Duke Energy Carolinas and Duke Energy Progress Effective Load Carrying Capability (ELCC) Study

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PREPARED FOR

Duke Energy

PREPARED BY

Nick Wintermantel
Cole Benson
Astrapé Consulting

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I. Summary of Methodology and Results

This study was requested by Duke Energy Carolinas (DEC) and Duke Energy Progress (DEP) to analyze the capacity value of solar, storage, and wind within each system. Capacity value is the reliability contribution of a generating resource and is the fraction of the rated capacity considered to be firm. Average seasonal capacity values are used for reserve margin calculation purposes and seasonal marginal values can be used for expansion planning. Both Companies are winter planning due to winter peak loads and the amount of solar on the systems. As more solar is added, Loss of Load Expectation (LOLE) is shifted to the winter when solar provides less reliability contribution. Because of this winter planning, the winter capacity values were the focus of the study which can then be used for reserve margin accounting and expansion planning purposes.[1]

Because solar and wind are intermittent resources, a solar or wind facility's ability to provide reliable capacity when it is needed is different from that of a fully dispatchable resource such as a gas-fired turbine, which can be called upon in any hour to produce energy, notwithstanding unit outages. Similarly, battery systems have limited energy storage capability and must be recharged, either from the grid or a dedicated generation resource. A battery's ability to reliably provide capacity when it is needed will also differ from that of a fully dispatchable resource. The study results provide the winter capacity value for solar, storage, and wind which are used in the Companies' Carbon Plan and Integrated Resource Plans.

[1] The Appendix includes one set of summer ELCC values for solar and wind for purposes of calculating DEC and DEP summer reserve margins. For determining marginal resources, the summer capacity values have no impact on plans because capacity needs are driven by the winter and resource adequacy risk is in the winter season given the level of solar being included in the plans.

A. Methodology

Astrapé performed this Effective Load Carrying Capacity (ELCC) study using the Strategic Energy Risk Valuation Model (SERVM) which is the same model used for DEC and DEP's past Resource Adequacy and ELCC Studies. The terms capacity value and ELCC are often used interchangeably for the purposes of this report. Additional details of the model setup and assumptions are included in the Technical Modeling Appendix of this report.

The Effective Load Carrying Capacity (ELCC) methodology was used to calculate the capacity value of the resource being studied. A "base" case of the system with no solar or storage was developed that resulted in the DEC and DEP systems achieving the 1 day in 10-year industry standard of 0.1 Loss of Load Expectation (LOLE). This is a common industry standard and ensures that these resources are being evaluated within a reliable system. Once the "base" case is established, battery, solar, and/or wind resources are added to the system. The additional resources improve LOLE to less than 0.1. Next, load is increased by adding a negative resource until the LOLE is returned to the same seasonal reliability as seen in the Base Case.[2] The ratio of the additional load to the additional resource being added is the reliability contribution or ELCC of the battery or renewable resource. For example, if 100 MW of battery is added and achieves the same Base Case seasonal LOLE after adding 90 MW of load, the ELCC is 90% (90 MW divided by 100 MW).

[2] Because it is difficult to return cases back to the exact seasonal reliability, several load levels were analyzed for each setup and interpolation was performed to determine the amount of load added to return to the Base Case seasonal LOLE.

As part of the 2020 IRP filed by the Companies, the Public Service Commission of South Carolina required the Companies to make several adjustments to its solar and storage ELCC studies. [3] For the Companies' Carbon Plan the following items have been taken into account in this study.

1. Perform Surface ELCCs for Solar and Storage –

   To accommodate the surface ELCC, Astrapé performed solar only ELCC analyses, storage only ELCC analyses, and storage and solar aggregated ELCC analysis to ensure any synergistic benefits were included. As laid out in the report, this analysis was performed over a broad range of capacity and storage durations. Previously, in the 2020 Storage ELCC Study, the storage ELCC analysis was performed with significant solar on the system, so all synergistic value was given to storage. Similar surface analysis was performed for wind and solar.

2. Use of 2035 Load Forecasts in the Analysis-

   Utilizing the 2035 load forecast captures a larger system and provides these resources more capacity value as the penetration increases.[4]

3. Use higher capacity factor solar resources –

   All future solar additions were modeled as bifacial, single-axis tracking resources.

4. Incorporate the Company's Winter Peak Demand Reduction Potential Assessment-

   The Winter Peak Study, which included additional demand response programs, adds demand response capacity in both winter and summer. [5]

[3] South Carolina Docket Nos. 2019-224-E and 2019-225-E, Order No. 2021-447, June 28, 2021, at 87.
[4] Given this assumption, ELCCs could potentially be overstated prior to 2035.
[5] The 2020 Winter Peak Demand Reduction Potential Assessment (also referred to as the Winter Peak Study) was prepared for Duke Energy by Dunsky Energy Consulting in partnership with Tierra Resource Consultants. The objective of the study was to identify the potential for new demand response programs and measures to reduce the

B. Solar and Storage Scope

Astrapé calculated the average ELCC of solar and battery energy storage systems as shown in Tables 1 and 2 for both Companies. These tables show the surface that was analyzed across solar and storage resources for each Company. The highlighted blue cells were simulated representing only solar, only storage, and aggregated solar and storage scenarios. Each of the matrices were duplicated for 2-hour, 4-hour, 6-hour, 8-hour, and 12-hour storage systems. The surface methodology allows modelers to understand the benefit of each resource alone and together to determine any synergistic values the resources may have with one another. There is synergistic benefit between solar and storage resources because the resources work together to increase their value from a resource adequacy perspective. After adding a fixed solar profile, the net peak load (gross load minus solar) is typically narrower allowing for short duration storage to better serve the new net load peak.

winter peak demand in each of the DEC and DEP systems. The Winter Peak Study reports were filed with the NCUC in Docket No. E-100, Sub 165.

