Reserve Margin and Effective Load Carrying Capability (ELCC) Study

Final Report Public

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PREPARED FOR

Santee Cooper

PREPARED BY

Astrapé Consulting

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ABBREVIATIONS USED IN REPORT

BAA	Balancing Authority Area
BESS	Battery Energy Storage System
CC	Combined Cycle Generator
CT	Combustion Turbine Generator
DR	Demand Response
EE	Energy Efficiency
EFOR	Equivalent Forced Outage Rate
EIA	Energy Information Authority
EIDB	Eastern Interconnection Data Base
ELCC	Effective Load Carrying Capability
EUE	Expected Unserved Energy
GADS	Generating Availability Data System
GDP	Gross Domestic Product
IRP	Integrated Resource Plan
LFE	Economic Load Forecast Error
LOLE	Loss of Load Expectation
MO	Maintenance Outage
NERC	North American Electric Reliability Corporation
NOAA	National Oceanic and Atmospheric Administration
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
ORDC	Operating Reserve Demand Curve
PO	Planned Maintenance Outage
PRM	Planning Reserve Margin
TTF	Time to Fail
TTR	Time to Repair
SAM	NREL System Advisory Model
SERVM	Astrapé’s Strategic Energy and Risk Evaluation Model
SEPA	Southeastern Power Administration

EXECUTIVE SUMMARY

This document provides details concerning a two-fold study performed by Astrapé Consulting for Santee Cooper to accomplish the following goals:

1. Determine the Planning Reserve Margin (PRM) associated with the Santee Cooper system.
2. Determine the Effective Load Carrying Capability (ELCC) for a range of solar and Battery Energy Storage System (BESS) penetrations on the Santee Cooper system.

The following summarizes the results of this study.

PRM RESULTS

The PRM of a system represents the amount of additional capacity in excess of forecasted peak load that a system would need in order to maintain an acceptable level of system reliability. In this study, this was accomplished by determining the amount of capacity that would be necessary to maintain a Loss of Load Expecation (LOLE) of 0.1 days/year. This level of reliability corresponds to an expectation of one loss of load event every 10 years, which is consistent with industry practice.

The base case PRM for the Santee Cooper system was performed for two different study years, 2026 and 2029. The 2026 study year represents the near term condition of the Santee Cooper system, while the 2029 study year corresponds with the retirement and subsequent replacement of the Winyah coal facility. The figure below shows the winter PRM produced from the analysis.

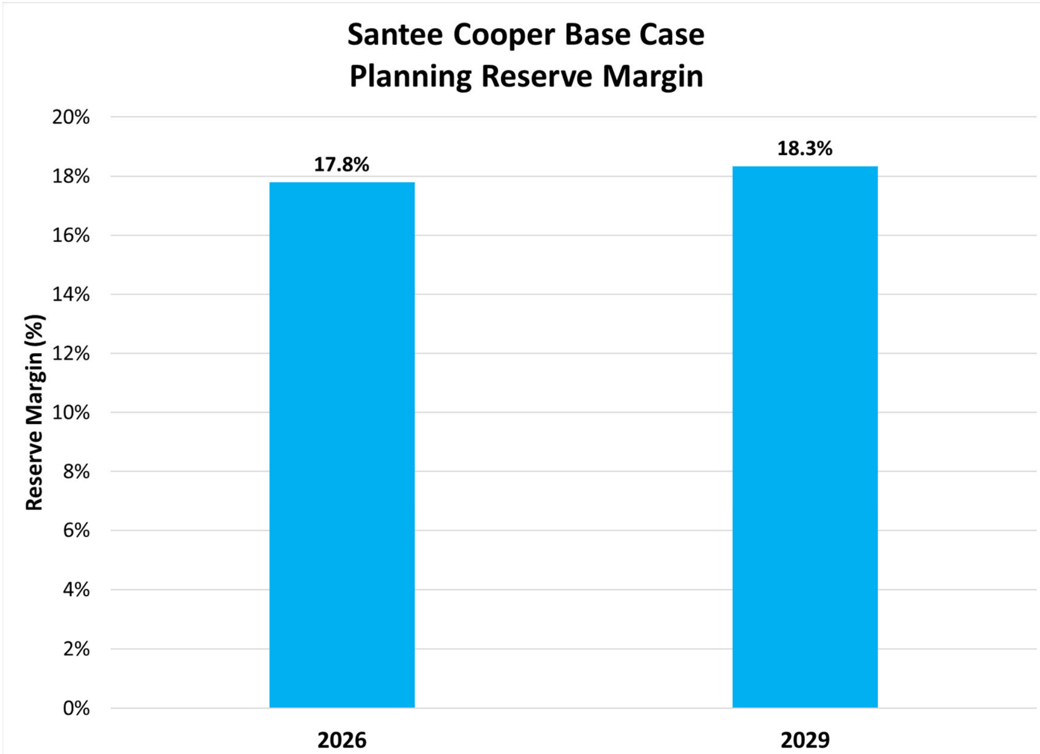

Figure ES 1. Planning Reserve Margin Results

The difference between the 2029 results and the 2026 results are driven primarily by differences in available capacity from the market and small changes system EFOR assoicated with a different capacity mix.

As shown in the figure below containing the monthly breakdown of LOLE at these established PRM levels, the overwhelming majority of LOLE occurs in the winter, making winter the dominant season for establishing reliability criteria.

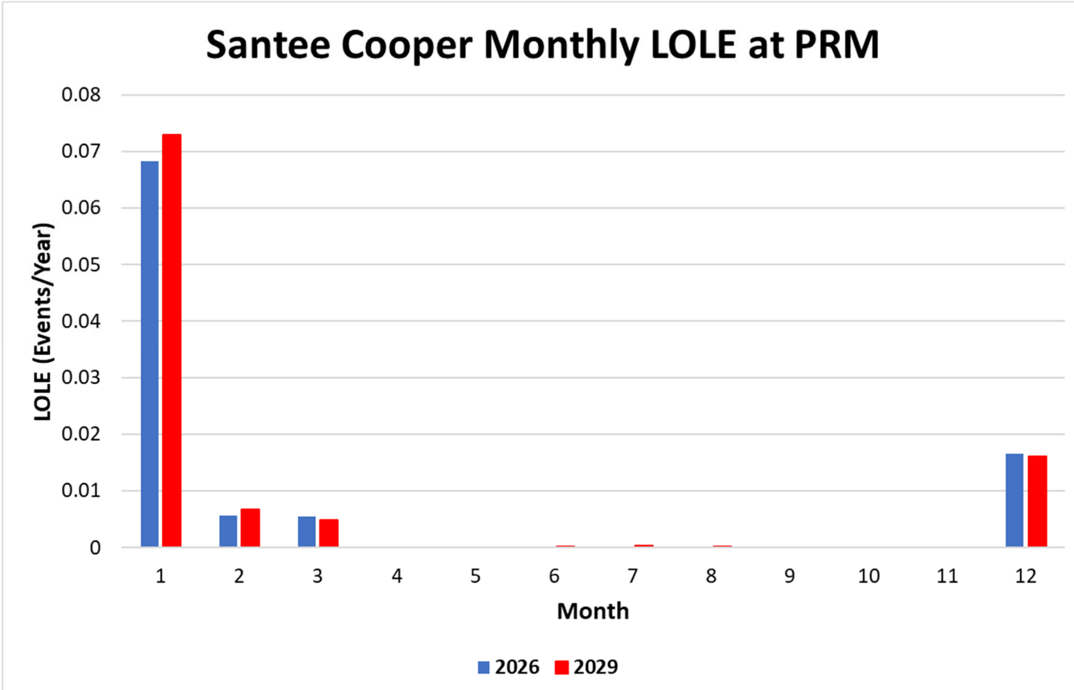

Figure ES 2. Monthly Breakdown of LOLE at PRM

To determine a reasonable summer planning target, an analysis of the summer LOLE was performed. That analysis indicated that a summer PRM in the 14-16% range would adequately maintain system reliability.

The following three items were primary drivers in the Reserve Margin Study.

1. The historical weather window included in the analysis,
2. Load response to extreme weather conditions, and
3. Available market assistance.

Based on these drivers, the following sensitivities were evaluated to test the robustness of the base case PRM:

1. Islanded Base Case (i.e., no market assistance),
2. Climate Change (i.e., compensate for the effects of increasing average temperatures),
3. Load response lower than base case assumptions,
4. Load response higher than base case assumptions, and
5. More restricted import capability.

The table below shows the results of each of these sensitities for both 2026 and 2029.

Table ES 1. PRM Results

	2026	2029
Base Case w/Market	17.8%	18.3%
Base Case Island	27.1%	27.7%
Climate Change	16.8%	17.2%
High Load Response	22.0%	22.9%
Low Load Response	14.2%	15.2%
Transmission Import	17.8%	18.5%

As indicated by the results in the table, there is a significant benefit to the interconnected Santee Cooper system, with the market providing approximately 10% benefit to the reserve margin requirement. The Climate Change sensitivity results in a reserve margin reduction of approximately 1% while the high and low load response sensitivities resulted in approximately +5% and -13% reserve margin adjustments, respectively. The lack of change in reserve margin for the transmission import sensitivity suggests that it is regional generation capacity, not transmission import capability, that is the limiting factor on the amount of market benefit that may be considered.

ELCC RESULTS

The ELCC of a renewable resource/portfolio represents the amount of dependable capacity that can be counted on by the renewable resource/portfolio for resource adequacy purposes. The ELCC is determined by finding the amount of additional load that can be served by the renewable resource/portfolio without adversely affecting system reliability as compared to a system without the renewable resource/portfolio. The ELCC is represented as a percent of nameplate capacity and is calculated by dividing the amount of additional peak load served by the nameplate capacity of the additional renewable resource/portfolio.

The table below shows the various levels of solar and BESS penetrations, as well as combined portfolios of solar and BESS, for which ELCCs were calculated.

Table ES 2. ELCC Scenarios

	BESS MW				
Solar MW ->	0	1,000	1,250	1,500	2,000
	200			200\1,500	
	400				400\2,000

The tables below show the winter and summer ELCCs, respectively that were calculated as part of this analysis.

Table ES 3. Winter ELCC Results

BESS\Solar	0	1000	1250	1500	2000
0		2.0%	1.8%	1.8%	1.4%
200	100.0%			100.0%\5.3%	
400	88.0%				93.8%\1.5%

Table ES 4. Summer ELCC Results

BESS\Solar	0	1000	1250	1500	2000
0		39.3%	36.6%	32.7%	26.9%
200	10.0%			100.0%/33.9%	
400	94.8%				100.0%/28.5%

CONCLUSIONS

Upon examination of the study analysis, including all the sensitivity results, it is evident that winter reliability is the driving factor in establishing an appropriate reserve margin requirement for Santee Cooper. Thus, Santee Cooper's primary reserve margin requirement should be a winter requirement. Furthermore, based on these results, it can be concluded that a winter reserve margin in the range of 17-18% can be justified. It is therefore recommended that the winter PRM requirement be set at 17%.

The summer reserve margin requirement should be considered a secondary requirement. Based on the analysis of the summer LOLE, it can be concluded that a summer reserve margin requirement in the 14-16% range is appropriate. It is therefore recommended that the summer PRM requirement be set at 15%.

INTRODUCTION

The purpose of this document is to report on the results of a study performed by Astrapé Consulting to determine the Planning Reserve Margin (PRM) necessary for Santee Cooper to maintain a Loss of Load Expectation (LOLE) of 0.1 Days/year or the equivalent of the common industry practice of one loss of load event in 10 years. The study examined the reserve margin requirements for two study years, 2026 and 2029.

In addition, this document will also report on the results of a study to determine the Effective Load Carrying Capability (ELCC) of the portfolio of solar resources expected to be installed on the Santee Cooper system for the two study years.

STUDY FRAMEWORK

This study was performed using the Strategic Energy & Risk Valuation Model (SERVM) and its associated study framework. The SERVM framework combines an hourly (i.e., 8760-hour) production cost model coupled with Monte Carlo outage simulation and comprehensive scenario management that considers load and weather uncertainty in order to determine key reliability parameters such as Loss of Load Expectation (LOLE). The following describes the key parameters and uncertainties that are considered and how they are applied within the study framework.

WEATHER UNCERTAINTY

To account for weather uncertainty, SERVM performs hourly production cost simulations using multiple load shapes representing historical weather years. The uncertainties that are modeled for each modeled weather year include load shapes, renewable profiles, and hydro availability. Load shapes for each weather year are developed to represent the expected future load response to the historical weather (temp). For example, a 1990 weather year represents how loads would respond if 1990 weather were to repeat itself in the future. These load shapes are then scaled so that the median of the peak demands from the various weather year load shapes equals the study year weather normal peak load forecast. Similarly, renewable profiles and hydro schedules are developed to represent the expected future availability associated with the historical weather profile. For purposes of this study, 41 weather year scenarios were simulated representing weather conditions for the years 1980-2020.

ECONOMIC LOAD FORECAST ERROR

Economic Load Forecast Error represents the potential error in the weather normal peak load forecast associated with uncertainty in economic forecasts. Using the Office of Congressional Budget's historical forecasts for Gross Domestic Product (GDP), it is possible to predict both the magnitude and probility of error in the forecast of the GDP economic indicator 3, 4, or 5 years out into the future. This probability of error can then be converted into a Load Forecast Error (LFE). For purposes of this study, 5 LFE scenarios were chosen. These are described in the Model Development section of this document. Each of the 41 weather year scenarios are combined with each of the 5 LFE scenarios to create 205 unique load scenarios, or "cases".

MONTE-CARLO OUTAGE ITERATIONS

SERVM uses monte-carlo techniques to simulate generator outages. Multiple hourly production cost simulations are run for each of the 205 load cases. With each outage iteration, random monte-carlo draws are made to determine the outage profile associated with that scenario. For purposes of this study, 100 outage draw iterations were made for each case. The specifics associated with how these outages were modeled are detailed in the Model Development section of this document.

As shown in the figure below, the SERVM uncertainty framework used for this study required at least 20,500 hourly (8760-hour) production cost simulations for a single analytical run of the Santee Cooper system and its first tier neighbors.

