ASTRAPÉ CONSULTING
innovation in electric system planning

Reserve Margin and Effective Load Carrying Capability (ELCC) Study

Final Report

10/24/2023

PREPARED FOR

Platte River Power Authority

PREPARED BY

Astrapé Consulting

TABLE OF CONTENTS

TABLE OF CONTENTS 1

TABLE OF FIGURES 3

TABLE OF TABLES 4

ABBREVIATIONS USED IN REPORT 5

EXECUTIVE SUMMARY 6

- BACKGROUND 6
- PRM RESULTS 6
- ELCC RESULTS 8
- APPLICATION OF AVERAGE VS MARGINAL ELCC 15
- CONCLUSIONS 16

INTRODUCTION 17

- STUDY FRAMEWORK 17
  - WEATHER UNCERTAINTY 17
  - ECONOMIC LOAD FORECAST ERROR 18
  - MONTE-CARLO OUTAGE ITERATIONS 18

MODEL DEVELOPMENT 19

- BASIS FOR MODEL DEVELOPMENT 20
- PEAK DEMAND FORECAST 20
- LOAD MODELING 21
- ECONOMIC FORECAST ERROR 26
- CONVENTIONAL RESOURCE MODELING 27
  - GENERATING CAPACITY 27
  - OUTAGE MODELING 28
  - HEAT RATES 29
  - FUEL COSTS 30
  - OTHER CONVENTIONAL DATA 31
- SOLAR RESOURCE MODELING 31
- WIND RESOURCE MODELING 35
- DARK CALM EVENTS 38
- STORAGE RESOURCE MODELING 41
- HYDRO RESOURCE MODELING 42
- DEMAND RESPONSE MODELING 42

FINAL COMPOSITION OF MARKET ... 42
ANCILLARY SERVICES MODEL ... 43
TRANSMISSION MODEL ... 44
MARKET ASSUMPTIONS ... 46

STUDY APPROACH AND RESULTS ... 47
ESTABLISHING MW ADJUSTMENT ... 47
EXISTING PORTFOLIO ELCC AND RESULTING PRM ... 47
DIVERSITY CONSIDERATIONS ... 53
ACCOUNTING CONSIDERATIONS ... 54
PRM RECOMMENDATION ... 54
TECHNOLOGY SPECIFIC ELCC ... 54
ELCC METHODOLOGY ... 56
SOLAR AND BATTERY ELCC SCENARIO RESLUTS ... 57
WIND ELCC SCENARIO RESULTS ... 63
ADDITIONAL ELCC SCENARIO RESULTS ... 64

CONCLUSIONS ... 72

APPENDIX ... 73

TABLE OF FIGURES

Figure ES 1. 2030 Base Case LOLE Analysis 7
Figure ES 2. Marginal Solar ELCC 9
Figure ES 3. Marginal Battery ELCC 11
Figure ES 4. Marginal Wind ELCCs 13
Figure ES 5. Side-By-Side Battery ELCC Comparison 15
Figure 1. SERVM Uncertainty Framework 18
Figure 2. Study Model Configuration 19
Figure 3. 2030 Peak Demand Forecast 21
Figure 4. Synthetic vs. Historical Daily Peak Loads 22
Figure 5. Summer Peak Load Variance 23
Figure 6. Winter Peak Load Variance 23
Figure 7. Summer Afternoon Extreme Temperature Regression 24
Figure 8. Winter Afternoon Extreme Temperature Regression 25
Figure 9. Winter Morning Extreme Temperature Regression 25
Figure 10. LFE Model 26
Figure 11. Plate River EFOR Rates 29
Figure 12. Platte River Heat Rates 30
Figure 13. Platte River Monthly Fuel Costs 31
Figure 14. Solar Model Locations 32
Figure 15. Average Summer Tracking Solar Profiles 33
Figure 16. Average Summer Fixed Axis Solar Profiles 34
Figure 17. Average Summer Bi-Facial Solar Profile 34
Figure 18. Wind Model Locations 36
Figure 19. July Wind Output Profiles 38
Figure 20. 24-Hour Correlated Dark Calm Event 40
Figure 21. 48-Hour Correlated Dark Calm Event 40
Figure 22. Extended Uncorrelated Wind Event 41
Figure 23. Regional Market Capacity Mix (MW) 43
Figure 24. Transmission Import/Export Limits 45
Figure 25. LOLE Analysis 49
Figure 26. LOLE by Weather Year at PRM 50
Figure 27. Net Peaks vs. Gross Peaks 51
Figure 28. LOLE by Month at PRM 52
Figure 29. Surface Plot of Solar/BESS Capacity Values 59
Figure 30. Marginal Solar ELCC 60
Figure 31. Marginal Battery ELCC 62
Figure 32. Marginal Wind ELCC Results 64
Figure 33. 8-Hour BESS ELCC Results 65
Figure 34. 100-Hour BESS ELCC Results 66
Figure 35. Comparison of Battery ELCC Results 67
Figure 36. DG Solar ELCC Results 68
Figure 37. Demand Response ELCC Results 69
Figure 38. BBE ELCC Results 70
Figure 39. EV Charging ELCC Results 71
Figure 40. Rawhide CT Ambient Temperature Multipliers 73
Figure 41. LMS 100 CT Ambient Temperature Multipliers 74
Figure 42. Average Winter Tracking Solar Profile 75
Figure 43. Average Winter Fixed Axis Solar Profile 75
Figure 44. January Wind Output Profiles 77
Figure 45. Operating Reserve Demand Curve 82

