CASE NO. 2022-00402

LIST OF EXHIBITS

TO THE DIRECT TESTIMONY OF MICHAEL GOGGIN
ON BEHALF OF SIERRA CLUB

Exhibit No.	Description of Exhibit	Protected Status	Format
MG-1	Michael Goggin Curriculum Vitae	Public	PDF
MG-2	Compiled Discovery Responses	Public	PDF
MG-3	List of Flowgates Used In LG&E and KU AFC, ATC Process	Public	PDF
MG-4	EIA Form 930 datafile for LGE, KU.xlsx	Public	Excel
MG-5	Interregional Transfer Requirement Analysis	Public	PDF
MG-6	Compiled Articles from Footnote 31	Public	PDF
MG-7	*Getting Capacity Right – How Current Methods Overvalue Conventional Power Sources*	Public	PDF
MG-8	Astrape ERCOT Reserve Margin	Public	PDF
MG-9	Brattle Estimation Market Equilibrium	Public	PDF

EXHIBIT MG-1

Michael Goggin

Education:

Harvard University class of 2004, B.A. *cum laude* in Social Studies

- Wrote thesis "Is it Time for a Change? Science, Policy, and Climate Change"

Experience:

Grid Strategies Vice President February 2018-present

- Serve as a consultant on electricity transmission, grid integration, reliability, market, and public policy issues for consumer, grid operator, non-profit, and industry clients
- Have testified before FERC and in over 25 state regulatory commission cases

AWEA Senior Director of Research, other titles February 2008-February 2018

- Led team responsible for all American Wind Energy Association (now American Clean Power Association) analysis
- Served as primary technical and economic expert for market design, transmission, grid integration, carbon policy, and other topics
- Authored regulatory filings at state (IRP and transmission siting cases), regional (ISO transmission and market design), and federal levels (FERC transmission, interconnection standard, grid integration, and market design cases; EPA carbon policy)
- Directed economic and power sector modeling to inform AWEA's policy strategy and support advocacy positions
- Communicated with the press and policy makers about wind energy
- Authored reports to promote AWEA's policy agenda, rebut misconceptions about wind energy, and explain complex energy topics to lay audiences
- Other titles included Electric Industry Analyst, Senior Analyst, Manager of Transmission Policy, Director of Research

Sentech, Inc. Research Analyst October 2005-February 2008

- Conducted economic analyses of solar, wind, geothermal, and energy storage technologies for U.S. Department of Energy officials
- Provided analytical support for DOE's renewable energy R&D funding decisions

Union of Concerned Scientists Clean Energy Intern May 2005-October 2005

- Worked with the legislative and field staff to promote the inclusion of pro-renewable energy measures in the Energy Policy Act of 2005

State Public Interest Research Groups Policy Analyst August 2004-May 2005

- Analyzed and advocated for clean energy policies at the state and federal level

Publications available at https://gridstrategiesllc.com/articles-2/

EXHIBIT MG-2

EXHIBIT MG-2

Public Company Responses to Data Requests

Data Requests

LG&E-KU Response to Sierra Club Request 1-5
LG&E-KU Response to Sierra Club Request 1-8
LG&E-KU Response to Sierra Club Request 1-19
LG&E-KU Response to Sierra Club Request 2-1
LG&E-KU Response to Sierra Club Request 2-7
LG&E-KU Response to Sierra Club Request 2-8

LG&E-KU Response to Joint Intervenor Request 1-88
LG&E-KU Response to Joint Intervenor Request 2-60

LG&E-KU Response to Attorney General Request 1-13

KENTUCKY UTILITIES COMPANY
AND
LOUISVILLE GAS AND ELECTRIC COMPANY

Response to Sierra Club's Initial Request for Information
Dated February 17, 2023

Case No. 2022-00402

Question No. 1-5

Responding Witness: Stuart A. Wilson

Q.1-5. Please refer to Exhibit SAW-1, sponsored by Stuart A. Wilson, at page D-12 (page 127 of the PDF), footnote 14.

a. Provide all documents, analyses, or forecasts that the Companies used to "ma[k]e" "adjustments . . . to the neighboring regions' generating portfolios as needed to reflect planned retirements and meet the neighboring regions' target reserve margins."

b. Describe how KU/LG&E made these adjustments in the reserve margin analysis.

A.1-5.

a. No workpapers were provided for the adjustments because they were made via the SERVM interface.

b. For MISO-Indiana, 24,552 MW of the region's generation resources were included to meet its target reserve margin of 18%. For PJM-West, 40,007 MW of the region's generation resources were included to meet its target reserve margin of 14.8%. For TVA, 35,648 MW of the region's generation resources were included to meet its target reserve margin of 17%. These levels were obtained by deactivating existing dispatchable resources in SERVM.

KENTUCKY UTILITIES COMPANY
AND
LOUISVILLE GAS AND ELECTRIC COMPANY

Response to Sierra Club's Initial Request for Information
Dated February 17, 2023

Case No. 2022-00402

Question No. 1-8

Responding Witness: Stuart A. Wilson

Q.1-8. Please refer to Exhibit SAW-1, sponsored by Stuart A. Wilson, at pages D-20 and D-21, figure 8 (pages 135 and 136 of the PDF). For the referenced SERVM scarcity price curve, provide:

a. All input and output files supporting the SERVM analysis (in electronic, machine-readable format with formulae intact).

b. For the analysis conducted by SERVM, provide all documents, analyses, or forecasts relied upon to calculate responses.

A.1-8.

a. See "\Reliability\SERVM\Inputs\ScarcityPricing\20220831_OperatingReserveDemandCurve.csv" in Exhibit SAW-2.[6]

b. See the response to part (a). The scarcity price curve was jointly developed by the Companies and Astrape Consulting, the developer of SERVM. The Companies do not possess any additional responsive documents.

During Winter Storm Elliott on December 23 and 24, the Companies purchased power at prices in excess of $3,000/MWh. These purchases corroborate the Companies' scarcity price curve.

[6] The public version of this data is available on the Commission's website in the zip file for Exh. SAW-2 Vol. 6.

KENTUCKY UTILITIES COMPANY
AND
LOUISVILLE GAS AND ELECTRIC COMPANY

Response to Sierra Club's Initial Request for Information
Dated February 17, 2023

Case No. 2022-00402

Question No. 1-19

Responding Witness: Lonnie E. Bellar / David S. Sinclair

Q.1-19. Please refer to the Direct Testimony of Stuart A. Wilson at page 9, stating, "Extreme weather conditions drive a need for additional reliability considerations"; Exhibit TAJ-1, sponsored by Tim A. Jones, at page 10, stating, "customers demand even greater load for a longer duration during extreme weather events"; and Exhibit SAW-1, sponsored by Mr. Wilson, at page D-12 (page 127 of the PDF), stating, "A key aspect in developing a target reserve margin is properly considering the likelihood of unit outages during extreme weather events."

a. Please provide documents, analyses, and workpapers sufficient to show the scope of service interruptions for KU/LG&E during Winter Storm Elliott in December 2022 (including but not limited to interruptions on December 23, 2022), including:

i. The number and percentage of customers affected hourly by service interruptions

ii. The amount and percentage of resources offline each hour on December 23, 2022, and any other times during Winter Storm Elliott, broken down by generation category (coal, NGCC, SCCT, solar, wind, hydro, etc.)

b Please provide documents sufficient to show the amount of power purchased hourly from the Midcontinent Independent System Operator ("MISO"), PJM Interconnection, and any and all other sources of power external to the Companies from December 21, 2022, to December 28, 2022, broken down by:

i. Hour

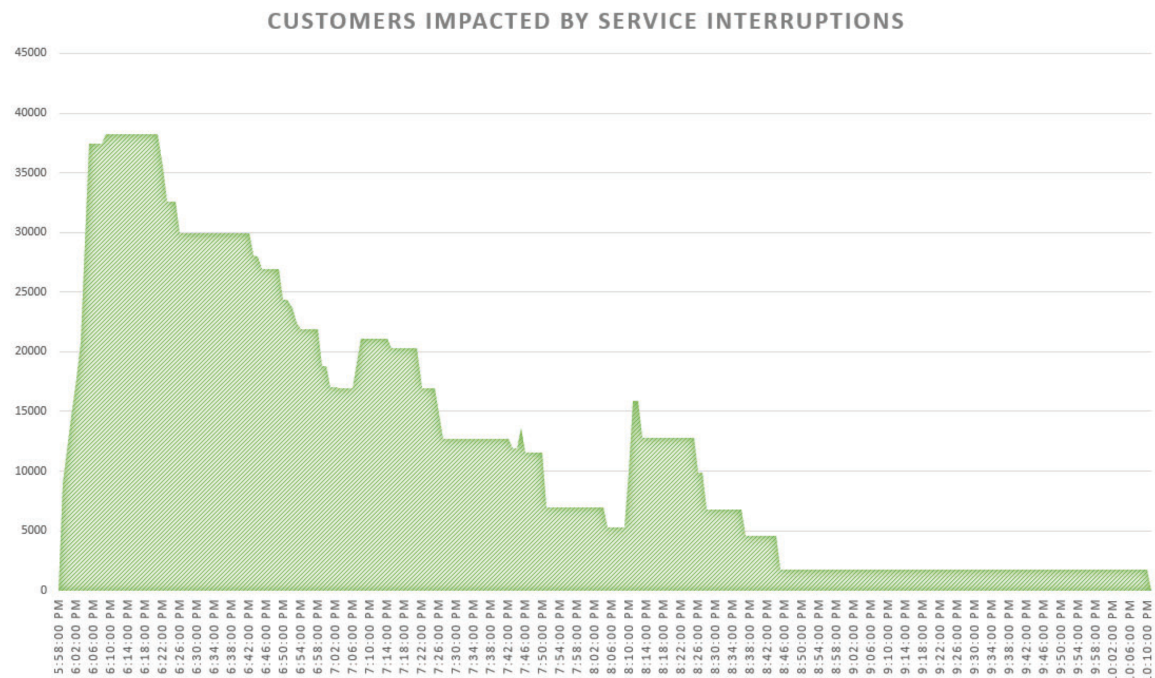
ii. Seller (i.e., MISO, PJM, or other), and

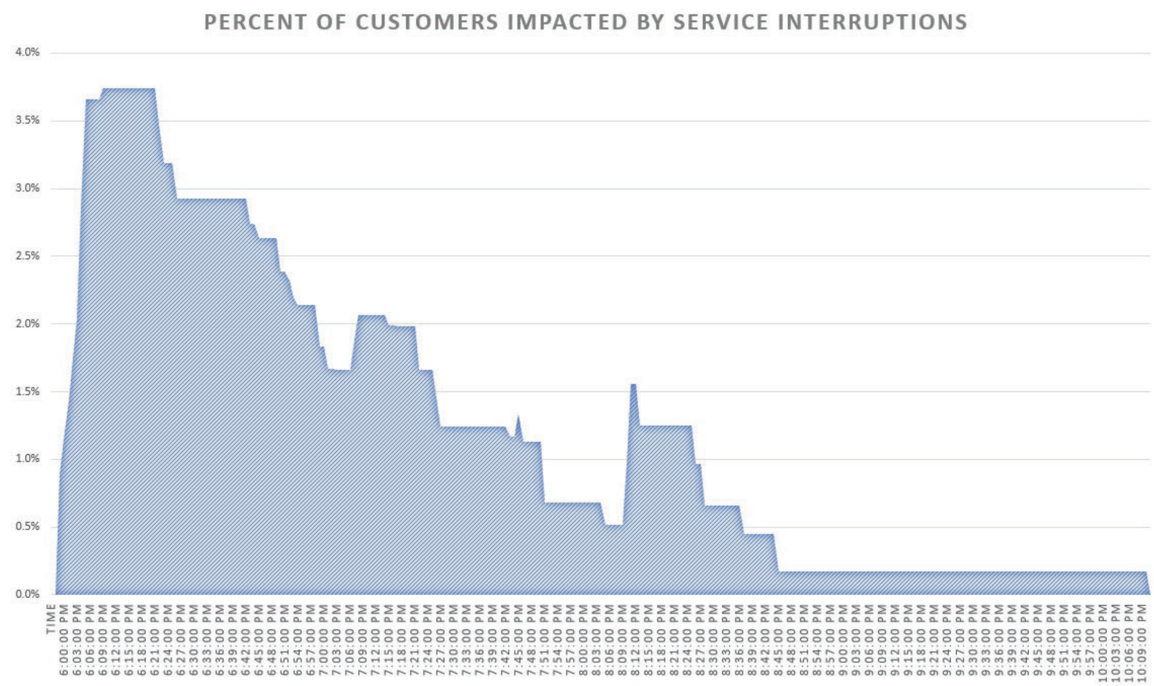
iii. Generation power source (i.e., coal, NGCC, SCCT, solar, wind, hydro, etc.).

A.1-19.

a.

i. Between 5:59pm and 10:11pm on December 23, 2022 approximately 54k customers were impacted by service interruptions (~5.3%). The highest amount of customers impacted by service interruptions at any given time was approximately 38k (~3.7%).





ii. See attached.

b. (i) - (iii) See the table below for the power purchased from MISO, PJM, and TVA during the period. There were also 391 MWh in total purchases during the period from other parties in the BA footprint through the OATT ancillary service schedules.

Flow Date	Hour Ending	Total Volume (MWh)	Seller	Power Source Type
12/23/2022	12:00	75	PJM	unknown
12/23/2022	12:00	100	PJM	unknown
12/23/2022	12:00	225	PJM	unknown
12/23/2022	13:00	266	PJM	unknown
12/23/2022	14:00	233	PJM	unknown
12/23/2022	15:00	107	PJM	unknown
12/23/2022	15:00	119	PJM	unknown
12/23/2022	15:00	200	PJM	unknown
12/23/2022	15:00	250	PJM	unknown
12/23/2022	16:00	142	PJM	unknown
12/23/2022	16:00	200	PJM	unknown
12/23/2022	16:00	250	PJM	unknown
12/23/2022	17:00	123	PJM	unknown
12/23/2022	17:00	125	PJM	unknown
12/23/2022	17:00	200	TVA	unknown
12/23/2022	22:00	100	PJM	unknown
12/23/2022	23:00	134	MISO	unknown
12/23/2022	24:00	260	MISO	unknown
12/23/2022	24:00	600	PJM	unknown
12/23/2023	18:00	400	TVA	unknown
12/24/2022	1:00	250	MISO	unknown
12/24/2022	1:00	250	PJM	unknown
12/24/2022	2:00	250	MISO	unknown
12/24/2022	2:00	150	PJM	unknown
12/24/2022	3:00	188	PJM	unknown
12/24/2022	4:00	250	PJM	unknown
12/24/2022	5:00	200	MISO	unknown
12/24/2022	6:00	50	PJM	unknown
12/24/2022	8:00	113	MISO	unknown

KENTUCKY UTILITIES COMPANY
AND
LOUISVILLE GAS AND ELECTRIC COMPANY

Response to Sierra Club's Supplemental Request for Information
Dated April 14, 2023

Case No. 2022-00402

Question No. 2-1

Responding Witness: Lonnie E. Bellar

Q.2-1. For each of the Companies' existing gas generating units, please indicate:

a. The gas line serving that generating unit.

b. Whether the generating unit has dual fuel capability with onsite fuel storage.

c. What percentage of the generating unit's peak gas consumption is supplied via firm gas transportation contracts.

d. The geographic area from which gas supply for that generating unit is sourced.

e. What percentage of the generating unit's peak gas consumption comes from supply contracts that are longer than one year in duration.

f. What, if any, impacts were observed on gas supply or transportation to that generating unit during Winter Storm Elliott (December 21-27, 2022)?

g. If there were any impacts to that generating unit during the period December 21- 27, 2022, please quantify the reduction in the generating unit's output due to the disruption to gas supply or transportation, and the start and end time for that reduction.

A.2-1.

a. The Texas Gas Transmission pipeline serves Cane Run 7, Paddy's Run 12-13, and Trimble County 5-10. Either the Texas Eastern or Tennessee Gas pipeline is capable of serving the seven E.W. Brown combustion turbines (Brown 5-11). Haefling 1-2 are connected to the Columbia Gas of Kentucky distribution system.

b. Four units at E.W. Brown, Brown 8-11 have dual fuel capability with onsite fuel oil storage.

KENTUCKY UTILITIES COMPANY
AND
LOUISVILLE GAS AND ELECTRIC COMPANY

Response to Sierra Club's Supplemental Request for Information
Dated April 14, 2023

Case No. 2022-00402

Question No. 2-7

Responding Witness: Stuart A. Wilson

Q.2-7. Please see the capacity contribution analysis described at pages D15-D16 of Exhibit SAW-1.

a. Please describe what if any assumptions for forced outage rates or derates were used to reduce the estimated capacity contribution of the 480 MW of SCCTs.

b. Please describe what if any assumptions for correlations in forced outage rates between the 480 MW of SCCTs and the Companies' other generating units were used to reduce the estimated capacity contribution of the 480 MW of SCCTs.

A.2-7.

a. The SCCTs were modeled with a 4.9% forced outage rate.

b. The analysis assumed no correlation between forced outage for these SCCTs and other units.

KENTUCKY UTILITIES COMPANY
AND
LOUISVILLE GAS AND ELECTRIC COMPANY

Response to Sierra Club's Supplemental Request for Information
Dated April 14, 2023

Case No. 2022-00402

Question No. 2-8

Responding Witness: Stuart A. Wilson

Q.2-8. Please provide any analysis the Companies directed to determine that retiring Haefling 1- 2 and Paddy's Run 12 in 2025 and replacing that capacity with new resources was more economic than continuing to operate those units. If that analysis was not conducted, please explain why.

A.2-8. These units are between 53 and 55 years old and operate very infrequently, averaging 12 operating hours per unit in 2022. The Companies have assumed that a mechanical failure will occur on these units and that it will likely be uneconomical to make the needed repairs, as has been the case in recent years with similar small-frame CTs. For an analysis comparing the retirement and repair of Paddy's Run 11, which LG&E retired in March 2021, see attached. The Companies have not performed a similar analysis for Halfling 1-2 and Paddy's Run 12 because the assumed failures of these units have not occurred. The Companies do not intend to retire these units until such failures occur. The timing and costs of such assumed failures are unknown but are assumed for the purposes of this analysis to occur by 2025.

KENTUCKY UTILITIES COMPANY
AND
LOUISVILLE GAS AND ELECTRIC COMPANY

Response to Metropolitan Housing Coalition, Kentuckians for the Commonwealth, Kentucky Solar Energy Society and Mountain Association's
Initial Request for Information
Dated February 17, 2023

Case No. 2022-00402

Question No. 1.88

Responding Witness: Stuart A. Wilson

Q-1.88. Please refer to the 2022 RFP Minimum Reserve Margin Analysis, page D-12, Footnote 14, which states: "In the reserve margin analysis, adjustments were made to the neighboring regions' generating portfolios as needed to reflect the planned retirements and meet the neighboring regions' target reserve margins."

a. Please list each adjustment(s) made to the generating portfolios for each of the following neighboring regions, as defined at pages D-11 to D-12 of Ex. SAW-1: (i) MISO-Indiana; (ii) PJM-West; and (iii) TVA.

b. In the reserve margin analysis, did the Companies make any adjustments for the addition of new resources in neighboring regions? If so, please list each such adjustment. If not, please explain why not in full.

c. Please explain in full each adjustment used to "meet the neighboring regions' target reserve margins," for each neighboring region.

d. In the reserve margin analysis, did the Companies make any adjustments to account for planned transmission projects in each of the neighboring regions? If so, please list each such adjustment. If not, please explain why not in full.

A-1.88.

a. See the response to SC 1-5(b).

b. No. See the response to SC 1-5(b).

c. See the response to part (a).

d. No. Planned transmission projects in neighboring regions are not intended to materially impact available transmission capacity ("ATC") between these

KENTUCKY UTILITIES COMPANY
AND
LOUISVILLE GAS AND ELECTRIC COMPANY

Response to Metropolitan Housing Coalition, Kentuckians for the Commonwealth, Kentucky Solar Energy Society and Mountain Association's Supplemental Request for Information Dated April 14, 2023

Case No. 2022-00402

Question No. 60

Responding Witness: Tim A. Jones / Stuart A. Wilson

Q-60. Regarding the files "20221028_LGELoad2028" and "Load2023PlanCC_IRA_DSM_20221026" please answer the following:

a. Please explain why the annual energy requirements in "Load2023PlanCC_IRA_DSM_20221026" fall below the energy requirements for all the weather years in "20221028_LGELoad2028".

b. Please explain why 31 of the 49 weather years in "20221028_LGELoad2028" contain annual peak values in excess of the 2028 peak contained in "Load2023PlanCC_IRA_DSM_20221026", i.e, why is the distribution of load modeled in SERVM distorted to the high side relative to the base load forecast?

c. Please provide any workbooks that support your response to the previous subparts with all formulas and links intact, changing nothing.

d. Please provide the workbooks with all formulas and links intact, changing nothing, that show how the hourly load shapes in "20221028_LGELoad2028" were updated from the 2021 IRP to the present docket.

A-60.

a. Weather year energy requirements inadvertently double counted forecast items that are layered onto the hourly forecasts separately due to their unique load shape. These "unique forecast items" include electric vehicle growth, distributed solar growth, and most significantly the BlueOval SK load. Fortunately, this double counting did not have a material impact on the weather year summer and winter peak demands and had no effect on the Companies' optimal resource portfolio or projected revenue requirements, which are based on the Companies' load forecast under normal weather conditions and not the weather year forecasts.

The weather year forecast models are specified for each company based on load data from 2012 to 2019 and cannot account for class-specific forecast trends in the base CPCN load forecast. In addition, the weather year forecast models cannot capture the unique impact of items like electric vehicle growth, distributed solar growth, and the addition of the BlueOval SK load. Therefore, the initial weather year load forecast results are scaled so that the mean of weather year energy requirements equals a version of the normal weather CPCN load forecast that excludes these "unique forecast items," and then these items are layered onto the forecast separately (a detailed summary of this process is attached as Attachment 1 to this response). The double counting of the BlueOval SK load occurred because the initial weather year load forecasts were inadvertently scaled to a version of the CPCN load forecast that included these unique forecast items, and then these items were effectively layered on a second time.

In the final step of the weather years process, the Companies tie the mean of the weather year summer and winter peaks to the CPCN forecast peaks through seasonal load factor adjustments that impact the distribution of peak demands but do not change total energy. Thus, the process produced a reasonable distribution of peak demands, but average weather year energy requirements and load factors were approximately 5.8% too high. The Companies did not detect this problem because an assessment of reliability and the calculation of LOLE in SERVM is significantly focused on peak events, and the Companies' review process was therefore focused on summer and winter peak demands, not annual energy requirements. The Companies have updated their review process to ensure this kind of error does not occur in the future.

Figure 1 compares the original and corrected ranges of peak demands and energy requirements at key steps in the weather years process. After scaling the initial weather year forecasts to equal CPCN energy requirements that exclude unique forecast items, the corrected ranges of peak demands and energy requirements are lower than the original (see "Energy Requirements Scaling" step in Figure 1). For both the original and corrected ranges, the impact of layering on the unique forecast items is the same (see "Addition of Unique Items" step in Figure 1). Finally, because of the double counting, the seasonal load factor adjustments in the original weather year forecasts are greater than in the corrected forecasts (see "Load Factor Adjustment" step in Figure 1). As a result, the corrected distributions of summer and winter peak demands are not materially different from the originals, but the corrected distribution of energy requirements is approximately 5.8% lower. Figure 2 contains the filed and corrected load duration curves for all weather years and further demonstrates that the impact of this correction is greater in non-peak hours.

Figure 1 – Weather Year Energy Requirements and Peak Demands[7]

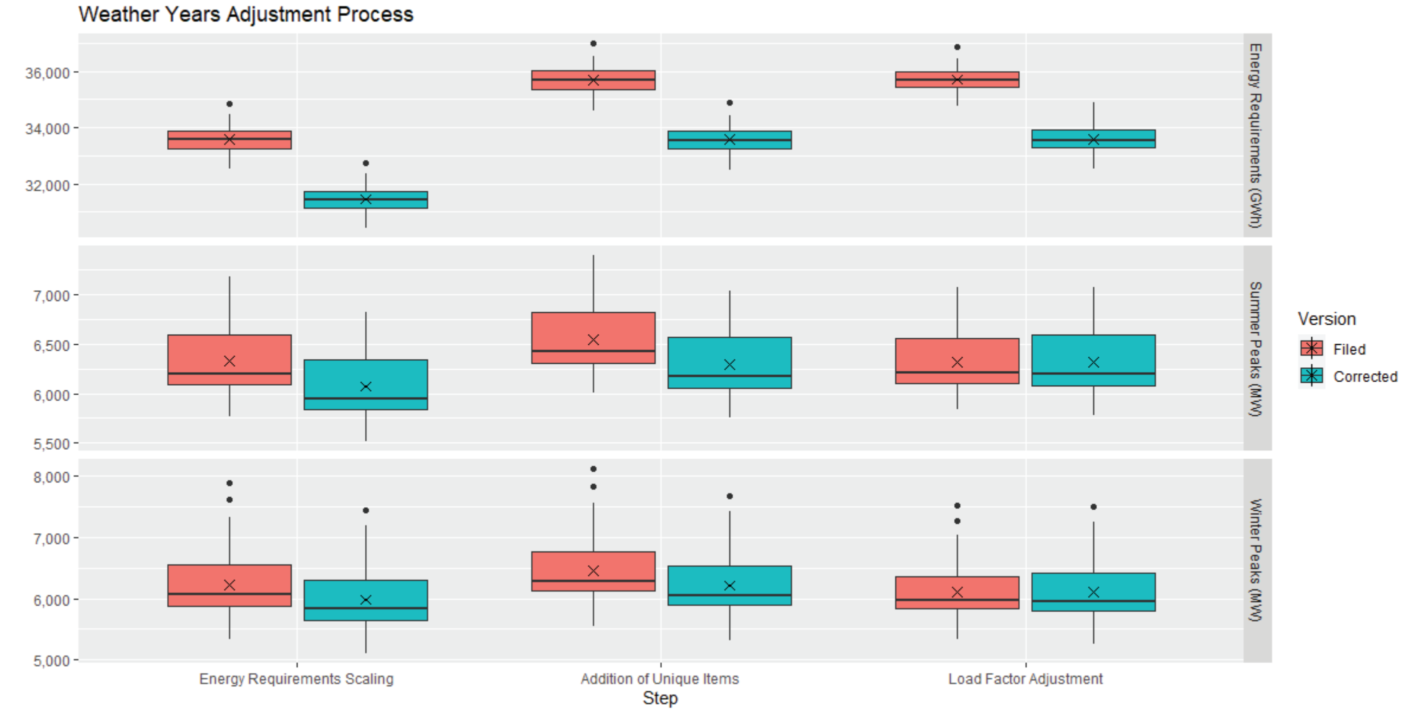
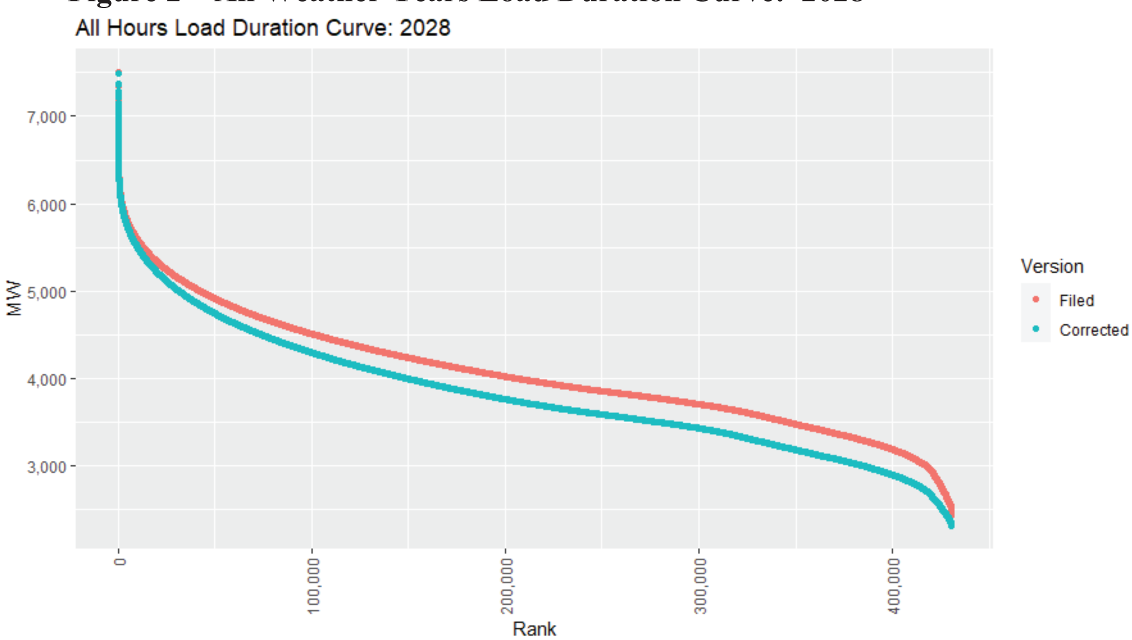


Figure 2 – All Weather Years Load Duration Curve: 2028



7 In Figure 1, the mean is marked with an "X."

Table 1 compares the original and corrected distributions of peak demands by quartile.[8] The seasonal load factor adjustment has a greater impact on hourly loads that are further from the mean, and a downward adjustment, as seen in the last two steps of Figure 1 for the filed version, has the effect of compressing the distribution of peak demands. With a smaller load factor adjustment, the corrected peak demand distributions are slightly less compressed. This is why the average of the top quartile demands in the corrected distributions are slightly higher than the original distribution. These minor differences are important to understand when assessing the impact of the corrected weather year forecasts on the Companies' analysis.

Table 1 – Weather Year Peak Demands by Quartile (MW)

Season	Quartile	Filed	Corrected	MW Change in Average Peak	% Change in Average Peak
Summer	**1**	6,751	6,801	50	0.74%
	2	6,361	6,369	8	0.12%
	3	6,166	6,148	-18	-0.29%
	4	6,024	5,987	-36	-0.61%
Winter	**1**	6,824	6,889	65	0.95%
	2	6,151	6,166	15	0.24%
	3	5,905	5,889	-17	-0.29%
	4	5,581	5,523	-58	-1.04%

Weather year load forecasts are key inputs to the Companies' minimum reserve margin analysis, the analysis to determine capacity contributions for limited-duration resources, the Stage Three, Step Two analysis that assesses dispatchable DSM and the Brown BESS as a means of increasing reliability, the Stage Three, Step Three analysis that assesses early retirement risk for OVEC, and the analysis that estimates LOLE for an all-DSM portfolio. An updated version of Exhibit SAW-1 is provided as Attachment 2 to this response. Certain information requested is confidential and proprietary and is being provided under seal pursuant to a petition for confidential protection. The corrected weather year forecasts impact only selected values in Appendix C (All-DSM Portfolio Analysis), Appendix D (Reserve Margin Analysis), and the Stage Three analysis. All updates are highlighted in blue.

[8] The 49 peaks for each season were ranked in descending order (the highest value given rank 1) and divided into quartiles of 12 with the bottom quartile containing 13 points. The value in the table represents the average of the peaks for each quartile. Values in the MW Change column may appear inaccurate due to rounding.

As noted earlier, the corrected weather year profiles had no impact on the Companies' optimal portfolio or projected revenue requirements, which are based on the Companies' load forecast under normal weather conditions and not the weather year forecasts. The following provides a summary of why this is true:

No Impact to Minimum Reserve Margin Targets

Minimum reserve margins are determined as the reserve margin at which an increase in load would cause the reliability and production cost benefits of adding SCCT capacity to exceed the cost of this capacity. The downward shift in the corrected weather year energy requirements reduced production costs in all weather year scenarios, but with only minor changes to the distributions of peak demands, there was only a small impact on reliability costs and no impact on the minimum reserve margin targets (i.e., the reserve margin at which SCCT capacity becomes economic).

Immaterial Impact to Capacity Contributions

Table 2 summarizes the impact of the corrected weather year forecasts on the capacity contributions for limited-duration resources. Capacity contribution for a limited-duration resource is computed as the ratio of that resource's impact on LOLE to the impact of a like-amount of SCCT capacity. With the corrected weather year forecasts, LOLE for the Reference portfolio is lower (i.e., LOLE for the Reference portfolio is 21.32 versus 25.13), but the capacity contributions of 4-hour and 8-hour battery storage are mostly unchanged. Unlike battery storage, the capacity contribution of dispatchable DSM is notably lower because the availability of dispatchable DSM is limited to only 100 hours and the top quartile of peak demands in the corrected weather year forecasts are slightly higher. Because the updated capacity contributions are immaterially lower for battery storage and because dispatchable DSM was not selected by PLEXOS in the Stage One or Stage Two analyses, the updated capacity contributions will have no impact on the rest of the Companies' analysis.

Table 2 – Filed and Corrected Capacity Contributions

	LOLE (Days in 10 Years)		LOLE Reduction (Days in 10 Years)		Capacity Contribution	
	Filed	Corrected	Filed	Corrected	Filed	Corrected
1: Reference	25.13	21.32	NA	NA	NA	NA
2: Reference + SCCT	3.87	3.57	21.26	17.75	NA	NA
3: Reference + 4-hr BESS	6.98	6.72	18.15	14.60	0.85	0.82
4: Reference + 8-hr BESS	5.13	4.88	20.00	16.44	0.94	0.93
5: Reference + Disp. DSM	10.49	15.14	14.64	6.18	0.69	0.35

Dispatchable DSM Remains the Most Economical Means of Enhancing Reliability

The Stage One and Two analyses and the analysis of capacity contributions summarized in Table 2 above demonstrate that dispatchable DSM is not a cost-effective means of meeting minimum reserve margin targets or customers' significant need for energy resulting from the retirement of coal units. However, at higher reserve margins where LOLE is lower and explained by fewer peak events, the limited availability of dispatchable DSM is less of a concern and dispatchable DSM continues to be a more cost-effective resource for improving reliability than SCCT or battery storage.

No Change in Conclusions to OVEC or All-DSM Analyses

As seen in Section 4.6.3 and Appendix C of the updated Exhibit SAW-1, the corrected weather year profiles have no impact on the conclusions reached regarding the implications of an early OVEC retirement or an all-DSM portfolio. The recommended portfolio will provide excellent reliability if OVEC retires early. Furthermore, with no replacement resources other than the proposed 2024-2030 DSM-EE Program Plan's dispatchable DSM programs, the Companies' LOLE is unacceptably high.

b. For the base load forecast, the Companies model peaks by season. Under normal peak weather conditions, the annual peak is expected to occur during the summer. However, from a load risk perspective, the Companies' system is dual peaking. Thirty-one of the 49 weather years contain annual peaks in excess of the 2028 summer peak demand under normal weather conditions because a number of the annual peaks are winter peaks. When evaluated on a seasonal basis, more than 50% of summer and winter weather year peaks are less than the 2028 summer and winter peak demands under normal weather conditions. Figure 1 provided in part (a) shows that for peaks in each season of each version of the weather year forecast, the median is below the mean, supporting the statement above that more than 50% of peaks in the distributions are below the mean.

c. See attached. Certain responsive files are too large for the Companies to upload to the Commission's website and are the subject of a Motion to Deviate being filed with these responses. Also, certain information requested is confidential and proprietary and is being provided under seal pursuant to a petition for confidential protection.

d. For any confidential workpapers relating to the IRP weather years forecast, see the response to Question No. 63. The public workpapers the Companies provided in response to JI 1-3 in Case No. 2021-00393 are available at https://highq.in/ous6sqhwi9.

2022 Resource Assessment

PPL companies

Generation Planning & Analysis

March 2023 Update

May 2023 Update

Table of Contents

1 Executive Summary

Louisville Gas & Electric Company ("LG&E") and Kentucky Utilities Company's ("KU") (collectively "Companies") Generation Planning & Analysis group conducted this 2022 Resource Assessment to ensure the Companies could continue to provide safe, reliable, and low-cost service to their customers while complying with the U.S. Environmental Protection Agency's ("EPA") recent Good Neighbor Plan across a variety of possible future fuel price and carbon price scenarios.

1.1 Good Neighbor Plan and Upcoming Capital Investments Require Revised Portfolio

The EPA promulgated the Good Neighbor Plan in April 2022. As drafted, the Good Neighbor Plan would effectively require two of the Companies' large coal-fired units, the 297 MW Mill Creek Unit 2 ("Mill Creek 2" or "MC2") and the 485 MW Ghent Unit 2 ("Ghent 2" or "GH2") to cease operating during the ozone season (May through September) each year beginning in 2026 unless the Companies install selective catalytic reduction ("SCR") equipment on the units to reduce the units' nitrogen oxides ("NO_x") emissions. SCRs have significant capital costs: $110 million for Mill Creek 2 and $126 million for Ghent 2.

Although unaffected by the Good Neighbor Plan, the 412 MW Brown Unit 3 ("Brown 3" or "BR3") is the Companies' coal unit with the highest operating costs and will require a $26 million overhaul in 2027 to operate safely beyond 2028.

Collectively, these units have a total capacity of 1,194 MW and typically produce 15% or more of customers' annual energy requirements, and they produce just over half of their annual energy during non-daylight hours. Simply retiring these units without reliably replacing their energy production or decreasing demand for the energy they supply would almost certainly result in unserved energy requirements—in other words, blackouts or brownouts.

Because such service would be unacceptable to customers and contrary to the Companies' obligation to provide safe, reliable, and low-cost service, the Companies conducted a holistic, comprehensive assessment of customers' anticipated needs and the available demand- and supply-side means of serving those needs. The result of this resource assessment is a reliability-, risk-, and cost-optimized portfolio of demand- and supply-side resources to meet customers' projected energy needs.

1.2 A Comprehensive Resource Assessment Results in an Optimal Portfolio

The Companies' Resource Assessment made the best use of the Companies' own experience and expertise and state-of-the-art modeling tools and techniques, including sophisticated portfolio development and screening, hourly dispatch, and reliability modeling software platforms.

The assessment began with:

- A fully updated thirty-year hourly load forecast, which accounted for the BlueOval SK Battery Park load (almost 260 MW summer, about 225 MW winter, almost 90% load factor),[1] the effects of the Inflation Reduction Act ("IRA"), and the energy efficiency effects of the Companies' proposed 2024-2030 DSM-EE Program Plan.

[1] As noted in the 2022 Load Forecast, Exhibit TAJ-1, the stated peak load figures represent BlueOval's non-coincident, peak hourly usage projections grossed up by a transmission loss factor of 1.02827. BlueOval's anticipated summer billing demand is 254 MW.

- Supply-side options resulting from the Companies' June 2022 RFP, which also accounted for IRA impacts and resulted in 22 respondents providing 101 proposals across 39 projects (which were later sub-divided into 110 proposals), including solar, wind, pumped hydro, battery energy storage, and natural gas units.
- Economic demand response programs and components from the Companies' 2024-2030 Demand-Side Management and Energy Efficiency ("DSM-EE") Program Plan.
- A full accounting of current environmental requirements, including the draft Good Neighbor Plan.

After screening the RFP responses for economics and practicability, 43 options proceeded to the assessment, in which the Companies evaluated the demand- and supply-side options in three basic stages:

1. **Creating an economically optimal portfolio consistent with minimum reliability and environmental compliance.** This stage involved using models to develop and screen optimal portfolios across six fuel price scenarios.

   Result: Retiring Mill Creek 2, Ghent 2, and Brown 3 and replacing them with 2 natural gas combined cycle ("NGCC") units, namely the 621 MW Mill Creek Unit 5 ("Mill Creek NGCC" or "MC5") and the 621 MW Brown Unit 12 ("Brown NGCC" or "BR12"), and 637 MW of solar power purchase agreements ("PPAs") is economically optimal at minimum reliability.

2. **Stress-testing the economically optimal portfolio.** This stage involved comparing the economically optimal portfolio to nine other possible portfolios across six fuel price scenarios and three CO_2 price scenarios to compare their economics and reliability.

   Result: Confirmation that retiring Mill Creek 2, Ghent 2, and Brown 3 and replacing them with Mill Creek NGCC, Brown NGCC, and 637 MW of solar PPAs remains economically optimal at minimum reliability.

3. **Fine tuning the portfolio to account for solar PPA execution risk, enhance reliability, and ensure reliability if OVEC retires early.** This stage consisted of three distinct fine-tuning analyses:

   a. **Solar PPA execution risk analysis.** The Companies' own experience with executed solar PPAs, negotiations of PPAs from the June 2022 RFP, and the state of the solar market broadly demonstrates there is real risk that PPA projects might not be built, at least not in a timely manner, at the agreed price. This analysis demonstrates the prudence of adding 240 MW of Companies-owned solar capacity to the optimal portfolio.

   b. **Analysis of reliability enhancements.** This analysis demonstrates that adding the dispatchable DSM programs in the Companies' proposed 2024-2030 DSM-EE Program Plan is a cost-effective reliability enhancement to the optimal portfolio. It further demonstrates that including the proposed Brown battery energy storage system ("Brown BESS") in the optimal portfolio adds reliability and notes that Brown BESS could offer quantifiable operational benefits, including possible reductions in required spinning reserves and reduced wear on fast-ramping units.

c. **Analysis of possible early retirement of Ohio Valley Electric Corp.'s ("OVEC") coal units.** This analysis demonstrates that the optimal portfolio maintains adequate reliability if OVEC retires as early as 2028 without replacement capacity.

Result: Retiring Mill Creek 2, Ghent 2, and Brown 3 and replacing them with Mill Creek NGCC, Brown NGCC, 637 MW of solar PPAs, 240 MW of Companies-owned solar capacity, the 2024-2030 DSM-EE Program Plan, and the Brown BESS is the portfolio that best optimizes reliability, cost, and risk-mitigation, and it positions the Companies to gain vital experience with utility-scale battery technology that is likely key to future large-scale renewable generation integration.

1.3 A No-Regrets Portfolio for Serving Customers Now and for Decades to Come

As discussed at length herein, the resource portfolio this Resource Assessment recommends optimally blends the reliability, cost, and lower-CO_2-emission benefits of NGCC units, the energy- and CO_2-cost hedging benefits of solar generation, and the demand-reducing and reliability-enhancing benefits of dispatchable DSM from the 2024-2030 DSM-EE Program Plan. It also hedges against the risks of the current solar market—namely that prices are rising and relatively few projects are actually being built—by including a mix of solar PPAs and solar capacity to be owned by the Companies. Finally, it includes Kentucky's first utility-scale battery energy storage system to provide additional reliability benefits and give the Companies invaluable first-hand experience with owning and operating at true utility scale an energy storage technology that will be vital to growing renewable energy generation in the decades to come.

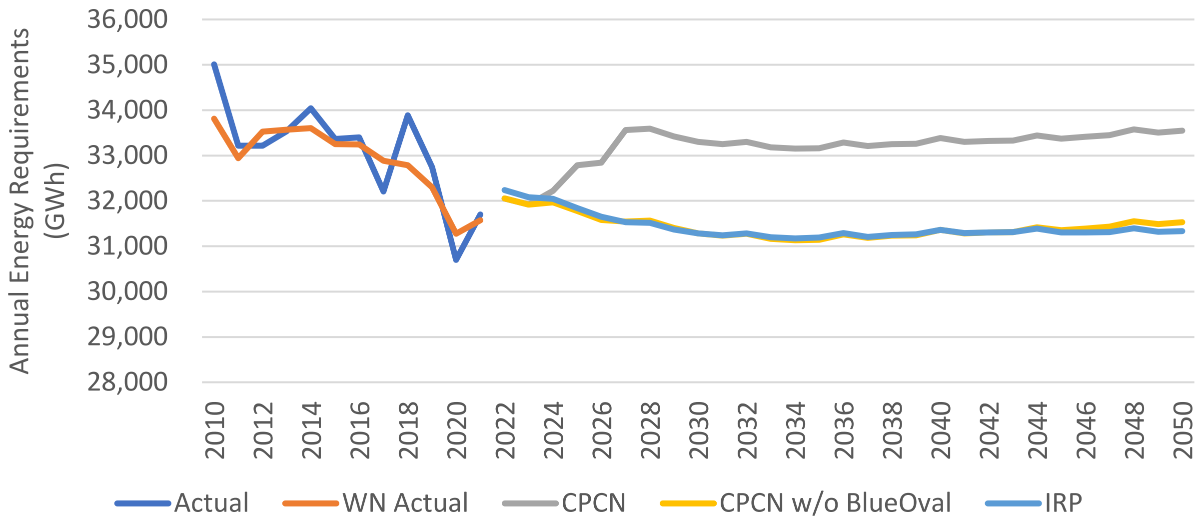
2 Objective: Reliably and Cost-Effectively Serving Customers' Projected Needs

The objective of this Resource Assessment is to develop a resource portfolio to ensure ongoing safe and reliable service at the lowest reasonable cost. An optimal resource portfolio must be able to serve customers' needs reliably at all times and in all seasons, weather, and daylight conditions. Achieving that objective begins with an understanding of customers' projected needs, as well as the reserve margins necessary to provide reliable service.

2.1 Customers' Projected Needs: The 2022 CPCN Load Forecast

The Companies' 2022 CPCN Load Forecast projects customers' energy and demand requirements.[2] Notably, the 2022 CPCN Load Forecast takes full account of IRA impacts, as well as the energy efficiency effects of the Companies' proposed 2024-2030 DSM-EE Program Plan. As shown in the annual energy requirements forecast below, the Companies project customers will require significantly more energy through 2050 than they have recently, due in large part to the BlueOval SK Battery Park to be located in KU's service territory in Glendale, Kentucky:

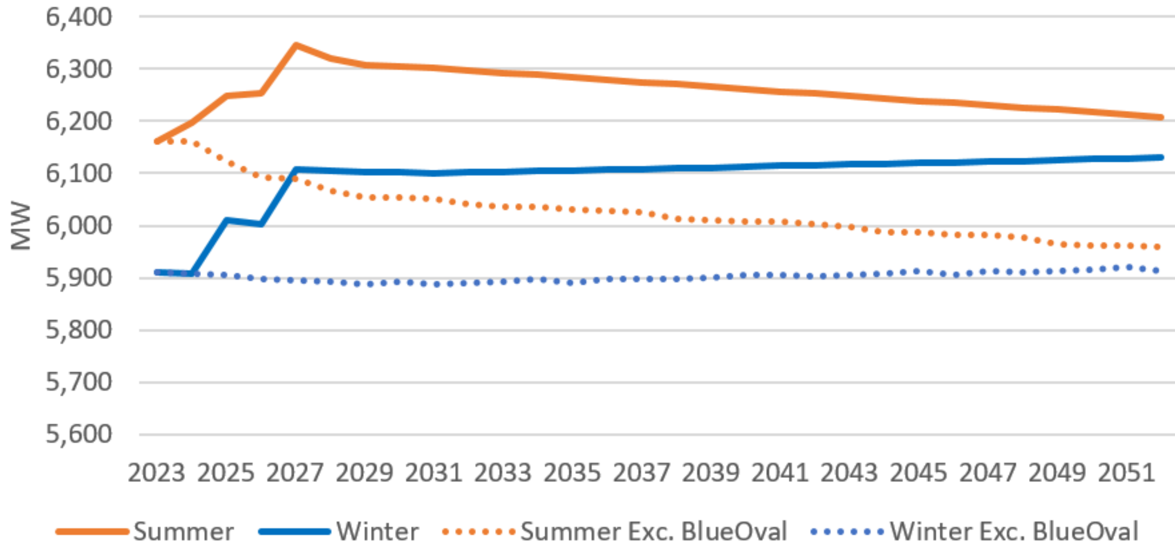
Figure 1: Annual Energy Requirements History and Forecast (exc. Departed Municipal Customers)



The Companies are also forecasting marked increases in seasonal peak demands, again largely driven by BlueOval, though the seasonal peaks converge over time as projected increases in electric heating load gradually increase winter peaks while increasing end-use efficiencies (including DSM-EE programs) and distributed solar generation steadily decrease summer peak load:

[2] Sponsored by Tim A. Jones as Exhibit TAJ-1.

Figure 2: Forecasted Seasonal Peaks



As shown in the following figures, customers will also continue to require significant amounts of energy in every hour and season, during daylight and non-daylight hours:

Figure 3: 2028 Proportion of Energy Consumed During Daylight and Non-Daylight Hours

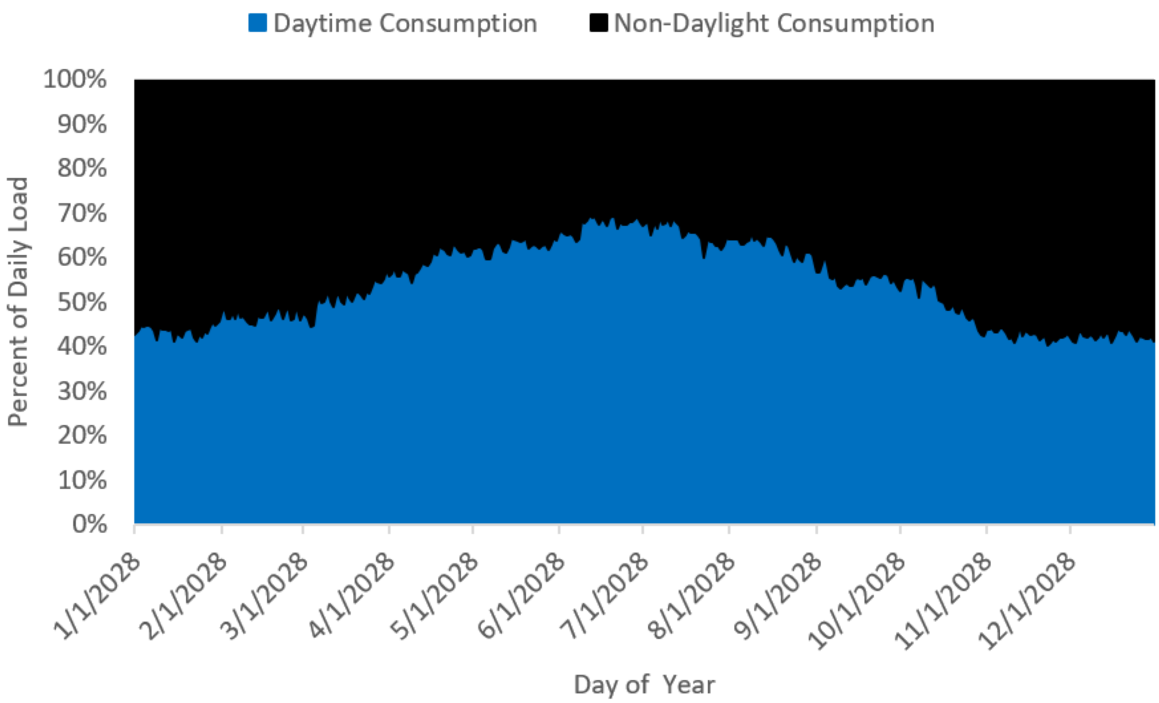
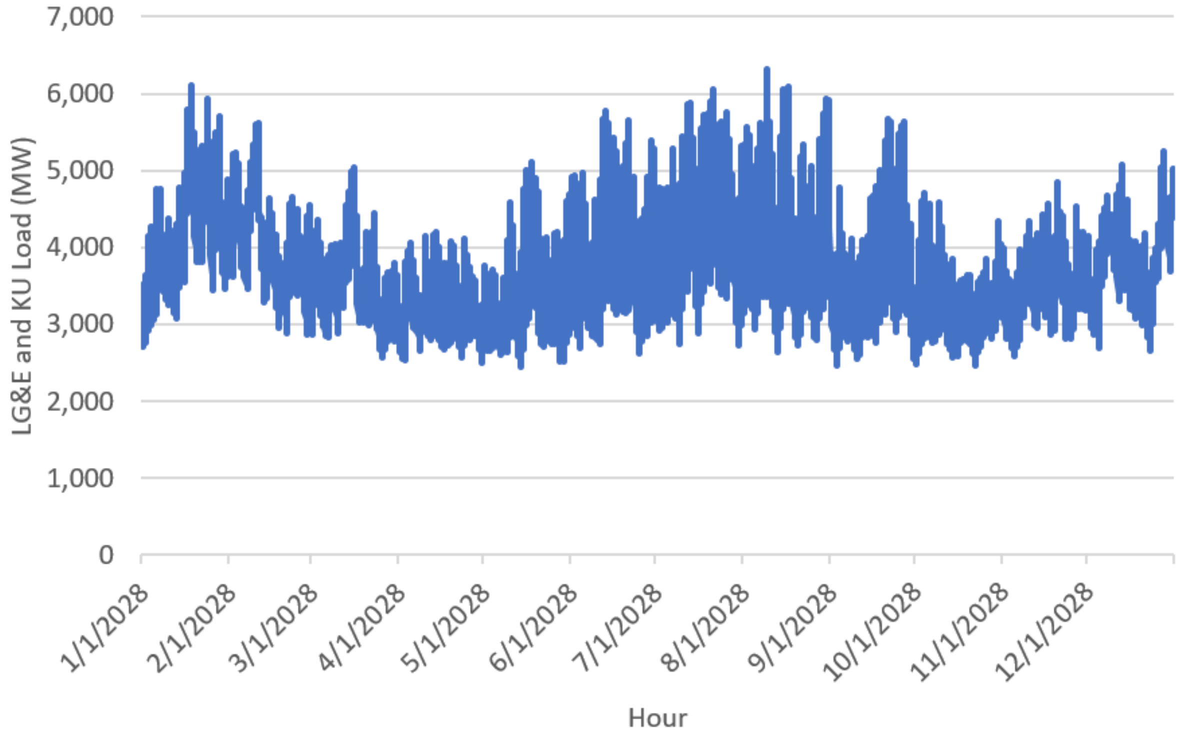


Figure 4: LG&E and KU 2028 Hourly Load

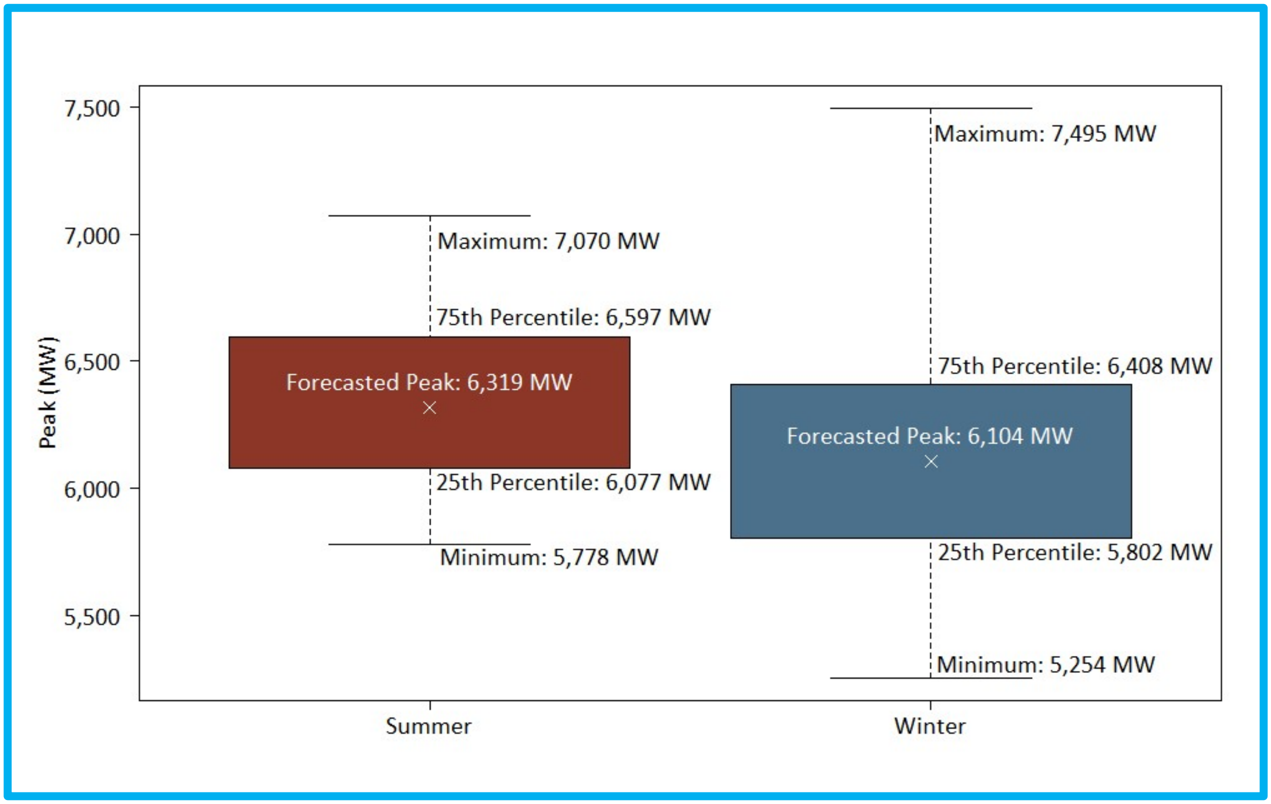


These figures show that an optimal resource portfolio must be able to serve customers' considerable energy requirements in all hours, seasons, and weather and daylight conditions. Notably, the Companies developed the figures above and the 2022 CPCN Load Forecast assuming normal weather. Extreme weather conditions drive a need for additional reliability considerations.

2.2 Serving Customers Reliably: Minimum Reserve Margins

To ensure reliable service, the Companies reanalyzed their reserve margins for this Resource Assessment. The full reserve margin analysis is Appendix D to this document. It demonstrates that the Companies' minimum reserve margins are 17% in the summer and 24% in the winter. This is consistent with the much greater variability of winter peak demands, as Figure 5 below shows:

Figure 5: Distributions of Summer and Winter Peak Demands, 2028



Note that the minimum reserve margins assume a mix of resources that are fully dispatchable for long durations and resources that are intermittent or can be dispatched for only limited durations (primarily solar and DSM). For example, the total summer minimum reserve margin assumes a 12% reserve margin that is fully dispatchable and a 5% reserve margin comprising intermittent and limited-duration resources. Therefore, any portfolio that achieves a total summer reserve margin of 17% but includes significantly less than a 12% reserve margin consisting of fully dispatchable resources raises reliability concerns.

2.3 Clarifying the Objective: Make Only the Decisions that Must Be Made Today

Finally, it is helpful to bear in mind that this is not the last time the Companies will make resource decisions. Thus, the objective of this Resource Assessment is not to prescribe the ideal resource mix through 2050, but rather to provide an optimal portfolio to address the decisions that must be made today due to upcoming environmental regulatory constraints (the Good Neighbor Plan) and major capital investments needed for Brown 3 to continue operating reliably in 2028 and beyond. It is inadvisable to attempt to prescribe today the resource portfolio for the entire period this Resource Assessment addresses; developments in resource technology and applicable regulations can and will affect resource decisions to be made five, ten, or even twenty years from now.

Therefore, the objective of this Resource Assessment is to formulate an optimal resource portfolio to meet customers' projected needs and address resource decisions that must be made today, but also to do so in a way that does not prejudice future resource decisions.

3 Meeting the Objective: Available Demand- and Supply-Side Resources

To meet customers' forecasted demand and energy requirements discussed above reliably and economically, the Companies gathered information about available supply- and demand-side resources in addition to their existing resources. They accomplished this on the supply side through a request for proposals ("RFP"). On the demand side, the Companies accomplished this through their own research and experience, engagement with a third-party consultant (Cadmus), and the Companies' DSM-EE Advisory Group. The result was a large array of potential supply-side resources and dispatchable DSM programs that advanced for further analysis in this Resource Assessment.

3.1 Supply Side: RFP Responses and Review

The Companies issued an RFP for new generation capacity and energy in June 2022.[3] In total, 22 parties responded to the RFP with 101 proposals across 39 different projects, some of which the Companies subdivided into a total of 110 proposals. Due to the timing of the responses relative to the passage of the federal Inflation Reduction Act, the Companies asked all respondents to update their responses to account for the IRA. The majority indicated they had already accounted for it or did not need to adjust their responses; five respondents provided updated information.

Appendix B contains a full listing of the 110 proposals; Table 1 below summarizes them by technology:

Table 1: Summary of RFP Responses

Technology	Number of Proposals by Start Year			Nameplate Capacity (MW)	Price
	<=2026	2027	2028+		
Solar	32	2	3	35-685	[redacted]
Solar w/ 4-hr Battery Option	26	16	-	100-750	[redacted]
Solar + 4-hr Battery	2	-	-	200	[redacted]
2-hr Battery	3	1	-	120-300	[redacted]
4-hr Battery	11	1	-	100-300	[redacted]
Pumped Hydro	-	-	1	287	[redacted]
Wind	1	-	-	143	[redacted]
NGCC	-	4	2	643-1,285	[redacted]
SCCT	2	1	-	556	[redacted]
Solar Asset Development	2	-	-	120-685	[redacted]

[3] The testimony of Charles R. Schram addresses the RFP at length, and it includes the RFP itself and all RFP responses as Exhibits CRS-1 and CRS-2, respectively.

The majority of the responses to the RFP were for solar PPAs or solar PPAs with battery storage options. The Companies' Project Engineering group submitted solar and battery storage proposals, as well as the only simple-cycle combustion turbine ("SCCT") and NGCC proposals.

The Companies reviewed the RFP responses and screened them to create a more manageable set of alternatives for modeling based on several factors, reducing the number of proposals evaluated to 43:

- For PPA proposals covering the same project but with different pricing options due to PPA term, start date, and price escalation, the Companies selected the proposal with the lowest levelized cost per MWh. For PPA proposals with similar levelized costs and flat or escalating price options, the Companies selected the proposals with flat prices.

- Certain of the Companies' self-build NGCC and SCCT proposals for the E.W. Brown Generating Station ("Brown") would have required additional land acquisitions. The Companies excluded those proposals due to the development risk associated with land acquisition.

- The NGCC proposals included both single units and sets of two units at both Brown and the Mill Creek Generating Station ("Mill Creek"). The Companies excluded sets of two NGCC units at each site due to the anticipated transmission capacity investment that would be required to accommodate two units at a single site and to allow for gas pipeline diversity among potential new NGCC units.

- The Companies excluded proposals for the purchase or development of solar and battery storage assets from advancing to the modeling analysis due to the economics of the proposals. The Companies revisited these proposals in Stage Three of the analysis described below.

- The Companies excluded a non-conforming self-build 35 MW solar proposal at Trimble County (note that the Companies considered all other non-conforming proposals).

- Some respondents rescinded certain proposals after submitting them. The Companies did not consider rescinded proposals.

The full set of 43 proposals that advanced for modeling analysis is also included in Appendix B. Two important observations concerning the RFP review and screening process are:

- **Solar PPA prices have increased significantly.** The most competitive solar PPA proposals were priced at \$36 to \$40/MWh, which is 30 to 40 percent higher than the pricing in the Rhudes Creek and Ragland PPAs the Companies executed in 2019 and 2021, respectively. These pricing increases are consistent with broader market indicators, such as the LevelTen Energy PPA Price Index for the third quarter of 2022, indicating that its Solar P25 Market-Averaged National Index rose to \$42.21/MWh, up 30.3% (\$9.82/MWh) year over year.[4]

[4] *See* LevelTen Energy "Q3 2022 PPA Price Index Executive Summary North America" at 7, available at: https://www.leveltenenergy.com/ppa.

- **The Companies' Muhlenberg Self-Build Solar Proposal Relocated to Mercer County.** One RFP response proposed to sell the Companies a solar project already in advanced stages of development, but not construction, located in Mercer County.[5] Because the proposal was not for a commercially executable transaction for a PPA or to acquire a solar facility per se, the Companies' Project Engineering group reviewed it and determined it would be a more suitable self-build solar site than their originally proposed site in Muhlenberg County, which had become problematic due to land acquisition issues. The Companies' Project Engineering group therefore revised their self-build proposal to suit the proposal at the Mercer County site, resulting in a 120 MW self-build solar proposal in Mercer County rather than a 145 MW self-build solar proposal in Muhlenberg County.

3.2 Demand Side: DSM Resources

Working with their DSM-EE Advisory Group and their outside expert consultant, Cadmus, the Companies formulated a proposed 2024-2030 DSM-EE Program Plan for which the Companies are seeking approval in this proceeding. As noted above, the Companies' 2022 CPCN Load Forecast fully accounts for the energy efficiency effects of the proposed 2024-2030 DSM-EE Program Plan. The dispatchable DSM portion of the 2024-2030 DSM-EE Program Plan, including the existing dispatchable DSM programs the Companies currently have in place, advanced for further analysis to determine their role in the optimal resource portfolio. A full listing of the dispatchable DSM programs and their relevant parameters are in Table 2 below, which is also located in Appendix B.

[5] *See* Response No. 110 in Table 43 in Appendix B.

Table 2: Dispatchable DSM Program Options

No.	Program Name	Variable Costs $/kWh		Time-Dependent Characteristic	2024	2025	2026	2027	2028	2029	2030
		Winter	Summer								
1	Peak Time Rebates	2.00	2.00	Summer Capacity MW	-	4	9	17	31	31	31
				Winter Capacity MW	-	4	9	17	31	31	31
				Fixed Cost $/kW-Year	-[6]	344	52	38	32	37	32
2	DLC-Water Heaters	2.50	2.50	Summer Capacity MW	3	3	3	2	2	2	2
				Winter Capacity MW	3	3	3	2	2	2	2
				Fixed Cost $/kW-Year	9	12	11	13	14	16	18
3	DLC-AC[7]	-	1.68	Summer Capacity MW	121	109	98	88	79	71	64
				Winter Capacity MW	-	-	-	-	-	-	-
				Fixed Cost $/kW-Year	9	12	11	13	14	16	18
4	BYOD-Smart Thermostats	4.17	4.93	Summer Capacity MW	1	3	6	10	17	23	29
				Winter Capacity MW	0.4	1	2	3	4	6	7
				Fixed Cost $/kW-Year	740	218	140	109	105	90	86
5	Non-residential Demand Response	7.55	7.55	Summer Capacity MW	29	36	45	56	67	79	79
				Winter Capacity MW	29	36	45	56	67	79	79
				Fixed Cost $/kW-Year	45	39	29	25	21	18	13

[6] The Peak Time Rebates program is projected to cost $250,000 in 2024 before realizing demand reductions starting in 2025.
[7] Summer capacity values are design-day values. Expected load reductions are lower on an average peak day.

3.3 The Companies' Existing Resources

The Companies have a suite of existing supply- and demand-side resources that would continue to serve the bulk of customers' demand and energy requirements over the Resource Assessment analysis period. This includes, for example, the Companies' interruptible load under their Curtailable Service Riders. To focus this analysis on the decision immediately at hand—namely, whether to retire and replace one or more of Mill Creek 2, Ghent 2, and Brown 3—the Companies have assumed that all of their existing resources will continue to operate throughout the analysis period with these exceptions: Mill Creek Unit 1 will retire as planned in 2024, Paddy's Run Unit 12 and Haefling Units 1-2 will retire in 2025, and OVEC will retire as planned in 2040.[8]

Also, as noted above, the Companies did not assume that existing dispatchable DSM programs would automatically continue for the entire Resource Assessment period; rather, those measures advanced for analysis in the Resource Assessment. Ultimately, those measures proved to be beneficial for reliability and are included in the optimal resource portfolio.

Finally, it is important to note the potential impact of retiring Mill Creek 2, Ghent 2, and Brown 3. Collectively, these units have a total capacity of 1,194 MW and typically produce 15% or more of customers' annual energy requirements, and they produce just over half of their annual energy during non-daylight hours:

Table 3: Operational Data for Mill Creek 2, Ghent 2, and Brown 3

Year	Total Energy (GWh)	% Night	% Day	Max Hourly Output (MW)	Average Hourly Output (MW)	% of Total Energy Requirements
2017	5,698	52%	48%	1,235	772	17%
2018	6,230	51%	49%	1,238	842	18%
2019	5,407	51%	49%	1,250	785	16%
2020	4,512	52%	48%	1,229	729	15%
2021	4,610	51%	49%	1,219	752	15%

Filling the energy gap these units will leave if they retire requires careful, thoughtful analysis to ensure the Companies have sufficient resources to continue to serve customers reliably and economically.

Appendix A contains a full discussion of existing resource assumptions.

[8] Due to their age and relative inefficiency, the Companies do not perform major maintenance on their small-frame simple-cycle combustion turbines ("SCCTs"), Paddy's Run Unit 12 and Haefling Units 1-2, but continue to operate them until they are uneconomic to repair. This analysis assumes that they will be retired in 2025 for planning purposes.

4 Meeting the Objective: Analysis to Achieve an Optimal Resource Portfolio

The Companies' Resource Assessment analysis described below brought together their 2022 CPCN Load Forecast, their existing resources, the 43 RFP proposals that advanced from the RFP review and screening, and all dispatchable DSM programs from the 2024-2030 DSM-EE Program Plan to achieve an optimal portfolio for meeting the potential capacity need in 2028. The Companies' analysis:

- Ensured compliance with the Good Neighbor Plan and other applicable environmental requirements while maintaining required reliability;

- Accounted for key uncertainties, such as fuel and CO_2 pricing; and

- Used a combination of sophisticated modeling tools (including PLEXOS, PROSYM, and SERVM), as well as the Companies' own expertise and experience.

The Companies conducted their analysis in three stages:

- **Stage One: Economic Optimization.** First, the Companies created an economically optimized portfolio across six fuel price cases that assured minimum reliability and Good Neighbor Plan compliance.

    - **Stage One Result:** An economically optimized portfolio of the 621 MW Mill Creek NGCC, the 621 MW Brown NGCC, and 637 MW of solar PPAs.

- **Stage Two: Stress Testing.** Next, the Companies stress-tested the results of the first stage by comparing the economically optimized portfolio to nine other portfolios, each of which the Companies designed to test whether adjusting in a particular way might improve the results (e.g., a portfolio that could replace any retired coal generation with only DSM, renewable energy resources, and battery storage). The Companies also tested the portfolios across all three CO_2 pricing scenarios and all six fuel price scenarios, all while maintaining minimum reliability.

    - **Stage Two Result:** The economically optimized portfolio of the Mill Creek NGCC, Brown NGCC, and 637 MW of solar PPAs remained optimal and resulted in lower CO_2 emissions than other tested portfolios.

- **Stage Three: Fine Tuning.** Third, the Companies fine-tuned the economically optimal portfolio to address three issues:

    - **Stage Three, Step One: Solar PPA Execution Risk.** The Companies' own experience with solar PPAs, as well as the broader market experience in recent years, is that it is increasingly difficult for contracted solar facilities to be built on time or at all, at least at the contracted price. To address this risk, the Companies demonstrate that adding two Companies-owned solar facilities to the portfolio helps address the risk that, given the current solar market, none of the solar PPAs might come to fruition, at least by 2028.

- **Stage Three, Step One Result:** Optimal portfolio of the Mill Creek NGCC, Brown NGCC, 240 MW of Companies-owned solar, and 637 MW of solar PPAs.

- **Stage Three, Step Two: Reliability Enhancement.** In this step, the Companies analyzed the value of adding reliability using dispatchable DSM from the 2024-2030 DSM-EE Program Plan, battery energy storage systems, and SCCT capacity. The Companies concluded that adding all of the dispatchable DSM in the 2024-2030 DSM-EE Program Plan provides cost-effective reliability. They further concluded that adding the proposed 125 MW, 500 MWh Brown BESS, though not as economical as SCCT, would further enhance reliability and provide the Companies valuable experience with battery technology at utility scale, which will likely be instrumental in reliably integrating large quantities of renewable generation in the future. In addition, Brown BESS might have quantifiable benefits that the Companies have not attempted to quantify here, such as reducing fast-ramping wear on gas turbine units and the ability to carry less spinning reserves.

  - **Stage Three, Step Two Result:** Optimal portfolio of the Mill Creek NGCC, Brown NGCC, 240 MW of Companies-owned solar, 637 MW of solar PPAs, 2024-2030 DSM-EE Program Plan, and Brown BESS.

- **Stage Three, Step Three: OVEC early retirement:** The final consideration was whether an early retirement of the OVEC coal units would reduce reliability such that the Companies would need additional resources solely to address the early retirement. Particularly because the Companies cannot unilaterally control the operation or retirement of OVEC's units, this was an important uncertainty to analyze. The results indicate that an OVEC early retirement, even in 2028, would not require additional resources (assuming no significant changes in actual versus forecasted load).

  - **Stage Three, Step Three Result:** Optimal portfolio remains the Mill Creek NGCC, Brown NGCC, 240 MW of Companies-owned solar, 637 MW of solar PPAs, 2024-2030 DSM-EE Program Plan, and Brown BESS.

The result is a resource portfolio that appropriately balances economics, reliability, and risk; provides valuable experience with new technologies to accommodate greater renewable power generation in the future; and reduces CO_2 emissions considerably, more than other portfolios analyzed, which reduces future regulatory risk and potential cost related to CO_2 emissions. It is a no-regrets portfolio:

- **Low load or increased efficiencies, no regrets.** If actual load is materially lower than projected load for any reason, including if technological advances or economic changes result in additional energy and demand savings (through DSM-EE programs or otherwise), retiring additional aging coal capacity would likely be the most economical option, further reducing CO_2 emissions.

- **High load, no regrets.** If actual load is materially higher than projected load, nothing in the Companies' proposed portfolio precludes adding demand- or supply-side resources to address the need. If the increased load results from electric space heating or electric vehicle charging, the proposed NGCC units could prove to be particularly valuable given their ability to economically produce energy at night.

- **Increased renewable generation or CO_2 constraints, no regrets.** The proposed portfolio's fast-ramping NGCC units and Brown BESS well position the Companies to provide reliable service if renewable energy generation increases, and the lower CO_2 emissions of NGCCs and zero emissions of solar and DSM-EE all improve the Companies' positioning to address any CO_2 emissions pricing or regulations that might eventuate.

4.1 Key Constraints and Uncertainties of Analysis

The Companies' Resource Assessment analysis included addressing a number of important constraints and uncertainties.

4.1.1 Key Constraints

All stages of the Resource Assessment's analysis assumed that compliance with the Good Neighbor Plan and all other environmental requirements and maintaining minimum reserve margins were absolute constraints. As proposed, the Good Neighbor Plan effectively requires installing SCR to operate Mill Creek 2 and Ghent 2 during the ozone season (May through September) beginning in 2026. But because replacement generation may not be available by 2026, the Companies have asked the EPA to extend the compliance deadline in the event that retiring and replacing a resource is lower cost than physical compliance with SCR. To achieve Good Neighbor Plan compliance, the Companies assumed in the Resource Assessment that non-SCR-equipped coal units could not operate during the ozone season beginning in 2026 unless the units were scheduled to be replaced. Specifically, the Companies assumed they could avoid the cost of installing SCR in 2026 if the non-SCR-equipped unit was replaced by the 2028 ozone season.

4.1.2 Key Uncertainty: Fuel Prices

Fuel prices are an important uncertainty in this analysis. To address it, the Companies used six different fuel price scenarios in which natural gas prices were the primary price setting factor, with coal prices derived from gas prices beginning in 2028 based on different historical coal-to-gas ("CTG") price ratios.

The Companies' three natural gas price cases (low, mid, and high) derive from Henry Hub forward prices in the near term (2023-2025), then interpolate to the Energy Information Administration's 2022 Annual Energy Outlook's corresponding natural gas price forecasts: High Oil and Gas Supply case (low gas price), Reference case (mid gas price), and Low Oil and Gas Supply case (high gas price).

In the first three fuel price scenarios the Companies analyzed, coal prices predominantly varied with gas prices by a ten-year average ratio of coal and gas prices. These cases are the most likely to occur over a long planning period and are called "Low Gas, Mid CTG Ratio," "Mid Gas, Mid CTG Ratio," and "High Gas, Mid CTG Ratio." Note that the Mid coal-to-gas price ratio approximates the ratio of NGCC and coal energy costs. Therefore, it is plausible to expect coal-to-gas price ratios to revert to this ratio over the long term, which is why the Companies refer to it as the "Expected CTG Price Ratio." Figure 6 below shows these three fuel price cases in nominal dollars per MMBtu through 2050:

Figure 6: Coal and Natural Gas Price Scenarios with a Mid Coal-to-Gas Price Ratio

[redacted]

The other three fuel price scenarios involve relationships between gas and coal prices that would be atypical for an extended time horizon, essentially as sensitivity cases: (1) low gas prices with a historically high coal-to-gas ratio (“Low Gas, High CTG Ratio”); (2) high gas prices with a historically low coal-to-gas ratio (“High Gas, Low CTG Ratio”); and (3) high gas prices with the current, historically aberrant coal-to-gas ratio (“High Gas, Current CTG Ratio”). Figure 7 below illustrates these three fuel price cases in nominal dollars per MMBtu through 2050:

Figure 7: Coal and Natural Gas Price Scenarios with Atypical Long-Term Coal-to-Gas Price Ratios

[redacted]

A full description of the formulation of these gas and coal prices and coal-to-gas price ratios is in the Coal and Natural Gas Prices discussion in Appendix A, as well as Appendix E.

4.1.3 Key Uncertainty: CO_2 Prices

The future of CO_2 regulation is a key uncertainty in this analysis. To address it, the Companies considered three different CO_2 prices as proxies for different possible CO_2 regulations, in accordance with the CO_2 prices Commission Staff asked the Companies to model in the 2021 IRP proceeding: $0/ton, $15/ton, and $25/ton.[9] These pricing cases are also reasonable based on prices in CO_2 markets like the Regional Greenhouse Gas Initiative ("RGGI") and others, as discussed in the CO_2 Prices discussion in Appendix A.

4.1.4 Key Uncertainty: Solar PPA Execution

The Companies' own experience with solar PPAs demonstrates the reality of solar PPA execution risk (i.e., the risk that a contracted facility will not be built on time or at all), as does the experience of the broader solar market in recent years. The Companies were able to execute two attractively priced PPAs (Rhudes Creek and Ragland) with reputable solar developers in 2019 and 2021, respectively. To date, neither project has obtained all necessary approvals to begin construction. Even if they were able to obtain necessary approvals, market prices of polysilicon needed for solar panels and related constraints on panel availability (owing largely to prohibitions on the ability to use certain solar panels made in China) make it

[9] *See* Case No. 2021-00393, Companies' Response to PSC 1-1(b) (Mar. 25, 2022).

unlikely the developers could obtain financing to build the projects at all, and certainly not at the prices prescribed in the PPAs.[10] The Companies address this risk in their analysis below.

But a solar risk the Companies do not directly address is solar intermittency: cloud risk. The modeling the Companies performed in this Resource Assessment took solar to be a resource with a fixed production profile. Although it is a reasonable profile and is correlated with the weather and solar irradiance underlying the load forecast, the models assume solar will reliably and consistently produce according to its profile.

4.1.5 Key Uncertainty: Early OVEC Retirement

A final key uncertainty the Companies' analysis considers is the possibility that the OVEC coal units that provide the Companies over 150 MW of dispatchable capacity might retire prior to the currently expected retirement date of 2040. At the end of the analysis below, the Companies evaluate the impact of OVEC retirement in 2028 on the reliability of the Companies' optimal resource portfolio.

4.2 Modeling Tools Used in the Analysis: PLEXOS, PROSYM, Financial Model, SERVM

The Companies used four primary software tools to aid them in their analysis:

- **Portfolio Development and Screening: PLEXOS.** The Companies used PLEXOS to develop least-cost resource portfolios over a range of fuel price scenarios. Using simplifying assumptions to increase speed, PLEXOS models and evaluate thousands of resource portfolios to determine which one minimizes the cost of serving customers' load while meeting minimum total summer and total winter reserve margin constraints. Notably, as the Companies use PLEXOS, although it evaluates thousands of possible resource portfolios in each run, its output for each run is only the least-cost portfolio for the assumptions entered; it does not provide a ranked listing or other comparison of runner-up portfolios. (Largely due to this limitation, Stage Two of the Companies' analysis involved comparing PLEXOS-selected portfolios to other portfolios formulated by the Companies to examine their relative reliability and economics.)

- **Production Cost Modeling: PROSYM.** Because production costs are an important component of total costs, after PLEXOS identifies which resources to include in a resource portfolio, the Companies modeled the portfolio's generation production costs in detail using PROSYM, an hourly chronological dispatch model. PLEXOS and PROSYM use the same inputs (e.g., they use the same natural gas and coal prices), but the Companies used PROSYM rather than PLEXOS for detailed production cost modeling because they have used and configured PROSYM over a number of years to do such modeling relatively quickly.

- **Present Value of Revenue Requirements ("PVRR"): Excel Financial Model.** The Companies used a Financial Model built in Excel to calculate and compare PVRR values for various portfolios. Inputs to the Financial Model include capital and fixed operating costs for new and existing resources as well as generation production costs. Table 4 below lists the primary costs included

[10] *See, e.g.,* "Polysilicon Prices Remain High, No Moderation Until 2023", EnergyTrend, September 2, 2022, available at: https://m.energytrend.com/news/20220902-29845.html#:~:text=While future polysilicon prices are,per kilogram polysilicon price drop.

in the Financial Model. Production costs are developed in PROSYM; the costs for new and existing resources are the same costs modeled in PLEXOS and used to develop the least-cost portfolio.

Table 4: Financial Model Costs

Cost Item	Description
Generation Production Costs	Variable fuel and reagent costs associated with power generation. Includes costs of purchased power such as OVEC and solar PPAs.
Existing Unit Stay-Open Costs	Ongoing capital and fixed O&M associated with existing generation assets.
Environmental Compliance Costs	Capital and O&M associated with compliance costs for new regulations, such as SCRs to comply with the Good Neighbor Plan.
New Generation Capital and Stay-Open Costs	Capital and O&M associated with new generation assets.

- **Reliability Analysis: SERVM.** The Companies used SERVM to evaluate portfolios' reliability across a wide range of weather and unit availability scenarios. Specifically, the Companies used SERVM to model generation production costs, reliability costs, and loss of load expectation ("LOLE") over 49 load scenarios and 300 unit availability scenarios. The load scenarios were developed based on the weather in each of the last 49 years. This allows the Companies to evaluate the economics of improving reliability considering the historical frequency and likelihood of extreme weather events.

4.3 Analytical Framework: Three Stages to Achieve an Optimal Resource Portfolio

As discussed above, the Companies conducted three stages of analysis using the 2022 CPCN Load Forecast, existing resources, RFP responses, dispatchable DSM programs from the 2024-2030 DSM-EE Program Plan, and modeling tools to address the potential retirements of Mill Creek 2, Ghent 2, and Brown 3, as well as the key uncertainties and risks also discussed above, and arrive at an optimal resource portfolio.

4.4 Stage One: Economic Optimization to Achieve Minimum Reliability

The objective of Stage One is an economically optimal resource portfolio across six fuel-price cases consistent with meeting minimum reserve margin requirements and complying with Good Neighbor Plan. All steps of this stage assumed a CO_2 price of zero; Stage Two analyzed other CO_2 prices.

4.4.1 Stage One, Step One: Portfolio Development and Screening with PLEXOS

The first step of Stage One consisted of allowing PLEXOS to create optimal resource portfolios for each of the Companies' six fuel price cases.

In this step, PLEXOS:

- Took the Companies' existing resources to be fixed (except Mill Creek 1 retiring by the end of 2024, the small-frame SCCTs retiring in 2025, OVEC retiring in 2040, and existing dispatchable DSM programs could be retained or retired);
- Could choose to add SCR to or retire either or both of Mill Creek 2 and Ghent 2;
- Could make the $26 million investment to continue operating Brown 3 or retire the unit; and

- Could add any RFP response or dispatchable DSM resource from the 2024-2030 DSM-EE Program Plan at any time, regardless of the operation date specified in the RFP response.

Table 5 below provides the portfolios PLEXOS selected with these assumptions for each fuel price scenario. As mentioned previously, as the Companies use PLEXOS, it provides only the economically optimal portfolio for each model run.

Table 5: Portfolio Development and Screening Results by Fuel Price Scenario

	Fuel Price Scenario (Gas, CTG Price Ratio)	Least-Cost Resource Portfolio: Changes to Dispatchable Resources by 2028	Least-Cost Resource Portfolio: Total New Renewables by 2028 (MW)	Least-Cost Resource Portfolio: Total New Renewables by 2035 (MW)
Expected CTG	Low Gas, Mid CTG Ratio	Replace MC2, GH2, BR3 w/ MC5 and BR12	N/A	N/A
Expected CTG	Mid Gas, Mid CTG Ratio	Replace MC2, GH2, BR3 w/ MC5 and BR12	104 Solar	384 Solar
Expected CTG	High Gas, Mid CTG Ratio	Replace MC2, BR3 w/ MC5; Add SCR at GH2	637 Solar	2,322 Solar
Atypical CTG	Low Gas, High CTG Ratio	Replace MC2, GH2, BR3 w/ MC5 and BR12	N/A	N/A
Atypical CTG	High Gas, Low CTG Ratio	Replace MC2, BR3 w/ MC5; Add SCR at GH2	384 Solar	2,322 Solar
Atypical CTG	High Gas, Current CTG Ratio	Replace MC2, GH2, BR3 w/ MC5 and BR12	2,322 Solar	2,717 Solar 143 Wind

Important observations from these results:

- **Adding NGCC capacity is optimal in all fuel price cases.** In four of the six fuel price cases, PLEXOS retired Mill Creek 2, Ghent 2, and Brown 3 and added Mill Creek NGCC and Brown NGCC. In two of the high gas price cases, PLEXOS chose to retire only Mill Creek 2 and Brown 3, add Mill Creek NGCC, and add SCR to Ghent 2. The level of fuel prices does not materially impact the need for resources that can economically produce large amounts of energy at night.

- **The desirability of solar predictably correlates with fossil fuel prices.** Only in the two low gas price cases did PLEXOS add no renewable generation, and it added more in the high gas price cases than it did in the mid gas price case. A significant amount of solar is added after 2028 in two of the three high gas price cases.

- **PLEXOS did not select DSM or batteries in any of the fuel-price cases.** This likely results from the cost of these resources relative to their limited duration, making them uneconomical to achieve minimum reliability and meet the significant need for energy created by coal unit retirements. Also, batteries do not produce energy, but rather move it in time.

4.4.2 Stage One, Step Two: Portfolio Optimization with Detailed Production Costs

The first step of Stage One revealed that only two basic combinations of retirements and replacement resources would be economically optimal in 2028: (1) retiring Mill Creek 2, Ghent 2, and Brown 3 and adding the Mill Creek NGCC, Brown NGCC, and solar PPAs; and (2) retiring Mill Creek 2 and Brown 3, adding SCR to Ghent 2, and adding the Mill Creek NGCC and solar PPAs.

In the second step of Stage One, the Companies sought to optimize the portfolio by evaluating actionable alternatives based on the results of Stage One, Step One.

To achieve this, the Companies identified all of the solar PPA proposals that PLEXOS selected by 2028 (a total of 2,322 MW), listed below in Table 6 in order of increasing PPA price per MWh:[11]

Table 6: Solar PPAs Selected in Portfolio Optimization

Response No. in Appx. B	Respondent	Project	Start Date	Term (Years)	Price ($/MWh)	Capacity (MW)	Cumulative Capacity (MW)
7	[redacted]						
70	[redacted]						
45	[redacted]						
29	[redacted]						
34	[redacted]						
39	[redacted]						
37	[redacted]						
74	[redacted]						
56	[redacted]						
36	[redacted]						

The Companies then created 11 PPA combination options, the first of which had 0 MW solar, with each subsequent PPA combination option adding the next most economical PPA from Table 6 above, resulting in each subsequent PPA combination having more cumulative PPA capacity that prior combinations, all the way to the 11th combination with 2,322 MW cumulative PPA capacity.

The Companies then used the 11 PPA combinations to create 22 total portfolios for detailed production cost runs in PROSYM. As shown in Table 7 below, each portfolio was a combination of one of the two NGCC combinations from the PLEXOS modeling (i.e., Mill Creek NGCC plus Brown NGCC and Mill Creek NGCC plus Ghent 2 with SCR) and one of the 11 PPA combinations described above (2 NGCC options x 11 PPA combinations = 22 portfolios to analyze).

[11] Note that only the first four proposals are at or below the $42.21/MWh P25 price for solar PPAs as reported by LevelTen and discussed in Section 3.1. Despite the higher price of the remaining proposals, they were evaluated in this step of the analysis.

Table 7: Resource Portfolios Evaluated in Detailed Production Cost Analysis

Portfolios Where MC2, GH2, BR3 Replaced w/ MC5 and BR12	**Portfolios Where MC2, BR3 Replaced w/ MC5; SCR Added to GH2**
MC5/BR12; 0 Solar	MC5/GH2 SCR; 0 Solar
MC5/BR12; 104 Solar	MC5/GH2 SCR; 104 Solar
MC5/BR12; 384 Solar	MC5/GH2 SCR; 384 Solar
MC5/BR12; 499 Solar	MC5/GH2 SCR; 499 Solar
MC5/BR12; 637 Solar	MC5/GH2 SCR; 637 Solar
MC5/BR12; 1,322 Solar	MC5/GH2 SCR; 1,322 Solar
MC5/BR12; 1,522 Solar	MC5/GH2 SCR; 1,522 Solar
MC5/BR12; 1,622 Solar	MC5/GH2 SCR; 1,622 Solar
MC5/BR12; 1,722 Solar	MC5/GH2 SCR; 1,722 Solar
MC5/BR12; 2,222 Solar	MC5/GH2 SCR; 2,222 Solar
MC5/BR12; 2,322 Solar	MC5/GH2 SCR; 2,322 Solar

The Companies then conducted detailed production cost runs in PROSYM for each of these 22 portfolios across all six fuel price cases (a total of 132 runs). Unlike the PLEXOS modeling, in this part of the analysis each solar contract was assumed to begin on its RFP-specified start date. Table 8 below lists the least-cost portfolio for each fuel price scenario.

Table 8: Portfolio Optimization Results

	Fuel Price Scenario (Gas, CTG Price Ratio)	**Least-Cost Resource Portfolio**
Expected CTG	Low Gas, Mid CTG Ratio	MC5/BR12; 104 Solar
	Mid Gas, Mid CTG Ratio	MC5/BR12; 637 Solar
	High Gas, Mid CTG Ratio	MC5/BR12; 2,322 Solar
	Average Low, Mid, High Gas w/ Mid CTG Ratio	MC5/BR12; 637 Solar
Atypical CTG	Low Gas, High CTG Ratio	MC5/BR12; 104 Solar
	High Gas, Low CTG Ratio	MC5/GH2 SCR; 2,222 Solar
	High Gas, Current CTG Ratio	MC5/BR12; 2,322 Solar
	Average Excluding High Gas, Current CTG Ratio	MC5/BR12; 637 Solar
	Average All Fuel Prices	MC5/BR12; 1,322 Solar

Important observations from these results:

- **Mill Creek NGCC and Brown NGCC portfolio appears optimal.** With detailed production cost modeling, only in the atypical fuel price scenario most favorable to coal (High Gas, Low Coal-to-Gas Ratio) is retiring only Mill Creek 2 and Brown 3, adding Mill Creek NGCC, and adding SCR to Ghent 2 least-cost.

- **Solar PPA capacity of 637 MW is optimal.** The three fuel price scenarios with a Mid coal-to-gas price ratio had an average optimal amount of solar of four PPAs totaling 637 MW. The Mid coal-to-gas price ratio is consistent with history and appears most likely to persist over a long analysis period. In addition, the most expensive of these PPAs is $40.02/MWh, which is consistent with broader solar PPA market pricing of solar.[12] Therefore, 637 MW of solar PPAs is the optimal amount to pursue given the responses to the RFP and current solar market conditions.

4.4.3 Stage One, Step Three: Ghent 2 SCR PVRR Analysis

The third step of Stage One built on the results of the previous two steps and sought to determine how long Ghent 2 would have to operate to justify equipping it with an SCR in the single fuel price case in which it was least cost. This would provide a more precise sense of the economics of adding SCR to Ghent 2.

To do this, the Companies evaluated cases where, after being retrofitted with SCR in 2028, Ghent 2 is replaced with the Brown NGCC later in the analysis period. The Companies' generation portfolio after Ghent 2 is replaced with the Brown NGCC is the same as the portfolio with the Mill Creek NGCC and Brown NGCC in 2028; the only material differences in revenue requirements after Ghent 2 is replaced result from the later-commissioned Brown NGCC having higher capital revenue requirements than commissioning it in 2028.

Table 9 compares the difference in PVRR between the portfolio with the Mill Creek NGCC, Ghent 2 with SCR, and 637 MW of solar ("MC5/GH2 SCR; 637 Solar") and the portfolio with the Mill Creek NGCC, Brown NGCC, and 637 MW of solar ("MC5/BR12; 637 Solar") over all six fuel price cases and four different eventual retirement dates for Ghent 2 with SCR.[13] Positive values in Table 9 indicate that the portfolio with the Ghent 2 SCR is more expensive.

Table 9: PVRR Difference; "MC5/GH2 SCR; 637 Solar" less "MC5/BR12; 637 Solar" ($M, 2022 Dollars)

		Year of GH2 Retirement in "MC5/GH2 SCR; 637 Solar" Portfolio				
	Fuel Price Scenario (Gas Price, CTG Price Ratio)	**2035**	**2040**	**2045**	**Indefinite Operation**	**SCR Break-Even Year**
Expected CTG	Low Gas, Mid CTG Ratio	77	121	107	96	N/A
	Mid Gas, Mid CTG Ratio	71	110	94	64	N/A
	High Gas, Mid CTG Ratio	75	116	104	91	N/A
Atypical CTG	Low Gas, High CTG Ratio	95	149	144	163	N/A
	High Gas, Low CTG Ratio	33	52	20	-77	2049
	High Gas, Current CTG Ratio	373	595	738	1,390	N/A

This analysis shows there are high costs to adding SCR to Ghent 2 in five of six fuel price scenarios and that adding SCR is unfavorable even in the fuel price scenario most favorable to coal (High Gas, Low CTG Ratio) unless Ghent 2 can continue to operate until at least 2049—all assuming no CO_2 pricing or other constraint. On balance, Stage One, Step Three indicates that the Mill Creek NGCC and Brown NGCC plus

[12] *See* LevelTen Energy "Q3 2022 PPA Price Index Executive Summary North America" at 7 (showing current LevelTen Energy PPA Price Index for third quarter of 2022, Solar P25 Market-Averaged National Index is at $42.21/MWh), available at: https://www.leveltenenergy.com/ppa.

[13] Focusing solely on the resource portfolio with the Mill Creek NGCC and SCR at Ghent 2, the optimal amount of solar over the fuel price scenarios with a Mid coal-to-gas price ratio is also 637 MW.

637 MW of solar PPAs is the economically optimal portfolio that satisfies both the Good Neighbor Plan and minimum reserve margin requirements.

4.5 Stage Two: Stress-Testing the Economically Optimal Portfolio

As noted above, the results of Stage One of the Companies' analysis strongly indicated that retiring Mill Creek 2, Ghent 2, and Brown 3 and adding the Mill Creek NGCC, Brown NGCC, and 637 MW of solar PPAs would be economically optimal based on fuel price scenario analysis alone.

In Stage Two, the Companies sought to stress-test the Stage One results in two ways simultaneously: (1) by evaluating different CO_2 price scenarios and (2) by comparing the apparently optimal portfolio to other portfolios created by the Companies to test whether certain portfolio constructs might offer additional insights. Particularly because PLEXOS, as the Companies use it, does not provide a listing or ranking of all the portfolios it evaluates, the Companies thought it was particularly important to explicitly evaluate other portfolios and compare their economics.

4.5.1 Stage Two, Step One: Portfolio Creation

As shown in Table 10 below, the Companies developed ten total portfolios to evaluate in Stage Two. The first two are familiar: Portfolio 1 is the apparently economically optimal portfolio from Stage One (Mill Creek NGCC, Brown NGCC, and 637 MW of solar PPAs); Portfolio 2 is the other potentially optimal portfolio from Stage One (Mill Creek NGCC, Ghent 2 with SCR, and 637 MW of solar PPAs). The other eight portfolios have varying levels of NGCC, coal unit retirements, SCR, dispatchable DSM from the 2024-2030 DSM-EE Program Plan, SCCT, and renewables, as well as options to operate non-SCR-equipped coal units only in non-ozone-season months. The Companies' reasoning for the other eight portfolios follows the table below.

Table 10: Stress Testing (Portfolios 1-10)

Port Num	Portfolio Name	Description	NGCC Units	Coal Units	New SCR
1	MC5 & BR12	Replace MC2 in 2027 w/ MC5 Replace BR3 & GH2 in 2028 with 1 NGCC at E.W. Brown Add 637 MW of solar	+2	-3	0
2	MC5/GH2 SCR	Replace MC2 in 2027 w/ MC5 Add SCR at GH2 and retire BR3 in 2028 Add 637 MW of solar	+1	-2	+1
3	MC5; Non-Ozone GH2	Replace MC2 in 2027 w/ MC5 No GH2 SCR; Operate GH2 in non-ozone season only Add optimal portfolio of renewables, battery storage, and dispatchable DSM	+1	-1	0
4	MC5; Non-Ozone GH2 Retire BR3	Replace MC2 in 2027 w/ MC5 No GH2 SCR; Operate GH2 in non-ozone season only Add optimal portfolio of renewables, battery storage, and dispatchable DSM Retire BR3	+1	-2	0
5	MC2/GH2 SCR	No coal retirements Add SCR at MC2 and GH2 in 2026 Complete BR3 overhaul in 2027 Add 637 MW of solar[14]	0	0	+2
6	Non-Ozone MC2/GH2	No SCRs and no coal retirements Operate MC2 and GH2 in non-ozone season only Complete BR3 overhaul in 2027 Add optimal portfolio of renewables, battery storage, and dispatchable DSM	0	0	0
7	Non-Ozone MC2/GH2; Retire BR3	No SCRs; Retire BR3 Operate MC2 and GH2 in non-ozone season only Add optimal portfolio of renewables, battery storage, and dispatchable DSM	0	-1	0
8	All Renewables	Replace MC2, BR3, and GH2 with optimal portfolio of renewables, battery storage, and dispatchable DSM	0	-3	0
9	SCCT + Renewables	Replace MC2, BR3, and GH2 with optimal portfolio of renewables, battery storage, dispatchable DSM, and SCCT	0	-3	0
10	DSM Only	Retire MC2, BR3, and GH2 Meet energy and capacity shortfall with DSM	0	-3	0

As noted in Table 10, Portfolios 3, 4, and 6-9 all required further specification of the renewable, dispatchable DSM from the 2024-2030 DSM-EE Program Plan, and battery resources to be added to address anticipated energy shortfalls (Portfolio 9 also included SCCT as an option). To do that optimally and meet the portfolio specifications, the Companies conducted a PLEXOS run for each portfolio in the high gas price, mid coal-to-gas price ratio case, which tends to favor renewables. As in Stage One, these PLEXOS runs included a zero CO_2 price and attempted to meet minimum reserve margin requirements.

The Companies' reasoning in creating Portfolios 3-10 follows:

[14] Portfolio 5 has the same amount of solar as Portfolios 1 and 2 because the economics of replacing generation that can economically serve nighttime energy requirements are not materially impacted by solar.

- Portfolios 3, 4, 6, and 7 explored different combinations of retaining Ghent 2 or Mill Creek 2 and Ghent 2 to serve only during non-ozone season months, with or without Brown 3. The purpose of these portfolios was to explore the relative reliability and economics of retaining one or both of these units without investing in SCR.
- Portfolio 5 tested the economics and reliability of investing in SCR for Mill Creek 2 and Ghent 2 and conducting the major overhaul of Brown 3, i.e., the reliability and economics of retaining all current coal units (other than Mill Creek Unit 1, which is already scheduled to retire by the end of 2024).
- Portfolio 8 tested the economics and reliability of retiring Mill Creek 2, Ghent 2, and Brown 3 and replacing their energy as needed with only renewables, batteries, and dispatchable DSM from the 2024-2030 DSM-EE Program Plan. The purpose was to test the reliability and economics of a replacement portfolio for complying with the Good Neighbor Plan that excluded all fossil fuel options.
- Portfolio 9 had the same retirements as Portfolio 8 but added SCCT to Portfolio 8's potential replacement resources. This was to test the impact of SCCT as a reliability resource in a replacement portfolio otherwise devoid of fossil fuel units.
- Portfolio 10 retires Mill Creek 2, Ghent 2, and Brown 3 and adds all dispatchable DSM from the 2024-2030 DSM-EE Program Plan for the purpose of assessing the reliability of the portfolio with no replacement resources other than DSM.[15]

Table 11 below summarizes the total generation changes (i.e., retirements and resource additions) in all ten portfolios:

Table 11: Stress Testing (Portfolios 1-10); Generation Changes by 2028 (Net Summer MW)

	Portfolio Name	**NGCC**	**Coal**	**SCCT**	**Solar**	**Wind**	**DSM[16]**	**Battery Storage[17]**
1	MC5 & BR12	+1,242	-1,194	-	+637	-	-46	-
2	MC5/GH2 SCR	+621	-709	-	+637	-	-46	-
3	MC5; Non-Ozone GH2	+621	-782[18]	-	+637	-	-46	-
4	MC5; Non-Ozone GH2; Ret BR3	+621	-1,194[19]	-	+637	-	-46	-
5	MC2/GH2 SCR	-	-	-	+637	-	-46	-
6	Non-Ozone MC2/GH2	-	-782[20]	-	+637	-	-46	-
7	Non-Ozone MC2/GH2; Ret BR3	-	-1,194[21]	-	+1,422	+143	-46	+400
8	All Renewables	-	-1,194	-	+1,972	+143	-46	+1,270
9	SCCT + Renewables	-	-1,194	+972	+1,522	-	-46	-
10	DSM Only	-	-1,194	-	-	-	+102	-

[15] Note that all portfolios effectively assume the full deployment of all non-dispatchable programs and measures in the 2024-2030 DSM-EE Program Plan because those effects are embedded in the 2022 Load Forecast.
[16] Values reflect expected load reductions under normal peak weather conditions.
[17] In Portfolio 7, battery storage consists of 300 MW of 2-hour duration batteries and 100 MW of 4-hour duration batteries. In Portfolio 8, all battery storage consists of 4-hour duration batteries.
[18] In Portfolio 3, MC2 is retired. GH2 is available only in the non-ozone season.
[19] In Portfolio 4, MC2 and BR3 are retired. GH2 is available only in the non-ozone season.
[20] In Portfolio 6, MC2 and GH2 are available only in the non-ozone season.
[21] In Portfolio 7, BR3 is retired. MC2 and GH2 are available only in the non-ozone season.

The reserve margins achieved by these portfolios are important to observe, which are shown in Table 12 below (note that "fully dispatchable resources" exclude intermittent and limited-duration resources):

Table 12: Stress Testing (Portfolios 1-10); 2028 Summer and Winter Reserve Margins

	Summer	Winter
Minimum Reserve Margin Target	17%	24%
Fully Dispatchable Reserve Margin		
Portfolio 1: MC5 & BR12	15.7%	25.1%
Portfolio 2: MC5/GH2 SCR	13.6%	22.6%
Portfolio 3: MC5; Non-Ozone GH2	12.4%	29.4%
Portfolio 4: MC5; Non-Ozone GH2; Retire BR3	5.9%	22.6%
Portfolio 5: MC2/GH2 SCR	15.0%	23.7%
Portfolio 6: Non-Ozone MC2/GH2	2.6%	23.7%
Portfolio 7: Non-Ozone MC2/GH2; Retire BR3	-3.9%	16.9%
Portfolio 8: All Renewables	-3.9%	4.1%
Portfolio 9: SCCT + Renewables	11.4%	21.0%
Portfolio 10: DSM Only	-3.9%	4.1%
Total Reserve Margin		
Portfolio 1: MC5 & BR12	30.1%	28.4%
Portfolio 2: MC5/GH2 SCR	28.0%	25.8%
Portfolio 3: MC5; Non-Ozone GH2	26.8%	32.6%
Portfolio 4: MC5; Non-Ozone GH2; Retire BR3	20.3%	25.8%
Portfolio 5: MC2/GH2 SCR	29.4%	27.0%
Portfolio 6: Non-Ozone MC2/GH2	17.0%	27.0%
Portfolio 7: Non-Ozone MC2/GH2; Retire BR3	27.1%	27.5%
Portfolio 8: All Renewables	47.7%	28.9%
Portfolio 9: SCCT + Renewables	36.9%	24.3%
Portfolio 10: DSM Only	4.9%	9.2%

Important observations concerning these results:

- **Dispatchable DSM from the 2024-2030 DSM-EE Program Plan is again uneconomical to meet minimum reserve margins.** PLEXOS again did not select any dispatchable DSM from the 2024-2030 DSM-EE Program Plan in any portfolio; rather, it retired existing dispatchable DSM in every portfolio it created as an uneconomical means of satisfying minimum reserve margins. To obtain dispatchable DSM in Portfolio 10, the Companies had to add it outside PLEXOS.

- **Some portfolios rely heavily on intermittent and limited-duration resources to meet reserve margins.** The non-ozone-operation portfolios and the renewables-only portfolio rely heavily on intermittent and limited-duration resources to meet summer reserve margins, and the renewables-only portfolio relies heavily on intermittent and limited-duration resources to meet *winter* reserve margins. Although these portfolios meet minimum reserve margin constraints in total, the differences in their fully dispatchable reserve margins indicate that the reliability of these portfolios is very different. As previously discussed, there is real risk to this approach, including solar execution risk and intermittency (cloud) risk.

- **Portfolio 10 (all DSM) did not meet any reserve margin requirement.** With no replacement resources other than the proposed 2024-2030 Program Plan's dispatchable DSM programs, Portfolio 10 does not meet any reserve margin requirement. The Companies' loss-of-load expectation with this portfolio increases to more than 130 days in ten years. Thus, Portfolio 10 did not advance to the next step of the Stage 2 analysis; if Mill Creek 2, Ghent 2, and Brown 3 are retired, the Companies must procure resources in addition to dispatchable DSM from the 2024-2030 DSM-EE Program Plan to reliably serve load. A further discussion of this portfolio is in Appendix C.

4.5.2 Stage Two, Step Two: CO_2 Pricing Analysis

Next, the Companies conducted detailed production cost modeling with PROSYM and developed revenue requirements for each of the nine portfolios that advanced from the first step of Stage 2. They performed PROSYM runs and developed revenue requirements for each portfolio across the six fuel price cases previously discussed and three CO_2 pricing cases ($0/MWh, $15/MWh, and $25/MWh) for a total of 18 cases analyzed per portfolio.

Table 13 below summarizes the differences in PVRR for Portfolios 1-9. Note that non-zero CO_2 prices begin in 2028 and that these results do not include all potential transmission system upgrade costs, which tends to favor Portfolios 3, 4, and 6 through 9.[22] As in Stage One, detailed production costs were modeled only for the renewables added in PLEXOS by 2028. For each fuel price scenario, the PVRR differences are presented as differences from the least-cost portfolio.

[22] To this point in the analysis, the Companies considered only transmission system upgrade costs associated with the fully dispatchable replacement resources (NGCCs and SCCTs at the Mill Creek and Brown stations). Due to the volume of RFP responses, it was not practical to evaluate transmission system upgrade costs for all proposals and potential retirements. Therefore, the evaluated transmission system upgrade costs for the other resources (e.g., solar, wind, and battery storage) was zero.

Table 13: Stress Testing Results (PVRR Difference from Best Case, $M, 2022 Dollars)

		Difference from Best Case (PVRR, $M, 2023-2050)								
		1	2	3	4	5	6	7	8	9
Fuel Price Scenario (Gas, CTG Price Ratio)	CO_2 Price	MC5 and BR12; 637 Solar	MC5 & GH2 SCR; 637 Solar	MC5; Non-Ozone GH2	MC5; Non-Ozone GH2; Ret BR3	MC2/ GH2 SCR	Non-Ozone MC2/ GH2	Non-Ozone MC2/ GH2 Ret BR3	All Renew	SCCT+ Renew
Low Gas, Mid CTG	0	0	96	561	117	604	697	1,019	2,375	1,568
Mid Gas, Mid CTG	0	0	64	540	126	583	728	844	2,096	1,580
High Gas, Mid CTG	0	0	91	499	218	571	844	428	1,521	1,712
Low Gas, High CTG	0	0	163	627	181	749	835	1,116	2,439	1,653
High Gas, Low CTG	0	77	0	372	166	265	599	216	1,301	1,620
High Gas, Curr CTG	0	0	1,390	1,885	1,376	3,459	3,481	2,379	2,958	3,212
Low Gas, Mid CTG	15	0	644	1,121	654	1,796	1,851	1,812	2,865	2,278
Mid Gas, Mid CTG	15	0	634	1,113	663	1,781	1,877	1,643	2,638	2,281
High Gas, Mid CTG	15	0	603	1,057	706	1,705	1,929	1,187	2,087	2,337
Low Gas, High CTG	15	0	714	1,188	720	1,940	1,987	1,920	2,927	2,361
High Gas, Low CTG	15	0	393	823	510	1,231	1,488	854	1,821	2,102
High Gas, Curr CTG	15	0	1,940	2,466	1,852	4,637	4,528	3,019	3,348	3,812
Low Gas, Mid CTG	25	0	1,009	1,511	997	2,591	2,609	2,291	3,154	2,703
Mid Gas, Mid CTG	25	0	996	1,493	1,010	2,569	2,651	2,117	2,980	2,736
High Gas, Mid CTG	25	0	979	1,447	1,056	2,488	2,678	1,696	2,433	2,800
Low Gas, High CTG	25	0	1,074	1,601	1,054	2,752	2,764	2,383	3,206	2,766
High Gas, Low CTG	25	0	755	1,202	856	2,012	2,239	1,367	2,189	2,553
High Gas, Curr CTG	25	0	2,269	2,834	2,131	5,385	5,237	3,437	3,544	4,124

Interestingly, the lowest-cost portfolio across 17 of 18 scenarios (Portfolio 1: Mill Creek NGCC, Brown NGCC, and 637 MW solar PPAs) is also the least CO_2-emitting, as shown in Table 14 below:

Table 14: 2030 CO_2 Emissions (Million Short Tons, Fuel Price Scenario: Mid Gas, Mid CTG Price Ratio)

		Total CO_2 Emissions	Difference from $0/MWh CO_2 Price Scenario	
Port Number	Portfolio Name	CO_2 Price: $0/MWh	CO_2 Price: $15/MWh	CO_2 Price: $25/MWh
1	MC5 & BR12; 637 Solar	22.8	-0.5	-0.5
2	MC5 & GH2 SCR; 637 Solar	25.4	-0.3	-0.3
3	MC5; Non-Ozone GH2	25.6	-0.3	-0.4
4	MC5; Non-Ozone GH2; Ret BR3	25.2	-0.3	-0.4
5	MC2/GH2 SCR	28.5	-0.2	-0.2
6	Non-Ozone MC2/GH2	28.1	-0.1	-0.2
7	Non-Ozone MC2/GH2; Ret BR3	25.9	-0.2	-0.2
8	All Renewables	24.3	-0.1	-0.1
9	SCCT + Renewables	25.1	-0.1	-0.1

These CO_2 emissions results tie directly to the energy mix each portfolio produces, as Table 15 below illustrates by comparing Portfolio 1 (Mill Creek NGCC, Brown NGCC, and 637 MW solar PPAs) to Portfolio 8 (all renewables):

Table 15: 2030 Energy Mix Comparison (Fuel Price Scenario: Mid Gas, Mid Coal-to-Gas Price Ratio)

	Portfolio 1: MC5 & BR12; 637 Solar			Portfolio 8: All Renewables		
Resource Type	\$0/MWh CO_2 Price	\$15/MWh CO_2 Price	\$25/MWh CO_2 Price	\$0/MWh CO_2 Price	\$15/MWh CO_2 Price	\$25/MWh CO_2 Price
Coal	50%	47%	47%	60%	59%	58%
NGCC	41%	42%	42%	15%	15%	15%
SCCT	2%	3%	4%	8%	10%	10%
Solar	6%	6%	6%	15%	15%	15%
Wind	0%	0%	0%	1%	1%	1%
Hydro	1%	1%	1%	1%	1%	1%

Important observations concerning these results:

- **The Stage One *apparently* optimal portfolio (Mill Creek NGCC, Brown NGCC, and 637 MW solar PPAs) is *clearly* optimal in non-zero CO_2 pricing scenarios.** This result is unsurprising; adding SCR to Ghent 2 allows a coal unit to continue operating, which is unfavorable in CO_2 pricing scenarios due to its higher CO_2 emissions per MWh.

- **The all-renewables replacement portfolio (Portfolio 8) is markedly more expensive than all other portfolios except the renewables plus SCCT portfolio (Portfolio 9), and then only with high gas price cases.** The cost of adding large amounts of renewables and batteries to serve load—under *normal* weather conditions—far exceeds the cost of paying even \$25/MWh in CO_2 costs for all other portfolios except the portfolio that adds only renewables and SCCT. Even that portfolio is less expensive than the all-renewables portfolio in all cases except high gas cost cases.

- **Increasing amounts of renewables require increasing dispatch of existing coal and SCCT generation, *increasing* CO_2 emissions relative to two NGCCs.** Table 14 shows that the inability of solar to provide energy in non-daylight hours, as well as its limited daylight production profile, requires more dispatch of coal and SCCT. This results in increased CO_2 emissions because coal and SCCT have higher CO_2 emissions per MWh than NGCC.

4.6 Stage Three: Fine-Tuning Optimal Portfolio for Risk and Reliability

In Stages One and Two, the Companies identified and confirmed the economically optimal portfolio that achieves Good Neighbor Plan compliance and satisfies minimum reserve margin requirements across a variety of fuel price and CO_2 price cases.

In Stage Three, the Companies sought to fine-tune the economically optimal portfolio to address certain risks not yet addressed and to add reliability to the extent it would be cost-effective or otherwise advisable to do so.

4.6.1 Stage Three, Step One: Mitigating Solar PPA Execution Risk through Solar Ownership

As previously discussed, one uncertainty associated with solar PPAs is execution risk, i.e., the risk that the contracted capacity is not built on time or at all. The modeling of Stages One and Two assumed the PPAs' capacity would be installed and operational as specified in the PPA proposal; it assumed zero solar PPA execution risk.

Other than the rights agreed to by the parties to the PPA, the Companies have no direct control over project development and construction. Project execution is a particularly acute risk in the current solar market, as the Companies have experienced with the two solar PPAs they executed in 2019 and 2021 (Rhudes Creek and Ragland, respectively); neither project has received all necessary approvals, neither is on schedule or has begun construction, and neither is likely to proceed any time soon because it will be difficult or impossible to finance the projects at the contracted price in today's solar market and interest rate environment. To help reduce the risk that future adverse changes in the solar market and interest rates negatively impact PPA project development, the Companies have negotiated a market price re-opener for the Grays Branch and Nacke Pike PPAs. This market price re-opener will also allow the Companies to request a lower price should the solar market and interest rates move lower.

One means of mitigating solar PPA execution risk would be to add solar capacity the Companies would be involved in developing and owning, either through acquisition or self-building. Ownership would allow the Companies and their customers to benefit from lower solar costs if the market changes favorably in the next several years when materials for the project would be purchased. This is especially important because the assumed costs for the owned solar projects are reflective of today's cost of materials, particularly solar panels.

Thus, this first step of Stage Three analyzes the economic impacts of adding a 120 MW self-build solar facility (originally Muhlenberg Solar, now Mercer County Solar Facility) and a 120 MW asset purchase facility (the BrightNight Frontier project, also called the Marion County Solar Facility) to a portfolio where Mill Creek 2, Ghent 2, and Brown 3 are replaced with two NGCC units and no solar PPAs, including the Rhudes Creek and Ragland PPAs. The portfolios the Companies analyzed are in Table 16 below. Portfolio 11 includes no solar PPAs. Portfolio 12 builds on Portfolio 11 as described in Table 16.

Table 16: Solar PPA Execution Risk (Portfolios 11-12); Solar Added (Nameplate MW)

Port Num	Portfolio Name	Description	Total Solar Added
11	MC5 & BR12; No Solar	Replace MC2 in 2027 w/ MC5 Replace BR3 & GH2 in 2028 with BR12 No Solar (i.e., No Rhudes Creek or Ragland PPAs)	-
12	Portfolio 11 +Asset Purchase +Self-Build	Portfolio 11 + 120 MW Solar Asset (Asset Purchase) + 120 MW Solar Asset (Self-Build)	+240

The Companies conducted PROSYM runs for the portfolios listed in Table 16 across all six fuel price cases and all three CO_2 price cases, then used the Companies' financial model to create revenue requirements for each portfolio in each run over three cases for the price of renewable energy certificates ("REC"), namely $0, $5, and $10 per REC. (Over the last three years, the Companies have sold Brown Solar RECs for between $8 and $13 per REC.) All proceeds from the sale of RECs are returned to customers. Table

17 below shows the results of adding the self-build and asset purchase resources to Portfolio 11 (with no solar). Negative values are highlighted in green and indicate that the solar self-build and asset purchase favorably impact PVRR, e.g., adding the solar self-build and asset purchase to Portfolio 11 in the High Gas, Mid CTG case with $0 CO_2 price decreases Portfolio 11's PVRR by $78 million.

