ASTRAPÉ CONSULTING
innovation in electric system planning

2023 Resource Adequacy Study for Duke Energy Carolinas & Duke Energy Progress

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PREPARED FOR

Duke Energy Carolinas & Duke Energy Progress

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Contents

Executive Summary

This study was performed by Astrapé Consulting (Astrapé) at the request of Duke Energy Carolinas (DEC) and Duke Energy Progress (DEP, and together with DEC, the Companies), as an update to the study performed in 2020.[1] The primary purpose of this study is to provide the Companies with information on physical reliability that could be expected with various reserve margin[2] planning targets. Physical reliability refers to the frequency of firm load shed events and is calculated using Loss of Load Expectation (LOLE). The one day in 10-year standard (LOLE of 0.1) is interpreted as one day with one or more hours of firm load shed every 10 years due to a shortage of generating capacity and is used across the industry[3] to set minimum target reserve margin levels. Astrapé determined the reserve margin required to meet the one day in 10-year standard for both DEC and DEP individually as well as a combined case which serves as the Base Case for this study.

Customers expect to have electricity during all times of the year but especially during extreme weather conditions such as cold winter days when resource adequacy[4] is at risk for the Companies' system[5]. In order to ensure reliability during these peak periods, the Companies maintain a

[1] Table A1 in Appendix A summarizes the changes in assumptions between the 2023 and 2020 studies.
[2] Throughout this report, winter and summer reserve margins are defined by the formula: (installed capacity - peak load) / peak load. Installed capacity includes capacity value for intermittent resources such as solar and energy limited resources such as battery energy storage.
[3] https://www.ferc.gov/sites/default/files/2020-05/02-07-14-consultant-report.pdf; See Table 14 in A-1. PJM, MISO, NYISO ISO-NE, Quebec, IESO, FRCC, APS, NV Energy all use the 1 day in 10 year standard. As of this report, it is Astrapé's understanding that Southern Company has shifted to the greater of the economic reserve margin or the 1 day in 10 year standard.
[4] NERC RAPA Definition of "Adequacy" - The ability of the electric system to supply the aggregate electric power and energy requirements of the electricity consumers at all times, taking into account scheduled and expected unscheduled outages of system components.
https://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/NERC_LTRA_2019.pdf, at 9.
[5] Section (b)(4)(iv) of NCUC Rule R8-61 (Certificate of Public Convenience and Necessity for Construction of Electric Generation Facilities) requires the utility to provide "… a verified statement as to whether the facility will

minimum reserve margin level to manage unexpected conditions including extreme weather, unanticipated changes in economic load growth, and significant forced outages. To understand potential reliability risks, a wide distribution of possible scenarios must be simulated at a range of reserve margins. To calculate the physical reliability of the Companies' system, Astrapé utilized its reliability model called SERVM (Strategic Energy and Risk Valuation Model) to perform thousands of hourly simulations for the 2027 study year at various reserve margin levels. Each of the yearly simulations was developed through a combination of deterministic and stochastic[6] modeling of the uncertainty of weather, economic growth, unit availability, and neighbor assistance.

In the 2020 study, reliability risk was concentrated in the winter and the study determined that a 16.0% reserve margin was required to meet the one day in 10-year standard (LOLE of 0.1) for DEC individually while DEP required a 19.25% reserve margin to meet the same level of reliability. In the combined case, the one day in 10-year standard was met with a 16.75% reserve margin. The recommendation was to maintain a 17% winter reserve margin based on the combined case in the 2020 study. This 2023 study updates all input assumptions to reassess resource adequacy for the Companies. As part of the update, a stakeholder meeting was conducted to provide an overview of the draft results and key assumptions. Results were presented to the stakeholders on May 31, 2023.

be capable of operating during the lowest temperature that has been recorded in the area using information from the National Weather Service Automated Surface Observing System (ASOS) First Order Station in Asheville, Charlotte, Greensboro, Hatteras, Raleigh or Wilmington, depending upon the station that is located closest to where the plant will be located."

[6] Deterministic modeling is represented with distinct scenarios and inputs that do not change such as the 40 weather years modeled in the resource adequacy framework. Stochastic Modeling allows for random variation in the inputs such as random generator outage draws.

Physical Reliability Results-Island Scenarios

Table ES1 and Table ES2 show the seasonal contribution of LOLE at various reserve margin levels for the Island Scenarios for both DEC and DEP. In the Island Scenarios, it is assumed that DEC and DEP are responsible for their own load and that there is no assistance from neighboring utilities including from each other. The summer and winter reserve margins differ for all scenarios due to seasonal demand forecast differences, weather-related thermal generation capacity differences, demand response seasonal availability, and seasonal solar capacity value. Using the one day in 10-year standard (LOLE of 0.1), which is used across the industry to set minimum target reserve margin levels, DEC would require a 28.5% winter reserve margin and DEP would require a 26.0% winter reserve margin in the Island Scenarios where no assistance from neighboring systems was assumed.

These reserve margin targets are required to cover the combined risks seen in load uncertainty, weather uncertainty, and generator performance for both systems. The reserve margin for DEC under its Island Scenario is higher than the reserve margin for DEP under its Island Scenario due to greater summer LOLE risk in DEC's Island Scenario. DEC also has lower penetrations of solar than DEP which results in more summer LOLE risk in an Island Scenario. In addition to this insight, DEC has more energy limited hydro and pump storage which typically will raise the reserve margin requirement in an island setup.

Table ES1. Island Physical Reliability Results DEC

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
21.0%	18.9%	0.718	0.411	0.307	3.41	3,857
22.0%	19.7%	0.556	0.332	0.224	2.54	2,835

23.0%	20.5%	0.425	0.266	0.159	1.84	2,023
24.0%	21.3%	0.320	0.212	0.108	1.30	1,396
25.0%	22.1%	0.239	0.168	0.071	0.89	930
26.0%	22.9%	0.179	0.133	0.045	0.60	600
27.0%	23.7%	0.135	0.106	0.028	0.41	382
28.0%	24.5%	0.104	0.085	0.019	0.29	252
29.0%	25.3%	0.084	0.070	0.014	0.23	185
30.0%	26.1%	0.070	0.057	0.013	0.20	158
31.0%	26.9%	0.060	0.047	0.012	0.18	146
32.0%	27.7%	0.049	0.038	0.011	0.15	125

Table ES2. Island Physical Reliability Results DEP

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
21.0%	35.9%	0.218	0.218	0.000	0.85	853
22.0%	36.9%	0.187	0.187	0.000	0.71	714
23.0%	37.8%	0.159	0.160	0.000	0.60	594
24.0%	38.7%	0.135	0.135	0.000	0.50	491
25.0%	39.6%	0.114	0.114	0.000	0.41	404
26.0%	40.5%	0.096	0.096	0.000	0.34	333
27.0%	41.4%	0.082	0.081	0.000	0.28	276
28.0%	42.3%	0.070	0.070	0.000	0.24	231
29.0%	43.2%	0.061	0.061	0.000	0.21	198
30.0%	44.1%	0.056	0.056	0.000	0.19	175
31.0%	45.1%	0.053	0.054	0.000	0.19	161
32.0%	46.0%	0.053	0.054	0.000	0.20	155

Physical Reliability Results-Island Combined Scenario

Table ES3 shows the seasonal contribution of LOLE at various reserve margin levels for the Island Combined Scenario where it is assumed that DEC and DEP are responsible for their own load and receive no assistance from neighboring utilities but can receive assistance from each other. Using the one day in 10-year standard (LOLE of 0.1), the Companies would require a 25.0% winter reserve margin in this Island Combined Scenario.

Table ES3. Island Combined Scenario Physical Reliability Results

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
20.0%	24.8%	0.257	0.257	0.00	0.90	1,835
21.0%	25.6%	0.211	0.211	0.00	0.73	1,490
22.0%	26.5%	0.173	0.173	0.00	0.59	1,210
23.0%	27.3%	0.143	0.143	0.00	0.48	982
24.0%	28.2%	0.118	0.118	0.00	0.39	797
25.0%	29.0%	0.098	0.098	0.00	0.32	645
26.0%	29.9%	0.083	0.083	0.00	0.27	514

Physical Reliability Results-Base Case Combined Scenario

Astrapé recognizes that DEC and DEP are part of the larger eastern interconnection and models the majority of all SEEM members and their respective loads and resources[7]. However, it is important to also understand that there is risk in relying on neighboring capacity that is less dependable than owned or contracted generation in which the Companies would have first call rights. A full description of the market assistance modeling and topology is available in the body of the report. Table ES4 shows the seasonal LOLE at various reserve margin levels for the Base Case Combined Scenario which is the Island Combined Scenario with neighbor assistance included as well as DEC and DEP being allowed to assist each other.[8] The various reserve margin levels simulated in the Combined Scenarios are calculated using the total amount of resources in both DEC and DEP and the combined coincident peak load of DEC and DEP.

[7] Due to the limited transmission capability from the Florida peninsula to Southern Company, Florida entities were excluded from the modeling.
[8] DEC and DEP intend to merge and as a result the Combined Case is the recommended scenario. The merged utility includes joint unit commitment, dispatch and ancillary services, and consolidates the balancing authorities and removes associated transmission constraints between existing individual BAs.
See https://starw1.ncuc.gov/NCUC/ViewFile.aspx?Id=801d9fbd-1b1d-456c-8439-6bfe8c9db339

Table ES4. Base Case Combined Physical Reliability Results

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
16.0%	21.4%	0.206	0.206	0	0.90	2,356
17.0%	22.3%	0.184	0.184	0	0.77	1,981
18.0%	23.1%	0.164	0.164	0	0.66	1,663
19.0%	24.0%	0.146	0.146	0	0.56	1,396
20.0%	24.8%	0.130	0.130	0	0.48	1,174
21.0%	25.6%	0.115	0.115	0	0.42	992
22.0%	26.5%	0.102	0.102	0	0.36	842
23.0%	27.3%	0.090	0.090	0	0.31	719
24.0%	28.2%	0.079	0.079	0	0.27	616
25.0%	29.0%	0.069	0.069	0	0.24	528
26.0%	29.9%	0.061	0.061	0	0.21	449
27.0%	30.7%	0.053	0.053	0	0.17	372

As the table indicates, the required reserve margin to meet the one day in 10-year standard (LOLE of 0.1), is 22.0% which is 3.0% lower than the required reserve margin for 0.1 LOLE in the Island Combined Scenario. Utilities around the country are continuing to retire and replace fossil-fuel resources with more intermittent or energy limited resources such as solar, wind, and battery capacity which will continue to shift risk to the winter season in the southeast region.

Physical Reliability Results - DEC and DEP Individual Cases

In addition to running the Island Scenarios, Island Combined Scenario and the Base Case Combined Scenario, DEC and DEP Individual Scenarios where DEC and DEP did not prioritize helping each other as they do in the Island Combined Scenario and Base Case Combined Scenario were simulated to understand the reliability impact. Table ES5 and Table ES6 show the results of the DEC and DEP Individual Scenarios at various reserve margin levels. The DEC winter reserve margin to meet the 1 day in 10 year standard is 21.5% while the DEP winter reserve margin to meet the 1 day in 10 year standard is 24.0%.

Table ES5. DEC Individual Scenario Physical Reliability Results

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
17.0%	15.7%	0.165	0.165	0.00	0.68	1,006
18.0%	16.5%	0.146	0.146	0.00	0.60	857
19.0%	17.3%	0.130	0.130	0.00	0.52	720
20.0%	18.1%	0.117	0.117	0.00	0.44	598
21.0%	18.9%	0.106	0.106	0.00	0.37	490
22.0%	19.7%	0.094	0.094	0.00	0.31	398
23.0%	20.5%	0.081	0.081	0.00	0.26	324

Table ES6. DEP Individual Scenario Physical Reliability Results

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
18.0%	33.2%	0.172	0.172	0.00	0.71	890
19.0%	34.1%	0.158	0.158	0.00	0.64	777
20.0%	35.0%	0.146	0.146	0.00	0.58	678
21.0%	35.9%	0.135	0.135	0.00	0.52	591
22.0%	36.9%	0.123	0.123	0.00	0.47	513
23.0%	37.8%	0.111	0.111	0.00	0.41	442
24.0%	38.7%	0.097	0.097	0.00	0.35	376

Recommendation

Based on the physical reliability results of the Base Case Combined Scenario, Astrapé recommends that the Companies maintain a 22% combined reserve margin for IRP purposes. Astrapé recognizes this is a 5% increase from the 17% reserve margin recommended in the 2020 Resource Adequacy and is being driven by three main factors including: a reduction in neighbor assistance, the assumption of long-term load forecast error, and generator performance especially during cold periods as described below. To ensure summer reliability is maintained, Astrapé recommends not allowing the summer reserve margin to drop below 15%.

When performing the 2023 Resource Adequacy study for the Companies, attention was given to accurately modeling the shifting neighbor resource portfolios including coal retirements and the buildout of solar, wind, and storage resources on other utilities' systems. This changing resource mix along with the cold weather load response has shifted the resource adequacy risk of the Companies' neighbors to the winter. Because of this, there is now less market assistance available to the Companies' during the winter extreme weather periods which increases the resources the Companies' need to carry to maintain a reliable system. Based on a comparison of net imports during extreme hours in the 2020 and 2023 studies, Astrapé estimates that this reduction in neighbor assistance translates to around a 1.75% increase in the reserve margin.

In the 2020 Resource Adequacy study, the economic load forecast error distribution model weighted over-forecasting more than under-forecasting load. The updated distribution that was modeled in the 2023 study was more symmetrical which leads to approximately a 0.75% increase in the reserve margin.

