Exhibit A-5.1

DTE Electric Resource Adequacy and LRZ7 ELCC Assessments

9/21/2022

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CC	Combined Cycle Generation
CO2	Carbon Dioxide
CT	Combustion Turbine Generation
DR	Demand Response
DTE	DTE Electric Company
EE	Energy Efficiency Programs
EFOR	Equivalent Forced Outage Rate
EFORd	Demand Equivalent Forced Outage Rate
EIA	Energy Information Administration
ELCC	Effective Load Carrying Capability
EUE	Expected Unserved Energy
GADS	Generating Availability Data System
ICAP	Installed Capacity
IC	Internal Combustion Generation
ISO	Independent System Operator
MISO	Midcontinent ISO
LOLE	Loss of Load Expectation
LOLH	Loss of Load Hours
LRZ	Local Resource Zone
LSE	Load Serving Entity
NREL	National Renewable Energy Laboratory
PCA	Proposed Course of Action
PRM	Planning Reserve Margin
PRMR	Planning Reserve Margin Requirement
PSH	Pumped Storage Hydro
SAM	System Advisory Model
SERVM	Strategic Energy Risk Valuation Model
TTF	Time to Fail
TTR	Time to Repair
UCAP	Unforced Capacity
VOM	Variable Operation and Maintenance

EXECUTIVE SUMMARY

To aid in their 2022 Integrated Resource Plan (IRP) filing, DTE Electric Company (DTE) contracted with Astrapé Consulting to determine the potential for new renewable and battery storage resources to reliably replace retiring conventional capacity. Using the Strategic Energy Risk Valuation Model (SERVM), DTE resources and load were modeled alongside non-DTE resources and load to construct a model of the Midcontinent ISO (MISO) Local Resource Zone 7 (LRZ7) for the future study year 2025[1]. This model was used to understand resource adequacy implications of the changing resource mix for DTE as it looks to retire significant fossil generation and add renewable and energy storage resources. The primary focus of this study was to understand the fungibility of various resource classes through the determination of Effective Load Carrying Capabilities (ELCC). Determining the ELCC values for resources such as solar, wind, and battery storage allow for appropriate accounting of the load and capacity balance of the system and ensures that the reliability value associated with the addition of these new variable energy resources adequately offsets the reliability value of conventional resources being retired.

For the purpose of this analysis, only LRZ7 was modeled, and the assumed unforced capacity (UCAP) needed to achieve a reliability value of 0.1 days/year Loss of Load Expectation (LOLE) was based on the published MISO 2025 UCAP planning reserve margin (PRM) value of 7.4%. A proxy unit was used in the resource adequacy assessment to reflect the expected market support LRZ7 receives from participating in the MISO market. The size of the proxy unit was compared against the LRZ7 market support implied by the latest MISO resource adequacy study for reasonableness. This established a base case from which the relative reliability contribution of proposed resource additions could be assessed against proposed resource retirements.

Two resource portfolios based on DTE's preliminary proposed course of action (PCA) at different points in time, one for 2028 and one for 2035, were modeled to assess their relative reliability impacts from the base case (i.e., the resource mix before major coal retirements and renewable resource additions). ELCC analysis was performed to accurately determine the reliability contribution of the proposed variable energy resource additions as an entire portfolio, as well as accurately allocating capacity values for each specific technology and across load serving entities. A summary of the base case and PCA portfolios are shown in Table 1 below. Both PCA portfolios were found to have LOLE values lower than 0.1 days/yr, meaning they were more reliable than the base case. An additional warm weather sensitivity analysis was performed to determine the impact of increased temperatures over time on the resulting LOLE and capacity surplus of the PCA portfolios. For both PCA portfolios, the impact of the warming weather sensitivity showed a slight increase in LOLE with a corresponding reduction to their estimated capacity surplus by approximately 40MW. For the base case, the warming weather sensitivity indicated the need for 143MW above the UCAP PRM requirement in order to achieve the 0.1 days/yr LOLE target. It should be noted that the non-DTE resources available in the LRZ7 model were adjusted for each PCA, such that non-DTE resources were

[1] A single study year was selected to isolate the effects of changing resource mix. The particular study year is not important. While some of the high renewable penetrations studied are not feasible by 2025, analyzing various portfolios against different fuel prices and different load forecasts for future years would produce more complicated reliability effects.

providing only the necessary capacity to meet the calculated UCAP PRM of 7.4%. Thus, the estimated surplus is attributable solely to DTE's obligation to meeting the UCAP PRM.

Table 1. PCA Resource Adequacy Assessment Results

	Base Case	2028 PCA	2035 PCA
LRZ7 Solar Installed Capacity (MW)	781	6,162	11,505
LRZ7 Wind Installed Capacity (MW)	3,836	3,936	4,513
LRZ7 Battery Storage Installed Capacity (MW)	1	435	572
LRZ7 Variable Energy Portfolio ELCC (MW)	1,215	3,265	3,930
Total DTE Variable Energy Portfolio ELCC (MW)	701	1,495	2,094
Incremental DTE Variable Energy Portfolio ELCC (MW)	0	794	1,393
Incremental DTE Demand Response (UCAP MW)	0	23	38
Incremental DTE Combined Cycle (UCAP MW)	0	0	902
DTE Retirements (UCAP MW)	0	1,462	2,888
LRZ7 LOLE	0.1	0.04	0.02
Estimated Surplus (UCAP MW; 7.4% PRM)	0	308	403
Weather Sensitivity Estimated Surplus (UCAP MW; 7.4% PRM)	-143	268	360

Second, to determine technology specific ELCC allocations in the PCA analysis, incremental ELCC curves were developed for solar and battery storage technologies. These curves represent the "Last In" ELCC values, which is defined as the ELCC attributable to an incremental capacity addition of a single technology class, assuming all other technology classes are already included in the system. This is distinguished from "First In" ELCC values, which is the ELCC attributable to an incremental capacity addition of a single resource class, assuming no other renewable/battery storage resources are in the system. Because resource classes can positively or negatively impact the reliability contribution of another resource class, the "First In" and "Last In" ELCC values may result in different ELCCs. This difference between "First In" and "Last In" is known as diversity impacts and can be accounted for by taking the average of the two ELCC values. The average of the "First In" and "Last In" ELCC values were calculated for this assessment in order to account for this diversity impact.

An example of a key diversity impact observed in the ELCC analysis of LRZ7 was the positive impact of increased solar penetration on battery storage ELCC. Because increased solar resources decreased the duration of the net load peak period, 4-hour duration battery storage resources were able to provide higher reliability contribution at the 50% solar penetration level compared to the 5% solar penetration level. The shift in net load peak periods is highlighted in the figure below (where net load peak is defined as the hours within 2,000MW of the daily net load peak).

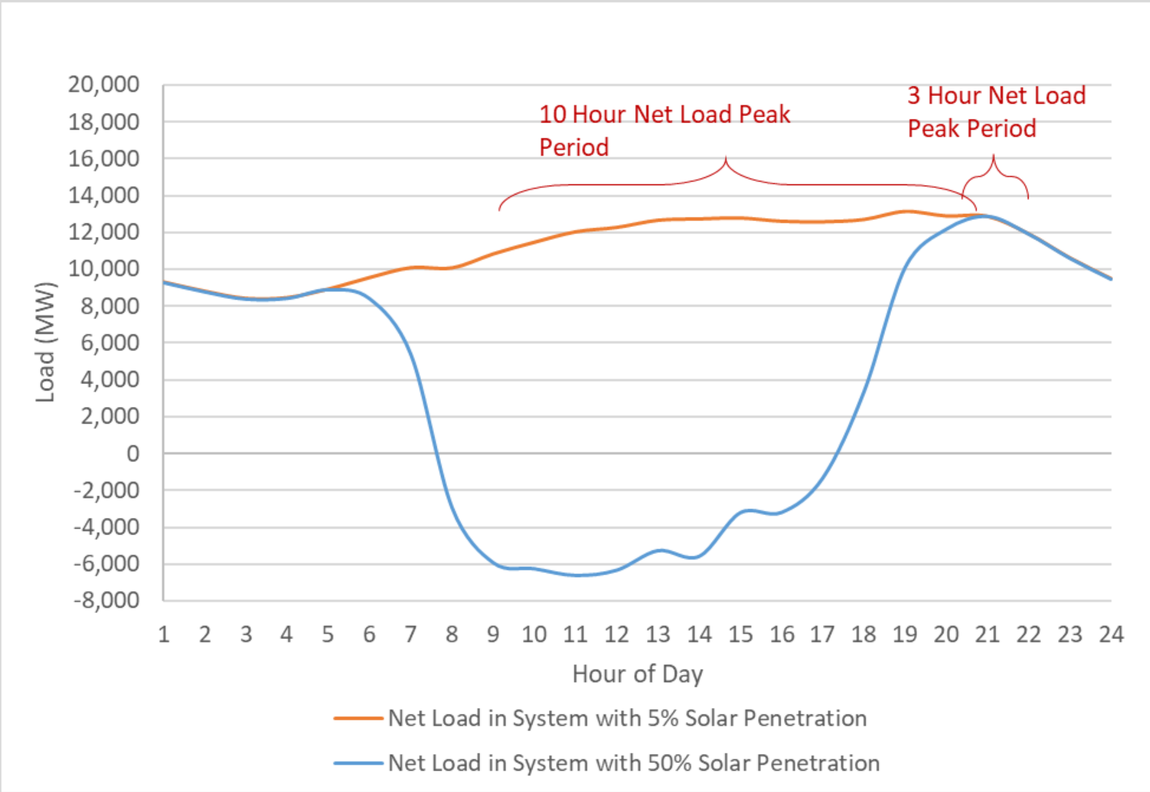

Figure 1. Solar + Battery ELCC Synergy

The resulting "Last In" incremental ELCC curves for each technology type from the portfolio ELCC analysis are shown in the figures below.

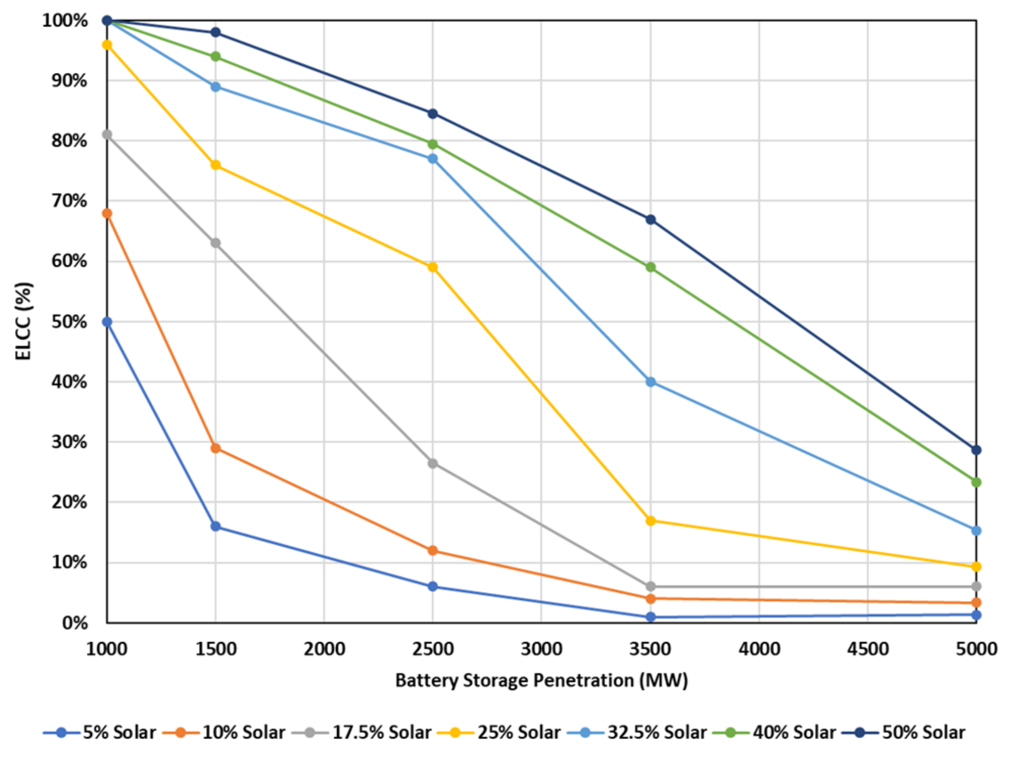

Figure 2. Last In Incremental Battery Storage ELCC (by Battery Storage Penetration, 12% Wind Penetration)

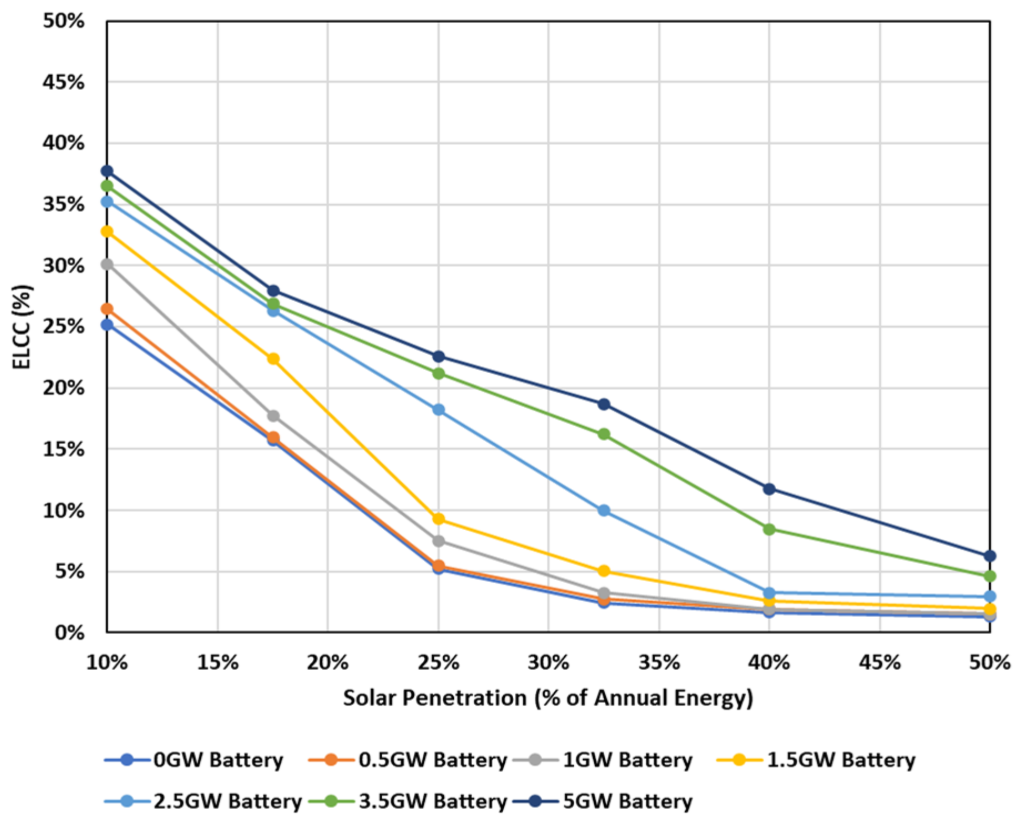

Figure 3. Incremental Last In Solar ELCC (by Solar Penetration, 12% Wind Penetration)

Finally, a renewable integration flexibility analysis was performed to determine the impact that increased renewable penetration has on the frequency of flexibility events (i.e., intra-hour imbalances between net load and generation due to solar, wind, and load volatility). The production cost of increased ancillary services required to mitigate the number of flexibility events down to the base case value (before increased renewable penetration) was determined both with and without battery storage resources included in the underlying portfolio mix. The difference in the cost to mitigate these flexibility events with and without battery storage was then used to quantify a flexibility benefit associated with increased battery storage penetration on a $/installed kW basis. The integration costs and associated battery storage benefit only considered the cost of mitigating additional flexibility violations and did not consider renewable integration costs associated with transmission and distribution. The results are summarized in the table below.

Table 2. Battery Storage Flexibility Benefit Results

	4GW Incremental Solar	8GW Incremental Solar	14GW Incremental Solar	2GW Incremental Wind	
Battery Storage Penetration (kW)	1,000,000	1,210,000	1,930,000	1,000,000	[A]
Incremental Renewable Energy (MWh)	7,644,296	15,395,217	27,009,997	6,132,386	[B]
Integration Cost Without Battery ($/MWh[2])	1.82	2.64	2.96	2.28	[C]
Integration Cost With Battery ($/MWh)	0.09	0	0	0.22	[D]
Integration Cost Reduction ($/MWh)	1.73	2.64	2.96	2.07	[E] = [D] – [C]
Total Battery Flexibility Benefit ($MM)	13.23	40.57	79.99	12.67	[F] = [E] * [B]
Battery Flexibility Benefit ($/kW)	13.23	33.41	41.38	12.67	[G] = [F] / [A]

Key takeaways from the analysis are listed below:

1. The 2028 and 2035 PCA portfolios were found to have a greater overall reliability value at the same UCAP PRM as the base case, corresponding to a capacity surplus of approximately 300-400MW.

[2] Incremental MWh produced by the incremental renewable installed capacity

a. The UCAP accreditation of the retired resources (Monroe) overestimates its reliability contribution relative to its ELCC value due to the large size of the individual units (approximately 750MW each). Large resources have disproportionate impacts on LOLE.
b. Replacing the UCAP value of Monroe with an equivalent ELCC value of renewable resources results in improved reliability[3] relative to the base case.

2. Technology specific average ELCC values are summarized in the table below, with a decline in solar ELCC from 50% at 781MW of installed capacity to 22% at 11,505MW of installed capacity. Wind and battery storage ELCC remain relatively static, with battery storage near 100% due to the penetration of solar resources (positive diversity benefit).

Table 3. Technology Specific Average ELCC % Values

	Base Case	2028 PCA	2035 PCA
Solar	50%	34%	22%
Wind	21%	19%	18%
Battery Storage	100%	99%	95%

3. The flexibility benefit of battery storage increases on a per kW installed capacity basis as solar penetration increases, ranging from $13.13/kW at 4GW of solar penetration to $41.38/kW at 14GW of solar penetration.

[3] Resource adequacy assessments assumes adequate transmission and distribution within LRZ7 to guarantee deliverability of incremental renewable energy

STUDY OVERVIEW

The scope of this analysis was restricted to modeling the loads and resources associated with MISO LRZ7 which covers the region in Michigan where DTE, as well as several other load serving entities (LSEs), are located. The map of LRZ7 is shown in Figure 4 below.

Figure 4. Map of MISO LRZ7

The analysis included three major scopes of work:

1. PCA Resource Adequacy Assessments
2. Variable Energy Resource Portfolio ELCC Assessments
3. Renewable Integration Flexibility Study

Each assessment was performed assuming the study year of 2025 using the SERVM modeling tool. An overview of SERVM and a summary of each assessment are described in the sections below.

SERVM OVERVIEW

SERVM (Strategic Energy & Risk Valuation Model) is a system-reliability planning and production cost model designed to analyze the capabilities of an electric system during a variety of conditions under thousands of different scenarios. While the production cost of the system is not relevant to the resulting reliability metrics of the system, using a full economic commitment and dispatch model results in a higher degree of accuracy of system reliability due to more realistic resource operational characteristics. The SERVM model chronologically simulates the economic commitment and dispatch of the system across all pre-defined scenarios, calculating numerous economic and reliability metrics for each. This process provides insight into risks and costs during these periods as well as the expectation of being able to meet peak load under various conditions. Understanding the results of the model helps a user understand and determine the amount of reserves an electric system requires to adequately meet peak demand. The model is also used for many other analyses including ELCC studies, fuel back up studies, Equivalent Forced Outage Rate (EFOR) improvement studies, and capacity valuations for upcoming peak seasons. SERVM also has the ability to conduct wind and solar integration studies as well as forecast production costs, energy margins, and market prices.

The major contributions to uncertainty considered in risk models such as SERVM include weather, economic forecast uncertainty, and unit performance. SERVM allows users to model future years based on historical weather patterns (typically 20 or more synthetic profiles[4]). The model is constructed using historical weather to predict loads and weather sensitive resource output (i.e., renewable and hydro) under these weather conditions based on projections of future customers and resources. For each weather year, 5 to 8 points of economic load forecast error are simulated, creating hundreds of distinct scenarios. Finally, each scenario is run with hundreds of unit outage draws creating thousands of iterations as a base case simulation. These results provide a comprehensive distribution of production costs, Expected Unserved Energy (EUE), Loss of Load Expectation (LOLE), Loss of Load Hours (LOLH), interruptible call summaries, and other metrics used for various types of studies. Expected values and confidence intervals can be calculated from the resulting distributions.

PCA RESOURCE ADEQUACY ASSESSMENT

The reliability assessment of three resource portfolios were performed in order to determine their reliability surplus or shortfall relative to the MISO LRZ7 UCAP PRM determination of 7.4%[5] for study year 2025. The analyzed portfolios were based on DTE's preliminary PCA portfolios for years 2028 and 2035, in addition to a base case portfolio representative of the current level of installed capacity of variable energy resources. The 2028 and 2035 portfolios correspond with significant retirements of coal resources, which are replaced with solar, wind, battery storage, and new combined cycle (CC) resources.