Table 1. DEC Solar Storage Surface Matrix[6]

		Solar MW						
	DEC	-	2,000	3,000	4,000	6,000	8,000	8,000
Battery MW	-							
	300							
	600							
	1,200							
	2,400							
	3,200							

Table 2. DEP Solar Storage Surface Matrix

		Solar MW						
	DEP	-	3,000	4,500	6,000	7,500	9,000	12,000
Battery MW	-							
	450							
	900							
	1,800							
	3,600							
	4,800							

C. Battery and Solar Modeling

For this study, battery resources were modeled in economic arbitrage mode. The objective of economic arbitrage mode is to maximize the economic value of the battery. In this mode, SERVM schedules the battery to charge at times when system energy costs are low, and to discharge when system energy costs are high. This type of dispatch aligns well with resource adequacy risks, meaning the battery will be available to discharge during peak net load conditions when loss of load events are most likely to occur. In this mode, SERVM offers recourse options during a

[6] The black highlighted areas were not simulated. If it became necessary, these values could be interpolated based on the simulated values.

reliability event. In other words, SERVM allows the schedule of the battery to be adjusted in real time, and discharge if its state of charge is greater than zero to avoid firm load shed. This method also assumes the utility has full control of the battery and best represents how batteries are expected to be operated on the DEC and DEP systems. Batteries were assumed to have no limits on ramping capability or constraints on number of cycles per day outside of the ability to charge the battery. Batteries were given an equivalent forced outage rate ("EFOR") of 2.4% compared to the negative resource (modeled as load) that was given a 4% outage rate.[7] By modeling resources with their unit specific EFOR values, all resources are captured on a level playing field. Solar was modeled with hourly profiles as described in the Technical Appendix, and a 2.7% outage rate. All new solar was based on bifacial single-axis tracking profiles.

D. Storage/Solar Surface Winter Results

Tables 3 and 4 show the average winter ELCC for battery without any solar included in the setup, solar without any battery included in the setup, and the synergistic ELCC's when both are included. For DEC, battery levels were modeled from 0 to 3,200 MW and solar resources from 0 to 8,000 MW. The synergistic values are higher than the single resource values especially as penetrations increase.

[7] The 4% outage rate represents the high end of new thermal resources such as new combined cycle or combustion turbine resources.

Table 3. DEC Winter Solar and Storage Results[8]

Solar MW	Battery MW	Duration Hours	Average Battery Capacity Value (no solar included)	Average Solar Capacity Value (no battery included)	Average Battery Capacity Value including any synergistic value	Average Solar Capacity Value including any synergistic value
2,000	200	2	99.2%	6.1%	100.0%	6.5%
3,000	400	2	97.8%	5.0%	100.0%	5.0%
4,000	600	2	96.4%	4.1%	98.7%	4.1%
5,000	800	2	95.1%	3.4%	95.7%	3.8%
2,000	300	4	99.5%	6.1%	99.9%	6.1%
3,000	600	4	99.8%	5.0%	99.8%	5.1%
4,000	1,200	4	98.5%	4.1%	98.8%	4.3%
5,000	2,400	4	87.3%	3.4%	94.0%	3.7%
6,000	3,200	4	73.5%	2.9%	88.4%	3.3%
8,000	3,200	4	73.5%	2.4%	88.6%	3.0%
2,000	300	6	99.8%	6.1%	100.0%	6.1%
3,000	600	6	99.4%	5.0%	100.0%	5.0%
4,000	1,200	6	97.4%	4.1%	99.3%	4.3%
5,000	2,400	6	88.7%	3.4%	95.6%	3.7%
6,000	3,200	6	79.2%	2.9%	91.7%	3.3%
8,000	3,200	6	79.2%	2.4%	91.8%	2.8%
2,000	300	8	99.6%	6.1%	99.6%	6.1%
3,000	600	8	99.6%	5.0%	99.6%	5.1%
4,000	1,200	8	98.1%	4.1%	98.3%	4.3%
5,000	2,400	8	89.6%	3.4%	94.7%	3.6%
6,000	3,200	8	79.8%	2.9%	91.0%	3.2%
8,000	3,200	8	79.8%	2.4%	92.6%	2.8%
2,000	300	12	99.8%	6.1%	100.0%	6.1%
3,000	600	12	99.5%	5.0%	99.8%	5.1%
4,000	1,200	12	97.7%	4.1%	98.3%	4.2%
5,000	2,400	12	90.2%	3.4%	94.8%	3.6%
6,000	3,200	12	82.1%	2.9%	92.1%	3.1%
8,000	3,200	12	82.1%	2.4%	92.7%	2.8%

[8] All values have been curve fitted to reflect smooth curves across the solar and storage penetrations resulting in minor adjustments for reporting purposes.

The same results are shown for DEP. The solar was simulated up to 12,000 MW and battery was simulated up to 4,800 MW.

Table 4. DEP Winter Solar and Storage Results[9]

Solar MW	Battery MW	Duration Hours	Average Battery Capacity Value (no solar included)	Average Stand-Alone Solar Capacity Value (no battery included)	Average Battery Capacity Value including any synergistic value	Average Solar Capacity Value including any synergistic value
3,000	300	2	97.7%	7.7%	100.0%	8.2%
4,500	600	2	91.2%	6.3%	96.2%	6.4%
6,000	900	2	84.8%	5.2%	90.4%	5.3%
7,500	1,200	2	78.4%	4.4%	83.3%	4.8%
3,000	450	4	100.0%	7.7%	100.0%	7.8%
4,500	900	4	95.8%	6.3%	96.6%	6.5%
6,000	1,800	4	86.9%	5.2%	88.4%	5.5%
7,500	3,600	4	68.3%	4.4%	73.4%	4.7%
9,000	4,800	4	55.3%	3.8%	64.5%	4.2%
12,000	4,800	4	55.3%	3.3%	64.5%	3.9%
3,000	450	6	100.0%	7.7%	100.0%	7.7%
4,500	900	6	97.5%	6.3%	98.3%	6.5%
6,000	1,800	6	93.5%	5.2%	94.5%	5.5%
7,500	3,600	6	78.2%	4.4%	84.1%	4.8%
9,000	4,800	6	62.5%	3.8%	75.1%	4.3%
12,000	4,800	6	62.5%	3.3%	75.1%	4.0%
3,000	450	8	100.0%	7.7%	100.0%	7.7%
4,500	900	8	97.8%	6.3%	98.8%	6.4%
6,000	1,800	8	95.0%	5.2%	96.4%	5.5%
7,500	3,600	8	81.6%	4.4%	87.3%	4.7%
9,000	4,800	8	66.9%	3.8%	78.0%	4.2%
12,000	4,800	8	66.9%	3.3%	78.0%	3.9%
3,000	450	12	100.0%	7.7%	100.0%	7.8%

