2016 LTRA Probabilistic Reliability Assessment

Final Report

November 21, 2016

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Summary

This study was performed by Astrapé Consulting at the request of the Electric Reliability Council of Texas (ERCOT). The study fulfills the requirements set forth by the North American Electric Reliability Corporation (NERC) to perform a 2016 Probabilistic Risk Assessment (PRA) in addition to the annual Long Term Reliability Assessment (LTRA). The purpose of this study is to calculate probabilistic reliability metrics for years 2018 and 2020 using 2016 LTRA resource and load data. The reliability metrics, calculated on a monthly and annual basis, include Expected Unserved Energy (MWh), Loss of Load Hours (hours/year), and Expected Unserved Energy (EUE) as percentage of Net Energy for Load.

Tables 1 through 4 display the annual and monthly base case results for forecast years 2018 and 2020. (Table 1 also includes the 2014 Probabilistic study's 2018 base case results for comparison purposes.) The reserve margins for 2018 and 2020 are 24.35% and 21.77%, respectively. As a result, 2018 has fewer loss of load events compared to 2020. Compared to the 2018 results for the 2014 PRA Assessment, LOLH decreased from 0.338 to 0.000004 while EUE decreased from 285.59 MWh to 0.005 MWh. These reductions are due to an increase in the anticipated reserve margin from 13.6% to 24.35% for the 2018 forecast year. This reserve margin increase is attributable to both a lower peak load forecast as well as an increase in anticipated resources relative to those included in the 2014 PRA.

Table 1. 2018 Base Case Annual Results

LOLH	EUE	EUE/Net Energy for Load
hours/year	**MWh**	**ppm**
2014 Probabilistic Assessment Results		
0.338	285.59	0.79
2016 Probabilistic Assessment Results		
0.000004	0.005	0.00001

As shown in Tables 2 and 4, the monthly results show all EUE events occurring in the summer months.

Table 2. 2018 Base Case Monthly Results

	LOLH, hours/year	EUE, MWh
January	-	-
February	-	-
March	-	-
April	-	-
May	-	-
June	0.00000*	0.00111
July	-	-
August	0.00004	0.00384
September	-	-
October	-	-
November	-	-
December	-	-
Total	0.00004	0.005

*Non-zero value

Table 3. 2020 Base Case Annual Results

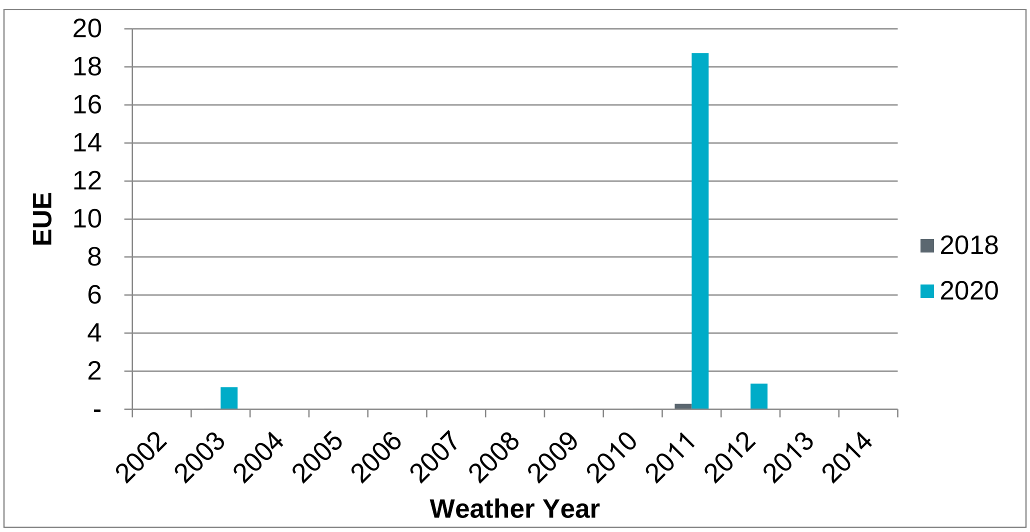
LOLH	EUE	EUE/Net Energy for Load
hours/year	MWh	ppm
0.0005	0.3945	0.001