VARIABLE ENERGY RESOURCE PORTFOLIO ELCC ANALYSIS

In order to understand DTE's overall capacity obligation and potential capacity surplus/shortfall associated with each PCA, the total variable energy resource portfolio ELCC values as well as individual technology specific ELCC values were required. Determining the ELCC values for resources such as solar, wind, and battery storage allow for appropriate accounting of the load and capacity balance of the system, and aid in the iterative capacity expansion modeling process to ensure that the reliability value of resources being added adequately offset the reliability value of resources being retired. Technology specific ELCC allocations were determined utilizing an ELCC portfolio

[4] Profiles constructed based on recent historical relationships. See the SERVM Model Development section below for more details.
[5] Page 26, Planning Year 2022-2023 Loss of Load Expectation Study Report, MISO https://cdn.misoenergy.org/PY%202022-23%20LOLE%20Study%20Report601325.pdf

analysis of dozens of LRZ7 resource mix scenarios at various levels of solar, wind, and battery storage penetration.

RENEWABLE INTEGRATION FLEXIBILITY STUDY

Lastly, a renewables integration study was developed to quantify the benefit that battery storage resources provide in mitigating intra-hour flexibility violations. Intra-hour flexibility violations are defined as an imbalance between the net load and generation due to the system's inability to ramp up resources to account for a sudden change in solar/wind production. As renewable penetration increases for a given system, the expected number of flexibility violations are expected to increase given a greater amount of energy is served by these volatile resources. The production cost of increased ancillary services required to mitigate the number of flexibility events down to the base case value (before increased renewable penetration) was determined both with and without battery storage resources included in the underlying portfolio mix. Battery storage resources can be used to resolve flexibility events at lower cost than fossil resources as they can provide spinning reserves with minimal associated variable O&M (VOM) costs. The difference in the cost to mitigate the additional flexibility events caused by increased renewables with and without battery storage was used to quantify a flexibility benefit associated with battery storage.

SERVM MODEL DEVELOPMENT

MISO LRZ7 was modeled and evaluated using the SERVM model as described in the subsections below.

UNCERTAINTY FRAMEWORK

Modeling inputs used to simulate the potential uncertainty associated with weather, unit performance, and load forecast error for the PCA portfolios, ELCC scenarios, and integration study are summarized in the sections below.

WEATHER YEARS

Key reliability and economic metrics were evaluated across a total of 41 weather years, representing weather conditions approximating the years 1980-2020.[6] For each weather year, loads were developed such that the median peak demand across the 41-year period would equal the expected weather-normal peak load. Each weather year was presumed to have the same probability of occurrence. An additional sensitivity was performed to determine the difference in LOLE that results in applying a higher probability weighting to warmer historical weather years to reflect historical trends in increased temperatures. This sensitivity is discussed in more detail in the Study Methodology and Results section.

PEAK DEMAND FORECAST UNCERTAINTY

For each weather year evaluated, a total of 5 peak demand forecast errors were modeled. Peak demand forecast uncertainty represents the economic component of demand uncertainty and represents the expected peak demand forecast error due to economic uncertainty when forecasting three years out.[7] All hours of load are adjusted by the peak demand uncertainty multipliers to reflect a higher or lower load condition for the particular economic condition, as appropriate. Each peak demand uncertainty has its own probability of occurrence. Thus, a total of 205 unique cases per scenario (41 weather years x 5 peak demand forecast errors) were evaluated. The table below shows the forecast uncertainty and probability of occurrence for the five peak demand error assumptions used in this study. Negative demand uncertainty indicates over forecast. Positive demand uncertainty indicates under forecast.

[6] By comparison, the MISO uncertainty framework only considers the 30 weather years comprising 1990-2019.
[7] The multipliers values were derived using the forward-looking error in Congressional Budget Office forecasts of GDP over the last 30 years. The probability of GDP error looking forward three years was developed and a 40% multiplier was applied to reflect the fact that electric growth is less than GDP. By comparison, the MISO uncertainty framework uses a 1-year out peak demand uncertainty matrix.

Table 4. Peak Demand Uncertainty

Peak Demand Uncertainty	Probability of Occurrence
-4%	6%
-2%	24.2%
0%	39.5%
2%	24.2%
4%	6%

OUTAGE UNCERTAINTY

For each scenario, each of the 205 weather/demand cases were then simulated multiple times (i.e., unique iterations), with a different random draw of unit outages. SERVM models outages by taking a random draw of "time to fail" and "time to repair" variables for each generating unit. The distributions of "time to fail" and "time to repair" are based on historical duration (expressed in hours) of failure and operating periods, respectively[8]. Each unit operates until it reaches its appointed time to fail and then remains on forced outage for the duration of the time to repair. Then another set of time to fail and time to repair variables are randomly drawn. These variables are developed in such a way that, with sufficient iterations, each unit and the system will converge to its expected EFOR value. Outage events can occur any hour of the day. In this analysis, 30 iterations were simulated for each of the 205 cases for the PCA portfolio analysis and ELCC analysis. For the integration study, 15 iterations were simulated.

PEAK DEMAND FORECAST

The zonal non-coincident peak load for MISO LRZ7 for the study year 2025 was modeled to be 20,742MW. Demand for DTE was provided by DTE. The non-DTE non-coincident peak demand was approximated to be equivalent to the DTE peak load as a simplifying assumption based on total LRZ7 peak load forecasts published by MISO[9]. This peak demand is inclusive of transmission losses and energy efficiency impacts.

LOAD SHAPES

Within SERVM, Astrapé modeled one load shape for the zone for each weather year. Since publicly available information for the balance of the zone was not available, it was assumed that the load shape of the zone is consistent with the DTE load shape. Therefore, the zonal load shape was developed using DTE historical hourly load shapes for the years 2015-2019 provided by DTE.

[8] Historical event durations sourced from GADS outage data for DTE units, described in more detail in the sections below

[9] Page 27, Planning Year 2022-2023 Loss of Load Expectation Study Report, MISO https://cdn.misoenergy.org/PY%202022-23%20LOLE%20Study%20Report601325.pdf

The following steps were used to develop the DTE load shapes. A similar process was used for the zonal shapes.

1. Historical hourly loads for 2015-2019 were grossed up based on economic indicators to a common economic year basis (2019). To gross up these values, a set of summer peak load hours for each year and winter peak load hours for each year were compared to determine the economic growth adjustment needed to gross each year up to the levels observed in 2019. The hourly load shape for each year was then adjusted by this economic adjustment factor.

2. The grossed up historical loads, along with corresponding temperature data from the National Oceanic and Atmospheric Administration (NOAA), were fed into a neural network model to create seasonal "networks". The seasons were defined as winter (December, January, and February), summer (June – September), and shoulder (all other months). The inputs for the neural network model were temperature, hour of week factor, and then rolling average temperature from the past 8, 24, and 48 hours.

3. Historical temperatures from the Detroit Metropolitan Wayne Country Airport weather station of NOAA for each of the 41 historical weather years (1980-2020) were fed into the Seasonal "networks" to create "synthetic" loads for each weather year. Where any gaps or errors in the Detroit Metropolitan Wayne County Airport weather station data were found, the Pontiac weather station was used as a secondary source to supplement the data.

4. The resulting synthetic loads were then adjusted to achieve more realistic results. First, based on the diversity within the historical data, a 3% "random walk" adder was applied to each hourly result. Second, for hours where temperatures were outside the reasonable range of the trained networks, loads were manually adjusted by using a MW/degree value determined from the historical data.

5. Because certain extreme temperatures occur so infrequently, the trained neural networks are unable to develop strong correlations between extreme temperature conditions and historical loads. To improve forecast accuracy for extreme conditions, linear correlations between daily peak loads and daily maximum temperatures (daily minimum temperatures for winter) were developed outside the neural network model to assess the change in load per degree change in the weather. The linear relationships were then applied to any summer daily peak load hour at or above 85 degrees or any winter daily peak load hour at or below 14 degrees in lieu of the of the neural network results. Additional smoothing of the daily load profile was applied to the 8 load hours before and after the extreme temperature daily peak. The figures below show the trend that resulted in the peak condition adjustment of 122.38 MW/Degree F for summer afternoons, winter peak condition adjustments of -23.69 MW/Degree F for winter afternoons, and winter peak condition adjustments of -18.22 MW/Degree F for winter mornings.

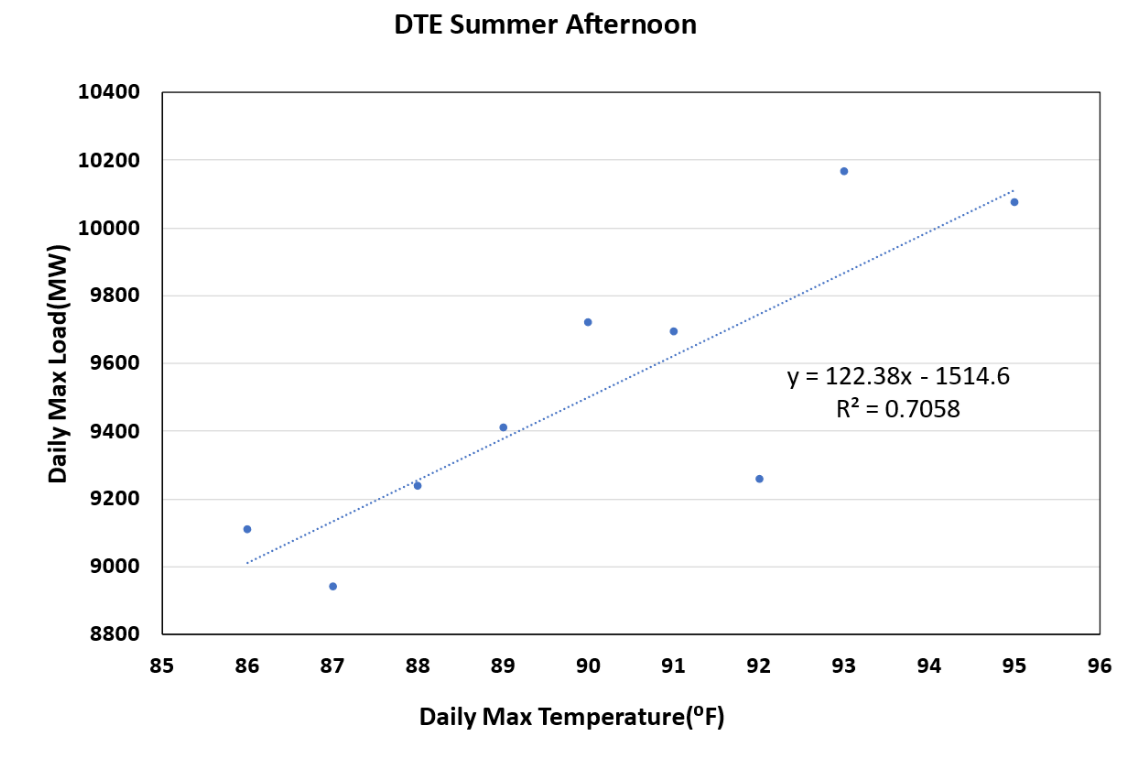

Figure 5. Summer Afternoon Extreme Temperature Load Trend

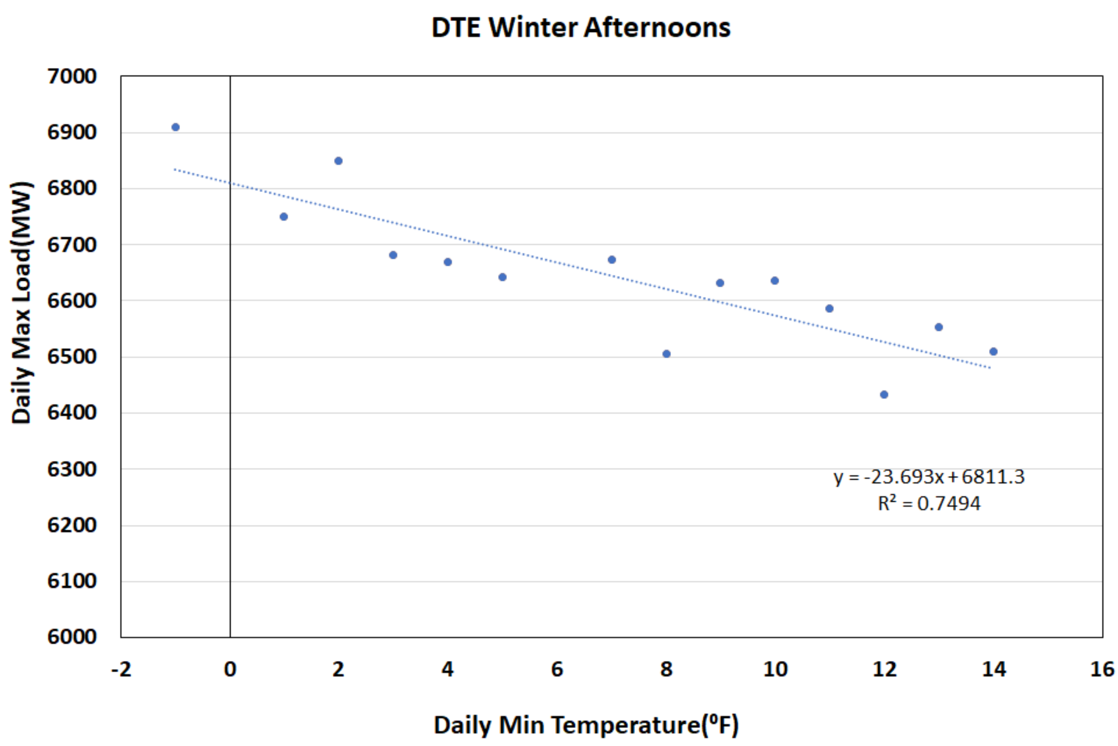

Figure 6. Winter Afternoon Extreme Temperature Load Trend

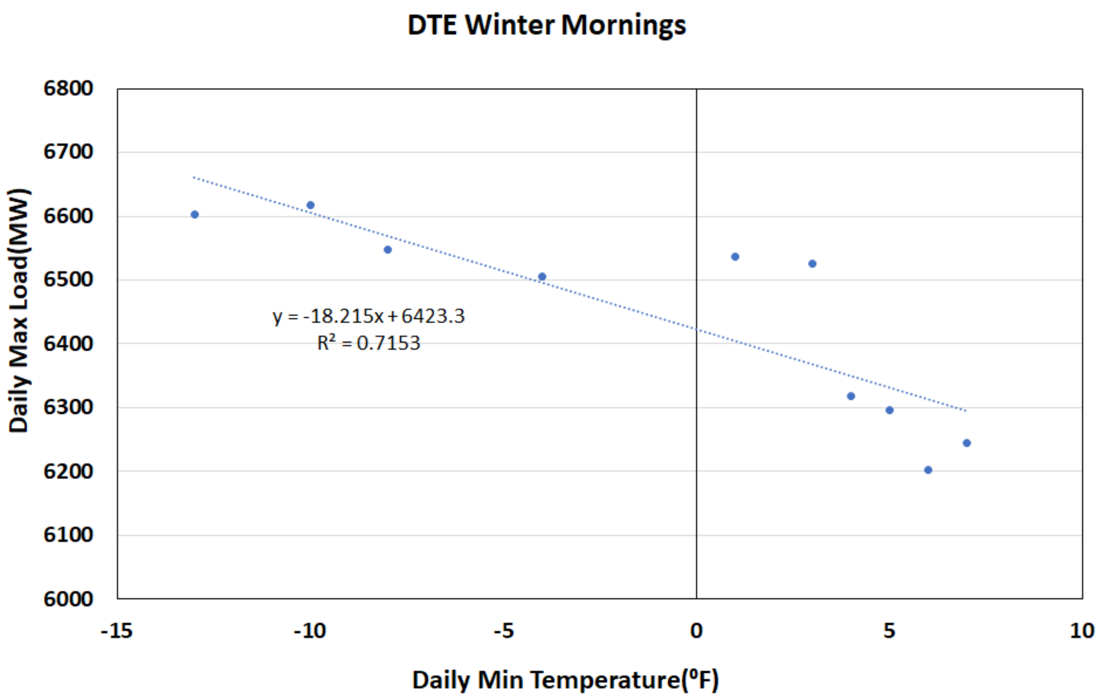

Figure 7. Winter Morning Extreme Temperature Load Trend

The two figures below show a comparison (for summer and winter, respectively) of the load shape for a typical day for the historical load and for an aggregation of all the synthetic weather years, demonstrating that the synthetic loads produce shapes consistent with historical load shapes.

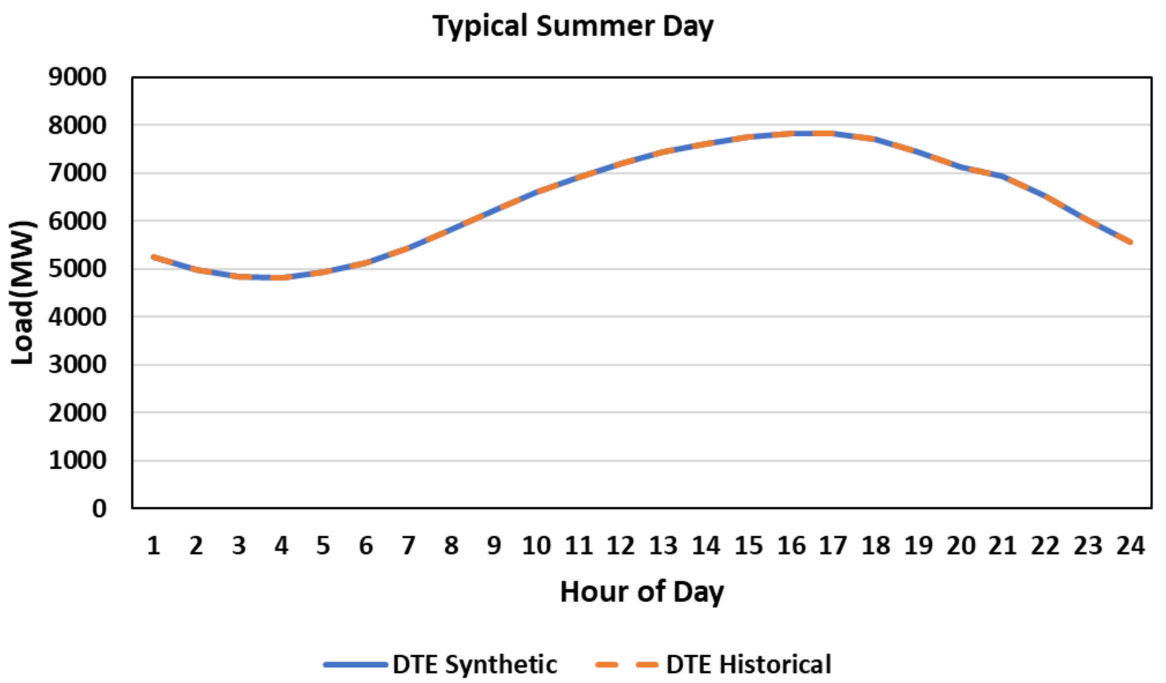

Figure 8. DTE Typical Summer Day Load Shape

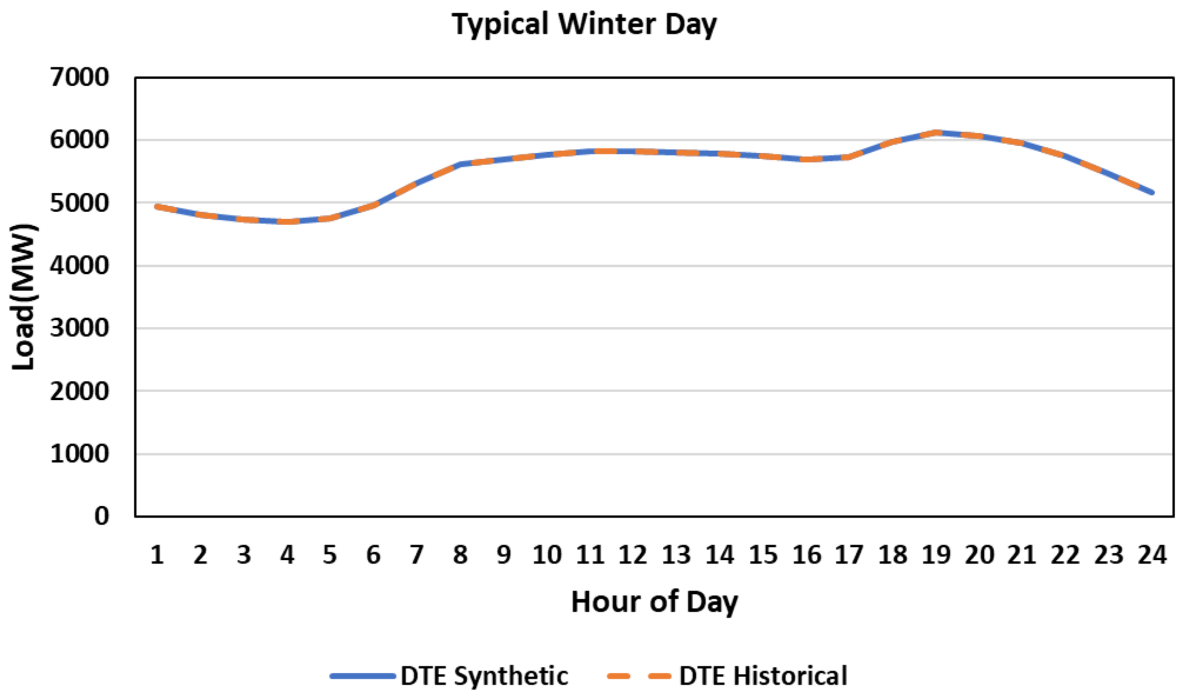

Figure 9. DTE Typical Winter Day Load Shape

Because temperature is such a driving factor in the development of the synthetic loads, the figure below shows a distribution of daily peak demands as a function of temperature as compared to the historical daily peak demands. The graph differentiates between weekdays and weekends/holidays to highlight why certain days with temperatures near or above 100 °F have loads below 10 GW. This figure demonstrates that the overall sensitivity of the synthetic loads to temperature is consistent with the sensitivity of the actual historical loads to temperature. Thus, the loads developed for a given weather year are shown to be a reasonable representation of the expected loads of the analyzed study year assuming the same weather conditions.