Table 17: Solar PPA Execution Risk Analysis Results (PVRR Differences, $M, 2022 Dollars)

	Fuel Price Scenario (Gas, CTG Price Ratio)	CO_2 Price	Impact of Adding Self-Build and Asset Purchase to Portfolio 11 (w/ No Solar) (Portfolio 12 minus Portfolio 11) REC Price $0/MWh	$5/MWh	$10/MWh
Expected CTG	Low Gas, Mid CTG	0	165	129	93
	Mid Gas, Mid CTG	0	93	57	21
	High Gas, Mid CTG	0	-78	-114	-150
	Avg Low-High, Mid CTG	0	60	24	-12
Atypical CTG	Low Gas, High CTG	0	153	117	81
	High Gas, Low CTG	0	-62	-98	-134
	High Gas, Curr CTG	0	-221	-257	-293
	Avg Excl High Gas, Curr CTG	0	54	18	-18
Expected CTG	Low Gas, Mid CTG	15	53	17	-19
	Mid Gas, Mid CTG	15	-12	-48	-84
	High Gas, Mid CTG	15	-181	-217	-253
	Avg Low-High, Mid CTG	15	-47	-83	-119
Atypical CTG	Low Gas, High CTG	15	47	11	-25
	High Gas, Low CTG	15	-151	-187	-224
	High Gas, Curr CTG	15	-297	-333	-369
	Avg Excl High Gas, Curr CTG	15	-49	-85	-121
Expected CTG	Low Gas, Mid CTG	25	-6	-43	-79
	Mid Gas, Mid CTG	25	-82	-118	-154
	High Gas, Mid CTG	25	-258	-294	-330
	Avg Low-High, Mid CTG	25	-115	-151	-188
Atypical CTG	Low Gas, High CTG	25	-14	-50	-86
	High Gas, Low CTG	25	-224	-260	-296
	High Gas, Curr CTG	25	-360	-396	-432
	Avg Excl High Gas, Curr CTG	25	-117	-153	-189

<u>**Important observations concerning these results**</u>:

- **Adding the solar self-build and asset purchase is favorable in the majority of cases evaluated.** In the nine cases comprising expected fuel prices (i.e., low, mid, and high gas prices with a mid coal-to-gas price ratio) and $0 to $10 REC prices, adding the solar assets is favorable in 3 of 9 cases with a $0/MWh CO_2 price, 7 of 9 cases with a $15/MWh CO_2 price, and 9 of 9 cases with a $25/MWh CO_2 price.

- **The economics of the solar self-build improve with higher gas prices, higher REC prices, and higher CO_2 prices.** The PVRR improves by approximately $35 million for every $5 increase in REC prices. Compared to cases with no CO_2 price, the favorability of the solar assets improves by approximately $100 million with a $15 CO_2 price.

On the whole, based on the PVRR results and given the uncertainties concerning the solar industry, gas prices, and future carbon regulations (for which CO_2 prices are a proxy), the Companies concluded that adding the solar asset purchase proposal (Marion County Solar Facility) and their self-build solar project (Mercer County Solar Facility) to the optimal portfolio of the Mill Creek NGCC, Brown NGCC, and 637 MW of solar PPAs is a reasonable hedge against these market uncertainties in the transition to a lower carbon future.

4.6.2 Stage Three, Step Two: Increasing Reliability through DSM and Battery Storage

All stages and steps of the Companies' analysis to this point have concerned optimizing the portfolio to achieve Good Neighbor Plan compliance and to satisfy *minimum* reserve margin requirements. The result is an optimized portfolio consisting of the Companies' existing resources and the Mill Creek NGCC, Brown NGCC, 637 MW of solar PPAs, the least-cost solar asset purchase proposal (Marion County Solar Facility), and the Companies' self-build solar project (Mercer County Solar Facility).

In the second step of Stage Three, the Companies' goal was to optimally enhance reliability. To do this, the Companies evaluated SCCT, batteries, and dispatchable DSM programs as potential reliability-enhancing resources.

The SCCT and battery options the Companies evaluated were the SCCT and Brown BESS proposals provided as RFP responses by the Companies' Project Engineering group with input from HDR, an engineering consulting firm. The Companies chose the Brown BESS to evaluate over other battery options because battery ownership will allow the Companies to gain valuable operational experience with such systems at utility scale, which will likely be an integral part of integrating increasing amounts of renewable generation in future.

The dispatchable DSM programs the Companies considered are the Companies' existing dispatchable DSM programs (DSM-2, DSM-3 and 20 MW of DSM-5 in Table 5 below) and the proposed dispatchable DSM programs included in the Companies' 2024-2030 DSM-EE Program Plan. In total, the capacity of the DSM programs is 192 MW in the summer and 102 MW in the winter. Note that in this analysis, the Companies treated all dispatchable DSM as being 100% available when needed.

Table 18 below lists the reliability resources evaluated in this step.

Table 18: Resources Evaluated in Reliability Assessment

Response No.	Resource	2028 Capacity (Summer/Winter MW)	2028 Carrying Cost ($M)	Max Operating Hours per Start/Event
107	SCCT	243/258	18.5	N/A
96	Brown BESS	125/125	$\boxed{16.9}$	4
DSM-1	Peak Time Rebates	30.8/30.8	1.0	25 4-hour events per year
DSM-2	DLC – Water Heaters	1.9/1.9	1.2	25 4-hour events per year
DSM-3	DLC - AC	79.0/0		20 4-hour events per year
DSM-4	BYOD – Smart Thermostats	16.7/4.2	1.7	25 4-hour events per year
DSM-5	Nonres Demand Response	67.1/67.1	1.4	25 4-hour events per year

The Companies then determined that, given the solar execution risk previously discussed, they would evaluate the resources in Table 18 in one case as additions to the Mill Creek NGCC and Brown NGCC only and in a second case as additions to the Mill Creek NGCC and Brown NGCC with 1,102 MW of solar consisting of the four new PPAs totaling 637 MW, the Rhudes Creek and Ragland PPAs, and two owned assets (Marion County Solar Facility and the Mercer County Solar Facility). Table 19 lists all the portfolios evaluated.

Table 19: Portfolios Evaluated in Reliability Assessment

Portfolios with 2 NGCCs Only	Portfolios with 2 NGCCs & Solar
MC5 & BR12	MC5 & BR12; 1,102 MW Solar
MC5 & BR12 + SCCT	MC5 & BR12; 1,102 MW Solar + SCCT
MC5 & BR12 + DSM	MC5 & BR12; 1,102 MW Solar + DSM
MC5 & BR12 + BESS	MC5 & BR12; 1,102 MW Solar + BESS
MC5 & BR12 + DSM + BESS	MC5 & BR12; 1,102 MW Solar + DSM + BESS

The Companies then used SERVM to model the loss of load expectation ("LOLE") impact and average reliability and production costs of each portfolio listed in Table 19 over a range of load and unit availability scenarios. Note that the industry standard reliability goal is an LOLE of no more than one day in ten years.

Table 20 below summarizes the results of this analysis for the portfolios without solar; Table 21 below summarizes the results of this analysis for the portfolios with solar.[23] Capacity costs reflect the annual carrying cost of each resource (e.g., the annual carrying cost of the SCCT in 2028 is $18.5 million). Average reliability and generation production costs were computed over all load and unit availability scenarios. Total costs are the sum of capacity costs and average reliability and generation production costs.

Table 20: Reliability Assessment Results without Solar

	LOLE (10 Years)			Difference from MC5/BR12 Portfolio:		
Generation Portfolio	Summer	Winter	Total	Capacity Cost ($M/year)	Average Reliability and Generation Production Costs ($M/year)	Total Cost: Capacity Costs + Avg Reliability and Generation Production Costs ($M/year)
MC5/BR12	1.39	0.57	2.11	-	-	-
MC5/BR12 + SCCT	0.49	0.21	0.74	19	-4	15
MC5/BR12 + DSM	0.74	0.43	1.22	5	0	5
MC5/BR12 + BESS	0.81	0.37	1.26	17	-3	14
MC5/BR12 + DSM + BESS	0.44	0.31	0.77	22	-2	20

[23] The modeling the Companies performed in this Resource Assessment took solar to be a resource with a fixed production profile (i.e., for a given load scenario, the Companies evaluated over 300 unit availability scenarios for dispatchable resources, but the generation profile for solar was assumed to be unchanging).

Table 21: Reliability Assessment Results with 1,102 MW Solar

Generation Portfolio	LOLE (10 Years)			Difference from MC5/BR12 + Solar Portfolio:		
	Summer	Winter	Total	Capacity Cost ($M/year)	Average Reliability and Generation Production Costs ($M/year)	Total Cost: Capacity Costs + Avg Reliability and Generation Production Costs ($M/year)
MC5/BR12 + Solar	0.08	0.48	0.58	-	-	-
MC5/BR12 + Solar + SCCT	0.02	0.19	0.22	19	-3	16
MC5/BR12 + Solar + DSM	0.04	0.40	0.44	5	0	5
MC5/BR12 + Solar + BESS	0.05	0.34	0.39	17	-2	15
MC5/BR12 + Solar + DSM + BESS	0.03	0.25	0.28	22	-1	21

<u>Important observations concerning these results</u>:

- **Adding dispatchable DSM from the 2024-2030 DSM-EE Program Plan is the most cost-effective means of enhancing reliability in these portfolios.** Table 20 shows that with only the Mill Creek NGCC and Brown NGCC, the Companies' expected LOLE is 2.11 days in 10 years, which is higher than the physical reliability guideline of one day in 10 years. Adding an SCCT reduces LOLE 65% to 0.74, but at a cost of $15 million per year, whereas adding dispatchable DSM from the 2024-2030 DSM-EE Program Plan reduces LOLE 42% to 1.22, but at one-third of the cost of SCCT ($5 million per year). Table 21 shows similar results: SCCT provides a 62% LOLE reduction, but dispatchable DSM provides a 24% LOLE reduction, again at approximately one-third of the SCCT cost. Dispatchable DSM from the 2024-2030 DSM-EE Program Plan is therefore markedly more cost-effective than SCCT for enhancing the reliability of these portfolios.

- **Adding Brown BESS further enhances reliability, but its primary value is in providing operational experience for integrating future renewable generation.** Table 20 and Table 21 show that Brown BESS adds reliability in portfolios with and without solar. But based on its cost, it is not the most cost-effective means of enhancing reliability as modeled. Therefore, the primary benefit of Brown BESS would be to provide the Companies valuable operational experience with a technology at utility scale that will likely be vital to integrating large amounts of renewable generation reliably in the future.

It is notable that Brown BESS might provide quantifiable benefits the Companies have not attempted to quantify here. For example, battery energy storage systems can provide instantaneous load following and compensation for fluctuations in intermittent generation that might otherwise require rapid ramping from the Companies' SCCT and NGCC units, reducing wear (and related costs) on such units. The Brown BESS might also allow the Companies to carry lower amounts of spinning reserves, which could also provide savings. Table 22 summarizes the impact of the Brown BESS on PVRR.

Table 22: Impact of Brown BESS on PVRR ($M, 2022 dollars, $0/MWh CO_2 price)

	Fuel Price Scenario (Gas, CTG Price Ratio)	PVRR Impact
Expected CTG	Low Gas, Mid CTG	130
	Mid Gas, Mid CTG	127
	High Gas, Mid CTG	95
Atypical CTG	Low Gas, High CTG	130
	High Gas, Low CTG	78
	High Gas, Curr CTG	79

Based on this analysis and given the uncertainty facing the solar industry, the Companies believe it is appropriate to add to the optimal resource portfolio (1) the dispatchable DSM programs from the 2024-2030 DSM-EE Program Plan, which are a cost-effective means of improving reliability, and (2) the Brown BESS project.

4.6.3 Stage Three, Step Three: Analyzing OVEC Early Retirement Risk

In this final step of the Companies' analysis, they evaluated the impact of a possible early retirement of OVEC on the optimal resource portfolio of existing resources plus two NGCCs, 637 MW of solar PPAs, the least-cost solar asset purchase proposal (Marion County Solar Facility), the Companies' self-build solar project (Mercer County Solar Facility), dispatchable DSM from the Companies' 2024-2030 DSM-EE Program Plan, and the Brown BESS.

In particular, the Companies sought to determine if an early OVEC retirement had a reliability impact that would require adding any demand- or supply-side resources to the optimal portfolio.

Therefore, as a final scenario, the Companies used SERVM to evaluate the LOLE impact on the optimal resource portfolio (both with and without solar) if the OVEC units ceased operating in 2028 rather than 2040 as currently forecasted. Table 23 below contains the results of this analysis.

Table 23: Impact of 2028 OVEC Retirement on Optimal Resource Portfolio

Portfolio	LOLE (10 Years)		
	Summer (Jun, Jul, Aug)	Winter (Dec, Jan, Feb)	Total Year
MC5/BR12 + DSM + BESS	0.44	0.31	0.77
MC5/BR12 + DSM + BESS - OVEC	0.93	0.55	1.56
MC5/BR12 + Solar + DSM + BESS	0.03	0.25	0.28
MC5/BR12 + Solar + DSM + BESS - OVEC	0.06	0.46	0.52

These results show that the optimal resource portfolio would provide excellent reliability even if OVEC retired early. Therefore, there was no reason to adjust the optimal portfolio solely to address the possibility of early OVEC unit retirements.

5 Objective Met: A No-Regrets Resource Portfolio to Serve Customers' Needs

As discussed previously, the objective of this Resource Assessment is not to make every resource decision for the Companies and their customers for through 2050; rather, it is only to provide an optimal resource portfolio for the decisions that the Companies must make today due to the Good Neighbor Plan and the upcoming major capital investment at Brown 3. In other words, the objective is to provide an optimal resource portfolio for the resource decisions that must be made now concerning possible unit retirements in the 2026 to 2028 timeframe, and to do so in a way that ensures safe and reliable service at the lowest reasonable cost—ideally with a no-regrets resource portfolio.

Part of having no regrets is recognizing that, as the 2022 CPCN Load Forecast shows, customers will continue to have significant energy needs in all hours, seasons, and weather and daylight conditions. Thus, a no-regrets portfolio must be able to serve customers reliably 8,760 hours every year, not just for a handful of peak hours, not just when the sun is shining, and not just when customers are willing to voluntarily reduce their load in response to pricing signals.

The Companies' optimal resource portfolio is such a no-regrets portfolio. It economically retires three large coal units (1,194 MW total) that provide around-the-clock energy. It replaces those units with an optimal blend of resources offered in the Companies' competitive RFP process and cost-effective dispatchable DSM programs from the Companies' 2024-2030 DSM-EE Program Plan:

<u>The 2022 Resource Assessment's Optimal Resource Portfolio</u>

- Reliable, dispatchable, around-the-clock generation (1,242 MW total)
    - Mill Creek NGCC (621 MW)
    - Brown NGCC (621 MW)
- Clean renewable generation, hedging fuel price and CO_2 risk (877 MW total)
    - Mercer County Solar Facility (self-build; 120 MW)
    - Marion County Solar Facility (asset purchase; 120 MW)
    - Song Sparrow PPA (Clearway Energy; 104 MW)
    - Gage Solar PPA (BrightNight; 115 MW)
    - Nacke Pike PPA (ibV; 280 MW)
    - Grays Branch PPA (ibV; 138 MW)
- Cost-effective dispatchable DSM programs (192 MW summer; 102 MW winter)
- Additional reliability and valuable operational experience with Brown BESS (125 MW, 500 MWh)

The Companies' rigorous three-stage analysis ensured that the optimal portfolio appropriately balances economics, reliability, and risk; provides valuable experience with new technologies to accommodate greater renewable power generation in the future; and reduces CO_2 emissions considerably, more than other portfolios analyzed, which reduces future regulatory risk and potential cost related to CO_2 emissions. It is a no-regrets portfolio:

- **Low load or increased efficiencies, no regrets.** If actual load is materially lower than projected load for any reason, including if technological advances or economic changes result in additional energy and demand savings (through DSM-EE programs or otherwise), retiring additional aging coal capacity would likely be the most economical option, further reducing CO_2 emissions.

- **High load, no regrets.** If actual load is materially higher than projected load, nothing in the Companies' proposed portfolio precludes adding demand- or supply-side resources to address the need. If the increased load results from electric space heating or electric vehicle charging, the proposed NGCC units could prove to be particularly valuable given their ability to cost-effectively serve nighttime energy requirements.

- **Increased renewable generation or CO_2 constraints, no regrets.** The proposed portfolio's rapid-ramping NGCC units and Brown BESS well position the Companies to provide reliable service if renewable energy generation increases, and the lower CO_2 emissions of NGCCs and zero emissions of solar and DSM-EE all improve the Companies' positioning to address any CO_2 emissions pricing or regulations that might eventuate.

In sum, the optimal resource portfolio this Resource Assessment recommends will help ensure that customers receive safe, reliable, and lowest-reasonable-cost service for years to come.

6 Utility Ownership

6.1 Background

Since the merger of LG&E and KU, the Companies have commissioned thirteen jointly-owned units: ten SCCTs at the Trimble County, E.W. Brown, and Paddy's Run stations, the Trimble County 2 coal unit, Cane Run 7, and Brown Solar. An ownership ratio for the jointly-owned SCCTs was determined so that each utility's projected reserve margin was equalized in the in-service year. Brown Solar's ownership was assigned by allocating its forecasted generation in each hour based on each company's forecasted share of native load energy requirements for the hour. Because Trimble County 2 and Cane Run 7 were expected to provide significant energy savings to customers, their ownership splits were based on the expected energy benefits to each company. To determine these benefits, the production costs associated with the Companies' existing generation portfolio and least-cost expansion plan were compared to the production costs associated with the Companies' generation portfolio and an expansion plan that included only SCCTs. This "all-SCCT" expansion plan represented the least-cost expansion plan when only considering capacity needs. The overall least-cost plan included the proposed unit (either Trimble County 2 or Cane Run 7) and was expected to result in significant energy savings over the "all-SCCT" plan. Because each company was expected to benefit differently from constructing the proposed unit due to each company's unique load profile and existing generation mix, the ownership split for the proposed unit was determined based on each company's share of the net present value of production cost savings.

6.2 Methodology

6.2.1 Solar Resources

The new solar resources were assigned to each company using a method similar to the method used for Brown Solar. This assignment was calculated by allocating the solar resources' forecasted generation in each hour based on each company's forecasted share of native load energy requirements for the hour. Each company's proposed assignment equals its allocated share of the total solar energy generated during the study period.

6.2.2 Mill Creek and Brown NGCC units

Depending on natural gas price levels and future CO_2 regulations, the Mill Creek and Brown NGCC units are expected to operate at a 60-85% capacity factor, generating significant amounts of energy. For this reason, the Companies calculated their ownership so that each company's ownership share matches its share of the anticipated energy benefits compared to an all-SCCT portfolio. This method is similar to the method used for TC2 and CR7 (see Section 6.1) as well as for the Green River NGCC unit proposed by the Companies in Case No. 2014-0002, which was later canceled.[24]

6.2.3 Battery Storage (Brown BESS)

Battery storage is considered to be a capacity resource because it does not produce energy in all hours but rather stores energy for when it is needed most. Therefore, the Brown BESS's ownership was assigned using a method similar to the method used for the jointly-owned CTs by better balancing 2028 summer

[24] *In the Matter of: Joint Application of Louisville Gas and Electric Company and Kentucky Utilities Company for Certificates of Public Convenience and Necessity for the Construction of a Combined Cycle Combustion Turbine at the Green River Generating Station and a Solar Photovoltaic Facility at the E.W. Brown Generating Station*.

reserve margins based on dispatchable and battery capacity, after assigning the NGCC units' ownership allocation.

6.3 Optimal Ownership

The optimal ownership allocations are shown in Table 24. For the Mill Creek and Brown NGCC units, the optimal ownership allocation is 69% for KU and 31% for LG&E. For the solar projects, the optimal allocation is 63% for KU and 37% for LG&E. Both of these ownership allocations are also close to the allocation of total energy between the Companies. KU's share of total energy is approximately 64%; LG&E's share is 36%. The Brown BESS is assigned 100% to LG&E to better balance the Companies' summer reserve margins.

Table 24: Optimal Ownership Allocations

	KU	LG&E
Solar Resources • 4 PPAs • Mercer County (self-build) • Marion County (asset purchase)	63%	37%
NGCC Units • Mill Creek NGCC • Brown NGCC	69%	31%
Brown BESS	0%	100%

7 Appendix A – Summary of Inputs

7.1 Load Forecast

Table 25 contains the Companies' load forecast, which was developed with the assumption that weather will be average or "normal" in every year.[25] The Companies' 2022 CPCN Load Forecast is Exhibit TAJ-1 to the testimony of Tim A. Jones.

Table 25: Load Forecast (Normal Weather)

Year	Annual Energy Requirements (GWh)	Peak Demand (MW)			Year	Annual Energy Requirements (GWh)	Peak Demand (MW)	
		Summer	Winter				Summer	Winter
2023	31,919	6,162	5,910		2037	33,207	6,275	6,108
2024	32,221	6,197	5,908		2038	33,254	6,271	6,110
2025	32,788	6,248	6,011		2039	33,258	6,266	6,111
2026	32,841	6,253	6,003		2040	33,382	6,262	6,113
2027	33,560	6,347	6,107		2041	33,302	6,257	6,114
2028	33,592	6,319	6,104		2042	33,321	6,253	6,116
2029	33,423	6,308	6,103		2043	33,330	6,249	6,117
2030	33,303	6,305	6,102		2044	33,439	6,244	6,118
2031	33,254	6,302	6,100		2045	33,375	6,240	6,120
2032	33,303	6,298	6,101		2046	33,411	6,235	6,121
2033	33,184	6,293	6,103		2047	33,451	6,231	6,123
2034	33,151	6,289	6,104		2048	33,576	6,226	6,124
2035	33,160	6,284	6,106		2049	33,506	6,222	6,125
2036	33,284	6,280	6,107		2050	33,547	6,218	6,127

7.2 Minimum Reserve Margin Target

The Companies' minimum reserve margin targets are 17% for summer and 24% for winter. A summary of the analysis for the Companies' minimum reserve margin targets is contained in Appendix D.

7.3 Capacity and Energy Need

Table 26 and Table 27 contain the Companies' summer and winter peak demand and resource summaries through 2050. These tables reflect the planned retirement of Mill Creek 1 at the end of 2024 and the assumed retirement of the small-frame SCCTs in 2025. Mill Creek 1 and 2 cannot be operated simultaneously during the ozone season due to NO_x limits, which results in a reduction of available summer capacity through 2024. Reserve margins are computed for 2028 with and without the retirements of Mill Creek 2, Ghent 2, and Brown 3.

[25] The Companies use 20 years of historical weather data to develop their normal weather forecast.

Table 26: Summer Peak Demand and Resource Summary (MW)

	2023	2024	2025	2026	2027	2028	2030	2040	2050
Peak Load	**6,162**	**6,197**	**6,248**	**6,253**	**6,347**	**6,319**	**6,305**	**6,262**	**6,218**
Dispatchable Generation Resources									
Existing Resources	7,583	7,612	7,612	7,612	7,612	7,612	7,612	7,612	7,612
Retirements/Additions									
Coal[26]	-300	-300	-300	-300	-300	-300	-300	-452	-452
Large-Frame SCCTs	0	0	0	0	0	0	0	0	0
Small-Frame SCCTs[27]	0	0	-47	-47	-47	-47	-47	-47	-47
Total	7,283	7,312	7,265	7,265	7,265	7,265	7,265	7,113	7,113
Reserve Margin	18.2%	18.0%	16.3%	16.2%	14.5%	15.0%	15.2%	13.6%	14.4%
Intermittent/Limited-Duration Resources									
Existing Resources	105	105	105	105	105	105	105	105	105
Existing CSR	128	128	128	128	128	128	128	128	128
Existing Disp. DSM[28]	62	60	56	52	49	46	42	28	24
Retirements/Additions									
Solar PPAs[29]	0	79	177	177	177	177	177	177	177
Total	294	371	466	462	459	456	451	438	434
Total Supply	**7,577**	**7,683**	**7,730**	**7,727**	**7,724**	**7,721**	**7,716**	**7,551**	**7,547**
Total Reserve Margin	**23.0%**	**24.0%**	**23.7%**	**23.6%**	**21.7%**	**22.2%**	**22.4%**	**20.6%**	**21.4%**
Dispatchable Generation Resources with Additional Coal Retirements									
Existing Resources	7,583	7,612	7,612	7,612	7,612	7,612	7,612	7,612	7,612
Retirements/Additions									
Coal[26,30]	-300	-300	-300	-300	-300	-1,494	-1,494	-1,646	-1,646
Large-Frame SCCTs	0	0	0	0	0	0	0	0	0
Small-Frame SCCTs	0	0	-47	-47	-47	-47	-47	-47	-47
Total	7,283	7,312	7,265	7,265	7,265	6,071	6,071	5,919	5,919
Reserve Margin	18.2%	18.0%	16.3%	16.2%	14.5%	-3.9%	-3.7%	-5.5%	-4.8%
Total Supply	**7,577**	**7,683**	**7,730**	**7,727**	**7,724**	**6,527**	**6,522**	**6,357**	**6,353**
Total Reserve Margin	**23.0%**	**24.0%**	**23.7%**	**23.6%**	**21.7%**	**3.3%**	**3.4%**	**1.5%**	**2.2%**

[26] Mill Creek 1 and 2 cannot be operated simultaneously during ozone season due to NO_x limits, which results in a reduction of available summer capacity through 2024. Mill Creek 1 will be retired by the end of 2024. OVEC's contract term ends in 2040.
[27] This analysis assumes Haefling 1-2 and Paddy's Run 12 are retired in 2025.
[28] Existing Dispatchable DSM reflects expected load reductions under normal peak weather conditions.
[29] This analysis assumes 100 MW of solar capacity is added in 2024 (Rhudes Creek), and an additional 125 MW of solar capacity is added in 2025 (Ragland). Capacity values reflect 78.6% expected contribution to summer peak capacity.
[30] Potential additional coal retirements include Mill Creek 2, Ghent 2, and Brown 3 in 2028.

Table 27: Winter Peak Demand and Resource Summary (MW)

	2023	2024	2025	2026	2027	2028	2030	2040	2050
Peak Load	**5,910**	**5,908**	**6,011**	**6,003**	**6,107**	**6,104**	**6,102**	**6,113**	**6,127**
Dispatchable Generation Resources									
Existing Resources	7,901	7,909	7,909	7,909	7,909	7,909	7,909	7,909	7,909
Retirements/Additions									
Coal[26]	-300	-300	-300	-300	-300	-300	-300	-458	-458
Large-Frame SCCTs	0	0	0	0	0	0	0	0	0
Small-Frame SCCTs[27]	0	0	-55	-55	-55	-55	-55	-55	-55
Total	7,601	7,609	7,554	7,554	7,554	7,554	7,554	7,396	7,396
Reserve Margin	28.6%	28.8%	25.7%	25.8%	23.7%	23.7%	23.8%	21.0%	20.7%
Intermittent/Limited-Duration Resources									
Existing Resources	72	72	72	72	72	72	72	72	72
Existing CSR	128	128	128	128	128	128	128	128	128
Existing Disp. DSM[28]	22	22	22	22	22	22	22	22	22
Retirements/Additions									
Solar PPAs[31]	0	0	0	0	0	0	0	0	0
Total	221	221	221	221	221	221	221	221	221
Total Supply	**7,822**	**7,830**	**7,774**	**7,774**	**7,774**	**7,774**	**7,774**	**7,616**	**7,616**
Total Reserve Margin	**32.3%**	**32.5%**	**29.3%**	**29.5%**	**27.3%**	**27.4%**	**27.4%**	**24.6%**	**24.3%**
Dispatchable Generation Resources with Additional Coal Retirements									
Existing Resources	7,901	7,909	7,909	7,909	7,909	7,909	7,909	7,909	7,909
Retirements/Additions									
Coal[26,30]	-300	-300	-300	-300	-300	-1,499	-1,499	-1,657	-1,657
Large-Frame SCCTs	0	0	0	0	0	0	0	0	0
Small-Frame SCCTs[27]	0	0	-55	-55	-55	-55	-55	-55	-55
Total	7,601	7,609	7,554	7,554	7,554	6,355	6,355	6,197	6,197
Reserve Margin	28.6%	28.8%	25.7%	25.8%	23.7%	4.1%	4.1%	1.4%	1.1%
Total Supply	**7,822**	**7,830**	**7,774**	**7,774**	**7,774**	**6,575**	**6,575**	**6,417**	**6,417**
Total Reserve Margin	**32.3%**	**32.5%**	**29.3%**	**29.5%**	**27.3%**	**7.7%**	**7.8%**	**5.0%**	**4.7%**

Table 28 summarizes generation from Mill Creek 2, Ghent 2, and Brown 3 over the last 5 years. In addition to approximately 1,200 MW of dispatchable capacity, these units provided 15-18% of total energy requirements (4.5 to 6.2 TWh) from 2017 to 2021.[32] Slightly more than half of this energy was produced at night which is consistent with the proportion of total electricity consumed by customers at night. On average, these units produce between 700 and 850 MW in every hour of the year. Even if Mill Creek 2,

[31] This analysis assumes 100 MW of solar capacity is added in 2024, and an additional 125 MW of solar capacity is added in 2025. Capacity values reflect 0% expected contribution to winter peak capacity.

[32] The decrease in energy production from 2019 to 2020 (and continuing into 2021) is due to a reduction in generation at the Mill Creek station during the ozone season as a result of an agreement with the Louisville Metro Air Pollution Control District. The generation reduction could be accomplished by either idling Unit 1 or Unit 2. In practice, Unit 2 was often idled. Unit 1 will be retired by the end of 2024, so Unit 2 will be required to run more than was the case in 2020 and 2021.

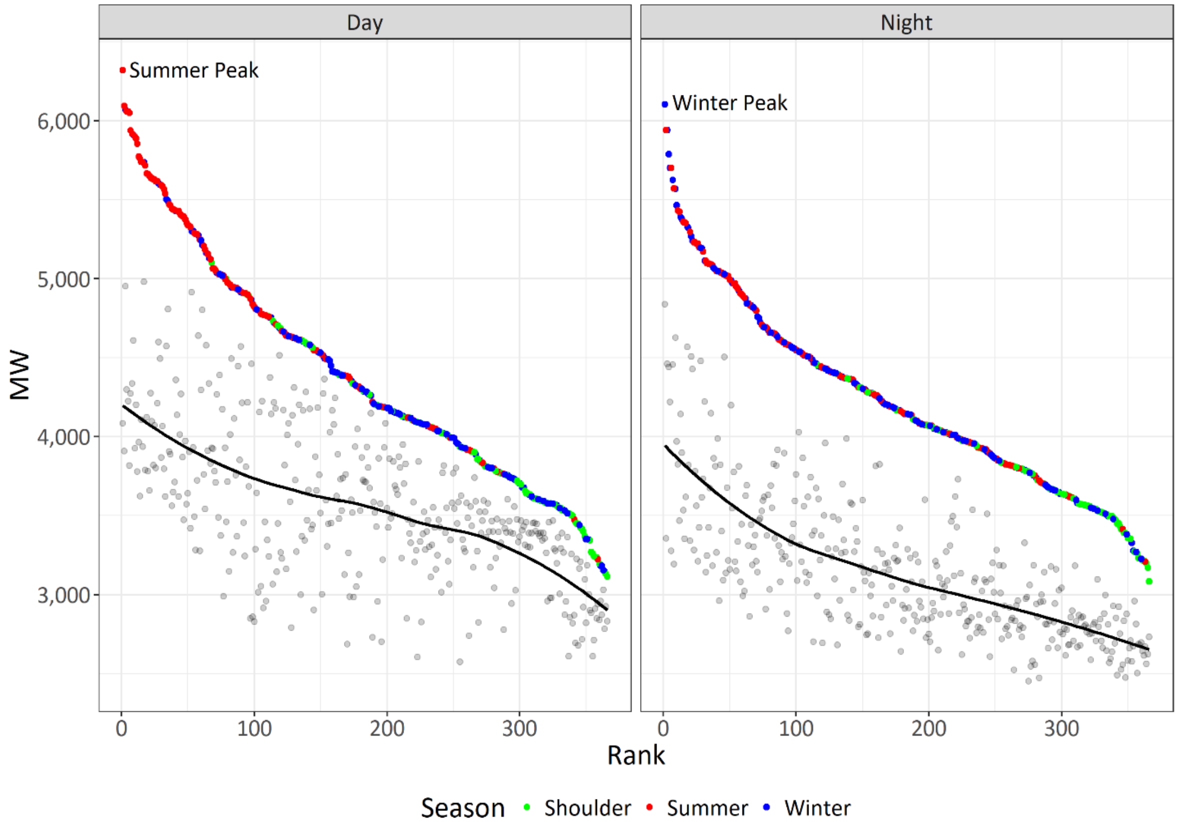
Ghent 2, and Brown 3 are not retired, the Companies' need for energy in 2028 will be exacerbated by the retirement of Mill Creek 1 and the addition of the BlueOval load.

Table 28: Mill Creek 2, Ghent 2, and Brown 3 Generation

Year	Total Energy (GWh)	% Night	% Day	Max Hourly Output (MW)	Average Hourly Output (MW)	% of Total Energy Requirements
2017	5,698	52%	48%	1,235	772	17%
2018	6,230	51%	49%	1,238	842	18%
2019	5,407	51%	49%	1,250	785	16%
2020	4,512	52%	48%	1,229	729	15%
2021	4,610	51%	49%	1,219	752	15%

Figure 8 shows the forecasted daily maximum and minimum loads during daytime and nighttime hours in 2028 under normal weather conditions. For each daytime and nighttime period, the daily maximum loads are sorted highest to lowest and are differentiated by season; the black lines are trend lines for the corresponding minimum daily loads. Notably, the generation capacity and load following capabilities needed to serve daytime and nighttime energy requirements are very similar. Under normal weather conditions, the forecasted winter peak demand (6,104 MW) occurs at night and is almost as high as the forecasted summer peak demand (6,319 MW), which occurs during the day. Importantly, the Companies' load is at least 2,450 MW in every hour of the year.

Figure 8: 2028 Daily Maximum and Minimum Loads during Daytime and Nighttime Hours[33]

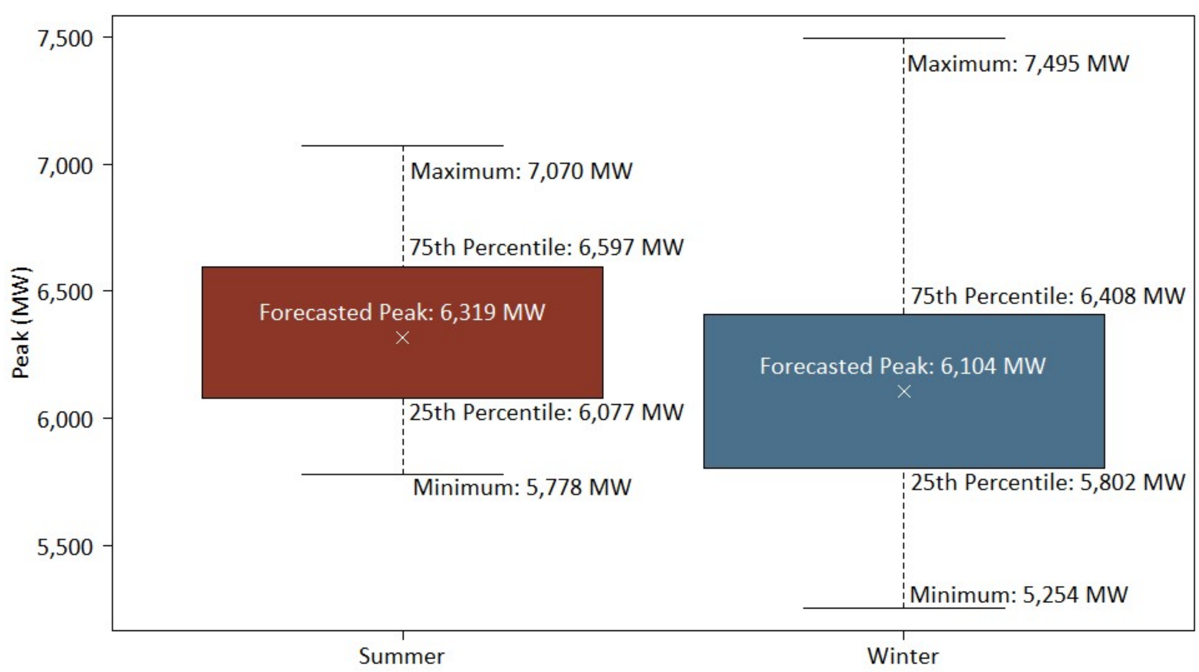


Whereas Figure 8 shows the variability in load throughout the year under normal weather conditions, Figure 9 shows the variability in summer and winter peak demands based on the range of weather that can occur in the Companies' service territories.[34] Under normal weather conditions, the Companies' summer peak demand is higher than the winter peak demand but the variability in peak demand is highest in the winter. This variability is driven in part by electric space heating demands when backup resistance heating is triggered under extremely cold weather conditions. The Companies plan generation to reliably serve customers in all hours of the year and in all weather scenarios.

[33] Data points in color represent daily maximum values; those in light grey represent daily minimums. The solid black line is a smoothed curve fit through the daily minimums.

[34] To assess generation portfolio reliability over a wide range of weather scenarios, the Companies develop hourly load forecasts based on weather in each of the last 49 years. The distributions in Figure 9 are based on the summer and winter peak demands from these forecasts.

Figure 9: Distribution of 2028 Summer and Winter Peak Demands



7.4 Existing Resource Inputs

Table 29 lists the Companies' forecasted existing generating resources as of 1/1/2025. Consistent with Table 26 and Table 27, resources that are fully dispatchable are listed separately from intermittent resources and resources that can be dispatched for only several hours at a time. The Companies' coal, NGCC, and SCCT resources are fully dispatchable. For example, while SCCTs typically operate less than 24 hours each time they are started due to their higher fuel costs, they can operate for longer periods if necessary. The Companies' solar and Ohio Falls hydro resources are intermittent. For example, the ability to generate power at the Ohio Falls station is entirely a function of water availability, which is managed by the Corps of Engineers. Finally, the Companies' dispatchable DSM and Curtailable Service Rider ("CSR") resources can be dispatched when needed but only for limited durations. The operating characteristics of supply-side and demand-side resources are an important consideration in resource planning.

Table 29: 2025 LG&E/KU Generating & DSM Portfolio[35]

Dispatchability	Resource Type	Resource Name	Net Max Summer Capacity (MW)	Net Max Winter Capacity (MW)
Fully Dispatchable[36]	Coal[37]	Brown 3	412	416
		Ghent 1	475	479
		Ghent 2	485	486
		Ghent 3	481	476
		Ghent 4	478	478
		Mill Creek 2	297	297
		Mill Creek 3	391	394
		Mill Creek 4	477	486
		Trimble County 1 (75%)	370	370
		Trimble County 2 (75%)	549	570
	Coal PPA	OVEC	152	158
	NGCC	Cane Run 7	691	691
	SCCT	Brown 5	130	130
		Brown 6	146	171
		Brown 7	146	171
		Brown 8	121	128
		Brown 9	121	138
		Brown 10	121	138
		Brown 11	121	128
		Paddy's Run 13	147	175
		Trimble County 5	159	179
		Trimble County 6	159	179
		Trimble County 7	159	179
		Trimble County 8	159	179
		Trimble County 9	159	179
		Trimble County 10	159	179
Intermittent/ Limited-Duration	Hydro	Dix Dam 1-3	31.5	31.5
		Ohio Falls 1-8	64	40
	Interruptible	CSR	128	128
	Dispatchable DSM	DCP[38]	56	22
	Solar	Brown Solar	8	0
		Business Solar	0.18	0
		Solar Share	1.7	0
		Rhudes Creek Solar PPA[39]	79	0
		Ragland Solar PPA[39]	98	0

[35] The Resource Assessment assumes Mill Creek 1, Haefling 1-2, and Paddy's Run 12 are retired in 2025.

[36] The Companies' simple-cycle combustion turbines at Brown and Paddy's Run have annual operating limits based on their emissions permits but are fully available to serve load for long stretches of time such as a weeklong period of extremely cold weather.

[37] Except Mill Creek 2 and Ghent 2, all of the Companies' coal units are equipped with SCR, flue gas desulfurization ("FGD"), and baghouses.

[38] Residential and Nonresidential Demand Conservation Program ("DCP"). Capacity values reflect expected load reductions under normal peak weather conditions.

As seen in Table 30, Mill Creek 2, Ghent 2, and Brown 3 are approximately 50 years old and approaching the end of their current book depreciation life. Although the units could theoretically operate beyond their depreciable book life, doing so would require a higher level of capital investments. To properly evaluate the economics of the existing fleet, the Companies identified the types of projects and associated costs that would be needed to extend the lives of units beyond their current depreciable book lives to 2050. To be clear, the Companies are not proposing to extend these units' lives; rather, this analytical approach is necessary to properly evaluate the fleet's economics.

Table 30: Age of Mill Creek 2, Ghent 2, and Brown 3

Unit	Age as of 1/1/2022	Age as of 1/1/2035	Age as of 1/1/2050	End of Book Depreciation Life
Mill Creek 2	47	60	75	2034
Ghent 2	44	57	72	2034
Brown 3	50	63	78	2035

Table 31 contains stay-open costs for Mill Creek 2, Ghent 2, and Brown 3. Stay-open costs for existing generating units include each unit's ongoing capital and fixed operating and maintenance ("O&M") costs. These costs are required to continue operating a unit and are avoided if a unit is retired. Costs that are shared by all units at a station (i.e., "common" costs) are allocated to units in proportion to how they would be reduced as units retire.[40] Stay-open costs include costs for routine maintenance and major overhauls, and do not include carrying costs for prior investments or costs for projects that would not be affected by unit retirements in this analysis, such as ash pond closures. In the case of Mill Creek 2 and Ghent 2, stay-open costs include the costs of SCR for Good Neighbor Plan Compliance. Finally, Table 31 differentiates between "standard" major overhaul costs and the costs for projects that would be needed to operate the unit through 2050.[41] When evaluating the retirement of these coal units, the Companies assume that costs for routine maintenance and major overhauls will be reduced in the years leading up to a unit's retirement and that all future spending would be avoided after a unit's retirement.

[39] The Rhudes Creek and Ragland solar projects have not received all of their necessary permits and are not yet under construction. Given current market conditions and interest rates, it is not clear whether these projects can be financed at the prices in their respective contracts.

[40] The allocation of common costs requires an assumed order of retirement at a given station. The lack of SCRs for Ghent 2 and Mill Creek 2 results in those units being retired first relative to other units at their respective stations. The remaining units have the same controls and similar efficiencies (with the exception of Trimble County 2, which is a supercritical unit and the most efficient in the Companies' coal fleet), so the likely retirement order would be driven by age of the units. At Ghent, this results in a retirement order of Ghent 2 first, followed by Ghent 1, then Ghent 3, and finally Ghent 4. At Mill Creek, this results in a retirement order of Mill Creek 2 first, followed by Mill Creek 3, and finally Mill Creek 4. At Trimble, this results in a retirement order of Trimble County 1 first, followed by Trimble County 2.

[41] Examples of projects that would be needed to extend the life of a generating unit are replacement of major high temperature components such as superheater and reheater headers and seamed main steam and hot reheat piping, condenser re-tubing, generator stator rewinds, generator step-up transformer replacements, and ID fan variable frequency drive replacements.

Table 31: Total Stay-Open Costs ($M)

Year	Mill Creek 2				Ghent 2				Brown 3		
	Ongoing Costs	Overhaul Costs (Standard)	Overhaul Costs (Life Extension)	Environmental Compliance Costs (SCR)	Ongoing Costs	Overhaul Costs (Standard)	Overhaul Costs (Life Extension)	Environmental Compliance Costs (SCR)	Ongoing Costs	Overhaul Costs (Standard)	Overhaul Costs (Life Extension)
2023	11	0	0	2	12	0	0	3	27	0	0
2024	21	0	0	16	23	0	0	30	30	0	0
2025	15	0	0	47	12	0	0	76	31	0	0
2026	18	11	0	45	22	0	0	18	35	0	0
2027	14	0	0	1	17	36	0	1	32	26	0
2028	18	0	0	1	13	0	0	1	32	0	0
2029	14	0	37	1	14	0	0	1	35	0	32
2030	21	0	23	1	25	0	0	1	36	0	38
2031	17	0	22	1	19	0	0	1	36	0	22
2032	21	0	0	1	19	0	0	1	38	0	0
2033	17	0	2	1	20	0	25	1	38	0	2
2034	22	16	18	1	20	0	42	1	40	0	0
2035	18	0	0	1	21	24	23	1	40	30	0
2036	22	0	0	1	21	0	42	1	41	0	0
2037	19	0	0	1	22	0	8	1	42	0	0
2038	25	0	0	2	22	0	0	2	43	0	14
2039	20	0	0	2	22	0	14	2	44	0	0
2040	24	0	0	2	23	0	0	2	45	0	0
2041	21	0	15	2	23	0	0	2	46	0	0
2042	25	19	0	2	24	0	0	2	48	0	11
2043	21	0	0	2	24	28	0	2	48	35	0
2044	27	0	0	2	25	0	0	2	50	0	0
2045	22	0	12	2	26	0	0	2	50	0	0
2046	30	0	0	2	26	0	0	2	52	0	0
2047	23	0	0	2	27	0	0	2	52	0	0
2048	29	0	0	2	27	0	0	2	55	0	0
2049	24	0	0	2	28	0	0	2	55	0	0
2050	25	23	0	2	30	0	0	2	57	0	0

7.4.1 CCR Revenue Assumptions

Coal combustion residuals ("CCR") include fly ash, bottom ash, and gypsum. CCR is either used for onsite construction projects, sold to third parties for use in the production of products like cement and wallboard, or stored in onsite landfills. When sold to third parties, the beneficial use of CCR materials is included in the Environmental Surcharge Mechanism as a credit to offset environmental compliance costs. In 2021, CCR sales revenues totaled over $15 million.

In recent years, as coal units have retired in the U.S., the market supply of CCR has decreased and the market price for CCR has increased. Table 32 lists the assumed sales prices for CCR in this analysis.[42] The 2022 values are weighted average prices based on existing contracts. CCR sales prices are expected to approach market prices as existing contracts expire. Market prices vary by station based on the station's proximity to local markets and are assumed to escalate at two percent per year.

Table 32: Sales Prices for CCR Sales ($/ton)

	Mill Creek			Ghent		Trimble	
Year	Fly Ash	Gypsum	Bottom Ash	Fly Ash	Gypsum	Fly Ash	Gypsum
2022	[redacted]						
2023							
2024							
2025							
2026							
2027							
2028							
2029							
2030							
2031							
2032							
2033							
2034							
2035							
2036							
2037							
2038							
2039							
2040							
2041							
2042							
2043							
2044							
2045							
2046							
2047							
2048							
2049							
2050							

Table 33 lists the percent of CCR produced at each station that is assumed to be sold to third parties. For Mill Creek, the values reflect current sales levels. For Ghent and Trimble County, the values are the assumed level of sales that will commence after current on-site pond closure projects are completed.[43] The Ghent station requires additional loading facilities to increase its fly ash sales after pond closure

[42] No sales prices for any CCR at Brown or for bottom ash at Ghent and Trimble are included because there is currently no market for these materials at these stations.
[43] Based on current progress of the active closure projects, completion is anticipated no later than December 2025.

projects are completed. The Companies continue to evaluate alternatives for doing this, but no costs or revenue impacts associated with these facilities are considered in this analysis.

Table 33: Percent of CCR Production Sold to Third Parties

Station	Fly Ash	Gypsum	Bottom Ash
Mill Creek	80%	97%	100%
Ghent	6%	70%	0%
Trimble County	80%	97%	0%
Brown	0%	0%	0%

7.5 Inflation Reduction Act Tax Incentives

As noted earlier, after the RFP proposals were received in August 2022, the Companies followed up with the respondents to ensure their proposals fully reflected the investment tax credits for renewables and battery storage in the Inflation Reduction Act. For PPAs, the impact of the IRA incentives is reflected in the PPA price. Table 34 summarizes the assumed tax incentives for solar and battery storage proposals that would require the Companies to own the assets. The solar projects that would require the Companies' ownership are expected to meet the IRA's prevailing wage and apprenticeship requirements. Additional incentives are available if construction materials (e.g., solar panels) are purchased from U.S. vendors or if the project is constructed on a coal mine or the site of a previously retired coal plant, but the proposed solar projects do not meet these requirements. The battery storage projects, on the other hand, do meet these requirements and are assumed to receive the maximum investment tax credit afforded by the IRA (50%).

Table 34: IRA Tax Incentives

	Production Tax Credit		
Resource Type	$/MWh	Term	Investment Tax Credit
Solar	27.50	10	N/A
Battery Storage	N/A	N/A	50%

7.6 Transmission System Upgrade Costs

In their analysis of the Mill Creek 2, Ghent 2, and Brown 3 retirements, the Companies are evaluating the addition of new generation at the Mill Creek and E.W. Brown generating stations. In a scenario where all three coal units are retired and new generation is added at both sites, the Companies would first add generation at Mill Creek (Mill Creek NGCC) in part to take advantage of existing emission permitting. Then, to serve customers reliably, Brown 3 would continue to operate until new generation at the Brown site is commissioned (Brown NGCC). In a scenario where Mill Creek 2 and Brown 3 are retired and SCR is added to Ghent 2, the Companies would still plan to add Mill Creek NGCC first. Then, to serve customers reliably, Brown 3 would continue to operate until SCR was added at Ghent 2. Because Brown 3 is needed in either case to maintain system reliability, new generation is always added first at the Mill Creek station.

The Companies have submitted Generator Interconnection Requests for the proposed self-build NGCC replacements in accordance with the LG&E/KU Open Access Transmission Tariff ("OATT"). Per the terms of the OATT, the Companies' Independent Transmission Organization ("ITO"), TranServ International, will perform studies to determine the proposed generators' impact to the transmission system. However, these studies are complex and time-consuming, and more importantly, cannot begin until all earlier queued Generator Interconnection Requests have been studied. Therefore, the results of the ITO's studies are not yet available.

Thus, for this Resource Assessment the Companies estimated costs for the identified transmission system upgrades that could be required to accommodate selected combinations of unit retirements and capacity replacements. Due to the volume of RFP responses, it was not practical to evaluate all proposals and potential retirements. The Companies initially developed least-cost resource plans considering transmission system upgrade costs for potential coal unit retirements and capacity replacements. Table 35 contains the transmission system upgrade cost estimates considered in this analysis.[44]

Table 35: Transmission System Upgrade Costs ($)[45]

Scenario	Cost (2022 Dollars)
Retirements: Mill Creek 1-2, Brown 3 Additions: SCCTs at Mill Creek	46,034,824
Retirements: Mill Creek 1-2, Brown 3 Additions: NGCC at Mill Creek	35,035,000
Retirements: Mill Creek 1-2, Brown 3, Ghent 2 Additions: NGCC or SCCTs at Mill Creek and Brown	3,420,000

7.7 Commodity Prices

7.7.1 Coal and Natural Gas Prices

Coal and natural gas prices are an important input to this analysis as the level of coal and natural gas prices impacts the economics of renewables and the relationship between coal and natural gas prices impacts the economics of installing SCR on a coal unit versus replacing the unit with natural gas-fired generation. The fuel price scenarios for this analysis were developed over a range of low, mid, and high natural gas prices based on recent market quotes and the Energy Information Administration's 2022 Annual Energy Outlook ("EIA's 2022 AEO") (see Figure 10). Appendix E contains a more detailed discussion of the natural gas price forecasts and demonstrates that these forecasts are consistent with forecasts prepared by industry consultants.

[44] Due to the uncertainties involved in estimates of solar projects' transmission costs, the Companies have not included these costs in their analysis.

[45] Consistent with the Companies' prior filings, the study assumed the retirements of Mill Creek 2 and Brown 3 and considered the potential for Ghent 2's retirement. Replacement capacity was assumed to be either NGCC or sets of three SCCT units, with generic individual summer net capacities of 645 MW and 220 MW, respectively, consistent with the Companies' 2021 IRP.

Figure 10: Natural Gas Price Forecasts (Henry Hub; Nominal $/MMBtu)

[redacted]

The majority of the Companies' coal supply is sourced from the Illinois Basin. The Companies developed Illinois Basin coal prices for the 2022 AEO natural gas prices based on the historical ratio of Illinois Basin coal and Henry Hub natural gas prices ("coal-to-gas price ratio" or "CTG price ratio") using publicly available historical price data. Figure 11 shows Illinois Basin coal prices and Henry Hub natural gas prices as well as the coal-to-gas price ratio since 2012. Coal and gas prices generally move together, but coal markets are slower to respond to changing market fundamentals than gas. As a result, periods of increasing gas prices are generally associated with lower coal-to-gas price ratios, and periods of decreasing gas prices are generally associated with higher coal-to-gas price ratios. In addition, the coal-to-gas price ratio is mean reverting (i.e., after hitting a high or low point, it reverts back toward the mean) and does not remain at high or low levels for long periods of time. In 2022, U.S. coal supply became tightly balanced with demand as export demand from Europe remained elevated due to reduction in the supply of Russian coal and gas. This resulted in the highest coal-to-gas ratio since before 2012, but this ratio is not expected to persist through 2050.

Figure 11: Illinois Basin Coal and Henry Hub Gas Prices (2012-2022)

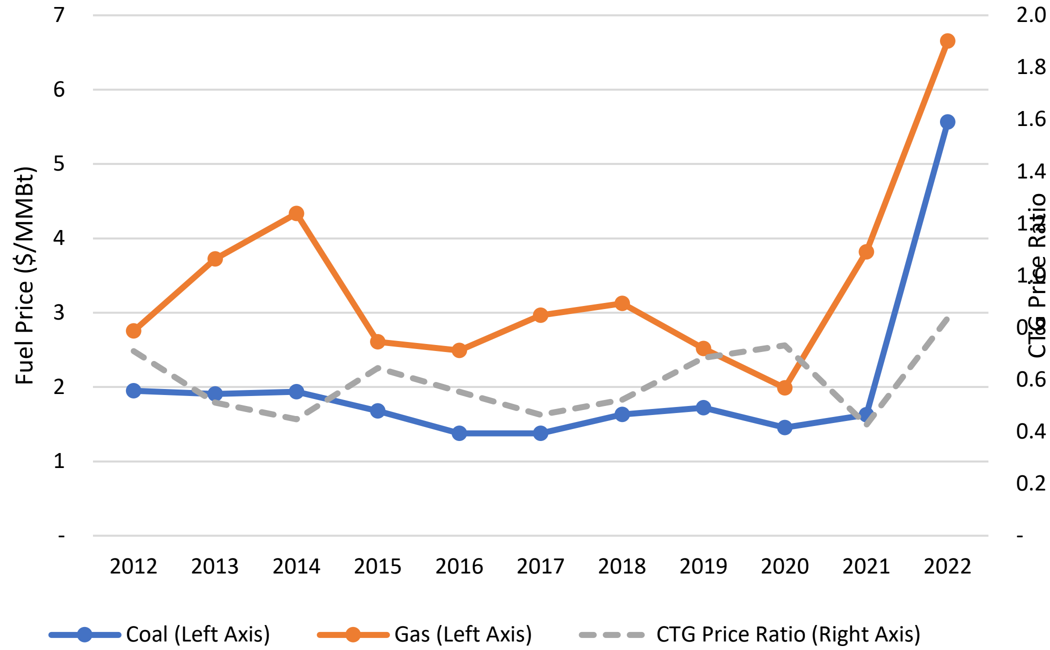


Table 36 summarizes the coal-to-gas price ratio in tabular form. Over the ten-year period from 2012 to 2021, the average coal-to-gas price ratio was 0.57. At this coal-to-gas price ratio, the cost of coal and NGCC energy is very similar, regardless of the level of gas prices. Furthermore, this average coal-to-gas price ratio is not surprising as coal and NGCC energy are economic substitutes, and a coal-to-gas price ratio of 0.57 approximates the ratio of NGCC and coal operating costs. Over a long analysis period, despite changing natural gas prices, the average coal-to-gas price ratio is expected to continue at this level. In addition to the 10-year average coal-to-gas price ratio, Table 36 contains the 6-year average ratios. These 6-year averages were used to evaluate short-term variations in the coal-to-gas price ratio.[46]

Table 36: Illinois Basis Coal to Henry Hub Natural Gas Price Ratio ("CTG Price Ratio")

Year	CTG Price Ratio	10-Year Average	6-Year Average
2012	0.71		
2013	0.51		
2014	0.45		
2015	0.64		
2016	0.55		
2017	0.46		0.55 (2012-2017)
2018	0.52		0.52 (2013-2018)
2019	0.68		0.55 (2014-2019)
2020	0.73		0.60 (2015-2020)
2021	0.43	0.57 (2012-2021)	0.56 (2016-2021)
2022	0.84		

[46] The Companies considered periods of five and six years to evaluate short-term variations in the average coal-to-gas ratio but a period of six years provides a wider range of ratios.

Table 37 summarizes the six fuel price scenarios considered in this analysis. For the first three fuel price scenarios (the "Mid" coal-to-gas price ratios), coal prices were forecasted beyond 2027 with the assumption that the coal-to-gas ratio would continue, on average, to approximate the average coal-to-gas price ratio from 2012 to 2021 (0.57). Again, note that the Mid coal-to-gas price ratio (0.57) approximates the ratio of NGCC and coal operating costs. Therefore, it is plausible to expect coal-to-gas price ratios to revert to this ratio over the long term, which is why the Companies refer to it as the "Expected CTG Price Ratio."

The last three fuel price scenarios were developed primarily to evaluate short-term, atypical variations in the coal-to-gas price ratio. Because periods of decreasing gas prices are generally associated with higher coal-to-gas price ratios, fuel scenario 4 pairs low gas prices with a high coal-to-gas price ratio. Likewise, fuel scenario 5 pairs high gas prices with a low coal-to-gas ratio. The High and Low coal-to-gas price ratios are the maximum and minimum, respectively, of the 6-year average coal-to-gas ratios in Table 36. Fuel price scenario 4 ("Low Gas, High CTG") is favorable to gas-fired generation; fuel price scenario 5 ("High Gas, Low CTG") is favorable to coal-fired generation. Fuel scenario 6 was developed to evaluate the continuation of current fuel prices in an energy-constrained world (i.e., high gas and coal prices with an unusually high coal-to-gas price ratio). This fuel price scenario is particularly not expected to persist over a long analysis period.

Table 37: Fuel Price Scenarios

Scenario Type	Scenario Number	Natural Gas Forecast	Coal-to-Gas Price Ratio	Fuel Price Scenario Name (Gas, CTG Price Ratio)
Expected CTG Price Ratio	1	Low (2022 AEO)	Mid (0.57)[47]	Low Gas, Mid CTG
	2	Mid (2022 AEO)	Mid (0.57)[47]	Mid Gas, Mid CTG
	3	High (2022 AEO)	Mid (0.57)[47]	High Gas, Mid CTG
Atypical CTG Price Ratios	4	Low (2022 AEO)	High (0.60)[48]	Low Gas, High CTG
	5	High (2022 AEO)	Low (0.52)[48]	High Gas, Low CTG
	6	High (2022 AEO)	Current (0.84)[49]	High Gas, Current CTG

Table 38 summarizes the coal and natural gas price scenarios evaluated in this analysis. These fuel prices reflect undelivered (Illinois Basin minemouth coal; Henry Hub gas) pricing for the Companies' open fuel positions (i.e., fuel not yet under contract). The Mid Gas, Mid CTG Ratio scenario reflects a blend of coal price bids and a third-party coal price forecast for 2023-2027 and a constant 0.57 CTG ratio thereafter. All other scenarios reflect constant CTG ratios in all years.

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[47] The mid coal-to-gas price ratio (0.57) is the average coal-to-gas ratio over the ten-year period from 2012 to 2021 and approximates the ratio of NGCC and coal operating costs.
[48] The High and Low coal-to-gas price ratios are the maximum and minimum, respectively, of the 6-year rolling average coal-to-gas ratio from 2012 to 2021. A six-year rolling average period was selected because the resource assessment contemplates retiring Mill Creek 2 and Ghent 2 six years before the end of their book deprecation lives (2034).
[49] The Current coal-to-gas price ratio is the coal-to-gas price ratio experienced in 2022 through mid-September.

Table 38 – Coal and Natural Gas Price Scenarios ($/mmBtu)

	Expected CTG Price Ratios						Atypical CTG Price Ratios					
	Low Gas, Mid CTG Ratio		Mid Gas, Mid CTG Ratio		High Gas, Mid CTG Ratio		Low Gas, High CTG Ratio		High Gas, Low CTG Ratio		High Gas, Current CTG Ratio	
Year	Coal	Gas	Coal	Gas	Coal	Gas	Coal	Gas	Coal	Gas	Coal	Gas
2023	[redacted]											
2024	[redacted]											
2025	[redacted]											
2026	[redacted]											
2027	[redacted]											
2028	[redacted]											
2029	[redacted]											
2030	[redacted]											
2031	[redacted]											
2032	[redacted]											
2033	[redacted]											
2034	[redacted]											
2035	[redacted]											
2036	[redacted]											
2037	[redacted]											
2038	[redacted]											
2039	[redacted]											
2040	[redacted]											
2041	[redacted]											
2042	[redacted]											
2043	[redacted]											
2044	[redacted]											
2045	[redacted]											
2046	[redacted]											
2047	[redacted]											
2048	[redacted]											
2049	[redacted]											
2050	[redacted]											

7.7.2 Ammonia Prices

Anhydrous ammonia ("ammonia") is used to reduce NO_x emissions from coal-fired generating units. Ammonia and natural gas prices are highly correlated given that natural gas is used to manufacture ammonia. Therefore, the Companies evaluated different levels of ammonia prices based on the level of natural gas prices.

Table 39 contains the ammonia price scenarios evaluated in this analysis. In the Mid Ammonia case, ammonia prices are assumed to increase by 5% from 2023 to 2024 and then escalate at 2% per year thereafter. "Current" Ammonia prices reflect recent high market ammonia prices corresponding to recent natural gas price spikes for 2023, increase by 5% from 2023 to 2024, and escalate at 2% per year thereafter. The Low and High Ammonia price cases reflect the relationship between the Mid Gas price forecast and the Low and High Gas Price forecasts, respectively.

Table 39 – Ammonia Prices (wholesale nominal $/ton)

	Low Ammonia		Mid Ammonia	High Ammonia		Current Ammonia
Year	Low Gas, Mid CTG Ratio	Low Gas, High CTG Ratio	Mid Gas, Mid CTG Ratio	High Gas, Mid CTG Ratio	High Gas, Low CTG Ratio	High Gas, Current CTG Ratio
2023	[redacted]					
2024						
2025						
2026						
2027						
2028						
2029						
2030						
2031						
2032						
2033						
2034						
2035						
2036						
2037						
2038						
2039						
2040						
2041						
2042						
2043						
2044						
2045						
2046						
2047						
2048						
2049						
2050						

7.7.3 CO_2 Prices

The Companies evaluated two non-zero CO_2 emissions price scenarios of $15 per short ton ("ton") and $25 per ton. These scenarios provide a reasonable range of future expectations of CO_2 prices based on the historical auction price trends of the two existing trading programs in North America: The Regional Greenhouse Gas Initiative ("RGGI") and the California-Quebec Cap-And-Trade Program.

RGGI, started in 2008, was the first CO_2 trading program in the U.S. and sets annual limits on CO_2 emissions by electric generation facilities in 11 states.[50] Though allowance pricing over the last five years (20 auctions) has averaged $7.38 per ton, prices have averaged $13.46 per ton over the last four quarterly auctions. The 3.5% annual emission cap decline, new state admittance to the program, and 7% annual escalation of the auction price ceiling and floor levels are expected to provide upward support to emission allowance prices going forward.

The California-Quebec Cap-And-Trade Program held the first joint auction in 2014.[51] The program seeks to reduce greenhouse gas emissions from the power, industrial, and fuel distribution sectors. Emission allowance prices have averaged $17.48 per ton over the last five years (20 auctions) and traded as high as $27.99 per ton in the May 2022 auction. The 2022 Auction Reserve Price (price floor) of $17.87 per ton is set to increase 12.75% in 2023 to $20.15 per ton due to annual escalation of 5% and inflation.[52]

7.7.4 Emission Allowance Prices

Table 40 summarizes the emission allowance price forecasts evaluated in this analysis. These forecasts were developed by IHS Markit/S&P Global in June 2022.

Table 40: Emission Allowance Prices (nominal $/ton)

Year	SO_2 Group 1	NO_x Seasonal Group 3	NO_x Annual	Year	SO_2 Group 1	NO_x Seasonal Group 3	NO_x Annual
2023	[redacted]	[redacted]	[redacted]	2037	[redacted]	[redacted]	[redacted]
2024	[redacted]	[redacted]	[redacted]	2038	[redacted]	[redacted]	[redacted]
2025	[redacted]	[redacted]	[redacted]	2039	[redacted]	[redacted]	[redacted]
2026	[redacted]	[redacted]	[redacted]	2040	[redacted]	[redacted]	[redacted]
2027	[redacted]	[redacted]	[redacted]	2041	[redacted]	[redacted]	[redacted]
2028	[redacted]	[redacted]	[redacted]	2042	[redacted]	[redacted]	[redacted]
2029	[redacted]	[redacted]	[redacted]	2043	[redacted]	[redacted]	[redacted]
2030	[redacted]	[redacted]	[redacted]	2044	[redacted]	[redacted]	[redacted]
2031	[redacted]	[redacted]	[redacted]	2045	[redacted]	[redacted]	[redacted]
2032	[redacted]	[redacted]	[redacted]	2046	[redacted]	[redacted]	[redacted]
2033	[redacted]	[redacted]	[redacted]	2047	[redacted]	[redacted]	[redacted]
2034	[redacted]	[redacted]	[redacted]	2048	[redacted]	[redacted]	[redacted]
2035	[redacted]	[redacted]	[redacted]	2049	[redacted]	[redacted]	[redacted]
2036	[redacted]	[redacted]	[redacted]	2050	[redacted]	[redacted]	[redacted]

7.8 Financial Inputs

Table 41 lists the financial inputs used to compute capital revenue requirements in this analysis.

[50] https://www.rggi.org/sites/default/files/Uploads/Fact%20Sheets/RGGI_101_Factsheet.pdf
[51] https://ww2.arb.ca.gov/sites/default/files/cap-and-trade/guidance/cap_trade_overview.pdf
[52] https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/cost-containment-information

Table 41: Financial Inputs

	Combined Companies
% Debt	47%
% Equity	53%
Cost of Debt	4.08%
Cost of Equity	9.43%
Tax Rate	24.95%
Property Tax Rate	0.15%
WACC (After-Tax)	6.43%

8 Appendix B – RFP Proposals and Dispatchable DSM Program Options

Table 42: RFP Proposals that Advanced to Modeling Analysis

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
Solar	1	[redacted]								
	3									
	7									
	12									
	21									
	23									
	29									
	34									
	36									
	37									
Solar w/ 4-hr Battery Option	39									
	40									
	45									
	46									
	56									
	57									
	60									
	61									

CONFIDENTIAL INFORMATION REDACTED

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
	70	[redacted]								
	71	[redacted]								
	74	[redacted]								
	75	[redacted]								
	78	[redacted]								
	79	[redacted]								
Solar + 4-hr Battery	80	[redacted]								
	81	[redacted]								
2-hr Battery	82	[redacted]								
	85	[redacted]								
4-hr Battery	86	[redacted]								
	87	[redacted]								
	88	[redacted]								
	91	[redacted]								
	92	[redacted]								
	93	[redacted]								
	94	[redacted]								
	95	[redacted]								

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
	97	[redacted]								
Pumped Hydro	**98**									
Wind	**99**									
NGCC	**101**									
	103									
SCCT	**107**									
	108									

Table 43: All RFP Proposals

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
Solar	**1**	[redacted]								
	2									
	3									
	4									
	5									
	6									
	7									
	8									
	9									
	10									
	11									

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
	12	[redacted]								
	13									
	14									
	15									
	16									
	17									
	18									
	19									
	20									
	21									
	22									
	23									
	24									
	25									

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
	26	[redacted]								
	27	[redacted]								
	28	[redacted]								
	29	[redacted]								
	30	[redacted]								
	31	[redacted]								
	32	[redacted]								
	33	[redacted]								
	34	[redacted]								
	35	[redacted]								
	36	[redacted]								
	37	[redacted]								
Solar w/ 4-hr Battery Option	38	[redacted]								
	39	[redacted]								
	40	[redacted]								
	41	[redacted]								
	42	[redacted]								
	43	[redacted]								
	44	[redacted]								

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
	45	[redacted]								
	46	[redacted]								
	47	[redacted]								
	48	[redacted]								
	49	[redacted]								
	50	[redacted]								
	51	[redacted]								
	52	[redacted]								
	53	[redacted]								
	54	[redacted]								
	55	[redacted]								
	56	[redacted]								
	57	[redacted]								
	58	[redacted]								
	59	[redacted]								
	60	[redacted]								
	61	[redacted]								
	62	[redacted]								
	63	[redacted]								

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
	64	[redacted]								
	65									
	66									
	67									
	68									
	69									
	70									
	71									
	72									
	73									
	74									
	75									
	76									
	77									
	78									
	79									
Solar + 4-hr Battery	**80**									
	81									
2-hr Battery	**82**									

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
	83	[redacted]								
	84									
	85									
4-hr Battery	**86**									
	87									
	88									
	89									
	90									
	91									
	92									
	93									
	94									
	95									
	96									
	97									
Pumped Hydro	**98**									
Wind	**99**									

Technology	No.	Resource ID and Respondent	Project Name	Location	Nameplate Capacity (MW)	Start Date	Term (Years)	Purchase Price ($/kW)	Capacity Price ($/kW-month)	Energy Price ($/MWh)
NGCC	100	[redacted]								
	101									
	102									
	103									
	104									
	105									
SCCT	106									
	107									
	108									
Solar Asset Development	109									
	110									

Table 44: Dispatchable DSM Program Options

No.	Program Name	Variable Cost $/kWh		Time-Dependent Characteristic	2024	2025	2026	2027	2028	2029	2030
		Winter	Summer								
1	Peak Time Rebates	2.00	2.00	Summer Capacity MW	-	4	9	17	31	31	31
				Winter Capacity MW	-	4	9	17	31	31	31
				Fixed Cost $/kW-Year	-	-	-	164	32	37	32
2	DLC-Water Heaters	2.50	2.50	Summer Capacity MW	3	3	3	2	2	2	2
				Winter Capacity MW	3	3	3	2	2	2	2
				Fixed Cost $/kW-Year	9	12	11	13	14	16	18
3	DLC-AC[53]	-	1.68	Summer Capacity MW	121	109	98	88	79	71	64
				Winter Capacity MW	-	-	-	-	-	-	-
				Fixed Cost $/kW-Year	9	12	11	13	14	16	18
4	BYOD-Smart Thermostats	4.17	4.93	Summer Capacity MW	1	3	6	10	17	23	29
				Winter Capacity MW	0.4	1	2	3	4	6	7
				Fixed Cost $/kW-Year	-	-	-	341	105	90	86
5	Non-residential Demand Response	7.55	7.55	Summer Capacity MW	29	36	45	56	67	79	79
				Winter Capacity MW	29	36	45	56	67	79	79
				Fixed Cost $/kW-Year	45	39	29	25	21	18	13

[53] Summer capacity values are design-day values. Expected load reductions are lower on an average peak day.

9 Appendix C – All-DSM Portfolio Analysis

To estimate the level of additional DSM programs required for Portfolio 10, the Companies modeled portfolio 10 in PROSYM and recorded the level of unserved energy in 2028.

Table 45: LOLE in 2028 with MC2, GH2, BR3 Retirements and Dispatchable DSM

	LOLE (10 Years)		
Portfolio	**Summer (Jun, Jul, Aug)**	**Winter (Dec, Jan, Feb)**	**Total Year**
Retire MC2, GH2, and BR3	76.58	13.01	101.37

2022 RFP

Minimum Reserve Margin Analysis

PPL companies

Generation Planning & Analysis

December 2022

May 2023 Update

Table of Contents

1 Executive Summary

The Companies' long-term load forecast is developed with the assumption that weather will be normal in every year.[1] While this is a reasonable assumption for long-term resource planning, weather from one year to the next is never the same. Therefore, to account for the possibility of extreme weather events and the uncertainty in generating unit availability, the Companies target a level of supply-side and demand-side resources that exceeds their forecasted peak demands. Reserve margin is the amount of resources carried in excess of forecasted peak demands and is typically expressed as a percentage of forecasted peak demands under normal weather conditions.

The Companies use PLEXOS, a generation portfolio optimization model, to develop least-cost resource plans over a range of scenarios. Minimum summer and winter reserve margins are key inputs to this analysis as these plans are developed to minimize the cost of serving customers' load while meeting minimum reserve margin targets. The Companies used the Equivalent Load Duration Curve Model ('ELDCM") and the Strategic Energy & Risk Valuation Model ("SERVM") to determine minimum reserve margin targets. SERVM is a licensed software from Astrape Consulting.

The 2021 IRP established minimum reserve margin targets of 17 percent in the summer and 26 percent in the winter. However, the 2021 IRP was finalized in October 2021, and the 2021 IRP load forecast did not contemplate the addition of the BlueOval SK Battery Park ("BlueOval SK") or the impacts of the Inflation Reduction Act ("IRA") and the Companies' proposed 2024-2030 Demand-Side Mangement and Energy Efficiency ("DSM-EE") Program Plan. Therefore, using the same methodology as the 2021 IRP, the Companies updated their minimum reserve margin targets based on an updated load forecast, which includes the BlueOval SK load as well as the impacts of the IRA and the 2024-2030 DSM-EE Program Plan.[2]

With the addition of the largely non-weather sensitive, summer peaking BlueOval SK load, the absolute level of reserve capacity needed for reliable service did not change materially, but the Companies' forecasted summer and winter peak demands increased, and the summer peak demand forecast increased more than the winter peak demand. The minimum reserve margin is the level of reserves below which the cost of adding additional generation capacity is economic. The cost of capacity for this analysis was based on a response to the Companies' June 2022 RFP for simple-cycle combustion turbine ("SCCT") capacity and was 34% lower than the cost of SCCT capacity used in the 2021 IRP Reserve Margin Analysis.

Based on the updated load forecast and after factoring in the updated cost of SCCT capacity, the minimum reserve margin target for the summer did not change from 17%, but the minimum winter reserve margin target decreased from 26% to 24%.

These reserve margin targets were developed based on a mix of (a) fully dispatchable resources (i.e., resources that can be dispatched any time and operated for days at a time) and (b) intermittent and limited-duration resources (i.e., resources like the Companies' dispatchable DSM programs that can only be dispatched for several hours at a time). Table 1 summarizes the portions of the minimum reserve margin targets that are made up of fully dispatchable and intermittent or limited-duration resources.

[1] The Companies use 20 years of historical weather data to develop their normal weather forecast.

[2] The Companies' 2022 CPCN Load Forecast is attached to the testimony of Tim A. Jones as Exhibit TAJ-1.

Total reserve margin will become less meaningful as a reliability metric as more intermittent and limited-duration resources are added to the generation portfolio.

Table 1 – Minimum Reserve Margin Targets

	Summer	Winter
Fully Dispatchable Resources	12%	21%
Intermittent/Limited-Duration Resources	5%	3%
Total	17%	24%

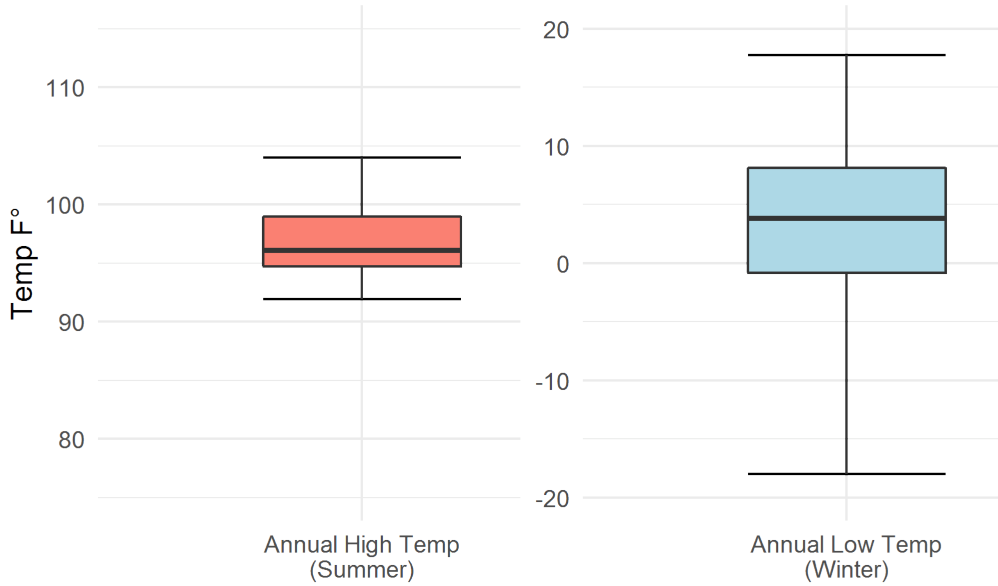
In addition to minimum reserve margins, the Companies used SERVM to determine the capacity contribution of limited-duration resources such as battery storage and the dispatchable DSM programs in the 2024-2030 DSM-EE Program Plan by comparing their impact on loss-of-load expectation ("LOLE") to that of a SCCT. This concept is similar to the effective load carrying capability that RTOs compute for limited-duration resources. PLEXOS uses these capacity contribution values to account for the fact that limited-duration resources do not contribute to reliability in the same way that fully dispatchable resources do. The capacity contributions for 4-hour battery storage, 8-hour battery storage, and dispatchable DSM are 82%, 93%, and 35%, respectively, of fully dispatchable resources.

2 Introduction

The reliable supply of electricity is vital to Kentucky's economy and public safety, and customers expect it to be available at all times and in all weather conditions. As a result, the Companies have developed a portfolio of demand- and supply-side resources with the operational capabilities and attributes needed to reliably serve customers' year-round energy needs at a reasonable cost. In addition to the ability to serve load during the annual system peak hour, the generation fleet must have the ability to produce low-cost baseload energy, the ability to respond to unit outages and follow load, and the ability to instantaneously produce power when customers want it.

An understanding of the way customers use electricity is critical for planning a generation, transmission, and distribution system that can reliably serve customers in every moment. Temperatures in Kentucky can range from below zero degrees Fahrenheit to above 100 degrees Fahrenheit. Figure 1 shows the distribution of annual high and low temperatures in Louisville over the last 49 years. From 1973 to 2021, the median annual high temperature was 96.1 degrees Fahrenheit and the median annual low temperature was 3.8 degrees Fahrenheit. Additionally, the variability of low temperatures in the winter is significantly greater than the variability of high temperatures in the summer.

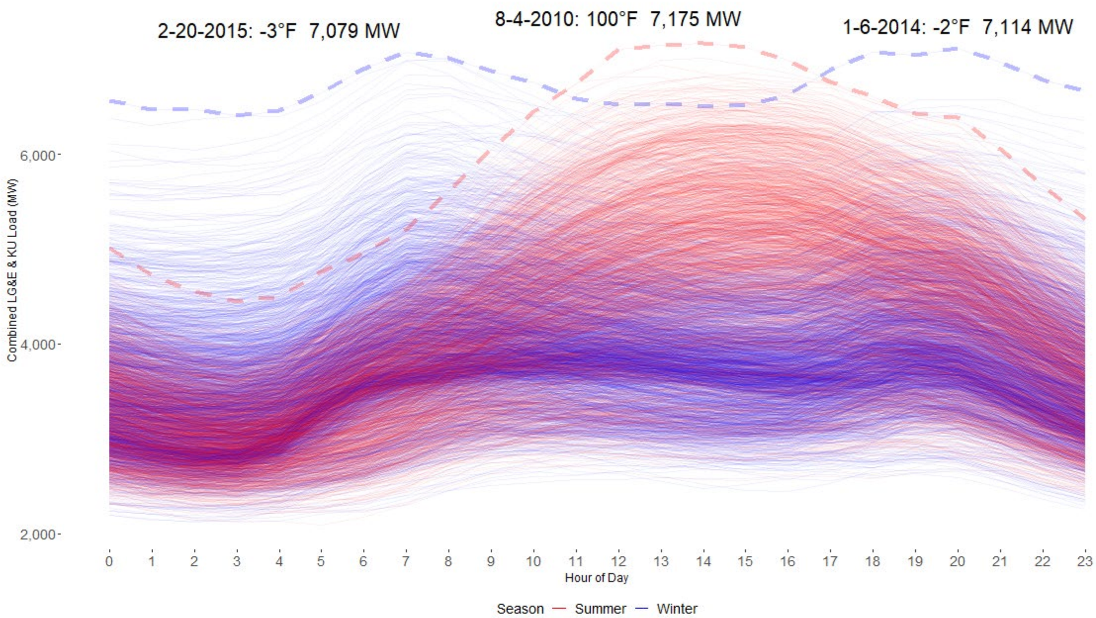
Figure 1: Louisville Annual High and Low Temperature Distributions (1973-2021)[3]



Because of the potential for cold winter temperatures and the increasing penetration of electric heating, the Companies are somewhat unique in that annual peak demands can occur in summer and winter months. The Companies' highest hourly demand occurred in the summer of 2010 (7,175 MW in August 2010). Since then, the Companies have experienced two annual peak demands in excess of 7,000 MW, both of which occurred during winter months (7,114 MW in January 2014 and 7,079 MW in February 2015). Figure 2 contains the Companies' hourly load profiles for every day from 2010 to 2020. Hourly demands can vary by as much as 600 MW from one hour to the next and by over 3,000 MW in a single day. Summer peak demands typically occur in the afternoons, while winter peaks typically occur in the mornings or evenings during nighttime hours.

[3] The limits of the box in the boxplots reflect the 25th and 75th percentiles while the "whiskers" represent the maximum and minimum.

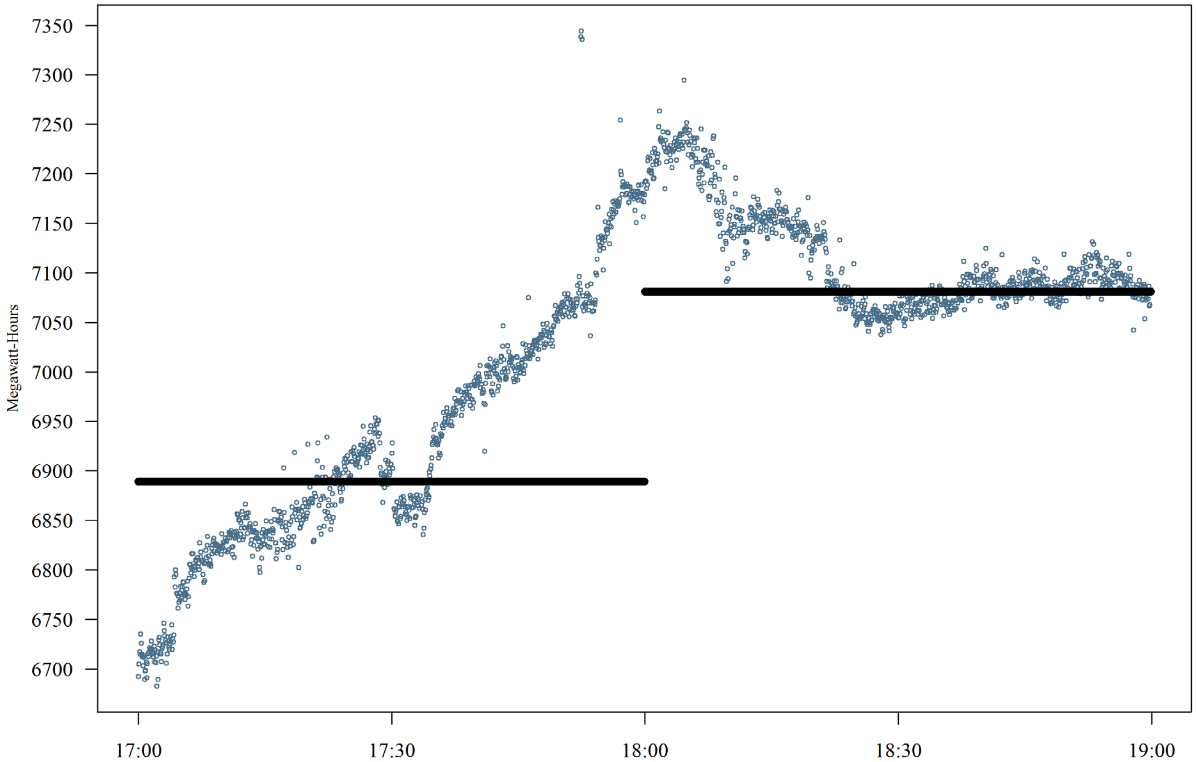
Figure 2: Hourly Load Profiles, 2010-2020



System demands from one moment to the next can be almost as volatile as average demands from one hour to the next. Figure 3 contains a plot of four-second demands from 5:00 PM to 7:00 PM on January 6, 2014 during the polar vortex event. The average demand from 6:00 PM to 7:00 PM was 7,114 MW but the maximum 4-second demand was more than 150 MW higher.[4]

[4] 7,114 MW is an hourly demand and is computed as the average demand over the hour. A 4-second demand is an instantaneous measure of demand taken every 4 seconds.

Figure 3: Four-Second Demands, 5:00-7:00 PM on January 6, 2014



In addition to being reliable, a generation portfolio must possess numerous other attributes to produce power when customers want it. For example, a generation portfolio must possess the ramping capabilities to follow abrupt changes in customers' energy requirements. In addition, the Companies must be able to dispatch at least a significant portion of their generating units when they are needed. Peaking units can start quickly and are needed to respond to unit outages. Baseload units take longer to start, but because their start times are predictable, the Companies can bring them online when they are needed. The size of a resource is also important. If a unit is too big, taking the unit offline for maintenance can be problematic. If a unit is too small, its value in responding to unit outages is limited. The Companies' resource planning decisions must ensure their generation portfolio has the full range of operational capabilities and attributes needed to serve customers in every moment.

Customers consume electricity every hour of the year, but no generating resource can be available at all times. Considering the need for maintenance, the Companies' baseload units and large-frame SCCTs are available to be utilized up to 90 percent of hours in a year. The Companies' Curtailable Service Rider ("CSR") limits the ability to curtail participating customers to hours when all large-frame SCCTs have been dispatched. As a result, the ability to utilize this program is limited to, at most, a handful of hours each year.

As the Companies evaluate integrating more renewables into their generation portfolio, they must consider that renewables lack many of the characteristics required to serve customers in every moment. Compared to coal- and natural gas-fired resources, the availability of renewables is less predictable and their fuel supply (e.g., sunshine, wind, or water) is more intermittent. Furthermore, because annual peak demands can occur during the winter months and because winter peaks typically occur during non-daylight hours, solar generation has virtually no value in the Companies' service territories as a source of winter capacity.

The following sections summarize the Companies' reserve margin analysis. Section 3 discusses the analysis framework. Section 4 provides a summary of key inputs and uncertainties in the analysis. Finally, Section 5 provides a summary of the analysis results.

3 Analysis Framework

Figure 4 illustrates the costs and benefits of adding capacity to a generation portfolio.[5] As capacity is added, reliability and generation production costs decrease (i.e., the generation portfolio becomes more reliable), but fixed capacity costs increase. The reserve margin for the generation portfolio where the sum of (a) capacity costs and (b) reliability and generation production costs ("total cost") is minimized is the economic reserve margin.

Figure 4: Costs and Benefits of Generation Capacity (Illustrative)

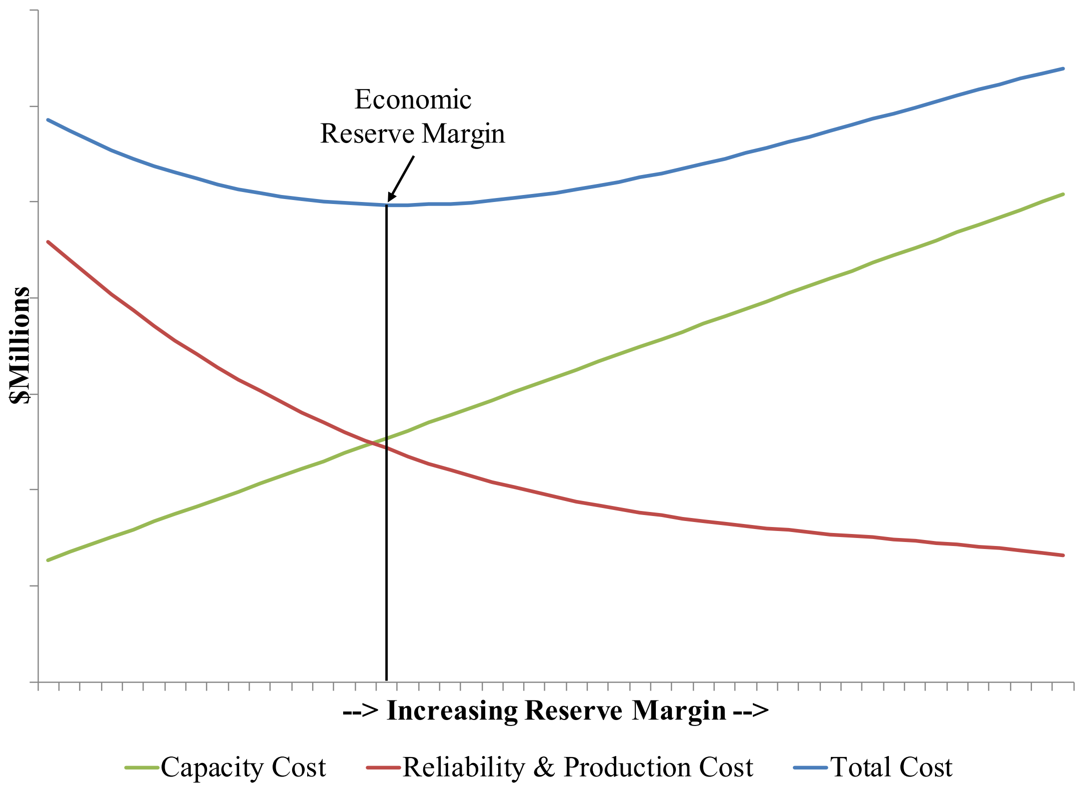


Figure 5 includes an alternative capacity cost scenario (dashed green line) for capacity with the same dispatch cost and reliability characteristics. The large dots mark the minimum of the range of reserve margins that is being evaluated. In this scenario, reliability and generation production costs are

[5] As mentioned previously, different types of generation resources play different roles in serving customers; not all resources provide the same reliability and generation production cost benefit.

unchanged but total costs (dashed blue line) are lower and the economic reserve margin is higher. This result is unsurprising; in an extreme case where the cost of capacity is zero, the Companies would add capacity until the value of adding capacity is reduced to zero.[6]

Figure 5: Economic Reserve Margin and Capacity Cost (Illustrative)

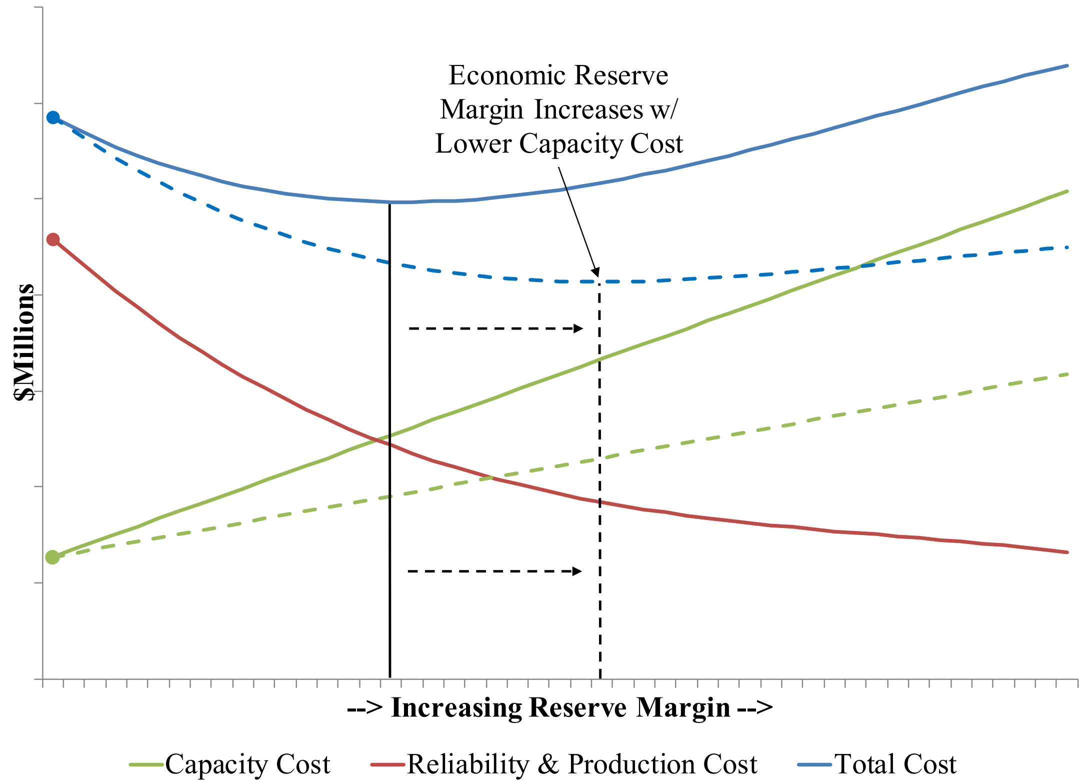


Table 2 contains the Companies' summer and winter reserve margin forecast for 2028. Generation resources have a higher capacity in the winter primarily because natural gas units can produce more power at lower ambient air temperatures. Mill Creek 1 and the Companies' small-frame SCCTs are assumed to be retired in 2025. Reserve margins are computed for 2028 with and without the Rhudes Creek and Ragland solar PPAs. These projects have not received all of their necessary permits and are not yet under construction. Given current market conditions and interest rates, it is not clear whether these projects can be financed at the prices originally proposed.

[6] In Figure 5, as more capacity is added to the generation portfolio, the value of adding the capacity decreases (i.e., the slope of the reliability and production cost line is flatter at higher reserve margins).

Table 2: Peak Demand and Resource Summary (MW, Base Energy Requirements Forecast)

	Summer	Winter
Peak Load	**6,319**	**6,104**
Dispatchable Generation Resources		
Existing Resources	7,612	7,909
Retirements/Additions		
Coal[7]	-300	-300
Large-Frame SCCTs	0	0
Small-Frame SCCTs[8]	-47	-55
Total	7,265	7,554
Reserve Margin (%)	15.0%	23.7%
Intermittent/Limited-Duration Resources		
Existing Resources	105	72
Existing CSR	128	128
Existing DLC	46	22
Retirements/Additions		
Solar PPAs[9]	177	0
Total	456	221
Total Supply w/ Solar	**7,721**	**7,774**
Total Reserve Margin w/ Solar (%)	**22.2%**	**27.4%**
Total Supply w/o Solar	**7,544**	**7,774**
Total Reserve Margin w/o Solar (%)	**19.4%**	**27.4%**

The Resource Assessment evaluates the retirement of dispatchable resources. Because reserve margin will become less meaningful as a reliability metric as more intermittent and limited-duration resources are added to the generation portfolio, reserve margins are computed in total as well as for fully dispatchable resources only. With no additional retirements beyond 2025 and with the Rhudes Creek and Ragland PPAs, the Companies' dispatchable reserve margin in 2028 is 15.0% in the summer and 23.7% in the winter; the Companies' total reserve margin in 2028 is 22.2% in the summer and 27.4% in the winter and stays above the minimum summer and winter reserve margin targets through 2040. Without the

[7] Mill Creek 1 and 2 cannot be operated simultaneously during ozone season due to NOx limits, which results in a reduction of available summer capacity through 2024. Mill Creek 1 will be retired at the end of 2024. OVEC's contract term ends in 2040.

[8] This analysis assumes Haefling 1-2 and Paddy's Run 12 are retired by 2025.

[9] This analysis assumes 100 MW of solar capacity is added in 2024 (Rhudes Creek), and an additional 125 MW of solar capacity is added in 2025 (Ragland). Capacity values reflect 78.6% expected contribution to summer peak capacity.

Rhudes Creek and Ragland PPAs, the Companies' dispatchable reserve margins are unchanged but the total reserve margins drop to 19.4% in the summer and 27.4% in the winter.

The Companies used the Equivalent Load Duration Curve Model ("ELDCM") and Strategic Energy Risk Valuation Model ("SERVM") to update the Companies' minimum reserve margin targets. SERVM was also used to compute capacity contributions for limited-duration resources based on their impact on loss of load expectation ("LOLE") in ten years. ELDCM estimates reliability and generation production costs based on an equivalent load duration curve.[10] SERVM is a simulation-based model and was used to complete the reserve margin studies for the 2011, 2014, 2018, and 2021 IRPs. SERVM models the availability of generating units in more detail than ELDCM, but ELDCM's simplified approach is able to consider a more complete range of unit availability scenarios. Given the differences between the models, their results should be consistent but not identical.

Key inputs to SERVM and ELDCM include load, unit availability, the ability to import power from neighboring regions, and other factors. SERVM separately models the ability to import power from each of the Companies' neighboring regions based on the availability of generation resources and transmission capacity in each region. In ELDCM, the Companies' ability to import power from neighboring regions is modeled as a single "market" resource where the availability of the resource is determined by the sum of available transmission capacity in all regions. Key analysis inputs and uncertainties are discussed in the following section.

4 Key Inputs and Uncertainties

Several factors beyond the Companies' control impact the Companies' planning reserve margin and their ability to reliably serve customers' energy needs. The key inputs and uncertainties considered in the Companies' reserve margin analysis are discussed in the following sections.

4.1 Study Year

The study year for this analysis is 2028. In the Resource Assessment, the Companies assumed they could comply with the Good Neighbor Plan if replacement generation was secured by 2028.

4.2 Neighboring Regions

The vast majority of the Companies' off-system purchase transactions are made with counterparties in MISO, PJM, or TVA. SERVM models load and the availability of excess capacity from the portions of the MISO, PJM, and TVA control areas that are adjacent to the Companies' service territory.[11] These portions of MISO, PJM, and TVA are referred to as "neighboring regions." The following neighboring regions are modeled:

- MISO-Indiana – includes service territories for all utilities in Indiana as well as Big Rivers Electric Corporation in Kentucky.

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[10] See https://www-pub.iaea.org/MTCD/Publications/PDF/TRS1/TRS241_Web.pdf beginning at page 219 for the modeling framework employed by ELDCM.

[11] As discussed previously, the ability to import power from neighboring regions is modeled as a single "market" resource in ELDCM.

- PJM-West – refers to the portion of the PJM-West market region including American Electric Power ("AEP"), Dayton Power & Light, Duke Ohio/Kentucky, and East Kentucky Power Cooperative service territories.
- TVA – TVA service territory.

Moving forward, uncertainty exists regarding the Companies' ability to rely on neighboring regions' markets to serve load. Approximately 20 GW of capacity was retired over the past five years in PJM and an additional 3 GW of retirements have been announced for the next five years. For the purpose of developing a minimum reserve margin for long-term resource planning, reserve margins in neighboring regions are assumed to be at their target levels of 18% (MISO[12]), 14.8% (PJM), and 17% (TVA[13]).[14]

4.3 Generation Resources

The unit availability and economic dispatch characteristics of the Companies' generating units are modeled in SERVM and ELDCM. SERVM also models the generating units in neighboring regions.

4.3.1 Unit Availability Inputs

Uncertainty related to the performance and availability of generating units is a key consideration in resource planning. From one year to the next, the average availability of generating units is fairly consistent. However, the timing and duration of unplanned outage events in a given year can vary significantly. A key aspect in developing a target reserve margin is properly considering the likelihood of unit outages during extreme weather events. Table 3 contains a summary of the Companies' generating resources along with their assumed equivalent forced outage rates ("EFORs"). The availability of units in neighboring regions was assumed to be consistent with the availability of units in the Companies' generating portfolio and not materially different from the availability of neighboring regions' units today.

[12] See NERC's "2020 Long-Term Reliability Assessment" at https://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/NERC_LTRA_2020.pdf.
[13] See TVA's "2019 Integrated Resource Plan" at https://www.tva.com/environment/environmental-stewardship/integrated-resource-plan.
[14] In the reserve margin analysis, adjustments were made to the neighboring regions' generating portfolios as needed to reflect planned retirements and meet the neighboring regions' target reserve margins.

Table 3: 2028 LG&E/KU Generating & DSM Portfolio

Resource	Resource Type	Net Max Summer Capacity (MW)[15]	Net Max Winter Capacity (MW)	EFOR
Brown 3	Coal	412	416	5.8%
Brown 5	SCCT	130	130	8.1%
Brown 6	SCCT	146	171	8.1%
Brown 7	SCCT	146	171	8.1%
Brown 8	SCCT	121	128	8.1%
Brown 9	SCCT	121	138	8.1%
Brown 10	SCCT	121	138	8.1%
Brown 11	SCCT	121	128	8.1%
Brown Solar	Solar	8	0	2.5%
Cane Run 7	NGCC	691	691	2.2%
Dix Dam 1-3	Hydro	32	32	N/A
Ghent 1	Coal	475	479	3.2%
Ghent 2	Coal	485	486	3.2%
Ghent 3	Coal	481	476	3.2%
Ghent 4	Coal	478	478	3.2%
Mill Creek 2	Coal	297	297	3.2%
Mill Creek 3	Coal	391	394	3.2%
Mill Creek 4	Coal	477	486	3.2%
Ohio Falls 1-8	Hydro	64	40	N/A
OVEC-KU	Power Purchase	47	49	N/A
OVEC-LG&E	Power Purchase	105	109	N/A
Paddy's Run 13	SCCT	147	175	8.1%
Trimble County 1 (75%)	Coal	370	370	3.2%
Trimble County 2 (75%)	Coal	549	570	5.1%
Trimble County 5	SCCT	159	179	4.9%
Trimble County 6	SCCT	159	179	4.9%
Trimble County 7	SCCT	159	179	4.9%
Trimble County 8	SCCT	159	179	4.9%
Trimble County 9	SCCT	159	179	4.9%
Trimble County 10	SCCT	159	179	4.9%
Business Solar	Solar	0.2	0	2.5%
Solar Share	Solar	1.7	0	2.5%
Rhudes Creek Solar	Solar	79	0	2.5%
Additional GT Option 3 Solar	Solar	98	0	2.5%
CSR	Interruptible	128	128	N/A
DCP[16]	DSM	46	22	N/A

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[15] Projected net ratings as of 2022. OVEC's capacity reflects the capacity that is expected to be available to the Companies at the time of the summer and winter peaks. The ratings for Brown Solar, Business Solar, Solar Share, Dix Dam 1-3, and Ohio Falls 1-8 reflect the assumed output for these facilities during the summer and winter peak demand. Cane Run 7 reflects the estimated impact of evaporative cooling under average summer ambient conditions.

[16] The Demand Conservation Programs include the Residential and Non-Residential Demand Conservation Programs. These programs are the Companies' only dispatchable demand-side management programs. The Companies did not evaluate the Curtailable Service Rider because the elimination of this rider would have no impact on total revenue requirements.

4.3.2 Fuel Prices

The forecasts of natural gas and coal prices for the Companies' generating units are summarized in Table 4 and Table 5. Those prices represent the Mid Gas, Mid Coal-To-Gas Ratio scenario. Fuel prices in neighboring regions were assumed to be consistent with the Companies' fuel prices. The natural gas price forecast reflects forecasted Henry Hub market prices plus variable costs for pipeline losses and transportation, excluding any fixed firm gas transportation costs.

Table 4: 2028 Delivered Natural Gas Prices (LG&E and KU; Nominal $/mmBtu)

Month	Value
1	[redacted]
2	
3	
4	
5	
6	
7	
8	
9	
10	
11	
12	

Table 5: 2028 Delivered Coal Prices (LG&E and KU; Nominal $/mmBtu)

Station	Value
Brown	[redacted]
Ghent	
Mill Creek	
Trimble County – High Sulfur	
Trimble County – PRB	

4.3.3 Interruptible Contracts

Load reductions associated with the Companies' Curtailable Service Rider ("CSR") are modeled as generation resources. Table 6 lists the Companies' CSR customers and their assumed load reductions. The Companies can curtail each CSR customer up to 100 hours per year.[17] However, because the Companies can curtail CSR customers only in hours when more than 10 of the Companies' large-frame SCCTs are being dispatched, the ability to utilize this program is limited to at most a handful of hours each year, and then the magnitude of load reductions depends on participating customers' load during the hours when they are called upon. The total assumed capacity of the CSR program is 128 MW.

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[17] See KU's Electric Service Tariff at https://psc.ky.gov/tariffs/Electric/Kentucky%20Utilities%20Company/Tariff.pdf and LG&E's at https://psc.ky.gov/tariffs/Electric/Louisville%20Gas%20and%20Electric%20Company/Tariff.pdf.

Table 6: Interruptible Contracts

CSR Customers	Assumed Hourly Load Reduction (MW)
[redacted]	

4.4 Available Transmission Capacity

Available transmission capacity ("ATC") determines the amount of power that can be imported from neighboring regions to serve the Companies' load and is a function of the import capability of the Companies' transmission system and the export capability of the system from which the power is purchased. For example, to purchase 50 MW from PJM, the Companies' transmission system must have at least 50 MW of available import capability and PJM must have at least 50 MW of available export capability. If PJM only has 25 MW of export capability, total ATC is 25 MW.

The Companies' import capability is assumed to be negatively correlated with load. Furthermore, because weather systems impact the Companies' service territories and neighboring regions similarly, the export capability from neighboring regions is oftentimes also limited when the Companies' load is high. Table 7 summarizes the sum of daily ATC between the Companies' system and neighboring regions on weekdays during the summer months of 2019 and 2020 and the winter months of 2020 and 2021. Based on the daily ATC data, the Companies' ATC for importing power from neighboring regions is zero 42% of the time. ATC is modeled in SERVM based on this distribution.

Table 7: Daily ATC

Daily ATC Range	Count of Days	% of Total
0	98	42%
1 – 199	2	1%
200 - 399	10	4%
400 - 599	17	7%
600 - 799	11	5%
800 - 999	21	9%
>= 1,000	73	31%
Total	232	

During peak hours when ATC is most likely needed to ensure reliable supply, ATC in ELDCM is assumed to be approximately 500 MW two-thirds of the time and zero MW one-third of the time.

4.5 Load Modeling

Uncertainty in the amount and timing of customers' utilization of electricity is a key consideration in resource planning. Uncertainty in the Companies' load is modeled in SERVM and ELDCM. SERVM also models load uncertainty in neighboring regions. Table 8 summarizes the summer peak demand forecast for the Companies' service territories and neighboring regions in 2028. The Companies' peak demand is taken from the base energy requirements forecast scenario and reflects the impact of the Companies' DSM programs. The forecasts of peak demands for MISO-Indiana, PJM-West, and TVA were taken from RTO forecasts and NERC Electricity Supply and Demand data.

Table 8: Peak Load Forecasts for 2028

	LG&E/KU	MISO-Indiana	PJM-West	TVA
Peak Load	6,319	20,809	34,677	30,442
Target Reserve Margin	N/A	18.0%	14.8%	17%

The Companies develop their long-term energy requirements forecast with the assumption that weather will be average or "normal" in each month of every year. In a given month, weather on the peak day is assumed to be the average of weather on the peak day over the past 20 years. While this is a reasonable assumption for long-term resource planning, weather from one month and year to the next is never the same. The frequency and duration of severe weather events within a year have a significant impact on load shape and reliability and generation production costs. For this reason, the Companies produced 49 hourly demand forecasts for 2028 based on actual weather in each of the last 49 years.

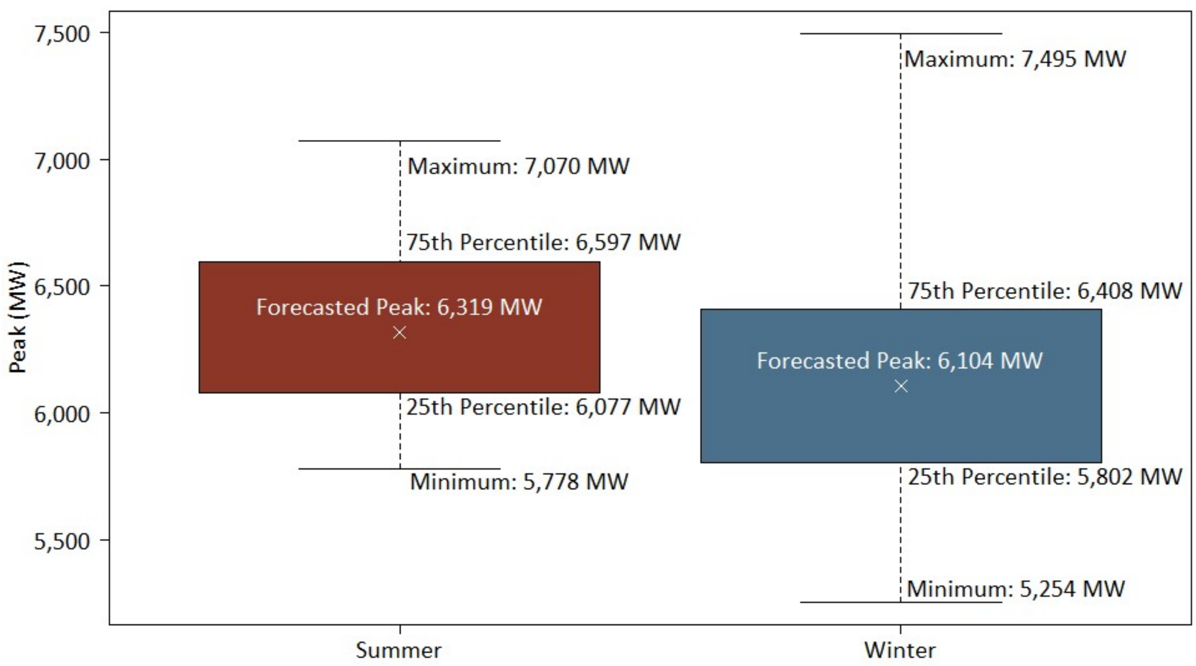
Table 9 summarizes the distributions of summer and winter peak demands for the Companies' service territory and coincident demands in the neighboring regions based on these "weather year" forecasts. Because each set of coincident peak demands is based on weather from the same weather year, SERVM captures weather-driven covariation in loads between the Companies' service territories and neighboring regions to the extent weather is correlated. Because the ability to purchase power from neighboring regions often depends entirely on the availability of transmission capacity, load uncertainty in the Companies' service territories has a much larger impact on resource planning decisions than load uncertainty in neighboring regions.

Table 9: Summer and Winter Peak Demand Forecasts, 2028

	Summer					Winter				
			Coincident Peak Demand in Neighboring Regions					Coincident Peak Demand in Neighboring Regions		
LG&E/ KU Load	Weather Year	LG&E/KU	MISO-Indiana	PJM-West	TVA	Weather Year	LG&E/KU	MISO-Indiana	PJM-West	TVA
Max	2007	7,070	20,045	32,361	32,639	1994	7,495	21,305	37,717	31,274
75th %-ile	2019	6,597	17,626	23,643	25,840	2003	6,408	17,718	32,037	24,089
Median	2013	6,198	18,806	28,498	27,090	2016	5,954	18,819	33,226	29,893
25th %-ile	1986	6,077	20,996	33,697	31,183	2011	5,802	16,905	33,525	26,061
Min	2004	5,778	17,591	28,155	22,179	1998	5,254	14,906	26,772	21,662

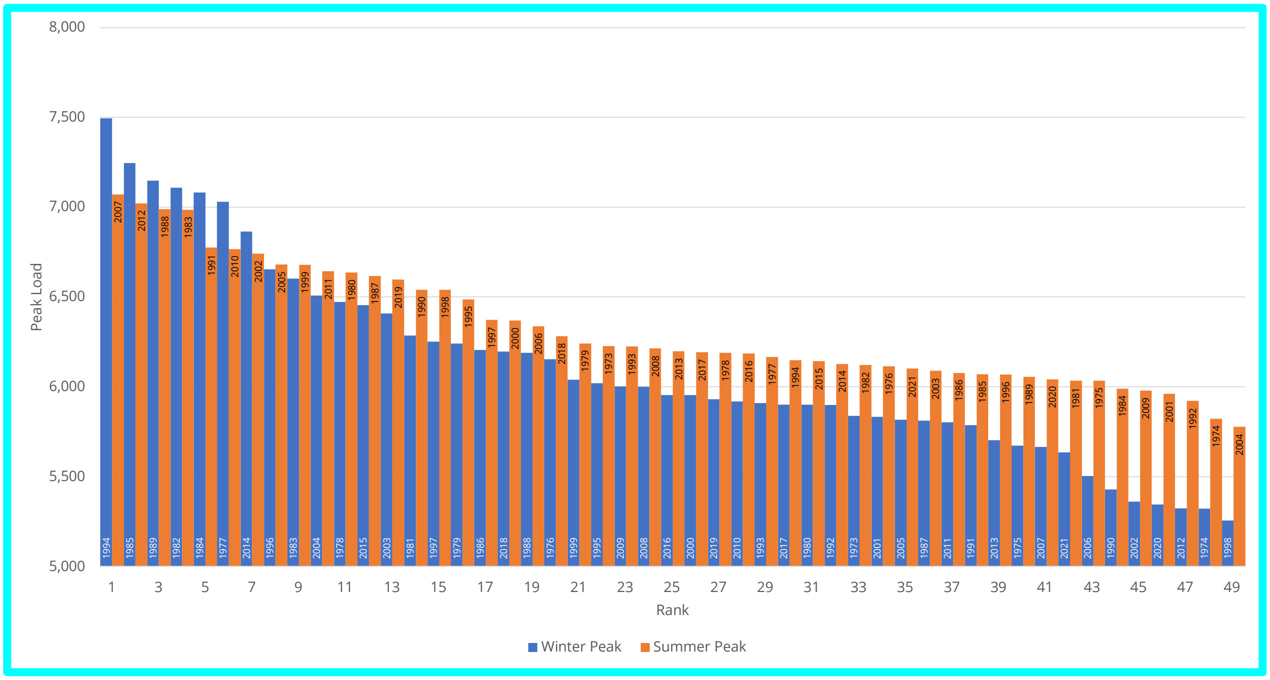
Figure 6 and Figure 7 contain graphical distributions of the Companies' summer and winter peak demands for 2028. The values in Figure 6 labeled "Forecasted Peak" (i.e., 6,319 MW in the summer and 6,104 MW in the winter) are the Companies' forecasts of summer and winter peak based on average peak weather conditions over the past 20 years. In Figure 7, the year labels indicate the weather years on which the seasonal peaks are based. The Companies' Forecasted Peak is higher in the summer, but the variability in peak demands is much higher in the winter.[18] This is largely due to the wider range of low temperatures that can be experienced in the winter and the fact that electric heating systems with heat pumps consume significantly more energy during extreme cold weather when the need for backup resistance heating is triggered.

Figure 6: Distributions of Summer and Winter Peak Demands, 2028



[18] The distributions in Table 9 do not reflect load reductions associated with the Companies' Curtailable Service Rider ("CSR") because this program is modeled as a generation resource; CSR load reductions are forecast to be 128 MW in 2028. The maximum winter peak demand (7,495 MW) is forecasted based on the weather from January 19, 1994 when the average temperature was -9 degrees Fahrenheit and the low temperature was -22 degrees Fahrenheit. For comparison, the Companies' peak demand on January 6, 2014 during the polar vortex event was 7,114 MW and the average temperature was 8 degrees Fahrenheit and the low temperature was -3 degrees Fahrenheit. CSR customers were curtailed during this hour and the departing municipals' load was 285 MW.

Figure 7: Distributions of Summer and Winter Peak Demands, 2028



4.6 Capacity Costs

For minimum reserve margin, the Companies estimated the change in load that would require the addition of generation resources. Specifically, the Companies estimated the load increase that would cause adding new SCCT to the portfolio to be less costly than the Existing portfolio. The cost of new SCCT capacity is based on a response to the Companies' June 2022 RFP and is summarized in Table 10 in 2028 dollars. Compared to the cost of SCCT capacity used in the 2021 IRP Reserve Margin Analysis, this cost is 34% lower.

Table 10: SCCT Cost (2028 Dollars)

Input Assumption	Value
Capital Cost ($/kW)	700
Fixed O&M ($/kW-yr)	3.6
Firm Gas Transport ($/kW-yr)	15.6
Escalation Rate	1.47%
Discount Rate	6.43%
Carrying Charge ($/kW-yr)	73.9

4.7 Cost of Unserved Energy (Value of Lost Load)

The impacts of unserved energy on business and residential customers include the loss of productivity, interruption of a manufacturing process, lost product, potential damage to electrical services, and inconvenience or discomfort due to loss of cooling, heating, or lighting.