Finally, the unit outage modeling was updated to be based on Generating Availability Data System (GADS) data from 2018-2022 including the performance of units during Winter Storm Elliot. Assumptions on capacity risk during winter weather events were also updated using the last five years of history. Both of these put upward pressure on reserve margin, and it is estimated these alone increased the reserve margin by 2.5%.

Given these factors outlined above, the 5% increase is reasonable and expected given the changing landscape over the last three to four years since the previous study was conducted. Recent events like Winter Storm Elliot show that it is increasingly difficult to rely on neighbor assistance during these extreme winter weather conditions especially as more and more of the Companies' neighbors have shifted away from summer resource adequacy risk to winter resource adequacy risk.

I. List of Figures

II. List of Tables

III. Input Assumptions

A. Study Year

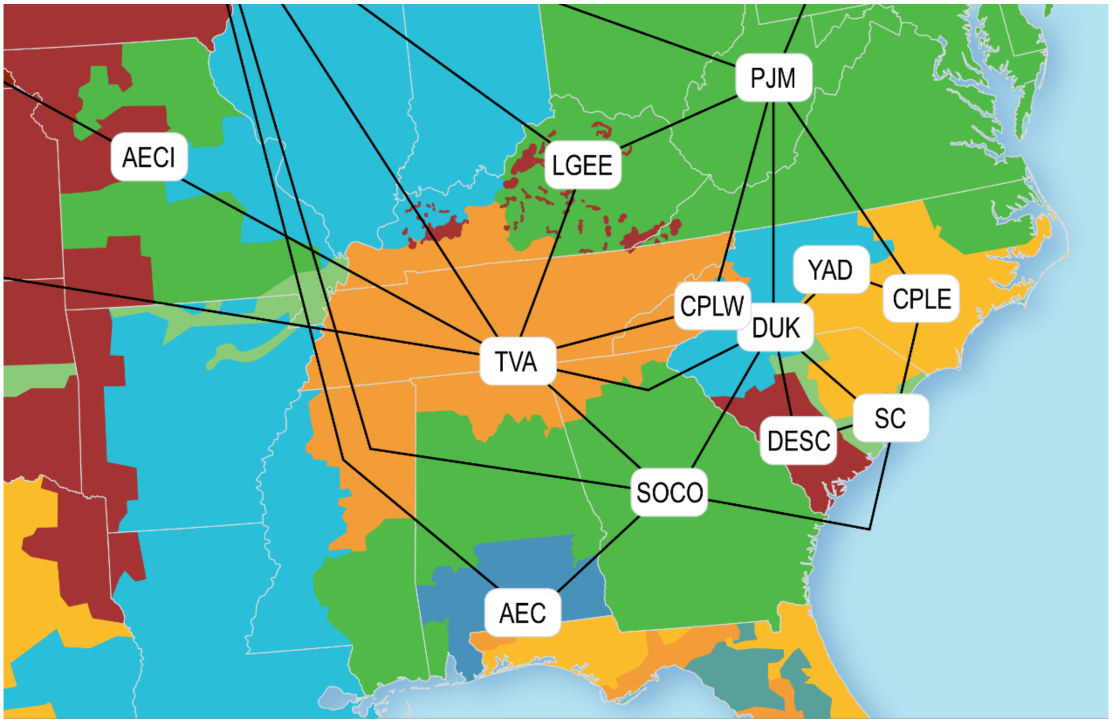
The selected study year is 2027.[9] The SERVM simulation results are broadly applicable to future years assuming that resource mixes and market structures do not change in a manner that shifts the reliability risk to a different season or different time of day.

B. Study Topology

Figure 1 shows the study topology that was used for the Resource Adequacy Study. While market assistance is not as dependable as resources that are utility owned or have firm contracts, Astrapé believes it is appropriate to capture the load diversity and generator outage diversity that DEC and DEP have with their neighbors. For this study, the DEC and DEP systems were modeled with nine surrounding regions. The surrounding regions captured in the modeling included Associated Electric Cooperative (AECI), Louisville Gas and Electric (LGE), Tennessee Valley Authority (TVA), Southern Company (SOCO), PJM West[10] & PJM South,[11] Yadkin (YAD), PowerSouth Energy Cooperative, Dominion Energy South Carolina (formally known as South Carolina Electric & Gas (SCEG)), and Santee Cooper (SC). SERVM uses a pipe and bubble representation in which energy can be shared based on economics but is subject to transmission constraints.

[9] The year 2027 was chosen because it is four years into the future which is indicative of the amount of time needed to permit and construct a new generating facility.
[10] PJM West is defined as the following PJM Zones: American Electric Power, East Kentucky Power Cooperative, ComEd, Duke Energy Ohio Kentucky, Allegheny Power Systems, Dayton Power and Light Company and Ohio Valley Electric Corporation
[11] PJM South is defined as the PJM DOM Zone.

Figure 1. Study Topology



C. Load Modeling

Table 1 displays SERVM's modeled seasonal peak forecast net of energy efficiency programs for 2027.[12]

Table 1. 2027 Forecast: DEC and DEP Seasonal Peak (MW)

2027	Summer	Winter
DEC	18,848	18,165
Progress East	12,773	13,778
Progress West	884	1,197
DEP	13,612	14,932
Combined System Coincident	32,298	32,765

[12] Load data reflects native load requirements and firm planning obligations and not total Balancing Authority load.

To model the effects of weather uncertainty, forty-three historical weather years (1980 - 2022) were developed to reflect the impact of weather on load. Based on the last five years of historical weather and load, a neural network program was used to develop relationships between weather observations and load.[13] A process chart displaying the detailed steps of the synthetic load shape development is included in Appendix A. The historical weather consisted of hourly temperatures from the following weather stations:

1) DEC
   a) Charlotte, NC-33.33%
   b) Greensboro, NC-33.33%
   c) Greenville, NC-33.33%
2) DEP-E
   a) Columbia, SC-10%
   b) Raleigh, NC-40%
   c) Wilmington, NC-30%
   d) Fayetteville, NC-20%
3) DEP-W
   a) Asheville, NC

Other inputs into the neural net model consisted of hour of week, eight hour rolling average temperatures, twenty-four hour rolling average temperatures, and forty-eight hour rolling average temperatures.[14] Different weather to load relationships were built for the summer, winter, and shoulder seasons. These relationships were then applied to the last forty-three years of weather to develop forty-three synthetic load shapes for 2027. Equal probabilities were given to each of the forty-three load shapes in the simulation. The synthetic load shapes were scaled to align the normal

[13] The historical load included years 2018 through 2022.
[14] The Neural Net Model is the NeuroShell Predictor provided by Ward Systems Group, Inc.

summer and winter peaks to the Company's projected thirty-year weather normal load forecast for 2027.

Figure 2, Figure 3, Figure 4, Figure 5, Figure 6, and Figure 7 show the results of the weather load modeling by displaying the peak load variance for both the summer and winter seasons for DEC, DEP-E, and DEP-W. The y-axis represents the percentage deviation from the average peak. For example, the 1985 DEC synthetic load shape would result in a summer peak load approximately 2% below normal and a winter peak load approximately 27% above normal. Thus, the bars represent the variance in projected peak loads based on weather experienced during the historic weather years. It should be noted that the variance for winter is much greater than summer. As an example and as seen in recent history, extreme cold temperatures can cause load to spike from additional electric strip heating and other heating sources. The highest summer temperatures typically are only a few degrees above the expected highest temperature and therefore do not produce as much peak load variation.

