STATE OF NORTH CAROLINA
UTILITIES COMMISSION
RALEIGH

DOCKET NO. E-100, SUB 190

BEFORE THE NORTH CAROLINA UTILITIES COMMISSION

In the Matter of Biennial Consolidated Carbon Plan and Integrated Resource Plans of Duke Energy Carolinas, LLC, and Duke Energy Progress, LLC, Pursuant to N.C.G.S. § 62-110.9 and § 62-110.1(c)	)))))))	**DIRECT TESTIMONY OF RICHARD NICHOLAS WINTERMANTEL AND COLE MICHAEL BENSON ON BEHALF OF DUKE ENERGY CAROLINAS, LLC AND DUKE ENERGY PROGRESS, LLC**

I. INTRODUCTION AND OVERVIEW

Q. MR. WINTERMANTEL, PLEASE STATE YOUR FULL NAME AND BUSINESS ADDRESS.

A. My name is Richard Nicholas ("Nick") Wintermantel, and my business address is 3000 Riverchase Galleria, Hoover, AL, 35224.

Q. BEFORE INTRODUCING YOURSELF FURTHER, WOULD YOU PLEASE INTRODUCE THE PANEL?

A. Yes. I am appearing on behalf of Duke Energy Carolinas, LLC ("DEC") and Duke Energy Progress, LLC ("DEP" and together with DEC, the "Companies" or "Duke Energy") together with Cole Michael Benson on the "Resource Adequacy Panel." Witness Benson will introduce himself.

Q. BY WHOM ARE YOU EMPLOYED AND IN WHAT CAPACITY?

A. I am a Principal at Astrapé Consulting ("Astrapé"). Astrapé is a consulting firm that provides expertise in resource planning and resource adequacy to utilities across the United States and internationally.

Q. DESCRIBE YOUR EDUCATIONAL BACKGROUND AND PROFESSIONAL EXPERIENCE.

A. I graduated summa cum laude with a Bachelor of Science in Mechanical Engineering from the University of Alabama in 2003. I also obtained a master's degree in business administration from the University of Alabama at Birmingham in 2007. I have worked in utility planning for over 20 years. I started my career at Southern Company Services, where I held several different positions. In my various roles, I was responsible for performing production cost simulations, financial modeling on wholesale power contracts, general integrated resource planning, and asset management. In 2009, I joined Astrapé as a Principal Consultant and have been responsible for resource adequacy and effective load carrying capability ("ELCC") studies across the United States and internationally.

Q. HAVE YOU PREVIOUSLY TESTIFIED BEFORE THE NORTH CAROLINA UTILITIES COMMISSION ("COMMISSION")?

A. Yes. I previously testified before the Commission in Docket No. E-100, Sub 158.

Q. BEFORE ADDRESSING YOUR SPECIFIC WORK FOR THE COMPANIES, PLEASE PROVIDE A SUMMARY OF YOUR AND YOUR FIRM'S EXPERTISE PERFORMING PLANNING RESERVE MARGIN AND ELCC STUDIES.

A. These resource adequacy studies and ELCC studies have used Astrapé's Strategic Energy & Risk Valuation Model ("SERVM"). In the Southeast, Astrapé has performed studies for utilities including the Companies, Tennessee Valley Authority, Entergy, Southern Company, Central Louisiana Electric Co-op, Georgia System Operations Corporation, Louisville Gas & Electric, Dominion Energy South Carolina, and Santee Cooper. Outside of the Southeast, Astrapé has used SERVM to perform planning reserve margin studies for large independent operators such as the Southwest Power Pool ("SPP"), Electric

Reliability Council of Texas ("ERCOT"), the Midwest Independent System Operator ("MISO"), and Alberta Electric System Operator ("AESO"). For many of these entities, I have also managed ELCC studies similar to the study my team performed for the Companies.

Q. HAVE YOU PERFORMED CONSULTING SERVICES FOR DUKE ENERGY CORPORATION BEFORE?

A. Yes. Most recently, Astrapé conducted the Solar Ancillary Service Study for the Companies in Docket No. E-100, Sub 158 and the Effective Load Carrying Capacity Study in Docket No. E-100, Sub 179.

Q. MR. BENSON, PLEASE STATE YOUR FULL NAME AND BUSINESS ADDRESS.

A. My name is Cole Michael Benson, and my business address is 3000 Riverchase Galleria, Hoover, AL, 35224.

Q. BY WHOM ARE YOU EMPLOYED AND IN WHAT CAPACITY?

A. I am a Managing Consultant at Astrapé.

Q. DESCRIBE YOUR EDUCATIONAL BACKGROUND AND PROFESSIONAL EXPERIENCE.

A. I graduated summa cum laude with a Bachelor of Science in Biochemistry from the University of New Mexico in 2017. I also graduated at the top of my class with my master's in business administration from the University of New Mexico in 2018. During my education, I interned for the Energy Storage Division at Sandia National Laboratories where I supported a team of engineers responsible for demonstrating the feasibility and uses of energy storage to accelerate the adoption of energy storage technologies. I joined Astrapé as a consultant in 2018 and have performed and supported a variety of resource adequacy and ELCC studies across the United States.

Q. HAVE YOU PREVIOUSLY TESTIFIED BEFORE THE COMMISSION?

A. No.

Q. PLEASE PROVIDE A SUMMARY OF YOUR EXPERTISE PERFORMING PLANNING RESERVE MARGIN AND ELCC STUDIES.

A. I have performed and supported a variety of resource adequacy and ELCC studies for utilities and system operators across the U.S. and internationally. These studies have used Astrapé's proprietary reliability model SERVM. I have performed resource adequacy work for entities including the Companies, Associated Electric Cooperative, Dominion Energy South Carolina, Santee Cooper, the Public Service Company of Colorado, SPP, MISO, and SERC Reliability Corporation.

Q. MR. WINTERMANTEL AND MR. BENSON, WHAT IS THE PURPOSE OF YOUR JOINT TESTIMONY?

A. The purpose of the Panel's testimony is to summarize the Companies' Resource Adequacy Study conducted by Astrapé on behalf of the Companies. We summarize the methodology, results, and major differences from the previous study which was conducted in 2020. We also describe the Wind ELCC study performed on behalf of the Companies. These studies are included as Attachments I and III, respectively, to the 2023-2024 Carbon Plan and Integrated Resource Plan ("CPIRP" or "the Plan").

Q. ARE YOU INCLUDING ANY EXHIBITS WITH YOUR TESTIMONY?

A Yes. Exhibit 1 and Exhibit 2 include our respective resumes. Exhibit 3 is the 2023 Resource Adequacy Study, Exhibit 4 is the 2022 ELCC Study, and Exhibit 5 is the 2023 Wind ELCC Study. Exhibits 3-5 are also attached to the CPIRP as Attachments I-III, respectively.

Q. PLEASE EXPLAIN HOW THIS PANEL'S TESTIMONY IS ORGANIZED.

A. Section II of the Panel's testimony identifies the portions of the CPIRP that we are sponsoring.

Section III of the Panel's testimony summarizes the key findings from the resource adequacy study.

Section IV of the Panel's testimony summarizes the key findings from the wind ELCC study.

II. SPONSORSHIP OF THE PLAN

Q. MR. WINTERMANTEL AND MR. BENSON, PLEASE IDENTIFY WHICH SECTIONS OF THE PLAN YOU ARE SPONSORING WITH YOUR DIRECT TESTIMONY.

A. We are sponsoring Attachments I (Resource Adequacy Study), II (ELCC Study), and III (2023 Wind ELCC Study) to the CPIRP.

III. RESOURCE ADEQUACY STUDY

Q. PLEASE DESCRIBE YOUR WORK FOR THE COMPANIES THAT IS THE SUBJECT OF YOUR TESTIMONY AS IT RELATES TO THE COMPANIES' RESOURCE ADEQUACY STUDY.

A. Astrapé was retained in early 2023 to perform the 2023 Resource Adequacy Study, which determines the planning reserve margin the Companies should plan for in their respective integrated resource plans ("IRPs"), as well as the wind ELCC study which determines the wind ELCC values to be used in the Companies' expansion planning modeling.

Q. PLEASE SUMMARIZE THE 2023 RESOURCE ADEQUACY STUDY THAT ASTRAPÉ PERFORMED.

A. This study was performed by Astrapé at the request of the Companies as an update to the resource adequacy studies performed by Astrapé for the Companies in 2020. The primary purpose of the 2023 Resource Adequacy Study is to provide the Companies' system planners with information on the physical reliability that could be expected with various reserve margin levels.

Q. WHAT DOES THE PHRASE "PHYSICAL RELIABILITY" REFER TO?

A. Physical reliability refers to the expected frequency of firm load shed events. A utility will have a firm load shed event in the scenario when it must reduce load on the system by turning off power because it does not have enough generation to serve the customers.

Q. HOW DOES A RESOURCE ADEQUACY STUDY CALCULATE LEVELS OF PHYSICAL RELIABILITY?

A. Physical reliability is calculated in the study by using Loss of Load Expectation ("LOLE"). LOLE is the expected number of days in a year when the utility will not have enough resources to meet load and will have a firm load shed event. The industry most commonly uses an LOLE standard of "one day in 10 years," which equates to an LOLE of 0.1 days/year. If a utility plans pursuant to this standard, it is expected to experience one day with one or more hours of firm load shed every 10 years due to a shortage of generating capacity.

Q. WHY IS IT IMPORTANT FOR UTILITIES TO SET AN ADEQUATE RESERVE MARGIN?

A. 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 is at risk for the Companies. In order to ensure reliability during these peak periods, the Companies each maintain a minimum reserve margin level to manage unexpected conditions including extreme weather, load growth, and significant forced outages. Further, as utilities continue to transition from conventional fossil fuels and rely more on intermittent and energy-limited resources, it is critical to ensure reliability during this transition. In general, the industry has relied on an LOLE of 0.1 days/year to determine an adequate reserve margin.

Q. HOW IS RESOURCE ADEQUACY RISK TYPICALLY CAPTURED IN A STUDY BY UTILITY PLANNERS?

A. Resource adequacy events are high-impact, low-probability events that are seen during periods of extreme weather, periods when the load forecast is missed, or periods when significant generation is unavailable. If only normal weather, expected loads, and expected generator performance were simulated, it is expected that little to no risks would surface. To understand resource adequacy risk, a representative sample of the full distribution of possible scenarios must be simulated at a range of reserve margins.

Q. HOW DID ASTRAPÉ CALCULATE PHYSICAL RELIABILITY FOR VARIOUS RESERVE MARGIN LEVELS FOR THE DUKE SYSTEM?

A. In order to capture the physical reliability risk for the Companies' systems, Astrapé utilized its proprietary reliability model SERVM to perform thousands of hourly simulations for the 2027 study year at various reserve margin levels. Each scenario modeled is developed between a combination of deterministic and stochastic modeling of various sources of uncertainty including weather, economic growth, unit availability, and neighbor assistance. Deterministic modeling refers to inputs that do not change during the simulations, and stochastic modeling refers to inputs that have random variation that change from simulation to simulation. For the 2023 Resource Adequacy Study, 43 weather years were simulated with three economic load forecast error points and 40 random unit outage draws, which results in 5,160 hourly simulations for each reserve margin simulated in the 2027 study year. Each of the simulation results are then weighted based on their probability of occurrence in order to calculate a set of weighted average reliability metrics for each reserve margin level.

Q. PLEASE DESCRIBE THE ISLAND CASE SCENARIOS MODELED BY ASTRAPÉ FROM AN INDIVIDUAL COMPANY PERSPECTIVE AND A COMBINED COMPANY PERSPECTIVE.

A. Astrapé evaluated the physical reliability of the DEC and DEP systems using an Island Scenario. In this scenario, it is assumed that each operating utility is responsible for serving its own load and there is no assistance from neighboring utilities. Under the DEC Island Scenario, DEC would require a 28.5% winter reserve margin to maintain the one day in 10-year standard (LOLE of 0.1). In the DEP Island Scenario, DEP would require a 26.0% winter reserve margin to maintain the one day in 10-year standard (LOLE of 0.1). In addition to the separate DEC and DEP Island Scenarios, Astrapé also modeled a scenario where the DEC and DEP systems are modeled together as an island without any assistance from the other neighboring systems. Together, the Companies would require a 25.0% winter reserve margin to maintain the one day in 10-year standard (LOLE of 0.1).

Q. PLEASE DESCRIBE THE INDIVIDUAL AND BASE CASE COMBINED SCENARIOS MODELED BY ASTRAPÉ.

A. In the Individual and Combined Base Cases, it is assumed that during capacity shortfalls, DEC and DEP are able to receive market assistance from the neighboring regions. In the Individual Base Cases, DEC would require a 21.5% winter reserve margin to maintain the 1 day in 10-year standard while the DEP winter reserve margin to meet the 1 day in 10 year standard is 24.0%. The Combined Base Case models DEC and DEP as a single balancing authority where they prioritize helping each other over their external neighbors but still retain access to the external market assistance. In this scenario, the Companies would require a 22% winter reserve margin to maintain the 1 day in 10-year standard.

Q. CAN ASTRAPÉ PLEASE EXPLAIN WHY THE RESULTS ARE BEING PRESENTED IN TERMS OF WINTER RESERVE MARGIN?

A. The results are being presented in terms of winter reserve margins as the Companies are winter planning utilities, which means most of their resource adequacy risk is concentrated during the winter months thus the importance of the level of reserves being maintained during the winter. The Companies are winter planning due to a variety of factors including the high penetration of solar on the system, increased winter load volatility, and the lack of neighbor assistance during the winter months.

Q. CAN ASTRAPÉ PLEASE EXPLAIN WHY THOSE FACTORS SHIFT THE RESOURCE ADEQUACY RISK TO THE WINTER?

A. The high penetration of solar on the Companies' systems provides a high amount of capacity contribution during the late afternoon peak load hours in the summer but relatively little capacity contribution during the early morning peak load hours seen during the winter. This means that the solar resources decrease summer resource adequacy risk substantially more than during peak winter periods. Additionally, the Companies' winter peak load volatility is much higher than summer peak load volatility which also leads to more resource adequacy risk during the winter. Finally, most of the Companies' first tier neighbors have also fully shifted to being winter planning which reduces the amount of available market assistance as the Companies neighbors are dispatching their fleets in order to deal with their own winter resource adequacy risks. Together, these factors lead to the Companies having almost exclusively winter resource adequacy risk.