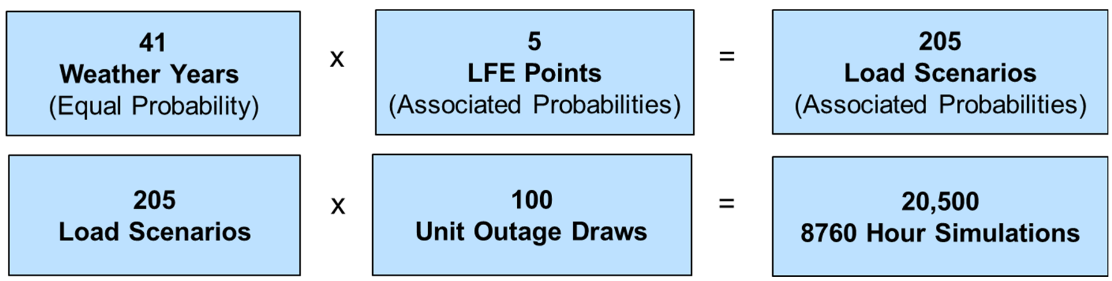

Figure 1. SERVM Uncertainty Framework

The Study Methodology section of this document describes the numerous “analytical runs” required to perform the reserve margin analysis, its associated sensitivities, as well as the ELCC analysis.

MODEL DEVELOPMENT

The SERVM data model utilized for this study was based upon load and resource profiles for the Santee Cooper Balancing Authority Area (BAA) and its immediate first tier interconnected BAAs, including the BAAs associated with Southern Company, Duke Energy Carolinas (DEC), Duke Energy Progress (DEP), and Dominion Energy SC (DESC). The figure below shows the configuration of the study model with its associated transmission interface connections using a pipe and bubble configuration.

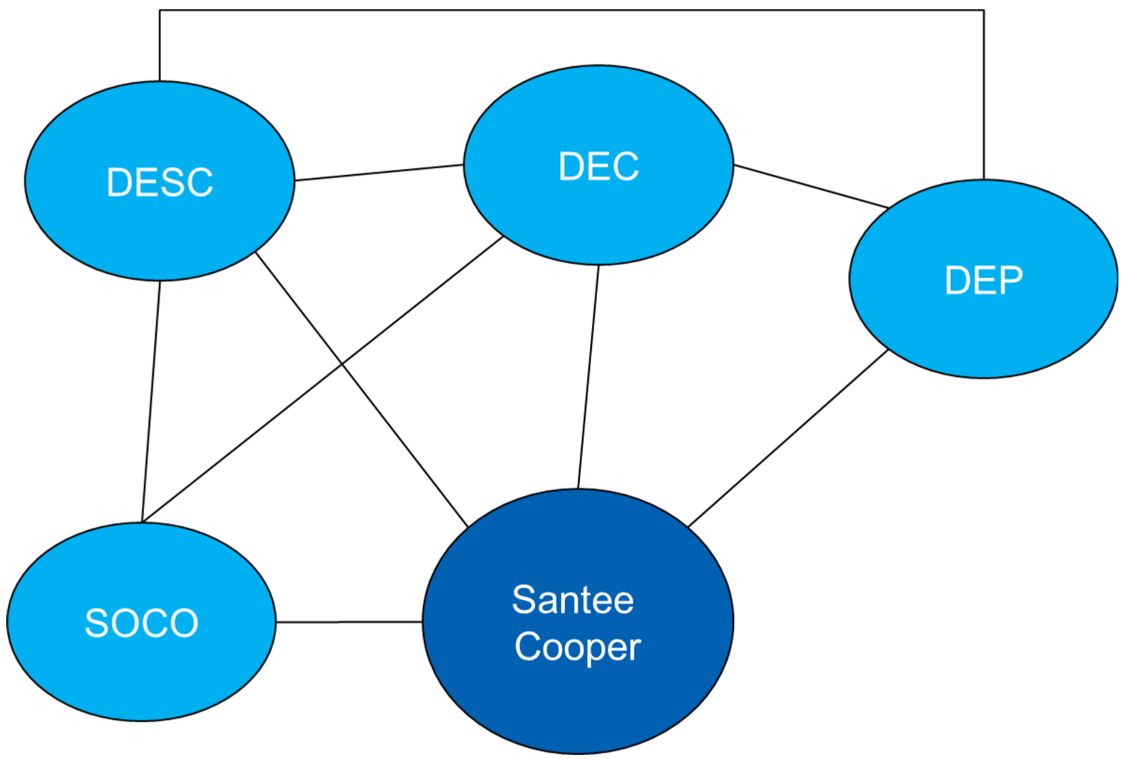

Figure 2. Study Model Configuration

BASIS FOR MODEL DEVELOPMENT

The basis for the SERVM model used in this study was the data included in Astrapé Consulting's Eastern Interconnection Database (EIDB) with revisions to the Santee Cooper region per data provided directly by Santee Cooper. Astrapé's EIDB was developed and is maintained using publicly available data from sources such as the Energy Information Authority (EIA) Form 860, available documents from the North Americal Reliability Corporation (NERC), various publicly available Integrated Resource Plans (IRPs), FERC Forms, and the like.

The following provides the specifics of the Santee Cooper data as provided by Santee Cooper for purposes of this study.

STUDY YEARS

As indicated in the Introduction section above, the study years chosen for this analysis included 2026 and 2029.

PEAK DEMAND FORECAST

For this study the peak demand forecast represented the gross load (i.e., before any reductions due to curtailable load or renewable load injections) reduced for anticipated Energy Efficiency (EE) impacts. The summer and winter peak demand forecasts as provided by Santee Cooper are shown in the figure below.

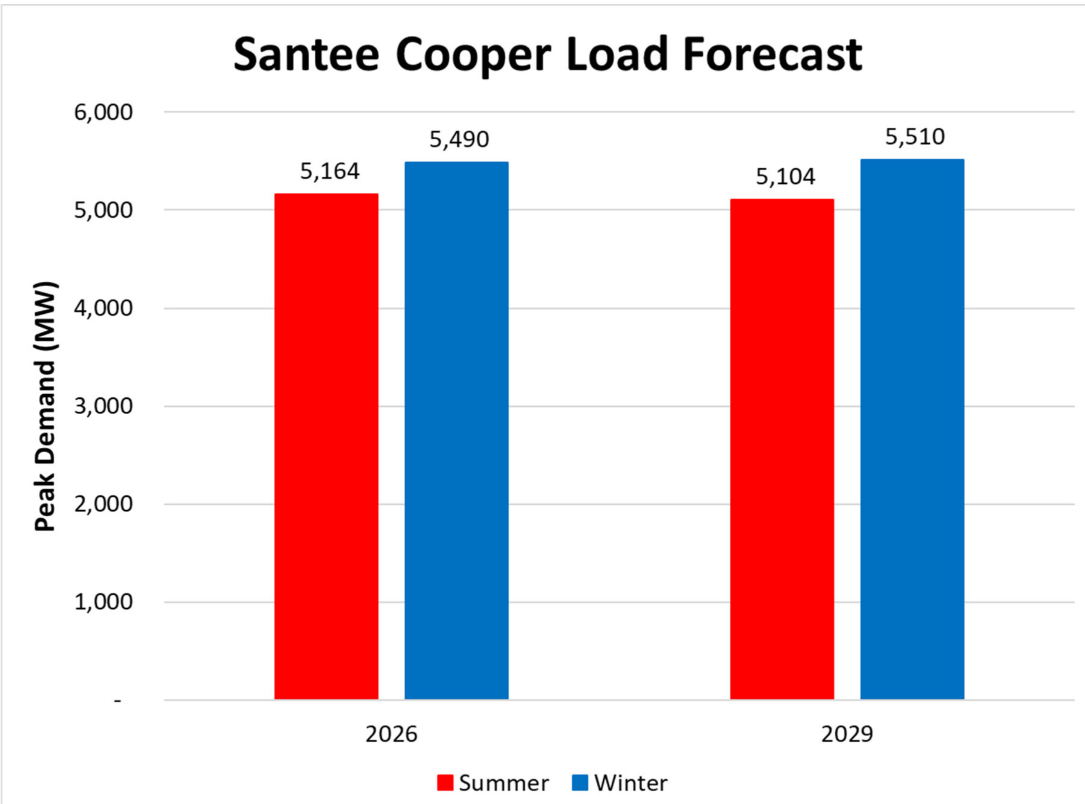

Figure 3. Peak Demand Forecast

LOAD MODELING

As described in the Study Framework subsection of the Introduction section above, load shapes were developed for each of the 41 study years 1980-2020. These load shapes were developed based on trends and relationships between load and weather for the years 2017-2021.

The five historical load shapes trended using a neural network that was trained using weighted hourly historical temperatures from the National Oceanic and Atmospheric Administration (NOAA) and other key variables. The following NOAA weather stations along with the indicated weighting were used to develop the temperature variables. Gaps in the weather data were filled using adjusted weightings of the remaining stations.

Table 1. NOAA Weather Stations and Weightings

Station	Weighting
Myrtle Beach	21.4%
Florence	15.7%
Charleston	10.7%
Columbia	41.7%
Savannah	10.5%

In addition to temperature, the neural net was provided with training variables that included day of week, hour of day, hour of week, 8-hour rolling average temperature, 24-hour rolling average temperature, and 48-hour rolling average temperature. “Networks” were created for Winter, Summer, and Shoulder periods. These trained networks were then applied to the NOAA weather data for the historical years 1980-2020 to develop synthetic load shapes for each of the 41 weather years.

Since the 41 years of historical weather data contains temperature data outside the range of that contained in the historical load set used to train the neural networks, those values were determined using peak load regressions developed outside the neural network. Peak load regressions were developed for summer afternoon, winter morning, and winter afternoon periods. These adjustment regressions were only applied to those hours in which the temperature fell outside the range of the 5-year historical data set.

The final load shapes were a combination of those hours developed using the neural net and those developed using the peak load regressions. The synthetic load shapes were then quality checked against the actual historical shapes to ensure their validity.

The figure below shows a plot of the daily peak loads as a function of either the daily max or daily min temperature as appropriate. The figure compares the 5 years of historical data with the 41 years of synthetic data.

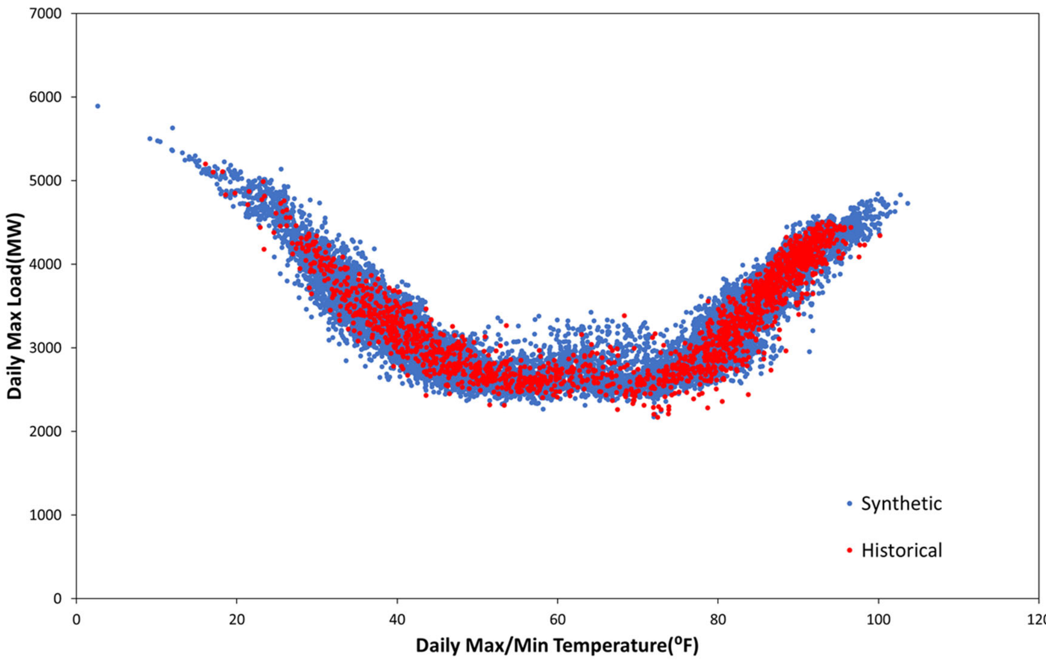

Figure 4. Synthetic vs. Historical Daily Peak Loads

The development of the 41 synthetic load shapes results in a diverse set of annual peak loads. Within SERVM, these shapes will be scaled such that the median of the annual peak loads will equal the weather normal peak load for both summer and winter. The figures below show the summer and winter peak load variance resulting from the 41 synthetic load shapes. The variance is shown in terms of its divergence from the weather normal peak load on a percentage basis.