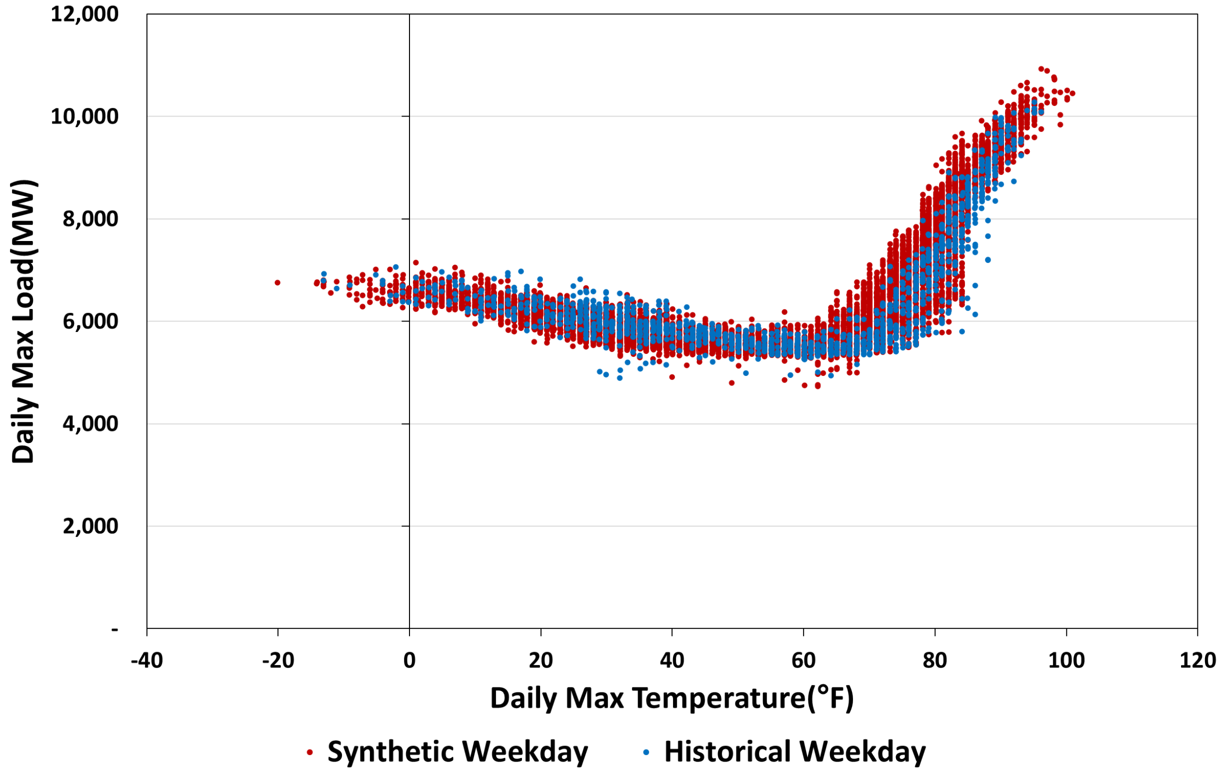

Figure 10. Comparison of Synthetic and Historical Daily Peak Loads

Finally, the figure below shows a distribution of the annual peak demand resulting from the development of the 41 years of synthetic loads, shown as a deviation from the forecasted value. This figure demonstrates the overall expected diversity of peak demand as a function of weather. Based on the 41 years of synthetic loads, peak demand can be expected to deviate (roughly) -7% to +8% from the weather normal forecast depending upon the weather. The figure also demonstrates that winter peak demand volatility is less than summer peak demand volatility. The 41 weather years that are modeled thus capture this weather diversity and its impact on reliability.

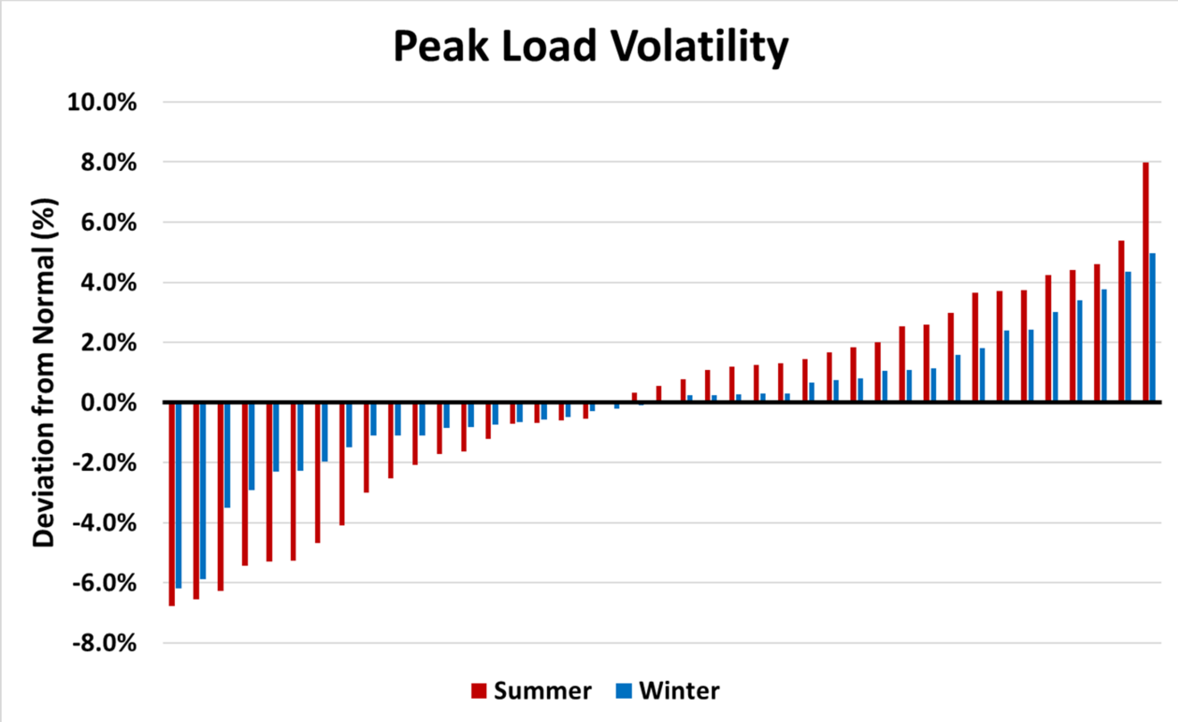

Figure 11. DTE Synthetic Load Peak Demand Volatility

RESOURCE MODELING

Resources were modeled based on a combination of publicly available information[10] as well as information provided by DTE. The figure below shows a summary by category of the total summer capacity modeled for LRZ7. Renewable resources are those presumed to be online by 2025 before any additional PCA portfolio planned additions. It also should be noted that the modeled generation reflects a significant amount of independently owned generation (i.e., not belonging to the major utilities within MISO LRZ7) as identified in the EIA Form 860.

[10] Primarily the Energy Information Administration (EIA) Form 860.

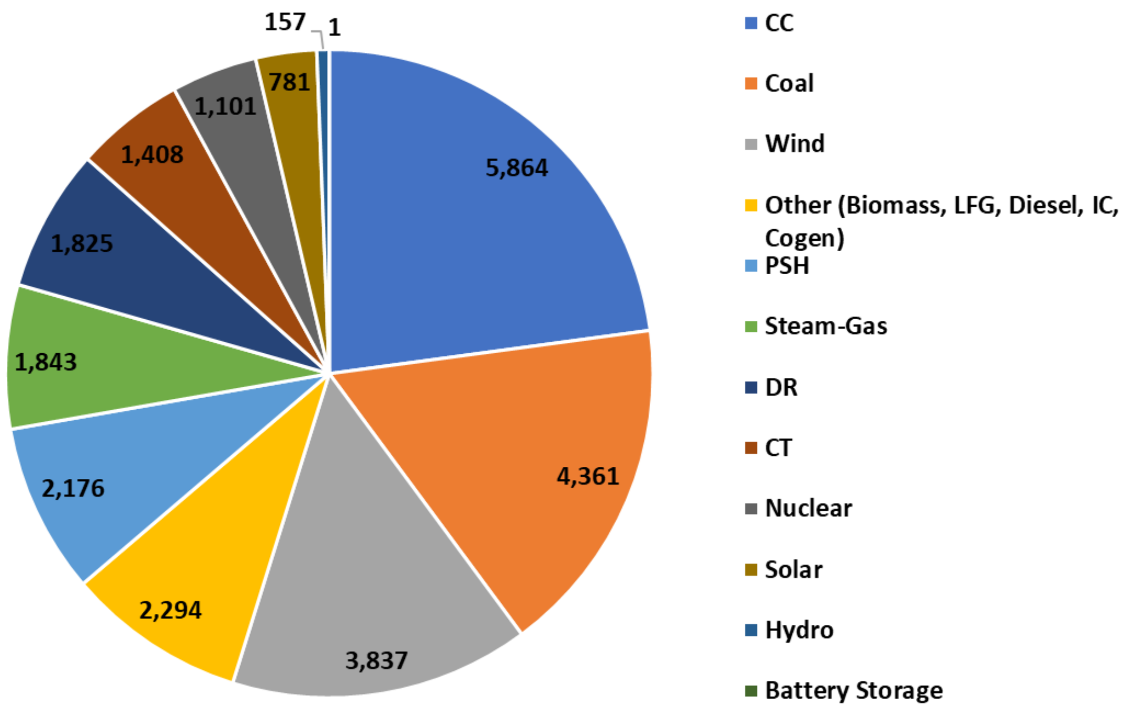

Figure 12. 2025 LRZ7 Base Case Resource Summary by Category (Installed Capacity MW)

The sub-sections below provide greater detail concerning the modeling of the different classes of resources as appropriate.

HYDRO RESOURCES

The hydro resources in LRZ7 were all aggregated into a single unit with monthly available hydro energies and a monthly daily minimum and maximum energy flow. SERVM schedules such available energy based on expected load conditions. Monthly values were developed using 5 years of hourly data (2016-2020) for the MISO central region and scaled to match hydro capacity for LRZ7. The hydro energy for 2016-2020 was averaged to obtain an average monthly energy to apply to the relationship between hydro energy and monthly maximum, daily average maximum, and daily average minimum. The figure below shows the relationship between dispatch capacity and monthly hydro energy for the monthly maximum, daily average maximum, and daily average minimum.

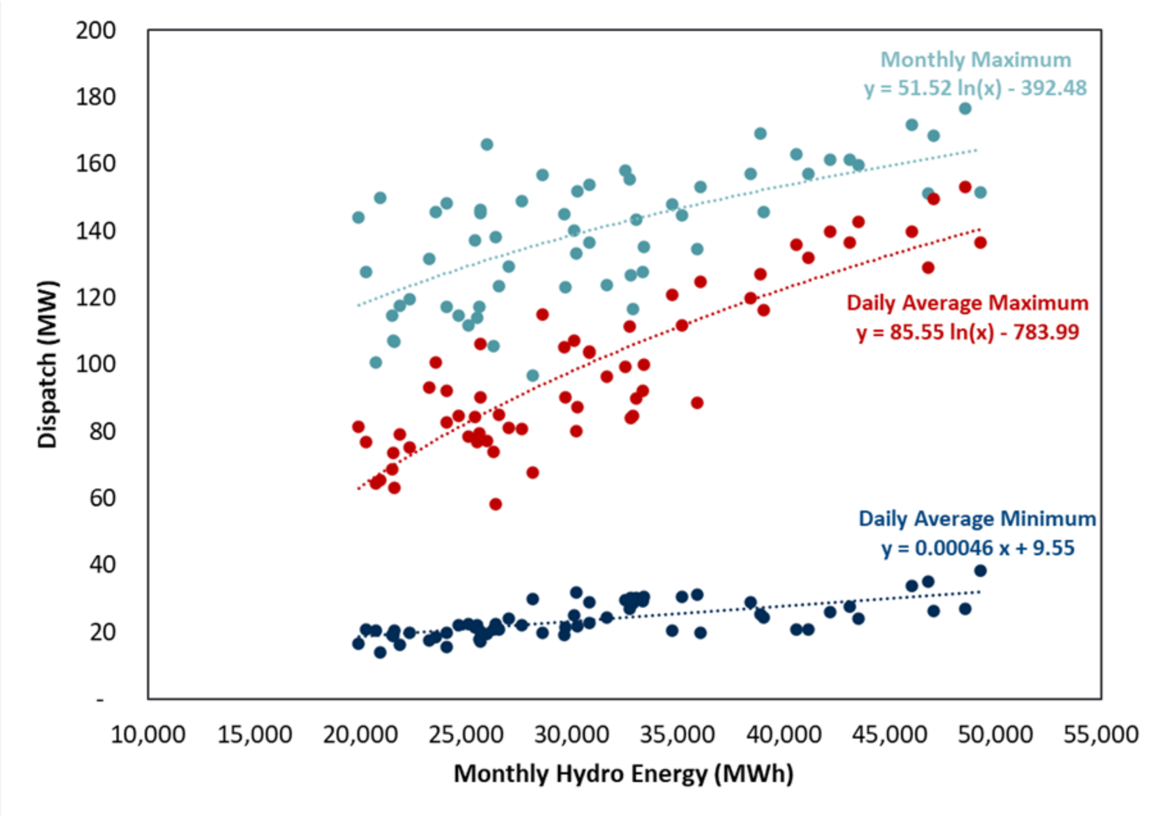

Figure 13. Relationship of Monthly Hydro Energy and Dispatch

From the relationships shown in the figure above and using historical available monthly hydro energies, the following hydro modeling parameters were developed for each month of each weather year: capacity values, average daily energy, total energy, and min and max schedule flow values.

CONVENTIONAL RESOURCES

The EIA 860 and the unit data provided by DTE served as the source of data for minimum and maximum capacities, heat rates, fuel sources, fuel costs, ramp rates, and forced and planned outage rates. To account for the differences in summer and winter output values, the temperature output curves in the figure below were applied to the unit capacity values.

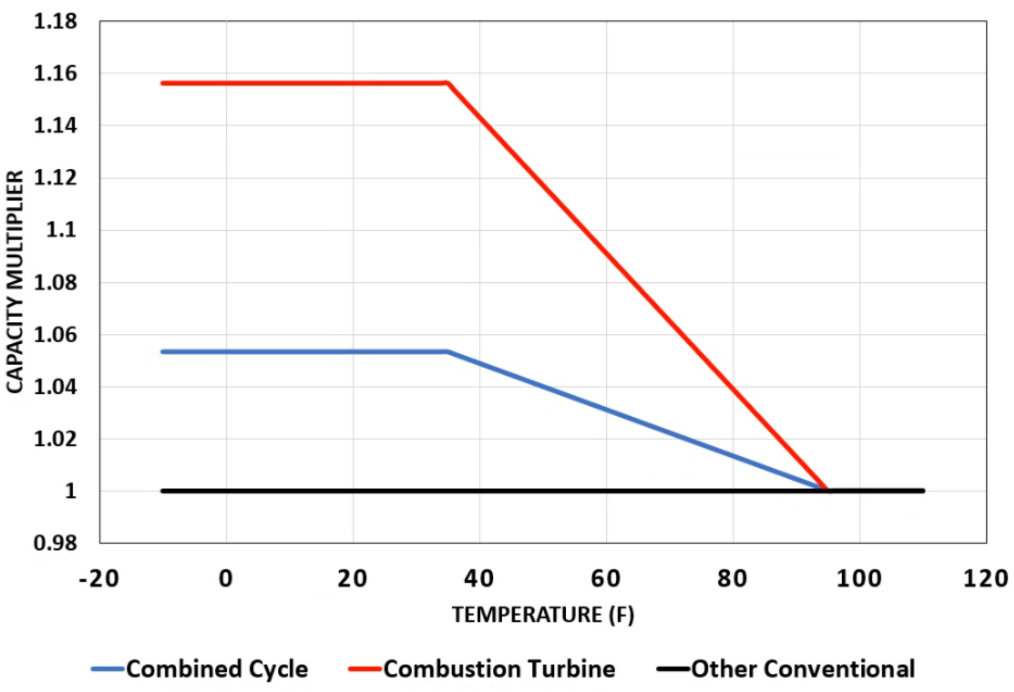

Figure 14. Temperature Output Curves by Technology

Because this analysis is focused more on reliability than production cost, it was determined that gaps in the generation data could be filled using generic values. Average heat rates were used where specific heat rate curves were not available. Where fuel costs were not available for non-DTE resources, fuel costs were based on similar unit types from DTE provided fuel cost data.

Table 5. 2025 Fuel Costs

Fuel Source	Price ($/MMBtu)
Uranium	0.69
Coal	1.95
Natural Gas	3.37
Oil	15.99
Biomass	2.1
Landfill Gas (LFG)	2.83

As described in the Uncertainty Framework section above, SERVM uses random draws of “time to fail” (TTF) and “time to repair” (TTR) variables to modeled forced outages. Multiple iterations of these random draws can converge to the desired EFOR for both the unit and the system if the TTF and TTR values have been developed appropriately. Using this model, the EFOR for any given unit would be determined using the following equations:

$$\frac{TTR}{(TTR + TTF)}$$

$$POR = \frac{POTTR}{(POTTR + POTTF)} * DP$$

$$EFOR = FOR + (1 - FOR) * POR$$

Where:

FOR= Forced Outage Rate

POR=Partial Outage Rate

DP= Partial Outage (Derate) Percentage

TTR=Time to Repair

TTF=Time to Fail

POTTR=Partial Outage Time to Repair

POTTF=Partial Outage Time to Fail

EFOR=Equivalent Forced Outage Rate

For this analysis, EFOR for DTE units was determined using 5 years of GADS data provided by DTE (2016-2020). From that data, a distribution of TTR, TTF, POTTR, and POTTF values were developed. Where GADS data was not available (particularly for non-DTE units), outage data referenced similar units for which GADS data was available. The above formulation often results in very high EFOR for units with very low capacity factors. Thus, for any unit whose GADS data resulted in an EFOR greater than 20%, the TTR and TTF data were adjusted so that EFOR would be targeted at 20% under reasonable operating conditions.

The resulting modeled EFORs by unit category are shown in the table below. The EFORs are approximate and may vary slightly from scenario to scenario, depending upon operation and whether resources of that class have been excluded, but remain generally in this range.

Table 6. Modeled Base Case EFOR by Unit Category

Unit Category	DTE	Non-DTE
Biomass	N/A	14.7
CC	3.6	3.6
Coal	7.3	N/A
CT	3.6	8.9
CT-Oil	22.5	N/A
Diesel	9.8	N/A
IC-Gas	17.9	10.5
IC-Oil	19.9	N/A
LFG	9.8	N/A
Nuclear	2.9	N/A
PSH	4.9	4.9
Steam-Gas	2.7	6.9

Planned outages were modeled using a planned maintenance rate calculated from the GADS data. Where GADS data was not available, a generic planned outage rates of 5% was used.

LOAD MODIFYING RESOURCES

Two types of load modifying resources[11] were modeled: demand response (DR) and energy efficiency (EE).

DR was modeled as curtailable resources with constraints dependent upon the particular program. The following table defines how the DTE and non-DTE interruptible loads were modeled. In addition to the constraints, annual hourly profiles were provided by DTE indicating the expected demand response potential as percent of its annual maximum capacity value. SERVM utilized these profiles to limit the dispatched capacity for a particular resource in a given hour if the resource was called during the simulation.

[11] This term is used generally and is not meant to be synonymous with MISO's definition of an LMR.

Table 7. Interruptible Load Summary

Program	Max Capacity	Allowable Dispatch Hours per Day	Time of Day	Seasonal	Max Calls per Year
DTE AC	255.66	8	HE1-24	Annual	N/A
DTE BYOD	61.22	24	HE13-20	Summer	14
DTE Capacity Release	61.22	24	HE1-24	Summer	N/A
CVR	51.7	24	HE1-24	Annual	N/A
DTE Hot Water	29.12	4	HE1-24	Annual	N/A
DTE Other (Legacy)	558.8	24	HE1-24	Annual	2
DTE SmartCurrents	16.7	4	HE16-19	Annual	14
CMS DR[12]	814	24	HE1-24	Annual	N/A

The amount of EE to model for the zone was determined by comparing the zonal peak demand forecast with and without the effects of EE. For the 2025 study year, this resulted in an EE resource with a capacity of 1,372 MW. The EE resource itself was modeled as an hourly injection into the system (similar to a renewable resource) with a load shape consistent with that provided by DTE. The table below represents the normalized average daily load reduction of the energy efficiency resource for each month of the year. Multipliers are applied to the maximum capacity value of 1,372 MW to determine the load reduction for each hour of the year in the simulation. EE was only modeled for the simulations used in developing the incremental last in ELCC curves for solar and battery storage, and the renewable flexibility integration study. For the PCA resource adequacy assessment, the modeled peak load was considered to be net of energy efficiency.