Q. PLEASE DESCRIBE ASTRAPÉ'S RECOMMENDED RESERVE MARGIN TARGET.

A. Astrapé recommends that the Companies maintain a 22% minimum winter reserve margin target for their IRP purposes based on the Base Case Combined Scenario.

Q. WHAT WAS THE RESERVE MARGIN RECOMMENDED BY ASTRAPÉ IN THE 2020 RESOURCE ADEQUACY STUDIES PERFORMED FOR THE COMPANIES?

A. Astrapé recommended a 17% minimum winter reserve margin for the Combined Case in the 2020 Resource Adequacy Studies.

Q. WHAT ARE THE MAIN DRIVERS OF THE FIVE PERCENT INCREASE IN RECOMMENDED MINIMUM RESERVE MARGIN FROM THE 2020 RESOURCE ADEQUACY STUDIES TO THE 2023 RESOURCE ADEQUACY STUDY?

A. Three major drivers have led to the 5% increase in the recommended minimum reserve margin:

1. Updated Generator Performance Assumptions;
2. Economic Load Forecast Error; and
3. Neighbor Assistance.

When performing the 2023 Resource Adequacy Study, Astrapé focused on, among others, accurately modeling the shifting neighbor resource portfolios including coal retirements and the buildout of solar, wind, and storage resources on other utilities' systems. This shifting resource mix coupled with cold weather load response increases the resources the Companies' need to carry to maintain a reliable system. Based on this, Astrapé recommended a 5% increase in the recommended minimum reserve margin.

Q. WHAT CHANGES WERE MADE TO THE UNIT PERFORMANCE ASSUMPTIONS?

A. In resource adequacy studies performed for the Companies, Astrapé based its unit outage modeling in SERVM on recent historical North American Electric Reliability Corporation ("NERC") Generating Availability Data System ("GADS") data. In the 2020 Resource Adequacy Studies, the unit outage modeling was based on 2014-2019 historical GADS data while in the 2023 Resource Adequacy Study, the unit outage modeling was based on 2018-2022 historical GADS data. This change in time horizon led to an upward trend in forced outage rates across the generation fleets of the Companies.

Q. WERE THERE OTHER CHANGES MADE TO THE UNIT PERFORMANCE ASSUMPTIONS?

A. Yes. As part of its review, Astrapé reviewed forced outages as a function of temperature similar to what was done in the 2020 resource adequacy studies. Given the recent extreme winter weather events like Winter Storm Elliot, outages related to cold weather on the system during the five-year historical window increased and were included in the modeling.

Q. HOW WERE COLD WEATHER-RELATED OUTAGES PREVIOUSLY MODELED IN THE 2020 STUDIES?

A. For the 2020 Resource Adequacy Studies, Astrapé assumed a discrete amount of incremental cold weather outages in its modeling which in the most extreme weather year added approximately 400 MW of cold weather outages between the two Companies.

Q. HOW WERE COLD WEATHER-RELATED OUTAGES MODELED IN THE 2023 STUDIES?

A. Astrapé worked with the Companies to review historic GADS data from 2018 through 2022 for instances identified as being caused by winter weather and then determined a probabilistic relationship between the temperature and these events. This relationship was modeled in SERVM as a weather dependent forced outage probability that increases as temperatures decrease. Partial outages were handled in a similar manner. Over the course of the thousands of simulations, an average level of cold weather outages based on historical data will be seen on the system but depending on the stochastic draw, they could be relatively mild or significant.

Q. WHAT IS THE ESTIMATED RESERVE MARGIN IMPACT OF THE UPDATED OUTAGE MODELING?

A. The updates made to base the unit outage modeling on 2018-2022 GADS data as well as updating the capacity risk during winter weather to be based on the last five years of history are estimated to have increased the reserve margin by 2.5%.

Q. WHAT IS ECONOMIC LOAD FORECAST ERROR AND HOW IS IT INCOPORATED IN THE STUDY?

A. Economic load forecast error captures economic uncertainty in load forecasts four years out. Economic load forecast error is modeled as a distribution in SERVM and each case is modeled with an amount of over or under forecasting error along with an associated probability. This distribution was developed using Moody's Analytics data and the resulting distribution is listed in the table below.

Table 1: Economic Load Forecast Error[1]

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

Q. HOW HAS THE ECONOMIC LOAD FORECAST ERROR DISTRIBUTION CHANGED COMPARED TO THE 2020 RESOURCE ADEQUACY STUDIES?

A. The updated economic load forecast error distributions represent a near symmetrical view of over and under forecasting whereas the bias in the 2020 resource adequacy studies was towards over forecasting load.

Q. HOW DOES THE UPDATED LOAD FORECAST ERROR DISTRIBUTION AFFECT THE MINIMUM PLANNING RESERVE MARGIN?

[1] Resource Adequacy Study at 28 (Table 4).

A. Since the distribution for the 2023 Resource Adequacy Study skews slightly towards under forecasting load growth, there is more resource adequacy risk modeled compared to the 2020 Resource Adequacy Studies. A sensitivity was performed and the updated load forecast error distribution results in approximately a 0.75% increase in the minimum planning reserve margin.

Q. HOW DID ASTRAPÉ MODEL NEIGHBOR ASSISTANCE IN SERVM FOR THE 2023 RESOURCE ADEQUACY STUDY?

A. SERVM allows for sharing resources between regions based on economics, but all purchases and sales are subject to transmission limits. 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 Forms, and reviews of IRP information from neighboring regions. Coal retirements, renewable portfolio buildouts, and cold weather outages were updated so that the changing resource mixes in the region were accurately captured and all regions were calibrated to 0.1 LOLE.

Q. WHY HAVE THESE CHANGES CAUSED A DECREASE IN MARKET ASSISTANCE IN THE 2023 RESOURCE ADEQUACY STUDY COMPARED TO THE 2020 RESOURCE ADEQUACY STUDIES?

A. Along with the high winter load response, both coal retirements and solar portfolio buildouts are causing Southeastern utilities to be winter planning utilities. As surrounding regions become more capacity constrained in extreme winter weather periods the Companies' market assistance has decreased since the 2020 resource adequacy studies. Astrapé estimates this decrease in winter market assistance is increasing the reserve margin by 1.75% compared to the 2020 resource adequacy studies. This impact is not surprising as purchases from surrounding regions were very limited during Winter Storm Elliot as those regions were also experiencing capacity constrained conditions due to higher than normal loads and increased forced outages.

IV. <u>WIND ELCC STUDY</u>

Q. PLEASE DESCRIBE THE PURPOSE OF THE WIND ELCC STUDY THAT ASTRAPÉ PERFORMED.

A. The Wind ELCC study was performed to analyze the capacity value of future wind resources on the Companies' systems. These values are ultimately used in the Companies' CPIRP.

Q. WHAT IS MEANT BY THE PHRASE "CAPACITY VALUE" AND HOW DOES IT RELATE TO RESOURCE ADEQUACY?

A. The "capacity value" of a resource is the reliability contribution of the said resource. Because wind resources are intermittent resources, the capacity value of a wind resource is often different than a conventional resource such as a gas-fired combustion turbine which outside of an outage can be called in any hour to produce energy.

Q. HOW WAS THE WIND ELCC STUDY PERFORMED?

A. The Wind ELCC study evaluated the wind ELCC's of the following table of portfolios.

Table 2: Wind and Solar Resource Tranches[2]

Solar Portfolios (MW)	DEC Onshore (MW)	DEP Onshore (MW)	DEP Offshore (MW)
7,411	300	300	800
10,000	600	600	1,600
15,000	900	900	2,400
20,000	1,200	1,200	3,200

The Wind ELCC study used the Base Case Combined Scenario from the 2023 Resource Adequacy Study along with the Solar Portfolios listed in the table above. The reliability of the study was targeted to a 0.1 LOLE standard, the wind portfolio being studied was added, and then varying levels of load are

[2] Wind ELCC Study at 2 (Table 1).

added until the reliability returns to 0.1 LOLE. The ratio of the resulting load added to the size of the portfolio is the ELCC.

Q. WHY WERE THERE DIFFERENT SOLAR PORTFOLIOS EVALUATED IN CONJUNCTION WITH THE WIND PORTFOLIOS?

A. Since renewable resources like wind and solar often have synergistic and deleterious effects on each other and any DEC and DEP wind portfolio expansion would likely be happening simultaneously with solar expansion, all wind portfolios were analyzed at different solar penetration levels to ensure those effects were captured.

Q. GENERALLY, SUMMARIZE THE RESULTS OF THE WIND ELCC RESULTS.

A. The tables below summarize the average and marginal ELCC, respectively, of each tranche of the wind portfolios. Average ELCC represents the ELCC over the total MW of the tranche while the marginal ELCC represents the ELCC of the next MW. Onshore wind provides winter marginal ELCC values in the 19%-44% % while offshore wind provides winter marginal ELCC values in the 64%-75% range.

Table 3: Average Wind ELCC Results[3]

DEC Onshore		DEP Onshore		DEP Offshore	
Wind Capacity	**Average ELCC (%)**	**Wind Capacity**	**Average ELCC (%)**	**Wind Capacity**	**Average ELCC (%)**
300	33.8%	300	43.8%	800	74.9%
600	29.0%	600	36.8%	1,600	72.9%
900	25.9%	900	32.8%	2,400	71.9%
1,200	24.6%	1,200	31.8%	3,200	70.3%

Table 4: Marginal Wind ELCC Results[4]

DEC Onshore		DEP Onshore		DEP Offshore	
Wind Capacity	**Marginal ELCC (%)**	**Wind Capacity**	**Marginal ELCC (%)**	**Wind Capacity**	**Marginal ELCC (%)**
First 300	33.8%	First 300	43.8%	First 800	74.9%
301st	23.9%	301st	28.2%	801st	74.9%
601st	22.2%	601st	27.7%	1601st	71.2%
901st	20.6%	901st	27.3%	2401st	67.5%
1201st	18.9%	1201st	26.8%	3201st	63.8%

Q. PLEASE EXPLAIN HOW THE METHODOLOGY OUTLINED EVALUATES THE WIND RESOURCES ON A LEVEL PLAYING FIELD WITH CONVENTIONAL RESOURCES.

[3] *Id.* at 4 (Table 2).

[4] *Id.* (Table 3).

A. Astrapé recognizes that gas resources do not provide 100% ELCC due to forced outages. To adjust for this, the wind portfolio wasn't compared against a perfect load but a load that reflected a 4% derate which increases the wind ELCC value and evaluates wind on a level playing field with a gas resource. The 4% outage rate represents the high end of new thermal resources such as a new combined cycle or combustion turbine.

Q. DOES THIS CONCLUDE YOUR TESTIMONY?

A. Yes. It does.

Richard Nicholas ("Nick") Wintermantel | Principal, Astrapé Consulting, LLC

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Mr. Wintermantel has over 20 years of experience in utility planning and electric market modeling, Areas of utility planning experience includes utility integrated resource planning (IRP) for vertically-integrated utilities, market price forecasting, resource adequacy modeling, RFP evaluations, environmental compliance analysis, asset management, financial risk analysis, and contract structuring. Mr. Wintermantel also has expertise in production cost simulations and evaluation methodologies used for IRPs and reliability planning. As a consultant with Astrapé Consulting, Mr. Wintermantel has managed reliability and planning studies for large power systems across the U.S. and internationally. Prior to joining Astrapé Consulting, Mr. Wintermantel was employed by the Southern Company where he served in various resource planning, asset management, and generation development roles.

Experience

Principal Consultant at Astrapé Consulting (2009 – Present)
Managed detailed system resource adequacy studies for large scale utilities
Managed ancillary service and renewable integration studies
Managed capacity value studies
Managed resource selection studies
Performed financial and risk analysis for utilities, developers, and manufacturers
Demand side resource evaluation
Storage evaluation
Served on IE Teams to evaluate assumptions, models, and methodologies for competitive procurement solicitations
Project Management on large scale consulting engagements
Production cost model development
Model quality assurance
Sales and customer service

Sr. Engineer for Southern Company Services (2007-2009)
Integrated Resource Planning and environmental compliance
Developed future retail projects for operating companies while at the Southern Company
Asset management for Southern Company Services

Sr. Engineer for Southern Power Company (Subsidiary of Southern Company) (2003-2007)
Structured wholesale power contracts for Combined Cycle, Coal, Simple Cycle, and IGCC Projects
Model development to forecast market prices across the eastern interconnect
Evaluate financials of new generation projects
Bid development for Resource Solicitations

Cooperative Student Engineer for Southern Nuclear (2000-2003)
Probabilistic risk assessment of the Southern Company Nuclear Fleet

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Industry Specialization

Resource Adequacy Planning	Resource Planning	Integrated Resource Planning
Competitive Procurement	Asset Evaluation	Financial Analysis
Environmental Compliance Analysis	Generation Development	Capacity Value Analysis
Renewable Integration	Ancillary Service Studies	

Education

MBA, University of Alabama at Birmingham – Summa Cum Laude
B.S. Degree Mechanical Engineering - University of Alabama - Summa Cum Laude

Relevant Experience

Resource Adequacy Planning and Production Cost Modeling

Tennessee Valley Authority: Performed Various Reliability Planning Studies including Optimal Reserve Margin Analysis, Capacity Benefit Margin Analysis, and Demand Side Resource Evaluations using the Strategic Energy and Risk Valuation Model (SERVM) which is Astrapé Consulting's proprietary reliability planning software. Recommended a new planning target reserve margin for the TVA system and assisted in structuring new demand side option programs in 2010. Performed Production Cost and Resource Adequacy Studies in 2009, 2011, 2013, 2015 and 2017. Performed renewable integration and ancillary service work from 2015-2017.

Southern Company Services: Assisted in resource adequacy and capacity value studies as well as model development from 2009 – 2018.

Louisville Gas & Electric and Kentucky Utilities: Performed reliability studies including reserve margin analysis for its Integrated Resource Planning process.

Duke Energy: Performed resource adequacy studies for Duke Energy Carolinas, LLC and Duke Energy Progress, LLC in 2012 and 2016. Performed capacity value and ancillary service studies in 2018. Performed ELCC analysis in 2022, and Resource Adequacy and ELCC Analysis in 2023.

California Energy Systems for the 21st Century Project: Performed 2016 Flexibility Metrics and Standards Project. Developed new flexibility metrics such as EUE_{flex} and $LOLE_{flex}$ which represent LOLE occurring due to system flexibility constraints and not capacity constraints.

Terna: Performed Resource Adequacy Study used to set demand curves in Italian Capacity Market Design.