Table 4. 2020 Base Case Monthly Results

	LOLH, hours/year	EUE, MWh
January	-	-
February	-	-
March	-	-
April	-	-
May	-	-
June	0.00018	0.1108
July	0.00004	0.0268
August	0.00030	0.2569
September	-	-
October	-	-
November	-	-
December	-	-
Total	0.0005	0.3945

To capture weather-related load uncertainty within the ERCOT Region, thirteen historical weather years were utilized. Figure 1 shows the resulting 2018 EUE by weather year. As can be seen in the Figure, 2011 had an extreme amount of EUE relative to other years due to anomalous weather; as a result, the 2011 weather year was only given a 1% probability of occurrence for the simulations.

Figure 1. EUE Study Results by Weather Year



To further understand the impact of load forecast error, a sensitivity was run where the peak load and energy for the two forecast years were scaled up by fixed percentages. For 2018, peak load and energy were scaled up by 2%, while for 2020, the peak load was scaled up by 4% and the energy was scaled up by 2%. Tables 5 and 6 compare the sensitivity and base case results.

Table 5. Load Sensitivities (2018)

	LOLH	EUE	EUE/Net Energy for Load	Reserve Margin
	hours/year	MWh	ppm	%
Base Case	0.000004	0.005	0.00001	24.4
Sensitivity	0.0002	0.243	0.0007	21.8

Table 6. Load Sensitivities (2020)

	LOLH	EUE	EUE/Net Energy for Load	Reserve Margin
	hours/year	MWh	ppm	%
Base Case	0.004	0.3945	0.001	20.8
Sensitivity	0.107	114.2	0.292	15.9

Software Model Description

This study used Astrapé CoOvernsulting's probabilistic resource adequacy assessment model called SERVM (Strategic Energy and Risk Valuation Model), which captures the uncertainty of weather, economic growth, unit availability, and external assistance from neighboring regions as stochastic variables. The model performed 19,500 hourly simulations for each study year to calculate the reliability metrics. The 19,500 hourly simulations are derived from 13 weather years, 5 load forecast multipliers and 300 Monte Carlo unit outage draws (13 x 5 x 300 = 19,500). SERVM is a reliability and hourly production cost simulation tool that performs an hourly chronological economic commitment and dispatch for multiple zones using a transportation/pipeline representation. The model allows zones to share energy based on economics and subject to import and export constraints. ERCOT was modeled as a single region with one external region to reflect historical import/export activity and potential assistance.

Demand Modeling

Table 7 shows the summer and winter peak and energy forecast for 2018 and 2020. Given that the ERCOT Region is a summer peaking system, the winter forecast is substantially lower than the summer forecast.

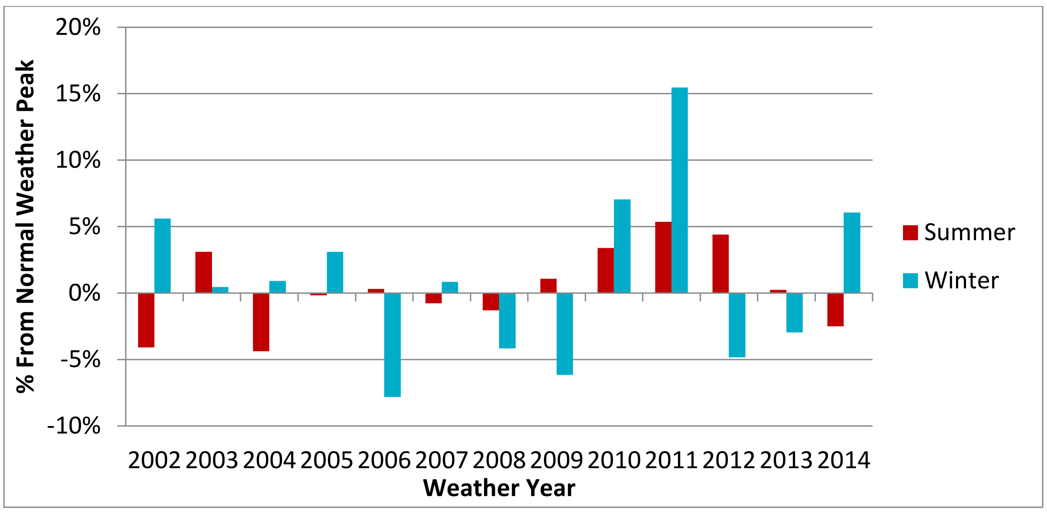
Table 7. Summer and Winter Peak and Energy Forecast (2018 and 2020)

