Estimation of the Market Equilibrium and Economically Optimal Reserve Margins for the ERCOT Region

2018 Update, Final Draft

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October 12, 2018

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, cooperation, and support. In particular, we would like to acknowledge the analytical, technical, and conceptual contributions of Peter Warnken, Kevin Hanson, and Julie Jin.

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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

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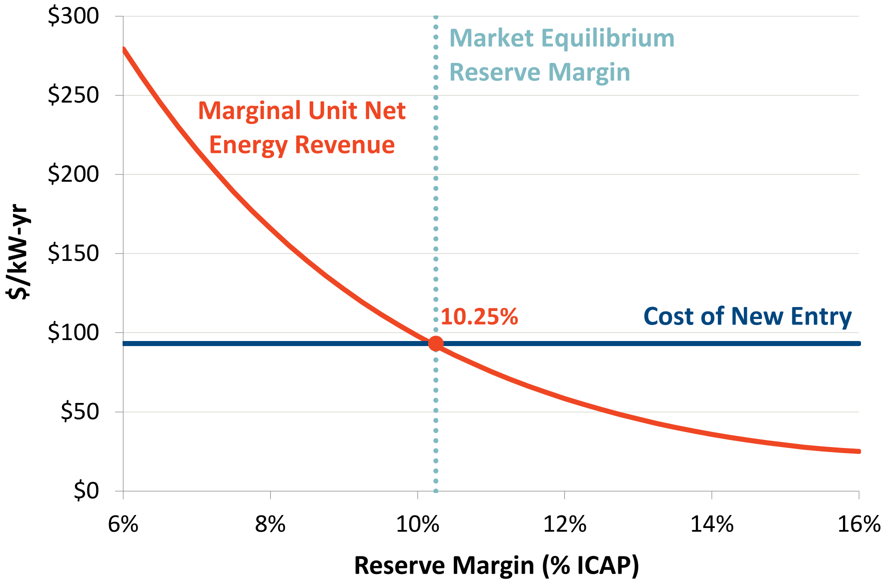
1 This estimate should not be interpreted as a precise forecast for 2022 or any other particular year, but as a reasonable expectation around which actual reserve margins may vary as market conditions fluctuate. To expect a persistently lower reserve margin would be to assume investors will forego profitable opportunities to add additional supply, and to expect a persistently higher reserve margin would be to assume investors will over-invest.

were 10.9% for the summer of 2018 (relative to forecasted firm peak load),[2] with 11.0% projected for 2019.[3]

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 is also interested in whether such a market outcome would be acceptable with respect 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-

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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.

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 prices higher than the marginal value of energy during scarcity conditions. This design intentionally creates additional incentives to invest that raise 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%) 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. An important uncertainty in our analysis is the likelihood of extreme weather. A base case assumption is that all 38 years of historical weather are assigned an equal probability of occurring for the 2022 simulation year. Assigning a greater likelihood to years with more extreme weather, such as 2011, impacts the reserve margin results. For example, assigning 10% weight to each of the last 10 weather years and 0% weight to each of the other 28 years increases the market equilibrium reserve margin by 1.5% due to the higher energy prices in these years. However, it would increase the number of scarcity events, resulting in similar reliability. Other key factors in our analysis are the estimated capital cost of building new generation, load forecasting error, coal and natural gas prices, the value of lost load (VOLL), and intermittent renewable penetration.

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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.

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.

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%**

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.

High renewable penetration reduces the net load duration curve, which decreases the annual average price at a given reserve margin. However, the high renewables scenario also has additional hours of low level scarcity prices, which limits annual average price decline. To estimate system reliability with higher renewable penetration, we analyzed a future scenario with an additional 10 GW of nameplate wind and 10 GW of nameplate solar photovoltaic (PV) capacity (with largely offsetting reductions in the amount of natural gas-fired capacity), reflecting half of the renewable capacity currently undergoing interconnection studies.[6] We estimate that with the higher renewable penetration the market equilibrium reserve margin decreases by 1.0%, resulting in an additional 0.25 expected load shed events per year, but the economic optimum reserve margin similarly decreases; thus the market would still be expected to attract more than sufficient reserves from an economic perspective. This analysis may seem to indicate a future of declining reliability with increasing renewable capacity (if there is no corresponding change in the ORDC), although it does not account for the likely offsetting effects of storage becoming more economic and/or gas prices potentially rising over time.

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-

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.

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 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 up-to-date 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

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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).

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 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.

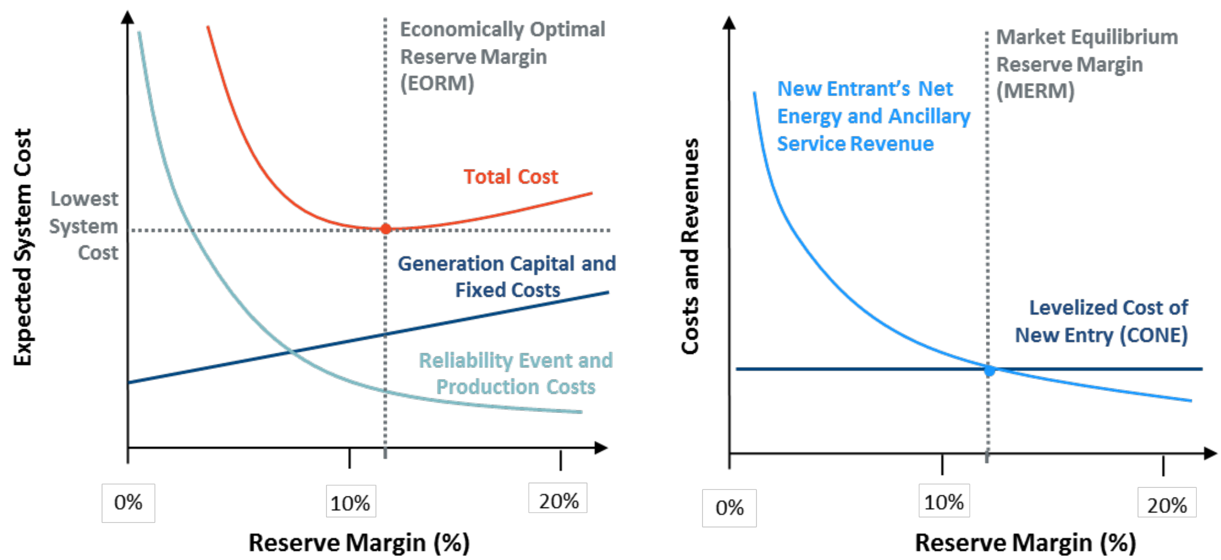
As the left panel of Figure 1 shows, higher reserve margins are associated with higher generation capital and fixed costs of building more capacity (dark blue line). The higher costs are offset by a reduction in the frequency and magnitude of costly reliability events, such as load-shed events, other 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.[8] The right part of Figure 1 shows how

[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

Continued on next page

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 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

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example, see Poland (1988), p.21; Munasinghe (1988), pp. 5–7, 12–13; and Carden, Pfeifenberger, and Wintermantel (2011).

9 See ERCOT (2017b). Note that the methodology described in the manual is derived from our 2014 study.

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 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 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

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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

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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.

tie lines with neighboring 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 peak demand.[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

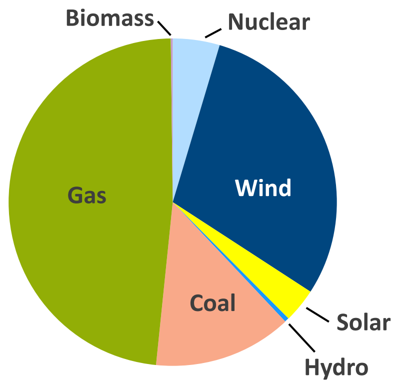
	Values from 2014 Study (MW) [A]	Re-expressed Values from 2014 Study (Using 2018 Accounting) (MW) [B]	Values from 2018 Study (MW) [C]	Difference Attributable to Accounting Changes (MW) [B-A]	Difference Attributable to Fundamentals Changes (MW) [C-B]
Modelled Year	**2016**	**2016**	**2022**		
Accounting 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]

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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.

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[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.

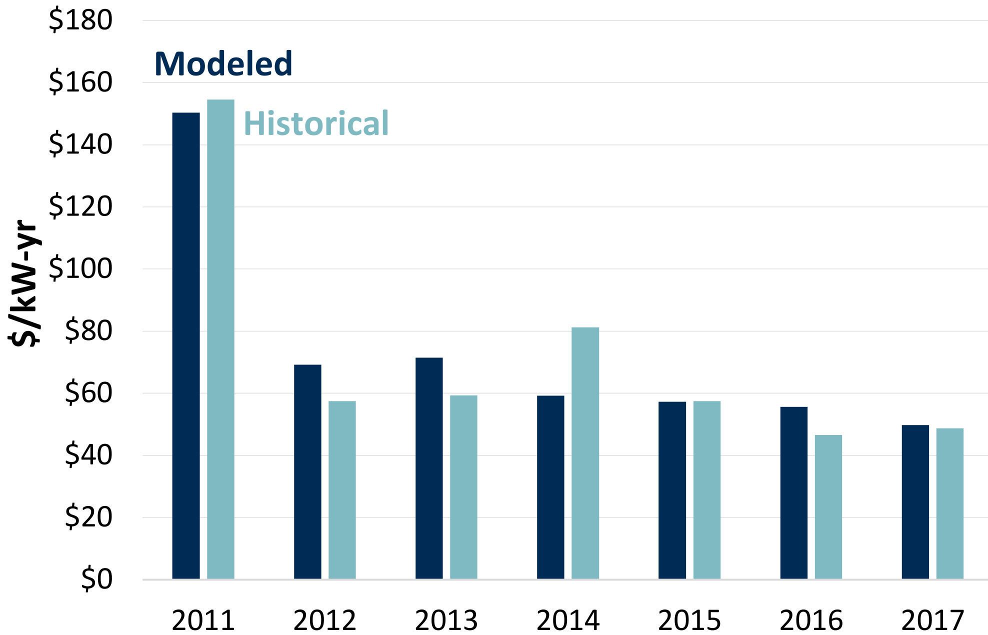
Table 5
Definition of Non-Modeled Sensitivities