TABLE OF TABLES

Table ES 1. Key Reliability Indices at PRM 8
Table ES 2. ELCCs To Be Used in the Resource Plan 8
Table ES 3. Subset of Marginal Solar ELCCs 10
Table ES 4. Subset of Marginal Battery ELCCs 12
Table ES 5. Additional ELCC Results 13

Table 1. LFE Model 26
Table 2. Platte River Resource Capacities 27
Table 3. UTILITIES Solar Facilities 31
Table 4. Wind Output as a Function of Load 37
Table 5. Historical Dark Calm Events 39
Table 6. Incremental Wind Lull Events 39
Table 7. Battery Storage Characteristics 41
Table 8. UTILITIES WAPA Hydro Purchases 42
Table 9. Platte River DR Characteristics 42
Table 10. Regional Market Peak Demands 43
Table 11. Base Ancillary Services Requirements 44
Table 12. PRM Calculation 48
Table 13. 12x24 Representation of LOLE Using WECC Criteria 53
Table 14. Solar and Battery ELCC Combination Scenarios 54
Table 15. Solar and Battery Scenario Average ELCC Results 58
Table 16. Subset of Solar/Wind Capacity Values 59
Table 17. Subset of Marginal Solar ELCCs 61
Table 18. Subset of Marginal Battery ELCCs 62
Table 19. Wind Scenario Average ELCC Results 63
Table 20. Additional ELCC Scenarios 64
Table 21. Solar Model Coordinates 74
Table 22. Solar Site Average Capacity Factors 76
Table 23. Platte River Solar Project Capacity Factors 76
Table 24. Wind Model Coordinates 76
Table 25. Wind Profile Capacity Factors 77
Table 26. Platte River Wind Project Capacity Factors 77
Table 27. Regional Market Resource List 78

ABBREVIATIONS USED IN REPORT

BAA	Balancing Authority Area
BBE	Building Beneficial Electrification
BESS	Battery Energy Storage System
BHC	Black Hills Corporation
CC	Combined Cycle Generator
CJD	Colorado Joint Dispatch
CT	Combustion Turbine Generator
DR	Demand Response
EE	Energy Efficiency
EFOR	Equivalent Forced Outage Rate
EFORd	Equivalent Forced Outage Rate Demand
EIA	Energy Information Authority
EIDB	Eastern Interconnection Data Base
ELCC	Effective Load Carrying Capability
EUE	Expected Unserved Energy
EV	Electric Vehicle
GADS	Generating Availability Data System
GDP	Gross Domestic Product
ICE	Reciprocating Internal Combustion Engine
IRP	Integrated Resource Plan
LFE	Economic Load Forecast Error
LOLE	Loss of Load Expectation
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
PSCo	Public Service Colorado
TTF	Time to Fail
TTR	Time to Repair
CSU	Colorado Springs Utilities
SAM	NREL System Advisory Model
SC	Electric Vehicle Supercharger
SERVM	Astrapé's Strategic Energy and Risk Evaluation Model
VOLL	Value of Lost Load
WAPA	Western Area Power Administration
WECC	Western Electricity Coordinating Council

EXECUTIVE SUMMARY

This document provides details concerning a two-fold study performed by Astrapé Consulting for Platte River Planning Authority (Platte River) to accomplish the following goals:

1. Determine the Planning Reserve Margin (PRM) for Platte River for 2030.
2. Determine the Effective Load Carrying Capability (ELCC) for a range of solar, wind, storage, and Distributed Energy Resources (DERs) for the Platte River system.