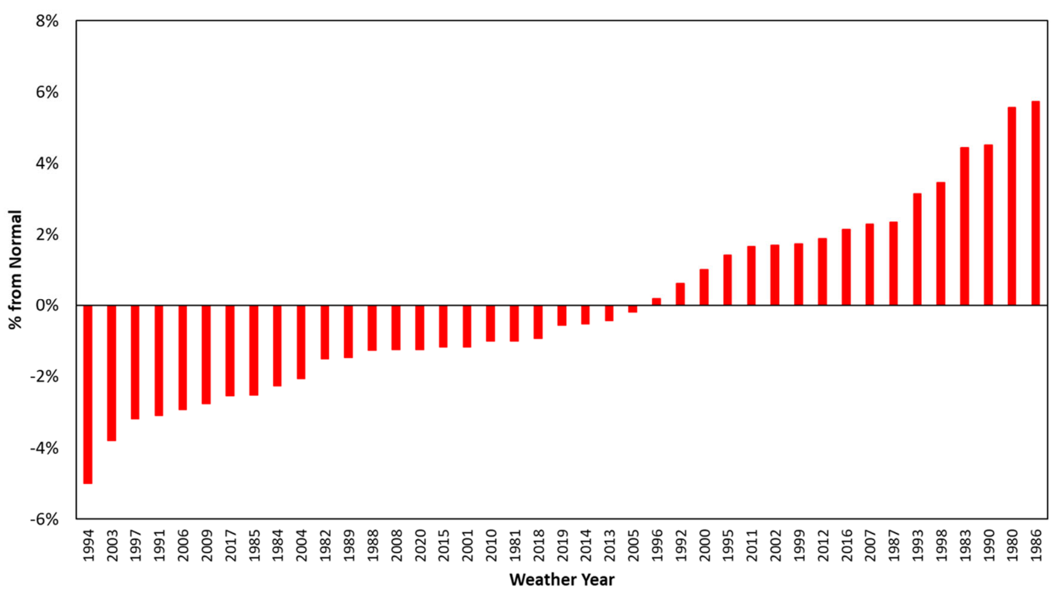

Figure 5. Summer Peak Load Variance

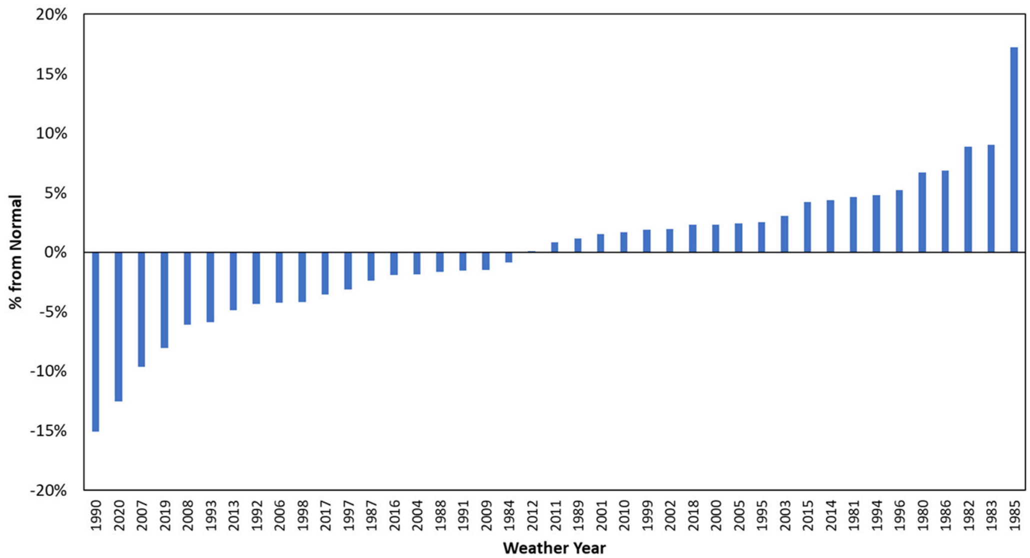

Figure 6. Winter Peak Load Variance

ECONOMIC FORECAST ERROR

As described in the Study Framework subsection of the Introduction section of this document, five Load Forecast Error (LFE) multipliers with their associated probabilities were applied to each of the 41 historical load shapes. The LFE multipliers simulate the expected probability that the peak demand forecast would be missed because of errors in the forecast of national economic indicators. The multipliers were developed by looking at the historical error in the 4-year out forecast GDP assuming a peak demand sensitivity to changes in GDP of 0.4% per 1% change in GDP. The set of LFE multipliers along with their probability of occurrence used in this study are shown in the table below with a graphic representation in the figure that follows.

Table 2. LFE Model

LFE	Probability
-4%	10.4%
-2%	23.3%
0%	32.5%
2%	23.3%
4%	10.4%

CONVENTIONAL RESOURCE MODELING

Resources for the first tier BAAs were developed using publicly available information. Resources for Santee Cooper were developed using data provided by Santee Cooper as outlined in the subsections below.

GENERATING CAPACITY

The following table shows the list of conventional resources and their corresponding summer and winter generating capabilities available to Santee Cooper for the 2026 study year.

Table 3. Santee Cooper Conventional Resource Capacities

Unit Name	Unit Category	Summer Capacity	Winter Capacity
Cross 1	Coal	580	585
Cross 2	Coal	565	570
Cross 3	Coal	610	610
Cross 4	Coal	615	615
Hilton Head 1	CT-Oil	16	20
Hilton Head 2	CT-Oil	16	20
Hilton Head 3	CT-Oil	52	60
John S Rainey CT2A	CT- Gas	146	180
John S Rainey CT2B	CT- Gas	146	180
John S Rainey CT3A	CT- Gas	75	90
John S Rainey CT3B	CT- Gas	75	90
John S Rainey CT4A	CT- Gas	75	90
John S Rainey PB1	GCC	460	520
Myrtle Beach 1	CT-Oil	8	10
Myrtle Beach 2	CT-Oil	8	10
Myrtle Beach 3	CT-Oil	19	20
Myrtle Beach 5	CT-Oil	21	25
V. C. Summer Nuclear Station	Nuclear	322	322
Winyah 1	Coal	275	280
Winyah 2	Coal	285	290
Winyah 3	Coal	285	290

For the 2026 study year, Winyah 4 is assumed idled/unavailable. For the 2029 study year, the remaining three coal units at Plant Winyah were assumed to be retired and a new 1,119 MW 2x1 Combined Cycle was assumed available as a replacement.

To model the transition from summer ratings to winter ratings, technology curves were developed for each unit that adjusted the maximum capacity of the resource based on ambient temperature. The figure below shows an example technology curve based on Hilton Head Unit 1. Other curves are similar.

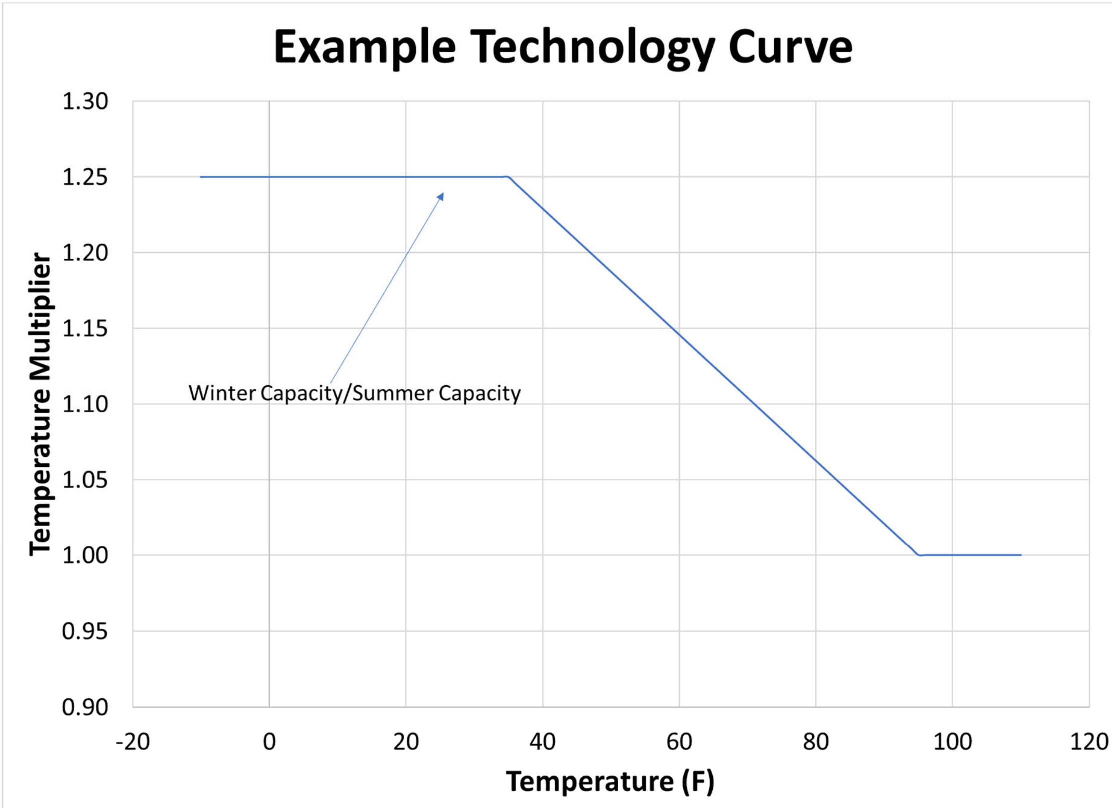

Figure 7. Example Technology Curve

In addition to these dispatchable resources, Santee Cooper also has access to output from 13 small landfill gas (LFG) resources as well as one biomass resource, which are owned by third parties. The capacities of these resources are shown in the table below below.

Table 4. LFG and Biomass Resource Capacity

Unit Name	Unit Category	Summer Capacity (MW)
Anderson Regional Landfill	LFG	3
Berkeley County Landfill	LFG	3
Georgetown LFGTE G1	LFG	1
Horry Landfill	LFG	3
Lee County Landfill	LFG	11
Richland County Landfill	LFG	8
EDF Renewable	Biomass	35.6

The LFG and biomass units were modeled as must-run units. See the outage section below for further discussion on their operation.

OUTAGE MODELING

Outage modeling consisted of three primary types of outages, planned maintenance, unplanned maintenance, and forced outages.

Planned Maintenance. SERVM can model planned maintenance, often called planned outages (PO), as either discrete schedules or an annual rate in percent of hours. If modeled as a PO rate, SERVM schedules planned maintenance in seasons where there would not typically be an expectation of reliability concerns. This determination is made by looking at all available weather year load shapes and developing a schedule that is least likely to cause reliability concerns. Thus, while it may be generally expected that planned maintenance will not create reliability issues, there may be some weather years in which that is not the case.

Santee Cooper provided explicit future planned outage schedules for several years into the future. However, because the two years evaluated in this study were considered representative years, planned maintenace was modeled using the annual rate method rather than the discrete schedules for the two study years, 2026 and 2029. The annul rate was developed by converting the specific future maintenance schedules into annual rates (in percent of hours per year) and then averaging all of these future annual rates by unit. This was done to ensure that the PRM is developed based on typical expected system conditions rather than specific system conditions associated with any one year. The figure below shows the result of this process and represents the maintenance rates modeled for the Santee Cooper resources.

[redacted]

Figure 8. Santee Cooper Resource PO Rates

See the discussion below on forced outages for LFG and biomass modeling.

Unplanned Maintenance. SERVM also models unplanned maintenance, often referred to as Maintenance Outages (MO), as a rate. SERVM uses these rates to determine the amount of time that a resource should be offline due to maintenance outages and attempts to schedule those hours during off-peak periods. However, because SERVM models these outages during hours without reliability risk, they have no material impact on the reserve margin study. MO rates for the Santee Cooper units were determined based on five years of historical NERC GADS data as provided by Santee Cooper.

Forced Outages. SERVM modeled forced outages using multiple sets of time to fail (TTF) and time to repair (TTR) inputs for both full and partial outages. Each resource has its own set of TTF and TTR inputs that are used to establish that resource's equivalent forced outage rate (EFOR). Using monte carlo techniques, a TTF value is chosen randomly for each generating resource. That resource is then allowed to operate until it reaches the TTF threshold, at which point it is forced offline. Once it is forced offline, a TTR value is chosen randomly to determine how long the resource will be unavailable. That resource remains offline until is reaches the TTR threshold, at which point it is once again made available and a new TTF variable is chosen for the resoruce.

TTF and TTR values for Santee Cooper were developed using five years of historical NERC GADS data. The EFOR values resulting from these TTF/TTR values were then examined by key experts at Santee Cooper and recommendations for the final EFOR values to be used in this study were made. The TTR and TTF values were then modified appropriately so that the resulting EFOR values would match the Santee Cooper recommendations. The figure below shows the final modeled EFOR rates by unit.

[redacted]

Figure 9. Santee Cooper EFOR Rates

Per recommendations from Santee Cooper and based on historical capacity factors, all LFG resources were modeled with TTRs and TTFs that could result in a 78% EFOR (i.e., a resulting 22% capacity factor).

Per recommendations from Santee Cooper and based on historical capacity factors, the EDF Renewable biomass resource was modeled with a 100% availability.

OTHER CONVENTIONAL DATA

Other conventional resources data provided by Santee Cooper included minimum capacities, minimum uptime, minimum downtime, and ramp rates. These were modeled as part of the analysis but had no direct bearing on the determination of the reserve margin.

SOLAR RESOURCE MODELING

SERVM models renewable resources as an hourly profile for each weather year. For this study, eight existing solar facilities were modeled and nine future solar facilities were modeled. The eight existing facilities, along with their tracking technology, assumed Inverter Loading Ratios (ILR), average expected capacity factors, and 2026/2029 installed capacities are shown in the table below.

Table 5. Solar Resource Summary

Resource	ILR	Average CF	2026 Capacity (MW)	2029 Capacity (MW)
Colleton (TIG)	1.0	20.3%	2.5	2.5
Allora	1.1	24.9%	75	0
Gunsight	1.1	25.5%	75	0
Landrace	1.0	18.8%	55	0
Chester White	1.4	31.4%	75	75
Lambert I & II	1.1	24.8%	200	200
Hemingway	1.3	29.1%	75	75
Watson Hill	1.2	27.1%	75	75
Future Solar	1.3	29.3%	370	825
Total			1,003	1,253

While the table above shows the future solar resources aggregated as a single row, future solar was modeled as nine discrete facilities at various geographic locations to capture expected geographic diversity of solar output. The nine locations modeled for the future solar were assumed to be at locations similar to the eight existing locations plus one additional location of an existing solar resource

(Centerfield Cooper; contract to expire before the 2026 study year). Thus, for modeling purposes, the nine site locations chosen are shown in the table below.

Table 6. Future Solar Facility Locations

Site	City	Reference Solar Resource
1	Walterboro, SC	Collteon (TIG)
2	Gilbert, SC	Allora
3	Swansea, SC	Gunsight
4	Conway, SC	Landrace
5	Aiken, SC	Chester White
6	Andrews, SC	Lambert I & II
7	Kingstree, SC	Hemingway
8	Summerville, SC	Watson Hill
9	Chesterfield, SC	Centerfield Cooper

To create the weather year profiles, irradiance data for these nine locations were downloaded from the National Renewable Energy Laboratory (NREL) National Solar Radiation Database (NSRDB) Data Viewer for the years 1998 to 2020.[1] The data obtained from the NSRDB Data Viewer was input into NREL's System Advisor Model (SAM)[2] for each year and location to generate the hourly solar profiles based on the solar weather data for fixed and tracking solar plants. Solar profiles for 1980 to 1997 were selected by using the daily solar profiles from the day that most closely matched the peak load for the Santee Cooper load out of all the days +/- 3 days of the source day for the 1998 to 2020 interval. The profiles for the remaining years 1998 to 2020 came directly from the solar shape output data from SAM. The figures below show the resulting summer and winter, respectively, average[3] daily output profiles for each of the eight existing solar facilities plus the aggregate average profile for the future solar.

[1] https://maps.nrel.gov/nsrdb-viewer/

[2] https://sam.nrel.gov/

[3] i.e., the average of all July/January days including all weather years.