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

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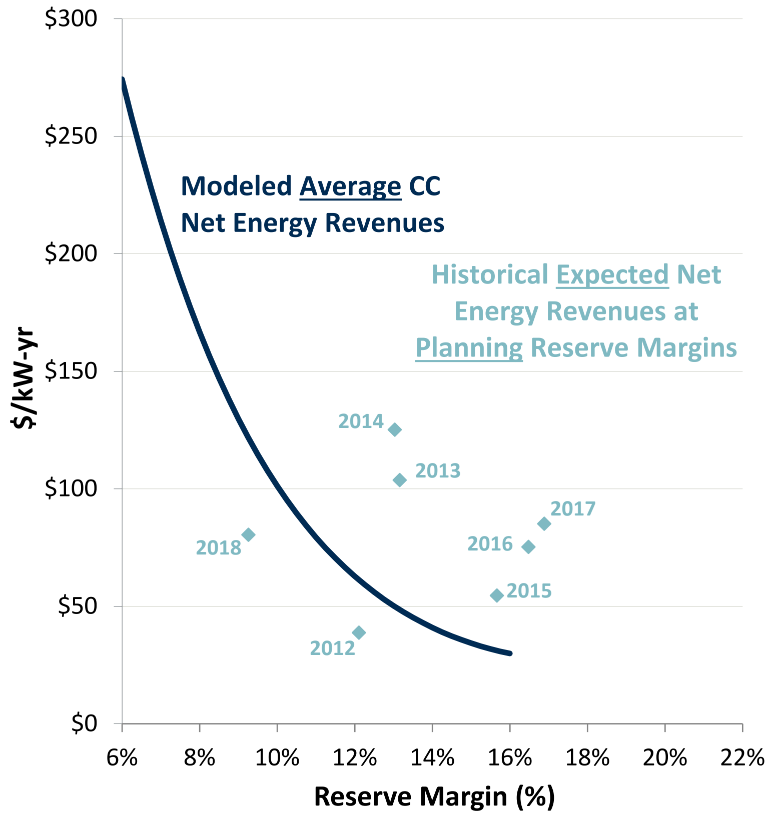
21 Note that pre-2013 price formation differed absent an ORDC, but the overall effect was similar on average as price cap was lower but it was activated more readily at higher levels of reserves.

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.

should reflect the distribution of possible weather and generation availability at a given planning reserve margin.[23] As the right panel on 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 but would fall above the curve if based on a forward view from a few months later, when forward prices spiked.

Figure 4
Average Modeled vs. Historical Expected Net Energy Revenues by Reserve Margin



Notes and Sources:

Net Energy Revenues are calculated using energy price and gas forwards as of the end of December before each respective year, using a marginal unit heat rate and VOM consistent with our modeled marginal unit. Planning Reserve Margins are from the December CDRs before each respective year. Energy and gas price forwards come from S&P Global Market Intelligence LLC; 2011 was not included due to insufficient 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.

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.

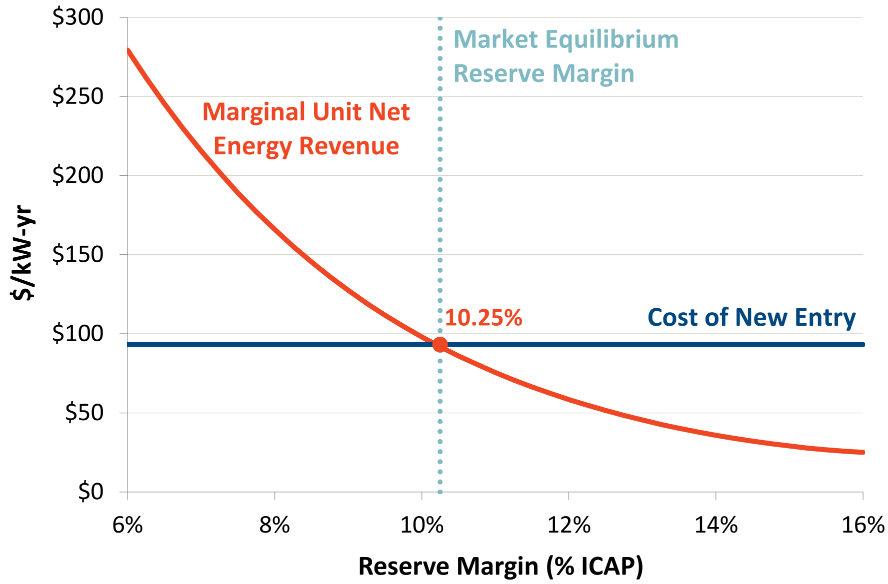
A. Market Equilibrium Reserve Margin

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

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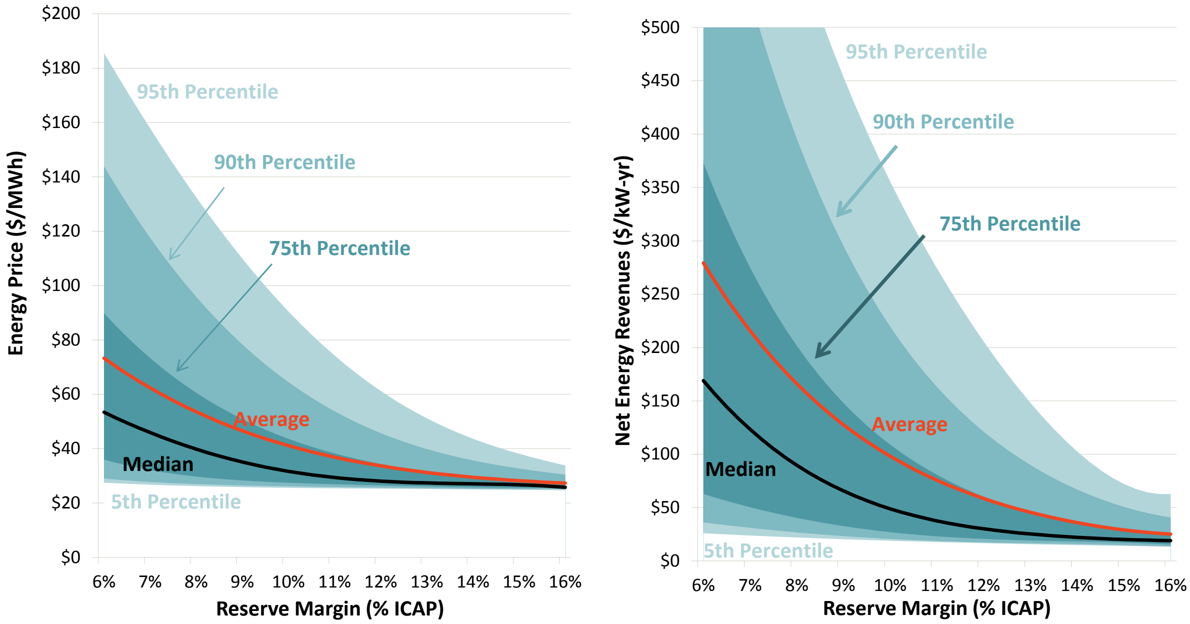
[24] Marginal Unit Net Energy Revenues represent net revenues from a mix of added CCs and CTs (77:23 ratio).

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 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 (90th percentile) and $334/kW-year (about 3.5 times CONE) once every two decades (95th percentile).[25]

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[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.

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 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 6.2% 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.

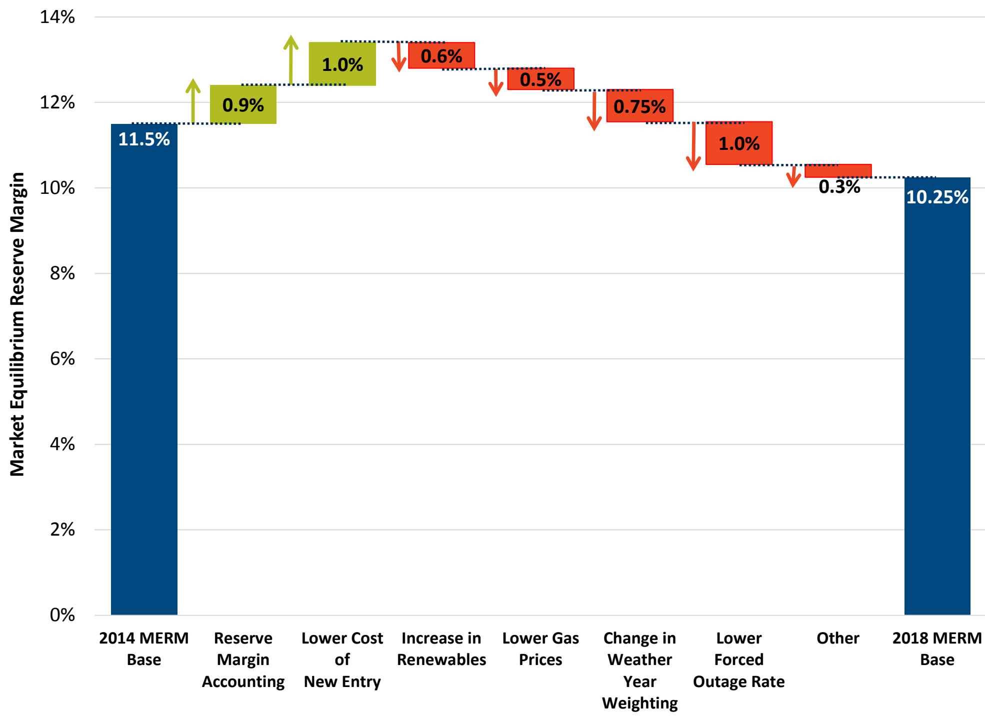
Variability in reserve margins may be moderated by short lead-time resources (including switchable units, mothballs, uprates, and demand response) that can exit or enter the market as expectations change between three years forward and delivery. By not simulating the effects of market exit and entry by short-term resources, our results would tend to overstate the range of 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% (10th to 90th 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