[9] At the low battery capacity levels (450-900 MW), additional Monte Carlo outage iterations are likely required to understand any clear differences between battery durations which are showing capacity values all near 100%. For reporting purposes, minor adjustments were made. For example, if the 450 MW 8 hour was interpolated at 99% it was adjusted to 100% since the 6-hour showed 100% for 450 MW. All values have been curve fitted to reflect smooth curves across the solar and storage penetrations resulting in minor adjustments for reporting purposes.

4,500	900	12	97.8%	6.3%	98.8%	6.4%
6,000	1,800	12	95.6%	5.2%	96.5%	5.4%
7,500	3,600	12	85.2%	4.4%	88.8%	4.6%
9,000	4,800	12	71.1%	3.8%	79.3%	4.1%
12,000	4,800	12	71.1%	3.3%	79.3%	4.0%

Tables 5 and 6 show the same ELCC results but calculated as the marginal ELCC. These include any synergistic value between the solar and storage. The marginal values were developed by curve fitting the average results to a polynomial and taking the first derivative. A single set of solar winter values were reported since all the values were similar across all the battery durations. The marginal ELCC represents the next MW at each point in the penetration. For example, the 2401st MW of 4-hour storage is worth 79.4%.

Table 5. DEC Winter Marginal Values

Solar	Battery	Duration	Marginal Battery including any synergistic values	Marginal Solar including any synergistic values
2,000	200	2	100.0%	
3,000	400	2	98.0%	
4,000	600	2	93.9%	
5,000	800	2	89.8%	
2,000	300	4	100.0%	3.1%
3,000	600	4	100.0%	2.4%
4,000	1,200	4	94.9%	1.8%
5,000	2,400	4	79.4%	1.2%
6,000	3,200	4	69.0%	1.1%
2,000	300	6	100.0%	
3,000	600	6	100.0%	
4,000	1,200	6	96.2%	
5,000	2,400	6	85.2%	
6,000	3,200	6	77.9%	
2,000	300	8	100.0%	
3,000	600	8	99.3%	
4,000	1,200	8	95.0%	
5,000	2,400	8	86.5%	
6,000	3,200	8	80.8%	

2,000	300	12	100.0%	[redacted]
3,000	600	12	98.7%	[redacted]
4,000	1,200	12	95.0%	[redacted]
5,000	2,400	12	87.6%	[redacted]
6,000	3,200	12	82.7%	[redacted]

Table 6 shows the same information for DEP. At some point, batteries will flatten the net load shape, removing the arbitrage opportunity, making the value of the next MW of short duration storage much less valuable.

Table 6. DEP Winter Marginal Values

Solar	Battery	Duration	Marginal Battery including any synergistic values	Marginal Solar including any synergistic values
3,000	300	2	100.0%	[redacted]
4,500	600	2	85.1%	[redacted]
6,000	900	2	70.2%	[redacted]
7,500	1,200	2	55.4%	[redacted]
3,000	450	4	93.7%	4.7%
4,500	900	4	86.8%	3.2%
6,000	1,800	4	73.1%	1.7%
7,500	3,600	4	45.8%	1.7%
9,000	4,800	4	27.5%	1.6%
3,000	450	6	100.0%	[redacted]
4,500	900	6	97.9%	[redacted]
6,000	1,800	6	84.9%	[redacted]
7,500	3,600	6	59.0%	[redacted]
9,000	4,800	6	41.6%	[redacted]
3,000	450	8	100.0%	[redacted]
4,500	900	8	100.0%	[redacted]
6,000	1,800	8	88.5%	[redacted]
7,500	3,600	8	62.2%	[redacted]
9,000	4,800	8	44.7%	[redacted]
3,000	450	12	100.0%	[redacted]
4,500	900	12	100.0%	[redacted]
6,000	1,800	12	90.4%	[redacted]
7,500	3,600	12	64.2%	[redacted]
9,000	4,800	12	46.7%	[redacted]

In addition to standalone solar and standalone storage resources, the Companies also include storage that is "DC coupled" with solar in their capacity expansion model. While not explicitly analyzed in this study, it is reasonable to assume that the ELCC of the solar resource and the ELCC of the storage resource are additive. As an example, a 100 MW solar facility that is DC-coupled with a 50 MW, 4-hour storage facility in DEP should have a firm capacity rating of approximately 52 MW (100 MW solar * 4.7% + 50 MW, 4-hour storage * 93.7%).

E. Sensitivity – 6-Hour Standalone Winter Battery Capacity Values Beyond 4-Hour Values

Additional surface analysis was performed to understand how 6-hour storage performed after significant 4-hour storage had already been added to the system. For these runs, storage and solar were added together as in the previous analysis to capture the synergistic value. The results are listed in Tables 7 and 8.