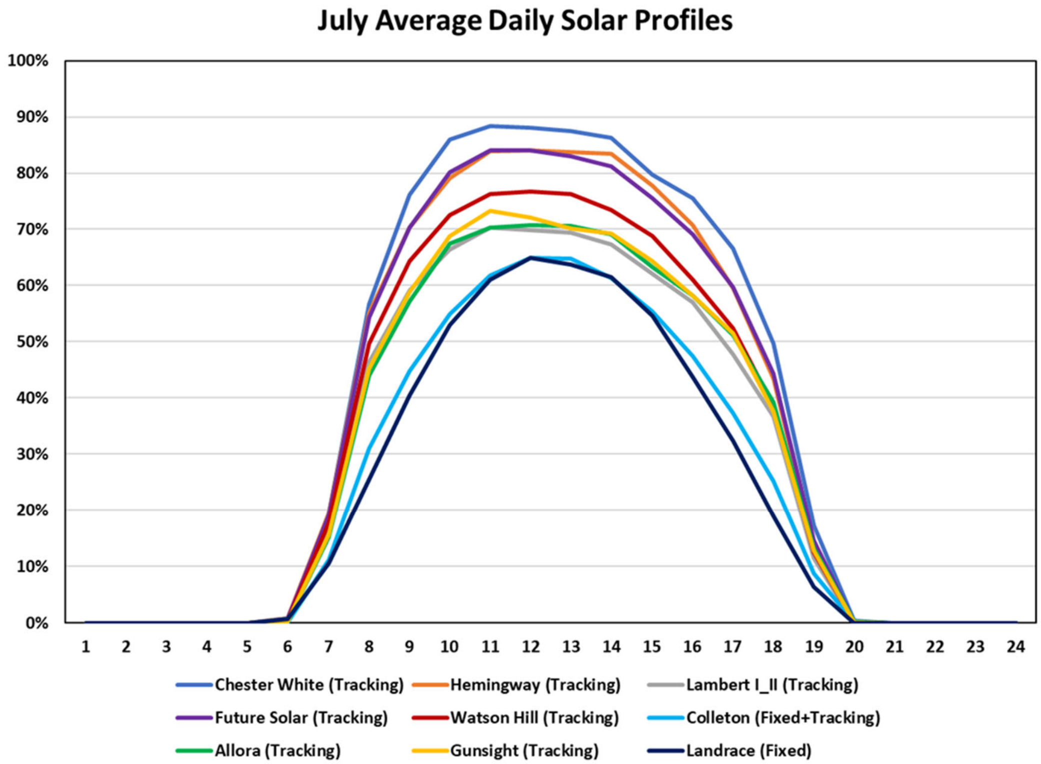

Figure 10. Average Summer Solar Profiles

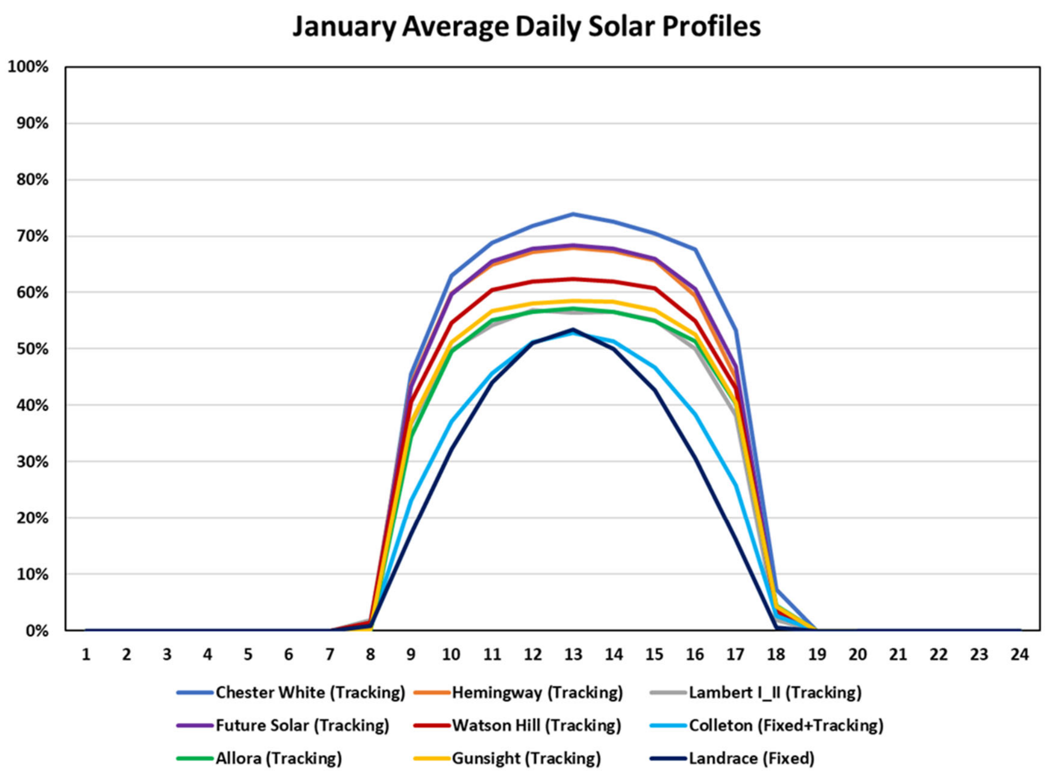

Figure 11. Average Winter Solar Profile

HYDRO RESOURCE MODELING

Hydro was modeled as two aggregate resources. Hydro facilities owned by Santee Cooper and the Corps of Engineers are referred to in this report as Santee Coooepr hydro resources. Hydro resources owned by the Southeastern Power Authority (SEPA), for which Santee Coooper has access for load serving purposes, are referred to as SEPA Hydro resources. The three Santee Cooper hydro facilities[4] total 226 MW and the SEPA facilities total 305 MW. SERVM models hydro facilities by scheduling available hydro energy to shave the daily net peak load using four different parameters for each month for each weather year. Those parameters include:

1. Monthly total energy output,
2. Daily scheduled maximum output,
3. Daily scheduled minimum output, and
4. Monthly maximum scheduled output.

The daily minimum hydro dispatch is scheduled at the minimum net load hour of the day, and the daily maximum hydro is scheduled at the maximum net load hour of the day, and the monthly maximum hydro is scheduled at the max load hour of the month, all while observing the monthly total energy output constraint. The monthly maximum scheduled output sets the available hydro capacity for that month.

To develop these parameters, available hydro energy data from 1980 to 2020 was collected from the EIA Form 923[5] and actual hourly hydro data was provided by Santee Cooper for the years 2018 to 2021. Using this data, average daily minimum and maximum dispatch levels, the total monthly energy, as well as the monthly maximum dispatch levels were identified from the historical hourly data and a regression of each was formed. These regressions were then applied to the historical monthly energy data obtained from EIA forms. The resulting parameters were then applied to the corresponding weather year as appropriate.

The following figures show the result of the regression analyses for the Santee Cooper and SEPA hydro facilities, respectively.

[4] Jefferies and Spillway are Santee Cooper owned while St. Stephens is owned by the Corps of Engineers.
[5] https://www.eia.gov/electricity/data/eia923/

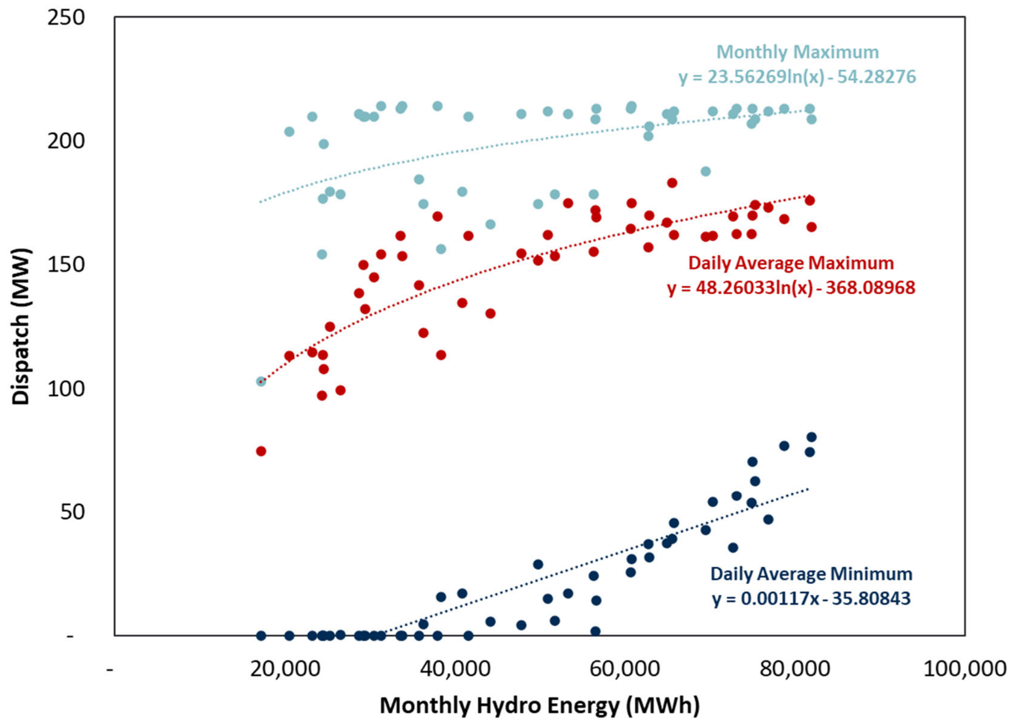

Figure 12. Santee Cooper Hydro Regression Results

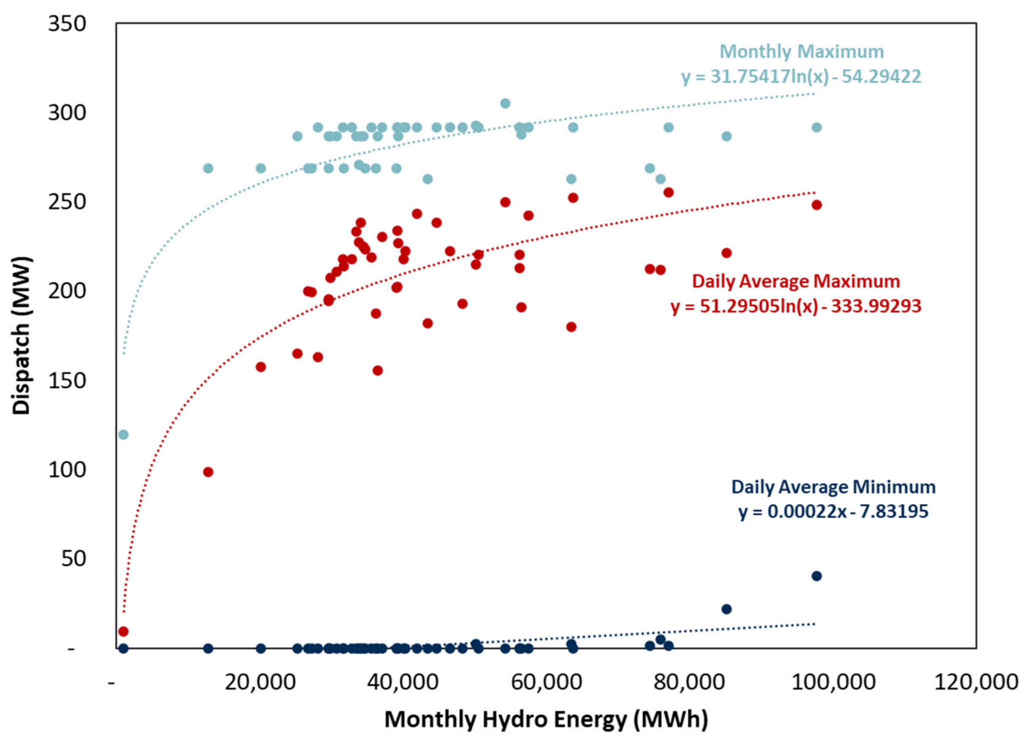

Figure 13.Santee Cooper SEPA Hydro Regression Results

The following figures show the available hydro energy by weather year for the Santee Cooper and SEPA hydro facilities, respectively.