Pacific Gas and Electric (PG&E): Performed flexibility requirement and ancillary service study from 2015–2017. Performed CES Study for Renewable Integration and Flexibility from 2015 – 2016.

PNM (Public Service Company of New Mexico): Managed resource adequacy studies and renewable integration studies and ancillary service studies from 2013 – 2023. Performed resource selection studies in 2017 and 2018. Additional IRP work from 2020 – 2023.

GASOC: Managed resource adequacy studies from 2015 – 2018.

MISO: Managed resource adequacy study in 2015 and performed ongoing seasonal resource adequacy analysis in 2020 and 2021. Provided ongoing support in regard to accreditation and LOLE studies in 2022 and 2023.

SPP: Managed resource adequacy study in 2017. Ongoing planned maintenance Study in 2020-2021.

SPP: Managed resource adequacy study in 2017. Ongoing planned maintenance Study in 2020-2021.

Santee Cooper: Managed resource adequacy, ELCC, and solar integration studies in 2022-2023.

Dominion Energy South Carolina: Managed resource adequacy and ELCC studies in 2022-2023.

NWPP: Managed resource adequacy study for the northwest power pool in 2022.

Malaysia (TNB, Sabah, Sarawak)): Performed and managed resource adequacy studies from 2015-2018 for three different Malaysian entities.

ERCOT: Performed economic optimal reserve margin studies in cooperation with the Brattle Group in 2014 and 2018. The report examined total system costs, generator energy margins, reliability metrics, and economics under various market structures (energy only vs. capacity markets). Completed a Reserve Margin Study requested by the PUCT, examining an array of physical reliability metrics in 2014 (See Publications: Expected Unserved Energy and Reserve Margin Implications of Various Reliability Standards). Probabilistic Risk Assessment for the North American Electric Reliability Corporation (NERC) in 2014, 2016, and 2018.

FERC: Performed economics of resource adequacy work in 2012-2013 in cooperation with the Brattle Group. Work included analyzing resource adequacy from regulated utility and structured market perspective.

EPRI: Performed research projects studying reliability impact and flexibility requirements needed with increased penetration of intermittent resources in 2013. Created Risk-Based Planning system reliability metrics framework in 2014 that is still in use today.

Independent Evaluator Work for RFPs: Served on independent evaluator teams for capacity RFPs in Georgia, Arizona, Oregon, and Colorado (2010-2023).

Evergy: Managed resource adequacy study in 2022.

Ameren: Managed resource adequacy, ELCC, and flexibility analysis for ongoing planning and IRP support (2019-2023).

Expert Witness Testimony

Dominion Energy South Carolina (2023): Testified on behalf of Dominion Energy South Carolina (2023) in South Carolina in regard to a resource adequacy and ELCC Study. DOCKET NO.2023-9-E.

New Mexico Public Regulation Commission (2021): Testified on behalf of Public Service Company of New Mexico in regard to the evaluation and recommendation of new generation resources. Case No. 21-00083-UT.

Public Service Commission of South Carolina (2021): Testified on behalf of Duke Energy in regard to the

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Resource Adequacy Study and Storage ELCC conducted by Astrapé Consulting. DOCKET NO.2019-224-E, NO.2019-225-E.

New Mexico Public Regulation Commission (2019 and 2020): Testified on behalf of Public Service Company of New Mexico in regard to the evaluation and recommendation of replacement resources for San Juan Generation Station Units 1 and 4. Case No 19-00195-UT.

Public Service Commission of South Carolina (2019): Testified on behalf of Duke Energy in regard to the Solar Integration Study Astrapé Consulting conducted for the Companies' Avoided Cost Filing. Docket No. 2019-185-E. Docket No. 2019-186-E.

North Carolina Public Service Commission (2019): Testified on behalf of Duke Energy in regard to the Solar Integration Study Astrapé Consulting conducted for the Companies' Avoided Cost Filing. Docket No. 1995-1192-E.

Georgia Public Service Commission (2014): Testified on behalf of the Commission Staff as an Independent Evaluator for the Advanced Solar Initiative RFP. Docket 38877.

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Mr. Benson has over 5 years of experience in resource adequacy and utility planning. As a consultant with Astrapé Consulting, Mr. Benson has managed and supported reliability and planning studies for large power systems across the U.S. and internationally. Prior to joining Astrapé Consulting, Mr. Wintermantel was employed by Sandia National Laboratories where he supported a team of engineers in the Energy Storage Division.

Experience

Managing Consultant, Junior Consultant at Astrapé Consulting (2018 – Present)

- Responsible for managing and using Astrapé's Strategic Energy & Risk Valuation Model ("SERVM") to perform a variety of resource adequacy related studies including reserve margin studies and ELCC studies for clients including: Duke Energy, Pacific Gas and Electric (PGE), Southern California Edison (SCE), San Diego Gas and Electric (SDGE), California Public Utilities Commission (CPUC), Midcontinent Independent System Operator (MISO), Southwest Power Pool (SPP), SERC Reliability Corporation, Public Service Company of Colorado (PSCo), Public Service Company of New Mexico (PNM), Georgia System Operations Corporation (GSOC), Associated Electric Cooperative (AECI), and Dominion Energy South Carolina (DESC);
- Wrote comprehensive reports and created presentations documenting study processes, input data, results, and conclusions for client consumption and any related filings;
- Developed synthetic load, solar, and wind profiles for clients across the US;
- Analyzed and parsed relevant resource adequacy data in Excel for usage in SERVM;
- Maintained the Astrapé server bank to run the SERVM simulations;
- Managde a team of analysts performing data analysis.

Graduate Intern for Sandia National Laboratories Energy Storage Division (2017-2018

- Provided project management support to the engineers within the Energy Storage Division including overseeing the installation of a 250kW/1MWh ESS;
- Presented a paper on improving energy storage data analysis at DOE Peer Review 2017;
- Gained a working knowledge of the energy storage industry and the RFP process through partnerships with energy storage companies, government officials, and utilities
- Conducted financial analysis of energy storage systems.

Industry Specialization

Resource Adequacy Planning	Ancillary Service Studies	Integrated Resource Planning
Renewable Integration	Financial Analysis	Capacity Value Analysis

Education

MBA, University of New Mexico – Summa Cum Laude
B.S. Degree Biochemistry - University of New Mexico - Summa Cum Laude
B.A. Degree Spanish – University of New Mexico- Summa Cum Laude

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Relevant Experience

Resource Adequacy Planning and Production Cost Modeling

Associated Electric Cooperative: Performed and managed resource adequacy studies in 2019, 2021, and 2023

Dominion Energy South Carolina: Supported resource adequacy and ELCC studies in 2022-2023.

Duke Energy: Performed and supported resource adequacy studies for Duke Energy Carolinas, LLC and Duke Energy Progress, LLC in 2020 and 2023.

GSOC: Performed and managed resource adequacy studies in 2018, 2021, and 2023

MISO: Performed ongoing seasonal resource adequacy analysis in 2020 and 2021. Provided ongoing support in regard to accreditation and LOLE studies in 2022 and 2023.

NWPP: Supported resource adequacy study for the Northwest Power Pool in 2022.

PG&E (Pacific Gas and Electric): Supported the ELCC studies performed for the California Joint IOU's in 2021 and 2022

PNM (Public Service Company of New Mexico): Supported resource adequacy studies from 2018 – 2020.

PSCo (Public Service Company of Colorado): Supported a resource adequacy and ELCC study in 2020 and performed an ELCC study in 2022

San Diego Gas and Electric (SDG&E): Supported the ELCC studies performed for the California Joint IOU's in 2021 and 2022

Santee Cooper: Supported resource adequacy, ELCC, and solar integration studies in 2022-2023.

SERC: Supported and performed the modelling for the 2022 Probabilistic Assessment

Southern California Edison (SCE) Supported the ELCC studies performed for the California Joint IOU's in 2021 and 2022

SPP: Managed ongoing planned maintenance Study in 2020-2021.

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

08/15/2023

PREPARED FOR

Duke Energy Carolinas & Duke Energy Progress

PREPARED BY

Nick Wintermantel
Cole Benson
Astrapé Consulting

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

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[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

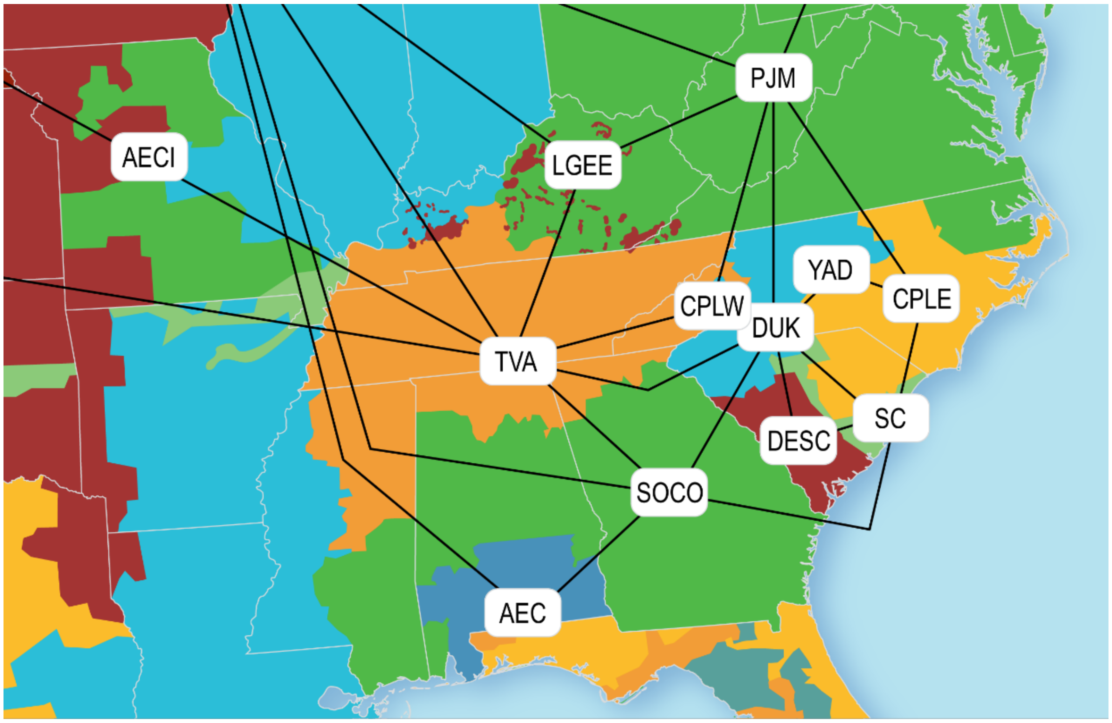
The selected study year is 2027.[9] The SERVM simulation results are broadly applicable to future years assuming that resource mixes and market structures do not change in a manner that shifts the reliability risk to a different season or different time of day.