Table 7. DEC Winter 6-Hour after 4-Hour Battery

Solar	Battery	Duration	Average Battery Capacity Value (including any synergistic value)	Marginal Battery Capacity Value (including any synergistic value)
2,000	300	4	100%	100%
3,000	600	4	100%	100%
4,000	1,200	4	99%	95%
5,000	2,400	4	94%	79%
6,000	3,200	4	88%	69%
8,000	4,000	6	81%	51%
8,000	5,000	6	74%	38%

Table 8. DEP Winter 6-Hour after 4-Hour Battery

Solar	Battery	Duration	Average Battery Capacity Value (including any synergistic value)	Marginal Battery Capacity Value (including any synergistic value)
3,000	450	4	100%	94%
4,500	900	4	97%	87%
6,000	1,800	4	88%	73%
7,500	2,300	6	90%	85%
7,500	2,800	6	87%	68%

One last sensitivity was performed for DEC evaluating the existing Bad Creek Pump Hydro Facility. DEC's existing Bad Creek (BC1) is modeled with 19 hours of storage and 1,640 MW of capacity. Because of its long duration, existing pump storage on the system was assumed to provide nearly 100% capacity value. DEC is evaluating adding a second powerhouse (Bad Creek 2 or BC2) at the existing Bad Creek 1 facility. In that case, Bad Creek 1 is reduced to 12 hours and an incremental 1,680 MW of 12-hour duration storage capacity is added. To assess the impact of reduced duration of Bad Creek 1 on the incremental 12-hour storage created by the addition of Bad Creek 2, the 12-hour surface analysis was rerun assuming a lower duration BC1. This analysis, depicted in Table 9, determined that the capacity value of incremental 12-hour storage decreases slightly with a reduction in BC1 storage duration.

Table 9. DEC Winter 12-Hour Bad Creek 2 Sensitivity

Solar	Battery	Duration	Average Battery Capacity Value BC1 @ 19 hours including any synergistic value	Marginal Battery Capacity Value BC1 @ 19 storage including any synergistic value	Average Battery Capacity Value BC1@ 12 hours including any synergistic value	Marginal Battery Capacity Value BC1@ 12 hours including any synergistic value
2,000	300	12	100.0%	100.0%	100.5%	100.0%
3,000	600	12	99.8%	98.7%	99.6%	98.3%
4,000	1,200	12	98.3%	95.0%	97.7%	93.6%
5,000	2,400	12	94.8%	87.6%	93.5%	84.1%
6,000	3,200	12	92.1%	82.7%	90.2%	77.8%

F. Wind Resources

Wind resources were modeled as hourly profiles provided by the Companies. The Technical Appendix provides more information surrounding these shapes. Wind profiles were provided assuming a 2.6% outage rate compared to the negative resource that was assumed to have a 4% outage rate.

G. Wind/Solar Surface Scope

Astrapé calculated the average ELCC of wind and solar as laid out in Tables 10 and 11 for both Companies. The highlighted blue cells were simulated representing only wind, only solar, and aggregated solar and wind scenarios. Each of the matrices were duplicated for offshore and onshore wind for both Companies.

Table 10. DEC Solar/Wind Surface Matrix

		Solar MW			
	DEC	-	2,000	4,000	6,000
Wind MW	-				
	1,000				
	2,000				
	3,000				

Table 11. DEP Solar/Wind Surface Matrix

		Solar MW			
	DEP	-	3,000	6,000	9,000
Wind MW	-				
	1,000				
	2,000				
	3,000				

H. Winter Wind/Solar Surface Results

Tables 12 and 13 show the average winter ELCC for wind without any solar included in the setup, solar without any wind included in the setup, and the ELCC's when both are included to capture any synergistic value the resources have. There was very little synergistic value seen in the onshore wind and solar analysis but a higher amount in the offshore wind and solar analysis. DEC was modeled with solar from 0 to 6,000 MW and wind from 0 to 3,000 MW. DEP was modeled with solar from 0 to 9,000 MW and wind from 0 to 3,000 MW. The profiles provided by the Company showed substantial output during cold winter mornings in the offshore wind profiles.[10] Even for winter values, to see ELCC's of this magnitude for offshore wind, particularly in DEC, is not intuitive and it is recommended that the Companies continue to understand offshore wind profiles especially during extreme cold periods.

Table 12. DEC Winter Wind Results

Solar MW	Wind MW	Offshore/ Onshore	Average Wind Capacity Value (no solar included)	Average Solar Capacity Value (no wind included)	Average Wind Capacity Value (including any synergistic value)	Average Solar Capacity Value (including any synergistic value)	Marginal Wind Capacity Value (including any synergistic value)
2,000	1,000	Onshore	39.9%	6.1%	40.7%	6.6%	29.1%
4,000	2,000	Onshore	36.9%	4.1%	36.9%	3.9%	32.0%
6,000	3,000	Onshore	35.8%	2.9%	34.9%	3.0%	35.0%
2,000	1,000	Offshore	89.5%	6.1%	94.9%	6.9%	86.6%
4,000	2,000	Offshore	84.2%	4.2%	89.3%	4.3%	80.7%
6,000	3,000	Offshore	76.4%	2.9%	85.5%	3.4%	74.8%

[10] Profiles are based on "ERA5" climate and weather data from the European Centre for Medium-Range Weather Forecasts. More information can be found at: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview

Table 13. DEP Winter Wind Results

Solar MW	Wind MW	Offshore/ Onshore	Average Wind Capacity Value (no solar included)	Average Solar Capacity Value (no wind included)	Average Wind Capacity Value (including any synergistic value)	Average Solar Capacity Value (including any synergistic value)	Marginal Wind Capacity Value (including any synergistic value)
3000	1000	Onshore	44.3%	7.7%	43.2%	7.8%	42.1%
6000	2000	Onshore	40.9%	5.2%	41.9%	5.4%	39.2%
9000	3000	Onshore	39.1%	3.8%	40.5%	4.1%	36.3%
3000	1000	Offshore	72.8%	7.7%	81.8%	6.9%	69.7%
6000	2000	Offshore	71.4%	5.2%	74.4%	5.5%	64.3%
9000	3000	Offshore	67.6%	3.8%	70.1%	4.1%	58.9%

I. Winter ELCC Conclusions

Winter ELCC's are a driver in resource plans for the Companies. Astrapé has taken an approach to recognize the synergistic value of combinations of resources. The winter storage ELCC's are at or near 100% for the first couple of battery tranches, but eventually these values will drop dramatically given winter load shapes can remain high across the day. Once enough storage is on the system, the net loads flatten to the point storage is needed in both the evening and morning peaks with limited reserve capacity available throughout the night to recharge the batteries. Solar values remain low during the winter as the risk of load shed is mostly during the early morning hours. The ELCC of onshore wind is in the 30-40% range while the ELCC of offshore wind was calculated to be north of 60%. This is driven by the ERA-5 shapes provided by the Company which show extremely high wind output during the coldest winter mornings. The average winter values should be used for reserve margin accounting and the marginal winter values should be used for marginal resource decision making since the needs of the Companies are in the winter.