The following summarizes the results of this study.

BACKGROUND

The state of Colorado requires all utilities in the state to reduce their carbon dioxide (CO2) emissions by 80% from the 2005 level by the year 2030. Furthermore, Platte River is working towards a 100% non-carbon supply portfolio as described by the resource diversification policy passed by its Board of Directors in 2018. This resource adequacy study is being performed in support of those initiatives.

PRM RESULTS

The PRM of a system represents the amount of capacity in excess of forecasted peak load that is needed to maintain an acceptable level of system reliability. This analysis was performed for the year 2030 and Platte River was assumed to be participating in a regional market. The regional market was assumed to consist of Platte River, Colorado Springs Utilities (CSU), Public Service Colorado (PSCO), and Black Hills Corporation (BHC). The market was assumed to be a "joint dispatch" market, therefore, the PRM was determined at the market level rather than at the Platte River level. Analyzing reliability under islanded conditions for Platte River would result in an inordinately high PRM because it would not capture the value of weather and generator outage diversity with other entities. Conversely, modeling the regional market but only analyzing the PRM requirement for Platte River would implicitly assign all diversity value to Platte River resulting in an inordinately low PRM. Identifying a market level PRM provides the proper analytical framework for all entities to share in the diversity value rather than individual entities subsidizing the reliability of others.

The PRM was set by determining the amount of capacity that would be necessary to maintain a Loss of Load Expectation (LOLE) of 0.1 days/year. This level of reliability corresponds to an expectation of one day of loss of load every 10 years, which is consistent with industry practice. The advent of renewable and battery technologies has sparked conversation on the appropriateness of this metric since limitations on dispatchability and constraints on energy will likely affect the duration and depth of loss of load events. However, in prior work, we have found that renewable and storage resources generally have offsetting effects on the duration and depth of events and the 0.1 LOLE standard is expected to yield a consistent relationship with most reliability metrics for a wide range of technology resource mixes. It will be important to continue to monitor these metrics however and recommend changes to reliability standards if the nature of reliability events does change.

The Western Electricity Coordinating Council (WECC) interprets the 0.1 LOLE standard as a 'maximum of 2.4 hours of risk allowed per year'[1]. Further, WECC divides this risk equally across all hours of the year and proposes a standard that limits the reliability risk in any individual hour to .02% Loss of Load Probability (LOLP). This implicitly supposes that reliability risk is spread uniformly across the year. However, since reliability risk is predominantly concentrated in a few critical hours each year (e.g., August weekday afternoons have significantly higher reliability risk than April weekend mornings), requiring each hour to meet this standard is quite onerous and requires a PRM much higher than that produced by a 0.1 LOLE standard. While we do not recommend the WECC standard for use in PRM calculations, we did quantify the required PRM to meet this standard as well.

The base case PRM assessment was performed for the year 2030.

Figure ES 1 below shows the result of the LOLE analysis for 2030 assuming the 1 day in 10 criteria, which shows the 0.1 LOLE falling at a *19.9%* reserve margin.