Figure 2. DEC Summer Peak Weather Variability

Figure 3. DEC Winter Peak Weather Variability

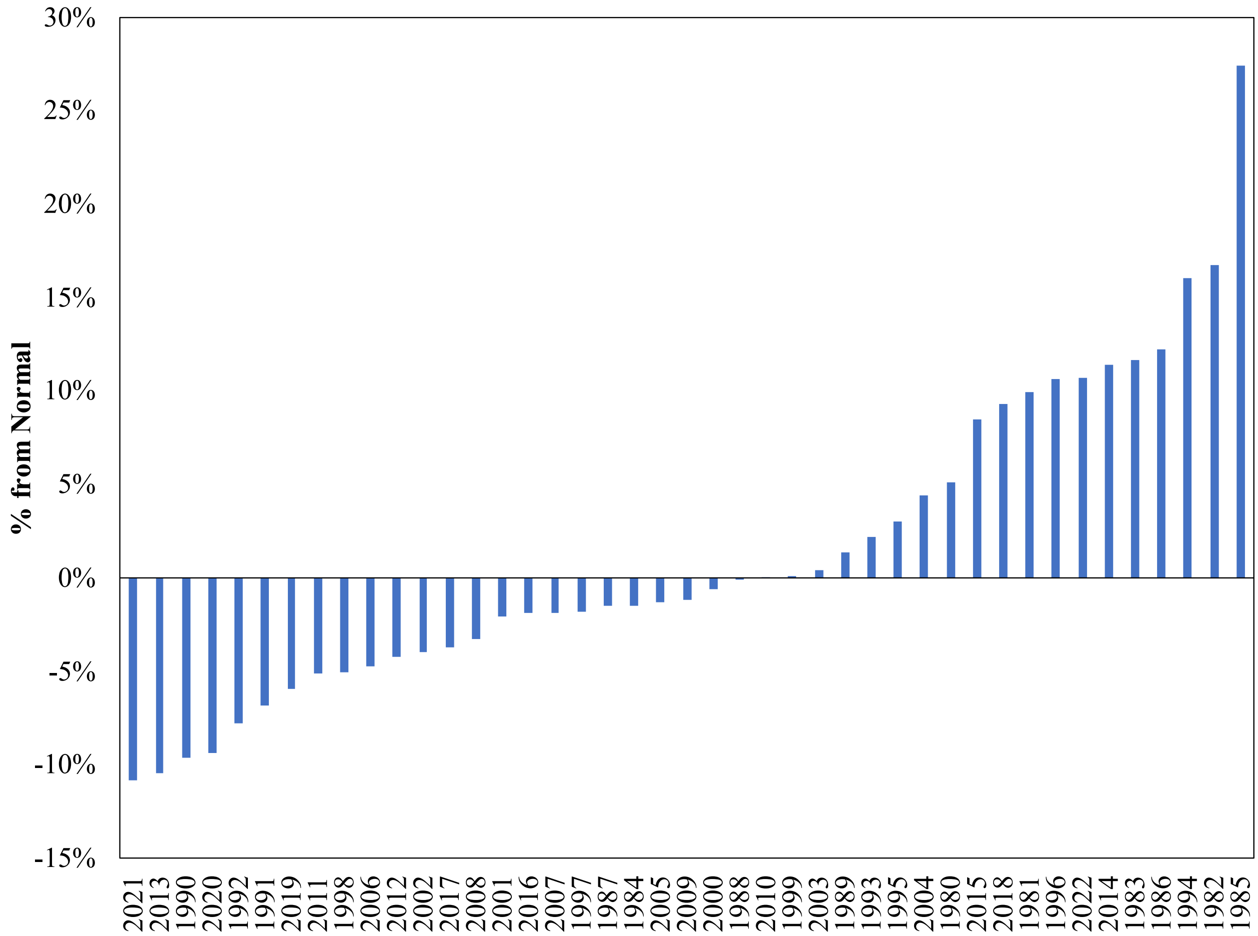


Figure 4. DEP-E Summer Peak Weather Variability

Figure 5. DEP-E Winter Peak Weather Variability

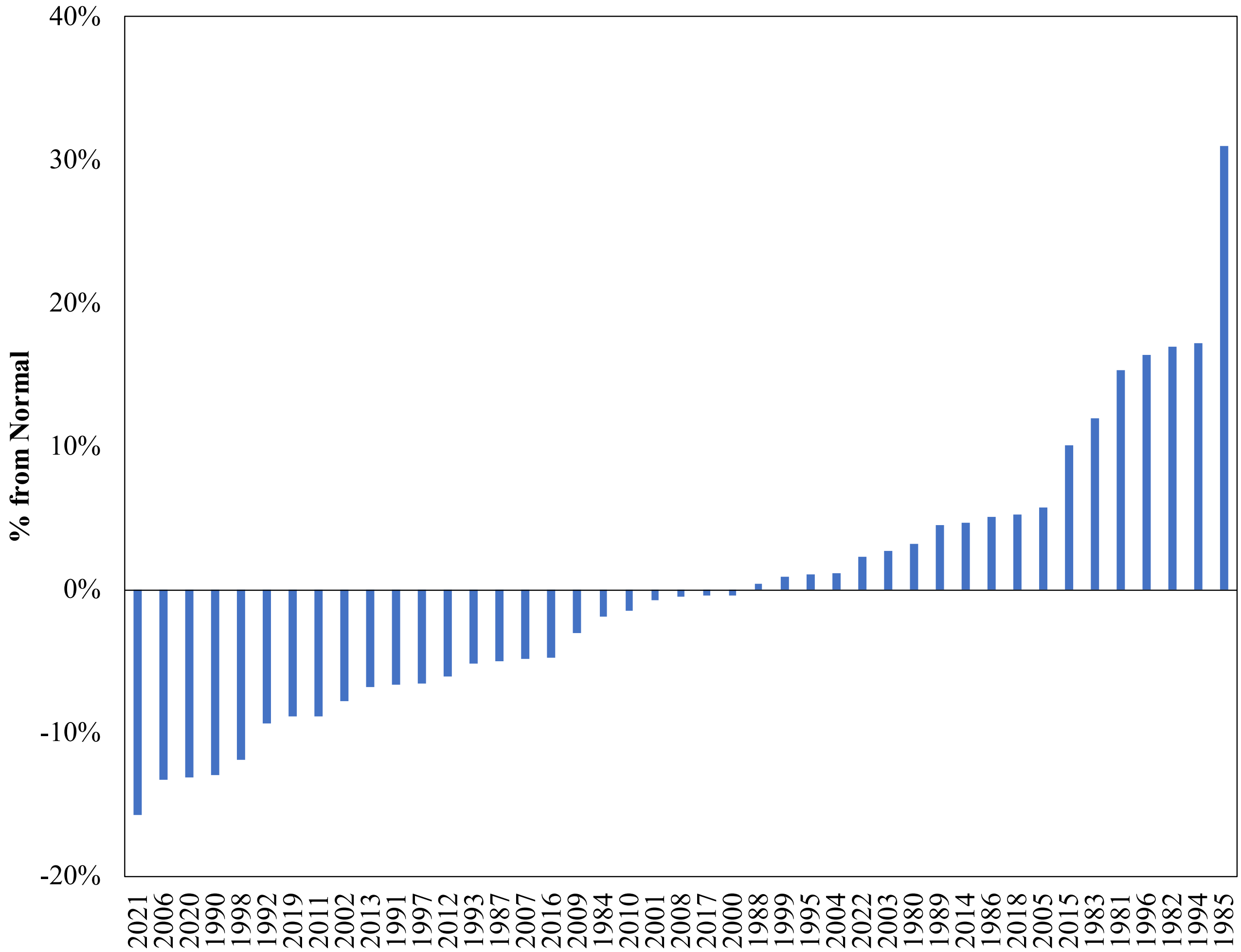


Figure 6. DEP-W Summer Peak Weather Variability

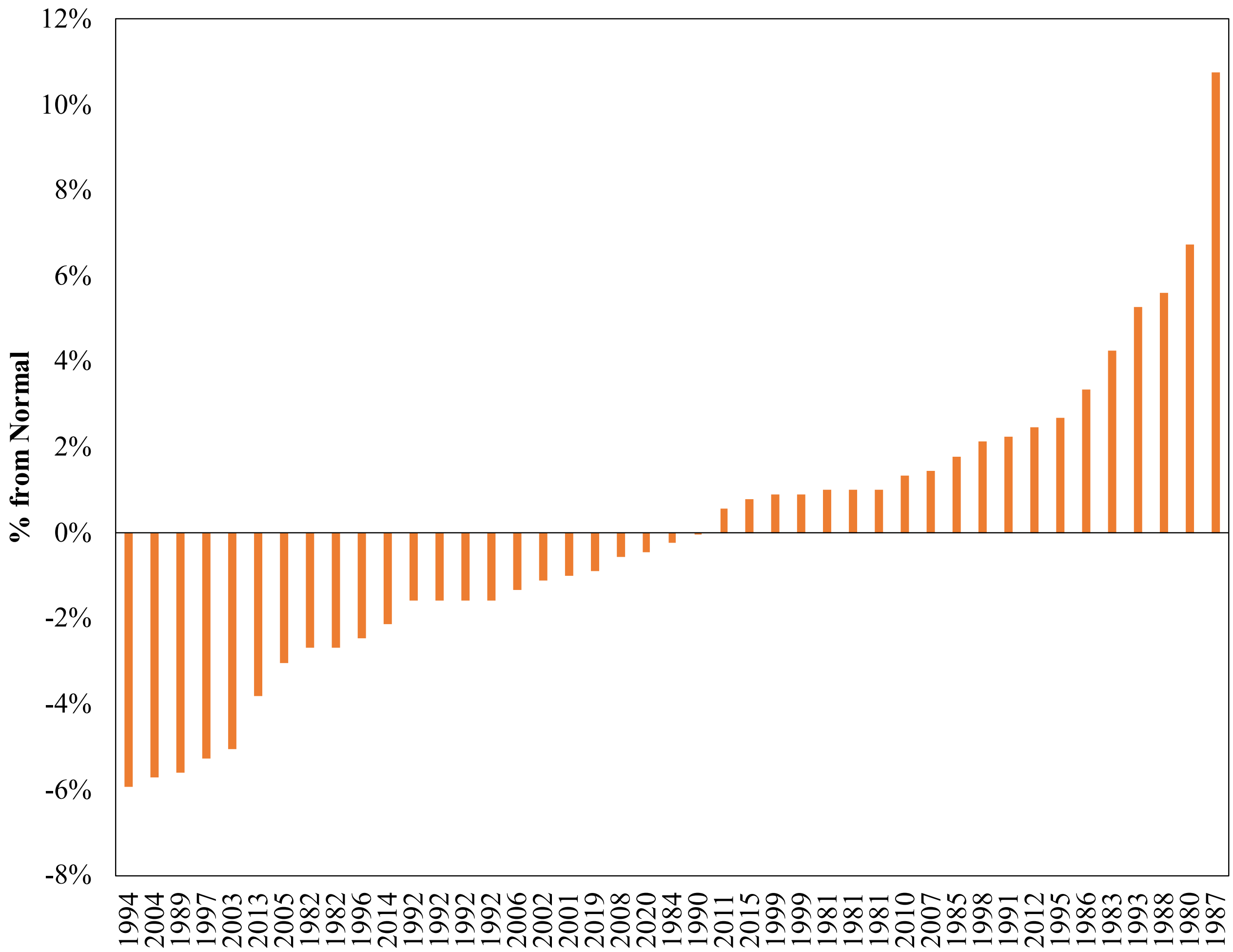
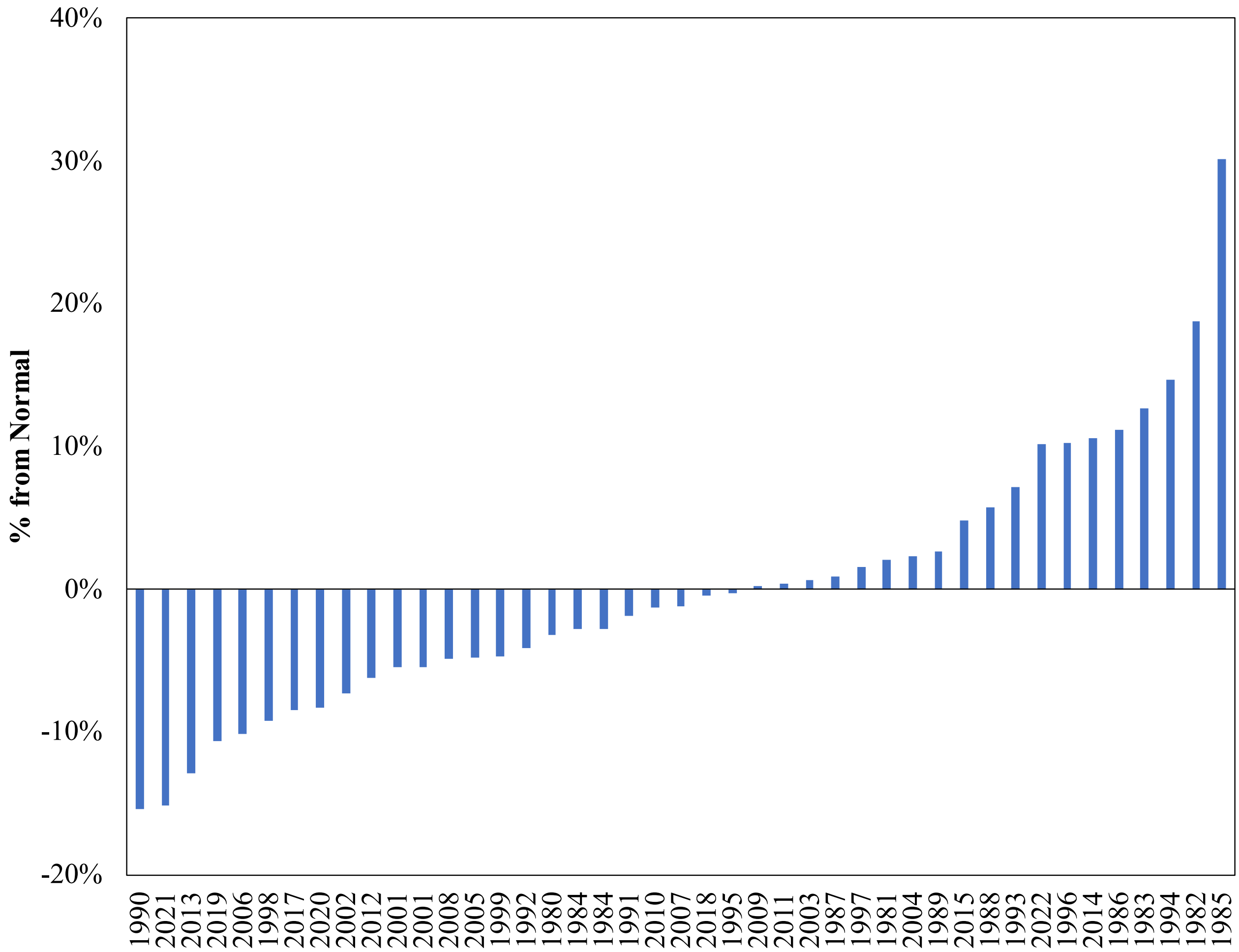


Figure 7. DEP-W Winter Peak Weather Variability



Figures 8-10 below show a weekday daily peak load comparison of the synthetic load shapes and history as a function of cold temperature for DEC, DEP-E, and DEP-W.