[12] Non-DTE resource limited to only 1000 hours of dispatch per year

Table 8. Heat Map of EE for LRZ7 (12 Months x 24 Hours)

	1	2	3	4	5	6	7	8	9	10	11	12
1	0.63	0.63	0.62	0.60	0.58	0.62	0.64	0.63	0.59	0.59	0.60	0.62
2	0.61	0.61	0.60	0.58	0.56	0.58	0.60	0.60	0.57	0.57	0.58	0.60
3	0.59	0.59	0.57	0.57	0.55	0.56	0.58	0.58	0.55	0.56	0.56	0.58
4	0.58	0.58	0.56	0.55	0.53	0.53	0.55	0.55	0.53	0.54	0.55	0.57
5	0.59	0.59	0.58	0.57	0.54	0.56	0.57	0.56	0.55	0.55	0.56	0.58
6	0.62	0.62	0.61	0.60	0.57	0.59	0.60	0.60	0.59	0.59	0.60	0.61
7	0.67	0.67	0.65	0.64	0.61	0.65	0.67	0.65	0.65	0.63	0.64	0.66
8	0.74	0.73	0.70	0.70	0.67	0.71	0.74	0.73	0.70	0.69	0.70	0.72
9	0.77	0.76	0.74	0.72	0.71	0.77	0.82	0.79	0.76	0.73	0.72	0.75
10	0.78	0.77	0.75	0.74	0.73	0.80	0.86	0.83	0.78	0.74	0.74	0.77
11	0.80	0.79	0.76	0.75	0.77	0.83	0.89	0.86	0.80	0.76	0.75	0.78
12	0.79	0.79	0.75	0.74	0.77	0.84	0.91	0.89	0.81	0.76	0.75	0.78
13	0.79	0.78	0.75	0.74	0.78	0.87	0.92	0.90	0.82	0.76	0.75	0.77
14	0.79	0.79	0.75	0.74	0.78	0.88	0.94	0.92	0.84	0.76	0.75	0.78
15	0.79	0.79	0.75	0.74	0.78	0.89	0.94	0.93	0.84	0.76	0.75	0.78
16	0.78	0.78	0.74	0.72	0.77	0.87	0.94	0.92	0.83	0.75	0.74	0.77
17	0.79	0.78	0.74	0.72	0.75	0.86	0.91	0.88	0.80	0.74	0.74	0.78
18	0.84	0.82	0.77	0.74	0.75	0.84	0.90	0.86	0.79	0.75	0.77	0.82
19	0.89	0.88	0.82	0.77	0.75	0.82	0.88	0.85	0.77	0.78	0.81	0.88
20	0.91	0.89	0.84	0.80	0.77	0.81	0.87	0.85	0.78	0.79	0.83	0.88
21	0.85	0.85	0.83	0.80	0.80	0.82	0.87	0.85	0.80	0.80	0.81	0.84
22	0.81	0.81	0.79	0.78	0.77	0.79	0.83	0.82	0.77	0.77	0.77	0.79
23	0.73	0.73	0.72	0.71	0.71	0.73	0.77	0.76	0.71	0.70	0.70	0.71
24	0.67	0.67	0.65	0.65	0.64	0.66	0.69	0.69	0.64	0.64	0.65	0.65

SOLAR RESOURCES

Base case solar resources (those expected by 2025) were identified as being at 32 locations in 12 "solar modeling" zones as identified in the figure below and the table following.

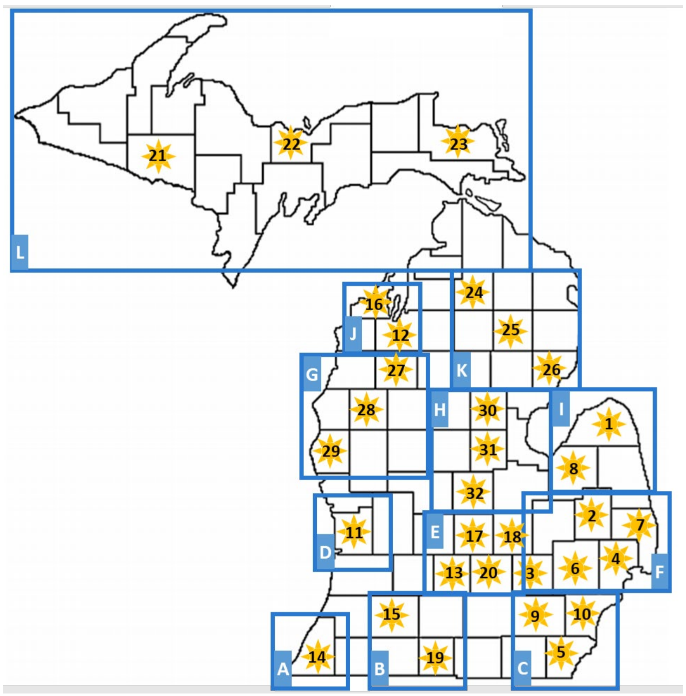

Figure 15. Solar Modeling Locations

Table 9. Existing Solar Project Locations

Map #	Map Letter	County Name	Latitude	Longitude
1	I	Huron	43.81	-82.98
2	F	Lapeer	43.05	-83.22
3	F	Livingston	42.57	-83.94
4	F	Macomb	42.65	-82.98
5	C	Monroe	41.89	-83.54
6	F	Oakland	42.61	-83.34
7	F	St. Clair	42.97	-82.70
8	I	Tuscola	43.45	-83.38
9	C	Washtenaw	42.25	-83.78
10	C	Wayne	42.25	-83.30
11	D	Ottawa	42.93	-86.02
12	J	Grand Traverse	44.65	-85.58
13	E	Eaton	42.61	-84.86
14	A	Berrien	41.93	-86.38
15	B	Kalamazoo	42.25	-85.58
16	J	Leelanau	44.85	-85.82
17	E	Clinton	42.93	-84.58
18	E	Shiawassee	42.93	-84.14
19	B	Branch	41.93	-85.02
20	E	Ingham	42.61	-84.38
21	L	Iron	46.17	-88.54
22	L	Alger	46.29	-86.90
23	L	Chippewa	46.33	-84.74
24	K	Ostego	45.01	-84.62
25	K	Oscoda	44.69	-84.14
26	K	Iosco	44.37	-83.66
27	G	Wexford	44.33	-85.54
28	G	Lake	43.93	-85.82

29	G	Oceana	43.61	-86.26
30	H	Gladwin	43.93	-84.38
31	H	Midland	43.57	-84.38
32	H	Gratiot	43.25	-84.66

For purposes of this analysis, fixed-axis and single-axis tracking profiles were developed for each of the 12 solar modeling zones. All solar resources within that zone were pointed to the fixed or tracking profile as appropriate.

For each of the 12 modeled locations, irradiance and weather data was downloaded from the NREL National Solar Radiation Database for the years 1998-2019. Fixed and tracking solar profiles were then developed using the System Advisor Model (SAM) and used as appropriate for the 1998-2018 weather years. Profiles for the remaining weather years were determined on a day-by-day basis from the source (i.e., SAM) solar profiles. For each day in the synthetic weather year, the daily peak load was compared to each day in the source data. For the day that most closely matched the synthetic load data, that day +/- 2 days (5 days total) were isolated and the daily solar profile from one of those 5 days was chosen at random to be the profile for the synthetic weather year day.

The following figures show the resulting average summer daily shape for each of the 12 fixed and tracking profiles, respectively. The table following the two figures shows the resulting capacity factor for each profile.

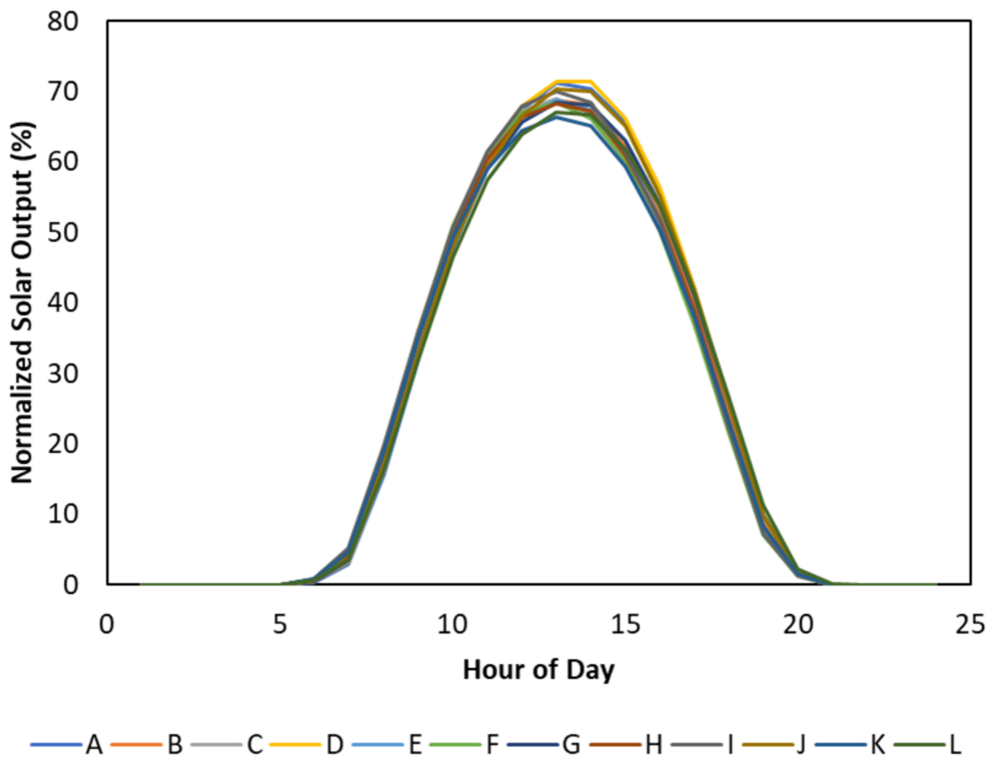

Figure 16. Fixed Profile Average Summer Daily Shape

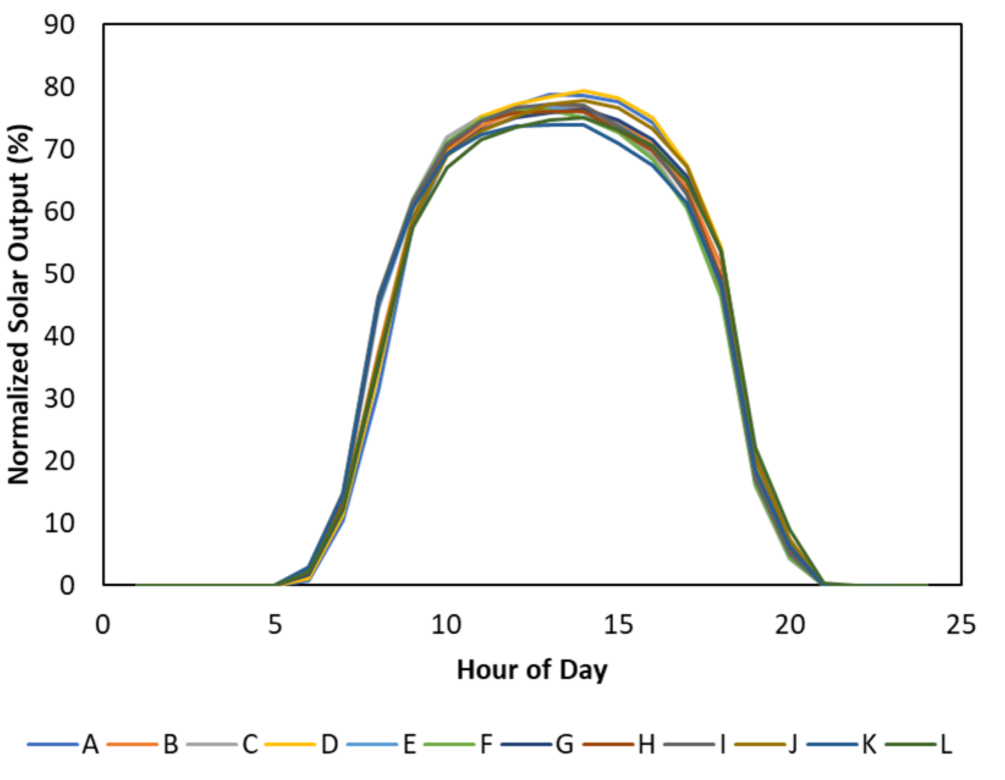

Figure 17. Tracking Profile Average Summer Daily Shape

Table 10. Solar Profile Annual Capacity Factors

Map Location	Tracking	Fixed
A	23.1	17.1
B	23.2	17.1
C	23.6	17.3
D	23.1	17.1
E	23.3	17.0
F	23.3	17.1
G	23.0	17.0
H	23.5	17.2
I	23.2	17.1
J	22.7	16.9
K	23.3	17.0
L	23.2	17.1

Future solar resources were only modeled as single-axis tracking resources and were assumed to be concentrated in southeastern Michigan (B, C, E, F, H, I, and K).

WIND RESOURCES

Wind shapes used in this analysis were those prepared for MISO for LRZ2 and LRZ7 and were used by permission of MISO.

These shapes were originally developed based on 2011-2019 historical data. Shapes for 1980-2010 were selected based on finding the most closely matched peak load from the synthetic load shapes during the 2011-2019 timeframe (within +/- 6 days of the source day). For example, if the synthetic peak load for 1/1/1980 most closely matched the synthetic peak load for 1/1/2019, then the daily load shape for 1/1/2019 was used as a proxy for 1/1/1980.

Since this analysis presumes the addition of a considerable amount of new wind, it is likely that such new wind will be more efficient with higher capacity factors. The target aggregate capacity factor of 35%, which represents the likely aggregate capacity factor including the newer resources, was used to adjust the per unit MISO wind profiles. To adjust the profiles, a gradient adjustment was applied for all per unit values below 65%. The gradient was applied such that the largest adjustments were made in the valley periods, with less towards the higher outputs up to 65% of nominal output. No adjustment was made for hours above 65% of nominal output. This adjustment was made to the hourly shapes until the aggregate capacity factor reached 35%. The figure below shows an example of a day in which this adjustment was made.

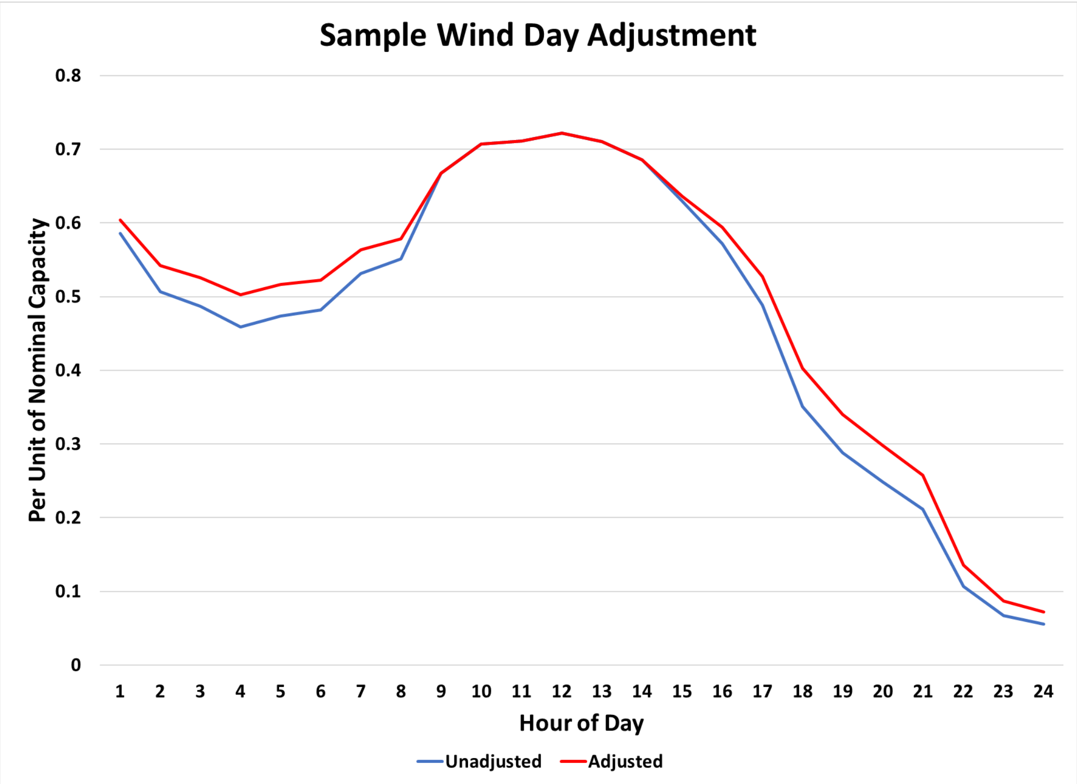

Figure 18. Example of Wind Shape Adjustment

As an indication of the magnitude of the adjustments made, the figure below shows the LRZ2/LRZ7 average summer wind shape before and after capacity factor adjustment.

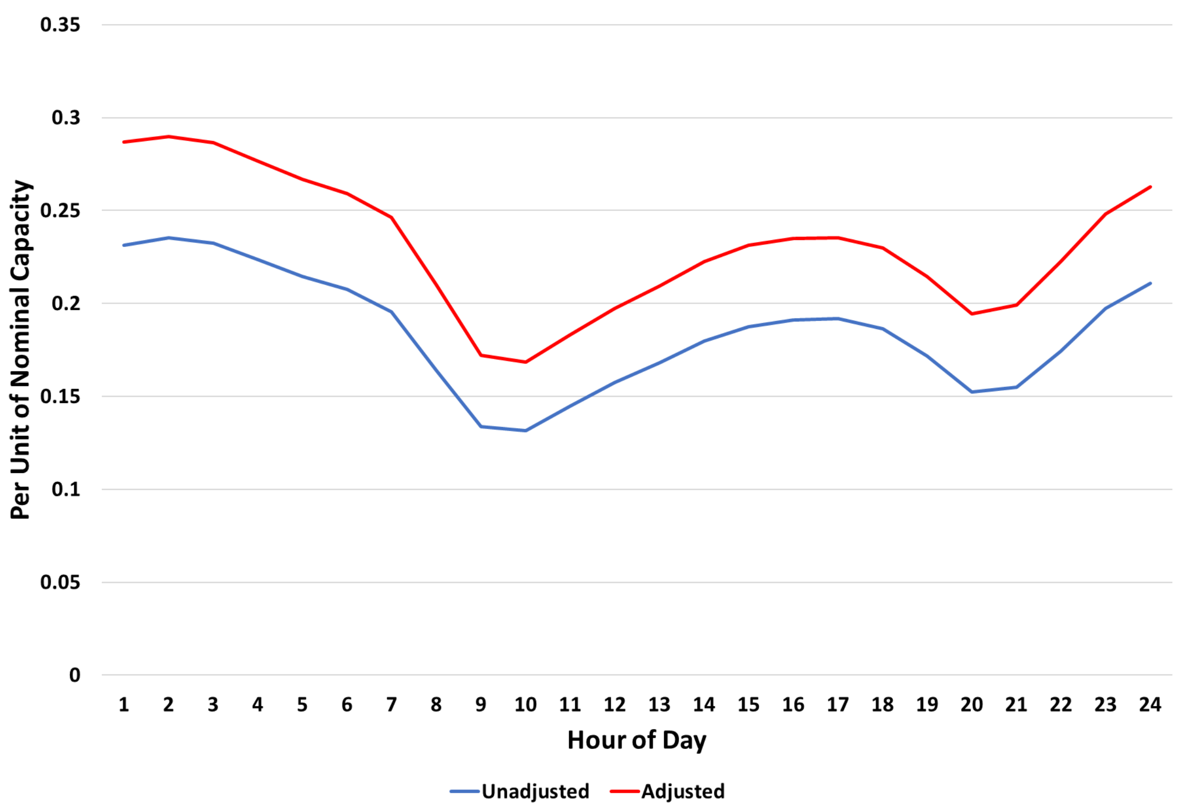

Figure 19. LRZ2/LRZ7 Summer Wind Shape Adjustment

The figure below shows the LRZ7 monthly aggregate wind shapes after final adjustments.

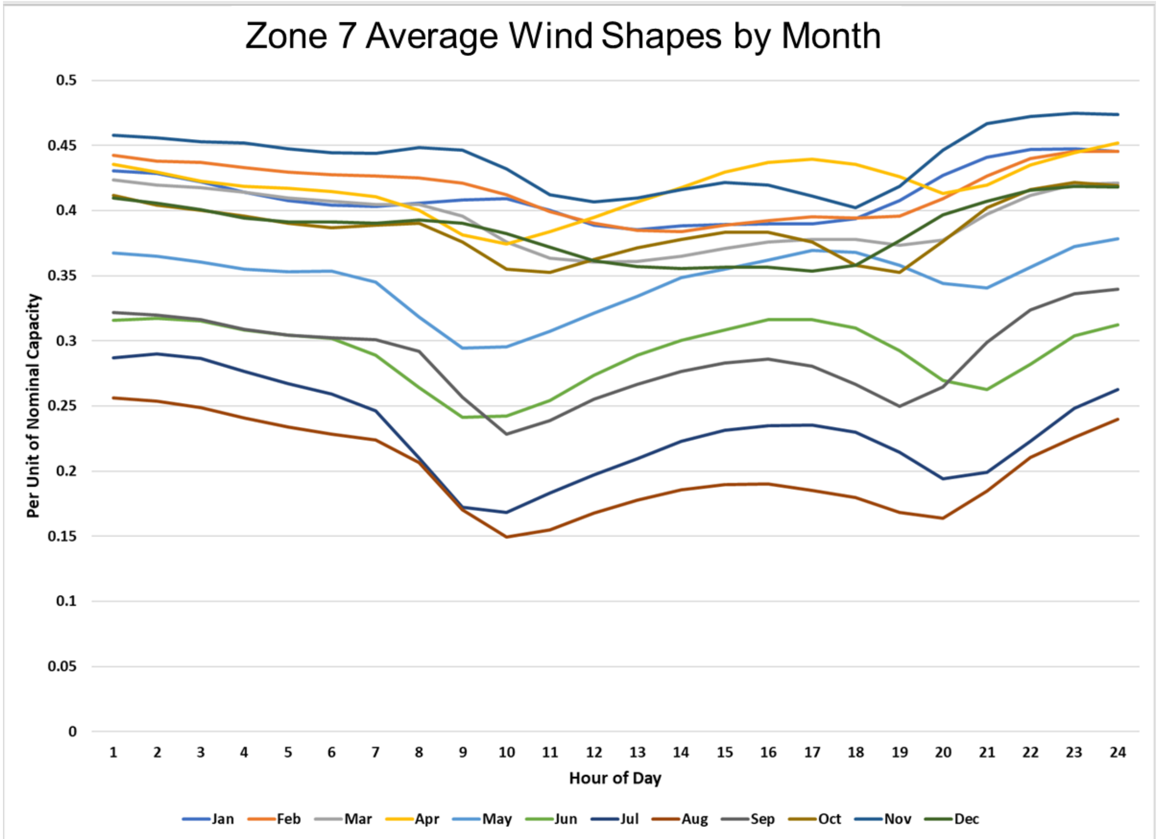

Figure 20. LRZ7 Monthly Wind Shapes

STORAGE RESOURCES

Several new battery storage resources are modeled similarly to Pumped Storage Hydro (PSH) facilities, but with different parameters. The basic parameters needed for modeling storage resources and the assumptions used in this analysis for those parameters are shown in the table below.