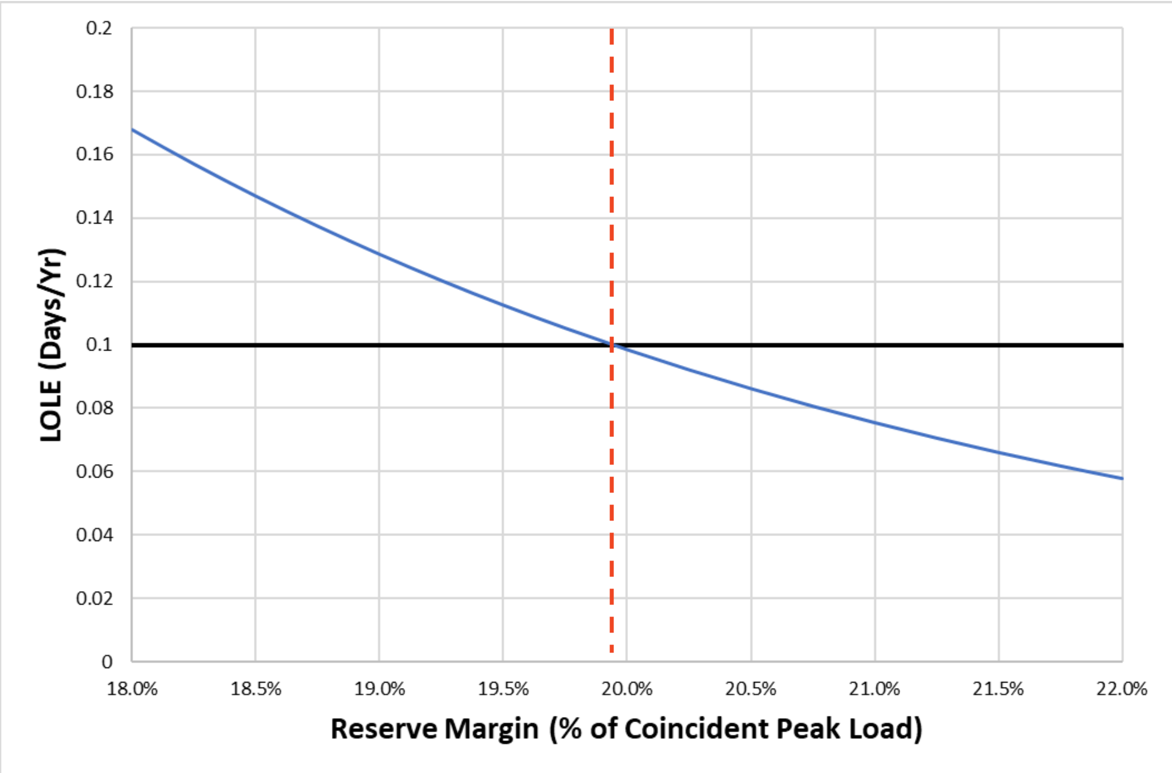

Figure ES 1. 2030 Base Case LOLE Analysis

As demonstrated in this graph, the expectation of LOLE decreases with increased reserve margin. In other words, as more capacity is added to the system, reliability improves. The point at which the graph crosses 0.1 days/year LOLE marks the target PRM.

[1] WECC One-day-in-ten-year metric explanation.pdf

However, to achieve the WECC criteria of 0.0002 LOLP in every hour would require a PRM of 30.3%.

The table below shows Platte River's anticipated LOLE, Loss of Load Hours (LOLH), Loss of Load Probability (LOLP) and Expected Unserved Energy (EUE) in MWh at the recommended 19.9% PRM.

Table ES 1. Key Reliability Indices at PRM

LOLE	0.10 Days/Year
LOLH	0.14 Hours/Year
LOLP	0.0011
EUE	12.2 MWh

At 0.1 Days/Year LOLE, the LOLH of 0.14 Hours/Year translates to 1.4 Hours/Event.[2]

ELCC RESULTS

The ELCC of a renewable resource/portfolio represents the amount of dependable capacity that can be counted on by the system 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.

Average and Marginal ELCC values were calculated in this study. The table below shows the solar, storage, and wind Average Incremental ELCCs values, derived from the Average and Marginal values, and recommended to be used in resource planning.

Table ES 2. ELCCs To Be Used in the Resource Plan

Year	Solar	Storage	Wind
2023	57%	89%	17%
2024	31%	75%	10%
2025	20%	74%	9%
2026	16%	70%	8%
2027	13%	66%	8%
2028	11%	62%	7%
2029	10%	59%	7%
2030	9%	58%	6%
2031	9%	56%	6%
2032	8%	54%	6%
2033	7%	52%	5%
2034	7%	51%	5%

[2] Event duration = LOLH/LOLE.

2035	7%	50%	5%
2036	7%	50%	5%
2037	7%	50%	5%
2038	7%	49%	5%

In addition to the base case portfolio ELCCs, the analysis included the calculation of average and marginal ELCCs by technology for solar, storage, and wind, which were the basis for the development of the ELCCs in the table above. Average ELCCs represent the aggregate capacity value of a portfolio of renewable resources. Marginal ELCCs represent the capacity value of the next increment of renewable capacity given an underlying portfolio. Solar and storage ELCC's were calculated for 2030 base case wind penetration assumptions of 6,280 MW for a range of penetrations up to 9,000 MW of solar and 3,000 MW of 4-hour batteries.

From the full matrix of capacity values, marginal solar and marginal battery ELCCs were calculated. Figure ES 3 shows the surface plot of marginal solar ELCC as a function of battery penetration.