For this study, unserved energy costs were derived based on information from four publicly available studies.[19] All studies split customers into residential, commercial, and industrial classes, which is a typical breakdown of customers in the electric industry. After escalating the costs from each study to 2028 dollars and weighting the cost based on LG&E and KU customer class weightings across all four studies, the cost of unserved energy was calculated to be $21.0/kWh.

Table 11 shows how the numbers were derived. The range for residential customers varied from $1.6/kWh to $4.0/kWh. The range for commercial customers varied from $28.4/kWh to $42.1/kWh while industrial customers varied from $14.7/kWh to $34.1/kWh. Not surprisingly, commercial and industrial customers place a much higher value on reliability given the impact of lost production and/or product. The range of system cost across the four studies is approximately $8.6/kWh.

Table 11: Cost of Unserved Energy (2028 Dollars)

	Customer Class Mix	2003 DOE Study $/kWh	2009 DOE Study $/kWh	Christian Associates Study $/kWh	Billinton and Wacker Study $/kWh
Residential	34%	1.8	1.6	4.0	3.4
Commercial	36%	42.1	38.3	28.4	29.5
Industrial	30%	24.3	34.1	14.7	29.5
System Cost of Unserved Energy		23.0	24.6	16.0	20.6
	Customer Class Mix	**Min $/kWh**	**Mean $/kWh**	**Max $/kWh**	**Range $/kWh**
Residential	34%	1.6	2.7	4.0	2.4
Commercial	36%	28.4	34.6	42.1	13.7
Industrial	30%	14.7	25.7	34.1	19.4
Average System Cost of Unserved Energy			21.0		

4.8 Spinning Reserves

Based on the Companies' existing resources, they are assumed to carry 243 MW of spinning reserves to meet their reserve sharing obligation and comply with NERC standards. The reserve margin analysis assumes the Companies would shed firm load in order to maintain their spinning reserve requirements.

[19] "Estimated Value of Service Reliability for Electric Utility Customers in the Unites States," Ernest Orlando Lawrence Berkeley National Laboratory, June 2009;
"Assessment of Other Factors: Benefit-Cost Analysis of Transmission Expansion Plans," Christensen Associates Energy Consulting, August 15, 2005;
"A Framework and Review of Customer Outage Costs: Integration and Analysis of Electric Utility Outage Cost Surveys," Ernest Orlando Lawrence Berkeley National Laboratory, November 2003;
"Value of Lost Load," University of Maryland, February 14, 2000.

4.9 Reserve Margin Accounting

The following formula is used to compute reserve margin:

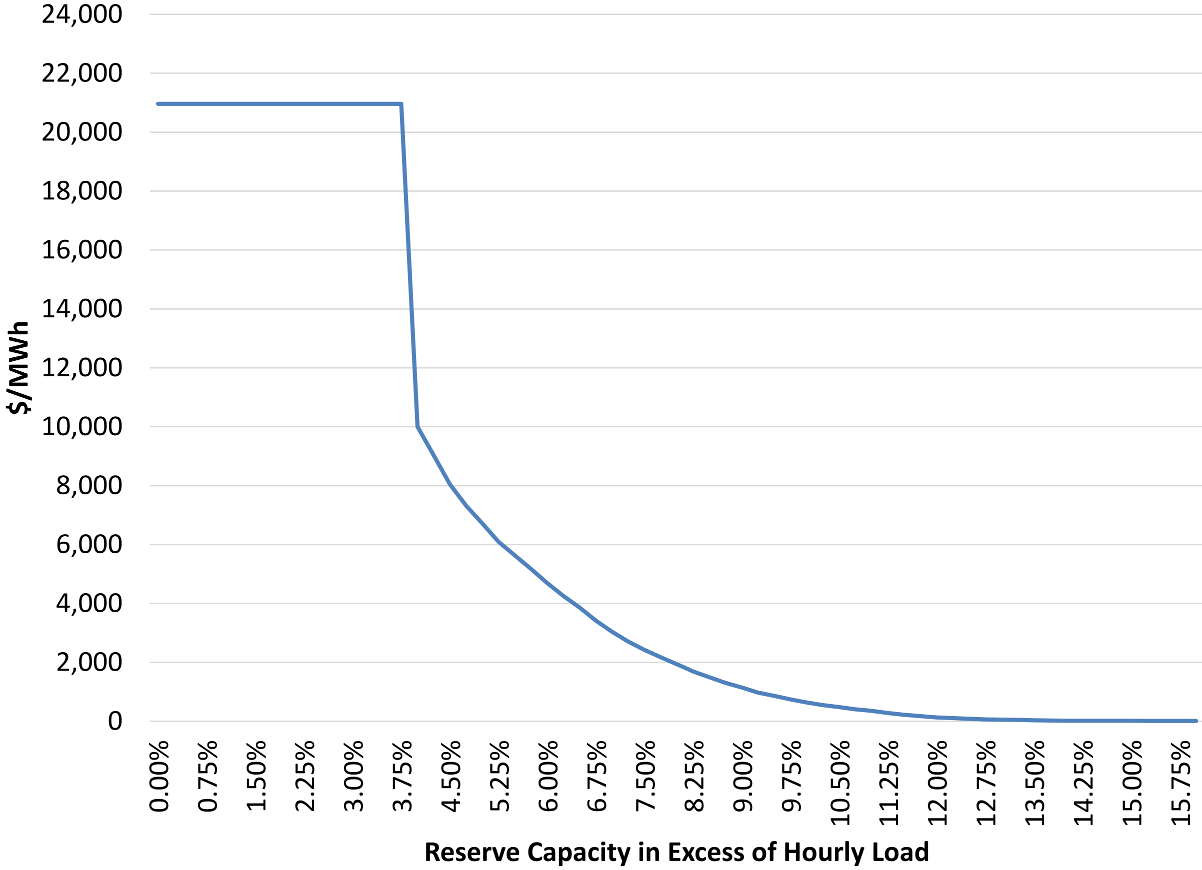
Reserve Margin = Total Supply/Peak Demand Forecast – 1

Total supply includes the Companies' generating resources and interruptible contracts. The peak demand forecast is the forecast of peak demand under normal weather conditions. The impact of the Companies' DSM programs is reflected in the Companies' peak demand forecast. While the Companies are assumed to carry 243 MW of spinning reserves to meet their reserve sharing obligation, this obligation is not included in the peak demand forecast nor as a reduction in generation resources for the purpose of computing reserve margin.

4.10 Scarcity Pricing

As resources become scarce, the price for market power begins to exceed the marginal cost of supply. The scarcity price is the difference between market power prices and the marginal cost of supply. Figure 8 plots the scarcity pricing assumptions in SERVM. The scarcity price is a function of reserve capacity in a given hour and is added to the marginal cost of supply to determine the price of purchased power. The Companies' assumed spinning reserve requirement (243 MW) is approximately 3.8% of the forecasted summer peak demand in 2028 (6,319 MW). At reserve capacities less than 3.8% of the hourly load, the scarcity price is equal to the Companies' value of unserved energy ($21,000/MWh; see Section 4.7). The remainder of the curve is estimated based on market purchase data.

Figure 8: Scarcity Price Curve



The scarcity price impacts reliability and generation production costs only when generation reserves become scarce and market power is available. In ELDCM, the scarcity price is specified as a single value ($100/MWh).

4.11 Summary of Scenarios

Reliability costs and loss-of-load events occur when loads are high or when supply is limited. To properly capture the cost of high-impact, low-probability events, the Companies evaluate thousands of scenarios that encompass a wide range of load and unit availability scenarios. Specifically, the Companies evaluated each generation portfolio over 49 load scenarios and 300 unit availability scenarios.

5 Analysis Results

5.1 Minimum Reserve Margin

To determine minimum summer and winter reserve margin targets, the Companies estimated the change in load that would cause the addition of generation capacity to be economic. To do this, the Companies modeled two generation portfolios:

- Existing: Existing portfolio except Mill Creek 1 (planned retirement in 2024) and the small-frame SCCTs (assumed retirement in 2025); Rhudes Creek and Ragland solar PPAs are not completed.
- Add SCCT: Existing portfolio plus 60 MW of SCCT.[20]

Specifically, the Companies estimated the load increase that would cause the total cost of the Add SCCT and Existing portfolios to be approximately equal. Total costs include generation capacity costs as well as reliability and generation production costs. The summer and winter reserve margins associated with this load increase are the minimum summer and winter reserve margin targets. Below this range, the Companies should seek to acquire additional resources to avoid reliability falling to levels that would likely be unacceptable to customers.

Because significant near-term load increases are most likely to be the result of the addition of one or more large industrial customers, the analysis evaluated the addition of large, high load factor loads. The results of this analysis from ELDCM and SERVM are summarized in Table 12 and Table 13, respectively. Consistent with the 2021 IRP reserve margin analysis, this analysis is focused on total costs that are estimated based on the 85th and 90th percentiles of the reliability and generation production cost distribution for the purpose of reducing volatility for customers. Based on ELDCM and assuming all other things equal, if the Companies' load increases by 150 MW (i.e., summer reserve margin decreases to 17 percent and winter reserve margin decreases to 24 percent), the reliability and production cost benefits from adding new SCCT capacity would more than offset the cost of the capacity. The results from SERVM are very similar.

Table 12: Minimum Reserve Margin Target (ELDCM)

Load Change	Summer Reserve Margin for Existing Portfolio	Winter Reserve Margin for Existing Portfolio	Total Cost w/ 85th %-ile Reliability and Production Costs ($M/year)			Total Cost w/ 90th %-ile Reliability and Production Costs ($M/year)		
			Existing	Add SCCT	Diff: Add SCCT less Existing	Existing	Add SCCT	Diff: Add SCCT less Existing
0	19.4%	27.4%	1,200	1,203	3	1,207	1,210	3
50	18.4%	26.4%	1,218	1,221	3	1,226	1,228	2
100	17.5%	25.3%	1,240	1,239	(1)	1,245	1,247	2
150	16.6%	24.3%	1,261	1,260	(1)	1,267	1,266	(1)
200	15.7%	23.4%	1,281	1,281	0	1,292	1,287	(5)

[20] 60 MW of capacity is approximately equal to 1% of reserve margin.

Table 13: Minimum Reserve Margin Target (SERVM)

Load Change	Summer Reserve Margin for Existing Portfolio	Winter Reserve Margin for Existing Portfolio	Total Cost w/ 85th %-ile Reliability and Production Costs ($M/year)			Total Cost w/ 90th %-ile Reliability and Production Costs ($M/year)		
			Existing	Add SCCT	Diff: Add SCCT less Existing	Existing	Add SCCT	Diff: Add SCCT less Existing
0	19.4%	27.4%	1,204	1,204	0	1,210	1,208	(2)
100	17.5%	25.3%	1,241	1,242	1	1,256	1,250	(6)
150	16.6%	24.3%	1,262	1,258	(4)	1,276	1,273	(4)
200	15.7%	23.4%	1,284	1,279	(5)	1,300	1,297	(3)

5.2 Capacity Contribution of Limited-Duration Resources

In the previous section, the Companies determined the minimum summer and winter reserve margin targets as 17% and 24%, respectively. For portfolio development and screening in PLEXOS, the Companies evaluate potential supply- and demand-side resources as generation replacement alternatives. Some supply- and demand-side resources such as battery storage and dispatchable DSM programs are limited-duration dispatchable resources which do not contribute to reliability in the same way that fully-dispatchable resources do. Therefore, the Companies use SERVM to determine the capacity contribution of limited-duration resources such as battery storage and the proposed new DSM programs by comparing their impact on LOLE to that of a SCCT. This concept is similar to the effective load carrying capability that RTOs compute for limited-duration resources.[21]

To complete this analysis, the Companies estimated LOLE for the generation portfolios in Table 14. The "Reference" portfolio (Portfolio 1) replaces Mill Creek 2, Ghent 2, and Brown 3 with one 621 MW NGCC and has reserve margins that are significantly lower than the minimum reserve margin targets. Portfolios 2-5 add 480 MW of various technologies to the Reference portfolio to achieve summer and winter reserve margins close to the minimum reserve margin targets.

Table 14: Generation Portfolios for Capacity Contribution Analysis

	Generation Portfolio	**2028 Reserve Margin Summer / Winter**
1	Reference: Replace Mill Creek 2, Ghent 2, and Brown 3 with 1 621 MW NGCC	10.3% / 17.6%
2	Reference + 480 MW of SCCT	17.9% / 26.0%
3	Reference + 480 MW of 4-hr BESS	
4	Reference + 480 MW of 8-hr BESS	
5	Reference + 480 MW of Dispatchable DSM	

[21] See PJM's Effective Load Carrying Capability (ELCC) at https://www.pjm.com/-/media/committees-groups/task-forces/ccstf/2020/20200407/20200407-item-04-effective-load-carrying-capability.ashx

Table 15 contains the results of this analysis. With summer and winter reserve margins significantly below the target minimums, the LOLE for the Reference portfolio is 21.32 days in 10 years, which is significantly higher than the reliability standard of 1 day in 10 years. When 480 MW of SCCT capacity is added to the Reference portfolio, LOLE decreases by 17.75 days. Alternatively, when 480 MW of 4-hour BESS is added to the Reference portfolio, LOLE decreases by 14.60 days. The capacity contribution for 4-hour BESS is computed as the ratio of the BESS LOLE impact to the SCCT LOLE impact (14.60/17.75 = 0.82). The capacity contributions for 4-hour BESS, 8-hour BESS, and dispatchable DSM are 82%, 93%, and 35%, respectively, of a SCCT or another fully dispatchable resource.

Table 15: Capacity Contribution for Limited-Duration Resources

Generation Portfolio	Reserve Margin Summer/Winter	LOLE (Days in 10 Years)	LOLE Reduction (Days in 10 Years)	Capacity Contribution
1: Reference	10.3% / 17.6%	21.32	NA	NA
2: Reference + SCCT	17.9% / 26.0%	3.57	17.75	NA
3: Reference + 4-hr BESS		6.72	14.60	0.82
4: Reference + 8-hr BESS		4.88	16.44	0.93
5: Reference + Disp. DSM		15.14	6.18	0.35

2022 Resource Assessment Fuel Price Forecasts

1 Summary

The 2022 Resource Assessment fuel price forecasts for Henry Hub natural gas and Ilinois Basin ("ILB") coal were developed in mid-2022. Using several combinations of these forecasts, the Companies developed the following six fuel price scenarios for the Resource Assessment:

- Expected Coal-to-Gas ("CTG") Ratio
    - Low Gas, Mid CTG Ratio
    - Mid Gas, Mid CTG Ratio
    - High Gas, Mid CTG Ratio
- Atypcial CTG Ratios
    - Low Gas, High CTG Ratio
    - High Gas, Low CTG Ratio
    - High Gas, Current CTG Ratio

The Companies' range of three gas price forecasts is based on the Energy Information Administration's ("EIA") forecasts in its 2022 Annual Energy Outlook ("AEO2022")[1] and is consistent with forecasts prepared by industry consultants, as discussed in Section 2.1. The gas price forecasts and the coal price forecasts with high gas paired with mid and current CTG ratios generally assume that some level of elevated demand in the international fuel markets will remain intact through the long-term period. The High Gas, Current CTG Ratio coal price forecast assumes a continuation of demand outstripping supply in global fuel markets. The Low Gas, Mid CTG and Mid Gas, Mid CTG coal price forecasts reflect a more domestic focus for coal demand. The High Gas, Low CTG and Low Gas, High CTG forecasts show scenarios where market conditions cause price trends to diverge between coal and natural gas.

The scenarios with Mid CTG ratio assume a return to the average historical ratio between ILB coal and gas prices experienced between 2012 and 2021, compared to the corresponding gas prices, as discussed in Section 2.2. Note that the Mid CTG price ratio approximates the ratio of NGCC and coal operating costs. Therefore, it is plausible to expect coal-to-gas price ratios to revert to this ratio over the long term, which is why the Companies refer to it as the "Expected CTG Price Ratio" throughout the Resource Assessment.

The High Gas, Current CTG coal price forecast assumes a continuation of the more recent ILB coal/gas price ratios experienced in 2022, as the coal and gas markets became extremely tight. The High Gas, Low CTG and Low Gas, High CTG price forecasts model variations from the long-term average in the ratio between the price of coal and natural gas.

2 Forecast Methodology

2.1 Natural Gas

The Henry Hub natural gas price forecasts were developed as combinations of short-term and long-term forecasts. The first three years (2023-2025) of the gas price forecasts reflect monthly forward market prices from NYMEX at various quote dates between March and July 2022. In the subsequent years, the market prices were interpolated to the endpoints of the AEO2022 forecasts (see Section 2.1.3).

[1] EIA released the AEO2022 in March 2022. See https://www.eia.gov/outlooks/aeo/.

2.1.1 Gas Price Scenario Assumptions

The first three years of each gas price forecast reflect market forward pricing as of three quote dates between March and July 2022, when the forecasts were being developed and as the forward gas market experienced high volatility.

- **Mid Gas**
  - **2023-2025**: Henry Hub Natural Gas forwards, 7/7/22 market quote date, reflecting the most recent forward market prices when the Companies' 2023 Business Plan forecasts were being finalized.
  - **2026+**: Interpolation to the endpoint in 2050 of the EIA's AEO2022 Reference case.
- **High Gas**
  - **2023-2025**: 6/9/22 quote date, reflecting the peak of forward gas prices during the forecast development period.
  - **2026+**: Interpolation to the endpoint in 2050 of the EIA's AEO2022 Low Oil and Gas Supply case.
- **Low Gas**
  - **2023-2025**: 3/21/22 quote date, reflecting a period of relatively low forward market prices as the current international market factors were still taking shape.
  - **2026+:** Interpolation to the endpoint in 2050 of the EIA's AEO2022 High Oil and Gas Supply case.

2.1.2 Conversion of annual price curves to monthly

Monthly/annual pricing ratios were calculated using NYMEX Henry Hub forwards for the respective market date in each case. These monthly average "factors" were then applied to the annual prices of each gas price case to derive a monthly price curve for years 2026 through 2050.

2.1.3 EIA AEO2022 Cases

2.1.3.1 EIA AEO2022 Reference case (Mid Gas Price Case)[2]

- **Supply.** Natural gas production grows by almost 24%, approximately twice as fast as consumption. U.S. natural gas production increases in all cases except in the Low Oil and Gas Supply case. More than half of the growth in natural gas production is associated with natural gas from tight oil plays with the remaining growth in production attributed to shale resources. Crude oil production returns to pre-pandemic levels in 2023 and peaks in the late 2020s. Production then remains relatively flat through 2050.
- **Demand.**
  - Projected U.S. natural gas exports rise through 2050, primarily driven by increased LNG capacity and growing global natural gas consumption. Increases in pipeline exports to Mexico also contribute to the increase in U.S. natural gas exports. LNG capacity expansions, coupled with high demand for natural gas abroad, result in an increase in LNG exports to 5.86 trillion cubic feet (16.1 Bcf/d) by 2033.
  - Natural gas consumption for space heating, which is the largest single contributor to both U.S. commercial and residential delivered energy consumption throughout the Reference case projection period, declines through 2050.
- **Electricity consumption.** U.S. annual average electricity growth rate remains below 1% over the projection period (2021-2050). Electricity is the fastest-growing fuel used for transportation, growing from less than 0.5% of total consumption in 2019 to nearly 2% in 2050.

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[2] https://www.eia.gov/outlooks/aeo/pdf/AEO2022_Narrative.pdf

- **Generation mix.** In all Cases, the EIA projects that renewable energy will be the fastest-growing U.S. energy source through 2050, more than doubling the current renewable electricity generation mix. Renewable electric generating technologies account for over 57% of the approximately 1,000 gigawatts (GW) of cumulative capacity additions. Solar capacity accounts for 47% of electric generating capacity additions, and wind accounts for about 10%. Solar's share of total U.S. capacity increases from 7% in 2020 to 29% in 2050. Natural gas generation makes up 39% of new capacity additions from 2021-2050. Significant projected coal and nuclear generating unit retirements cause the shares from those sources to drop by half.

2.1.3.2 EIA AEO2022 Low Oil and Gas Supply Case (High gas price case)

- Compared with the Reference case, the Low Oil and Gas Supply case assumes the following are all 50% lower: the estimated ultimate recovery per well for tight oil, tight gas, or shale gas in the United States; the undiscovered resources in Alaska and the offshore lower 48 states; and the rates of technological improvement that reduce costs and increase productivity in the United States.
- The Low Oil and Gas Supply case assumes higher costs and less resource availability, which increases natural gas prices, so LNG exports begin to decline in the mid-2030s.
- In 2050, the projected natural gas price is almost twice as high in the Low Oil and Gas Supply case as in the Reference case.

2.1.3.3 EIA AEO2022 High Oil and Gas Supply Case (Low gas price case)

- Compared with the Reference case, the High Oil and Gas Supply case assumes the following are all 50% higher: the estimated ultimate recovery per well for tight oil, tight gas, or shale gas in the United States; the undiscovered resources in Alaska and the offshore lower 48 states; the rates of technological improvement.
- Shale gas and associated natural gas from tight oil plays are the primary contributors to the long-term growth of U.S. natural gas production through 2050.
- In 2050, the price is approximately 29% lower than in the Reference case.

2.1.4 Gas Price Forecasts Reasonableness

The range of natural gas price forecasts compares reasonably to the market expectations of reputable industry consultants, as shown in Figure 2.[3] The range between the Low and High scenarios reasonably bounds these consultants' forecasts, while the Mid scenario approximates the AEO's Reference case in the long term.

[3] The constultant's forecasts were published in June and August 2022.

Figure 1 - Comparison of Henry Hub Natural Gas Price History and Forecasts (Nominal $/MMBtu)

[redacted]

2.2 ILB Coal

The Illinois Basin ("ILB") coal open position price forecasts were created using the following inputs.

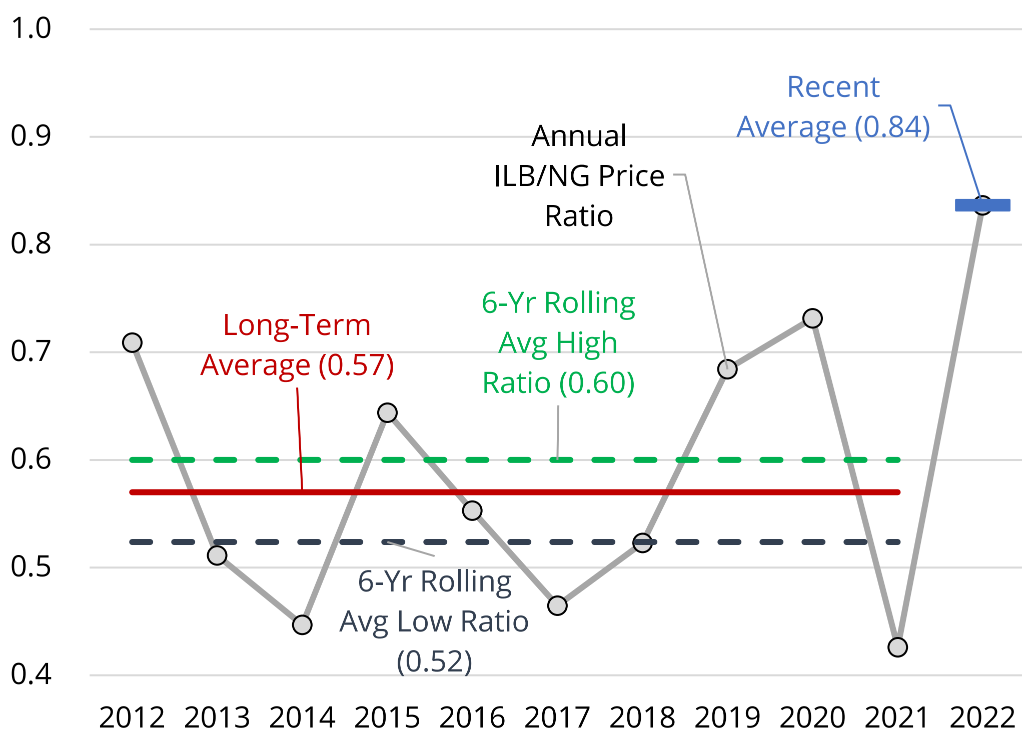
- Bid prices solicited by LG&E/KU's Fuels group
- S&P Global's ("SPG") price forecast
- Historical ILB coal/gas price ratios

For the Mid Gas, Mid CTG coal price forecast, bid pricing sourced from LG&E/KU's Fuels group reflects minemouth quotations supplied by coal suppliers for delivery in each year through 2027. The fuels group received these quotations in response to a request for quotation (RFQ) issued in Q2 2022. Bid pricing for 2027 was estimated by inflating 2026's price by 2%, due to low bid 2027 volume.

SPG was contracted to produce a coal price forecast to complement the Companies' bid pricing. SPG produced this forecast in Q1 2022 just before a steep increase in commodity prices, so the forecast was adjusted in July 2022 to reflect current natural gas futures prices, which had increased by 25%-30% due to production being tightly balanced with demand as export demand from Europe remained elevated as the supply of Russian coal and gas was reduced.

The long-term ILB price forecasts comprise 6 scenarios that were developed by applying historical relationships between ILB coal and natural gas prices to the natural gas price forecasts. Figure 3 shows that relationship over the past decade.

Figure 2 - Historical ILB Coal/Henry Hub Gas Ratios (CTG)



The ILB coal/Henry Hub natural gas ratio (referred to as "CTG") is the ratio between yearly average ILB coal prices and natural gas prices. The long-term average CTG of 0.57 over the decade through 2021 (referred to as the "Mid CTG") reflects a relatively stable coal market with ample supply vs. demand as depicted by the red line on Figure 3. This average is the basis for the Mid CTG coal price forecasts. As noted above, the Mid coal-to-gas price ratio (0.57) approximates the ratio of NGCC and coal energy costs. Therefore, it is plausible to expect coal-to-gas price ratios to revert to this ratio over the long term, which is why the Companies refer to it as the "Expected CTG Price Ratio" throughout the Resource Assessment.

The remaining CTG ratios are atypical. The first such atypical CTG ratio is the recent average ratio (referred to as the "Current CTG"), at 0.84, is the 2022 January through mid September average CTG. This ratio reflects a volatile market and is the basis for the High Gas, Current CTG coal price forecast, which assumes that strong demand for ILB coal continues in both domestic and export markets and that the coal industry constrains supply increases by maintaining low capital expenditures.

The High and Low rolling 6-yr average ratios (referred to as the "High CTG" and "Low CTG") depicted on the graph at 0.60 and 0.52, respectively, are also atypical. They are the maximum and minimum rolling 6-year average ILB coal/Henry Hub gas price ratio over the past decade. These ratios are used to create the High Gas, Low-CTG and Low-Gas, High CTG coal price forecasts, which are intended to model a range of scenarios where coal and gas prices diverge from their historical correlation.

2.2.1 ILB Coal Price Scenario Assumptions

- **Mid Gas, Mid CTG**
  - **2023-2027**: blend of bid prices and the adjusted SPG forecast using the following weightings.
    - 2023: 100% bid pricing
    - 2024: 75% bid pricing/25% adjusted SPG forecast
    - 2025-2027: 50% bid pricing/50% adjusted SPG forecast

Figure 4 shows the resulting near-term ILB price forecast and its components.

Figure 3 - Mid ILB Coal Price Forecast, 2023-2027 (Nominal $/MMBtu)

[redacted]

  - **2028-2050:** The Mid gas price forecast multiplied by the long-term average CTG ratio of 0.57.

- **Low Gas, Mid CTG and High Gas, Mid CTG:** The Low and High gas price forecasts, respectively, were multiplied by the Mid CTG of 0.57 throughout the planning period.
- **High Gas, Current CTG** was developed by multiplying the High gas price forecast by the Recent CTG, which is 0.84.
- **High Gas, Low CTG** was developed by multiplying the High gas price forecast by the Low CTG ratio, which is 0.52.
- **Low Gas, High CTG** was developed by multiplying the Low gas price forecast by the High CTG ratio, which is 0.60.

KENTUCKY UTILITIES COMPANY
AND
LOUISVILLE GAS AND ELECTRIC COMPANY

Response to Attorney General's Initial Request for Information
Dated February 17, 2023

Case No. 2022-00402

Question No. 13

Responding Witness: Lonnie E. Bellar

Q-13. Provide a detailed, thorough and comprehensive explanation regarding the causes of the rolling blackouts the Companies instituted during Winter Storm Elliott ("the Storm"), from Dec. 23-25, 2022. Include in your discussion, at a minimum, the following issues set forth below. For each issue identified below, and for any additional issues the Companies identify, explain also, where applicable, the potential future impact as to both of the proposed NGCC plants:

a. The performance of each one of the Companies' generating units, including the capacity factor of all of the Companies' existing solar units;

b. Whether the Companies had secured adequate fuel, and whether the Companies, and/or their pipeline suppliers, may need to obtain additional storage for both the LG&E LDC operations and the Companies' joint electric generation operations. Include in your response whether the Companies can identify any infrastructure needs that would help increase the reliability of their gas supply;

c. Whether pipelines that provide gas to the Companies' generating units were affected in any manner by the Storm, and if so, how;

d. Whether the Brown Station combustion turbines ("CTs") were operated off of the Texas Eastern or Tennessee Gas pipelines, or perhaps both;

e. Identify the pipeline and the supplier that provide gas to the Trimble Station CTs;

f. Explain whether any of the issues that may have affected the Brown CTs also affected the Trimble CTs. If so, provide a discussion on whether a redundant gas supply to Trimble should be investigated;

g. Whether any of the gas suppliers and/or owners of any such affected pipelines declared a force majeure as a result of the Storm, and if so, the impact this had on the Companies, in terms of cost and otherwise;

h. Whether the Companies maintain any hedging or insurance products designed to reduce the risk of gas and/or other fuel shortages;

i. If the supplier the Companies use was unable to supply gas, explain whether any other suppliers are allowed to supply gas on the Texas Gas pipeline, and if so, explain whether the Companies either currently have a back-up supply contract with any other supplier, or if not, whether they will consider doing so in the future;

j. Explain whether any of the Companies' CTs have dual-fuel capability, and if so, whether the Companies have investigated installing on-site tanks to store a second fuel supply, such as Duke Energy, Kentucky and East Kentucky Power Cooperative ("EKPC") have;

k. Whether the Companies were able to make any off-system purchases to help mitigate the rolling outages;

l. Provide all studies / internal analyses, evaluations or reports the Companies performed regarding the performance of their generation and transmission facilities during the Storm, including any "lessons learned" studies. Include in your response whether the Companies plan to retain any external consultants to perform any such studies or analyses, and if so, provide timelines for the completion of such studies;

m. Explain whether in light of the Storm, the Companies believe that their generation reserve margin should be re-evaluated;

n. The Storm's impact on the Fuel Adjustment Charge (i.e., will there be any significant increases or decreases), and whether there will be any significant impact on base rates;

o. Provide the total time duration during which rolling blackouts were instituted, the total number of ratepayers affected, and the average length of time the blackouts lasted.

p. In the aftermath of the Storm, do the Companies believe it is more important to preserve their remaining coal fleet?

q. Explain whether the Companies believe they did an adequate job of communicating with their customers regarding the rolling blackouts. Explain also whether the Companies could provide more enhanced communications, including via a phone or computer app.

A-13.

a. See the response to JI 1-22d. During December 23-25, 2022, the Brown Solar capacity factor was 11.5%, while the Simpsonville Solar capacity factor was 13.6%.

   The Brown Solar and Simpsonville Solar facilities were not operating during the hours that load was curtailed.

b. LG&E's gas distribution business had adequate natural gas supplies including storage to serve its customers during the Storm. LG&E's gas business has not identified any infrastructure needs that would increase reliability as a result of its operating experience during the Storm. The Companies secured adequate natural gas supply for generation during Winter Storm Elliott and those supplies were not cut by suppliers. The Texas Gas Transmission pipeline serving Cane Run and Trimble County experienced equipment issues that caused reductions in gas pressure affecting the Companies' ability to operate generating units at full output at those sites. Texas Gas is taking steps to upgrade equipment and update operational procedures to ensure transportation reliability.

c. See the response in part (b) for the interstate pipeline impact on the Companies generating units. LG&E's gas distribution business serves coal-fired generation units at Mill Creek with gas for unit start-up and stabilization. LG&E's gas distribution pipeline serving Mill Creek was not impacted by the Storm.

d. The Brown Station CTs were operated on the Texas Eastern pipeline during Winter Storm Elliott.

e. Texas Gas Transmission provides natural gas transportation to the Trimble Station CTs.

f. The interstate pipeline pressure issue affecting the Trimble County CTs did not affect the Brown CTs, where gas was delivered via a different interstate pipeline. There is not another interstate pipeline in the vicinity of the Trimble County plant for potentially developing a secondary interstate pipeline connection.

g. The Companies did not receive force majeure notices from any gas suppliers or interstate pipelines providing gas to the Companies' generation assets. LG&E's gas distribution business receives gas from suppliers on Texas Gas Transmission, LLC ("Texas Gas") and Tennessee Gas Pipeline, LLC

("Tennessee"). There were no Force Majeures issued by LG&E's suppliers, Texas Gas or Tennessee during the Storm.

h. LG&E's gas distribution company does not maintain any hedging or insurance products designed to reduce the risk of gas shortages. LG&E's gas supply plan includes a reserve margin to mitigate the risk of forecast error, LG&E compressor station equipment issues, or the loss of pipeline supply. The reserve margin is provided by LG&E's on-system storage.

   The Companies do not maintain hedging or insurance products designed to reduce the risk of gas shortages for generation. The Companies' firm gas transport agreement services, gas purchasing practices, and dual fuel capability for some of the Brown CTs are designed to ensure that adequate fuel is available and deliverable to the Companies' generating units.

i. See the response to part (b). The Companies purchase gas from multiple suppliers on the spot and forward markets for generation gas supply.

   None of the suppliers to LG&E's gas distribution system declared Force Majeure. However, LG&E's gas distribution business has contracts in place with several suppliers that allow it purchase gas a day at a time. If one supplier fails to perform, LG&E could attempt to purchase gas "intra-day" from another supplier. However, there is no guaranty that "intra-day" supply will be available.

j. The Companies currently have dual fuel capabilities for 4 CTs at the Brown Station, which has both fuel oil storage and demineralized water storage to support operation on fuel oil.

k. See the response to PSC 1-58(b).

l. The investigation into the events of Winter Storm Elliott are ongoing. Attached are two completed reports, a comprehensive event summary report for Generation, Transmission and Distribution, and a summary report for Gas Operations. The Companies have not retained the services of an external consultant to review the event.

m. The Companies review of storm events, see the response to AG 1-13(l), will inform any decision to change the Companies Reserve Margin requirements. Currently, we do not expect a change in Reserve Margin requirements.

n. The issues that impacted the Companies' ability to meet its load requirements during Winter Storm Elliott did result in the Companies' making high cost energy purchases. Based on Commission precedent, $3.4 million of KU's purchases were excluded from FAC recovery for the month of December.

None of LG&E's purchases were excluded from FAC recovery, as they did not exceed the cost of LG&E's highest cost unit available during the month of December. There will be no impact to current base rates, as they can only be changed through an application with the Commission.

o. Total time duration during which rolling blackouts were instituted: 5:59PM to 10:11PM December 23, 2022 (4 hours, 12 minutes). Total customers Affected: 54,637. Average length of outage per customer: 59 minutes.

p. See the response to PSC 1-58(a). Also, it is important to note that one of the Companies' coal units was on a forced outage on December 23 and several coal units experienced derates during the course of the storm event. The Companies are confident that the new generation resources proposed in this CPCN case will provide reliable, low-cost service to our customers for many decades into the future.

q. The Companies are always seeking to improve performance and are reviewing their communications during the storm to identify opportunities for future improvements.

Winter Storm Elliott
Events in the LG&E and KU Balancing Authority Area (BAA)
December 23-24, 2022

Executive Summary

Winter Storm Elliott hit the Eastern Interconnect December 23-25, straining the grid, and resulting in load shedding events across the region. As the storm moved across Kentucky, it transitioned from rain to ice then snow. Elliot's conditions included:

- Temperatures as low as -8 degrees, the lowest in the Louisville area since 1994.
- Windchills exceeding 30 degrees below zero and wind gusts of 30-40 miles per hour.
- Snowfall of 1-5 inches.

The storm set new all-time December electric peaks within the LG&E and KU BAA on Friday, Dec. 23rd.

- Total Daily Energy Usage was 141,613 MWh, breaking the prior record of 134,600 MWh set on Dec. 14, 2010.
- Over half-a-billion cubic feet of gas was delivered to customers on December 23. This was the second highest amount of gas delivered to customers on record for December. 42% of that gas came from LG&E gas storage fields.

On the evening of December 22 temperatures began to drop rapidly across the state. In Louisville the temperatures dropped from the mid-40s at 16:00 to single digits by midnight and below zero by 04:00. Over the course of the next two days, the LG&E and KU BAA experienced significant challenges including interstate gas pipeline pressure limitations, mechanical and other cold weather issues.

This narrative is intended to provide a high-level overview with real time event history as it impacted the LG&E and KU BAA.

On the morning of December 22, the 14-day projected net peak was forecasted to be 5,899 MW on December 23 at 20:00. On December 23 at 00:00 there was 4,761 MW of generation in service and 7,239 MW available capacity (excluding contingency reserves). The actual peak was 6,559 MW on December 23 at 17:58, well within the projected available capacity. TC1, BR10 and Dix1 (444 MW net total) were offline to address pre-existing mechanical issues and were not expected to be needed.

EW Brown Station's fuel gas was supplied by Texas Eastern Transmission Pipeline ("TETCO") throughout the event and was unaffected by external supply issues.

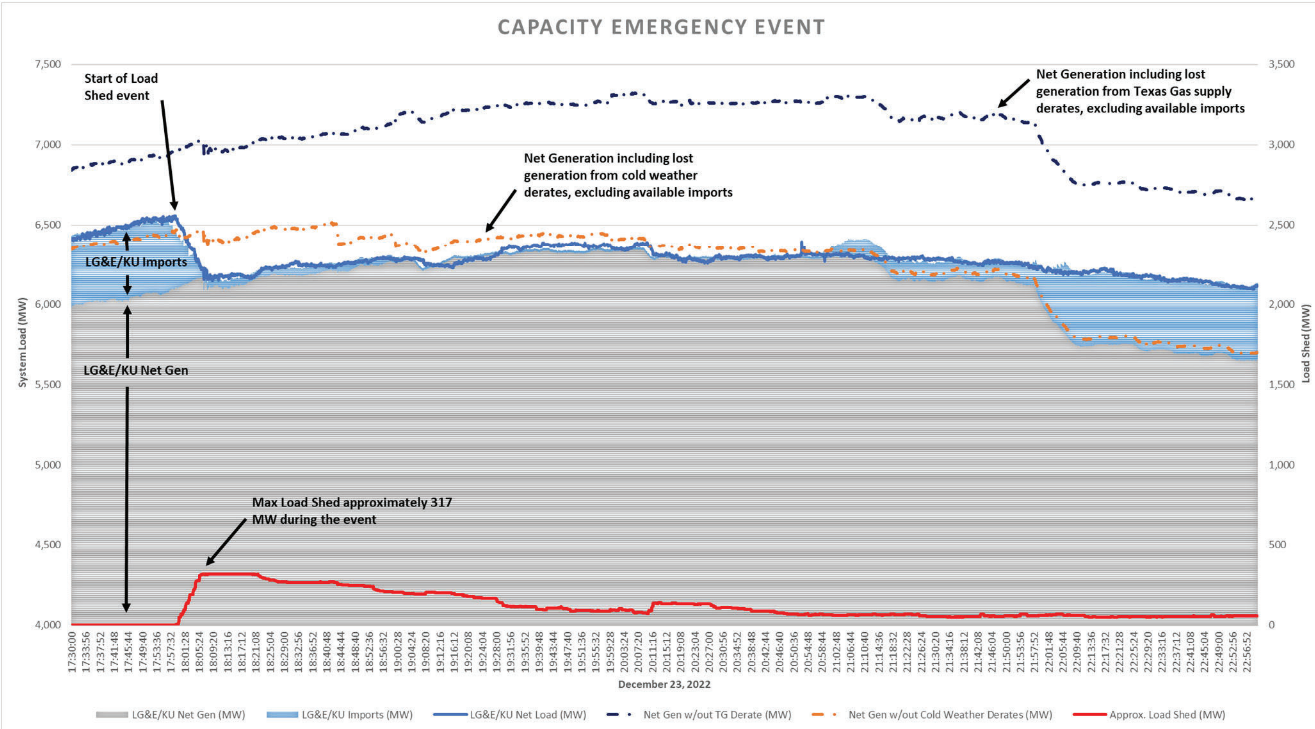
Cane Run and Trimble County plants are supplied by the Texas Gas Transmission Pipeline ("Texas Gas"). The companies' transportation contracts with Texas Gas specify minimum pressure for deliveries to Cane Run at 550 psi and Trimble County at 530 psi. Texas Gas deliveries to Cane Run fell below the minimum required pressure at 11:09 on 12/23. As a result, Cane Run experienced derates between 12/23 at 13:08 and 12/25 at 04:06. Deliveries to Cane Run did not return to full contracted pressure until 12/25 at approximately 13:00. Texas Gas deliveries to Trimble County fell below the minimum required pressure at approximately 11:15 on 12/23, requiring several derates at the plant between 12/23 at 13:47 and 12/25 at approximately 16:00, when the deliveries returned to full contracted pressure. Note that per NERC GADS rules, 'Failure of fuel supplier to fulfill contractual obligations' is considered 'Outside Plant Management Control' and does not contribute to the plant EFOR. See appendix A for fuel gas supply pressure trends.

Further contributing to the shortfall was the interruption in energy deliveries from OVEC, which was projected to supply 156 MW on 12/23 but in fact ranged from 91 MW to as little as 6 MW over the course of the event. Additionally, several times during the event TVA could not support its contingency reserve requirements, withdrawing its contribution to the Contingency Reserve Sharing Group ("CRSG") and necessitating LG&E/KU to cover a significantly increased amount of contingency reserve for our BAA (equal to our Most Severe Single Contingency, or MSSC, of 710 MW – an increase of over 450 MW in contingency reserve requirements).

As conditions across the regional grid began deteriorating on December 23, LG&E and KU executed the Capacity and Energy Emergency Operating Plan (which includes NERC required measures). The urgent actions required when facing these rare, emergency conditions necessitate swift, thoughtful response to restore system balance as quickly as possible or risk wide scale impacts over an extended period. The LG&E and KU Balancing Authority ("BA") had to shed load on 12/23 from 17:58 through 22:11 by as much as 317 MW. While this event impacted less than 5% of LG&E and KU customers, it was a first-of-its kind occurrence within the LG&E and KU system. See Appendix B for graph of customers affected by utility.

During the time of the load shedding event, derates attributable to the inability of Texas Gas to meet contractual delivery obligations ranged from 785MW to 943 MW. Derates unrelated to Texas Gas supply ranged from 45MW to 361MW.

The following graph demonstrates the impact that the gas supply issue had on the system in conjunction with the load shedding event. This graph covers the period of 12/23 from 17:30 to 22:58 and encompasses the entirety of the load shedding event. It also reflects the impact of the non-gas supply derates.



Generation Events

This narrative details the events across the LG&E and KU Generation Fleet over the course of the cold weather event. It does not directly reflect customer impact. Starting Friday, 12/23 the following generating issues developed:

- 12/23/22 at 00:00 the generation fleet condition was as follows:
  - Per Generation Dispatch there was 4,761 MW of generation in service and 7,239 MW available capacity.
  - **TC1** (370 MW net exclusive of partners) had been in outage since 12/22/22 at 15:35 due to failure of submerged drag chain conveyor hydraulic gearbox. Repairs were in progress at the time of this event, but the unit was available for up to 75 MW (exclusive of partners) firing gas only.
  - **BR10** (138 MW net) had been in an outage since 12/3/22 when a borescopic inspection identified issues with turbine seals. Repairs were in progress at the time of this event.
  - **Dix 1** (11 MW net) had been in a planned outage since 11/14/22. The unit could not be commissioned at the available lake level.
- 01:28 **BR5** (130 MW net) and **BR8** (128 MW net) tripped offline due to an interruption in fuel gas. This same failure rendered **BR9** (138 MW net) and **BR11** (128 MW net) unavailable. A pilot light that preheats fuel gas to act as control gas for fuel gas supply regulators blew out, making the regulators to the BR CT's inoperable and stopping fuel gas supply to the units. Station Maintenance built enclosures, installed heat trace, and

wrapped in insulating blanket. This system was released back into service 12/23 at 16:58.

  - **BR9** came online firing fuel oil at 03:50.
  - **BR11** was made available at 03:50 and came online firing fuel oil at 07:40. It tripped at 15:39 due to a flame scanner issue and returned to service at 17:03 firing gas.
  - **BR8** came online firing fuel oil at 07:02. It hit a controls alarm for emissions limitations at 10:51, derating it to 100 MW.

- 03:10 **TC2** derated by 37 MW net (exclusive of partners) due to low inlet air temperature into the air heater. With the very low ambient air temperatures the water coil air heater could not provide sufficient heat input to maintain full load. This variable derate continued through 12/27/22 at 16:30.
- OF (45 MW net) The Army Corps lost power to the dams due to inclement weather issues. OF units were taken offline between 04:32 and 15:20 by order of Army Corps as a method of regulating the pool.
- 05:10 Generation Dispatch went into Alert Status, an internal status requesting that plant personnel avoid unnecessary risks with generating units.
- 05:15 PR13 (175 MW net) online. Tripped at 06:36 due to low generator gas temperature. This was caused by a manual valve in the cooling water circuit. The valve was set to its winter flow setting, but the extreme cold necessitated an additional adjustment. The unit came back online at 07:13.
- Secondary CT's:
  - 06:15 the HA units (2x14 MW net) were requested. Note that this site is unmanned and requires local operation. The delay to start was based on dispatching personnel to the site.
  - HA1 came on at 10:33 and ran until 12/24/22 at 14:57
  - HA2 was made unavailable from 10:33 until 14:57 due to a substation breaker issue, at which point the lube oil temperature to the unit could not make minimum temperature due to the extreme cold.
  - 07:52 PR12 (28 MW net) online.
  - 09:46 Dix2 and 09:52 Dix3 (11 MW net each) online.
- 07:17 BR3 (400 MW net) derated by 62 MW due to problems with combustion process instrumentation (not believed to be weather related at this time). This led to additional combustion related issues and derates through 12/25/22 at 21:15 when the unit was taken offline due to excessive slagging. The maximum derate prior to coming offline was 76 MW.
- At 11:09 gas pressure CR dropped below their contract limit of 550psi and soon after TC dropped below their contract limit of 530psi. By 13:08 this began to affect generating units, first when TC5 tripped (179 MW) followed by a derate at CR7 at 13:47 (253 MW). This derate varied as gas supply pressure changed over the course of the event. At

13:48 the operating gas turbines at TC collectively took a 439 MW derate to manage dropping gas pressure. As previously noted, TC1 was available for 100 MW firing gas had supply been available.

- 15:48 TC2 experienced a derate of 269 MW net due to a frozen boiler feed pump transmitter. This caused a unit runback that tripped a coal mill. The mill needed to be manually purged before returning to service. This lasted until 22:26 when the unit returned to its previous 37 MW derate due to inlet air temperature.
- At 16:13 MC4 lost a coal feeder due to cold weather-related bunker issues (coal tripper froze up) and took a 121 MW derate. This was resolved as of 18:44 and the unit returned to full load.

External Impacts

The timeline below details the interaction between LG&E/KU BA and the external entities whose actions impacted the LG&E/KU system including times when customers were impacted. For simplicity and readability, it excludes real time LG&E/KU generation status information.

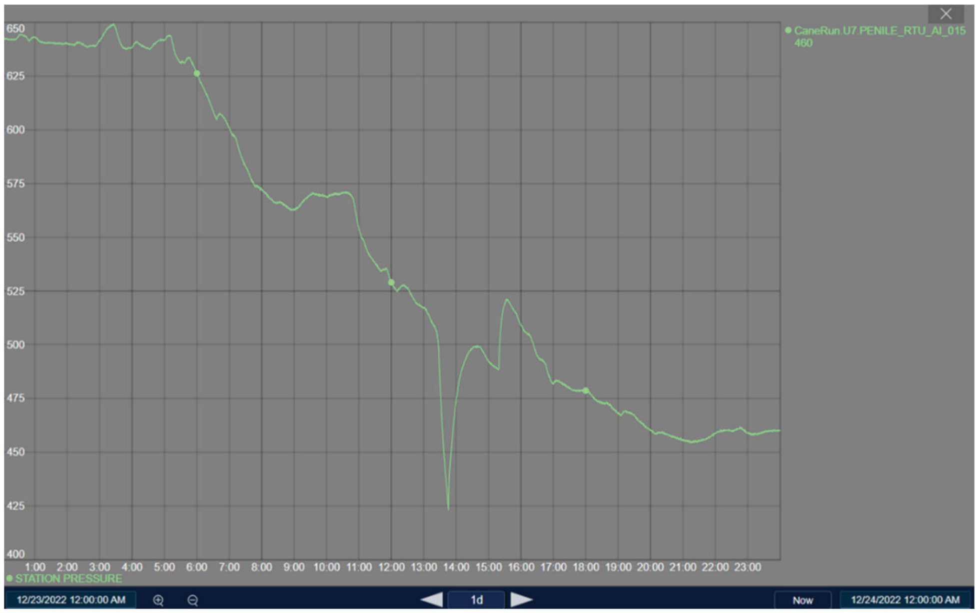
- 12/23/22
    - 05:07 TVA declared EEA-1
    - 05:38 TVA declared EEA-2
    - 06:12 TVA declared EEA-3
    - 06:26 LG&E/KU Out of CRSG - carrying 700 MW reserves for CR7 (at current time MSSC)
    - 09:00 LKE Curtailable Service Rider (CSR) customers - directed to reduce load consistent with their contract and tariff.
    - 10:15-11:45, 11:50-13:30 requested CSR assistance, LKE supplied 243 MW contingency reserves
    - 11:09-11:15 Texas Gas supply pressure to TC and CR dropped below the contract limit
    - 13:08 Generation derates due to Texas Gas supply pressure issues begin
    - 13:36 LG&E/KU BA declared EEA 3, pulled reserves from the CRSG
    - 13:51 TVA declared EEA-2
    - 14:48 TVA supplied extra 243 MW to CRSG
    - 14:52 LG&E/KU BA changes from EEA 3 to EEA 2 and supplied our 243 MW to CRSG
    - 16:29 PJM curtailed import to LG&E/KU for 400 MW
    - 16:29 ARS called for 400 MW
    - 16:45 LG&E/KU BA declares EEA 3
    - 17:18 TVA declares EEA-3
    - 17:58 LG&E/KU BA starts Load Shed process. The peak system load of 6,552 MW with a system capacity of 6,129 MW was achieved at this point
    - 18:05 End of TVA curtailment tag

  - 21:30 TETCO force majeure issue in Ohio (no impact to Brown as supply was coming from the south).
  - 22:11 Per BA/TO all breakers opened during load shed were back closed
- 12/24/22
  - 00:53 LG&E/KU BA declares EEA 2
  - 01:55 LG&E/KU BA declares EEA 3
  - 06:00 PJM adjusted OVEC tags by as much as 59 MW between 06:00 and 12:00. The GO worked with the BA and TVA RC to resolve but it is unknown at this time why PJM was changing tags.
  - 12:10 TVA declares EEA 2
  - 12:22 LG&E/KU BA declares EEA 2
  - 13:07 TVA declares EEA 1
  - 13:45 TVA declares EEA 0
  - 14:06 LG&E/KU BA declares EEA 0
- 12/25/22
  - 13:15 LG&E/KU ended Generation Alert Status
  - 16:00 Generation derates due to Texas Gas supply pressure issues end

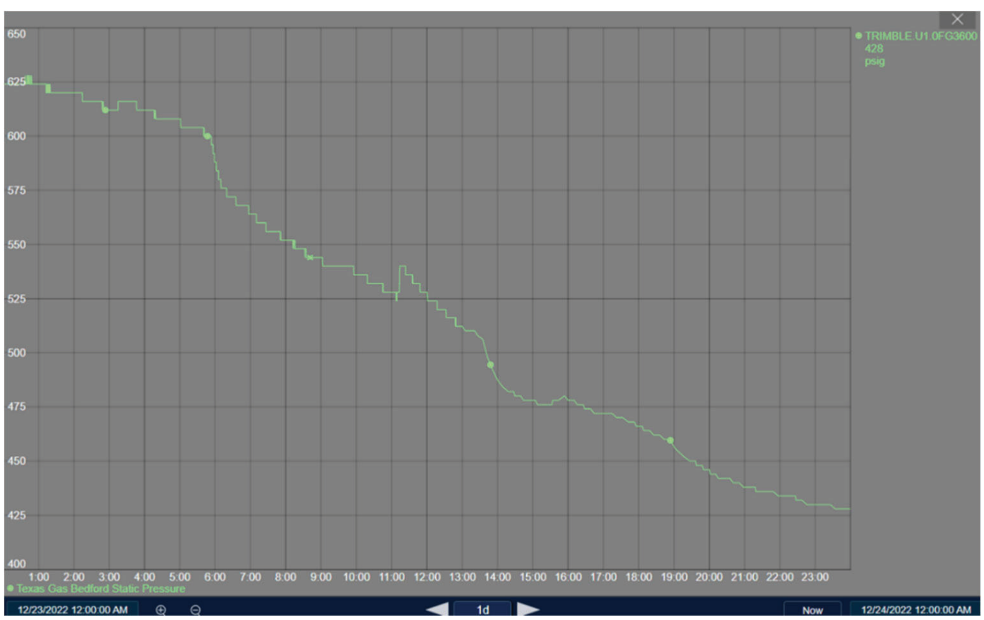
Appendix A:

Supplied Gas Pressure from Texas Gas on 12/23/22 at 00:00 through 23:59

Cane Run



Trimble County



Supplied Gas Pressure from Texas Gas on 12/22/22 at 08:00 through 12/26 at 04:00

Cane Run (Low pressure persisted until 12/25/2022 at approximately 13:00)

Trimble County (Low pressure persisted until 12/25/2022 at approximately 16:00)

Appendix B:

LG&E/KU Customer Outages

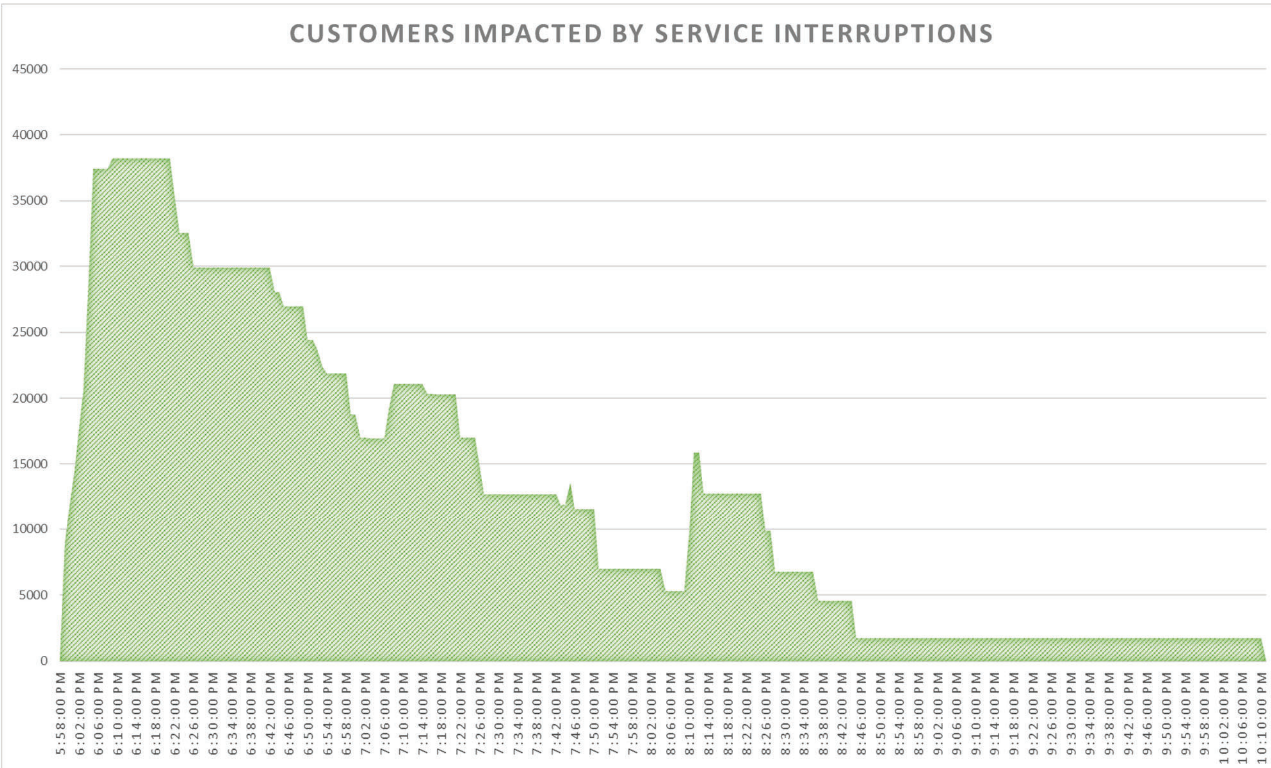


EXHIBIT MG-3

List of Flowgates used in LG&E and KU AFC/ATC process

FG ID	Flowgate	FG Shortname	FG Owner
1023	Volunteer-PhippsBend 500 kV (flo) Jefferson-Rockport 765 kV	VOLPHBJEFROC	TVA
1024	Volunteer-PhippsBend 500 kV (flo) Conasauga-Mosteller 500 kV	VOLPHBCONMOS	TVA
1025	Trimble Co.-Clifty Creek 345-Rockport-Jefferson 765	TRMCLFROCJEF	LGEE
1095	Smith 345/138 kV XFMR (flo) Wilson - Daviess 345 kV	SMIXFRWILDAV	OMU
1613	Volunteer - Phipps Bend 500	VOLPHB__PTDF	TVA
1644	Bull Run - Volunteer 500kV	BLLVOL__PTDF	TVA
1660	Coleman Tap-Paducah Primary 161 kV (flo) Shawnee-Marshall 500 kV	GRASPDSHNMRS	LGEE
1661	Livingston Co-North Princeton 161 kV (flo) Livingston Co-Crittenden Co-Morganfield 161 kV	LIVERLLIVCRD	LGEE
2047	Gibson_Petersburg_345_flo_Gibson_Bedford_345	GIBPETGIBBDF	MISO
2089	Clifty Creek-Trimble Co. 345	CLFTRM__PTDF	LGEE
2092	Cloverport - Green River Steel 138	CVPGRS__PTDF	LGEE
2192	Pineville 500/345 Tr.	PINXFM__PTDF	LGEE
2201	Brown South-Fawkes 138 kV	BRNFWK__PTDF	LGEE
2244	Paddys-Summershade 161 (flo) Baker-Broadford 765	PDRSSHBAKBRO	TVA
2268	Smith-Green River Steel 138 (flo) Smith 345/138 Xfmr	SMIGRSSMIXFM	LGEE
2277	Avon-Loudon 138 (flo) Ghent-West Lexington-Brown 345	AVNLDNGHEWLX	LGEE
2285	Paddys West - Paddys Run 138	PDWPDR__PTDF	LGEE
2294	Clifty Creek-Carrollton 138 (flo) Baker-Broadford 765	CLFCARBAKBRO	LGEE
2484	Northside - Clifty Creek 138 (flo) Trimble County - Clifty Creek 345	NSICLFCLFTRM	LGEE
2525	W Frankfort - E Frankfort 138 (flo) Ghent - W Lexington - Brown N 345	FFWFFEGHEWLX	LGEE
2614	Bull Run-Volunteer 500kV (flo) WBN-Volunteer 500 kV	BULVOLWBNVOL	TVA
2801	Brown N-Alcalde 345 (flo) Baker-Broadford 765	BNNALCBAKBRO	LGEE
2802	Buckner-Middletown 345 (flo) Trimble County-Clifty Creek 345	BUKMIDTRMCLF	LGEE
2803	Calvert-Livingston 161 (flo) Kentucky Dam-Livingston 161	CVELIVKYDLIV	LGEE
2804	Green River-River Queen Tap 161 (flo) Green River-Corydon Tap 161	GRVRQTGRVCDT	LGEE
2805	Hardinsburg-Black Branch 138 kV (flo) Daviess Co-Hardin Co 345 kV	HBGHCODVCHCO	LGEE
2806	Hardinsburg-New Hardinsburg 138 (flo) Cloverport-New Hardinsburg 138	HBGNHBCVPNHB	LGEE
2807	Kentucky Dam-Livingston 161 (flo) Calvert-Livingston 161	KYDLIVCVELIV	LGEE
2808	Livingston-Crittenden 161 kV (flo) Livingston-North Princeton 161 kV	LIVCRDLIVERL	LGEE
2809	Pineville 345/500 Xfm (flo) Baker-Broadford 765	PINXFMBAKBRO	LGEE
2810	River Queen Tap-Earlington North 161 kV (flo) Green River-Corydon Tap-Morganfield 161 kV	RQTERLGRVCDT	LGEE
2811	Trimble County-Buckner 345 (flo) Trimble County-Middletown 345	TRMBUKTRMMID	LGEE
2812	Trimble County-Middletown 345 (flo) Buckner-Middletown 345	TRMMIDBUKMID	LGEE
2813	West Lexington 345-138 kV (flo) Brown North - West Lexington 345 kV	WLXXFMBNNWLX	LGEE
2816	Trimble County - Clifty Creek 345 kV (flo) Trimble County - Ghent 345 kV	TRMCLFTRMGHE	LGEE
2818	Clifty Creek - Trimble County 345 kV (flo) North Clark - Spurlock 345 kV	CLFTRMNCSPRL	LGEE
2819	Clifty Creek - Carrollton 138 kV (flo) Clifty Creek - Trimble County 345 kV	CLFCARCLFTRM	LGEE

Note: Rating values can be found in OASIS under AFC initialization impacts detail report for LGEE owned Flowgates. For Flowgates with owner other than LGEE, please refer to the respective owner's OASIS for updated values.

FG ID	Flowgate	FG Shortname	FG Owner
2820	Clifty Creek - Carrollton 138 kV (flo) Trimble County - Ghent 345 kV	CLFCARTRMGHT	LGEE
2821	Clifty Creek - Northside 138 kV (flo) Clifty Creek - Trimble County 345 kV	CLFNRSCLFTRM	LGEE
2822	Smith - Daviess County 345 kV (flo) Green River Steel - Smith 138 kV	SMIDCGRVSSMI	LGEE
2824	North Princeton - Earlington North 161 kV (flo) Morganfield - Crittenden Co - Livingston Co 161 kV	NPRELNMGCCLC	LGEE
2826	Cloverport - Tip Top 138 kV (flo) Daviess County - Hardin County 345 kV	CLVPTPTPDCHC	LGEE
2830	Trimble County - Clifty Creek 345 kV	TRMCLF__PTDF	LGEE
2833	Green River Steel - Cloverport 138 kV (flo) Coleman - Daviess County 345 kV	GRSCLVCOLDCO	LGEE
2834	Wilson - Matanzas 161 kV (flo) Green River - Wilson 161 kV	WILMATGRVWIL	LGEE
2837	Wilson - Green River 161 kV (flo) Matanzas - Wilson 161 kV	WILGRVMATWIL	MISO
2838	Matanzas - Wilson 161 kV (flo) Green River - Wilson 161 kV	MATWILGRVWIL	LGEE
2872	East Frankfort - Tyrone 138 (flo) Ghent - West Lexington - Brown 345	FFETYRGHEWLX	LGEE
2883	Green River-River Queen Tap 161	GRVRQT__PTDF	LGEE
2884	Green River Steel-Cloverport 138 (flo) Smith 345-138 kV	GRSCVPSMIXFM	LGEE
2973	Smith 138-345 (flo) Hardinsburg - Hardin Co. 138	SMIXFMHBGHCO	OMU
2977	Buckner-Middletown 345 (flo) Trimble Co-Middletown 345	BUKMIDTRMMID	LGEE
2979	Ghent-NAS 138 (flo) Ghent - W Frankfort 345	GHENASGHEFFW	LGEE
3322	Cloverport-N. Hardinsburg 138 kV flo Cloverport-Hardinsburg 138 kV	4CL4NH4CL4HA	MISO
17564	Volunteer - Phipps Bend 500 kV (flo) Mountaineer Unit 1	VOLPHIMOUNTA	TVA
17884	Volunteer - Phipps Bend 500kV (flo) Culloden - Wyoming 765kV	VOLPHBCULWYO	TVA
19146	Smith 138/345 Xfmr flo Green River_Cloverport 138	SMTXFRGRSCLV	OMU
20603	OMU Smith 138/345 kV XFMR (flo) Coleman-Newtonville 161 kV	SMTXFRCOLNEW	OMU
22061	Ghent - Fairview 138kV (flo) Ghent - Batesville 345kV	GHEFAIGHEBVL	LGEE
23687	Volunteer - Phipps Bend (flo) Gavin Unit 2	VOLPHIGAVIN2	TVA
24408	Trimble County - Clifty Creek 345kV l/o Jefferson-Rockport 765kV + Rockport U1	TRICLIJEFROC	LGEE
24409	Trimble County - Clifty Creek 345kV l/o Jefferson-Rockport 765kV + Rockport U2	TRICLIJEFRO2	LGEE
24411	Blue Lick 345/161 kV (flo) Hardin County - Mill Creek 345 Kv	BLULICHARMIL	LGEE
24583	Volunteer - Phipps Bend 500kv flo Antioch - Jackson Ferry 765/500kv	VOLPHIANTJAC	TVA
91008	Brown Plant - Fawkes 138 (flo) Brown N - Alcalde - Pineville 345	BRNFWKBNNALC	LGEE
91047	Brown North - Tyrone 138 kV (flo) Ghent - West Frankfort 345 kV	BNNTYRGHEFFW	LGEE
91050	Brown Plant - Fawkes 138 kV (flo) Brown North 345-138 kV	BRPFWKBNNXFM	LGEE
91052	Green River Steel - Smith 138 kV (flo) Smith 345-138 kV	GRSSMISMIXFM	LGEE
91057	Northside - Clifty Creek 138 kV (flo) Rockport - Jefferson 765 kV	NSICLFROCJEF	LGEE
91128	Ghent - Blackwell 138 kV (flo) Clifty Creek - Trimble County 345 kV	GHTBLWCLFTRM	LGEE
91129	Brown Plant - Fawkes 138 kV (flo) Brown North - West Garrard 345 kV	BRPFWKBRNWGA	LGEE
91130	Brown Plant - Fawkes 138 kV (flo) JK Smith - West Garrard 345 kV	BRPFWKJKSWGA	LGEE
91133	Danville North Tap - Lebanon 138 kV (flo) Brown North 345/138 kV	DNTLEBBRNXFM	LGEE
91136	Coleman Tap - Paducah Primary 161 kV	COLTPP__PTDF	LGEE
91137	Pineville - Pineville Switching 161 kV (flo) Pocket North - Phipps Bend 500 kV	PINPNSPCKNPB	LGEE
91149	Alcalde 345/161 kV (flo) Pineville 345/161 kV	ALCXFMPINXFM	LGEE

Note: Rating values can be found in OASIS under AFC initialization impacts detail report for LGEE owned Flowgates. For Flowgates with owner other than LGEE, please refer to the respective owner's OASIS for updated values.

FG ID	Flowgate	FG Shortname	FG Owner
91150	Cloverport - Green River Steel 138 kV (flo) Daviess County - Smith 345 kV	CLVGRSDVCSMI	LGEE
91151	Avon - Loudon 138 kV (flo) JK Smith - West Garrard 345 kV	AVNLDNJKSWGA	LGEE
91152	Alcalde - Elihu 161 kV (flo) Wolf Creek - Russell County - Cooper 161 kV	ALCELIWCRCCP	LGEE
91154	Brown North 138/345 kV (flo) Brown Plant - Fawkes 138 kV	BNNXFMBRPFWK	LGEE
91155	Pineville 345/500 kV (flo) Broadford - Sullivan 500 kV	PINXFMBRFSUL	LGEE
91158	Clifty Creek - Trimble County 345 (flo) Ramsey - Kenzig Road 345	CLFTRMRAMKNZ	LGEE
91160	Gallagher - Paddys West 138 (flo) Kenzig Road - Paddys West 345	GALPDWKNZPDW	LGEE
91161	Paddys West - Gallagher 138 (flo) Trimble County - Clifty Creek 345	PDWGALTRMCLF	LGEE
91162	Hardinsburg - Black Branch 138 (flo) Hardin Co 345/138	HBGBLBHCOXFM	LGEE
91163	Matanzas - Green River 138 (flo) Matanzas - Wilson 161	MATGRVMATWIL	LGEE
91164	Smith - Daviess 345 (flo) Wilson - Daviess 345	SMIDCOWILDCO	LGEE
91165	Daviess - Smith 345 (flo) Cloverport - Green River Steel 138	DCOSMICLVGRS	LGEE
91166	Daviess - Smith 345 (flo) Green River Steel - Smith 138	DCOSMIGRSSMI	LGEE
91172	Artemus Tap - Farley 161 (flo) Brown North - Alcalde - Pineville 345	ARTFARBRNALC	LGEE
91173	Livingston - Crittenden 161 (flo) North Princeton - Earlington North 161	LIVCRDNPRERL	LGEE
91174	Green River 161/138 TR3 (flo) Wilson - Matanzas 161	GRVXF3WILMAT	LGEE
91178	Wilson - Matanzas 161 (flo) Wilson - Daviess 345	WILMATWILDCO	LGEE
91179	BR Tap - Matanzas 161	BRTMAT__PTDF	LGEE
91180	BR Tap - Matanzas 161 (flo) Hardin - Daviess 345	BRTMATHCODCO	LGEE
91181	Matanzas - BR Tap 161 (flo) Wilson - Daviess 345	MATBRTWILDCO	LGEE
91182	BR Tap - Matanzas 161 (flo) Livingston - North Princeton 161	BRTMATLIVNPR	LGEE
91183	BR Tap - Matanzas 161 (flo) Morganfield - Crittenden - Livingston 161	BRTMATMGCCLC	LGEE
91184	Matanzas - BR Tap 161 (flo) N. Hardinsburg Transformer 161/138	MATBRTHBGXFM	LGEE
91185	BR Tap - Matanzas 161 (flo) N. Hardinsburg Transformer 161/138	BRTMATHBGXFM	LGEE
91186	Matanzas - BR Tap 161	MATBRT__PTDF	LGEE
91187	Brown CT - Bardstown 138 (flo) Hardin County 345/138	BRCBRDHCOXFM	LGEE
91188	Brown North - Tyrone 138 (flo) Brown North 138/345	BRNTYRBRNXFM	LGEE
91192	Paddys West - Paddys Run 138 (flo) Paddys West - Cane Run CT - Mill Creek 345	PDWPDRPDCRMC	LGEE
91193	Paducah Primary - South Paducah 161	PDPSPD__PTDF	LGEE
91195	Buckner - Trimble County 345kV (flo) Buckner - Middletown 345kV	BUKTRMBUKMID	LGEE
91196	Blue Lick - Cedar Grove Tap 161kV (flo) Hardin County 345/138kV XFMR	BLUBULHCOXFM	LGEE
91199	Grahamville - Coleman Road Tap 161kV	GRACLT_PTDF	LGEE
91200	Livingston Co - Crittenden 161kV	LIVCRD_PTDF	LGEE
91201	Livingston Co - North Princeton 161kV	LIVNPR_PTDF	LGEE
91202	Pocket North - Harlan Y 161kV (flo) Pineville - Pocket North 500kV	PCKNHYPINPOC	LGEE
91203	South Paducah - Livingston Co 161kV (flo) Grahamville-Coleman Road Tap-Paducah Primary 161kV	SPDLIVGRAPDP	LGEE
91204	South Paducah - Livingston Co 161kV (flo) Shawnee - Marshall 500kV	SPDLIVSHNMRS	LGEE
91205	South Paducah - Livingston Co 161kV	SPDLIV_PTDF	LGEE
91206	Matanzas - BR Tap 161kV (flo) Hardin County - Daviess County 345kV	MATBRTDVCHCO	LGEE

Note: Rating values can be found in OASIS under AFC initialization impacts detail report for LGEE owned Flowgates. For Flowgates with owner other than LGEE, please refer to the respective owner's OASIS for updated values.

FG ID	Flowgate	FG Shortname	FG Owner
91207	Cloverport - Tip Top 138 kV (flo) Trimble County-Clifty Creek 345 kV	CVPTPTTRMCLF	LGEE
91208	Elizabethtown - Nelson County 138kV (flo) Hardin County - Brown North 345kV	ETNNCOHCOBRN	LGEE
91209	Fawkes KU - Clark County 138kV (flo) Boonesboro North - Avon-Dale 138kV	FWKCLKBBNDAL	LGEE
91210	Green River Steel - Cloverport 138kV (flo) Hardin County - Daviess County 345kV	GRSCVPHCODCO	LGEE
91211	Hardin County - Elizabethtown 138kV (flo) Hardin County - Brown North 345kV	HCOETNHCOBRN	LGEE
91212	Lake Reba Tap - Fawkes Tap 138kV (flo) Fawkes KU - Fawkes EK 138kV	LRTFWTFWKFWE	LGEE
91213	Paddys West - Gallagher 138kV (flo) Speed 345/138kV XFMR	PDWGLGDSPXFM	LGEE
91214	Meredith TVA Tap - Bonnieville 138kV (flo) Hardin County - Daviess County 345kV	MRDBVLDCOHCO	LGEE
91215	Paducah Primary - South Paducah 161kV (flo) Shawnee - Marshall 500kV	PDPSPDSHNMRS	LGEE
91216	Paducah Primary - Coleman Road Tap 161kV (flo) South Paducah - Paducah Primary 161kV	PDPCLTSPDPDP	LGEE
91217	New Hardinsburg - Hardinsburg 138kV (flo) Hardin County - Daviess County 345kV	NHBHBGDCOHCO	LGEE
91218	BRTap - Matanzas 161kV (flo) Reid - Wilson 345kV	BRTMATREIWIL	LGEE
91220	Union City Tap - Lake Reba Tap 138kV (flo) Fawkes KU - Fawkes EK 138kV	UCTLRTFWKFWE	LGEE
91221	Cooper - Elihu 161kV (flo) Laurel County - Laurel Dam 161kV	CPRELIELCLCD	LGEE
91225	Ohio County - Shrewsbury 138kV (flo) Daviess County - Hardin County 345kV	OCOSHRWDCHC	LGEE
91226	Jeffersonville Tap - Beargrass 138kV (flo) Beargrass - Northside 138kV	JFTBRGBRGNSD	LGEE
91227	Brown North 138/345kV XFMR (flo) Brown North - West Lexington 345kV	BNNXFMBNNWLX	LGEE
91228	Clifty Creek - Carrollton 138kV (flo) North Clark - Spurlock 345kV	CLFCARNCSPRL	LGEE
91229	Elihu - Cooper 161kV (flo) Wolf Creek - Russell County - Cooper 161kV	ELICPRCPRRCW	LGEE
91230	Green River - Matanzas 138kV (flo) Matanzas - Wilson 161kV	GRVMATWLSMAT	LGEE
91231	New Hardinsburg - Hardinsburg 138kV (flo) Hardin County 345/138 kV	NHGHBGHCOXFM	LGEE
91232	Paducah Primary - South Paducah 161 (flo) Grahamville - Paducah Primary 161	PDPSPDGRAPDP	LGEE
91233	Pineville 500/345 (flo) AEP Sullivan - Broadford 500	PINXFMSULBRF	LGEE
91234	Ramsey - Kenzig Road 345 (flo) AEP Rockport - Jefferson 765	RAMKNZROCJEF	LGEE
91237	Ghent - Blackwell 138 (flo) Ghent - West Lexington - Brown North 345	GHTBLWGHEWLX	LGEE
91238	Brown North 345/138 (flo) Ghent - West Lexington - Brown North 345	BNNXFMGHEWLX	LGEE
91242	Brown CT - Brown T2 138 (flo) Brown North - Brown CT - Brown South 138	BNCBNTBNBCBS	LGEE
91243	Pineville Switch - Artemus Tap 161 (flo) Brown North - Alcalde - Pineville 345	PNSARTBNALPV	LGEE
91244	Crittenden - Morganfield 161 (flo) Livingston - North Princeton 161	CRDMORLIVNPR	LGEE
91245	New Hardinsburg - Hardinsburg 138 (flo) Cloverport - Hardinsburg 138	NHBHBGCLVHBG	LGEE
91246	Hardin County 345/138 (flo) Hardin County - Brown North 345	HCOXFMHCOBNN	LGEE
91248	Trimble County - Ghent 345 (flo) EK Bullitt County - Shelby County 161	TCOGHEBULSHC	LGEE
91249	West Lexington 345/138 (flo) Brown North 345/138	WLXXFMBNNXFM	LGEE
91250	Green River Steel - Smith 138 (flo) Daviess County - BR Wilson 345	GRSSMIDCOWIL	LGEE
91251	Tip Top - Cloverport 138 (flo) Mill Creek - Hardin County 345	TPTCVPMLCHCO	LGEE
91252	Buckner - Middletown 345 (flo) Buckner - Trimble County 345	BUKMIDBUKTRM	LGEE
91254	Green River 161/138 TR2 (flo) Matanzas - Wilson 161	GRVXF2MATWIL	LGEE
91255	Elihu - Alcalde (flo) EK Laurel County - Laurel Dam 161	ELIALCEKLLDM	LGEE
91257	Brown CT - Brown T1 138 (flo) Brown North - Brown CT - Brown Plant 138	BCTBRTBRNBRP	LGEE

Note: Rating values can be found in OASIS under AFC initialization impacts detail report for LGEE owned Flowgates. For Flowgates with owner other than LGEE, please refer to the respective owner's OASIS for updated values.

FG ID	Flowgate	FG Shortname	FG Owner
91258	Higby Mill - Reynolds 138 (flo) Haefling - West Lexington 138	HIGREYHAELEX	LGEE
91259	Brown North - Tyrone 138	BRNTYR__PTDF	LGEE
91260	Morganfield - Corydon Tap 161 (flo) Morganfield 161/69	MORCORMORXFR	LGEE
91261	Hardin County - Elizabethtown 138 (flo) Hardin County 138/69	HCOETNHCOXFR	LGEE
91262	Cannelton Tap - Cloverport 138 (flo) Daviess County - Coleman 345	CANCLVDAVCOL	LGEE
91264	Avon - Loudon Ave 138 (flo) Brown North - West Garrard 345	AVOLOUBRNGAR	LGEE
91265	Spurlock - Kenton 138 (flo) EK North Clark - Spurlock 345	SPUKENCLKSPU	LGEE
91266	Haefling - IBM North Tap 138 (flo) EK JK Smith - West Garrard 345	HAEIBMGARJKS	LGEE
91267	Ramsey - Kenzig Road 345 (flo) Trimble County - Clifty Creek 345	RAMKENCLFTRM	LGEE
91268	Brown T1 - Brown Plant (flo) Brown North - Brown CT - Brown Plant 138	BRNBRPBRNBRP	LGEE
91269	Kenzig Road - Paddys West 345 (flo) Daviess County - Hardin County 345	KENPDWDAVHAR	LGEE
91271	Pineville Switch - Pineville 161 (flo) TVA Volunteer - Phipps Bend 500	PWSPVLVOLPHP	LGEE
91272	Galagher - Paddys West 138 (flo) Kenzig Road - Ramsey 345	GLGPDWKENRAM	LGEE
91273	BR Tap - Matanzas 161 (flo) TVA Volunteer - Phipps Bend 500	BRTMATVOLPHP	LGEE
91274	Spurlock - Kenton 138	SPUKEN_PDF	LGEE
91275	Phipps Bend - Pocket North 500 (flo) Broadford - Sullivan 500	PHBPOCBRFSUL	LGEE
91276	Nelson County - Bardstown 138 (flo) Hardin County - Brown North 345	NCOBRDHCOBRN	LGEE
91277	Brown T2 - Brown Plant 138 (flo) Brown North - Brown CT - Brown Plant 1 138	BR2BRPBRNBRP	LGEE
91278	Ghent - Blackwell 138 (flo) EK JK Smith - West Garrard 345	GHTBLWJKSWGA	LGEE
91279	Ghent - Blackwell 138 (flo) EK North Clark - Spurlock 345	GHTBLWNCSPRL	LGEE
91280	Trimble County - Ghent 345 (flo) Hardin County - Brown North 345	TCOGHEHCOBRN	LGEE
91281	Pineville Switch - Pineville 161 (flo) Pocket North - Phipps Bend 500	PWSPVLPCKNPB	LGEE
91282	Pineville 500/345 (flo) Pocket North 500/161	PINXFMPCKNXF	LGEE
91283	W Lexington 345/138 (flo) EK JK Smith - W Garrard 345	WLEXFMEKJWGA	LGEE
91284	Blue Lick - Cedar Grove IP 161 (flo) Mill Crk - Hardin co 345	BLUCEDMILHAR	LGEE
91285	Blue Lick - Cedar Grove 161 (flo) Mill Crk - Hardin Co 345	BLUCEDMILHA2	LGEE
91286	Paddys Run - Lebanon Jct 161 (flo) Mill Crk - Hardin Co 345	PADLEBMILHAR	LGEE
91287	Cane Run SW - Paddys Run 138 (flo) Cane Run SW - Campground 138	CANPADCANCAM	LGEE
91288	Green River - Smith Tap 138 (flo) Daviess - Smith 345	GRESMIDAVSMI	LGEE
91289	Green River - Smith Tap 138 (flo) Daviess - BR Wilson 345	GRESMIDAVWIL	LGEE
91290	Pond Creek - Tip Top 138 (flo) Mill Crk - Hardin Co 345	PONTIPMILHAR	LGEE
91291	Spurlock - Kenton 138 (flo) EKPC Goddard 138/69	SPUKENGODXFM	LGEE
91292	TVA Pineville KY - Pineville SW 161 (flo) Pocket North - Phipps Bend 500	PINPINPCPHB	LGEE
91293	Blue Lick - Cedar Grove Ta 161kV (flo) Hardin County 345/138kV XFMR	BLUCEDHARFMR	LGEE

Note: Rating values can be found in OASIS under AFC initialization impacts detail report for LGEE owned Flowgates. For Flowgates with owner other than LGEE, please refer to the respective owner's OASIS for updated values.

EXHIBIT MG-4

EIA Form 930 datafile for LGE, KU.xlsx

(Excel File Provided Separately)

EXHIBIT MG-5

QUANTIFYING A MINIMUM INTERREGIONAL TRANSFER CAPABILITY REQUIREMENT

MAY 2023

FOR

Americans for a Clean Energy Grid

BY

Grid Strategies

MICHAEL GOGGIN, ZACH ZIMMERMAN,
AND ABBY SHERMAN,
GRID STRATEGIES LLC

INTRODUCTION

This report demonstrates a straightforward method by which a minimum interregional transfer capability requirement can be set based on objective historical data. Applying this approach to historical data from the last decade indicates that a minimum interregional transfer capability requirement equivalent to 20-25% of peak load conservatively approximates the need for and reliability benefit of interregional transmission in all regions.

The minimum transfer requirement can be calculated based on how transmission accesses geographic diversity across regions in the timing of peak demand, generator output, and correlated generator outages. The methodology compares the capacity need if sources of electricity supply and demand are aggregated across the Interconnect, which accounts for how geographic diversity in hourly electricity demand and supply patterns decreases the need for capacity, against the larger sum of the component regions' stand-alone capacity needs. Interregional transmission reduces the amount of generating capacity that is needed to achieve the same level of reliability, mostly by canceling out the weather's localized and short-lived impacts on electricity supply and demand.

That geographic diversity benefit should set the interregional transfer capability requirement. This reflects that a certain megawatt (MW) amount of interregional transmission allows the component regions to achieve the same level of reliability with that many fewer MW of generating capacity by accessing geographic diversity. This method was applied to nine years of historical data, which captures the largest reliability threats over the last decade: Winter Storm Elliott in December 2022, Winter Storm Uri in February 2021, the South Central event in January 2018, and the Polar Vortex event in January 2014.

That analysis indicates that the Federal Energy Regulatory Commission specifying a default minimum interregional transfer capacity requirement in the range of 20-25% of peak load would conservatively approximate the need for and reliability benefit of interregional transmission in all regions. This report also outlines a similar methodology a region can use if it seeks to demonstrate its need for transfer capacity differs from that default. However, a specific default transfer capacity requirement applied uniformly to all regions is likely superior to more complex region-specific analytical approaches due to 1. Significant intractable uncertainty about factors including future weather and climate patterns, the generation mix and location, load patterns, and the geography of gas supply and demand and pipeline networks, 2. The fact that future severe weather and other extreme events will never perfectly replicate past events, 3. Challenges that arise from individual regions using different methodologies and assumptions to determine their interregional transfer capacity needs, and 4. The fact that all regions within an Interconnect are inherently affected by power flows resulting from the balancing of electricity supply and demand across all other regions in the Interconnect.

A straightforward requirement applied uniformly to all regions reflects that interregional transmission functions like an insurance policy against unexpected events, in that it is

impossible to precisely predict when, where, or for what that insurance policy will be needed, but over the long term all regions will be affected by such an event and will benefit from that interregional transfer capacity. Favoring an elegant uniform requirement over more complex methods is consistent with the use of default standards to approximate other reliability and resilience needs, like the 1-day-in-10-year Loss of Load Expectation standard that serves as the foundation for resource adequacy planning in most regions. A minimum interregional transfer capability requirement set in the range of 20-25% of peak demand would ensure high levels of reliability and resilience in the face of evolving threats to the bulk power system. Transmission is bidirectional so it provides a capacity benefit to both interconnected regions, and transmission is largely immune to the correlated outages that affect many types of generation. As a result, expanding interregional transmission can increase electric reliability and resilience more effectively and at lower cost than increasing the redundancy of generating resources. Europe has set a similar target for each country's interregional transfer capacity to cover 15% of its installed generating capacity by 2030.[1] In the U.S. installed capacity is about 67% greater than peak load2 and increasing, so Europe's 15% installed capacity requirement is roughly equivalent to a transfer capability requirement for 25% of peak load.

1 European Commission, "Electricity interconnection targets," available at https://energy.ec.europa.eu/topics/infrastructure/electricity-interconnection-targets_en

2 1,241,578 MW installed capacity over a peak demand of approximately 742,000 MW = 1.6733, per installed capacity for 2021 https://www.eia.gov/electricity/data/eia860/ and recent peak demand https://www.eia.gov/electricity/gridmonitor/expanded-view/custom/pending/ElectricityOverview-2/edit

RESULTS

A minimum interregional transfer capacity requirement can be calculated from publicly available hourly electricity supply and demand data. This methodology was applied to 9 years of historical data for ERCOT and the U.S. portion of the Eastern Interconnect, a time period that captures the largest reliability threats over the last decade: Winter Storm Elliott in December 2022, Winter Storm Uri in February 2021, the South Central cold weather event in January 2018, and the Polar Vortex event in January 2014. The results of this analysis are shown below.

TABLE 1. *Reduced capacity need from interregional transmission in Eastern and ERCOT Interconnections*

Reduction in capacity needs, as a share of peak load	21%
Reduction in capacity needs, in MW	137,146
Economic value of reduced capacity needs	$113 billion

Aggregating electricity supply and demand across ERCOT and the U.S. portion of the Eastern Interconnect over this time period reduced the peak need for capacity by 137,146 MW,[3] with the vast majority of this benefit accruing from geographic diversity within the Eastern Interconnect. This geographic diversity benefit equates to 20.99% of the sum of the peak loads of the component regions over the last five years, supporting the creation of a default minimum requirement for all regions somewhere in the range of 20-25% of peak load. The reduced capacity need from interregional transmission can be translated to $113 billion in economic savings based on the avoided capital cost of an equivalent amount of gas combustion turbine capacity.[4]

This geographic diversity benefit results from the timing mismatch in when regions experience peak demand and reductions in generator output, typically because individual severe weather events do not affect all regions equally and move over time. As summarized in the table below, and shown in more detail in the maps in Appendix A, when some regions are experiencing generation shortfalls during a severe weather event, other regions tend to have abundant spare capacity available. Each row in the table shows the net load[5] of each region during one hour of a severe weather event, as a percent of the maximum net load that region experienced across all nine years of the analysis. Regions at or near 100% and shown in red are experiencing their maximum shortfall in generation supply, while regions with low percentages shown in green tend to have abundant spare capacity at that point in time. By aggregating regions with spare

3 This refers to MW of unforced generating capacity, generating capacity that has been derated to account for outages and derates during peak periods, and thus equates to theoretical capacity that is perfectly dependable.

4 Conservatively using an assumed $785/kW cost of a frame combustion turbine from U.S. Energy. Info. Admin., *Cost and Performance Characteristics of New Generating Technologies, Annual Energy Outlook 2022* (March 2022), available at https://www.eia.gov/outlooks/aeo/assumptions/pdf/table_8.2.pdf and the conservative assumption that a new combustion turbine offers 95% of its nameplate capacity as dependable capacity value. To be conservative, ongoing fixed O&M costs for maintaining that gas capacity were also not accounted for.

5 As explained in Appendix B, "net load" is defined as electricity demand minus renewable output plus conventional generator forced outages, to reflect the impact of conventional generator forced outages and changes in renewable output on the need for other capacity.

capacity with regions experiencing shortfalls, interregional transmission is an effective tool for countering the localized reliability impacts of extreme events.

TABLE 2. *Each region's net load during severe weather events, as a percent of that region's maximum net load across all nine years*

	ERCOT	SPP	MISO S	TVA	MISO N	PJM	NYISO	ISO-NE	Carolinas	SOCO	Florida
1/17/2014 7 AM ET	58%	60%	74%	86%	75%	100%	68%	64%	88%	87%	60%
1/17/2018 10 AM ET	60%	67%	100%	81%	61%	70%	61%	63%	56%	85%	61%
1/18/2018 6 AM ET	58%	50%	65%	76%	55%	66%	51%	55%	63%	100%	79%
2/15/2021 10 AM ET	100%	99%	83%	61%	69%	63%	56%	59%	58%	68%	55%
12/23/2022 6 PM ET	68%	87%	88%	99%	86%	85%	60%	56%	88%	91%	65%
12/24/2022 6 AM ET	63%	87%	87%	91%	77%	85%	49%	50%	100%	95%	66%

This analysis was based on data for the years 2012-2015 and 2018-2022. As documented in Appendix B, the period 2012-2015 was included because data tracking hourly conventional generator forced outage rates by NERC regional entity are available for that time period from Murphy et al. 2018-2022 was chosen because that time period captures three severe weather events (the 2018 South Central event and Winter Storms Uri and Elliott) for which FERC-NERC reports or other public data sources tracking hourly generator forced outages are available, and because EIA Form 860 began to track Balancing Authorities' hourly generation by fuel type in July 2018.

Our analysis also evaluated how several sensitivities affected the need for and reliability benefit of interregional transmission, relative to the results presented above which are repeated in bold in the table below. First, we found that the need for interregional transmission is only slightly lower if diversity benefits within the Eastern Interconnect are evaluated without accounting for diversity benefits with ERCOT. Second, we found that renewable output diversity is currently a small contributor to the total reliability benefit of interregional transmission, confirming that geographic diversity in electricity demand and conventional generator correlated outages drive more than 87% of the need for a minimum interregional transfer capability requirement. These results are presented in the following table, and were derived using the same general methodology described above and documented in Appendix B.

TABLE 3. *Reduced capacity need from geographic diversity as a share of peak load, under different assumptions*

	With Renewables	Without Renewables
With ERCOT	20.99%	18.35%
Without ERCOT	18.25%	14.42%

In addition to this analysis of the Eastern Interconnect and ERCOT, Grid Strategies previously conducted analysis for the U.S. portion of the Western Interconnect that examines geographic diversity in demand and renewable output. Grid Strategies presented analysis on behalf of the American Clean Power Association at the Commission's December 2022 workshop[6] indicating that in 2021, aggregating demand and renewable output across the Western Interconnect reduced peak net load by 14% or 19,400 MW, relative to the sum of individual Balancing Authorities' peak net loads.

This is a conservative estimate of the total geographic diversity benefit in the West, as it does not account for geographic diversity in correlated conventional generator outages, even though it has been publicly reported that Winter Storms Elliott, Uri, and the cold snap that caused the 2011 Southwest outages did cause parts of the West to experience high forced outage rates. Geographic diversity in correlated outages of conventional generators was not included in that analysis as Murphy et al.'s 2012-2015 dataset tracks outages at the NERC Regional Entity level, so forced outage rates are reported uniformly for all of WECC, precluding analysis of geographic diversity in conventional generator forced outage rates within that region.

Based on localized forced outage rates observed in parts of the West during recent events, as well as geographic diversity in forced outages observed in the Eastern Interconnect, it is likely that the West sees at least a 5-10% additional benefit from geographic diversity in conventional generator forced outages. As a result, 20-25% of peak load is a conservative estimate of the total geographic diversity benefit of aggregating supply and demand in the Western Interconnect.

These results indicate a uniform minimum interregional transfer requirement of 20-25% of peak load for all parts of the Eastern, Western, and ERCOT Interconnections would conservatively approximate the need for and reliability benefit of interregional transmission. As explained above, a universal default requirement based on objective data offers many advantages over more complex region-specific analyses, and these results indicate a single universal requirement in the range of 20-25% of peak load is a conservative approximation of the need in all regions. If a region wants to conduct a more complex analysis to justify a different requirement, the next section discusses minimum criteria for inputs and methodology that FERC should require for such an analysis.

These results are almost certain to be a conservative underestimate of the value of and need for interregional transmission for several reasons. First, hourly forced outage data is not publicly

6 See https://www.ferc.gov/media/panel-3-opening-statement-michael-goggin-grid-strategies-acpa and https://www.ferc.gov/media/panel-3-michael-goggin-grid-strategies-acpa

available for 2018-2022, unlike 2012-2015, as explained in Appendix B. Due to a lack of data, it was conservatively assumed that forced outages were at the same uniform rate (3% for NYISO and ISO-NE, and 5% for all other regions) for regions for which information on forced outages during the cold snap events was not available, and for all regions in all hours outside of the three major cold snaps. This greatly understates the actual geographic diversity in forced outages rates across these regions seen in the 2012-2015 data.

In addition, our analysis does not attempt to model specific interregional power flow needs because future events will not exactly replicate the relatively small sample of events observed over the last decade. However, because power flows often cross multiple regions during such an event and flows to and from larger regions may cross smaller regions, it is more likely for peak power flows into and across some regions to be greater than that region's pro rata share of the Interconnect-wide diversity benefit. As a result, setting each region's requirement as a share of its peak load is more likely to understate than overstate the transmission need in some regions.

The net load analysis of the Western Interconnect is also likely to be conservative as it is based on only one year of data. Analysis over a longer time horizon would likely indicate a larger need and reliability benefit from interregional transmission in the West, as extreme events tend to drive the transmission need and more such events are captured by a longer time horizon.

Finally, the above analysis was based entirely on historical data to keep it founded in incontrovertible objective data, given the inherent uncertainty with projections of the future generation mix and load patterns. However, multiple trends are further coupling electricity supply and demand to the weather, further increasing the value of transmission for tapping into geographic diversity that mitigates the impact of localized weather events. The largest trend in the generation mix over the last 15 years has been the increasing penetration of gas. Multiple cold snap events over that period have shown gas generators are more prone to correlated outages during cold weather than other fuel sources. Peak winter electricity demand coincides with peak demand for gas to meet building heating demand, straining gas supply and pipeline capacity, particularly when supply from gas fields is reduced due to wellhead freeze-offs.[7]

The growth of wind and solar generation is also increasing the impact of localized weather on electric supply, though wind and solar output tend to be negatively correlated during most extreme weather events, increasing the chance that one resource will be available if the other is not.[8] Finally, electrifying heating will further tie electricity demand to the weather and increase electricity demand during extreme cold weather events, further increasing the value of transmission for tapping into geographic diversity that helps cancel out localized weather impacts.

7 A drop in fuel supply to gas generators in at least some affected regions appears to have been a major factor in all of the cold weather electricity reliability events discussed in this report. For example, see the FERC-NERC reports for Winter Storm Uri (https://www.ferc.gov/media/february-2021-cold-weather-outages-texas-and-south-central-united-states-ferc-nerc-and) and the 2018 South Central cold weather event (https://www.nerc.com/pa/rrm/ea/Documents/South_Central_Cold_Weather_Event_FERC-NERC-Report_20190718.pdf), the NERC report for the 2011 Southwest outages (https://www.nerc.com/pa/rrm/ea/February%202011%20Southwest%20Cold%20Weather%20Event/SW_Cold_Weather_Event_Final.pdf), the NERC report on the 2014 Polar Vortex (https://www.nerc.com/pa/rrm/January%202014%20Polar%20Vortex%20Review/Polar_Vortex_Review_29_Sept_2014_Final.pdf) as well as press reports on Winter Storm Elliott (https://fortune.com/2022/12/27/america-electrical-grid-barely-escaped-a-calamity-as-massive-storm-exposes-a-vulnerable-natural-gas-infrastructure/)

8 For example, wind output has been high during most recent cold snap events, while solar output is often high during summer high pressure heat dome events that often coincide with low wind output but high electricity demand.

As a result, the Commission may want to set the default minimum transfer capability requirement at or above the high end of the 20-25% range, as the 21% of peak load requirement calculated from conservative analysis of data from the last decade likely understates the need going forward.

Methodology for Regions Proposing to Deviate from the Default Minimum

As explained above, a straightforward default transfer capacity requirement applied uniformly to all regions is likely to be superior to more complex analytical approaches developed by each region, due to intractable uncertainty in key inputs into the analysis and challenges that arise from regions using different methodologies and assumptions to determine their interregional transfer capacity needs. However, this section offers a method by which a region can calculate a different requirement if it believes its needs significantly differ from the default minimum requirement. FERC establishing minimum requirements for the assumptions and methods used in such an analysis, and particularly requiring that such an analysis look across the Interconnect, will help ensure that any analyses conducted by regions are compatible.

For geographic scope, FERC should require that regions look at geographic diversity in load, generator output, and generator forced outage rates across the Interconnect. This geographic scope reflects the physical reality that all regions within an Interconnect are inherently affected by power flows resulting from the balancing of electricity supply and demand across all other regions in the Interconnect. For example, during Winter Storm Uri, SPP was importing power from MISO which was importing from PJM, while during Winter Storm Elliott the Southeast was importing from MISO which was importing from Canada and other regions. The power system is a network of interdependent regions, so looking at a small number of regions in isolation misses the benefits of aggregation across a larger area.

For chronological scope, FERC should require a region to use enough historical data to capture extreme events that tend to drive the long-term need for capacity. For example, this could include a requirement that the region use data for at least the last 10 years, but that time period could be expanded to ensure that at least one severe event (as indicated by an anomaly in peak load, temperature, etc.) in each region is included in the dataset.

While the default requirement presented above was calculated solely based on historical data to keep the calculation straightforward and incontrovertible, if a region proposes to add complexity by doing analysis to justify deviating from that default, it should be required to account for expected future trends in the resource mix and load patterns.[9] On the demand side, this should account for the impacts of climate change[10] and increasing electrification on hourly patterns of electricity demand. On the supply side, historical rates of conventional generator correlated outage rates by fuel type could be applied to the expected future generation mix. Existing renewable output profiles can be scaled up using statistical techniques that account for the inherent geographic diversity from adding new resources, or the output from additions of wind and solar capacity can be even more accurately modeled using synthetic hourly resource profiles.[11] The future generation mix in that region and across the Interconnect can be projected based on inputs like the 10-year outlooks in NERC's annual Long-Term Reliability Assessment,[12] with reasonable assumptions for the expected completion rate for planned resources. Utility

9 FERC could make this requirement consistent with the requirements it sets in its pending rulemaking on Regional Transmission Planning and Cost Allocation, available at https://ferc.gov/media/rm21-17-000.

10 To conduct this analysis, planners could use inputs such as this 50-year historical dataset of hot and cold snaps that has been adjusted for the impacts of climate change to develop a forward projection.https://www.osti.gov/servlets/purl/1885888

11 For example, see https://www.nrel.gov/grid/wind-integration-data.html

12 https://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/NERC_LTRA_2022.pdf

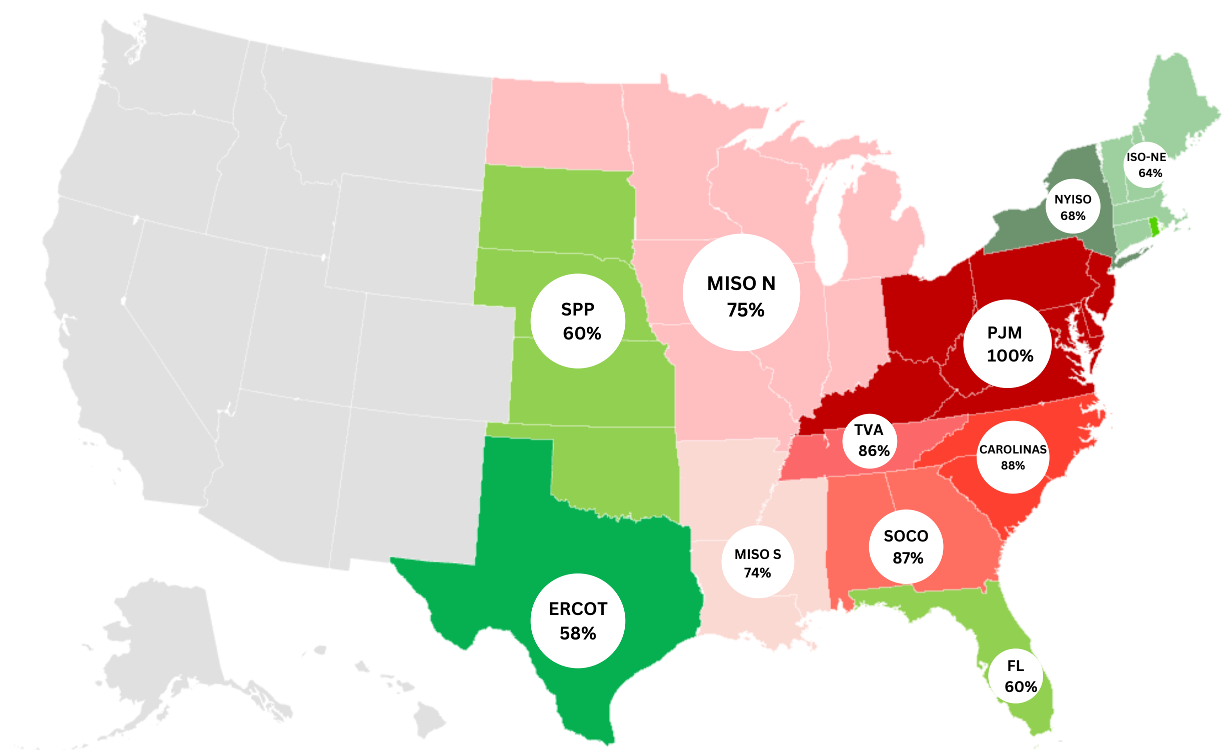
Integrated Resource Plans and utility and state carbon and renewable targets should also be accounted for, where they exist. Regions should be required to file their analysis justifying a different requirement in a contested proceeding at FERC, where intervenors and FERC staff should be given discovery rights that allow them to critically review the model and input assumptions.

APPENDIX A

MAPS OF NET LOAD DIVERSITY DURING SEVERE WEATHER EVENTS

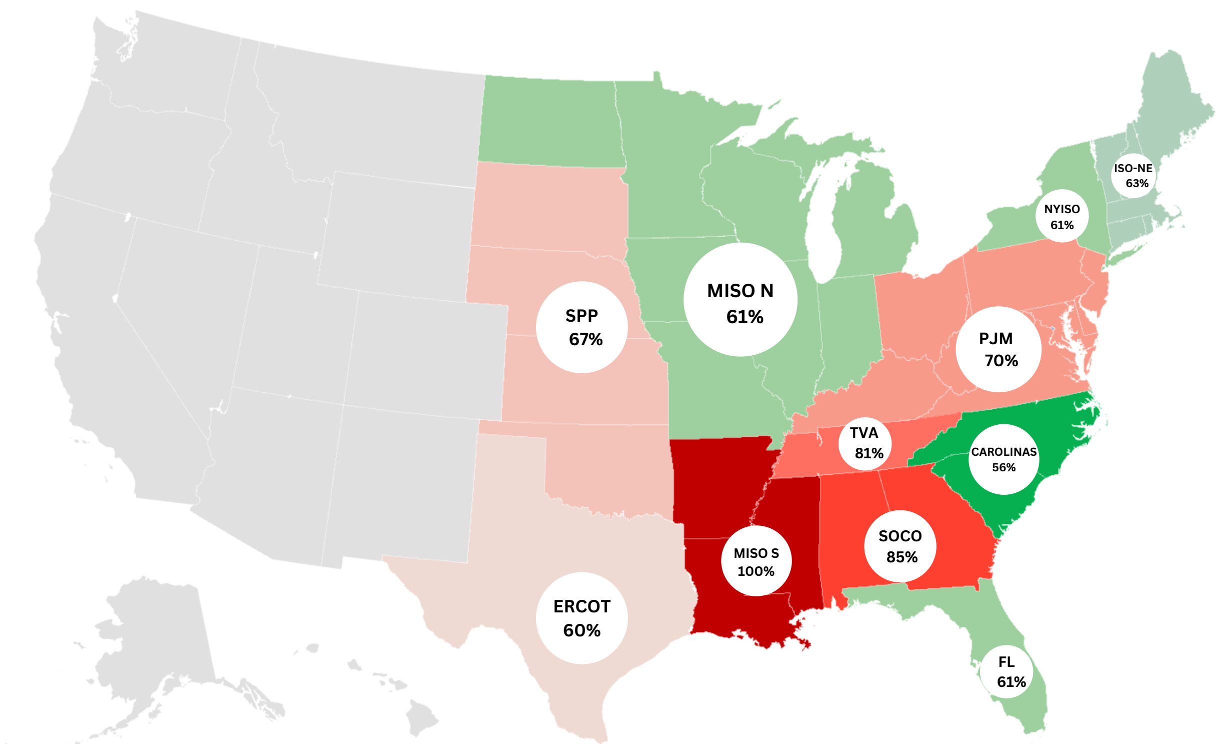
As explained above, geographic diversity benefits result from the timing mismatch in when regions experience peak demand and reductions in generator output, typically because individual severe weather events do not affect all regions equally and move over time. As summarized in the maps below, when some regions are experiencing generation shortfalls, other regions tend to have abundant spare capacity available. Each map shows the net load (defined as electricity demand - renewable output + conventional generator forced outages) of each region during one hour of a severe weather event, as a percent of the maximum net load that region experienced across all nine years of the analysis. Regions at or near 100% and shown in red are experiencing their maximum shortfall in generation supply, while regions with low percentages shown in green tend to have abundant spare capacity at that point in time.[13] By aggregating regions with spare capacity with regions experiencing shortfalls, interregional transmission is an effective tool for countering the localized reliability impacts of severe weather events.

2014 POLAR VORTEX EVENT, JANUARY 17, 2014, AT 7 AM ET

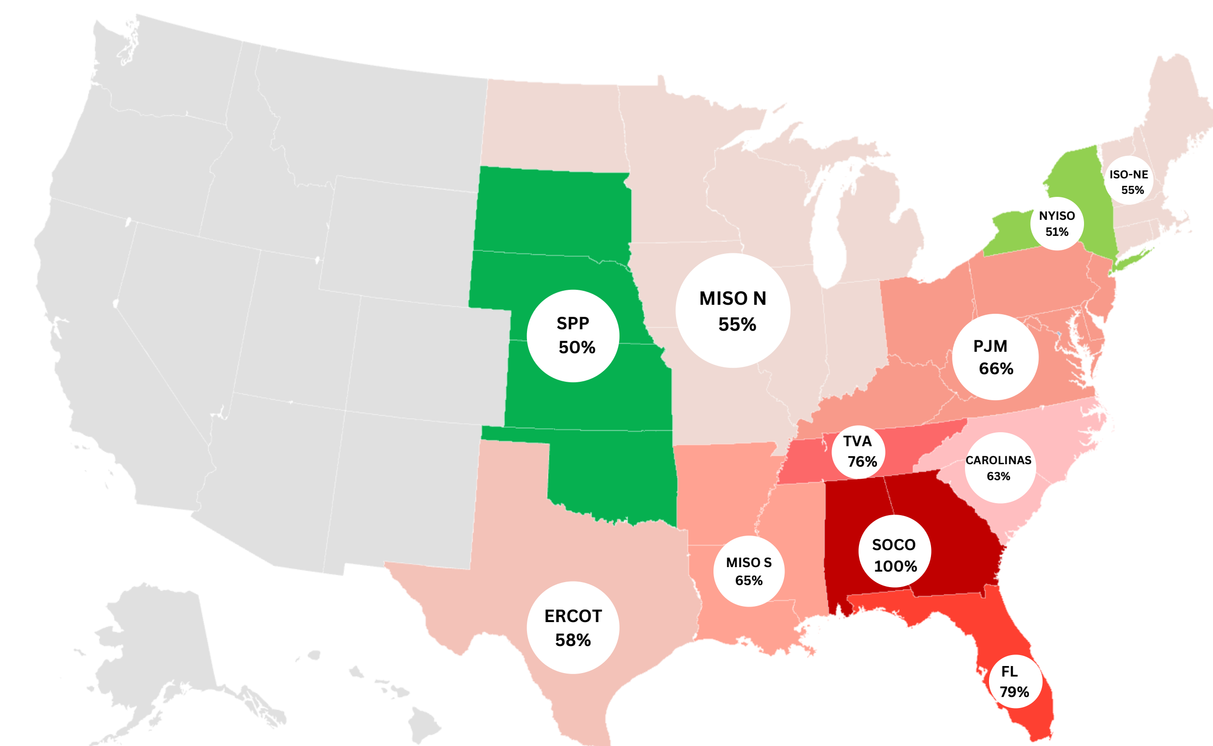


13 These maps approximate the boundaries of grid operators and other regions to the nearest state border for graphical simplicity. The analysis was conducted on data for each grid operator and thus reflects their actual boundaries.

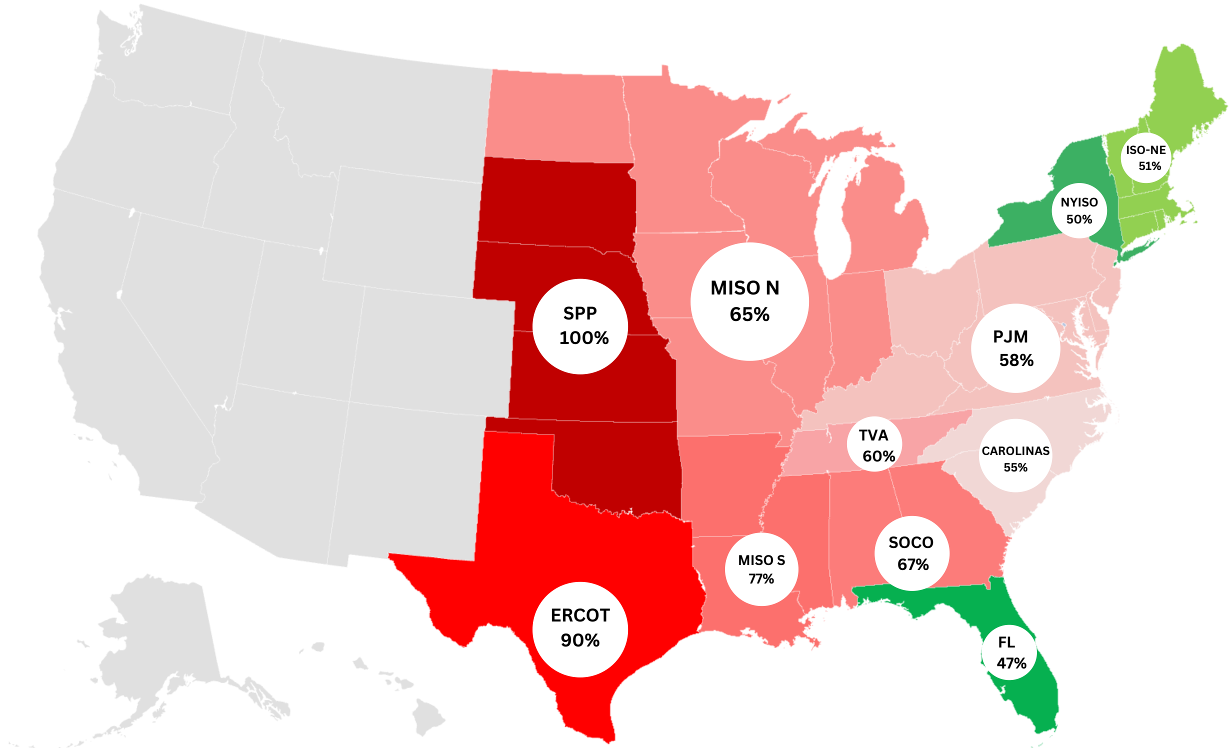
2018 SOUTH CENTRAL COLD WEATHER EVENT, JANUARY 17, 2018, AT 10 AM ET



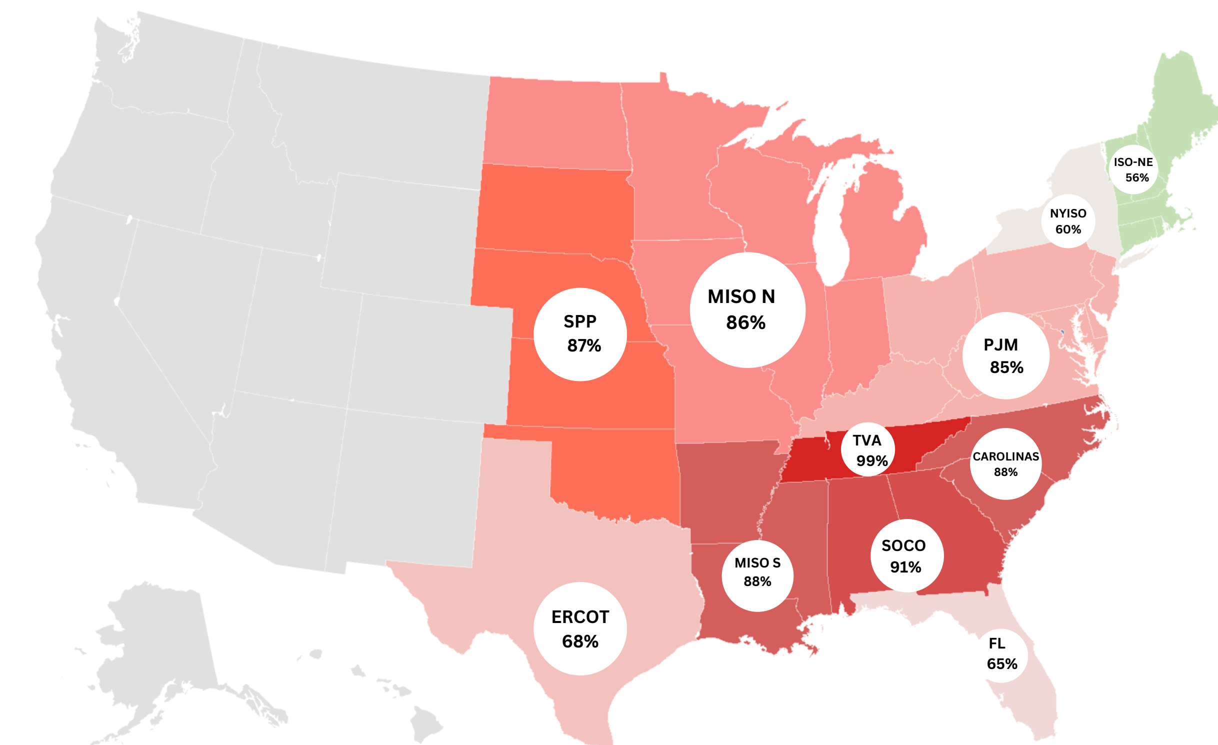
2018 SOUTH CENTRAL COLD WEATHER EVENT, JANUARY 18, 2018, AT 6 AM ET



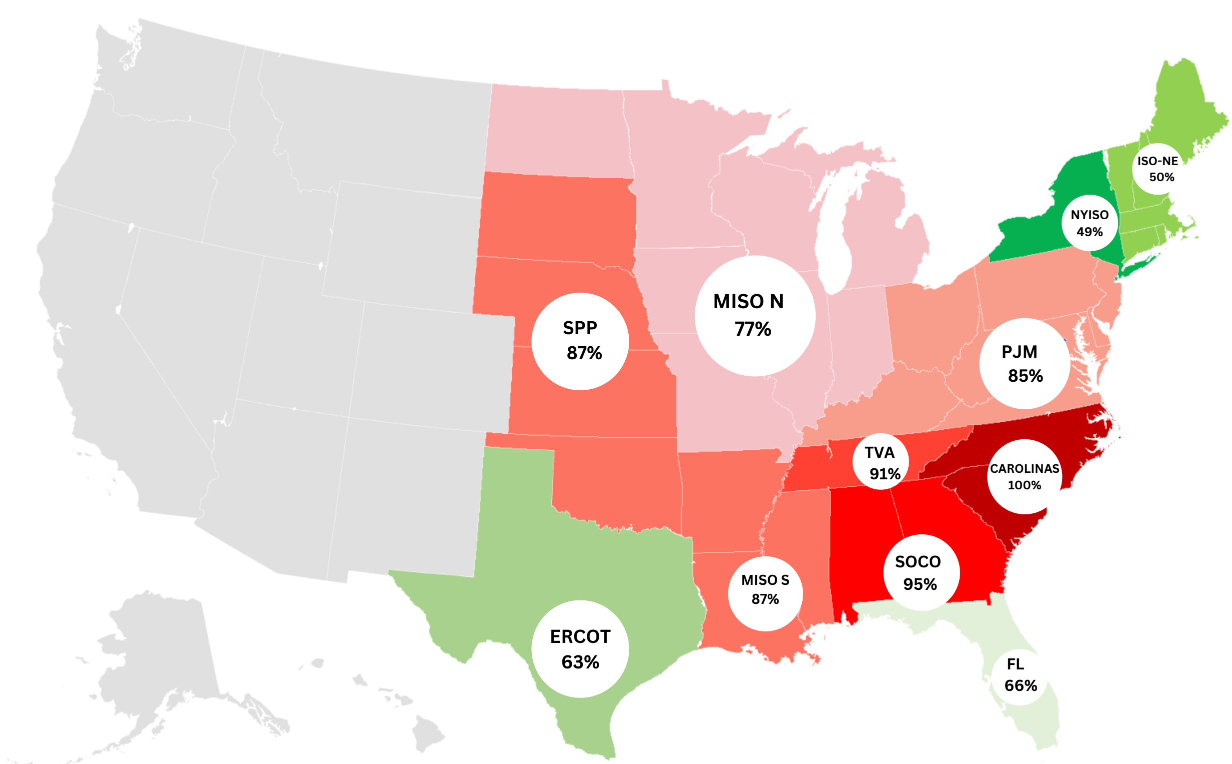
2021 WINTER STORM URI, FEBRUARY 15, 2018, AT 10 AM ET



2022 WINTER STORM ELLIOTT, DECEMBER 23, 2022, 6 PM ET



2022 WINTER STORM ELLIOTT, DECEMBER 24, 2022, 6 AM ET



APPENDIX B
DETAILED METHODOLOGY FOR ANALYSIS OF EASTERN U.S. AND ERCOT

The analysis of geographic diversity across the U.S. portions of the Eastern Interconnection plus ERCOT was conducted for the periods 2012-2015 and 2018-2022. As noted above, the time period 2012-2015 was chosen because data tracking hourly conventional generator forced outages by NERC regional entity are available for that time period from Murphy et al.[14] 2018-2022 was chosen because that time period captures three severe weather events (the 2018 South Central event and Winter Storms Uri and Elliott) for which FERC-NERC reports or other public data sources tracking hourly generator forced outages are available, and because EIA Form 860 began to track Balancing Authorities (BAs') hourly generation by fuel type in July 2018.