Table 11. Storage Modeling Assumptions

Characteristic	Battery Storage	PSH
Maximum Discharge Capacity	Nominal MW	Nominal MW
Minimum Discharge Capacity	0 MW	60% of capmax
Storage Capability	4 Hours	8.5-9 Hours
Cycle Efficiency	85%	90%
Maximum Charge Capacity	Nominal MW	Nominal MW
Minimum Charge Capacity	0 MW	Nominal capmax
Quick Start Capability	Yes	No
Emergency Dispatch Price	$1000/MWh	$500/MWh

Storage capacity is generally related to the maximum capacity and is based on the “number of hours of storage” being studied. For example, a 100 MW battery storage resource that has 4 hours of storage would have a storage capability of 400 MWhs. For battery storage resources, minimum capacity is set to zero (0) and automatic generation control (AGC) capability is enabled so that the battery storage resource can provide ancillary services. Storage resources are economically scheduled on a day ahead basis to optimize the load shape by shaving the peak. However, the emergency dispatch price is the market price at which storage resources will deviate from the day ahead schedule to resolve a potential reliability issue.

The base case had one battery storage resource of 1.1 MW, and 2,179MW of PSH resources (Ludington). However, additional storage resources were modeled for Incremental resources defined in the PCA portfolios.

ANCILLARY SERVICES MODELING

Ancillary services were modeled using the assumptions in the table below

Table 12. Ancillary Services Assumptions

Characteristic	Assumption
Regulating Reserves	1% of Load
Spinning Reserves	3% of Load
Quick Start Reserves	1% of Load
Load Following Up Target	1% of Load

In addition, per methods consistent with other MISO analyses, ancillary services were allowed to fully deplete before load was shed (i.e., no ancillary services were held in reserve during load shed conditions).

STUDY METHODOLOGY AND RESULTS

PCA RESOURCE ADEQUACY ASSESSMENTS

MISO LRZ7 UCAP PRMR

Within the MISO resource adequacy framework, the Planning Reserve Margin Requirement (PRMR) determines the required procurement volume of UCAP capacity to meet reliability obligations across all of MISO. For an individual LSE, the PRMR is calculated by taking an LSE's coincident peak load and multiplying it by the UCAP PRM. The UCAP PRM was 7.4% in the 2022-2023 Loss of Load Expectation Study.[13] This PRM is determined by MISO using their probabilistic loss of load expectation assessment performed annually. The PRMR calculation for LRZ7 for the study year 2025 is shown in the table below.

Table 13. MISO LRZ7 UCAP Obligation (Study Year 2025)

LRZ7 Non-Coincident Peak Load Forecast (MW)	20,742[14]	[A]
Coincidence Factor	0.9577	[B]
LRZ7 Forecasted Coincident Peak Demand, Including losses (MW)	19,864	[C] = [A]*[B]
UCAP PRM (%)	7.4%[15]	[D]
LRZ7 UCAP PRMR (MW)	21,334	[E] = [C] * (1 + [D])
DTE UCAP PRMR (MW)	10,667	[F] = [E] * .5
Non-DTE UCAP PRMR (MW)	10,667	[G] = [E] * .5

COMPARISON OF MODELING METHODOLOGIES WITH MISO

A key difference between the reliability assessment performed in this study and the MISO resource adequacy study used to determine the 2025 UCAP PRMR is the availability of imports. In this assessment, LRZ7 is treated as an islanded zone without any transmission import capability, whereas the MISO study determines the PRMR based on an aggregated simulation of all of MISO to achieve 0.1 LOLE. Since this study models LRZ7 as an island and does not have access to market purchases, reliability is worse than 0.1 LOLE before any adjustments. This study estimates that the necessary

[13] Page 26, Planning Year 2022-2023 Loss of Load Expectation Study Report, MISO https://cdn.misoenergy.org/PY%202022-23%20LOLE%20Study%20Report601325.pdf

[14] The non-coincident peak demand for DTE was provided by DTE. The non-DTE non-coincident peak demand was approximated to be equivalent to the DTE peak load as a simplifying assumption based on total LRZ7 peak load forecasts published by MISO.

[15] Page 26, Planning Year 2022-2023 Loss of Load Expectation Study Report, MISO https://cdn.misoenergy.org/PY%202022-23%20LOLE%20Study%20Report601325.pdf

market support to maintain 0.1 LOLE is 2,049MW, and a proxy unit with this capacity is included in all analyses to represent the reliability benefit of the market. For reasonableness, this shortfall can be compared to the implied generator outage and load diversity benefit for LRZ7 determined by MISO in its latest published resource adequacy assessment. Per the 2022-2023 Loss of Load Expectation Study report published by MISO in October 2021, the reliability need for LRZ7 in planning year 2025-2026 is reduced from 23,857MW UCAP assuming an islanded case to 21,603MW UCAP[16] assuming full interconnection with MISO. This indicates a reliability value of 2,254MW for imports into LRZ7. Additional modeling differences between MISO and this assessment are summarized in the table below.

Table 14. MISO vs Astrapé Modeling Differences

Category	MISO	Astrapé
Peak Load	21,003	20,742
Load Shapes	MISO-developed zonal load shape	Astrapé-developed DTE shape used as proxy for zone
Weather Years	1990-2019	1980-2020
Resource Set	MISO's planning data set	Units from EIA 860 for lower MI with future capacity adjustments per DTE as well as the CMS IRP
Treatment of EE	A mix of load adjustments and resource modeling	EE shapes provided by DTE used to scale load shapes for reduced total annual energy consumption
Planned Outage	Use of "realistic" planned outage schedules	Outage schedules optimized across the average load shape for all weather years
Modeling Approach	Must run using EFORd	Economic Dispatch using EFOR
Wind Resource Modeling	Constant monthly values using MISO wide ELCC with per unit adjustments using monthly capacity factors	Hourly wind profiles unique to each weather year
Solar Resource Modeling	Future solar given 50% capacity credit	Hourly solar profiles unique to each weather year

After modeling the base case portfolio tuned to the 2025 UCAP PRMR, change cases that involve adding renewable resources and retiring existing resources can be modeled. An improvement in reliability from 0.1 LOLE indicates the new portfolio has excess capacity relative to need. Because the PCA portfolios are designed to replace the amount of retired UCAP capacity of conventional

[16] 21,003MW peak demand reduced by a coincidence factor of .9577, multiplied by the 7.4% UCAP PRM

resources with the same amount of ELCC capacity for new renewable resources, any excess capacity identified is driven by MISO capacity accreditation practices. UCAP capacity accounting implies the reliability value of any generator is equal to 1-EFORd. However, some large generators' actual reliability value is less than implied by this formula due to the impact of the loss of those large generators. In other words, 5 small generators would provide more reliability value than 1 large generator due to outage diversity, but this effect is not captured in UCAP accounting currently.

Capacity accreditation in the base case and change cases is based on the UCAP rating for conventional resources and the ELCC values calculated using SERVM for solar, wind, and battery storage resources. By accrediting solar, wind, and battery storage at more accurate ELCC values determined by SERVM at their respective penetration levels (as opposed to relying on published MISO ratings), it ensures that all portfolios accurately account for correlated risks associated with renewable resource unavailability (e.g., solar unavailability on cloudy days or large correlated low wind output periods).

MODELED PORTFOLIO SUMMARY

The UCAP/ELCC capacity of the three modeled portfolios for this reliability assessment are summarized in the tables below. Additional tables highlight the key changes in installed capacity across the portfolios and the calculated technology specific ELCC percentages values used for capacity accreditation.

Table 15. DTE Modeled Portfolios (UCAP/ELCC MW)

	Base Case	2028 PCA	2035 PCA
Conventional Resources[17]	8,986	8,160	7,593
DR	973	996	1,009
Solar	306	772	1,291
Wind	395	367	462
Battery Storage	0	355	341
Total UCAP	10,660	10,651	10,696

[17] Accounting reflects adjustments for units with joint ownership (49% DTE ownership of Ludington 1-6, and 81.39% DTE ownership of Belle River 1 & 2)

Table 16. Non-DTE Modeled Portfolios (UCAP/ELCC MW)

	Base Case	2028 PCA	2035 PCA
Conventional Resources[17]	9,311	8,035	7,965
DR	814	814	814
Solar	84	1,318	1,268
Wind	429	379	367
Battery Storage	1	74	201
Total UCAP	10,640	10,619	10,614

Table 17. Variable Energy Resource ELCC % Values

	Base Case	2028 PCA	2035 PCA
Solar	50%	34%	22%
Wind	21%	19%	18%
Battery Storage	100%	99%	95%

Key differences between the base case and PCA portfolios include the retirement of the Monroe coal fired power plants and an increase in solar, wind, and battery installed capacity. 2028 PCA assumes a total solar penetration for LRZ7 of approximately 13%, and 2035 PCA assumes a total solar penetration of approximately 24% (penetration defined as a percent of load by total annual energy). Non-DTE retirements of conventional resources was done for modeling purposes to maintain the total UCAP/ELCC value near the non-DTE 2025 UCAP PRM requirement after the addition of non-DTE renewable resources.

Table 18. 2028 PCA Resource Retirements and Additions (Installed Capacity MW)

	DTE	Non-DTE
Retirements	1,540 (Monroe 3&4)	1,295[18]
Incremental Solar	1,664	3,718
Incremental Wind	100	0
Incremental Battery	360	74
Incremental DR	23	0

[18] Non-DTE peaking resource units were retired based on UCAP accreditation to offset the incremental ELCC of the solar and battery additions.

Table 19. 2035 PCA Resource Retirements and Additions (Installed Capacity MW)

	DTE	Non-DTE
Retirements	3,073 (Monroe 1-4)	1,398[19]
Incremental Solar	5,192	5,532
Incremental Wind	677	0
Incremental Battery	360	211
Incremental DR	38	0
Incremental CC	946	0

RESULTS

The results of the reliability assessment are shown in the table below. Without market support, DTE would face significant reliability risk for each portfolio as shown in the DTE Island and LRZ7 Island scenarios. The calculated base case market dependence for LRZ7 was determined to be 2,049MW, with 1,420MW of this support allocated to DTE.[20] The DTE specific market dependence is based on the DTE Island shortfall, net of intrazonal LRZ7 generator outage diversity benefits DTE receives from non-DTE resources. Comparing the 2,049MW market dependence to the MISO value of 2,254MW described in the section above indicates a slightly conservative estimate of market support for the LRZ7 island assessment. The market support from the MISO analysis for LRZ7 for 2027/2028 remains close to 2,254 MW so the declining market dependence over time identified in this assessment represents a capacity surplus for LRZ7 in general and DTE in particular.

Table 20. DTE Reliability Assessment Results (Market Support)

	Base Case	2028 PCA	2035 PCA	
DTE Island Shortfall (MW)	1,840	1,490	1,270	[A]
Intrazonal Generator Outage Diversity Benefit (MW)	420	378	253	[B]
DTE Market Dependence (MW)	1,420	1,113	1,018	[C] = [A]-[B]
DTE Surplus (MW)	0	308	403	[D] = $[C]_{(Base)}$ – $[C]_{(2028/2035\ PCA)}$

[19] Non-DTE peaking resource units were retired based on UCAP accreditation to offset the incremental ELCC of the solar and battery additions. Dan Karn 3 & 4 steam-gas units were also retired.
[20] The total shortfall of LRZ7 relative to 0.1LOLE was allocated to DTE and non-DTE in proportion to their individual shortfall. The portfolio composition for non-DTE showed lower shortfall than DTE primarily due to smaller units. Thus, non-DTE was allocated a smaller portion of the shortfall.

Table 21. DTE Reliability Assessment LOLE Results (days/yr)

	Base Case	2028 PCA	2035 PCA
DTE Island	11.2	6.13	3.94
LRZ7 Island	2.68	2.76	1.45
LRZ7 With Base Case Levels of Market Support	0.1	0.04	0.02

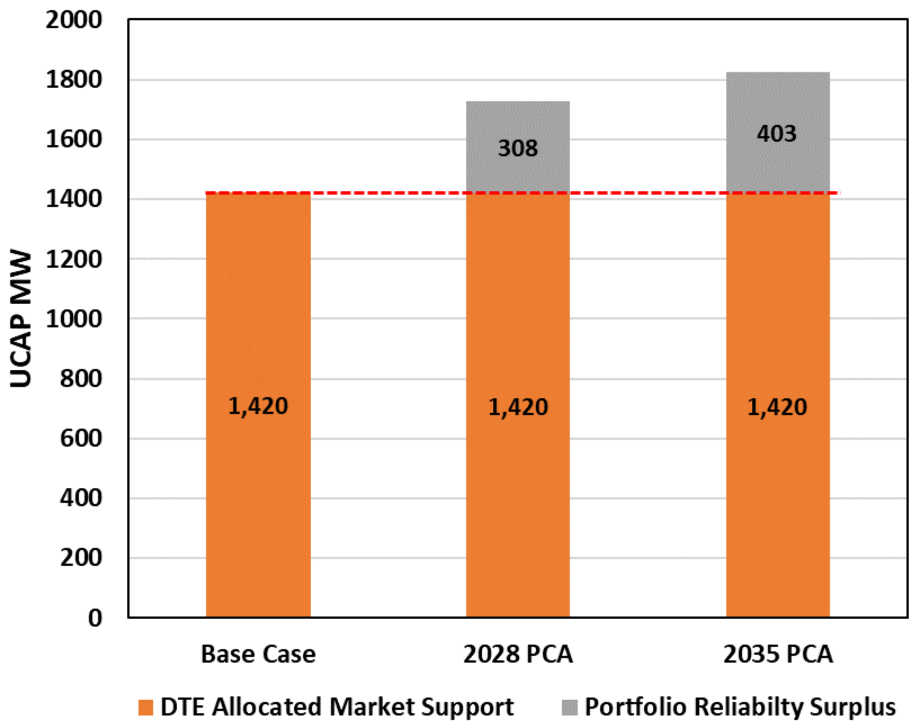

Figure 21. DTE Portfolio Surplus Comparison

Both the 2028 PCA and 2035 PCA indicate a reduced reliance on the MISO market compared to the base case with a net reduction of 308MW and 403MW respectively. A key driver in the increased reliability of the 2028 and 2035 PCA portfolios is due to the retirement of large conventional resources accredited at their UCAP capacities which are replaced with variable energy resources that are accredited at their ELCC values. Both UCAP and ELCC capacity accreditation attempt to incorporate generator availability into the capacity rating (i.e., express a resource's reliability contribution as its perfectly available capacity equivalent value). While UCAP may be a good proxy for the perfectly available capacity equivalent value for smaller resources, an outage of a single large generator (such as the retired Monroe coal units at approximately 750MW each) tends to have a greater impact on reliability than what is implied by its EFORd rating. The ELCC of the retired Monroe units was calculated in SERVM and compared to its UCAP accreditation to quantify this impact.

Table 22. Monroe UCAP vs. ELCC Comparison (MW)

	Monroe 1 - 4
ICAP	3,072
xEFORd	0.06
UCAP	2,888
ELCC	2,325 (76%)
Delta	563

Overall, the lower ELCC value of Monroe 1-4 implies that when replacing its accredited UCAP capacity with incremental ELCC capacity of variable energy resources results in a higher reliability value at the same UCAP PRM. The allocation of surplus among entities in LRZ7 is subject to change as MISO reviews and updates its accounting practices, but a shift by DTE toward smaller units while constructing portfolios compliant with UCAP PRM will exhibit better reliability outcomes.

RISK DISTRIBUTIONS

The results discussed above reflect the weighted average LOLE values across all combinations of load forecast error and weather years. The LOLE risk distribution associated with each individual weather year are shown in the figure below for the Base Case, 2028 PCA, and 2035 PCA. The weather years are rank ordered by the base case LOLE value, from highest value to lowest value.

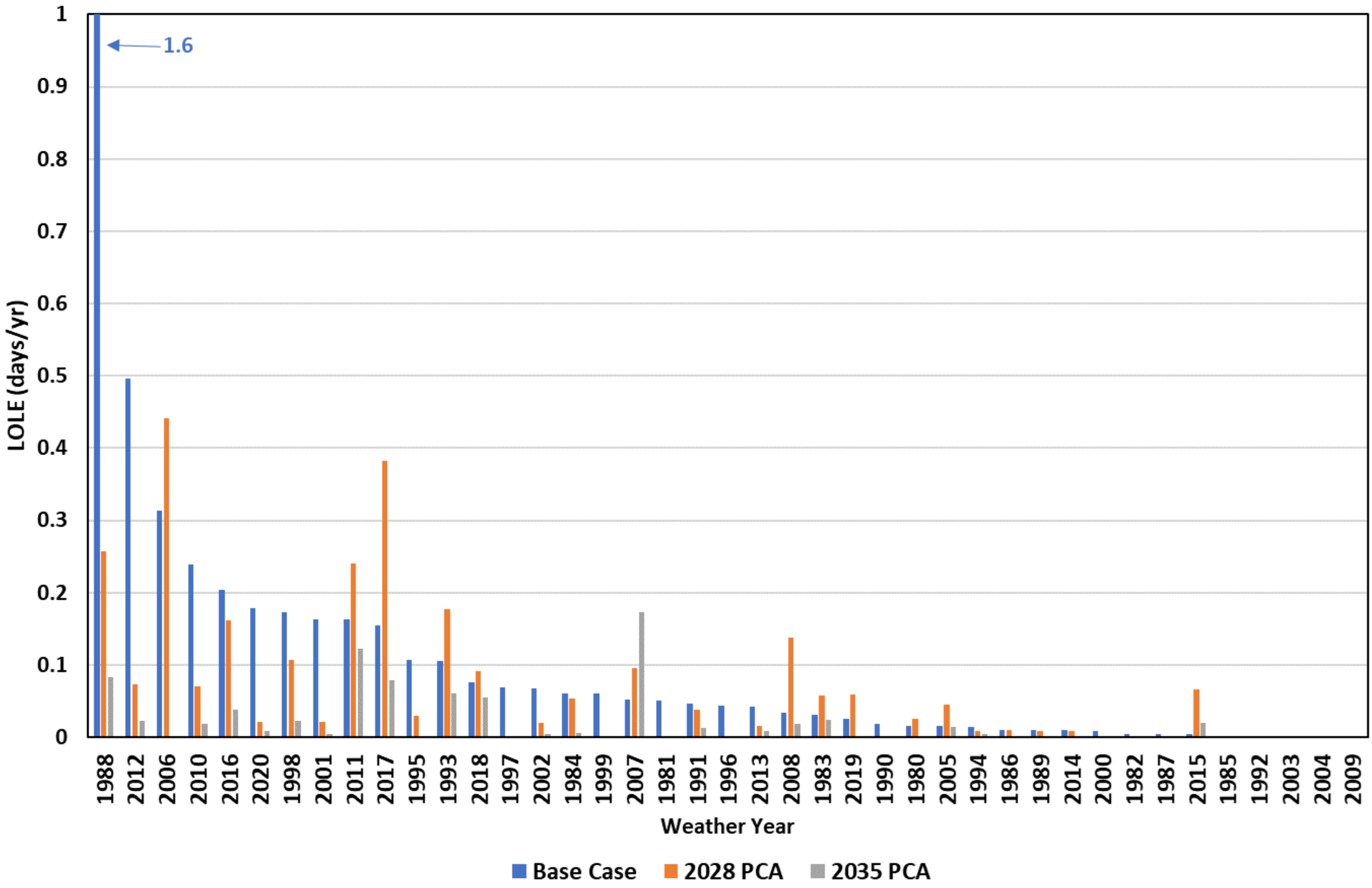

Figure 22. LOLE Distribution by Weather Year

The maximum LOLE for the base case was found to be 1.6 days/yr associated with the weather year 1988 due to a large number of warm days (daily maximum temperatures above 85F). For the 2028 and 2035 PCA portfolios, the maximum LOLE values were found to be 0.44 and 0.17 respectively when assuming 1,420MW of MISO market support to DTE.