II. Technical Modeling Appendix

The following sections include a discussion on the setup and assumptions used to perform the ELCC study. The Study utilized the framework from the 2020 Resource Adequacy study and updated the following inputs.

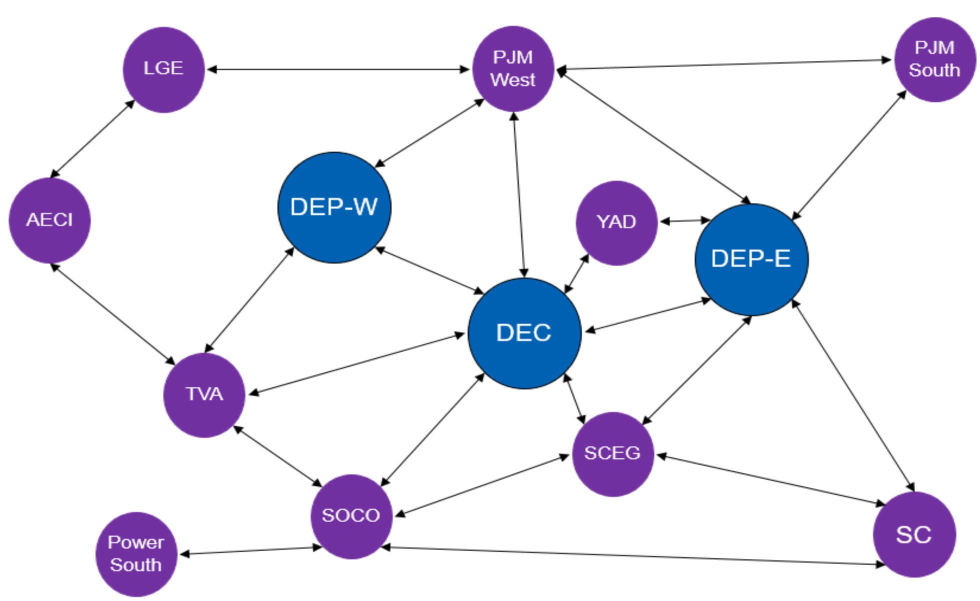
A. SERVM Framework and Cases

The study uses the same framework as the Base Case 2020 Resource Adequacy Study but was updated to model study year 2026 and included forty-one weather years (1980 – 2020), five load forecast error multipliers, and Monte Carlo generator outages.

B. Study Topology

The 2020 Resource Adequacy study was updated to include the additional SEEM entities Louisiana Gas and Electric (LGE), Associated Electric Cooperative Incorporated (AECI), and Power South. The study topology is shown below in Figure 1.

Figure 1. Study Topology



In order to reduce the simulation time for the ELCC analysis, the neighbors were tuned to 0.1 reliability in a calibration study. Purchases were derived from this calibration study to simulate the benefit received from the market. This allowed DEC and DEP to be simulated as islands for all the ELCC analyses.

C. Load Modeling

The load modeling was updated to model forty-one historical weather years (1980- 2020). The same methods used in the 2020 Resource Adequacy Study were used for this update. 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. The historical weather consisted of hourly temperatures from weather stations across the DEC and DEP service territories. 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. Different weather to load relationships were built for the summer, winter, and shoulder seasons. These relationships were then applied to the last forty-one years of weather to develop forty-one synthetic load shapes for 2026. Extreme peaks were corrected based on regression analysis examining extreme peak periods for both winter and summer. Equal probabilities were given to each of the forty-one load shapes in the simulation. The synthetic load shapes were scaled to align the normal summer and winter peaks to the Company's projected thirty-year weather normal load forecast for 2026.

D. Economic Load Forecast Error

Economic load forecast error multipliers from the 2020 Resource Adequacy were updated to reflect additional historical data. The updated values are shown in Table 14. Because the system is driven to 0.1 before the analysis begins, these assumptions don't drive the ELCC analysis significantly.

Table 14. Load Forecast Error

Load Forecast Error Multipliers	Probability %
0.96	10.4%
0.98	23.3%
1.00	32.5%
1.02	23.3%
1.04	10.4%

E. Conventional Resource Modeling

The resource mixes for DEC, DEP-E, and DEP-W were all updated to reflect any changes in the fleets since the 2020 Resource Adequacy Study was performed. Additionally, all modeled outage rates for the thermal fleet were updated to reflect the five most recent years of GADS data.

F. Renewable Resource Modeling

The solar units were modeled with updated forty-one solar shapes that represent forty-one years of weather data. 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 2 below shows the county locations that were used and then Figure 3 shows the average August output for different fixed-tilt and single-axis-tracking inverter loading ratios.