The basic methodology was to compare the difference between the aggregated capacity need across the Eastern Interconnect and ERCOT, which accounts for how geographic diversity in hourly electricity demand and supply patterns decreases the need for capacity, against the larger sum of the component regions' stand-alone capacity needs. To calculate capacity needs, hourly renewable output was subtracted from demand and hourly forced outages were added to demand, reflecting that those factors decrease or increase the amount of generation that must be supplied by other resources on a 1:1 basis, equivalent to an identical change in demand.[15] The difference between the maximum aggregated capacity need across the Eastern Interconnect and ERCOT over the nine years versus the sum of the component regions' maximum stand-alone capacity needs over the nine years was then calculated (a difference of 137,146 MW) and reported as a percentage of the sum of the regions' stand-alone peak demands (20.99%).

2012-2015 Hourly Net Load Analysis

For 2012-2015 we collected hourly load and wind generation data from ERCOT,[16] ISO-NE,17 NYISO,[18] PJM,[19] and SPP.[20] We then multiplied the GADS hourly forced outage rate (the sum of hourly derates, start failures, and forced outages) by the installed conventional generator

14 https://www.sciencedirect.com/science/article/pii/S0306261917318202; Supplementary data file available at https://ars.els-cdn.com/content/image/1-s2.0-S0306261917318202-mmc1.zip

15 In this appendix, "net load" is used to refer to hourly load minus wind and solar output plus conventional generator forced outages. "Outages" or "forced outages" is used to refer to conventional generator forced outages, and includes conventional generator failures to start, derates, and forced outages.

16 Hourly Load: https://www.ercot.com/gridinfo/load/load_hist. Hourly Wind: https://www.ercot.com/gridinfo/generation

17 Hourly Load: https://www.iso-ne.com/isoexpress/web/reports/load-and-demand/-/tree/zone-info. Hourly Wind: https://www.iso-ne.com/isoexpress/web/reports/operations/-/tree/daily-gen-fuel-type

18 Hourly Load: https://www.nyiso.com/custom-reports. Hourly Wind: Did not use wind generation for 2012-2015.

19 Hourly Load: https://dataminer2.pjm.com/feed/inst_load. Hourly Wind: https://dataminer2.pjm.com/feed/wind_gen/definition

20 Hourly Load: https://marketplace.spp.org/pages/hourly-load. Hourly Wind: https://marketplace.spp.org/pages/generation-mix-historical

capacity (Table 1 from Murphy et al.)[21] for each region. Because the GADS outage rate and installed capacity data in Murphy et al. is reported at the NERC region level, which groups ISO-NE and NYISO into NPCC along with the eastern Canadian provinces, we used the installed capacity for NYISO[22] and ISO-NE[23] as reported by those regions' Independent Market Monitors (IMMs) for 2012-2015, but assumed that the NPCC GADS hourly outage rate applied for both regions.

For the entire analysis we separated MISO N and MISO S to account for the limited transmission ties between those areas, and the fact that Entergy was its own BA prior to joining MISO on December 19, 2013. For MISO N a similar issue arose as with NYISO and ISO-NE due to the misalignment of MRO and MISO. To account for this misalignment, we pulled hourly load and wind generation for the entire MISO region for 2012-2015[24] and used IMM reported installed capacity for MISO for 2012-2015.[25] To account for the addition of MISO S at the end of 2013 we subtracted hourly load and MISO S installed capacity from our MISO N hourly load and installed capacity. MISO S is discussed further below. For MISO N, we assumed that the MRO GADS hourly outage rate would apply uniformly across MISO N and multiplied the MRO GADS Hourly Outage by MISO N installed capacity.

To collect Entergy hourly load data before it joined MISO and its load was included in MISO zonal data, we used FERC Form Number 714 data to pull Entergy hourly load for 2012 through December 18, 2013.[26] We then added MISO S reported load for December 19, 2013, through the end of 2015 using MISO's reported load data. For MISO S installed capacity, we used 2012-2015 EIA 860 nameplate capacity (MW) data for Entergy.[27] We then applied Murphy's SERC hourly forced outage rate to Entergy's (MISO S) installed capacity for 2012-2015 to get hourly outages in MISO. No renewable generation was included as MISO S and Entergy had limited installed renewable capacity during this period.

For the non-RTO parts of the Eastern Interconnection we divided it up into four regions: the Southeast,[28] TVA, the Carolinas,[29] and Florida.[30] We again pulled hourly load data from FERC Form Number 714 for the Balancing Authorities that make up each of those regions.[31]

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21 Murphy's installed capacity in Table 1 did not include wind or solar capacity. Throughout this appendix we use the term "installed capacity" to refer to conventional generator capacity which does not include wind or solar generating capacity.

22 2012-2015 installed wind capacity, page 66, https://www.nyiso.com/documents/20142/2226467/2015-Load-Capacity-Data-Report-Gold-Book.pdf/63d6d932-7a50-4972-1cc9-e3f1eaa7ab90; 2012-2012 installed capacity, page 339, https://www.potomaceconomics.com/wp-content/uploads/2017/02/NYISO-2015-SOM-Report.pdf

23 For ISO-NE's installed capacity we used FCM results, see page 80, https://www.iso-ne.com/static-assets/documents/markets/mkt_anlys_rpts/annl_mkt_rpts/2012/amr12_final_051513.pdf

24 Hourly Load: https://www.misoenergy.org/markets-and-operations/real-time--market-data/market-reports/market-report-archives/#nt=%2FMarketReportType%3ASummary%2FMarketReportName%3AArchived%20Historical%20Regional%20Forecast%20and%20Actual%20Load%20%20(zip)&t=10&p=0&s=MarketReportPublished&sd=desc. Hourly Wind: https://www.misoenergy.org/markets-and-operations/real-time--market-data/market- reports/market-reportarchives/#nt=%2FMarketReportType%3ASummary%2FMarketReportName%3AArchived%20Historical%20Hourly%20Wind%20Data%20%20(zip)&t=10&p=0&s=MarketReportPublished&sd=desc

25 2012 installed capacity, page 11, https://www.potomaceconomics.com/wp-content/uploads/2017/02/2012-State-of-the-Market-Report.pdf; 2013 installed capacity, page 23, https://www.potomaceconomics.com/wp-content/uploads/2017/02/2014-State-of-the-Market-Report.pdf; 2014-2015 installed capacity, page 26, https://www.potomaceconomics.com/wp-content/uploads/2017/02/2015-State-of-the-Market-Report.pdf

26 https://www.ferc.gov/industries-data/electric/general-information/electric-industry-forms/form-no-714-annual-electric/data

27 https://www.eia.gov/electricity/data/eia860/

28 The Southeast region is composed of all Southern Company Power Companies (including Gulf Power Co) Balancing Authorities (BAs).

29 The Carolinas region is comprised of the following BAs in North and South Carolina: Duke, Dominion, South Carolina Public Service Authority, and Yadkin.

30 Florida is composed of the following BAs: City of Tallahassee, Florida Municipal Power Agency, Florida Power & Light, Gainesville Regional Utilities, Gulf Power Co (2018-2022 only), JEA, Lakeland Electric, Orlando Utilities Commission, Duke Energy Florida, Seminole Electric Cooperative, and Tampa Electric.

31 The BAs that comprise each region are based on the footnotes above and EIA 930 designations, per https://www.eia.gov/electricity/gridmonitor/dashboard/electric_overview/US48/US48.

For Florida we used Murphy et al.'s installed capacity MW for 2012-2015.[32] For the Carolinas, Southeast, and TVA's installed capacity we used Nameplate Capacity MW from EIA 860 for each Balancing Authority for 2012-2015 and summed it to get a total installed capacity for each region. We then applied Murphy's SERC GADS hourly all outage rate to the Southeast, TVA, and the Carolinas and multiplied it by the installed capacity in each region to Total Hourly MW Outages. No renewable generation was included for any of the three regions as each had limited installed renewable capacity during this period.

All regions were standardized to the Eastern Time Zone and then Total Hourly Outages (MW) were calculated by multiplying Installed Capacity by the NERC region GADS Hourly Outage Percent. We then calculated Total Hourly Net Load by subtracting Hourly Wind Generation from Hourly Load and then adding Total Hourly Outages (MW).

2018-2022 Analysis

For 2018-2022 a similar methodology was used with some changes to the data sources to analyze the Eastern Interconnection and ERCOT. 2018-2022 hourly load and 2019-2022 hourly wind and solar generation was compiled using EIA 930 data for ERCOT, ISO-NE, NYISO, PJM, SPP, TVA, and the Southeast, Carolinas, and Florida regions.[33] EIA 930 did not start reporting hourly wind and solar generation until July 1, 2018, so regionally reported hourly wind and solar generation for 2018 was used for ERCOT, ISO-NE, PJM, and SPP using the same sources as the 2012-2015 analysis. For TVA, Southeast, Carolinas, and Florida, the renewable generation for January 1, 2018, through June 30, 2018, was not included due to limited installed capacity. Hourly MISO data which separates load, wind, solar generation into MISO N and MISO S was used instead of EIA 930 data, which does not distinguish between MISO N and S.[34]

For the RTO regions (except MISO), we again used installed capacity for ERCOT,[35] ISO-NE,[36]

32 Table 1 from Murphy et al.

33 https://www.eia.gov/electricity/gridmonitor/dashboard/electric_overview/US48/US48

34 2021-2022 Load: https://www.misoenergy.org/markets-and-operations/real-time--market-data/market-reports/#nt=%2FMarketReportType%3ASummary%2FMarketReportName%3AHistorical%20Daily%20Forecast%20and%20Actual%20Load%20by%20Local%20Resource%20Zone%20(xls)&t=10&p=0&s=MarketReportPublished&sd=desc; 2018-2020 Load: https://www.misoenergy.org/markets-and-operations/real-time--market-data/market-reports/market-report-archives/#nt=%2FMarketReportType%3ASummary%2FMarketReportName%3AArchived%20Historical%20Regional%20Forecast%20and%20Actual%20Load%20%20(zip)&t=10&p=0&s=MarketReportPublished&sd=desc; 2021-2022 Wind and Solar: https://www.misoenergy.org/markets-and-operations/real-time--market-data/market-reports/#nt=%2FMarketReportType%3ASummary%2FMarketReportName%3AHistorical%20Generation%20Fuel%20Mix%20(xlsx)&t=10&p=0&s=MarketReportPublished&sd=desc ; 2018-2020 Wind and Solar: https://www.misoenergy.org/markets-and-operations/real-time--market-data/market-reports/market-report-archives/#nt=%2FMarketReportType%3ASummary%2FMarketReportName%3AArchived%20Historical%20Generation%20Fuel%20Mix%20%20%20(zip)&t=10&p=0&s=MarketReportPublished&sd=desc

35 2022: Assumed same installed capacity in 2022 as 2021. 2021: Wind, page 35; Solar, page 32; Installed capacity based on estimate from Figure A16, page A-26, https://ftp.puc.texas.gov/public/puct-info/industry/electric/reports/ERCOT_annual_reports/2021annualreport.pdf; 2020: Wind page 25; Solar page 23; Installed capacity based on estimate from Figure A-14, page A-20; https://ftp.puc.texas.gov/public/puct-info/industry/electric/reports/ERCOT_annual_reports/2020annualreport.pdf; 2019: Solar based on stated additions in 2020 report, page 22; Wind, page 24; Installed capacity based on estimate from Figure A14, page A-18; https://ftp.puc.texas.gov/public/puct-info/industry/electric/reports/ERCOT_annual_reports/2019annualreport.pdf.; 2018: Solar based on estimate from page A-18 in 2019 report; Wind page 80; Installed capacity based on estimate from Figure 64, page 77; https://ftp.puc.texas.gov/public/puct-info/industry/electric/reports/ERCOT_annual_reports/2018annualreport.pdf.

36 For ISO-NE's installed capacity we used FCM results, see page 205. For 2018-2020 wind and solar we used a MW of installed capacity that also included DR, Coal, Other, and Battery Storage, Figure 6-2, page 195, https://www.iso-ne.com/static-assets/documents/2022/05/2021-annual-markets-report.pdf.

NYISO,[37] PJM,[38] and SPP[39] as reported by the IMM. For ERCOT, ISO-NE, and SPP, 2021 installed capacity was used for 2022.

For MISO N[40] we used IMM reported total installed capacity minus MISO S installed capacity, which we calculated by summing the EIA 860 nameplate installed capacity for all Entergy Utilities for 2018-2022. For MISO N and S, 2021 installed capacity was used for 2022.

For the Carolinas, Southeast, and TVA, installed capacity was calculated using Nameplate Capacity MW from EIA 860 for each Balancing Authority for 2018-2021 which was then summed to get a total installed capacity for each region. 2021 installed capacity was used for 2022 as 2022 EIA 860 data is not yet available. For Florida, we used installed capacity from the Southern Alliance for Clean Energy's SENFO database for Florida BAs for 2018-2021, which were then summed to get a total installed capacity for Florida for 2018-2021. For Florida's installed renewable capacity we summed the installed nameplate renewable capacity from EIA's 860 data for 2018-2021. For the Carolinas, Southeast, TVA, and Florida installed capacity for 2021 was used for 2022.

For 2018-2022, we did not have access to NERC GADS Hourly Outage data, but we did have hourly outage data for some regions for three extreme weather events during that time period: 2022 Winter Storm Elliott, 2021 Winter Storm Uri, and the 2018 South Central Cold Weather Event. For each of these events there was often post-event reports that tracked outage MWs in the affected regions. We compiled this data to track hourly MW of forced outages at the regional level during those events.

For the 2018 South Central Cold Weather Event, the best outage data came from the FERC-NERC report.[41] Figure 22 from the report details outages for MISO S, SPP, TVA and SERC for January 17, 2018. We manually extracted the numerical hourly MW outages for each region during the event from the figure. For MISO S and TVA, we assumed outages did not include any renewable outages since both regions had limited installed renewables. For SPP and SERC (our Southeast region) a 5% outage rate was assumed for installed renewables during the event and these outages were subtracted from the FERC-NERC Figure 22 outages. For the rest of the Eastern Interconnection Regions and ERCOT we did not have actual hourly outages and an hourly outage rate of 5% was used, except for ISO-NE and NYISO where a 3% outage rate was assumed, approximating those regions' average forced outage rate over the 2012-2015 period per Murphy et al.

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37 2022 Installed capacity, wind, and solar assumed same as 2021. 2020-2021 Installed capacity, wind, and solar, page 71, https://www.nyiso.com/documents/20142/2226333/2021-Gold-Book-Final-Public.pdf/b08606d7-db88-c04b-b260-ab35c300ed64. 2018-2019 Installed capacity, wind, and solar, page 43, https://www.nyiso.com/documents/20142/2226333/2019-Gold-Book-Final-Public.pdf/a3e8d99f-7164-2b24-e81d-b2c245f67904?t=1556215322968.

38 2022 Installed capacity, wind and solar, page 313, https://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2022/2022-som-pjm-vol2.pdf. 2021 Installed capacity, wind, and solar, page 295, https://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2021/2021-som-pjm-vol2.pdf. 2020 Installed capacity, wind, and solar, page 272, https://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2020/2020-som-pjm-vol2.pdf. 2019 Installed capacity, wind, and solar, page 262, pg 262; https://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2019/2019-som-pjm-volume2.pdf. 2018 Installed capacity, wind, and solar, page 262, https://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2018/2018-som-pjm-volume2.pdf

39 2019-2021 installed capacity, wind, and solar, page 52, https://www.spp.org/documents/67104/2021%20annual%20state%20of%20the%20market%20report.pdf. 2018 installed capacity, wind and solar, page 30, https://www.spp.org/documents/65161/2020%20annual%20state%20of%20the%20market%20report.pdf

40 2020-2021 installed capacity, wind, and solar, page 6, https://www.potomaceconomics.com/wp-content/uploads/2022/06/2021-MISO-SOM_Report_Body_Final.pdf. 2018-2019 installed capacity, wind, and solar, page 6, https://www.potomaceconomics.com/wp-content/uploads/2020/06/2019-MISO-SOM_Report_Final_6-16-20r1.pdf

41 Pg 46, https://www.nerc.com/pa/rrm/ea/Documents/South_Central_Cold_Weather_Event_FERC-NERC-Report_20190718.pdf

For 2021 Winter Storm Uri, the best data also came from the FERC-NERC report for that event.[42] Figure 66b from the report details outages for ERCOT, MISO, and SPP for February 8-20, 2021. From the figure, we manually extracted the numerical MW outages for approximately each 12-hour interval for each region during the event, and then the hourly outages within each 12-hour period were interpolated linearly. However, the report does not include renewable outage rates during the event. For MISO S a 5% outage rate was assumed for installed renewables during the event and these outages were subtracted from the interpolated FERC Figure 66b hourly outages for February 13-20, 2021. For ERCOT, EIA 930 Forecasted Load was used for February 14, 2021 through February 20, 2021, as this better reflected what load would have been without the large loss of load during that period.

Generator outage data for ERCOT and SPP were compiled from those RTOs' outage reports. Both RTOs' reports provide forward-looking projections of outages, which tend to have decreasing accuracy over time. As a result, only the initial hours from each report were used and a linear interpolation was used to fill in the gaps between reports. To account for renewable outages during February 13-20, 2021, 10 real-time ERCOT outage reports from February 13-17, 2021 were used to interpolate renewable outages. The first 6 hours from each report was used and a linear interpolation was used to fill in the gaps between reports. From February 17 at 14:00 through the end of the day February 20th a thermal outage rate was extrapolated using the ratio of the previous total hourly outage compared to thermal outages. For SPP, wind outages were pulled from the first hour of SPP forecasted generator outage reports for February 13, 2021.[43] The first hour of renewable outages from the report was linearly interpolated to February 14th. For February 14th through February 20th, reported wind outages were used from Figure 23 of an SPP report.[44] From the figure we manually extracted the numerical MW outages roughly every 12 hours for SPP wind outages and then the hourly outages in between were interpolated linearly. For the rest of the Eastern Interconnection, we did not have hourly forced outage data, so as above, an hourly forced outage rate of 5% was used, except for ISO-NE and NYISO where a 3% forced outage rate was assumed.

For Winter Storm Elliott, conventional generator correlated outage data was pieced together from preliminary event reports from different regions. For SPP, slide 22 of an SPP Staff Presentation[45] shows outages by generator type for December 19th through December 26th. From the slide we manually extracted the numerical MW outages for roughly every 12 hours during the event, and then the hourly outages in between were interpolated linearly for each 12-hour period. We only used Gas and Coal outages from the chart as outages from other fuel types were negligible and the impact of renewable forced outages is captured in the EIA 930 hourly renewable output data. For PJM, we used Slide 2 from a PJM Winter Storm Elliott Presentation,[46] which shows outages by generator fuel type for December 23rd through December 25th on a two-hour basis. From the slide we manually extracted the numerical MW outages for two-hour blocks during the event. MISO reported system-wide daily average

42 Pg 126, https://www.ferc.gov/media/february-2021-cold-weather-outages-texas-and-south-central-united-states-ferc-nerc-and

43 https://marketplace.spp.org/pages/capacity-of-generation-on-outage

44 Pg 48, https://spp.org/documents/65037/comprehensive%20review%20of%20spp%27s%20response%20to%20the%20feb.%202021%20winter%20storm%202021%2007%2019.pdf

45 SPP, "DECEMBER 2022 WINTER STORM ELLIOTT," Staff Presentation by C.J. Brown, January 17, 2023, slide 22.

46 Slide 2, https://www.pjm.com/-/media/committees-groups/committees/oc/2023/20230413/20230413-item-04---winter-storm-elliott-fuel-supply-issues.ashx

unplanned generation outages by fuel type for December 22nd through December 24th.[47] The reported daily averages were entered for Hour 12 of December 22, 23, and 24, and then a linear interpolation was done between those hours. The outages were then split proportionally between MISO N and MISO S based on installed capacity. For TVA and the Carolinas, outages were determined by taking the difference between the EIA 860 installed thermal capacity for the region in 2022 and comparing it to the lowest hour of thermal generation (coal, gas, and nuclear) during each region's rolling blackout period(s) during Winter Storm Elliott, based on the assumption that all thermal generation would have been fully dispatched during this period.[48] We did not have hourly outage data for the rest of the Eastern Interconnection and ERCOT, so as above an hourly outage rate of 5% was used, except for ISO-NE and NYISO where a 3% outage rate was assumed.

All hourly data for demand, renewable output, and forced outages were converted to the Eastern Time Zone. Total Hourly Outages (MW) were then calculated outside of the three extreme weather events by multiplying by the assumed 5% or 3% outage rate discussed above. We then calculated Total Hourly Net Load for 2018-2022 by subtracting Hourly Wind and Solar Generation from Hourly Load and then adding Total Hourly Outages (MW).

47 Slide 10, https://cdn.misoenergy.org/20230117%20RSC%20Item%2005%20Winter%20Storm%20Elliott%20Preliminary%20Report627535.pdf

48 Reported rolling blackouts for both TVA and Duke during Winter Storm Elliot from this article: https://rmi.org/wasted-wind-and-tenable-transmission-during-winter-storm-elliott/

EXHIBIT MG-6

Joule

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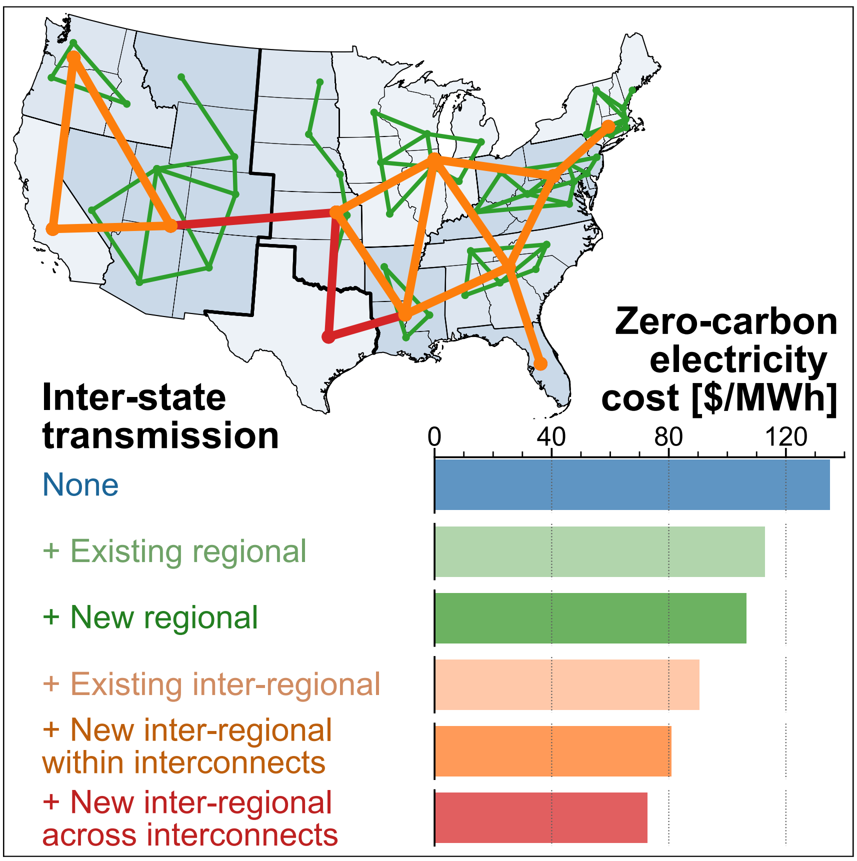
Article

The Value of Inter-Regional Coordination and Transmission in Decarbonizing the US Electricity System



Rapid decarbonization of electricity is a critical component of climate change mitigation. We model zero-carbon electricity systems for the continental US using technologies currently deployed at gigawatt-scale—solar, wind, existing hydropower, lithium-ion batteries, and transmission. Inter-state operational coordination reduces the cost of decarbonization; allowing new inter-state transmission reduces cost further. Nuclear power and long-duration energy storage have the potential to reduce system cost but are not necessary for decarbonization; all sensitivity cases deploy hundreds of gigawatts of new solar and wind.

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HIGHLIGHTS

US electricity demand can be met with currently available zero-carbon technologies

Inter-regional coordination and transmission construction significantly reduce cost

Nuclear, if available, plays a smaller role than renewables at central cost projections

Nationally planned decarbonization is more efficient than state or regional approaches

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Joule

CellPress

Article

The Value of Inter-Regional Coordination and Transmission in Decarbonizing the US Electricity System

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SUMMARY

Preventing global warming in excess of 1.5°C–2°C requires a transition to zero-carbon electricity systems by midcentury along with the widespread electrification of other sectors. Current state-level renewable portfolio standards and regional transmission arrangements do not capture the benefits of inter-regional transmission or coordination of planning and dispatch for renewable-energy integration. Here, using a co-optimized capacity-planning and dispatch model over 7 years of hourly operation, we show that inter-state coordination and transmission expansion reduce the system cost of electricity in a 100%-renewable US power system by 46% compared with a state-by-state approach, from 135 \$/MWh to 73 \$/MWh. Sensitivity analyses show that reductions in the cost of photovoltaics, wind, and lithium-ion batteries lead to the lowest electricity costs for systems in which transmission expansion is allowed, while cost reductions for nuclear power or long-duration energy storage lead to greater electricity cost reductions for isolated systems.

Context & Scale

Averting the worst effects of climate change requires decarbonizing the electricity sector as rapidly as possible. Given the urgency of action and the uncertainty inherent in new technology development, it is prudent to explore zero-carbon electricity systems limited to technologies currently being deployed at gigawatt-scale. Here, we model zero-carbon electricity systems for the continental US using solar photovoltaics, wind power, existing hydropower, lithium-ion batteries, and transmission, incorporating 7 years of hourly weather data from tens of thousands of available sites. New and existing long-distance transmission significantly reduces the system cost of electricity and the amount of energy storage required for reliable zero-carbon electricity. Streamlining the planning and permitting process for new transmission and coordinating decarbonization at the national (rather than state) level could enable a more efficient and rapid transition to a zero-carbon electricity system.

INTRODUCTION

Stabilizing global warming below 1.5°C–2°C necessitates reducing net anthropogenic greenhouse gas emissions to zero by the middle of this century.[1] Many analyses suggest that the electricity sector will need to decarbonize most rapidly, concomitant with electrification of other sectors.[2] Given the short time frame for power-system decarbonization and the long development times for new technologies and supply chains, there is a need for analyses demonstrating zero-carbon power-system pathways using technologies currently deployed at gigawatt-scale to prepare for the possibility that nascent technologies, including next-generation nuclear fission, carbon capture and long-term sequestration (CCS), and grid-connected hydrogen turbines or fuel cells, are delayed or unavailable at a large scale. Zero-carbon technologies currently deployed at gigawatt-scale in the United States (US) include onshore wind power (104 GW installed capacity at the end of 2019), nuclear power (103 GW), hydropower (80 GW), photovoltaics (36 GW), geothermal (3.8 GW), and concentrated solar thermal power (1.6 GW), and ancillary technologies including alternating-current (AC) and direct-current (DC) transmission, pumped-hydropower storage (PHS) (22 GW), and electrochemical batteries (1.0 GW).[3]

Modeling zero-carbon electricity systems for the US, particularly those relying on high penetrations of variable renewable energy (VRE, including wind and solar power) and storage, presents numerous challenges.[4,5] Large (continent-scale) geographic coverage is necessary to represent spatiotemporal correlation in weather systems and the long-range interconnected nature of the US electricity grid;[6–8] large (multi-year) temporal coverage is required to account for interannual weather variability and ensure resource adequacy during uncommon low-resource weather events;[8–11] fine ($\leq 1h$) temporal resolution is required to represent VRE variability and storage operation; and chronological time coupling is required to represent storage energy constraints, the combined capacity value of VRE and storage, and generator ramp rates in systems employing nuclear power.

Numerous optimization models[12,13] and a significant body of literature[4,5,14] address the optimal design of low- and zero-carbon electricity systems for the US. These models and studies can roughly be divided into two classes. One class employs high geographic resolution (10–100 zones), explicit representation of transmission investment and power flow, relatively low temporal resolution for capacity planning (typically tens to hundreds of ''time slices''), and a multi-period sequential-investment framework, typically to model systems up to ~80% decarbonization.[15–20] The second class tends to employ low geographic resolution (often a single-zone ''copper-plate'' system), limited or no representation of transmission, high temporal resolution (hourly chronological time steps, often for a single year but sometimes over multiple years), and a single-period steady-state framework to model systems up to 100% decarbonization—in some cases for the entire US,[8,21] and in others for isolated sites,[10] states,[22] or regions.[23,24] MacDonald et al. partially bridge this divide,[25] combining hourly resolution with zonal transmission expansion, but do not exceed 80% decarbonization. Other studies explore zero-carbon systems for Europe,[26–29] including the recent work of Tröndle et al.,[30] which explores the impact of VRE siting policy and transmission availability on system cost (albeit for a single year at four-hour resolution). For the reasons noted above, both high temporal resolution and an explicit representation of transmission are necessary for accurately modeling low- and zero-carbon electricity systems for the US.

Here, we employ a linear optimization model with hourly resolution over 7 years of historical weather (2007–2013) to explore zero-carbon electricity systems for the US, co-optimizing capacity investments and hourly operation of generation, storage, and transmission to meet projected electricity demand in 2040. Transmission costs and constraints at the national scale are addressed using a hierarchical approach, first determining inter-state transmission investment within 11 regional planning areas (PAs), then optimizing inter-PA transmission investment and hourly flows for an interconnected US system. We find that a zero-carbon power system is feasible at the level of hourly system balancing using technologies deployed today (photovoltaics [PV], wind, transmission, Li-ion batteries, and hydropower) at all spatial scales considered, from isolated states to PAs to the interconnected US system. Inter-state and inter-regional coordination of capacity-planning and dispatch, as well as the construction of new inter-state transmission capacity, significantly reduce the cost of decarbonization. Sensitivity analyses show that, while flexible nuclear power and ''long-duration'' (low-energy-cost and low-self-discharge-rate) storage have the potential to reduce the cost of decarbonization, they are not required to reach a zero-carbon system and have less impact on system cost than continued reduction in the price of PV, wind, and Li-ion batteries when full transmission expansion is allowed.

Analytical Approach

Renewable-Energy Supply Curves

Modeling the expansion of PV and wind capacity requires assessing the available land area for new deployment. We develop supply curves of available land area for PV and wind development, excluding water bodies,[31] national parks,[32] urban

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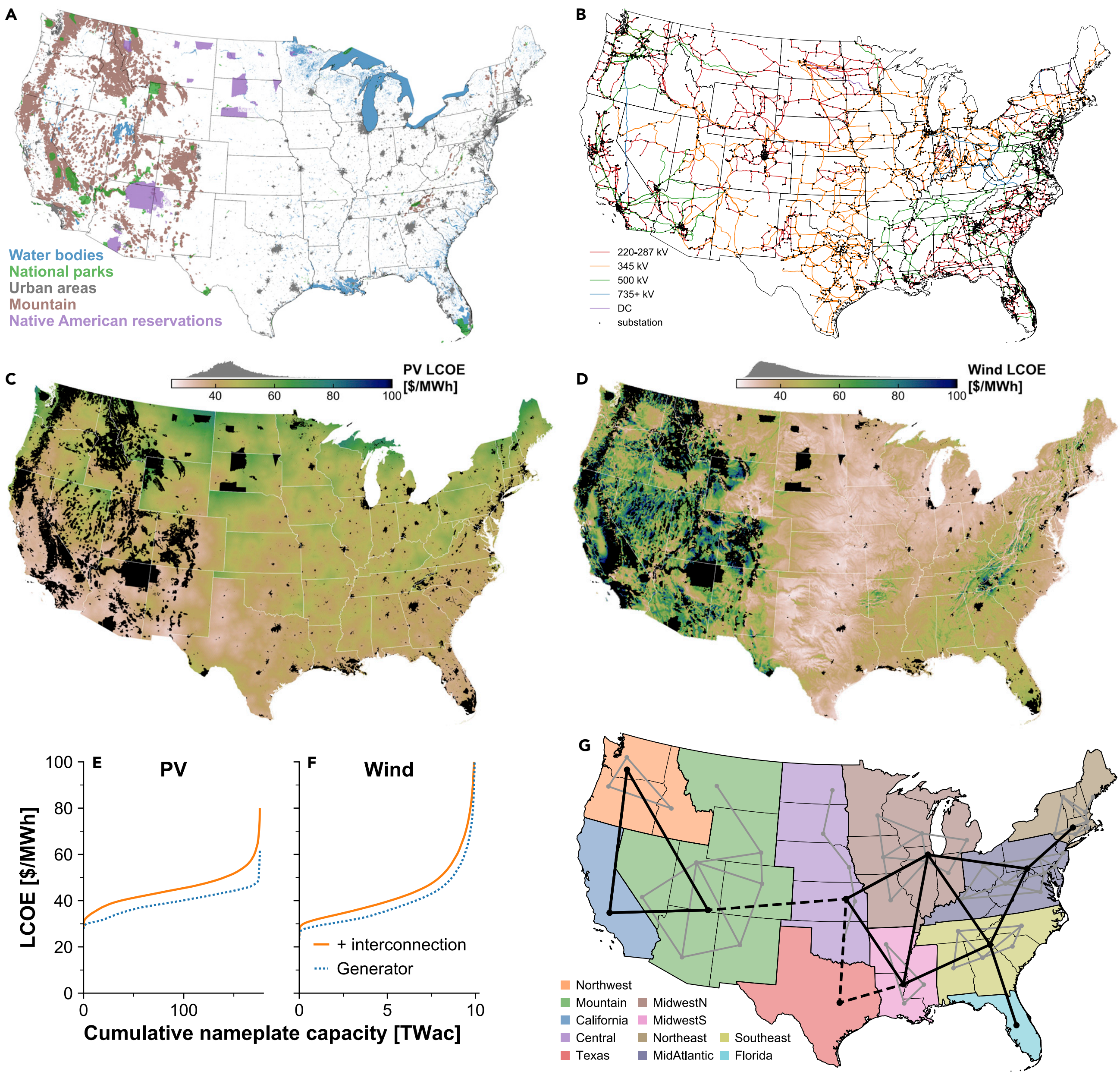

Figure 1. Geospatial Input Assumptions for VRE Availability and Power System Topology for the Continental US.

(A) Land exclusions.[31–35] Excluded areas are indicated by colored areas; white areas are assumed to be available for solar and wind deployment.

(B) Existing transmission lines (colored lines) and transmission substations (black circles).[76] Interconnection costs are calculated based on the distance from solar and wind sites to substations and the distance from substations to urban boundaries in (A), as described in the Supplemental Information.

(C and D) Maps of the LCOE for 41,990 PV sites (C) and 416,859 wind sites (D), including the site-specific cost of interconnection to in-state substations.

(E and F) Supply curves of PV sites (E) and wind sites (F) sorted by site-specific LCOE, excluding (blue dotted lines) and including (orange solid lines) interconnection costs.

(G) PA boundaries and transmission system topology assumed for the capacity-planning model in this study. Inter-state intra-PA transmission is denoted by gray lines; inter-PA transmission is denoted by black lines. Solid lines denote AC connections; dashed lines denote DC connections. All costs in (C)–(F) and in the remainder of this work are in 2017 US dollars.

areas,[33] mountain ranges,[34] and Native American territories[35] from development (Figure 1A) and quantifying the interconnection cost of "spur lines" to connect to existing transmission infrastructure (Figure 1B).

The hourly capacity factor (CF) of horizontal 1-axis-tracking PV over 2007–2013 is simulated using satellite data from the National Solar Radiation Database (NSRDB)[36,37] for 41,990 sites across the continental US; the hourly CF of wind is simulated using climate reanalysis data from the WIND Toolkit and manufacturer power curve data for the Gamesa:G126/2500 turbine at 100-meter height for 416,859 sites. Figures 1C and 1D show maps of the calculated levelized cost of electricity (LCOE) across the modeled sites assuming 2030 "mid" cost projections from the 2019 NREL Annual Technology Baseline (ATB),[38] and Figures 1E and 1F show the cumulative available capacity sorted by LCOE, applying areal power densities representative of current installations. Further details are provided in the Supplemental Information (Note S2).

Capacity-Planning Model

The capacity-planning model minimizes the sum of annualized capital costs and hourly operational costs over 7 years of hourly operation using 2007–2013 weather data, subject to constraints on hourly demand balance, hourly VRE availability, available PV and wind capacities, storage energy balance, transmission flows, and hydropower availability. Using the "steady-state" framework discussed above, we include-long-lived "brownfield" hydropower and transmission assets while treating all other generators as "greenfield" assets, and we do not consider limits on annual capacity deployment. The model improves upon previous work by combining hourly resolution, interannual variability (across 7 years in central cases and up to 21 years in the Supplemental Information [Note S5.2]), explicit modeling of transmission flows, and site-specific VRE interconnection costs with an extensive sensitivity analysis over more than 370 independent cases. Details regarding the model formulation, assumptions, and input data are provided in the Supplemental Information (Note S3), with open-source computer code available in the associated repository.

Hourly electricity demand projections by state are obtained from the NREL Electrification Futures Study, using the 2040 "reference" electrification scenario with "slow" technology advancement.[39,40] Cost and performance assumptions for generation and storage technologies are provided in Table 1; we use 2030 "mid" cost projections from the 2019 NREL ATB unless noted otherwise, reflecting the fact that most capacity in the modeled demand year of 2040 will be installed in years prior to 2040. Cost and performance assumptions for transmission are taken from the NREL ReEDS model[15] and are provided in Table S3; existing transmission capacity is assumed to be available at no cost. PV and wind sites are aggregated into five LCOE classes within each zone to reduce the model size. No existing ("brownfield") VRE capacity is included, given that most installations are likely to be repowered by 2040. The power and energy costs of Li-ion battery systems are disaggregated,[41,42] allowing the model to optimize the duration (energy-to-power ratio) of storage within each modeled zone. Existing reservoir and run-of-river (ROR) hydropower facilities are included, using monthly historical generation from 2007–2013.[3,43,44] Existing hydropower is considered to be fully paid off, with zero capex cost; no new hydropower construction is allowed.

Nuclear power represents a special case when compared with other currently deployed technologies; while nuclear power produced roughly 20% of US electricity in 2019, only a single unit has been built in the US in the last 24 years.[3,43] There are two operational power-generating carbon-capture plants worldwide at the time of this writing, with a

Table 1. Cost and Performance Assumptions for Generation and Storage Technologies

Technology	Qualifier	Capex Cost (Power)	Capex Cost (Energy)	Lifetime	WACC (Real)	FOM Cost (Power)	FOM Cost (Energy)	Ramp Rate	Minimum Generation
		[$/kWac]	[$/kWh]	[Years]	[%]	[$/kWac-yr]	[$/kWh-yr]	[%/h]	[% capacity]
PV	2018	1,442	-	25	4.2	26	-	100	0
PV	2030 "Mid"	1,118	-	25	4.2	13	-	100	0
PV	2030 "Low"	733	-	25	4.2	9	-	100	0
Wind	2018	1,623	-	25	4.2	44	-	100	0
Wind	2030 "Mid"	1,262	-	25	4.2	39	-	100	0
Wind	2030 "Low"	1,134	-	25	4.2	34	-	100	0
Nuclear	Noflex	6,180*	-	25	4.5	101	-	0	100
Nuclear	Midflex	6,180*	-	25	4.5	101	-	25	50
Nuclear	Fullflex	6,180*	-	25	4.5	101	-	25	0
Nuclear	Existing	0	-	-	-	234	-	5	85
Hydro	Reservoir	-	-	-	-	36	-	100	10
Hydro	Run-of-River	-	-	-	-	36	-	0	100
CCGT	2030 "Mid"	850	-	25	4.5	11	-	50	0
OCGT	2030 "Mid"	849	-	25	4.5	12	-	100	0
Li-Ion	2018	287	300	15	4.2	6	7	100	0
Li-Ion	2030 "Mid"	158	165	15	4.2	3	4	100	0
Li-Ion	2030 "Low"	95	99	15	4.2	2	2	100	0
LDES		1,757	5–50*	25	4.2	16	0	100	0
PHS	Existing	0	0	-	-	16	0	100	0

All monetary quantities are in 2017 US dollars and are taken, where possible, from the NREL Annual Technology Baseline (ATB).[38] Capital expenditure (capex) costs for nuclear power and long-duration energy storage (LDES), marked with a "*", vary across sensitivity cases and are noted in Figure 4 for cases in which they are included. LDES cost and performance assumptions are derived from estimates for PHS. Reservoir and run-of-river hydropower are included in all simulations, but no capacity additions are allowed. Figures 2 and 3 and the "default" row in Figure 4 include only PV "2030 mid," wind "2030 mid," Li-ion "2030 mid," and transmission as new investment options; other rows in Figure 4 include the additional technologies listed here where noted. Additional cost and performance assumptions are given in Tables S10 and S11. Abbreviations are defined in the Supplemental Information (Note S1).

combined capacity of 0.35 GW; both utilize the captured CO_2 for enhanced oil recovery,[45] and cannot be classified as zero-carbon given the sub-100% CO_2-capture efficiency of CCS. While offshore wind is currently deployed at gigawatt-scale in Europe, the deployed US capacity is 0.03 GW at the time of this writing.[3] Given our focus on technologies currently being deployed at gigawatt-scale in the US, only PV, wind, Li-ion batteries, existing hydropower, and transmission are included in the base case; nuclear power is considered separately in the sensitivity analysis described below, while offshore wind and carbon capture are excluded given their sub-gigawatt capacity. Geothermal and CSP currently demonstrate relatively limited regional availability and deployment, and are thus excluded to reduce the model size and computation time (computational details are provided in Supplemental Information section S4). Three additional sources of flexibility are considered in the sensitivity analysis: flexible nuclear, long-duration energy storage (LDES, with cost assumptions and technical parameters derived from PHS), and load shedding during periods of peak net demand.

Table 2. Regional Coordination and Transmission Assumptions

Scenario	Zones	Independent Simulations	Coordination Boundary	Existing Inter-State Transmission?	New Inter-State Transmission?
States	States	48	State	No	No
PA – AC	States	11	PA	Within each PA	No
PA + AC	States	11	PA	Within each PA	AC between states within PA
USA – AC – DC	PAs	1	USA	Between adjacent PAs	AC between states within PA No new AC/DC between PAs
USA + AC – DC	PAs	1	USA	Between adjacent PAs	AC between states within PA New AC between synchronous PAs
USA + AC + DC	PAs	1	USA	Between adjacent PAs	AC between states within PA New AC between synchronous PAs New DC between asynchronous PAs

The transmission system topology for the "PA" and "USA" scenarios is shown in Figure 1G. Each PA contains between 1 and 8 states. "+" and "–" symbols in scenario names indicate whether new transmission of the indicated type (AC or DC) is allowed (+) or disallowed (–) between the constituent zones (states for PA scenarios, PAs for USA scenarios). There are three groups of synchronous PAs: the western interconnect (Northwest, Mountain, and California), the eastern interconnect (Central, MidwestN, MidwestS, Northeast, MidAtlantic, Southeast, Florida), and Texas; AC transmission is included between PAs within the same synchronous interconnect, while DC transmission is only included between interconnects.

Regional Coordination and Transmission Scenarios

In this work, "coordination" is defined to include all of the functions that would be performed by a cost-minimizing centrally-planned electric system operator within an isolated coordination area: generation and transmission capacity planning and procurement, balancing of supply and demand through hourly dispatch, and (in the relevant sensitivity cases discussed below) procurement of operating reserves. We consider three different boundaries for regional coordination: individual states, multi-state PAs, and the interconnected US system. Two "PA" and three "USA" scenarios are considered, differing in their allowance of new transmission construction. The "States" and "PA" scenarios entail independent optimizations of each state or PA, balancing hourly supply and demand using only generation assets sited within the borders of the relevant state or PA, while the "USA" scenarios entail a single optimization of the full 11-PA system. These six scenarios are summarized in Table 2.

While existing transmission capacity is most closely approximated by the "USA – AC – DC" scenario, this scenario does include new intra-PA inter-state transmission to balance VRE generation with demand within the PA. Independent system operators (ISOs) currently coordinate extensively between states within their service territory, while inter-ISO coordination is comparatively more difficult;[46] coordination of generation capacity-planning and day-ahead unit commitment between ISOs is limited, and wheeling charges disincentivize inter-regional power flows. The names and boundaries of the 11 PAs considered here, in addition to the assumed intra-PA inter-state grid topology and inter-PA topology, are shown in Figure 1G. To accommodate our high temporal resolution (>60,000 chronological hourly timesteps over 7 years), the 11 PAs used here are larger in size and smaller in number than the ~70 balancing authorities of the continental US.[47]

Limitations

Before describing our results, we first note several limitations in our analysis. We do not model sub-hourly resource variability (although the hourly operating reserves cases suggest that doing so would not substantially increase costs); transmission is modeled in a highly aggregated fashion, without AC or DC optimal power flow; we do not include connections to Canada or Mexico, offshore wind, geothermal,

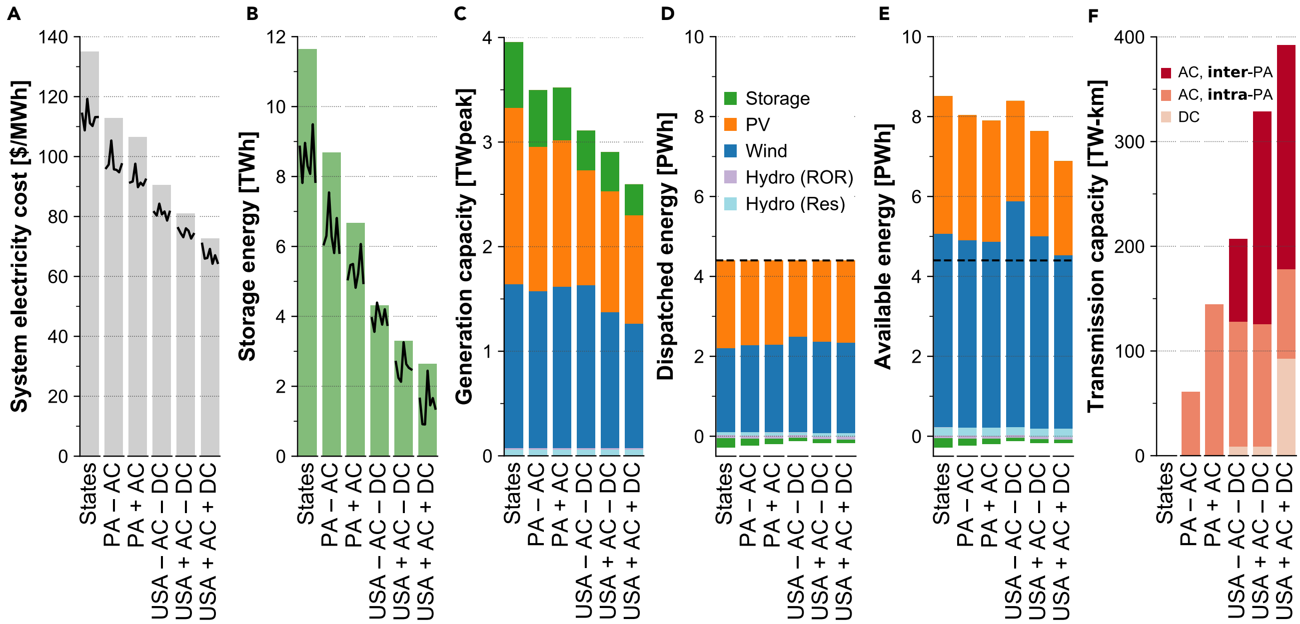

Figure 2. Cost, Capacity, and Annual Operation of Optimized Zero-Carbon Power Systems

Results are shown for isolated states ("States"); isolated PAs without ("PA – AC") and with ("PA + AC") new inter-state AC transmission; and the full-US system without new inter-PA transmission ("USA – AC – DC"), with new inter-PA AC transmission ("USA + AC – DC"), and with new inter-PA AC and DC transmission ("USA + AC + DC"). New DC transmission capacity is only allowed between nodes connected by dashed lines in Figure 1G.

(A) Average SCOE, given by the optimized value of the objective function divided by the summed hourly system demand. Gray bars denote optimized solutions for the full 2007–2013 period; black lines denote optimized individual yearly solutions for the 7 years between 2007 and 2013, with 2007 on the left and 2013 on the right.

(B) Installed energy capacity of storage. As in (A), green bars denote solutions optimized for the full 2007–2013 period and black lines denote individual yearly solutions for the 7 years between 2007 and 2013.

(C) Installed power capacity of generation and storage optimized for the full 2007–2013 period.

(D) Annual dispatched energy for systems optimized for the full 2007–2013 period. Bars start from a negative value that corresponds to the energy used to charge storage, in addition to storage and transmission losses. The sum of dispatched energy from storage and dispatched energy from hydropower, wind, and PV equals the annual demand, denoted by the black dashed line.

(E) Annual available energy for systems optimized for the full 2007–2013 period, with annual demand denoted by the black dashed line. As in (D), bars start from a negative value to account for storage charging and losses from storage and transmission. The available energy from wind and PV is given by the 7-year average CF multiplied by the installed capacity. The available energy from reservoir hydropower is given by historical generation over 2007–2013, assuming no spilled power.

(F) Installed inter-state transmission capacity. Bars include both existing and new-build transmission capacity. Interconnection "spur lines" associated with PV and wind sites are not included. Intra-PA transmission for the "USA" scenarios is calculated using the method described in the Supplemental Information (Note S3.2.1).

CSP, demand response (outside of the bounding "$9000/MWh load shedding" sensitivity case discussed below), unit commitment for nuclear or CCGT, security constraints, or nonlinearities arising from wind wake effects and storage degradation. Our approach can be characterized as "perfect hindsight," showing that historical demand profiles (scaled up to account for demand growth and electrification) can be met under historical weather conditions; we do not model forecast uncertainty in VRE availability or demand, or the impact of climate change on weather patterns. We also do not address issues of system inertia or transient stability (although recent work shows that PV,[48] wind,[49] and batteries[50] can provide such services). These areas should be considered in future work. Including additional generation technologies or demand response would decrease estimated electricity costs, while modeling optimal power flow, security constraints, inertia, or unit commitment would tend to increase costs.[51]

RESULTS

Impacts of Regional Coordination and Transmission

Figure 2 shows the system cost of electricity (SCOE, defined as the total annualized capex and operational costs of generation, storage, and transmission divided by the yearly system-wide demand; distribution and administration costs are not included), installed capacity, and dispatched and available energy for the six central zero-carbon scenarios described in Table 2. Zero-carbon systems are feasible with today's VRE and storage technologies in all scenarios, even for the "States" scenario requiring each state to balance hourly electricity supply and demand from generators within its own borders. Yet as regional coordination increases along the horizontal axis, the SCOE and installed generation and storage capacity decrease substantially. Benefits are derived both from increasing coordination without installing new transmission capacity (the SCOE decreases by 22 $/MWh from "States" to "PA – AC" and by 16 $/MWh from "PA + AC" to "USA – AC – DC") and from allowing new transmission installations at the same level of coordination (in the "USA" scenarios, allowing new AC transmission reduces the SCOE by 10 $/MWh, and allowing new DC transmission across the three asynchronous interconnects reduces SCOE by a further 8 $/MWh).

The decline in storage deployment is even more pronounced: The "USA + AC + DC" case deploys 40% of the storage used in the "PA + AC" case and 23% of the storage used in the "States" case. Projected average 2040 electricity demand is 0.50TW, so the installed energy capacity of storage (Figure 2B) divided by average demand equates to roughly 23 hours in the "States" case, 13 hours in the "PA + AC" case, and 5.3 hours in the "USA + AC + DC" case. Inter-state transmission capacity (including both intra-PA and inter-PA capacity) increases by roughly 90% between the "USA – AC – DC" and "USA + AC + DC" cases.

These results corroborate previous studies showing that a single weather year is insufficient for modeling zero-carbon systems with high reliability.[8–11] The 7-year simulations over 2007–2013 always entail higher SCOE (Figure 2A) and typically employ larger storage capacity (Figure 2B) than simulations over individual weather years, even the "worst" years, although interannual weather variability is smaller at the continent scale than at the scale of states or PAs (Note S5). Because the worst year varies across states (Figure S19) and storage deployment tends to be sized for the worst year (where "worst" roughly indicates the severity and duration of synchronized low-availability periods for wind, PV, and hydropower), the gap between the optimal 7-year and 1-year storage capacities (and SCOE) is larger for the geographically-isolated "States" and "PA" scenarios than for the "USA" scenarios.

Given the currently available technologies modeled here, the intermittency of VRE is primarily managed by sizing VRE capacity to provide sufficient generation during the lowest-resource times (cloudy winters for PV and calm summers for wind) and curtailing generation to match demand during other times.[22,52] Increased regional coordination and transmission reduce the necessary capacity and the incidence of curtailment (Figures 2D and 2E). As shown in Figure 3, storage duration (defined by the energy-to-power ratio of the optimized storage capacity in a given zone) is lower in the "USA + AC + DC" scenario than in the "USA – AC – DC" scenario. Construction of new transmission capacity thus has two primary benefits—it allows increased VRE deployment at higher-quality sites, reducing the capacity investment required to produce a given amount of energy (Figure 2C); it also reduces VRE intermittency by integrating generation from distant sites spanning different cloud and weather systems,[6,7] thus reducing the amount and duration of storage required (Figures 2B, 3C, and 3G).

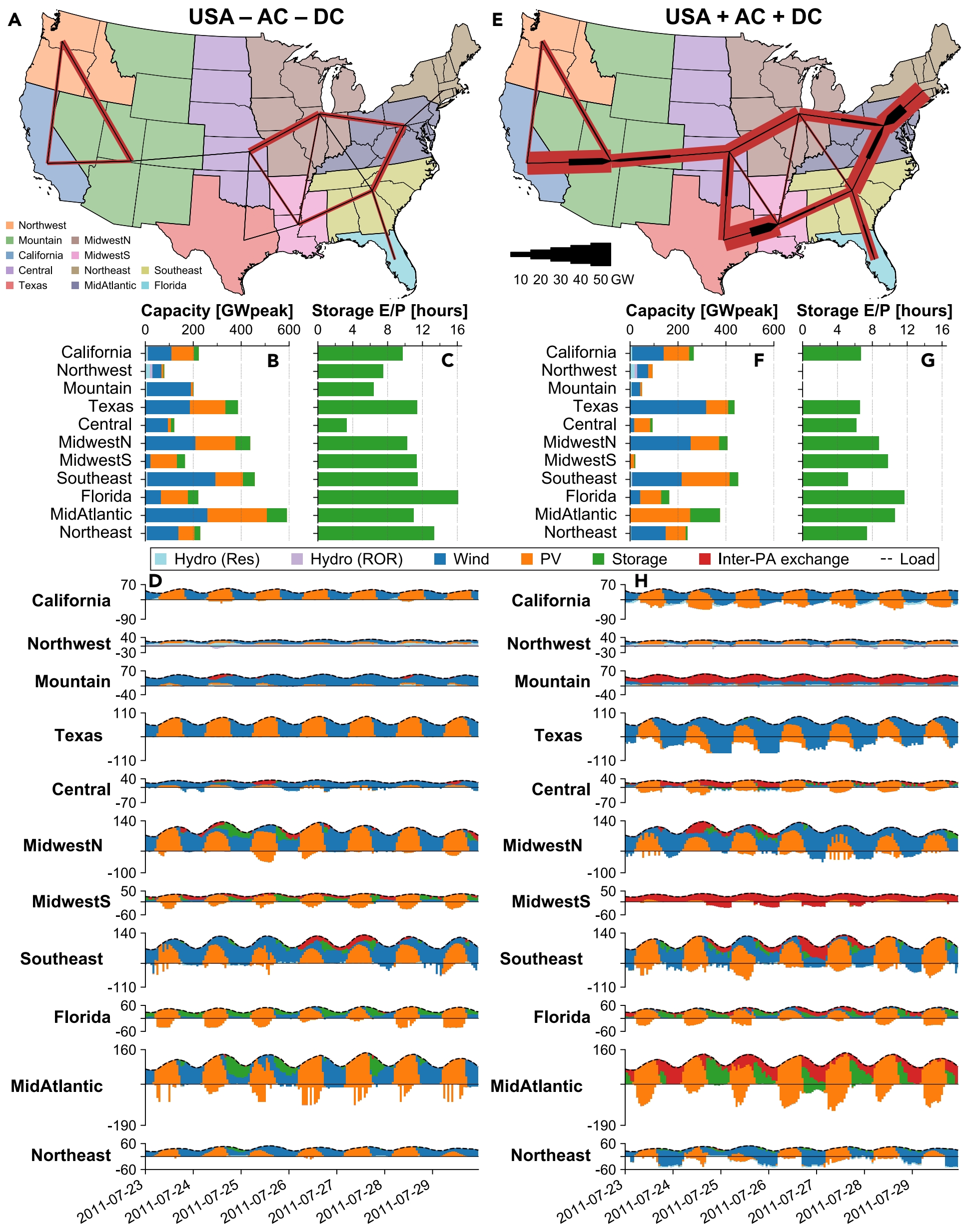

Figure 3. Capacity and Operation of Optimized Zero-Carbon Systems Disaggregated by PA for the "USA – AC – DC" (Left) and "USA + AC + DC" (Right) Scenarios

Power capacity and dispatch are optimized for the full 2007–2013 period.

(A and E) Installed inter-PA transmission capacity (red) and average hourly power flow (black), with capacity and flow indicated by line thickness. Each link shows the average flow in both directions, with the average flow into a node shown by the thickness of the black line on the side of the link closest to that node.

(B and F) Installed power capacity of generation and storage disaggregated by PA.

(C and G) Energy/power ratio of storage for each PA. Storage energy in GWh is given by the product of storage power in (B and F) and energy/power ratio in (C and G).

(D and H) Hourly dispatch by PA for the week from 2011-07-23-00:00 to 2011-07-29-23:00, shown in US central standard time. Negative values indicate charging of storage or power flow out of the PA; red areas indicate transmission power flow into the PA. Curtailment of wind and PV and spillage of reservoir hydropower are not shown.

Alternative Technology Assumptions

While the analysis described thus far indicates the feasibility of zero-carbon systems and the value of inter-regional coordination and transmission, the assumed future technology costs and demand levels are far from certain. It is also possible that technologies excluded thus far—including nuclear power and long-duration storage—could be economically viable in the future. Figure 4 presents the results of a sensitivity analysis across 48 different cases (41 zero-carbon cases and 7 "no-policy" cases), taking the "USA + AC + DC" scenario described above as the base case. Numerical and methodological assumptions for the alternative cases are provided in Table 1 and in Note S3.2.5.

Three zero-carbon cases result in a SCOE that is at least 10 $/MWh cheaper than the default case: "2030low VRE&S prices" (-17 $/MWh difference with the default case), "LDES ($5/kWh)" (-13 $/MWh), and "fullflex nuclear_$4000/kW" (-12 $/MWh). In addition to the "States" and "PA" scenarios described above, eight cases produce a SCOE that is at least 10 $/MWh more expensive than the default case: "2018 VRE&S prices," "no new AC or DC" (the same scenario as "USA – AC – DC" described above), "WTKclass2" (representing a higher-specific-power wind turbine model), "5× Li-ion cost," "Vestas:V110/2000" (another higher-specific-power wind turbine model), "0.1× VRE available," "5× interconnection cost," and "6% WACC." Combining changes from multiple sensitivity cases would lead to greater differences from the default case.

New Nuclear

The impact of nuclear is sensitive to cost and technical assumptions. At a capex cost of $12,000/kW$_{ac}$—roughly the estimated cost of the Georgia Vogtle nuclear plant expansion, still incomplete at the time of this writing[53]—no new nuclear capacity is installed ("noflex nuclear_$12000/kW"). At the 2030 ATB cost projection of $6,180/kW$_{ac}$, between 70 GW ("noflex nuclear_$6180/kW") and 190 GW ("fullflex nuclear_$6180/kW") of nuclear capacity is installed depending on the flexibility assumptions, but the system cost is only reduced by 0.2–2 $/MWh compared with the default case without nuclear. System cost reductions greater than 5 $/MWh are only observed once the nuclear capex cost drops to $5,000/kW$_{ac}$, roughly 10% below the ATB cost projection for 2050. "Fullflex" nuclear at $4,000/kW$_{ac}$ does significantly reduce the SCOE (-12 $/MWh) but to a lesser extent than achieving the 2030 "low" cost projections for PV, wind, and Li-ion batteries (-17 $/MWh). While the impact of nuclear at central cost projections is low, nuclear and VRE can coexist, even in the "noflex" nuclear cases: VRE generators are highly rampable within their temporal availability limits, so when paired with inflexible nuclear, VRE and storage perform load-following to complement nuclear baseload.

VRE Availability / Wind Turbine

Results are relatively robust to assumptions regarding the available land area for VRE development and regional cost variability: uniformly reducing the available land area by 80% ("0.2× VRE available") only raises the SCOE by 2 $/MWh, and applying regional cost scalers from the EIA Annual Energy Outlook 2020[54] raises the SCOE by 1 $/MWh. VRE prices are comparatively much more important, along with technical assumptions regarding wind power: utilizing the power curve for the high-specific-power "WTKclass2" model increases the SCOE by ~16 $/MWh relative to the low-specific-power Gamesa:G126/2500 (used as the default) or Leitwind:LTW90/1000 models. These results corroborate previous studies reporting an increased value for low-specific-power wind turbines at lower wind penetrations.[55,56] Additional details on wind modeling are provided in the Supplemental Information (Note S2).

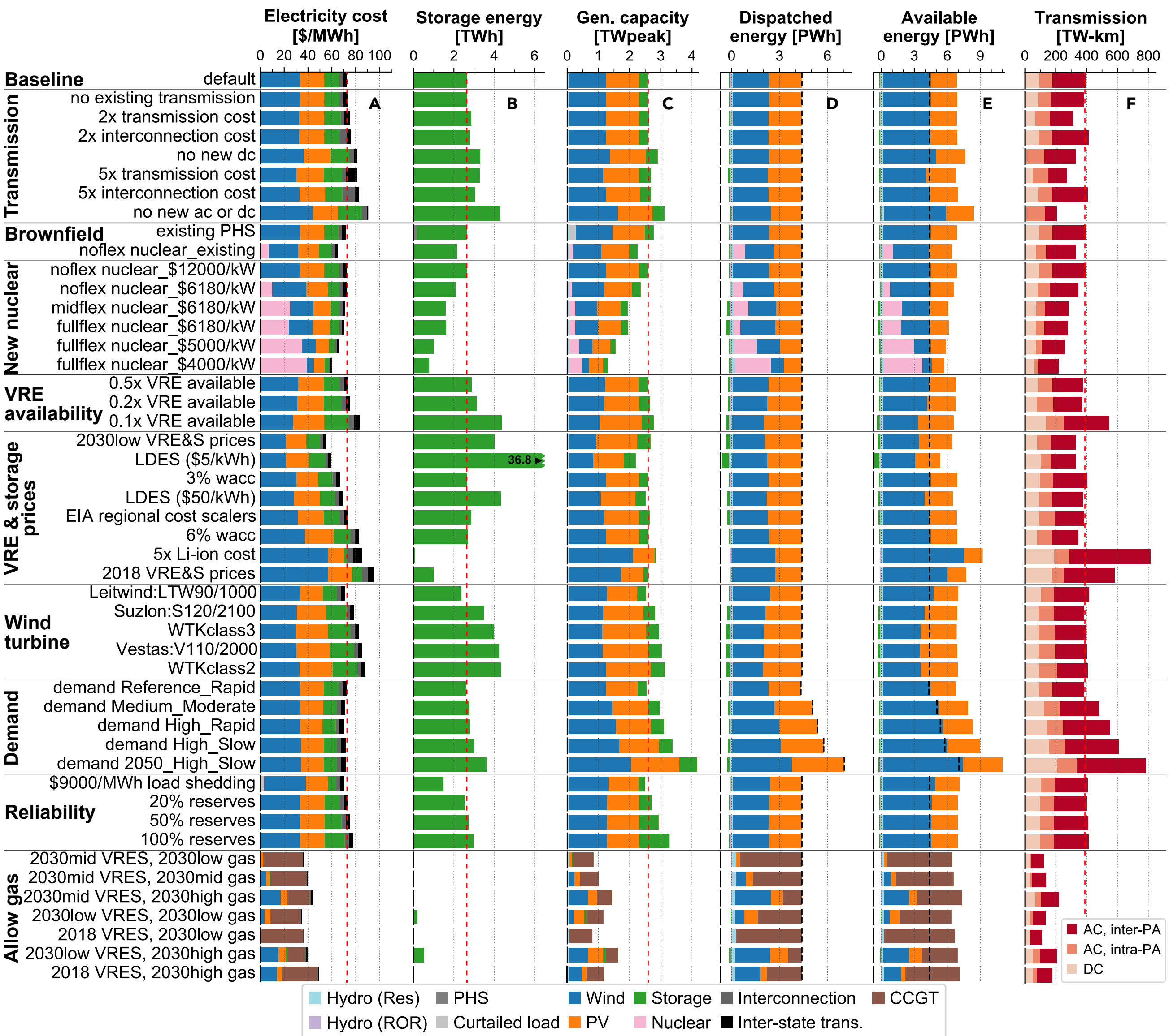

Figure 4. Sensitivity of Cost, Capacity, and Annual Operation to a Range of Assumptions

All results are for the interconnected US system; default assumptions correspond to the scenario labeled "USA + AC + DC" in Figure 2.

(A) Average SCOE

(B) Installed storage energy capacity

(C) Installed power capacity of storage and generation

(D) Annual dispatched energy

(E) Annual available energy

(F) Installed transmission capacity.

Plotting conventions follow Figure 2, but only results for the full 2007–2013 period are shown here. Panel (A) disaggregates the SCOE into contributions from different sources; here, "Inter-state trans." includes the cost of new intra-PA and inter-PA transmission, while "Interconnection" includes site-specific interconnection costs for PV and wind. The dotted red line in (A), (B), (C), and (F) indicates the value for the "default" case as a guide to the eye, and the dotted black line in (D) and (E) indicates the yearly electricity demand. Low, medium, and high gas prices for "Allow gas" rows are 3.40, 4.11, and 5.82 $/MMBtu, respectively (3.22, 3.90, and 5.52 $/GJ); complete details on other different sensitivity cases are provided in Table 1 and in the Supplemental Information (Note S3.2.5). Social costs associated with emissions of greenhouse gases and particulate matter in the "Allow gas" cases are not included.

VRE & Storage Prices / Transmission

Regional scope is still more important than VRE/storage cost assumptions: assuming constant VRE and storage costs for the full-US "USA + AC + DC" scenario ("2018 VRES prices" in Figure 4) results in a SCOE that is 11 $/MWh *lower* than assuming the baseline projected 2030 "mid" cost reductions for the transmission-constrained "PA + AC" scenario (Figure 2A). Reductions in the cost of either PV or storage tend to increase the deployment of PV and storage at the expense of wind and inter-PA transmission, while reductions in the cost of either wind or transmission tend to have the opposite effect (Note S6.1). Even in the "5× transmission cost" case there are substantial transmission additions: optimized inter-PA transmission capacity in this case increases 30% over the "no new AC or DC" ("USA – AC – DC") case, reducing the SCOE by 6 $/MWh.

Demand

The SCOE is relatively insensitive to the assumed electricity demand. While significantly more generation capacity and storage are built in the high-demand cases ("Demand" in Figure 4), the increased capex cost is levelized over an increased electricity demand, such that the SCOE of all alternative demand scenarios is roughly equivalent to the baseline SCOE. Given the greater degree of electrification of heating and transportation in the high-demand cases, these cases represent a greater reduction in economy-wide emissions than the baseline case and may enable increased flexibility from price-responsive demand (not considered here).

Reliability

Results are also relatively insensitive to changes in the reliability assumptions. Implementing load shedding at a cost of $9,000/MWh ("$9000/MWh load shedding," matching the scarcity price currently used in the ERCOT system) reduces the SCOE by 2 $/MWh, resulting in load shedding equivalent to 0.10 days of average system-wide demand per year (Figure S25). Results for individual states and PAs are much more sensitive to assumptions regarding load shedding, as shown in the Supplemental Information (Note S6.3). Implementing an hourly operating reserve margin requirement, which can be met by curtailed VRE or by energy held in storage, also has relatively little impact on cost: SCOE increases by 0.7 $/MWh, 2 $/MWh, and 5 $/MWh in the "20% reserves," "50% reserves," and "100% reserves" cases, where the reserve level indicates the percentage of hourly demand for which operating reserves must be procured.

Alternative Assumptions for Regional Coordination and Transmission

The sensitivity analysis shown in Figure 4 applies to the "USA + AC + DC" scenario allowing transmission expansion between all adjacent PAs. Figure 5 shows the SCOE for a subset of sensitivity cases for each of the six coordination and transmission scenarios described in Table 2. In each case, costs increase monotonically as inter-regional coordination and the ability to deploy new transmission capacity are reduced. In general, cost differences across sensitivity cases are accentuated in the transmission-constrained "States" and "PA" scenarios. While the directionality of most trends across sensitivity cases is similar within each of the six coordination and transmission scenarios, low-cost flexible nuclear and long-duration storage reduce the SCOE to a much larger extent in the "States" and "PA" scenarios than in the "USA" scenarios and, when available, reduce the relative benefits of inter-regional coordination and transmission. While the "2030low VRE&S prices" case gives the lowest SCOE in the "USA + AC + DC" and "USA + AC – DC" scenarios (and accordingly gives the lowest SCOE across all sensitivity-case/transmission-

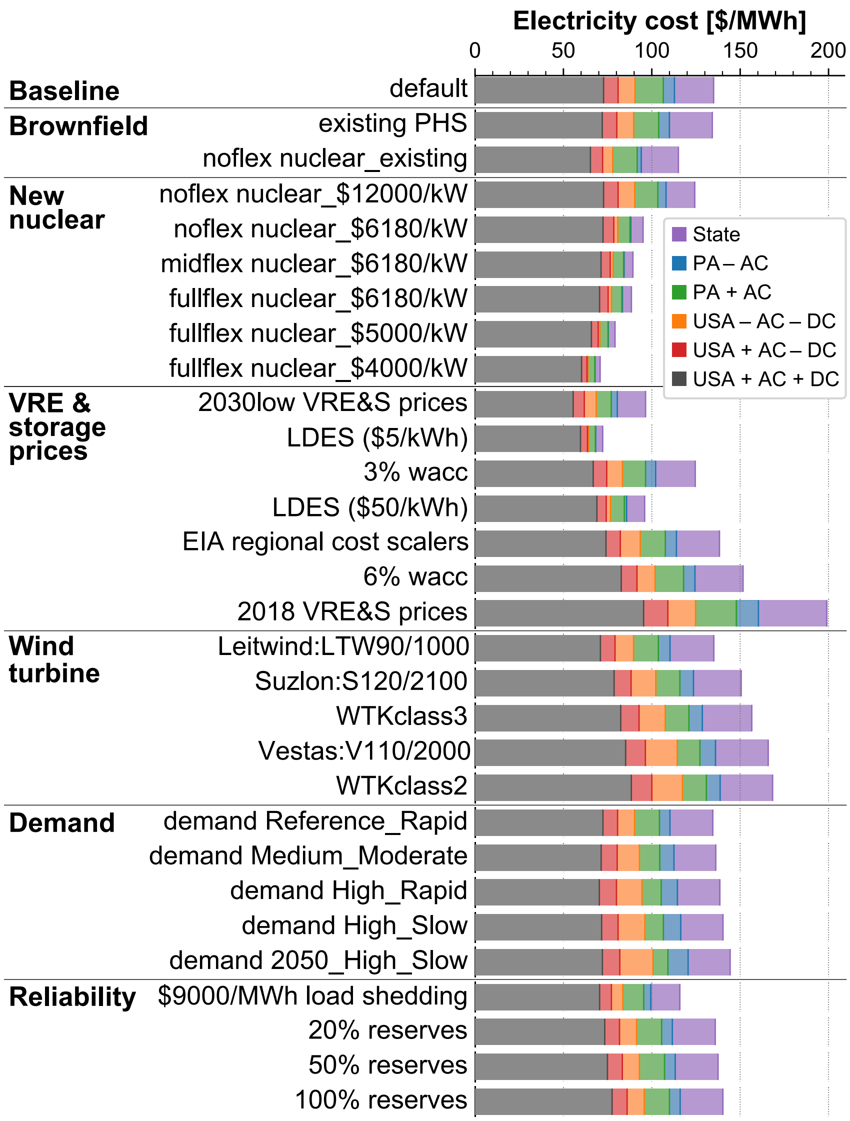

Figure 5. Sensitivity of Electricity Cost to Technical Assumptions under Different Scenarios for Regional Coordination and Transmission

Regional coordination and transmission scenarios are described in Table 2. Sensitivity cases represent a subset of the cases included in Figure 4 and are described in Note S3.2.5. The dark gray "USA + AC + DC" bars reproduce the total SCOE shown in Figure 4A.

scenario pairs considered in this study), "LDES ($5/kWh)" and "fullflex nuclear_$4000/kW" give lower costs in the "PA" and "States" scenarios.

These results emphasize that there are multiple potentially viable paths to a zero-carbon system at costs below those presented in Figure 2 under default assumptions: low-cost renewables and Li-ion batteries coupled with new transmission construction give the lowest cost, but if either are unavailable, the development of low-cost flexible nuclear or low-cost long-duration storage would provide an alternative at only moderately higher cost. Electricity costs would be further reduced if all technology options (low-cost renewables, Li-ion batteries, nuclear, LDES, and transmission) were available.

Additional sensitivity cases and results are discussed in the Supplemental Information (Note S6), including the impact of interannual weather variability over longer periods and alternative assumptions for nuclear power and load shedding.

"No-Policy" Decarbonization

The discussion thus far has focused on zero-carbon electricity systems. To illustrate the trajectory of electricity cost between a "no-policy" case (unconstrained carbon emissions) and zero carbon, we here allow investment in combined-cycle gas turbines (CCGT) and open-cycle gas turbines (OCGT). The "Allow gas" rows in Figure 4 demonstrate the characteristics of the optimized system in the no-policy case with three different natural gas price assumptions: 3.40, 4.11, and 5.82 \$/MMBtu (or 3.22, 3.90, and 5.52 \$/GJ) for the "low," "mid," and "high" cases, taken from the NREL ATB for 2030.[38] Using 2030 "mid" prices for all technologies results in 31% of demand being met by non-fossil resources (Figure 4D). As noted in other studies,[25,57] the economic level of decarbonization in a no-policy case is highly sensitive to assumptions regarding the capex cost of VRE and fuel price of natural gas: "no-policy" decarbonization ranges from 6% in the "2018 VRES, 2030 low gas" scenario to 81% in the "2030 low VRES, 2030 high gas" scenario.

From "No-Policy" to "Zero-Carbon"

Figure 6 bridges the gap between the no-policy and zero-carbon cases by applying an escalating clean-energy standard (CES, equivalent to a renewable portfolio standard [RPS] in this nuclear-free case) in each of the isolated states (blue bars), isolated PAs (green bars), and the interconnected US system (orange and red bars). The current implementation of most RPS policies lies between our "States" and "PA" scenarios; some states allow out-of-state generation capacity to contribute to the state's RPS if generation is delivered to the state, while other states have quotas or benefits for in-state generation siting.[58] Other studies have noted that system cost increases nonlinearly as decarbonization approaches 100%;[10,19,24] while our results support this finding, the cost increase is much smaller for an interconnected US system than for isolated systems. Achieving 95%, 99%, and 100% decarbonization adds 24 \$/MWh, 44 \$/MWh, and 93 \$/MWh, respectively, to the no-policy SCOE when the CES is applied at the level of isolated states, compared with 10 \$/MWh, 18 \$/MWh, and 33 \$/MWh when applied to the full US allowing new inter-PA transmission capacity. For context, 33 \$/MWh was roughly the difference in retail electricity price between Michigan and Oklahoma in 2018.[59] As noted in Figure 4A, achieving low-cost targets for VRE and Li-ion, LDES, or nuclear would reduce the electricity cost premium for 100% decarbonization relative to the middle "no-policy" case to 16 \$/MWh, 20 \$/MWh, or 20 \$/MWh, respectively.

DISCUSSION

Curtailment

It is notable that the level of curtailment—defined as the total nameplate capacity times hourly availability of each generator minus annual demand, shown by the gap between the black dotted line and the sum of the colored bars in Figure 4E—is roughly the same between the zero-carbon and no-policy cases. Given that peak demand nationwide is ~1.6 × mean demand,[40] a system reliant on fully dispatchable generation would feature ~37% $(1-1/1.6)$ curtailment. This level of curtailment is observed across most of the zero-carbon and no-policy sensitivity cases considered in Figure 4 (with the exception of the "LDES (\$5/kWh)" and "fullflex nuclear" cases, which exhibit 20%–30% curtailment, and the "no new AC or DC" and "5× Li-ion cost" cases, which exhibit ~50% curtailment). Just as natural gas peaking capacity lies idle during off-peak periods (with most open-cycle gas peakers

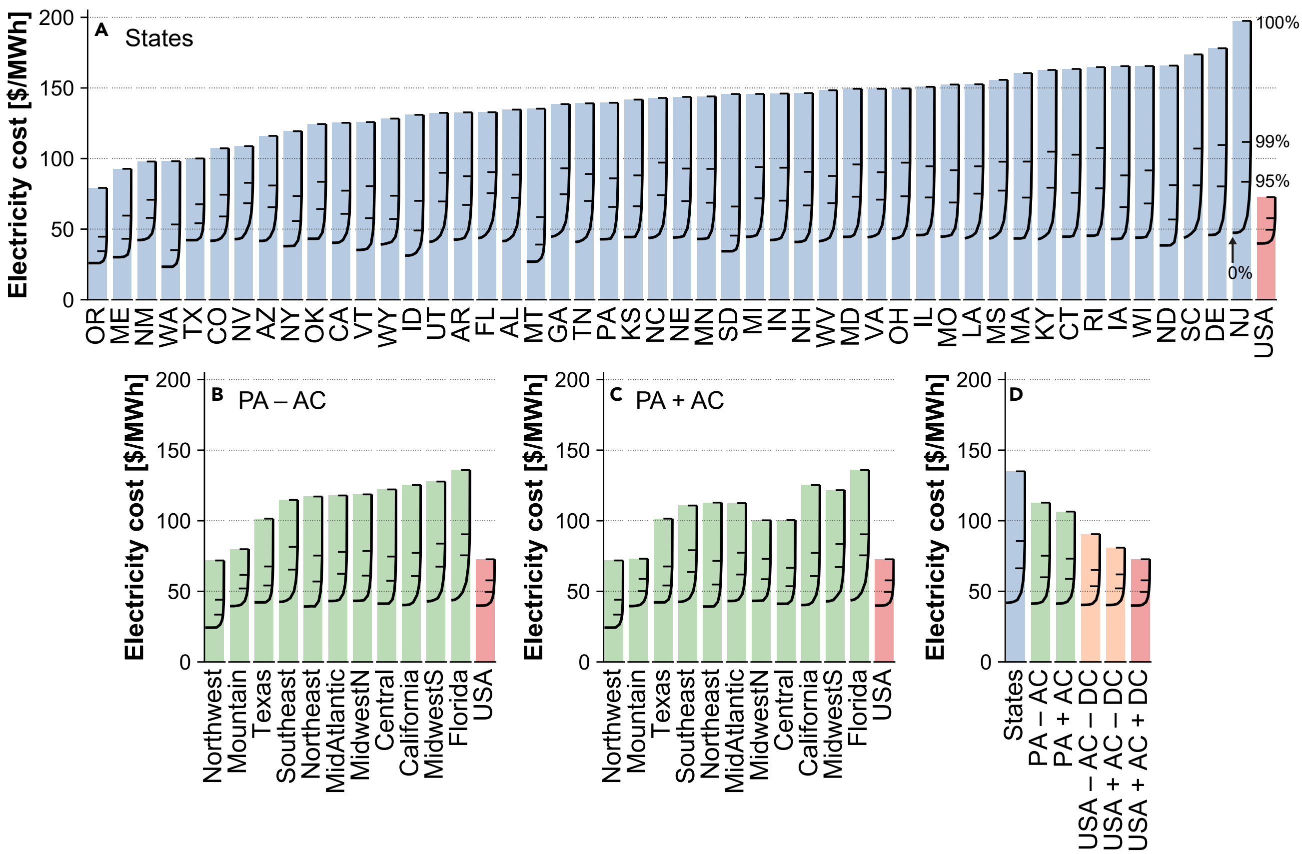

Figure 6. System Cost of Electricity As a Function of Clean-Energy Standard (CES) *En Route* to 100%

Colored bars indicate the SCOE for zero-carbon (100% CES) systems. Each bar is overlaid with a subplot (black lines) indicating the SCOE for systems allowing natural gas generation and employing an escalating CES, with 0% CES on the left of each bar and 100% CES on the right of each bar. The three horizontal ticks in each bar indicate the SCOE at 95%, 99%, and 100% CES, as shown in the "NJ" bar in (A). The SCOE of the interconnected US system allowing construction of new inter-state and inter-PA transmission is shown on the right of each subplot in red for context.

(A) SCOE for each of the 48 states in the continental US if each state were to meet its hourly electricity demand within its own borders (corresponding to scenario "States" in [D] and Figure 2), sorted by SCOE at 100% CES.

(B) SCOE for each of the isolated PAs without new inter-state transmission ("PA − AC" in [D] and Figure 2), sorted by SCOE at 100% CES.

(C) SCOE for each of the isolated PAs allowing new inter-state transmission ("PA + AC" in [D] and Figure 2), in the same order as (B).

(D) Combined SCOE across all isolated states (blue), isolated PAs (green), and the interconnected US system (orange and red). Colored bars in this plot indicate the same values as in Figure 2A. Social costs associated with emissions of greenhouse gases and particulate matter in the sub-100% CES cases are not included.

exhibiting capacity factors <10%, or >90% "curtailment"),[60] some VRE capacity lies idle during high-resource low-demand periods in a cost-optimized system (albeit without fuel-based cost savings). Including demand response through flexible charging of electric vehicles or other forms of inter-sector coupling (not modeled here) could significantly reduce the curtailment of zero-marginal-cost VRE.

It is also notable that curtailment is higher in the "USA – AC – DC" scenario than in the "PA + AC" scenario (Figure 2E), even though wind and solar capacity is higher in "PA + AC" (Figure 2C). As the "USA" scenarios have access to higher-quality wind and solar sites, more energy can be generated from less capacity, thus reducing cost while increasing curtailment. While curtailment is a feature of a cost-minimized system, it does lead to market-design implications and would increase the importance of capacity markets and/or scarcity pricing for cost recovery.

Expanding Transmission versus Generation Capacity

The roughly 90% increase in transmission capacity in the cost-optimized "USA + AC + DC" scenario compared with the "USA – AC – DC" scenario (Figure 2F) is in line with other studies showing roughly a doubling in installed transmission capacity to be cost-optimal for electricity decarbonization in the USA[61] and the EU.[29,30] While large, the relative expansion in transmission capacity is considerably smaller than the expansion in wind (~10×) and PV (~28×) capacity in the default case or the ~3× expansion in nuclear capacity in the most-aggressive nuclear case (Figure 4C).[3] Note also that the ~90% increase in transmission capacity [TW-km] does not necessarily imply a similar increase in transmission-line-miles; a double-circuit 500kV line can carry roughly 7.5× the power of a single-circuit 230kV line over a given distance.[62]

MacDonald et al. also present the benefits of nationwide transmission expansion for decarbonization; as MacDonald et al. utilize a "no-policy" scenario reaching ~80% decarbonization, they report lower benefits from inter-regional transmission than are observed in our 100%-decarbonized scenarios.[25] The 13 $/MWh reduction in SCOE observed here for the "LDES ($5/kWh)" case is roughly in line with the 10–20 $/MWh reduction in SCOE from LDES observed by Dowling et al.[63] for a full-US model without transmission constraints. Shaner et al.[8] report that hourly US electricity demand over 36 years could be met by a 50/50 wind/solar resource mix with an available-energy/demand ratio of ~1.3× and storage equivalent to 4 days of mean demand; this result is in line with our "LDES ($5/kWh)" case (Figure 4), which employs 3 days of storage and an available-energy/demand ratio of 1.2×. Other studies over small geographic areas report a larger role for LDES[10] and nuclear power[24] in zero-carbon systems; as shown in Figure 5, we also find that nuclear and LDES significantly reduce the SCOE in isolated and transmission-constrained zero-carbon systems, but their impact is diminished when new transmission deployment is fully allowed.

Conclusions and Policy Implications

The results described here suggest that a zero-carbon electricity system for the US based on VRE and storage is feasible at 1-hour resolution over many years of operation, accounting for the costs and constraints of transmission and land availability, using technologies currently being deployed at gigawatt-scale. Moreover, we demonstrate that, while decarbonization of the electricity system is feasible at the level of individual states and regions, it can be accomplished at a significantly lower cost when implemented at the national level.

Even in the absence of new inter-regional transmission, inter-state coordination of generation capacity planning and dispatch reduces system cost substantially in decarbonized electricity systems. Historical experience with the western Energy Imbalance Market (EIM) shows that inter-regional coordination of real-time dispatch alone can reduce operational costs, renewable curtailment, and CO_2 emissions;[64] this work shows that as the geographic and operational bounds of coordination are expanded, even further benefits can be realized. Relaxing in-state siting requirements for renewable portfolio standards would deliver similar benefits.[65] While increased coordination delivers system-wide cost reductions, the relinquishing of local operational control alongside the potential for locally increased electricity prices in low-priced regions upon coordination with higher-priced regions can lead to localized opposition.[66]

While this study demonstrates that transmission expansion is a cost-effective enabler of electricity system decarbonization, transmission construction—particularly inter-state and inter-regional transmission—faces multiple challenges in the US. Transmission lines typically require permits from multiple federal agencies and from each state and local jurisdiction within their path;[67] the multi-party benefits of transmission make cost allocation difficult;[68] and like any type of energy infrastructure, transmission can engender local opposition.[69] There are a number of strategies for streamlining the planning, permitting, and construction of new inter-state transmission to overcome such barriers: increasing utilization of existing transmission rights-of-way through reconductoring of existing lines, increasing line voltage, or adding additional circuits;[70] converting existing AC transmission corridors to DC;[71] implementing federally identified transmission corridors;[72] and building social acceptance through public engagement[73] or community ownership[74,75] could accelerate and reduce the cost of transmission expansion and power-system decarbonization. While innovation in long-duration energy storage and nuclear power has the potential to reduce system costs, all zero-carbon systems modeled here deploy substantial capacities of wind and PV (>670 GW in all cases and >2,200 GW in the base case), demonstrating the importance of near-term deployment of available technologies in the pursuit of urgent climate targets.

EXPERIMENTAL PROCEDURES

Resource Availability

Lead Contact

Requests for further information should be directed to the Lead Contact, Patrick R. Brown (prbrown@alum.mit.edu).

Materials Availability

No materials were used in this study.

Data and code availability

Computer code, input data, and results are available as a Zenodo repository at https://doi.org/10.5281/zenodo.4268878.

Full experimental procedures are given in the Supplemental Information.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.joule.2020.11.013.

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AUTHOR CONTRIBUTIONS

P.R.B. conceived the study, built the model, collected data, performed the analysis, and wrote the manuscript. A.B. provided guidance on model design and technical assumptions and edited the manuscript.

DECLARATION OF INTERESTS

Both authors are affiliated with the MIT Energy Initiative, which receives funding from a variety of external sources, including oil and gas producers, utility companies, renewable energy companies, private philanthropic organizations, and environmental non-profits, listed at http://energy.mit.edu/membership/#current-members. P.R.B. is also at the National Renewable Energy Laboratory, and A.B. is also at Argonne National Laboratory. None of these organizations were involved with the development of the work reported here. The authors declare no other competing financial interests.

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The Value of Increased HVDC Capacity Between Eastern and Western U.S. Grids: The Interconnections Seam Study

Preprint

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The Value of Increased HVDC Capacity Between Eastern and Western U.S. Grids: The Interconnections Seam Study

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***Abstract*—The Interconnections Seam Study examines the potential economic value of increasing electricity transfer between the Eastern and Western Interconnections using high-voltage direct-current (HVDC) transmission and cost-optimizing both generation and transmission resources across the United States. The study conducted a multi-model analysis that used co-optimized generation and transmission expansion planning and production cost modeling. Four transmission designs under eight scenarios were developed and studied to estimate costs and potential benefits. The results show benefit-to-cost ratios that reach as high as 2.9, indicating significant value to increasing the transmission capacity between the interconnections under the cases considered, realized through sharing generation resources and flexibility across regions.**

***Index Terms*— HVDC transmission, Interregional transmission, Power generation dispatch, Power system economics, Power system reliability, Power system planning, Resource adequacy, Solar power generation, Wind power generation.**

I. Introduction

At the western edge of the American prairie, just east of the Rocky Mountains, lies a collection of electrical transmission resources that tie together the otherwise segregated U.S. and Canadian Eastern and Western Interconnections (EI and WI). These seven back-to-back (B2B) high-voltage direct-current (HVDC) facilities enable 1,320 megawatts (MW) of electricity to flow between the U.S. EI and WI.[1] This transfer capability between the interconnections is very small compared to the networks they connect—the larger EI is home to 700,000 MW of generating capacity, and the WI roughly 250,000 MW. But as small as these B2B facilities may be, they are important: they are located strategically at the "seam" where the East meets the West—and with the U.S. resource portfolio in transition, the ability to share additional resources across the seam could be economically attractive under a variety of possible futures. At the same time, these facilities are aging, and thus their continued use will require additional investment for keeping them in service. These observations suggest that increasing cross-seam transmission capacity may represent a timely and impactful opportunity for utilities, developers, regulators, and policy makers to modernize and strengthen the U.S. electric grid.

Over the last 95 years, a number of entities have indicated interest in developing additional cross-seam transmission. The earliest [1], in 1923, was motivated by a desire to integrate the continent's hydro and coal resources. Subsequent studies [2, 3, 4, 5] investigated joining the existing systems for economic and/or reliability benefits. An HVDC overlay of the U.S. western and Midwestern grids was proposed in [6]. Reference [7] argued for an integrated alternating-current/direct-current (AC/DC) approach and illustrated a national overlay design of predominantly 765 kV AC lines. More recent work [8, 9, 10] applied generation and transmission co-optimization on a set of geographically aggregated electric nodes across the United States to design a national transmission network that was shown to be economically attractive under various futures. A variety of challenges have prevented nationwide HVDC overlays from development so far. References [11, 12] describe transmission planning efforts around the world, including HVDC overlay designs.

Here we present the Interconnections Seam Study, a coordinated transmission planning analysis of the two major U.S. interconnections. The study co-optimizes capacity expansion and systems operations to quantify the potential value of increasing the transmission capacity between the EI and WI using HVDC technology to facilitate more economically efficient exchange of power and adequacy throughout the United States. The work described in this paper differs from previous efforts in three ways:
(1) *Study objective*: The objective was to identify the value of increased cross-seam transmission capacity; as a result, several HVDC designs were studied—one of which, called the macrogrid, has features similar to those of previously developed overlays.
(2) *Analysis fidelity*: The study uniquely captures capacity expansion and production cost at an unprecedented geographic scale and detail, all performed with consistent data inputs. The production cost modeling deploys a novel geographic decomposition computational method to more precisely represent operational constraints, enable increased modeling resolution, and reduce solve time.
(3) *HVDC and AC transmission*: In each cross-seam transmission design, HVDC capacity was co-optimized not only with generation investments but also with AC transmission investments; this process ensured that AC transmission investment needs were satisfied.

II. Approach

To ensure the technical rigor of this study, a technical review committee (TRC) including more than 20 organizations met on six occasions to discuss the approach, methods, scenarios, data, assumptions, and results. The study provides initial valuations of increasing connection between the interconnections but should not be referenced as reporting final ready-to-build designs. It also does not take the place of regional planning studies, but can provide

[1] An additional 150 MW of B2B transmission capacity is in Alberta, Canada; it was modeled, but not considered for expansion.

analysis of potential ways regions can benefit from inter-regional planning efforts. Similarly, the study does not obviate the need for state and federal siting review. The study did not consider the impact on wholesale rates set by the Federal Energy Regulatory Commission or North American Electric Reliability Corporation (NERC) reliability standards under Federal Power Act Sections 203, 205, and 206.

The first step of the study was to conduct a detailed capacity expansion analysis for four future (through 2038) transmission designs and eight different generation scenarios developed using differing assumptions regarding transmission costs, renewable generation, wind and solar costs, gas prices, and retirements (see Table 1). Each of the 32 simulated power systems (four transmission designs applied to eight scenarios) meet long-term simplified, single-year, consistent, resource adequacy requirements. In the base case, the systems are expanded cost-optimally based on state renewable portfolio standards existing in 2017 and business-as-usual assumptions for generation technology cost improvement. We then created detailed nodal transmission models to evaluate the ability of the power system to reliably schedule and dispatch generation to meet demand at all hours of the year for select scenarios.

TABLE 1
Description of the Scenarios*

Scenario	Key assumption differences
Base Case	AEO 2017 gas price, state RPS laws
Low Gas Price	AEO 2017 High Gas Resource (regionally and temporally varying around $4/mmbtu)
High Gas Price	AEO 2017 Low Gas Resources gas prices (varying around $6/mmbtu)
High AC Trx Cost (1.5x)	50% higher than base transmission cost. Base transmission cost from [16]
High AC Trx Cost (2x)	Double the base transmission cost
No retirements	Model does not retire any generating units beyond announced retirements
Low-cost renewables	ATB 2017 Low-Cost VG
High VG	Least-cost generation mix when using a carbon cost from $3/tonne in 2024 to $45/tonne in 2038**

*Acronyms used here include Energy Information Administration (EIA) Annual Energy Outlook (AEO); Renewable Portfolio Standard (RPS); Annual Technology Baseline (ATB) (atb.nrel.gov); Variable Generation (VG)
**: The study TRC recommended this approach (consistent with cost estimates in [17]) as a proxy for potential growth in wind and solar in light of uncertainty in traditional deployment forecasts [18].

Table 2 summarizes the four interregional transmission designs considered in the generation scenarios. In all designs, new AC transmission and generation are co-optimized to minimize system-wide costs in addition to the HVDC and B2B facility expansions allowed under each transmission design. For co-optimized generation and transmission expansion, we used Iowa State University's co-optimized generation and transmission plan (CGT-Plan) model [14]. Energy Exemplar's PLEXOS was used for production cost modeling (PCM).

TABLE 2
Summary of Transmission Designs

Design Name	Description
Design 1 (D1)	Existing B2B facilities are maintained at their 2017 capacity
Design 2a (D2a)	Existing B2B facilities are allowed to expand in the optimization
Design 2b (D2b)	Three HVDC transmission segments (along with the expansion of the B2Bs) are built between the EI and WI
Design 3 (D3)	A national-scale HVDC transmission network, or macrogrid, is built

III. INPUT DATA AND ASSUMPTIONS

A variety of input data and assumptions were used to build power system representation of the EI and WI. The near-term expected generation and transmission for the EI and WI was obtained from NERC regional entities. The Eastern Interconnection Reliability Assessment Group's (ERAG) Multiregional Modeling Working Group (MMWG) 2026 summer case and the Western Electricity Coordinating Council (WECC) Transmission Expansion Planning Policy Committee (TEPPC) 2024 common case were chosen as the starting point for creating an updated nodal representation of the 2024 EI and WI. Additional information on the 2024 data can be found in [13]. Both capacity expansion and production cost modeling used consistent data for the transmission topology, existing and expanded generation fleet, thermal plant operating characteristics, load forecasts, and time-series data for wind and solar resources.

A. Capacity Expansion Modeling

The capacity expansion model, CGT-Plan, determines the location, size, and technology type for generation and transmission built in each scenario. It does this by minimizing generation and transmission investment costs, generation retirement costs and generation production cost over time from 2024-2038 using 169 buses reduced from the 98,000 nodal 2024 U.S. EI and WI transmission networks. Production costs include, for new and existing resources, fixed and variable operating and maintenance costs, fuel cost and operational reserve cost (regulation up/down and contingency reserve). Constraints imposed include: power balance at each node; "DC" angle constraints across each existing line; upper and lower limits on generation dispatch and line flows; lower limits on available up/down regulation reserves and available contingency reserves; upper limits on up/down regulation (contingency) reserves by the unit's 1-minute (10-minute) ramp rate; capacity in excess of the NERC-recommended 115% of peak [14] (all units contributed to the planning reserve according to each units capacity value which, for wind and solar, varied locationally as described in [15] but were independent of renewable penetration); and the definition of the particular transmission design being studied. Operational reserves were imposed system-wide; a capacity constraint was imposed in each of four regions:

West, Northwest, Midwest, and East. A full description of the model is available at [15].

CGT-Plan was run 32 times, for each of the four designs, D1, D2a, D2b, and D3 under the eight scenarios. CGT-Plan identified investments in two-year increments to minimize net present value of investments plus operational costs occurring during the 15-year decision horizon, plus operating costs occurring for another 20 years thereafter. Operations were simulated for every year using 19 conditions; wind and solar were dispatched using a P_{max} set by their capacity factor (for energy blocks) or capacity value (for peak blocks) and were redispatched down under congested conditions as necessary; flexibility requirements were modeled as a function of net-load variability. The 19 conditions included 15 "energy blocks" capturing five time periods in each of three seasons (summer, winter, and shoulder): 1–7 a.m., 8 a.m.–12 p.m., 1–4 p.m., 5–6 p.m., and 7 p.m.–12 a.m. The remaining four conditions were "peak net-load blocks" to capture one-hour annual peak conditions in each of four regions. The peak blocks were used to model the capacity constraint; because different regions peak at different times of the year, this enabled analysis of interregional reserve-sharing subject to transmission-related deliverability constraints [15].

Decision variables included investment in various generation and transmission technologies, as well as retirement of existing generation. Percentage of load served by VG ranged from approximately 30% to 40% in the base case and high VG case, respectively. All generation assets were based on commercially available technologies in 2017 and were modeled with appropriate maturation rates at all buses. The natural gas price assumption for the Base Case was adopted from the U.S. Energy Information Agency's (EIA) 2017 AEO [19]; the nominal price for electric generation ranged by region from $4.2/million British thermal units (MBTU) to $5.1/MBTU in 2024; these assumed prices are similar to those projected in the "low oil and gas supply curve" of the 2020 EIA AEO [20]. Battery energy storage was not an investment option. At each bus, the wind resources available for selection included three 100-meter wind technologies, each having different costs and the ability to be optimized for unique wind resource characteristics by geography. This included three different capacity factor categories that identified the investment potential at a particular range of capacity factor. Investments in solar photovoltaics (PV) were limited to utility scale and were split evenly between single-axis tracking and fixed-tilt. Distributed PV capacity projections for 2024 came from the 2016 NREL Standard Scenarios [21], and a 3% per year growth rate [19] was applied until 2038.

Investment options among transmission technologies included additional AC capacity on any existing branch at the voltage of that branch, at a cost per mile appropriate for that voltage and the geography of the region. Table 1 summarizes the additional HVDC investments that are allowed in D2a, D2b, and D3. In D2a and D2b, B2B facilities could expand independently of one another. In D2b, the three additional HVDC lines connecting the EI and WI are required to develop equal capacity. Similarly, in D3, all segments of the macrogrid are required to maintain equal capacity. Although the N-1 reliability criterion was not explicitly imposed, the "equal capacity" constraints for the HVDC lines in D2b and D3 were employed as proxies to avoid significant violation of this criterion. For example, three equal-capacity parallel HVDC bipole lines can be loaded to capacity and withstand a monopole loss of any one of them (considered to be an N-1 outage) if the remaining five poles can each provide an additional 20% capacity for a short time on their emergency overload ratings. Based on analysis of discount rates recommended by the White House Office of Management and Budget and other studies [21 - 23], we chose a nominal discount rate of 7.7% and an inflation rate of 2%, resulting in a real discount rate of 5.7%. Demand growth was set within each region consistent with recent studies [24, 25]; technology costs and regional multipliers for all generation resources and AC and HVDC transmission were based on [16, 26-29]. A capacity credit is given to each generator type and is the percent of that unit's capacity that can be applied towards satisfying the annual peak [30, 31]. Other data and associated sources are identified in [15, 32]. After the translation (III.B) and PCM (III.C) were completed on the penultimate CGT-Plan runs, the CGT-Plan was re-run for analysis presented in the results section on costs and benefits (IV.C), this time allowing a comprehensive set of transmission interfaces to be expanded and considering load growth end effects beyond 2038 in the optimization.

B. *Translation from Capacity Expansion to Production Cost Modeling*

CGT-Plan developed year-2038 aggregated zonal transmission and generation for the EI and WI. In order to study the year-2038 operation of these systems and determine operational savings (in perpetuity) due to the HVDC and B2B facilities, a nodal production cost model (PCM) of the 2038 system was created. This required a translation of the CGT-Plan zonal generation and transmission results to the nodal PCM network. This is a two-step process that begins with a 2024 nodal transmission model. Step 1 distributes generation investments and retirements identified by CGT-Plan according to the 2024 nodal model, using the following criteria: (i) Individual generating units are retired in the 2024 model based on heat rate until the CGT-Plan retirement amounts are satisfied; (ii) CGT-Plan new thermal generators are added at locations in the 2024 model where thermal plants were retired; and (iii) wind and PV investments identified by CGT-Plan were added to the high-voltage node (≥230 kV) in the PCM that is geographically closest to the wind and PV sites.

Step 1 resulted in a nodal model that contained 2038 load and generation for the PCM (from CGT-Plan) but did not update the transmission system. For step 2, we developed a transmission expansion planning (TEP) optimization program and applied it to the nodal PCM obtained from Step 1. This optimization is non-linear, given each transmission investment changes the circuit capacity and the circuit reactance. To address this, we developed the TEP as a sequence of linear programs (LPs), where each LP minimized the total transmission investment cost (subject to DC power flow equations), and only circuit capacity was treated as a decision variable, while circuit reactance was held constant. Following the LP solution, the reactance of each invested circuit was updated to reflect the change in capacity, after which the LP was rerun. The iterations were terminated when the circuit with the largest change in capacity relative to the previous iteration was within a specified tolerance. This two-step process results in a nodal version of the 2038 systems created by CGT-Plan, which is used in the PCM.

C. Production Cost Modeling

The nodal PCM that resulted from the capacity expansion scenarios was used to simulate a full year of continuous operation in the year 2038. The simulation has two phases, a day-ahead unit commitment, made up of 365 serial optimizations, and a real-time dispatch in which 8,760 serial optimizations are completed. Each day-ahead unit commitment optimization is a mixed integer linear program that considers 24 hourly decisions with additional 24-hours of look-ahead information. The look-ahead is used to improve decisions about the operations of energy-limited resources and units with long minimum online/offline times. The real-time dispatch is also a mixed integer linear program that only considers a single hourly decision at a time.

Barrows et al. [33] summarizes the system of equations that define the optimization problem for each phase of the PCM. The objective function minimizes the total cost to operate the system, while deciding which generating units to start or shut down and how much power online units should generate. Constraints to the objective functions include requiring total system generation meet total system load, the technical limitations of generators (such as ramp rates and minimum up/down times), temporal energy limits, nodal power balance, and linearized power flow equations, among others.

We adopted a new decomposition method described in [34] to complete the day-ahead unit commitment phase to improve representation of realistic operations for multiple regions and reduce solve times by three orders of magnitude. This method enables the unit commitment and dispatch to be simulated independently for each region (independent system operator (ISO)/regional transmission organization (RTO) equivalent).

The 2038 PCM includes approximately 13,000 generating units, 98,000 transmission nodes, and 96,000 transmission lines and transformers. Wind data is from the Wind Integration National Dataset (WIND) Toolkit, and solar data is from the National Solar Radiation Database (NSRDB).[2] Load data is from multiple sources, including the various RTOs, ISOs, and Federal Energy Regulatory Commission (FERC) [13]. Weather conditions for the years 2007–2013 were evaluated for use in the PCM. A geospatial analysis of wind and solar resource availability identified 2012 as the closest to average across the seven-year data set, so the 2012 data was used for wind, solar, and load to maintain correlations and time synchronicity between these data sets.

Thermal plant assumptions were adopted from [35] and enabled detailed modeling of every thermal generator. When possible, existing thermal plants that are still in operation in 2038 have unit-specific plant flexibility characteristics that were extracted by analyzing the Environmental Protection Agency's Continuous Emissions Monitoring System. When unit-specific data was unavailable, generic assumptions were made based on the generator vintage and type.

Contingency and regulation reserves are held regionally, either by ISO/RTO boundary or by FERC Order 1000 planning region. The amount of regulation required is calculated using the method described in Ibanez et al. [36]. The method determines the amount of reserves required to cover the uncertainty and variability of the load, wind, and solar.

IV. Results

A. Costs and Benefits

In this section, we describe the results of the generation and transmission expansion through 2038, for the four transmissions designs in the base case (Table 3) and then the suite of eight scenarios (Tables 4 and 5). The capacity expansion model was used to assess the costs and benefits of each of the study scenarios and designs, using the investment costs and operating costs for the years 2024–2038, plus 20 years with no load or generation growth after 2038 in order to reduce the impacts of end effects. Because D1 was the only design that did not allow cross-seam transmission investment, it is reference for comparison for the other three designs; positive numbers indicate cost increases and negative indicates cost decreases. The investment and operational costs for each transmission design in the base case are presented in Table 3, where we observe that the 35-year net cost change (total transmission and generation investment costs plus operational cost, relative to D1) is greatest for D2b and D3 in each scenario.

An important observation from Table 3 is that the benefit-to-cost (B/C) ratio, calculated as the change (relative to D1) in the generation investment and operational cost divided by the change in the transmission investment cost, is well above the industry threshold of 1.25 considered necessary to justify transmission investments [37]. Most of the benefit occurs as a result of reduction in generation operational costs enabled by increased transfer capability provided by transmission builds. The values shown may be considered as lower bounds on B/C ratios since they do not reflect externalities nor non-quantified benefits such as increased resiliency of the electric system to continue supplying low-cost energy during catastrophes such as large hurricanes and widespread wildfires. While including these details could increase overall costs of the scenarios, transmission would likely continue to have additional benefits.

TABLE 3
Summary of CGT-Plan Benefit/Cost Results for Base Scenario

Capacity or Cost Item	D1	ΔD2a	ΔD2b	ΔD3
Transmission Investment Cost, $B	40.03	2.57	6.76	8.19
Generation Investment Cost, $B	555.23	3.6	10.44	4.17
Operational cost, $B	2376.50	-8.79	-21.70	-15.30
35-yr Net Cost change, $B	-	-2.62	-4.5	-2.94
35-yr B/C ratio	-	2.02	1.66	1.36

Note: D1 results are shown as absolute costs; D2a, D2b, and D3 results are shown relative to D1.

[2] https//www.nrel.gov/grid/wind-toolkit.html; http://nsrdb.nrel.gov/

Tables 4 and 5 show the 35-year net cost savings and benefit to cost ratios for D2a, D2b and D3, relative to D1 for the various scenarios. The cost (net present value) of the D1 design under the base case conditions is $B29,712. Though D2a consistently produces the highest B/C ratio among the three cases per sensitivity, D2b results in the greatest potential net cost savings.

TABLE 4
35-year Net Cost Savings for Sensitivities ($B)

Sensitivity	ΔD2a	ΔD2b	ΔD3
Base Case	-2.62	-4.5	-2.94
Low Gas Price	-2.91	-4.15	-2.38
High Gas Price	-4.67	-9.51	-5.88
High AC Trx Cost (1.5x)	-2.23	-5.35	-4.56
High AC Trx Cost (2x)	-2.08	-5.46	-5.48
No retirements	-1.24	-1.58	-0.82
Low-cost renewables	-2.87	-4.78	-3.00
High VG	-18.35	-28.83	-23.04

Note: D2a, D2b, and D3 results are shown as savings relative to D1. Emission costs included in the High VG scenario are not included in Net Costs.

TABLE 5
35-year Benefit/Cost Ratio for Sensitivities

Sensitivity	ΔD2a	ΔD2b	ΔD3
Base Case	2.02	1.66	1.36
Low Gas Price	1.81	1.52	1.22
High Gas Price	1.76	1.84	1.46
High AC Trx Cost (1.5x)	1.87	1.45	1.29
High AC Trx Cost (2x)	2.26	1.52	1.37
No retirements	1.98	1.72	1.33
Low-cost renewables	2.53	1.77	1.56
High VG	2.09	2.89	1.80

Note: D2a, D2b, and D3 results are shown relative to D1. Emission costs included in the High VG scenario are not included in ratio.

The B/C ratio in almost every case (except D3 for the low gas price case) remains above the 1.25 threshold mentioned above. In most cases, it is significantly higher.

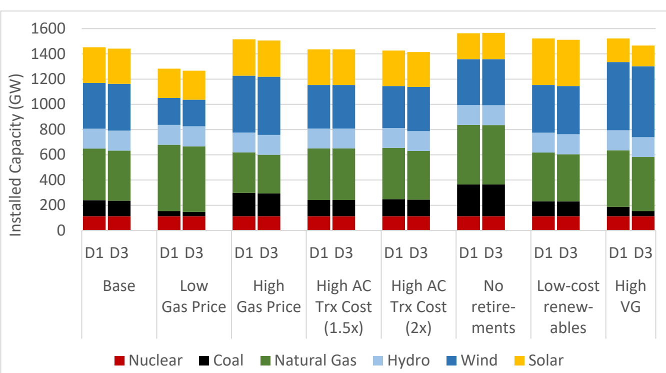

Fig. 1. Installed generation capacity by resource type in 2038. The installed capacity was determined using CGT-Plan.

The 2038 installed generation capacity from CGT-Plan is presented in Fig. 1 for D1 and D3. Maps of the resulting AC and DC (post-translation) transmission additions are shown in Fig. 2. Fig. 1 reveals a slight decrease in installed capacity in all scenarios in designs D3, relative to D1 (D2a and D2b, not shown, are all between D1 and D3). The High VG scenario has the largest capacity reduction and the most transmission. Tables 6 and 7 identify the additional transmission capacity added in the Base and High VG scenarios. Each design requires significant AC transmission expansion, but this AC transmission expansion is less for the designs with high HVDC capacity (D2b and D3). Additional details on the CGT-Plan modeling are provided in [15].

TABLE 6
Transmission Investment Summary, Base Scenario

Design→	D1	D2a	D2b	D3
HVDC-B2B (GW)	0	6.7	6.3	0
HVDC-Line (GW-miles)	0	0	14,487	29,062
AC Line (GW-miles)	18,409	19,357	17,778	16,076

Note: New transmission investments are identified, for B2B in terms of GW increased capacity between B2B terminals; and also, for lines, in terms of GW-miles, which is the GW capacity multiplied by the path distance.

TABLE 7
Transmission Investment Summary, High VG Scenario

Design→	D1	D2a	D2b	D3
HVDC-B2B (GW)	0	25.7	7.5	0
HVDC-Line (GW-miles)	0	0	31,335	63,156
AC Line (GW-miles)	52,737	60,141	50,964	43,190

B. System Operations

We use hourly PCM to help evaluate the operability of a given scenario by simulating an entire year of hourly operations, as opposed to the time slices used for capacity expansion. The PCM simulated the operations of the 2038 power systems built by the penultimate (and largely similar to the final) version of CGT-Plan buildout. We compare the base case to the high VG scenario, as they showed the most differences in B/C ratio, net cost savings, and overall generation buildout. In those simulations, all of the power systems met all load in all hours and met 99.69%–99.97% of all contingency and regulation reserve requirements. In both of the capacity scenarios, D1, the design with the least cross-seam transmission capacity, had the largest total reserve shortage. In the PCM modeling, nuclear generation did not change across the scenarios. Fossil fuels provided 36% of generation in the four Base designs and approximately 26% in the four High VG designs. Wind and solar increased from just under 30% in the Base designs to just under 40% in the High VG designs.

VG curtailment ranged from 11%–15% across all scenarios and designs. A review of curtailment outcomes indicates that congestion on AC transmission lines is a significant driver of curtailment. Other options, such as additional energy storage investment or additional demand response, may also become economically attractive at these curtailment levels, but they were not considered as an investment option. Additional analysis is necessary to understand the tradeoffs between curtailment, transmission, storage, and other options.

In addition to assessing overall system performance in 2038, the PCM was also used to conduct a detailed analysis of extreme time periods based on 2012 load and meteorology. We present two such cases that reflect periods of high net-loads and ramping, as well as the value of cross-seam transmission in potentially mitigating them. The first period is the three-day period in August around the coincident peak load across the EI and WI. The hourly cross-seam flow across the B2B and HVDC lines during this period is displayed in Fig. 3. There is a strong diurnal pattern in the aggregate power flow across the interconnections seam during this period in all transmission designs. In the afternoon, the load in the EI begins to peak. At the same time, solar PV generation is high in the WI, while the WI load is still relatively low. Cross-seam lines are nearly fully loaded and are used to flow power from the WI to EI. As the sun begins to set on the West Coast, load decreases in the EI and wind in the Midwest increases its output. The flow on the cross-seam lines changes direction, delivering power from the EI to the WI. The lines export Midwestern wind power and power from thermal units that otherwise would have turned off after the EI peak load.