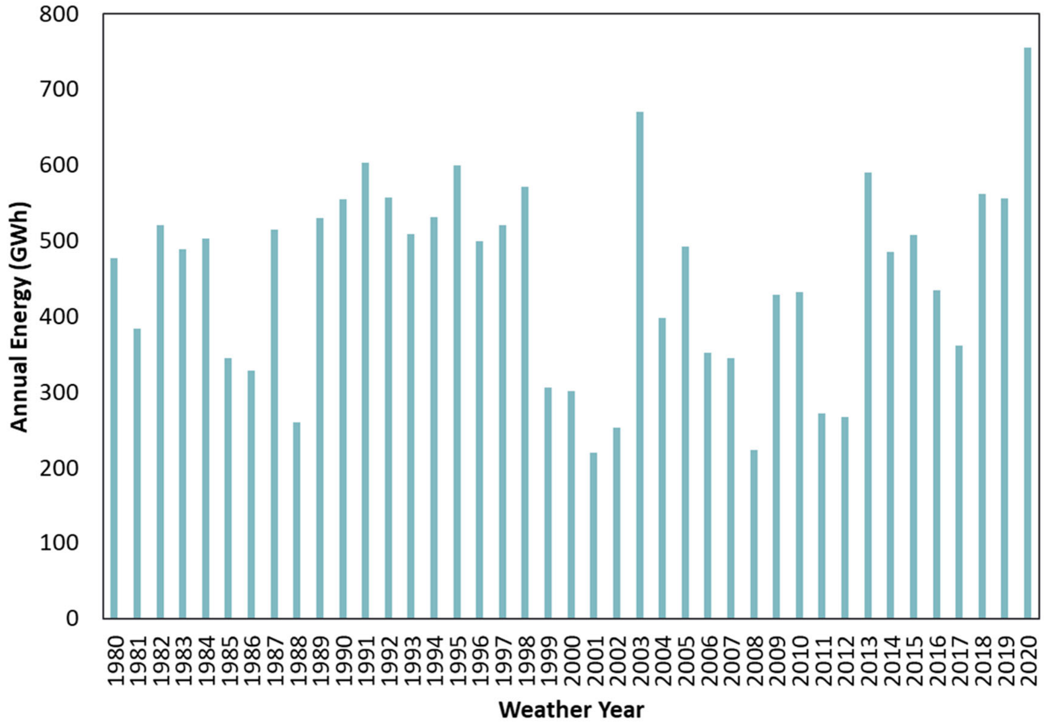

Figure 14. Santee Cooper Energy by Weather Year

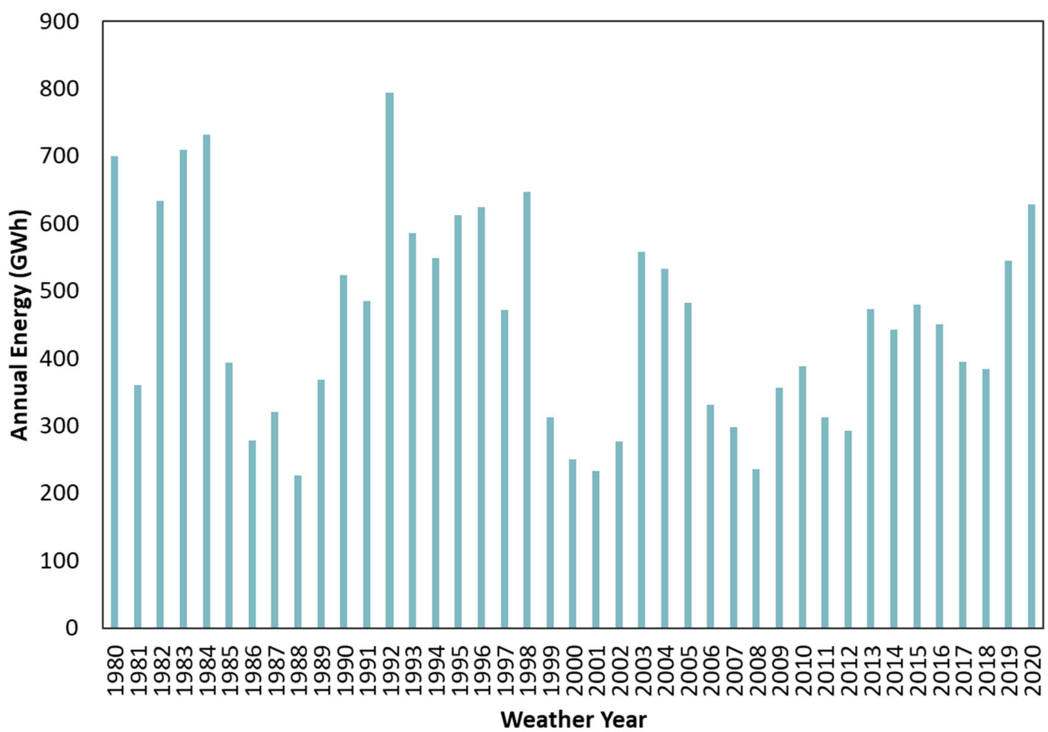

Figure 15. Santee Cooper SEPA Hydro Energy by Weather Year

The following figures show the monthly available capacity for Santee Cooper and SEPA hydro, respectively.

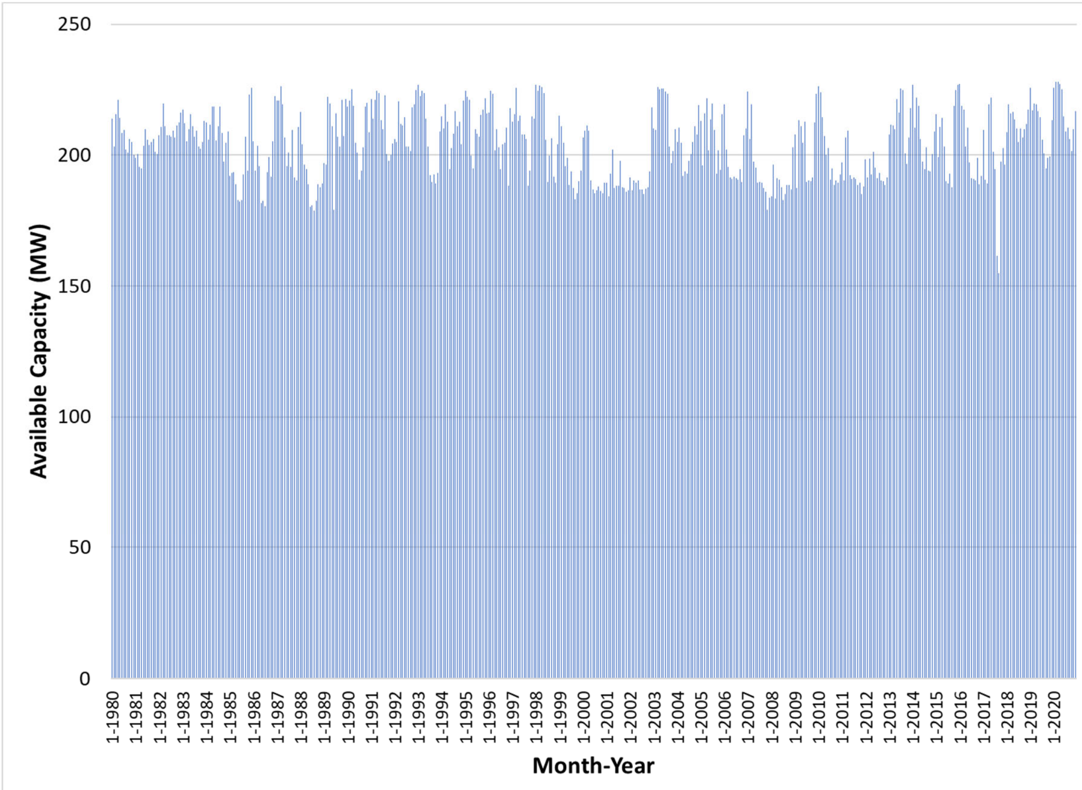

Figure 16. Santee Cooper Monthly Hydro Capacity

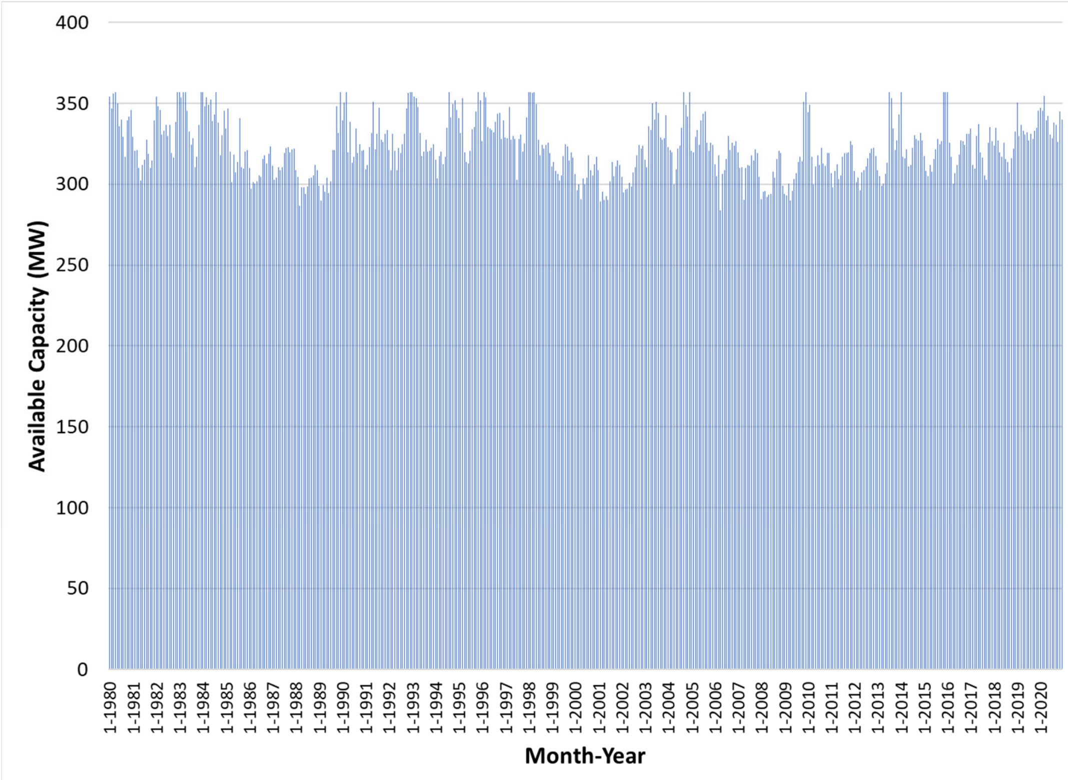

Figure 17. Santee Cooper SEPA Monthly Hydro Capacity

DEMAND RESPONSE MODELING

For purposes of this study, Energy Efficiency (EE) is modeled as a reduction in load. All load shapes and peak demand forecasts were developed net of EE.

Santee Cooper has four active Demand Response (DR) programs available to respond to reliability conditions, including:

1. Interruptible (I) customers,
2. Economy Power (EP) customers,
3. Direct Load Control (DLC) customers, and
4. Conservation Voltage Reduction (CVR).

Additional DR is available through Santee Cooper's largest customer, Central Electric Power Cooperative (Central).

While each of these programs has its own tariff provisions, all have in common the unlimited ability to curtail the customer for purposes of avoided a firm load shed event. The following table shows the capacity modeled for each of the programs as well as for Central.

Table 7. Santee Cooper DR Assumptions

	2026 Summer	2026 Winter	2029 Summer	2029 Winter
I & EP	371.0	330.0	371.0	330.0
DLC	20.4	28.8	28.5	40.2
CVR	16.5	14.5	16.5	14.5
Central	20.0	20.0	30.0	30.0
Total	427.9	393.3	446.0	414.7

FIRM SYSTEM PURCHASES

To meet its existing reserve margin requirements, Santee Cooper has placeholders in its plan for potential firm purchase agreements with third-party providers of capacity. For purposes of this study to determine Santee Cooper's PRM requirements, these purchases were not modeled. Instead CT capacity was added to achieve the target LOLE as discussed in the methodology section.

RESOURCE CAPACITY MIX

The model of the system described above resulted in a system with the mix of resources shown in the figures below for the 2026 and 2029 study years. All values are in MW representing summer capacity values with solar resources shown with nameplate values.

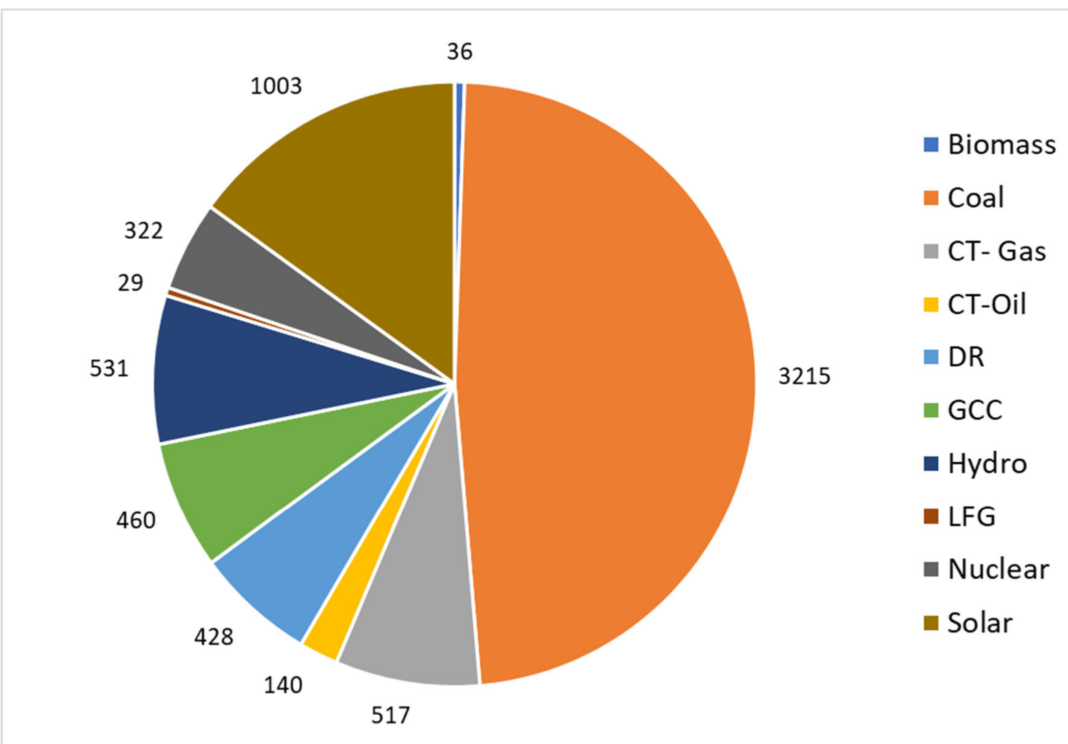

Figure 18. 2026 Resource Capacity Mix (Summer Ratings)

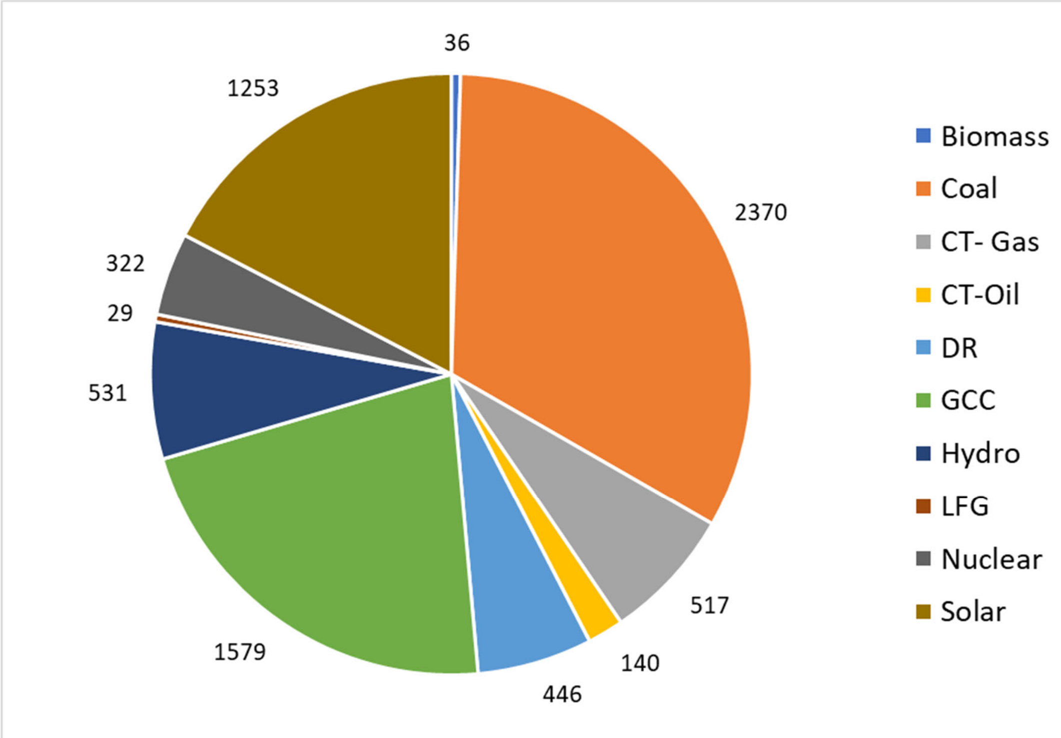

Figure 19. 2029 Resource Capacity Mix (Summer Ratings)

ANCILLARY SERVICES MODEL

The ancillary services model included as part of this study included the modeling of regulating reserves, contingency reserves spinning (spinning reserves), and contingency reserve supplemental (non-spinning reserves). SERVM will commit the system to maintain all ancillary services requirements. However, per guidance provided by Santee Cooper, spinning and non-spinning reserves would be allowed to deplete to zero to avoid a load shedding event. Regulating reserves would be maintained during load shedding events. Based on information provided by Santee Cooper, the following baseline set of operating reserves were modeled.