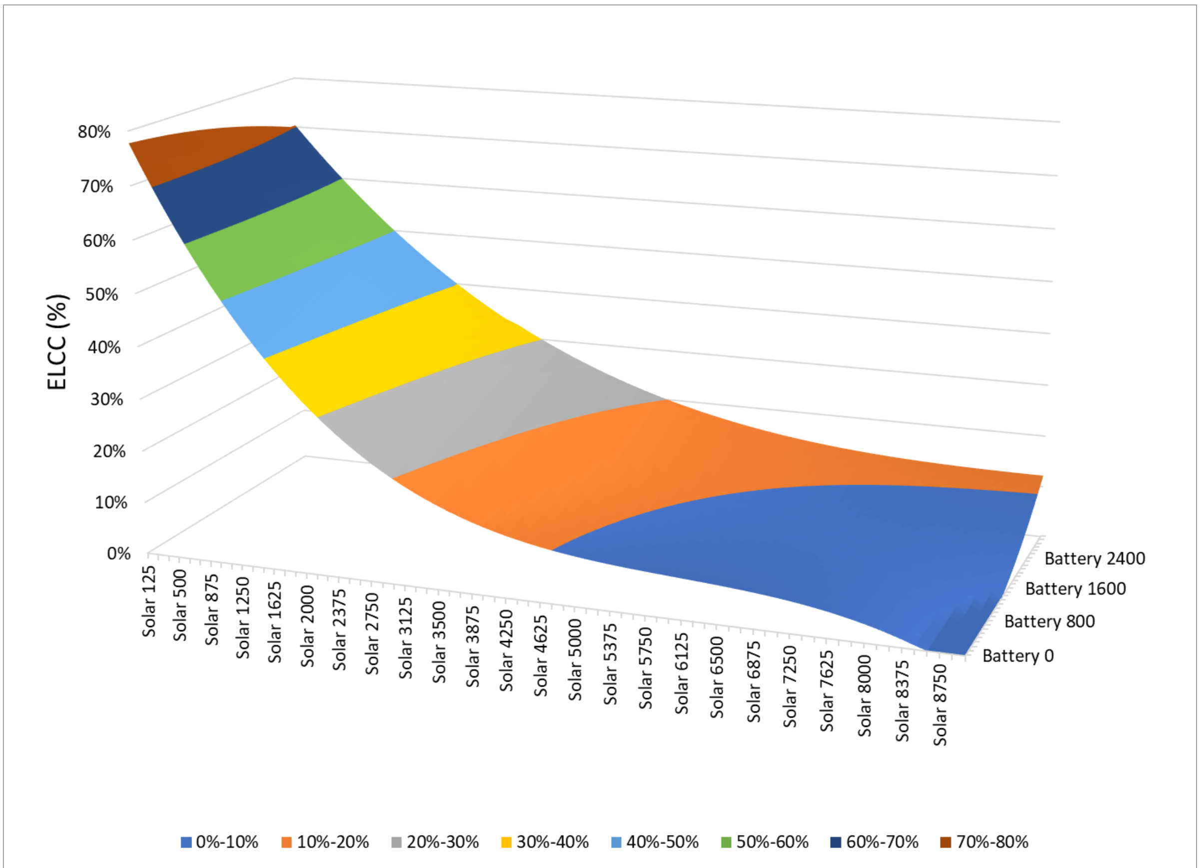

Figure ES 2. Marginal Solar ELCC

The surface plot is a visual representation of how marginal solar ELCC varies across various penetrations of batteries. The marginal solar ELCC values decline with increased penetrations of solar because the incremental solar additions move the system "net peak" further out into the evening until such time that the net peak occurs after the sun has set. At that point, the marginal solar ELCC approaches zero. However, the synergies associated with adding battery resources to a system with significant solar resources cause an increase in marginal solar ELCC. Both effects are evident on the surface plot as the slope decreases with increasing solar penetration and increases with increasing battery penetration. Note that at very low penetrations, solar has a flattening effect on load which is antagonistic with storage resources. This drives the downward slope in solar ELCC from 77% to 70% at the lowest solar penetrations. This effect is resolved once solar capacity exceeds 500 MW and solar has persistently higher ELCC with increasing storage penetration for all higher penetrations.

To determine the marginal solar ELCC for any combination of solar and battery penetrations on the system, find the point on the surface associated with that combination of penetrations. For example, to find the marginal solar ELCC at 5,000 MW of solar penetration and 800 MW of battery penetration, you would find the point on the surface corresponding to “Solar 5000” on the x axis and “Battery 500” on the y-axis. This value falls in the blue range on the z-axis, which is 0-10% ELCC. Since it is difficult to pull precise values from this visualization, a tool was developed that provides the ELCC for any given portfolio combination. Table ES 3 shows a subset of actual marginal solar ELCCs as determined using that tool. Based on the table, a marginal ELCC of 5,000 MW of solar at 500 MW of battery penetration is 9.7%. This table, which is illustrative of the type of data provided by the tool, was developed assuming base case wind penetration assumptions of 6,280 MW.