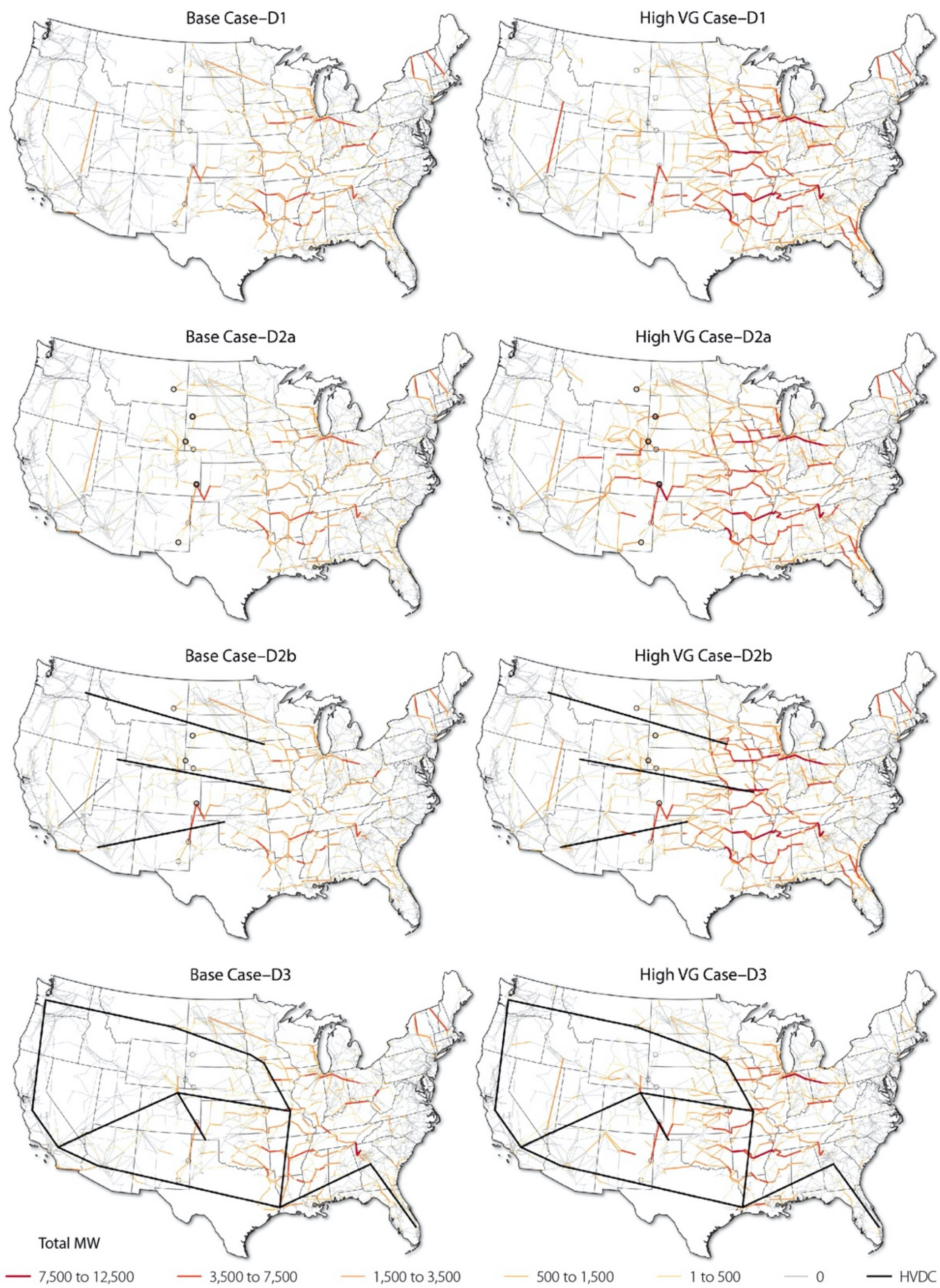

Fig. 2. Maps of the resulting AC and DC transmission additions between 2024 and 2038 from the TEP (i.e., post-translation and as modeled in the PCM). On the left are the four transmission designs in the base scenario. The results for the designs in the high VG scenario are on the right.

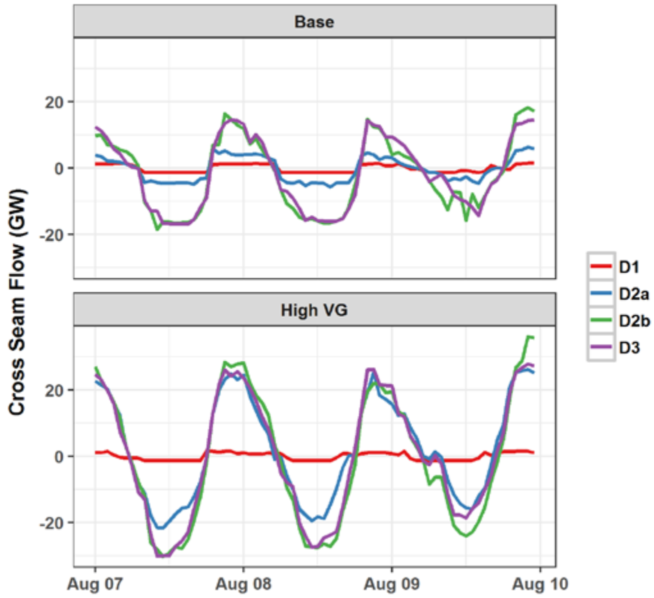

Fig. 3. Cross-seam transmission power flow (B2B and HVDC) during the coincident peak load period. A positive flow is a net export from the EI to the WI; a negative flow is a net import into the EI from the WI. Times are Eastern Standard Time.

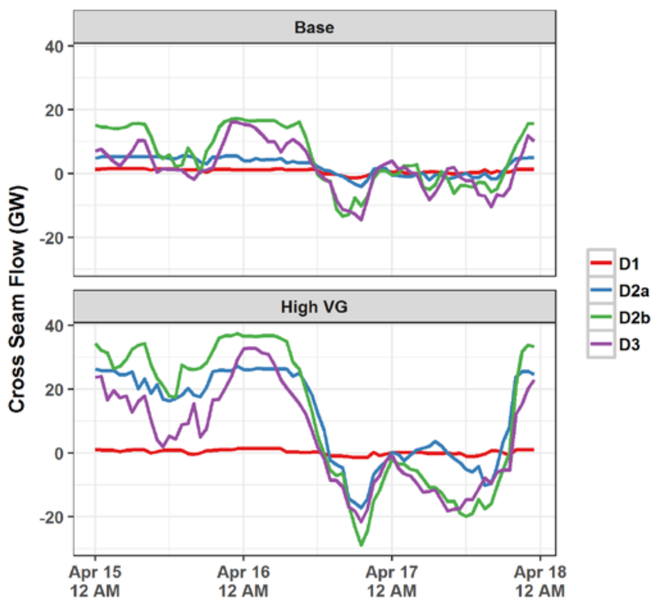

Fig. 4. Cross-seam transmission power flow (B2B and HVDC) during a large down-ramp in Midwest wind generation. A positive flow is a net export from the EI to the WI; a negative flow is a net import into the EI from the WI. Times are Eastern Standard Time.

We also analyzed a three-day period in April. On the first day of this period, April 15th, the VG instantaneous penetration hovers around 60% of total generation for all designs in both scenarios. VG curtailment is also significant throughout the day. However, in the late morning hours of the next day, April 16th, Southwest Power Pool (SPP) wind begins a steady ramp down, and a decrease in Midcontinent Independent System Operator (MISO) wind follows. Fig. 4 shows how cross-seam transmission helps respond to this event. On April 15th, the cross-seam HVDC is used to export wind from SPP and MISO to the WI. But as the wind power drops off on the morning of April 16th, the flow changes direction, and the WI begins exporting to the EI. Rather than requiring SPP and MISO to deal with the down-ramp in wind on their own, cross-seam transmission allows lower-cost resources in the WI to help balance the loss of the wind power on the other side of the seam.

V. Conclusions/Next Steps

This study demonstrates significant novelty in its multi-model approach. Combining CGT-Plan and PCM allowed for a thorough assessment and evaluation of the benefits and costs of four alternative cross-seam transmission designs in the United States and eight generation and transmission cost scenarios. The study also deploys novel modeling techniques to 1) characterize the value of capacity sharing, and 2) enable a nodal simulation of every generator and transmission line in the two largest North American Interconnections.

The study shows with increased intercontinental transmission that the system was able to balance generation and load with less total system installed capacity across each of the generation scenarios, due to load and generation diversity, and increased operating flexibility. The results show benefit-to-cost ratios ranging from 1.2 to 2.9, indicating significant value to increasing the transmission capacity between the interconnections and sharing generation resources for of all the cost futures studied. Production cost modeling identified that new lines would likely have high utilization during challenging operational periods throughout the year.

While fundamental elements of transmission and generation were represented throughout the study, additional modeling and analysis is required to further examine the alternative grid designs and evaluate the technical and economic benefits. Contingency analysis, particularly for new HVDC designs D2a, D2b, and D3, is an essential step in going forward. Industry review and input will remain vital to further evaluation of potential transmission expansion across the interconnections, as studies often present the most optimal solution given the model inputs. Additionally, this study does not address market adoption feasibility as well as other technical details needed to develop a more thorough understanding of system reliability implications (e.g. dynamic power flow, voltage stability, more complete contingency analysis). Full exploration of the potential benefits and costs of cross-seam transmission to the continent will require additional multi-model analysis.

This study provides a platform for conducting additional research at a large geographic scale. Potential reliability and resilience benefits of transmission could be explored through AC power flow studies with steady-state and stability modeling; consideration of system resilience and security requirements related to weather and extreme conditions; and incorporation of natural gas delivery infrastructure and gas-electric operational coordination. Additional analyses could estimate additional system- and local-level costs and benefits (e.g., economic and environmental impacts).

VI. Acknowledgment

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ARTICLES
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nature climate change

Future cost-competitive electricity systems and their impact on US CO_2 emissions

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Carbon dioxide emissions from electricity generation are a major cause of anthropogenic climate change. The deployment of wind and solar power reduces these emissions, but is subject to the variability of the weather. In the present study, we calculate the cost-optimized configuration of variable electrical power generators using weather data with high spatial (13-km) and temporal (60-min) resolution over the contiguous US. Our results show that when using future anticipated costs for wind and solar, carbon dioxide emissions from the US electricity sector can be reduced by up to 80% relative to 1990 levels, without an increase in the levelized cost of electricity. The reductions are possible with current technologies and without electrical storage. Wind and solar power increase their share of electricity production as the system grows to encompass large-scale weather patterns. This reduction in carbon emissions is achieved by moving away from a regionally divided electricity sector to a national system enabled by high-voltage direct-current transmission.

Carbon dioxide (CO_2) release from burning fossil fuels is a major contributor to climate change[1]. Without significant action to curb these emissions, humans and the natural world will face increasing penalties[2–5]. In contrast with the negative effects of CO_2 emissions are the benefits of cheap energy; electricity in particular is strongly linked to advanced national economies and high living standards[6]. Any solution to mitigate CO_2 must be economical for it to succeed.

Wind and solar power have very low life-cycle CO_2 emissions[7]. Integrating large amounts of wind and solar would decrease CO_2 emissions drastically; however, they are dependent on the weather. The variability of the weather has led to the assumption that all weather-dependent renewable energy technologies need to be supported by backup fossil fuel generation or storage on a significant basis, causing costs to soar[8]. Paradoxically, the variability of the weather can provide the answer to its perceived problems.

Because Earth's mid-latitude weather systems cover large geographic areas, the average variability of weather decreases as size increases[9]; if wind or solar power are not available in a small area, they are more likely to be available somewhere in a larger area. Even more importantly, access to electricity over a large region allows locations with rich wind and solar resources to supply cheap power to distant markets. The key enabling technology for the large geographic domains favoured for wind and solar power is a network of high-voltage direct-current (HVDC) transmission lines. Electrical storage can also reduce the intermittency of wind and solar, but at a higher cost than HVDC transmission lines.

Our study targets the contiguous US electricity sector to find cost-optimal networks of wind and solar generators that fulfil the requirements of an electrical power system. We show that the US can reduce CO_2 emissions from the electricity sector by 33–78% at approximately the same cost of electricity as in 2012. In recent years, similar tools have been developed that deal with electrical power ystem optimization, for example, MARKAL, NEMS, WEM, ReEDS, SWITCH, US-REGEN and ReNOT (refs 10–18). Our National Electricity with Weather System (NEWS) model differs from these models in its use of weather data with high temporal and spatial resolution, broad geographic areas, and extended time periods. Further, it co-optimizes dispatch, transmission and capacity expansion, allowing cost savings from geographic diversity, load smoothing, transmission expansion, reserve pooling and decreased energy density requirements. We integrate complex weather data over continental-scale geography while still handling the salient features of an electrical power system. NEWS implicitly computes the security-constrained unit commitment and economic dispatch, explicitly determines the planning reserves, load-following reserves and calculates the hourly transmission power flow, the capacity expansion of generators as well as transmission expansion. These constraints can be found in Supplementary Information Section 1.6.

Several studies have appeared over the past few years examining very high penetration levels of variable generation (close to 100%); these studies model renewable energy domination of the electricity sector. Two of these use subsets of the US, both spatially and temporally[19,20]. To get very high penetrations of variable generation they either constrain the fossil fuels or assume low-cost storage. Further, transmission is assumed to be perfect, an assumption that we do not make. A further study[21] considers the entire contiguous US is considered, but with large amounts of spatial aggregation along with a longer time series. However, the longer time series is simplified by utilizing only a small subset of those data. Also, they cost-optimize predetermined resource sites to balance the load. Aside from the resource data, the critical difference in these models compared with NEWS is the co-optimized structure of the NEWS model, which solves for the minimum total system cost, including both generation and transmission simultaneously.

The NEWS model is intended to be a hybrid capacity expansion and production cost model. The hybrid approach allows for cost reductions because the capacity expansion is decided in parallel with the dispatch of the generators instead of in serial. Supplementary Information Section 1 provides more

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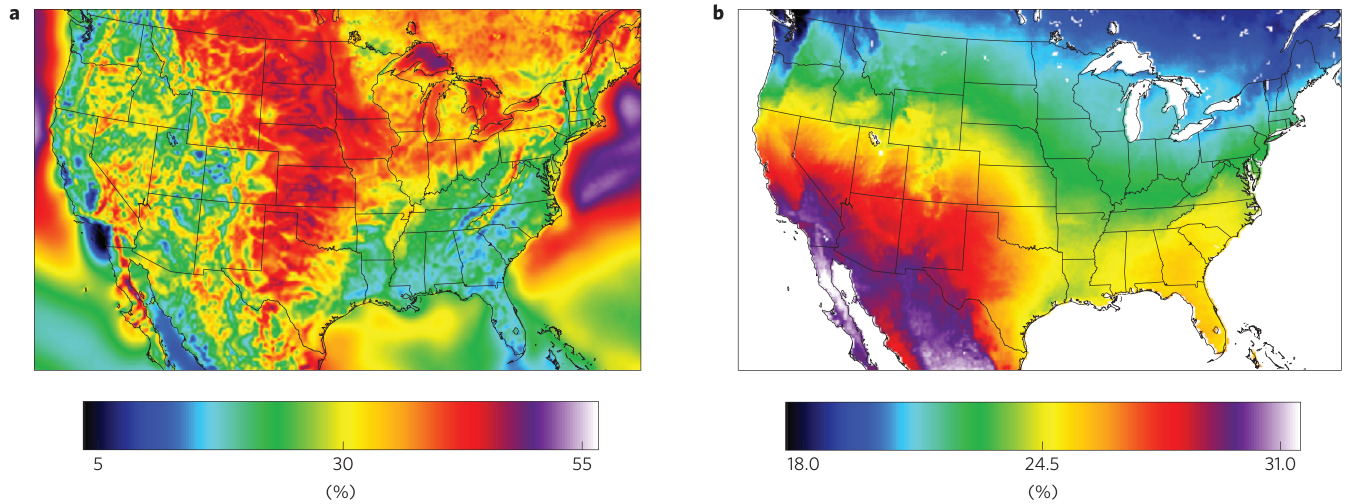

Figure 1 | The wind and solar PV power potential over the contiguous US. a,**b**, Wind at 90 m above ground level (**a**) and solar PV resource potential (**b**) over the US using the high-resolution weather data and power-modelling algorithms for 2006–2008. The potential is presented as the expected percentage of installed capacity power (capacity factor). Black/blue represents very low resource potential whereas red/violet indicate very good resource potential for that technology. The range of values is different for wind and solar PV. The description of the wind and solar PV power modelling is given in Supplementary Information Section 1.1.2.

details on the mathematics of the optimization. Further discussion of the optimization technique can also be found in ref. 22. The study uses hourly wind speed and solar irradiance for the years 2006–2008 using an advanced weather assimilation model on a 13-km grid[23]. The weather assimilation model extrapolates extensive weather observations over a uniformly spaced grid utilizing mathematical operators consistent with atmospheric dynamics and physics. We convert the weather data into electrical power output for wind turbines and solar photovoltaic (PV) panels with sophisticated power-modelling algorithms to mimic current technology behaviour (see Supplementary Information Section 1 for the methods).

Figure 1 shows the wind and solar PV resource potential over the US. It demonstrates the high level of detail contained in the weather and power data sets; there are ~152,000 spatial grid points in the data set. The panels in Fig. 1 show the temporal averages for 2006–2008; the data set contains ~27,000 hourly time steps. Figure 1a highlights that the locations across the US that have a high wind resource potential are predominantly away from densely populated regions, whereas Fig. 1b shows that the best solar PV resources are located in the desert southwest. The wind power data set is described in more detail in ref. 24. We did not explicitly treat wake effect interactions between wind turbines because the number of wind turbines is a dependent variable within the optimization and doing so would have made the problem intractable. The resulting distribution of wind turbines across the US does not extract more than 0.5 W m^{-2} on average from their grid cells.

Because weather is a major driver of electrical power use, we compiled the concurrent electricity demand for each market area and each hour of 2006–2008 (ref. 25). It is recognized that electrical power system dispatch includes timescales shorter than one hour, and that sub-hourly variability of wind and solar PV can be significant. However, the current NEWS model cannot address these high-frequency fluctuations because current data sets of electricity demand, as well as output from weather assimilation models, are not available at higher temporal resolution for the geographic scales we are modelling. Furthermore, the geographic scales considered in the present study effectively eliminate sub-hourly variability due to aggregation[26].

We selected 2030 as the reference year to create a cost-minimized electrical power system, and included a 14% increase in electricity demand above our baseline years of 2006–2008. The main reason for choosing a reference year of 2030 is that the cost estimates for all of the technologies become increasingly uncertain at longer time horizons. The increase in electricity demand is found by tracking GDP growth and contraction to 2011, then estimating a 0.7% growth per annum, in line with EIA estimates[27]. Supplementary Fig. 4 shows the aggregated hourly US electricity demand. Cost estimates for generators are continually evolving, so to provide rigorous estimates we compiled cost projections from numerous studies available at the time of the simulation runs and constructed three 2030 scenarios that span a range of future costs. The reader can refer to Supplementary Information Section 1.4 (Supplementary Fig. 6 and Supplementary Table 3) for a detailed description of the cost estimates used. The first was the high-cost renewable and low-cost natural gas (HRLG) scenario, which is similar to costs in 2012. The second was the low-cost renewable and high-cost gas (LRHG) scenario, in which the US achieves future expected cost reductions for renewable energy and faces increased demand for natural gas. Finally, we took the average of those two estimates to create the mid-cost renewable and mid-cost natural gas (MRMG) scenario. We assume that generator and transmission purchase costs are fully amortized over thirty years with a real discount rate of 6.6%. The costs are socialized equally among all of the different geographic regions of the contiguous US. Further, there are no increased capacity payments in the model because the purchases are simply assumed to be all debt repaid over the thirty years.

The study focused on three main generation technologies; wind turbines, solar PV, and natural gas combined cycle turbines, while one simulation also included coal plants. Natural gas is an effective complement to wind and solar PV because it has lower greenhouse gas emissions than other fossil fuels, and has the advantage of being able to rapidly change power output. Starting from nuclear, hydroelectric (no pumped hydroelectric is considered), wind, and solar PV plants that existed in 2012, our optimization model designs a new cost-optimal electrical power system for the entire contiguous US. The solution comprises wind, solar PV, natural gas, nuclear and hydroelectric generators. It also includes an HVDC transmission network that can transmit electricity over long distances, which high-voltage alternating current (HVAC) cannot do. In addition, HVDC is more efficient and cheaper than HVAC (ref. 28). Our model's key constraint is that it must provide electrical

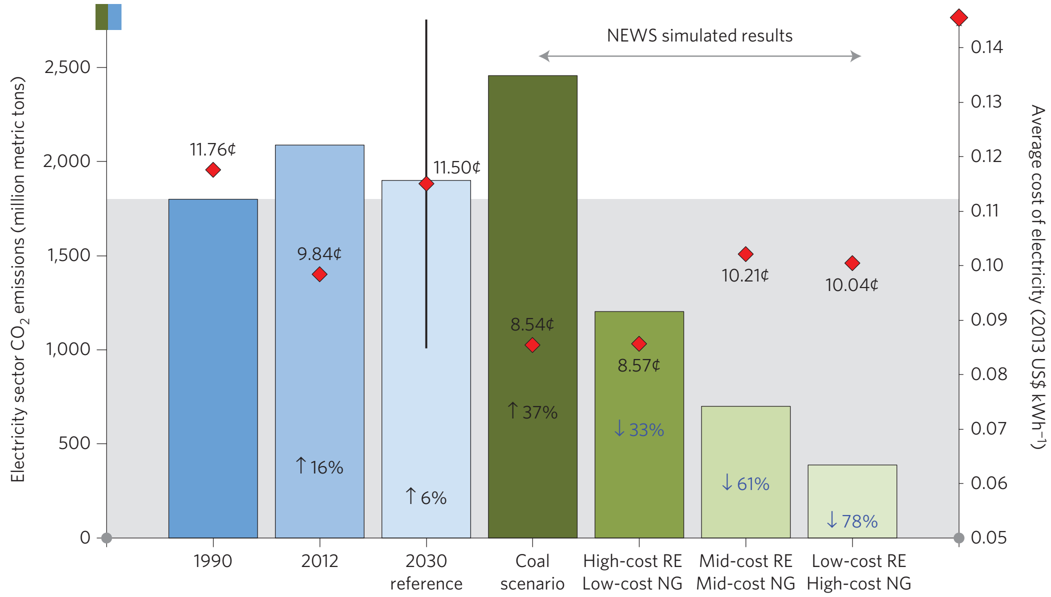

Figure 2 | The US electricity sector CO_2 emissions (left axis, bars) and levelized cost of electricity (right axis, diamonds). The blue bars are for historical data and an International Energy Agency projection to 2030 (ref. 6). The green bars represent results from our optimization model (the values are the average of the three years of simulations). The coal scenario is identical to the HRLG scenario, but with the inclusion of coal plants. The red diamonds represent the levelized cost of electricity per kilowatt-hour (kWh) to consumers in 2013US$. The percentages show the change of CO_2 emissions relative to 1990 levels.

power for every hour to every market while operating within current technology limits (see Supplementary Information Section 1 for methods).

The IEA World Energy Outlook (WEO) 2013 estimates that the levelized cost of electricity (LCOE), in 2013US$, to US customers will be 11.5¢, with a range between 8.5¢ and 14.5¢, per kWh by 2030, and CO_2 emissions will be 6% higher than in 1990 (ref. 6). The EIA Annual Energy Outlook (AEO) 2015 also estimates that the LCOE to US customers will be 11.5¢ per kWh (ref. 29). The LCOE to US customers includes the generation, transmission, distribution, O&M and fuel costs. The same applies to results from the NEWS model. Although our study focused on three main technologies, coal at present plays a major role in electricity generation in the US. In Fig. 2 we show results from optimization model runs that included coal (without carbon capture and sequestration (CCS)); CO_2 emissions were 37% higher than 1990 levels and the LCOE was 8.5¢ kWh^{-1} (ref. 29). The cost of electricity for comparison is estimated using the optimization model output and assuming that the split of costs remains the same as at present—that is, 68% for generation and transmission and 32% for distribution. The costs of nuclear and hydroelectric generation are 6¢ kWh^{-1} and 2¢ kWh^{-1}, respectively. Although somewhat less expensive than the other NEWS solutions, the coal scenario does not mitigate CO_2 emissions. Any proposed solution to mitigate CO_2 emissions cannot have substantial coal without CCS. Storage was considered and available in the optimization model; however, in preliminary simulations it was not selected in national solutions at a cost of US$1.50 per watt installed (more can be found in Supplementary Information Section 1.4). Therefore, for simplicity we removed it from the model. All other generation technologies were excluded from the optimization on the basis of cost projections that make them non-cost-competitive, or because of their current lack of large-scale commercial availability; including geothermal, concentrating solar power, and marine-hydro-kinetics. Further, the NEWS scenarios do not model fossil fuel generator stranded assets. However, we note that there is a significant turnover of fossil fuel generators on decadal timescales and, in particular, large numbers of coal plants are at present being retired for age, economic or environmental reasons.

Figure 2 indicates that, with current technologies, CO_2 emissions would be reduced by 33%, 61% and 78% relative to 1990 levels according to the HRLG, MRMG and LRHG scenarios, respectively. With a LCOE at 8.6¢, 10.2¢ and 10.0¢ kWh^{-1}, the three scenarios are below the 2030 reference LCOE of 11.5¢ kWh^{-1}, estimated by both the WEO 2013 and AEO 2015. Therefore, with existing technologies, the US electricity sector can substantially reduce its CO_2 emissions by 2030 without an increase in the LCOE, assuming learning curve cost reductions in wind and solar PV and the facilitation of a national HVDC transmission grid overlay. Using the LRHG scenarios (2006–2008), US power consumers could save an estimated US$47.2 billion annually with a national electrical power system versus a regionally divided one (~1.1¢ kWh^{-1}). This amounts to almost three times the cost of the HVDC transmission per year.

The model-produced electrical power system is a complex amalgam of variable and conventional generators, HVDC transmission lines and varying electrical load. Another component of the optimization model is that it simultaneously computes the locations of each generator and the capacity of each HVDC transmission line, dispatches each generator every hour at each location, and calculates the power flow (with losses) within the HVDC transmission network. The HVDC transmission network is a web of lines that connects 32 nodes, allowing power to flow between each region. The siting of the generators is bounded by numerous constraints, and care was taken to incorporate these restrictions within the model. For example, the nuclear and hydroelectric power plants are placed where they existed in 2012, the optimization can select to build natural gas and coal plants only where a fossil fuel plant existed in 2012 (to ensure the necessary infrastructure exists), and wind and solar PV plants cannot be built on protected lands, within urban areas or on steep slopes. See Supplementary Information Section 2.2 for details.

The selected locations of the wind and solar PV plants in the cost-optimized solutions are geographically dispersed over the entire contiguous US (Fig. 3). The electrical power system shown in Fig. 3 is for the LRHG scenario using data year 2007. It includes 523 gigawatts (GW) of wind (22 MW offshore, seen

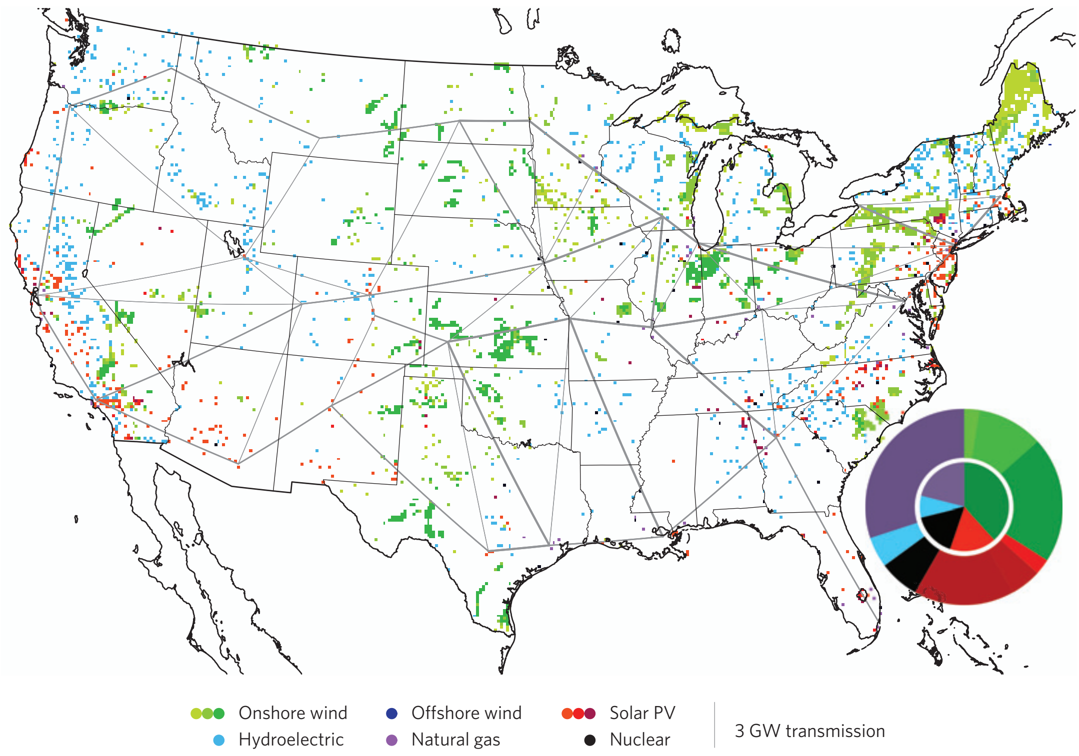

Figure 3 | Cost-optimized single electrical power system for the contiguous US, using data year 2007. The colours indicate that a model grid cell has a technology sited within it. Onshore wind and solar PV are split into three bins to designate the density of installations. For wind the bins are: less than 0.5 W m^{-2}; between 0.5 W m^{-2} and 1.5 W m^{-2}; above 1.5 W m^{-2}. For solar the bins are: less than 5 W m^{-2}; between 5 W m^{-2} and 10 W m^{-2}; above 10 W m^{-2}. The grey lines show the HVDC transmission network. The outer pie chart represents the installed capacity, whereas the inner pie chart shows the electricity demand met by each technology.

halfway down the Maine coastline), 371 GW of solar PV, 461 GW of natural gas, 100 GW of nuclear, and 74 GW of hydroelectric, for a total of 1,529 GW installed capacity. The very small amount of offshore wind (22 MW) demonstrates the cost efficiency of HVDC transmission to be able to transmit the power from the high plains to the coast rather than building wind turbines offshore. Compared with 2012 that represents a total increase in capacity of 31%. Natural gas capacity falls by 25 GW, whereas wind and solar PV rise by 463 GW (a factor of eight) and 368 GW (a factor of 62), respectively[27]. The inner pie chart in Fig. 3 shows that wind provides the dominant share of electricity at 38%, natural gas contributes 21%, solar PV 17%, and the remainder is fulfilled by nuclear and hydroelectric (16% and 8%, respectively). In other words, natural gas reduces its contribution by 9% relative to 2012, whereas wind and solar PV substantially increase their share to replace the other fossil fuels and displace some natural gas. The reader is encouraged to compare this result with those found in Supplementary Information Section 2 for all the other scenario runs.

The land taken out of its current uses and converted into power production is 6,570 km^2 (460 km^2 for wind and 6,110 km^2 for solar PV), or 0.08% of the contiguous US. The HVDC transmission network provides the access to these distant areas at a share of 4% of the cost of the electricity. A further benefit from this scenario is a significant drop of 65% in water consumption for electricity generation relative to 2012, predominantly because fewer steam turbines and cooling towers are needed[30]. More detailed results are presented in the Supplementary Information Section 2.

In the current US electricity sector there is no single electrical power system; there are three large connected regions known as interconnects, which are further divided into balancing authority areas (BAAs) that are designed to maintain supply and demand of electricity within their respective areas. Small, self-contained areas will diminish the efficacy of power generation from wind and solar PV because the local resources will be more correlated in time than geographically separated sites. In Fig. 4a the dependency on electrical power system size can be observed. As the size of the connected system grows, the amount of wind and solar PV generation increases. Moreover, the cost of electricity decreases as the area increases, because the system has access to more remote, rich resources and the correlation between connected sites weakens. The amounts by which the wind and solar PV installations grow and the costs decrease vary by scenario, but the trend persists in each. It is worth mentioning that, even in the single connected electrical power system, there can be thirty-two asynchronous subsystems that are connected by the HVDC. The HVDC reduces the potential of whole electrical power system blackouts because the entire system does not need to operate at the exact same frequency. Therefore, when faults occur, regions of the electrical power system can be isolated from the remainder.

Natural gas is a commodity and its cost to the electricity sector fluctuates continuously. During the decade of 2004–2014 the average monthly cost of natural gas for electricity has been as low as US$2.81 and as high as US$12.41 per million British thermal units (MM Btu). One MM Btu is equivalent to 1.054615 GJ. (ref. 31). Because the NEWS model minimizes the total system cost, the deployment of wind and solar PV in our model is linked to the cost of natural gas; as it increases so does the installed capacity of wind and solar PV. There is always a critical cost of natural gas where the system rapidly installs more wind and solar PV. Figure 4a,b can be used together to estimate the additional amounts of carbon-emission-free generation that could be economically deployed in 2030 for the same LCOE if a national HVDC-enabled system were implemented. For example, for ~11¢ kWh^{-1} there is ~75% carbon-emissions-free generation for the mid renewable costs in the

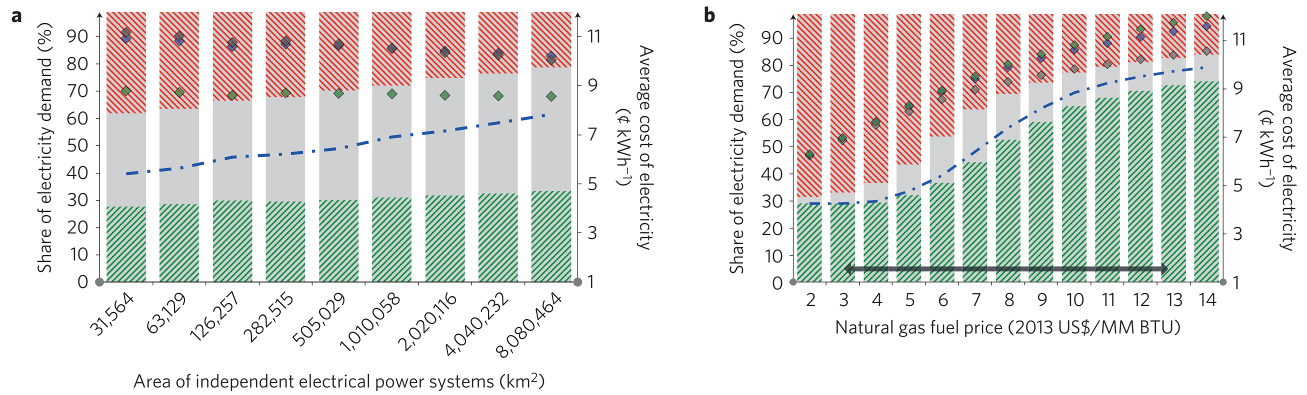

Figure 4 | Sensitivity to geographic scale and natural gas price. a,**b**, Influence of area (**a**) and natural gas cost (**b**) on the amount of carbon-emission-free generation. The green-hashed area represents the carbon-emissions-free generation of the HRLG scenario, whereas the grey area shows extra carbon-emissions-free generation created in the LRHG scenario. The blue dot-dashed line is the midrange (MRMG) value of the share of demand met by non-fossil fuel generation. The grey, blue and green diamonds show the LRHG, MRMG and HRLG cost scenarios LCOE to customers, respectively. The values shown are the three-year averages. The shaded arrow in **b** denotes natural gas costs to electricity utilities over the past decade (2004–2014).

national system (from Fig. 4b, columns for US$12–13 per million British thermal units (MM BTU)), but only ~40% with systems on the scale of the 2012 BAAs (from Fig. 4a, 63,129 km^2 column).

The formidable challenges associated with a large transformation of the US electrical power system by the 2030s include: the integration of variable generators; changes to the existing regulatory, commercial and legal system; and investments in a HVDC network and new power plants. Importantly, if the electricity sector is decarbonized, there are good prospects that electrical vehicles, heat pumps, and other electricity-based technologies can similarly reduce CO_2 across the entire energy sector. Although it would be a difficult transition, the challenges are not dissimilar to previous US projects for the creation of national markets, such as the transcontinental railroads of the nineteenth century, and the interstate highway system of the twentieth century.

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Author contributions
A.E.M. developed the original concept. C.T.M.C. wrote the majority of the paper along with help from all the other authors. C.T.M.C. produced all the figures and associated data. C.T.M.C. devised, ran and computed the results for all of the experiments, created and developed the mathematical optimization along with the associated software, and wrote the Supplementary Information. C.T.M.C. also finalized the spatial, load and transmission data sets for the optimization routine. A.A. created the initial spatial availability and electrical load data sets, and compiled the original weather data sets. A.D. computed the costs for each technology. J.W. verified the weather data and assisted extensively with editing the paper. Y.X. helped with the initial optimization approach and verified the mathematical approach. All authors contributed to data review and consistency checks.

Additional information
Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to A.E.M. or C.T.M.C.

Competing financial interests
The authors declare no competing financial interests.

EXHIBIT MG-7

GETTING CAPACITY RIGHT

HOW CURRENT METHODS OVERVALUE CONVENTIONAL POWER SOURCES

Advanced Energy Economy
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GETTING CAPACITY RIGHT: HOW CURRENT METHODS OVERVALUE CONVENTIONAL POWER SOURCES

Acceleration of the clean energy transition is dramatically shifting the types of electric generation technologies used to meet electricity demand and reliably operate the grid. Rapid cost declines in advanced energy technologies like wind, solar, and energy storage are making them increasingly competitive choices for new generation additions. The thriving clean energy market, combined with state policies and customer demand for such technologies, is causing these technologies to begin overtaking conventional generation sources like coal and natural gas that have traditionally been relied upon. This trend will accelerate as state clean energy targets, climate laws, and sustainability commitments by consumers and local governments call for their replacement.

These advanced energy technologies have different operating characteristics than the conventional power plant fleet. As a result, there has been considerable attention devoted to establishing the performance metrics and resource adequacy accreditation methods (e.g., determining their reliability value) applied to these new resource types, particularly renewables and energy storage. However, the methods used to evaluate the resource adequacy, or capacity, value of conventional thermal generating resources (including coal, natural gas, and oil-fired power plants) have not been formally reexamined or updated in decades.

In addition, recent extreme weather events have raised important questions about whether uncertainties in resource availability and correlated outage risks – those that affect multiple generators at the same time – are captured in current resource accreditation metrics. These events, which are increasing in frequency, have a significant impact on grid reliability. While methodologies recently adopted in some regions to determine the resource adequacy value of renewable resources and energy storage include such uncertainties and outage risks, the methodologies currently applied to conventional resources may not. Ensuring that the reliability contributions of all resources sufficiently take into account known reliability risks, and reflect them in their resource adequacy value determination, is critical to ensuring reliability and a level playing field in the markets.

With these factors in mind, Advanced Energy Economy (AEE) engaged Astrapé Consulting to conduct an analysis of the prevailing methodology for accrediting resource adequacy for thermal generating resources.[1] The report compared the methods applied to value the capacity of thermal power plants to their actual performance under various conditions.

[1] Accrediting Resource Adequacy Value to Thermal Generation, Astrapé Consulting, March 2022

The analysis shows that the traditional valuation method can overstate the capacity value of these resources by 2.7% to over 20% in winter and 4.6% to over 10% in summer, depending on regional conditions and other relevant factors These findings demonstrate that improvements in methodology are needed to accurately reflect the contributions to system reliability of these resources when determining their resource adequacy value and the amount of capacity they can bid into and receive revenues for in capacity markets. Putting in place methodologies that consider all types of outage risks would improve incentives for all generators to take steps to improve their accredited value, add new incentives for demand response and flexible load to enter the market, and send a signal for inefficient and poor performing thermal generators to retire, all of which can lower the total costs for capacity that customers pay to ensure reliability.

RESOURCE ADEQUACY AND CAPACITY MARKETS

Ensuring that electric power systems have sufficient resources available to reliably serve customers is accomplished through a combination of planning analyses to assess system needs, and procurement mechanisms that obtain the resources needed to meet those needs. Every system operator, regardless of whether it is a regional transmission organization (RTO) or a vertically integrated utility outside an RTO region, calculates a Planning Reserve Margin (PRM) that expresses the quantity of capacity needed to meet a system's peak demand. Planners typically use inputs such as expected demand growth, seasonal patterns in demand, historic and anticipated outages, and availability of supply to determine the required PRM.

Procuring resources needed to meet the PRM requires the application of methods to accredit (i.e., calculate) the capacity value of particular generating units, taking into account the amount of time they are expected to be available to produce energy. No generating resource is available 100% of the time to achieve its maximum potential output; these methods determine the "discount" from a generating unit's nameplate capacity to determine how much value it provides toward meeting resource adequacy needs. The RTOs in the Northeast (namely PJM Interconnection, ISO New England, and New York Independent System Operator) operate centralized capacity markets where generators compete to sell capacity needed to meet the RTO's PRM. In those regions, capacity accreditation methods are important because they determine the amount of capacity generators can sell into the market.

To accredit the capacity value of thermal generators, these regions generally apply a methodology called Equivalent Forced Outage Rate Demand (EFORd), which considers a unit's historical forced outage rate during periods the unit was in demand. EFORd assumes that a generating unit's performance is independent of other similar resources (i.e., outages are not correlated).

This is very different from how the capacity of advanced energy resources like wind, solar, and energy storage are now assessed in PJM and other regions using an Effective Load Carrying Capability (ELCC) methodology. ELCC is a probabilistic method that determines the capacity value of these resources by evaluating their contribution to meeting the reliability objective of no more than one day of outage in 10 years. ELCC capacity values are determined for groups (or classes) of resources based on their characteristics and output profiles; unlike EFORd, this grouping captures the potential for correlated periods of unavailability among similar resources and assigns capacity value accordingly. ELCCs have not typically been quantified for thermal resources since they are dispatchable and presumed to not have energy constraints. The only reduction in the reliability contribution of these resources would be due to unplanned outages.

	PJM	CAISO	MISO	SPP	ERCOT
Onshore Wind	15.0%	16.3%	16.6%	16.8%	21.0%
Offshore Wind	40.0%	N/A	N/A	N/A	31.0%
Solar Fixed	38.0%	8.7%	50.0%	85.1%	74.0%
Solar Tracking	54.0%	11.0%	50.0%	85.1%	74.0%
4-Hr Battery	83.0%	90.6%	100.0%	N/A	N/A

SOURCE: Astrapé Consulting, "Accrediting Resource Adequacy Value to Thermal Generation," March 2022

In PJM, EFORd continues to be used for conventional thermal resources, while ELCC is now in place for renewables, energy storage, hydro, and similar variable or limited duration resources. This difference in treatment of resources has been identified by market participants and at least one FERC commissioner[2] as problematic. PJM is now considering revisiting conventional thermal resource accreditation. Other regions are in various stages of moving to an ELCC methodology (for some or all resources) to determine capacity value as they anticipate expected increases in the development of renewables and storage putting pressure on conventional generation, and in response to recent extreme weather events like Winter Storm Uri, which raise new questions about outage risks facing the generation fleet.

ACCOUNTING FOR KNOWN OUTAGE RISKS OF THERMAL GENERATORS

In the report, Astrapé assesses the extent to which the existing EFORd methodology adequately accounts for the actual risks of outages of thermal resources that were observed in prior extreme weather events, and whether EFORd appropriately values capacity in light of those outage risks. To perform this assessment, Astrapé constructed a model based on the demand and generation resource profile of the PJM South region. Incorporating historic extreme weather events and publicly available data, the model ran different simulations

[2] Commissioner Christie's Dissent from Order Concerning PJM's proposed ELCC, Federal Energy Regulatory Commission, July 20, 2021.

weighing thousands of simulated years of outages (including both winter and summer) to compare how the EFORd methodology performs in accounting for these uncertainties when compared to an ELCC-equivalent methodology.

Based on this modeling, Astrapé determined that the existing EFORd accreditation methodology does not fully account for these risks when assigning capacity value to thermal generation resources. Specifically, the report describes four categories of outage uncertainty and risk that the EFORd methodology fails to fully capture when compared to an ELCC-equivalent:

1. Outage variability: Existing EFORd and Unforced Capacity (UCAP) determination methodologies implicitly presume an annual average rate of outages, but Astrapé's modeling shows that at any given time actual outages will vary and often can exceed those averages. Using an annual average masks these higher outage rates and results in a higher capacity accreditation than is justified.
2. Common mode failures: Existing methodologies like EFORd generally assume that generator outages are independent from one another. However, modeling shows correlated outages of multiple resources can occur in certain instances, such as when they share equipment like a step-up transformer.
3. Weather-dependent outages: The modeling further showed that thermal generation resources can suffer correlated outages due to the acute impacts of extreme weather, such as frozen equipment or heat stress, causing them to perform below their EFORd-based rating in a statistically significant manner.
4. Fuel availability: Modeling and anecdotal evidence reviewed by Astrapé showed that cold weather events can impact availability of fuel supply itself (such as natural gas) independent of particular acute impacts on generation resources themselves and result in correlated outages that may not be captured in the EFORd average availability calculation.

Based on these findings, the report presents an illustrative range of the downward adjustments to EFORd-based accreditations that could be made to account for these risks. While precise adjustments to capacity accreditation require further study and analysis, the range presented in the report illustrates the potential magnitude by which the existing EFORd-based methodology overstates the capacity value of thermal resources. The table below summarizes illustrative adjustments from model simulations, showing potential downward adjustments of 2.7% to over 20% in winter and 4.6% to over 10% in summer.

Thermal Generator SUMMER	Outage Factor	Accreditation Impact (Incremental)	Capacity Credit (Cumulative)
Standard Practice	Forced Outage Rate	5.0%	95.0%
Proposed Additional Factors	Outage Variability	4.6%	90.4%
	Common Mode Outage	N/A	
	Weather Dependent Outage	5.6%	84.7%
	Fuel Supply Outages	N/A	
Adjusted Summer Thermal Capacity Credit:		**84.7%**	

SOURCE: Astrapé Consulting, "Accrediting Resource Adequacy Value to Thermal Generation," March 2022

Thermal Generator WINTER	Outage Factor	Accreditation Impact (Incremental)	Capacity Credit (Cumulative)
Standard Practice	Forced Outage Rate	5.0%	95.0%
Proposed Additional Factors	Outage Variability	2.7%	92.3%
	Common Mode Outage	2.3%	90.0%
	Weather Dependent Outage	10.0%	82.3%
	Fuel Supply Outages	6.2%	76.1
Adjusted Winter Thermal Capacity Credit:		**76.1%**	

SOURCE: Astrapé Consulting, "Accrediting Resource Adequacy Value to Thermal Generation," March 2022

IMPLICATIONS FOR REGIONAL MARKET OPERATORS AND REGULATORS

The report findings suggest that existing EFORd-based resource adequacy and capacity accreditation methodologies should be carefully reviewed and revised to ensure that they adequately consider all relevant uncertainties. To the extent these methodologies do not account for these outage uncertainties, they may be over-accrediting capacity value to thermal resources and requiring consumers to pay for capacity contributions to reliability they are not actually receiving. Further, given that ELCC-based methodologies now applied to renewables, energy storage, and similar technologies in PJM already account for correlated unavailability, failure to revisit existing EFORd-based methodologies applied to thermal resources may result in undue discrimination among resources within RTO centralized capacity markets.

The modeling results in the report do not necessarily imply that PRM requirements should be increased. Some of these risks are already accounted for when setting the reserve margin requirement but they are not considered in the capacity values of generation resources using EFORd. This essentially shifts the cost of these risks to customers (who pay the costs of all capacity acquired to meet the PRM), rather than assigning those risks to generators by adjusting the amount of capacity they can sell. Other unaccounted for risks may be offset by other conservative assumptions.

Putting that risk back on the generators, where it belongs, would improve incentives for generators to take steps to improve their accredited value (adding storage, improving weatherizing, obtaining firm fuel supply, etc.), add new incentives for demand response and flexible load to enter the market, and send a signal for inefficient and poor performing thermal generators to retire, all of which can in turn lower the total costs customers must pay for capacity to meet PRM requirements.

While the report presents a range of illustrative downward adjustments to EFORd-based thermal capacity accreditations, further analysis is necessary to translate the results of the modeling into a fair accreditation and valuation methodology for use in markets.

To arrive at a new methodology, regional market operators should consider, among other things, how to account for and adjust outage assumptions based on individual unit size, age, and performance characteristics (including fuel supply arrangements or other technical specifications). Seasonal impacts on outage risks may also need to be addressed.

A methodology that fairly quantifies the capacity value of traditional energy sources becomes increasingly important as the transition to advanced energy technologies like solar, wind, and energy storage accelerates and these technologies replace thermal generation resources. A clear understanding of the true load-carrying capability of all resources is necessary to ground conversations about the potential reliability implications of this shift and solutions to identified reliability challenges.

EXHIBIT MG-8

ASTRAPÉ CONSULTING
innovation in electric system planning

Estimation of the Market Equilibrium and Economically Optimal Reserve Margins for the ERCOT Region for 2024

FINAL

1/15/2021

PREPARED FOR

Electric Reliability Council of Texas ("ERCOT")

PREPARED BY

Kevin Carden
Alex Krasny Dombrowsky

Astrapé Consulting

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Acknowledgement: We acknowledge the valuable contributions of many individuals to this report and to the underlying analysis, including peer review and input offered by ERCOT staff and members of the ERCOT stakeholder groups. In particular, we would like to acknowledge the analytical, technical, and conceptual contributions of Julie Jin, Kevin Hanson and Peter Warnken. We are deeply indebted to the Brattle Group for developing the framework for addressing many off the topics covered in the report and would like to acknowledge the input and review for this report from Kathleen Spees, Sam Newell and Michael Hagerty.

TABLE OF CONTENTS

EXECUTIVE SUMMARY

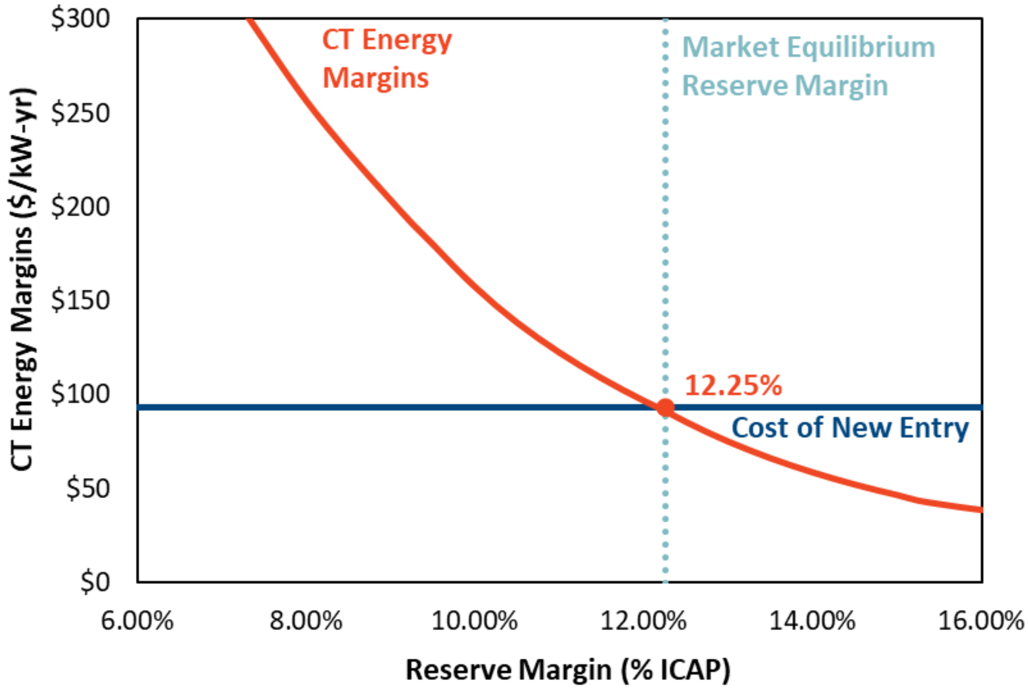
We have been asked by the Electric Reliability Council of Texas (ERCOT) to estimate the market equilibrium reserve margin (MERM) and the economically optimal reserve margin (EORM) for ERCOT's wholesale electric market. For this analysis, Astrapé Consulting simulated the ERCOT market using its Strategic Energy & Risk Valuation Model (SERVM). The model captures ERCOT's wholesale market design and projected system conditions for 2024; it probabilistically simulates the economic and reliability implications of a range of possible reserve margins under a range of weather and other conditions. The MERM concept is relevant in ERCOT because, unlike all other electricity systems in North America, ERCOT does not have a resource adequacy reliability standard or reserve margin requirement. In ERCOT, the reserve margin is ultimately determined by suppliers' costs and willingness to invest based on market prices, where prices are determined by market fundamentals and by the administratively-determined Operating Reserve Demand Curve (ORDC) during tight market conditions. This approach creates a supply response to changes in energy market prices towards a "market equilibrium"; low reserve margins cause high energy and ancillary service (A/S) prices and attract investment in new resources, and investment will continue until high reserve margins result in prices too low to support further investment.

We estimate a market equilibrium reserve margin of 12.25% under projected 2024 market conditions, as shown in Figure ES-1.[1] This is higher than our MERM projection of 10.25% in our 2018 study, however, the projections of system reliability are nearly identical at 0.5 Loss of Load Expectation (LOLE).[2]

[1] This estimate should not be interpreted as a precise forecast for 2024 or any other particular year, but as a reasonable expectation around which actual reserve margins may vary as market conditions fluctuate. To expect a persistently lower reserve margin would be to assume investors will forego profitable opportunities to add additional supply, and to expect a persistently higher reserve margin would be to assume investors will over-invest.

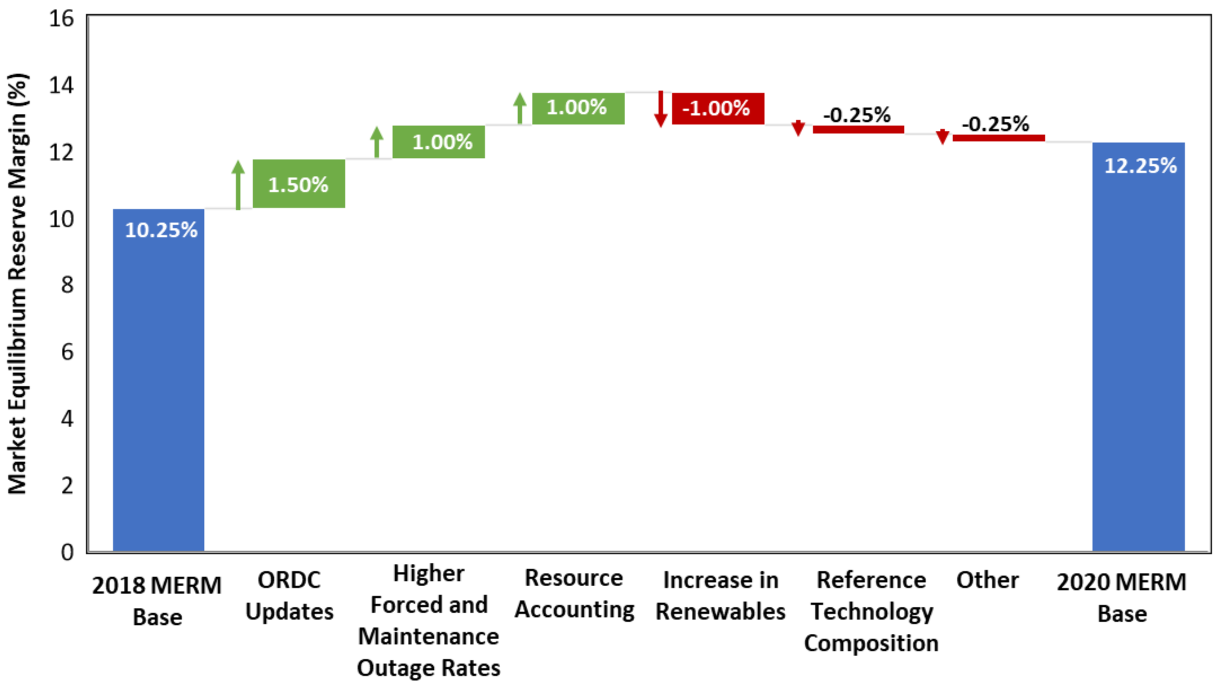
[2] The 2018 Report can be found at Newell, et al. (2018b).

Figure ES-1. Market Equilibrium Reserve Margin



Input and reserve margin accounting changes with both upward and downward effects have been introduced since 2018. An increase in renewable penetration put downward pressure on MERM, while the changes in resource accounting increased the MERM. The PUCT administered changes to the ORDC which put upward pressure on MERM, and higher forced outage rates also put upward pressure on MERM. The change in marginal resource composition put slight downward pressure on MERM. The waterfall chart in Figure ES-2 quantifies the magnitude of the impact of each of these factors.

Figure ES-2. Base MERM Changes from 2018 to 2020 Study

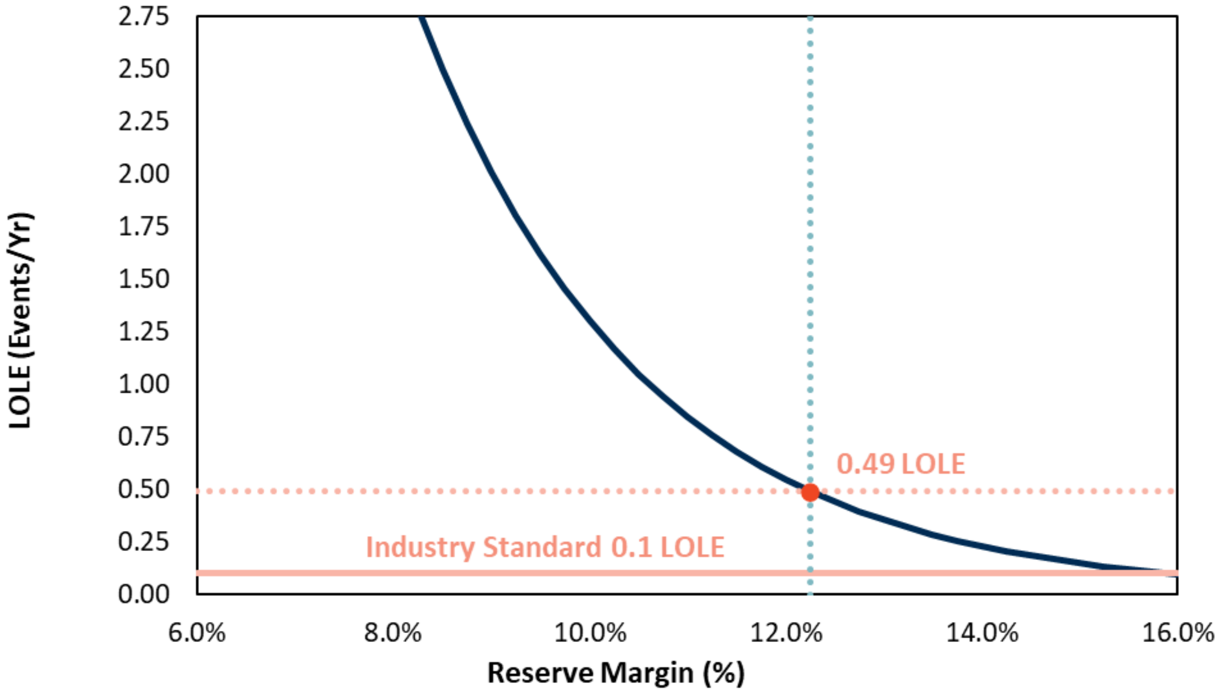


In terms of reliability, our probabilistic simulations indicate that under base case assumptions with a market equilibrium reserve margin of 12.25%, the system is expected to experience 0.5 days per year Loss of Load Expection (LOLE).[3] As shown in Figure ES-3, this is significantly higher than the 0.1 events per year LOLE standard used by most electric systems in North America for planning purposes. It is also important to note that this LOLE is the same value reported in the 2018 study at the MERM of 10.25%. Intuitively, the higher MERM in this study would supply higher reliability. However, the higher Equivalent Forced Outage Rate (EFOR) assumptions, combined with a discrepancy between the renewable credit (or reliability contribution) estimated for CDR[4] reserve margin reporting and the actual reliability value provided by these resources, increase the MERM without an improvement to reliability.

[3] For the simulations, a loss-of-load (LOL) event occurs when the hourly load, plus a minimum operating reserve level of 1,000 MW, is greater than available resource capacity. A LOL event is recorded for each day of the simulation if one LOL hour occurs in the 24-hour span, or if there are more than one non-contiguous LOL hours during the day. For a given reserve margin level, the LOLE is the mean number of LOL events for 10,000 simulations (40 weather years, 5 load error levels, 50 outage draws).

[4] CDR is the "Report on Capacity, Demand and Reserves for the ERCOT Region," typically released in May of each year, with an update released in December.

Figure ES-3. Loss-of-Load Expectation at Varying Reserve Margins



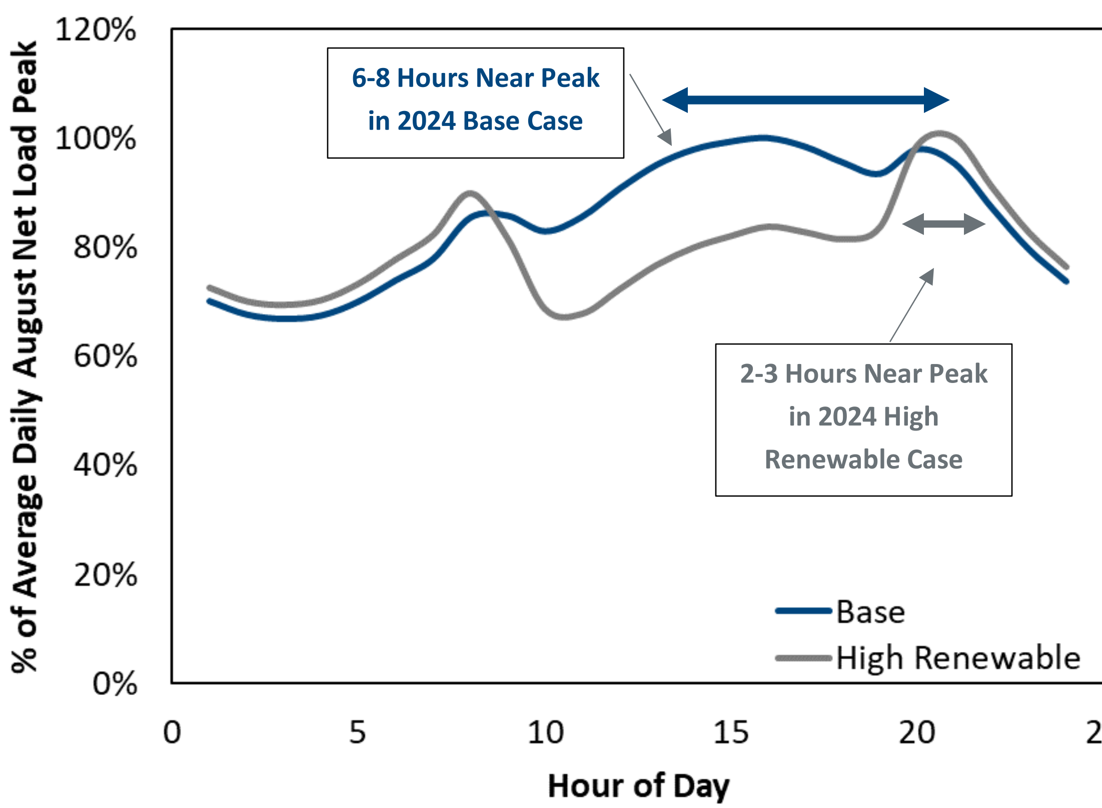
Determination of the economic potential of marginal resources in an energy-only market is complex. The potential energy margins of any generating resource are a function of the load profile, the technological composition of the entire generation fleet, the reserve margin of the fleet, the fuel prices to operate those generators, and other factors. The MERM for marginal peaking capacity then is in part determined by the characteristics of the other resources on the system. While this study is designed to analyze only marginal peaking capacity decisions, the ramifications of that equilibrium penetration can inform the calculus for other resource classes making investment or retirement decisions as well.

One interaction among resources that is analyzed in detail for this study is the impact of renewable penetration on MERM for marginal peaking capacity. Since the introduction of renewable generation, with its *de minimis* variable operating costs, will tend to depress market prices[5], we find that the MERM will be reduced by increases in renewable penetration. This downward pressure on the MERM from increasing renewables is initially small. For the 2018 study, Astrapé and Brattle quantified that an increase of 20 GW of renewable capacity would shift MERM down by only 0.75 percentage points, or approximately 500 MW. The magnitude of the impact however grows as the penetration of renewable grows, and is particularly sensitive to solar capacity. The size of the impact is primarily

[5] The volatility of renewable output could lead to more frequent periods of scarcity pricing if the system is not able to respond quickly enough. However, we assume this effect is mitigated by carrying additional operating reserves to be able to respond to the renewable volatility. As such, the addition of renewable generation is expected to depress market prices.

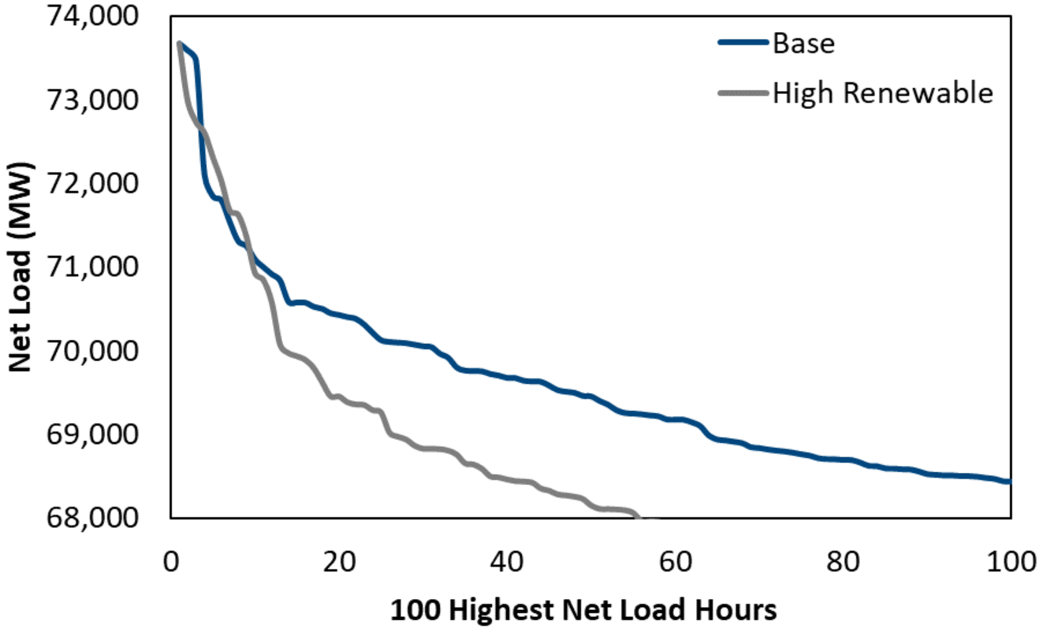
dependent on how the renewable fleet affects the frequency of hours with high electricity market prices. In an extremely high solar penetration scenario, the net load shape is very steep, so there are very few hours with very high loads, and commensurately high market price hours are infrequent. Up to projected penetrations in 2024 however, the net load shape is quite flat. There are eight or more hours every day within a few thousand MW of the daily peak load. Figure ES-4 compares the net load shape in the base case and in a high renewable scenario. Both scenarios require the same reserve margin to maintain the same reliability, but the high renewable scenario will have many fewer hours with high market prices.

Figure ES-4. Average August Daily Net Load Comparison



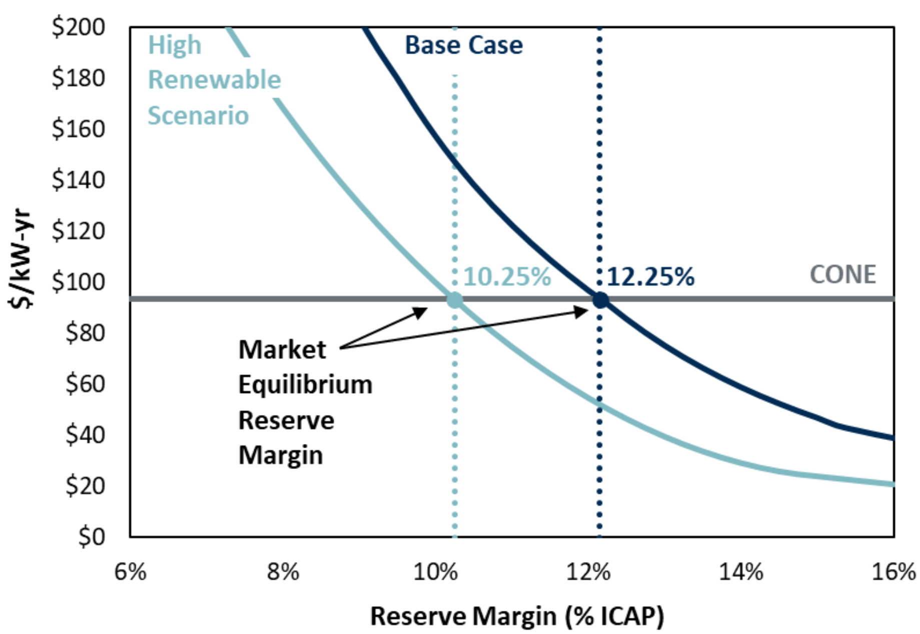
The moderation of net load peak frequency can be seen clearly in the annual net load duration curve shown in Figure ES-5. Scarcity conditions and associated high prices are most likely when net load is near its annual peak. The addition of another 15 GW of solar capacity dramatically steepens the net load duration curve near the annual peak. This steepening translates to lower frequency of scarcity conditions and high prices, depressing MERM.

Figure ES-5. Net Load Duration Curve Comparison



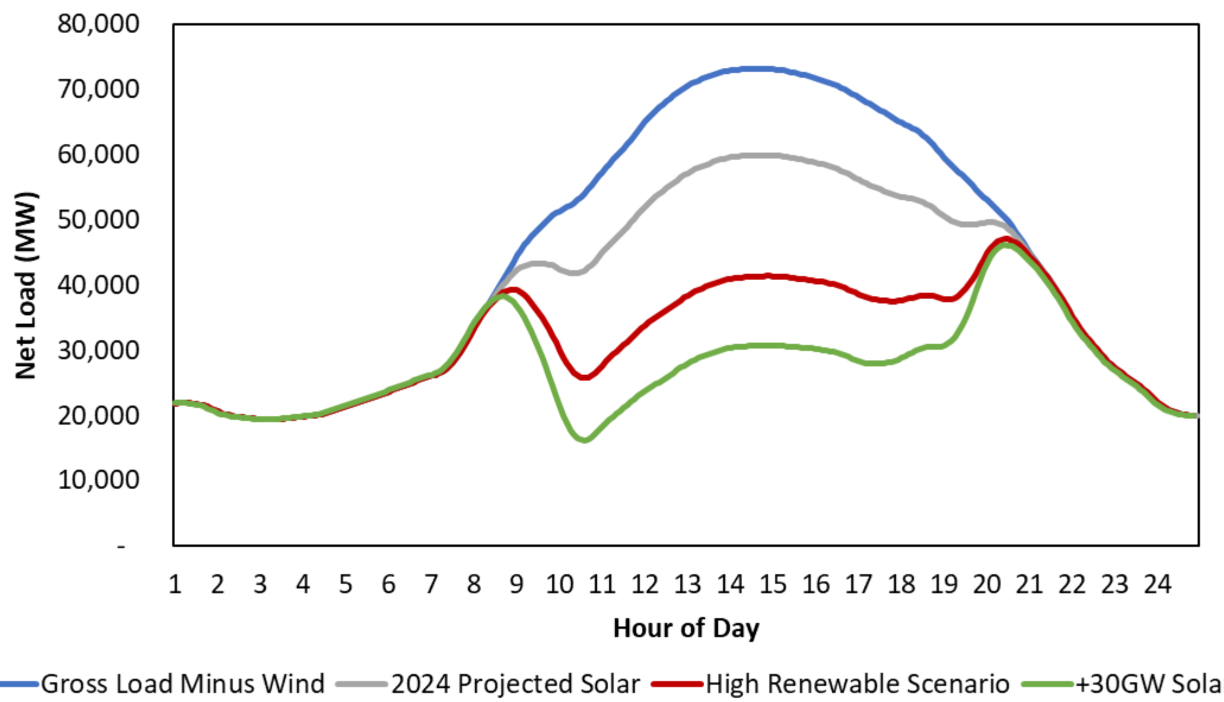
From the waterfall chart (Figure ES-2), the impact of the 20 GW of renewable additions from the 2018 study to the 2020 study was to reduce the MERM by 1.00 percentage points. Because of the more pronounced effect on load shape of additional solar from the projected 2024 penetration, the next 20 GW of renewable additions analyzed in the high renewable scenario are expected to reduce MERM by 2.00 percentage points to 10.25%, as shown in Figure ES-6. At this level, the reliability implications of a different MERM are significant with firm load shed occurring 0.5 days per year at MERM in the base case, but more than 1.3 days every year in the high renewable case.

Figure ES-6. Marginal Unit Net Energy Revenues



While the change in net load shape reduces the frequency of scarcity pricing, it creates opportunities for other classes of resources, namely battery storage, as shown in Figure ES-7. Prior to the introduction of any solar, the load peak in ERCOT spans several hours; the net load is within a few thousand MW of the daily peak for six to eight hours. Even after the addition of over 16 GW of solar projected to be online by 2024, the net load shape is still quite flat near the peak, and consequently batteries would need to supply long duration storage. Subsequent additions begin to produce steeper net loads near the daily peak, and at the penetrations in the high renewable scenario, the steepness of the net load shape results in significant four-hour battery capacity[6] being able to supply capacity value.

Figure ES-7. Net Load Shape Impact of Solar[7]



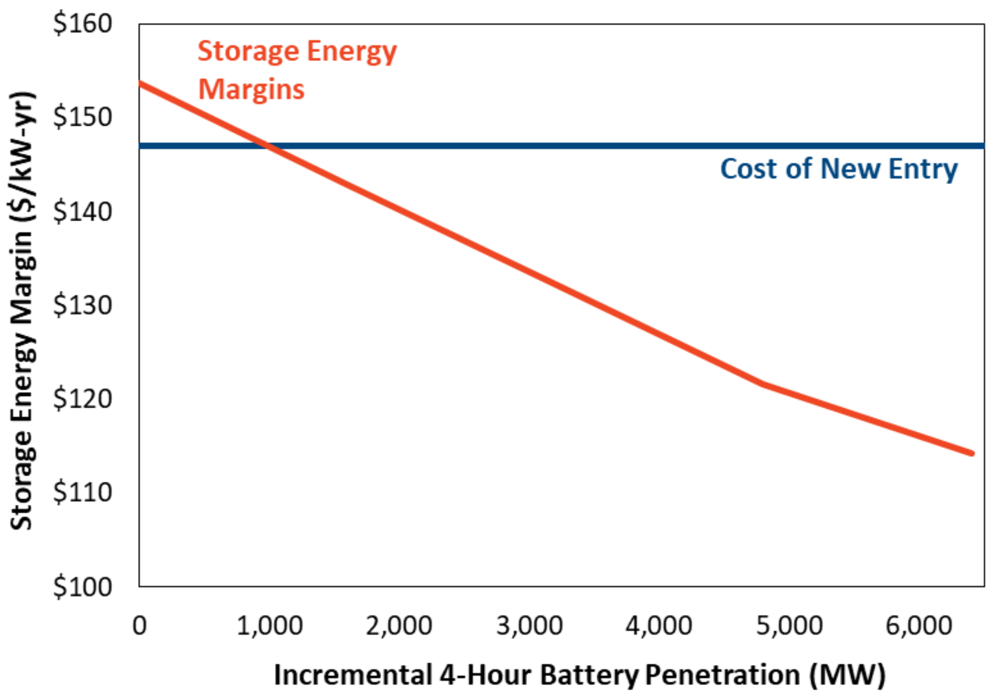
While the capital cost of batteries is higher than that of conventional combustion turbine (CT) capacity, the economic benefits of batteries are substantial in the high renewable scenario. At the high renewable MERM of 10.25%, incremental batteries can expect to earn a return in excess of their fixed and variable costs from the energy and ancillary service market. Swapping out new CTs for new

[6] Batteries of shorter duration than 4 hours can provide some capacity value, but as the penetration increases, the capacity value potential declines. This study focused on higher penetrations of storage which require average durations of 4 hours or longer. We note that much of the current battery capacity development activity in ERCOT is of shorter duration, but our analysis is focused on future portfolios when longer durations will be needed to supply capacity value.

[7] Profiles developed from a single example weather day with varying solar penetration.

four-hour batteries yields the energy margins[8] shown in Figure ES-8 for incremental battery capacity, and demonstrates a breakeven incremental penetration of 1,100 MW.[9] The energy margin decline is modest and if technology improvements lead to a battery capital cost decline to $115/kw-yr, up to 6.5 GW of incremental four-hour battery capacity could be economic in ERCOT in a high renewable scenario with the reserve margin at 10.25%. These results are contingent on a number of assumptions including the bidding behavior of renewable resources and the qualification for providing ancillary services, and they do not include other potential value streams for storage including locational benefits, but they provide indications of the economic potential for storage in ERCOT in the future.

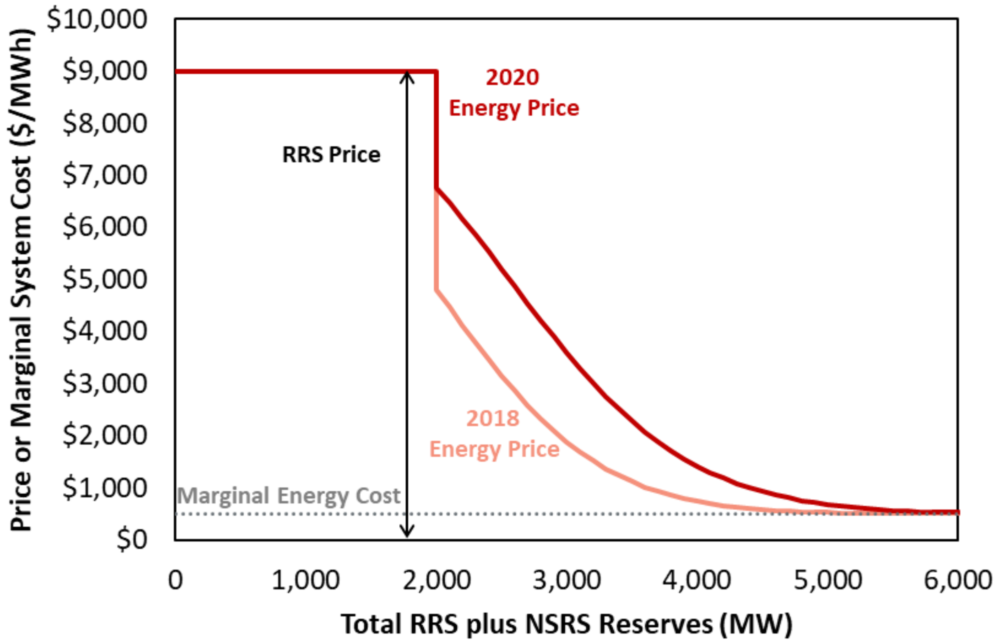
Figure ES-8. Storage Energy Margins



Another key difference from the 2018 study is an increase to ORDC pricing.[10] A comparison of the 2018 and 2020 ORDC adders is illustrated in Figure ES-9. At the same level of reserves, market participants will realize higher energy and ancillary service prices which will increase MERM.

[8] Energy margins as referenced in this report are calculated as total revenue from energy and ancillary service markets minus variable operating costs.
[9] The base case has 1,103 MW of batteries. Battery analysis is incremental to that capacity.
[10] See PUCT (2019b).

Figure ES-9. ORDC Curve Comparison



As shown in the waterfall chart (Figure ES-2), the ORDC curve change increased the MERM by 1.5 percentage points. In isolation this administrative change would improve reliability. However, the increase of renewable penetration in the base case almost completely offsets this effect.

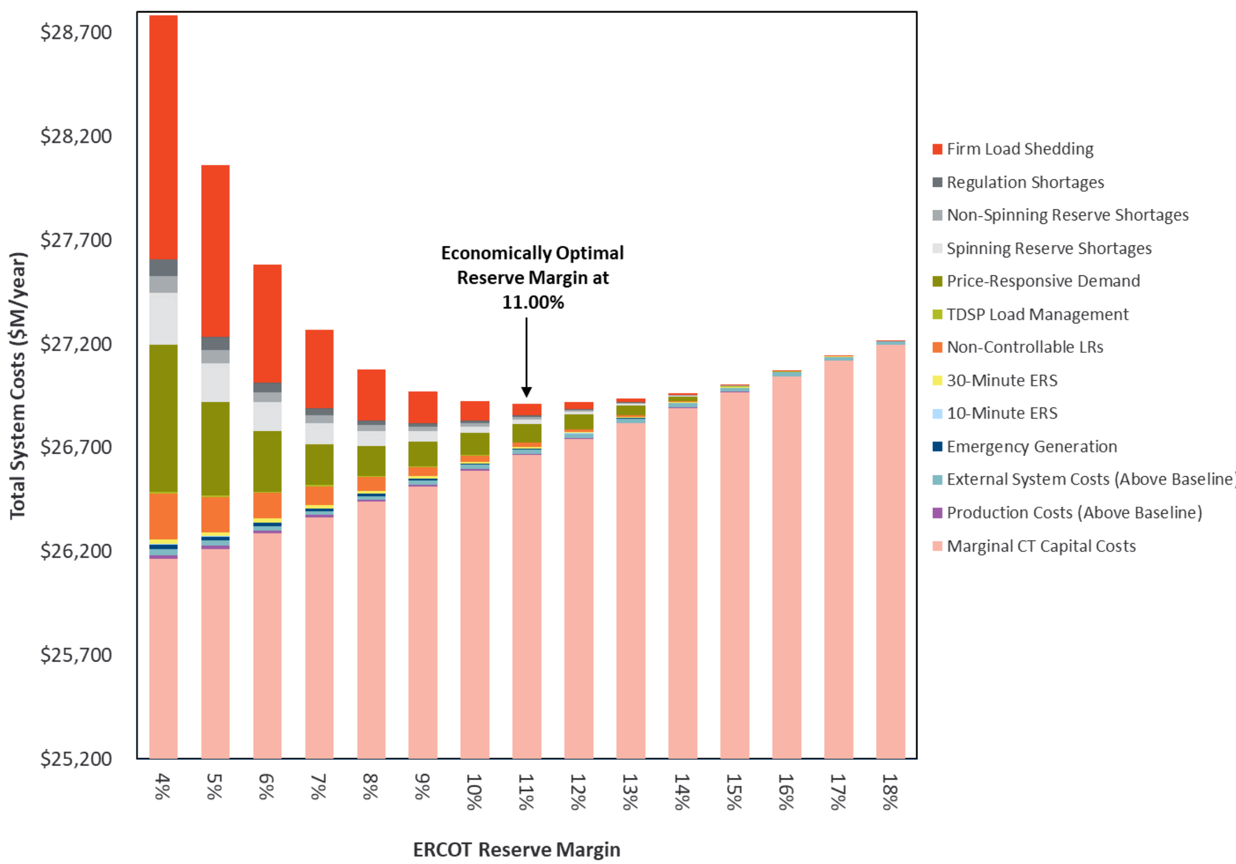
Other key differences from the 2018 study include higher forced outages rates in the more recent outage data used for this study and the effect of the change in the reference technology.

While the MERM tests market outcomes, ERCOT stakeholders may be interested in the associated economic optimality outcomes. The economic optimum occurs at the reserve margin that minimizes societal costs net of all supply costs and the lost value from any disruptions in electric service. We calculate the economically optimal reserve margin (EORM) by finding the balance between the marginal costs and marginal benefits of adding capacity. The marginal costs are simply the levelized capital costs and fixed costs of a new generator. Marginal benefits include lower production costs and reduced load shedding (at an assumed cost of $9,000/MWh), reserve shortages, demand-response calls, and other costly emergency events. Our simulations quantify how scarcity event frequencies decrease (at a diminishing rate) as reserve margins increase. As shown in Figure ES-10 below, we estimate 11.00% as the EORM, based on the risk-neutral, probability-weighted-average cost of 80,000 simulations.[11] However, the estimated societal costs are relatively flat with respect to reserve margin near the minimum, with only modest variation between reserve margins of 10.00% and 12.00%. There is also a noticeable asymmetry in costs on either side of the EORM, suggesting risk

[11] 40 weather years, each at 5 levels of non-weather-based load forecast error, with 50 generator outage draws, at 8 modeled reserve margins.

adjustment value to consumers to maintaining a reserve margin higher than EORM. While the asymmetry was present in previous EORM analyses, the magnitude is more pronounced in this study due to a higher penetration of energy limited resources that can be exhausted more rapidly at very low reserve margins and the recognition of additional reliability risks in the SERVM modeling. The mechanism to achieve a higher reserve margin than economically optimum in an energy-only market is through market pricing constructs.

Figure ES-10. Total System Costs across Planning Reserve Margins



Our analysis shows that the market equilibrium of 12.25% is greater than the economically optimal level of capacity by 1.25 percentage points. The market equilibrium is higher than the economic optimum because the ORDC as currently designed sets prices higher than the marginal value of energy during scarcity conditions. The size of the gap is lower than suggested by current ORDC values and the gaps identified in previous studies because of the presence of more energy-limited resources. In certain reliability-constrained hours in the simulation, additional capacity can provide more value than its nameplate multiplied by the value of lost load (VOLL). This is because in addition to being available during the peak hour, the incremental resource can preserve the energy from the energy limited resources such as battery and demand response[12] for availability during peak conditions. This means that the system savings in some extreme hours will be larger than the market price benefit the marginal CT realizes.

Table ES-1 shows the MERM and EORM for the base case as well as for sensitivity and scenario analyses conducted for this study. Some of the key assumptions we test are the estimated capital cost of new generation, load forecasting error, coal and natural gas prices, VOLL, intermittent renewable penetration, and weather distributions. Regarding weather, our base case assumption is that all 40 years of historical weather are assigned an equal probability of occurring for the 2024 simulation year, and this reliance on long term history is consistent with the EORM Manual.[13] More recent weather has been hotter (especially 2011) and may be more representative of future weather. Assuming accordingly that each of the last 15 weather years has a 1/15th chance of reoccurring (with 0% weight on each of the prior 25 years) leads to higher simulated prices and reliability events at a given reserve margin; but the higher prices would attract more investment, resulting in a 1% higher market equilibrium reserve margin and similar reliability to the base case.

Table ES-1. Market Equilibrium and Economically Optimal Reserve Margins and Reliability

Scenario/Sensitivity	**MERM** (%)	**EORM** (%)
Base Case	**12.25**	**11.00**
Vary Cost of New Entry (CONE)	11.25 – 13.25	10.00 – 12.00
Vary VOLL	12.25	10.25 – 13.25
Vary Probability of Weather Years	13.25	12.00
Vary Forward Period and Load Forecast Uncertainty	11.25 – 12.00	10.00 – 10.75
High Renewables Scenario	**10.25**	**9.00**
Lower EFOR	**11.25**	**10.00**

Notes:
Table reflects all scenarios and sensitivities analyzed, as described in Section C; Current practice has VOLL set to the max of the ORDC but the sensitivity which varies to VOLL does not change the ORDC curve and therefore does not affect the MERM.

These estimates must not be interpreted as deterministic, since actual market conditions will fluctuate from year-to-year. In reality, the reserve margin will vary as plants enter and exit. Moreover, even at a given reserve margin, realized reliability and price outcomes can deviate far from the expected value, primarily due to weather and variations in wind generation. For example, with a projected market equilibrium reserve margin of 12.25%, we estimate that in the 90th percentile outcome—representing relatively hot weather and low generation availability—energy prices would more than double, marginal units could have net energy revenues reaching $246/kW-year, with 1.2 load-shed events per year (compared to a mean of 0.5 across all conditions modeled).

[12] Two demand response categories – TDSP and ERS – have annual, seasonal, or daily call constraints.
[13] See ERCOT (2017b). Note that the methodology described in the manual is derived from our 2014 study.

I. BACKGROUND AND CONTEXT

We have been asked to estimate the market equilibrium reserve margin (MERM) and the economically optimal reserve margin (EORM) for ERCOT's wholesale electric market.

The MERM describes the reserve margin that the market can be expected to support in equilibrium, as investment in new supply resources responds to expected market conditions. This concept is relevant in ERCOT because, unlike all other electricity systems in North America, ERCOT does not have a reserve margin requirement. In ERCOT, the reserve margin is ultimately determined by suppliers' costs and willingness to invest based on market prices, where prices are determined by market fundamentals and by the administratively-determined Operating Reserve Demand Curve (ORDC) during tight market conditions. This approach creates a supply response to changes in energy market prices toward a "market equilibrium"; low reserve margins cause high energy and ancillary service (A/S) prices and attract investment in new resources, and investment will continue until high reserve margins result in prices too low to support further investment. The PUCT also wants to know whether the market outcome will be acceptable with respect to economic optimality. The EORM is the benchmark for establishing the sufficiency of the expected MERM, where the marginal benefits of new supply are just equal to the marginal costs of new supply.

As the left panel of Figure 1 shows, higher reserve margins are associated with higher generation capital and fixed costs of building more capacity (dark blue line). The higher costs are offset by a reduction in the frequency and magnitude of costly reliability events, such as load-shed events, other emergency events, and demand-response curtailments, and the reduced production costs (light blue line). The tradeoff between increasing capital costs and decreasing reliability-related operating costs results in a U-shaped societal cost curve (red line), with costs minimized at what we refer to as the "economically optimal" reserve margin.[14] The right chart of Figure 1 shows how we derive the "market equilibrium" reserve margin. The marginal cost of capacity is known as the "Cost of New Entry" (CONE), which depends on technology costs and economic conditions such as tax structures and remains stable across reserve margins (dark blue line). A marginal unit's net revenues from energy markets and ancillary services (light blue line) quickly decrease with less scarcity pricing at higher reserve margins. The intersection point of a marginal unit's net revenue and CONE represent the "market equilibrium" reserve margin where the marginal unit breaks even.

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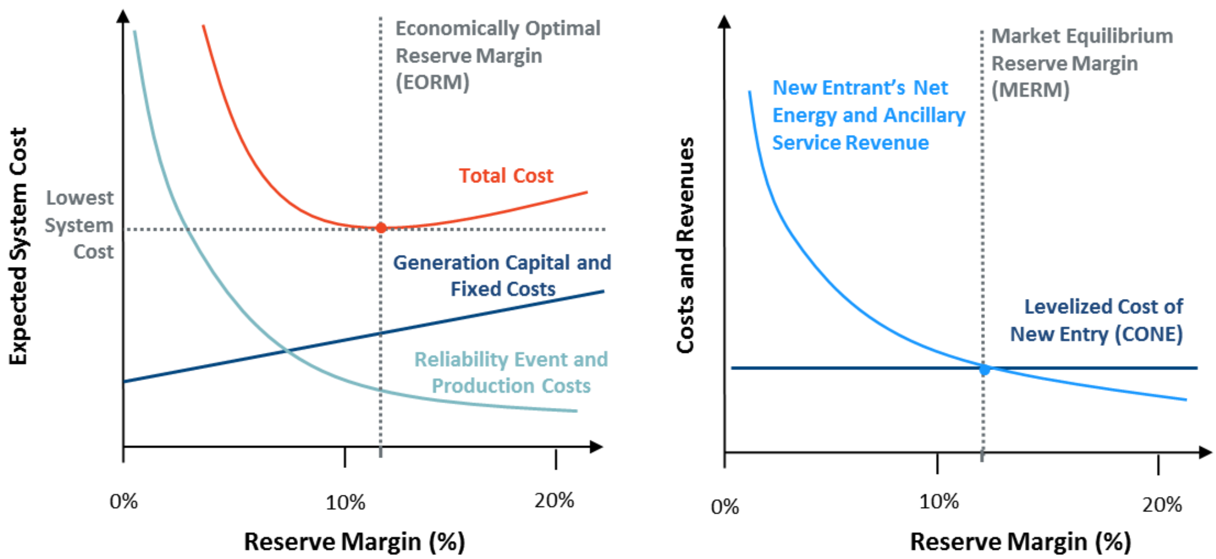
[14] In developing our approach to calculating the economically optimal reserve margin, we draw upon a large body of prior work conducted by ourselves and others, although the majority or all of this prior work was relevant in the context of regulated planning rather than restructured markets. For example, see Poland (1988), p.21; Munasinghe and Sanghvi (1988), pp. 5–7, 12–13; and Carden, Pfeifenberger, and Wintermantel (2011).

Figure 1. Economically Optimal Reserve Margin and Market Equilibrium Reserve Margin Concepts
(Illustrative Schematics, Not Simulation Results)



This study estimates the MERM and the EORM for the ERCOT market given the currently formulated scarcity pricing mechanism and expected market conditions. It estimates the reliability at each of those levels of reserves, but strictly for informational purposes since there is no reliability requirement. Our study methodology follows the ERCOT manual for estimating the EORM and MERM.[15] The primary analytical tool in this study is energy market simulations using the SERVM model. SERVM simulates hourly energy demand (under a range of weather conditions), energy production, and energy prices given the marginal cost of available supply and the Operating Reserve Demand Curve (ORDC). By analyzing the results of simulations conducted at many possible levels of investment, we can identify which of the reserve margins represents the MERM and which level represents the EORM.

This study was previously performed in 2014 and 2018. The present study incorporates updated market conditions regarding the projected resource mix, the CONE for a reference generation resource, ORDC, maintenance outages, and gas prices; different assumptions regarding weather; higher forced outage rates based on recent data; and current conventions for describing peak load and accounting for intermittent resources in expressing the reserve margin.

[15] See ERCOT (2017b).

II. STUDY ASSUMPTIONS AND APPROACH

Our simulations rely on a detailed representation of the ERCOT system, including: load and weather patterns and their probabilistic variations; the cost and performance characteristics of ERCOT's generation and demand-response resources; the mechanics of the ERCOT energy and ancillary services markets, including a unit commitment and economic dispatch of all generation resources, demand-response resources, and the transmission interties with neighboring markets. Assumptions on the generation fleet, demand-response penetration, fuel prices, and energy market design reflect expected conditions in 2024.

A. MODELING FRAMEWORK

We use the Strategic Energy & Risk Valuation Model (SERVM) to estimate the economically optimal reserve margin, the market equilibrium reserve margin, and associated reliability in the ERCOT system.[16] Like other reliability models, SERVM probabilistically evaluates the reliability implications of any given reserve margin. 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 events (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. SERVM estimates hourly and annual production costs, customer costs, market prices, net import costs, load shed costs, and generator net energy revenues as a function of the planning reserve margin. These results allow us to compare these variable costs against the incremental capital costs required to achieve higher planning reserve margins, such that the optimal reserve margin can be identified. The MERM can be identified by comparing potential new generators' net revenues to their levelized fixed costs.

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, as explained in Appendix 1. 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

[16] SERVM software is a product of Astrapé Consulting, which authored this report. See Astrapé (2020).

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 as explained further in Appendix 1.E

To examine a full range of potential economic and 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 40 weather years, 5 levels of economic load forecast error,[17] and 50 draws of generating unit performance for a total of 10,000 iterations for each simulated reserve margin case. Each individual iteration simulates 8,760 hours for the year 2024. The large number of simulations is necessary to accurately assess the reliability and economic implications of varying reserve margins. A probabilistic approach is needed to characterize the distribution of possible outcomes, particularly because the majority of reliability-related costs are associated with infrequent and sometimes extreme scarcity events. Such reliability events are typically triggered by rare circumstances that reflect a combination of extreme weather-related loads, high load-growth forecast error, and unusual combinations of generation outages.

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.[18]

B. PRIMARY INPUTS

The projected resource mixes in ERCOT have shifted and load has grown since completion of the 2018 study report. This section focuses on those changes and discusses their implications for the MERM and EORM.

Load and resource accounting for the base case is based on ERCOT's conventions in the May 2020 CDR, as summarized in column C of Table 1. Peak load is reduced for non-controllable load resources (LRs), 10-minute and 30-minute emergency response service (ERS), and Transmission/Distribution Service

[17] The five discrete levels of load forecast error we model are equal to 0%, +/−2%, and +/−4% above and below the 50/50 ERCOT load forecast.

[18] 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.

Providers (TDSP) energy efficiency and load management. On the supply side, most resources are counted toward the reserve margin at their summer ratings, except for coastal wind, panhandle wind, other wind, solar, and storage counting at 63%, 29%, 16%, 76%, and 0% of nameplate respectively, and the High Voltage Direct Current (HVDC) ties counting at approximately 31% of the path ratings, consistent with the CDR. The capacity credit estimation process for renewable resources is discussed further in section II.A.

Table 1. Components of Supply and Demand in Current 2020 Study vs. 2018 Study

	Values from 2018 Study (MW) [A]	**Re-expressed Values from 2018 Study (Using 2020 Accounting)** (MW) [B]	**Values from 2020 Study** (MW) [C]	**Difference Attributable to Accounting Changes** (MW) [B-A]	**Difference Attributable to Fundamentals Changes** (MW) [C-B]
Modelled Year	**2022**		**2024**		
Accounting Methodology Year	**2018**		**2020**		
Peak Load	**79,027**	**79,027**	**82,982**	**0**	**3,955**
Load Reduction	**2,173**	**2,173**	**2,202**	**0**	**29**
LRs serving RRS	1,119	**1,119**	1,172	0	53
10-Minute ERS	140	**140**	76	0	-64
30-Minute ERS	632	**632**	692	0	60
TDSP Curtailment Programs	282	**282**	262	0	-20
Supply	**85,919**	**86,813**	**93,979**	**894**	**7,166**
Conventional Generation	72,441	72,441	68,395	0	-4,046
Hydro	467	467	474	0	7
Wind	6,331	7,052	9,137	721	2,085
Solar	2,708	2,744	12,161	36	9,417
Storage	324*	0	0**	-324	0
PUNs	3,259	3,259	2,962	0	-297
Capacity of DC Ties	389	850	850	461	0
Reserve Margin	**11.80%**	**12.96%**	**16.34%**	**1.16%**	**3.38%**

*Notes: *The 324 MW of storage capacity represents a CAES unit. Batteries were also given 0% capacity credit in the 2018 study.*

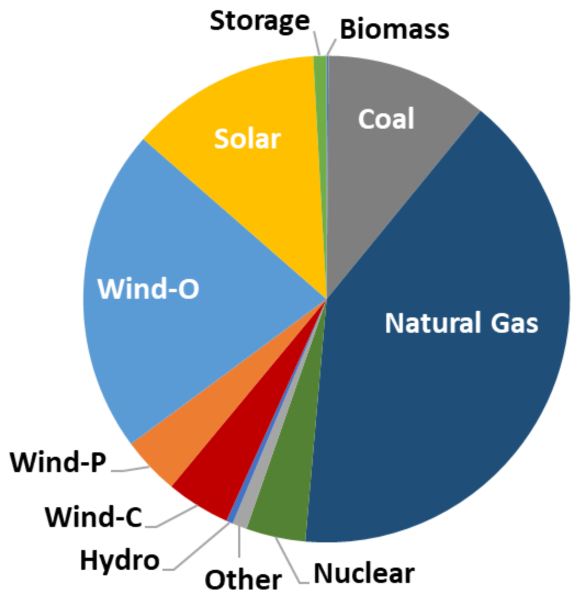
**1,103 MW of nameplate capacity of storage is included in the 2020 study but given a 0% capacity credit in the reserve margin calculation.

The base 2024 supply fleet, as summarized in column C of Table 1 is consistent with the 2020 North American Electric Reliability Corporation (NERC) Long-Term Reliability Assessment (LTRA) report.[19] The fleet summary developed by ERCOT staff for the NERC LTRA was the most recent data available when this study was developed. When compared to the 2020 CDR values for 2024, the supply fleet fluctuates by a relatively modest 129 MW of thermal capacity, 115 MW of wind, and 620 MW less of solar installed

[19] We include or exclude new units and retirements starting in the specified year and completely exclude units that have been mothballed. We model switchable units as internal resources. Data was provided, as submitted to NERC, by ERCOT staff.

capacity (reflecting reported delays in planned solar projects by developers). The composition of installed capacity in the 2020 LTRA is summarized in Figure 2.

Figure 2. Installed Capacity by Resource Type



Sources and Notes: Most recent LTRA data supplied by ERCOT staff and ERCOT, 2020a.The LTRA data was comparable to the capacities provided in the May 2020 CDR.

We conducted simulations over a wide range of reserve margins by adding or removing capacity from this supply fleet. To analyze higher reserve margins, we add gas CT capacity, assuming the characteristics shown in Table 2 below that were derived from a recent study Brattle conducted. To analyze lower reserve margins, we selectively retired coal units and excluded planned thermal units.[20] We assume the CONE for the new CT units are $93,500/MW-year.[21]

[20] More detail on the reference technology can be found in Appendix 1.B.1.

[21] The CONE value is based on the results from the 2018 PJM CONE study (Newell, *et al.* 2018a)

Table 2. Reference Technology Cost and Summer Performance Characteristics

Characteristic	Unit	Simple Cycle
Plant Configuration		
Turbine		GE 7HA.02
Configuration		1 x 0
Heat Rate (HHV)		
Base Load		
Non-Summer	(Btu/kWh)	9,138
Summer	(Btu/kWh)	9,274
Installed Capacity		
Base Load		
Non-Summer	(MW)	371
Summer	(MW)	352
CONE	($/kW-yr)	93.5

Sources and Notes: Based on ambient conditions of 92°F Max. Summer (55.5% Humidity).

On the demand side, this study starts with ERCOT's peak load forecast for 2024, and then uses hourly shapes under many possible weather patterns. We simulate each of 40 weather years, from 1980 through 2019 (with corresponding wind and solar conditions from the same years). When calculating expected values, we assume an equal probability for each year's weather. 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. (Other possibilities are considered in the Section 45. below.)

A. RENEWABLE ACCOUNTING

The CDR methodology used for determining the renewable capacity contribution is calculated by the following process:

- Wind Capacity Contribution Values: Values are calculated for three zones--Coastal, Panhandle, and Other—based on average telemetered dispatch limits (HSLs) during the highest 20 seasonal peak load hours for each season for each of the last ten years (2010-2019). They are re-calculated after each season with the new seasonal historical data. In addition to including a new Panhandle zone for calculating contribution values, another change introduced in 2019 was to use weighted averaging of the historical seasonal nameplate capacities. This approach reduces the influence of older wind turbine technologies installed in the earlier years of the estimation period, and thereby increased the contribution values relative to the ones based on the original methodology.

- Solar Capacity Contribution Values: Values are based on average telemetered HSLs during the highest 20 seasonal peak load hours for each season for each of the last three years (2017-2019).

They are re-calculated after each season with new seasonal historical data. Weighted-averaging of the seasonal nameplate capacities is also applied to the solar contribution values.

However, the value from this calculation will not match the calculated reliability contribution from SERVM simulations for the same resources. Table 3 illustrates the apparent disconnect between the reported capacity value and the true reliability contribution of renewable resources.[22]

Table 3. Potential ELCC Methods: Average Output Versus Peak Net Load Reduction

	Wind		Solar	
	Avg Output During Top 20 Load Hours (ERCOT Accounting Method)	**Peak Net Load Reduction (Modeled Reliability Contribution)**	**Avg Output During Top 20 Load Hours (ERCOT Accounting Method)**	**Peak Net Load Reduction (Modeled Reliability Contribution)**
2010	12%	8%	78%	75%
2011	24%	12%	83%	72%
2012	13%	6%	80%	72%
2013	24%	13%	82%	80%
2014	24%	16%	80%	68%
2015	18%	13%	81%	76%
2016	30%	21%	76%	71%
2017	24%	18%	75%	68%
2018	20%	16%	76%	70%
2019	27%	16%	79%	65%
Average	**22%**	**14%**	**79%**	**72%**

This disconnect means that the reserve margin needed to maintain the same reliability will shift. Since the reliability contribution is less than the average output during high gross load hours, the reserve margin will increase. This disconnect is not new. The 2018 study also used CDR accounting practices, and likewise the renewable capacity credit did not match its reliability contribution either. In order to isolate the impact of the renewable accounting on changes in MERM from the 2018 study to this study, only the incremental disconnect is quantified.

The magnitude of the incremental disconnect is about 1,800 MW or a 2% increase in reserve margin.[23] Other reserve margin accounting related changes from the 2018 study include the addition of 1,103 MW of battery storage capacity. These resources are not given any capacity credit in CDR accounting, but they

[22] The modeled peak net load reduction represents the analytical reduction in annual net load peak between gross load and gross load minus modeled wind or solar output. Other factors can affect the simulated reliability benefits of wind and solar, so the peak net load reduction is only an approximation of the reliability contribution of the respective renewable portfolios, but it is more accurate than using an average output methodology.

[23] Increase in counted wind capacity in CDR from values used in the 2018 study to those in this study was 2,728 MW. Increase in reliability contribution was approximately 950 MW, resulting in an incremental disconnect of 1,778 MW.

provide reliability benefits in the SERVM simulations, offsetting the increase in reserve margin due to renewable penetration. The net impact of the resource accounting treatment from the 2018 study to this study is an increase in reserve margin of one percentage point. For the higher renewable penetration analyzed in this study, the reserve margin accounting was normalized such that the capacity credit of incremental renewable resources matched its simulated reliability contribution. Given the complexity of reserve margin accounting and reliability contributions, ERCOT commissioned the calculation of Effective Load Carrying Capability (ELCC) for each renewable resource category to rigorously quantify the dynamic of declining capacity contributions as a function of increasing renewable penetration. This analysis is documented in Appendix 2.

B. SCARCITY PRICING AND DEMAND RESPONSE MODELING

A number of different types of demand-side resources contribute to resource adequacy and price formation in ERCOT. Table 4 summarizes these resources, explaining how we model their characteristics, their assumed marginal costs when utilized, and how they are accounted for in the reserve margin. We developed these assumptions in close coordination with the ERCOT staff, who provided assumptions regarding the appropriate quantities for modeling.

The marginal costs of these demand-side resources are highly uncertain, although the marginal costs we report in the table are in the general range that we would anticipate given the sparse data availability. Most of these resources including TDSP load management, emergency response service (ERS), and load resources (LRs) are dispatched for energy based on an emergency event trigger rather than a price-based trigger consistent with marginal cost. We use ERCOT's administrative scarcity pricing mechanism, the ORDC, to reflect the willingness to pay for spinning and non-spinning reserves in the real-time market. We make the simplifying assumption that these resources are triggered in order of ascending marginal cost, and at the time when market prices are equal to their marginal curtailment cost, as explained further in Appendix 1.E.4 below.

Energy efficiency (EE) is not explicitly modeled because the load shapes already reflect their projected impact as a function of historical energy reduction trends. These resources are appropriately accounted for using the conventions of ERCOT's CDR report as explained further in Appendix 1.A.1 below.

Two programs with overlapping response were modeled explicitly in both load and resources: four coincident peak (4CP) and price-responsive demand (PRD). Both programs had strong response in 2019 when the reserve margin was lower than typically experienced. A single model for the aggregate response was constructed to gross up the synthetic load shapes. For simulating the respective response, separate functions were developed since PRD response varies with price while 4CP is primarily expected to vary as a function of load only. At low reserve margins then, PRD response is expected to be higher with the corresponding higher prices while 4CP response is the same at all reserve margin levels.

Table 4. 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	2,884	Not explicitly modeled.	*n/a*	None	Load reduction
Load Management	262	Emergency trigger at EEA Level 1	$2,469	None	Load reduction
Emergency Response Service (ERS)					
30-Minute ERS	691	Emergency trigger at EEA Level 1	$1,372	None	Load reduction
10-Minute ERS	76	Emergency trigger at EEA Level 2	$2,469	None	Load reduction
Load Resources (LRs)					
Non-Controllable LRs	1,172	Economically dispatch for Responsive Reserve Service (most hours) or energy (few peak hours). Emergency deployment at EEA Level 2	$2,469	None	Load reduction
Controllable LRs	0	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 - $9,000/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. See corresponding sections in the Appendix for more detail.

C. STUDY SENSITIVITIES AND SCENARIOS

In addition to the base case analysis described above, we simulated three alternative scenarios and several "sensitivity" analyses to inform how the MERM and EORM could vary under different plausible conditions. The three scenarios are "High Renewables Penetration," "Storage Potential at the High Renewables Penetration," and "Lower Equivalent Forced Outage Rate (EFOR)". The high renewable penetration scenario adds much more wind and solar generation to explore the implications of understating renewable penetration in 2024 (or beyond). The storage scenario evaluates the economic potential for batteries using the renewable penetrations in the high renewable scenario. The Lower EFOR study uses the class average forced outage rate assumptions from the 2018 study to isolate the impact of more recent outage data. The assumptions for each scenario are summarized in Table 5 below.

Table 5. Description of Modeled Scenarios

Scenario Name	Base Case Assumption	Alternate Scenario Assumption	Expected EORM Impact
High Renewables Penetration	Only include CDR-eligible wind and solar from CDR	Include some of the wind and solar from the interconnection queue that has not met all requirements for CDR (15 GW of new solar, 5 GW of new wind)	Downward pressure on prices and therefore lower EORM
Storage Potential at the High Renewables Penetration	1,100 MW of battery storage	Test various battery penetrations at MERM from the High Renewables Scenario	
Lower EFOR	Last 3 years used to populate outage rates for all units	Use class average EFORs from 2018 study	2018 modeled EFOR was lower, so the reversion will decrease EORM

The other sensitivity analyses that we conducted, defined in Table 6, examine the impacts of: (a) varying the assumed cost of building new plants; (b) adjusting the value of lost load (VOLL)[24]; (c) adjusting the likelihood of recent weather years compared to historic values; and (d) varying the associated load forecast uncertainty not attributable to weather conditions.

Table 6. Definition of Non-Modeled Sensitivities

Sensitivity	Base Case Assumption	Sensitivity Range
CONE	$93.5/kW-year	-25% / +25%
VOLL	$9,000/MWh	$5,000 to $30,000/MWh
Weighting of Historical Weather Years	Equal probability assigned to all 40 weather years	Equal probability assigned to the last 15 weather years
Forward Period and Load Forecast Uncertainty	4 years	0 years to 3 years

[24] Our VOLL sensitivity adjusts the VOLL but it does not adjust the ORDC, which is set by the Public Utility Commission of Texas based on the system-wide offer cap and not directly set based on customer VOLL. Because the ORDC curve does not change, the VOLL sensitivity does not affect market prices and the MERM (which is solely based on market prices) does not change. The EORM is affected because the higher VOLL implies customers place a higher value on avoiding loss-of-load events and therefore prefer higher reserve margins, all else equal.

D. MODEL VALIDATION

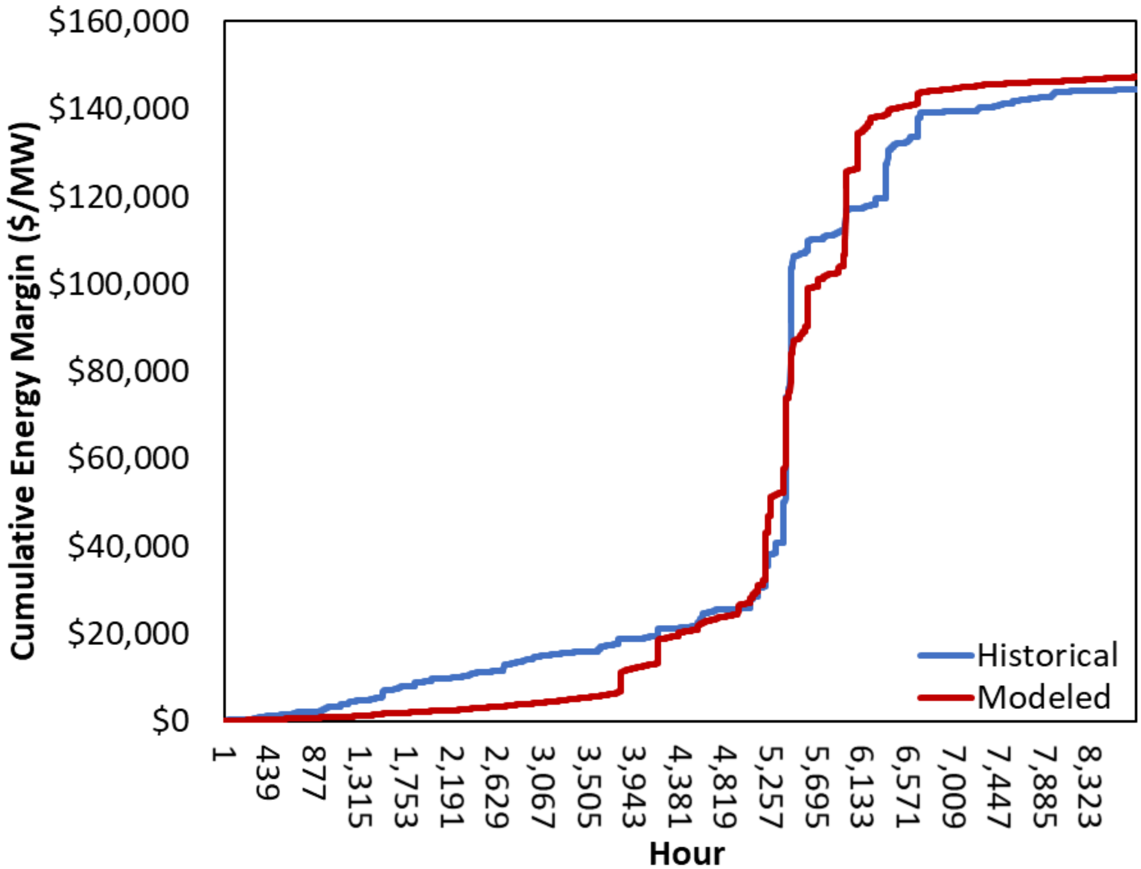
In addition to carefully constructing realistic inputs to the model, we validated that the model's outputs are reasonable by comparing them to real-world market observations. In the 2018 study, Astrapé and Brattle introduced calibration efforts to ensure modeled economic and reliability results corresponded to historical conditions. The approach primarily looked at Peaker Net Margin (PNM); careful tuning of the annual market price duration curve was not performed. Since the economics of the marginal resource were primarily influenced by hours where the market cleared above the dispatch cost of CTs, this was adequate. In the 2020 EORM study, hybrid battery and solar resources are a potential marginal resource, making the market prices throughout the year critical to the conclusions of this analysis. Also, the higher penetrations of renewable resources are expected to make low price conditions more impactful. For this calibration, a number of benchmarks were considered:

- Market price duration curve
- Monthly peak and off-peak pricing
- Scarcity pricing timing, magnitude, and frequency

The typical drivers of the market prices throughout the year are fuel prices, the underlying reserve margin, the resource mix and economic parameters of generators, and generator forced outage rates. Through the calibration process, a number of other drivers were identified including planned and maintenance outages, day ahead load and wind forecast error, and generator bidding strategies.

An example of the outcome of the SERVM calibration for 2019 is shown below in Figure 3. The chart reflects the cumulative energy margin for CTs with a 10,000 btu/kwh heat rate. The historical load, renewable profiles, and generators were input into the model. The simulations were run for five iterations of random generator outages, market support, and day ahead forecast error. Planned and maintenance outages were modeled with historical averages rather than forcing exact 2019 conditions. The modest slope in most months of the years reflect limited energy margins for CTs when scarcity is not present in the market. The steep ramp during the summer reflects the historical and modeled scarcity conditions where market prices approached $9,000/MWh. Another period of increasing energy margins starting around hour 5,800 reflects September conditions when loads remained high, but maintenance and planned outages began to take place.