Table 8. Base Ancillary Services Requirements

Reserve Component	Requirement (MW)
Regulating Reserves	100
Spinning Reserves	110
Non-Spinning Reserves	110

In addition to the base ancillary services requirement, Santee Cooper requires an additional amount of regulating reserves for hour ending (HE) 9-22 to accommodate the intermittent nature of solar resources. The additional regulating reserves amount to roughly 30% of nameplate solar capacity. However, these reserves would not be maintained to avoid a load shedding event. Thus for modeling purposes within SERVM, these additonal reserve requirements were modeled as spinning reserves, so that they would be depleted prior to load curtailment. The total spinning reserves modeled (base plus solar requirement) for 2026 for HE 9-22 was 410 MW and the total spinning reserves modeled for 2029 for HE 9-22 was 485 MW.

TRANSMISSION MODEL

The values used for the non-Santee Cooper interconnections were taken directly from the SERC Long Term Working Group 2026 Summer Future Year Study, dated December 16, 2021. The table below depicts the Santee Cooper import limit assumptions used in this study.

Table 9. Santee Cooper Transmission Import Limits

[redacted]

The values for the Santee Cooper interconnects were also based upon the values from that study, but were modified by Santee Cooper to reflect expectations on simultaneous import.

MARKET ASSUMPTIONS

As SERVM performs its 8760-hour production cost simulation, it makes a determination each hour as to the availability and price of potential market transactions between BAAs. This determination is made through development of both a day ahead and an hourly market price for each region that is based on a combination of an energy price and a scarcity price according to the equation

$$MP = MEP + ORDC$$

Where
MP= Market Price
MEP= Marginal Energy Price (a.k.a, the marginal dispatch price), and
ORDC=the Operating Reserve Demand Curve price.

The ORDC price simplys provies a scarcity price signalbased on the amount of remaining undispatched operarating reserves.

SERVM allows economic transactions based on each region's resulting market price subject to transmission constraints.

STUDY METHODOLOGY

The two objectives of this study were to (a) establish the PRM for the Santee Cooper system and (b) determine the ELCC for various penetrations of solar and battery energy storage system (BESS) resources. The sections below describe the approach for each of these two objectives.

ESTABLISHING MW ADJUSTMENT

The PRM for the Santee Cooper system was determined for two separate study years, 2026 and 2029. The establishment of the PRM should be fairly stable with minor changes in system configuration. Thus the 2026 study year should be reasonably representative of existing and near future PRM. However, the retirement of the three Winyah coal units and its replacement with a single 2x1 CC in 2029 was significant enough to warrant performing the analysis for 2029 as well to determine the extent to which the PRM might change. In addition, if any major changes in the system occur prior to conducting another PRM study then the conclusions of this study should be reconsidered. Major changes in the system refer to any significant changes in the demand or resources of the system. This may include but are not limited to changes in load beyond the load forecast projections, unit retirements, or unit additions.

To determine the PRM, expansion CTs were iteratively added to the base case system until the annual LOLE reached 0.1 days/year. Practically speaking, because of the size of the expansion CT relative to the size of the Santee Cooper system[6], this required making multiple runs with differing amounts of expansion CTs (e.g., 1 CT, 2 CTs, etc.) and trending the resulting LOLE so that the 0.1 LOLE point could be interpolated. The result of this extrapolation was the MW adjustment necessary to achieve 0.1 LOLE. This analysis was performed on both an islanded basis as well as a regional basis that included the Santee Cooper first tier BAAs.

Converting the results of this analysis into a resulting PRM required the establishment of an ELCC for the existing solar resources as described in the next subsection below. The final determination of the PRM (in %) was determined as follows:

PRM = [(Existing Capacity[7,8] + Adjustment Capacity) / Peak Load – 1] * 100.

[6] One expansion CT (355 MW in the winter) represents approximately 6.5% of system load.
[7] For PRM calculation purposes, demand response and hydro are treated as a resource, and solar resources are applied at the appropriate ELCC value.
[8] For the reserve margin calculation and simulations, interruptible load is included as a resource and not subtracted from load. The interruptible load is called before a firm load shed event when calculating LOLE. If non-firm load increases significantly from what is assumed in this study then the PRM should be reviewed through a study update or sensitivity.

DETERMINING ELCC

To calculate ELCC values for Santee Cooper, the 2026 study year was chosen as representative for all future years. The figure below shows the general approach taken to calculate ELCC.

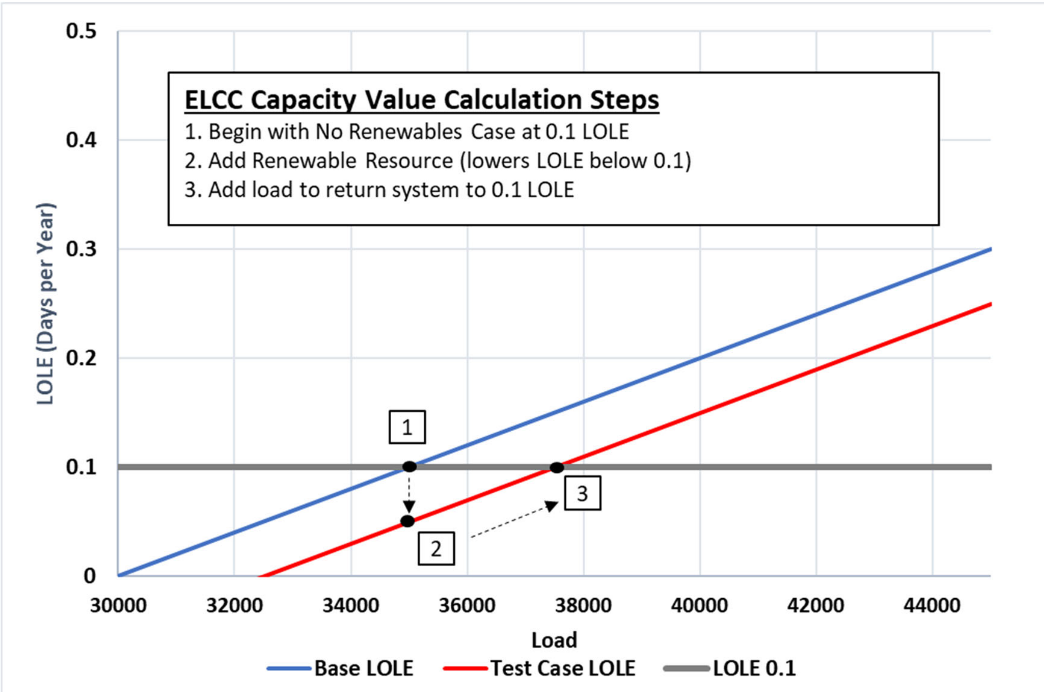

Figure 20. Generic ELCC Methodology

As indicated by the figure, an ELCC base case is established that contains no renewable resources but has been tuned to 0.1 days/year LOLE. When the renewable resources are added to that system, LOLE drops below 0.1 days/year. The system is then returned to the 0.1 days/year LOLE point by adding load (generally accomplished by injecting negative generation into the system).

This figure, however, shows how ELCC is calculated on an annual basis. For purposes of this study, ELCC was calculated seasonally for summer (June-September) and winter (January, February, and December). In this case, rather than targeting a 0.1 days/year annual LOLE, the monthly LOLE of the base case is grouped by season and each becomes the associated target for that season.

Seasonal ELCCs were calculated for 1000 MW of solar (approximately equal to the solar modeled in the 2026 PRM analysis), 1250 MW of solar (approximately equal to the solar modeled in the 2029 PRM analysis), 1500 MW of solar, and 2000 MW of solar. In addition, ELCCs were calculated for 200 MW of BESS and 400 MW of BESS. Finally, ELCCs were calculated for a 200/1500 MW combination of of BESS and Solar as well as a 400/2000 MW combination of BESS and Solar. The figure below shows a representation of the ELCC scenarios evaluated.

Table 10. ELCC Scenarios

	BESS MW				
Solar MW ->	0	1,000	1,250	1,500	2,000
	200			200\1,500	
	400				400\2,000

STUDY RESULTS

The following outlines the results of the base case PRM analysis as well as the ELCC analysis.

BASE CASE ISLANDED PRM

As described in the Study Methdology section above, the Santee Cooper system PRM was evaluated in 2026 and 2029. In each study year, the system was simulated with the addition of multiple CTs as necessary to find the capacity necessary to achieve 0.1 days/year LOLE.

The table below shows the scenarios simulated as well as the resulting LOLE for the Santee Cooper system on an islanded basis.

Table 11. Islanded PRM Simulated Results

No CTs	Winter MW	2026 LOLE	2029 LOLE
2	710	N/A	0.1743
3	1,066	0.1093	0.0352
4	1,421	0.0190	0.0076
5	1,776	0.0043	N/A

The figure below shows the Santee Cooper annual LOLE for 2026 and 2029 as a function of winter reserve margin[8].

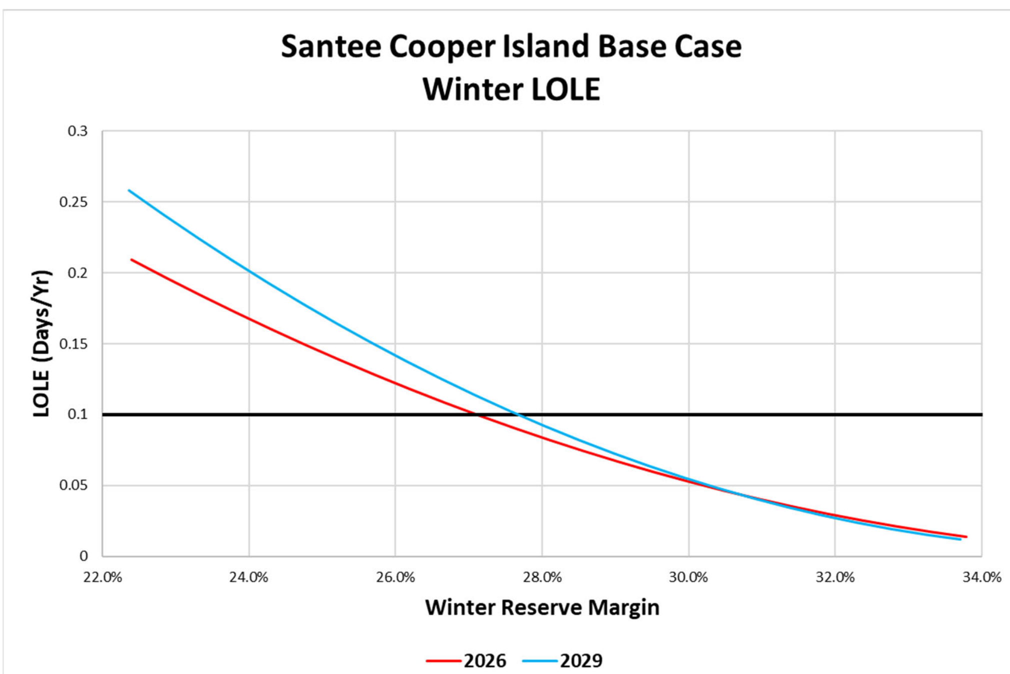

Figure 21. Islanded LOLE as a Function of PRM

[8] Winter ELCC for the solar resources per the ELCC results calculated during the ELCC analysis.

The final MW adjustment and resulting PRM for the islanded Santee Cooper system is shown in the table below.

Table 12. Islanded PRM Interpolated Results

Year	Winter MW Adjustment	Winter PRM
2026	1,092	27.1%
2029	865	27.7%

It should be expected that the islanded PRM would not significantly change from one year to another unless there is a significant difference in the underlying system. The difference between the 2026 and 2029 results shown here are driven primarily by minor differences in outages.

BASE CASE INTERCONNECTED PRM

The table below shows the scenarios simulated as well as the resulting LOLE for the Santee Cooper interconnected system that included first tier Balancing Authorities.

Table 13. Interconnected PRM Simulated Results

No CTs	Winter MW	2026 LOLE	2029 LOLE
1	355	0.1614	0.0988
2	710	0.0721	0.0300
3	1,066	0.0232	0.0122

The figure below shows the Santee Cooper annual LOLE for 2026 and 2029 as a function of winter reserve margin[9].

[9] Winter ELCC for the solar resources per the ELCC results calculated during the ELCC analysis.