Figure 8. DEC Winter Weekday Calibration

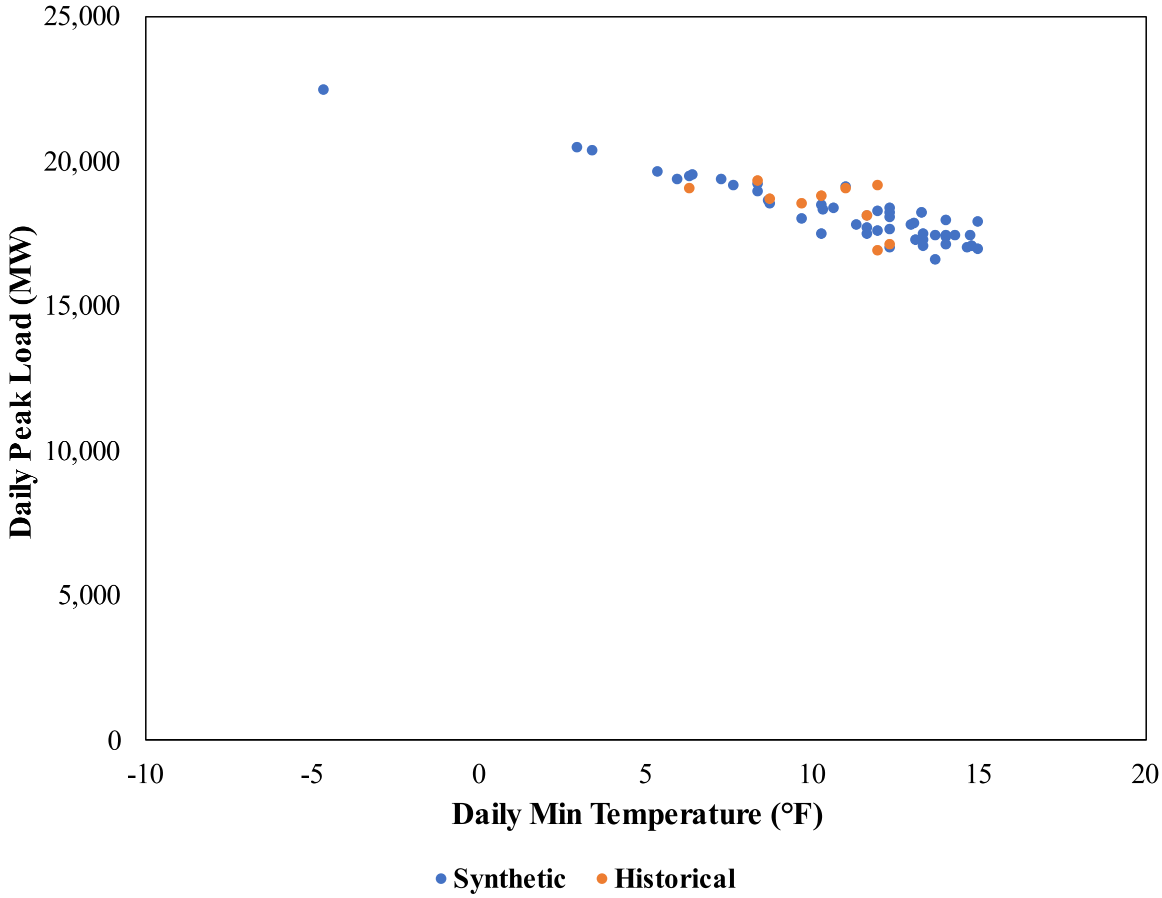


Figure 9. DEP-E Winter Weekday Calibration

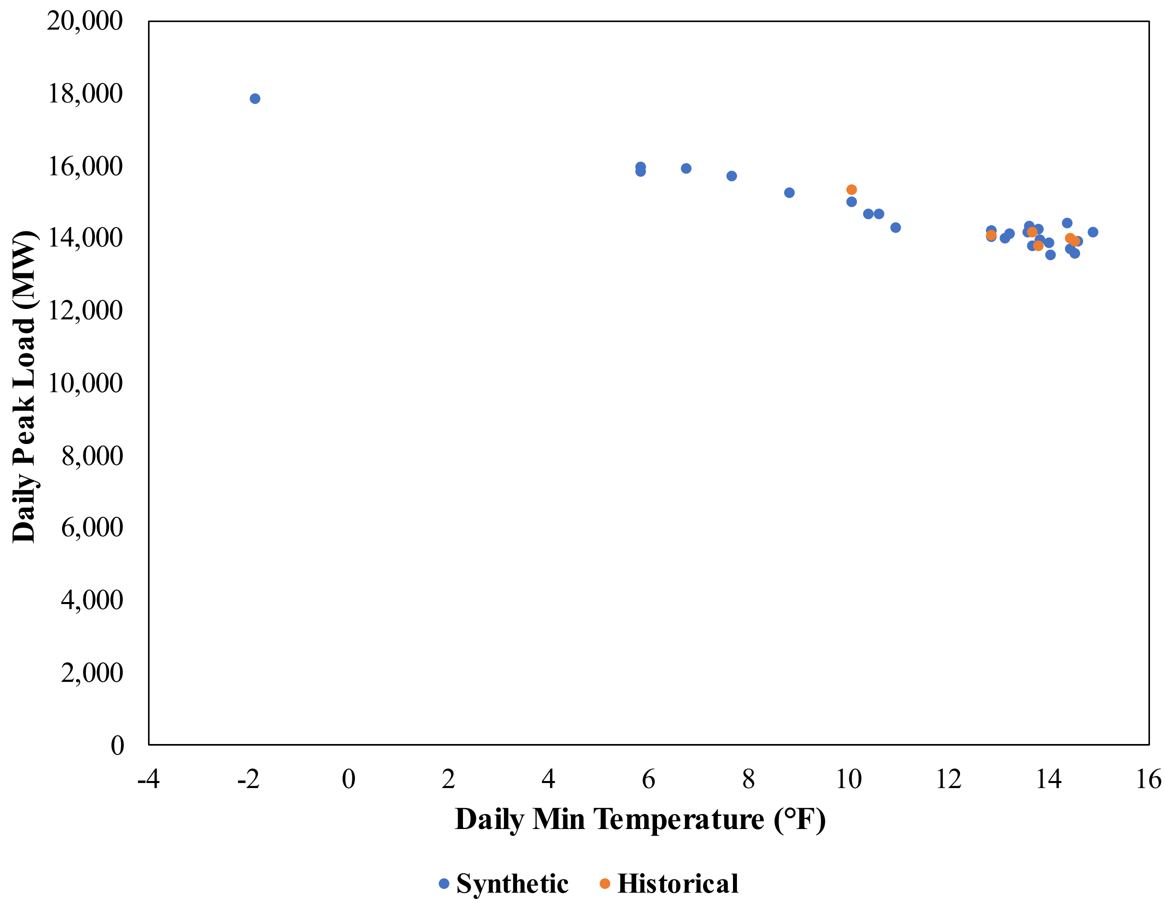
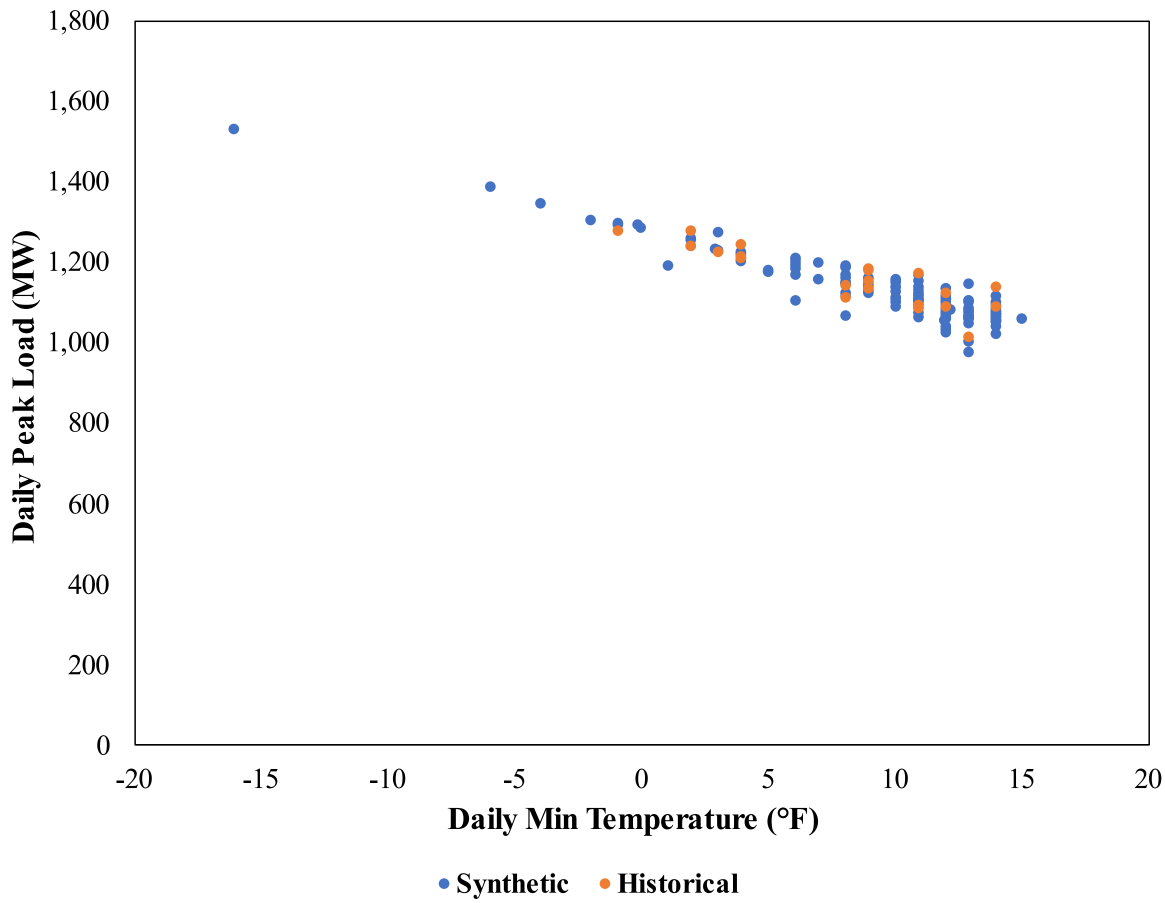


Figure 10. DEP-W Winter Weekday Calibration



Given the recent extreme winter weather, special attention was given to ensuring that the winter load relationship was accurately captured especially at the temperature points that have not been seen in recent history. While the neural nets referenced above were trained on 2018-2022 load data, peak load and temperature data from 2014-2022 were used to extrapolate out the load behavior at extreme temperatures. Including the number of cold days preceding the extreme cold weather was considered as well as examining whether the slope of the cold weather load response to temperature has increased over time. Attempting to incorporate either of these factors did not improve the analysis and it was determined the methodology used in the 2020 study still remained the best option for extrapolating out the extreme load behavior especially given the load response seen in the recent Winter Storm Elliot event. More discussion on this process is located in Appendix A.

The synthetic shapes described above were then scaled to the forecasted seasonal energy and peaks within SERVM. Because DEC and DEP's load forecasts are based on thirty years of weather, the shapes were scaled so that the average of the last thirty years equaled the forecast.

Synthetic loads for each external region were developed in a similar manner as the DEC and DEP loads. A relationship between hourly weather and publicly available hourly load[15] was developed based on recent history, and then this relationship was applied to forty-three years of weather data to develop forty-three synthetic load shapes. Table 2 and Table 3 show the resulting weather diversity between the combined DEC and DEP systems and external regions for both summer and winter loads. When the system, which includes all regions in the study, is at its winter peak, the individual regions are approximately 2% - 13% below their non-coincidental peak load on average over the forty-three-year period. At the time of the Carolinas (combined DEC and DEP) winter peak as shown in Table 3, all neighboring regions excluding AECI are 5% - 10% below their non-coincidental peak load. These values represent the average of mild and extreme years.

Table 2. External Region Summer Load Diversity

Load Diversity (% below non coincident average peak)	At System Coincident Peak	At CAR Peak
CAR	2.6%	-
AECI	13.1%	19.4%
LGE	4.7%	9.0%
PJM_South	5.6%	7.4%

[15] Federal Energy Regulatory Commission (FERC) 714 Forms were accessed during January of 2023 to pull hourly historical loads for all neighboring regions.

Load Diversity (% below non coincident average peak)	At System Coincident Peak	At CAR Peak
PJM_West	2.1%	11.2%
PowerSouth	10.8%	10.5%
SC	7.9%	5.3%
SCEG	7.5%	6.0%
SOCO	5.3%	5.1%
TVA	4.3%	6.4%
System	-	3.6%

Table 3. External Region Winter Load Diversity

Load Diversity (% below non coincident average peak)	At System Coincident Peak	At CAR Peak
CAR	2.4%	-
AECI	13.4%	20.3%
LGE	5.0%	9.5%
PJM_South	6.6%	5.4%
PJM_West	3.6%	7.3%
PowerSouth	6.8%	8.9%
SC	8.0%	6.5%
SCEG	7.2%	5.3%
SOCO	3.0%	6.0%
TVA	3.2%	7.3%
System	-	2.1%

D. Economic Load Forecast Error

Economic load forecast error multipliers were developed to isolate the economic uncertainty that the Companies have in their four year ahead load forecasts. The economic load forecast error distribution was developed using Moody's Analytics data. To estimate the economic load forecast error, the forecasts of both state population and Gross Domestic Product (GDP) for different economic scenarios were used to determine the percent change from each economic scenario to the baseline scenario. The Moody's estimated likelihood of these percent changes was then applied, and the percent changes were adjusted by a factor of 0.4 which acknowledges that the load does not grow at a one-to-one ratio with GDP. The final distribution used in the study is provided in Table 4.

Table 4. Economic Load Forecast Error

Economic Load Forecast Error Multipliers	Probability %
0.9806	27.0%
1.00	46.0%
1.0231	27.0%

E. Conventional Thermal Resources

DEC and DEP thermal resources are outlined in Table 5 and Table 6 and represent summer and winter ratings. All thermal resources are committed and dispatched to load economically. The capacities of the units are defined as a function of temperature in the simulations. For temperatures in between the winter and summer temperature rating provided for each unit, capacity was linearly scaled between the summer and winter rating for each unit.

Table 5. DEC and DEP Baseload and Intermediate Resources

DEC[16]				DEP			
Unit	**Primary Fuel**	**Winter Capacity (MW)**	**Summer Capacity (MW)**	**Unit**	**Primary Fuel**	**Winter Capacity (MW)**	**Summer Capacity (MW)**
Belews Creek 1	Coal	1,110	1,110	Asheville CC_1	Natural Gas	292	248
Belews Creek 2	Coal	1,110	1,110	Asheville CC_2	Natural Gas	292	248
Buck CC	Natural Gas	718	668	Brunswick 1	Nuclear	975	938

[16] The listed amounts for Catawba 1 & 2 and W.S. Lee are the portions of these units that DEC owns.

DEC[16]				DEP			
Unit	**Primary Fuel**	**Winter Capacity (MW)**	**Summer Capacity (MW)**	**Unit**	**Primary Fuel**	**Winter Capacity (MW)**	**Summer Capacity (MW)**
Catawba 1	Nuclear	294	260	Brunswick 2	Nuclear	953	932
Catawba 2	Nuclear	294	260	H. F. Lee CC 1	Natural Gas	1,079	863
Cliffside 6	Coal	849	844	Harris 1	Nuclear	1,009	964
Dan River CC	Natural Gas	718	662	Mayo 1	Coal	746	727
Marshall 1	Coal	380	370	Richmond CC 4	Natural Gas	570	475
Marshall 2	Coal	380	370	Richmond CC 5	Natural Gas	697	591
Marshall 3	Coal	658	658	Robinson 2	Nuclear	793	759
Marshall 4	Coal	660	660	Roxboro 1	Coal	380	379
McGuire 1	Nuclear	1,199	1,158	Roxboro 2	Coal	673	668
McGuire 2	Nuclear	1,187	1,158	Roxboro 3	Coal	698	694
Oconee 1	Nuclear	865	847	Roxboro 4	Coal	711	698
Oconee 2	Nuclear	872	848	Sutton CC 1	Natural Gas	658	536
Oconee 3	Nuclear	881	859				
W.S. Lee CC	Natural Gas	709	686				

Table 6. DEC and DEP Peaking Resources

DEC				DEP			
Unit	**Primary Fuel**	**Winter Capacity (MW)**	**Summer Capacity (MW)**	**Unit**	**Primary Fuel**	**Winter Capacity (MW)**	**Summer Capacity (MW)**
Lee CT_7	Oil	48	42	Asheville CT 3	Natural Gas	185	160
Lee CT_8	Oil	48	42	Asheville CT 4	Natural Gas	185	160
Lincoln CT_1	Natural Gas	94	73	Blewett CT 1	Oil	17	13
Lincoln CT_10	Natural Gas	96	73	Blewett CT 2	Oil	17	13
Lincoln CT_11	Natural Gas	95	73	Blewett CT 3	Oil	17	13
Lincoln CT_12	Natural Gas	94	73	Blewett CT 4	Oil	17	13
Lincoln CT_13	Natural Gas	93	72	Darl CT 12	Natural Gas	131	118
Lincoln CT_14	Natural Gas	94	72	Darl CT 13	Natural Gas	133	116
Lincoln CT_15	Natural Gas	94	73	Richmond CT 1	Natural Gas	192	157
Lincoln CT_16	Natural Gas	93	73	Richmond CT 2	Natural Gas	192	156
Lincoln CT_17	Natural Gas	402	365	Richmond CT 3	Natural Gas	192	155
Lincoln CT_2	Natural Gas	96	74	Richmond CT 4	Natural Gas	192	159
Lincoln CT_3	Natural Gas	95	73	Richmond CT 6	Natural Gas	192	145
Lincoln CT_4	Natural Gas	94	73				
Lincoln CT_5	Natural Gas	93	72				
Lincoln CT_6	Natural Gas	93	72				
Lincoln CT_7	Natural Gas	95	72				

DEC				DEP			
Unit	**Primary Fuel**	**Winter Capacity (MW)**	**Summer Capacity (MW)**	**Unit**	**Primary Fuel**	**Winter Capacity (MW)**	**Summer Capacity (MW)**
Lincoln CT_8	Natural Gas	94	72				
Lincoln CT_9	Natural Gas	94	71				
Mill_Creek_CT_1	Natural Gas	94	71				
Mill_Creek_CT_2	Natural Gas	94	70				
Mill_Creek_CT_3	Natural Gas	95	71				
Mill_Creek_CT_4	Natural Gas	94	70				
Mill_Creek_CT_5	Natural Gas	94	69				
Mill_Creek_CT_6	Natural Gas	92	71				
Mill_Creek_CT_7	Natural Gas	95	70				
Mill_Creek_CT_8	Natural Gas	93	71				
Rockingham CT_1	Natural Gas	179	165				
Rockingham CT_2	Natural Gas	179	165				
Rockingham CT_3	Natural Gas	179	165				
Rockingham CT_4	Natural Gas	179	165				
Rockingham CT_5	Natural Gas	179	165				

F. Unit Outage Data

Unlike typical production cost models, SERVM does not use an Equivalent Forced Outage Rate (EFOR) for each unit as an input. Instead, historical GADS data events for the period 2018-2022 are entered in for each unit and SERVM randomly draws from these events to simulate the unit outages. Units without historical data use history from similar technologies in the Companies' fleets. The events are entered using the following variables:

Full Outage Modeling
Time-to-Repair Hours
Time-to-Fail Hours

Partial Outage Modeling
Partial Outage Time-to-Repair Hours
Partial Outage Derate Percentage
Partial Outage Time-to-Fail Hours

Maintenance Outages
Maintenance Outage Rate - % of time in a month that the unit will be on maintenance outage. SERVM uses this percentage and schedules the maintenance outages during off peak periods.