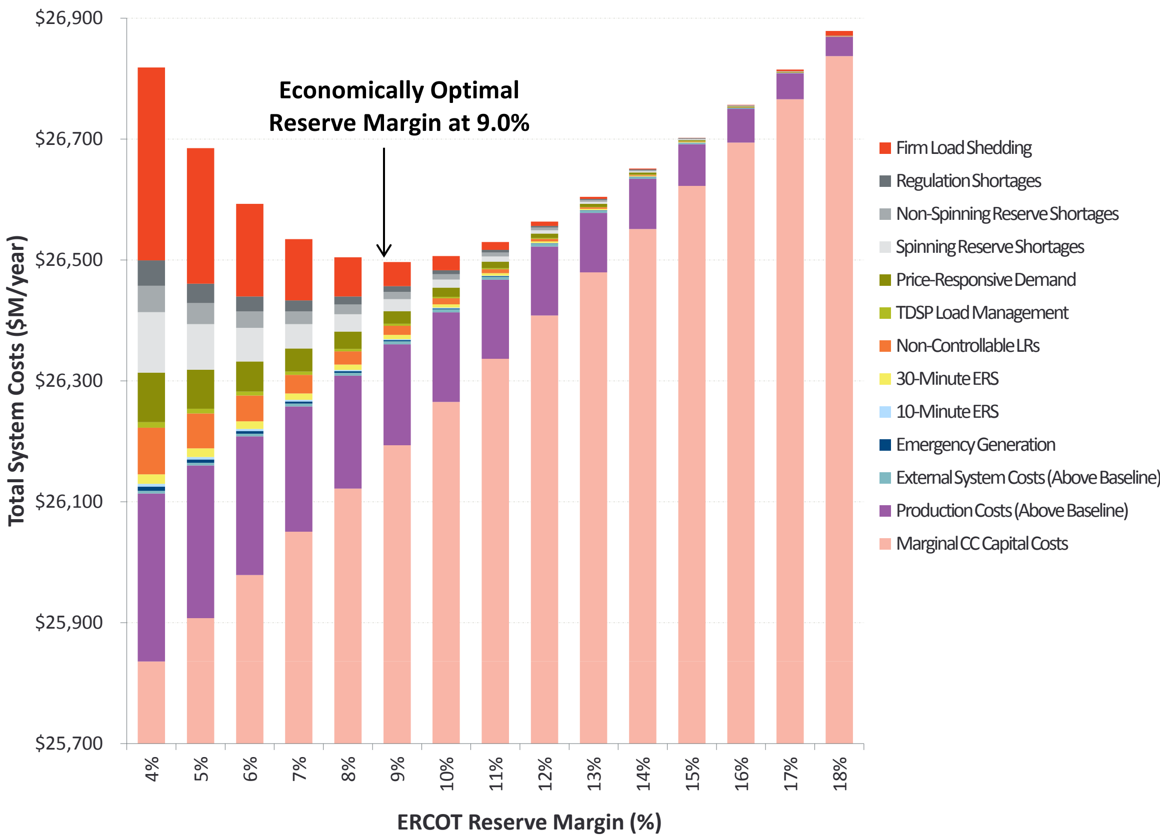
B. Economically Optimal Reserve Margin

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.

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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.

- **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.
- **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.

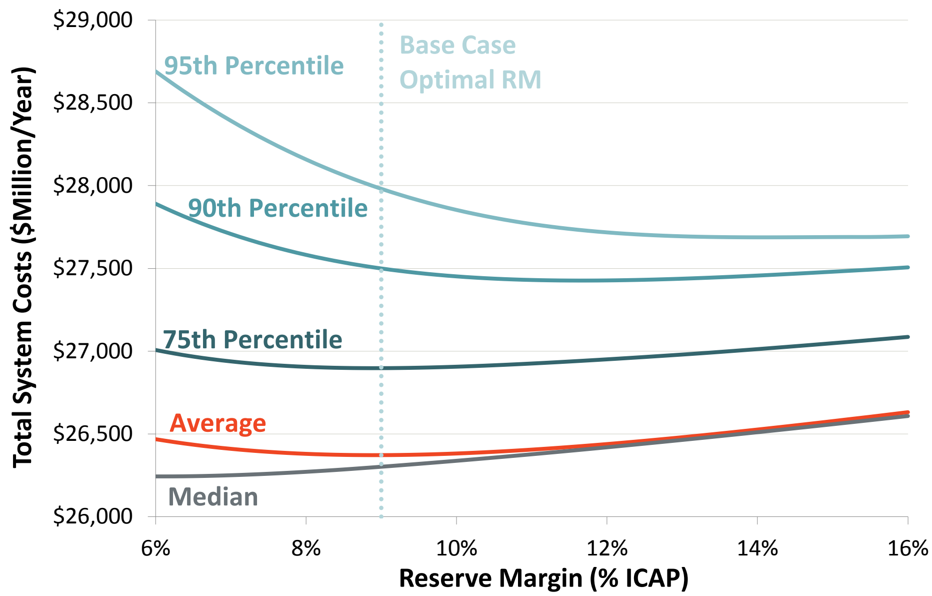
2. Exposure to Extreme Scarcity Events

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.

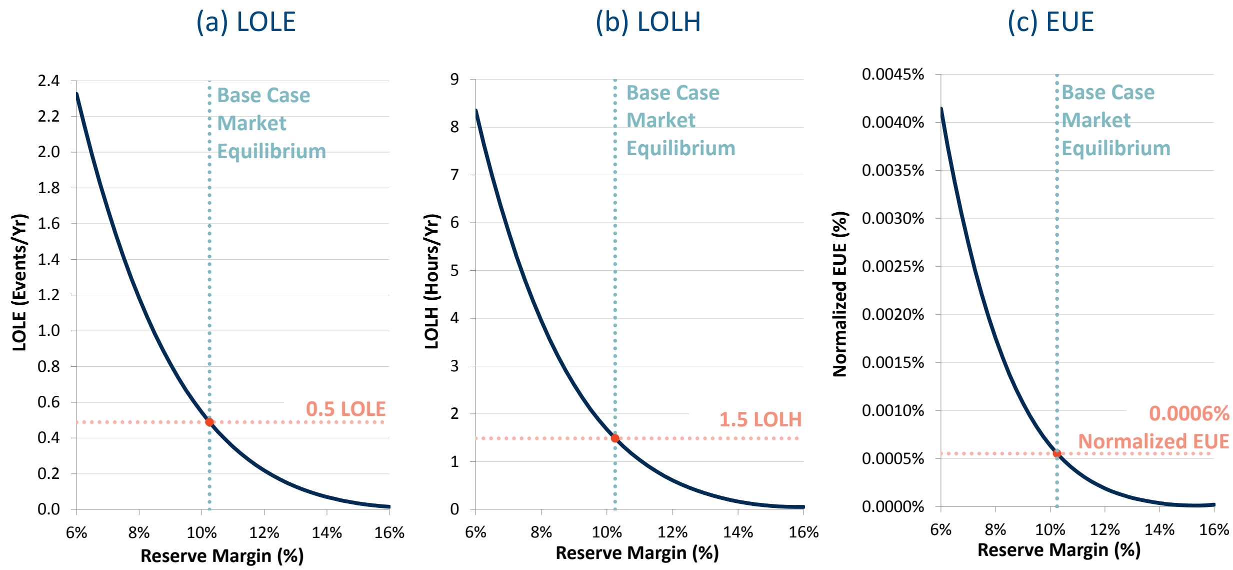
C. System Reliability

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 of all 38 weather 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	0.05	80	3.40	5,295	1,558

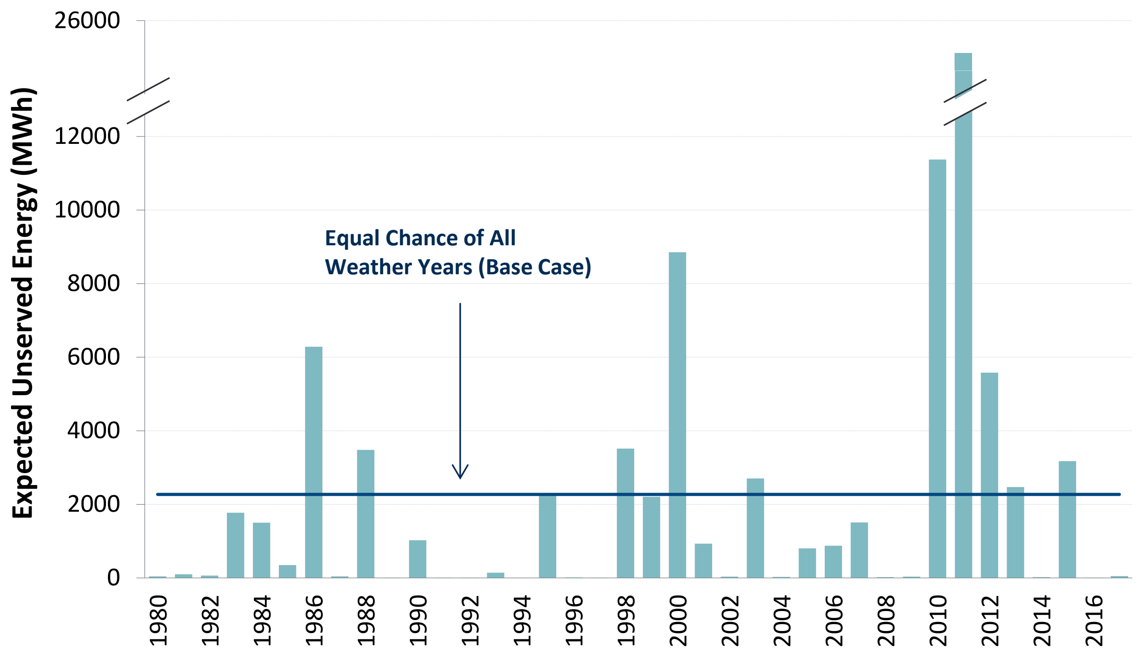
Most US areas set reliability metrics on the "1-in-10" standard, *i.e.*, a probability-weighted average of 0.1 loss-of-load events (LOLE) per year. Under base case conditions a 13.5% reserve margin would be required to achieve 0.1 LOLE, which is 3.25% higher than MERM. However, another common interpretation 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 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