	2018		2020	
ENERGY	Annual		Annual	
Net Energy for Load - Annual (GWh)	362,255		376,149	
	2018		2020	
Peak Demand	Winter	Summer	Winter	Summer
Total Internal Demand (MW)	59,597	72,277	61,845	74,288

To capture load uncertainty within the ERCOT Region, thirteen historical weather years were simulated with five different economic load forecast multipliers resulting in 65 full-year load scenarios. The thirteen load shapes were scaled so the weighted average of the summer and winter peaks equaled the peak demand forecasts for the study year. Each weather year was given equal probability in the simulations with the exception of 2011, which was assigned a 1% probability of occurrence to account for the outlier status of weather that occurred in that year. ERCOT derived the 1% probability value for 2011 weather by evaluating summer mean temperature “probability-of-exceedance” data published by the National Oceanic and Atmospheric Administration’s Climate Prediction Center.

Figure 2 shows the variability in summer and winter peak load across the thirteen weather years simulated. The most severe summer peak is 5.37% above the normal weather summer peak, whereas the most severe winter peak is 15.56% above the normal weather winter peak. While the winter shows significantly more weather uncertainty, the expected forecast is much lower resulting in higher reliability in the winter.

Figure 2. Peak Load Variance by Weather Year



Economic load forecast error multipliers were developed to isolate the economic component of uncertainty of forecasting load two years and four years in advance for the 2018 and 2020 study years. The following assumptions were based on a comparison of Congressional Budget Office (CBO) GDP forecasts two and four years ahead with actual GDP data. The standard deviation of the forecast error was calculated and used to develop a normal distribution. Because electric load grows at a slower rate than GDP, a 40% multiplier was applied to the raw CBO forecast error. This normal distribution was broken into a discrete distribution with five points and their associated probabilities (shown in Table 8). The table demonstrates that 0.5% of the time it is expected that load will be under-forecasted by 4% in 2018. In 2020, there is an 11.1% probability that load will be under-forecasted by 4%. The error distribution on a two-year ahead forecast is smaller than the error distribution of a four-year ahead forecast reflecting increasing load forecast uncertainty over time. The SERVM model created 65 distinct cases consisting of each of the thirteen weather years matched with each of the five load forecast error points for 2018 and 2020. For example, the 2011 weather year load shape consisting of 8,760 hours was converted into five load shapes for simulation purposes by multiplying each hour by each of the five load forecast error multipliers.

Table 8. Peak Load Variance by Weather Year

Load Forecast Error Multipliers	Two-Year-Ahead Probability (%)	Four-Year-Ahead Probability (%)
0.96	0.5%	11.1%
0.98	18.9%	23.1%
1.00	61.1%	31.6%
1.02	18.9%	23.1%
1.04	0.5%	11.1%

Controllable Capacity Demand Response Modeling

Interruptible load and demand response resources are captured as resources with specific price thresholds at which each resource is dispatched. These resources are also modeled with call limits and priority as shown in Table 9.