Planned Outages
Estimates based on future scheduled maintenance were utilized in the modeling.

To illustrate the outage logic, assume that from 2018 – 2022, a generator had 12 full outage events and 30 partial outage events reported in the GADS data. The Time-to-Repair and Time-to-Fail between each event is calculated from the GADS data. These multiple Time-to-Repair and Time-to-Fail inputs are the distributions used by SERVM. Because there may be seasonal variances in EFOR, the data is broken up into seasons such that there is a set of Time-to-Repair and Time-to-Fail inputs for summer, shoulder, and winter, based on history. Further, assume the generator is online in hour 1 of the simulation. SERVM will randomly draw both a full outage and partial outage Time-to-Fail value from the distributions provided. Once the unit has been economically committed for that amount of time, it will fail. A partial outage will be triggered first if the selected Time-to-Fail value is lower than the selected full outage Time-to-Fail value. Next, the model will draw a Time-to-Repair value from the distribution and be on outage for that number of hours. When the repair is complete it will draw a new Time-to-Fail value. The process repeats until the end of the iteration when it will begin again for the subsequent iteration. The full outage counters and partial outage counters run in parallel. This more detailed modeling is important to capture the tails of the distribution that a simple convolution method would not capture.

Additional steps were taken to accurately model the incremental cold weather outages seen in the 2018-2022 historical GADS data. Incremental cold weather outage rates derived from historical cold weather events including Winter Storm Elliot were also applied to the thermal fleet.

G. Winter Weather Capacity Risk

The threat that winter weather poses to the Companies' generating fleet has been considered in studies Astrapé performs on behalf of the Companies since 2016. After Winter Storm Elliot in December of 2022, there has been a renewed emphasis on capturing the additional risk posed by winter weather. To do this, historic GADS data from 2018 through 2022 was reviewed for instances identified as being caused by winter weather specifically.[17]

A probabilistic relationship between the temperature and these events caused by winter weather was then determined. This relationship was modeled in SERVM as a weather dependent forced

[17] Key words in the GADS event description such as: "Froze", "Freezing", "snow", "ice", etc.

outage probability that increases as temperatures decrease. Partial outages were handled in a similar manner.

H. Solar and Battery Modeling

Table 7 and Table 8 show the solar and battery resources captured in the study.

Table 7. DEC and DEP Solar Resources

Unit Type	Inverter Loading Ratio (ILR)	DEC Capacity (MW)	DEP Capacity (MW)
Solar Fixed	1.3	1,142	3,161
Solar Fixed	1.6	121	239
Solar Single-Axis Tracking	1.3	575	179
Solar Single-Axis Tracking	1.6	258	164
Solar Bifacial Single-Axis Tracking	1.4	809	765
Total		2,905	4,507

Table 8. DEC and DEP Storage Resources

Unit	Capacity (MW)	Duration (hours)	Cycle Efficiency
DEP 2HR Composite Battery	182	2	85%
DEP 4HR Composite Battery	55	4	85%
DEP Solar Plus Storage 2 HR	32	2	85%
DEP Solar Plus Storage 4 HR	20	4	85%
DEC 2HR Composite Battery	60	2	85%
DEC 4HR Composite Battery	52	4	85%
DEC CPRESS Guilford	41	4	85%
DEC CPRESS Orange	36	4	85%
DEC Solar Plus Storage 2 HR	27	2	85%

The solar units were simulated with forty-three solar shapes representing forty-three years of weather. The solar shapes were developed by Astrapé from data downloaded from the National Renewable Energy Laboratory (NREL) National Solar Radiation Database (NSRDB) Data Viewer. The data was then input into NREL's System Advisor Model (SAM) for each year and county to generate hourly profiles for both fixed and tracking solar profiles. Figure 11 shows the county locations that were used and Figure 12, Figure 13, and Figure 14 show the average January output for fixed, monofacial tracking and, bifacial tracking for the various sites. All future solar resources were modeled as bifacial single axis tracking.