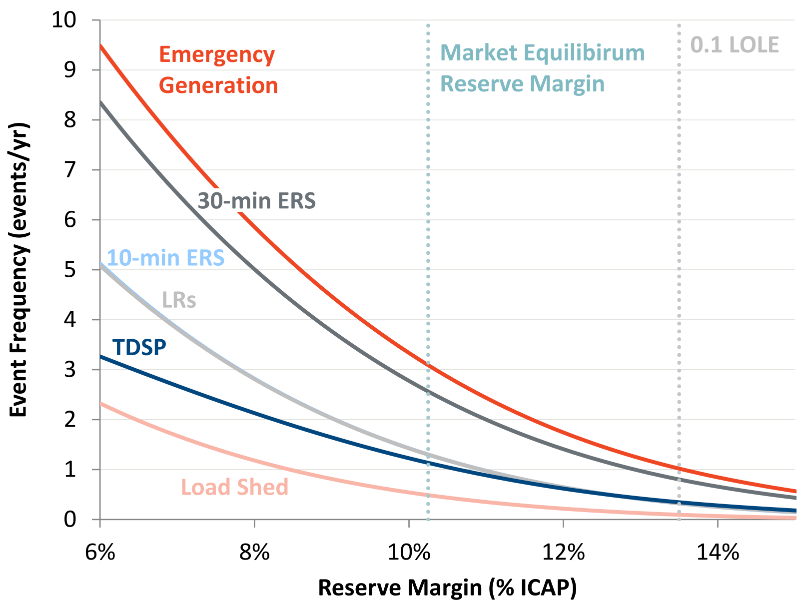
Notes:
Figure reflects Base Case 3-Year forward LFE assumption and the Base Case equal weather weight for all 38 years.

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.[30]

Running all of the simulations under these alternative scenarios does indeed affect the MERM. In the High Renewables scenario, the MERM falls by one percentage point, to 9.25%. In the Low Renewables scenario, the MERM rises 0.5 percentage points, to 10.75%. 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.[31] The addition of these new and more efficient marginal resources increases the overall ERCOT thermal resource fleet efficiency and offsets the effects of lower renewables on the average market prices compared to the 2014 EORM study. This offsetting effect limits the impact of the

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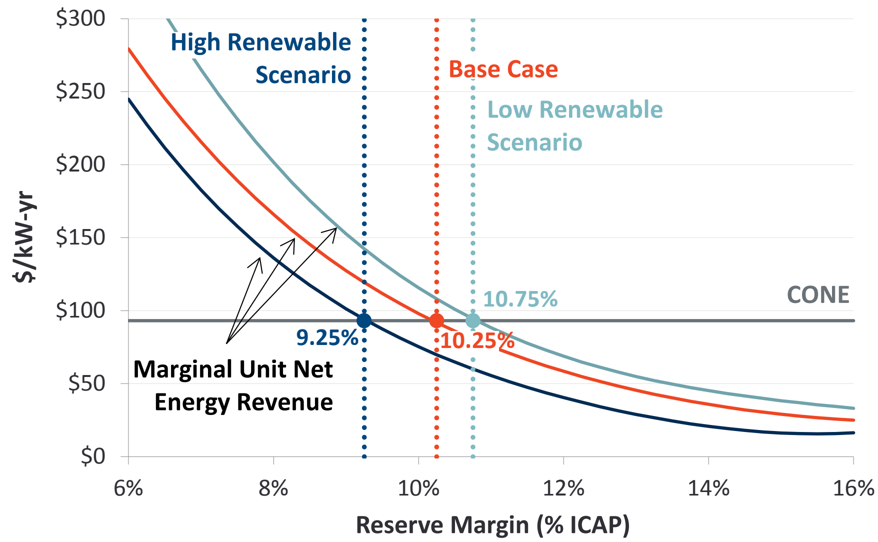
30 The capacity contribution of renewables was adjusted in the high and low scenarios so that an LOLE of 0.1 events per year occurs at a reserve margin of 13.75%, which is the consistent with the base case reliability under ERCOT's current renewable capacity contributions. Capacity contribution decreased in the high renewables scenario, and increased in the low renewable scenario.

31 The characteristics of Marginal Technology Resources are described in Appendix 1.B.1.

Low Renewables scenario on the market equilibrium reserve margin.[32] On the other hand, the High Renewable scenario displaces 9 GW of existing conventional generators to incorporate the renewables at the modeled reserve margins. This change in the thermal resource fleet increases the efficiency of the ERCOT fleet and further decreases market prices in most hours. While both of these effects of higher renewables (decreased net load and the more efficient thermal fleet) tend to reduce market prices and reduce the net energy revenues for attracting new resources, we find that there is a slightly higher frequency of scarcity prices that limits the impact on annual average prices and MERM.

Figure 13
Market Equilibrium Reserve Margin Sensitivity to Renewable Penetration



Furthermore, our study of resource adequacy 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 we recognize 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 setting commitment and dispatch. These

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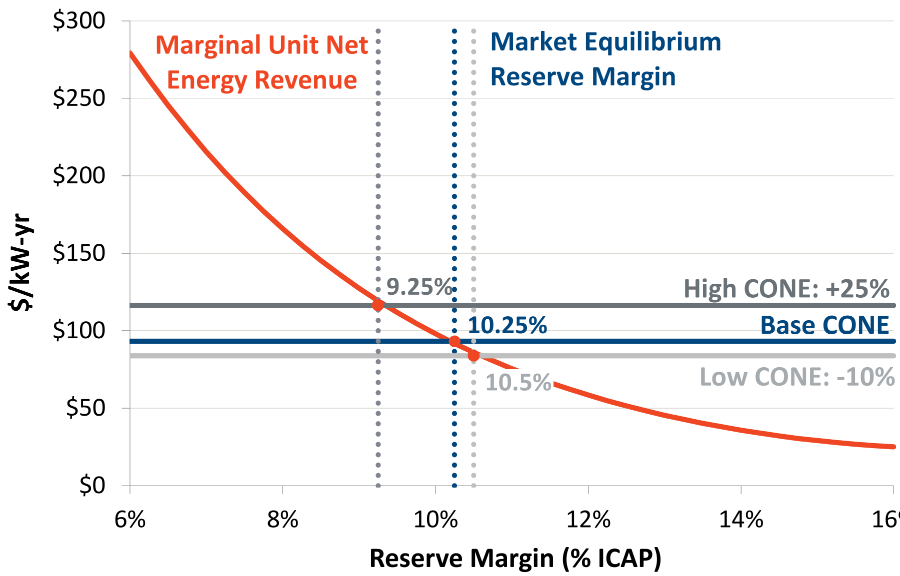
32 The 2014 EORM included several GW of traditional generators that have retired.

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.[33] 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 Years 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

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33 We assumed a larger sensitivity on high end of the range of CONE values due to the potential for higher financing costs in the ERCOT energy-only market relative to the PJM energy and capacity market design and the potential for recent tariffs to increase costs more so than what the market prices already reflect.

distribution, assuming that distribution is representative of future weather patterns. We also examined the expected MERM under three alternative sets of weighting factors: (1) assign weights based on the number of consecutive days of greater than 100-degree weather using a Pareto distribution;[34] (2) equal weights to only the most recent 10 years of weather data and no weighting to the earlier years; (3) the same weights applied in the 2014 EORM study, a 1% weight to 2011 and equal weight to the remaining years from 1998 to 2012. This analysis shows that the MERM could vary over a range of 10.0% to 11.75% based on these alternative weighting schemes.

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.[35] 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.

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

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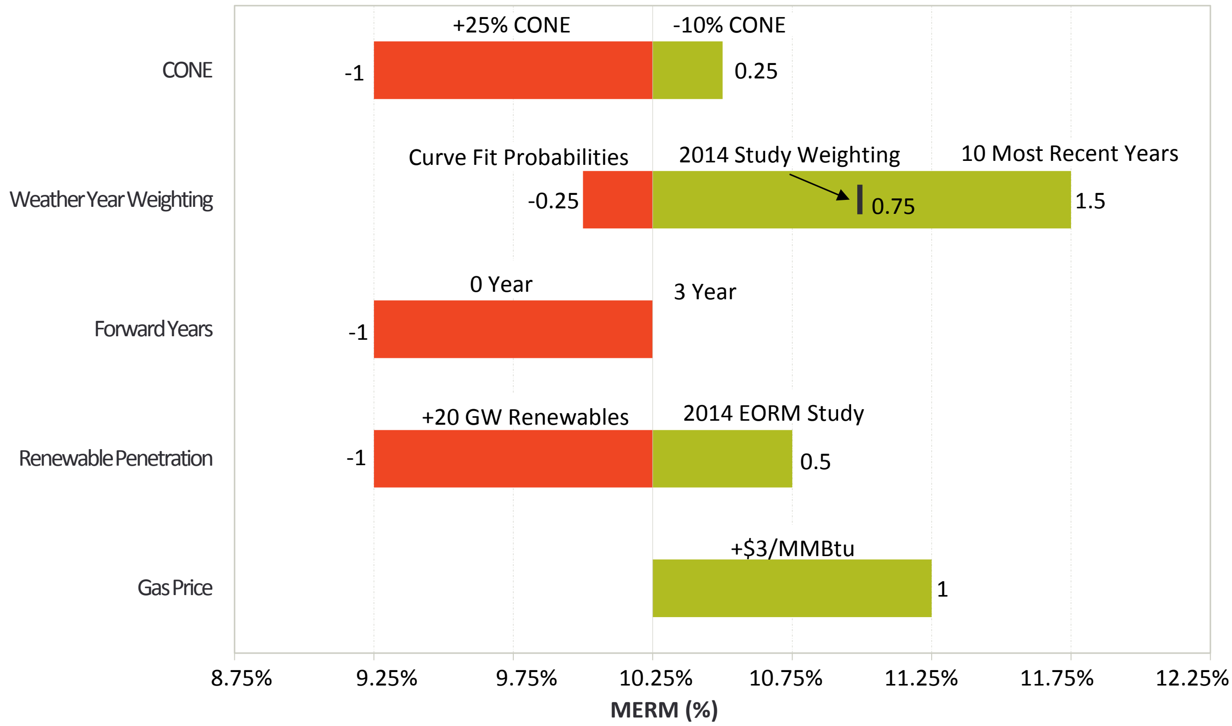
34 This is an updated version of the Weather-risk Index weighting discussed in Section 10.2.1 of ERCOT 2017b.