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

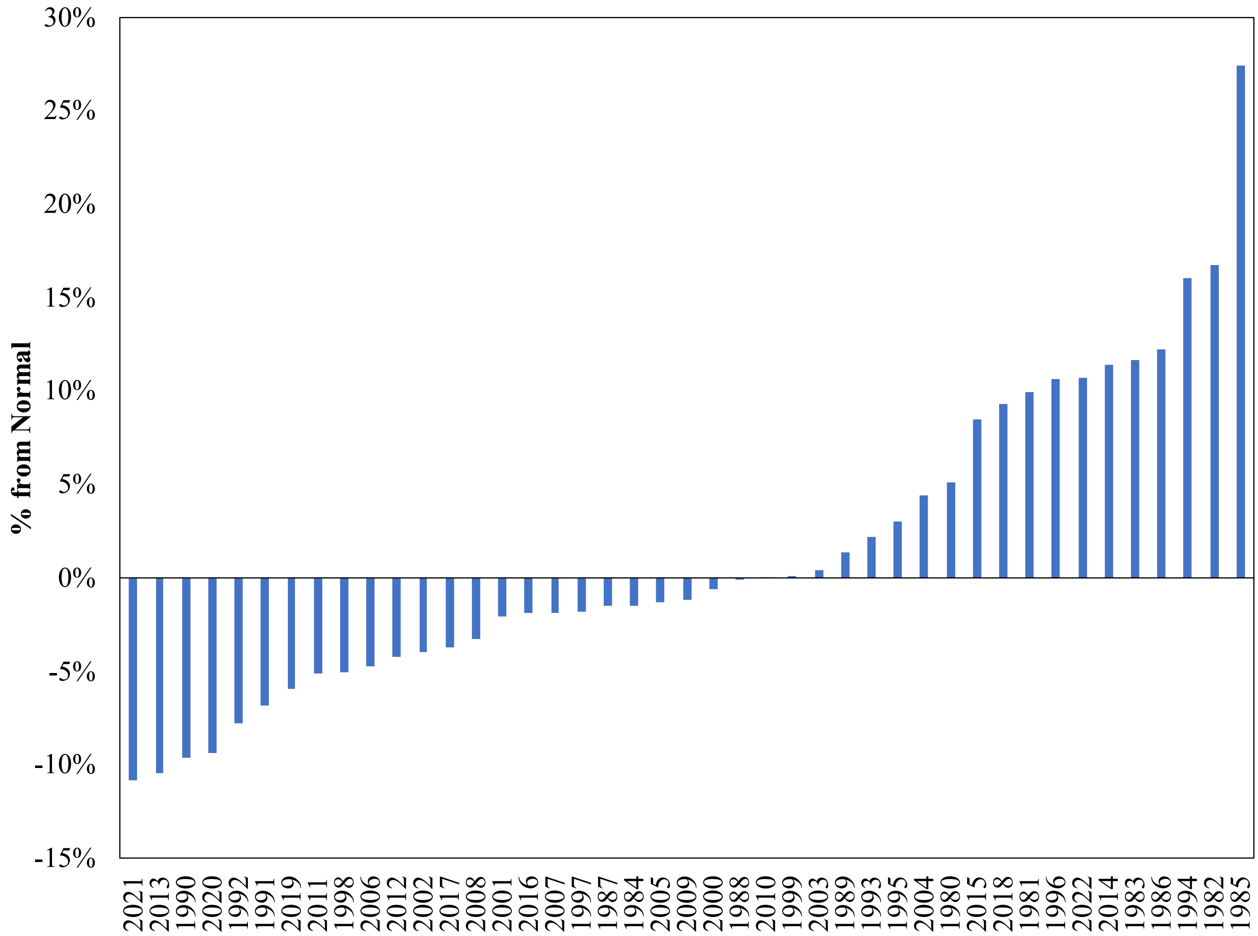


Figure 4. DEP-E Summer Peak Weather Variability

Figure 5. DEP-E Winter Peak Weather Variability

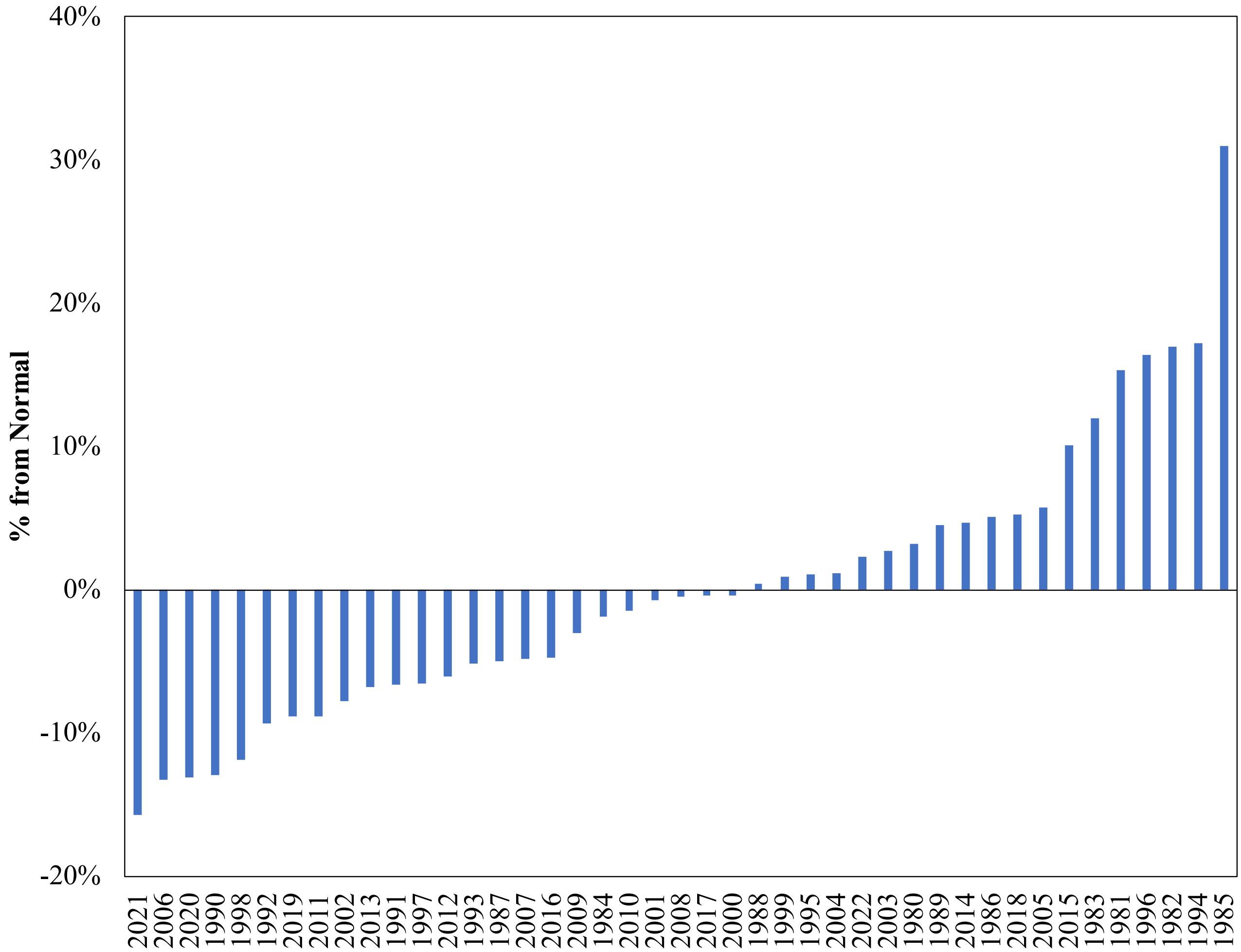


Figure 6. DEP-W Summer Peak Weather Variability

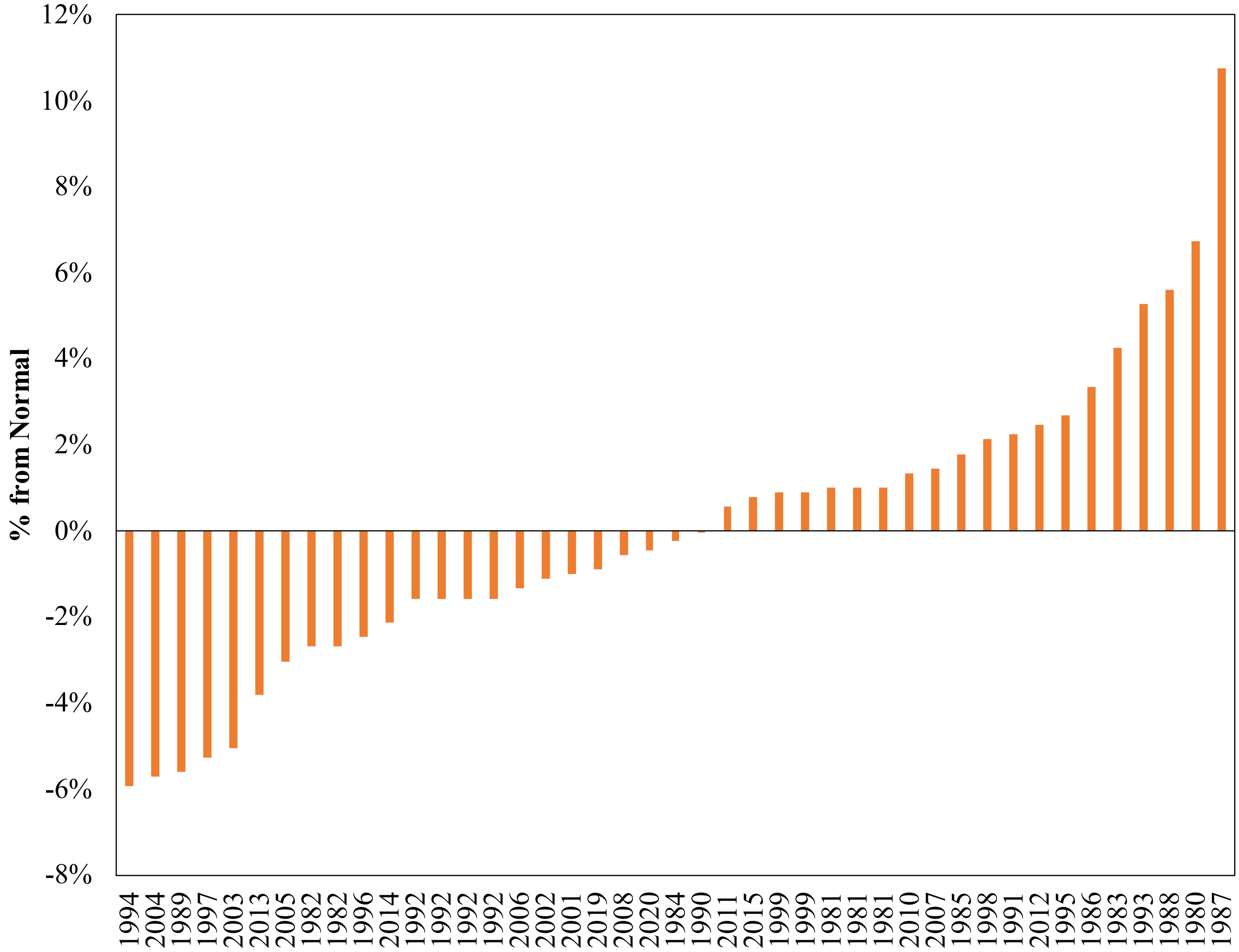
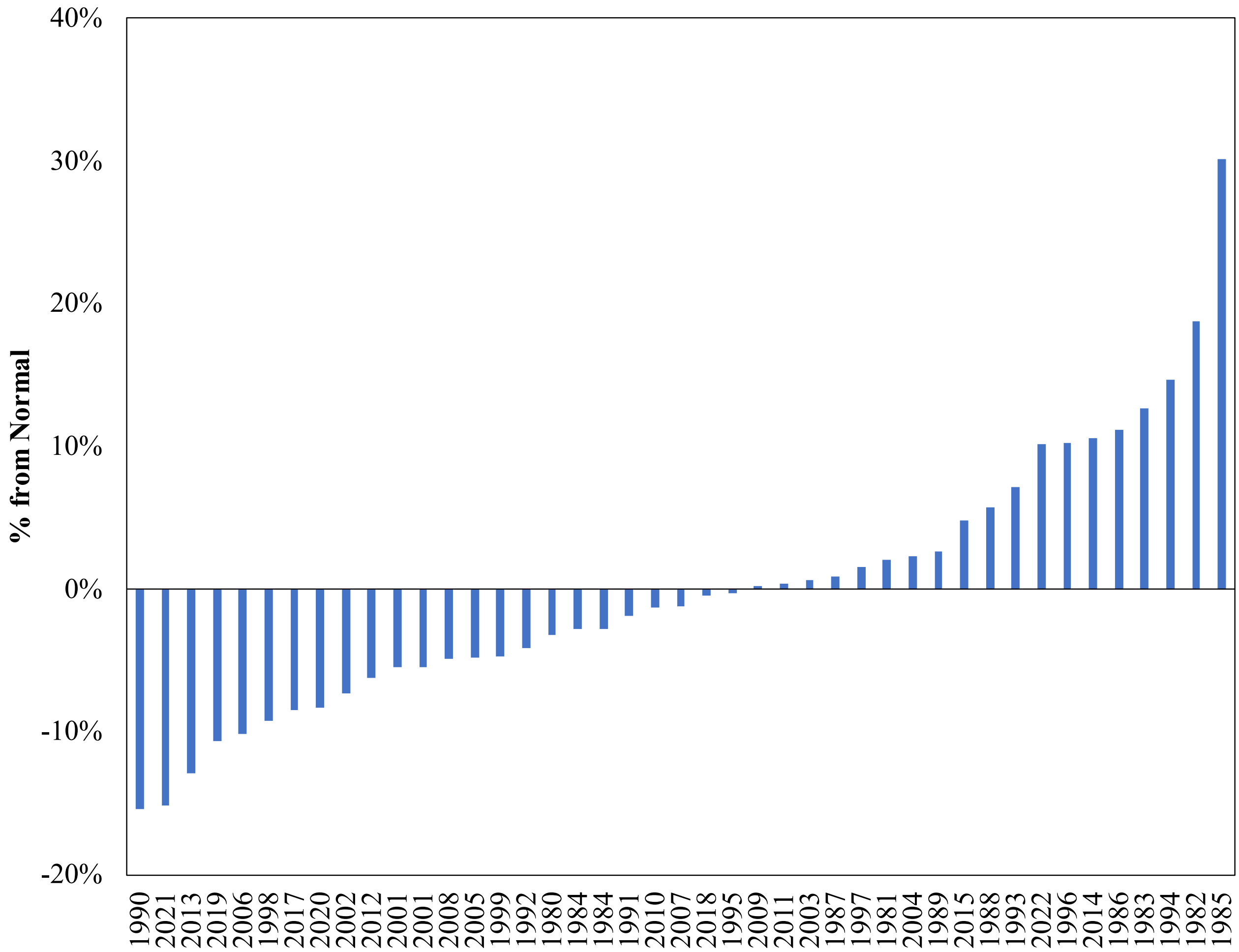


