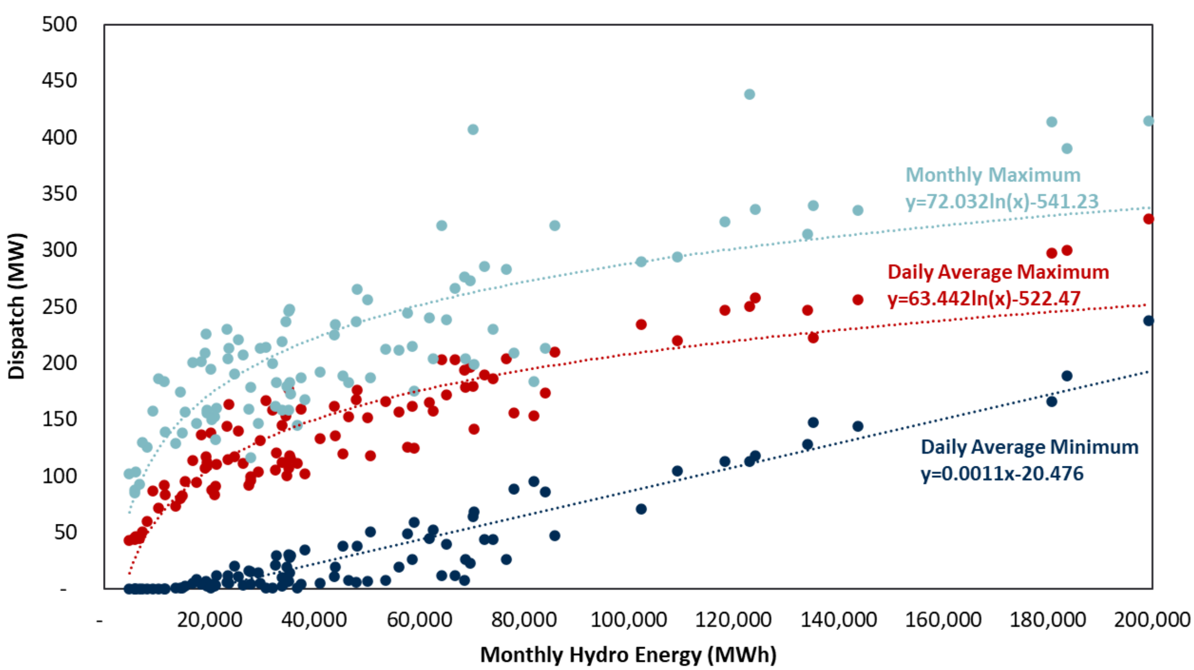
A. GENERATION RESOURCES

1. HYDROELECTRIC

We include 557.4 MW of hydroelectric resources, consistent with ERCOT's May 2022 CDR report. We characterize hydro resources using eight years of hourly data over 2012-2019 provided by ERCOT, and 42 years of monthly data over 1980-2021 from Form EIA-923.[18] 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



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

2. FUEL PRICES

We used the natural gas future quotes for the 2024 study year.[19] The average fuel prices used in the study are presented in Table A1.