Figure 3. SERVM Energy Margin Calibration for 2019



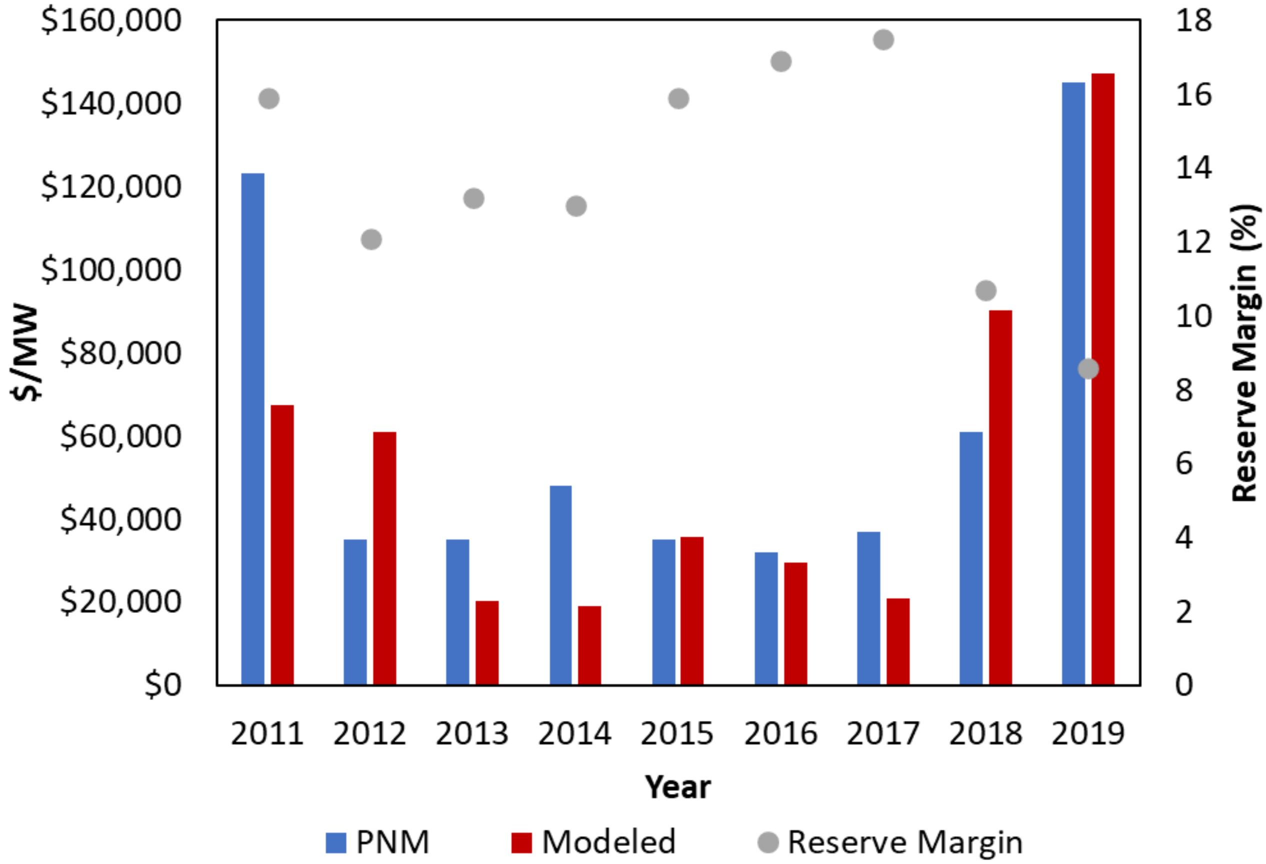
Not all years calibrated this well, but the intent of the process was not to force the model to replicate history but to understand how random drivers may influence market prices. In 2018 for instance, reserve margins were relatively low, but energy margins did not reflect significant scarcity. This was primarily driven by better than expected performance of conventional generation as shown in Table 7.

Table 7. Average Megawatts Forced Offline for Modeled Versus Historical in Top 3 Load Days of 2018

Date	Modeled Forced Outages (MW)	Historical from NERC Generating Availability Data System (MW)
7/23/2018	3,231	2,272
7/19/2018	3,383	1,891
7/20/2018	3,041	2,141

More distant history also did not calibrate as well. In 2011-2014, the modeled energy margins were mostly lower than those experienced in history. This may be due to the retirement of old generating capacity with high heat rates that may have set market prices for some hours in those years. Figure 4 below compares the simulated and historical CT net energy revenues for 2011 to 2019.

Figure 4. Modeled vs. Actual Combustion Turbine Net Energy Revenues



Future enhancements to the commitment and dispatch practices in ERCOT were not captured in these simulations. Significant price reduction benefits of more advanced optimization have been quantified by the Independent Market Monitor for ERCOT.[25] If these benefits are realized, the MERM would likely shift downward.

[25] See Puct 2019b.

III. RESULTS

This section first presents the results of our study under base case assumptions, including the estimated 2024 MERM and EORM and the associated reliability statistics, and then describes how the results could differ under alternative market conditions captured in the scenarios and sensitivities described above. This section explains why the MERM and EORM results differ with respect to the result from the 2018 study.

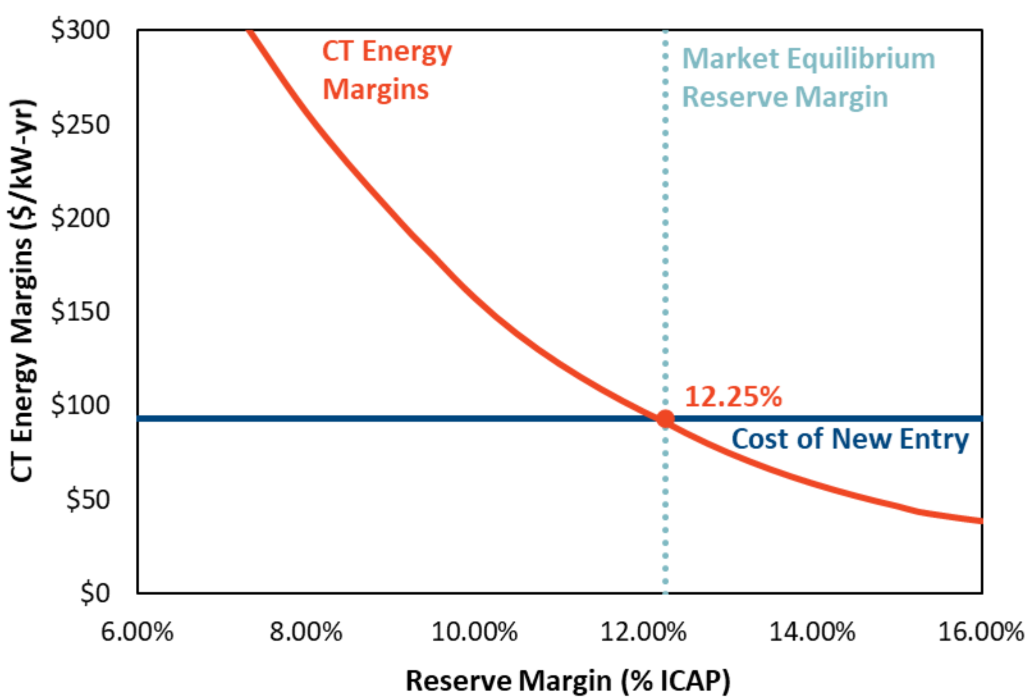
A. MARKET EQUILIBRIUM RESERVE MARGIN

We describe here the anticipated equilibrium conditions under ERCOT's current market design by: (1) estimating the market equilibrium for our base case assumptions and several sensitivity cases; (2) summarizing the volatility in realized prices and net revenues across reserve margins; and (3) describing the likely year-to-year variation in realized reserve margins.

1. AVERAGE EQUILIBRIUM RESERVE MARGIN

As described above, the MERM occurs at the level of capacity where the net revenues of new capacity from our simulations just equal the marginal costs of capacity, which is equal to CONE. As shown in Figure 5 below, CT net energy revenues tend to decrease with higher reserve margins due to lower energy prices and few scarcity hours that occur when there is additional supply available on the system. We find that the MERM, where marginal costs of new capacity intersect with the marginal revenues for that capacity, is 12.25%.

Figure 5. ERCOT Projected 2024 Market Equilibrium Reserve Margin



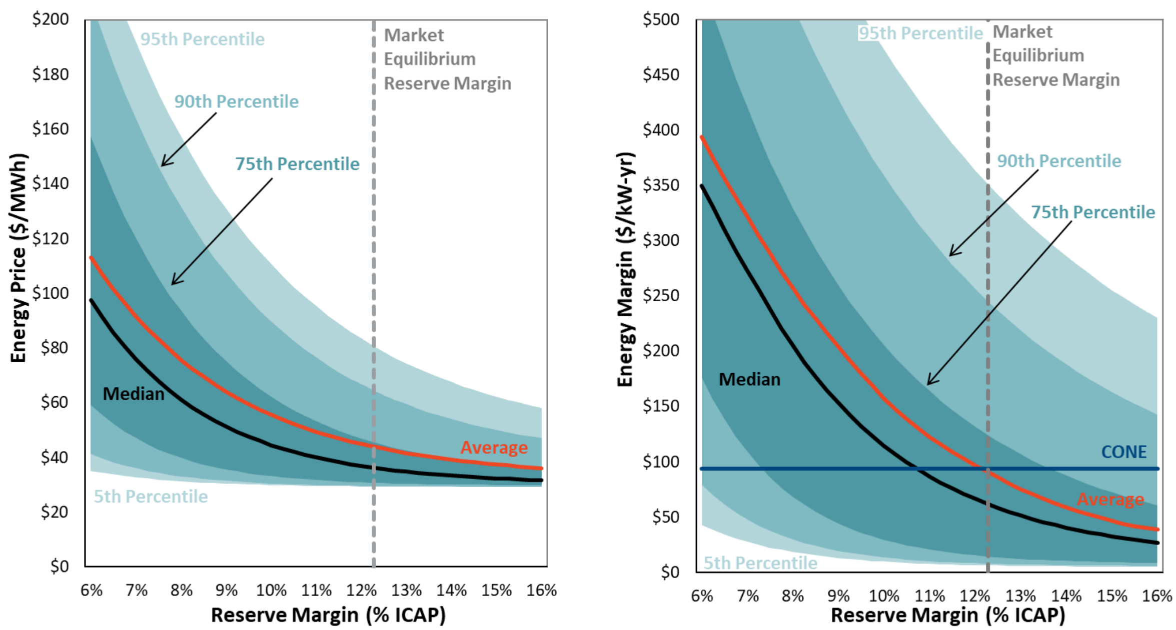
However, the single average MERM of 12.25% does not provide a complete story of the expected reliability of the ERCOT system or the expected revenues for new entrants. In the remainder of this section we discuss the volatility in realized prices in our simulations and the year-to-year variability in the reserve margin. In Section 0 we compare this market equilibrium to an economically optimal reserve margin, and in Section C we examine the sensitivity of our analysis to uncertainties in future market conditions.

2. VOLATILITY IN REALIZED PRICES AND GENERATOR REVENUES

Our estimate of the average MERM is strongly influenced by the assumed peak load and generator outage probability distributions, especially the most extreme scarcity events at the tails of those distributions. As the reserve margin declines, these tails become more likely to produce scarcity resulting in high prices, high system-wide costs, and high generator margins.

Figure 6 shows the range of annual energy prices (left) and marginal unit net energy revenues (right) for the base case across the reserve margins analyzed.[26] The upper percentile curves show that prices and supplier margins in the tails of the distribution can be much higher in any given year than their median or overall weighted average values.

Figure 6. Distribution of Spot Energy Prices (Left) and Net Energy Revenues for a Marginal Unit (Right)



Note: Marginal Unit Net Energy Revenues represent net revenues from added CTs.

The years reflected in the tails of the distribution have a substantial effect on the MERM. For example, at the base case MERM value of 12.25%, we estimate that once per decade (90th percentile) energy prices would exceed \$65/MWh (78% higher than the median price at this reserve margin). Once every two

[26] Marginal Unit Net Energy Revenues represent net revenues from added CTs.

decades (95th percentile), prices would exceed $81/MWh (123% above the median price). Similarly, new gas plant net revenues in the median year are only $62/kW-year, which is just 66.5% of CONE, but occasional high-priced years would elevate the average to CONE. Assuming full exposure to spot market prices (*i.e.*, no hedging) net revenues of marginal units would exceed $246/kW-year (about 2.6 times CONE) once in a decade (90th percentile) and $353/kW-year (about 3.8 times CONE) once every two decades (95th percentile).[27] All simulation results reflect scarcity pricing rules that reduce the systemwide offer cap from $9,000/MWh to $2,000/MWh when net operating profit exceeds three times the cost of new entry (assumed at $93.5/kw-yr).

3. YEAR-TO-YEAR RESERVE MARGIN VARIABILITY

The uncertainty in future load growth can have significant impacts on reserve margins and reliability. Our base case simulations assume that the market invests based on the expected load growth and resulting prices on a four-year forward basis. However, realized load growth will generally differ from four-year expectations, resulting in a range of reserve margins that differ from the equilibrium reserve margins shown above.

We simulate this effect by assuming alternative load growth projections based on the distribution of non-weather forecast error in projecting future load, as described in Appendix 1.A.1 below. Even if the four-year-ahead planning reserve margin is exactly at the market equilibrium of 12.25%, realized shorter-term planning reserve margins can be higher or lower as load growth uncertainty resolves itself over the next four years. The planning reserve margins projected going into each summer would thus vary around the equilibrium from 10.7% to 13.8% in 50% of all years and drop below 9.25% approximately once per decade (i.e., below the 10th percentile). Once weather-related load fluctuations are considered as well, after-the-fact realized reserve margins will vary even more substantially and will drop below 9.4% approximately once per decade (i.e., below the 10th percentile). However, realized reserve margins, particularly the lows that largely reflect realized weather extremes, should not be compared to more familiar planning reserve margin benchmarks.

Variability in reserve margins may be moderated by short lead-time resources (including switchable units, mothballs, uprates, and demand response) that can exit or enter the market as expectations change between four years forward and delivery. By not simulating the effects of market exit and entry by short-term resources, our results would tend to overstate the range of realized reserve margins. However, our simulations do not account for the countervailing effects of additional supply-side uncertainties, such as unanticipated retirements, construction delays, and lumpiness in uncoordinated new entry, which would tend to increase the variability of reserve margins. Furthermore, uncertainties about anticipated fuel prices, the capacity contribution of renewables, and other modeling assumptions would further widen the

[27] However, generators are generally not fully exposed to spot markets, since they hedge by selling most of their output in forward markets. Forward prices reflect *ex ante* market expectations of all possibilities rather than spot realizations. Selling forward dramatically smooths revenues closer to the expected values we estimate.

distribution of realized reserve margins. Overall, we estimate that with a four-year forward period, load forecast uncertainty would result in equilibrium reserve margins ranging from 9.25% to 15.25% (10^{th} to 90^{th} percentiles).

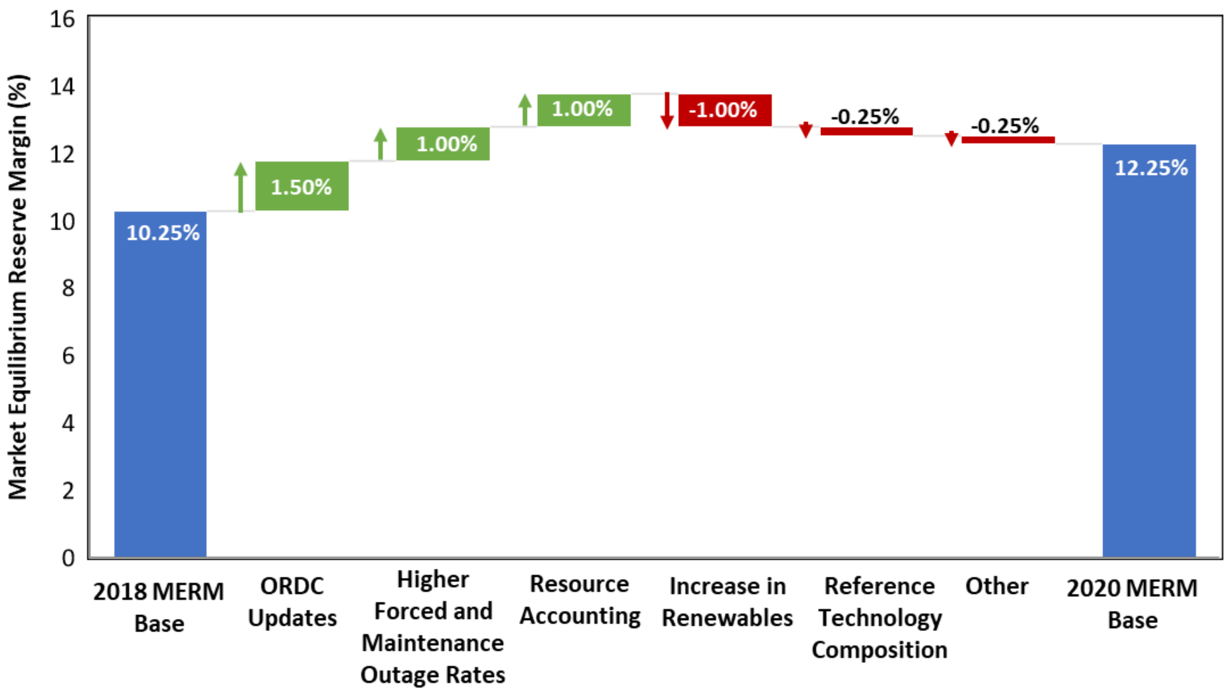
4. COMPARISON TO 2018 STUDY RESULTS

The 2018 study estimated a market equilibrium reserve margin for 2022 of 10.25%, which is 2.00 percentage points lower than current base case results of 12.25%. There are several offsetting factors that result in a 2.00% net change in the MERM, shown in Figure 7 below. While changes in the ORDC and forced outage rate assumptions increase the MERM, these changes are somewhat offset by an increase in renewables, and a change to the reference technology from a blended CT and combined-cycle to just a CT.

The largest drivers that had upward effects on the MERM are the higher ORDC, the higher forced outage rates for conventional generators, and renewable accounting procedures. The economic effects of higher renewable penetration and the composition of the reference technology reduced the MERM. While sensitivity simulations were not performed to assess the implications for a change in reference technology to an alternative gas-fired technology, the small difference in capital costs between combined cycles and combustion turbines is likely slightly more than offset by the production cost savings of the more efficient technology. This likely contributes to a small reduction in the MERM.

Since the base case uses the renewable accounting methodology applied in ERCOT's CDR development process, any discrepancy between the renewable capacity in the CDR and the reliability contribution in the simulations will also affect the MERM. The largest discrepancy between the capacity credit for incremental resources was for wind resources. The net change in capacity credit for wind in the CDR between the two studies was 2,806 MW, while the reliability contribution of wind only changed by 1,142 MW in the SERVM simulations. Offsetting this effect was the fact that storage resources were not given any capacity credit in the CDR, but in the simulations they did provide reliability value. The net effect of these accounting practices is a 1.00% increase in MERM.

Figure 7. Drivers of the Market Equilibrium Reserve Margin Change from 2018 to 2020 Study



Given the MERM in this study is 2.00 percentage points higher than the MERM found in the 2018 study, intuition suggests that ERCOT would be more reliable at MERM now. However, since the one percentage point increase in forced outage rates and one percentage point renewable accounting impact do not correspond to reliability improvements, projected reliability actually stayed the same between the 2018 study MERM and the 2020 study MERM. Absent the administrative boost to ORDC prices, reliability would have degraded at MERM. Since the effects reducing MERM are projected to escalate with additional renewable, it will be important to carefully monitor projected reliability going forward.

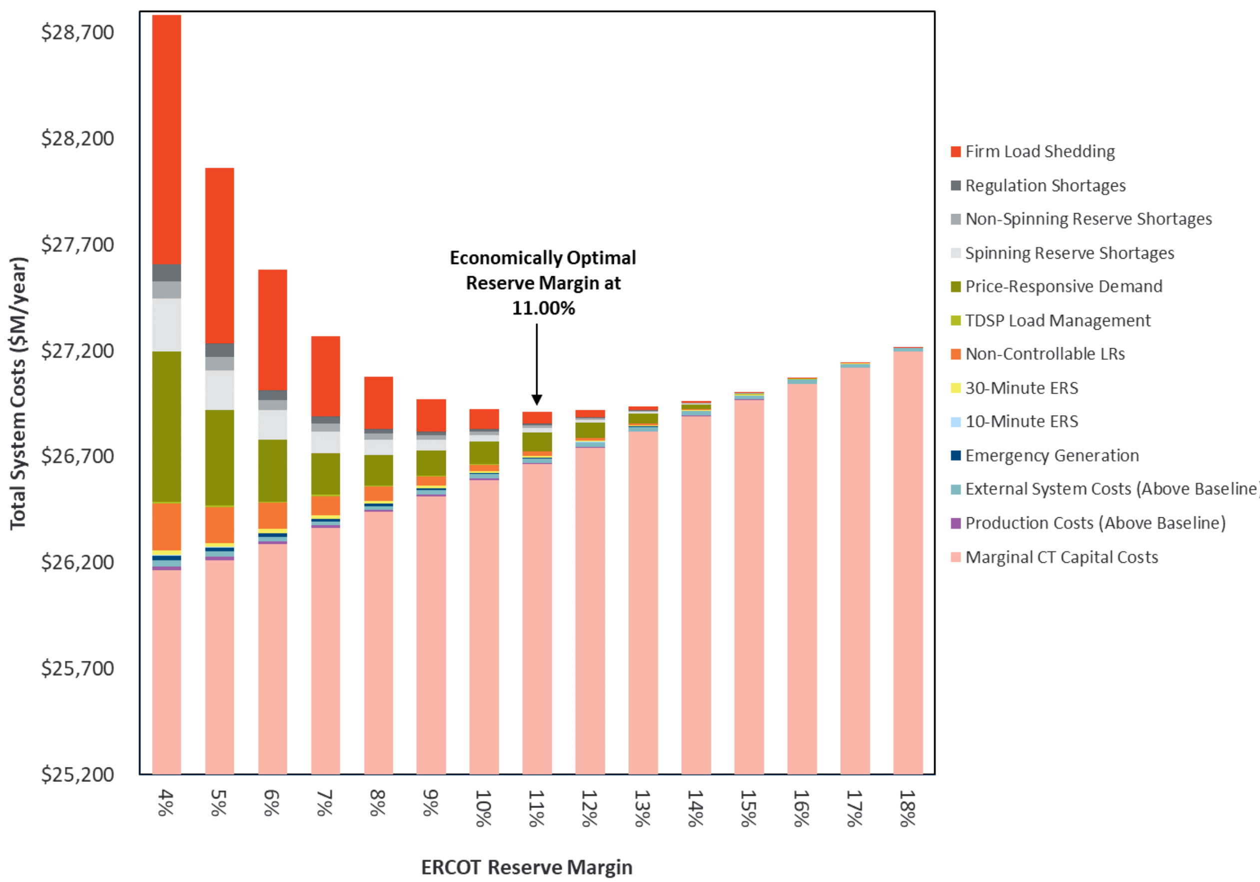
B. ECONOMICALLY OPTIMAL RESERVE MARGIN

1. SYSTEM COST-MINIMIZING RESERVE MARGIN

The EORM is the level of capacity that minimizes total system capital and production costs. As shown in Figure 8 below, we estimated the annual average of reliability-related costs over a range of planning reserve margins and found the EORM under base case assumptions to be 11.00%.

At the lowest reserve margins analyzed, the average annual reliability costs are high, driven by the cost of firm load shedding (red bar), regulation and reserve scarcity (grey bars), and production costs of emergency and conventional resources. As reserve margins increase, total reliability costs drop due to the decrease in scarcity events and production costs. These costs decrease more quickly than the increases in capital costs associated with adding additional CTs resulting in a decrease in total system costs. This continues at higher reserve margins until the "economically optimal" quantity of capacity has been added at a reserve margin of 11.00%. After crossing this minimum cost point, the capital costs of adding more CTs exceed the benefits from reducing reliability-related costs, so total costs increase.

Figure 8. Total System Costs across Planning Reserve Margins



Notes:

Total system costs include a large baseline of total system costs that do not change across reserve margins, including $13.4B/year in transmission and distribution (assumption not updated from 2018 study), $7.5B/year in external system costs, and $5.2B/year in production costs.

The total cost curve shown above has a shape similar to those we have observed in value-of-service studies for many other electric systems.[28] The curve is relatively flat near the minimum average cost point, indicating that expected total costs do not vary substantially between reserve margins of 10%–12%. However, the lower end of that range (10%) is associated with much more uncertainty in realized annual reliability costs, which we discuss in the next section, and a much larger number of severe, high-cost reliability events. At the 12% reserve margin, a greater proportion of total annual costs is associated with the costs of adding new units (which has less uncertainty), and a smaller proportion of the average annual costs are from uncertain, low-probability, but high-cost reliability events.[29] One notable difference from

[28] For example, see Poland (1988), p.21; Munasinghe and Sanghvi (1988), pp. 5–7 and 12–13; and Carden, Pfeifenberger, and Wintermantel (2011).

[29] Reliability across planning reserve margins is discussed in Section 1.

the components of the EORM curve is the smaller magnitude of production cost savings. Since CTs have relatively high dispatch costs, increasing penetration does not provide much incremental production cost savings. While there is significant capacity in ERCOT with dispatch costs higher than that of the marginal CT additions, the differential is dwarfed by the difference in costs between CTs and the emergency products. At the capacity factor of the marginal CTs of 9%, a cost differential of $8/MWh between the CT and an older gas generator would produce annual savings of only $6/kw-yr. In contrast, avoiding a single hour of firm load shed would provide $9/kw-yr. Since there are several emergency categories that are activated multiple times per year when the system reserve margin is near the EORM, the economic benefits of the CT are more concentrated in emergency savings than in production cost savings.

At each reserve margin level in Figure 8, we show the weighted-average costs across all 10,000 annual simulations for several components of system costs that change with reserve margins. We estimated each of the components of system costs based on the following assumptions:

- **Marginal CT Capital Costs** are the annualized fixed costs associated with building CT plants at a cost of $93.5/kW-year in the Base Case.
- **Production Costs (Above $5.2 billion per year Baseline)** are total system production costs of all resources above an arbitrary baseline cost of $5.2 billion. We show only a portion of total system costs as an individual slice on the chart in order to avoid having production costs dwarf the magnitude of other cost components and subtract the same $5.2 billion at all reserve margins shown. Production costs decrease at higher reserve margins because adding efficient new gas CTs reduces the need to dispatch higher-cost peakers.
- **External System Costs (Above Baseline)** include production and scarcity costs in neighboring regions above an arbitrary baseline, which drop by a small amount with increasing reserve margins because ERCOT will rely less on imports from high-cost external peakers during internal scarcity events, and may be able to export more supply during external scarcity events.[30]
- **Emergency Generation** is the price-driven dispatch of units outputting at high levels above their summer peak ratings at an assumed cost of $1,372/MWh, see Appendix 1.E.3.
- **10-Minute and 30-Minute ERS** is the cost of dispatching these resources during emergency events at assumed costs of $2,469 and $1,372/MWh for 10-minute and 30-minute ERS respectively, see Appendix 1.C.1.
- **Non-Controllable LR** costs reflect the cost of administratively re-dispatching LRs from supplying Responsive Reserve Service (RRS) to supplying energy at a cost of $2,469/MWh during emergencies, see Appendix 1.C.2.

[30] The baseline level of external production costs is not included in our total system cost. This differs from our reporting of ERCOT-internal production costs, for which we do include baseline costs (that do not vary with reserve margin) in order to produce a meaningful total cost estimate for the ERCOT system.

- **TDSP Load Management** costs are incurred when ERCOT administratively orders these demand-side resources to curtail during emergencies at an assumed cost of $2,469/MWh, see Appendix 1.E.2.
- **Price Responsive Demand** costs are determined by the hourly market price in the hours during which the demand response occurred.
- **Spinning and Non-Spinning Reserve Scarcity** costs are calculated as the area under the ORDC curve, calculated assuming load would be shed at X = 1,000 MW, see Appendix 1.E.4.
- **Regulation Scarcity** costs are calculated according to the Power Balance Penalty Curve (PBPC) assuming that this curve accurately reflects the marginal cost of running short on regulating reserves, see Appendix 1.E.5.
- **Firm Load Shedding** costs are the customer costs imposed during load-shed events at a cost at the assumed VOLL of $9,000/MWh.

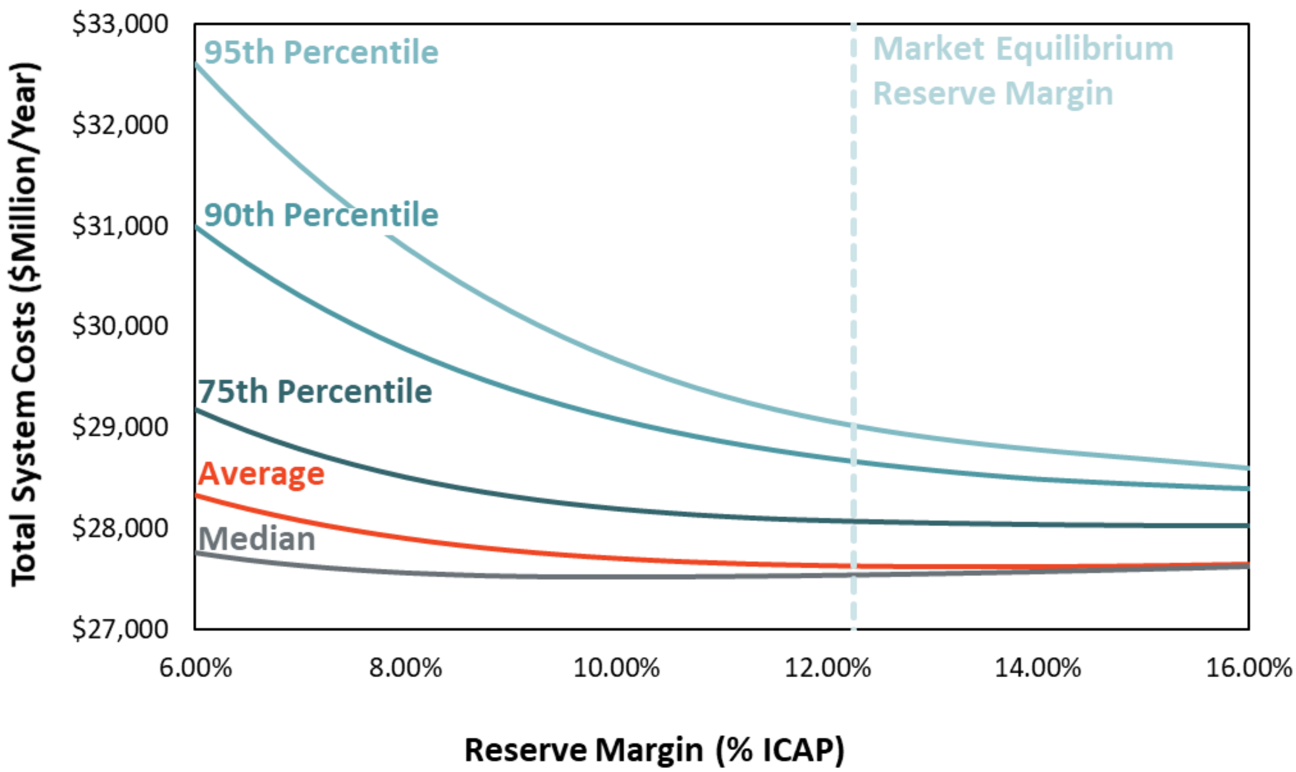
2. EXPOSURE TO EXTREME SCARCITY EVENTS

The economic results shown above assume risk neutrality with respect to the uncertainty and volatility of reliability-related costs. Figure 8 compares total costs at different reserve margins as the probability-weighted average of annual reliability costs for all 10,000 simulation draws. However, there is substantial volatility around the average level of possible reliability cost outcomes. Most simulated years will have very modest reliability costs, while a small number of years have very high costs. These high-cost outcomes account for the majority of the weighted-average annual costs shown as the individual bars in Figure 8 above.

Figure 9 below summarizes this risk exposure by comparing the weighted-average costs for different reserve margins (red line, which is equal to the height of the individual bars in Figure 8) to annual costs under the most costly possible outcomes, represented by the 75th, 90th, and 95th percentiles of annual reliability costs across all 10,000 simulated scenarios.

Considering the higher-cost uncertainty exposure at lower reserve margins, some policymakers prefer reserve margins to exceed the risk-neutral economic optimum. As the simulation results show, a several percentage point increase in the reserve margin would only slightly increase the average annual costs, but more significantly reduce the likelihood of experiencing very high-cost events. Total average costs change by a relatively modest amount over a range of planning reserve margins (*e.g.*, average system costs increase by just $5 million with an increase in reserve margin from 10% to 15%). However, lower planning reserve margins have a significantly larger uncertainty in reliability costs and the likelihood of high-cost outcomes than can be encountered in any particular year. For example, at a 7% reserve margin, costs are expected to be $2.2 billion higher than average once every ten years, while at 11% they would increase with a similar frequency by $1.2 billion.[31]

Figure 9. Year-to-Year Possible Realizations of Total Annual System Costs



Notes:

Total system costs include scarcity-related and production costs (that decrease with reserve margin), generation capital costs (that increase with reserve margin), and T&D costs (which remain constant across reserve margins. Additional detail on the individual components of total system costs is available in Section 1.

C. SYSTEM RELIABILITY

In this section, we compare the expected reliability of the market equilibrium reserve margin to traditional reliability metrics.

1. PHYSICAL RELIABILITY METRICS

At a market equilibrium reserve margin of 12.25% ERCOT can expect a probability-weighted average of 0.5 loss-of-load events (LOLE) per year. Our simulations find that there is likely to be a loss-of-load event about every two years in the range of 1,541 MW of load being shed for 2.9 hours on average, for a total expected unserved energy of 4,507 MWh.[32] Such events would be more frequent, longer, and deeper at lower reserve margins and less so at higher reserve margins. Figure 10 depicts how three physical

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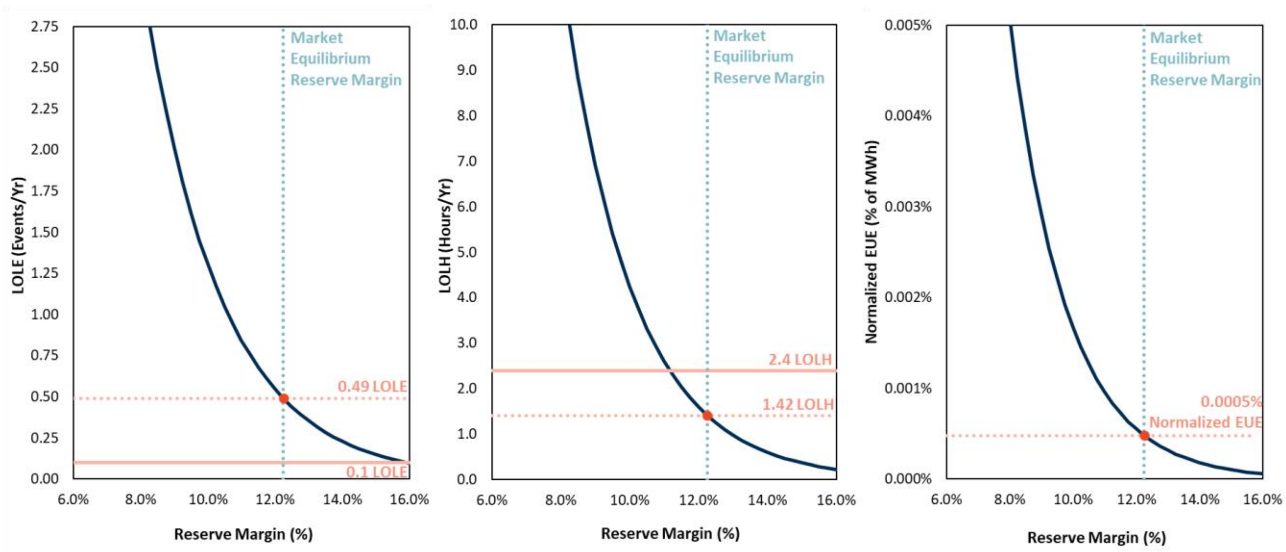
[31] These values are calculated as the difference between the weighted average and 90th percentile total system costs at 7% and 11% reserve margins.

[32] Load, duration, and energy are calculated for each firm load shed event which occurs approximately once every two years. The LOLH and EUE in Figure 10 are annual metrics.

reliability metrics vary with reserve margin: (1) LOLE on the left; (2) loss of load hours (LOLH) in the middle; (3) Normalized Expected Unserved Energy (EUE) on the right.[33]

Figure 10. Reliability Metrics that Vary with Reserve Margins

(a) LOLE *(b) LOLH* *(c) EUE*



Notes: Reflects Base Case assumptions, including 4-Year Forward LFE, and equal weather weights of all 40 weather years.

Table 8 shows the same information in tabular form, along with additional information describing the magnitude of outage events when they occur.

[33] For our simulations, the reported reliability metrics are the mean for 10,000 simulations (40 weather years, 5 load error levels, 50 outage draws). A LOLE event is recorded for each day with at least one hour of lost load. LOLH is calculated as the total hours in the simulation with lost load, without accounting for persistence of a particular outage event. Normalized EUE is calculated as the expected quantity of unserved energy over the year divided by the net energy for load multiplied by 1,000,000.

Table 8. Detailed Reliability Metrics across Planning Reserve Margins in Base Case

Reserve Margin (%)	Total Annual Loss of Load			Average Outage Event		
	LOLE (events/yr)	LOLH (hours/yr)	EUE (MWh)	Duration (hours)	Energy Lost (MWh)	Depth (MW)
4%	17.61	79.45	209,338	4.51	11,890	2,635
5%	11.41	48.76	120,154	4.27	10,532	2,464
6%	7.39	29.93	68,964	4.05	9,329	2,304
7%	4.79	18.37	39,583	3.83	8,264	2,155
8%	3.10	11.27	22,720	3.63	7,320	2,015
9%	2.01	6.92	13,040	3.44	6,484	1,885
10%	1.30	4.25	7,485	3.26	5,744	1,762
11%	0.84	2.61	4,296	3.09	5,088	1,648
12%	0.55	1.60	2,466	2.92	4,507	1,541
13%	0.35	0.98	1,415	2.77	3,992	1,441
14%	0.23	0.60	812	2.62	3,536	1,348
15%	0.15	0.37	466	2.49	3,132	1,260
16%	0.09	0.23	268	2.35	2,775	1,179
17%	0.06	0.14	154	2.23	2,458	1,102
18%	0.04	0.09	88	2.11	2,177	1,031

Most US areas set reliability metrics on the "1-in-10" standard, *i.e.*, a probability-weighted average of 0.1 loss-of-load events (LOLE) per year.[34] Under base case conditions a 15.75% reserve margin would be required to achieve 0.1 LOLE, which is 3.5 percentage points higher than MERM.

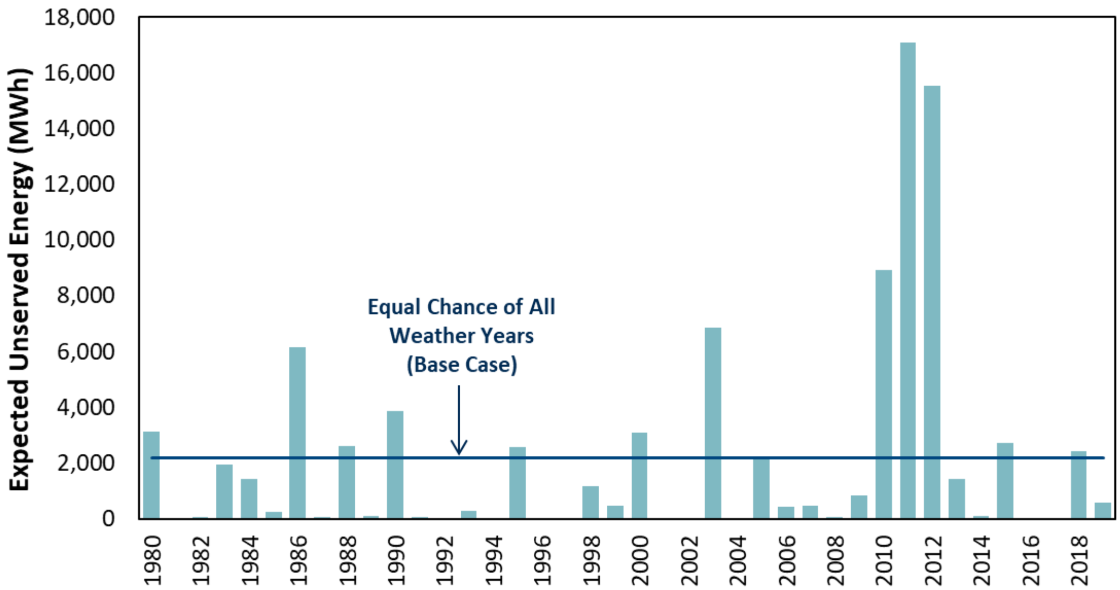
All of the reliability metrics shown above reflect the average over many possible outcomes at a given reserve margin. Average statistics provide a convenient summary of a large amount of data, but they can obscure the wide distribution of possible outcomes around the average, as shown in the sections above. Realized reliability in any given year will depend strongly on the weather and on generation availability.

To illustrate the distribution of possible outcomes, Figure 11 below shows how reliability varies with weather, as measured by the annual expected unserved energy. The teal bars show the total MWh of load shed during each of the 40 weather years for the Base Case simulations at a 12.25% reserve margin corresponding to the market equilibrium reserve margin. The reoccurrence of 2011 weather conditions could lead to almost 17,080 MWh of expected involuntary curtailment of firm load, far above the equal-probability-weighted average of 2,171 MWh over all 40 years depicted by the blue horizontal line. By contrast, 25 out of the 40 years have much milder weather, with substantially less load shed than the average. Thus, the actual reliability will vary. In addition, the expected value of reliability would differ if

[34] LOLE standards refer only to loss-of-load events due to shortages of bulk power supplies. Customer outages caused by disturbances on distribution infrastructure are much more frequent and longer in duration.

different probability weights were assigned to the various weather patterns, as discussed in the next section.

Figure 11. Expected Unserved Energy by Weather Year at 12.25% Reserve Margin



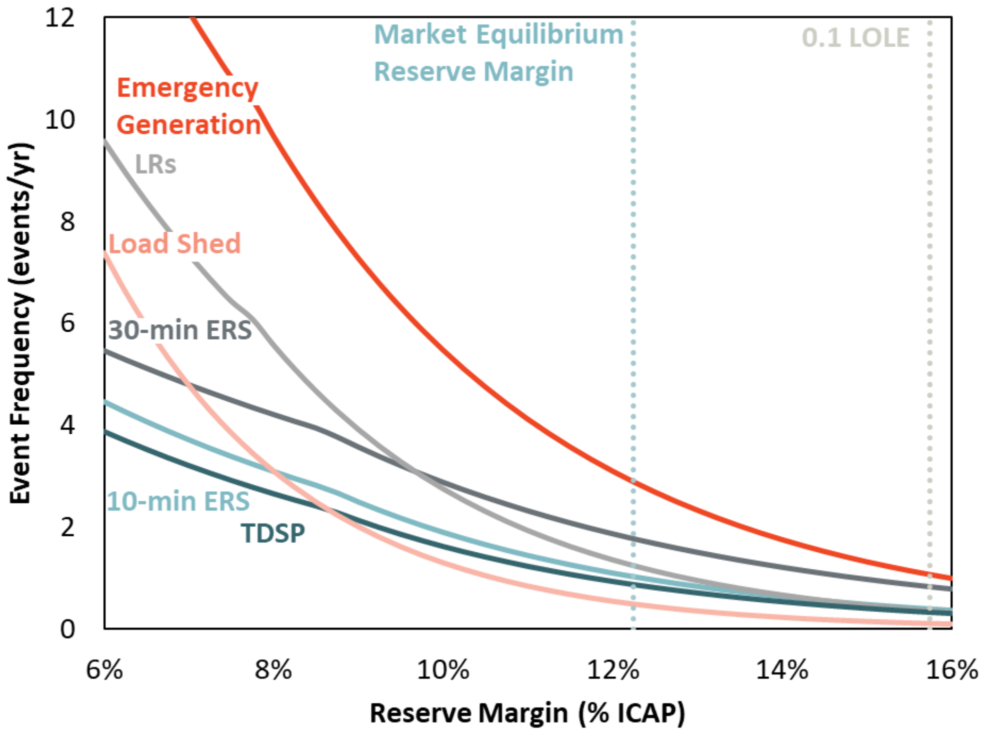
Notes: Figure reflects Base Case 4-Year forward LFE assumption and the Base Case equal weather weight for all 40 years.

2. EMERGENCY EVENT FREQUENCY

Figure 12 summarizes the frequency of six types of emergency events for the base case simulations as a function of the reserve margin. The emergency events, in increasing order of severity, are: (1) the economic dispatch of emergency generation (red line); (2) calling 30-minute ERS (dark gray line); (3) calling TDSP load curtailments (dark blue line); (4) re-dispatching LRs from RRS to energy (light gray line); (5) calling 10-minute ERS (light blue line); and, finally, (6) shedding firm load (light red line). As shown, at a 15.75% reserve margin corresponding to 1-event-in-10-years (0.1 LOLE), emergency generation would be dispatched approximately one time a year on a weighted-average basis across all simulated years. At a reserve margin of 8.5%, the system faces two load shed events per year on average, most years without load shed events and some years with several. At the same 8.5% reserve margin, the various types of demand resources would have to be called from two to four times on average each year (depending on the resource type), and emergency generation would be dispatched approximately nine times on average each year. At the market equilibrium reserve margin of 12.25%, emergency generation would be dispatched about three times on average per year, and other demand resources would average about one time per year.

All types of emergency events become more frequent at lower reserve margins, but the frequency of load shed and emergency generation decline faster than several of the other categories of emergency events. Some of the emergency products in ERCOT are summer-only so any reliability events that occur in non-summer months will only entail emergency generation and load shed.

Figure 12. Average Annual Frequency of Emergency Events



Notes: Results from Base Case (4-Year Forward LFE, equal weighting of weather years).
Inflections in the series data reflect the fact that some emergency procedures are not available in all seasons or they have other call constraints.

D. SENSITIVITY OF MARKET EQUILIBRIUM RESERVE MARGIN TO STUDY ASSUMPTIONS

If investors have different beliefs about load and other factors affecting revenues, or if they face different costs, the MERM could differ from our estimates. Here we examine several important uncertainty factors affecting the MERM, including: (1) the amount of intermittent renewable generation installed; (2) the reference technology moving to four-hour battery storage; (2) the forced outage rate of conventional generators; (3) the assumed cost of building new natural gas-fired plants; (3) the value of lost load; (4) the assumed probabilities of the historical weather years used to model hourly loads and renewable generation; (5) and load forecast uncertainty.

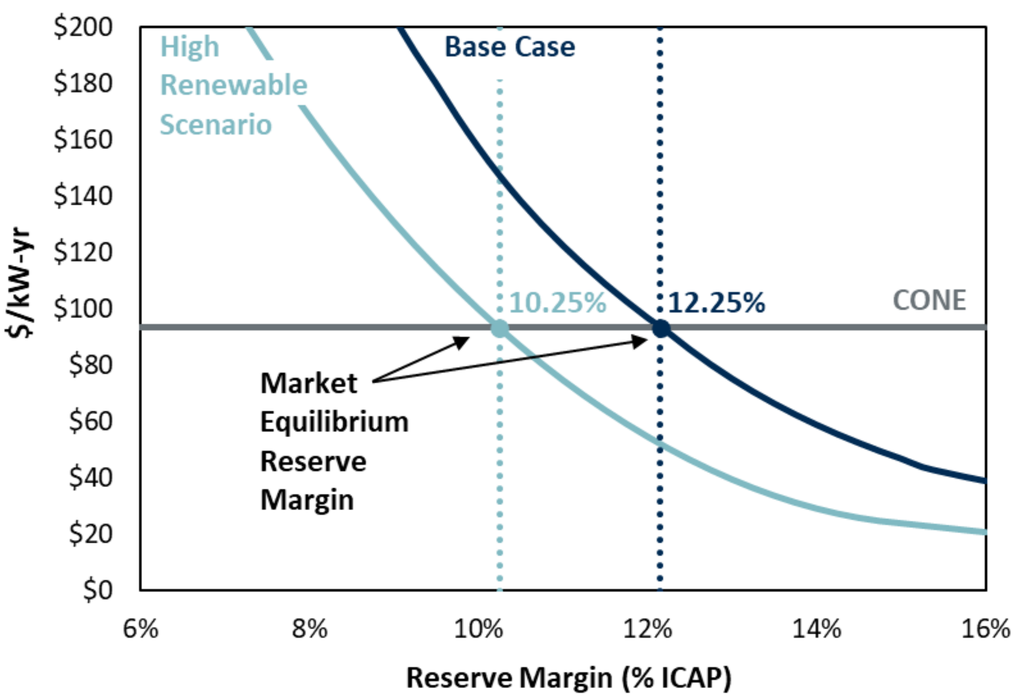
Changing the values for these variables over a plausible range results in market equilibrium reserve margins ranging from 10.25% to 13.25%. The actual uncertainty could be even wider, however, when considering other possibilities such as extreme weather events, broader distributions of intermittent renewable generation coinciding with the highest load years (rather than always taking the 2011 wind patterns with 2011 loads, for example), or different beliefs about future market and regulatory conditions. This range of equilibrium reserve margins would produce a range of reliability outcomes, which we estimate to be 0.32 to 1.17 LOLE.

1. RENEWABLES PENETRATION SCENARIOS

The base case analysis assumes 37.4 GW of wind and 16 GW of solar online by 2024, based on the existing fleet and planned resources that have met the criteria to be included in the CDR. Our alternative "High Renewables" scenario adds wind and solar capacity that has not yet met all the requirements to be included in the May 2020 CDR, resulting in an additional five GW of wind and 15 GW of solar.

All else equal, adding renewable generation would decrease prices; but lower prices should force out conventional generation, until the market re-equilibrates at approximately the same reserve margin. However, we do estimate that equilibrium reserve margins would decrease slightly with higher renewable penetration because the net load duration curve becomes steeper. A steeper net load duration curve causes prices to fall faster from the peak hour. That would reduce generators' net revenues, so reserve margins have to tighten slightly to re-equilibrate, with a slight increase in high-priced ORDC hours. As discussed in the Executive Summary, the load shape impact of increasing renewables is becoming significant given projected 2024 penetrations. Solar capacity additions to date have not materially steepened the net load shape since solar afternoon output has not reduced the net load below the load after sunset. Once the net load in late afternoon hours is below the post-sunset net load, subsequent additions of solar will make the net load much steeper late in the day. This steep net load shape means that few hours will be close to the daily peak load, and correspondingly few hours will be close to the annual peak load. In the 2018 study, the High Renewables scenario reduced the MERM by 1 percentage point. In this study, a commensurate 20 GW increase in renewable capacity reduces the MERM by 2.00 percentage points, as illustrated in Figure 13.

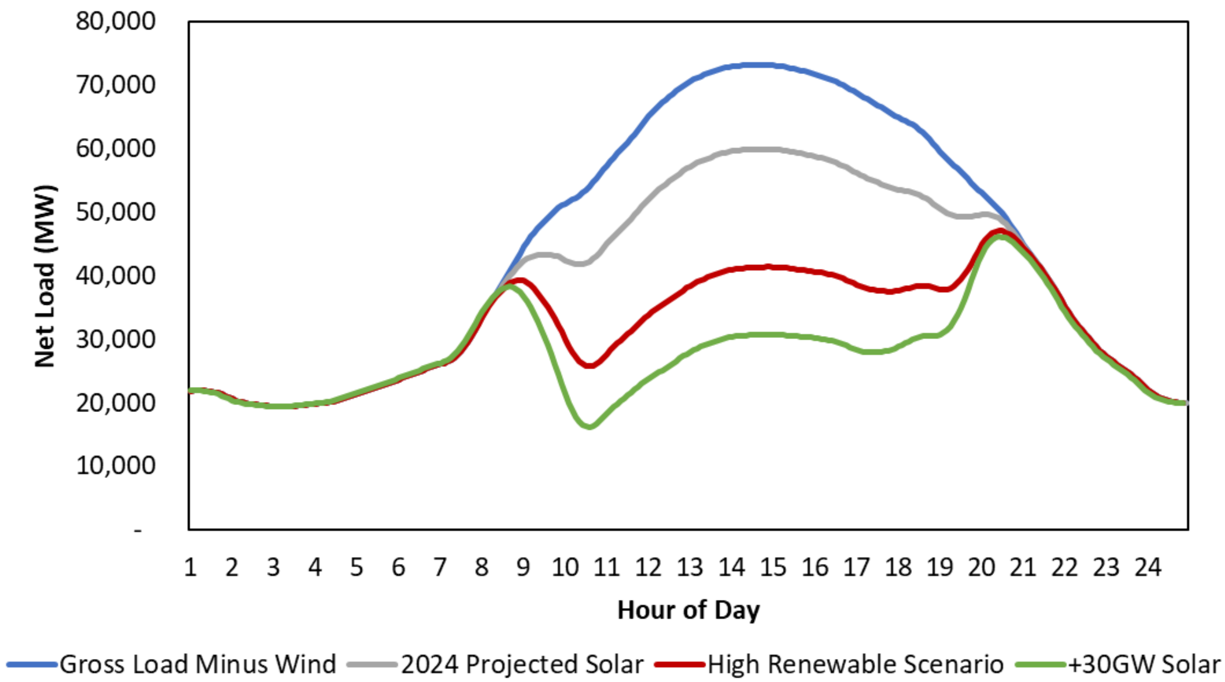
Figure 13. Market Equilibrium Reserve Margin Sensitivity to Renewable Penetration



2. STORAGE POTENTIAL AT THE HIGH RENEWABLES PENETRATION

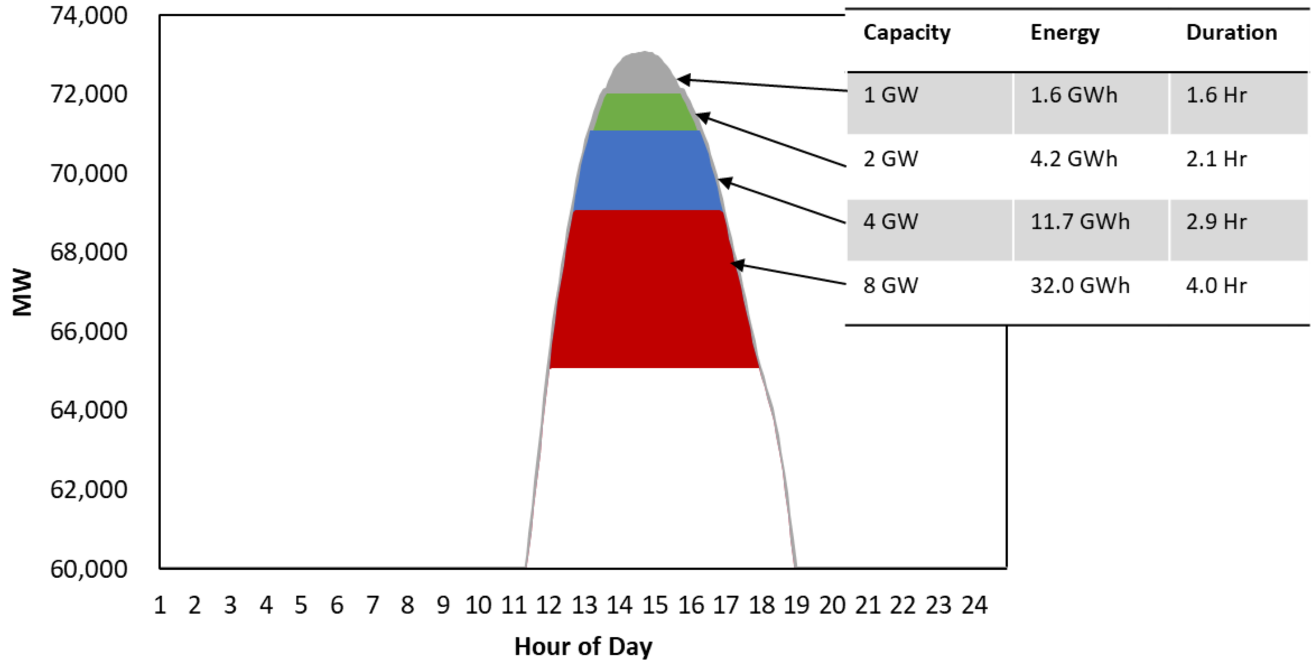
The net load shape effect of increasing renewable resources provides an opportunity for short duration resources to provide capacity value. The area under the net load curve during peak days that could be served by four-hour duration resources increases from the penetration expected in the base case in 2024 to a higher renewable scenario which includes an additional 15 GW of solar capacity. An illustration of this shift is shown in Figure 14. It is important to note that the 2024 base case net load shape has many hours near the daily peak which results in limited opportunity for short-duration batteries to provide energy arbitrage. It was for this reason that we only studied battery potential for a high renewable scenario.

Figure 14. Net Load Shape Impact of Solar Generation



To quantify the capacity of storage that can contribute to reliability, the area under each net load curve is analyzed. The area under the series labeled 'Gross Load Minus Wind' within one GW of the daily net load peak is approximately 1.6 GWh. This means that one GW of load can be served reliably with 1.6 hours of energy from a battery resource. Within two GW of the daily net load peak a longer duration is required and that area represents 2.1 hours of energy. Figure 15 contains a visual illustration of this example. The area under the curve for the 'Gross Load Minus Wind' series at four-hours of duration corresponds to 8,000 MW of capacity and is shown as the far left point on Figure 16.

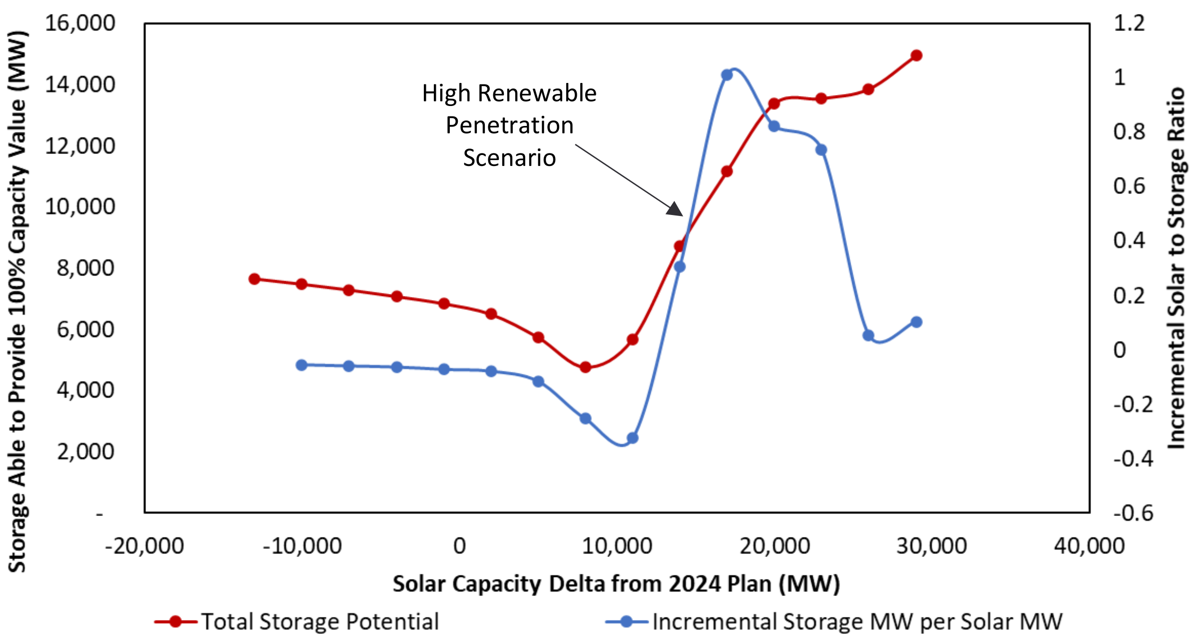
Figure 15. Battery Storage Duration Analysis Example



Capacity	Energy	Duration
1 GW	1.6 GWh	1.6 Hr
2 GW	4.2 GWh	2.1 Hr
4 GW	11.7 GWh	2.9 Hr
8 GW	32.0 GWh	4.0 Hr

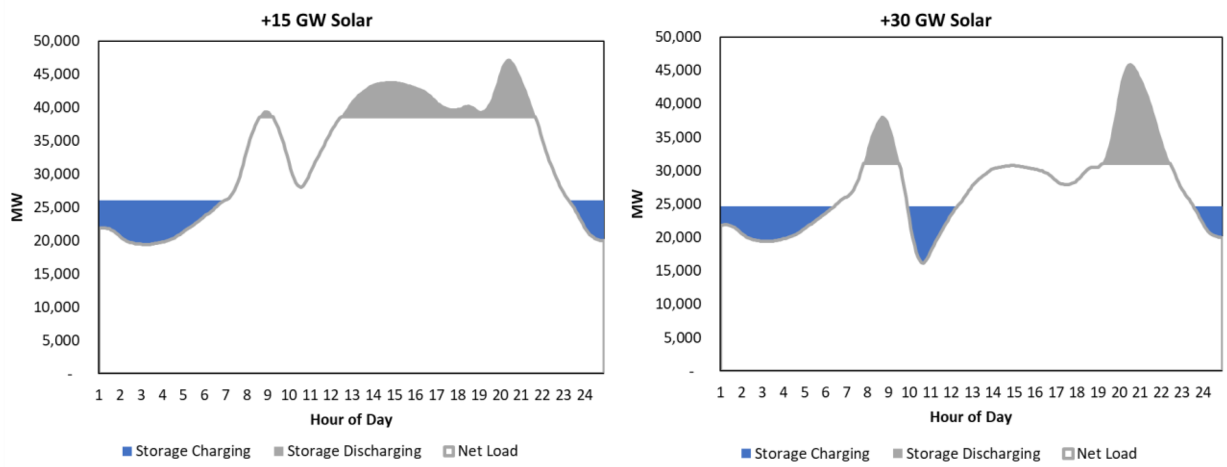
Performing this calculation for a wide range of solar penetrations yields the remaining points on this series. Initial incremental solar flattens the net load shape, reducing the potential for storage to supply reliability to ERCOT. At approximately 30 GW of total solar penetration, the net load shape begins to steepen and storage potential begins to increase. In the high renewable penetration scenario (additional 15 GW of solar and 5 GW of wind added to the system) analyzed, approximately 10 GW of four-hour battery storage has the potential to supply reliability value to ERCOT.

Figure 16. Storage Potential to Contribute to Reliability



Example charging and discharging schedules, in Figure 17, illustrate the flatness or steepness of the respective daily load shapes under different solar penetrations.

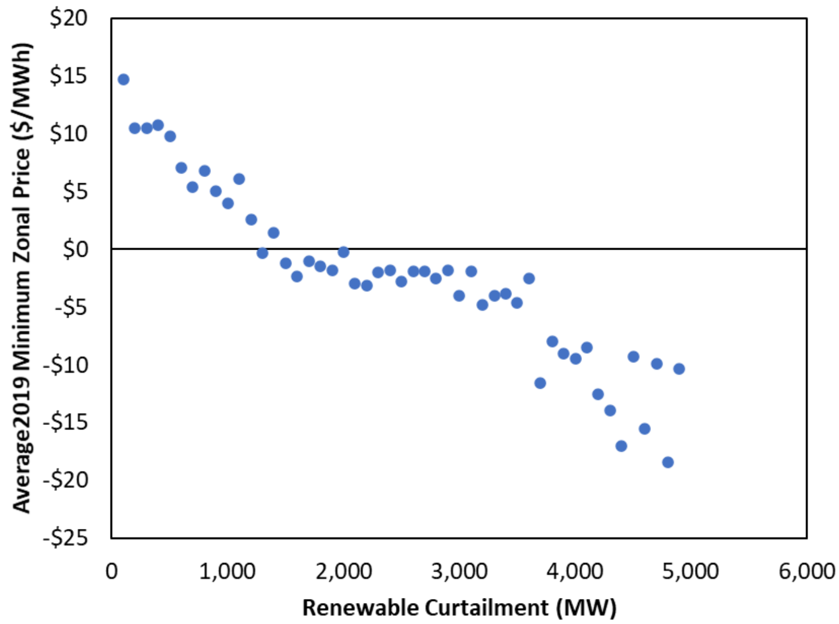
Figure 17. Storage Charging Potential



Since the load shape in the 2024 Base Case did not support significant incremental short duration storage capacity, all economic analysis of batteries was performed with the portfolios from the 2024 High Renewable scenario. The economic opportunity quantified in the following sections would be lower for batteries in the Base Case although the magnitude of the difference was not quantified.

The economic opportunity for battery storage is limited by the daily arbitrage opportunity throughout the year. The significant penetrations of renewable resources in ERCOT create frequent low market price hours where most conventional generation is either turned off or dispatched near minimum. During these periods, renewable generation can even be curtailed. The bidding strategies of renewable generator owners may entail bidding at negative prices since they have a financial incentive in terms of tax credits to continue to produce. Batteries are able to charge during these periods and capture significant arbitrage opportunities. To assess the potential for batteries to earn an economic return in future high renewable scenarios, the bidding behavior of these resources must be modeled. The historical relationship between curtailment and the average minimum zonal price is reflected in Figure 18.

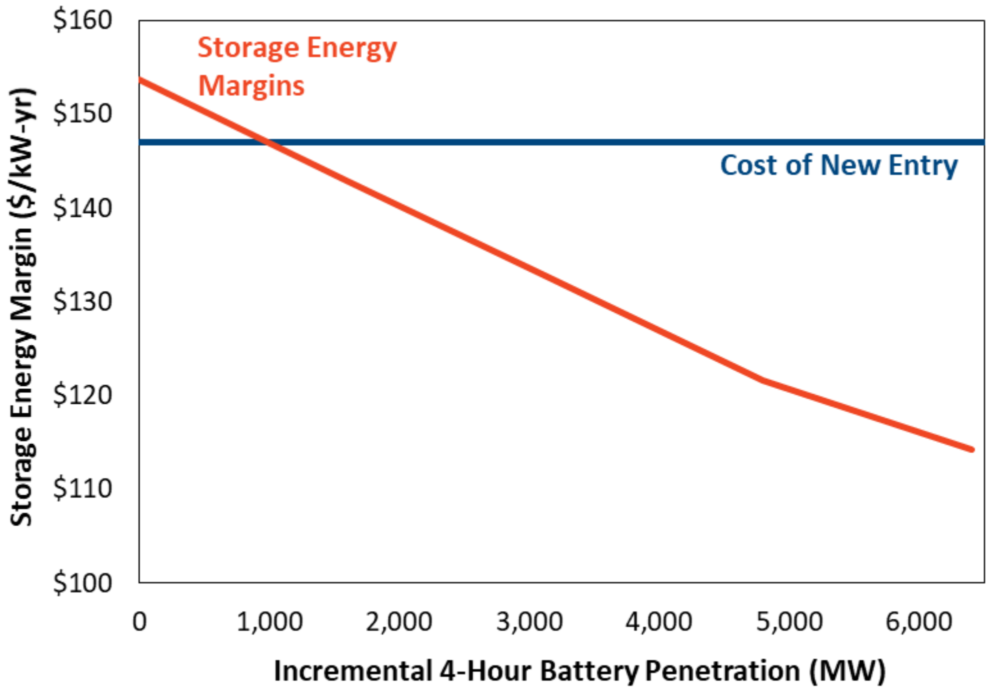
Figure 18. Historical Relationship Between Curtailment and the Average Minimum Zonal Price



Unfortunately the behavior is likely influenced by penetration and composition of renewable resources that will be on the system in the future and extrapolating from historical relationships is challenging. Assuming that market prices in these low net load periods will continue to be correlated to system renewable curtailment, the historical relationship was modeled in SERVM. A sensitivity reflecting moderation of negative pricing bidding strategies demonstrated that energy margins for battery resources could decline by 10%.

Even with frequent negative pricing, the economic arbitrage opportunity is still limited and declines as the penetration of storage increases. On days in which combined-cycle generators are on the margin in low load hours and CTs are on the margin in high load hours, the arbitrage opportunity is less than $10/MWh with gas prices below $3/MMBtu. Simulations of mild weather years with a reserve margin near MERM suggest energy arbitrage opportunities over the course of the year approaching $30/kw-yr. After inclusion of ancillary service market opportunity and scarcity pricing periods, the economic margins of the first tranches of energy storage exceed those of marginal CTs, but decline as the penetration increases. As shown in Figure 19, with capital carrying costs of $147/kw-yr, the economic potential for batteries at the high renewable penetration is only 2,100 MW, and approximately 1,100 MW of batteries is already expected to be in the system in 2024. This opportunity also presumes that other conventional resources would economically retire to maintain the system reserve margin near MERM. Otherwise, if reserve margins increased with increasing penetration of storage, returns would drop much faster. If battery capital costs decline to $115/kw-yr, up to 6.5 GW of incremental 4-hour battery capacity could be economic at the high renewable penetration.

Figure 19. Storage Charging Potential at the High Renewable Penetration



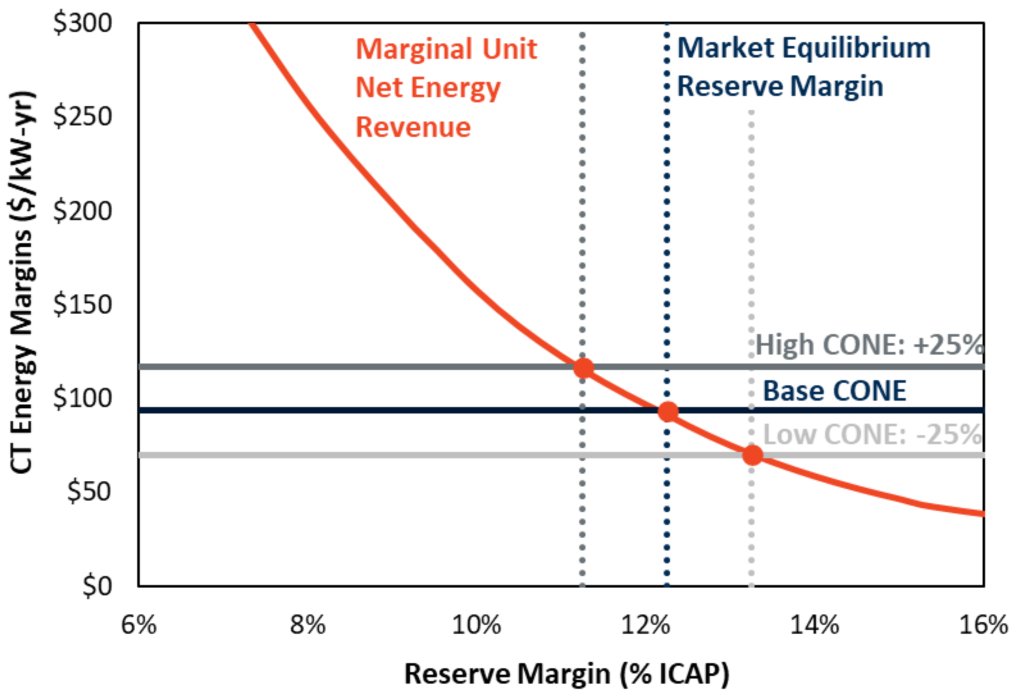
3. COST OF NEW ENTRY SENSITIVITY

The base case simulations assume that a natural gas-fired CT is the marginal resource with industry standard assumptions for capital costs. However, industry experience suggests that there is a range of uncertainty around technology cost estimates.

Figure *20* shows the impact of varying CONE from −25% to +25% relative to our base assumptions. The base case CONE estimate was adapted from a Brattle Group study from 2018.[35] A more recent report from Lazard gives a range of estimates for installed capital costs with a lower end of $700/kW.[36] This is approximately 22% lower than the comparable installed cost in the Brattle report. Accordingly, we selected a range of -25% to +25% relative to our base assumptions. Overall, the MERM could vary over a range of 11.25% to 13.25% depending on the range of CONE uncertainty.

[35] See Newell, et al. (2018 a)
[36] See Lazard (2020)

Figure 20. Market Equilibrium Reserve Margin Sensitivity to Cost of New Entry



4. PROBABILITY WEIGHTING OF WEATHER SENSITIVITY

The high impact of weather on net energy revenue means that different weather expectations will influence the market equilibrium reserve margin. The base case assumes equal probability for all 40 weather years because 40 years should be a sufficient sample of the underlying distribution, assuming that distribution is representative of future weather patterns. This reliance on long history is consistent with the EORM Manual. However, more recent weather has, on average, been hotter (especially in 2011) and may be assumed to be more representative of future weather, as discussed in Section D above. Assuming accordingly that each of the last 15 weather years has a 6.66% chance of reoccurring (with 0% weight on each of the prior 25 years) leads to higher simulated prices and reliability events at a given reserve margin; but the higher prices would attract more investment, resulting in a 1% higher market equilibrium reserve margin of 13.25%. With that higher MERM protecting against the effects of hotter weather, the simulated reliability is approximately the same as in the base case.

5. FORWARD PERIOD AND LOAD FORECAST UNCERTAINTY SENSITIVITY

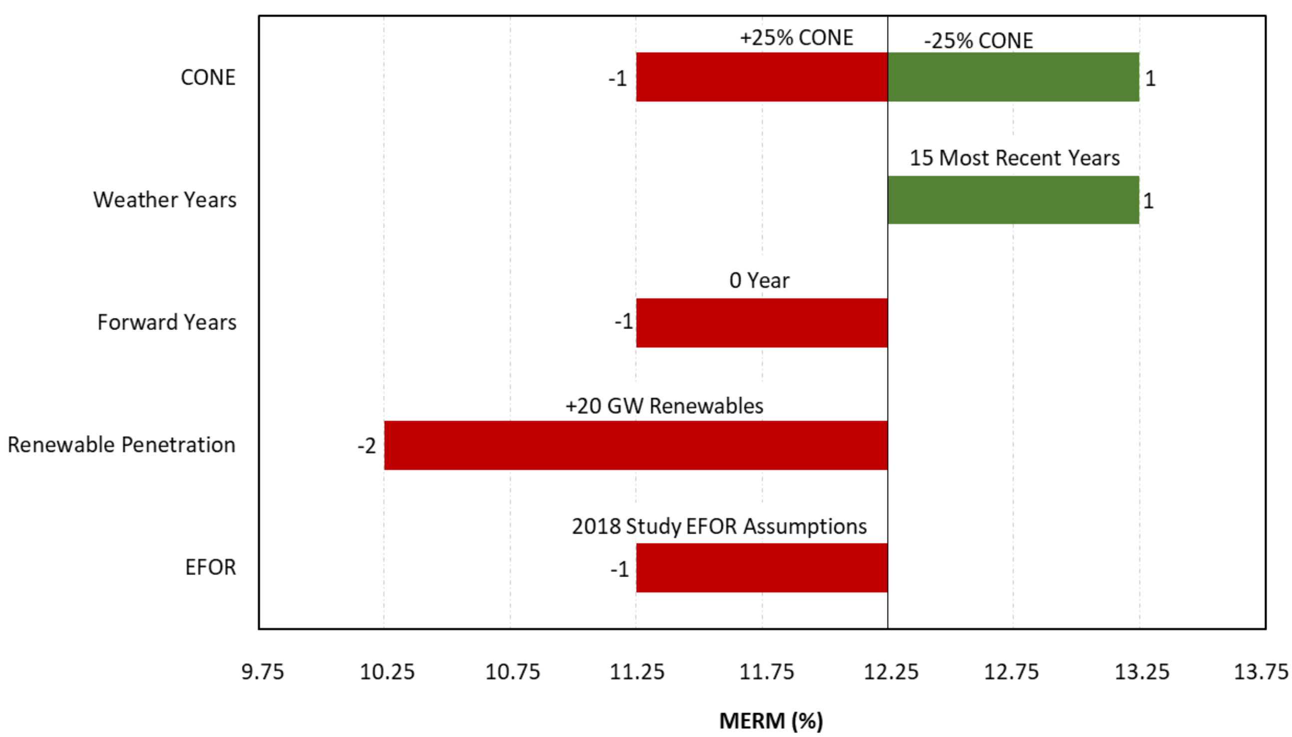
In our base case analysis, we assume that all future supply decisions must be locked in four years in advance, approximately consistent with the lead time needed to construct new natural gas-fired generation resources. However, unlike weather-related load uncertainty, non-weather load forecasting error (LFE) increases with the forward period. The forward period may increase if investors require a longer planning period and decrease if there are significant short-term resources (such as demand response, switchable units, mothballed units, and even renewable resources) to respond more quickly to market conditions than traditional new builds. Depending on the expected forward periods the market equilibrium will vary from 11.25% to 12.25%.

6. SUMMARY OF SENSITIVITIES

Our estimate of the MERM is sensitive to a number of study assumptions as explained in previous sections, and summarized in Figure 21 and Table 9. As shown in the table, the MERM is between 10.25% and 13.25% for all sensitivities.

The change in the VOLL is not considered to shift the operating reserves demand curve (ORDC) and will not affect the MERM.[37] Moving from a four-year LFE forward period to no forward period reduces the MERM by one percentage point. Each one-year increase in the forward period increases the MERM by 0.25%. Weighting more recent weather years more heavily increases MERM since recent data exhibits higher loads on average. And the effects of CONE pricing are symmetrical, but even a reasonably large shift of 25% only moves MERM by one percentage point.

Figure 21. Sensitivity of the Market Equilibrium Reserve Margin to Study Assumptions



Notes: Varying the VOLL is not shown because it does not affect the MERM.

[37] The ORDC is discussed in Appendix 1.E.4; varying the VOLL to range from $5,000 to $30,000 changes the EORM to range from 10.25% to 13.25%, respectively.

Table 9. Sensitivity of the Market Equilibrium Reserve Margin to Study Assumptions

Scenario/Sensitivity	Market Equilibrium Reserve Margin (%)	Base Assumptions	Low/High Sensitivity
Base Case	**12.25**		
Vary CONE	11.25 – 13.25	$93.5/kW-yr	$70.1 - $116.9/kW-yr
Vary VOLL	12.25	$9,000/MWh	$5,000-$30,000/MWh
Vary Probability of Weather Years	13.25	Equal probability to all 40 weather years	Equal probability to last 15 weather years
Vary Forward Period and Load Forecast Uncertainty	11.25 – 12.00	4 years	0 years to 3 years
High Renewables Scenario	**10.25**	**May 2020 CDR values for 2024 study year**	**15 GW of new solar and 5 GW of new wind**
Lower EFOR	**11.25**	**Last 3 years to populate outage rates for all units**	**2018 study class average EFORs**

Notes: Varying the VOLL does not affect the MERM.

IV. DISCUSSION OF RESULTS

As shown in Table 10, the reported MERM from the 2018 study increased from 10.25% to 12.25%, but the increase is associated with forced outage rate changes and reserve margin reporting artifacts which do not translate to improvements in reliability. The base case in this study, as in the 2018 study, projects 0.5 LOLE days per year, a level 5 times higher than the industry standard of 0.1 LOLE. If renewable deployments continue to increase to the level in the high renewable scenario analyzed, firm load shed frequency will rise 160% to 1.3 days per year. This high renewable scenario demonstrates a MERM of 10.25%. Since further renewable penetration increases have a more dramatic impact on the shape of the net load curve, the impact on MERM will escalate, further reducing reserve margins and increasing the frequency of reliability events.

Table 10. MERM and Reliability Comparison Between Scenarios

Scenario	MERM	Reliability at MERM (LOLE in Days per Year)
2018 Study	10.25%	0.5
2020 Study	12.25%	0.5
2020 Study, High Renewable	10.25%	1.3

However, other factors, which have in recent history mostly resulted in realized reserve margins in ERCOT above MERM, may continue to exert an influence on reserve margin levels. Renewable resource investments motivated by alternate economic or other decision criteria have continued to be added at a pace that maintains a reserve margin above the market equilibrium even after economic retirements are accounted for. Storage deployment costs have dropped dramatically in recent years and after consideration of current and potential governmental incentives for storage devices, may support significant investment and result in the continuation of reserve margins that support high levels of reliability. However, the design of an energy-only market does not inherently protect system reliability. Future reserve margin studies will continue to analyze the implications of not only marginal conventional technology, but also the interactions of all resource classes and other market conditions that may result in realized reliability higher than projected by MERM.

In addition to highlighting the potential market and reliability outcomes of the ERCOT system, this report has provided information on the impact of accounting treatment of renewable resources. While the reserve margin is primarily only a reporting indicator, it can communicate the wrong message with respect to reliability if the disconnect between capacity credit and reliability contribution continues to grow. In fact, if current CDR accounting was applied to the high renewable scenario, the reported MERM would rise to 19.25%, even though the projected reliability for this scenario is 160% worse than that of the base case. In order to provide market participants with the most meaningful information, it is important that the reliability contribution calculations and capacity accounting be synchronized.

The results presented throughout this report consider a range of possibilities for a number of uncertain variables. To the extent history provides guidance for the distribution of uncertainty, rigorous analysis was performed to quantify it. Load shapes, renewable output profiles, and generator outages all have histories that give reasonable representations for how the future may materialize.

LIST OF ACRONYMS

4CP	Four Coincident Peak
ATWACC	After-Tax Weighted Average Cost of Capital
AEO	Annual Energy Outlook
CC	Combined Cycle
CDR	Capacity, Demand, and Reserves (report)
CONE	Cost of New Entry (Gross)
CT	Combustion Turbine
EFOR	Equivalent Forced Outage Rate
EE	Energy Efficiency
EORM	Economically Optimal Reserve Margin
ERCOT	Electric Reliability Council of Texas
ERS	Emergency Response Service
EUE	Expected Unserved Energy
GADS	Generation Availability Data System
HCAP	High System-Wide Offer Cap
HVDC	High Voltage Direct Current
LCAP	Low System-Wide Offer Cap
LFE	Load Forecast Error
LTRA	Long-Term Reliability Assessment
LOL	Loss-of-Load
LOLE	Loss-of-Load Event
LOLH	Loss-of-Load Hour
LOLP	Loss of Load Probability
LRs	Load Resources
MERM	Market Equilibrium Reserve Margin
MW	Megawatt(s)
NERC	North American Electric Reliability Corporation
ORDC	Operating Reserve Demand Curve
PBPC	Power Balance Penalty Curve
PNM	Peaker Net Margin
PRD	Price Responsive Demand
PUCT	Public Utility Commission of Texas
PUN	Private Use Network
RRS	Responsive Reserve Service
SCED	Security Constrained Economic Dispatch
SERVM	Strategic Energy Risk Valuation Model

SWOC	System-Wide Offer Cap
TDSP	Transmission/Distribution Service Providers
VOLL	Value of Lost Load
VOM	Variable Operations and Maintenance

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APPENDIX 1: MODELING ASSUMPTIONS

This Appendix describes in more detail the representation of the ERCOT system, including: load and weather patterns and their probabilistic variations; the cost and performance characteristics of ERCOT's generation and demand-response resources; the mechanics of the ERCOT energy and ancillary services markets, including a unit commitment and economic dispatch of all generation resources, demand-response resources, and the transmission interties with neighboring markets. We also explain assumptions developed to reflect expected conditions of 2024 on the generation fleet, demand-response penetration, fuel prices, and energy market design.

A. DEMAND MODELING

This section describes the data and modelling of the demand in the model, specifically peak load, weather uncertainty, non-weather forecast uncertainty, and demand shapes.

1. PEAK DEMAND AND REGIONAL DIVERSITY

The peak load forecast normalizes for weather by identifying a 50th percentile peak load ("50/50") forecast for each weather zone. The 50/50 peak load for each weather zone represents the average peak load from 40 synthetic load profiles, each representing the expected load in a future year given the weather patterns from each of the last 40 years of history. To develop a system 50/50 peak load forecast, the load in each weather zone must be identified at the time of the system peak. To do so, an average load duration curve is constructed for each weather zone by averaging each hour of the load duration curves from 40 years of historical data. Then, the zonal load duration curves are mapped to a single historical year. The single historical year ERCOT uses for the 2020 CDR is 2008 because it was a generally "normal" weather year. The mapping is completed by identifying the peak load hour in 2008 and setting its load to the peak load from the average zonal load duration curve. Then the second highest load hour in 2008 is assigned the second highest load in the average zonal load duration curve. This continues until all of the hours in 2008 are assigned a load level based on their rank and the equivalent load at that rank in the average load duration curve. The resulting hourly load profile constructed for each zone is then used to aggregate the individual zonal loads into the system peak load.

However, 2008 experienced less peak diversity between weather zones than ERCOT normally experiences. Expressing the "50/50" peak from the many years of historical data using 2008 as a base shape therefore understates typical load diversity and may overstate the 50/50 system peak load. It results in a 82,982 MW system peak load rather than 81,793 MW 50/50 peak when using the median system peak across the study years (1980–2019).[38] For the purposes of this study, this is only a reporting issue and does not affect the underlying hourly weather patterns and loads used in our simulations. It does cause the EORM and

[38] Provided by ERCOT staff.

MERM to appear lower than they would if expressed against a 50/50 peak load using typical diversity, by about 1.4% (since the reserve margin is expressed relative to a 83 GW reported peak load when the actual 50/50 corresponding to the same underlying data may be closer to 82 GW).

2. DEMAND SHAPES AND WEATHER UNCERTAINTY MODELING

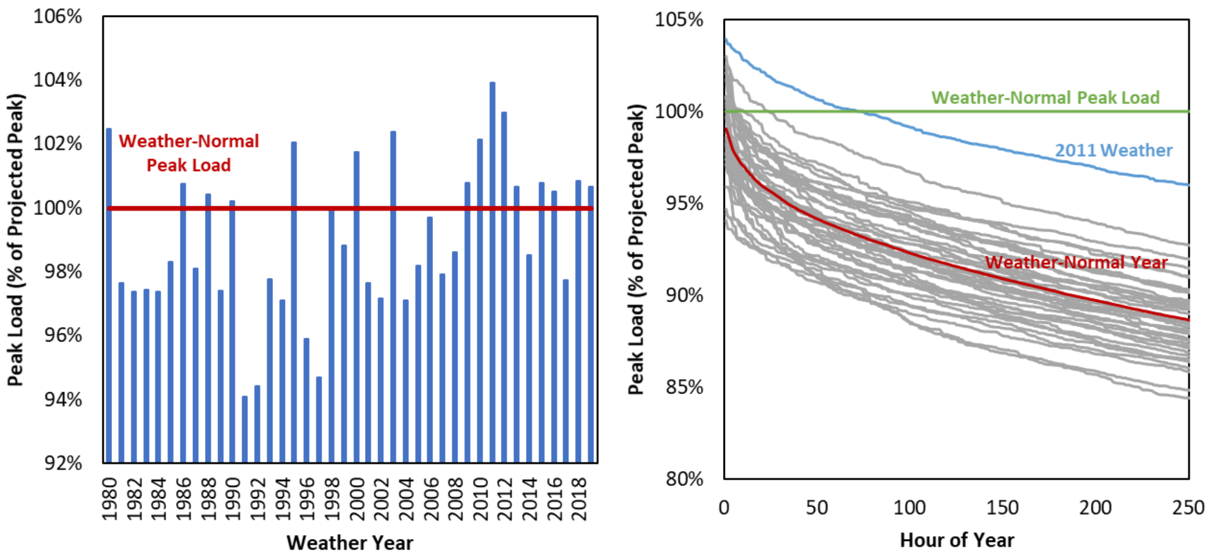
We represent weather uncertainty in the projected ERCOT 2024 peak load by modeling 40 load forecasts based on 40 historical weather years from 1980–2019, as summarized in Figure A1-1.[39] ERCOT staff used these 40 weather years as inputs into its 2020 load forecasting model, which produced the range of hourly load forecasts for 2024 we used in the SERVM model for this study.[40]

The left chart shows projected 2024 peak load for each weather year relative to the weather-normal peak load. The chart illustrates asymmetry in the distribution of peak loads, with the highest projected peak load (based on 2011 weather) at 3.9% above the weather-normal peak loads, compared to a peak load in the mildest weather year that is only 5.9% below weather-normal peak load.

The right chart in Figure A1-1 shows the 2024 load duration curves for the 250 highest-load hours in each of the 40 weather years. The light blue load duration curve is based on the extreme and extended hot summer weather in 2011. As shown, the entire load duration curve from 2011 weather is far above all other weather years in the top 250 hours. This extreme heat resulted in a number of emergency events and price spikes during the summer of 2011, which is described by some as a 1-in-100 weather year. Despite this, our base case assigns equal probability to all 40 weather years because the sample set is large enough to be reasonably representative of weather patterns. We also report the MERM and EORM under an alternative weather weight of equal probability of the last 15 years.

[39] This is different than the previous EORM study, which used 38 weather years (1980–2017).
[40] Details on the load forecast model methodology in ERCOT (2019a).

Figure A1-1. ERCOT Peak Load (Left) and Peak Load Duration Curve (Right) by Weather Year



Sources and Notes: ERCOT load shapes provided by ERCOT staff.

3. NON-WEATHER DEMAND FORECAST UNCERTAINTY AND FORWARD PERIOD

Forward-looking "planning" or "target" reserve margins differ from actually-realized reserve margins because both realized peak load and actual available resources can differ from projections. One cause of forecast error is simply the weather. Another is due to uncertainties in population growth, economic growth, efficiency rates, and other factors. These non-weather drivers of load forecast errors (LFEs) differ from weather-related LFEs because they increase with the forward planning period, while weather uncertainties will generally remain constant and be independent with the forward period.

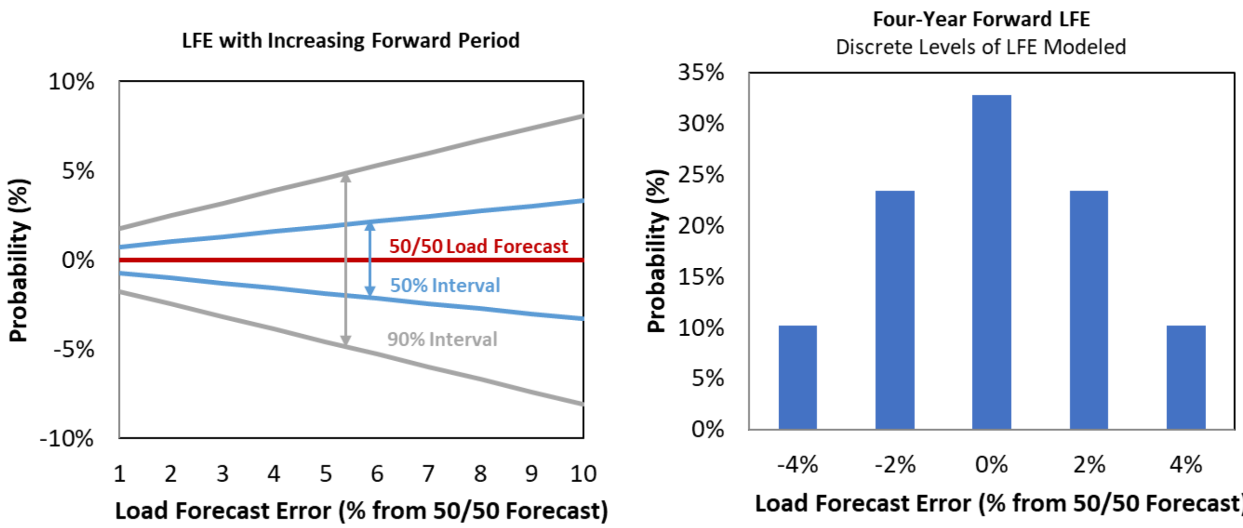
As shown in the left chart of Figure A1-2, we assume that non-weather LFE is normally distributed with a standard deviation of 0.43% on a 1-year forward basis, increasing by 0.66% with each additional forward year.[41] The distribution includes no bias or asymmetry in non-weather LFEs, unlike the weather-driven LFE in ERCOT, which has more upside than downside uncertainty.

For our purposes, the relevant forward period for characterizing non-weather LFEs is the period at which investment decisions must be finalized. We assume investment decisions must be finalized four years prior to delivery, consistent with the approximate construction lead time for new generation resources. This means that available supply and the expected planning reserve margin are "locked in" at four years forward, and the realized reserve margin may differ substantially as both weather and non-weather uncertainties are resolved as the delivery year approaches. The right-hand chart of Figure A1-2 shows the five discrete levels of LFE we model, equal to 0%, +/−2%, and +/−4% above and below the forecast. The

[41] 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.

largest errors are the least likely, consistent with a normal distribution. We also conduct a sensitivity analysis, examining the implications on economically optimal and reliability-based reserve margins if the forward period is varied between zero and four years forward.

Figure A1-2. Non-Weather Load Forecast Error



4. EXTERNAL REGION DEMAND

We independently developed external regions' peak load and load shapes based on publicly-available peak load projections, historical hourly weather profiles, and historical hourly load data. Table A1-1 summarizes the peak load for the ERCOT system and the load diversity relative to the interconnected neighboring regions. Consistent with the peak load reporting conventions used in ERCOT's CDR report, these peak loads are reported: (a) net of anticipated load reductions from price-responsive demand (PRD) and load resources (LRs); and (b) prior to any potential reductions from transmission and distribution service provider (TDSP) load management or energy efficiency (EE) programs.[42]

[42] See May 2020 CDR in ERCOT (2020a).

Table A1-1. Peak Loads and Diversity Used in Reserve Margin Accounting

		ERCOT	Entergy	SPP	Mexico	Total
Summer Peak Load Forecast						
Non-Coincident	*(MW)*	82,982	33,658	54,012	12,950	183,601
Coincident	*(MW)*	80,572	32,618	52,893	12,651	178,734
At ERCOT Peak	*(MW)*	82,982	30,809	48,605	12,872	175,268
Load Diversity						
At Coincident Peak	*(%)*	2.99%	3.19%	2.11%	2.36%	2.72%
At ERCOT Peak	*(%)*	0.00%	9.25%	11.12%	0.61%	4.75%
Reserve Margin at Criterion						
At Non-Coincident Peak	*(%)*	n/a	16.80%	12.00%	15.00%	n/a
At ERCOT Peak	*(%)*	n/a	27.60%	24.46%	15.00%	n/a

Sources and Notes:
Non-Coincident Peak represents each individual region's peak load.
Coincident Peak represents the load in each region at the maximum total model area peak.
At ERCOT Peak represents the load in each region at the time of the ERCOT system peak.
SPP 50/50 peak load forecast is from the NERC *2019 Long-Term Reliability Assessmen*t.[43]
Entergy's 50/50 peak load forecast is from the MISO *Planning Year 2020-2021 Loss of Load Expectation Study Report*. [44]
Load shapes in SPP and Entergy are based on our independently-developed statistical relationship between hourly weather and load estimated over five years of load data and 40 years of weather data.[45]
Mexico's peak load and load shape were unavailable. The peak is assumed at a 15% reserve margin above the currently-installed generation fleet). Load shapes in Mexico are assumed identical to those in ERCOT.

As shown in the table above, there is a substantial amount of load diversity between ERCOT and the neighboring systems, indicating that ERCOT may have access to substantial import quantities during shortages to the extent that sufficient intertie capability exists. For example, at the time of ERCOT's peak load, SPP load is likely to be at only 90% of its own non-coincident peak load. This load diversity results in having more than 11,500 MW of excess generation available for export in hours where ERCOT is shedding firm load. However, most of these excess supplies will not be imported because ERCOT is relatively isolated from neighboring systems with only 820 MW of intertie capability with SPP and 400 MW with Mexico.

[43] See NERC (2019).
[44] See MISO (2019).
[45] See FERC (2020) and NOAA (2020).

B. GENERATION RESOURCES

We model the economic, availability, ancillary service capability, and dispatch characteristics of all generation units in the ERCOT fleet, using unit ratings and online status consistent with ERCOT's May 2020 CDR report. In this section we describe our approach for modeling conventional generation, private use networks (PUNs), and intermittent wind and solar. We also describe the assumed cost and technical specifications of the CT reference technology.

1. MARGINAL RESOURCE TECHNOLOGY

The quantity of installed generating capacity must vary to simulate ERCOT's system costs, market prices, and reliability across different reserve margins. We add gas CT plants in our base case, roughly reflecting the types of capacity resources that have been added or proposed for the ERCOT market. Our technology choices for the gas CT plants is consistent with assumptions from the 2018 study.

The costs and performance characteristics of the reference CT are summarized in Table A1-2 and Table A1-3 respectively. These characteristics are based on GE 7HA technology for the CT plants, which is the same as the CT reference technology from EORM 2018.[46] We use updated cost of new entry (CONE) assumptions consistent with this technology, as well as an updated after-tax weighted-average cost of capital (ATWACC) for a merchant developer based on current financial market conditions. These updates result in an estimated CONE of $93,500/MW-year for the gas CT, which is 5.65% higher than in EORM 2018, as shown in Table A1-2.

Table A1-2. Cost of New Entry

	ATWACC	**CONE**	
		Simple Cycle	**Combined Cycle**
	(%/yr)	($/MW-yr)	($/MW-yr)
From 2018 Study (2022 Online Date)			
Low: Base Minus 10%	n/a	$79,700	$85,100
Base: Merchant ATWACC	7.80%	$88,500	$94,500
High: Base Plus 25%	n/a	$110,600	$118,100
Updated Estimate (2024 Online Date)			
Low: Base Minus 25%	n/a	$70,100	[redacted]
Base: Merchant ATWACC	7.80%	$93,500	[redacted]
High: Base Plus 25%	n/a	$116,90	[redacted]

Sources and Notes:
2018 study numbers and current numbers are adapted from CONE studies for PJM, with adjustments applied as relevant for ERCOT; see Spees, *et al.* (2011) and Newell, *et al.* (2018a), respectively. CONE values determined with adjustments to technology characteristics within an area that most closely resemble ERCOT, as outlined in Table A1-3. The updated CONE estimate was developed based on the values in the 2018 PJM CONE report before adjustments were made to the assumed discount rate and exemption from paying sales taxes.

[46] See Newell, *et al.* (2018a).

Table A1-3. Performance Characteristics

Characteristic	Unit	Simple Cycle
Plant Configuration		
Turbine		GE 7HA.02
Configuration		1 x 0
Heat Rate (HHV)		
Base Load		
Non-Summer	(Btu/kWh)	9,138
Summer	(Btu/kWh)	9,274
Installed Capacity		
Base Load		
Non-Summer	(MW)	371
Summer	(MW)	352
CONE	($/kW-yr)	93.5

Sources and Notes:

Technical and performance parameters use region EMAAC as most closely resembling ERCOT in altitude and ambient conditions from Newell, *et al.* (2018a).

Based on ambient conditions of 92°F Max. Summer (55.5% Humidity) and 59°F Non-Summer.

2. 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.[47]

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

[47] Capturing the possibility of such low-probability, high-impact events is an advantage of the unit-specific Monte Carlo outage modeling used in SERVM. The simpler convolution method, which is a common alternative outage modeling method, results in a distribution of outages that may under-estimate the potential for extreme events, especially in small systems.

provided by ERCOT where unit-specific data were unavailable. Table A1-4 summarizes fleet-wide and asset-class outage rates, including both partial and forced outages.

Table A1-4. Forced Outage Rates by Asset Class and Fleet Average

Unit Type	Equivalent Forced Outage Rate *(%)*	Mean Time to Fail *(hours)*	Mean Time to Repair *(hours)*
Gas Combined Cycle	3.7	1,312	32
Gas Combustion Turbine	8.3	967	74
Gas Steam	14.0	687	58
Coal	5.9	833	39
Nuclear	0.2	16,467	330
Fleet Weighted Average	**5.9**		

Sources and Notes: Parameter distributions based on two years (2018-2019) of unit-specific GADS data and asset class average outage rates from ERCOT.

3. 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

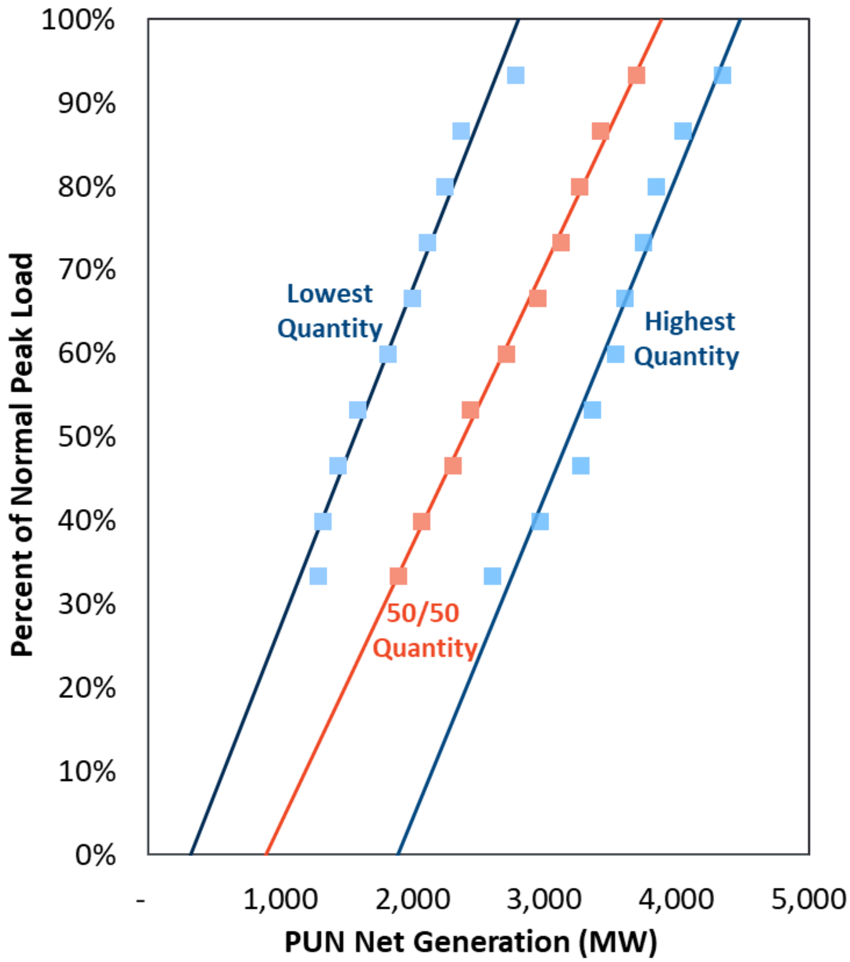
Figure *A1-3*. At any given load, the realized net PUN generation has a probabilistic quantity, with 10 different possible quantities of net generation within each of 10 different bands of system load.[48] Each of the 10 possible quantities has an equal 10% chance of materializing, although

Figure *A1-3* reports only the lowest, median, and highest possible quantity. We developed this probabilistic net PUN supply curve based on aggregate hourly historical net output data within each range of peak load percentage. During scarcity conditions with load at or above 93% of normal peak load, PUN output produces at least 2,776 MW of net generation with an average of 3,691 MW.

We observe a pattern of availability and responsiveness consistent with: (a) gross generation, much of which is fully integrated into ERCOT's economic dispatch and security constrained economic dispatch (SCED), resulting in substantial increases in the expected quantities over moderate price levels, minus (b) gross load, which introduces some probabilistic uncertainty around net generation, minus (c) some apparent load price-responsiveness, which likely contributes to some small additional increase in net PUN generation at very high prices.

[48] Hourly net PUN output data gathered from ERCOT, hourly load data from Velocity Suite, ABB Inc.

Figure A1-3. PUN Net Generation



Sources and Notes:

Hourly net PUN output data gathered from ERCOT, hourly load data from Velocity Suite, ABB Inc.
Individual data points represent summary of data in a series of data binned by system load level, within each load bin, the points on the chart represent the lowest 10%, middle 10%, and top 10% of realized quantities in 2012 to 2020.

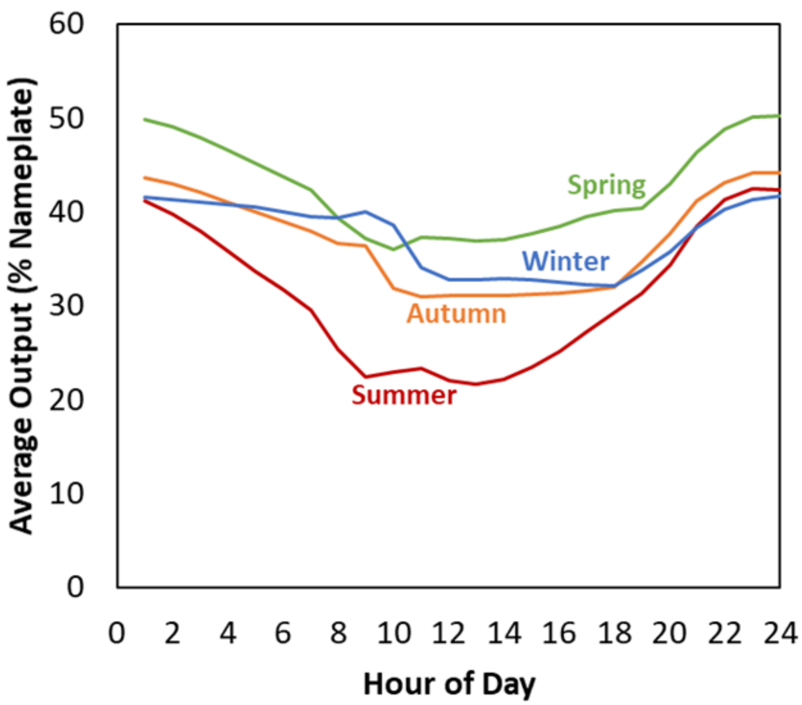
4. INTERMITTENT WIND AND SOLAR

We model a total quantity of intermittent wind and solar photovoltaic resources that reflects what ERCOT reported to NERC for its 2020 LTRA report, including the installed capacity of all existing and planned resources as of 2024.[49] This includes 37,396 MW nameplate capacity of wind and 16,001 MW nameplate of solar, with intermittent output based on hourly generation profiles that are specific to each weather year.

[49] Provided by ERCOT staff.

We developed our system-wide hourly wind profiles by aggregating 40 years of synthesized hourly wind shapes for each location of individual units across the system wind shapes over 1980 to 2019, as provided by ERCOT staff.[50] Figure A1-4 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 is 36.4%; although we calculate reserve margins assuming an ELCC of 63% for coastal wind, 29% for panhandle wind, and 16% for other wind, consistent with the ERCOT May 2020 CDR convention.[51] In EORM 2018, wind units were given an ELCC of 14% for non-coastal wind and 59% for coastal wind, consistent with the ERCOT May 2018 CDR convention.

Figure A1-4. Average Wind Output by Month and Time of Day



Sources and Notes:
Average of 40 years' hourly wind profiles provided by ERCOT, originally from UL (formerly AWS Truepower).

We similarly model hourly solar photovoltaic 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 2019.[52] In aggregate, solar resources have a capacity factor of 27.3% across all years, and we assign a 76%

[50] We aggregated location-specific output profiles for all units, including traditional and coastal units. ERCOT obtained the original wind profiles from UL (formerly AWS Truepower).
[51] See ERCOT (2020a).
[52] Individual county output profiles for 1980-2019 were provided by ERCOT, obtained through UL (formerly AWS Truepower).

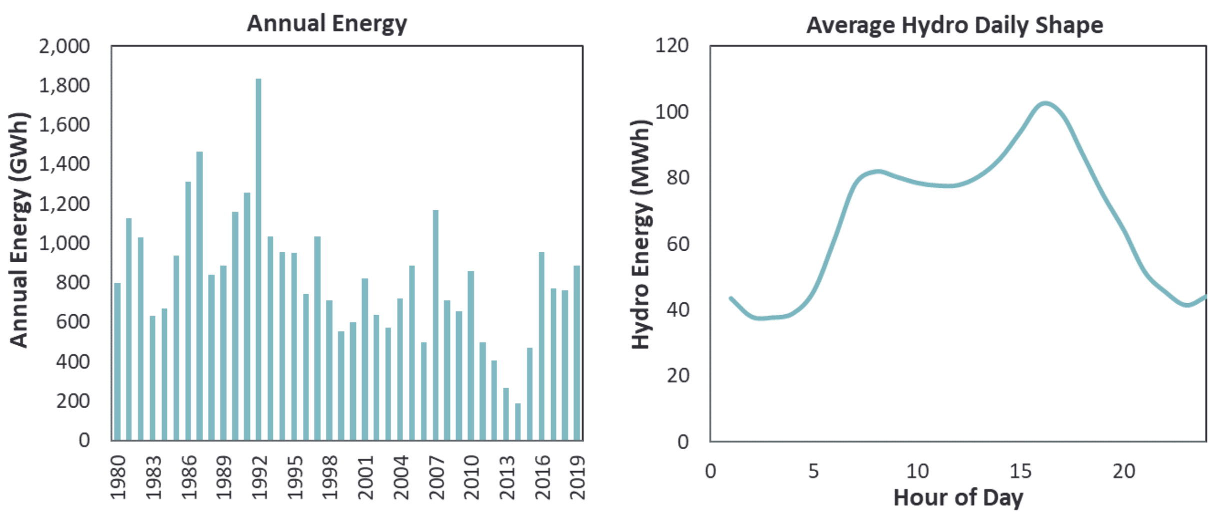
of nameplate contribution toward the reserve margin consistent with ERCOT's CDR accounting convention.[53]

5. HYDROELECTRIC

We include 558.1 MW of hydroelectric resources, consistent with ERCOT's May 2020 CDR report.[54] We characterize hydro resources using six years of hourly data over 2012–2019 provided by ERCOT, and 40 years of monthly data over 1980–2019 from EIA form 923.[55] For each month, SERVM uses four parameters for modeling hydro resources, as summarized in Figure A1-5: (1) monthly total energy output and (2) monthly maximum output, as drawn from historical data consistent with each weather year; and (3) daily maximum output and (4) daily minimum output, as estimated from historical hourly 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 A1-5. Hydro Annual Energy (left) and Average Hydro Daily Shape (right)



Sources and Notes:
Monthly and annual energy data from EIA form 923, peak shaving capability based on eight years of historical hourly data from ERCOT.

6. FUEL PRICES

We use the 2020 Annual Energy Outlook Low Economic Growth case for our gas price future inputs. These gas prices are consistent with fuel prices used in other ERCOT analysis, and are comparable to gas price forwards, as shown in Figure A1-6. Alternative gas prices are explored as sensitivities, but do not make a

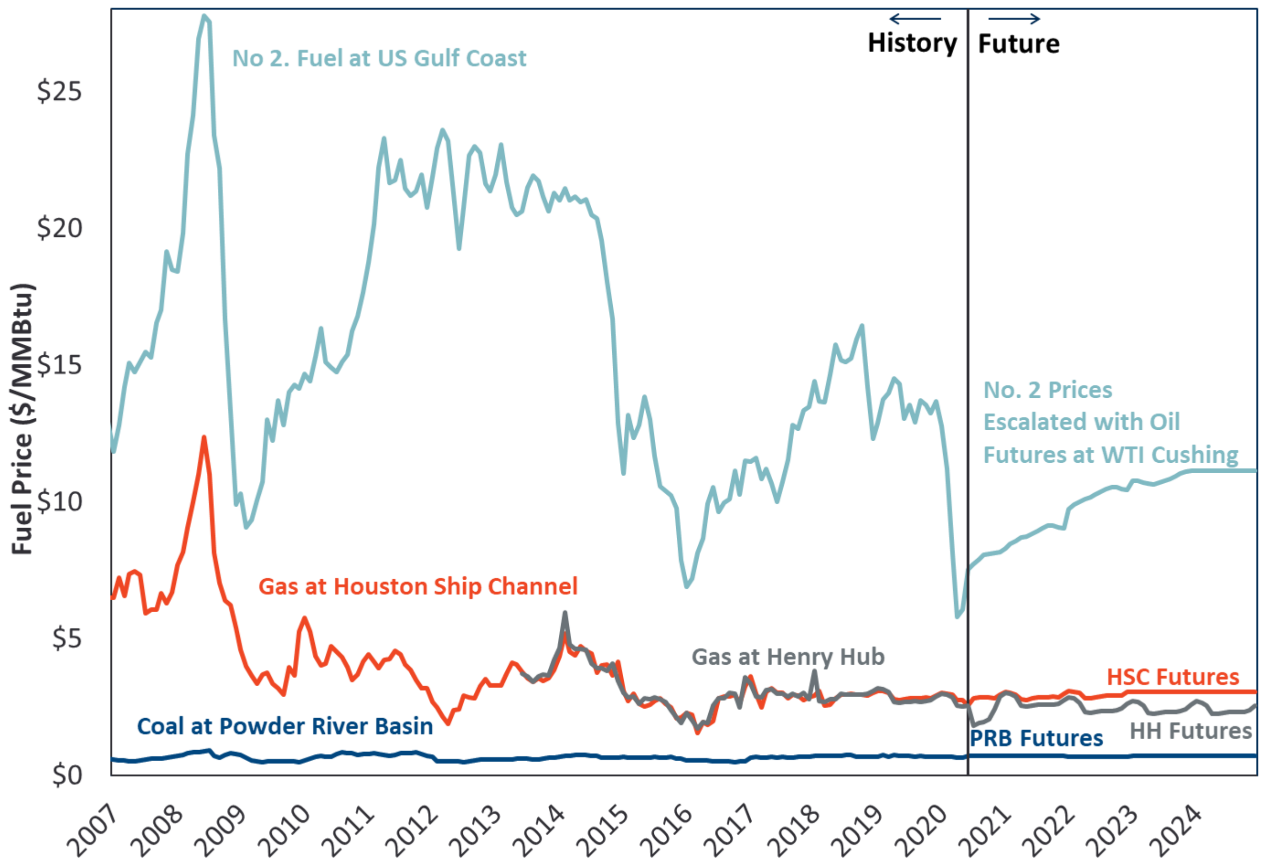
[53] See ERCOT (2020a). For the 2018 study, solar was given a 75% contribution to reserve margin consistent with ERCOT's 2018 CDR accounting conventions.
[54] See ERCOT (2020a).
[55] See Form 923 in EIA (2020).

substantial difference in results. We estimate monthly fuel prices for ERCOT coal units based on the average 2019 historical prices. For external coal units and all oil-fired plants, we use futures prices for the year 2024 and after applying a delivered fuel price basis. We use U.S. Gulf Coast and Powder River Basin as the market price points for historical and futures prices as shown in Figure A1-6.[56] To estimate a delivered fuel price basis for each market, we calculated the historical difference between that market price point and prices as delivered to plants in that region and then escalated the delivered price basis with inflation to the year 2024.[57] This locational basis is inclusive of both market price basis as well as a delivery charge and therefore may be positive or negative overall as shown in

Table A1-5.

[56] Oil futures at WTI Cushing were used to escalate No. 2 fuel oil prices into the future due to lack of data on No. 2 futures at U.S. Gulf Coast. Data from S&P Global Market Intelligence LLC and Bloomberg.
[57] Fuel price basis varies by region by not among individual plants. Historical delivered fuel prices from Bloomberg, SNL Energy, and EIA.

Figure A1-6. Historical and Futures Prices for Gas, Coal, and No. 2 Distillate



Sources and Notes:

No. 2 prices escalated using a linear relationship with WTI Cushing and escalated with WTI futures.
Prices for the base case are from the 2020 Annual Energy Outlook (AEO) Low Economic Growth Case.
Natural gas and coal historical prices and coal futures prices from Bloomberg, SNL Energy, and EIA.

Table A1-5. ERCOT 2024 Delivered Fuel Prices

Coal Fuel Price ($/MMBtu)	Gas Fuel Price ($/MMBtu)	Diesel Fuel Price ($/MMBtu)
1.65	2.96	11.14

Sources and Notes:
Coal Fuel Price is averaged from 2019 EIA 923 and FERC Form 1 data.

Gas Fuel Price from the 2020AEO Low Economic Growth Case.

C. DEMAND-SIDE RESOURCES

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 types differ from each other in whether they are triggered by price-based or emergency actions, and restrictions on availability and call hours. Below we describe the assumptions and modeling approach for each type of resource.

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 *A1-6*. 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 2019, with the 2024 summer peak quantity assumption provided by ERCOT.[58] 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.[59]

Table A1-6. Assumed ERS Quantities Available in 2024

[58] For total ERS procurement quantities by product type and season, see ERCOT (2020b).
[59] See ERCOT (2018a) and ERCOT (2020a-c).

Contract Period	Quantity			
	10-Min NWS *(MW)*	30-Min NWS *(MW)*	30-Min WS *(MW)*	Total *(MW)*
June - September				
TP1: Weekdays HE 6 AM - 8 AM	86	767		853
TP2: Weekdays HE 9 AM - 1 PM	91	820		911
TP3: Weekdays HE 2 PM - 4 PM	90	780	26	896
TP4: Weekdays HE 5 PM - 7 PM	76	666	26	767
TP5: Weekdays HE 8 PM - 10 PM	81	784		865
TP6: All Other Hours	76	710		785
October - January				
TP1: Weekdays HE 6 AM - 9 AM	95	829	5	930
TP2: Weekdays HE 10 AM - 1 PM	88	799		887
TP3: Weekdays HE 2 PM - 4 PM	88	804		892
TP4: Weekdays HE 5 PM - 7 PM	96	849	5	950
TP5: Weekdays HE 8 PM - 10 PM	93	832		925
TP6: Weekend and Holidays HE 6 AM - 9 AM	66	746	-	812
TP7: Weekend and Holidays HE 4 PM - 9 PM	66	742	-	808
TP8: All Other Hours	67	729		795
February - May				
TP1: Weekdays HE 6 AM - 9 AM	96	843	5	945
TP2: Weekdays HE 10 AM - 1 PM	89	833		922
TP3: Weekdays HE 2 PM - 4 PM	87	834		921
TP4: Weekdays HE 5 PM - 7 PM	94	877	5	976
TP5: Weekdays HE 8 PM - 10 PM	93	851		945
TP6: Weekend and Holidays HE 6 AM - 9 AM	56	740	-	795
TP7: Weekend and Holidays HE 4 PM - 9 PM	54	743	-	796
TP8: All Other Hours	65	750		816

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 2024 LTRA summer quantity (767 MW), based on availability in 2019, from ERCOT (2020a).

2. LOAD RESOURCES PROVIDING ANCILLARY SERVICES

Consistent with ERCOT's published minimum Responsive Reserve Service (RRS) requirements, we model 1,172 MW of non-controllable load resources (LRs) that actively participate in the RRS market.[60] All 1,172 MW are modeled as responsive to Energy Emergency Alert, Level 2.