Figure 11. Solar Map

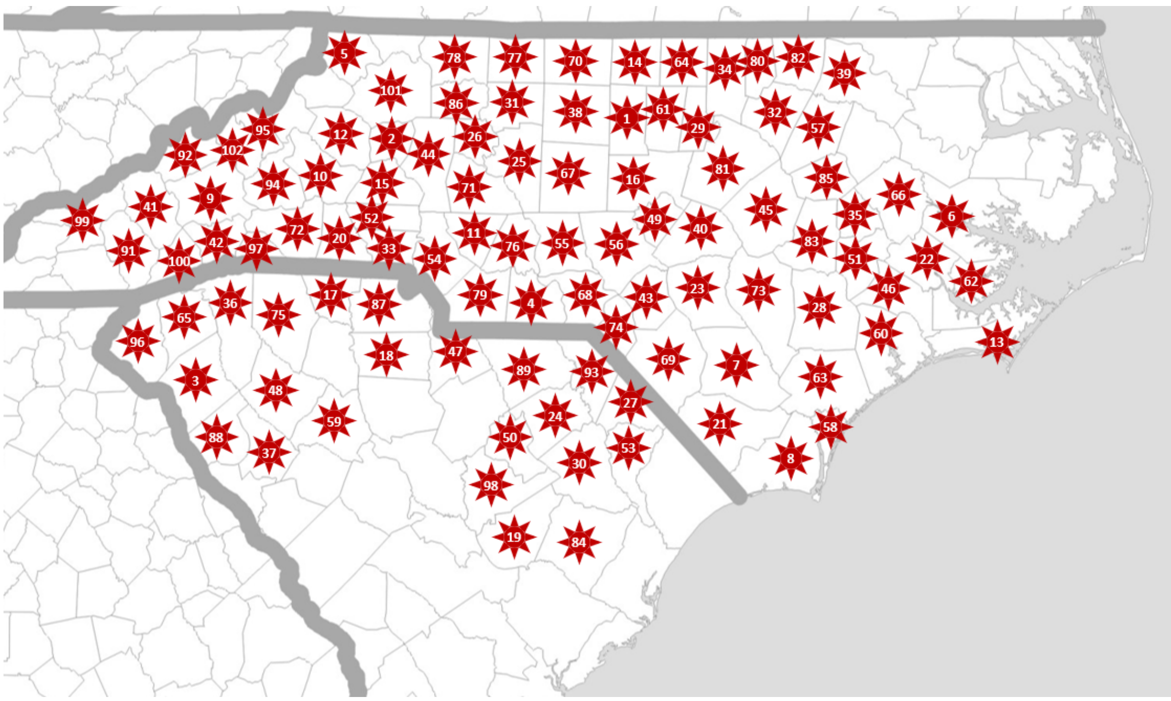


Figure 12. Average January Output for Fixed Tilt

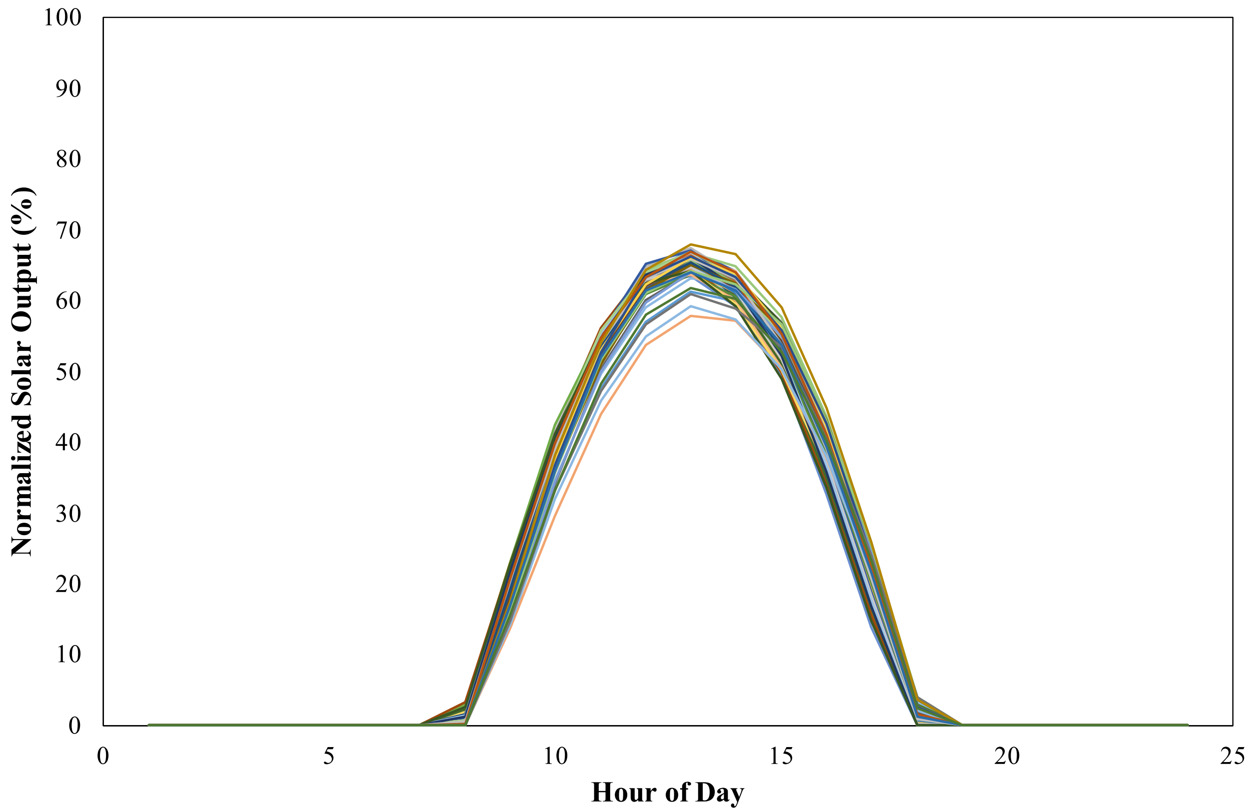


Figure 13. Average January Output for Monofacial Single Axis Tracking

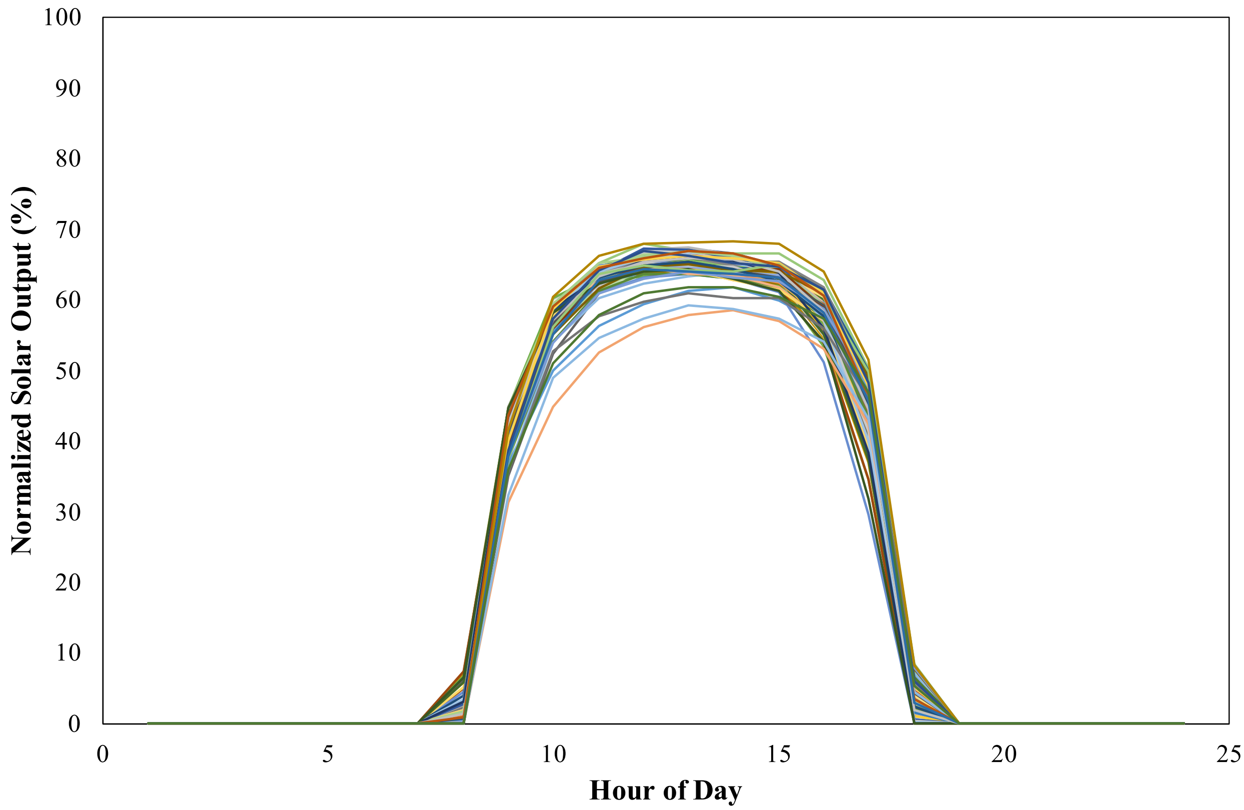
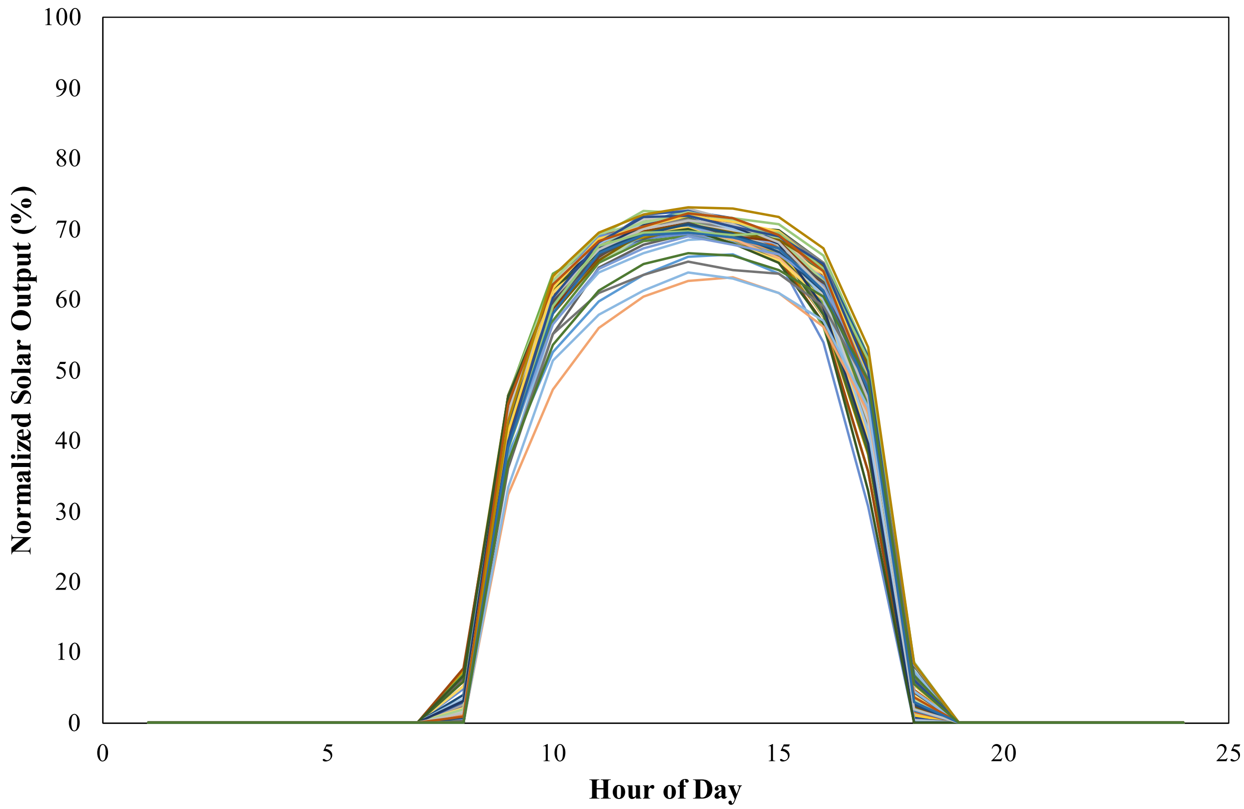


Figure 14. Average January Output for Bifacial Single Axis Tracking



I. Hydro Modeling

The scheduled hydro is used for shaving the daily peak load but also includes minimum flow requirements. Figure 15 and Figure 16 show the total breakdown of scheduled hydro based on the last forty-three years of weather for DEC and DEP.

Figure 15. DEC Scheduled Capacity

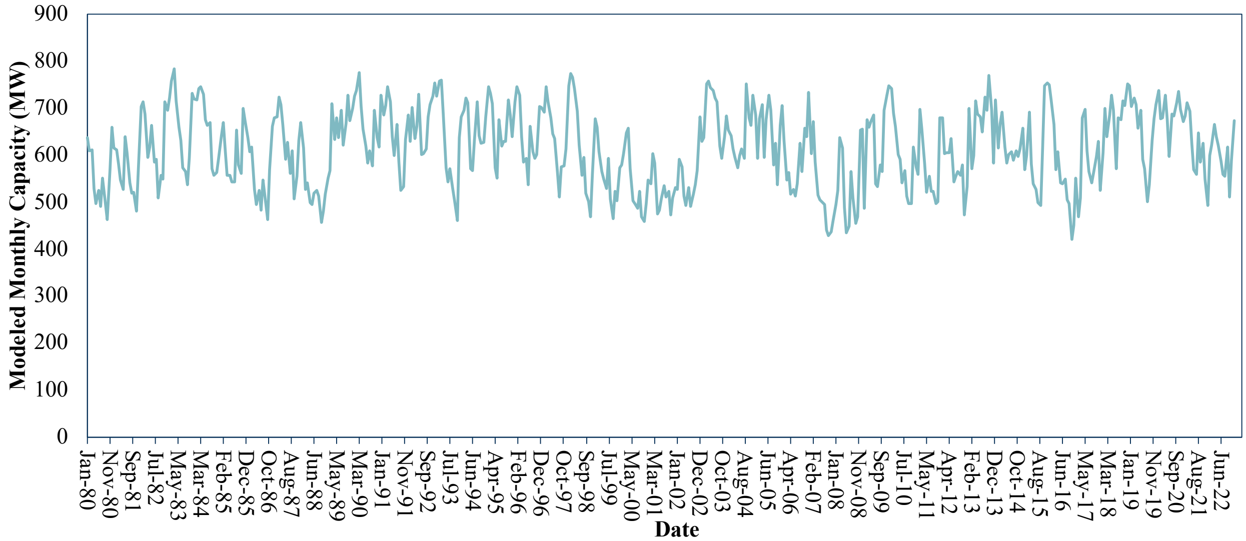


Figure 16. DEP Scheduled Capacity

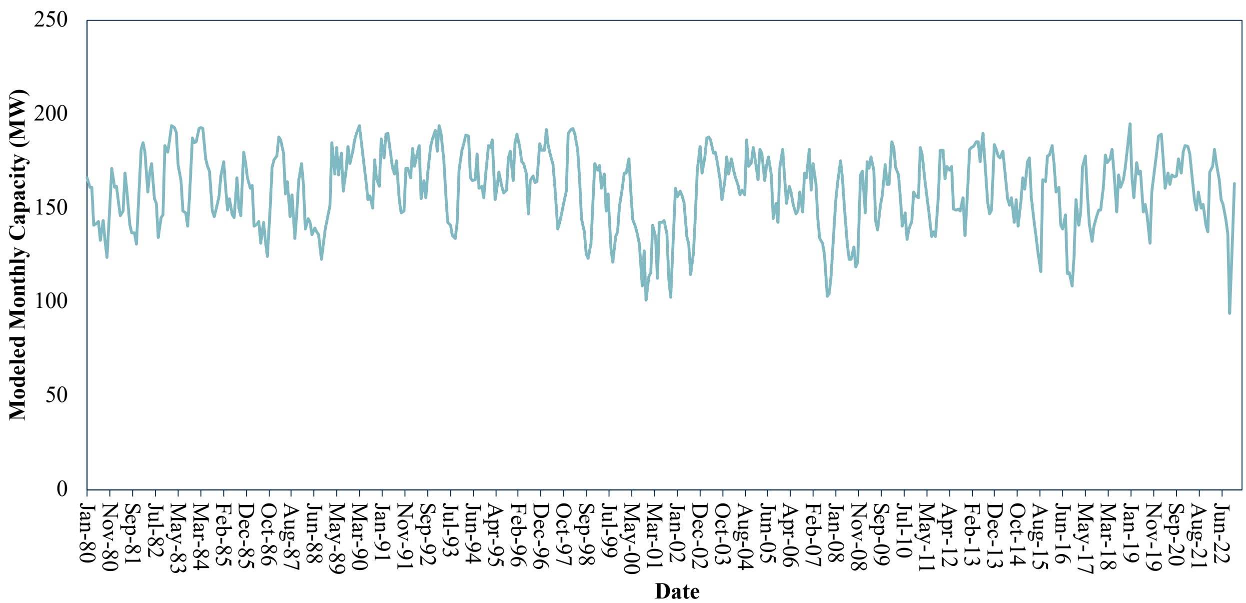


Figure 17 and Figure 18 demonstrate the variation of hydro energy by weather year which is input into the model. The lower rainfall years such as 2001, 2007, and 2008 are captured in the reliability model with lower peak shaving.

Figure 17. DEC Hydro Energy by Weather Year

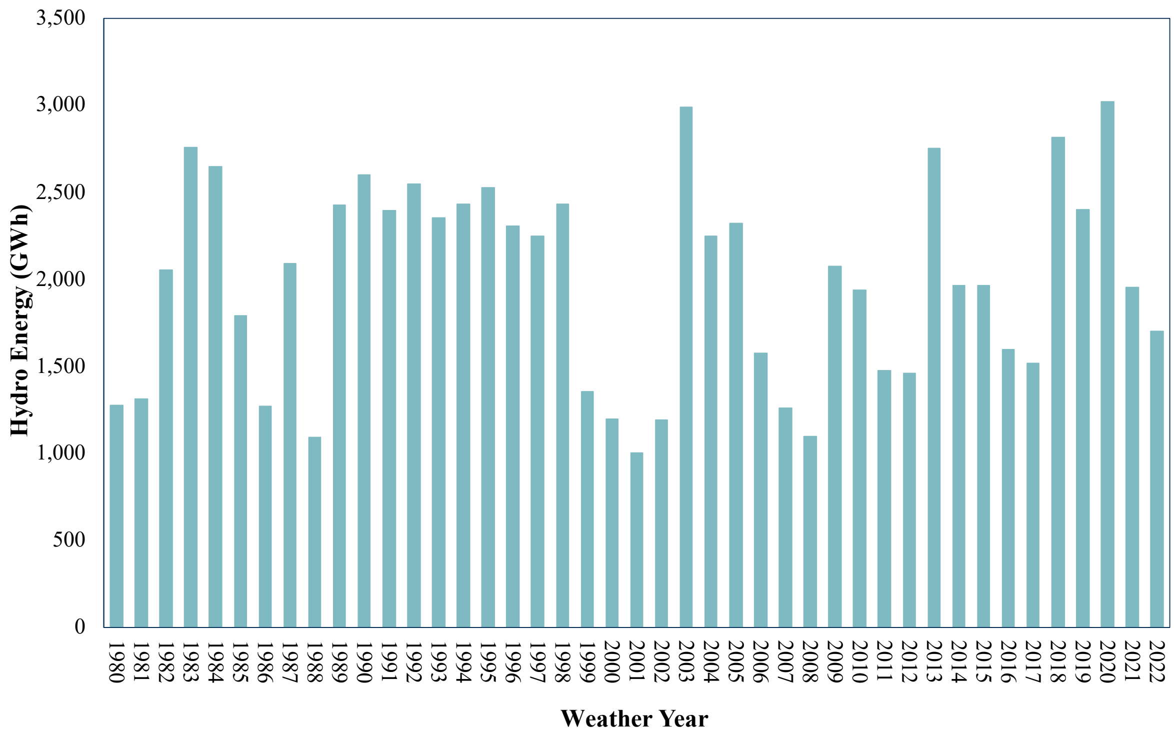
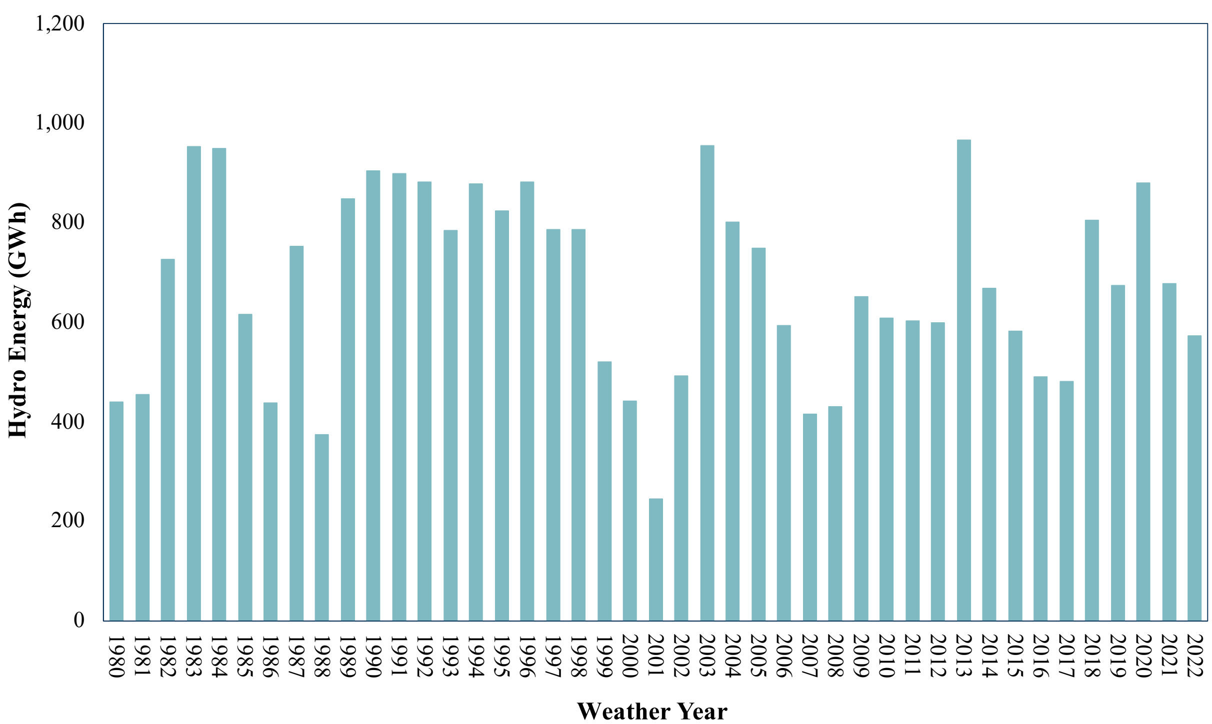


Figure 18. DEP Hydro Energy by Weather Year



In addition to conventional hydro, DEC owns and operates a pump hydro fleet consisting of 2,420 MW. The fleet consists of two pump storage plants: (1) Bad Creek at a 1,680 MW summer/winter rating[18] and (2) Jocassee at a 780 MW summer/winter rating. These resources are modeled with reservoir capacity, pumping efficiency, pumping capacity, generating capacity, and forced outage rates. SERVM uses excess capacity to economically fill up the reservoirs to ensure the generating capacity is available during peak conditions.