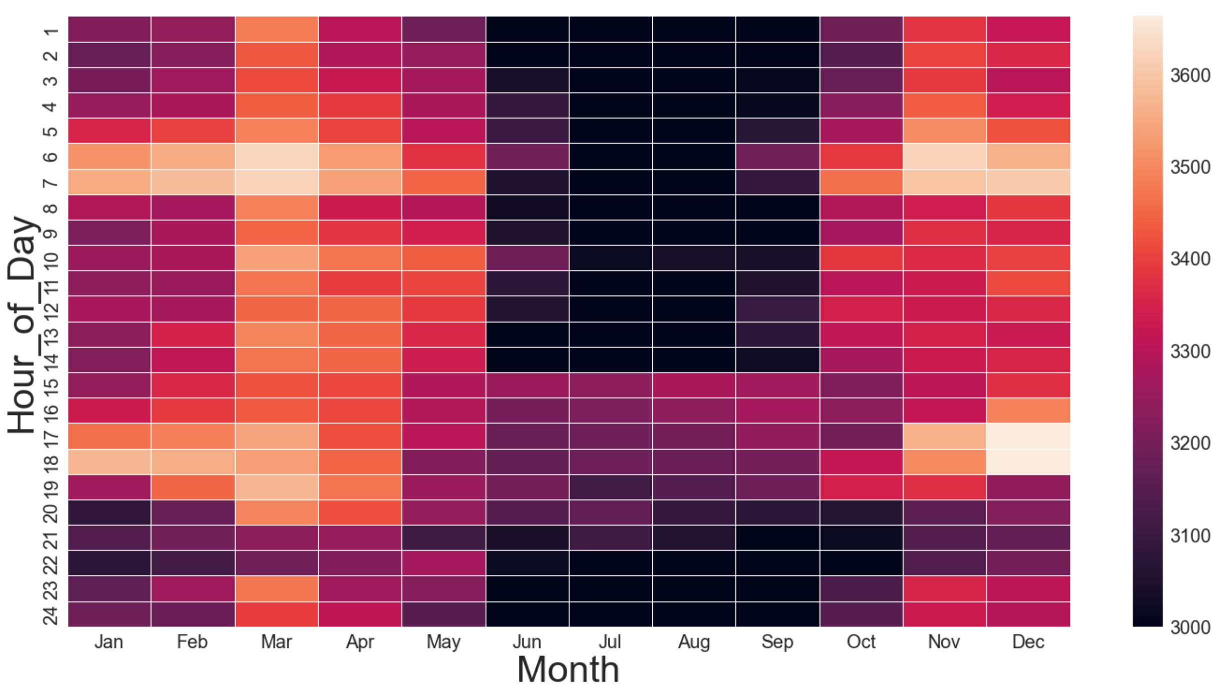
Table A1. ERCOT Fuel Forecasts

Coal Fuel Price ($/MMBtu)	Gas Fuel Price ($/MMBtu)	Diesel Fuel Price ($/MMBtu)
2.52	3.38	11.14

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. A heatmap of the monthly and hourly online upward reserve minimums is shown in Figure A2.

Figure A2. Upward Reserve Requirements



[19] https://www.cmegroup.com/markets/energy/natural-gas/natural-gas.quotes.html

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	Marginal Curtailment Cost	Adjustments to ERCOT Load Shape	Reserve Margin Accounting
TDSP Programs					
Energy Efficiency	3,681	Not explicitly modeled.	*n/a*	None	Load reduction
Load Management	307	Emergency trigger at EEA Level 1	$2,543	None	Load reduction
Emergency Response Service (ERS)[20]					
30-Minute ERS	890	Emergency trigger at EEA Level 1	$1,721	None	Load reduction
10-Minute ERS	35	Emergency trigger at EEA Level 2	$2,543	None	Load reduction
Load Resources (LRs)					
Non-Controllable LRs	1,591	Economically dispatch for Responsive Reserve Service (most hours) or energy (few peak hours). Emergency deployment at EEA Level 2	$2,543	None	Load reduction
Controllable LRs		Currently no controllable LRs modeled in ERCOT	*n/a*	*n/a*	*n/a*
Voluntary Self-Curtailments					
4 CP Reductions	1,700	Load shapes grossed up for projected response and corresponding response modeled on the resource side	*n/a*	None	None; excluded from reported peak load
Price Responsive Demand	Variable	Load shapes explicitly grossed up for expected response. Economic self-curtailment modeled on resource side	$5,000 - $5,000/MWh	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 2021 and 2022, with the 2024 summer peak quantity assumptions provided by ERCOT.[21] Demand resources enrolled under ERS

[20] New rules allow ERCOT to deploy ERS prior to an EEA Level declaration.
[21] For total ERS procurement quantities by product type and season, see https://sa.ercot.com/misapp/GetReports.do?reportTypeId=11465&reportTitle=ERS%20Procurement%20Results&showHTMLView=&mimicKey

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.