WEATHER SENSITIVITY

A weather sensitivity was performed to determine the impact of climate change on the expected reliability results for the base case and PCA portfolios. The number of days where the daily maximum temperature exceeded 85F was plotted across all 41 weather years and a linear trend was developed. The average number of warm weather days across the 41 weather years was then compared against the extrapolated trended value for the study year 2025, which were found to be 28 days and 34 days respectively. Using a linear scaling adjustment, the weather year probabilities were reweighted such that the probability weighted average number of warm weather days was increased to 34 days. The new weightings were then applied to the case level specific results from the PCA analysis to determine weather adjusted expected average LOLE results.

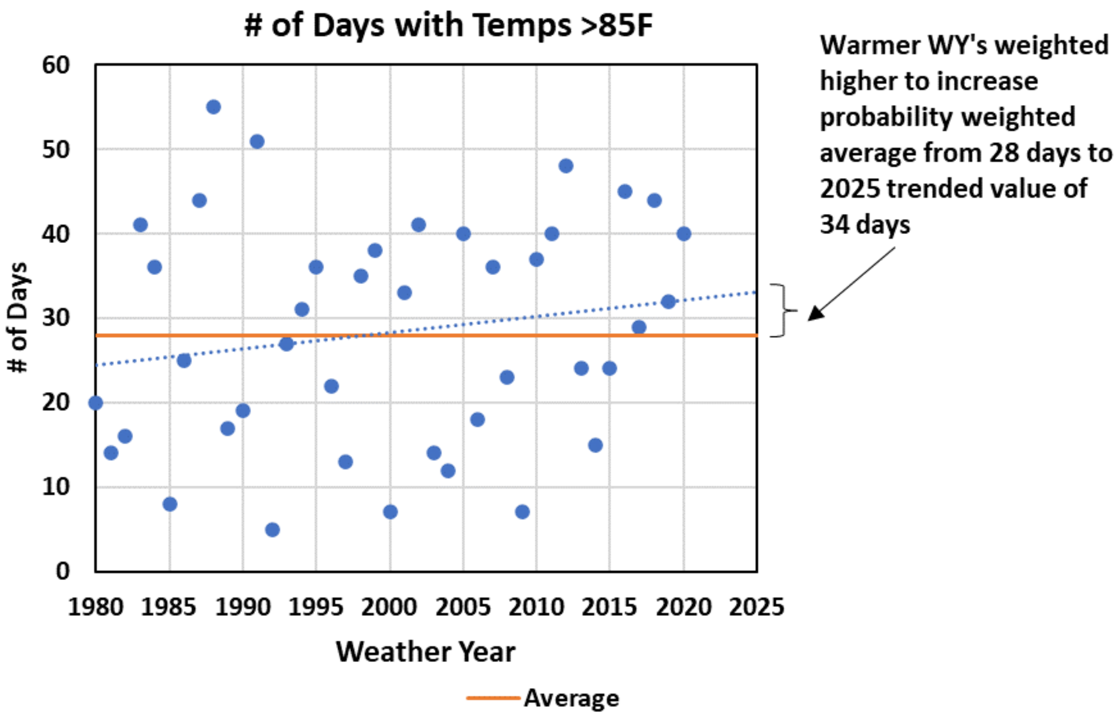

Figure 23. Weather Year Probability Reweighting Basis

Table 23. Warm Weather Sensitivity Results

	Base Case	2028 PCA	2035 PCA
LRZ7 With Base Case Levels of Market Support (Equal WY Weighting)	0.1	0.04	0.02
LRZ7 With Base Case Levels of Market Support (Warm Weather Adjusted)	0.16	0.05	0.03
Estimated Capacity Surplus/(Deficit) (MW)	(143)	268	360

The warm weather sensitivity results showed an increase in LOLE as expected given the higher weighting assigned to warmer weather years. However, for the 2028 and 2035 PCA portfolios the LOLE results were still below the 0.1 days/yr threshold. Compared to the equally weighted weather year analysis, the 2028 and 2035 PCA capacity surpluses decreased by approximately 40MW.

IMPACTS OF INCREASED RENEWABLE PENETRATION IN NEIGHBORING REGIONS

Astrapé analyzed the impact that a divergence in renewable penetration trajectory between LRZ7 and the rest of MISO could have on reliability in LRZ7. Any zone within MISO building out renewable capacity more quickly than another zone will create additional reliability diversity. For instance, net loads will be highest late in the day for a zone with high solar and early for a zone with little solar, allowing both zones to provide more reliability support to each other. This diversity benefit would be seen with either a more rapid build-out or slower build-out for neighboring zones when compared to the trajectory of LRZ7. Our reliability analysis used a conservative assumption that neighboring zones would follow a similar renewable build-out trajectory and market benefits would be limited to generator outage diversity and load diversity. Of course, even more conservative market assumptions could be made such as inadequate reserve margins or over-estimates of the ELCCs for resource expansion plans, but our market representation reasonably balances benefits and risks and is consistent with general reliability modeling practices.

VARIABLE ENERGY PORTFOLIO ELCC ANALYSIS

The following ELCC analysis was used to generate technology specific cumulative ELCC curves for solar and battery storage resources, as well as total variable energy portfolio ELCC values assuming various levels of solar, wind, and battery storage. These results were used as input into DTE's iterative capacity expansion modeling. It should be noted that these ELCC results were generated from an older version of the LRZ7 SERVM database that was utilized in previous project work with DTE. This database included slightly different base case installed capacity assumptions related to renewable resource penetration and different assumptions regarding the summer ratings of conventional unit resources. Any discrepancies between the results from the older database and the most recent database used to perform the PCA portfolio reliability assessment were reconciled with a direct ELCC calculation of the variable energy resource portfolios defined in the PCA portfolios. These direct ELCC calculations were performed using a similar methodology as what is described below. However, the incremental ELCC curves associated with this analysis were used in allocating technology specific ELCC values for solar, wind, and battery storage for the purposes of UCAP/ELCC resource accounting between DTE and non-DTE.

SERVM METHODOLOGY

The ELCC of a variable energy resource (i.e., solar, wind, and battery storage) is the capacity value (expressed in MW) associated with the resource's reliability contribution to the system. The ELCC can also be expressed as a percentage of the calculated capacity value relative to the nameplate capacity value of the resource.

The first step in the ELCC analysis was to determine the ELCC of the base case variable energy resource portfolio. The calculation process is summarized in the steps below:

1. Begin with the base case LRZ7 system for study year 2025, including existing variable energy resources, calibrated to 0.1 LOLE by removing excess non-DTE owned generators in descending CO2 emission rate order (i.e., units with higher CO2 emission rates were removed first).
2. Remove all variable energy resources (solar, wind, and battery storage) and determine the impact on LOLE (LOLE increases due to the reduction in resources)
3. Add in perfect[21] resources until 0.1 LOLE is achieved.
4. The MW of perfect resources added to the system is equal to the ELCC of the base case variable energy resource portfolio.

[21] Capacity resource with no modeled outages (i.e., 100% availability).

5. To isolate the ELCC value of base case solar, begin with the base case LRZ7 system and remove solar capacity and determine impact on LOLE (LOLE increases due to a reduction in resources)
6. Add in perfect resources until 0.1LOLE is achieved
7. The MW of perfect resources added to the system is equal to the ELCC of the base case solar portfolio
8. The difference between base case variable energy portfolio ELCC and the base case solar ELCC is assumed to be the base case wind ELCC.

The base case installed capacity values for solar, wind, and battery storage are summarized in the table below.

Table 24. Base Case Variable Energy Portfolio ELCC

Solar Installed Capacity	768	[A]
Wind Installed Capacity	3,933	[B]
Battery Storage Installed Capacity	0	[C]
Total Variable Energy Installed Capacity	4,701	[D] = [A]+[B]+[C]
Total Variable Energy Portfolio ELCC	1,300	[E] = From Step 4 above
Solar ELCC	410 (53%[22])	[F] = From Step 6 above
Wind ELCC	890 (23%[22])	[G] = [E] – [F]

Once the base case variable energy resource portfolio ELCC was calculated, the portfolio ELCCs for various proposed scenarios, each with varying levels of solar, wind, and battery storage penetration, were calculated utilizing the following steps:

1. Begin with the base case LRZ7 system for study year 2025, including existing variable energy resources, calibrated to 0.1 LOLE by removing excess non-DTE owned generators in descending CO2 emission rate order (i.e., units with higher CO2 emission rates were removed first).
2. Add the incremental renewable/intermittent resources (solar, wind, and battery storage) associated with the proposed ELCC scenario and determine the impact on the LOLE (LOLE decreases due to the increase in renewable/intermittent resources)
3. Increase load[23] to the system until the 0.1 LOLE is achieved
4. The MW amount of load added to the system is equal to the incremental ELCC of the added variable energy resource portfolio for the analyzed scenario

[22] Not identical to PCA Base Case ELCC value due to modeling differences discussed at the beginning of the Variable Energy Portfolio ELCC Analysis section
[23] For study purposes, load additions were simulated using a “perfect MW” with negative capacity (i.e., a negative capacity resource with 100% load factor). This effectively shifts load by the amount of the negative resource)

5. The total portfolio ELCC of the proposed variable energy resource portfolio is calculated by adding the base case variable energy resource portfolio ELCC and the incremental scenario portfolio ELCC

Error! Reference source not found. Figure 24 below illustrates the ELCC calculation process.

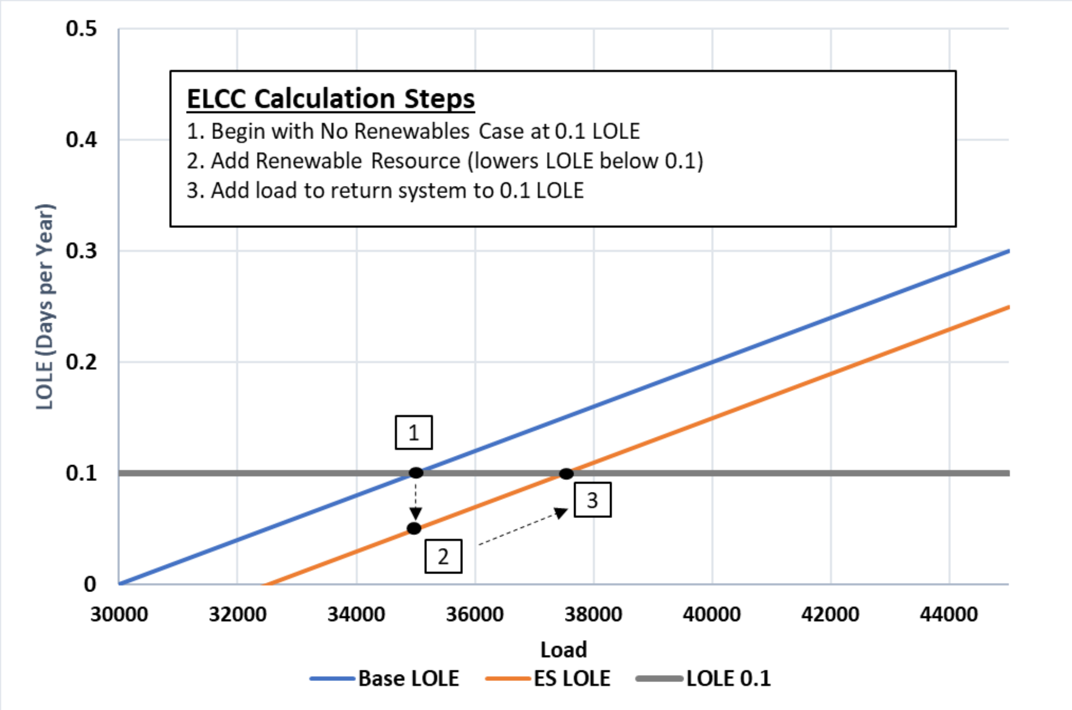

Figure 24. ELCC Methodology

The ELCC scenarios analyzed are summarized in Table 25 below. Each of the 49 scenarios represents a different combination of penetrations of solar (measured in % of load by energy), wind (measured in % of load by energy), and battery storage capacity (measured in GW). Wind penetration was fixed at 12% for all scenarios based on an assumed 3,933MW installed capacity of wind. The installed capacity values associated with the various levels of solar penetration are provided for reference in Error! Reference source not found. Table 26 below.

Table 25. Portfolio Evaluation Matrix

Scenarios	1-7	8-14	15-21	22-28	29-35	36-42	43-49
Solar	**Battery (GW)**						
(% of Load)	**0**	**0.5**	**1**	**1.5**	**2.5**	**3.5**	**5**
5	5/12/0	5/12/0.5	5/12/1	5/12/1.5	5/12/2.5	5/12/3.5	5/12/5
10	10/12/0	10/12/0.5	10/12/1	10/12/1.5	10/12/2.5	10/12/3.5	10/12/5
17.5	17.5/12/0	17.5/12/0.5	17.5/12/1	17.5/12/1.5	17.5/12/2.5	17.5/12/3.5	17.5/12/5
25	25/12/0	25/12/0.5	25/12/1	25/12/1.5	25/12/2.5	25/12/3.5	25/12/5
32.5	32.5/12/0	32.5/12/0.5	32.5/12/1	32.5/12/1.5	32.5/12/2.5	32.5/12/3.5	32.5/12/5
40	40/12/0	40/12/0.5	40/12/1	40/12/1.5	40/12/2.5	40/12/3.5	40/12/5
50	50/12/0	50/12/0.5	50/12/1	50/12/1.5	50/12/2.5	50/12/3.5	50/12/5

Table 26. Solar Penetration % and Corresponding Installed Capacity

% Solar Penetration	Installed Capacity (GW)
5%	2.4
10%	4.9
17.5%	8.5
25%	12.2
32.5%	15.9
40%	19.5
50%	24.4

The individual contribution of each renewable/intermittent resource type to the total portfolio ELCC value was assessed by comparing ELCC results relative to other scenarios. For example, the incremental ELCC impact of solar from 10% penetration to 17.5% penetration assuming 2.5GW of battery storage and 12% wind penetration can be isolated by comparing the ELCC results of Scenarios 30 and 31. Between these two scenarios, only the assumed amount of solar capacity is changed, and thus its impact can be isolated. These types of comparisons were calculated to generate incremental ELCC curves for each technology type.

DIVERSITY INTERACTIONS

When determining the ELCC values of individual technologies within a total variable energy resource portfolio, adjustments must be made to account for diversity interactions between the resources. Diversity interactions occur when resources of one technology type improves or reduces the reliability contribution of another technology type. One common diversity interaction occurs between solar and storage resources, where increasing solar penetration improves the ELCC of storage and vice versa. This is due to the impact solar has on the net load peak during a typical day. Increasing solar penetration results in excess generation during the middle of the day when solar resources typically produce at their highest output, resulting in a shorter net peak load period. Shorter net peak load periods reduce the number of hours required for storage resources to shave the net load peak and improve their reliability contribution. Conversely, lower solar penetration results in longer net load peak periods where storage resources of equivalent duration may not be able to fully shave the peak. This results in a lower storage ELCC. An illustration of this effect is shown below. In the 5% solar penetration case, the net load peak period (defined as the period where net load is within 2,000MW of peak) lasts 10 hours, vs. the 50% solar case which has a net load peak period of 3 hours. A typical 4-hour duration battery resource with a maximum capacity of 2,000MW would be able to provide full reliability contribution in the 50% solar case assuming adequate state of charge levels, whereas it would not be able to fully shave the peak in the 5% solar case.

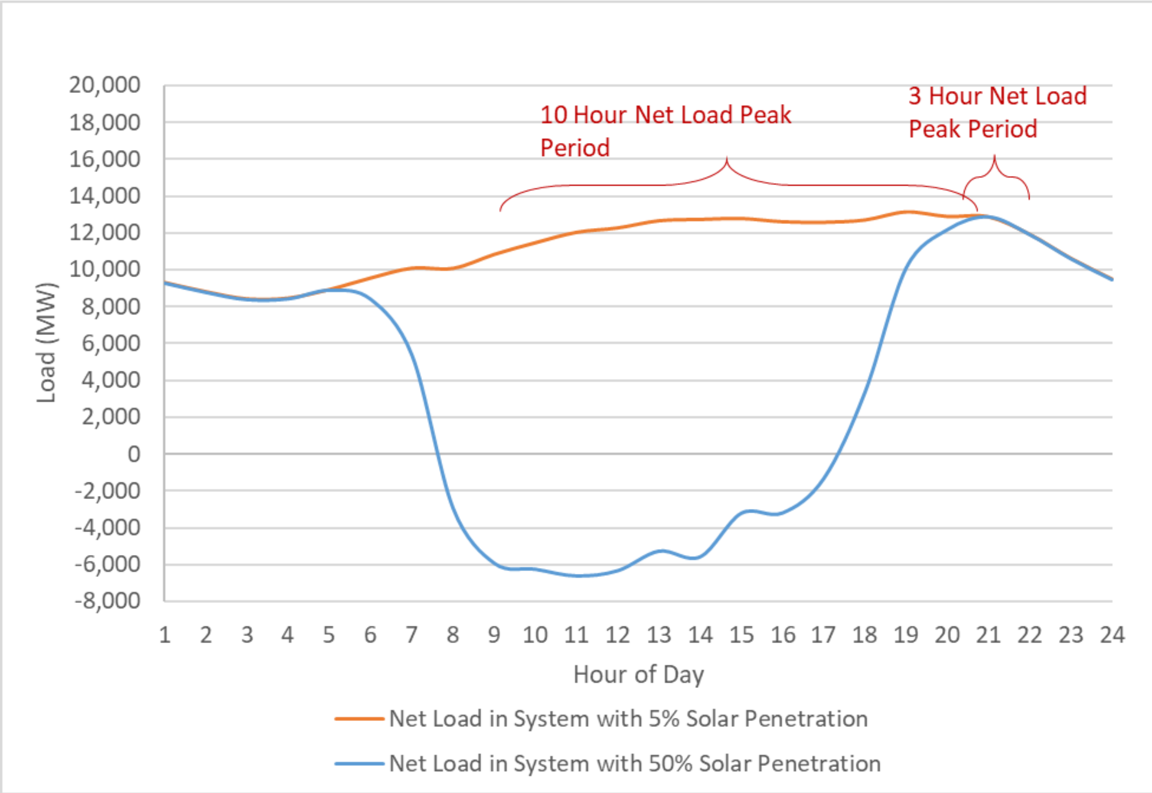

Figure 25. Solar + Battery ELCC Synergy

These positive diversity benefits result in the total ELCC of the combined solar and battery portfolio to be greater than the sum of the individual ELCC values of solar and storage. Thus, the individual contribution allocated to each resource requires a scaling adjustment such that the sum of the individual solar and storage ELCCs equals the total portfolio ELCC.

To account for this diversity, the average of the "Last In" and "First In" ELCC values were calculated for solar, battery storage, and wind resources. "Last In" incremental ELCC is defined as the ELCC attributable to an incremental capacity addition of a single technology class, assuming all other technology classes are already included in the system. "First In" incremental ELCC values are defined as the ELCC attributable to an incremental capacity addition of a single resource class, assuming no other renewable/battery storage resources are in the system. The following sections describe the incremental "Last In" ELCC results for battery storage and solar. The Base Case, including existing solar, wind, and storage (PSH resources) was used as the starting point for adding the incremental variable energy resource capacity.

INCREMENTAL BATTERY ELCC RESULTS

As battery penetration in a given system increases, the expected marginal reliability contribution decreases. This is due to the impact increased battery penetration has on the net load shape. As more batteries are deployed to shave the peak load, the net load peak duration period increases. This necessitates a longer duration battery to provide the same level of reliability contribution. An illustrative example is shown in the figure below.

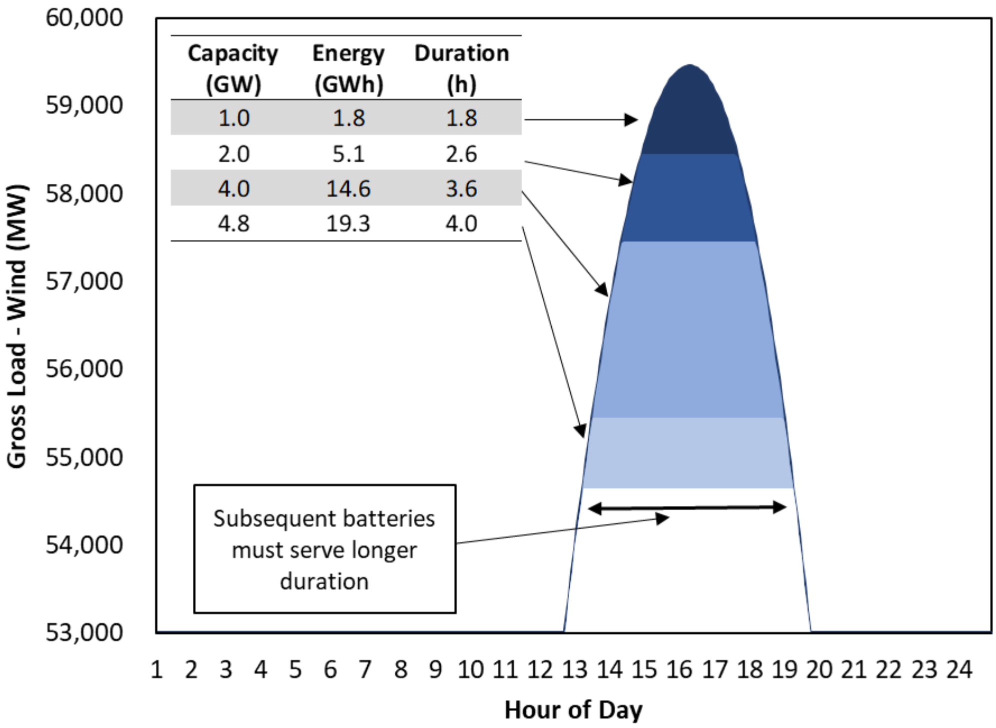

Figure 26. Required Duration at Increasing Battery Penetration

The results of the LRZ7 portfolio ELCC analysis are consistent with expected declining incremental battery ELCC trends. Holding wind and solar penetration values constant, the impact of battery storage penetration was isolated for the various scenarios. The figure below shows the incremental (i.e., "last in") ELCC % of battery storage as penetration increases, with wind penetration constant at 12%.