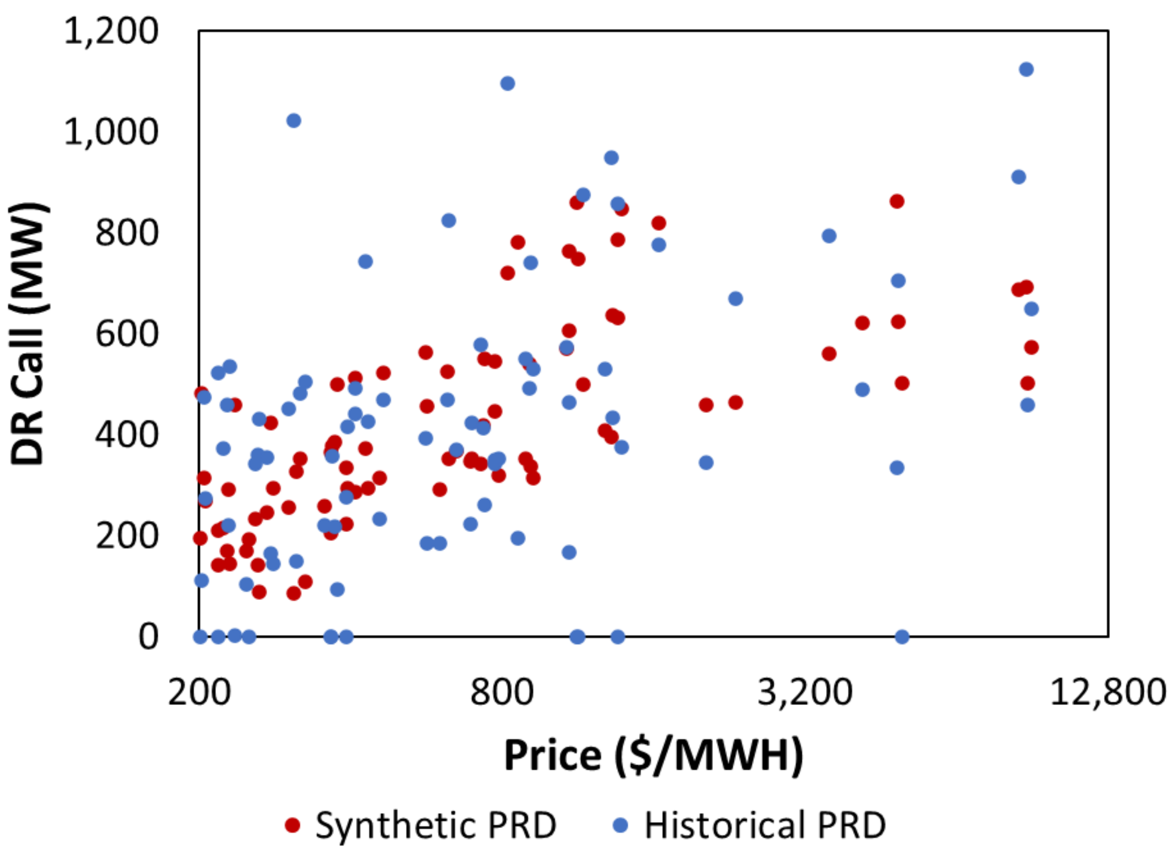
3. PRICE RESPONSIVE DEMAND AND 4 COINCIDENT PEAK

2019 historical demand response was used to develop modeling inputs to replicate stochastic demand-side response for price responsive and 4-coincident peak demands. A comparison of historical and synthetic PRD calls is shown in Figure A1-7 The aggregate of these shapes was used to gross up all 40 synthetic weather shapes.

[60] 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.

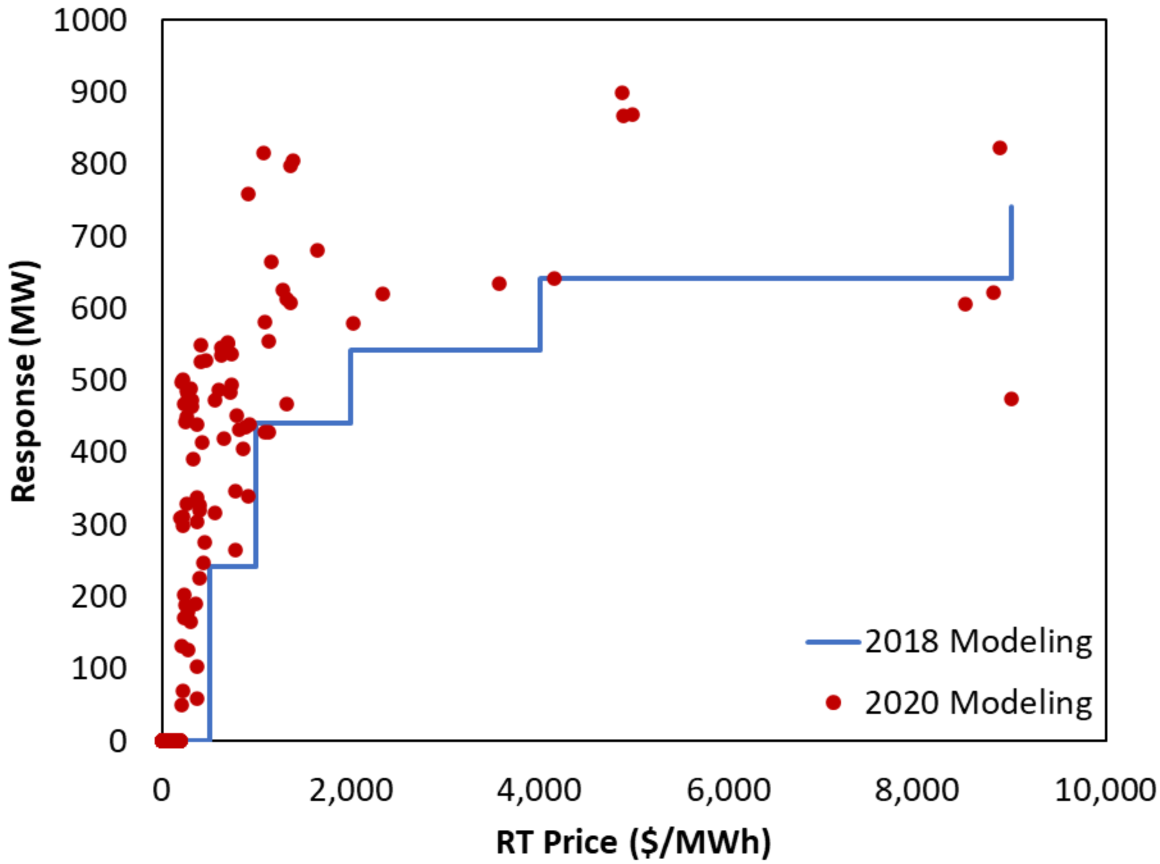
To model the price responsive demand (PRD) in SERVM, a curtailable unit was created that points to a price responsive demand curve. The demand curve has 4 pricing points based on the segments above ($200, $400, $800, and $1,500). For each of the 4 pricing points, 50 data points were created using the segment formulas specified. Within SERVM, whenever price reached one of the specified threshold points, SERVM randomly picked a DR value from that list of 50 data points. The Price Responsive Demand unit was available in all months.

Figure A1-7. Comparison of Historical and Synthetic PRD Calls



This stochastic representation in 2020 modeling differs from the discrete representation in the 2018 study, as shown in Figure A1-8.

Figure A1-8. PRD Modeling Comparison Between 2018 and 2020 Studies

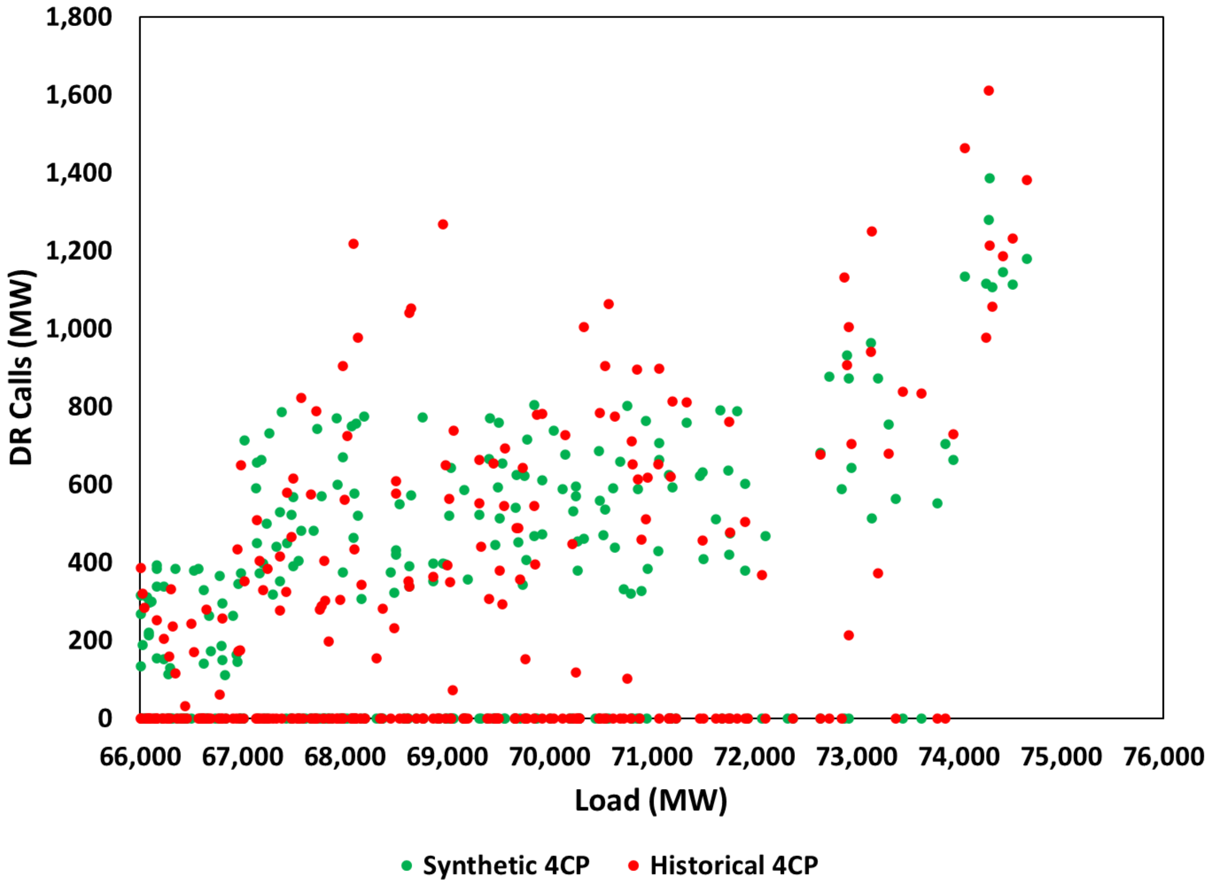


Similarly, 4CP was modeled as a load responsive unit. A comparison of historical and synthetic 4CP calls is provided below in Figure A1-9. Historical hourly 4CP was calculated as the sum of the following 4CP programs:

- 4CP Competitive
- 4CP NOIE

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

Figure A1-9. Comparison of Historical and Synthetic 4CP Calls



D. TRANSMISSION SYSTEM MODELING AND EXTERNAL RESOURCE OVERVIEW

This section provides an overview of the system interconnection topology, intertie availability, ERCOT and neighboring regions' supply curves.

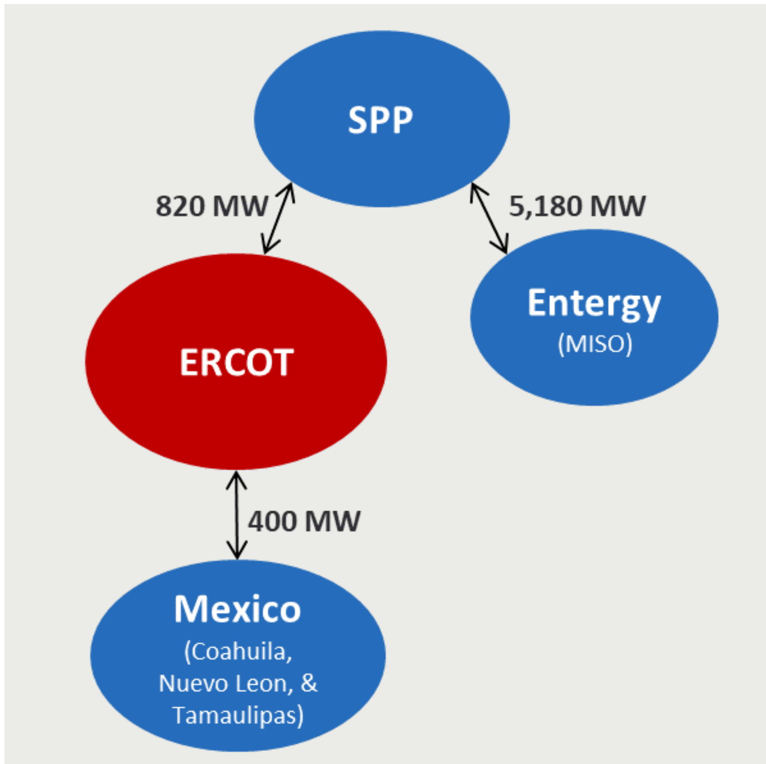
1. TRANSMISSION TOPOLOGY

ERCOT is a relatively islanded system with only 1,220 MW of high voltage direct current (HVDC) interties; the majority of that intertie capacity is with SPP.[61] As described in Section A, SERVM runs a multi-area economic dispatch and will schedule imports or exports from ERCOT depending on the relative cost of production compared to the neighboring systems. During peaking conditions, ERCOT will generally import power due to the high internal prices, unless imports cannot be realized. ERCOT may not be able to import during peak conditions because either: (a) the neighboring system experiences a simultaneous scarcity

[61] In some ERCOT studies the South DC Tie between ERCOT and Mexico is modeled with a capacity of 36 MW. However, we retired the 30 MW South Tie (Eagle Pass Tie) on April 2020 consistent with the ERCOT DC-Tie Operations Manual. See ERCOT (2020e) and ERCOT (2020a).

and will prioritize meeting its own load, or (b) insufficient intertie capability exists to support the desired imports. The intertie capacities assumed for this study are shown in Figure A1-10 below.

Figure A1-10. System Topology and Modeled Interties



Sources and Notes:
ERCOT intertie ratings from ERCOT (2020e)

2. EXTERNAL SYSTEMS' RESOURCE OVERVIEW

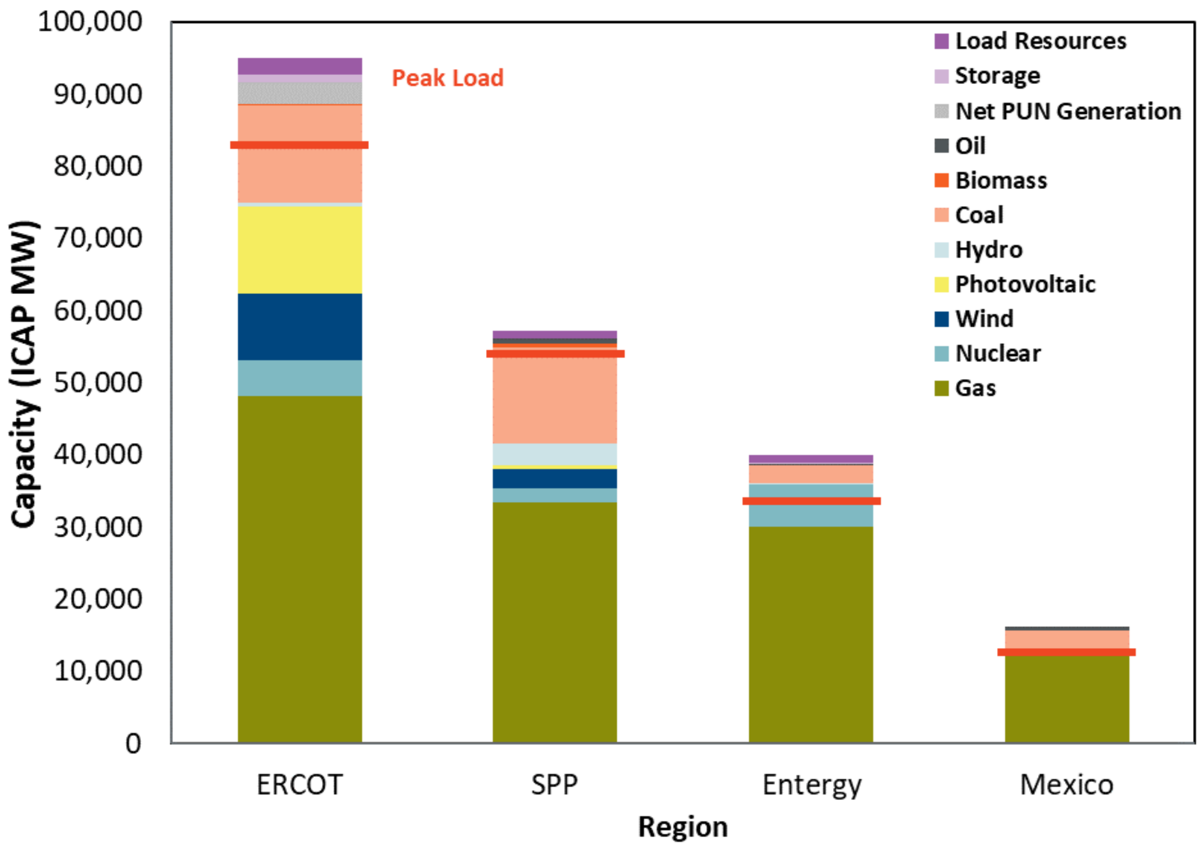
This section of our report provides an overview of the neighboring regions resource mixes.[62] Appendix A.1 summarizes the supply resource mix that we model in ERCOT, SPP, Entergy, and Mexico. For the neighboring regions, we rely on public data sources for the fleet makeup and demand-response penetrations.[63] As shown in Figure A1-11, we model each external region *at criterion*, meaning that we treat them exactly at their respective reserve margin targets of 12.0%, 16.8%, and 15% for SPP, Entergy, and Mexico, respectively.[64] Because these regions are currently capacity long, we adjusted their resource base downward by removing individual units of different resource types in order to maintain the current overall resource mix.

[62] More information on the ERCOT supply mix can be found in B.

[63] Specifically, we take external regions' resource mix from publicly available data and external regions' demand-response penetrations from NERC (2019).

[64] See MISO (2019), NERC (2019), SPP (2018). For Mexico we use an assumed reserve margin above the peak load.

Figure A1-11. Resource Mix for ERCOT and Neighboring System



3. AVAILABILITY OF EXTERNAL RESOURCES FOR ERCOT

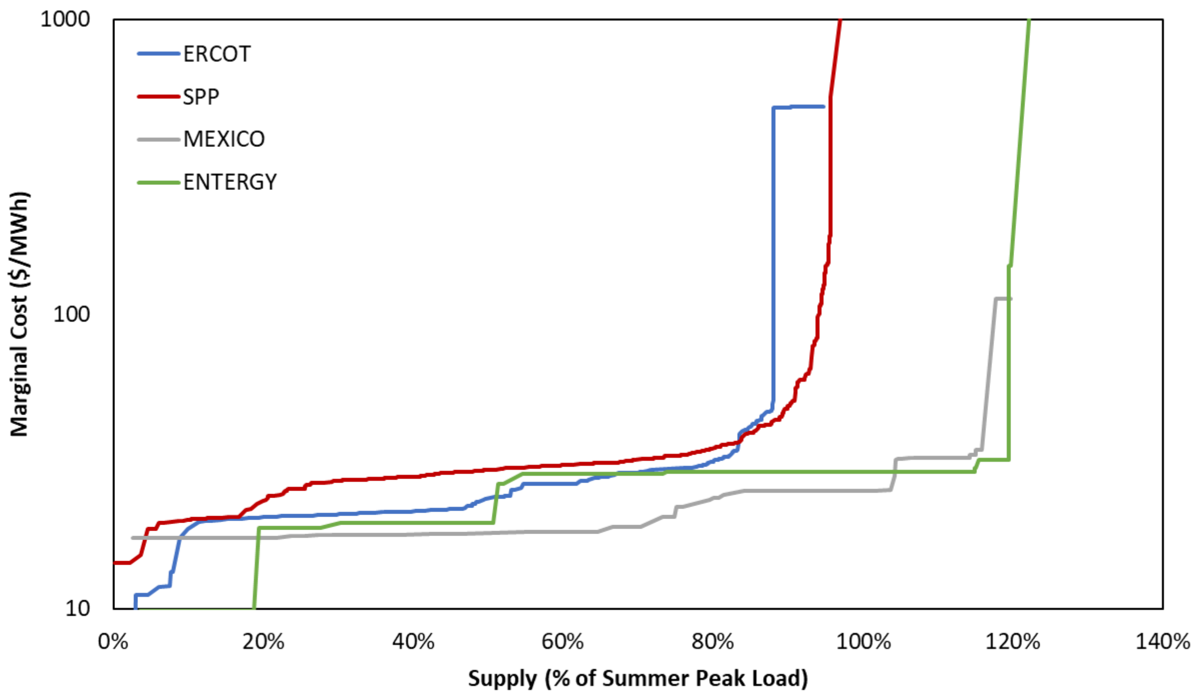
Imports to ERCOT depend on the conditions in the neighboring systems; even if transmission is available, ERCOT may not be able to import in emergency situations if the external region is peaking at the same time. To provide intuition regarding anticipated prices and intertie flows during normal conditions, we summarize the ERCOT and neighboring regions' supply curves in Figure A1-12. The curve reports energy dispatch costs consistent with year 2024, accounting for unit-specific heat rates, variable operations and maintenance (VOM) costs, and locational fuel prices from Appendix 1.0.6. For ERCOT, we gathered unit-specific information representing heat rate curves, VOM, ancillary service capabilities, ramp rates, startup fuel, non-fuel startup costs, and run-time restrictions from ERCOT. For external regions, we gathered unit-specific heat rates from public data sources, supplemented by class-average characteristics similar to those in ERCOT for other unit characteristics.[65] For all thermal resources, we model a seasonal capacity value which results in increased available capacity from the fleet during colder periods.

Overall, ERCOT's supply curve is similar to Mexico's but is relatively tight compared to SPP and Entergy. However, interchange will be limited because of ERCOT's relatively small quantity of HVDC interties, having

[65] Heat rates from ABB Velocity Suite (2018).

only 820 MW of interties with SPP and 400 MW with Mexico.[66] Some factors affecting the quantity and economic value of interchange include that: (a) SPP has more lower-cost coal that is somewhat cheaper than ERCOT-internal resources that are dominated by efficient but somewhat higher-cost gas combined-cycles, which will lead to ERCOT being a net importer, and (b) Mexico has a substantial proportion of relatively high-cost oil-fired peaking units, which will make such imports unlikely except at high prices in scarcity conditions. Further, the regions experience some amount of load diversity that will change the relative economics of supply in each region and lead to inter-regional flows.

Figure A1-12. 2024 System Supply Curves



Sources and Notes:
ERCOT is shown at 9.57% reserve margin, with resource mix consistent with 2020 LTRA as explained in Appendix 1.B, using unit-specific heat rates, VOM, and other characteristics obtained from ERCOT.
External systems resource mix from publicly available data.
Supply curves reflect VOM and fuel costs, with fuel prices from Appendix 1.B.6 above.

E. SCARCITY CONDITIONS

Increasing the reserve margin provides benefits primarily by reducing the frequency and severity of high-cost emergency events. Calculating the economically optimal reserve margin requires a careful examination of the nature, frequency, trigger order, and cost of each type of market-based or administrative emergency action implemented during such events.

[66] Based on several years of historical hourly intertie ratings supplied by ERCOT.

1. ADMINISTRATIVE MARKET PARAMETERS

We developed a representation of the 2024 ERCOT market using the parameters summarized in Table A1-7. We assume that the administrative Value of Lost Load (VOLL) is equal to the true market VOLL and the High System-Wide Offer Cap (HCAP) at $9,000/MWh.[67] We also conduct a sensitivity analysis for a reasonable range of VOLL.

Consistent with current market rules, we tabulate the Peaker Net Margin (PNM) over the calendar year and reduce the System-Wide Offer Cap (SWOC) to the Low System-Wide Offer Cap (LCAP) of $2,000/MWh after the PNM threshold is exceeded.[68] However, we stress that this mechanism will have a small impact on the MERM since the PNM threshold is rarely exceeded at reserve margins near MERM. We ran a simulation scenario which did not adjust the SWOC after the PNM threshold was exceeded, and the MERM changed by less than .25% from the result in our base case. We further explain our implementation of the ORDC PBPC in Sections 4 and 5 below.

Table A1-7. ERCOT Scarcity Pricing Parameters Assumed for 2024

Parameter	Value	Notes
Value of Lost Load (VOLL)	$9,000/MWh	Administrative and actual
High System-Wide Offer Cap (HCAP)	$9,000/MWh	Applied to PBPC and ORDC
Low System-Wide Offer Cap (LCAP)	$2,000/MWh	Applies to PBPC and ORDC when PNM threshold exceeded
Peaker Net Margin (PNM) Threshold	$280,500/MW-yr	3 x CT CONE

Sources and Notes:
HCAP, LCAP, and VOLL parameters consistent with PUCT (2019a).
PNM threshold is set at three times CT CONE consistent with current market rules and our updated CONE.

The offer cap and PNM parameters determine the maximum offer price for small suppliers in ERCOT's market under its monitoring and mitigation framework. However, we do not explicitly model these dynamics and instead assume that suppliers always offer into the market at price levels reflective of their marginal costs, including commitment costs.

2. EMERGENCY PROCEDURES AND MARGINAL COSTS

Table *A1-8* summarizes our modeling approach and assumptions under all scarcity and non-scarcity conditions depending on what type of marginal resource or administrative emergency procedure would

[67] See PUCT (2019a).
[68] See PUCT (2019a).

be implemented to meet an incremental increase in demand. These marginal resources are listed in the approximate order of increasing marginal costs and emergency event scarcity, although in some cases the deployment order overlaps.

We distinguish between market-based responses to high prices in scarcity conditions and out-of-market administrative interventions triggered by emergency conditions. Among market-based responses, we include generation, imports, and price-responsive demand, including some very high-cost resources that will not economically deploy until prices are quite high. We also model reserve scarcity that is administrative in nature but triggered on a price basis consistent with the ORDC and PBPC as explained in the following sections.

A final category of emergency interventions encompasses out-of-market actions including ERS, LR, TDSP load management, and firm load shed deployments that are triggered for non-price reasons during emergency conditions. We implement each of these actions at a particular scarcity level as indicated by the quantity of reserves capability available according to the ORDC x-axis, a measure similar to the physical responsive capacity (PRC) indicator used by ERCOT to monitor system operations. To estimate the approximate ORDC x-axis at which each action would be implemented, we reviewed ERCOT's emergency operating procedures, evaluated the PRC level coinciding with each action during historical emergency events, and confirmed these assumptions with ERCOT staff.[69] These trigger levels are in line with historical emergency events, although actual emergency actions are manually implemented by the system operator based on a more complex evaluation of system conditions, including frequency and near-term load forecast.

We also describe in the table below the marginal system costs of each type of scarcity event as well as the prevailing market price during those events. In a perfectly-designed energy market, prices would always be equal to the marginal cost that would theoretically lead to optimal response to scarcity events and an optimal level of investments in the market. In ERCOT, prices are reflective of marginal costs in most cases but not all. Specifically, the ORDC curve is designed based on an assumption that load would be shed at X = 2,000 MW, while our review of historical events indicates that load shedding is more likely to occur at a lower level of X = 1,000 MW. This discrepancy results in prices above marginal costs during moderate scarcity events, as discussed further in Appendix 1.E.4 below.

[69] The PRC metric is calculated with some accounting nuances that make it a somewhat different number from the ORDC Spin x-axis, we do not consider these nuances in our modeling, for the formula for calculating PRC, see ERCOT (2020d), Section 6.5.7.

Table A1-8. Emergency Procedures and Marginal Costs

Emergency Level	Marginal Resource	Amount of Resource (MW)	Trigger	Price	Marginal System Cost
n/a	Generation	Variable	Price	Approximately $20 - $250	Same
n/a	Imports	Variable	Price	Approximately $20-$250 Up to $1,000 during load shed	Same
n/a	Non-Spin Shortage	700	ORDC x-axis = 3,000 MW	$4,627 (from ORDC)*	$1,025*
n/a	Price-Responsive Demand	Variable	Price	$500 - $9,000	Same
n/a	Emergency Generation	469.8	ORDC x-axis = 2,300 MW	$5,850 (from ORDC)	$1,372
n/a	PBPC	200	Price	$1,000 - $9,000	Same
EEA 1	30-Minute ERS	691**	Spin ORDC x-axis = 2,300 MW	$5,850 (from ORDC)	$1,372
EEA1	Spin Shortage A	550	Spin ORDC x-axis = 2,300 MW	$7,492 (from ORDC)*	$1,856*
EEA 2	TDSP Load Curtailments	262	Spin ORDC x-axis = 1,750 MW	$9,000 (from ORDC)	$2,469
EEA 2	Load Resources in RRS	1,172***	Spin ORDC x-axis = 1,750 MW	$9,000 (from ORDC)	$2,469
EEA 2	10-Minute ERS	76**	Spin ORDC x-axis = 1,750 MW	$9,000 (from ORDC)	$2,469
EEA3	Spin Shortage B	750	Spin ORDC x-axis = 1,750 MW	$9,000 (from ORDC)	$3,562*
EEA 3	Load Shed	Variable	Spin ORDC x-axis = 1,000 MW	VOLL = $9,000	Same

Sources and Notes:

*: Price reflects the average price between the upper and lower level of each resource.

**: 76 10NWS + 666 30NWS + 26 30WS = 767 total ERS (CDR Value). Both NWS and WS are included in the 30-Minute ERS.

***: 60% of RRS

Developed based on review of historical emergency event data, input from ERCOT staff, and ERCOT's emergency procedure manuals; see ERCOT (2020d), Section 6.5.9, and ERCOT (2020f), Section 4.

3. EMERGENCY GENERATION

During severe scarcity conditions, there are out-of-market instructions by ERCOT as well as strong economic incentives for suppliers to increase their power output to their emergency maximum levels for a short period of time.[70] During these conditions, suppliers can output power above their normal capacity ratings, although doing so is costly because it may impose additional maintenance costs and may put the unit at greater risk of failure.

[70] See Section 6.5.9, ERCOT 2020d.

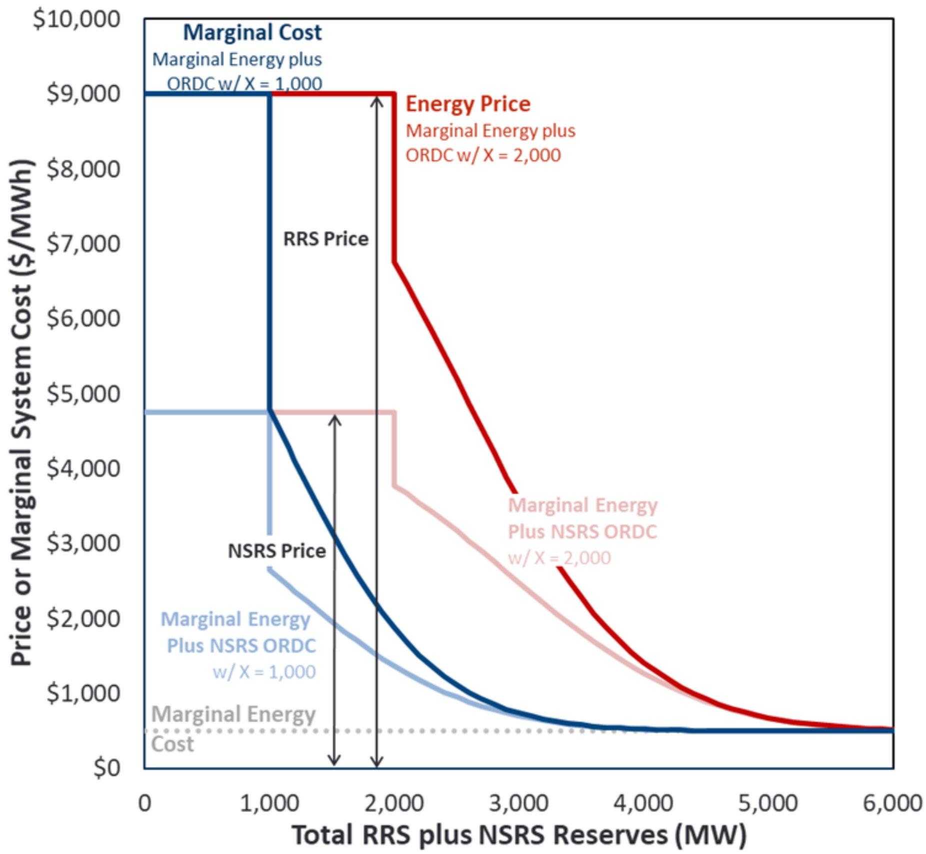
According to ERCOT's emergency maximum ratings, the aggregate ERCOT fleet should be able to produce approximately 469.8 MW in excess of summer CDR ratings.[71] We estimate the marginal cost of emergency output at approximately \$2,752/MWh, consistent with ERCOT's procedures for calling emergency generation.

4. OPERATING RESERVES DEMAND CURVE

The most important and influential administrative scarcity pricing mechanism in ERCOT is the operating reserves demand curve (ORDC) that reflects the willingness to pay for spinning and non-spinning reserves in the real-time market. Figure A1-13 illustrates our approach to implementing ORDC in our modeling, which is similar to ERCOT's implementation, although with some simplifications.[72] We implement distinct ORDC curves for each of the four seasons each year, and for each of two types of operating reserves.[73]

Figure A1-13. Operating Reserve Demand Curves

Example: Summer Hours 15-18



Sources and Notes:

ORDC curves developed consistent with ERCOT (2013).

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[71] This number excludes private use network resources, which we model separately as explained in Section 3 above.

[72] For a detailed explanation of ERCOT's ORDC implementation see their whitepaper on the methodology for calculating ORDC at ERCOT (2013).

[73] See ERCOT (2013).

The ORDC curves are 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.[74] 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.

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 A1-9 provides a summary of the resources that are always available to contribute to the ORDC x-axis unless they have been dispatched for energy although the realized ORDC x-axis 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).[75]

Table A1-9. Resources Always Contributing to ORDC X-Axis Unless Dispatched for Energy

Spin X-Axis		
Hydrosynchronous Resources	(MW)	245
Non-Controllable Load Resources	(MW)	1,172
Non-Spin X-Axis		
30-Minute Quickstart	(MW)	5,206
Total Spin + Non-Spin	**(MW)**	**6,623**

The red and pink curves in Figure A1-13 show the ORDC curves used for price-setting purposes, calculated as if ERCOT would shed load at an ORDC x-axis of X = 2,000 MW. However, as we explained in Appendix 1.E.2 above, we assume that load shedding will actually occur at X = 1,000 MW based on our analysis of historical emergency events and consistent with the blue curves below. In other words, we model a discrepancy between marginal costs (blue) and market prices (red) that will create some inefficiency in realized market outcomes.

[74] Note that the lost load implied by this function and caused by operating reserve scarcity is additive to the lost load that we report elsewhere in this study. 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. We also do not change the ORDC when varying the VOLL in our model sensitivities.

[75] We assume that the CT reference unit is capable of providing non-spin from an offline position.

As in ERCOT's ORDC implementation, we calculate: (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 do not scale the ORDC curves in proportion to VOLL minus marginal energy in each hour.[76] Instead, we treat the ORDC curves as fixed with a maximum total price adder of VOLL minus $500, which causes prices to rise to the cap of $9,000/MWh in scarcity conditions, because $500 is the cap placed on marginal energy prices in the model. Higher-cost demand-response resources will be triggered in response to high ORDC prices and therefore prevent prices from going even higher, but do not affect the "marginal energy component" of price-setting. We model the ORDC curves out to a maximum quantity of 8,000 MW where the prices are near zero, although they never drop all the way to 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 model unit commitment in three steps: (1) a week-ahead optimal unit commitment over the fleet, with the result determining which long-lead resources will be committed[77]; (2) a four-hour ahead unit commitment (updated hourly) with an updated fleet outage schedule, with the result determining the preliminary commitment and decommitment schedules for combined cycle units; and (3) an hourly economic dispatch that dispatches online baseload units, and can commit 10-minute and 30-minute quickstart units if energy and spin prices are high enough to make it more profitable than remaining offline (similarly, if prices are not high enough these units will economically self-decommit).[78] 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. These resources will not self-commit unless doing so would result in greater energy and spin payments (net of variable and commitment costs) than would be available from an offline position. We use a similar logic to economically commit or de-commit units until the incentives provided by the ORDC are economically consistent with the quantity of resources turned on.

5. POWER BALANCE PENALTY CURVE

The Power Balance Penalty Curve (PBPC) is an ERCOT 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 A1-14.[79] Whenever a PBPC is dispatched for

[76] See ERCOT's implementation in ERCOT (2013).

[77] 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.

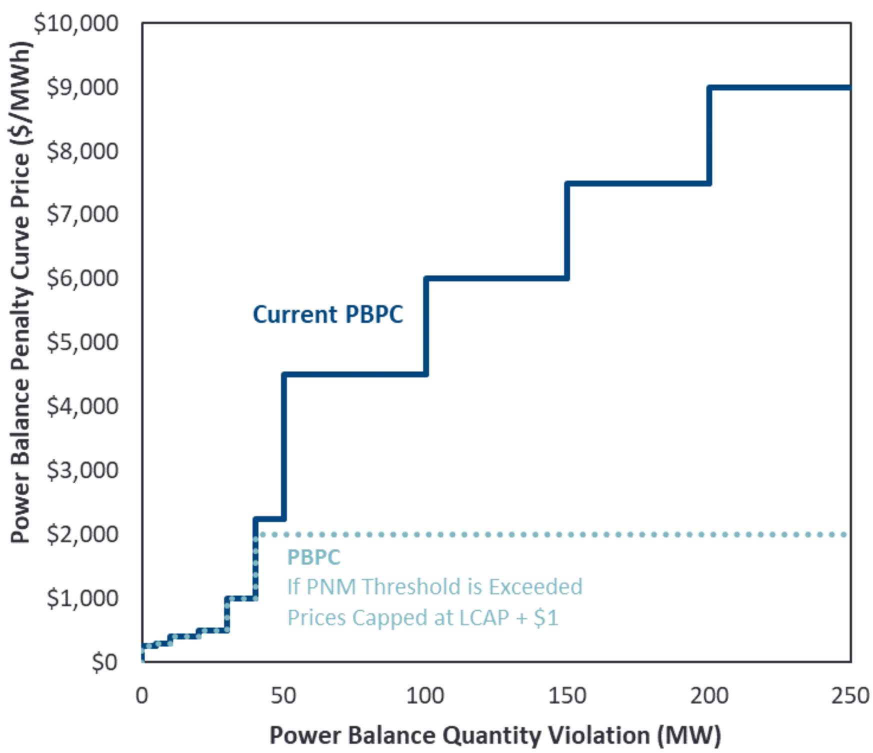
[78] These week-ahead and day-ahead commitment algorithms minimize cost subject to meeting load as well as ERCOT's administratively-determined regulation up and spinning reserve targets, with non-spinning reserve targets not considered at the unit commitment phase.

[79] See ERCOT (2019b).

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. At 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 as explained in Appendix 1.E.1 above.

We similarly model the PBPC as phantom supply that may influence the realized price, and that will cause a reduction in available regulating reserves whenever called. However, we model only the first 200 MW of the curve at prices below the cap, and assume that all price points on the PBPC will increase according to the scheduled SWOC.[80] We also assume that the prices in the PBPC are reflective of the marginal cost incurred by going short of each quantity of regulating reserves.[81] 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.[82] Note that even after the maximum PBPC price is reduced, ERCOT market prices may still rise to a maximum value of VOLL equal to $9,000/MWh during scarcity conditions because of the ORDC as explained in the following section.

Figure A1-14. Power Balance Penalty Curve



Sources and Notes:
PBPC numbers from ERCOT (2019b), p. 22-23.

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[80] See ERCOT (2019b).
[81] Once the PNM is exceeded and the PBPC is reduced, these prices are no longer reflective of marginal cost but are instead lower than marginal cost at regulation shortage quantities greater than 40 MW.
[82] See ERCOT (2019b).

APPENDIX 2: EFFECTIVE LOAD CARRYING CAPABILITY

The reserve margin is the sum of all dependable generating capacity divided by expected peak load. Dependable generating capacity varies for non-dispatchable or energy-limited resources and generally depends on simulations which calculate the comparable conventional capacity for the resource being evaluated. Very constrained resources such as 1-hour energy storage or low capacity factor wind would be expected to have ratios much lower than 100% while very dependable resources such as long duration storage would have ratios close to 100%.

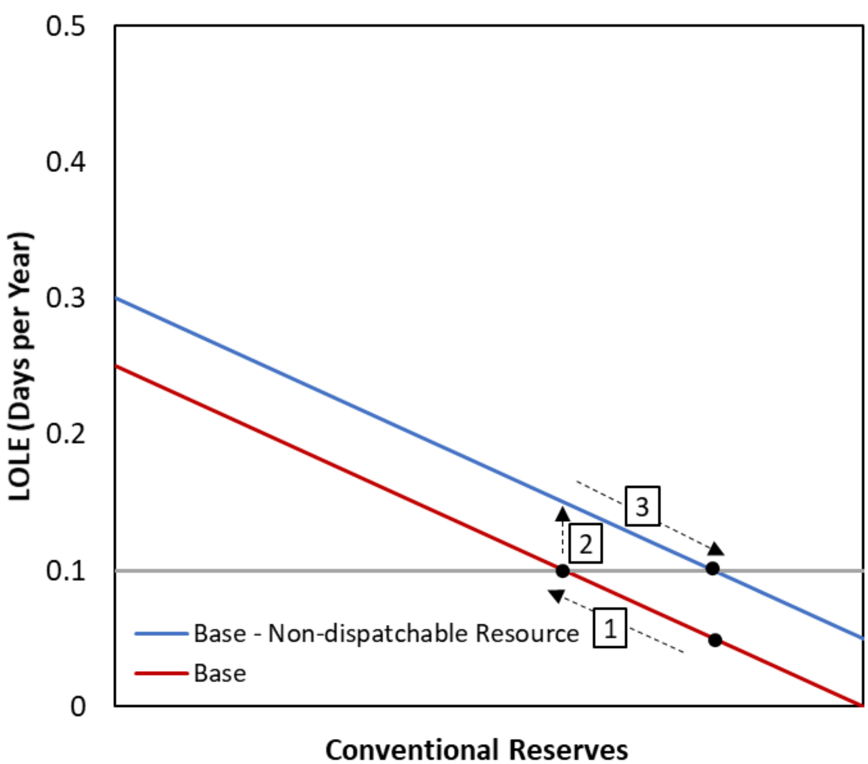
The actual steps to determine these ratios are as follows:

1. Calibrate system reliability to 0.1 LOLE by removing or adding conventional capacity.
2. Remove the non-dispatchable or energy-limited resource portfolio in question. This will increase the frequency of LOLE events.
3. Restore LOLE to 0.1 by adding conventional capacity.
4. Calculate the ELCC:

$$ELCC = \frac{Conventional\ Capacity\ Added\ (Step\ 3)}{Non\text{-}Dispatchable\ or\ Energy\text{-}Limited\ Resource\ Capacity\ Removed\ (Step\ 2)}$$

Figure A2-1 contains a visual example of the process described above.

Figure A2-1. ELCC Visual Example

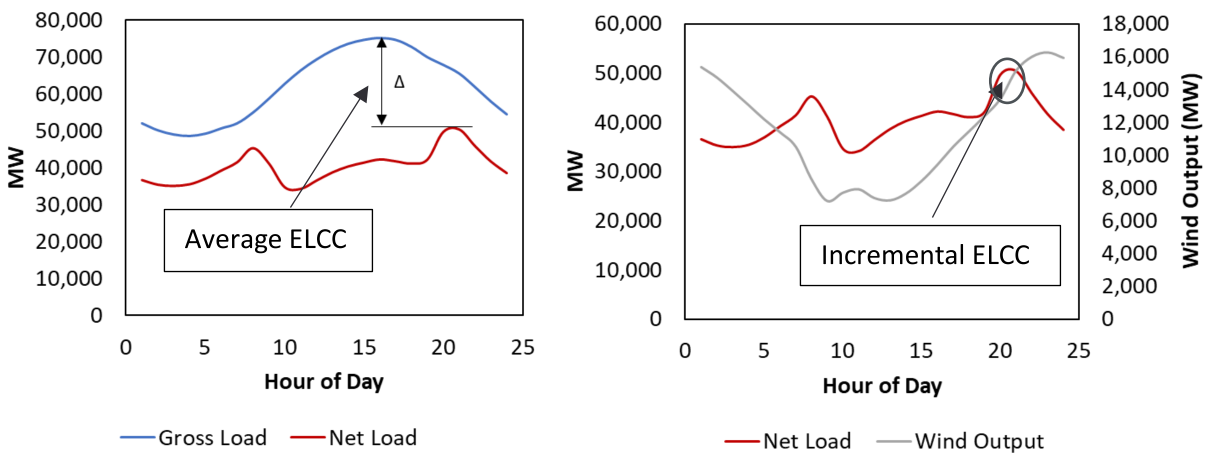


AVERAGE ELCC VERSUS INCREMENTAL ELCC

The calculation steps explained above are for average ELCC. It determines the value of an entire portfolio. Calculations for incremental ELCC would typically be done in reverse. Add a small resource to a calibrated system and determine the capacity to remove to determine ELCC. Average ELCC would be used for reserve margin accounting. Incremental ELCC is used for procurement decisions.

In Figure A2-2, the average ELCC illustration on the left shows the reduction in net load which would approximately correspond to the average ELCC value. The illustration on the right shows the renewable profile of an incremental resource against the net load profile of a system with an existing penetration of renewable capacity. The Incremental ELCC value would approximately correspond to the average output during the net load peak.

Figure A2-215. Average ELCC Versus Incremental ELCC



Both of these methods differ from the implicit ELCC calculations in the CDR accounting in ERCOT. The capacity credit given to wind and solar in CDR is based on the average of the top 20 gross load hours. Since this method doesn't consider that the net load may have shifted due to the renewable output, it will overstate the ELCC of the renewable resources. Table A2-1 shows a comparison of methods of ELCC calculation using synthetic data for both wind and solar.

Table A2-1. Average Output and Net Load Reduction ELCC Comparison

	Wind		Solar	
	Avg Output During Top 20 Load Hours (ERCOT Accounting Method)	Net Load Reduction (True Reliability Contribution)	Avg Output During Top 20 Load Hours (ERCOT Accounting Method)	Net Load Reduction (True Reliability Contribution)
2010	12%	8%	78%	75%
2011	24%	12%	83%	72%
2012	13%	6%	80%	72%
2013	24%	13%	82%	80%
2014	24%	16%	80%	68%
2015	18%	13%	81%	76%
2016	30%	21%	76%	71%
2017	24%	18%	75%	68%
2018	20%	16%	76%	70%
2019	27%	16%	79%	65%
Average	**22%**	**14%**	**79%**	**72%**

ELCC RESULTS

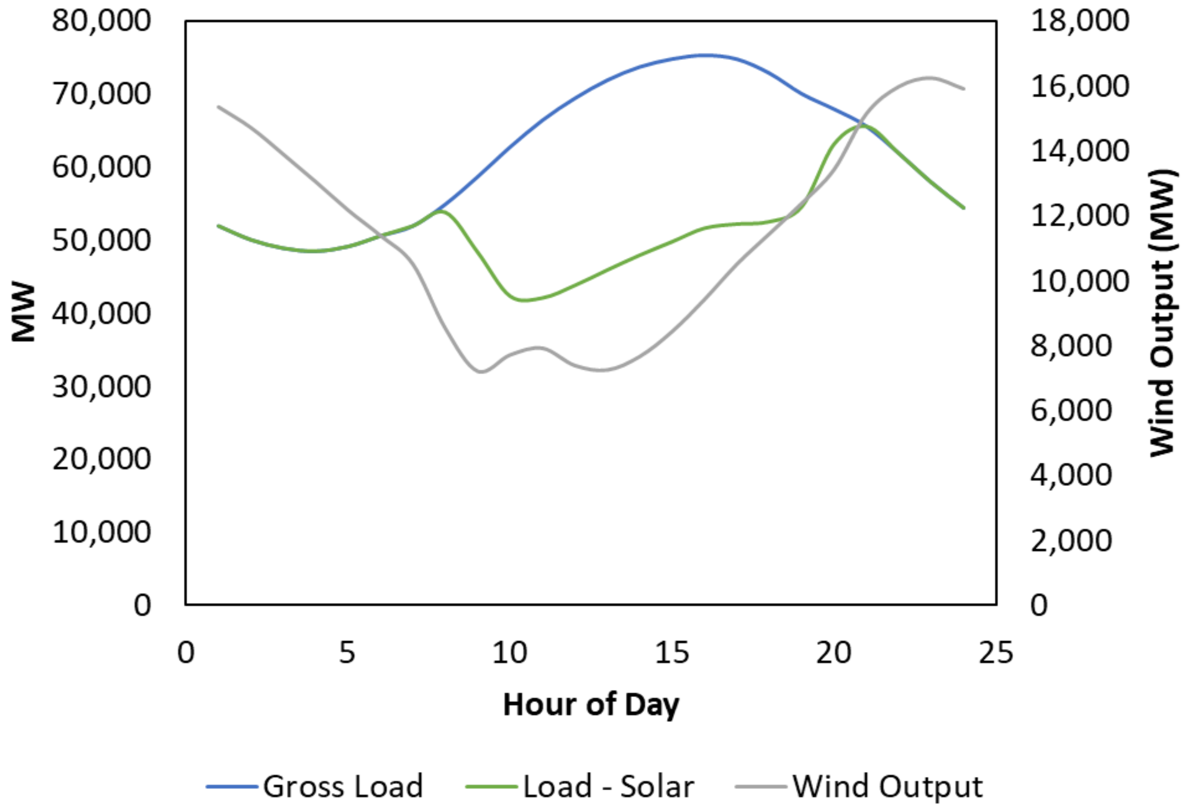
The net load reductions in Table A2-1 indicate the true reliability contribution, but SERVM simulations are required to get precise values. Performing the average ELCC simulations results in ELCCs for the entire renewable portfolio in Table A2-2.

Table A2-2. Average ELCC Simulation Results for Entire Renewable Portfolio

	2020	2024	2024 High Renewable
All Renewable ELCC (MW)	9,436	18,693	22,844
All Renewable Installed Capacity (MW)	37,923	53,397	73,397
All Renewable ELCC (%)	25%	35%	31%

These renewable portfolio totals will be used in later steps since the sum of individual technology or zonal ELCCs cannot exceed the renewable portfolio total. Technology specific ELCCs are calculated by removing only the study resource. Since wind and solar exhibit some synergy for reliability contribution, the sum of the raw ELCCs for wind and solar is greater than the entire portfolio ELCC. Figure A2-3 shows how the addition of solar pushes the net load to late in the day when the aggregate ERCOT wind output is expected to produce more energy. The higher energy translates to higher ELCC. In reverse, wind would push the net load peak to earlier in the day, increasing the ELCC for solar as well.

Figure A2-316. Effects of Addition of Solar to Net Load Shape



The resulting raw ELCCs for each technology are shown in Tables A2-3 and A2-4. As expected the sum of the individual technology ELCCs is larger than the entire portfolio ELCC, since the standalone analyses include the full synergistic benefits from the other technology. This would be double counting the benefit by assigning it to each of wind and solar.

Table A2-3. Wind Technology Raw ELCC Values

	2020	2024	2024 High Renewable
Wind Raw SERVM ELCC (MW)	5,422	7,045	9,194
Wind Installed Capacity (MW)	32,026	37,396	42,396
Wind ELCC (%)	17%	19%	22%

Table A2-4. Solar Technology Raw ELCC Values

	2020	2024	2024 High Renewable
Solar Raw SERVM ELCC (MW)	4,711	12,529	17,095
Solar Installed Capacity (MW)	5,897	16,001	31,002
Solar ELCC (%)	80%	78%	55%

Since the sum is larger, the total portfolio ELCC needs to be allocated to each respective technology according to the following formulas:

- $Wind\ ELCC = \frac{Wind\ ELCC}{(Wind\ ELCC+Solar\ ELCC)} * Renewable\ ELCC$
- $Solar\ ELCC = \frac{Solar\ ELCC}{(Wind\ ELCC+Solar\ ELCC)} * Renewable\ ELCC$

The results of these calculations are shown in Tables A2-5 and A2-6.

Table A2-5. Wind Technology Allocated ELCC Values

	2020	2024	2024 High Renewable
Wind Raw SERVM ELCC (MW)	5,422	7,045	9,194
Wind Allocated ELCC (MW)	5,049	6,728	7,989
Wind ELCC (%)	16%	18%	19%

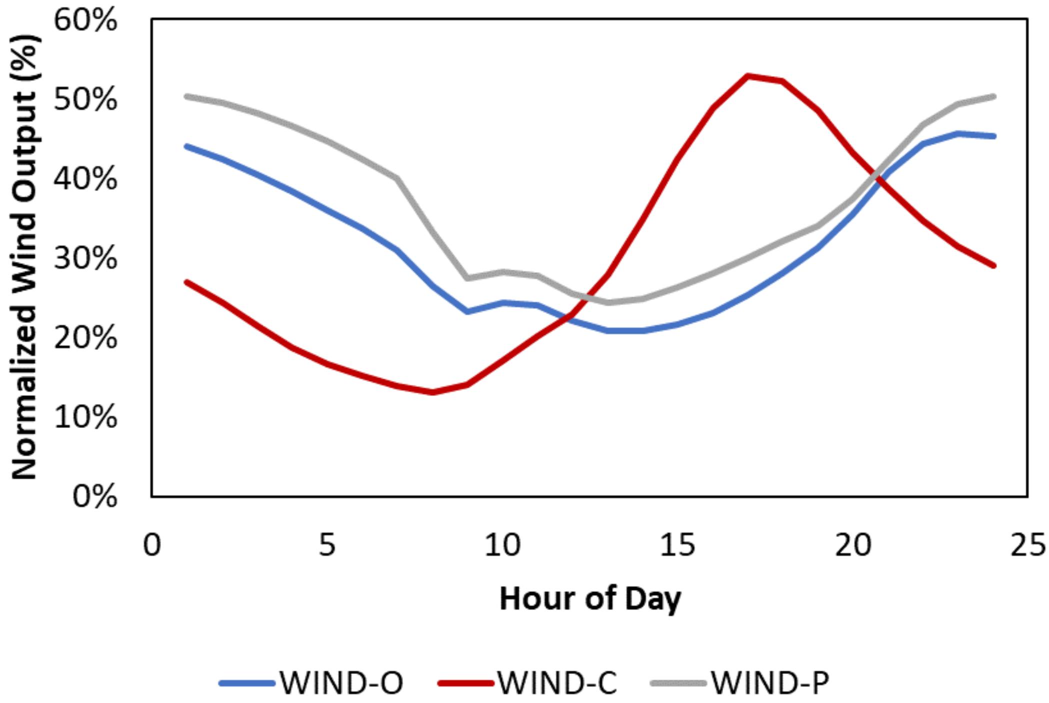
Table A2-6. Solar Technology Allocated ELCC Values

	2020	2024	2024 High Renewable
Solar Raw SERVM ELCC (MW)	4,711	12,529	17,095
Solar Allocated ELCC (MW)	4,387	11,965	14,855
Solar ELCC (%)	74%	75%	48%

The synergy can be seen in both the allocation calculation as well as the change from year to year. The wind capacity value increases from 2020 to 2024 and to 2024 High Renewable as solar shifts the net load profile to later in the day. Solar ELCC doesn't decline much between 2020 and 2024, but additions after the penetrations assumed in the 2024 portfolio have a rapidly declining ELCC. The average ELCC for solar increases from approximately 12 GW in 2024 to 15 GW 2024 with High Renewable. The 3 GW increase in ELCC corresponds to a 15 GW solar increase, so on a relative basis, the solar added between these scenarios only achieves a 20% ELCC.

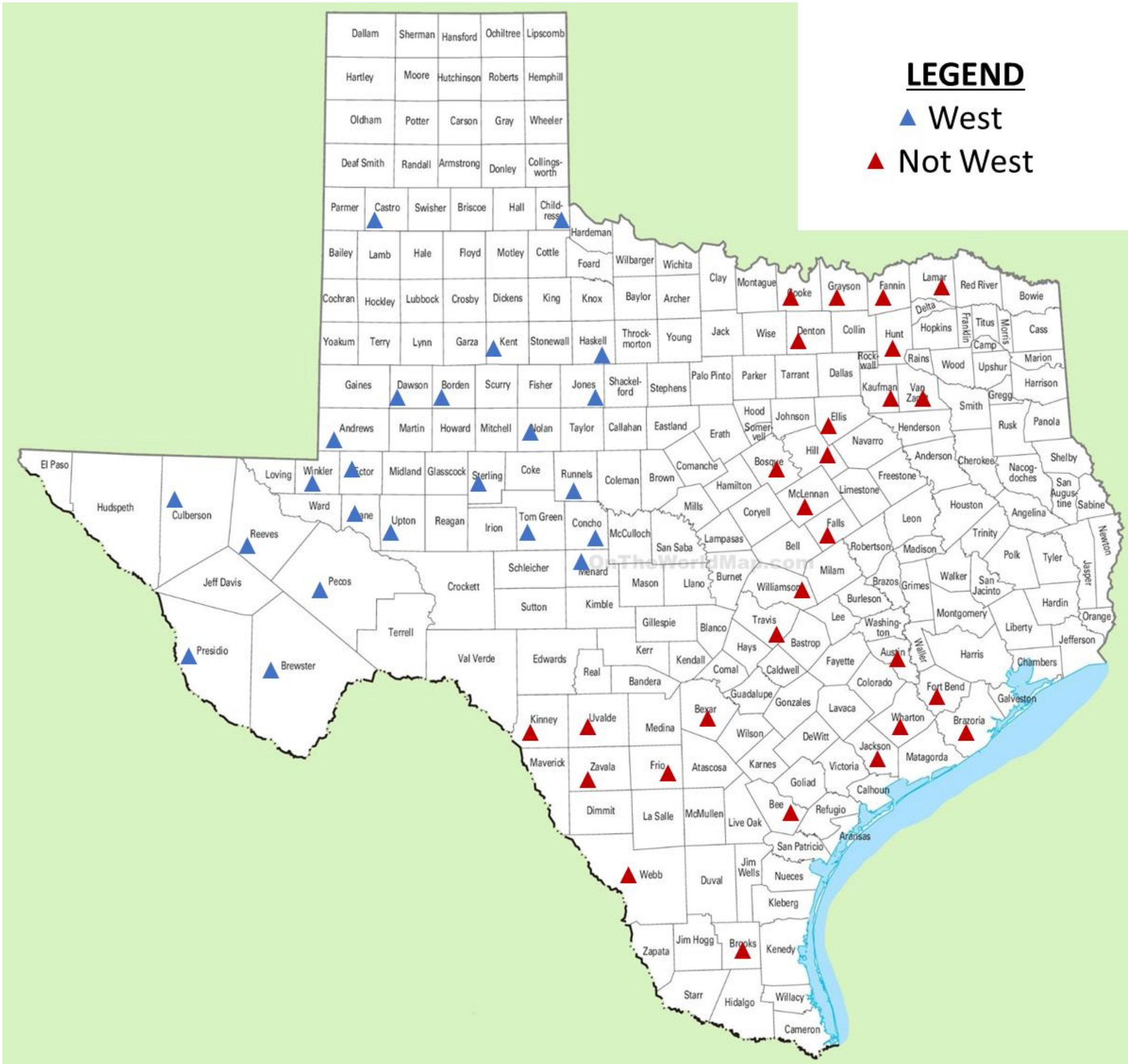
We performed further calculations to isolate locational ELCCs for both wind and solar. Wind is divided into Wind Coastal (Wind-C), Wind Other (Wind-O), and Wind Panhandle (Wind-P). A typical summer profile is shown for each wind location in Figure A2-4.

Figure A2-417. Typical Daily Summer Profile for Each Wind Subcategory



Solar is divided into West and Non-West according to the geographic grouping shown in the map in Figure A2-5.

Figure A2-518. Geographic Grouping for Solar West and Non-West



As expected, the coastal wind which exhibits higher capacity factor and higher diversity with load has a higher ELCC than the other two locational categories. However, it is not as high as suggested by the average output calculations performed by ERCOT. Table A2-7 compares the ELCCs for different years and portfolios and the ERCOT CDR methodology.

Table A2-7. Wind ELCC by Location

	May 2020 CDR Summer Peak Average Capacity Contribution	2020	2024	2024 High Renewable
Wind-C	63%	31%	37%	24%
Wind-O	16%	11%	13%	18%
Wind-P	29%	21%	22%	17%
All Wind		16%	18%	19%

Solar ELCC is in part determined by longitude. Projects further to the west would be expected to have higher ELCCs in the summer since they would continue to produce output late into the afternoon. Since summer is the predominant reliability risk season, this effect drives the ELCC for solar, but in winter peaking regions across the country, eastern projects could produce higher ELCCs if early morning peaks are a reliability concern. The difference in ELCCs by location is 3-4%, as shown in Table A2-8, but more granular analysis comparing ELCCs for single locations in far West Texas vs far East Texas might show slightly larger disparities.

Table A2-8. Solar ELCC by Location

	May 2020 CDR Summer Peak Average Capacity Contribution	2020	2024	2024 High Renewable
Solar Non-West	76%	71%	72%	46%
Solar West	76%	75%	76%	49%
All Solar		74%	75%	48%

Until 2024, the CDR accounting methodology roughly approximates the ELCC results from SERVM. However, further expansion of the solar fleet will sharply reduce ELCCs creating a disconnect with CDR methodology.

EXHIBIT MG-9

Estimation of the Market Equilibrium and Economically Optimal Reserve Margins for the ERCOT Region

2018 Update

PREPARED FOR

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Acknowledgement: We acknowledge the valuable contributions of many individuals to this report and to the underlying analysis, including Michael Hagerty, Katie Mansur, and other members of The Brattle Group for peer review. The authors would also like to thank the ERCOT staff for their input. In particular, we would like to acknowledge the analytical, technical, and conceptual contributions of Peter Warnken, Kevin Hanson, and Julie Jin.

Table of Contents

Executive Summary

We have been asked by the Electric Reliability Council of Texas (ERCOT), on behalf of the Public Utility Commission of Texas (PUCT), to estimate the market equilibrium reserve margin (MERM) and the economically optimal reserve margin (EORM) for ERCOT's wholesale electric market. We undertook this analysis with Astrapé Consulting simulating the ERCOT market using its Strategic Energy Risk Valuation Model (SERVM). The model reflects ERCOT's wholesale market design and projected system conditions for 2022; it probabilistically simulates the economic and reliability implications of a range of possible reserve margins under a range of weather and other conditions.

The MERM describes the reserve margin that the market can be expected to support in equilibrium, as investment in new supply resources responds to expected market conditions. This concept is relevant in ERCOT because, unlike all other electricity systems in North America, ERCOT does not have a resource adequacy reliability standard or reserve margin requirement. In ERCOT, the reserve margin is ultimately determined by suppliers' costs and willingness to invest based on market prices, where prices are determined by market fundamentals and by the administratively-determined Operating Reserve Demand Curve (ORDC) during tight market conditions. This approach creates a supply response to changes in energy market prices towards a "market equilibrium"; low reserve margins cause high energy and ancillary service (A/S) prices and attract investment in new resources, and investment will continue until high reserve margins result in prices too low to support further investment.

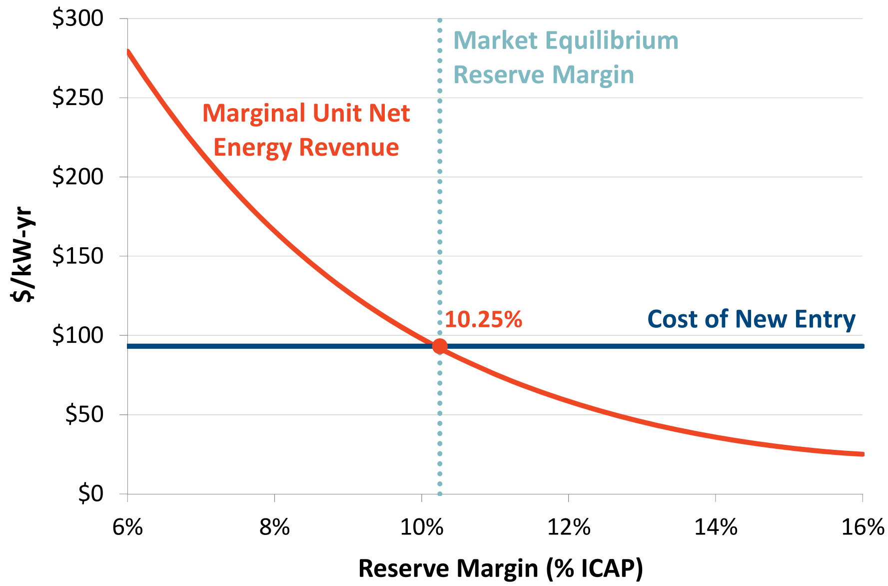
We estimate a market equilibrium reserve margin of 10.25% under projected 2022 market conditions, as shown in Figure ES-1.[1] This is much lower than historical reserve margins, but close to the reserve margins from ERCOT's latest resource adequacy reports. Reserve margins were 10.9% for the summer of 2018 (relative to forecasted firm peak load),[2] with 11.0% projected for 2019.[3]

1 This estimate should not be interpreted as a precise forecast for 2022 or any other particular year, but as a reasonable expectation around which actual reserve margins may vary as market conditions fluctuate. To expect a persistently lower reserve margin would be to assume investors will forego profitable opportunities to add additional supply, and to expect a persistently higher reserve margin would be to assume investors will over-invest.

2 Final 2018 Summer SARA. Adjusted Peak Demand reduced by Load Resources, Emergency Response Service, and TDSP according to the May 2018 Capacity, Demand and Reserves (CDR) report to calculate the reserve margin.

3 May 2018 CDR.

Figure ES-1



Note: Marginal Unit Net Energy Revenue represents the net revenue from a mix of added combined-cycle and simple-cycle combustion turbine plants (77:23 ratio); the Cost of New Entry shown at $93.1/kW-yr reflects this mix.

The PUCT may be interested in whether such a market outcome would be acceptable to economic optimality. The economic optimum occurs at the reserve margin that minimizes societal costs net of all supply costs and the lost value from any disruptions in electric service. We calculate the economically optimal reserve margin by finding the balance between the marginal costs and marginal benefits of adding capacity. The marginal costs are simply the levelized capital costs and fixed costs of a new generator. Marginal benefits include lower production costs and reduced load shedding (at an assumed cost of $9,000/MWh), reserve shortages, demand-response calls, and other costly emergency events. Our simulations quantify how scarcity event frequencies decrease (at a diminishing rate) as reserve margins increase. We estimate 9.0% as the economically optimal reserve margin, based on the risk-neutral, probability-weighted-average cost of 57,000 simulations.[4] However, the estimated societal costs are relatively flat with respect to reserve margin near the minimum, with only modest variation between reserve margins of 7% and 11%.

Our analysis shows that the market equilibrium of 10.25% is greater than the economically optimal level of capacity by 1.25%. Based on these results, we conclude that the current market design will support more than sufficient reserve margins from an economic perspective. The market equilibrium is higher than the economic optimum because the ORDC as currently designed sets

[4] 38 weather years, each at 5 levels of non-weather-based load forecast error, with 50 generator outage draws, at six modeled reserve margins.

prices higher than the marginal value of energy during scarcity conditions. This design intentionally creates additional incentives to invest and thereby raises reserve margins somewhat above the economic optimum. When ERCOT implemented the ORDC in June 2014 per PUCT orders, it right-shifted the curve by 1,000 MW (slightly more than 1% of peak load) relative to the curve that more accurately reflected the expected value of lost load.[5] The right-shift accounted for the additional cost of emergency actions, but it may have reflected some risk aversion to lower reliability.

Table ES-1 shows these for the base case as well as for sensitivity and scenario analyses conducted for this study. Some of the key assumptions we test are the estimated capital cost of new generation, load forecasting error, coal and natural gas prices, the value of lost load (VOLL), intermittent renewable penetration, and weather distributions. Regarding weather, our base case assumption is that all 38 years of historical weather are assigned an equal probability of occurring for the 2022 simulation year, and this reliance on long history is consistent with the EORM Manual. More recent weather has been hotter (especially 2011) and may be assumed to be more representative of future weather. Assuming accordingly that each of the last 10 weather years has a 10% chance of reoccurring (with 0% weight on each of the prior 28 years) leads to higher simulated prices and reliability events at a given reserve margin; but the higher prices would attract more investment, resulting in a 1.5% higher market equilibrium reserve margin and similar reliability to the base case.

Table ES-1
Market Equilibrium and Economically Optimal Reserve Margins and Reliability

	MERM *(%)*	EORM *(%)*
Base Case	**10.25%**	**9.0%**
Vary Gross CONE	9.25% - 10.50%	8.0% - 9.25%
Vary VOLL	10.25%	8.25% - 10.5%
Vary Probability of Weather Years	10.0% - 11.75%	8.75% - 10.5%
Vary Forward Years	9.25% - 10.25%	8.5% - 9.0%
High Renewables Scenario	**9.25%**	**8.25%**
Low Renewables Scenario	**10.75%**	**9.50%**
High Gas Price	**11.25%**	**10.25%**

5 Specifically, the ORDC was set as if load would be shed (or other emergency actions taken at an equivalent cost) at an operating reserve level of 2,000 MW. This is above the 1,000 MW estimated level at which load is shed, with prior emergency actions incurring costs below the value of lost load.

Notes:
Table reflects all scenarios and sensitivities analyzed, as described in Section II.D; Current practice has VOLL set to the max of the ORDC but the sensitivity which varies to VOLL does not change the ORDC curve and therefore does not affect the MERM.

In an alternative High Renewable scenario with 10 GW more wind and 10 GW more solar photovoltaic capacity (nameplate) than the base case,[6] renewable resources economically displace a roughly offsetting amount of conventional generation, resulting in only a small change in the market equilibrium reserve margin. We estimate a 1% reduction in the market equilibrium reserve margin. The decrease is caused by a steeper net load (load minus renewable generation) duration curve causing prices to fall faster beyond the peak hour. Such lower prices would reduce generators' net revenues, so reserve margins have to tighten slightly (increasing high-priced ORDC hours) for investment to re-equilibrate. The reduction in market equilibrium reserve margin is matched, however, by an equal reduction in the economically optimal reserve margin. Thus the market would still be expected to attract more than sufficient reserves from an economic perspective.

In terms of reliability, our probabilistic simulations indicate that under base case assumptions with a market equilibrium reserve margin of 10.25%, the system could be expected to experience 0.5 events per year loss-of-load expectation (LOLE).[7] This compares favorably to 0.8 events per year LOLE at the economically optimum level, but is above the 0.1 events per year LOLE standard used by most electric systems in North America for planning purposes.

These estimates must not be interpreted as deterministic, since actual market conditions will fluctuate from year-to-year. In reality, the reserve margin will vary as plants enter and exit. Moreover, even at a given reserve margin, realized reliability and price outcomes can deviate far from the expected value, primarily due to weather and variations in wind generation. For example, with a projected market equilibrium reserve margin of 10.25%, we estimate that in the 90th percentile outcome—representing relatively hot weather and low generation availability—energy

6 The high renewables case adds roughly 50% of the wind and solar capacity from the July 2018 Generator Interconnection Status (GIS) report that has not yet met all the requirements to be included in ERCOT's May 2018 CDR report.

7 For the simulations, a loss-of-load (LOL) event occurs when the hourly load, plus a minimum operating reserve level of 1,000 MW, is greater than available resource capacity. A LOL event is recorded for each day of the simulation if one LOL hour occurs in the 24-hour span, or if there are more than one non-contiguous LOL hours during the day. For a given reserve margin level, the LOLE is the mean number of LOL events for 9,500 simulations (38 weather years, 5 load error levels, 50 outage draws).

prices would double, marginal units could have net energy revenues reaching $200/kW-year, with 1.2 load-shed events per year (compared to a mean of 0.5 across all conditions modeled).

Compared to the 2014 study, both the estimated market equilibrium reserve margin and economically optimal reserve margin are 1.25% lower in spite of a lower Cost of New Entry (CONE) and reserve margin accounting changes that would lead to higher reserve margins. Factors driving down reserve margins are low gas prices, higher renewable penetration, and updated assumptions on generator forced outages and weather. Correspondingly, reliability under the estimated market equilibrium reserve margin is worse than the estimated LOLE in the last study, at 0.5 events per year vs. 0.33 events per year in the previous study. The two biggest drivers of a lower MERM, and the corresponding lower reliability, are lower forced outage rates and changes in weather weights.

These conclusions are based on a well-tested model, whose structure and updated inputs have been carefully constructed in collaboration with ERCOT staff, and whose outputs (particularly prices) have been validated against real-world conditions. However, as in any analysis of complex problems, this analysis has its limitations that must be understood to properly interpret the results. One limitation is the uncertainty surrounding the assumptions. Although we believe the most important uncertain assumptions are examined through our sensitivity analyses, others are also uncertain, such as the average availability of the generation fleet. Another limitation is that we did not consider how high prices under tight market conditions might attract more renewable generation, energy storage, and price-responsive demand that could help support reliability.

I. Background and Context

We have been asked by the Public Utility Commission of Texas (PUCT) and the Electric Reliability Council of Texas (ERCOT) to estimate the market equilibrium reserve margin (MERM) and the economically optimal reserve margin (EORM) for ERCOT's wholesale electric market.

The MERM describes the reserve margin that the market can be expected to support in equilibrium, as investment in new supply resources responds to expected market conditions. This concept is relevant in ERCOT because, unlike all other electricity systems in North America, ERCOT does not have a reserve margin requirement. In ERCOT, the reserve margin is ultimately determined by suppliers' costs and willingness to invest based on market prices, where prices are determined by market fundamentals and by the administratively-determined Operating Reserve Demand Curve (ORDC) during tight market conditions. This approach creates a supply response to changes in energy market prices toward a "market equilibrium"; low reserve margins cause high energy and ancillary service (A/S) prices and attract investment in new resources, and investment will continue until high reserve margins result in prices too low to support further investment. The PUCT also wants to know whether the market outcome will be acceptable to economic optimality. The EORM is the benchmark for establishing the sufficiency of the expected MERM, where the marginal benefits of new supply are just equal to the marginal costs of new supply.

As the left panel of Figure 1 shows, higher reserve margins are associated with higher generation capital and fixed costs of building more capacity (dark blue line). The higher costs are offset by a reduction in the frequency and magnitude of costly reliability events, such as load-shed events, other emergency events, and demand-response curtailments, and the reduced production costs (light blue line). The tradeoff between increasing capital costs and decreasing reliability-related operating costs results in a U-shaped societal cost curve (red line), with costs minimized at what we refer to as the "economically optimal" reserve margin.[8] The right part of Figure 1 shows how we derive the "market equilibrium" reserve margin. The marginal cost of capacity is known as the "Cost of New Entry" (CONE), which depends on technology costs and economic conditions such

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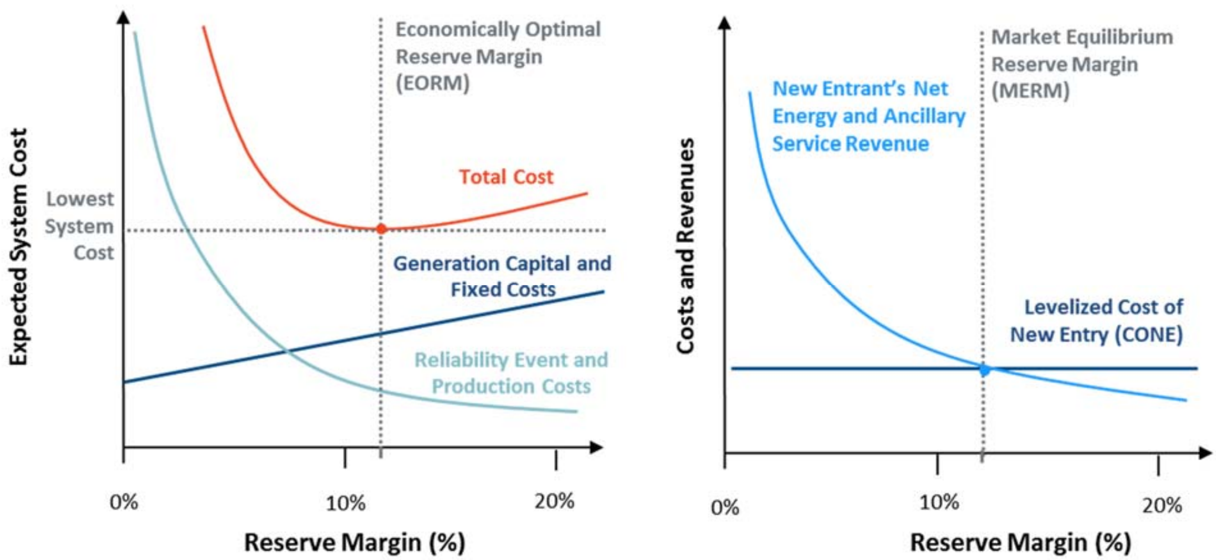
8 In developing our approach to calculating the economically optimal reserve margin, we draw upon a large body of prior work conducted by ourselves and others, although the majority or all of this prior work was relevant in the context of regulated planning rather than restructured markets. For example, see Poland (1988), p.21; Munasinghe (1988), pp. 5–7, 12–13; and Carden, Pfeifenberger, and Wintermantel (2011).

as tax structures and remains stable across reserve margins (dark blue line). A marginal unit's revenues from energy markets and ancillary services (light blue line) quickly decrease with less scarcity pricing at higher reserve margins. The intersection point of a marginal unit's revenue and CONE represent the "market equilibrium" reserve margin where the marginal unit breaks even.

Figure 1
Economically Optimal Reserve Margin and Market Equilibrium Reserve Margin Concepts
(Illustrative Schematics, Not Simulation Results)



This study estimates the MERM and the EORM for the ERCOT market given the currently formulated scarcity pricing mechanism and expected market conditions. It estimates the reliability at each of those levels of reserves, but strictly for informational purposes, since there is no reliability requirement. Our study methodology follows the ERCOT manual for estimating the EORM and MERM.[9] The primary analytical tool in this study is energy market simulations using the SERVM model. SERVM simulates hourly energy demand (under a range of weather conditions), energy production, and energy prices given the marginal cost of available supply and the Operating Reserve Demand Curve (ORDC). By analyzing the results of simulations conducted at many possible levels of investment, we can identify which of the reserve margins represents a MERM and which level represents the EORM.

In the 2014 study, we found a MERM of 11.5% and an EORM of 10.2%, with corresponding reliability of 0.5 and 0.8 expected load-shed events per year, respectively. The present study

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9 See ERCOT (2017b). Note that the methodology described in the manual is derived from our 2014 study.

incorporates updated market conditions regarding the projected resource mix, CONE, and gas prices; different assumptions regarding weather; lower forced outage rates based on recent data; and current conventions for describing peak load and accounting for intermittent resources in expressing the reserve margin.

II. Study Assumptions and Approach

Our simulations rely on a detailed representation of the ERCOT system, including: load and weather patterns and their probabilistic variations; the cost and performance characteristics of ERCOT's generation and demand-response resources; the mechanics of the ERCOT energy and ancillary services markets, including a unit commitment and economic dispatch of all generation resources, demand-response resources, and the transmission interties with neighboring markets. Assumptions on the generation fleet, demand-response penetration, fuel prices, and energy market design reflect expected conditions in 2022.

A. Modeling Framework

We use the Strategic Energy Risk Valuation Model (SERVM) to estimate the economically optimal reserve margin, the market equilibrium reserve margin, and the associated reliability in the ERCOT system.[10] Like other reliability models, SERVM probabilistically evaluates the reliability implications of any given reserve margin. 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 events (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. SERVM estimates hourly and annual production costs, customer costs, market prices, net import costs, load shed costs, and generator net energy revenues as a function of the planning reserve margin. These results allow us to compare these variable costs against the incremental capital costs required to achieve higher planning reserve margins, such that the optimal reserve margin can be identified. The MERM can be identified by comparing potential new generators' net revenues to their levelized fixed costs.

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

10 SERVM software is a product of Astrapé Consulting, co-authors of this report. See Astrapé (2018).

and time to repair, as explained in Appendix 1. 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 as explained further in Appendix 1.E

To examine a full range of potential economic and 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 38 weather years, 5 levels of economic load forecast error,[11] and 50 draws of generating unit performance for a total of 9,500 iterations for each simulated reserve margin case. Each individual iteration simulates 8,760 hours for the year 2022. The large number of simulations is necessary to accurately assess the reliability and economic implications of varying reserve margins. A probabilistic approach is needed to characterize the distribution of possible outcomes, particularly because the majority of reliability-related costs are associated with infrequent and sometimes extreme scarcity events. Such reliability events are typically triggered by rare circumstances that reflect a combination of extreme weather-related loads, high load-growth forecast error, and unusual combinations of generation outages.

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,

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[11] The five discrete levels of load forecast error we model are equal to 0%, +/–2%, and +/–4% above and below the 50/50 ERCOT load forecast.

accounting for energy and call-hour limitations, dispatch prices, operating reserve depletion, dispatch of economic and emergency demand-response resources, and administrative scarcity pricing.[12]

B. PRIMARY INPUTS

Market conditions and ERCOT's reserve margin accounting conventions have both shifted since the 2014 EORM report was completed. This section focuses on those changes and discusses their implications for the MERM and EORM.

Our reserve margin accounting is consistent with the reserve margin accounting conventions in ERCOT's 2018 CDR, as summarized in column C of Table 1. 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. On the supply side, most resources are counted toward the reserve margin at their summer ratings, except for non-coastal wind, coastal wind, and solar counting at 14%, 59%, and 75% of nameplate respectively, and the High Voltage Direct Current (HVDC) ties counting at approximately 31% of the path ratings, consistent with the CDR.

There have been several changes in reserve margin accounting since the 2014 EORM report. Table 1 columns A and B summarize the effects of the reserve margin accounting changes on the assumptions used in EORM 2014. Most notably, ERCOT now counts more capacity value for wind generation after having refined its methods based on historical operating data. The contribution of wind generation is now divided by region, coastal versus non-coastal, and both areas have higher contributions than the previous 8.7%, increasing the accounting for wind.[13] This increase in nominal capacity contributions (and reserve margins) is partially offset by having reduced solar generation's nominal capacity contribution from full nameplate capacity down to 75%. Similarly, ERCOT now counts less summer peak capacity available on ERCOT's tie lines with neighboring

---

12 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.

13 Non-coastal wind has a 14% capacity contribution, and coastal wind has a 59% capacity contribution during summer peak loads.

regions based on historical contributions, rather than the prior assumption that they could be expected to contribute 50% of their line ratings.

A more subtle accounting change is that ERCOT's system peak load forecast is now expressed as a higher number for the same underlying loads because the historical year ERCOT used to shape its forecast had less inter-zonal load diversity than in the 2014 study (and we understand that this was chosen by ERCOT staff to create more conservative load forecasts, so we characterize it as an "accounting" change).[14] This means that the ERCOT system peak forecast appears higher than it would have been under previous calculations, and this decreases apparent reserve margins, all else equal.

In addition to accounting changes, ERCOT's system has been experiencing many changes in market fundamentals since the previous study (for study year 2016). First, load has been growing about 1.5% per year due to economic and population factors. Second, much more wind and solar generation has entered or will enter the system by 2022—approximately 15 GW more wind and 3 GW more solar than prior expectations for 2016. Third, ERCOT has seen increased participation in load reduction programs.[15] Fourth, private use network (PUN) units are expected to have a lower contribution to supply during peak demand periods.[16]

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14 There is an additional accounting effect in that ERCOT uses the most recent 15 years in its load forecasting, so the current load forecasts are based on a different set of historical years than those for the 2014 EORM study.

15 Participation has decreased in RRS, 10-minute ERS, and TDSP programs, but this is offset by an increase in 30-minute ERS participation.

16 PUNs are behind-the-fence loads at generation facilities and frequently operate with zero net energy injection into the ERCOT system, but contribute to system inertia; PUN generation in ERCOT is mainly comprised of Combined Cycle, Combustion Turbine Simple Cycle, and Gas Steam units (ERCOT, 2018k).

Table 1
Components of Supply and Demand in Current 2018 Study vs. 2014 Study

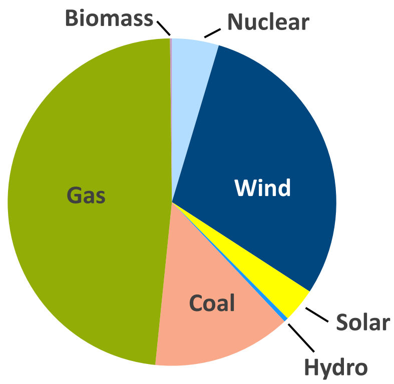
	Values from 2014 Study (MW) [A]	Re-expressed Values from 2014 Study (Using 2018 Accounting) (MW) [B]	Values from 2018 Study (MW) [C]	Difference Attributable to Accounting Changes (MW) [B-A]	Difference Attributable to Fundamentals Changes (MW) [C-B]
Modelled Year	**2016**	**2016**	**2022**		
Accounting Methodology Year	**2013**	**2018**	**2018**		
Peak Load	**70,618**	**71,353**	**79,027**	**735**	**7,674**
Load Reduction	**1,869**	**1,869**	**2,173**	**0**	**304**
LRs serving RRS	1,205	1,205	1,119	0	-86
10-Minute ERS	347	347	140	0	-207
30-Minute ERS	77	77	632	0	555
TDSP Curtailment Programs	240	240	282	0	42
Supply	**76,659**	**78,114**	**85,919**	**1,455**	**7,805**
Conventional Generation	69,700	69,700	72,441	0	2,741
Hydro	521	521	467	0	-54
Wind	1,319	3,044	6,331	1,725	3,287
Solar	124	93	2,708	-31	2,615
Storage	36	36	324	0	288
PUNs	4,331	4,331	3,259	0	-1,072
Capacity of DC Ties	628	389	389	-239	0
Reserve Margin	11.51%	12.42%	11.80%	0.91%	-0.63%

Sources and Notes: Reserve Margin = Supply/ (Peak Load – Load Reductions) – 1
Conventional Generation includes new units. CC and CT capacity is treated as a key variable in this study, controlling reserve margins.

The base 2022 supply fleet, as summarized in column C of Table 1 is consistent with the forthcoming 2018 North American Electric Reliability Corporation (NERC) Long-Term Reliability Assessment (LTRA) report.[17] The fleet summary developed by ERCOT staff for the NERC LTRA was the most recent data available when this study was developed. When compared to the 2018 CDR values for 2022, the supply fleet adds a relatively modest 986 MW of wind and 251 MW of solar installed capacity. The composition of installed capacity in the 2018 LTRA is summarized in Figure 2.

[17] We include or exclude new units and retirements starting in the specified year and completely exclude units that have been mothballed. We model switchable units as internal resources. Data was provided, as submitted to NERC, by ERCOT staff.

Figure 2
Installed Capacity by Resource Type



Sources and Notes: Most recent LTRA data supplied by ERCOT staff and ERCOT, 2018a.The LTRA data was comparable to the capacities provided in the May 2018 CDR.

We conduct simulations over a wide range of reserve margins by adding or removing capacity from this existing supply fleet. To analyze higher reserve margins, we add a combination of gas CC and gas CT capacity, assuming the characteristics shown in Table 2 below that were derived from a recent study Brattle conducted. CCs and CTs are added in a 77:23 megawatt ratio, roughly reflecting the types of resources that have been added or proposed for the ERCOT market. To analyze lower reserve margins, we exclude planned new resources that are similar to our reference technology.[18] We assume the CONE for the new units are $94,500/MW-year for the gas CC and $88,500/MW-year for the gas CT.[19]

18 More detail on the reference technology can be found in Appendix 1.B.1.

19 The CONE values are based on the results from the 2018 PJM CONE study (Newell, *et al.* 2018.), but do not account for adjustments to the assumed discount rate and exemption from paying sales taxes that occurred following the release of the report. Changing the CONE for ERCOT to be consistent with the higher discount rate would increase the CC CONE to $97.5/kW-year and the CT CONE to $91.2/kW-year, which is within the high end sensitivity range (+25%).

Table 2
Reference Technology Cost and Summer Performance Characteristics

		Simple Cycle	Combined Cycle
Plant Configuration			
Turbine		GE 7HA.02	GE 7HA.02
Configuration		1 x 0	2 x 1
Heat Rate (HHV)			
Base Load	*(Btu/kWh)*	9,274	6,312
Max Load w/ Duct Firing	*(Btu/kWh)*	n/a	6,553
Installed Capacity			
Base Load	*(MW)*	352	1,023
Max Load	*(MW)*	n/a	1,152
Gross CONE	*($/kW-yr)*	**$89**	**$95**

Sources and Notes: Based on ambient conditions of 92°F Max. Summer (55.5% Humidity). (Newell, *et al.* 2018). After the initial report, Brattle made two (largely offsetting) updates with higher ATWACC (8%) and incorporating state sales tax exemptions.

On the demand side, this study starts with ERCOT's peak load forecast for 2022, but then develops hourly shapes under many possible weather patterns. We simulate each of 38 weather years, from 1980 through 2017 (with corresponding wind and solar conditions from the same years). When calculating expected values, we assume equal probabilities of each year's weather. 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. (Other possibilities are considered in the Section III.D.3. below.) This differs from the 2014 EORM study base assumptions, which applied a 1% weight to 2011 weather and assigned the remaining 99% equally among weather conditions for 15 other years (1998 to 2012). The effect of using 38 years provides a greater variation in weather uncertainty, and while it puts more weight on 2011, the more recent weather history simulated for the 2014 EORM study resulted in more reliability issues than the full 38-year distribution on average. The net effect of the change in weather assumptions reduces the market equilibrium reserve margin relative to the level reported in the 2014 EORM study.

C. Scarcity Pricing and Demand Response Modeling

A number of different types of demand-side resources contribute to resource adequacy and price formation in ERCOT. Table 3 summarizes these resources, explaining how we model their characteristics, their assumed marginal costs when interrupted, and how they are accounted for in the reserve margin. We developed these assumptions in close coordination with the ERCOT staff, who provided assumptions regarding the appropriate quantities for modeling.

The marginal costs of these demand-side resources are highly uncertain, although the marginal costs we report in the table are in the general range that we would anticipate given the sparse data availability. Most of these resources including TDSP load management, emergency response service (ERS), and load resources (LRs) are dispatched for energy based on an emergency event trigger rather than a price-based trigger consistent with marginal cost. We use ERCOT's administrative scarcity pricing mechanism, the operating reserves demand curve (ORDC), to reflect the willingness to pay for spinning and non-spinning reserves in the real-time market. We make the simplifying assumption that these resources are triggered in order of ascending marginal cost, and at the time when market prices are equal to their marginal curtailment cost, as explained further in Appendix 1.E.4 below.

Two types of demand-side resources, energy efficiency (EE) and self-curtailment to avoid four coincident peak (4CP) transmission charges, are not explicitly modeled because the historical effect of these load reductions are included in the load shapes. However, these resources are appropriately accounted for using the conventions of ERCOT's CDR report as explained further in Appendix 1.A.1 below.

Table 3
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
Load Management					
Energy Efficiency	2,389	Not explicitly modeled.	*n/a*	None	Load reduction.
TDSP Programs	282	Emergency trigger at EEA Level 1.	$2,456	None	Load reduction.
Emergency Response Service (ERS)					
30-Minute ERS	632	Emergency trigger at EEA Level 1.	$1,365	None	Load reduction.
10-Minute ERS	140	Emergency trigger at EEA Level 2.	$2,456	None	Load reduction.
Load Resources (LRs)					
Non-Controllable LRs	1,119	Economically dispatch for Responsive Reserve Service (most hours) or energy (few peak hours). Emergency deployment at EEA Level 2.	$2,456	None	Load reduction.
Controllable LRs	0	Currently no controllable LRs modeled in ERCOT.	*n/a*	*n/a*	*n/a*
Voluntary Self-Curtailments					
4 CP Reductions	1,700	Not explicitly modeled (assume 4CP behavior will persist in all circumstances).	*n/a*	None	None; excluded from reported peak load.
Price Responsive Demand	741	Economic self-curtailment	$5,000 - $9,000/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. See corresponding sections in the Appendix for more detail.

No adjustments are made to the ERCOT load shapes because they are estimated assuming no curtailments, except for 4CP for which the load shapes are already reduced, and Price Responsive Demand which is assumed to have a negligible historical response.

For 10-Minute ERS and 30-Minute ERS there is an 8-hour call limit per Contract Period. See Table A1-6 below.

TDSP Load Management Programs have a 16-hour call limit from June to September.

Previously, the 2014 EORM Report also had 36 MW of Controllable LRs attributed to the Notrees Battery; both the CDR and the LTRA listed Notrees battery as 0 MW for summer 2022 so no controllable LRs were modeled in ERCOT for this study.

D. Study Sensitivities and Scenarios

In addition to the base case analysis described above, we simulated three alternative scenarios and several "sensitivity" analyses to inform how the MERM and EORM could vary under different plausible conditions. The three scenarios are "High Renewables Penetration," "Low Renewables Penetration," and "High Gas Prices." The high renewable penetration scenario adds much more wind and solar generation to explore the implications of understating renewable penetration in 2022 (or beyond). The low renewable penetration scenario assumes the same level of renewable penetration as 2014 and is included to inform the differences between the current EORM study and the 2014 study, not because we find it to be a realistic future scenario. The High Gas Price scenario is considered due to the impact gas prices have on the economics of investing in new plant. We do not consider a low gas price scenario since the base case gas prices are near historic lows. The assumptions for each scenario are summarized in Table 4 below.

Table 4
Description of Modeled Scenarios

Scenario Name	Base Case Assumption	Scenario Assumption	Expected Impact
High Renewables Penetration	Consistent with the 2018 LTRA, 1.2 GW new solar and 5.4 GW new wind	In addition, add ~50% of the wind and solar capacity from the July 2018 interconnection queue that has not yet met all the requirements to be included in the LTRA (10 GW new solar, 10 GW new wind)	Steeper net load curve may reduce MERM and EORM and slightly degrade reliability
Low Renewables Penetration	Consistent with the 2018 LTRA, 1.2 GW new solar and 5.4 GW new wind	Model wind and solar capacity equal consistent with the values used in the 2014 EORM Report	Increase MERM and EORM. Helps explain the effect of net load changes from previous report
High Gas Price	Consistent with the 2018 EIA AEO High Oil and Gas Resource and Technology Case	Consistent with the 2018 EIA AEO Low Oil and Gas Resource and Technology Case	Increase EORM

The other sensitivity analyses that we conducted examine the impacts of: (a) varying the assumed cost of building new plants; (b) adjusting the value of lost load (VOLL);[20] (c) adjusting the likelihood of recent weather years compared to historic values; and (d) varying the associated load forecast uncertainty not attributable to weather conditions.

[20] Our VOLL sensitivity adjusts the VOLL but it does not adjust the ORDC, which is set by the Public Utility Commission of Texas based on the system-wide offer cap and not directly set based on customer VOLL. Because the ORDC curve does not change, the VOLL sensitivity does not affect market prices and the MERM (which is solely based on market prices) does not change. The EORM is affected because the higher VOLL implies customers place a higher value on avoiding loss-of-load events and therefore prefer higher reserve margins, all else equal.

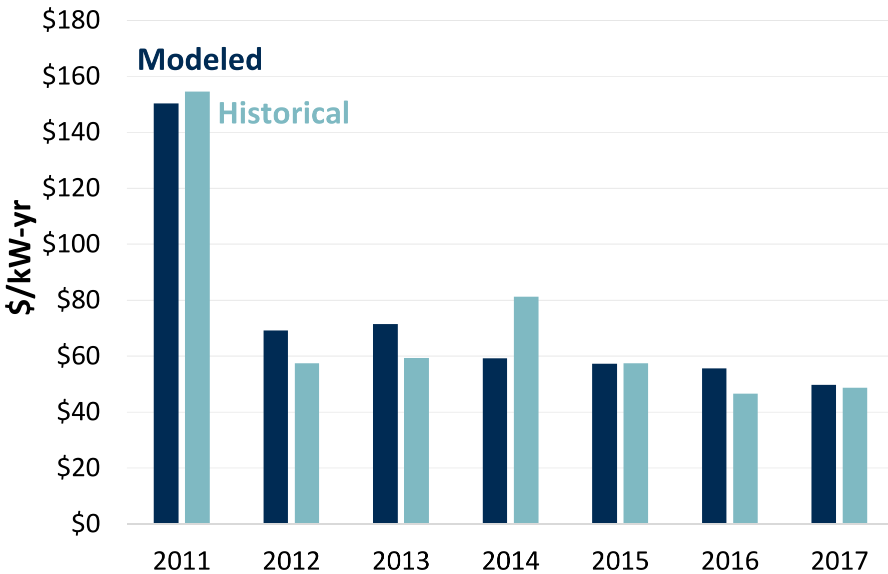
Table 5
Definition of Non-Modeled Sensitivities

Sensitivity	Base Case Assumption	Sensitivity Range
Gross CONE	CT: $89/kW-year CC: $95/kW-year	−10% / +25%
VOLL	$9,000/MWh	$5,000 to $30,000/MWh
Weighting of Historical Weather Years	Equal probability assigned to all 38 weather years	(1) Assign equal probability to 10 most recent years and zero probability to first 28 years (2) Assign probabilities based on Pareto distribution fit to weather years based on number of consecutive days with weather over 100 degrees (3) Set probabilities equal to 2014 EORM base case
Forward Period and Load Forecast Uncertainty	3 years	0 years to 2 years

E. Model Validation

In addition to carefully constructing realistic inputs to the model, we validated that the model's outputs are reasonable by comparing them to real-world market observations. Figure 3 below compares the simulated and historical combined-cycle net energy revenues for 2011 to 2017. The historical bars reflect the net energy revenues for a new combine-cycle based on historical energy and natural gas price. The modeled bars reflect the simulated net energy revenues for the same combined-cycle with energy prices determined by SERVM based on market and weather conditions corresponding to the actual year, assuming renewable capacity consistent with the "low renewable" scenario.

Figure 3
Modeled vs. Actual Combined-Cycle Net Energy Revenues



The simulated net energy revenues are similar to the historical values with discrepancies primarily reflecting differences in supply availability. This suggests that the model characterizes the price formation in the market reasonably well.[21]

Note that, the chart above does not include 2018 data since not all the data is available. Instead, we calculated the net energy revenues for a new combined-cycle over the most recent twelve month period based on realized energy and gas prices (similar to the historical bars in the figure above) and compared it to the median of simulated combined-cycle net revenues at the realized 2018 reserve margin.[22] The comparison indicates the proxy 2018 value is also reasonably calibrated.

Another useful benchmark is a comparison of the *average* simulated net energy revenues against historically expected net energy revenues (corresponding to forward prices), both of which should reflect the distribution of possible weather and generation availability at a given planning reserve

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21 Note that pre-2013 price formation differed absent an ORDC, but the overall effect was similar on average as price cap was lower but it was activated more readily at higher levels of reserves.

22 This simpler comparison adjusts the realized load in the peak hour for demand-side resources, but not all hours as was done in the comparison above. The demand-side resources adjustments for each year are consistent with December 2017 CDR values. This assumes that the resources were not deployed to help meet the peak demand.

margin.[23] As Figure 4 shows, the historical data points fall above and below the curve across a range of reserve margins, suggested that the distribution of possibilities represented in the model is reasonably similar to the distributions underlying energy traders' and generation investors' views. The 2018 point shown, calculated consistently with the other years, falls below the curve. However, the 2018 point based on revenues using forward prices from May 2018, when prices spiked, falls above the curve.

Although the fit is decent, the fit would be even closer if the curve shifted 1.5 percentage points to the right. Such a shifted curve is approximately what we simulate under alternative weather assumptions drawn equally from each of the last 10 years instead of the last 38 in our base case. On average the last 10 years have been hotter than the prior period, suggesting a trend. The fact that the curve based on recent, hotter weather appears more consistent with futures prices suggests that perhaps traders in the electricity futures markets place more weight on the recent hot weather data.

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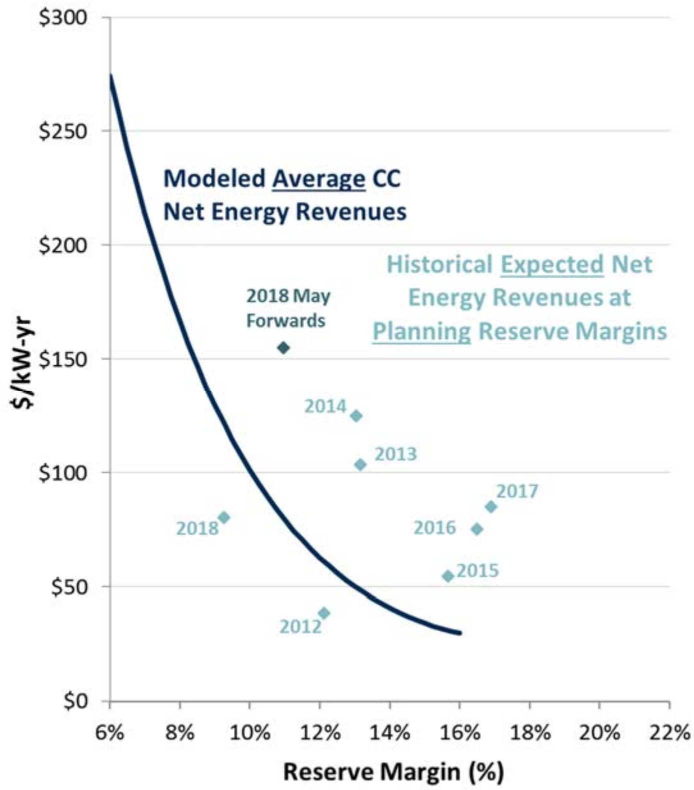
[23] Planning reserve margins are from the December CDR report prior to each year shown in the chart; forwards prices are from contemporaneous trade dates, also in December.

Figure 4
Average Modeled vs. Historical Expected Net Energy Revenues by Reserve Margin



Notes and Sources:

Net Energy Revenues are calculated based on energy and gas forward prices as of the end of December before each respective year, from S&P Global Market Intelligence LLC. Planning Reserve Margins shown along the x-axis are taken from the December CDRs before each respective year. The dark teal "2018 May Forwards" point is a similar calculation as of May, using updated forward prices and updated supply and demand information from the SARA report and load adjustments (LRs, ERS, TDSP) from the December 2017 CDR; we show that because it is so different from December expectations. Note that net energy revenues shown here likely understate what an actual unit would expect to earn because they do not account for hourly volatility within on-peak and off-peak periods. 2011 was not included due to insufficient data.

III. Results

This section first presents the results of our study under base case assumptions, including the estimated 2022 MERM and EORM and the associated reliability, and then how the results could differ under alternative market conditions captured in the scenarios and sensitivities described above. This section explains why the MERM and EORM results differ with respect to the result from the 2014 EORM study.

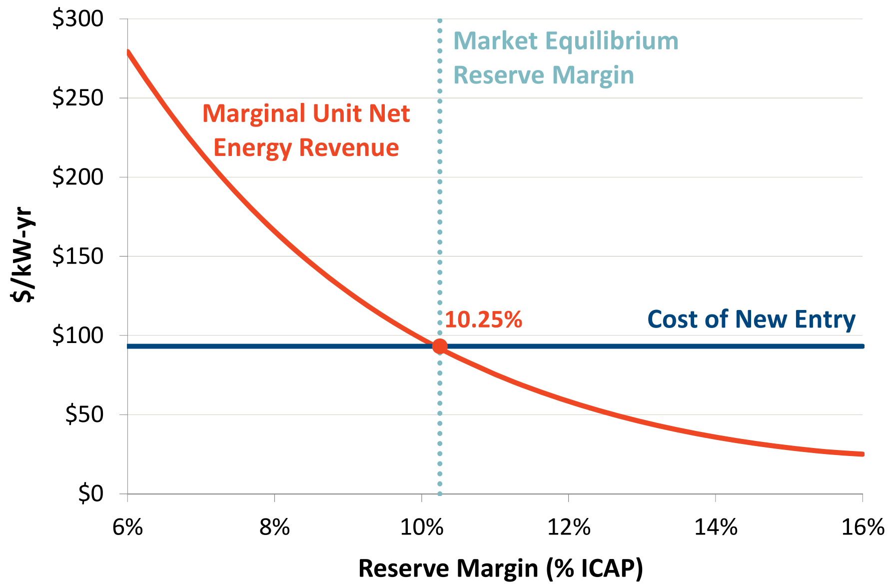
A. Market Equilibrium Reserve Margin

We describe here the anticipated equilibrium conditions under ERCOT's current market design by: (1) estimating the market equilibrium for our base case assumptions and several sensitivity cases; (2) summarizing the volatility in realized prices and net revenues across reserve margins; and (3) describing the likely year-to-year variation in realized reserve margins.

1. Average Equilibrium Reserve Margin

As described above, the market equilibrium reserve margin occurs at the level of capacity where the net revenues of new capacity from our simulations just equal the marginal costs of capacity, which is equal to CONE. As shown in Figure 5 below, CC/CT net energy revenues tend to decrease with higher reserve margins due to lower energy prices and few scarcity hours that occur when there is additional supply available on the system. We find that the market equilibrium reserve margin, where marginal costs of new capacity intersect with the marginal revenues for that capacity, is 10.25%.

Figure 5
ERCOT Projected 2022 Market Equilibrium Reserve Margin



Note: Marginal Unit Net Energy Revenue represents the net revenue from a mix of added CCs and CTs (77:23 ratio); the CONE shown at $93.1/kW-yr reflects this mix as well.

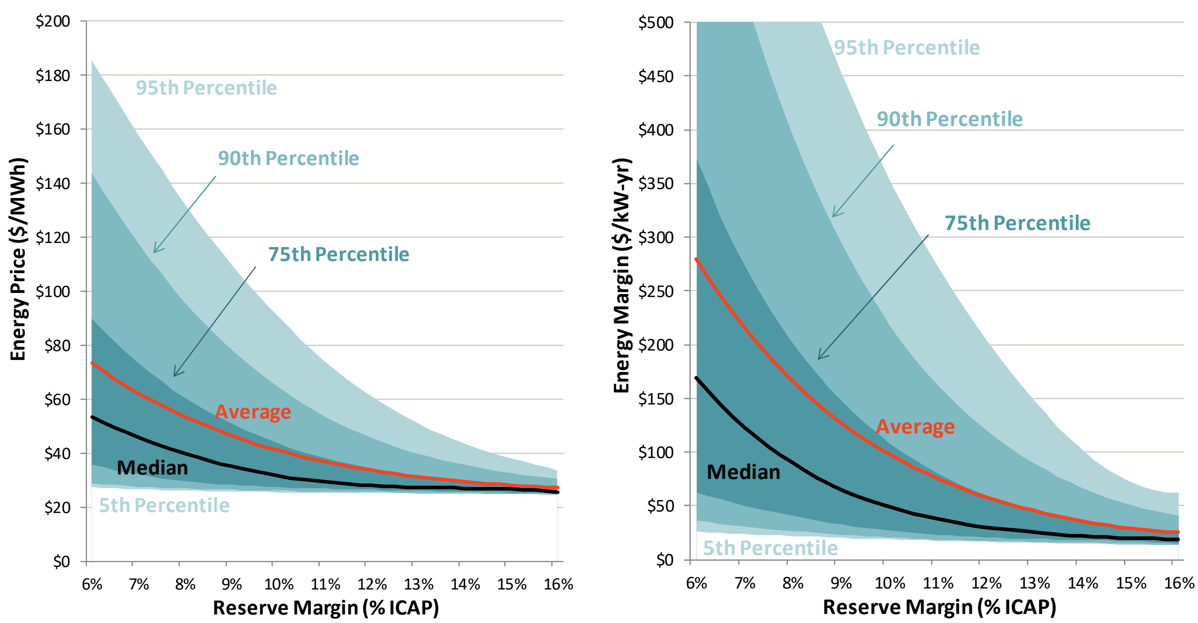
However, the single average market equilibrium reserve margin of 10.25% does not provide a complete story of the expected reliability of the ERCOT system or the expected revenues for new entrants. In the remainder of this section we discuss the volatility in realized prices in our simulations and the year-to-year variability in the reserve margin. In Section III.B we compare this market equilibrium to an economically optimal reserve margin, and in Section III.C we examine the sensitivity of our analysis to uncertainties in future market conditions.

2. Volatility in Realized Prices and Generator Revenues

Our estimate of the average market equilibrium reserve margin is strongly influenced by the assumed peak load and generator outage probability distributions, especially the most extreme scarcity events at the tails of those distributions. As the reserve margin declines, these tails become more likely to produce scarcity resulting in high prices, high system-wide costs, and high generator margins.

Figure 6 shows the range of annual energy prices (left) and marginal unit net energy revenues (right) for the base case across the reserve margins analyzed.[24] The upper percentile curves show that prices and supplier margins in the tails of the distribution can be much higher in any given year than their median or overall weighted average values.

Figure 6
Distribution of Spot Energy Prices (Left) and Net Energy Revenues for a Marginal Unit (Right)



Note: Marginal Unit Net Energy Revenues represent net revenues from a mix of added CCs and CTs (77:23 ratio).

The years reflected in the tails of the distribution have a substantial effect on the market equilibrium reserve margin. For example, at the base case market equilibrium reserve margin of 10.25%, we estimate that once per decade (90th percentile) energy prices would exceed $62/MWh (100% higher than the median price at this reserve margin). Once every two decades (95th

[24] Marginal Unit Net Energy Revenues represent net revenues from a mix of added CCs and CTs (77:23 ratio).

percentile), prices would exceed \$86/MWh (180% above the median price). Similarly, new gas plant net revenues in the median year are only \$46/kW-year, which is just 50% of CONE, but occasional high-priced years would elevate the average to CONE. Assuming full exposure to spot market prices (*i.e.*, no hedging) net revenues of marginal units would exceed \$204/kW-year (about 2 times CONE) once in a decade (90^{th} percentile) and \$334/kW-year (about 3.5 times CONE) once every two decades (95^{th} percentile).[25]

3. Year-to-Year Reserve Margin Variability

The uncertainty in future load growth can have significant impacts on reserve margins and reliability. Our base case simulations assume that the market invests based on the expected load growth and resulting prices on a three-year forward basis. However, realized load growth will generally differ from three-year expectations, resulting in a range of reserve margins that differ from the equilibrium reserve margins shown above.

We simulate this effect by assuming alternative load growth projections based on the distribution of non-weather forecast error in projecting future load, as described in Appendix 1.A.1 below. Even if the three-year-ahead planning reserve margin is exactly at the market equilibrium of 10.25%, realized shorter-term planning reserve margins can be higher or lower as load growth uncertainty resolves itself over the next three years. The planning reserve margins *projected going into each summer* would thus vary around the equilibrium from 8.4% to 12.1% in 50% of all years and drop below 6.7% approximately once per decade (*i.e.*, below the 10^{th} percentile). Once weather-related load fluctuations are considered as well, after-the-fact *realized reserve margins* will vary even more substantially and will drop below 6.2% approximately once per decade (*i.e.*, below the 10^{th} percentile). However, realized reserve margins, particularly the lows that largely reflect realized weather extremes, should not be compared to more familiar planning reserve margin benchmarks.

Variability in reserve margins may be moderated by short lead-time resources (including switchable units, mothballs, uprates, and demand response) that can exit or enter the market as expectations change between three years forward and delivery. By not simulating the effects of market exit and entry by short-term resources, our results would tend to overstate the range of

25 However, generators are generally not fully exposed to spot markets, since they hedge by selling most of their output in forward markets. Forward prices reflect *ex ante* market expectations of all possibilities rather than spot realizations. Selling forward dramatically smooths revenues closer to the expected values we estimate.

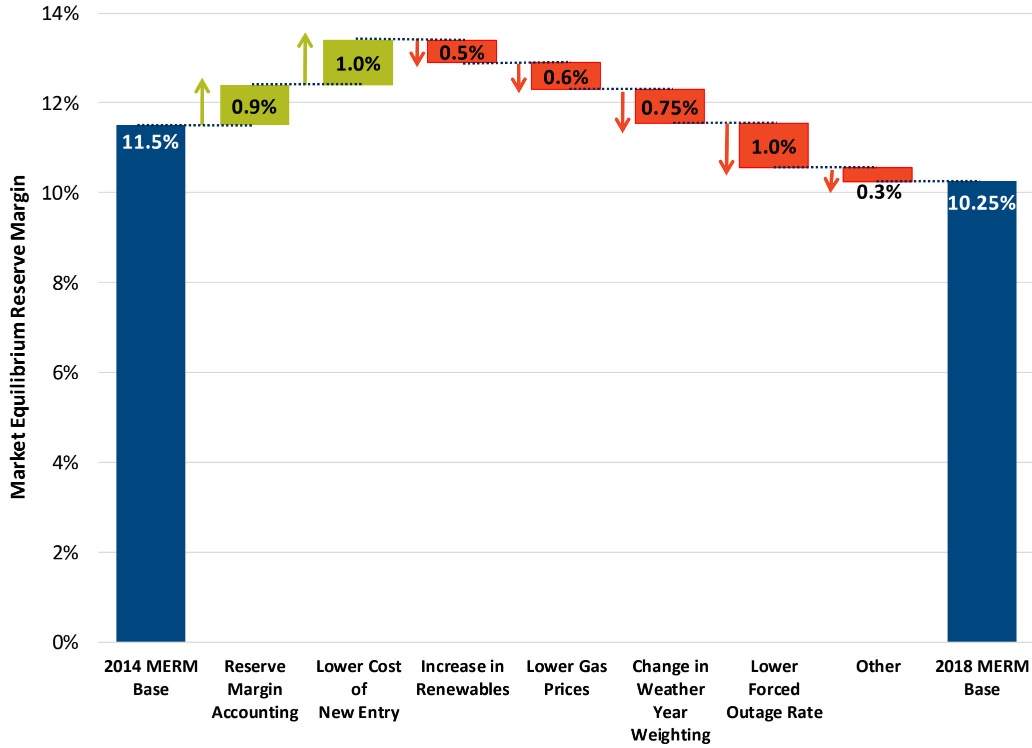
realized reserve margins. However, our simulations do not account for the countervailing effects of additional supply-side uncertainties, such as unanticipated retirements, construction delays, and lumpiness in uncoordinated new entry, which would tend to increase the variability of reserve margins. Furthermore, uncertainties about anticipated fuel prices, the capacity contribution of renewables, and other modeling assumptions would further widen the distribution of realized reserve margins. Overall, we estimate that with a three-year forward period, load forecast uncertainty would result in equilibrium reserve margins ranging from 6.7% to 13.8% (10^{th} to 90^{th} percentiles).

4. Comparison to 2014 EORM Study Results

The 2014 EORM study estimated a market equilibrium reserve margin for 2016 of 11.5%, which is 1.25% higher than the current base case results of 10.25%. There are several offsetting factors that drive the change in results, shown in Figure 7 below. While changes in the ERCOT reserve margin accounting and a lower CONE tend to increase the MERM, these changes are primarily offset by an increase in renewables, lower gas prices, a lower assumed fleet-wide forced outage rate, and adjustments to the weighting we applied to historical weather years.

The two largest drivers behind the market equilibrium reserve margin reduction are the lower CONE projected for 2022 and the lower forced outage rate seen in recent data, which offset each other by changing market equilibrium reserve margin up by 1.0% and down by 1.0%, respectively. As discussed in Section II.B, ERCOT has made several changes to reserve margin accounting, including: the diversity benefit of peak load, the capacity contribution of renewable generation, and the contribution of DC Ties; together these changes increase the market equilibrium reserve margin reported in the 2014 EORM study by 0.90%. The increase in renewable installed capacity, lower predicted gas prices, and the change in the base case weather year weighting each have a 0.6%, 0.5%, and a 0.75% decrease on the market equilibrium reserve margin, respectively. Each of these aforementioned drivers is explored as a sensitivity to the results, discussed in Section III.D.5. Other, more nuanced differences between the 2014 EORM study and the current study, such as the change in renewable generation shapes lining up with peak load hours, account for the remaining 0.3% decrease in the market equilibrium reserve margin. For the same reasons, the EORM, as discussed in Section III.B, decreases with roughly the same percentage point magnitudes.