Table A3. Assumed ERS Quantities Available in 2024

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	47.1	991.3	-	1,038.4
TP2: Weekdays HE 10 AM - 1 PM	46.8	1,154.3	-	1,201.1
TP3: Weekdays HE 2 PM - 4 PM	38.3	1,040.1	41.8	1,120.2
TP4: Weekdays HE 5 PM - 7 PM	35.3	847.9	41.8	925.0
TP5: Weekdays HE 8 PM - 10 PM	42.4	985.7	-	1,028.2
TP6: Weekend and Holidays HE 6 AM - 9 AM	45.8	823.4	-	869.2
TP7: Weekend and Holidays HE 4 PM - 9 PM	40.8	818.8	-	859.6
TP8: All Other Hours	44.2	863.5	-	907.6
October - November				
TP1: Weekdays HE 6 AM - 9 AM	105.9	1,073.5	-	1,179.4
TP2: Weekdays HE 10 AM - 1 PM	95.1	1,032.4	-	1,127.5
TP3: Weekdays HE 2 PM - 4 PM	96.3	1,038.0	-	1,134.4
TP4: Weekdays HE 5 PM - 7 PM	107.6	1,109.1	-	1,216.8
TP5: Weekdays HE 8 PM - 10 PM	105.6	1,089.0	-	1,194.6
TP6: Weekend and Holidays HE 6 AM - 9 AM	103.2	956.8	-	1,060.0
TP7: Weekend and Holidays HE 4 PM - 9 PM	105.2	971.7	-	1,077.0
TP8: All Other Hours	57.6	900.1	-	957.8
December - March				
TP1: Weekdays HE 6 AM - 9 AM	97.8	994.7	5.5	1,098.0
TP2: Weekdays HE 10 AM - 1 PM	98.5	1,004.1	-	1,102.6
TP3: Weekdays HE 2 PM - 4 PM	99.8	1,010.9	-	1,110.7
TP4: Weekdays HE 5 PM - 7 PM	97.4	1,014.2	5.5	1,117.2
TP5: Weekdays HE 8 PM - 10 PM	96.7	996.5	5.5	1,098.8
TP6: Weekend and Holidays HE 6 AM - 9 AM	32.4	764.0	5.5	802.0
TP7: Weekend and Holidays HE 4 PM - 9 PM	33.8	802.6	-	836.4
TP8: All Other Hours	92.2	887.8	-	979.9
April - May				
TP1: Weekdays HE 6 AM - 9 AM	386.3	736.3	2.2	1,124.7
TP2: Weekdays HE 10 AM - 1 PM	345.7	771.5	-	1,117.3
TP3: Weekdays HE 2 PM - 4 PM	342.5	770.6	19.9	1,133.1
TP4: Weekdays HE 5 PM - 7 PM	375.4	752.5	27.7	1,155.6
TP5: Weekdays HE 8 PM - 10 PM	378.1	733.9	19.9	1,132.0
TP6: Weekend and Holidays HE 6 AM - 9 AM	332.5	530.6	-	863.1
TP7: Weekend and Holidays HE 4 PM - 9 PM	327.0	536.5	22.2	885.6
TP8: All Other Hours	336.5	643.3	-	979.9

Sources and Notes:
Total available ERS MW for 2024 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 2021-2022.