Table ES 3. Subset of Marginal Solar ELCCs

Solar Penetration \ Battery Penetration	-	500	1,000	1,500	2,000	2,500	3,000
1,000	52.8%	53.8%	54.5%	55.1%	55.4%	55.5%	55.4%
2,000	32.8%	34.5%	36.2%	37.8%	39.2%	40.6%	41.6%
3,000	20.1%	21.8%	23.6%	25.4%	27.4%	29.4%	31.6%
4,000	12.9%	14.0%	15.4%	17.1%	19.1%	21.4%	24.0%
5,000	9.4%	9.7%	10.5%	11.8%	13.6%	15.9%	18.6%
6,000	7.8%	7.4%	7.6%	8.5%	10.1%	12.3%	15.2%
7,000	6.4%	5.6%	5.5%	6.2%	7.8%	10.1%	13.3%
8,000	3.4%	2.7%	2.9%	3.9%	5.9%	8.7%	12.4%
9,000	0.0%	0.0%	0.0%	0.7%	3.7%	7.5%	12.2%

A similar surface plot is available for marginal battery ELCCs. Figure ES 4 below shows the surface plot of the marginal 4-hour battery ELCC as a function of solar penetration. As with the solar ELCCs above, these were developed assuming base case wind penetrations.

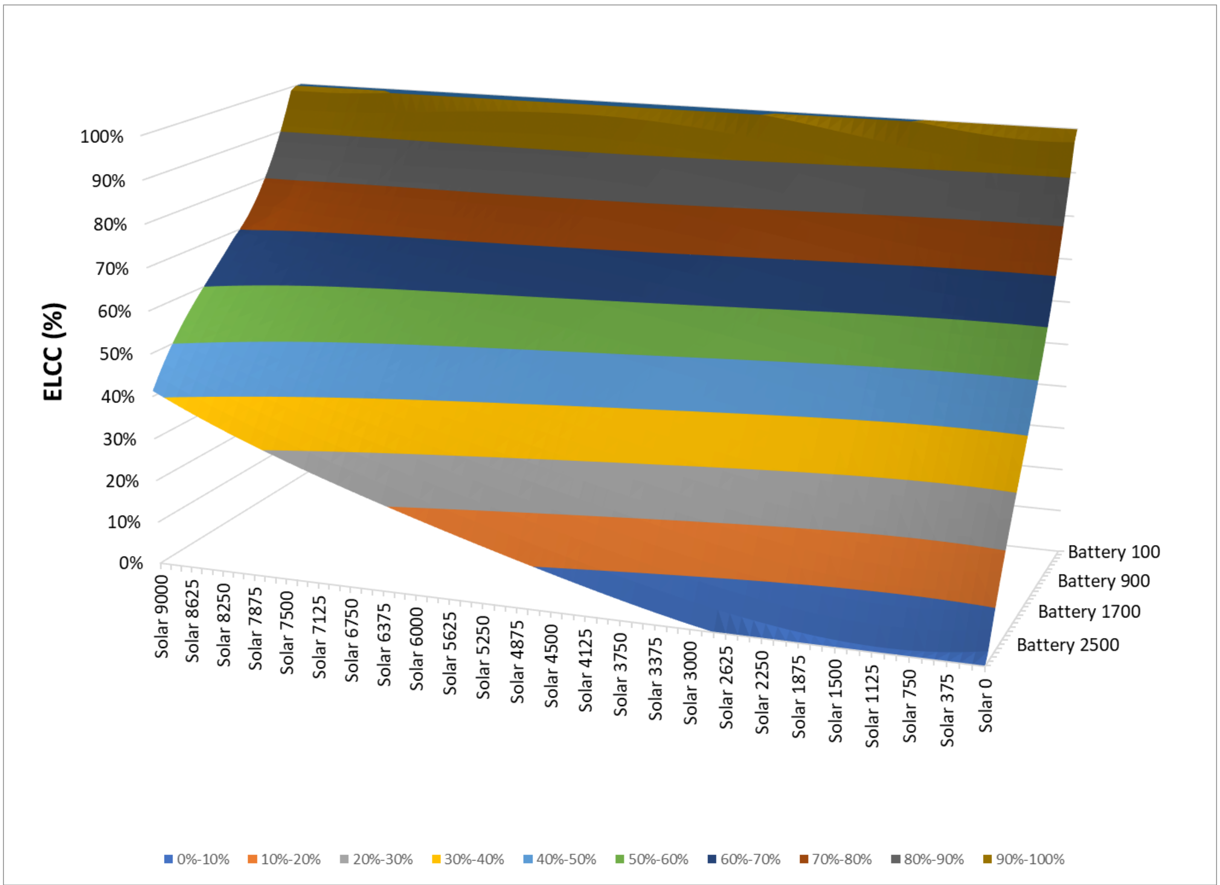

Figure ES 3. Marginal Battery ELCC

As with the marginal solar surface plot, the marginal battery surface plot is merely a visual representation that shows how marginal battery ELCC varies across various penetrations of solar. The marginal battery ELCC values decline with increased penetrations of battery because of a flattening of the overall net peak that results from the batteries. This flattening of the peak makes incremental additions of battery resources less effective. This decline decreases until a 4-hour battery can no longer contribute to improving reliability. However, because adding large penetrations of solar has the effect of sharpening the net peak, the synergies associated with adding solar resources to the battery resources cause an increase in marginal battery ELCC with increasing solar penetration. Both effects are evident on the surface plot. The slope decreases with increasing battery penetration but increases with increasing solar penetration. Note: The orientation of the surface plot has been reversed so that the slope is visually evident. To determine the marginal battery ELCC for any combination of solar and battery