Figure 7. DEP-W Winter Peak Weather Variability



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

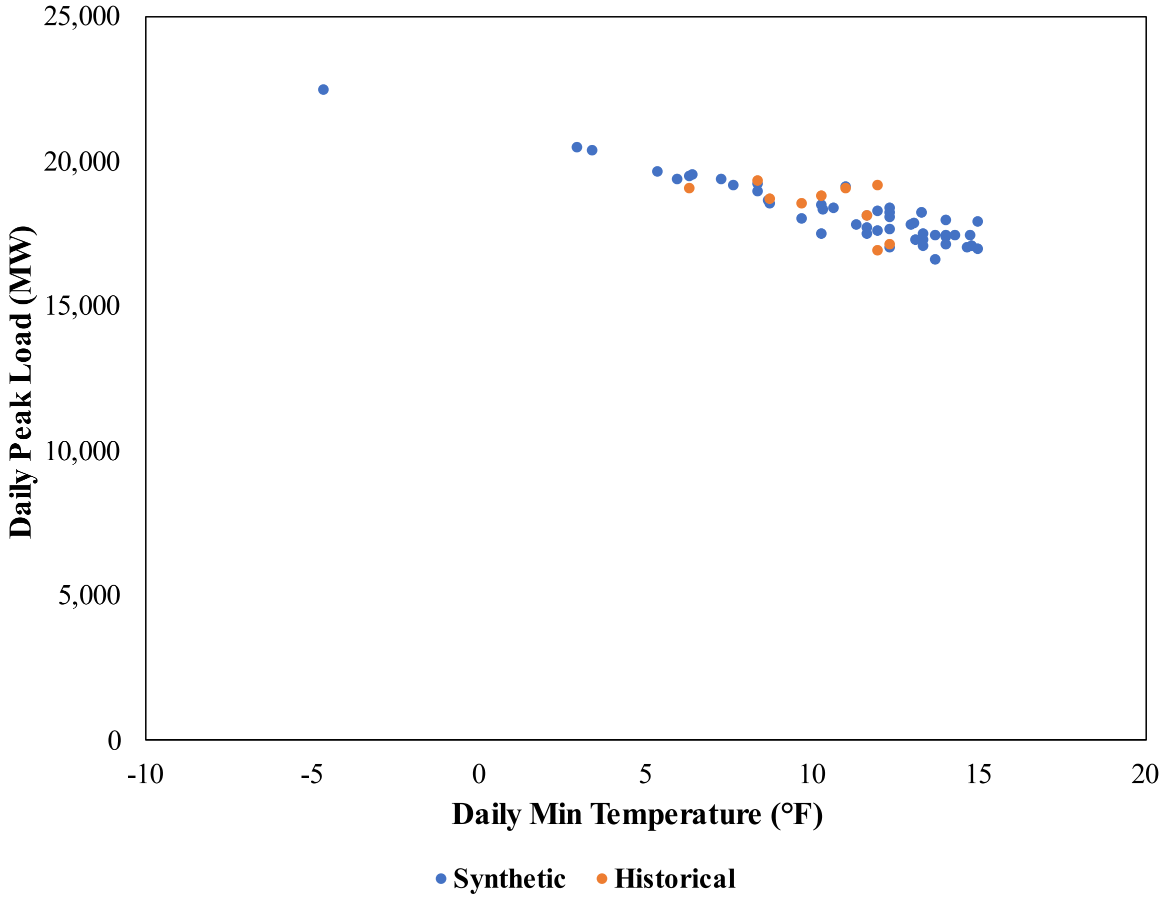


Figure 9. DEP-E Winter Weekday Calibration

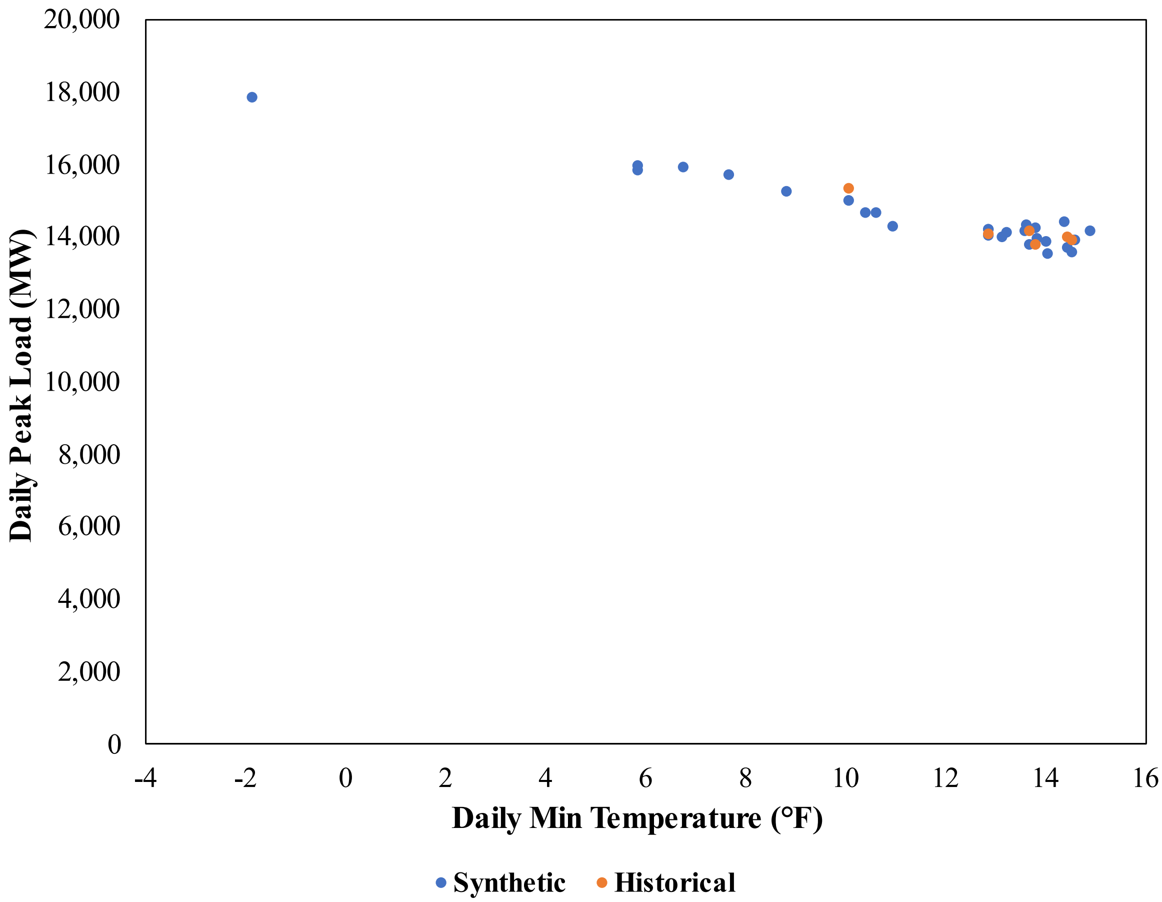
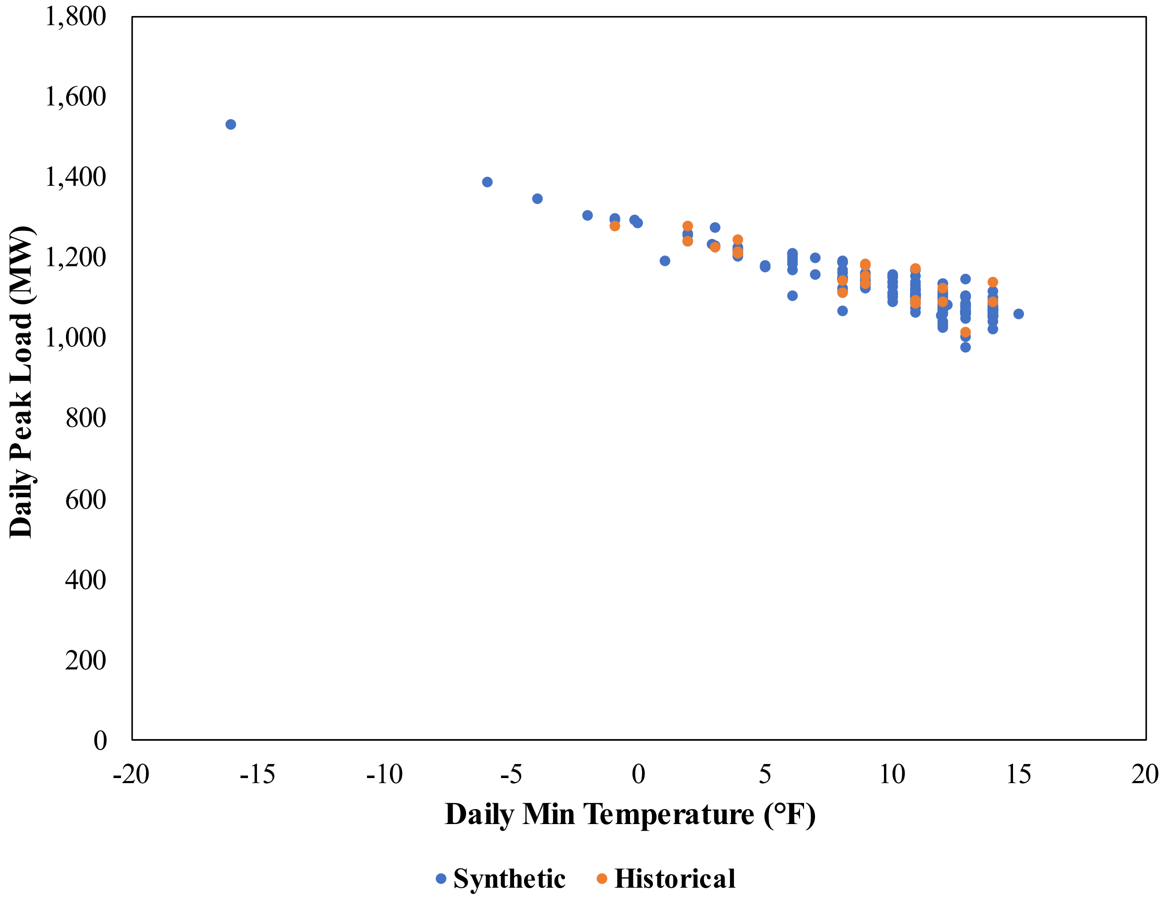