35 This construction timeframe is why the PJM and ISO-NE capacity markets rely on a three-year forward period.

affect the MERM.[36] 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.

36 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.

The most important uncertainties are the likelihood of extreme 2011-like weather (*i.e.*, many days over 100 degrees). Assigning a greater weight on 2011 weather by only using weather from the last 10 years would increase the market equilibrium by 1.5%—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 key 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.[37] 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 true economic value.

37 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 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 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).[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 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.[39] 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.[40]

The left chart shows projected 2022 peak load for each weather year relative to the weather-normal peak load.[41] 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

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38 Provided by ERCOT staff.

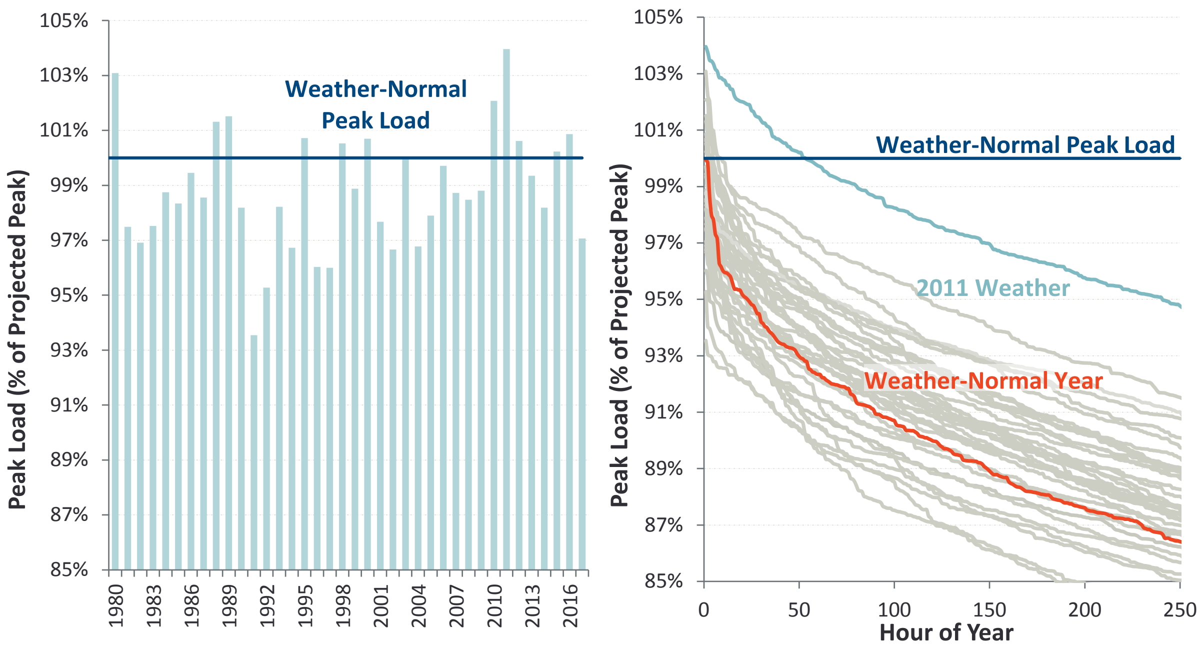
39 This is different than the previous EORM study, which used 15 weather years (1998–2012)

40 Details on the load forecast model methodology in (ERCOT, 2017c).

41 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.

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 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.

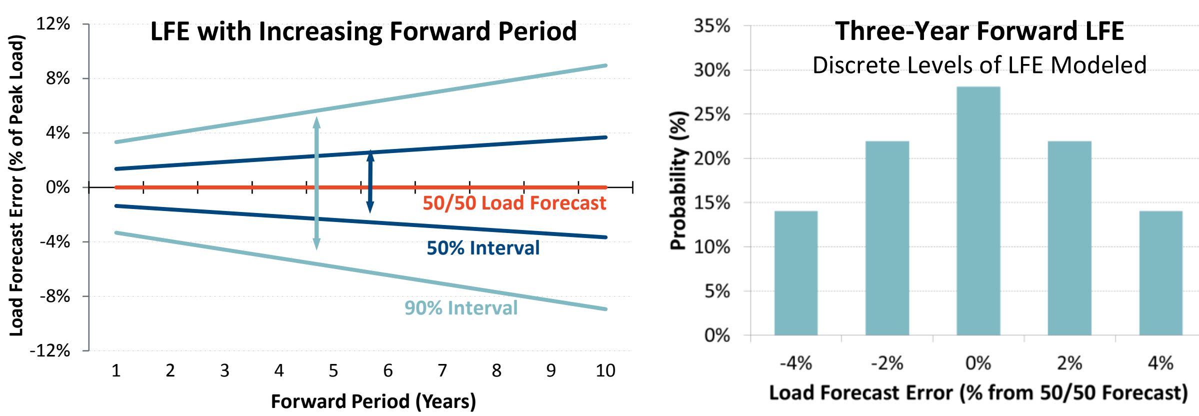
3. Non-Weather Demand Forecast Uncertainty and Forward Period

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.[42] 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



42 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.

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.[43]

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.

[43] See May 2018 CDR.

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.

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.[44]

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.[45] 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

---

44 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.

45 See Newell, *et al.* (2018).

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.

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.[46]

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 distributions based on three years (2015-2017) of unit-specific GADS data and asset class average outage rates from ERCOT.[47]

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

46 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.

47 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.

historical data and as summarized in Figure A1-3.[48] At any given load, the realized net PUN generation has a probabilistic quantity, with 11 different possible quantities of net generation within each of 15 different bands of system load.[49] 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.

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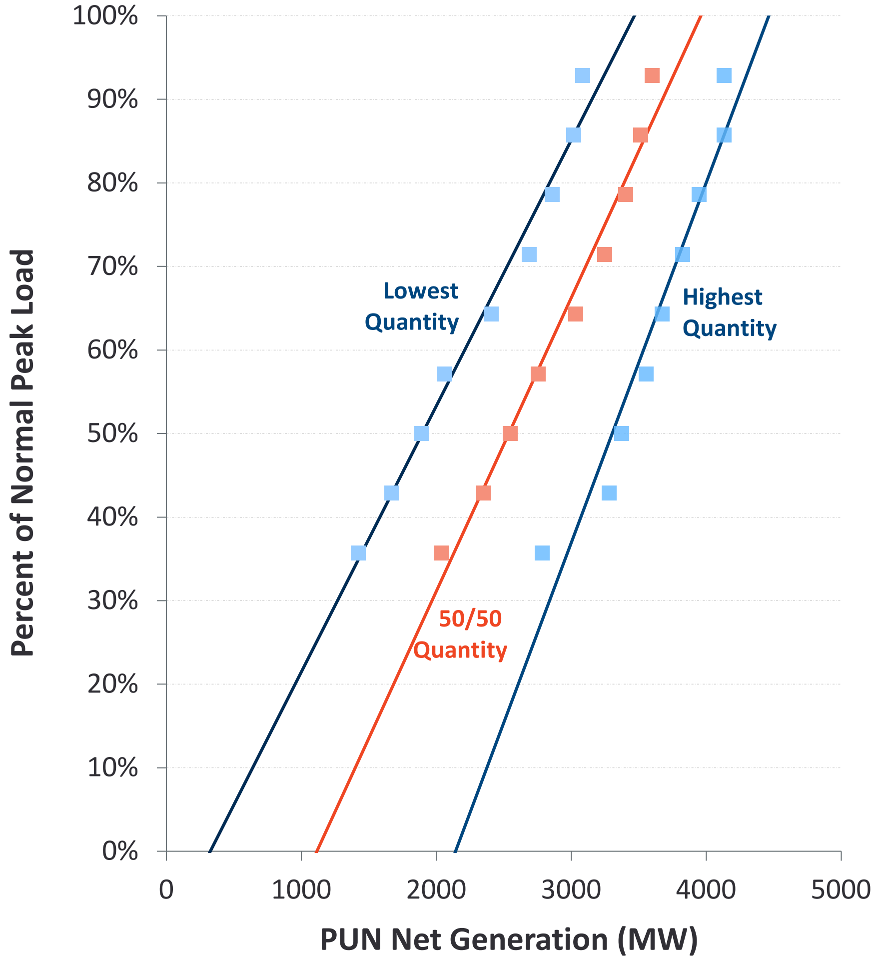
48 The representation of PUN generation as correlated with load is a slight change to the modeling from the previous EORM report, which used system energy prices to predict PUN generation, without a realized change in results. Load and prices are also correlated, but PUN decisions are more likely to be made based on load forecasts.