2. LOAD RESOURCES PROVIDING REAL-TIME RESERVES

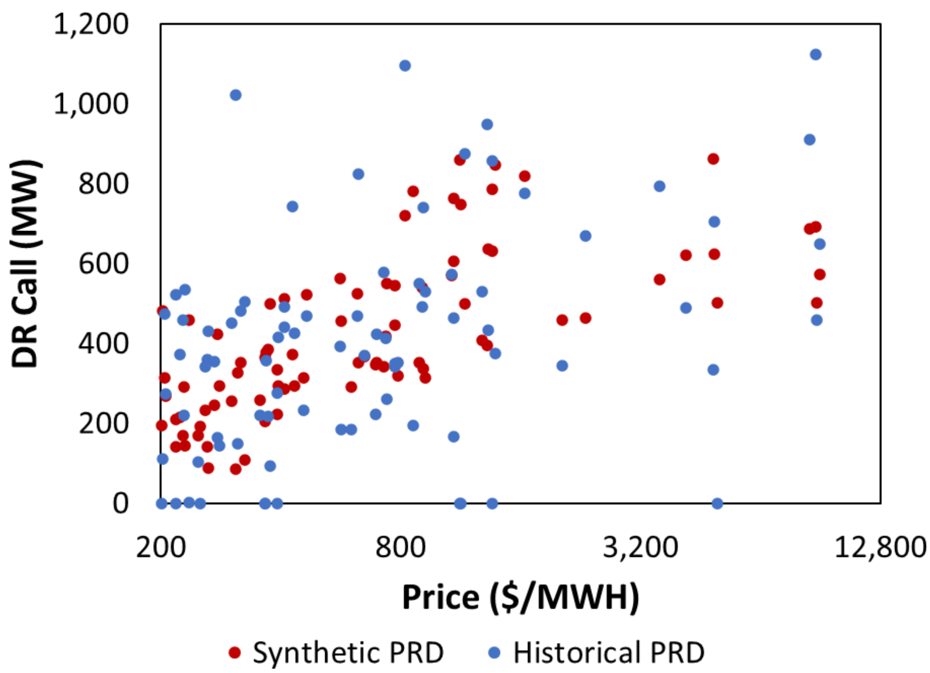
Consistent with ERCOT's published minimum Responsive Reserve Service (RRS) requirements, we modeled 1,591 MW of non-controllable load resources (LRs) that actively participate in the RRS market.[22] All 1,591 MW were modeled as responsive to Energy Emergency Alert, Level 2.

[22] 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. PRICE RESPONSIVE DEMAND AND 4-COINCIDENT PEAK

2019 historical demand response was used to develop modeling inputs to replicate stochastic demand-side response for price responsive and 4-coincident peak (4CP) demands. A comparison of historical and synthetic PRD calls is shown in Figure A3. The aggregate of these shapes was split by zone and used to gross up all 42 synthetic weather shapes.

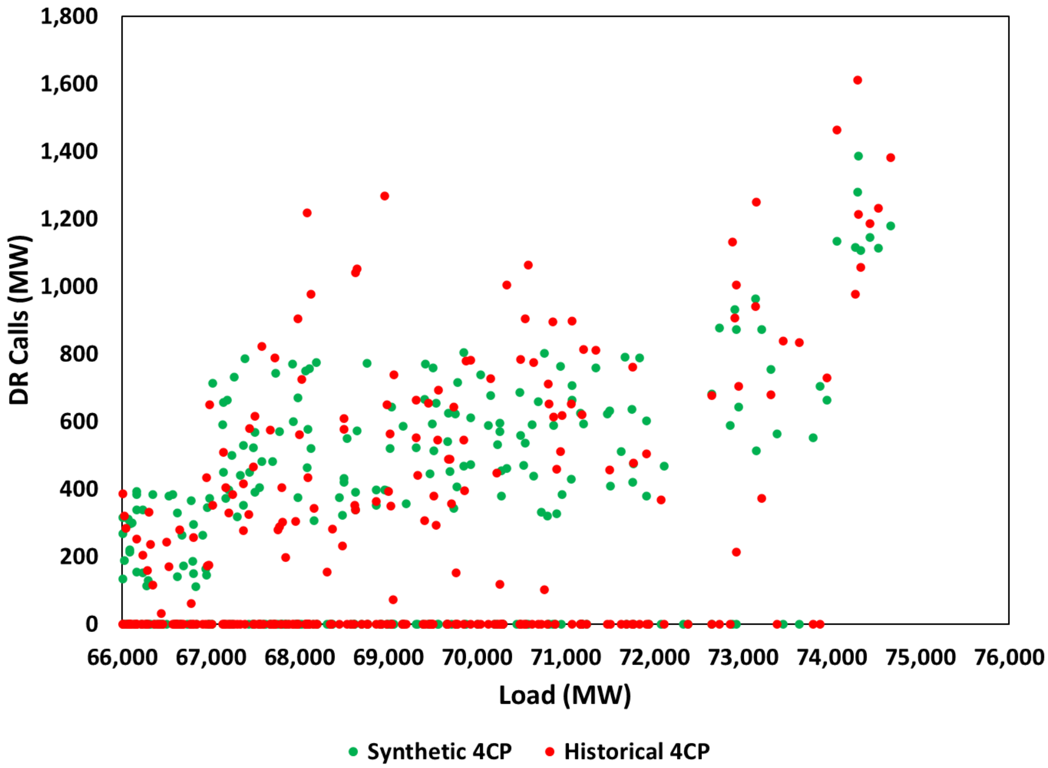
Figure A3. Comparison of Historical and Synthetic PRD Calls