Table 9. Load Management and Demand Response Resources

	Summer Capacity (MW)	Call Limits	Call Priority
TDSP Standard Load Management Programs	208	16 hours per year, during hours 14-20	1
Load Resources Serving as Responsive Reserve	1,153	Unlimited	2
10-Minute Emergency Response Service	609	8 hours per season and per hourly intervals; Seasons: Winter, Spring, Summer, Fall; Hourly intervals: week day hours 1-8 and 21-24 and weekends, week day hours 9-13, week day hours 14-16, week day hours 17-20	3
30-Minute Emergency Response Service	898	8 hours per season and per hourly intervals; Seasons: Winter, Spring, Summer, Fall; Hourly intervals: week day hours 1-8 and 21-24 and weekends, week day hours 9-13, week day hours 14-16, week day hours 17-20	4

Capacity Modeling

Conventional generators were modeled in detail with maximum capacities, minimum capacities, heat rate curves, startup times, minimum up and down times, and ramp rates. Table 10 provides a summary of ERCOT resources for the 2018 and 2020 study years. The winter and summer ratings are based on ERCOT's 2016 LTRA data submission.

For the Capacity Expected On-Peak section of Table 10, the summer capacity credit for coastal wind is 55% and 12% for non-coastal wind. (Coastal wind covers resources located in eleven contiguous counties that border the Gulf Coast.) The winter capacity credit for coastal wind is 35% and 20% for non-coastal wind. All solar is given an 80% capacity credit in the summer and 5% in the winter. ERCOT developed these capacity credit values using a multi-year average of historical unit output during the highest peak load hours for each applicable season. Conventional resources are not discounted for expected forced outages in this table. Note that the probabilistic modeling used the hourly wind and solar output profiles described below, whereas LTRA renewable resource reporting used the capacity credit percentages summarized above.

Table 10. ERCOT Resource Summary (MW Capacity)

	2018		2020	
CAPACITY	**Winter**	**Summer**	**Winter**	**Summer**
Capacity Installed (Nameplate)	**114,280**	**116,374**	**118,621**	**118,380**
Coal	20,796	20,796	20,796	20,796
Petroleum	0	0	0	0
Gas	54,716	56,732	58,110	58,110
Nuclear	5,268	5,268	5,268	5,268
Hydro	544	544	544	544
Pumped Storage	0	0	0	0
Geothermal	0	0	0	0
Biomass	210	210	210	210
Wind	26,231	26,231	26,934	26,934
Solar	2,053	2,053	2,053	2,053
Behind the Meter Generation Capacity	4,462	4,540	4,706	4,465
Capacity Expected On-Peak (Existing Certain + Tier 1)	**86,092**	**86,068**	**88,374**	**86,456**
Coal	18,545	19,209	17,705	18,369
Petroleum	0	0	0	0
Gas	51,362	50,649	54,301	51,867
Nuclear	5,164	4,981	5,164	4,981
Hydro	444	437	444	437
Pumped Storage	0	0	0	0
Geothermal	0	0	0	0
Biomass	199	199	199	199
Wind	5,568	4,411	5,824	4,495
Solar	102	1,642	103	1,642
Behind the Meter Generation Capacity	4,710	4,540	4,635	4,465

Since conventional generators are able to run their units at slightly higher outputs for short periods during capacity shortages, a synthetic emergency generation unit was modeled with a capacity of 494 MW and a $500/MWh dispatch price. The capacity for this unit was determined by compiling differences between telemetered High Sustained Limits (HSLs) and High Emergency Limits (HELs) reported by each unit's scheduling entity during the 2016 peak load hour. This unit was designed to capture the additional short-duration capacity from the entire fleet. To model the uncertainty of the dependability of this additional capability, a stochastic response factor was applied which allowed the synthetic generator to achieve full capacity when called 50% of the time and 360 MW the other 50% of the time. (The 360 MW lower limit is based on an analysis of historical generator output levels during high market price events.) The $500/MWh dispatch price was based on an analysis of historical prices occurring at times when generators exceeded their sustained seasonal capacity ratings.