49 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 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.[50] 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.

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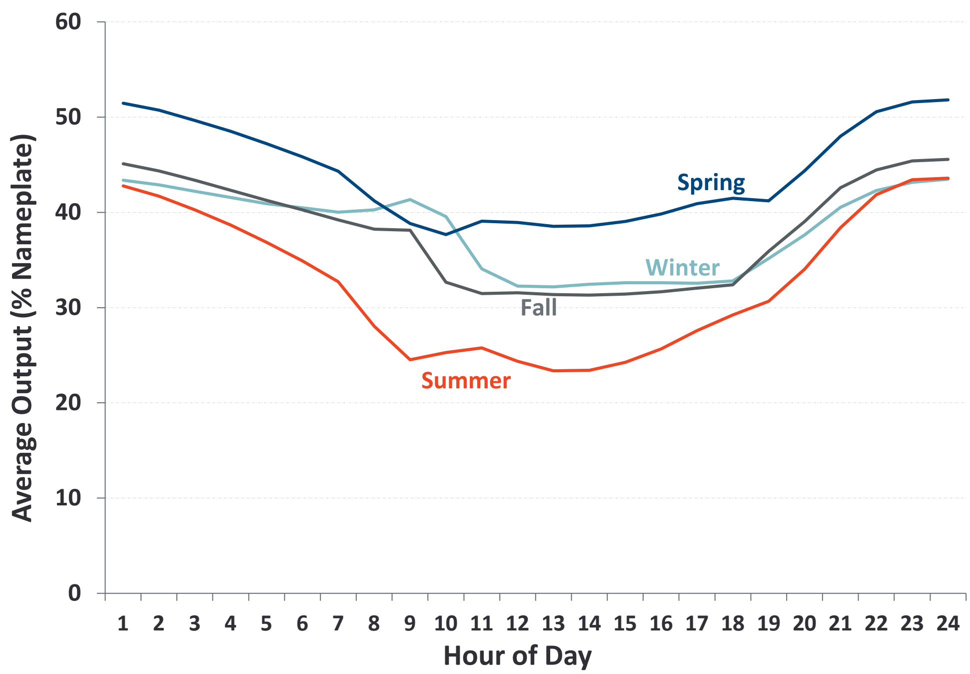
50 Provided by ERCOT staff.

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.[51] 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.[52] 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

[51] 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).

[52] See ERCOT (2018a), p. 8.

years 1997 to 2015.[53] 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.[54]

5. Hydroelectric

We include 555 MW of hydroelectric resources, consistent with ERCOT's May 2018 CDR report.[55] 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.[56] 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.

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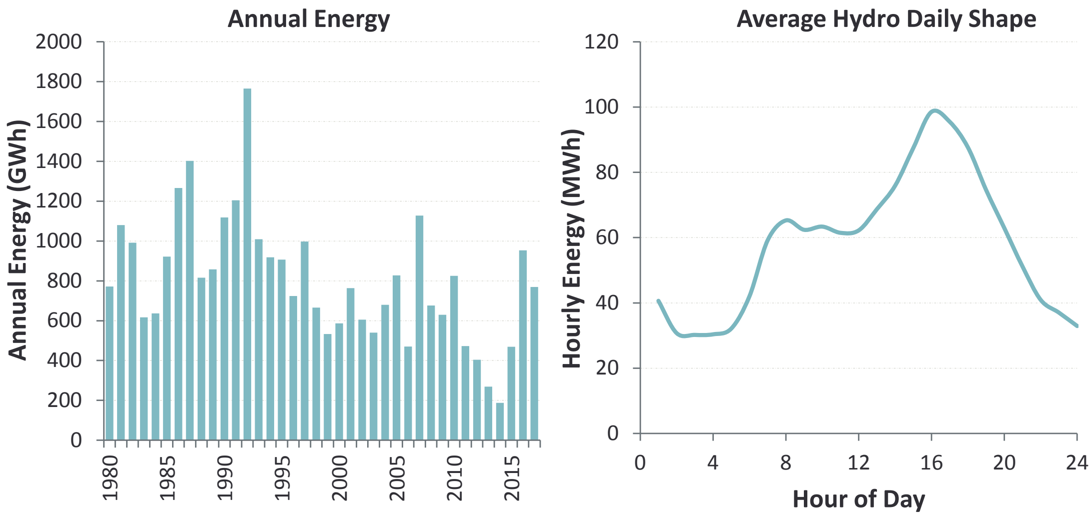
53 Individual county output profiles for 1997-2015 were provided by ERCOT, obtained through UL (formerly AWS Truepower). In conjunction with ERCOT, profiles were developed for the other synthetic weather years by inserting solar profiles from the 1997-2015 dataset for days with similar load patterns in the same time of year.

54 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.

55 See ERCOT (2018a).

56 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.[57] 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.[58] 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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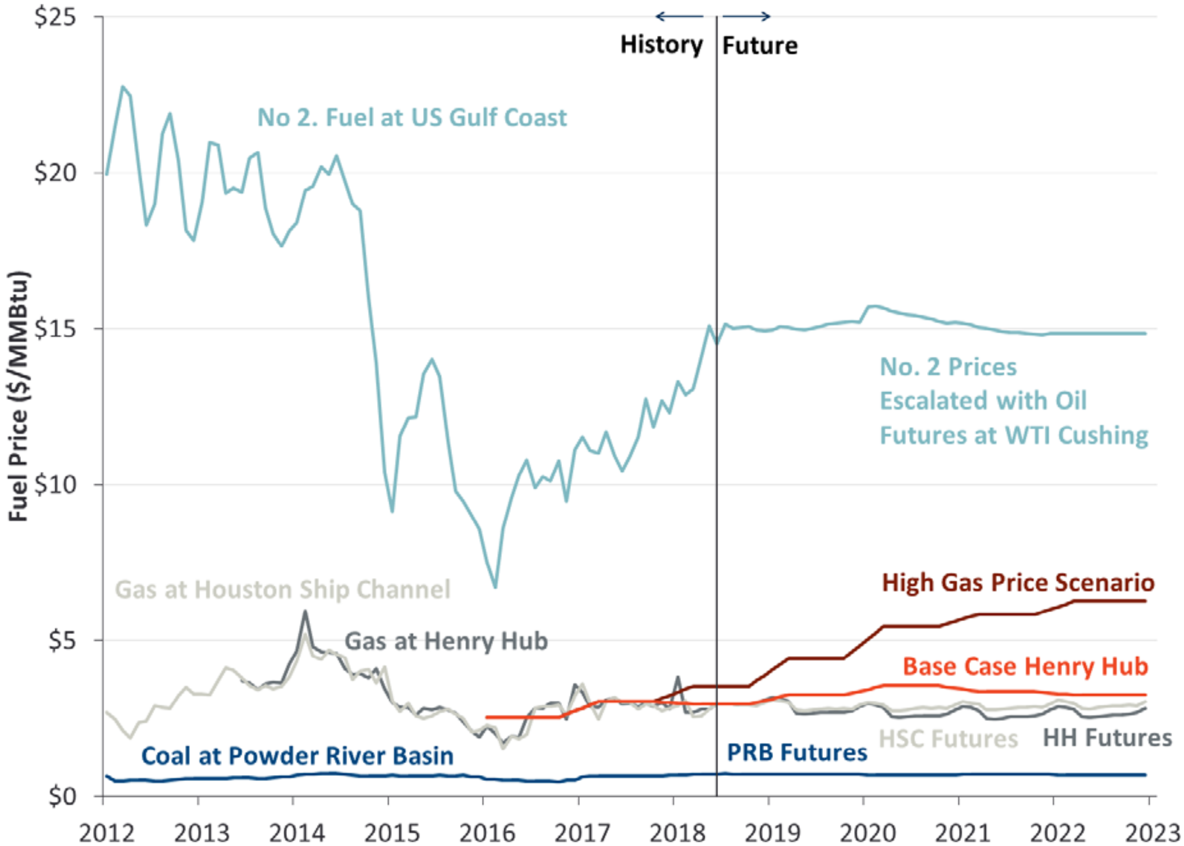
[57] Oil futures at WTI Cushing were used to escalate No. 2 fuel oil prices into the future due to lack of data on No. 2 futures at U.S. Gulf Coast. Data from S&P Global Market Intelligence LLC and Bloomberg.

[58] 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



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.[59] 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.[60]

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59 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.

60 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.[61] All 1,119 MW are modeled as responsive to Energy Emergency Alert, Level 2.[62]

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

3. Price Responsive Demand

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.[63] 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.[64]

Table A1-7
PRD by Program Type

Program Type	Enrolled Quantity (MW) Response	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