To model the price responsive demand (PRD) in SERVM, a curtailable unit was created that points to a price responsive demand curve. The demand curve has four pricing points based on the segments: $200, $400, $800, and $1,500. For each of the four pricing points, 50 data points were created using created synthetic formulas. Within SERVM, whenever price reached one of the specified threshold points, SERVM randomly picked a DR value from the list of 50 data points. The PRD unit was available in all months.

Similarly, 4CP was modeled as a load responsive unit. A comparison of historical and synthetic 4CP calls is provided below in Figure A4. Historical hourly 4 CP was calculated as the sum of the 4CP Competitive and 4CP NOIE programs.

Figure A4. Comparison of Historical and Synthetic 4CP Calls

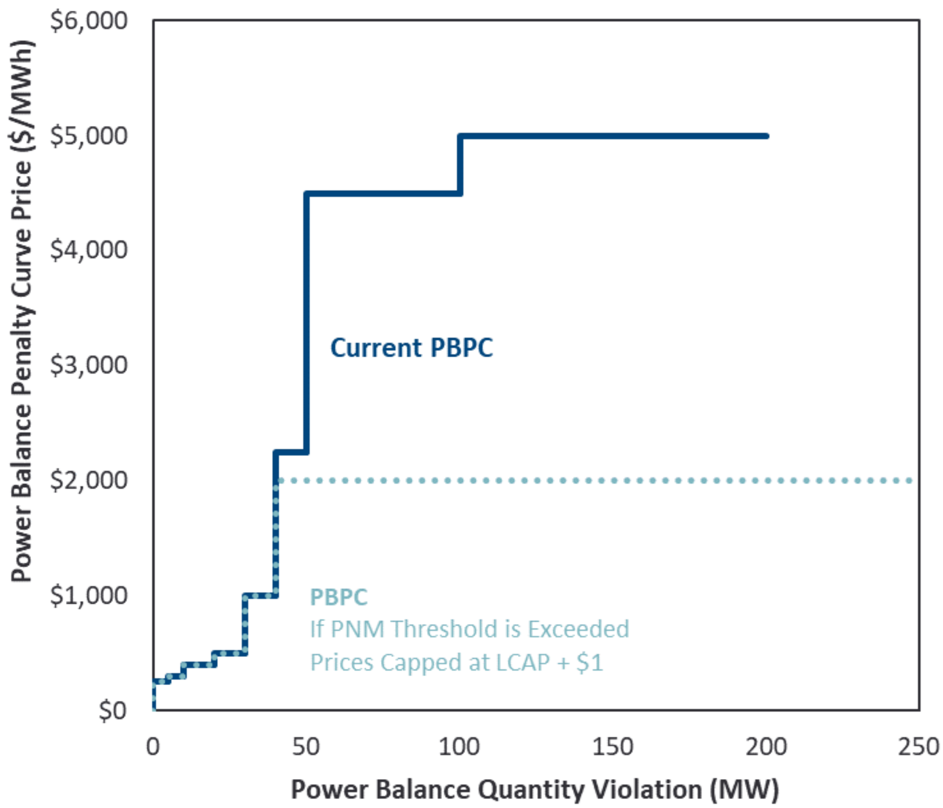


To model the 4CP program in SERVM, a curtailable unit was created in each region that pointed to a load responsive demand curve. The demand curve had four load points based on the segments 66,000 MW, 67,000 MW, 72,000 MW, and 74,000 MW. For each of the four load points, 50 data points were created using segment formulas. Within SERVM, whenever load reached one of the specified threshold points, SERVM randomly picked a DR value for each unit from that list of 50 data points. The 4CP units were only available during the months of June to September.