J. Demand Response Modeling

Demand response programs are modeled as resources in the simulations. They are modeled with specific contract limits including hours per year, days per week, and hours per day constraints. Table 9 and Table 10 contain the capacities of the DEC and DEP demand response portfolios.

Table 9. DEC Demand Response Modeling

	Summer Capacity (MW)	Winter Capacity (MW)
DEC Energy Wise Business	12	17
Interruptible Service	53	51
Power Manager Residential	658	125
PowerShare Generator	5	4
PowerShare Mandatory	468	435
Integrated Voltage / VAR Control	190	190
Total	1,386	822

[18] The Bad Creek station is modeled with a maximum capacity of 1,640 MW (410 MW per unit). Each of the four units can individually run at a maximum rated capacity of 420 MW. However, due to power tunnel limitations, all four units cannot run at their maximum rated capacity simultaneously. Therefore, if all four units were called to operate at maximum possible generation they would be de-rated by 10 MW each with the highest possible station output at 1,640 MW.

Table 10. DEP Demand Response Modeling

	Summer Capacity (MW)	Winter Capacity (MW)
Demand Response Automation	48	30
Integrated Voltage / VAR Control	149	149
Energy Wise Home	497	77
Energy Wise Business	5	10
Large Load Curtailable	207	168
Total	906	434

K. Operating Reserve Requirements

Operating Reserve Requirements (also known as Ancillary Service Requirements) were created for each Company and the combined Base Case using the Companies' Ancillary Quartile Regression (AnQR) tool which is based on the Electric Power Research Institute (EPRI) Dynamic Assessment and Determination of Operating Reserve (DynaDOR) tool[19].

Operating Reserve Requirements also denote when firm load shed occurs. For the Companies' studies, firm load shed is set to occur when the model would otherwise be unable to serve regulation reserves. Put another way, the model will maintain regulation reserves in all hours of the study.

[19] *See* EPRI, Program 173: Bulk Integration of Renewables and Distributed Energy Resources, Dynamic Reserve Determination Tool,
https://www.epri.com/research/programs/067417/results/3002020168

L. External Assistance Modeling

The external market plays a significant role in planning for resource adequacy. If several of the DEC and DEP resources were experiencing an outage at the same time, and they did not have access to surrounding markets, there is a high likelihood of unserved load. To capture a reasonable amount of assistance from surrounding neighbors, each neighbor was modeled at the one day in 10-year standard (LOLE of 0.1) level representing the target for many entities. By modeling in this manner, only weather diversity and generator outage diversity benefits are captured. The market representation used in SERVM is based on Astrapé's proprietary dataset which is developed based on publicly available information including FERC Forms, Energy Information Administration (EIA) Forms, and reviews of IRP information from neighboring regions. Specific attention was given to coal retirements and renewable portfolio buildouts so that the changing resource mixes in the region were accurately captured.

SERVM allows for sharing between regions based on economics but subject to transmission limits. The cost of transfers between regions is based on marginal costs. In cases where a region is short of resources, scarcity pricing is added to the marginal costs. As a region's hourly reserves approach zero, the scarcity pricing for that region increases.

IV. Simulation Methodology

Since most reliability events are high impact, low probability events, a large number of scenarios must be considered. For the Companies, SERVM utilized forty-three years of historical weather and load shapes, three points of economic load growth forecast error, and forty iterations of unit outage draws for each scenario to represent a distribution of realistic scenarios. The number of yearly simulation cases equals 43 weather years * 3 load forecast errors * 40 unit outage iterations = 5,160 total iterations for the Base Case. This Base Case, comprised of 5,160 total iterations, was re-run at different reserve margin levels by varying the amount of CT capacity.

A. Case Probabilities

An example of probabilities given for each case is shown in Table 11. Each weather year is given equal probability and each weather year is multiplied by the probability of each load forecast error point to calculate the case probability.

Table 11. Case Probability Example

Weather Year	Weather Year Probability (%)	Load multipliers Due to Load Economic Forecast Error (%)	Load Economic Forecast Error Probability (%)	Case Probability (%)
1980	2.33	98.06	27	0.629
1980	2.33	100	46	1.0718
1980	2.33	102.31	27	0.629
1981	2.33	98.06	27	0.629
1981	2.33	100	46	1.0718
1981	2.33	102.31	27	0.629
...	…	...	...	...
...	…	...	...	...
2022	2.33	102.31	27	0.629
			Total	100

For this study, LOLE is defined in number of days per year and is calculated for each of the 129 load cases and weighted based on probability. When counting LOLE events, only one event is counted per day even if an event occurs early in the day and then again later in the day. Across the industry, the traditional 1 day in 10 year LOLE standard is defined as 0.1 LOLE. Additional reliability metrics calculated are Loss of Load Hours (LOLH) in hours per year and Expected Unserved Energy (EUE) in MWh.

B. Reserve Margin Definition

For this study, winter and summer reserve margins are defined as the following:

- (Resources – Demand) / Demand
  - Demand is 50/50 peak forecast
  - Demand response programs are included as resources and not subtracted from demand
  - Solar capacity is counted at 5% capacity credit for winter reserve margin calculations, 39% for summer reserve margin calculations, the 4-hour storage capacity was counted at 100%, and the 2-hour storage capacity was counted at 50%.

As previously noted, the Base Case Combined Scenario was simulated at different reserve margin levels by varying the amount of CT capacity in order to evaluate the impact of reserves on LOLE. Table 12 shows a comparison of winter and summer reserve margin levels for the Base Case Combined Scenario. As an example, when the winter reserve margin is 20%, the resulting summer reserve margin is 24.8% due to the solar on the system which provides greater summer capacity contribution.

Table 12. Relationship Between Winter and Summer Reserve Margin Levels (Base Case Combined)

Winter Reserve Margin (%)	Summer Reserve Margin (%)
17.0%	22.3%
18.0%	23.1%
19.0%	24.0%
20.0%	24.8%
21.0%	25.6%
22.0%	26.5%
23.0%	27.3%
24.0%	28.2%
25.0%	29.0%

V. Physical Reliability Results

Physical Reliability Results-Island Scenarios

Table 13 and Table 14 show the seasonal contribution of LOLE at various reserve margin levels for the Island Scenarios for both DEC and DEP. In this scenario, it is assumed that DEC and DEP are responsible for their own load and that there is no assistance from neighboring utilities including its sister utility. The summer and winter reserve margins differ for all scenarios due to seasonal demand forecast differences, weather-related thermal generation capacity differences, demand response seasonal availability, and seasonal solar capacity value. Using the one day in 10-year standard (LOLE of 0.1), which is used across the industry to set minimum target reserve margin levels, DEC would require a 28.5% winter reserve margin and DEP would require a 26.0% winter reserve margin in the Island Scenario where no assistance from neighboring systems was assumed.

These reserve margin targets are required to cover the combined risks seen in load uncertainty, weather uncertainty, and generator performance for both systems. As discussed below, when compared to Base Case results which recognizes neighbor assistance, results of the Island Scenarios illustrate both the benefits and risks of carrying lower reserve margins through reliance on neighboring systems.

The reserve margin for DEC under its Island Scenario is higher than the reserve margin for DEP under its Island Scenario due to greater summer LOLE risk in DEC's Island Scenario. DEC also has lower penetrations of solar than DEP which results in more summer LOLE risk in an Island Scenario. In addition to this insight, DEC has more energy limited hydro and pump storage which typically will raise the reserve margin requirement in an island setup.

Table 13. Island Physical Reliability Results DEC

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
21.0%	18.9%	0.718	0.411	0.307	3.41	3,857
22.0%	19.7%	0.556	0.332	0.224	2.54	2,835
23.0%	20.5%	0.425	0.266	0.159	1.84	2,023
24.0%	21.3%	0.320	0.212	0.108	1.30	1,396
25.0%	22.1%	0.239	0.168	0.071	0.89	930
26.0%	22.9%	0.179	0.133	0.045	0.60	600
27.0%	23.7%	0.135	0.106	0.028	0.41	382
28.0%	24.5%	0.104	0.085	0.019	0.29	252
29.0%	25.3%	0.084	0.070	0.014	0.23	185
30.0%	26.1%	0.070	0.057	0.013	0.20	158
31.0%	26.9%	0.060	0.047	0.012	0.18	146
32.0%	27.7%	0.049	0.038	0.011	0.15	125

Table 14. Island Physical Reliability Results DEP

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
21.0%	35.9%	0.218	0.218	0.000	0.85	853
22.0%	36.9%	0.187	0.187	0.000	0.71	714
23.0%	37.8%	0.159	0.160	0.000	0.60	594
24.0%	38.7%	0.135	0.135	0.000	0.50	491
25.0%	39.6%	0.114	0.114	0.000	0.41	404
26.0%	40.5%	0.096	0.096	0.000	0.34	333
27.0%	41.4%	0.082	0.081	0.000	0.28	276
28.0%	42.3%	0.070	0.070	0.000	0.24	231
29.0%	43.2%	0.061	0.061	0.000	0.21	198
30.0%	44.1%	0.056	0.056	0.000	0.19	175
31.0%	45.1%	0.053	0.054	0.000	0.19	161
32.0%	46.0%	0.053	0.054	0.000	0.20	155

Physical Reliability Results-Island Combined Scenario

Table 15 shows the seasonal contribution of LOLE at various reserve margin levels for the Combined Island where it is assumed that DEC and DEP are responsible for their own load and receive no assistance from neighboring utilities but can receive assistance from their sister utility. Using the one day in 10-year standard (LOLE of 0.1), the Companies would require a 25.0% winter reserve margin.

Table 15. Island Combined Physical Reliability Results

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
20.0%	24.8%	0.257	0.257	0.00	0.90	1,835
21.0%	25.6%	0.211	0.211	0.00	0.73	1,490
22.0%	26.5%	0.173	0.173	0.00	0.59	1,210
23.0%	27.3%	0.143	0.143	0.00	0.48	982
24.0%	28.2%	0.118	0.118	0.00	0.39	797
25.0%	29.0%	0.098	0.098	0.00	0.32	645
26.0%	29.9%	0.083	0.083	0.00	0.27	514

Physical Reliability Results-Base Case Combined Scenario

Table 16 shows the seasonal LOLE at various reserve margin levels for the Base Case Combined Scenario which is the Island Combined scenario with neighbor assistance included. The various reserve margin levels are calculated as the total resources in both DEC and DEP using the combined coincident peak load, and reserve margins are increased together for the combined utilities.

Table 16. Base Case Combined Physical Reliability Results

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
16.0%	21.4%	0.206	0.206	0	0.90	2,356
17.0%	22.3%	0.184	0.184	0	0.77	1,981
18.0%	23.1%	0.164	0.164	0	0.66	1,663
19.0%	24.0%	0.146	0.146	0	0.56	1,396
20.0%	24.8%	0.130	0.130	0	0.48	1,174
21.0%	25.6%	0.115	0.115	0	0.42	992
22.0%	26.5%	0.102	0.102	0	0.36	842
23.0%	27.3%	0.090	0.090	0	0.31	719
24.0%	28.2%	0.079	0.079	0	0.27	616
25.0%	29.0%	0.069	0.069	0	0.24	528
26.0%	29.9%	0.061	0.061	0	0.21	449
27.0%	30.7%	0.053	0.053	0	0.17	372

As the table indicates, the required reserve margin to meet the one day in 10-year standard (LOLE of 0.1), is 22.0% which is 3.0% lower than the required reserve margin for 0.1 LOLE in the Island scenario. Table B1 located in Appendix B outlines the 12 months by hour of day table (12 x 24) of the LOLE seen at the reserve margin level with the reliability closest to the 0.1 LOLE standard.