Continued from previous page

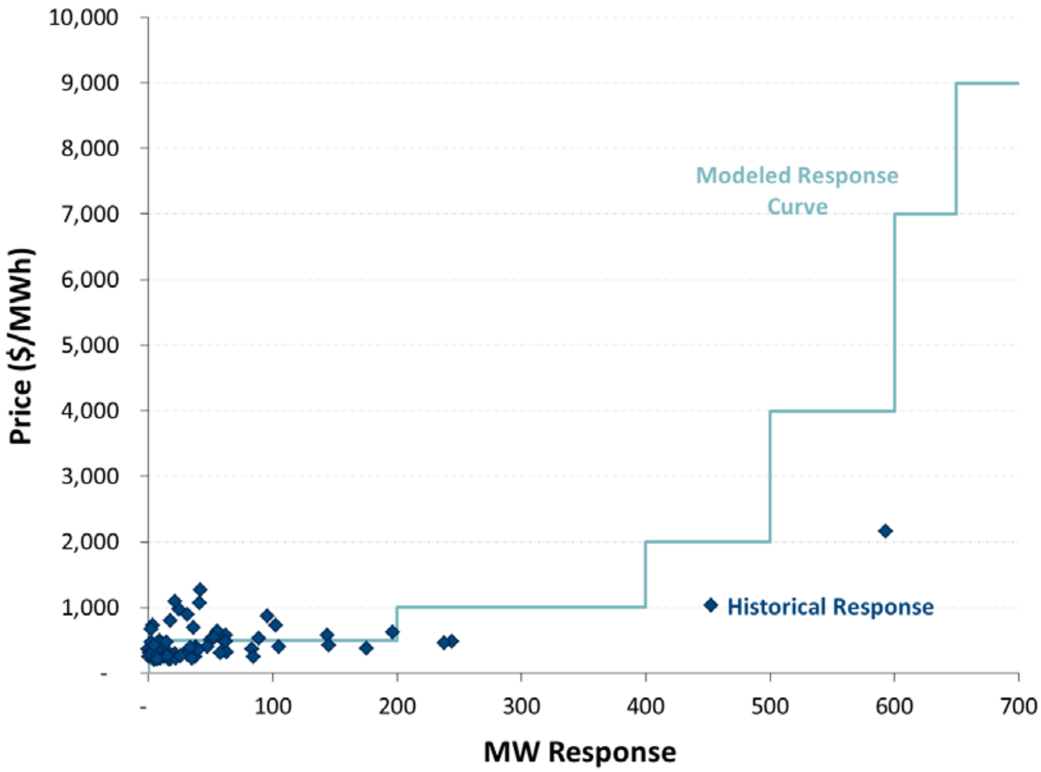
62 Our non-controllable load resource modeling deviates from the previous EORM report prepared in 2014. In that report 1,400 MW of LRs were modeled, consistent with the maximum amount allowed to clear in the RRS market. The LRs were divided into 2 blocks, a smaller block that responded at an energy "strike 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.

63 See ERCOT (2017a and 2018e).

64 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.

response, historical load shapes are not grossed up for PRD.[65] Furthermore, we analyzed the 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.[66]

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.

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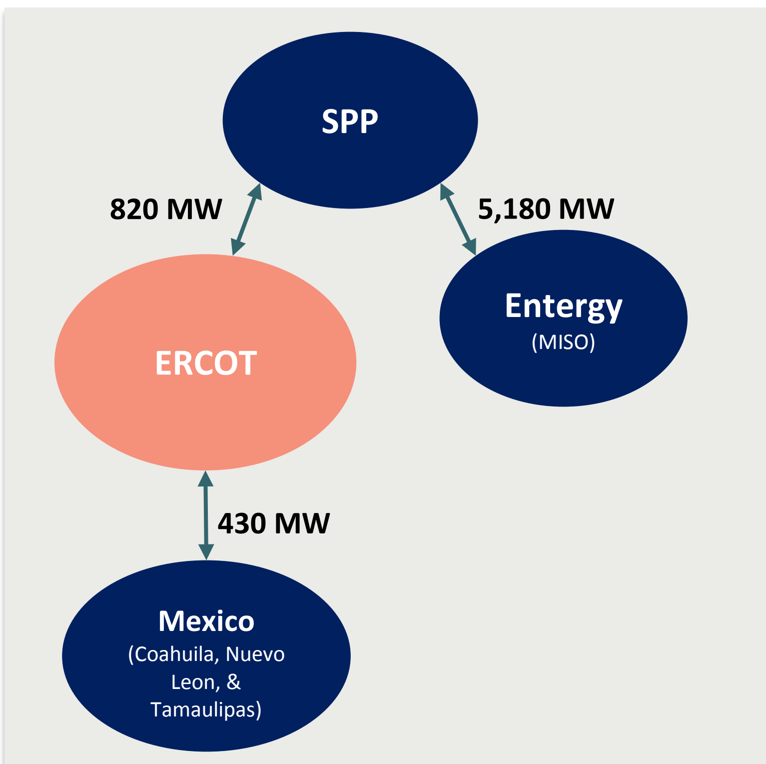
65 The prior EORM study (2014) did gross up load shapes for PRD, on the expectation that the PRD response under 2011 scarcity conditions was representative of long-term PRD behavior. However, ERCOT has had additional time to study historical PRD response, and has found that historical load shapes have not been greatly affected by PRD deployments.

66 The 2014-2017 PRD response and price behavior is consistent with our analysis of PRD response in 2008–2012 as studied in EORM 2014.

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.[67] As described in Section II.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 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).

[67] 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).

2. External Systems' Resource Overview

This section of our report provides an overview of the neighboring regions resource mixes.[68] 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.[69] 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.[70] 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.

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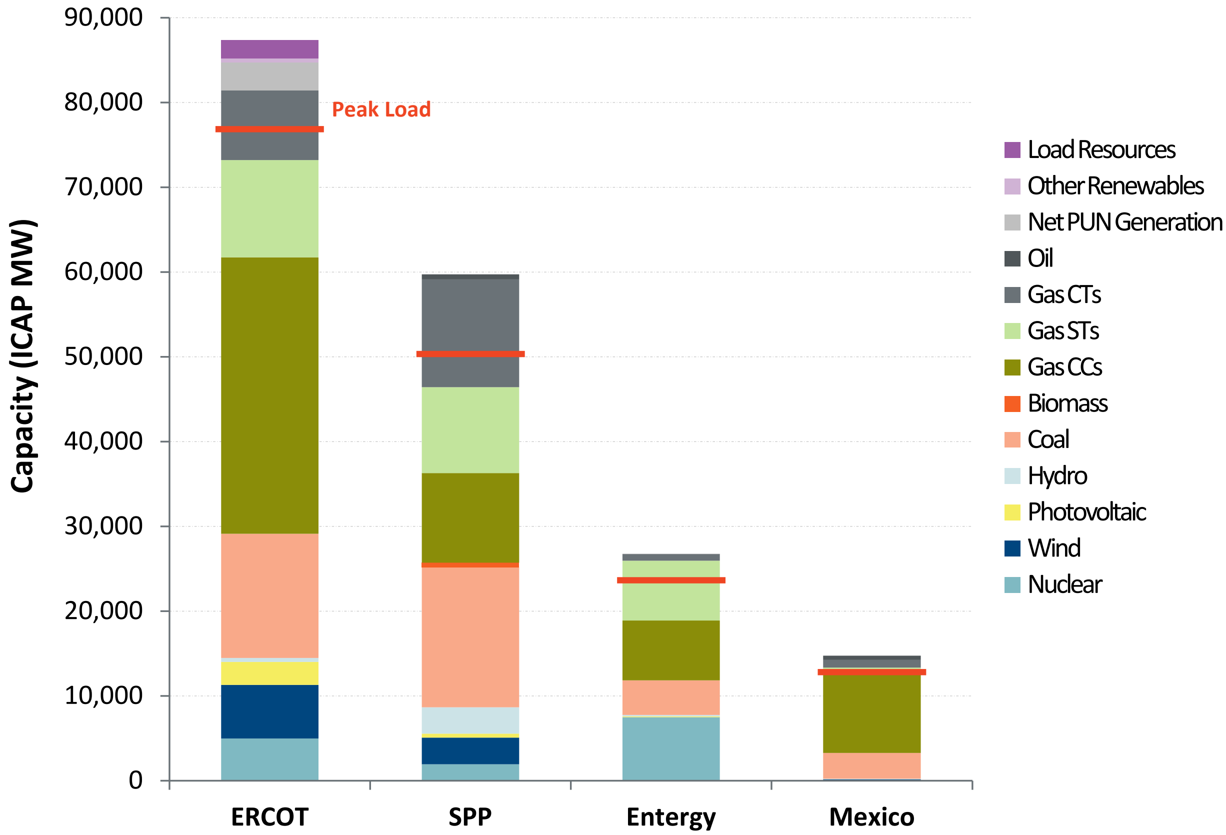
68 More information on the ERCOT supply mix can be found in II.B.

69 Specifically, we take external regions resource mix from ABB, Inc. Velocity Suite (2018) and external regions' demand-response penetrations from NERC (2017).

7070 See MISO (2016), NERC (2017), SPP (2015). For Mexico we use an assumed reserve margin above the peak load.

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 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.[71]