Figure 2. Solar Location Map

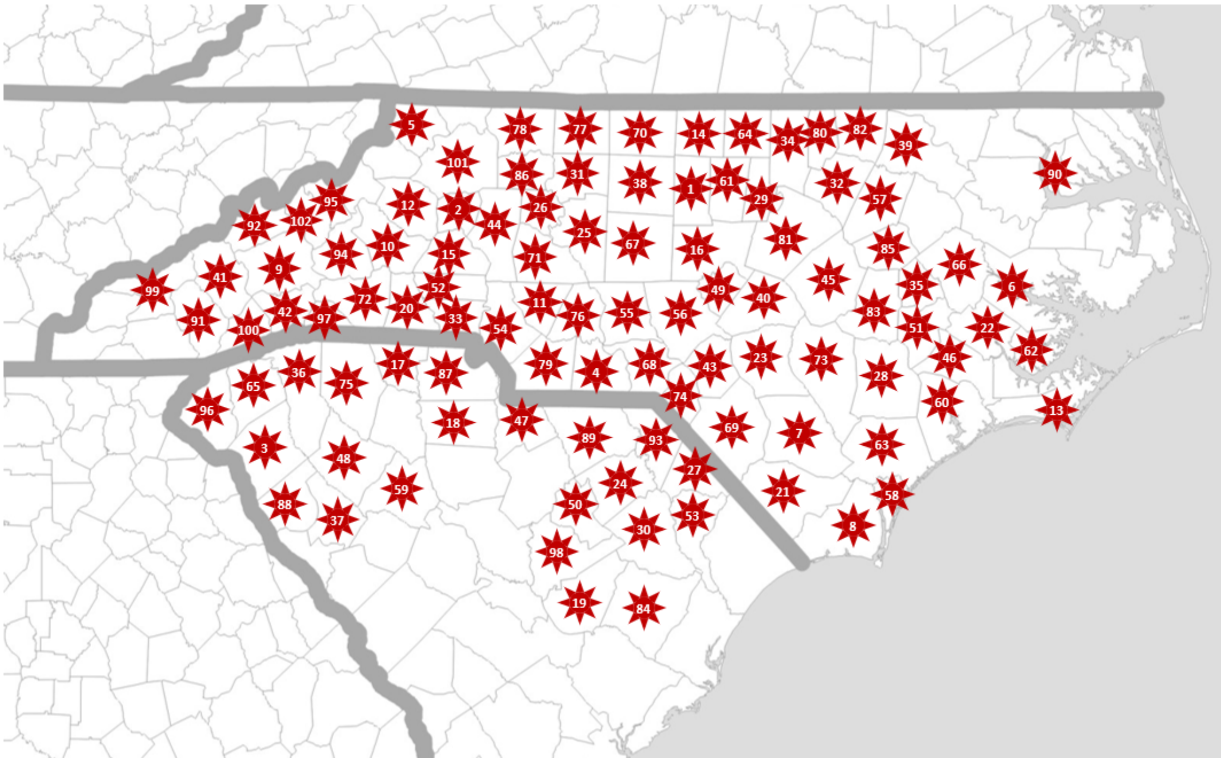
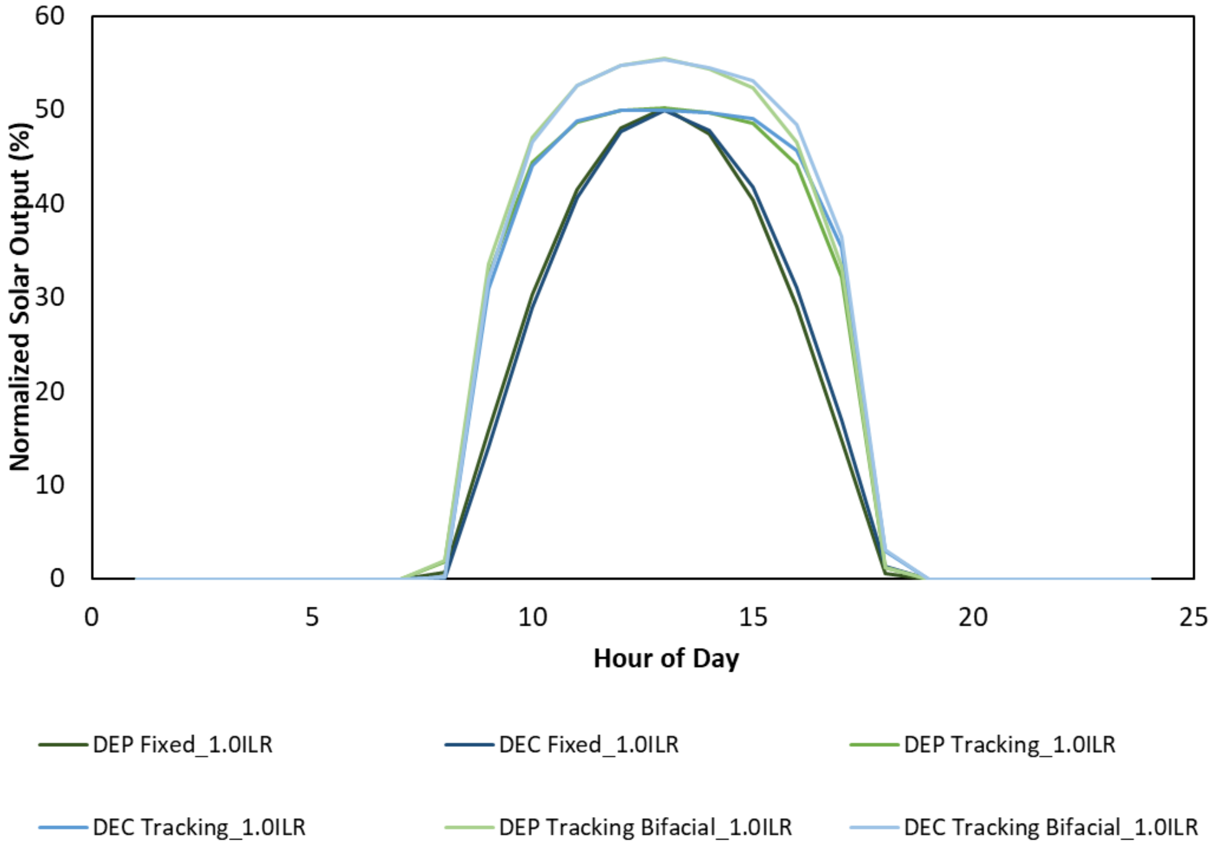


Figure 3. Average January Solar



The onshore and offshore wind profiles were provided by DEC and DEP and were derived from ERA-5 meteorological data. Figures 4 and 5 outline their average output and then a comparison of their output on peak days. Given the high output of offshore profiles on peak days, it is understandable that these profiles would result in a high ELCC value.