4. 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 A5. 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 A5. Power Balance Penalty Curve



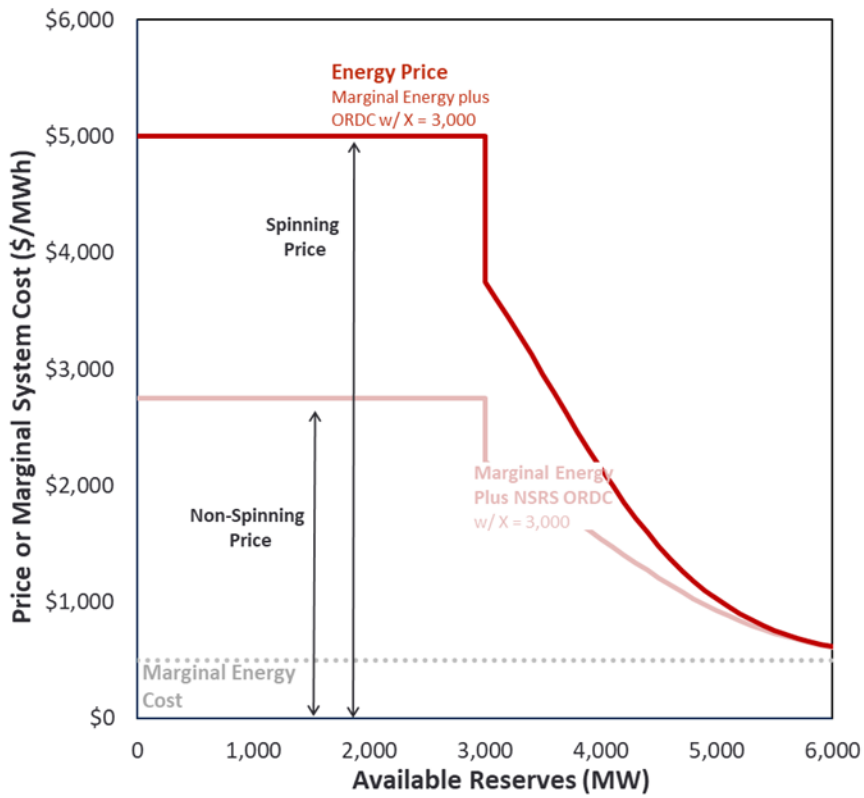
Within SERVM, PBPC is modeled similarly as a phantom supply that may influence the realized price, and that will cause a reduction in available regulating reserves whenever called. However, only the first 200 MW of the curve at prices below the cap are modeled, and it is assumed that all price points 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.[23] 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.

[23] 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

5. 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 A6 illustrates our approach to implementing ORDC in our modeling, which is similar to ERCOT's implementation, with some simplifications.

Figure A6. 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.[24] 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.

[24] 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	1,591
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.[25] 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

[25] 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;[26] 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.[27] 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.

[26] 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.

[27] 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.