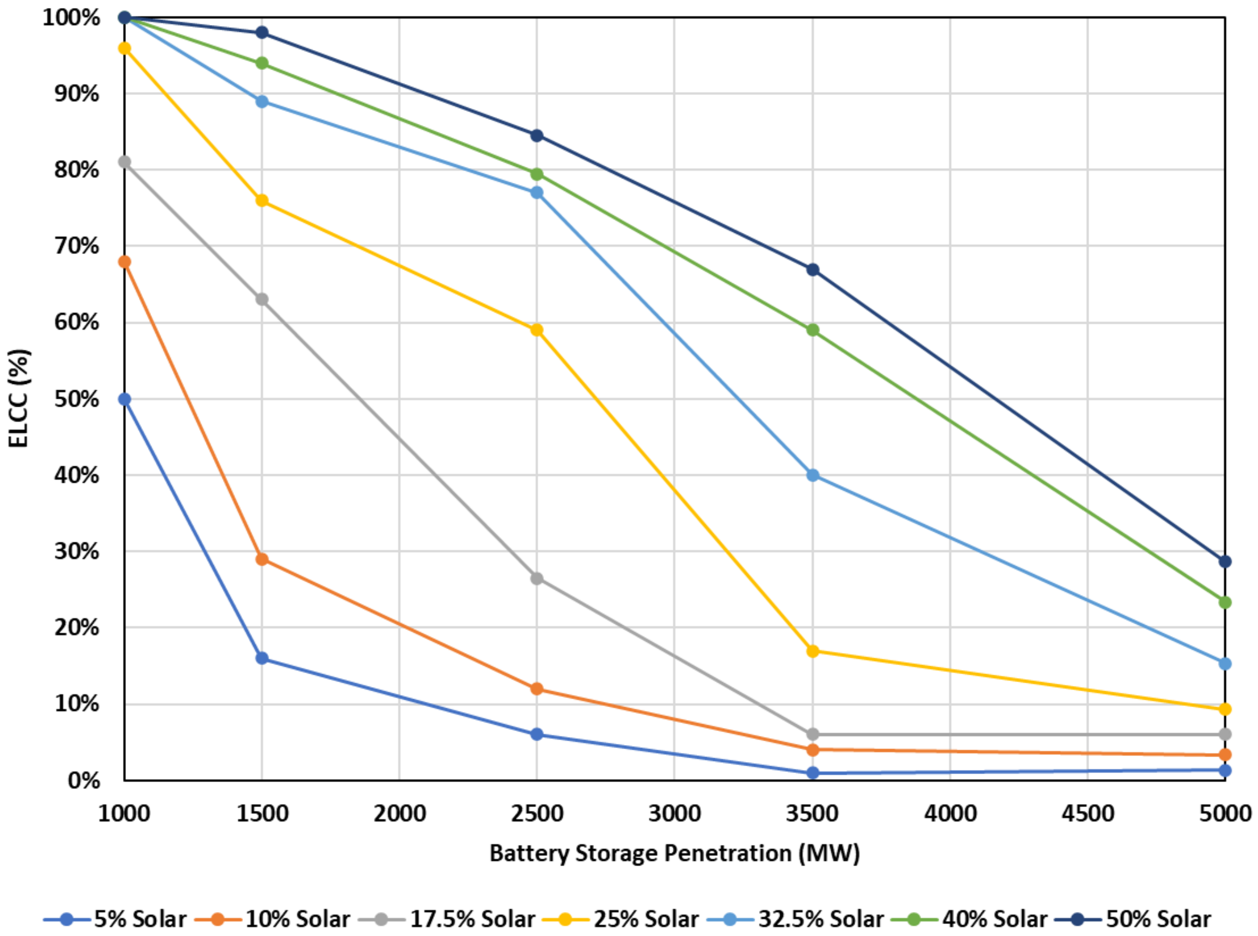

Figure 27. Last In Incremental Battery Storage ELCC (12% Wind Penetration)

The first 1GW of battery storage was found to have an ELCC% between 50%-100% across all scenarios. As battery storage penetration increases beyond the first 1GW, the lower solar penetration scenarios (5% and 10% solar penetration) were found to have a sharp decrease in ELCC%. At higher solar penetrations, the decrease in ELCC% occurs at higher levels of battery penetration and decreases at a slower rate. This reflects the positive diversity impact solar has on battery storage, where excess solar generation preceding the net load peak allows for charging the battery fleet and a narrowing of the net load peak period, such that the battery fleet can be fully utilized during net load peak.

INCREMENTAL SOLAR ELCC RESULTS

Holding wind and battery penetration values constant, the impact of solar penetration was isolated for the various scenarios. The figure below shows the incremental (i.e., “last in”) ELCC% of solar as penetration increases, holding wind penetration constant at 12%.

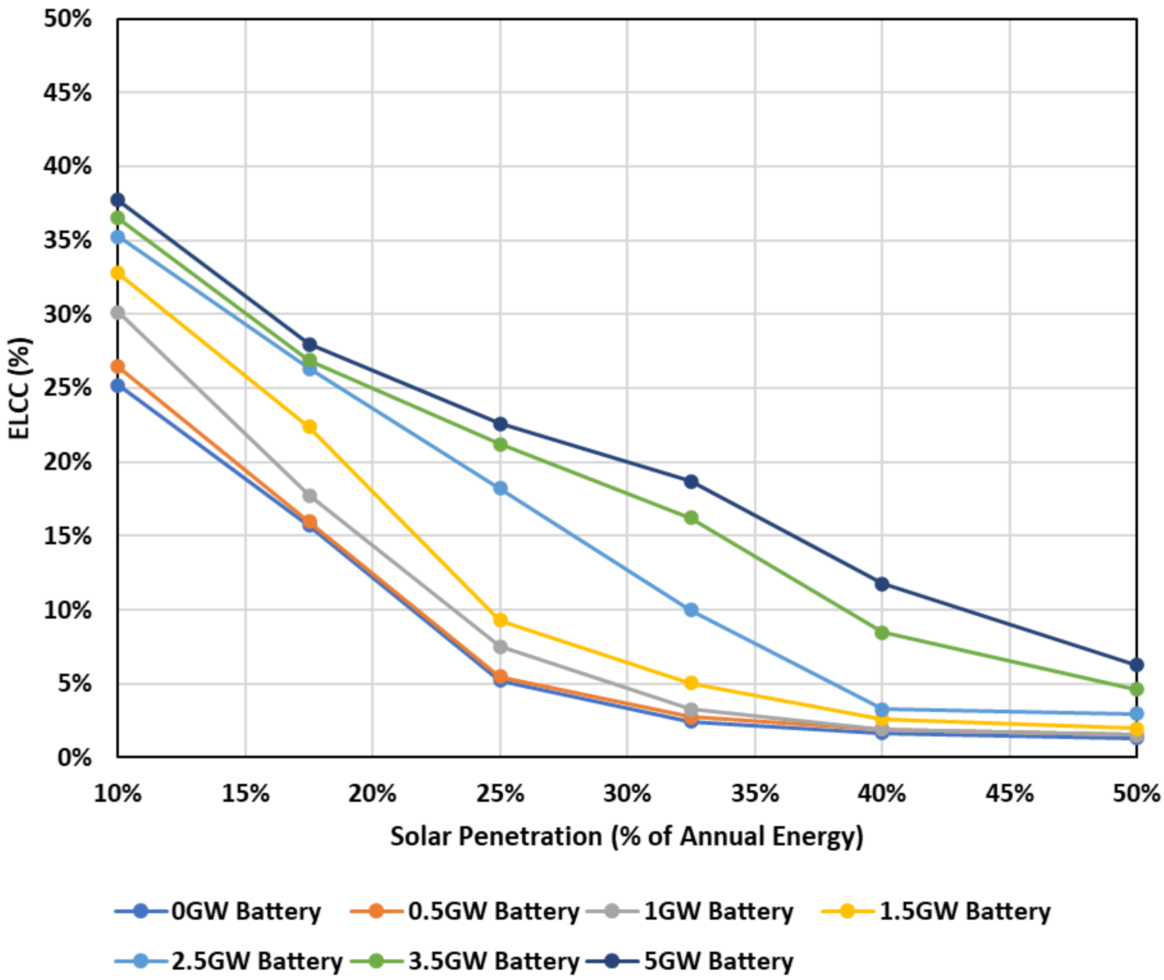

Figure 28. Incremental Last In Solar ELCC (by Solar Penetration)

Higher battery penetration scenarios were shown to have a slower decline in solar ELCC%, reflecting the positive diversity impact between solar and storage.

PORTFOLIO ELCC RESULTS

The portfolio ELCC and ELCC% values for the 49 scenarios analyzed as part of the Variable Energy Portfolio ELCC Analysis are shown in the tables below. The MW values associated with the various levels of solar and wind penetration are also provided as reference.

Table 27. Total Variable Energy Portfolio ELCC Values (MW)

Total Capacity Value (MW)

	Scenarios	1-7	8-14	15-21	22-28	29-35	36-42	43-49
Solar	Wind	Battery (GW)						
(% of Load)	(% of Load)	0	0.5	1	1.5	2.5	3.5	5
5	12	2,150	2,650	2,900	2,980	3,040	3,050	3,070
10	12	2,765	3,295	3,635	3,780	3,900	3,940	3,990
17.5	12	3,340	3,880	4,285	4,600	4,865	4,925	5,015
25	12	3,530	4,080	4,560	4,940	5,530	5,700	5,840
32.5	12	3,620	4,180	4,680	5,125	5,895	6,295	6,525
40	12	3,680	4,250	4,750	5,220	6,015	6,605	6,955
50	12	3,745	4,325	4,825	5,315	6,160	6,830	7,260

TECHNOLOGY SPECIFIC ELCC ALLOCATION

The following is a step-by-step methodology of how the technology specific ELCC allocations were determined for the PCA analysis. Incremental last in ELCC curves for solar and battery storage were developed based on the analysis described above and were utilized in conjunction with direct total portfolio ELCC and wind ELCC calculations by SERVM for each PCA.

1. Calculate the “First In” solar ELCC
    a. Develop a curve fit for the incremental solar ELCC data (solar ELCC% vs. installed solar nameplate capacity) at a fixed wind penetration (12%) and 0GW battery penetration. Solar nameplate capacity analyzed ranged from 2.4GW – 24.4GW.
    b. Calculate the expected solar ELCC capacity given the installed nameplate capacity of the PCA being analyzed. This is done by calculating the area under the incremental solar ELCC curve up to the installed capacity value of the given PCA portfolio (integral of the incremental ELCC% curve is equivalent to the total solar ELCC MW)
2. Calculate the “Last In” solar ELCC
    a. Develop a curve fit for the incremental solar ELCC data at a fixed wind penetration and a higher battery penetration. Solar nameplate capacity analyzed ranged from 2.4GW – 24.4GW.
    b. Calculate the expected solar ELCC capacity using the higher battery penetration incremental solar ELCC curve. Interpolate as necessary between the incremental solar ELCC curves developed for the various battery penetration levels based on the specified amount of battery penetration for a given PCA portfolio.
3. Calculate the “Average” solar ELCC by taking the average of the first in and last in solar ELCC values. The ELCC % is determined by the ELCC divided by the total installed capacity value for the given LRZ7 PCA portfolio.

4. Repeat steps 1-3 for battery ELCC by developing a family of curves for the incremental battery ELCC data at a fixed wind penetration and various levels of solar penetration. Scenarios assuming the base case amount of installed nameplate solar capacity of 767MW were used to develop the "First In" curves
5. Calculate the "Average" wind ELCC %. Wind ELCC was not shown to be sensitive to varying levels of solar and battery storage penetration. Instead of utilizing predeveloped curve fits for incremental ELCC results discussed above, the wind ELCC % was calculated directly from the PCA portfolio.
    a. Calculate the "First In" wind ELCC
        i. Remove all solar, wind, and battery storage resources from the PCA portfolio and retune model back to 0.1LOLE with perfect capacity.
        ii. Add in wind resources and record the decrease in LOLE (due to an addition of resources)
        iii. Remove perfect capacity until 0.1LOLE is reached
        iv. The amount of perfect capacity removed is equivalent to the first in ELCC
    b. Calculate the "Last In" wind ELCC
        i. Remove wind resources from the PCA portfolio and retune model back to 0.1LOLE with additional perfect capacity.
        ii. The amount of perfect capacity required to be added is equivalent to the last in ELCC
    c. Calculate the "Average" ELCC by taking the average of the first in and last in values. ELCC % is expressed by the ELCC divided by the installed capacity of wind associated with the PCA portfolio.
6. Calculate the total portfolio ELCC by summing the individual technology ELCC values determined from Steps 1-5 above.
7. Compare the total portfolio ELCC in Step 6 to the total portfolio ELCC determined via SERVM.
    a. Remove all solar, wind, and battery storage resources from the PCA portfolio and retune model back to 0.1LOLE with perfect capacity.
    b. The amount of perfect capacity required to be added is equivalent to the total variable energy resource portfolio ELCC
    c. The difference between the sum of the individual ELCC values and the total variable energy resource portfolio ELCC represents any remaining diversity impacts not accounted for in the First In/Last In ELCC analysis described in Steps 1-5
8. Scale the individual technology ELCC values such that their sum equals the total portfolio ELCC value determined via SERVM to account for additional diversity impacts.

RENEWABLE INTEGRATION FLEXIBILITY STUDY

BACKGROUND

The use of non-dispatchable renewable resources such as wind and solar in bulk electric systems results in an increase in net load volatility, creating a need for a flexible system that can respond with rapid increases or decreases in generation. The SERVM model has the capability of performing intra-hour simulations (5-minute time intervals) to quantify the frequency and magnitude of flexibility violations defined as the inability to follow net load with dispatchable generation. The primary flexibility violation metric measured by SERVM and used to compare the flexibility of various portfolios and operating practices is the count of days with one or more 5-minute interval where there is an imbalance in load and generation due to ramping constraints or required generator startup times. While generation and load imbalances due to capacity shortfalls are recorded as Loss of Load Expectation (LOLE) in traditional reliability analyses and have more severe consequences, the events identified in this flexibility analysis are generally absorbed in deviations in Area Control Error or in momentary reductions in the operating reserves that are carried. While these events are not as severe, it is important that all portfolios provide the same level of flexibility such that the introduction of new resources does not force a system to be more reliant on interchange or to expect more frequent NERC balancing obligations. Figure 29 and Figure 30 show two different types of flexibility violation examples. Figure 29 shows a multi-hour ramping problem, whereas Figure 30 shows an intra-hour ramping problem. The vast majority of flexibility violations events fall under the intra-hour problems seen in Figure 30. These events are typically very short in duration and are caused by a rapid decline in solar or wind resources over a short time interval. Increasing online spinning reserves or adding fast ramping capability resources can help resolve these issues.

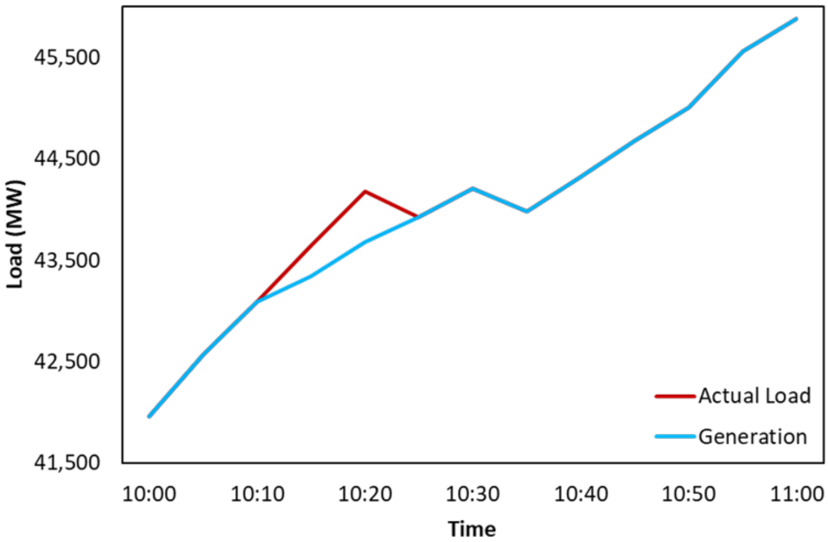

Figure 29. Multi-Hour flexibility violations Example

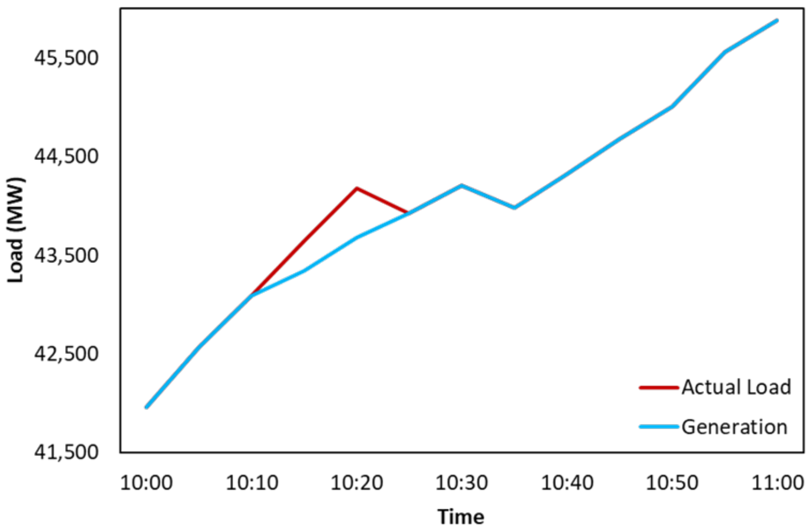

Figure 30. Intra-Hour flexibility violations Example

SCOPE AND METHODOLOGY

PORTFOLIO SETUP

A renewable integration flexibility needs analysis for LRZ7 was performed to determine how various levels of incremental renewable penetration impact the frequency of flexibility violations within the zone, and what level of increased ancillary services requirements would be necessary to maintain the same frequency of flexibility violations as was observed in the base case. This analysis was performed with a base case with no battery storage resources and a sensitivity case that included the addition of battery storage resources in order to determine the economic benefit of battery storage in mitigating the increase in flexibility violations.

The base case portfolio for the integration study was based on the resource adequacy base case portfolio utilized in the PCA Resource Adequacy assessment. Two key differences from the PCA Resource Adequacy Base Case were reflected in the integration study base case. First, the MISO Market Unit Adjustment was changed from a perfect capacity resource to generic CT resources with their associated production cost variables and forced outage rate. This was done to not overestimate the flexibility of the base case system. Second, 500MW of non-DTE wind were removed from the portfolio which was associated with future LRZ7 wind resource expansion. This was done to better reflect the flexibility violations associated with the current level of renewable resource penetration.

The various levels of incremental renewable penetration tested against the base case are summarized in Table 28 below.

Table 28. Integration Study Incremental Renewable Portfolios

Portfolio Name	LRZ7 Solar (MW)	LRZ7 Wind (MW)	Load Addition for 0.1LOLE Tuning (MW)	Incremental Renewable Energy Production (GWh)
Base Case	781	3,337	0	0
4GW Incremental Solar	4,781	3,337	1,150	7,644
8GW Incremental Solar	8,781	3,337	1,850	15,395
14GW Incremental Solar	14,781	3,337	1,850	27,010
2GW Incremental Wind	781	5,337	250	6,132

Each of the four incremental renewable portfolios were tuned to approximately 0.1 days/yr LOLE via uniform load additions[24] and simulated at 5-minute intervals to capture intra-hour uncertainty associated with solar and wind resource production. No changes were made to the ancillary services requirements across the four portfolios. As discussed in more detail in the results section below, the frequency of flexibility violations naturally increases from the base case as the volatility associated with the renewable resource output results in greater volatility in the overall net load at higher renewable penetrations. These results are considered “unmitigated” flexibility violations as no

[24] Negative output units

changes to the ancillary services requirements were made to mitigate the additional flexibility events.

After determining the unmitigated flexibility violation frequency, the portfolios with incremental renewable resource additions were then simulated with various levels of increased load following reserves until the base case level of flexibility violations was reached. These results are considered the "mitigated" flexibility violations and returns the system to an expected level of flexibility events experienced at current levels of renewable penetration. The increase in load following reserves were added uniformly to every hour of the year.

VOLATILITY DISTRIBUTIONS

In order to accurately capture the intra-hour volatility associated with solar and wind resource output, and as well as load volatility, volatility distributions were developed based on historical data.

LOAD VOLATILITY

Load volatility occurs as a result of the minute-by-minute changes in load associated with customer response. To model this uncertainty, SERVM applies a 5-minute load volatility (or load divergence) metric to a smoothed, 5-minute load shape. The 5-minute load volatility data is developed using one year's worth of historical 5-minute load data. The smoothed 5-minute load shape is developed from the hourly load shape. SERVM then develops a set of normalized volatility draws from the historical load volatility data and applies that to the smoothed load shape for each 5-minute interval, depending upon the normalized load during that interval.