Figure 4. Average January Onshore and Offshore Wind Output

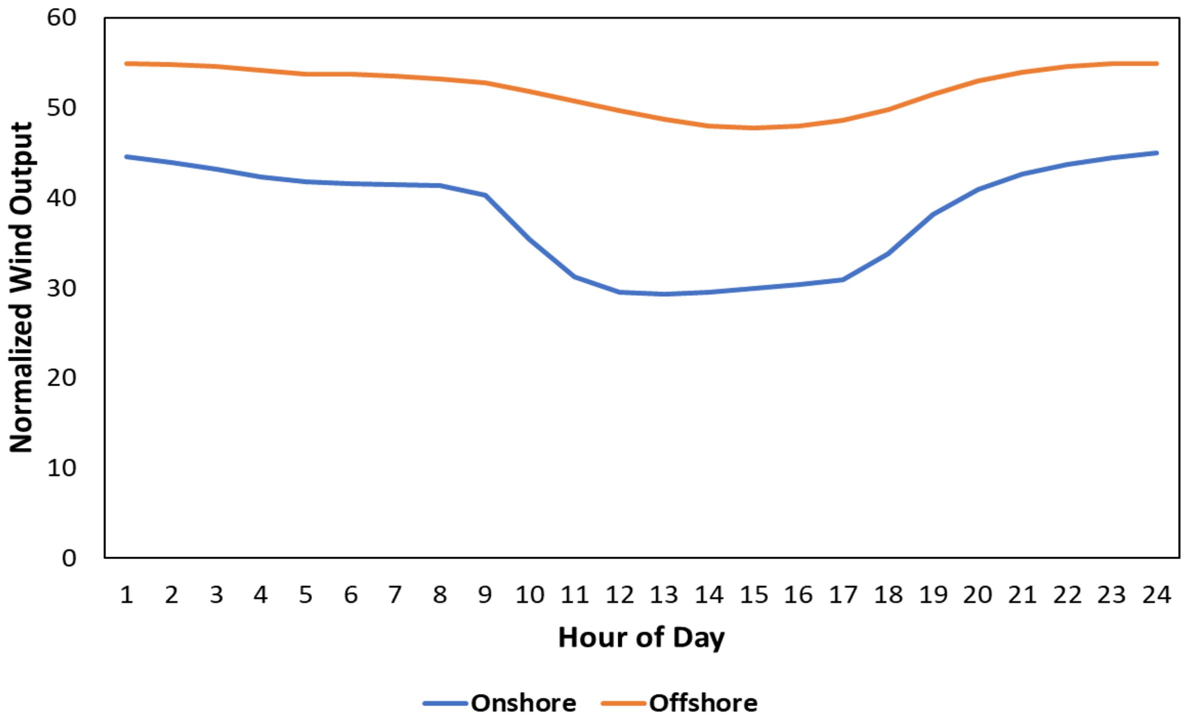
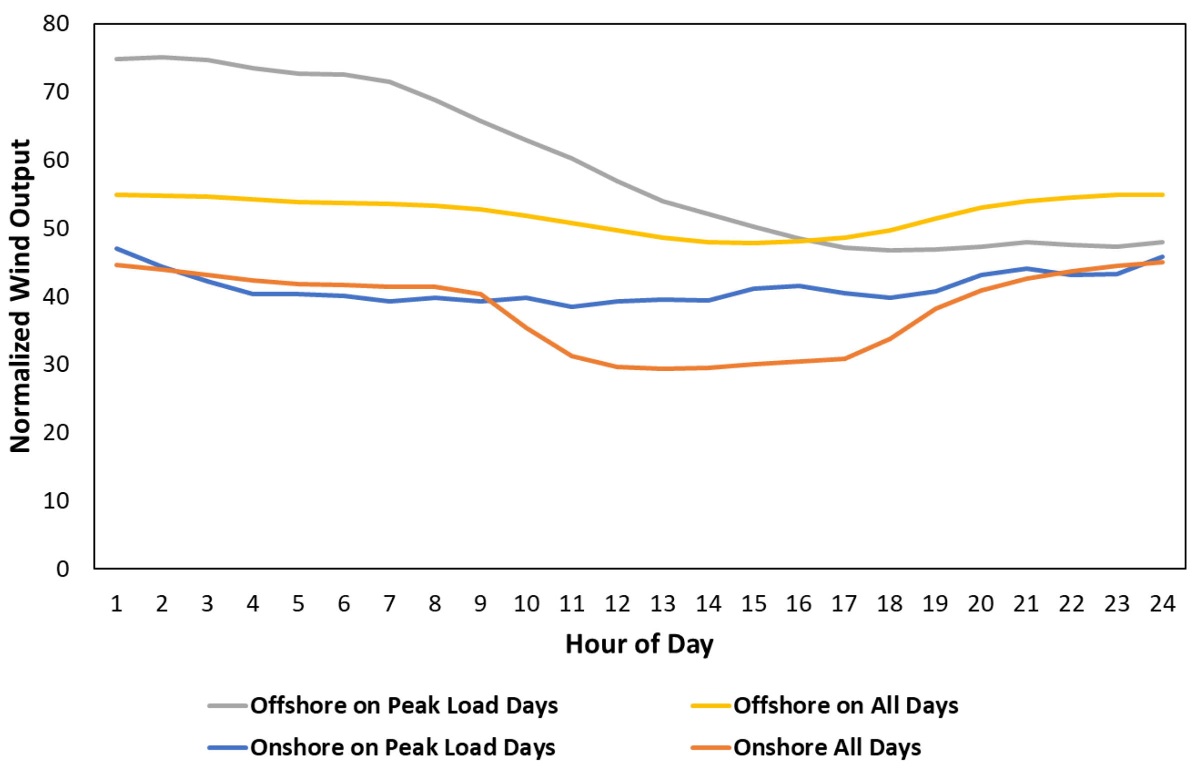


Figure 5. Peak Load Day January Onshore/Offshore Wind Output



G. Summer Solar and Wind ELCC Values

While summer was not the focus of this study, summer ELCC values were calculated for solar and wind for reserve margin accounting purposes. The Solar ELCC values are listed in Table 15 below. This analysis was only performed for DEC since there was summer LOLE in the Base Case before any solar was added. There was essentially zero LOLE in the summer in DEP even before solar is added so additional runs were not performed DEP because it would require manipulating the Base Case further to produce summer LOLE. These summer values give reasonable estimates for reserve margin accounting purposes and can be reasonably used for both Companies. But as discussed previously, because solar increases summer capacity more than winter capacity, summer reserve margins are increasing faster making future resource decisions driven by winter capacity need.