Physical Reliability Results-DEC and DEP Individual Cases

In addition to running the Island Scenarios, Island Combined Scenario and the Base Case Combined Scenario, DEC and DEP Individual Scenarios where DEC and DEP did not prioritize helping each other as they do in the Island Combined Scenario and Base Case Combined Scenario were simulated to understand the reliability impact. Table 17 and Table 18 show the results of the DEC and DEP Individual Scenarios at various reserve margin levels. The DEC winter reserve margin to meet the 1 day in 10 year standard is 21.5% while the DEP winter reserve margin to meet the 1 day in 10 year standard is 24.0%.

Table 17. DEC Individual Physical Reliability Results

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
17.0%	15.7%	0.165	0.165	0.00	0.68	1,006
18.0%	16.5%	0.146	0.146	0.00	0.60	857
19.0%	17.3%	0.130	0.130	0.00	0.52	720
20.0%	18.1%	0.117	0.117	0.00	0.44	598
21.0%	18.9%	0.106	0.106	0.00	0.37	490
22.0%	19.7%	0.094	0.094	0.00	0.31	398
23.0%	20.5%	0.081	0.081	0.00	0.26	324

Table 18. DEP Individual Physical Reliability Results

Winter Reserve Margin (%)	Summer Reserve Margin (%)	LOLE (events/year)	Winter LOLE (events/year)	Summer LOLE (events/year)	LOLH (hours/year)	EUE (MWh/year)
18.0%	33.2%	0.172	0.172	0.00	0.71	890
19.0%	34.1%	0.158	0.158	0.00	0.64	777
20.0%	35.0%	0.146	0.146	0.00	0.58	678
21.0%	35.9%	0.135	0.135	0.00	0.52	591
22.0%	36.9%	0.123	0.123	0.00	0.47	513
23.0%	37.8%	0.111	0.111	0.00	0.41	442
24.0%	38.7%	0.097	0.097	0.00	0.35	376

VI. Conclusions

Based on the physical reliability results of the Base Case Combined Scenario, Astrapé recommends that the Companies maintain a 22% combined reserve margin for IRP purposes. Astrapé recognizes this is a 5% increase from the 17% reserve margin recommended in the 2020 Resource Adequacy and is being driven by three main factors including: a reduction in neighbor assistance, the assumption of long-term load forecast error, and generator performance especially during cold periods as described below. To ensure summer reliability is maintained, Astrapé recommends not allowing the summer reserve margin to drop below 15%, but as the results show if the winter reserve margin is maintained at 22% then the summer reserve margin will be well above 15%.

When performing the 2023 Resource Adequacy study for the Companies, attention was given to accurately modeling the shifting neighbor resource portfolios including coal retirements and the buildout of solar, wind, and storage resources on other utilities' systems. This changing resource mix along with the cold weather load response has shifted the resource adequacy risk of the Companies' neighbors to the winter. Because of this, there is now less market assistance available to the Companies' during the winter extreme weather periods which increases the resources the Companies' need to carry to maintain a reliable system. Based on a comparison of net imports during extreme hours in the 2020 and 2023 studies, Astrapé estimates that this reduction in neighbor assistance translates to around a 1.75% increase in the reserve margin.

In the 2020 Resource Adequacy study, the economic load forecast error distribution model weighted over-forecasting more than under-forecasting load. The updated distribution that was modeled in the 2023 study was more symmetrical which leads to approximately a 0.75% increase in the reserve margin.

Finally, the unit outage modeling was updated to be based on GADS data from 2018-2022 including the performance of units during Winter Storm Elliot. Assumptions on capacity risk during winter weather events were also updated using the last five years of history. Both of these put upward pressure on reserve margin, and it is estimated these alone increased the reserve margin by 2.5%.

Given these factors outlined above, the 5% increase is reasonable and expected given the changing landscape over the last three to four years since the previous study was conducted. Recent events like Winter Storm Elliot show that it is increasingly difficult to rely on neighbor assistance during these extreme winter weather conditions especially as more and more of the Companies' neighbors have shifted away from summer resource adequacy risk to winter resource adequacy risk.

VII. Appendix A

Table A1. Base Case Assumptions and Sensitivities

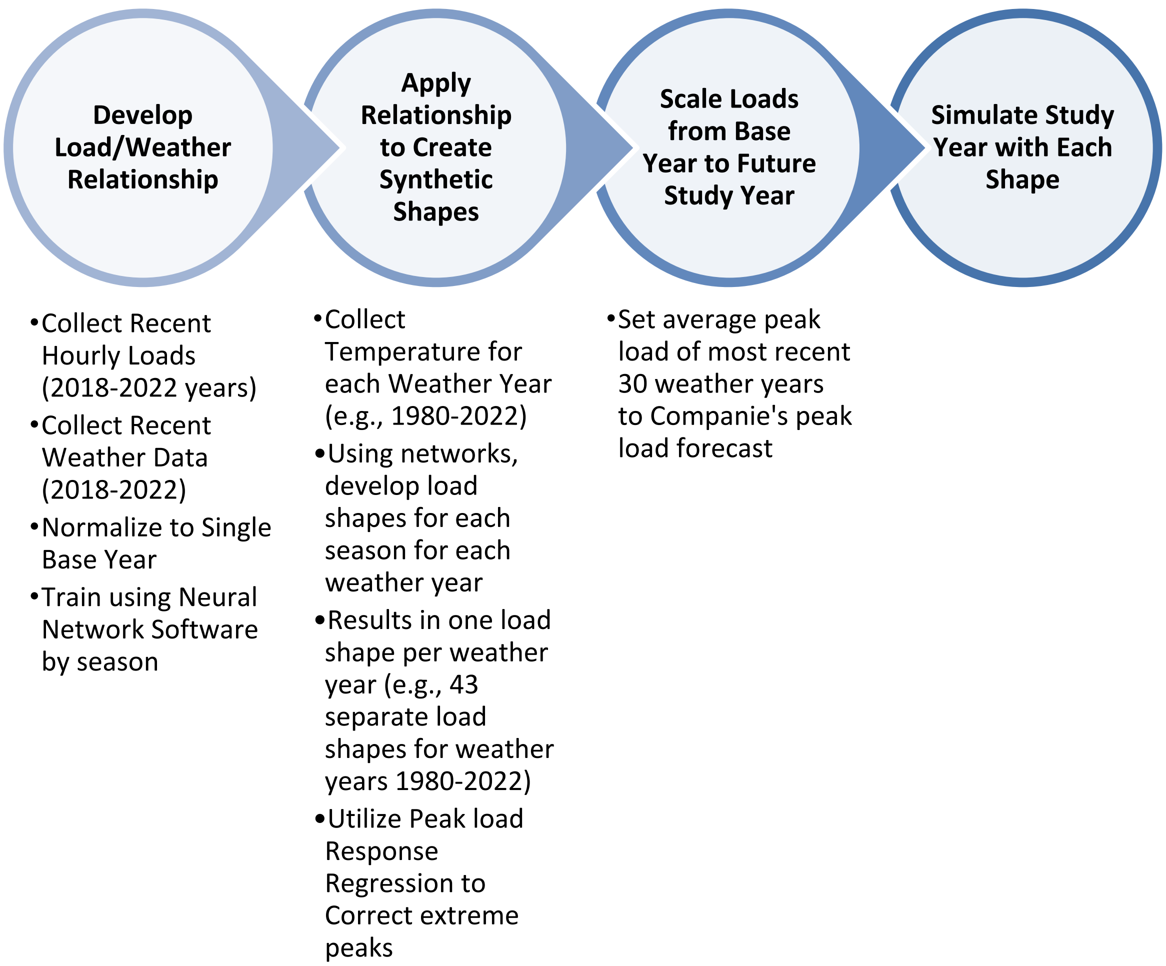
Assumption	Base Case Value	Value in 2020 Study	Comments
Weather Years	1980-2022	1980-2018	Added 4 additional weather years and updated all load, hydro, and renewable processes to be based on latest data
Synthetic Load Shapes	1980-2022	1980-2018	Updated the load/temperature relationship based on latest data. Considered other load extrapolation methods including, number of cold days preceding event, load slope over time
LFE	3 point near symmetrical distribution	Asymmetrical distribution biased towards over forecasting load	Based the distribution on Moody's GDP and population growth scenarios for North and South Carolina
Unit Outages	Based on 2018-2022 GADS Data	Based on 2015-2019 GADS Data	-
Cold Weather Outages	Modeled stochastic incremental outages that increased as temperature decreased	Modeled 400 MW of incremental outages below 10 degrees	-
Hydro/PSH	Based on 2018-2022 Hourly Hydro Data and 1980-2022 EIA Data	Based on 2015-2019 Hourly Hydro Data and 1980-2018 EIA Data	-
Solar	1980-2022	1980-2018	See Above
Demand Response	As documented in Full Report	As documented in Full Report	-
Neighbor Assistance	As documented in Full Report	As documented in Full Report	Special attention was given to neighbor coal retirement and renewable buildouts in order to accurately model the shifting seasonal risk

Assumption	Base Case Value	Value in 2020 Study	Comments
Operating Reserves	As documented in Full Report	As documented in Full Report	-
Study Topology	As documented in Full Report	As documented in Full Report minus AECI, LGE, and Power South	Modeled all SEEM except Florida entities

Synthetic Load Shape Modeling Process Chart

As described in detail in the report, the distinct steps for developing the forty-three synthetic load shapes are shown in the following figure. The neural network used for the process is NeuroShell Predictor developed by Ward Systems[20].

Figure A.1. Synthetic Load Shape Development Process



[20] Advanced Neural Network and Genetic Algorithm Software, http://www.wardsystems.com/predictor.asp.

Cold Weather Peak Load Response Modeling

During the 2023 Study, Astrapé and the Companies made a concerted effort to look for ways to improve its extreme cold weather peak load modeling as requested by the PSCSC Order. Astrapé's approach that has been utilized in jurisdictions across the country and the Companies during the 2020 studies uses regression splines produced by averaging the daily max loads based on the daily minimum temperature seen on those days. These regression splines are then used to "predict" the maximum peak load seen at minimum temperatures that are lower than what was seen during the recent historical period. Astrapé believes this is a robust approach given its usage in multiple jurisdictions but considered integrating other variables and methods to improve this process as it is a key input in the reserve margin study. The main goal of this process was to investigate other trends or factors that could be contributing to cold weather load response.

The first potential method Astrapé explored was integrating the number of previous cold days preceding the current day and creating different regression splines to be applied based on how many proceeding days to the current day had a minimum temperature that dropped below 30 °F. Based on Astrapé's analysis, there was no clear relationship where increasing the number of proceeding cold days either consistently increases or decreases the slope of the resulting regression splines.

Astrapé also reviewed whether there were major changes in the load response over the 2014 – 2022 time period to see if some additional relationship should be incorporated. Much like the number of previous cold days method, Astrapé saw no consistent relationship with the cold weather load response increasing over time.

One potential driver of the non-intuitive results of these additional analytical methods is the lack of data points. By increasing the number of criteria, the amount of data points that fit those criteria are reduced and the resulting splines are sourced from fewer data points. Given that Astrapé has already taken the step of including peak load behavior back to 2014 to increase the available number of data points, it did not seem helpful to include the additional criteria as not only did it reduce the number of data points, the inclusion did not seem to indicate a more accurate picture of the load response.

Astrapé does recognize that given the relatively low amount of data points at these extreme temperatures, the ones that do exist are especially valuable for guiding the analysis. Winter Storm Elliot and the load response seen on December 24th, 2022 serve as a valuable check of whether or not the resulting splines are a good predictor of load behavior at extreme temperatures. If the December 24th, 2022 events in DEC, DEP-E, and DEP-W are removed from the dataset and the resulting splines without December 24th, 2022 included are used to predict the maximum peak load on December 24th, they predict the morning peak within a 5% accuracy.

Astrapé believes that working through this process reinforced that its method of developing regression equations utilizing temperature and load across recent historical weather years is a robust method to project load response for temperatures not seen in over a decade.

VIII. Appendix B

Table B.1 Percentage of Loss of Load by Month and Hour of Day for the Combined Base Case

	Month											
Hour of Day	1	2	3	4	5	6	7	8	9	10	11	12
1	1.8%	-	-	-	-	-	-	-	-	-	-	-
2	1.8%	-	-	-	-	-	-	-	-	-	-	0.9%
3	1.8%	-	-	-	-	-	-	-	-	-	-	-
4	3.6%	-	-	-	-	-	-	-	-	-	-	0.9%
5	6.3%	1.8%	-	-	-	-	-	-	-	-	-	-
6	7.1%	4.5%	-	-	-	-	-	-	-	-	-	0.9%
7	9.8%	4.5%	-	-	-	-	-	-	-	-	-	2.7%
8	12.5%	4.5%	-	-	-	-	-	-	-	-	-	3.6%
9	5.4%	-	-	-	-	-	-	-	-	-	-	1.8%
10	5.4%	-	-	-	-	-	-	-	-	-	-	0.9%
11	4.5%	-	-	-	-	-	-	-	-	-	-	0.9%
12	1.8%	-	-	-	-	-	-	-	-	-	-	-
13	-	-	-	-	-	-	-	-	-	-	-	-
14	-	-	-	-	-	-	-	-	-	-	-	-
15	-	-	-	-	-	-	-	-	-	-	-	-
16	-	-	-	-	-	-	-	-	-	-	-	-
17	-	-	-	-	-	-	-	-	-	-	-	-
18	-	-	-	-	-	-	-	-	-	-	-	-
19	-	-	-	-	-	-	-	-	-	-	-	-
20	0.9%	-	-	-	-	-	-	-	-	-	-	-
21	1.8%	-	-	-	-	-	-	-	-	-	-	-
22	1.8%	-	-	-	-	-	-	-	-	-	-	-
23	2.7%	-	-	-	-	-	-	-	-	-	-	-
24	2.7%	-	-	-	-	-	-	-	-	-	-	0.9%
SUM	71.4%	15.2%	-	-	-	-	-	-	-	-	-	13.4%