Figure 7
Drivers of the Market Equilibrium Reserve Margin Change from 2016 to 2022 Model



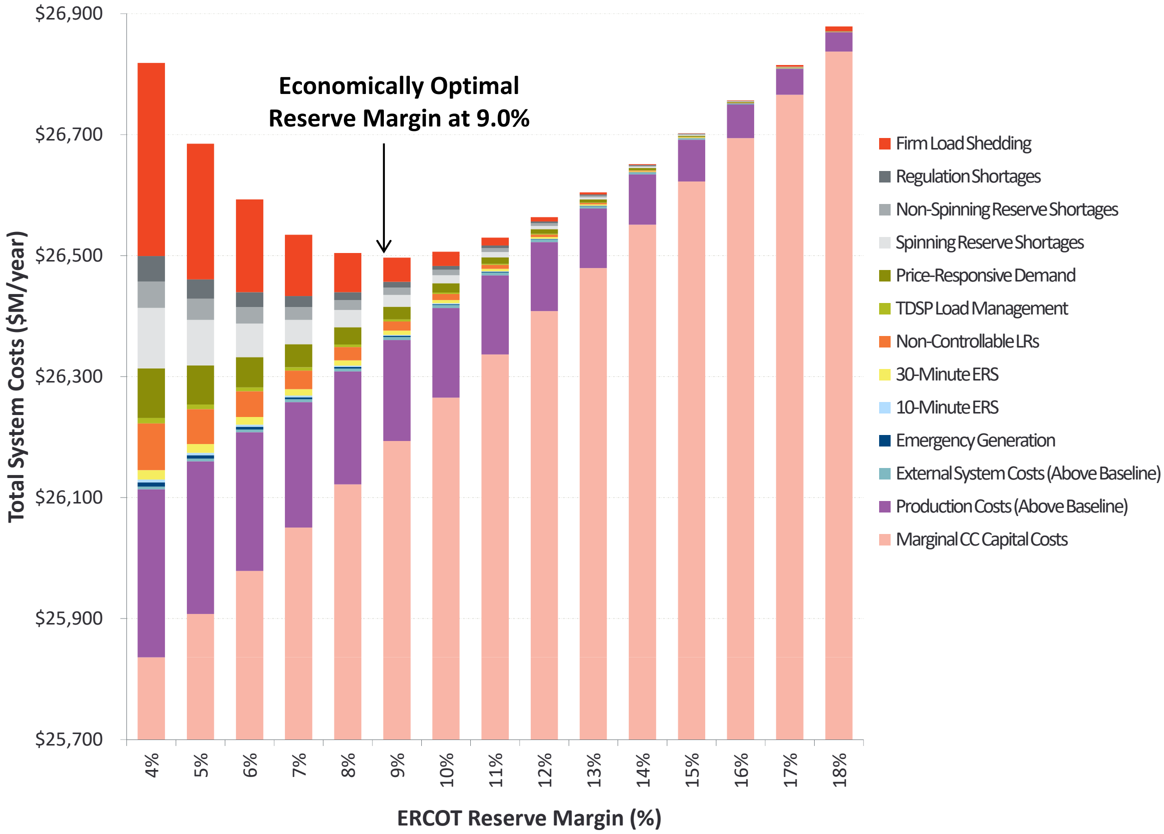
B. Economically Optimal Reserve Margin

1. System Cost-Minimizing Reserve Margin

The EORM is the level of capacity that minimizes total system capital and production costs. As shown in Figure 8 below, we estimated the annual average of reliability-related costs over a range of planning reserve margins and found the EORM under base case assumptions to be 9.0%.

At the lowest reserve margins analyzed the average annual reliability costs are high, driven by the cost of firm load shedding (red bar), regulation and reserve scarcity (grey bars), and production costs (purple bar). As reserve margins increase, total reliability costs drop due to the decrease in scarcity events and production costs. These costs decrease more quickly than the increases in capital costs associated with adding additional CCs and CTs resulting in a decrease in total system costs. This continues at higher reserve margins until the "economically optimal" quantity of capacity has been added at a reserve margin of 9.0%. After crossing this minimum cost point, the capital costs of adding more CCs and CTs exceed the benefits from reducing reliability-related costs, so total costs increase.

Figure 8
Total System Costs across Planning Reserve Margins



Notes:
Total system costs include a large baseline of total system costs that do not change across reserve margins, including $13.4B/year in transmission and distribution, $6.7B/year in external system costs, and $5.8B/year in production costs.

The total cost curve shown above has a shape similar to those we have observed in value-of-service studies for many other electric systems.[26] The curve is relatively flat near the minimum average cost point, indicating that expected total costs do not vary substantially between reserve margins of 7%–11%. However, the lower end of that range (7%) is associated with much more uncertainty in realized annual reliability costs, which we discuss in the next section, and a much larger number of severe, high-cost reliability events. At the 11% reserve margin, a greater proportion of total annual costs is associated with the costs of adding new units (which has less uncertainty), and a smaller proportion of the average annual costs are from uncertain, low-probability, but high-cost reliability events.[27]

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26 For example, see Poland (1988), p.21; Munasinghe (1988), pp. 5–7 and 12–13; and Carden, Pfeifenberger, and Wintermantel (2011).

27 Reliability across planning reserve margins is discussed in Section III.C.1.

At each reserve margin level in Figure 8, we show the weighted-average costs across all 9,500 annual simulations for several components of system costs that change with reserve margins. We estimated each of the components of system costs based on the following assumptions:

- **Marginal CC and CT Capital Costs** are the annualized fixed costs associated with building a mix of CC and CT plants, at a cost of $95/kW-year for the CC and $89/kW-year for the CT in the base case.
- **Production Costs (Above $6 billion per year Baseline)** are total system production costs of all resources above an arbitrary baseline cost of $6 billion. We show only a portion of total system costs as an individual slice on the chart in order to avoid having production costs dwarf the magnitude of other cost components, and subtract the same $6 billion at all reserve margins shown. Production costs decrease at higher reserve margins because adding efficient new gas CCs and CTs reduces the need to dispatch higher-cost peakers.
- **External System Costs (Above Baseline)** include production and scarcity costs in neighboring regions above an arbitrary baseline, which drop by a small amount with increasing reserve margins because ERCOT will rely less on imports from high-cost external peakers during internal scarcity events, and may be able to export more supply during external scarcity events.[28]
- **Emergency Generation** is the price-driven dispatch of units outputting at high levels above their summer peak ratings at an assumed cost of $1,365/MWh, see Appendix 1.E.3.
- **10-Minute and 30-Minute ERS** is the cost of dispatching these resources during emergency events at assumed costs of $2,456 and $1,365/MWh for 10-minute and 30-minute ERS respectively, see Appendix 1.C.1.
- **Non-Controllable LR** costs reflect the cost of administratively re-dispatching LRs from supplying Responsive Reserve Service (RRS) to supplying energy at a cost of $2,456/MWh during emergencies, see Appendix 1.C.2.
- **TDSP Load Management** costs are incurred when ERCOT administratively orders these demand-side resources to curtail during emergencies at an assumed cost of $2,456/MWh, see Appendix 1.E.2.

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[28] The baseline level of external production costs is not included in our total system cost. This differs from our reporting of ERCOT-internal production costs, for which we do include baseline costs (that do not vary with reserve margin) in order to produce a meaningful total cost estimate for the ERCOT system.

- **Spinning and Non-Spinning Reserve Scarcity** costs are calculated as the area under the ORDC curve, calculated assuming load would be shed at X = 1,000 MW, see Appendix 1.E.4.
- **Regulation Scarcity** costs are calculated according to the Power Balance Penalty Curve (PBPC) assuming that this curve accurately reflects the marginal cost of running short on regulating reserves, see Appendix 1.E.5.
- **Firm Load Shedding** costs are the customer costs imposed during load-shed events at a cost at the assumed VOLL of $9,000/MWh.

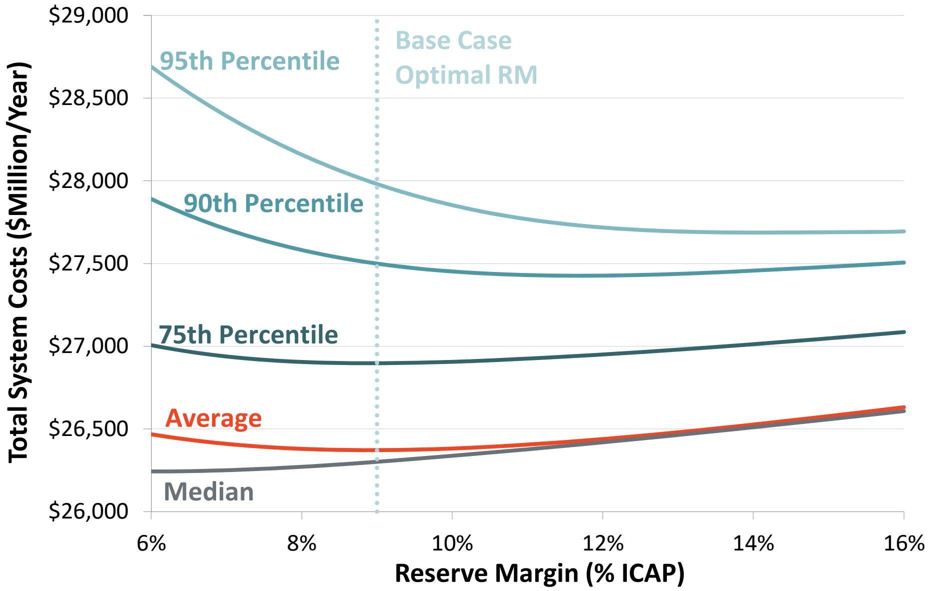
2. Exposure to Extreme Scarcity Events

The economic results shown above assume risk neutrality with respect to the uncertainty and volatility of reliability-related costs. Figure 8 compares total costs at different reserve margins as the probability-weighted average of annual reliability costs for all 9,500 simulation draws. However, there is substantial volatility around the average level of possible reliability cost outcomes. Most simulated years will have very modest reliability costs, while a small number of years have very high costs. These high-cost outcomes account for the majority of the weighted-average annual costs shown as the individual bars in Figure 8 above.

Figure 9 below summarizes this risk exposure by comparing the weighted-average costs for different reserve margins (red line, which is equal to the height of the individual bars in Figure 8) to annual costs under the most costly possible outcomes, represented by the 75th, 90th, and 95th percentiles of annual reliability costs across all 9,500 simulated scenarios.

Considering the higher-cost uncertainty exposure at lower reserve margins, some policymakers prefer reserve margins to exceed the risk-neutral economic optimum. As the simulation results show, a several percentage point increase in the reserve margin would only slightly increase the average annual costs, but more significantly reduce the likelihood of experiencing very high-cost events. Total average costs change by a relatively modest amount over a range of planning reserve margins (*e.g.*, average system costs increase by just $200 million with an increase in reserve margin from 10% to 15%). However, lower planning reserve margins have a significantly larger uncertainty in reliability costs and the likelihood of high-cost outcomes than can be encountered in any particular year. For example, at a 7% reserve margin costs are expected to be $1.3 billion higher than average once every ten years, while at 11% they would increase with a similar frequency by 1.0 billion.

Figure 9
Year-to-Year Possible Realizations of Total Annual System Costs



Notes:
Total system costs include scarcity-related and production costs (that decrease with reserve margin), generation capital costs (that increase with reserve margin), and T&D costs (which remain constant across reserve margins. Additional detail on the individual components of total system costs is available in Section III.B.1.

C. System Reliability

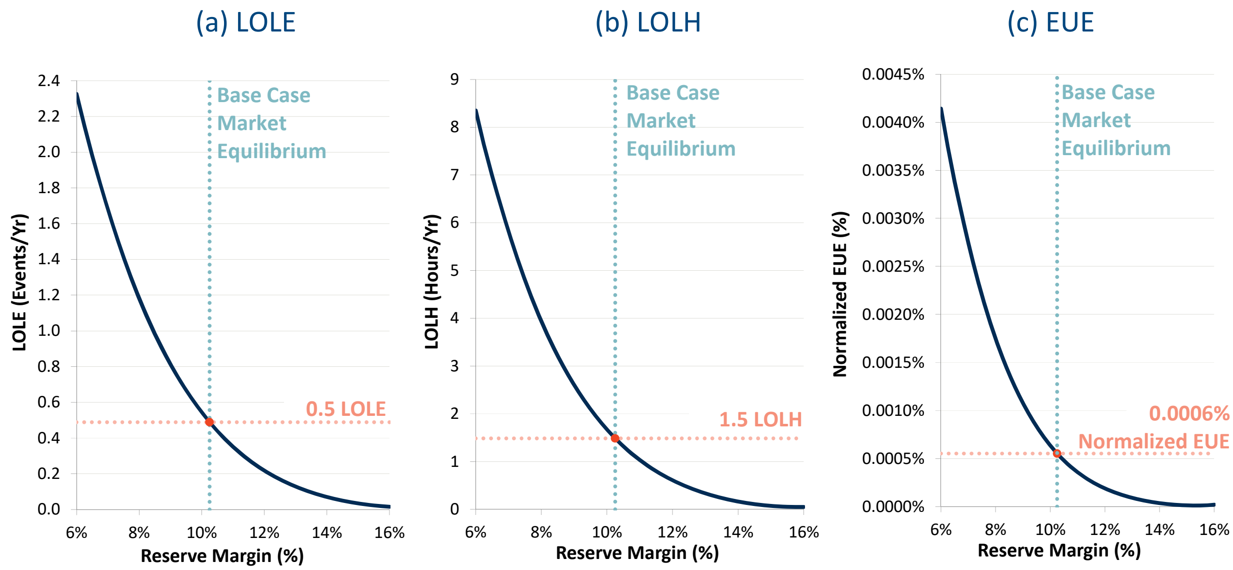
Although assessing planning reserve margins based on physical reliability standards is not within the scope of this study, it is still important to address the expected physical reliability metrics associated with our study results. Most notably, we compare the expected reliability of the market equilibrium reserve margin to traditional reliability metrics.

1. Physical Reliability Metrics

At a market equilibrium reserve margin of 10.25% ERCOT can expect a probability-weighted average of 0.5 loss-of-load events (LOLE) per year. Our simulations find that there is likely to be a loss-of-load event about every two years in the range of 1,527 MW of load being shed for 3.2 hours on average, for a total expected unserved energy of 4,647 MWh. Such events would be more frequent, longer, and deeper at lower reserve margins and less so at higher reserve margins. Figure 10 depicts how three physical reliability metrics vary with reserve margin: (1) LOLE on the left;

(2) loss of load hours (LOLH) in the middle; (3) Normalized Expected Unserved Energy (EUE) on the right.[29]

Figure 10
Reliability Metrics that Vary with Reserve Margins



Notes:
Reflects base case assumptions, including 3-Year Forward LFE and equal weather weights for all 38 years.

Table 6 shows the same information in tabular form, along with additional information describing the magnitude of outage events when they occur.

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[29] For our simulations, the reported reliability metrics are the mean for 9,500 simulations (38 weather years, 5 load error levels, 50 outage draws). A LOLE event is recorded for each day with at least one hour of lost load. LOLH is calculated as the total hours in the simulation with lost load, without accounting for persistence of a particular outage event. Normalized EUE is calculated as the expected quantity of unserved energy over the year divided by the net energy for load multiplied by 1,000,000. More information on these reliability metrics can be found in NERC 2010.

Table 6
Detailed Reliability Metrics across Planning Reserve Margins in Base Case

Reserve Margin (%)	Total Annual Loss of Load LOLE (events/yr)	LOLH (hours/yr)	EUE (MWh)	Average Outage Event Duration (hours)	Energy Lost (MWh)	Depth (MW)
6%	2.33	8.35	17,015	3.59	7,315	2,038
7%	1.68	5.81	11,263	3.46	6,714	1,938
8%	1.18	3.95	7,198	3.34	6,086	1,824
9%	0.81	2.61	4,426	3.21	5,444	1,698
10%	0.54	1.67	2,610	3.08	4,805	1,562
11%	0.35	1.03	1,468	2.94	4,182	1,421
12%	0.22	0.61	778	2.80	3,571	1,277
13%	0.13	0.33	374	2.61	2,919	1,118
14%	0.07	0.16	148	2.34	2,117	903
15%	0.03	0.07	48	2.09	1,409	673
16%	0.02	0.03	18	1.90	1,017	535

Most US areas set reliability metrics according to the "1-in-10" standard, *i.e.*, a probability-weighted average of 0.1 loss-of-load events (LOLE) per year.[30] Under base case conditions a 13.5% reserve margin would be required to achieve 0.1 LOLE, which is 3.25% higher than MERM. However, another common interpretation of a one "day" in 10 years resource adequacy standard is 24 hours per 10 years, or 2.4 loss of load hours (LOLH) per year, for which the reserve margin would only need to be 9.2%, which is 1.05% lower than MERM.

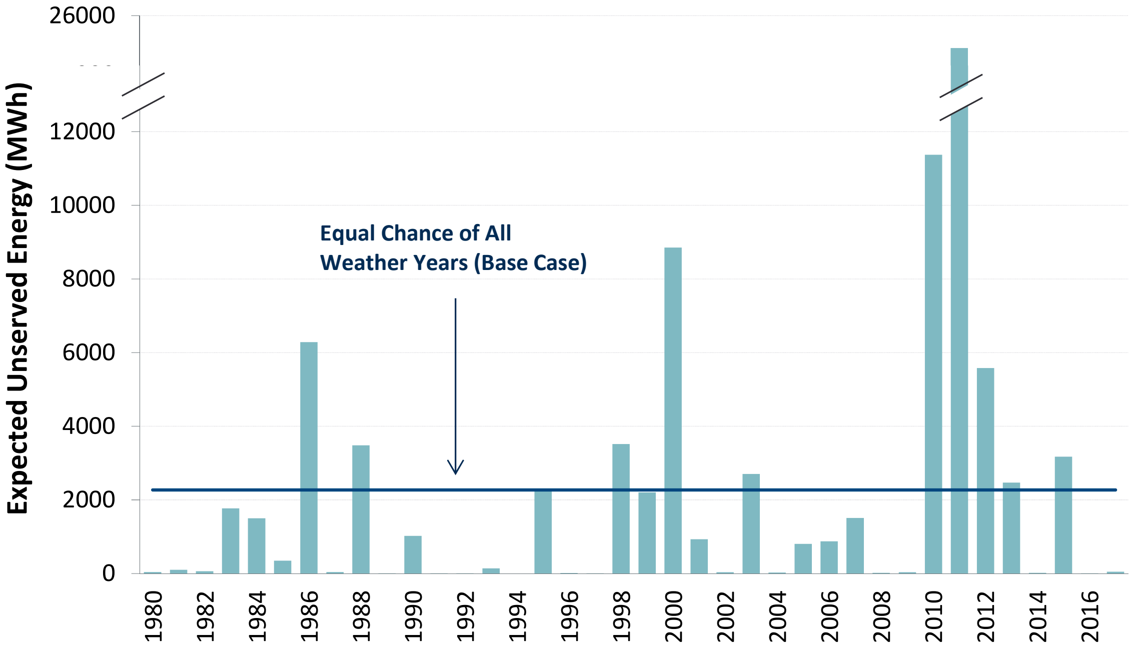
All of the reliability metrics shown above reflect the average over many possible outcomes at a given reserve margin. Average statistics provide a convenient summary of a large amount of data, but they can obscure the wide distribution of possible outcomes around the average, as shown in the sections above. Realized reliability in any given year will depend strongly on the weather and on generation availability.

To illustrate the distribution of possible outcomes, Figure 11 below shows how reliability varies with weather, as measured by the annual expected unserved energy. The teal bars show the total MWh of load shed during each of the 38 weather years for the base case simulations at a 10.25% reserve margin corresponding to the market equilibrium reserve margin. The reoccurrence of 2011 weather conditions could lead to almost 25,000 MWh of expected involuntary curtailment of firm

[30] LOLE standards refer only to loss-of-load events due to shortages of bulk power supplies. Annual customer service interruption hours caused by distribution outages are orders of magnitude greater, as discussed in Newell 2012.

load, far above the equal-probability-weighted average of 2,300 MWh over all 38 years depicted by the blue horizontal line. By contrast, 28 out of the 38 years have much milder weather, with substantially less load shed than the average. Thus the actual reliability will vary. In addition, the expected value of reliability would differ if different probability weights were assigned to the various weather patterns, as discussed in the next section.

Figure 11
Expected Unserved Energy by Weather Year at 10.25% Reserve Margin



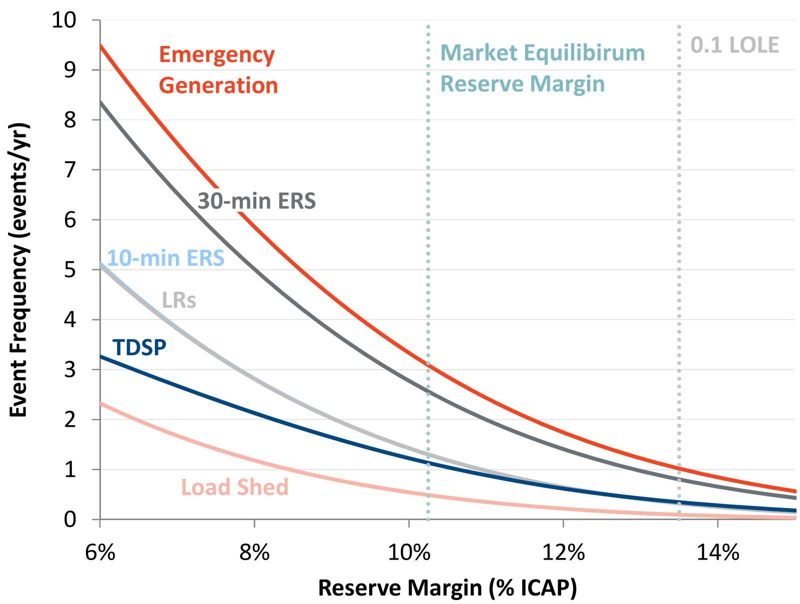
Notes:
Figure reflects the base case 3-Year forward LFE assumption and equal weather weights for all 38 years.

2. Emergency Event Frequency

Figure 12 summarizes the frequency of six types of emergency events for the base case simulations as a function of the reserve margin. The emergency events, in increasing order of severity, are: (1) the economic dispatch of emergency generation (red line); (2) calling 30-minute ERS (dark gray line); (3) calling TDSP load curtailments (dark blue line); (4) re-dispatching LRs from RRS to energy (light gray line); (5) calling 10-minute ERS (light blue line); and, finally, (6) shedding firm load (light red line). As shown, at a 13.5% reserve margin corresponding to 1-event-in-10-years (0.1 LOLE), emergency generation would be dispatched approximately 1 time a year on a weighted-average basis across all simulated years. At a reserve margin of 8.5%, the system faces one load shed event per year on average, most years without load shed events and some years with several. At the same 8.5% reserve margin, the various types of demand resources would have to be called from two to five times on average each year (depending on the resource type), and emergency generation would be dispatched approximately five times on average each year. At the market equilibrium reserve margin of 10.25%, emergency generation would be dispatched about three times on average per year, and other demand resources would average between once and 2.5 times per year.

All types of emergency events become more frequent at lower reserve margins, but the frequency of re-dispatching LRs that provide RRS to energy increases faster than TDSP calls. This is because at lower reserve margins the hours-per-year constraints on TDSP demand-side resources bind in more cases, which diminishes their reliability value and requires ERCOT to rely more heavily on other measures and resources.

Figure 12
Average Annual Frequency of Emergency Events



Notes:
Results from base case (3-Year Forward LFE, equal weighting of weather years).

D. Sensitivity of Market Equilibrium Reserve Margin to Study Assumptions

If investors have different beliefs about load and other factors affecting revenues, or if they face different costs, the market equilibrium reserve margin could differ from our estimates. Here we examine the most important uncertainty factors affecting the MERM, including: (1) the amount of intermittent renewable generation installed; (2) the assumed cost of building new natural gas-fired plants; (3) the value of lost load; (4) the assumed probabilities of the historical weather years used to model hourly loads and renewable generation; (5) load forecast uncertainty; and (6) gas prices.

Changing the values for these variables over a plausible range results in market equilibrium reserve margins ranging from 9.25% to 11.75%. The actual uncertainty could be even wider, however, when considering other possibilities such as extreme weather events, broader distributions of intermittent renewable generation coinciding with the highest load years (rather than always taking the 2011 wind patterns with 2011 loads, for example), or different beliefs about future market and regulatory conditions. This range of equilibrium reserve margins would produce a range of reliability outcomes, which we estimate to be 0.44 to 0.74 LOLE.

1. Renewables Penetration Scenarios

The base case analysis assumes 32.0 GW of wind and 3.6 GW of solar online by 2022, based on the existing fleet and planned resources that have met the criteria to be included in the CDR. Our alternative "High Renewables" scenario adds 50% of the wind and solar capacity from ERCOT's July 2018 Generator Interconnection Status report that has not yet met all the requirements to be included in the May 2018 CDR, resulting in an additional 10 GW of wind and 10 GW of solar. The alternative "Low Renewables" scenario makes wind and solar capacities consistent with the 2014 EORM Study by removing approximately 16.8 GW of wind and 3.5 GW of solar—not because this is realistic but because it informs how much of the change in MERM from one study to the other can be attributed to the additional renewables.[31]

All else equal, adding renewable generation would decrease prices; but lower prices should force out conventional generation, until the market re-equilibrates at approximately the same reserve margin. However, we do estimate that equilibrium reserve margins would decrease slightly with higher renewable penetration because the net load (load minus renewable generation) duration curve becomes steeper. A steeper net load duration curve causes prices to fall faster beyond the peak hour. That would reduce generators' net revenues, so reserve margins have to tighten slightly to re-equilibrate, with a slight increase in high-priced ORDC hours. In the High Renewables scenario, the MERM falls by one percentage point, to 9.25%, and reliability worsens slightly, increasing LOLE by 0.25.

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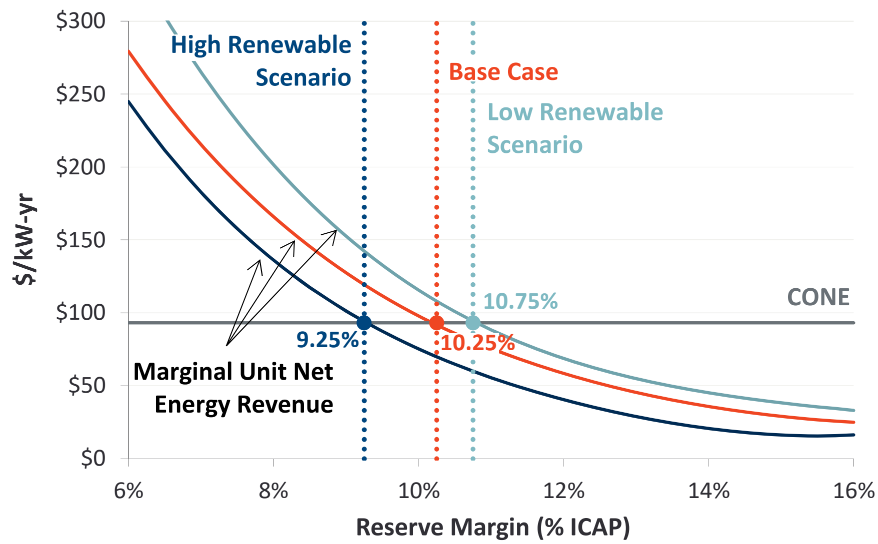
31 The capacity contribution of renewables was adjusted in the high and low scenarios so that an LOLE of 0.1 events per year occurs at a reserve margin of 13.75%, which is the consistent with the base case reliability under ERCOT's current renewable capacity contributions. Capacity contribution decreased in the high renewables scenario, and increased in the low renewable scenario.

In the Low Renewables scenario, the MERM rises 0.5 percentage points, to 10.75%—a smaller increase than the decrease estimated for the High scenario. Although both renewable penetration scenarios add or decrease about 20 GW of renewable nameplate capacity, they have asymmetric effects on the MERM because of the impact of renewables penetration on the remaining fleet, which can be seen in Figure 13. In the Low Renewables scenario, additional gas-fired generation is necessary to maintain the reserve margin at base case levels.[32] These relatively efficient new resources operate frequently and reduce prices in many hours, thus limiting the amount of investment that can be supported.[33] By contrast, the High Renewable scenario displaces 9 GW of existing generation that is not as efficient.

Figure 13
Market Equilibrium Reserve Margin Sensitivity to Renewable Penetration



This resource adequacy study does not account for numerous *operational* challenges that can arise with greater penetration of intermittent renewable generation, such as providing enough operating reserves to compensate for wind and solar forecast errors, providing enough ramping capability to compensate for rapid changes in wind and solar output, and maintaining enough inertia to slow the rate of change of frequency following the loss of a large (usually thermal) generator. While these problems can be addressed to avoid deteriorating operational reliability, it is likely they result in both more hours with low (or negative) market prices as well as more hours with high market prices than produced by our simulations, which assume perfect foresight in

32 The characteristics of Marginal Technology Resources are described in Appendix 1.IV.B.1.

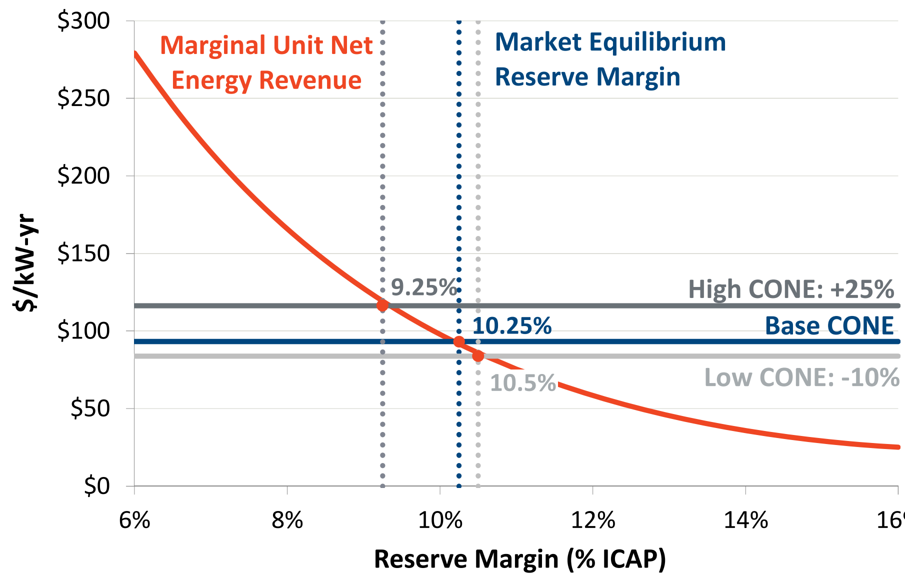
33 The 2014 EORM included several GW of traditional generators that have retired.

setting commitment and dispatch. These challenges could affect reliability if not addressed adequately, and they are not expressed in the small change in MERM we estimate.

2. Cost of New Entry Sensitivity

The base case simulations assume that a combination of natural gas-fired CCs and CTs are the marginal resource with industry standard assumptions for capital costs. However, industry experience suggests that there is a range of uncertainty around technology cost estimates. Figure 14 shows the impact of varying gross CONE from –10% to +25% relative to our base assumptions.[34] Overall, the market equilibrium reserve margin could vary over a range of 9.25% to 10.50% depending on the range of gross CONE uncertainty.

Figure 14
Market Equilibrium Reserve Margin Sensitivity to Cost of New Entry



Note: Marginal Unit Net Energy Revenue reflects a mix of CCs and CTs. This ratio is applied in each sensitivity.

3. Probability Weighting of Weather Sensitivity

The high impact of weather on net energy revenue means that different weather expectations will influence the market equilibrium reserve margin. The base case assumes equal probability for all 38 weather years because 38 years should be a sufficient sample of the underlying distribution,

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34 We tested an asymmetric range with more upside because CONE estimates are substantially lower than in the past, and to account for the possibility that developers may require higher, more front-loaded payments to enter given the prospect of a high-renewable future that limits future revenues.

assuming that distribution is representative of future weather patterns. This reliance on long history is consistent with the EORM Manual. However, more recent weather has, on average, been hotter (especially in 2011) and may be assumed to be more representative of future weather as discussed in Section II.E above. Assuming accordingly that each of the last 10 weather years has a 10% chance of reoccurring (with 0% weight on each of the prior 28 years) leads to higher simulated prices and reliability events at a given reserve margin; but the higher prices would attract more investment, resulting in a 1.5% higher market equilibrium reserve margin of 11.75%. With that higher MERM protecting against the effects of hotter weather, the simulated reliability is approximately the same as in the base case.

We also examined the effects of two other sets of weighting factors: (1) assign weights based on the number of consecutive days of greater than 100-degree weather using a Pareto distribution, resulting in a 0.25% lower MERM;[35] and (2) apply the same weights as in the 2014 EORM study, with a 1% weight to 2011 and equal weight to the remaining years from 1998 to 2012, resulting in a 0.75% higher MERM.

4. Forward Period and Load Forecast Uncertainty Sensitivity

In our base case analysis, we assume that all future supply decisions must be locked in three years in advance, approximately consistent with the lead time needed to construct new natural gas-fired generation resources.[36] However, unlike weather-related load uncertainty, non-weather load forecasting error (LFE) increases with the forward period. The forward period may increase if investors require a longer planning period and decrease if there are significant short-term resources (such as demand response, switchable units, mothballed units, and even renewable resources) to respond more quickly to market conditions than traditional new builds. Depending on the expected forward periods the market equilibrium will vary from 9.25% to 10.25%.

5. Summary of Sensitivities

Our estimate of the MERM is sensitive to a number of study assumptions as we have explained in previous sections, and summarized in Figure 15 and Table 7. As shown in the table, the MERM is between 9.25% and 11.75% for all sensitivities.

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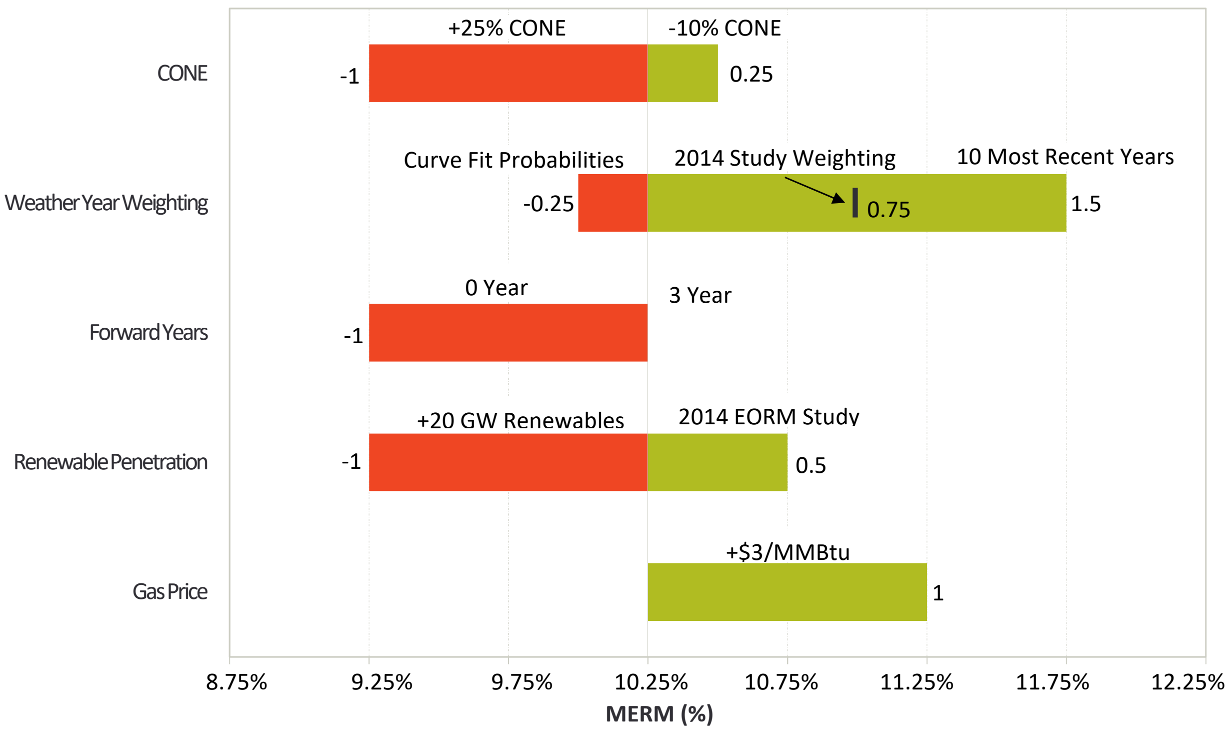
35 This is an updated version of the Weather-risk Index weighting discussed in Section 10.2.1 of ERCOT 2017b.

36 This construction timeframe is why the PJM and ISO-NE capacity markets rely on a three-year forward period.

Each sensitivity does not necessarily have a symmetric effect on the MERM. As discussed in Section III.D.1, the resource mix of renewable additions influences the effect on the MERM. Having a higher ratio of solar to wind installed in the high renewable penetration case decreases the MERM more than the low renewable penetration case decreases the MERM. The change in the VOLL is not considered to shift the operating reserves demand curve (ORDC), and will not affect the MERM.[37] Moving from a three-year LFE forward period to no forward period reduces the MERM by one percentage point. Each one-year increase in the forward period increases the MERM by 0.5%, but each additional year of LFE has a smaller incremental effect on the MERM.

Figure 15
Sensitivity of the Market Equilibrium Reserve Margin to Study Assumptions



Notes:
Varying the VOLL is not shown because it does not affect the MERM.

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37 The ORDC is discussed in Appendix 1.E.4; varying the VOLL to range from $5,000 to $30,000 changes the EORM to range from 8.25% to 10.5%, respectively.

Table 7
Sensitivity of the Market Equilibrium Reserve Margin to Study Assumptions

	Reserve Margin *(%)*	**Base Assumptions**	**Low/High Sensitivity**
Base Case	**10.25%**		
Vary Gross CONE	9.25% - 10.50%	$88.5/kW-yr (CT) $94.5/kW-yr (CC)	$79.7-$110.6/kW-yr (CT) $85.1-$118.1/kW-yr (CC)
Vary VOLL	10.25%	$9,000/MWh	$5,000-$30,000/MWh
Vary Probability of Weather Years	10.0% - 11.75%	Equal Probability to all 38 weather years	Equal Probability to last 10 years; 2014 EORM Base Case Weather Probability; Consecutive Days >100 Pareto Distribution
Vary Forward Years	9.25% - 10.25%	3 years	0 years to 2 years
High Renewables Scenario	**9.25%**		10 GW of new solar, 10 GW of new wind
Low Renewables Scenario	**10.75%**		Wind and Solar capacities equal to those in the 2014 EORM report.
High Gas Price	**11.25%**		$3.00 increase in Gas price.

Notes:

Varying the VOLL does not affect the MERM.

IV. Discussion of Results

Our analysis shows a market equilibrium reserve margin of 10.25%, which exceeds the economic optimum by 1.25%, as discussed in Section III.B. Based on these results, we conclude that the current market design will support more than sufficient reserve margins from an economic perspective, with some excess. In terms of reliability, our probabilistic simulations indicate that at the market equilibrium reserve margin of 10.25%, the system could be expected to experience 0.5 events per year loss-of-load expectation (LOLE). This compares favorably to 0.8 events per year LOLE at the economic optimum, but is greater than the 0.1 events per year LOLE standard used by most electric systems in North America for planning purposes. Table 8 shows these and other metrics, as well as alternative estimates under different uncertain assumptions and future scenarios.

One of the most important sources of uncertainty is the likelihood of extreme 2011-like weather (*i.e.*, many days over 100 degrees) and hot weather generally. Assigning a 10 percent weight to each of the last 10 years would increase the market equilibrium by 1.5% from the base case that assumes equal weight on each of the last 38 years—but it would also increase the number of scarcity events at a given reserve margin, resulting in similar reliability at the higher market equilibrium reserve margin.

Other uncertainty factors are the estimated capital cost of building new generation, load forecasting error, natural gas prices, and renewable penetration. We estimate that the market equilibrium decreases by 1.0% with an additional 10 GW of nameplate wind and 10 GW of nameplate PV capacity, with reliability deteriorating by 0.25 events/year for that amount of additional capacity (and offsetting reductions in the amount of gas-fired capacity). This observation may seem to point to a future of declining reliability, but perhaps not if storage becomes more economic and/or if gas price rise from their current low levels.

Table 8
Market Equilibrium and Economically Optimal Reserve Margins

	MERM *(%)*	EORM *(%)*
Base Case	**10.25%**	**9.0%**
Vary Gross CONE	9.25% - 10.50%	8.0% - 9.25%
Vary VOLL	10.25%	8.25% - 10.5%
Vary Probability of Weather Years	10.0% - 11.75%	8.75% - 10.5%
Vary Forward Years	9.25% - 10.25%	8.5% - 9.0%
High Renewables Scenario	**9.25%**	**8.25%**
Low Renewables Scenario	**10.75%**	**9.50%**
High Gas Price	**11.25%**	**10.25%**

Notes:

Table reflects all scenarios and sensitivities studied, as described in Section II.D; Current practice has VOLL set to the max of the ORDC but the sensitivity which varies to VOLL does not change the ORDC curve and therefore does not affect the MERM.

These estimates must not be interpreted as deterministic, since actual conditions will fluctuate from year-to-year. In reality, the reserve margin will vary as plants enter and exit. Moreover, even at a given reserve margin, realized reliability and price outcomes can deviate far from the expected value, primarily due to weather and variations in wind generation. For example, with a projected reserve margin of 10.25% (the market equilibrium), we estimate that the 90th percentile outcome—representing relatively hot weather, higher than expected non-weather related load, and low generation availability—energy prices would double, marginal units could have net energy revenues reaching $200/kW-yr, and reliability would be expected to fall to 1.2 firm load shed events per year

The market equilibrium is higher than the economic optimum because the ORDC sets prices higher than the marginal value of energy during scarcity conditions, creating additional incentives to invest that raise reserve margins somewhat above the optimal level. This is by design. When ERCOT implemented the ORDC in June 2014 per PUCT orders, it was deliberately right-shifted by 1,000 MW (slightly more than 1%) relative to an original curve that reflected the expected value of lost load.[38] The right-shift recognized the additional cost of emergency actions, but it also may have reflected some risk aversion to lower reliability.

Our base case market equilibrium estimate of 10.25% is above the 9.0% economically optimal reserve margin, discussed in Section III.B. This 10.25% market equilibrium value exceeds the economically optimal reserve margin because the base case ORDC produces energy prices that sometimes exceed marginal system cost (as explained in Appendix 1.E) and, therefore, provides investment incentives that slightly exceed the resource's risk-neutral economic value.

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[38] Specifically, the ORDC was set as if load would be shed (or other emergency actions taken at an equivalent cost) at an operating reserve level of X = 2,000 MW. This is above the 1,000 MW estimated level at which load is shed, with prior emergency actions incurring costs below the value of lost load.

List of Acronyms

4CP	Four Coincident Peak
ATWACC	After-Tax Weighted Average Cost of Capital
AEO	Annual Energy Outlook
CC	Combined Cycle
CDR	Capacity, Demand, and Reserves (report)
CONE	Cost of New Entry
CT	Combustion Turbine
EFOR	Equivalent Forced Outage Rate
EE	Energy Efficiency
EORM	Economically Optimal Reserve Margin
ERCOT	Electric Reliability Council of Texas
ERS	Emergency Response Service
EUE	Expected Unserved Energy
GADS	Generation Availability Data System
GIS	Generator Interconnection Status
HCAP	High System-Wide Offer Cap
HVDC	High Voltage Direct Current
LCAP	Low System-Wide Offer Cap
LFE	Load Forecast Error
LTRA	Long-Term Reliability Assessment
LOL	Loss-of-Load
LOLE	Loss-of-Load Event
LOLH	Loss-of-Load Hour
LOLP	Loss of Load Probability
LRs	Load Resources
MERM	Market Equilibrium Reserve Margin
NERC	North American Electric Reliability Corporation
ORDC	Operating Reserve Demand Curve
PBPC	Power Balance Penalty Curve
PNM	Peaker Net Margin
PRD	Price Responsive Demand
PUCT	Public Utility Commission of Texas

PUN	Private Use Network
RRS	Responsive Reserve Service
SARA	Seasonal Assessment of Resource Adequacy
SCED	Security Constrained Economic Dispatch
SERVM	Strategic Energy Risk Valuation Model
SWOC	System-Wide Offer Cap
TDSP	Transmission/Distribution Service Providers
VOLL	Value of Lost Load
VOM	Variable Operations and Maintenance

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Appendix 1: Modeling Assumptions

This Appendix describes in more detail the representation of the ERCOT system, including: load and weather patterns and their probabilistic variations; the cost and performance characteristics of ERCOT's generation and demand-response resources; the mechanics of the ERCOT energy and ancillary services markets, including a unit commitment and economic dispatch of all generation resources, demand-response resources, and the transmission interties with neighboring markets. We also explain assumptions developed to reflect expected conditions of 2022 on the generation fleet, demand-response penetration, fuel prices, and energy market design.

A. Demand Modeling

This section describes the data and modelling of the demand in the model, specifically peak load, weather uncertainty, non-weather forecast uncertainty, and demand shapes.

1. Peak Demand and Regional Diversity

We developed a weather-normal ERCOT peak load forecast for expressing the reserve margin (as [supply – peak] / peak) consistent with the May 2018 Capacity and Demand Report (CDR). The peak load forecast normalizes for weather by identifying a 50^{th} percentile peak load ("50/50") forecast for each weather zone. The 50/50 peak load for each weather zone represents the average peak load from 15 synthetic load profiles, each representing the expected load in a future year given the weather patterns from each of the last 15 years of history. To develop a system 50/50 peak load forecast, the load in each weather zone must be identified at the time of the system peak. To do so, an average load duration curve is constructed for each weather zone by averaging each hour of the load duration curves from 15 years of historical data. Then, the zonal load duration curves are mapped to a single historical year. The single historical year ERCOT uses for the 2018 CDR is 2003 because it was a generally "normal" weather year. The mapping is completed by identifying the peak load hour in 2003 and setting its load to the peak load from the average zonal load duration curve. Then the second highest load hour in 2003 is assigned the second highest load in the average zonal load duration curve. This continues until all of the hours in 2003 are assigned a load level based on their rank and the equivalent load at that rank in the average load duration curve. The resulting hourly load profile constructed for each zone is then used to aggregate the individual zonal loads into the system peak load.

However, 2003 experienced less peak diversity between weather zones than ERCOT normally experiences. Expressing the "50/50" peak from the many years of historical data using 2003 as a base shape therefore understates typical load diversity and may overstate the 50/50 system peak load. It results in a 79,568 MW system peak load rather than 78,079 MW 50/50 peak when using the average system peak across the study years (1980–2017).[39] For the purposes of this study, this is only a reporting issue and does not affect the underlying hourly weather patterns and loads used in our simulations. It does cause the EORM and MERM to appear lower than they would if expressed against a 50/50 peak load using typical diversity, by about 1.2% (since the reserve margin is expressed relative to a 79 GW reported peak load when the actual 50/50 corresponding to the same underlying data may be closer to 78 GW).

2. Demand Shapes and Weather Uncertainty Modeling

We represent weather uncertainty in the projected ERCOT 2022 peak load by modeling 38 load forecasts based on 38 historical weather years from 1980–2017, as summarized in Figure A1-1.[40] ERCOT staff used these 38 weather years as inputs into its 2018 load forecasting model, which produced the range of hourly load forecasts for 2022 we used in the SERVM model for this study.[41]

The left chart shows projected 2022 peak load for each weather year relative to the weather-normal peak load.[42] The chart illustrates asymmetry in the distribution of peak loads, with the highest projected peak load (based on 2011 weather) at 5.9% above the weather-normal peak loads, compared to a peak load in the mildest weather year that is only 4.6% below weather-normal peak load.

The right chart in Figure A1-1 shows the 2022 load duration curves for the 250 highest-load hours in each of the 38 weather years. The light blue load duration curve is based on the extreme and extended hot summer weather in 2011. As shown, the entire load duration curve from 2011 weather is far above all other weather years in the top 250 hours. This extreme heat resulted in a number of emergency events and price spikes during the summer of 2011, which is described by some as a 1-in-100 weather year. Despite this, our base case assigns equal probability to all 38

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39 Provided by ERCOT staff.

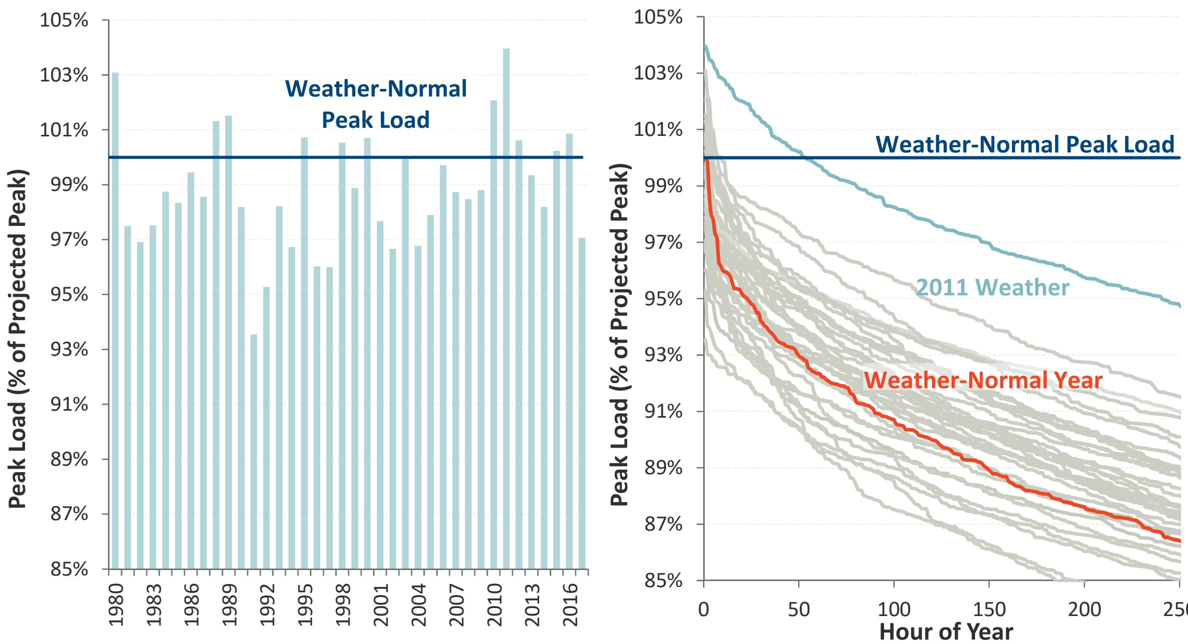
40 This is different than the previous EORM study, which used 15 weather years (1998–2012)

41 Details on the load forecast model methodology in (ERCOT, 2017c).

42 In this study there is no peak load gross-up for PRD and LRs because there has not been significant historical response from these resources so the historical load shape has not been reduced by their deployment.

weather years because the sample set is large enough to be reasonably representative of weather patterns. We also report the MERM and EORM under alternative weather weights consistent with the 15 weather years used in the 2014 EORM study and placing higher probability on the last 10 years to represent recent trends in weather patterns, which tend to emphasize the 2011 weather and its impacts on load.

Figure A1-1
ERCOT Peak Load (Left) and Peak Load Duration Curve (Right) by Weather Year



Sources and Notes:
ERCOT load shapes provided by ERCOT staff.

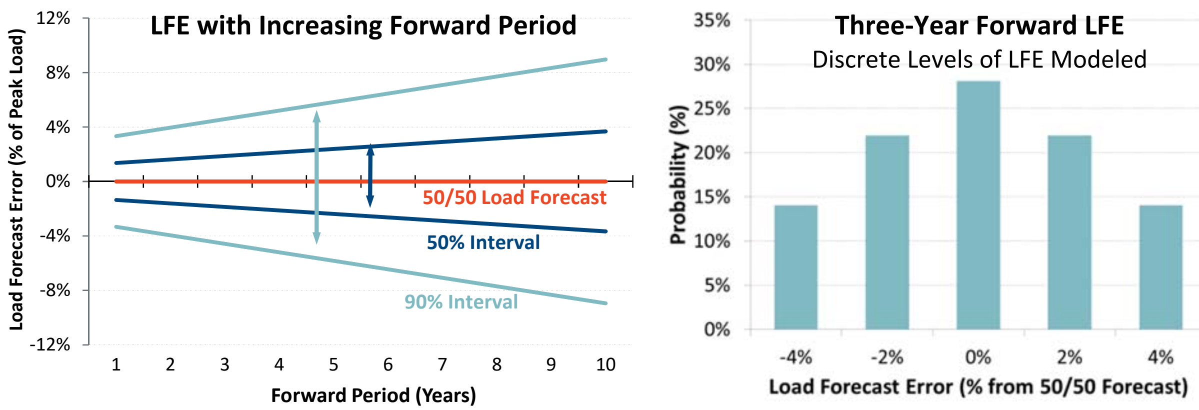
3. Non-Weather Demand Forecast Uncertainty and Forward Period

Forward-looking "planning" or "target" reserve margins differ from actually-realized reserve margins because both realized peak load and actual available resources can differ from projections. One cause of forecast error is simply the weather. Another is due to uncertainties in population growth, economic growth, efficiency rates, and other factors. These non-weather drivers of load forecast errors (LFEs) differ from weather-related LFEs because they increase with the forward planning period, while weather uncertainties will generally remain constant and be independent with the forward period.

As shown in the left chart of Figure A1-2, we assume that non-weather LFE is normally distributed with a standard deviation of 0.8% on a 1-year forward basis, increasing by 0.6% with each additional forward year.[43] The distribution includes no bias or asymmetry in non-weather LFEs, unlike the weather-driven LFE in ERCOT, which has more upside than downside uncertainty.

For our purposes, the relevant forward period for characterizing non-weather LFEs is the period at which investment decisions must be finalized. We assume investment decisions must be finalized three years prior to delivery, consistent with the approximate construction lead time for new generation resources. This means that available supply and the expected planning reserve margin are "locked in" at three years forward, and the realized reserve margin may differ substantially as both weather and non-weather uncertainties are resolved as the delivery year approaches. The right-hand chart of Figure A1-2 shows the five discrete levels of LFE we model, equal to 0%, +/–2%, and +/–4% above and below the forecast. The largest errors are the least likely, consistent with a normal distribution. We also conduct a sensitivity analysis, examining the implications on economically optimal and reliability-based reserve margins if the forward period is varied between zero and four years forward.

Figure A1-2
Non-Weather Load Forecast Error



4. External Region Demand

We independently developed external regions' peak load and load shapes based on publicly-available peak load projections, historical hourly weather profiles, and historical hourly load data. Table A1-1 summarizes the peak load for the ERCOT system and the load diversity relative to the interconnected neighboring regions. Consistent with the peak load reporting conventions used in

43 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.

ERCOT's CDR report, these peak loads are reported: (a) net of anticipated load reductions from price-responsive demand (PRD) and load resources (LRs); and (b) prior to any potential reductions from transmission and distribution service provider (TDSP) load management or energy efficiency (EE) programs.[44]

Table A1-1
Peak Loads and Diversity Used in Reserve Margin Accounting

		ERCOT	Entergy	SPP	Mexico	Total
Summer Peak Load Forecast						
Non-Coincident	*(MW)*	79,027	23,644	50,326	12,679	165,677
Coincident	*(MW)*	76,700	22,965	49,488	12,306	161,459
At ERCOT Peak	*(MW)*	79,027	21,894	48,219	12,679	161,819
Load Diversity						
At Coincident Peak	*(%)*	3.0%	3.0%	1.7%	3.0%	2.6%
At ERCOT Peak	*(%)*	0.0%	8.0%	4.4%	0.0%	2.4%
Reserve Margin at Criterion						
At Non-Coincident Peak	*(%)*	n/a	15.8%	13.6%	15.0%	n/a
At ERCOT Peak	*(%)*	n/a	25.1%	18.6%	15.0%	n/a

Sources and Notes:

Non-Coincident Peak represents each individual region's peak load.

Coincident Peak represents the load in each region at the maximum total model area peak.

At ERCOT Peak represents the load in each region at the time of the ERCOT system peak.

SPP 50/50 peak load forecast is from the NERC *2017 Long-Term Reliability Assessment*.

Entergy's 50/50 peak load forecast is from the MISO *Planning Year 2017-2018 Loss of Load Expectation Study Report*. Load shapes in SPP and Entergy are based on our independently-developed statistical relationship between hourly weather and load estimated over five years of load data from FERC and 38 years of weather data from NOAA (2017).

Mexico's peak load and load shape were unavailable. The peak is assumed at a 15% reserve margin above the currently-installed generation fleet, see NERC (2017) and ABB, Inc. Velocity Suite (2018). Load shapes in Mexico are assumed identical to those in ERCOT's South Zone, as estimated by ERCOT staff.

As shown in the table above, there is a substantial amount of load diversity between ERCOT and the neighboring systems, indicating that ERCOT may have access to substantial import quantities during shortages to the extent that sufficient intertie capability exists. For example, at the time of ERCOT's peak load, SPP load is likely to be at only 96% of its own non-coincident peak load. This load diversity results in having more than 6,000 MW of excess generation available for export in hours where ERCOT is shedding firm load. However, most of these excess supplies will not be imported because ERCOT is relatively isolated from neighboring systems with only 800 MW of intertie capability with SPP.

[44] See May 2018 CDR.

B. GENERATION RESOURCES

We model the economic, availability, ancillary service capability, and dispatch characteristics of all generation units in the ERCOT fleet, using unit ratings and online status consistent with ERCOT's May 2018 CDR report. In this section we describe our approach for modeling conventional generation, private use networks (PUNs), and intermittent wind and solar. We also describe the assumed cost and technical specifications of the gas combined cycle and combustion turbine reference technologies.

1. Marginal Resource Technology

The quantity of installed generating capacity must vary to simulate ERCOT's system costs, market prices, and reliability across different reserve margins. We add gas combined cycle (CC) and combustion turbine (CT) plants in our base case at a 77:23 ratio, roughly reflecting the types of resources that have been added or proposed for the ERCOT market. Our technology choices for the gas CC and CT plants are also consistent with recent developer announcements.[45]

The costs and performance characteristics of the reference CC and CT are summarized in Table A1-2 and Table A1-3 respectively. These characteristics are based on GE 7HA technology for both the CC and CT plants, which is different than the reference GE 7FA technology from EORM 2014.[46] We use updated cost of new entry (CONE) assumptions consistent with this technology, as well as an updated after-tax weighted-average cost of capital (ATWACC) for a merchant developer based on current financial market conditions. These updates result in an estimated CONE of $94,500/MW-year for the gas CC and $88,500/MW-year for the gas CT, which is 22.6% and 8.8% lower than in EORM 2014, as shown in Table A1-2.

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[45] Recent orders of GE turbines show that future CCs are almost exclusively using the H-class turbines from GE Power & Water's H-Class Gas Turbine Experience List from November 2016 and the 7F.05 Gas Turbine Experience List from June 2016.

[46] See Newell, *et al.* (2018).

Table A1-2
Gross Cost of New Entry

	ATWACC	Gross CONE	
		Simple Cycle	Combined Cycle
	(%/yr)	*($/MW-yr)*	*($/MW-yr)*
From 2014 Study (2016 Online Date)			
Low: Base minus 10%	n/a	$87,300	$109,900
Base: Merchant ATWACC	8.0%	$97,000	$122,100
High: Base plus 25%	n/a	$121,300	$152,600
Updated Estimate (2022 Online Date)			
Low: Base minus 10%	n/a	$79,700	$85,100
Base: Merchant ATWACC	7.8%	$88,500	$94,500
High: Base plus 25%	n/a	$110,600	$118,100

Sources and Notes:

2014 Study numbers and current numbers are adapted from CONE studies for PJM, with adjustments applied as relevant for ERCOT; see Spees, *et al.* (2011) and Newell, *et al.* (2018), respectively. CONE values determined with adjustments to technology characteristics within an area that most closely resemble ERCOT, as outlined in Table A1-3. The updated CONE estimate was developed based on the values in the 2018 PJM CONE report before adjustments were made to the assumed discount rate and exemption from paying sales taxes. Changing the CONE for ERCOT to be consistent with the higher discount rates would increase the Base CC CONE to $97.5/kW-year and the Base CT CONE to $91.2/kW-year, which is well within the sensitivity range, as described in Section III.D.2.

Table A1-3
Performance Characteristics

		Simple Cycle	Combined Cycle
Plant Configuration			
Turbine		GE 7HA.02	GE 7HA.02
Configuration		1 x 0	2 x 1
Heat Rate (HHV)			
Base Load			
Non-Summer	*(Btu/kWh)*	9,138	6,270
Summer	*(Btu/kWh)*	9,274	6,312
Max Load w/ Duct Firing			
Non-Summer	*(Btu/kWh)*	n/a	6,503
Summer	*(Btu/kWh)*	n/a	6,553
Installed Capacity			
Base Load			
Non-Summer	*(MW)*	371	1,073
Summer	*(MW)*	352	1,023
Max Load			
Non-Summer	*(MW)*	n/a	1,202
Summer	*(MW)*	n/a	1,152
Gross CONE	*($/kW-yr)*	**$89**	**$95**

Sources and Notes:
Technical and performance parameters use region EMAAC as most closely resembling ERCOT in altitude and ambient conditions from Newell, *et al.* (2018).

2. 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.[47]

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 A1-4 summarizes fleet-wide and asset-class outage rates, including both partial and forced outages.

Table A1-4
Forced Outage Rates by Asset Class and Fleet Average

Unit Type	Equivalent Forced Outage Rate *(%)*	Mean Time to Fail *(hours)*	Mean Time to Repair *(hours)*
Nuclear	5.3%	7,580	339
Coal	5.0%	863	38
Gas Combined Cycle	2.3%	3,182	27
Gas Combustion Turbine	7.1%	1,486	66
Gas Steam Turbine	9.7%	784	61
Fleet Weighted Average	**4.8%**		

Sources and Notes:
Parameter distribution based on three years (2015-2017) of unit-specific GADS data and asset class average outage rates from ERCOT.[48]

3. 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 A1-3.[49] At any given load, the realized net PUN generation has a

47 Capturing the possibility of such low-probability, high-impact events is an advantage of the unit-specific Monte Carlo outage modeling used in SERVM. The simpler convolution method, which is a common alternative outage modeling method, results in a distribution of outages that may under-estimate the potential for extreme events, especially in small systems.

48 Significant forced outages of the Comanche Peak Nuclear Power Plant increased the Equivalent Forced Outage Rate (EFOR) of nuclear plants as compared to EORM 2014. The EFOR of combined cycle and combustion turbines decreased, bringing the Fleet Weighted Average down by two percentage points from EORM 2014.

49 The representation of PUN generation as correlated with load is a slight change to the modeling from the previous EORM report, which used system energy prices to predict PUN generation, without a

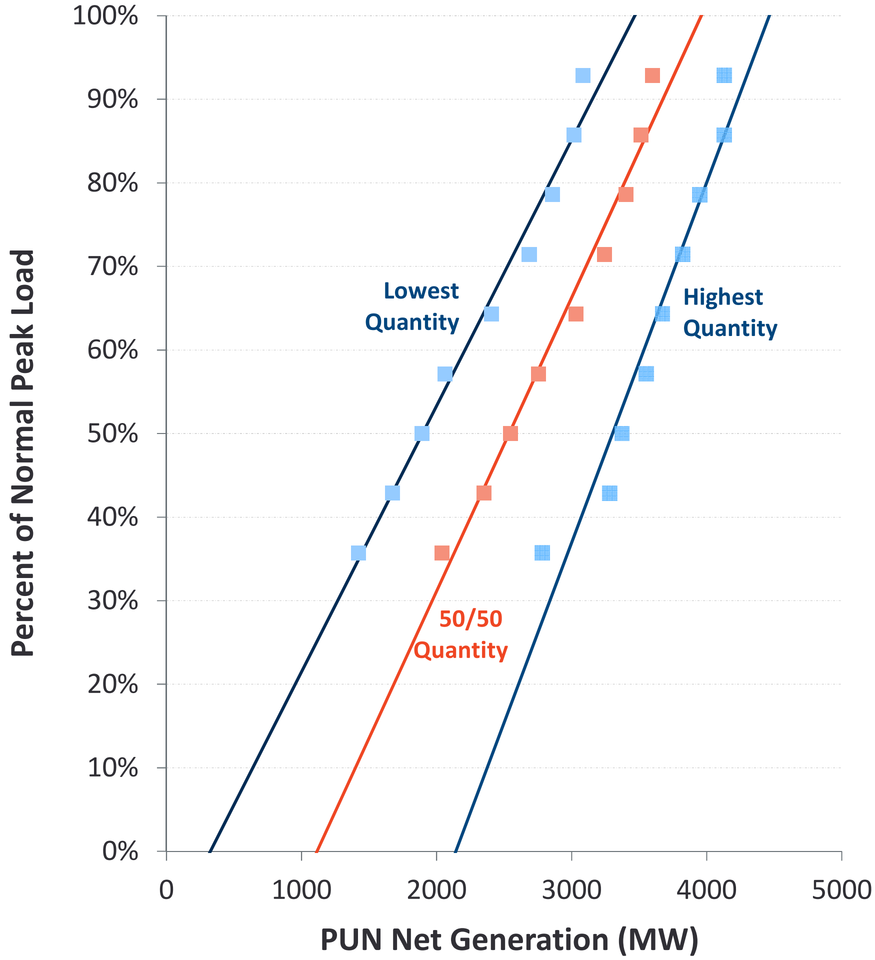
probabilistic quantity, with 11 different possible quantities of net generation within each of 15 different bands of system load.[50] Each of the 11 possible quantities has an equal 9.1% chance of materializing, although Figure A1-3 reports only the lowest, median, and highest possible quantity. We developed this probabilistic net PUN supply curve based on aggregate hourly historical net output data within each range of peak load percentage. During scarcity conditions with load at or above 93% of normal peak load, PUN output produces at least 3,100 MW of net generation with an average of 3,600 MW.

We observe a pattern of availability and responsiveness consistent with: (a) gross generation, much of which is fully integrated into ERCOT's economic dispatch and security constrained economic dispatch (SCED), resulting in substantial increases in the expected quantities over moderate price levels, minus (b) gross load, which introduces some probabilistic uncertainty around net generation, minus (c) some apparent load price-responsiveness, which likely contributes to some small additional increase in net PUN generation at very high prices.

realized change in results. Load and prices are also correlated, but PUN decisions are more likely to be made based on load forecasts.

[50] Hourly net PUN output data gathered from ERCOT, hourly load data from ABB Inc. Velocity Suite (2018).

Figure A1-3
PUN Net Generation



Sources and Notes:
Hourly net PUN output data gathered from ERCOT, hourly load data from Velocity Suite, ABB Inc.
Individual data points represent summary of data in a series of data binned by system load level, within each load bin, the points on the chart represent the lowest 9.1%, middle 9.1%, and top 9.1% of realized quantities in 2012 to 2017.

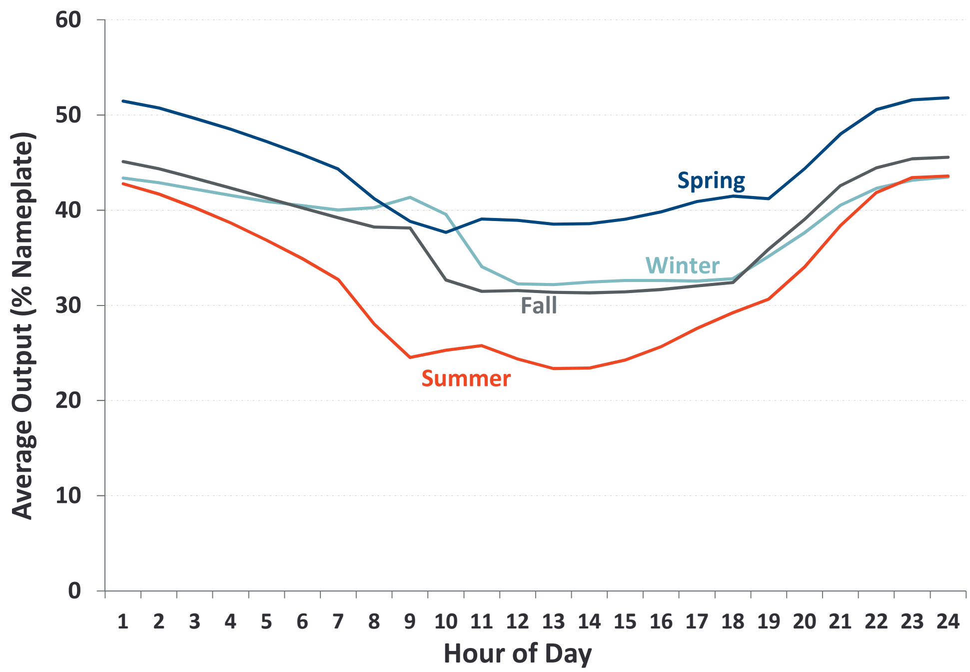
4. Intermittent Wind and Solar

We model a total quantity of intermittent wind and solar photovoltaic resources that reflects what ERCOT reported to NERC for its 2018 LTRA report, including the installed capacity of all existing and planned resources as of 2022.[51] This includes 31,806 MW nameplate capacity of wind and 3,623 MW nameplate of solar, with intermittent output based on hourly generation profiles that are specific to each weather year.

[51] Provided by ERCOT staff.

We developed our system-wide hourly wind profiles by aggregating 38 years of synthesized hourly wind shapes for each location of individual units across the system wind shapes over 1980 to 2017, as provided by ERCOT staff.[52] Figure A1-4 plots the average wind output by month 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 is 37.7%; although we calculate reserve margins assuming an effective load-carrying capability of 14% for non-coastal wind and 59% for coastal wind, consistent with the ERCOT May 2018 CDR convention.[53] In EORM 2014, all wind units were given an ELCC of 8.7%, consistent with the 2013 CDR convention. ERCOT updated this convention as wind penetration has increased and more historical output data became available.

Figure A1-4
Average Wind Output by Month and Time of Day



Sources and Notes:
Average of 38 years' hourly wind profiles provided by ERCOT, originally from UL (formerly AWS Truepower).

We similarly model hourly solar photovoltaic output based on hourly output profiles that are specific to each weather year, as aggregated from county-specific synthesized output profiles over

[52] We aggregated location-specific output profiles for all units, including traditional and coastal units. ERCOT obtained the original wind profiles from UL (formerly AWS Truepower).

[53] See ERCOT (2018a), p. 8.

years 1997 to 2015.[54] In aggregate, solar resources have a capacity factor of 33.5% across all years, and we assign a 75% of nameplate contribution toward the reserve margin consistent with ERCOT's CDR accounting convention.[55]

5. Hydroelectric

We include 555 MW of hydroelectric resources, consistent with ERCOT's May 2018 CDR report.[56] We characterize hydro resources using six years of hourly data over 2012–2017 provided by ERCOT, and 38 years of monthly data over 1980–2017 from EIA form 923.[57] For each month, SERVM uses four parameters for modeling hydro resources, as summarized in Figure A1-5: (1) *monthly total energy output* and (2) *monthly maximum output*, as drawn from historical data consistent with each weather year; and (3) *daily maximum output* and (4) *daily minimum output*, as estimated from historical hourly 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 100 MW of additional hydro for 20 hours per year.

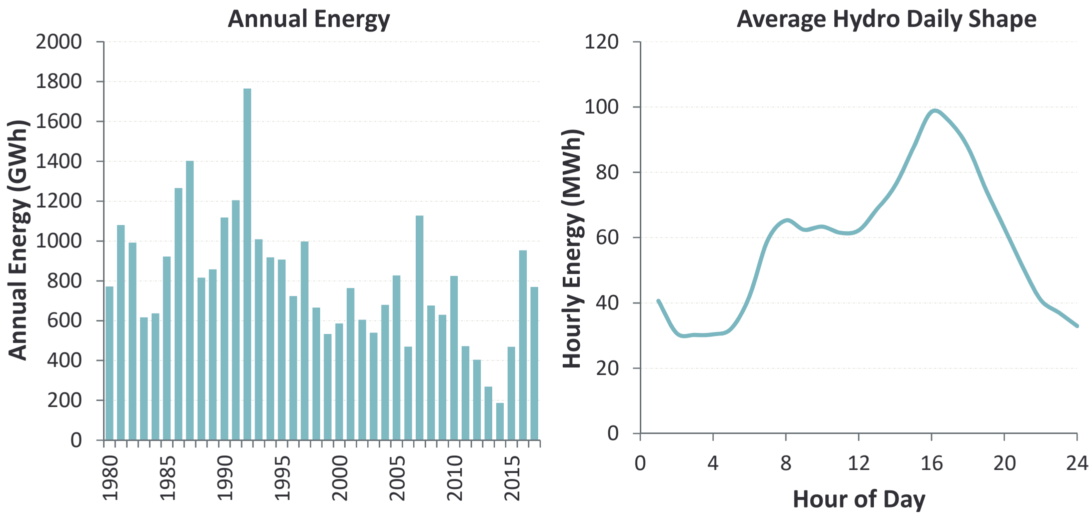
54 Individual county output profiles for 1997-2015 were provided by ERCOT, obtained through UL (formerly AWS Truepower). In conjunction with ERCOT, profiles were developed for the other synthetic weather years by inserting solar profiles from the 1997-2015 dataset for days with similar load patterns in the same time of year.

55 See ERCOT (2018a), p. 8. For the 2014 EORM study, solar was given a 100% contribution to reserve margin consistent with ERCOT's 2013 CDR accounting conventions.

56 See ERCOT (2018a).

57 See EIA-923.

Figure A1-5
Hydro Annual Energy (left) and Average Hydro Daily Shape (right)



Sources and Notes:
Monthly and annual energy data from FERC (2013b), peak shaving capability based on six years of historical hourly data from ERCOT.

6. Fuel Prices

We use 2018 AEO High Resource Case for our gas price future inputs. These gas prices consistent with fuel prices used in other ERCOT analysis, and are comparable to gas price forwards, as shown in Figure A1-6. Alternative gas prices are explored as sensitivities, but do not make a substantial difference in results. We estimate monthly fuel prices for ERCOT coal units based on the average 2017 historical prices. For external coal units and all oil-fired plants, we use futures prices for the year 2022 and after applying a delivered fuel price basis. We use U.S. Gulf Coast and Powder River Basin as the market price points for historical and futures prices as shown in Figure A1-6.[58] To estimate a delivered fuel price basis for each market, we calculated the historical difference between that market price point and prices as delivered to plants in that region and then escalated the delivered price basis with inflation to the year 2022.[59] This locational basis is inclusive of both market price basis as well as a delivery charge and therefore may be positive or negative overall as shown in Table A1-5.

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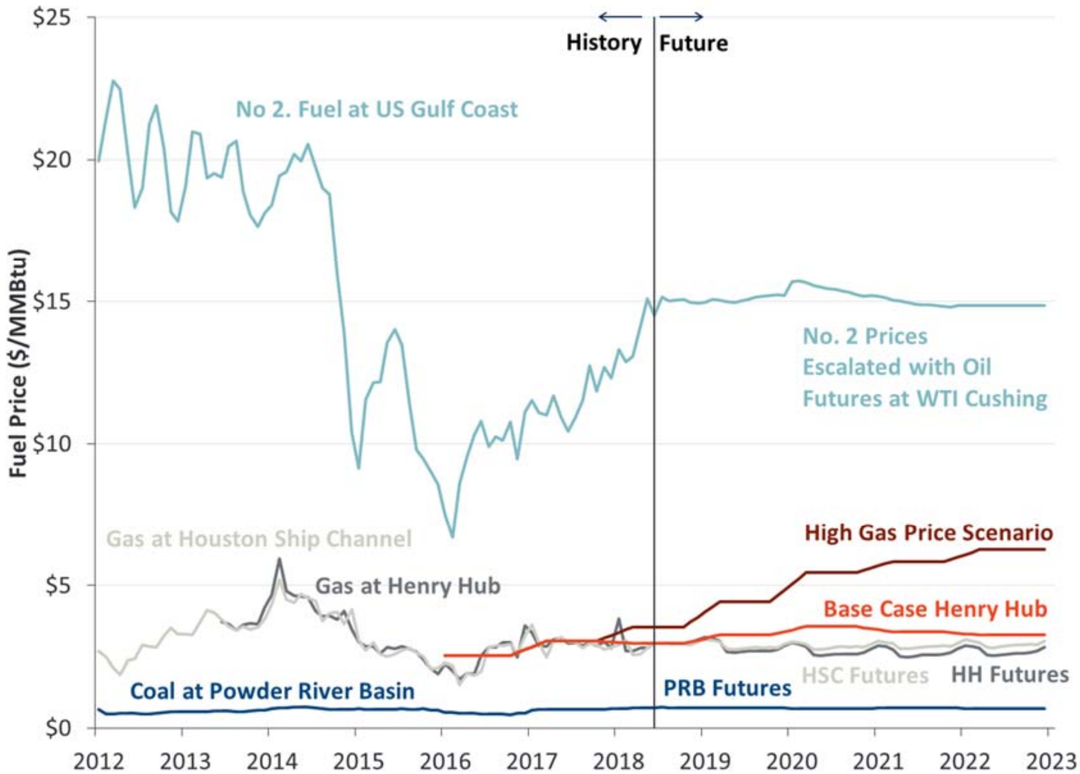
58 Oil futures at WTI Cushing were used to escalate No. 2 fuel oil prices into the future due to lack of data on No. 2 futures at U.S. Gulf Coast. Data from S&P Global Market Intelligence LLC and Bloomberg.

59 Fuel price basis varies by region by not among individual plants. Historical delivered fuel prices from S&P Global Market Intelligence LLC and EIA.

Figure A1-6
Historical and Futures Prices for Gas, Coal, and No. 2 Distillate



Sources and Notes:

No. 2 prices escalated using a linear relationship with WTI Cushing and escalated with WTI futures.

Prices for the base case and High Gas Price Scenario from the 2018 Annual Energy Outlook (AEO) High Resource Case and 2018 AEO Low Resource Case, respectively.

Natural gas and coal historical prices and coal futures prices from S&P Global Market Intelligence LLC and Bloomberg.

Table A1-5
ERCOT 2022 Delivered Fuel Prices

Coal Fuel Price ($/MMBtu)	Gas Fuel Price ($/MMBtu)	Diesel Fuel Price ($/MMBtu)
$1.70	$3.26	$14.85

Sources and Notes:
Coal Fuel Price is averaged from 2017 EIA 923 and FERC Form 1 data.
Gas Fuel Price from the 2018 AEO High Resource Case.

C. Demand-Side Resources

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 types differ from each other in whether they are triggered by price-based or emergency actions, and restrictions on availability and call hours. Below we describe the assumptions and modeling approach for each type of resource.

1. Emergency Response Service

Emergency Response Service (ERS) includes two types of products, 10-minute and 30-minute ERS, with the quantity of each product available changing by time of day and season as shown in Table A1-6. 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 2018, with the 2022 summer peak quantity assumption provided by ERCOT.[60] 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 twelve hours total per season.[61]

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60 For total ERS procurement quantities by product type and season, see ERCOT (2018b). In EORM 2014 we grossed-up ERS quantities from the CDR for losses in the model, but the 2018 CDR ERS quantities include losses.

61 See ERCOT (2018b–d).

Table A1-6
Assumed ERS Quantities Available in 2022

Contract Period	Quantity 10-Min *(MW)*	30-Min *(MW)*	Total *(MW)*
June - September			
TP1: Weekdays 5 AM - 8 AM	159	732	891
TP2: Weekdays 8 AM - 1 PM	165	776	941
TP3: Weekdays 1 PM - 4 PM	142	709	851
TP4: Weekdays 4 PM - 7 PM	140	632	772
TP5: Weekdays 7 PM - 10 PM	156	750	905
TP6: All Other Hours	150	653	803
October - January			
TP1: Weekdays 5 AM - 8 AM	202	632	835
TP2: Weekdays 8 AM - 1 PM	213	671	885
TP3: Weekdays 1 PM - 4 PM	211	659	870
TP4: Weekdays 4 PM - 7 PM	206	654	860
TP5: Weekdays 7 PM - 10 PM	202	624	826
TP6: All Other Hours	193	647	839
February - May			
TP1: Weekdays 5 AM - 8 AM	185	650	835
TP2: Weekdays 8 AM - 1 PM	196	701	896
TP3: Weekdays 1 PM - 4 PM	192	686	878
TP4: Weekdays 4 PM - 7 PM	189	677	866
TP5: Weekdays 7 PM - 10 PM	184	655	839
TP6: All Other Hours	171	585	756

Sources and Notes:
Total available ERS MW for 2022 June-Sept. TP4 provided by ERCOT staff.
ERS 10-min and 30-min MW for other contract periods scaled proportionally to the 2022 LTRA summer quantity (772 MW), based on availability in 2018, from ERCOT (2018a).
ERS resources have an eight-hour call limit applies to both product types and are not callable outside contracted hours, see ERCOT (2018d)

2. Load Resources Providing Ancillary Services

Consistent with ERCOT's published minimum Responsive Reserve Service (RRS) requirements, we model 1,119 MW of non-controllable load resources (LRs) that actively participate in the RRS market.[62] All 1,119 MW are modeled as responsive to Energy Emergency Alert, Level 2.[63]

62 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.

63 Our non-controllable load resource modeling deviates from the previous EORM report prepared in 2014. In that report 1,400 MW of LRs were modeled, consistent with the maximum amount allowed to clear in the RRS market. The LRs were divided into 2 blocks, a smaller block that responded at an

3. Price Responsive Demand

ERCOT has conducted several studies to understand the quantity and behavior of price responsive demand (PRD), whereby customers respond to retail prices that may track spot prices to some extent.[64] Retail programs that enable customers to respond to spot wholesale market conditions include Block & Index, Real Time Pricing, NOIE Price Response, Peak Rebate, DG, and others. We model all such programs combined into a 741 MW of resource based on analysis provided by ERCOT staff of existing PRD enrollments and likely responses.[65]

Table A1-7
PRD by Program Type

Program Type	Enrolled Quantity (MW) Response	Enrolled Quantity (MW) Estimated Undeployed
Block & Index	194	
Real Time Pricing	25	
NOIE Price Response	299	
Other	27	
DG	181	
Other Direct Load Control	2	5
Peak Rebate	13	144
Total	741	149
Total (Including Undeployed)		890

The past several years have experienced few scarcity events and limited dispatch response from PRD under emergency conditions. Given the infrequency of scarcity events and limited PRD response, historical load shapes are not grossed up for PRD.[66] Furthermore, we analyzed the

energy "strike price" of $380/MWh and the rest. The smaller block represented units that had commonly been withdrawing from the RRS market in times of high prices, in order to self-curtail. In this year's study we did not see the same common behave of self-curtailments.

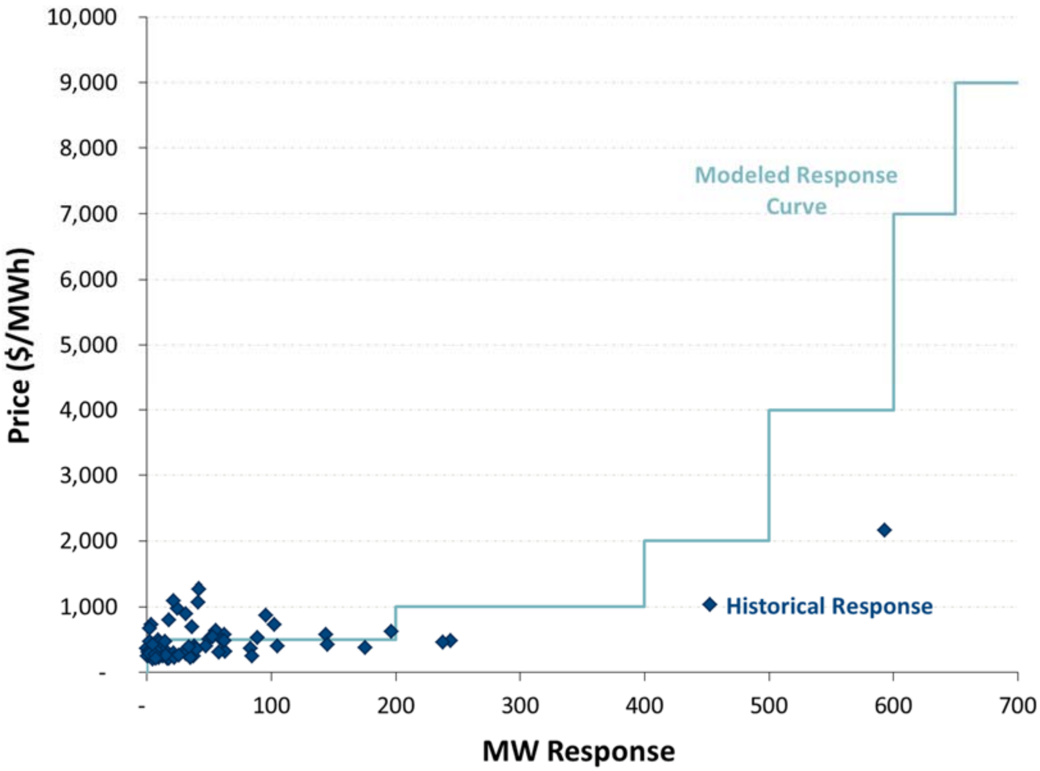
64 See ERCOT (2017a and 2018e).

65 We do not forecast growth in PRD programs for 2022, because historical enrollment analysis shows a low correlation between both load growth and prices and actual enrollment changes.

66 The prior EORM study (2014) did gross up load shapes for PRD, on the expectation that the PRD response under 2011 scarcity conditions was representative of long-term PRD behavior. However, ERCOT has had additional time to study historical PRD response, and has found that historical load shapes have not been greatly affected by PRD deployments.

response of PRD from 2014 to 2017 and model the likely MW response at various market prices based on the supply curve shown in Figure A1-7 below.[67]

Figure A1-7
Historic and Modeled Price Responsive Demand



D. Transmission System Modeling and External Resource Overview

This section provides an overview of the system interconnection topology, intertie availability, ERCOT and neighboring regions' supply curves.

1. Transmission Topology

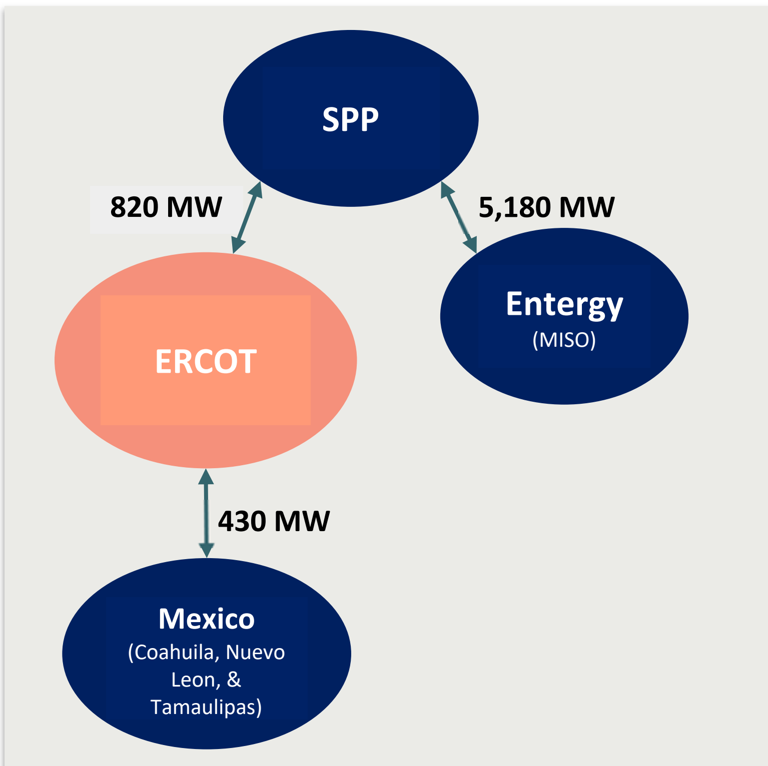
ERCOT is a relatively islanded system with only 1,250 MW of high voltage direct current (HVDC) interties; the majority of that intertie capacity is with SPP.[68] As described in Section II.A, SERVM runs a multi-area economic dispatch and will schedule imports or exports from ERCOT depending

67 The 2014-2017 PRD response and price behavior is consistent with our analysis of PRD response in 2008–2012 as studied in EORM 2014.

68 In some ERCOT studies the South DC Tie between ERCOT and Mexico is modeled with a capacity of 36 MW. However, we model the South Tie with a 30 MW capacity consistent with the ERCOT DC-Tie Operations Manual (2018h).

on the relative cost of production compared to the neighboring systems. During peaking conditions, ERCOT will generally import power due to the high internal prices, unless imports cannot be realized. ERCOT may not be able to import during peak conditions because either: (a) the neighboring system experiences a simultaneous scarcity and will prioritize meeting its own load, or (b) insufficient intertie capability exists to support the desired imports. The intertie capacities assumed for this study are shown in Figure A1-8 below.

Figure A1-8
System Topology and Modeled Interties



Sources and Notes:
ERCOT intertie ratings from ERCOT (2018h), SPP-Entergy path rating from OATI (2013).

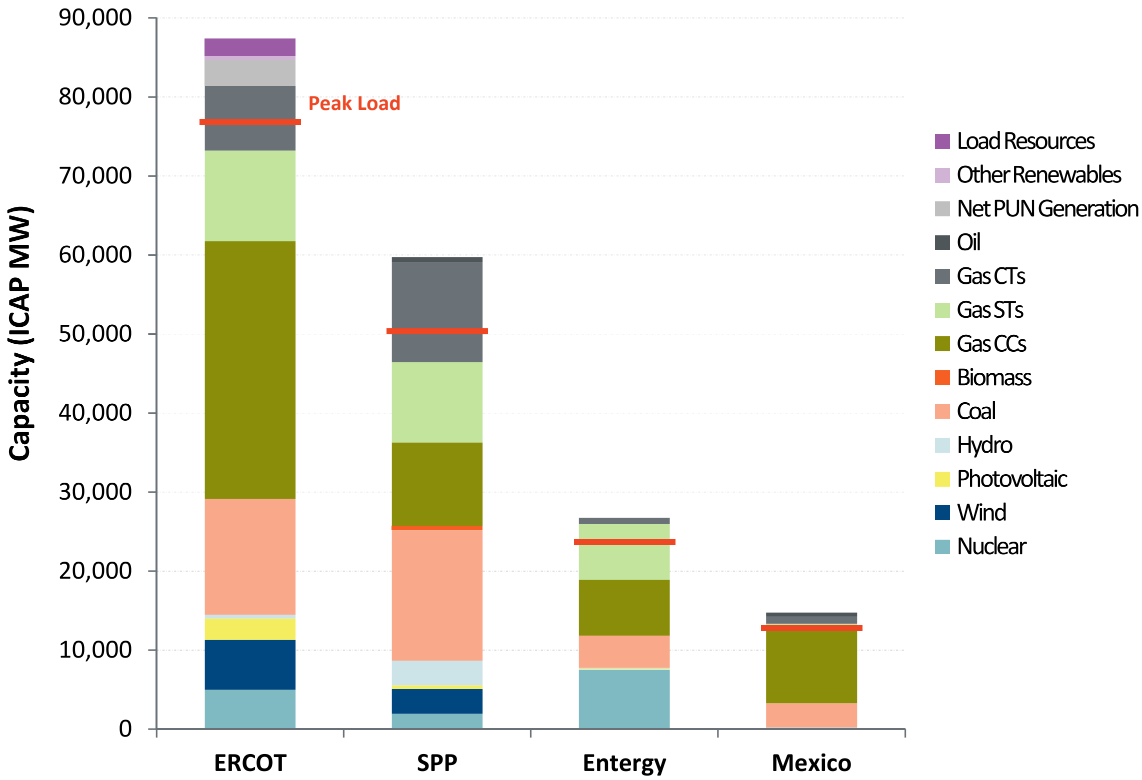
2. External Systems' Resource Overview

This section of our report provides an overview of the neighboring regions resource mixes.[69] Appendix A.1 summarizes the supply resource mix that we model in ERCOT, SPP, Entergy, and Mexico. For the neighboring regions, we rely on public data sources for the fleet makeup and

[69] More information on the ERCOT supply mix can be found in II.B.

demand-response penetrations.[70] We model each external region *at criterion*, meaning that we treat them exactly at their respective reserve margin targets of 13.6%, 12%, and 15% for SPP, Entergy, and Mexico, respectively.[71] Because these regions are currently capacity long, we adjusted their resource base downward by removing individual units of different resource types in order to maintain the current overall resource mix.

Figure A1-9
Resource Mix for ERCOT and Neighboring System



3. Availability of External Resources for ERCOT

Imports to ERCOT depend on the conditions in the neighboring systems; even if transmission is available, ERCOT may not be able to import in emergency situations if the external region is peaking at the same time. To provide intuition regarding anticipated prices and intertie flows during normal conditions, we summarize the ERCOT and neighboring regions' supply curves in Figure A1-10. The curve reports energy dispatch costs consistent with year 2022, accounting for

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70 Specifically, we take external regions resource mix from ABB, Inc. Velocity Suite (2018) and external regions' demand-response penetrations from NERC (2017).

7171 See MISO (2016), NERC (2017), SPP (2015). For Mexico we use an assumed reserve margin above the peak load.

unit-specific heat rates, variable operations and maintenance (VOM) costs, and locational fuel prices from Appendix 1.0.6. For ERCOT, we gathered unit-specific information representing heat rate curves, VOM, ancillary service capabilities, ramp rates, startup fuel, non-fuel startup costs, and run-time restrictions from ERCOT. For external regions, we gathered unit-specific heat rates from public data sources, supplemented by class-average characteristics similar to those in ERCOT for other unit characteristics.[72]

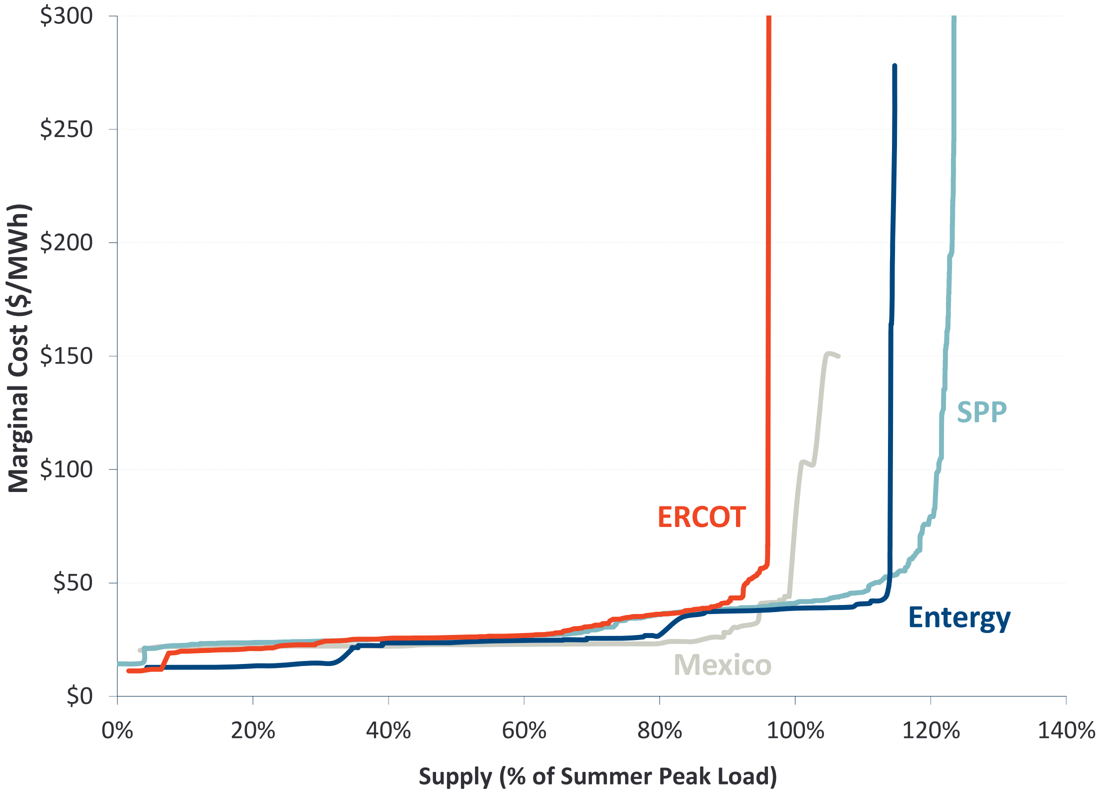
For all thermal resources, we model a relationship between capacity and hourly temperature which results in increased available capacity from the fleet during colder periods. Each unit is designated a specific weather station in which the hourly temperature determines the rating of the unit for that hour. By doing this, we simulate the real-world correlation among load, thermal generation, wind, and solar across the 38 weather years that are simulated.

Overall, ERCOT's supply curve is similar to Mexico's but is relatively tight compared to SPP and Entergy. However, interchange will be limited because of ERCOT's relatively small quantity of HVDC interties, having only 820 MW of interties with SPP and 430 MW with Mexico.[73] Some factors affecting the quantity and economic value of interchange include that: (a) SPP has more lower-cost coal that is somewhat cheaper than ERCOT-internal resources that are dominated by efficient but somewhat higher-cost gas CCs, which will lead to ERCOT being a net importer, and (b) Mexico has a substantial proportion of relatively high-cost oil-fired peaking units, which will make such imports unlikely except at high prices in scarcity conditions. Further, the regions experience some amount of load diversity that will change the relative economics of supply in each region and lead to inter-regional flows.

72 Heat rates from ABB, Inc. Velocity Suite (2018).

73 Based on several years of historical hourly intertie ratings supplied by ERCOT.

Figure A1-10
2022 System Supply Curves



Sources and Notes:
ERCOT is shown at 11.8% reserve margin, with resource mix consistent with 2018 LTRA as explained in Appendix 1.B, using unit-specific heat rates, VOM, and other characteristics obtained from ERCOT.
External systems resource mix from with resource attributes from ABB, Inc. Velocity Suite (2018).
Supply curves reflect VOM and fuel costs, with fuel prices from Appendix 1.B.6 above.

E. Scarcity Conditions

Increasing the reserve margin provides benefits primarily by reducing the frequency and severity of high-cost emergency events. Calculating the economically optimal reserve margin requires a careful examination of the nature, frequency, trigger order, and cost of each type of market-based or administrative emergency action implemented during such events.

1. Administrative Market Parameters

We developed a representation of the 2022 ERCOT market using the parameters summarized in Table A1-8. We assume that the administrative Value of Lost Load (VOLL) is equal to the true market VOLL and the High System-Wide Offer Cap (HCAP) at $9,000/MWh.[74] We also conduct a sensitivity analysis for a reasonable range of VOLL.

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74 See PUCT (2012).

Consistent with current market rules, we tabulate the Peaker Net Margin (PNM) over the calendar year and reduce the System-Wide Offer Cap (SWOC) to the Low System-Wide Offer Cap (LCAP) of $2,000/MWh after the PNM threshold is exceeded.[75] However, we stress that this mechanism will have a small impact on the market because the LCAP only affects the Power Balance Penalty Curve (PBPC) and suppliers' offers, but does not affect the Operating Reserves Demand Curve (ORDC). Therefore, prices will still rise gradually to the VOLL of $9,000 in scarcity conditions even after the PNM threshold is exceeded, thereby rendering the LCAP far less important. We further explain our implementation of the ORDC and PBPC in Sections IV.E.4 and IV.E.5 below.

Table A1-8
ERCOT Scarcity Pricing Parameters Assumed for 2022

Parameter	Value	Notes
Value of Lost Load (VOLL)	$9,000/MWh	Administrative and actual
High System-Wide Offer Cap (HCAP)	$9,000/MWh	Always applied to ORDC
Low System-Wide Offer Cap (LCAP)	$2,000/MWh	Applies only to PBPC
Peaker Net Margin (PNM) Threshold	$266,000/MW-yr	3 x CT CONE

Sources and Notes:
HCAP, LCAP, and VOLL parameters consistent with scheduled increases by 2016, see PUCT (2012).
PNM threshold is set at three times CT CONE consistent with current market rules and our updated CONE estimate from Appendix.B.1, but is lower than the $300,000/MW-yr value applicable for 2013, see PUCT (2012).

The offer cap and PNM parameters determine the maximum offer price for small suppliers in ERCOT's market under its monitoring and mitigation framework. However, we do not explicitly model these dynamics and instead assume that suppliers always offer into the market at price levels reflective of their marginal costs, including commitment costs.

2. Emergency Procedures and Marginal Costs

Table A1-9 summarizes our modeling approach and assumptions under all scarcity and non-scarcity conditions depending on what type of marginal resource or administrative emergency procedure would be implemented to meet an incremental increase in demand. These marginal resources are listed in the approximate order of increasing marginal costs and emergency event scarcity; although in some cases the deployment order overlaps.

We distinguish between market-based responses to high prices in scarcity conditions and out-of-market administrative interventions triggered by emergency conditions. Among market-based

75 See PUCT (2012).

responses, we include generation, imports, and price-responsive demand, including some very high-cost resources that will not economically deploy until prices are quite high. We also model reserve scarcity that is administrative in nature, but triggered on a price basis consistent with the ORDC and PBPC as explained in the following sections.

A final category of emergency interventions encompasses out-of-market actions including ERS, LR, TDSP load management, and firm load shed deployments that are triggered for non-price reasons during emergency conditions. We implement each of these actions at a particular scarcity level as indicated by the quantity of reserves capability available according to the ORDC x-axis, a measure similar to the physical responsive capacity (PRC) indicator used by ERCOT to monitor system operations. To estimate the approximate ORDC x-axis at which each action would be implemented, we reviewed ERCOT's emergency operating procedures, evaluated the PRC level coinciding with each action during historical emergency events, and confirmed these assumptions with ERCOT staff.[76] These trigger levels are in line with historical emergency events, although actual emergency actions are manually implemented by the system operator based on a more complex evaluation of system conditions, including frequency and near-term load forecast.

We also describe in the table below the marginal system costs of each type of scarcity event as well as the prevailing market price during those events. In a perfectly-designed energy market, prices would always be equal to the marginal cost that would theoretically lead to optimal response to scarcity events and an optimal level of investments in the market. In ERCOT, prices are reflective of marginal costs in most cases but not all. Specifically, the ORDC curve is designed based on an assumption that load would be shed at X = 2,000 MW, while our review of historical events indicates that load shedding is more likely to occur at a lower level of X = 1,000 MW. This discrepancy results in prices above marginal costs during moderate scarcity events, as discussed further in Appendix 1.E.4 below.

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76 The PRC metric is calculated with some accounting nuances that make it a somewhat different number from the ORDC Spin x-axis, we do not consider these nuances in our modeling, for the formula for calculating PRC, see ERCOT (2018f), Section 6.5.7.5.

Table A1-9
Emergency Procedures and Marginal Costs

Emergency Level	Marginal Resource	Amount of Resource (MW)	Trigger	Price	Marginal System Cost
n/a	Generation	Variable	Price	Approximately $20 - $250	Same
n/a	Imports	Variable	Price	Approximately $20-$250 Up to $1,000 during load shed	Same
n/a	Non-Spin Scarcity	700	ORDC x-axis = 3,000 MW	$2,753 (from ORDC)*	$1,020*
n/a	Price-Responsive Demand	741	Price	$500 - $9,000	Same
n/a	Emergency Generation	237	ORDC x-axis = 2,300 MW	$3,787 (from ORDC)	$1,365
n/a	PBPC	200	Price	$1,000 - $9,000	Same
EEA 1	30-Minute ERS	632	Spin ORDC x-axis = 2,300 MW	$3,787 (from ORDC)	$1,365
EEA1	Spin Scarcity A	550	Spin ORDC x-axis = 2,300 MW	$6,394 (from ORDC)*	$1,847*
EEA 2	TDSP Load Curtailments	282	Spin ORDC x-axis = 2,300 MW	$3,787 (from ORDC)	$2,456
EEA 2	Load Resources in RRS	1,119	Spin ORDC x-axis = 1,750 MW	$9,000 (from ORDC)	$2,456
EEA 2	10-Minute ERS	140	Spin ORDC x-axis = 1,750 MW	$9,000 (from ORDC)	$2,456
EEA3	Spin Scarcity B	750	Spin ORDC x-axis =1,750 MW	$9,000 (from ORDC)*	$3,544*
EEA 3	Load Shed	Variable	Spin ORDC x-axis = 1,000 MW	VOLL = $9,000	Same

Sources and Notes:
*Price reflects the average price between the upper and lower level of each resource
Developed based on review of historical emergency event data, input from ERCOT staff, and ERCOT's emergency procedure manuals; see ERCOT (2018f), Section 6.5.9.4, and ERCOT (2018i), Section 4.

3. Emergency Generation

During severe scarcity conditions, there are out-of-market instructions by ERCOT as well as strong economic incentives for suppliers to increase their power output to their emergency maximum levels for a short period of time.[77] During these conditions, suppliers can output power above their normal capacity ratings, although doing so is costly because it may impose additional maintenance costs and may put the unit at greater risk of failure.

To estimate the approximate quantity and cost of emergency generation, we reviewed ERCOT data on units' emergency maximum ratings.[78] According to ERCOT's emergency maximum ratings, the aggregate ERCOT fleet should be able to produce approximately 237 MW in excess of summer CDR ratings.[79] We estimate the marginal cost of emergency output at approximately $1,365/MWh, consistent with ERCOT's procedures for calling emergency generation.

4. Operating Reserves Demand Curve

The most important and influential administrative scarcity pricing mechanism in ERCOT is the operating reserves demand curve (ORDC) that reflects the willingness to pay for spinning and non-spinning reserves in the real-time market.[80] Figure A1-11 illustrates our approach to implementing ORDC in our modeling, which is similar to ERCOT's implementation, although with some simplifications.[81] We implement all 48 distinct ORDC curves that reflect four seasons each year, six periods each day, and two types of operating reserves.[82]

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77 See Section 6.5.9, ERCOT 2018f.

78 EORM 2014 also analyzed actual realized output levels during high price events in August of 2011, but there were not enough such events to meaningfully analyze for the purpose of this study.

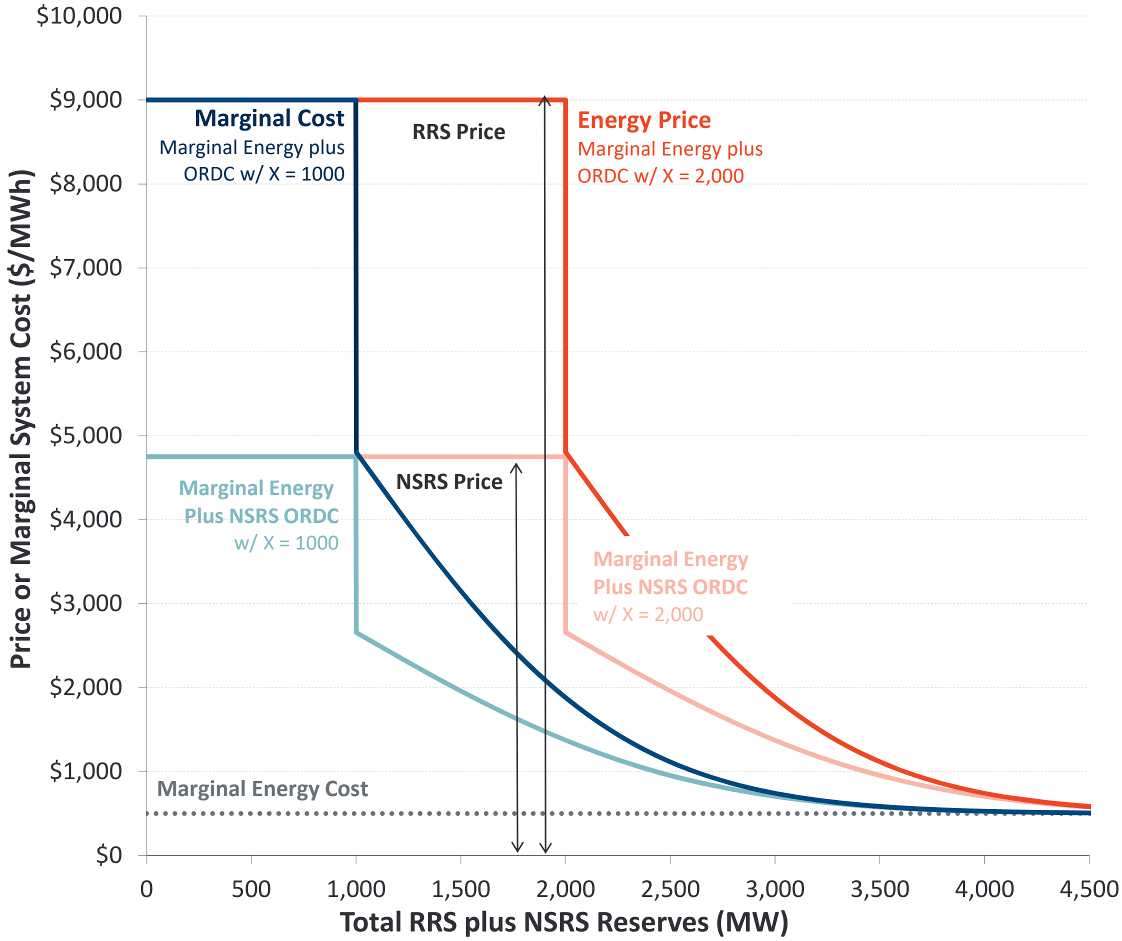
79 This number excludes private use network resources, which we model separately as explained in Section IV.B.3 above. This number is significantly lower than the EORM 2014 rating of 360 MW because ERCOT updated the reporting standards of HSL and emergency limits, which reduced the MW above HSL.

80 Note that the ORDC is not planned to be co-optimized with the energy market at this time, but the real-time spinning and non-spinning prices they produce are used to settle against the day-ahead RRS (Spin) and NSRS (Non-Spin) markets.

81 For a detailed explanation of ERCOT's ORDC implementation see their whitepaper on the methodology for calculating ORDC at ERCOT (2013).

82 See ERCOT (2013), p. 15.

Figure A1-11
Operating Reserve Demand Curves
Example: Summer Hours 15-18



Sources and Notes:
ORDC curves developed consistent with ERCOT (2013).

The ORDC curves are 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.[83] This curve reflects the incremental cost imposed by running short of

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[83] Note that the lost load implied by this function and caused by operating reserve scarcity is additive to the lost load that we report elsewhere in this study. 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. We also do not change the ORDC when varying the VOLL in our model sensitivities.

reserves and is added to the marginal energy cost to estimate the total marginal system cost and price.

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 quick start; 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 quick start units. Table A1-10 provides a summary of the resources that are always available to contribute to the ORDC x-axis unless they have been dispatched for energy although the realized ORDC x-axis 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).[84]

Table A1-10
Resources Always Contributing to ORDC X-Axis
Unless Dispatched for Energy

Spin X-Axis		
Hydrosynchronous Resources	*(MW)*	240
Non-Controllable Load Resources	*(MW)*	1,119
Non-Spin X-Axis		
30-Minute Quickstart	*(MW)*	7,767
Total Spin + Non-Spin	***(MW)***	**9,126**

Sources and Notes: Controllable Load Resources and 10-Minute Quickstart not shown, compared to EORM 2014, because they are modeled at zero.

The red and pink curves in Figure A1-11 show the ORDC curves used for price-setting purposes, calculated as if ERCOT would shed load at an ORDC x-axis of X = 2,000 MW. However, as we explained in Appendix 1.E.2 above, we assume that load shedding will actually occur at X = 1,000 MW based on our analysis of recent emergency events and consistent with the blue curves below. In other words, we model a discrepancy between marginal costs (blue) and market prices (red) that will create some inefficiency in realized market outcomes.

84 We assume that the CC reference unit is not capable of providing either spin or non-spin from an offline position, although we assume that the CT reference unit is capable of providing non-spin from an offline position.

As in ERCOT's ORDC implementation, we calculate: (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 do not scale the ORDC curves in proportion to VOLL minus marginal energy in each hour.[85] Instead, we treat the ORDC curves as fixed with a maximum total price adder of VOLL minus \$500, which causes prices to rise to the cap of \$9,000/MWh in scarcity conditions, because \$500 is the cap placed on marginal energy prices in the model. Higher-cost demand-response resources will be triggered in response to high ORDC prices and therefore prevent prices from going even higher, but do not affect the "marginal energy component" of price-setting. We model the ORDC curves out to a maximum quantity of 8,000 MW where the prices are near zero, although they never drop all the way to 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 model unit commitment in three steps: (1) a week-ahead optimal unit commitment over the fleet, with the result determining which long-lead resources will be committed;[86] (2) a four-hour ahead unit commitment (updated hourly) with an updated fleet outage schedule, with the result determining the preliminary commitment and decommitment schedules for combined cycle units; and (3) an hourly economic dispatch that dispatches online baseload units, and can commit 10-minute and 30-minute quick start units if energy and spin prices are high enough to make it more profitable than remaining offline (similarly, if prices are not high enough these units will economically self-decommit).[87] Note that 10-minute quick start units can earn spin payments from an offline position while 30-minute quick start units can earn non-spin payments from an offline position. These resources will not self-commit unless doing so would result in greater energy and spin payments (net of variable and commitment costs) than would be available from an offline position. We use a similar logic to economically commit or de-commit units until the incentives provided by the ORDC are economically consistent with the quantity of resources turned on.

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85 See ERCOT's implementation in ERCOT (2013).

86 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.

87 These week-ahead and day-ahead commitment algorithms minimize cost subject to meeting load as well as ERCOT's administratively-determined regulation up and spinning reserve targets, with non-spinning reserve targets not considered at the unit commitment phase.

5. Power Balance Penalty Curve

The Power Balance Penalty Curve (PBPC) is an ERCOT 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 A1-12.[88] Whenever a 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. At 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 as explained in Appendix 1.E.1 above.

We similarly model the PBPC as phantom supply that may influence the realized price, and that will cause a reduction in available regulating reserves whenever called. However, we model only the first 200 MW of the curve at prices below the cap, and assume that all price points on the PBPC will increase according to the scheduled SWOC.[89] We also assume that the prices in the PBPC are reflective of the marginal cost incurred by going short of each quantity of regulating reserves.[90] 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.[91] Note that even after the maximum PBPC price is reduced, ERCOT market prices may still rise to a maximum value of VOLL equal to $9,000/MWh during scarcity conditions because of the ORDC as explained in the following section.

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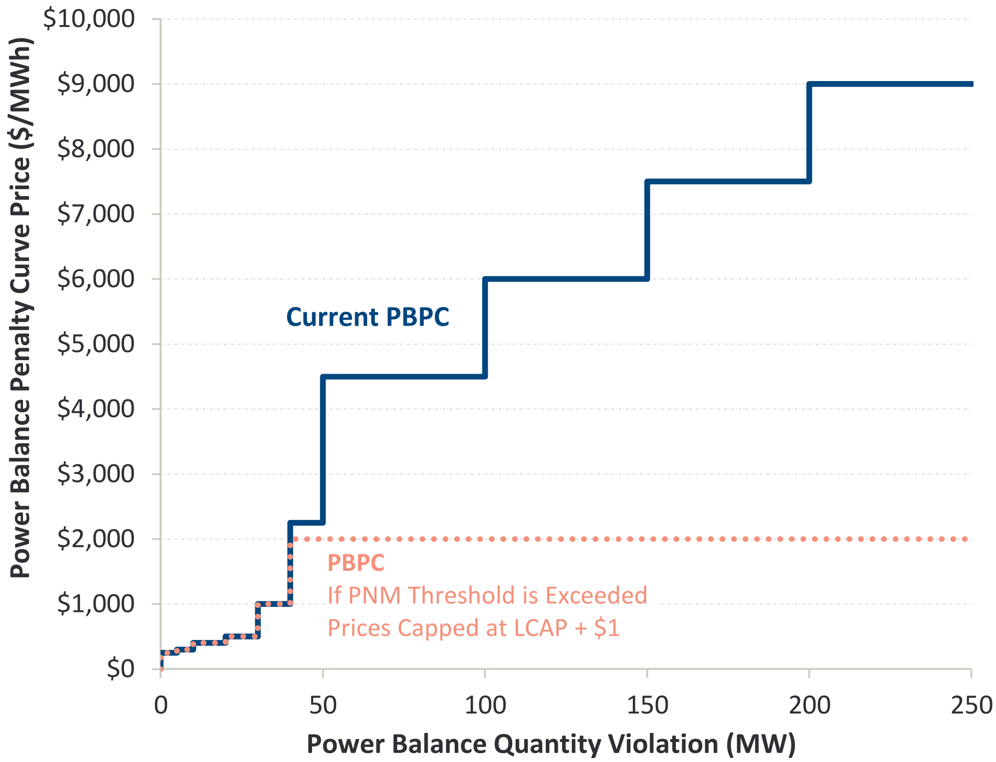
88 See ERCOT (2018g).

89 See ERCOT (2018g).

90 Once the PNM is exceeded and the PBPC is reduced, these prices are no longer reflective of marginal cost but are instead lower than marginal cost at regulation shortage quantities greater than 40 MW.

91 See ERCOT (2018g).

Figure A1-12
Power Balance Penalty Curve



Sources and Notes:
PBPC numbers from ERCOT (2018g), p. 22-23.

BOSTON
NEW YORK
SAN FRANCISCO
WASHINGTON
TORONTO
LONDON
MADRID
ROME
SYDNEY

THE Brattle GROUP