Figure 10. DEP-W Winter Weekday Calibration



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

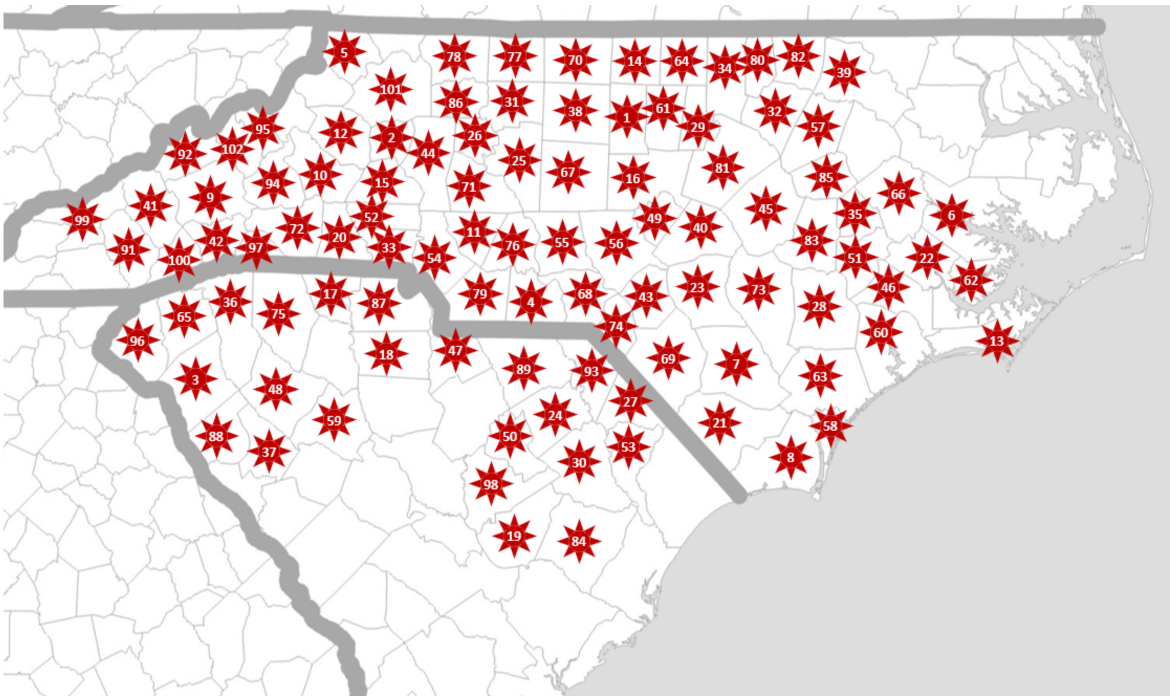


Figure 12. Average January Output for Fixed Tilt

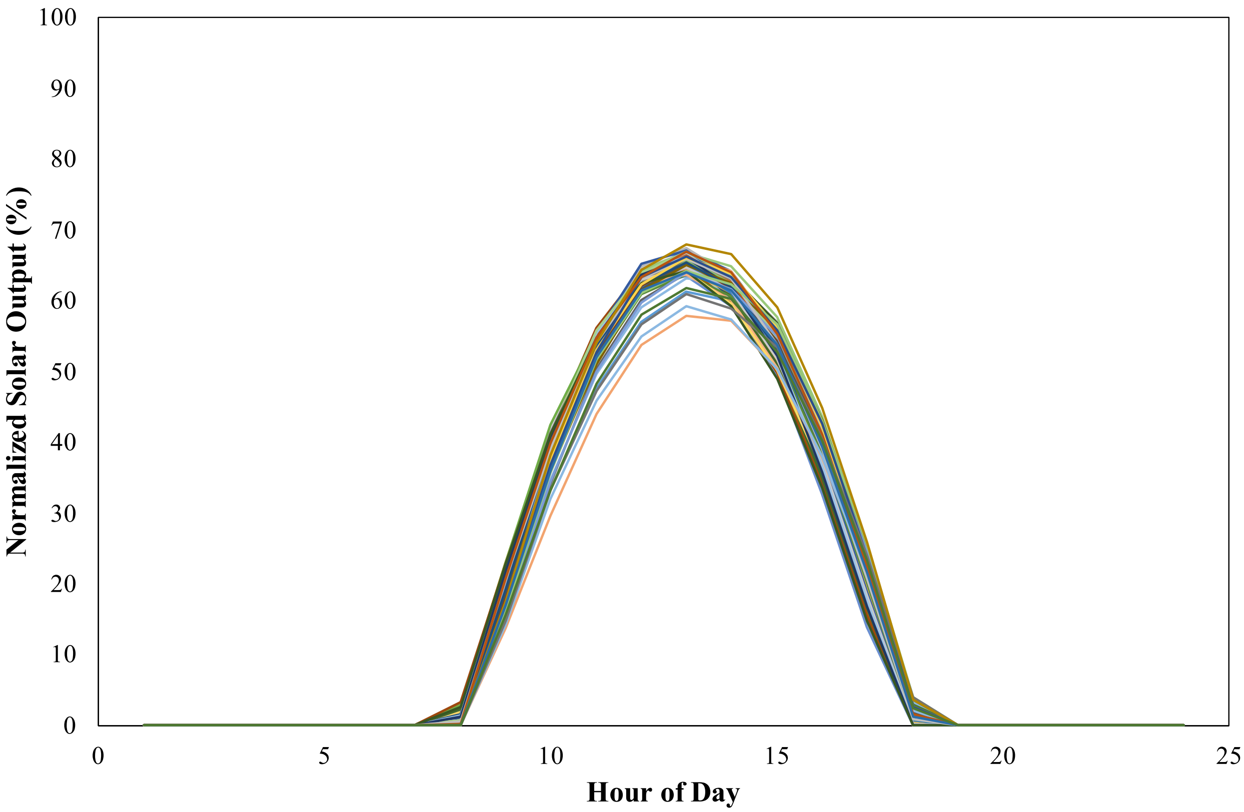


Figure 13. Average January Output for Monofacial Single Axis Tracking

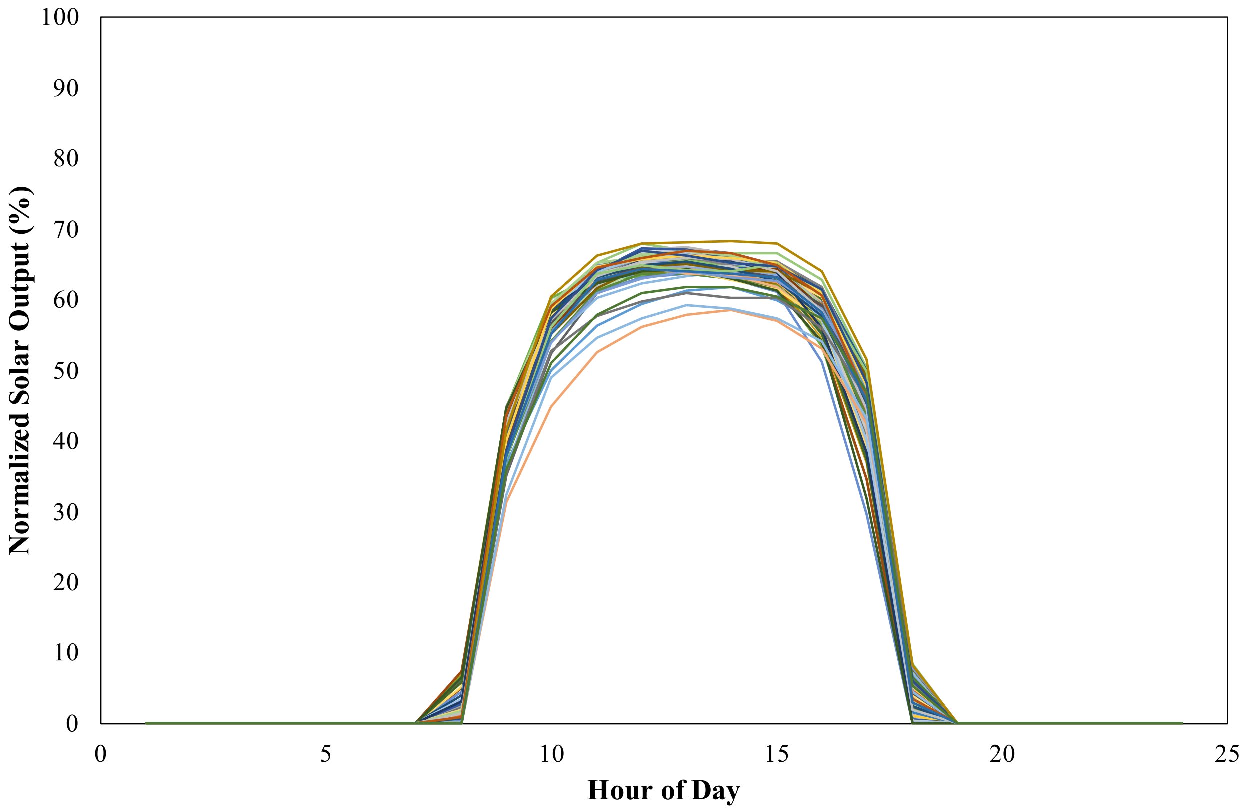
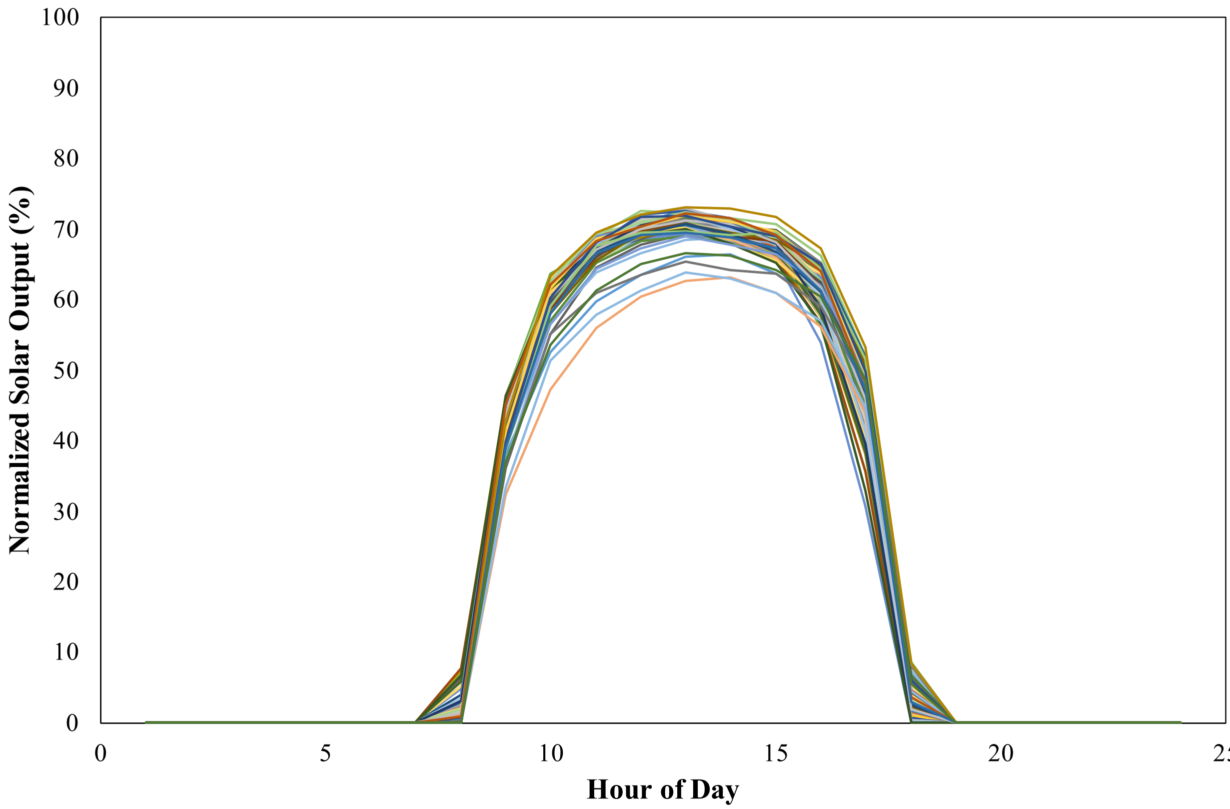


Figure 14. Average January Output for Bifacial Single Axis Tracking



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

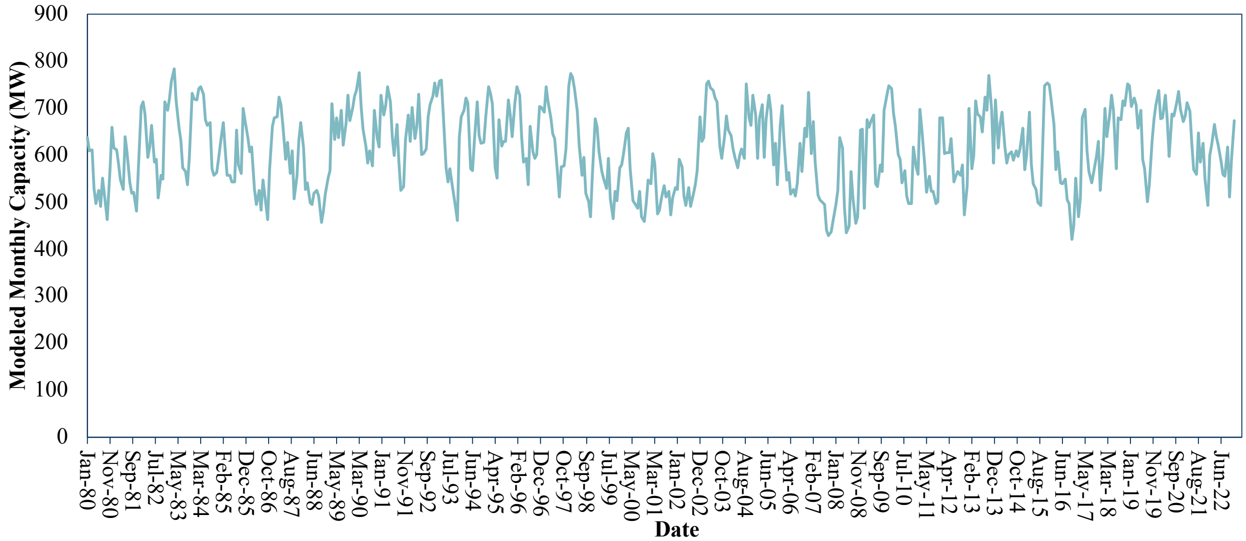


Figure 16. DEP Scheduled Capacity

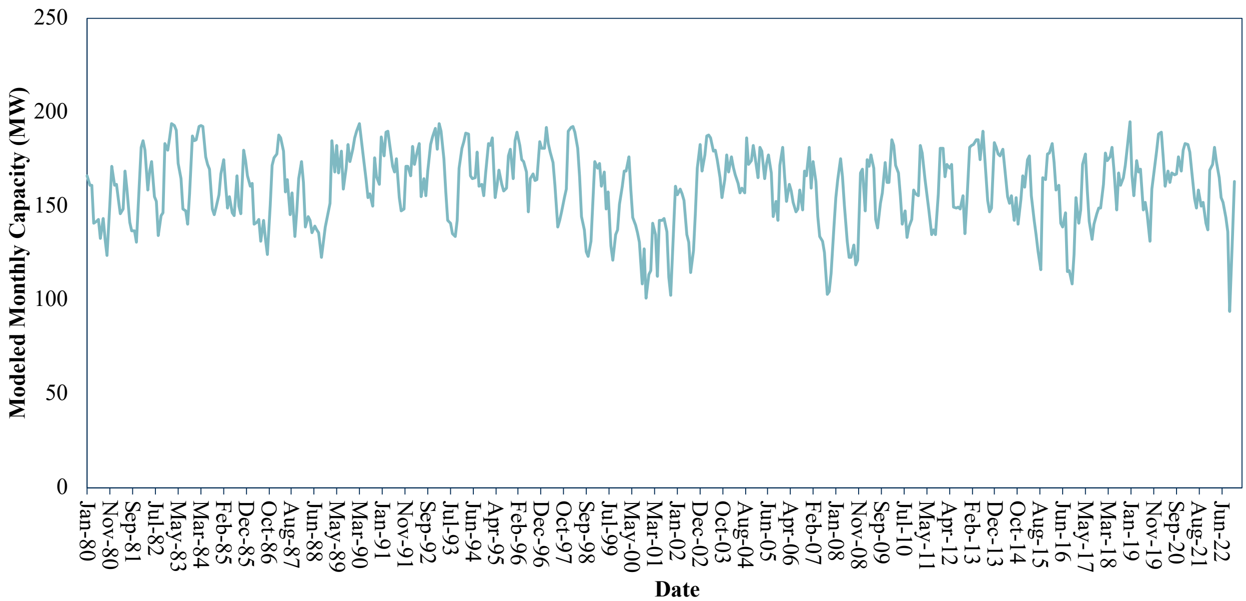


Figure 17 and Figure 18 demonstrate the variation of hydro energy by weather year which is input into the model. The lower rainfall years such as 2001, 2007, and 2008 are captured in the reliability model with lower peak shaving.

Figure 17. DEC Hydro Energy by Weather Year

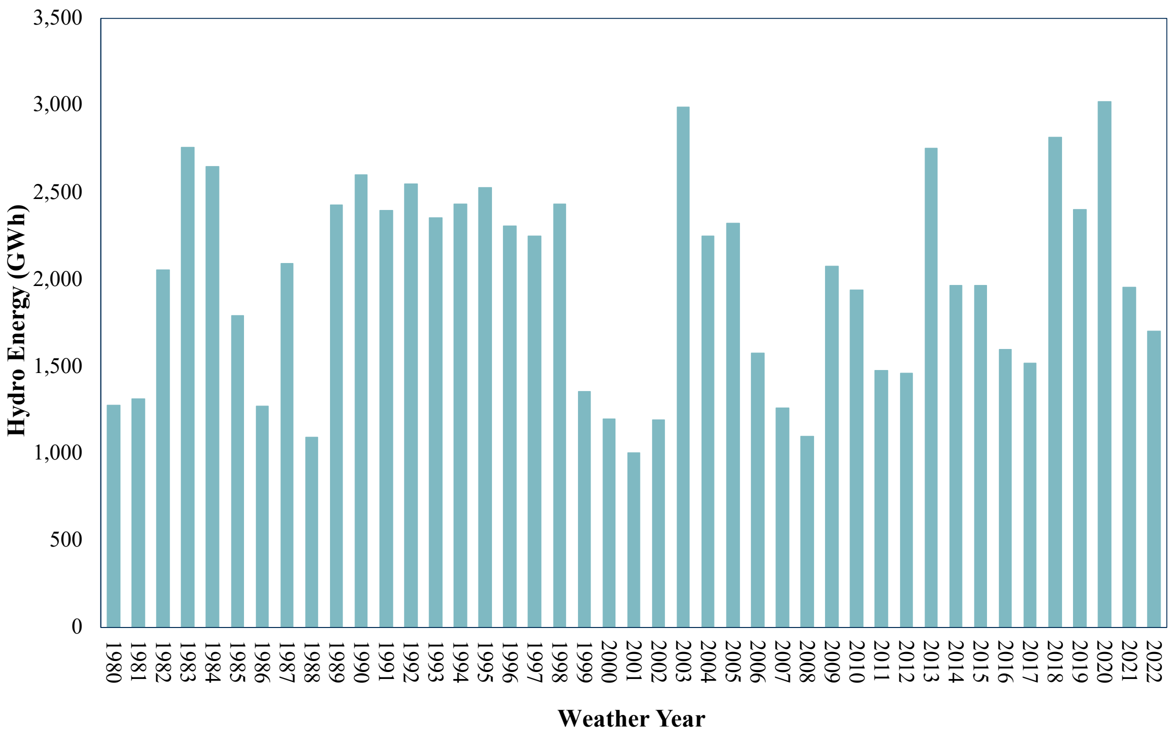
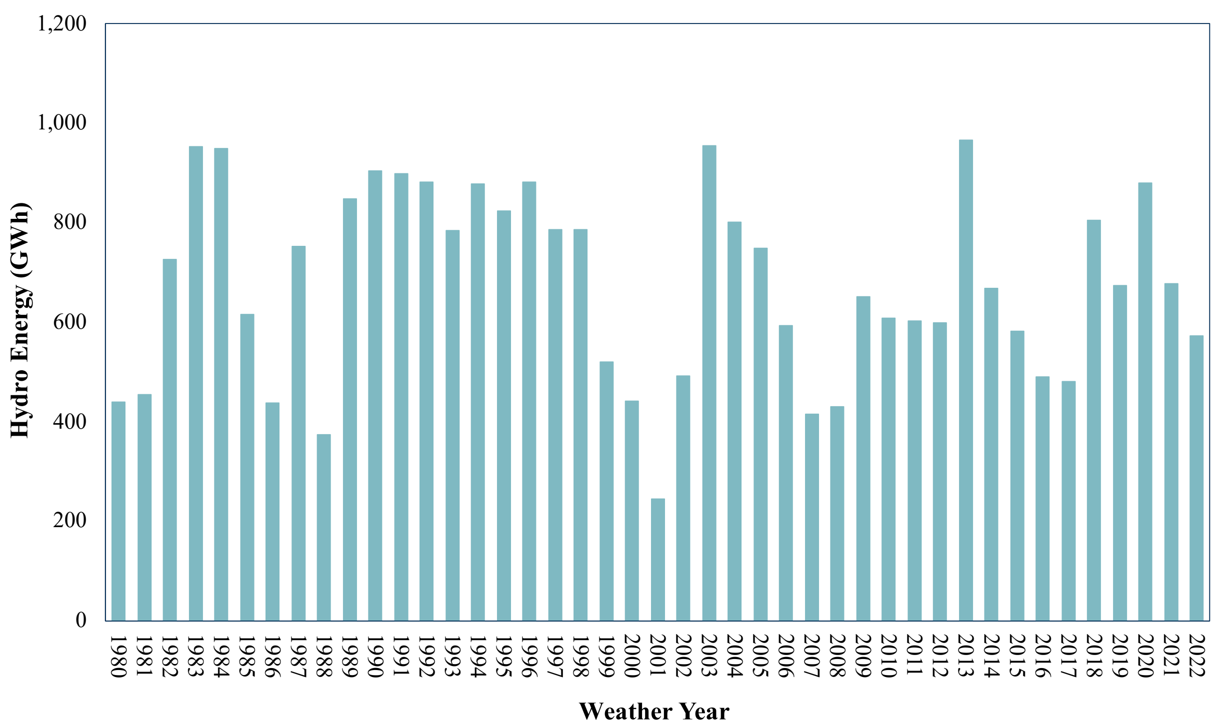