Private Use Network (PUN) resources—generators that serve load that is not directly metered by ERCOT and typically are located at industrial facilities—were modeled as load-responsive resources based on historical data. Depending on the maximum load level of the day, the PUN resources provide an expected response with an uncertainty band around the response. Table 11 shows how the probabilistic PUN resource output levels are represented in SERVM. Output levels represent just the amount of net generation capacity available to the ERCOT grid rather than total generation capacity. Similarly, ERCOT's load forecast only accounts for PUN load that is served through the ERCOT grid. (That is, PUN self-serve load is not accounted for in the forecast.)

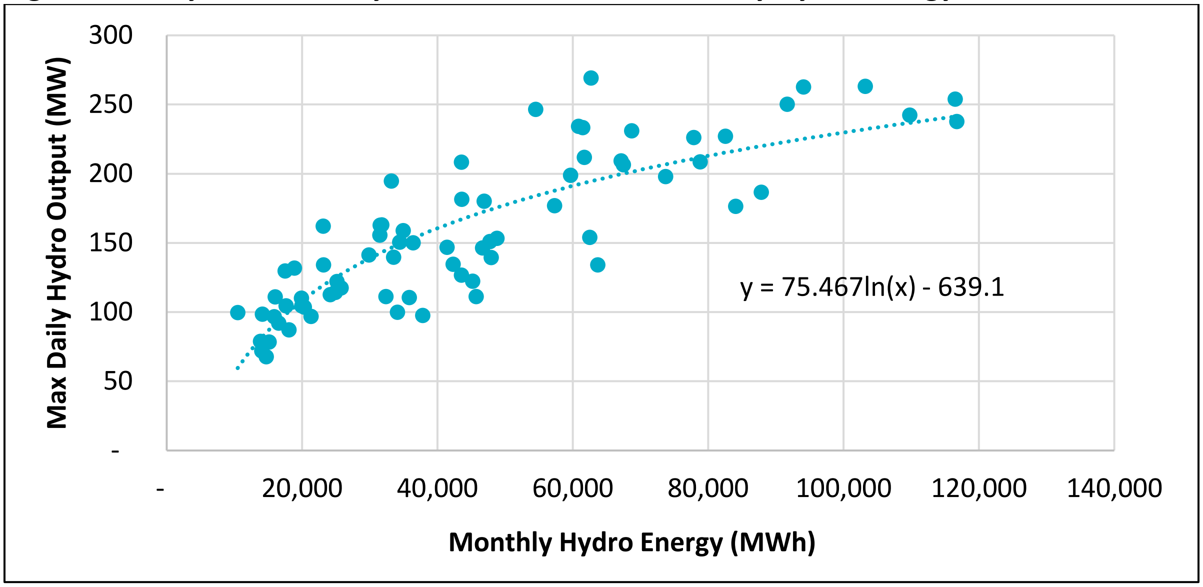
Table 11. Private Use Network Output Probabilistic Representation

Draw Probability	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
Load Level	Net Output to the ERCOT Grid (MW)									
Above 100% of Peak Forecast	3,631	3,800	3,822	3,875	3,885	3,885	3,916	3,927	3,991	4,090
95% - 100% of Peak Forecast	3,042	3,222	3,403	3,583	3,764	3,809	4,026	4,243	4,459	4,676
90% - 95% of Peak Forecast	3,042	3,201	3,360	3,519	3,677	3,723	3,938	4,154	4,370	4,585
85% - 90% of Peak Forecast	2,633	2,860	3,087	3,314	3,541	3,587	3,825	4,063	4,302	4,540
70% - 85% of Peak Forecast	2,270	2,531	2,792	3,053	3,314	3,360	3,655	3,950	4,245	4,540
Below 70% of Peak Forecast	999	1,044	1,067	1,441	2,497	2,542	2,985	3,428	3,870	4,313