penetrations on the system, find the point on the surface associated with that combination of penetrations. For example, to find the marginal battery ELCC at 1,000 MW of battery penetration and 3,000 MW of solar penetration, you would find the point on the surface corresponding to “Solar 3000” on the x axis and "Battery 100" on the y-axis. Although difficult to see, this value falls in the dark blue range on the z-axis, which is 60-70% ELCC. Since it is difficult to pull precise values from this visualization, a tool was developed that provides the ELCC for any given portfolio combination. Table ES 4 shows a subset of actual marginal solar ELCCs as taken from that tool.

Table ES 4. Subset of Marginal Battery ELCCs

Battery Penetration	Solar Penetration 1,000	2,000	3,000	4,000	5,000	6,000	7,000	8,000	9,000
100	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
500	82.0%	84.9%	88.4%	91.4%	93.1%	93.3%	92.4%	91.4%	91.3%
1,000	60.9%	63.5%	67.0%	70.4%	72.9%	74.3%	74.9%	75.6%	76.7%
1,500	44.4%	46.7%	50.2%	54.0%	57.3%	59.9%	62.1%	64.5%	68.3%
2,000	29.9%	31.8%	35.4%	39.6%	43.7%	47.5%	51.1%	55.3%	60.9%
2,500	14.7%	16.3%	19.9%	24.5%	29.4%	34.4%	39.6%	45.4%	52.7%
3,000	0.0%	0.0%	1.1%	6.1%	11.8%	18.0%	24.6%	32.2%	41.3%

As shown from the table, the marginal battery ELCC for 1,000 MW of battery and 3,000 MW of solar is 67%.

Although there is some minor synergy between solar and wind ELCCs, battery ELCCs remain relatively stable with wind penetration. However, calculating the variance of solar and battery ELCCs across multiple penetrations of wind was not within the scope of this analysis.

Wind ELCCs were calculated for penetrations of 3,000 MW, 6,000 MW, and 9,000 MW at base case solar and battery penetrations; at solar and battery penetrations of 7,000 MW and 2,000 MW, respectively; and at solar and battery penetrations of 9,000 MW and 1,000 MW, respectively. These results were then trended and expanded and marginal ELCC values calculated as shown in Figure ES 5 below.