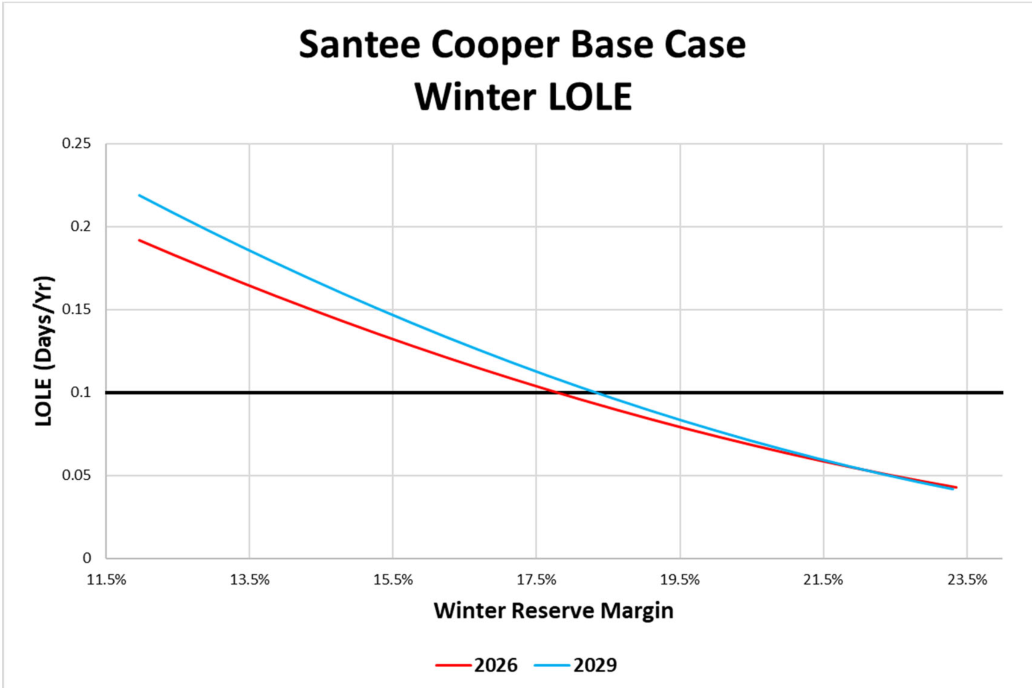

Figure 22. Interconnected LOLE as a Function of PRM

The final MW adjustment and resulting PRM for the interconnected Santee Cooper system is shown in the table below.

Table 14. Interconnected PRM Interpolated Results

Year	Winter MW Adjustment	Winter PRM
2026	580	17.8%
2029	351	18.3%

The difference between the 2029 results and the 2026 results are driven primarily by differences in available capacity from the market and small changes system EFOR assoicated with a different capacity mix.

The following figure shows the monthly breakdown of LOLE at PRM.

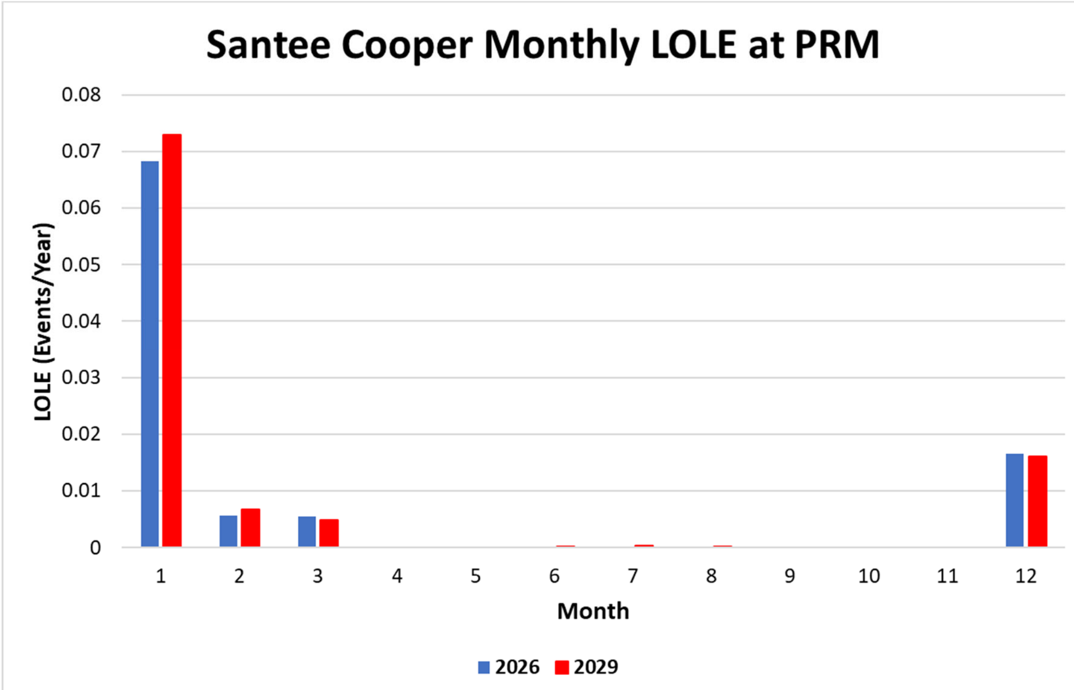

Figure 23. Monthly LOLE at PRM

As the figure demonstrates, the overwhelming majority of the LOLE occurs during the winter months of January, February, and December. There is also a noticable risk in March. This is due to an overlap of planned maintenance, forced outages, and the potential for unusally cold weather. Despite the risk of extremely hot weather, the lower summer peak loads, regional solar penetrations, and the availability of purchases from the market make reliability concerns in the summer low.

This can also be seen by examining the hourly EUE profile. The tables below show the probability weighted average hourly 12x24 EUE profile (as a percent of the total EUE for the year) for 2026 and 2029, respectively. These tables also demonstrate that the greatest risk for reliability events is not just on winter mornings, but in the overnight and early morning hours of the winter as well.

Table 15. 2026 Weighted LOLE by Hour

2026 12x24 EUE (Percent of Annual Expecation)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
3	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
4	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
5	5%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%
6	10%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	1%
7	16%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	3%
8	20%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	5%
9	5%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	4%
10	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%
11	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
12	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
13	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
14	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
15	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
16	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
17	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
18	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
19	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
20	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
21	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
22	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
23	5%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
24	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table 16. 2029 Weighted EUE by Hour

2029 12x24 EUE (Percent of Annual Expecation)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
3	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
4	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
5	5%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%
6	10%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	1%
7	16%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	3%
8	20%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	5%
9	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	3%
10	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
11	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
12	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
13	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
14	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
15	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
16	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
17	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
18	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
19	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
20	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
21	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
22	5%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
23	5%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
24	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

BASE CASE SUMMER PRM

As discussed above, the constraining season in this PRM study is winter. Meeting the winter PRM requirement will result in a summer reliability that is considerably more reliable than 0.1 days/year LOLE.[10] As shown in Figure 24 above, the LOLE in the summer months (June-September) is almost non-existent. This can also be seen in the hourly EUE tables above, Tables 15 and 16. Because such a high percentage of the LOLE is in the winter months, developing a summer PRM in which the summer PRM was allowed to increase significantly would result in an unacceptably high annual LOLE. For example, if both the summer and the winter were each allowed to approach 0.1 days/year LOLE, the total annual LOLE would approach 0.2 days/year or 1 event every 5 years. This would not meet industry practice for acceptable system reliabilily.

To establish a summer PRM requires finding the reserve margin in which summer LOLE begins to appreciably materialize and yet total annual LOLE does not increase unacceptably. As shown in the figure below, summer LOLE increases slightly once summer PRM falls below 17%.

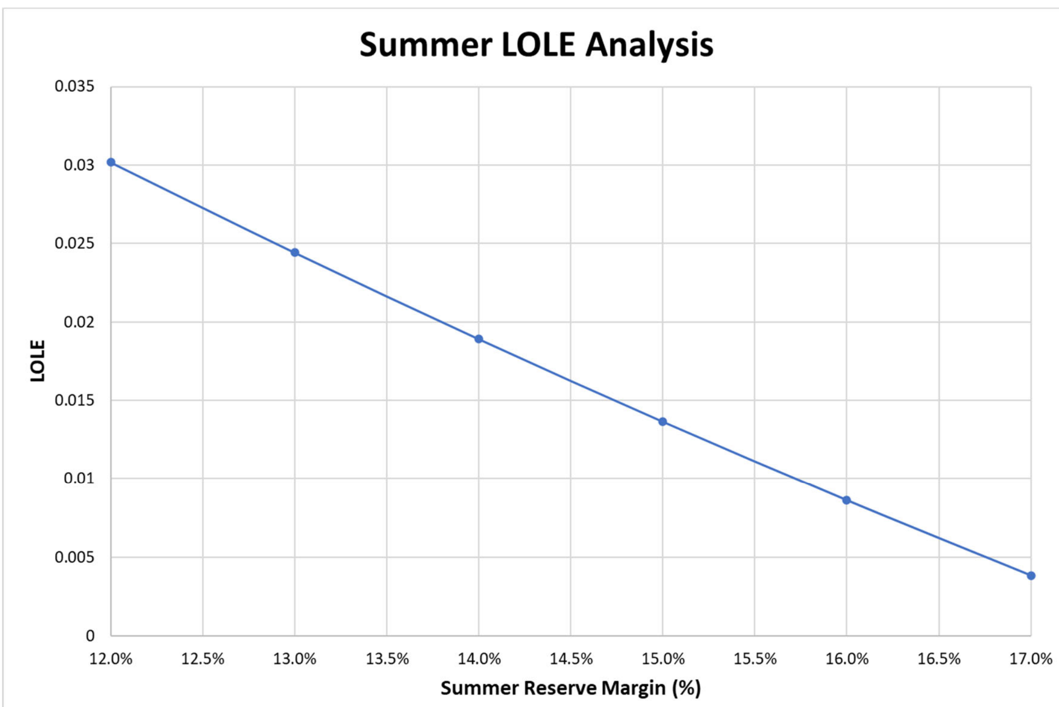

Figure 24. Summer LOLE Analysis

At a summer reserve margin of 16%, the summer LOLE is approximately 0.009 days/year; at a summer reserve margin of 15% the summer LOLE is approximately 0.014 days/year; and at a summer reserve margin of 14% the summer LOLE is approximately 0.019 days/year. These levels of seasonal LOLE will not significantly increase the overall annual LOLE. Thus, it would be reasonable to establish

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[10] For example, meeting the 2026 winter PRM of 17.1% will result in a system with a summer reserve margin of roughly 28%.

a summer reserve margin requirement somewhere in this range. It should be noted that given current portfolios and the anticipated addition of solar resources, Santee Cooper will automatically meet this requirement so long as they are meeting the established winter target. For this reason, the summer reserve margin target should be considered a secondary constraint.

BASE CASE RESULTS DRIVERS

There are a number of factors driving the Base Case results. The primary ones are as follows:

WEATHER WINDOW

The 40-year weather window was chosen as representative of long term weather patterns and includes periods of both mild and cold weather for consideration in the PRM determination. The following graph shows the resulting weighted average LOLE by weather year.

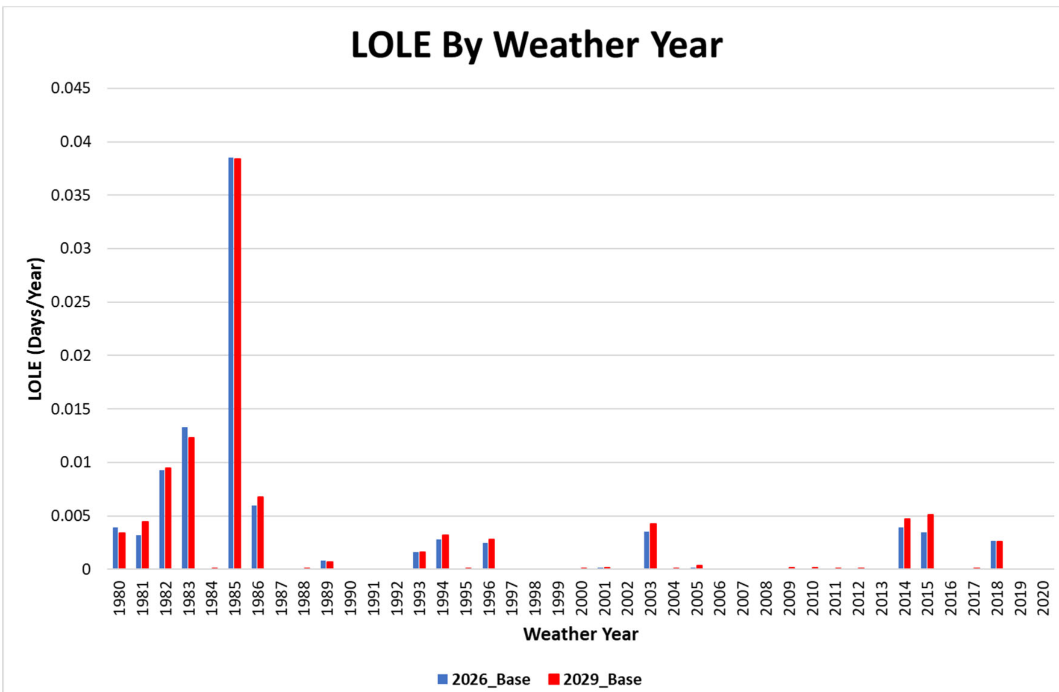

Figure 25. LOLE By Weather Year

LOAD RESPONSE ASSUMPTIONS

As discussed in the Load Modeling section of this report, the historical temperatures used to train the neural networks that were employed to develop the weather year load data did not contain some of the most extreme temperatures. Thus, a MW/degree load response assumption was developed based on the historical data so that loads could be extrapolated on those days. On cold winter mornings, this load response assumption was 57 MW/degree. It is this load response that drives the +18% peak demand variance from the normal winter forecast.

There is uncertainty as to whether this response holds true at colder temperatures or whether saturation is experienced such that the load reponse under extreme conditions is actually less than 57 MW/degree. Experience from other regions of the country suggests that little saturation exists for extreme cold temperatures. In fact, as a result of recent extreme cold weather events in other regions of the country[11], some regions have experienced load variance significantly higher that what was assumed in this analysis, suggesting that load response actually increases at much colder temperatures. As a result, both a high and low load response sensitivity were performed to determine the impacts of load response to PRM results (see sensitivities section below).

MARKET INFLUENCE

As demonstrated through comparison of the islanded PRM vs. the integrated PRM, the market is a significant driver in the results of this analysis, contributing a significant reliability benefit of almost 10%. Although the transmission import assumptions were based upon regional studies and expectations of simultaneous import, there is some concern that the combined import capabilities of Santee Cooper and DESC may be overstated due to the highly interconnected and interdependent nature of the Total Transfer Capabilities of those systems. As a result, a sensitivity was performed that considered a more restrictive joint import capability for DESC and Santee Cooper to determine if transmission capability is allowing too great a market influence (see sensitivities section below).

[11] e.g., ERCOT in February 2021.

SENSITIVY RESULTS

The following sensitivities were performed, with the results from each sensitivity analysis presented in the sub-sections that follow:

- Climate Change Sensitivity
- Low Load Sensitivity
- High Load Sensitivity
- Transmission Sensitivity

CLIMATE CHANGE SENSITIVITY

There is general consensus that there has been a gradual increase in average temperatures over the last several decades. According to a climate change study[12] performed by the National Oceanic and Atmospheric Administration (NOAA), global temperatures have increased since 1981 at a rate of approximately 0.3 degrees Farenheight per decade.