For purposes of this analysis and due to the lack of available 5-minute load data for MISO LRZ7, generic load volatility data constructed by Astrapé[25] was used as a proxy for MISO LRZ7 load volatility. Load volatility is not a significant driver of flexibility events.

The figure below shows the normalized load divergence (i.e., the percent change in load over a 5-minute interval) as a function of normalized load utilized for MISO LRZ7. Each dot in the chart represents one of the 5-minute intervals in the historic data set.

[25] Since load volatility data cannot be entered in per unitized values (i.e., values less than 1), this load data was normalized to approximately 1000MW.

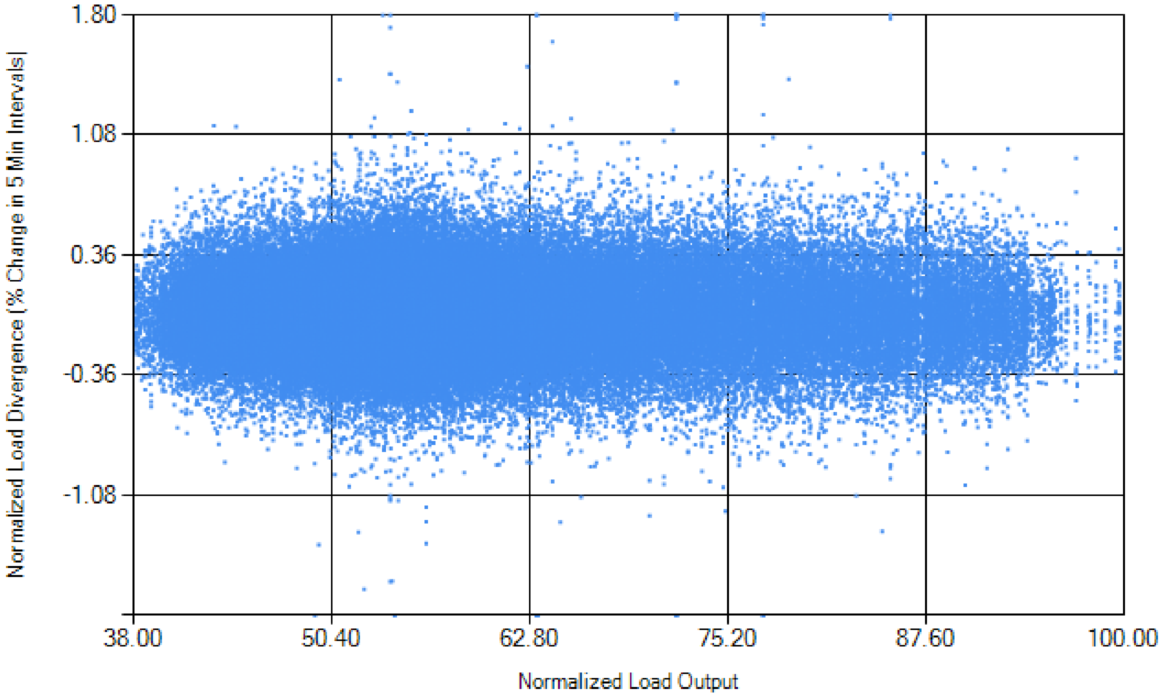

Figure 31. Load Divergence as a Function of Load

As the chart demonstrates, the maximum expected load divergence is just under 2%, with most occurrences, and thus the prevailing load volatility expectation, being under 1%.

SOLAR VOLATILITY

Solar volatility occurs due to moment-to-moment changes in solar irradiance resulting from atmospheric cloud cover at the solar facility site. Like load volatility, solar volatility was also determined using one year's worth of 5-minute generation data. However, due to effects of geographic diversity, solar volatility declines with increasing solar penetration. Thus, a separate set of load volatility data was required for the base case solar penetration (approximately 780 MW) and for each of the incremental solar penetration tranches (4GW, 8GW, and 14GW) evaluated in the study. The source of the data used was publicly available 1-minute solar output data from the California ISO.[26]

The data showed a significant drop in volatility from the base case to 4GW of solar due to geographic diversity. Above 4GW, the majority of the volatility occurrences are contained within the +/- 3% range. However, with increased penetration, geographic diversity continues to reduce the number of extreme volatility occurrences, resulting in fewer outliers and less overall normalized divergence. This can be demonstrated in the figure below, which shows the frequency of divergent values for each of the solar tranches.

[26] https://stakeholdercenter.caiso.com/RecurringStakeholderProcesses/Flexible-capacity-needs-assessment-2023

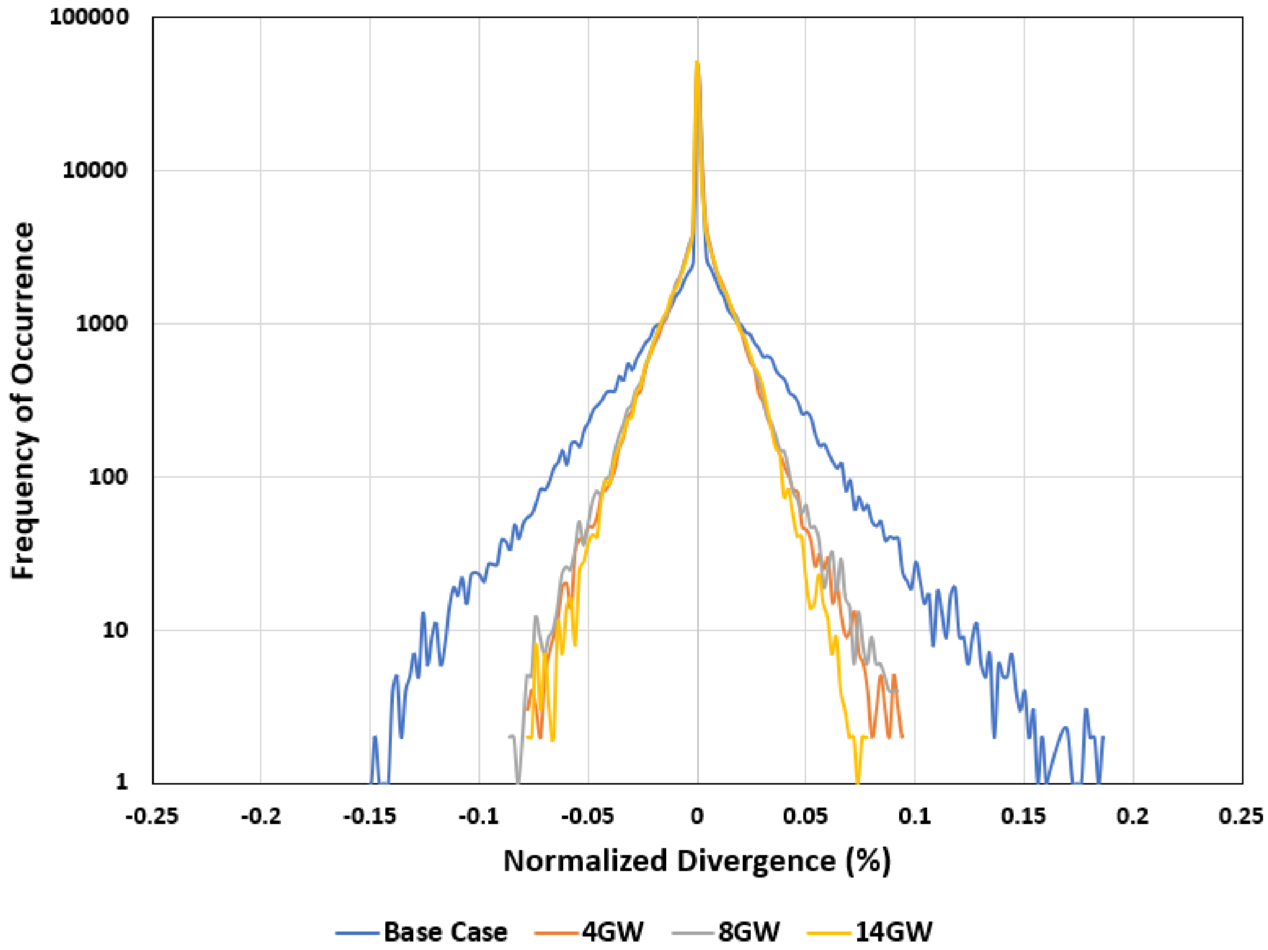

Figure 32. Solar Diversity Frequency of Occurrence

WIND VOLATILITY

Wind volatility occurs because of moment-to-moment changes in wind gradients at a given location. Like solar, wind volatility decreases with penetration as a result of geographic diversity. Using available wind volatility data from a nearby region (Tennessee Valley Authority), wind volatility data was developed for two tranches of wind, the base case (approximately 3,340 MW) and the base case plus 2GW. The reduction in volatility can also be seen in the frequency of occurrence chart below.

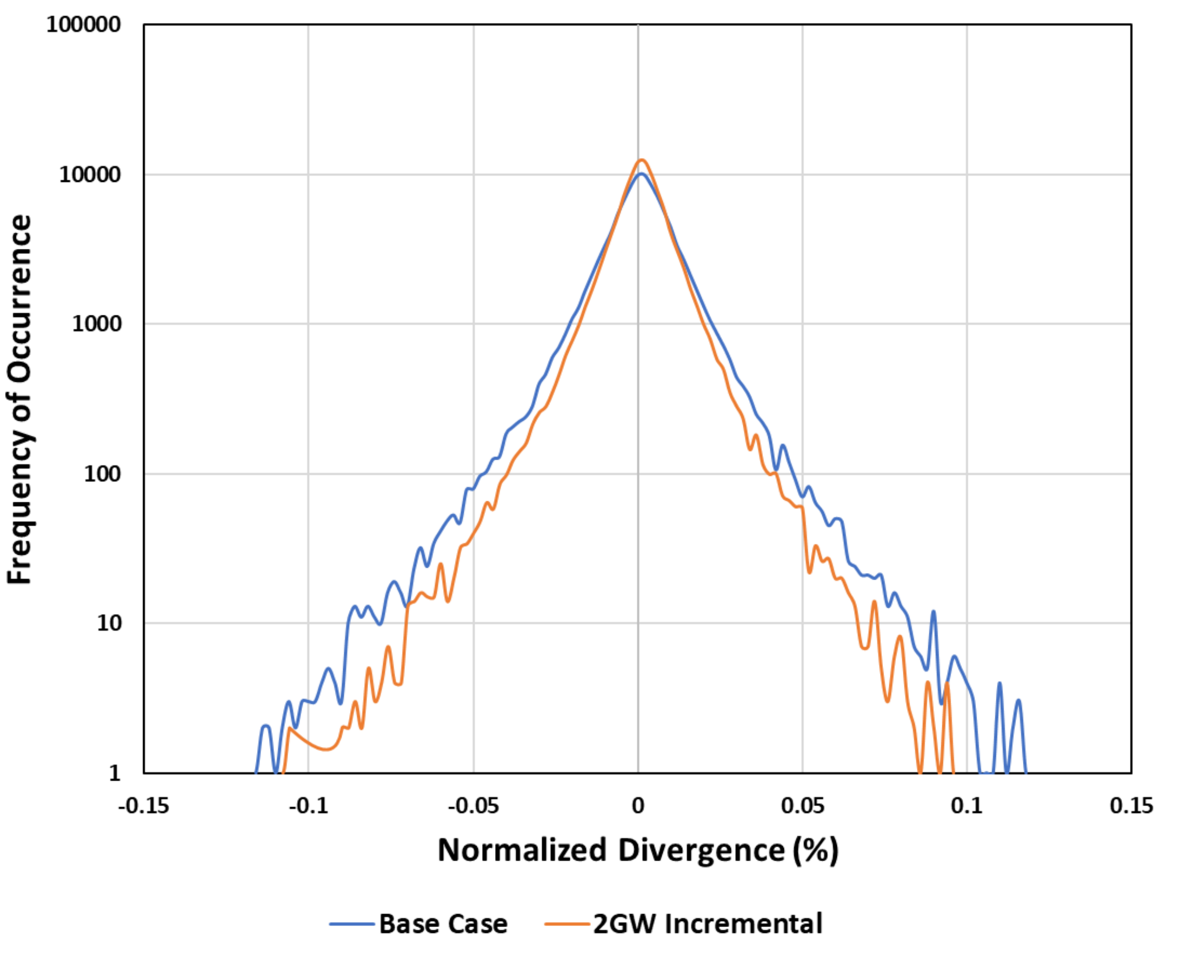

Figure 33. Wind Diversity Frequency of Occurrence

INTEGRATION COST AND BATTERY STORAGE FLEXIBILITY BENEFIT

The increase in ancillary services requirements necessary to mitigate the increase in flexibility violations associated with incremental renewable resource penetration results in an increase in total system production costs. Total system production costs are calculated in SERVM as the sum of fuel costs, startup costs, and variable O&M costs based on the economic dispatch of resources in the simulation. Therefore, this cost increase is defined as the integration cost for each incremental renewable portfolio and can be calculated using the formula below (using the 4GW Incremental Solar portfolio as an example).

$$\begin{aligned} Total\ Integration\ Cost_{4GW\ Inc.\ Solar}(\$) \\ &= Total\ Production\ Cost_{4GW\ Inc.\ Solar,Mitigated}(\$) \\ &- \ Total\ Production\ Cost_{4GW\ Inc.\ Solar,Unmitigated}(\$) \end{aligned}$$

A sensitivity analysis was performed to determine how this integration cost decreases with an increase in battery storage resources in the underlying portfolio mix. Battery storage resources can be used to resolve flexibility events at lower cost than fossil resources as they can provide spinning reserves with minimal associated VOM costs. This flexibility benefit can then be assigned to battery storage resources and factored into a total life cycle cost analysis for the purpose of capacity expansion planning.

The following portfolios were analyzed with the same ancillary services requirements and renewable resource penetrations as the initial analysis, but with the addition of battery storage. The portfolios were tuned to 0.1 LOLE using load additions and the flexibility violations were calculated in SERVM (i.e., unmitigated cases). Next, the portfolios were tuned by increasing the load following minimum up reserve targets until the base case level of flexibility violations was reached (i.e., mitigated cases). Where it was found that the increase in battery storage penetration alone resulted in lower flexibility violations than the base case, the battery storage penetration was iteratively reduced to determine at what penetration level results in the base case value of flexibility violations.

Table 29. Battery Storage Sensitivity Portfolio Setup

Portfolio Name	LRZ7 Solar (MW)	LRZ7 Wind (MW)	LRZ7 Battery Storage (MW)	Load Addition for 0.1LOLE Tuning (MW)
4GW Incremental Solar	4,781	3,337	1,000	1,775
8GW Incremental Solar	8,781	3,337	1,214[27]	2,950
14GW Incremental Solar	14,781	3,337	1,933[28]	4,275
2GW Incremental Wind	781	5,337	1,000	875

The battery flexibility benefit was then calculated by comparing the integration cost without battery storage to the integration cost with battery storage. This calculation is expressed in the formulas below.

$$\begin{aligned} &Total\ Integration\ Cost_{4GW\ Inc.Solar+1GW\ Battery}(\$) \\ &\quad = Total\ Production\ Cost_{4GW\ Inc.\ Solar+1GW\ Battery,Mitigated}(\$) \\ &\quad - Total\ Production\ Cost_{4GW\ Inc.\ Solar+1GW\ Battery,Unmitigated}(\$) \end{aligned}$$

$$\begin{aligned} &Total\ Battery\ Flexbility\ Benefit\ (\$) \\ &\quad = Total\ Integration\ Cost_{4GW\ Inc.\ Solar}(\$) \\ &\quad - Total\ Integration\ Cost_{4GW\ Inc.Solar+1GW\ Battery}(\$) \end{aligned}$$

The battery flexibility benefit was also calculated on a per unit of installed battery storage capacity ($/kW) for use in capacity expansion planning modeling.

RESULTS

The number of flexibility violations in the base case portfolio was determined to be 9.29 days/yr and established the target flexibility violations value for the mitigated cases. The frequency of flexibility violations quantified is not meant to be a proxy for any NERC-monitored performance obligation.

[27] 1,500MW of battery storage was originally tested but resulted in the number of flexibility violations below the base case value 9.29 days/yr. Battery storage penetration was reduced until the base case value was reached.

[28] 2,500MW of battery storage was originally tested but resulted in the number of flexibility violations below the base case value 9.29 days/yr. Battery storage penetration was reduced until the base case value was reached.

Since SERVM does not have a full network representation, it is not feasible in this analysis to estimate such a metric. Rather, since current system operations maintain compliance with NERC standards, the goal of the analysis is simply to ensure that the alternate portfolios being studied have the capability to follow net load as effectively as today's portfolio. The table below summarizes the unmitigated flexibility violations values, incremental load following requirements for flexibility event mitigation, and total production costs for each of the incremental renewable portfolios. The total integration costs are normalized on a per MWh of incremental renewable energy production for each portfolio for the sake of comparison.

Table 30. Integration Study Results

	4GW Incremental Solar	8GW Incremental Solar	14GW Incremental Solar	2GW Incremental Wind	
Unmitigated flexibility violations(days/yr)	64.95	151.89	214.17	49.63	[A]
Incremental LF Reserves for Mitigation (MW)	230	614	1,017	235	[B]
Unmitigated Total Production Costs ($MM)	2,148	2,129	1,977	1,946	[C]
Mitigated Total Production Costs ($MM)	2,162	2,169	2,057	1,960	[D]
Total Integration Cost ($MM)	13.9	40.6	80	14	[E] = [D] – [C]
Incremental Renewable Energy (MWh)	7,644,296	15,395,217	27,009,997	6,132,386	[F]
Total Integration Cost ($/MWh)	1.82	2.64	2.96	2.28	[G] = [E] / [F]

The simulation results showed that as the solar penetration increases, the unmitigated flexibility violations increase. This is because as solar penetration increases, the solar production volatility has a greater impact on the net load volatility and reduces the system's ability to ramp accordingly. Therefore, the amount of load following reserves needed to mitigate the flexibility events increases as penetration increases.

The results of the battery storage sensitivity analysis are summarized in the table below. The addition of battery storage alone for the 8GW and 14GW portfolios was sufficient in maintaining the same number of flexibility violations observed in the base case. Therefore, there was no need for incremental load following reserves and the total integration costs were found to be $0.

Table 31. Battery Storage Sensitivity Integration Study Results

	4GW Incremental Solar	8GW Incremental Solar	14GW Incremental Solar	2GW Incremental Wind	
Battery Storage Penetration (GW)	1	1.21	1.93	1	[A]
Unmitigated flexibility violations(days/yr)	14.28	9.29	9.29	18.81	[B]
Incremental LF Reserves for Mitigation (MW)	74	0	0	84	[C]
Unmitigated Total Production Costs ($MM)	2,328	2,385	2,463	2,118	[D]
Mitigated Total Production Costs ($MM)	2,329	2,385	2,463	2,120	[E]
Total Integration Cost ($MM)	0.7	0	0	1.3	[F] = [E] – [D]
Incremental Renewable Energy (MWh)	7,644,296	15,395,217	27,009,997	6,132,386	[G]
Total Integration Cost ($/MWh)	0.09	0	0	0.22	[H] = [F] / [G]

A summary of the battery storage flexibility benefit is shown in the table below. The flexibility benefit increases from $13.23/kW for a 4GW solar portfolio to $41.38/kW for a 14GW solar portfolio.

Table 32. Battery Storage Flexibility Benefit Summary

	4GW Incremental Solar	8GW Incremental Solar	14GW Incremental Solar	2GW Incremental Wind	
Battery Storage Penetration (kW)	1,000,000	1,210,000	1,930,000	1,000,000	[A]
Integration Cost Without Battery ($/MWh)	1.82	2.64	2.96	2.28	[B]
Integration Cost With Battery ($/MWh)	0.09	0	0	0.22	[C]
Integration Cost Reduction ($/MWh)	1.73	2.64	2.96	2.07	[D] = [A] – [B]
Total Battery Flexibility Benefit ($MM)	13.23	40.57	79.99	12.67	[E] = [D] * Inc. MWh
Battery Flexibility Benefit ($/kW)	13.23	33.41	41.38	12.67	[F] = [E] / [A]

CONCLUSIONS

Conclusions from the PCA reliability assessment, ELCC analysis, and renewable integration flexibility study are listed below:

1. The 2028 and 2035 PCA portfolios were found to have a greater overall reliability value at the same UCAP PRM as the base case, corresponding to a capacity surplus of approximately 300-400MW.
    a. The UCAP accreditation of the retired resources (Monroe) overestimates its reliability contribution relative to its ELCC value due to the large size of the resources (approximately 750MW each). Large resources have disproportionate impacts on LOLE.
    b. Replacing the UCAP value of Monroe with an equivalent ELCC value of renewable resources results in improved reliability relative to the base case.

2. When factoring in warming weather into the reliability assessment, the 2028 and 2035 PCA Portfolios were still shown to have a capacity surplus relative to the 2025 UCAP PRM requirement. The surplus was slightly reduced by approximately 40MW for each portfolio.

3. Technology specific average ELCC values are summarized in the table below, with a decline in in solar ELCC from 50% at 781MW of installed capacity to 22% at 11,505MW of installed capacity. Wind and battery storage ELCC remain relatively static, with battery storage near 100% due to the penetration of solar resources (positive diversity benefit).

Table 33. Technology Specific Average ELCC % Values

	Base Case	2028 PCA	2035 PCA
Solar	50%	34%	22%
Wind	21%	19%	18%
Battery Storage	100%	99%	95%

4. The flexibility benefit of battery storage increases on a per kW installed capacity basis as solar penetration increases, ranging from $13.13/kW at 4GW of solar penetration to $41.38/kW at 14GW of solar penetration.