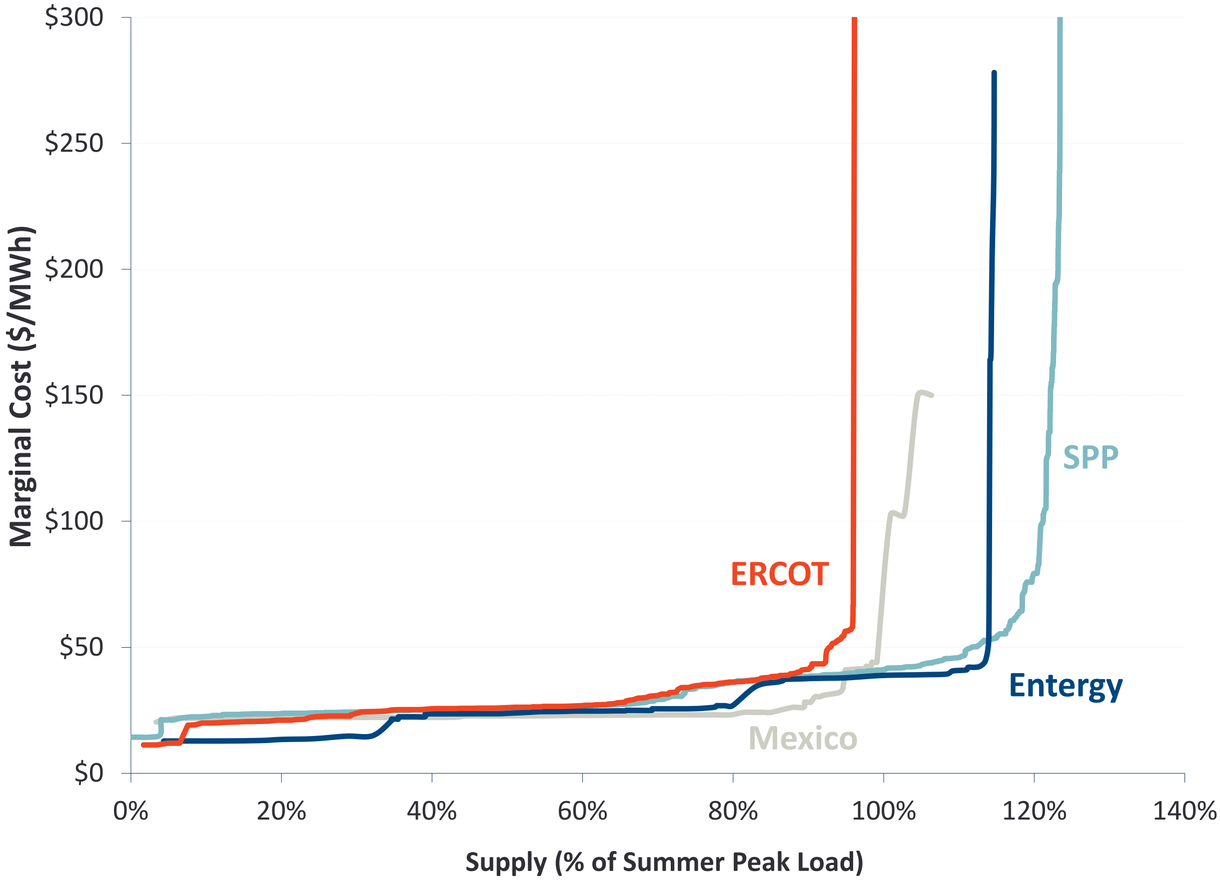
For all thermal resources, we model a relationship between capacity and hourly temperature which results in increased available capacity from the fleet during colder periods. Each unit is designated a specific weather station in which the hourly temperature determines the rating of the unit for that 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.[72] 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.

71 Heat rates from ABB Velocity Suite (2018).

72 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 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.[73] 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.[74] 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

73 See PUCT (2012).

74 See PUCT (2012).

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 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.[75] 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

75 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.

MW. This discrepancy results in prices above marginal costs during moderate scarcity events, as discussed further in Appendix 1.E.4 below.

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	700	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	920	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	203	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.[76] 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.[77] 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.[78] 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.[79] Figure A1-11 illustrates our approach to implementing ORDC in our modeling, which is similar to ERCOT's implementation, although with some simplifications.[80] We implement all 48 distinct ORDC curves that reflect four seasons each year, six periods each day, and two types of operating reserves.[81]

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76 See Section 6.5.9, ERCOT 2018f.

77 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.

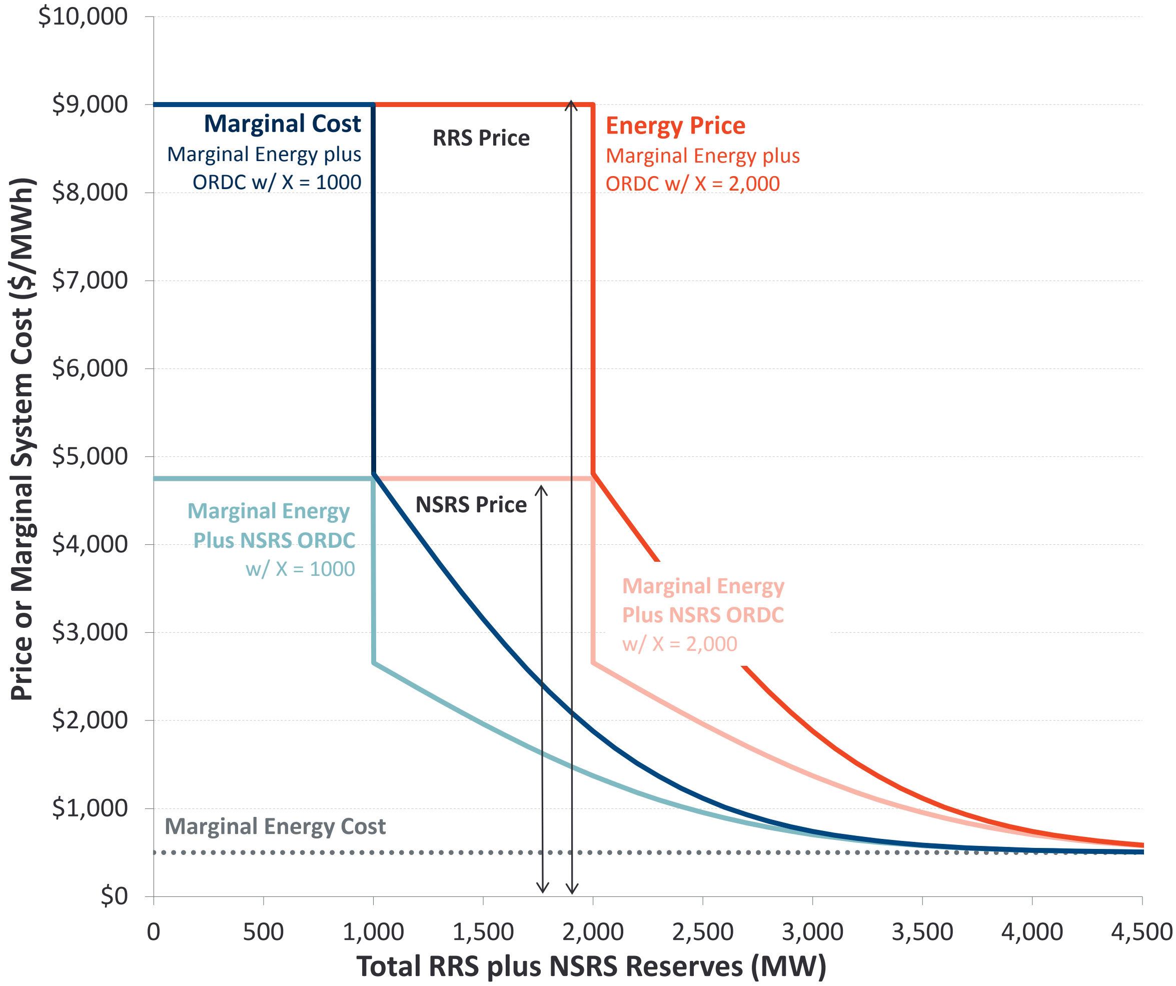
78 This number excludes private use network resources, which we model separately as explained in Section IV.B.3 above. This number is significantly lower than the EORM 2014 rating of 360 MW because ERCOT updated the reporting standards of HSL and emergency limits, which reduced the MW above HSL.

79 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.

80 For a detailed explanation of ERCOT's ORDC implementation see their whitepaper on the methodology for calculating ORDC at ERCOT (2013).

81 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.[82] This curve reflects the incremental cost imposed by running short

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82 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

Continued on next page

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 A1-10 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).[83]

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

Continued from previous page

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.

83 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.

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.

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.[84] 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;[85] (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).[86] 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

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[84] See ERCOT's implementation in ERCOT (2013).

[85] 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.

[86] 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.

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 A1-12.[87] 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.[88] 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.[89] 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.[90] 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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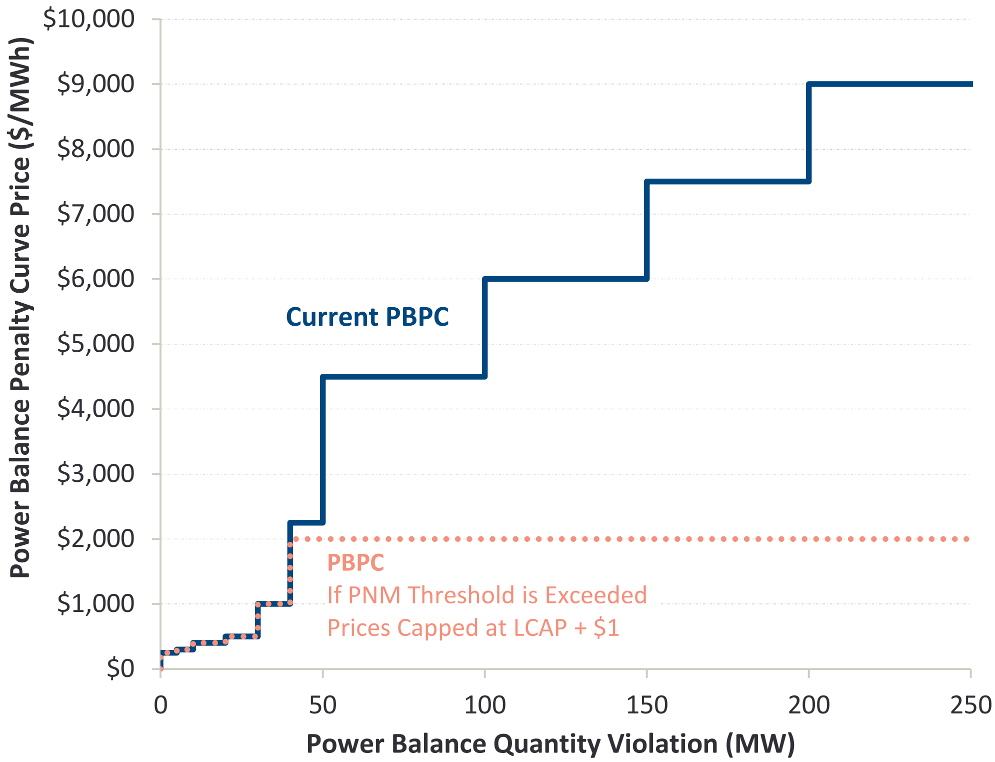
87 See ERCOT (2018g).

88 See ERCOT (2018g).

89 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.

90 See ERCOT (2018g).

Figure A1-12
Power Balance Penalty Curve



Sources and Notes:
PBPC numbers from ERCOT (2018g), p. 22-23.

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