Figure 18. DEP Hydro Energy by Weather Year



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

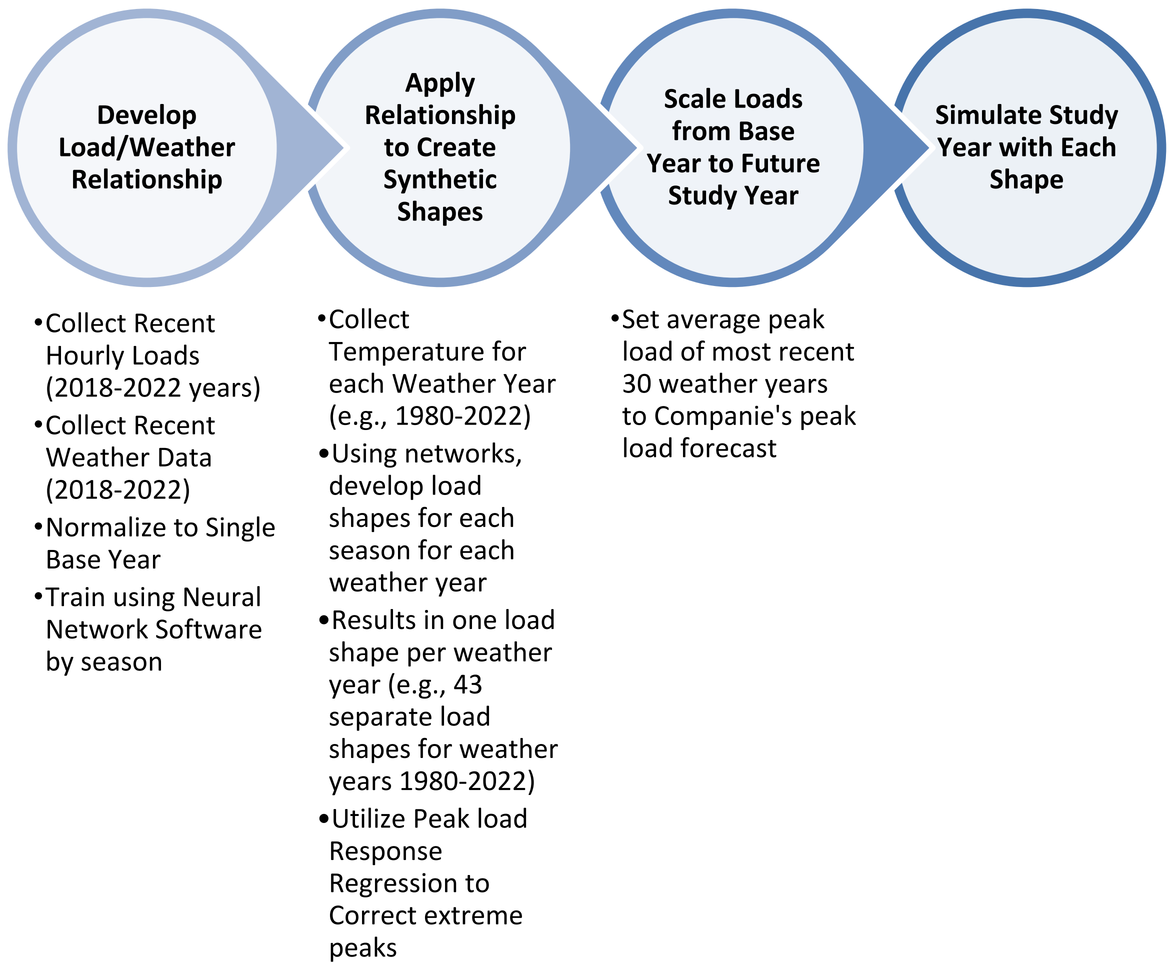
Assumption	Base Case Value	Value in 2020 Study	Comments
Weather Years	1980-2022	1980-2018	Added 4 additional weather years and updated all load, hydro, and renewable processes to be based on latest data
Synthetic Load Shapes	1980-2022	1980-2018	Updated the load/temperature relationship based on latest 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%

ASTRAPÉ CONSULTING
innovation in electric system planning

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

4/25/2022

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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.

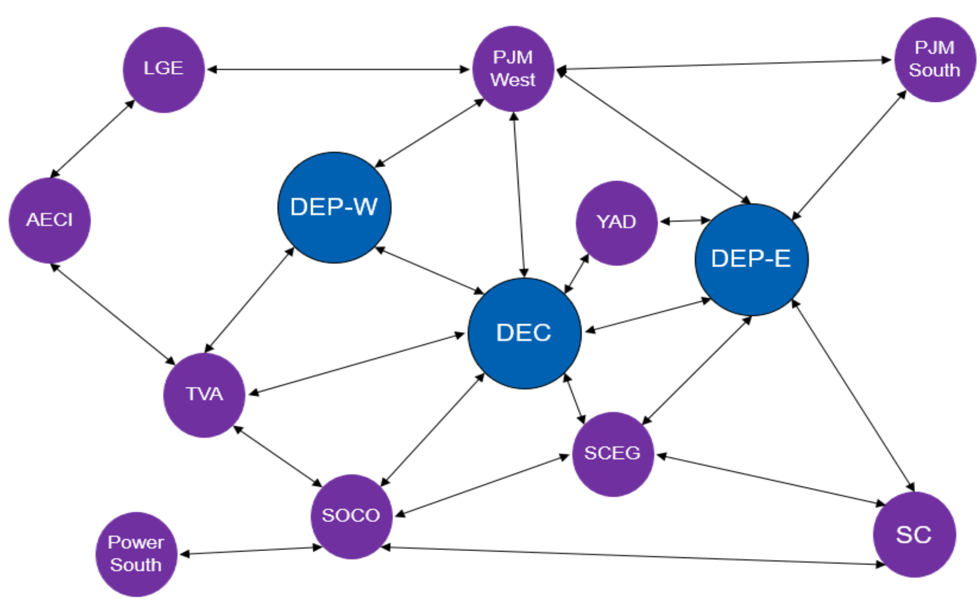
A. SERVM Framework and Cases

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

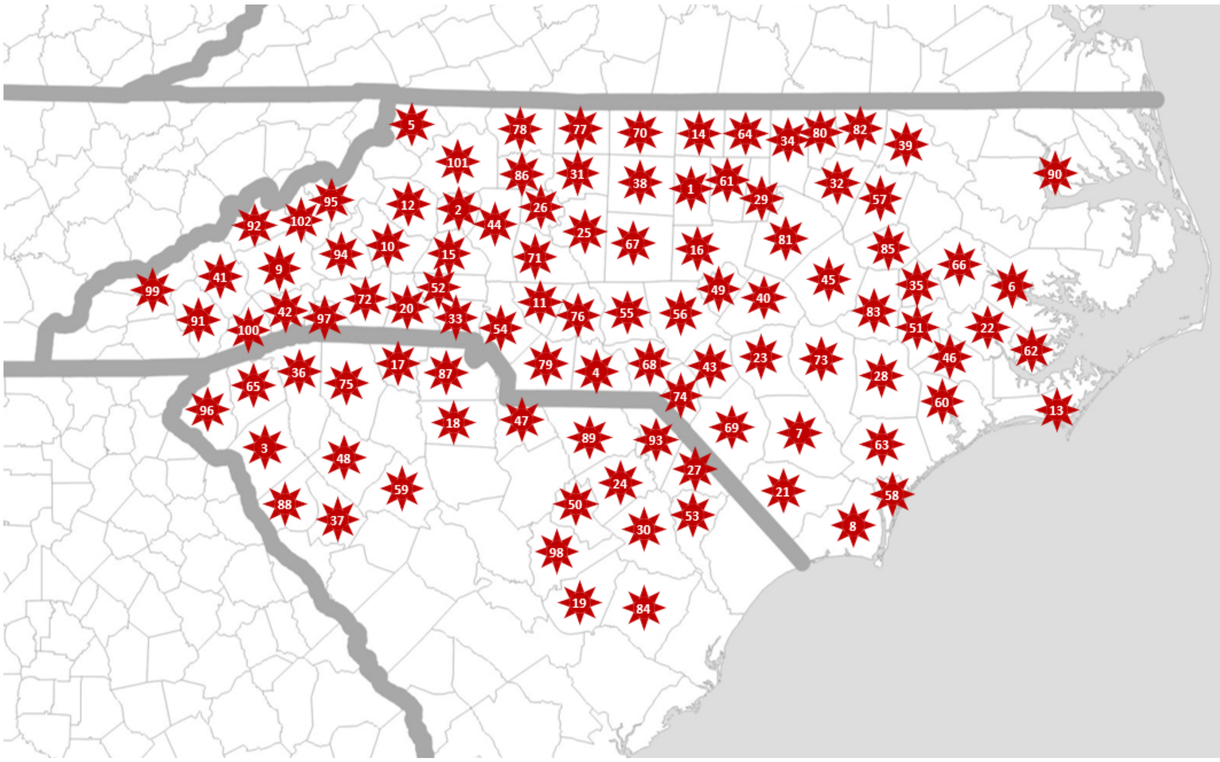
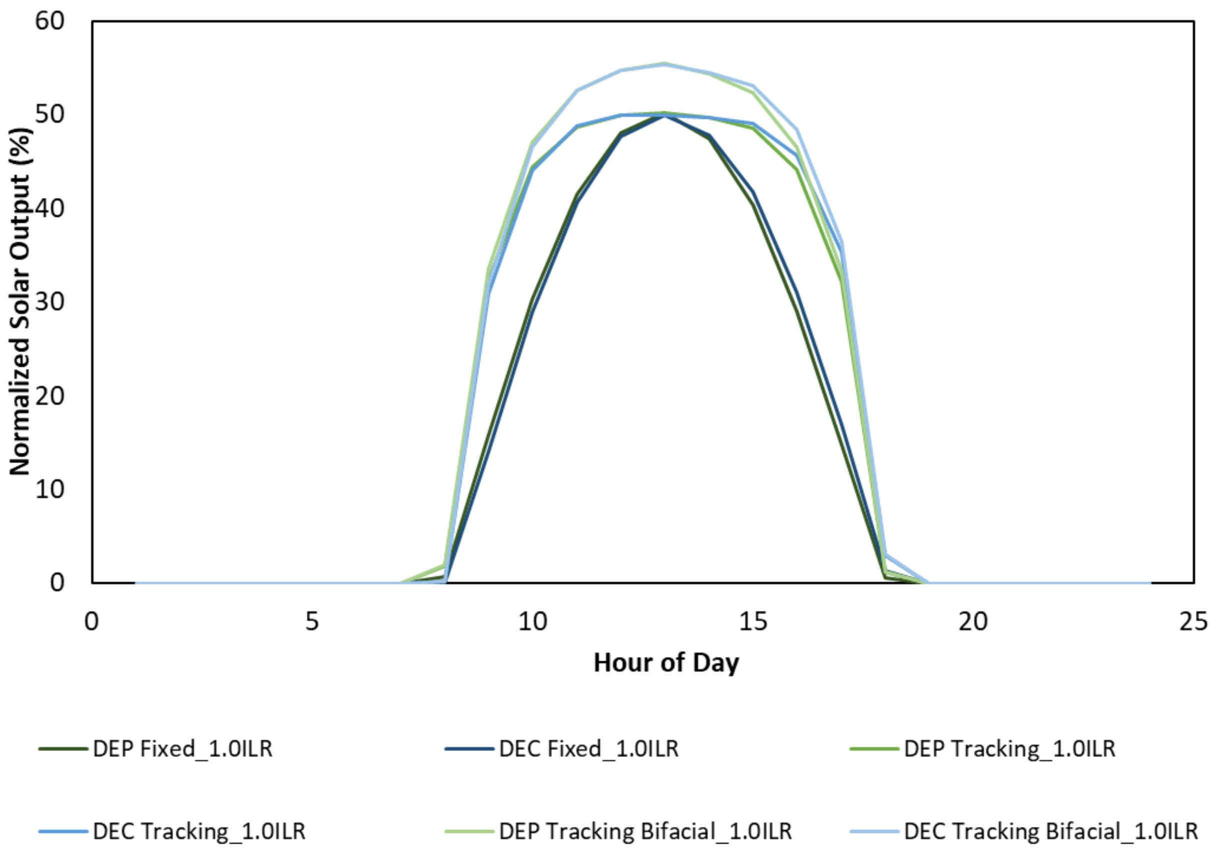