For hydro resources, 13 years of historical monthly hydro energies and capacities are modeled. A relationship determined from a comparison of total monthly hydro energy and daily hydro dispatch parameters is used to define monthly inputs in SERVM. This relationship is shown in Figure 3. As can be seen in the Figure, months with higher total hydro energy have higher average maximum daily hydro outputs. A similar relationship is seen for daily minimum hydro output. In addition to average daily minimum and maximum output, days with higher load generally have higher hydro output. In months with significant total hydro energy, the maximum hydro output on the maximum load day is 300-350

MW. A separate energy-limited hydro resource with a capacity of 100 MW is modeled to represent additional capability during emergency conditions. This is only allowed for approximately 20 hours per year. The variation in hydro energy combined with the constraints on the hydro system's dispatch result in an average of 330 MW during modeled EUE events.

Figure 3. Daily Maximum Hydro as a Function of Monthly Hydro Energy



Intermittent wind and solar resources were modeled using hourly output profiles that coincide with the 13 historical weather years used for load and hydro modeling. The wind profiles were developed by outside consultants contracted by ERCOT and are summarized in Figure 4. The solar profiles were constructed by Astrapé Consulting using available National Renewable Energy Laboratory (NREL) data and are summarized in Figure 5.

Figure 4. Aggregated Wind Profiles

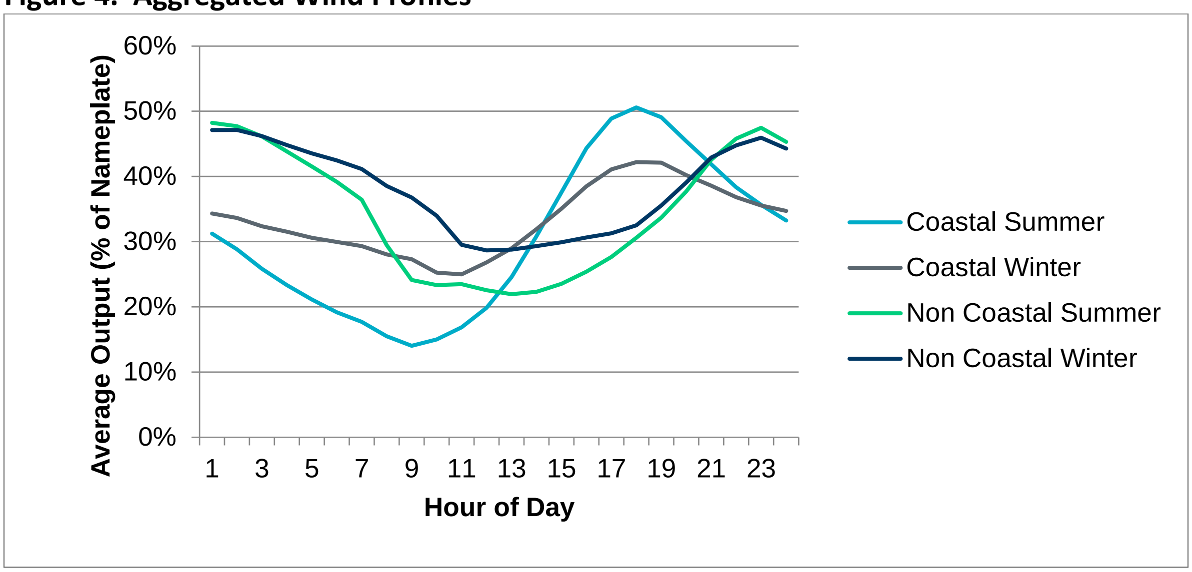
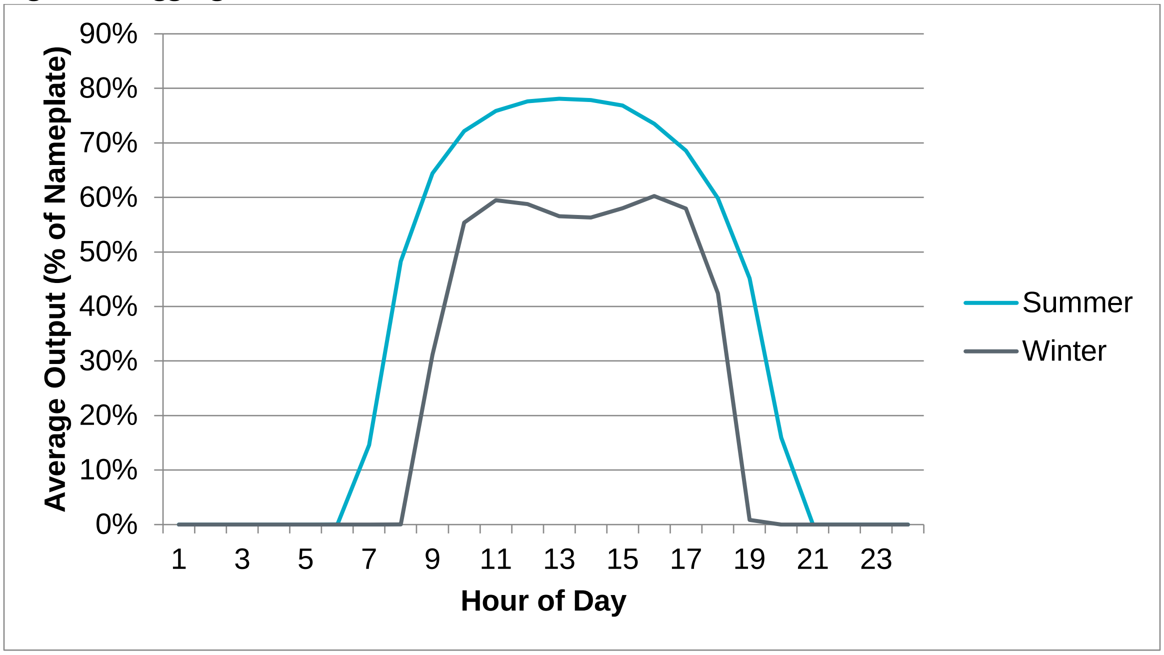