Thus, to better understand the impact of rising temperatures on reserve margin requirements, a sensitivity was performed by increasing historical temperatures according to this 0.3°F/decade heuristic. Thus, temperatures were simply increased on a graduated scale, with 1980 temperatures increased most significantly by 1.2°F. Loads were then re-developed based on these revised temperatures and the PRM analysis repeated.

The figure below shows the results of this sensitivity analysis as compared to the basecase and demonstrates that rising temperatures would result in a slight decrease in PRM of approximately 1%.

[12] NOAA. “Global Climate Report – 2020.” Accessed 4/8/2022 from https://www.ncei.noaa.gov/access/monitoring/monthly-report/global/202013

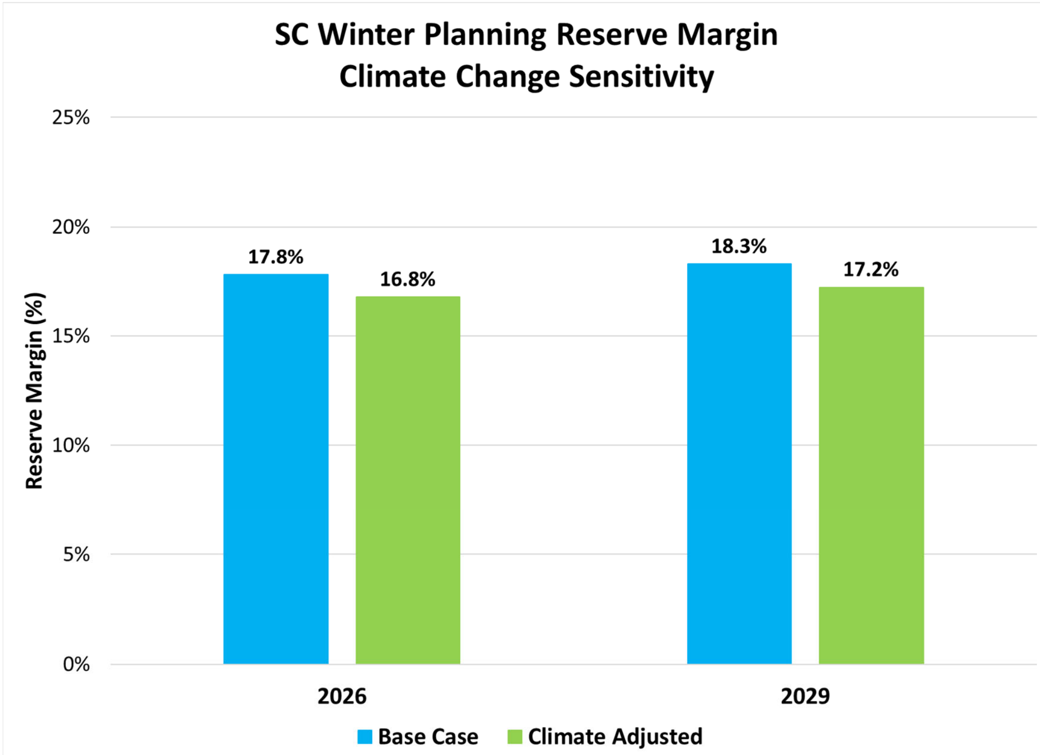

Figure 26. Climate Change Sensitivity Results

LOW LOAD RESPONSE SENSITIVITY

To simulate a low load response sensitivity, loads were re-developed in such a way that loads for Santee Cooper were never allowed to exceed that seen in the five year historical data used to train the neural networks, representing a load response of 0 MW/degree at temperatures below approximately 13°F. Although extreme, this represents a low sensitivity as it is certain there will be some increase in loads at lower temperatures. The results of that analysis are shown in the figure below.

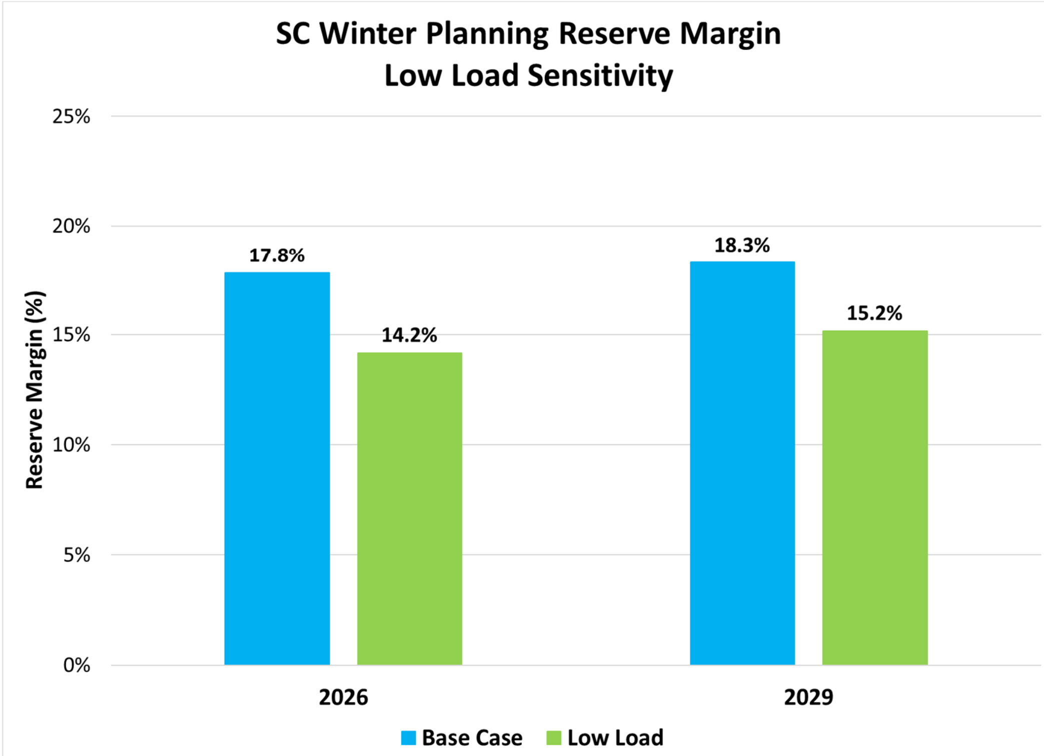

Figure 27. Low Load Response Sensitivity Results

HIGH LOAD RESPONSE SENSITIVITY

In February of 2021, ERCOT experienced load variance due to extreme cold weather of approximately +30%[13] versus the normal weather forecast To simulate a high load response sensitivity, loads were re-developed with an increased load response assumption such that the maximum peak load variance for Santee Cooper reached +30%. This sensitivity represents a high bookend for load response. The results of that analysis are shown in the figure below.

[13] Data from ERCOT shows that the winter peaks in February 2021 were approximately 29% above the weather normal forecast. The weather normal forecast going into the winter was 59,567 MW and while actual loads at the coldest temperature were not known precisely due to load shedding procedures, ERCOT projected a peak load of 76,819 MW.   This represents a load volatility of 29% (76,819 MW / 59,567 MW)-1) above the weather normal forecast developed prior to the winter season.

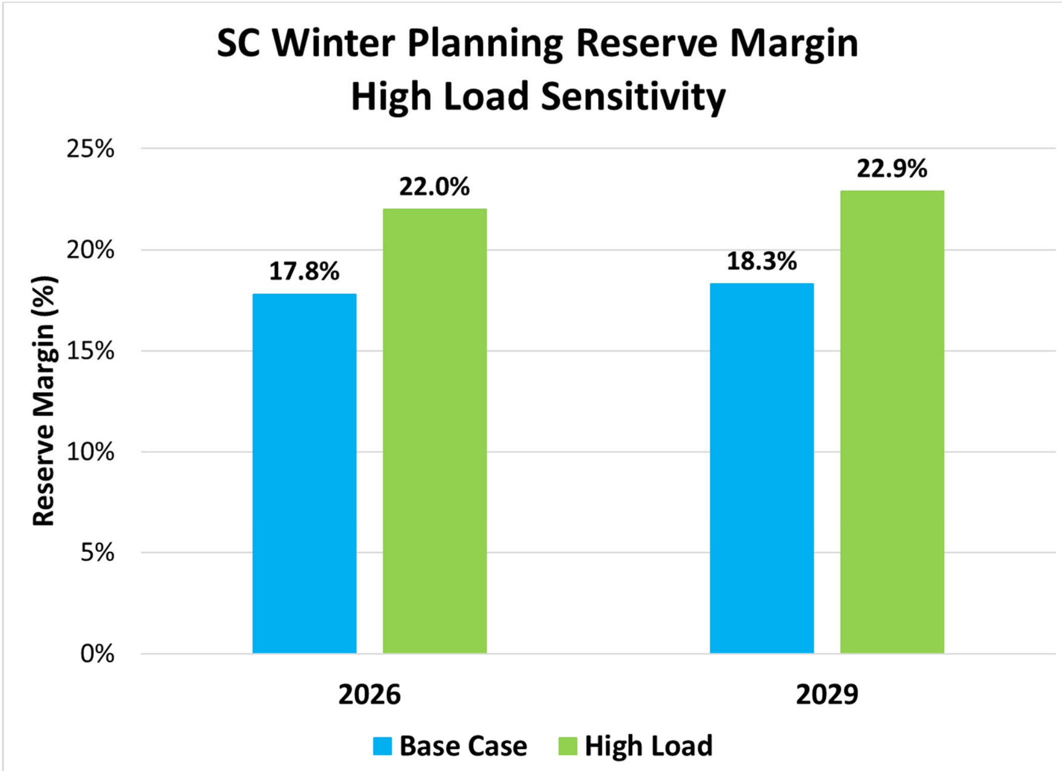

Figure 28. High Load Response Sensitivity Results

TRANSMISSION SENSITIVITY

To simulate a more constrained import capability between DESC and Santee Cooper, a sensitivity was performed in which the combined import capability was limited to a total of 1,500 MW. The result is shown in the figure below.

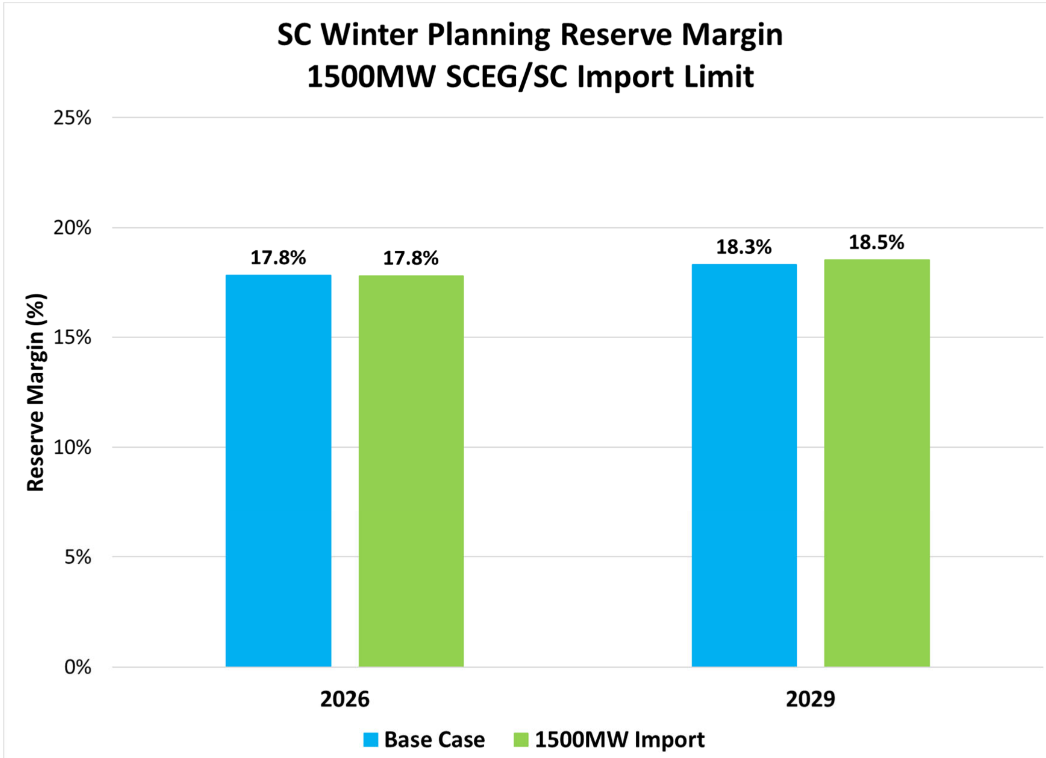

Figure 29. Transmission Sensitivity Results

The lack of increase in PRM suggests that regional capacity constraints, not transmission import capability is the limiting factor driving results in the analysis.

ELCC RESULTS

The process used in determining the ELCC of renewables on the Santee Cooper system was described in the Determining ELCC subsection of the Study Methodology section of this report above. The results of the ELCC analysis are as follows.

The table below shows the resulting allocated winter and summer ELCC's respectively. Any synergistic value between the resources was allocated based on the individual value of each resource as measured in the BESS only and Solar only cases. For this analysis, the BESS resources are operated in a conservative manner on cold winter days providing them their maximum value.

Table 17. Allocated Winter Portfolio ELCC

BESS\Solar	0	1000	1250	1500	2000
0		2.0%	1.8%	1.8%	1.4%
200	100.0%			100.0%\5.3%[14]	
400	88.0%				93.8%\1.5%

Table 18. Allocated Summer Portfolio ELCC

BESS\Solar	0	1000	1250	1500	2000
0		39.3%	36.6%	32.7%	26.9%
200	10.0%			100.0%/33.9%	
400	94.8%				100.0%/28.5%

[14] First Value is BESS ELCC, and second value is solar ELCC.

CONCLUSIONS

Upon examination of the study analysis, including all the sensitivity results, it is evident that winter reliability is the driving factor in establishing an appropriate reserve margin requirement for Santee Cooper. Thus, Santee Cooper's primary reserve margin requirement should be a winter requirement. Furthermore, based on these results, it can be concluded that a winter reserve margin in the range of 17-18% can be justified. It is therefore recommended that the winter PRM requirement be set at 17%.

The summer reserve margin requirement should be considered a secondary requirement. Based on the analysis of the summer LOLE, it can be concluded that a summer reserve margin requirement in the 14-16% range can be justified. It is therefore recommended that the summer PRM requirement be set at 15%.