Table 15. Summer Solar ELCC Values

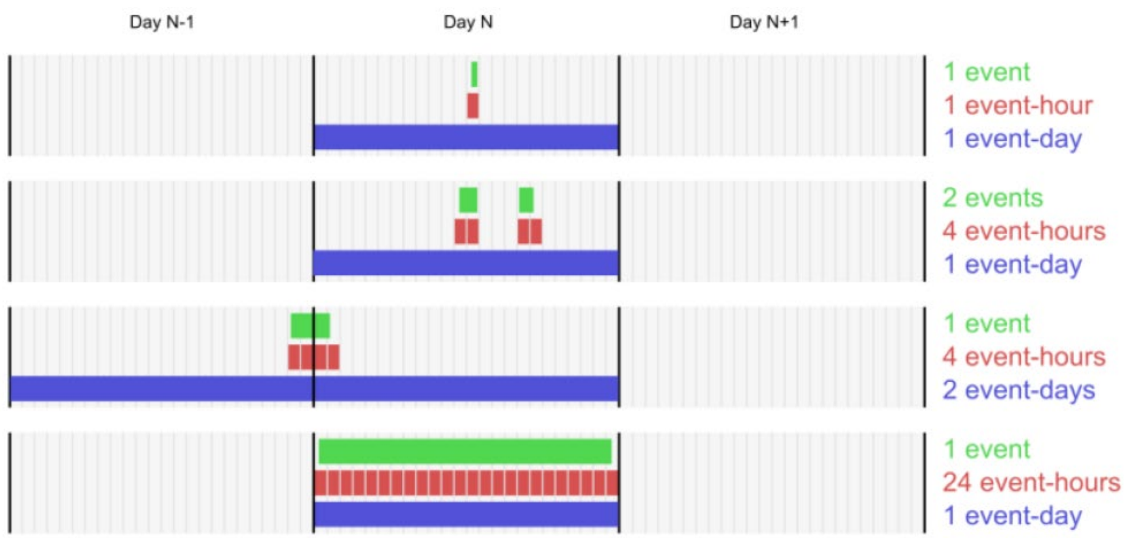
Solar MW	Storage (MW)	Summer Solar Average ELCC	Summer Solar Marginal ELCC
2000	300	67%	37.9%
3000	600	56%	34.3%
4000	1,200	51%	30.8%
5000	2,400	46%	24.0%
6000	3,200	42%	18.6%
8000	3,200	35%	7.9%

Onshore wind was found to provide approximately 11% in the summer and offshore wind was found to provide approximately 37% in the summer.

H. Discussion of Reliability Metrics (LOLE vs. EUE)

As part of the analysis, Astrapé did examine the impact the reliability metric used had on the ELCC values. Traditional resource adequacy only considers LOLE which counts the number of days customers are not served. LOLE is counted as one day whether the day has one hour or ten hours of load shed. Under this metric, two portfolios can have the same number of days of load shed but one portfolio could have substantially more load shed from an energy standpoint. This is illustrated in Figure 6 below where the first, second and fourth portfolios have the same number of days from a LOLE perspective but may differ in the number of hours and customer energy unserved.

Figure 6. LOLE Illustration[11]



Expected Unserved Energy (EUE) is another reliability metric which measures all customer energy demand not served. To better understand the impact a change in reliability metric may have on the results, Astrapé analyzed battery capacity values using EUE instead of LOLE as the ELCC

[11] Clarifying the Interpretation and Use of the LOLE Resource Adequacy Metric-2021 NERC Probabilistic Analysis Forum October 5th, 2021

metric. The winter results seen in Table 16 show that for short term storage, the capacity values based on EUE are substantially lower than of the LOLE results. This is logical because a 2-hour battery may still eliminate some events that a fully dispatchable resource can eliminate, but during events that remain it is likely that there will be more EUE with short duration battery. This is an interesting finding of the study that should be noted for future analysis. The opposite occurs for solar because solar cannot typically eliminate the entire event since most of the load shed in the winter events are before the sun rises, but it can eliminate EUE in hours 8 and 9. These results are shown in Table 17. For this reason, using EUE as the metric actually benefits solar. Planning reserve margin studies across the industry have used LOLE and the 1-day in 10-year standard so changing metrics for ELCC would create an accounting disconnect that would require further adjustments to the overall resource adequacy framework.

Table 16. DEC LOLE vs EUE Winter Battery ELCC Results

Battery (MW)	Duration(hours)	Average Battery Capacity Values with no solar included LOLE Base Results	Average Battery Capacity Values with no solar included EUE Results	Delta (EUE - LOLE)
400	2	97.8%	60.7%	-37.1%
600	2	96.4%	60.0%	-36.4%
800	2	95.1%	57.8%	-37.3%
600	4	99.8%	82.1%	-17.8%
1,200	4	98.5%	77.5%	-21.0%
2,400	4	87.3%	75.4%	-11.9%
3,200	4	73.5%	59.6%	-14.0%
600	6	99.4%	93.4%	-6.1%
1,200	6	97.4%	90.1%	-7.3%
2,400	6	88.7%	78.3%	-10.4%
3,200	6	79.2%	70.2%	-9.0%
600	8	99.6%	95.1%	-4.4%
1,200	8	98.1%	94.0%	-4.1%
2,400	8	89.6%	84.7%	-4.9%
3,200	8	79.8%	69.7%	-10.1%
600	12	99.8%	98.2%	-1.7%
1,200	12	99.5%	93.1%	-6.4%
2,400	12	97.7%	93.7%	-4.0%
3,200	12	90.2%	84.4%	-5.8%

Table 17. DEC LOLE vs EUE Winter Solar ELCC Results

Solar (MW)	Average Solar Capacity Value with no storage included LOLE Results	Average Solar Capacity Value with no storage included EUE Results
2,000	6.1%	8.2%
3,000	5.0%	6.2%
4,000	4.1%	5.7%
5,000	3.4%	5.1%
5,000	2.9%	4.9%
5,000	2.4%	3.8%