Figure 3. Average January Solar



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

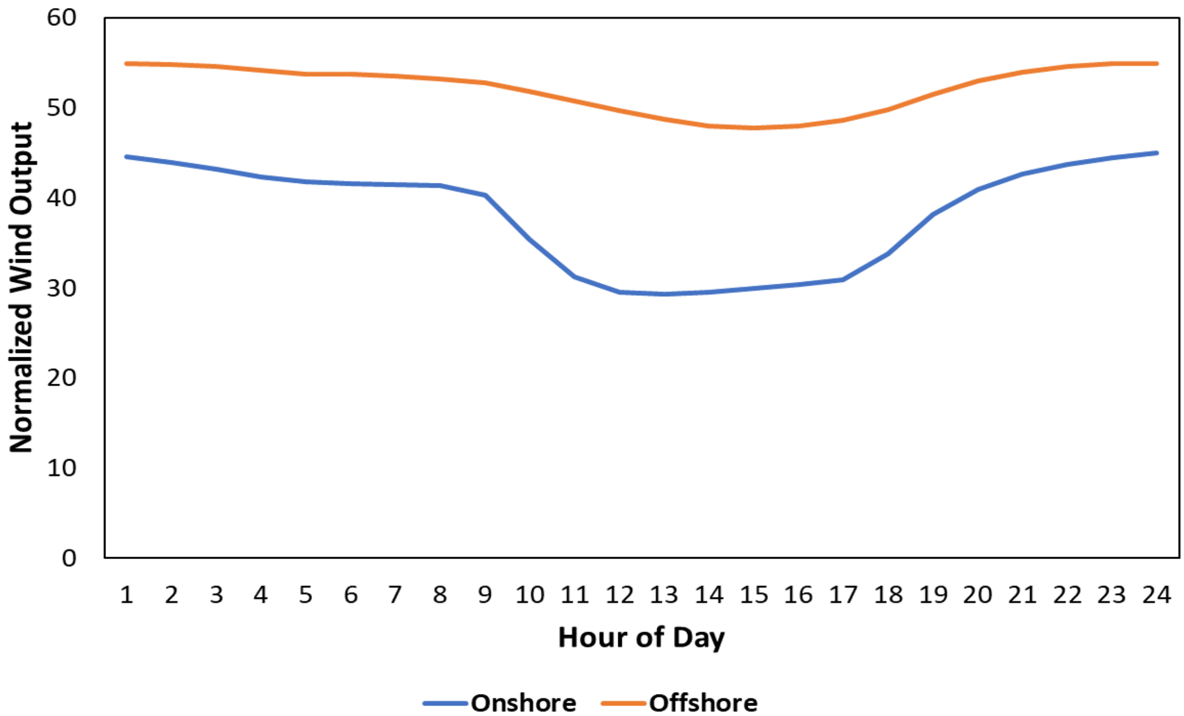
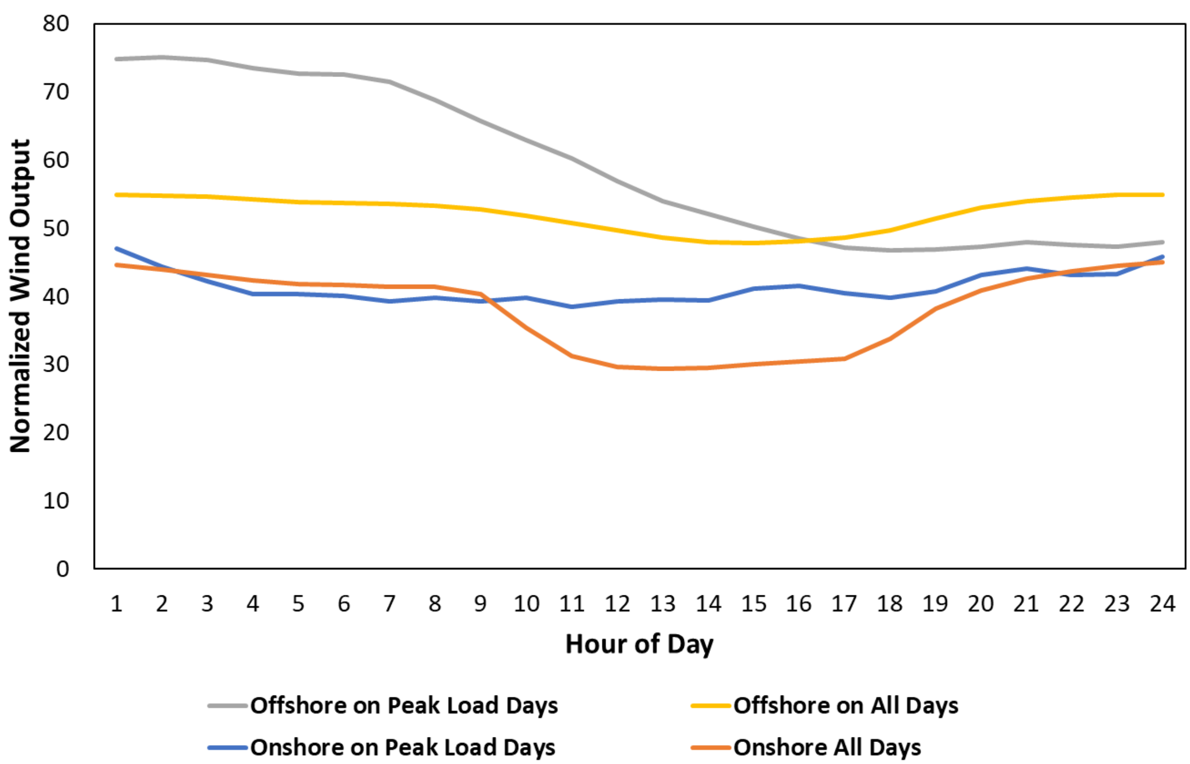


Figure 5. Peak Load Day January Onshore/Offshore Wind Output



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

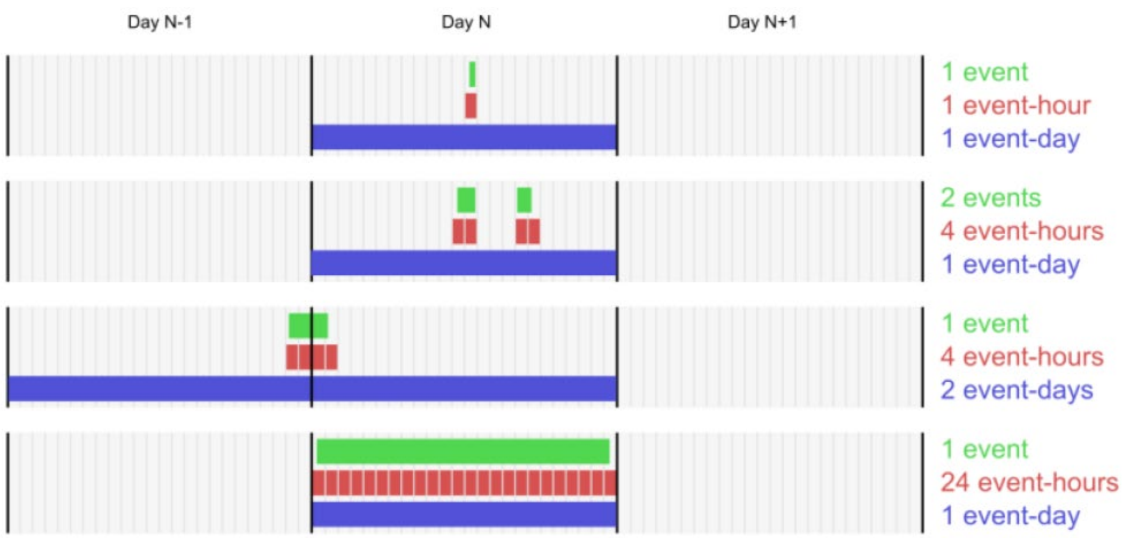
Solar MW	Storage (MW)	Summer Solar Average ELCC	Summer Solar Marginal ELCC
2000	300	67%	37.9%
3000	600	56%	34.3%
4000	1,200	51%	30.8%
5000	2,400	46%	24.0%
6000	3,200	42%	18.6%
8000	3,200	35%	7.9%

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%

ASTRAPÉ CONSULTING
innovation in electric system planning

2023 Wind Effective Load Carrying Capability (ELCC) Study for Duke Energy Carolinas & Duke Energy Progress

8/15/2023

PREPARED FOR

Duke Energy Carolinas & Duke Energy Progress

PREPARED BY

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Wind ELCC Study Results

In addition to the 2023 Resource Adequacy Study performed for Duke Energy Carolinas & Duke Energy Progress, a wind resources ELCC study was conducted in order to determine the winter capacity value for future wind resources on the Companies' system which are ultimately used in the Companies' Resource Plan. All inputs used in the Wind ELCC Study are documented in the 2023 Resource Adequacy Study Report.

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.

The Wind ELCC study utilized the Base Case Combined Scenario as a starting point and then evaluated three different wind portfolios at four different capacity levels in conjunction with the 7,411 MW existing solar portfolio, and expanded solar portfolios that totaled 10,000 MW, 15,000 MW, and 20,000 MW. The wind resources were simulated along with the different solar portfolios in order to determine Surface ELCCs for the wind portfolios which is an ELCC methodology that captures the synergistic or deleterious effects of different classes of resources on each other and then allocates that to the appropriate resource type.

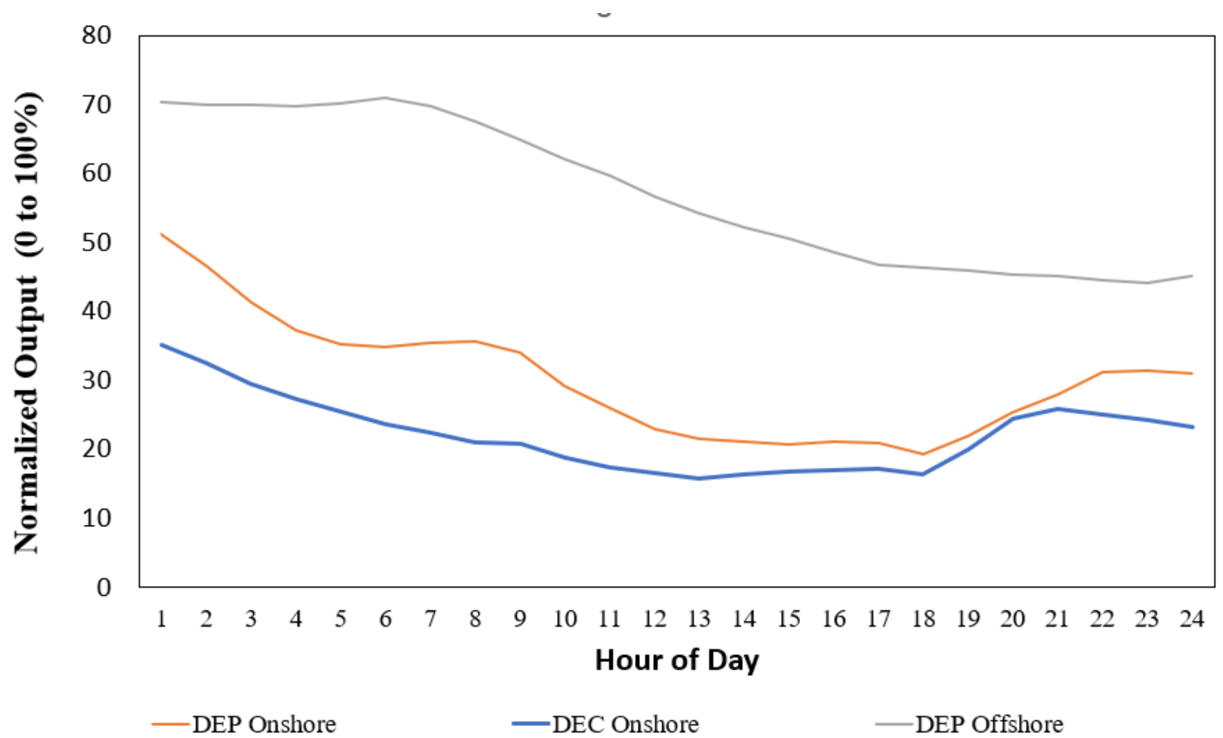
Table 1 lists the types of wind resources and their capacities along with the differing solar levels. Each capacity level of each wind portfolio is simulated along with each solar portfolio level. Figure

1 below shows the average output across all forty-three weather years of each wind resource type during winter high load hours.

Table 1. Wind and Solar Resource Tranches

Solar (MW)	DEC Onshore (MW)	DEP Onshore (MW)	DEP Offshore (MW)
7,411	300	300	800
10,000	600	600	1,600
15,000	900	900	2,400
20,000	1,200	1,200	3,200

Figure 1. Wind Shape by Hour of Day During High Load Periods



The ELCC of each tranche is calculated by first calibrating a base case system with no solar or wind that resulted in the DEC and DEP systems achieving a 1 day in 10-year industry standard of 0.1 LOLE. Once the base case is established, then the varying wind and solar tranches are added to the system. Reliability will increase and LOLE will improve to less than 0.1. Then, load will be added to the system using a negative resource until the LOLE returns to the 0.1 reliability seen in the base case. The ratio of the load added to the capacity of the portfolio added is the ELCC of the portfolio. For example, if the 300 MW portfolio of DEC Onshore Wind is added and achieves the 0.1 LOLE reliability level when 100 MW of load is added, the ELCC of the portfolio is 33%. Wind resources were modeled with a 2.6% equivalent forced outage rate (EFOR). Astrapé recognizes that gas resources do not provide 100% ELCC due to forced outages. To adjust for this, the wind portfolio wasn't compared against a perfect load but a load that reflected a 4% derate which evaluates wind on a level playing field with a gas resource. The 4% outage rate represents the high end of new thermal resources such as new combined cycle or combustion turbine resources.

The resulting ELCC's of each wind/solar tranche are then post processed to allocate any synergistic benefits and a final average and marginal ELCC for each wind tranche is determined. These wind results are listed in Table 2 and Table 3 below. The results for each tranche below are represented in two forms: marginal and average. Average ELCC represents the ELCC over the total MW of the tranche while marginal ELCC represents the ELCC of the next MW. For example, the average ELCC of the 300 MW of DEC Onshore wind is 33.8% while the 301st MW has an ELCC OF 23.9%.

Table 2. Average Wind ELCC Results

DEC Onshore		DEP Onshore		DEP Offshore	
Wind Capacity	Average ELCC (%)	Wind Capacity	Average ELCC (%)	Wind Capacity	Average ELCC (%)
300	33.8%	300	43.8%	800	74.9%
600	29.0%	600	36.8%	1,600	72.9%
900	25.9%	900	32.8%	2,400	71.9%
1,200	24.6%	1,200	31.8%	3,200	70.3%

Table 3. Marginal Wind ELCC Results

DEC Onshore		DEP Onshore		DEP Offshore	
Wind Capacity	Marginal ELCC (%)	Wind Capacity	Marginal ELCC (%)	Wind Capacity	Marginal ELCC (%)
First 300	33.8%	First 300	43.8%	First 800	74.9%
301st	23.9%	301st	28.2%	801st	74.9%
601st	22.2%	601st	27.7%	1601st	71.2%
901st	20.6%	901st	27.3%	2401st	67.5%
1201st	18.9%	1201st	26.8%	3201st	63.8%