Figure 5. Aggregated Solar Profiles



Outage Modeling

SERVM's Monte Carlo forced outage logic incorporates full and partial outages based on 2011-2016 historical operations of units in the ERCOT Region. Time-to-Fail and Time-to-Repair distributions are entered for each unit based on historical events, and SERVM uses Monte Carlo draws to generate random forced outages based on this data. The actual Equivalent Forced Outage Rate (EFOR) is an output of the simulation rather than a direct input. (Note that this EFOR does not represent an Equivalent Forced Outage Rate – Demand (EFORd) value since the model economically commits and dispatches resources to load.) Table 12 shows the resulting EFOR by unit technology type in the simulations.

Table 12. Equivalent Forced Outage Rates by Technology Type

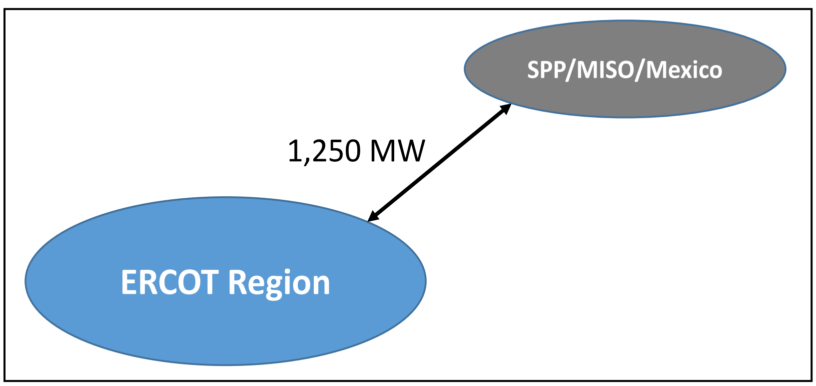
Technology Type	Capacity Weighted Equivalent Forced Outage Rate (%)
Nuclear	4.04%
Coal	6.32%
Gas Combined Cycle	4.27%
Gas Combustion Turbine	19.42%
Gas Steam Turbine	20.03%
Fleet Capacity Weighted Average EFOR	**8.50%**

Planned maintenance rates were entered for each unit as annual percentages. SERVM optimized planned maintenance events using the average of the thirteen load shapes input for weather uncertainty. This results in all planned maintenance events occurring in the winter, spring, and fall months with none occurring during the summer.

Transmission

As noted above, SERVM captures the transmission system using a transportation/pipeline representation allowing energy to be shared among all zones. Figure 6 shows the topology used for the ERCOT Region. ERCOT was treated as a single zone for the 2016 assessment since the 2014 results showed virtually no difference in reliability metrics between multi-zone and single zone analyses. (The 2014 probabilistic study used three internal zones defined using power transfer capability analysis for 2016 and 2018.) An external region was modeled with no load and 1,250 MW of generation to reflect the aggregate net import capability of the five DC ties connected to the SPP and Mexican grids. These resources were given a probabilistic distribution to reflect a range of purchase availability that calibrated with historical purchase activity.

Figure 6. Study Topology



Assistance from External Resources

The external region consisted of five generators totaling 1,250 MW of generation capacity and no load assumptions. To reflect the availability of market assistance seen in history, these resources were each given a 63% EFOR. While the market assistance averages between 500 MW to 700 MW (approximately 1% in reserve margin) during peak periods, there are hours where there is zero capacity and hours where there is 1,250 MW of capacity. The decision to simplify the external modeling was due to the small amount of ERCOT import capability.

Definition of Loss-of-Load Event

SERVM dispatches resources to meet regulation, spin, and non-spin requirements. This study assumes that load would be shed to maintain 500 MW of regulation and 500 MW of spinning reserve across the ERCOT Region.

Sensitivity Modeling

Two additional load scenarios were modeled for the probabilistic assessment. The first scenario increased 2018 peak load and energy by 2%, and the second increased 2020 peak load by 4% and 2020 energy by 2%. All other input assumptions were identical to those used for the base case simulations. Testing incrementally higher load levels in this way indicates that LOLH and EUE begin to increase exponentially as the reserve margin falls below 17%.

Tables 13 reports the monthly and annual results for the two alternative load growth scenarios. Results for the base case scenario are also provided for comparison purposes.

Table 13. Load Sensitivity Results

Base Case	2018												
PROBABILISTIC STATISTICS	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Expected Unsupplied Energy (EUE) (MWh)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0011	0.0000	0.0038	0.0000	0.0000	0.0000	0.0000	0.0050
Loss of Load Hours (LOLH) (hours/year)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Base Case	2020.0000												
PROBABILISTIC STATISTICS	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Expected Unsupplied Energy (EUE) (MWh)	0.0000	0.0000	0.0000	0.0000	0.0000	0.1108	0.0268	0.2569	0.0000	0.0000	0.0000	0.0000	0.3945
Loss of Load Hours (LOLH) (hours/year)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	0.0003	0.0000	0.0000	0.0000	0.0000	0.0005

Sensitivity Case	2018.0000												
PROBABILISTIC STATISTICS	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Expected Unsupplied Energy (EUE) (MWh)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0215	0.0015	0.2186	0.0013	0.0000	0.0000	0.0000	0.2429
Loss of Load Hours (LOLH) (hours/year)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0002

Sensitivity Case	2020.0000												
PROBABILISTIC STATISTICS	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Expected Unsupplied Energy (EUE) (MWh)	0.0000	0.0000	0.0000	0.0000	0.0000	44.0717	8.1095	61.2672	0.7373	0.0000	0.0000	0.0000	114.1857
Loss of Load Hours (LOLH) (hours/year)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0415	0.0084	0.0566	0.0008	0.0000	0.0000	0.0000	0.1074