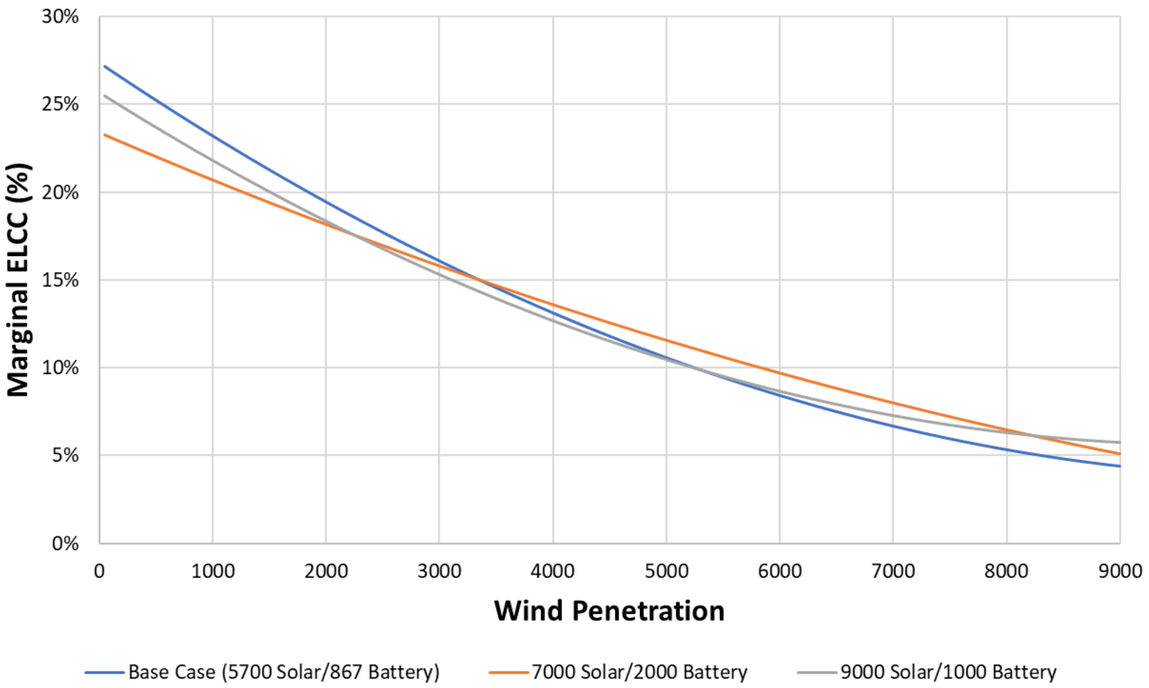

Figure ES 4. Marginal Wind ELCCs

This graph demonstrates very little variance in ELCCs across solar and battery penetrations.

ELCC scenarios were also evaluated for various penetrations of 8-hour batteries, 100-hour batteries, distributed generation (DG) solar, Building Beneficial Electrification (BBE), electric vehicle (EV) charging, and demand response (DR). Table ES 5 shows the average and marginal ELCCs for each of these scenarios after being smoothed with trending with base case solar (5,700 MW including 3,880 MW utility scale and 1,820 MW of distributed), wind (6,280 MW) and 4-hour battery (867MW) penetrations.

Table ES 5. Additional ELCC Results

Technology	Penetration (MW)	Average ELCC (%)	Marginal ELCC (%)
8-hour batteries	500	92.7%	91.6%
8-hour batteries	1000	90.5%	84.4%
8-hour batteries	1500	87.0%	75.6%
100-hour batteries	500	92.7%	91.6%
100-hour batteries	1000	91.9%	90.8%
100-hour batteries	1500	91.4%	90.0%
DG Solar	500	8.5%	7.9%
DG Solar	1000	8.0%	7.2%
DG Solar	2000	7.2%	5.8%
DG Solar	4000	5.8%	2.9%
BBE	100	6.9%	7.4%
BBE	200	7.3%	8.2%

BBE	300	7.8%	9.0%
EV	100	32.0%	33.6%
EV	200	33.8%	37.3%
EV	300	35.7%	41.0%
DR	100	92.3%	87.3%
DR	200	87.1%	77.8%
DR	300	82.6%	70.4%

The BBE, EV, and DR ELCCs were calculated assuming base case modeling assumptions without Platte River's deployment of that component. For example, the DR ELCC was calculated assuming no Platte River DR, but all other base case modeling assumptions remained unchanged. The high DR ELCCs relative to 4-hour batteries are due primarily to the fact that the model calls storage before it calls DR. For energy limited resources such as DR and storage, the longer the resource is held in reserve before being called, the greater its overall capacity value will be. Having 4-hour batteries called prior to 4-hour DRs will preserve the DR and thus increase its relative capacity value. This ordering is appropriate given that storage can be recharged but DR cannot be recharged. Thus, it is likely that this curtailment order is such that the frequency of DR calls is not exceeding its calls per year limit, which further boosts its value. A reversing of the curtailment order between storage and DR would result in DRs being called first, resulting in its exhaustion of yearly calls. This scenario, while not recommended, would have the effect of storage having a higher capacity value than DR. While the reported ELCCs are not wrong as modeled, it may be prudent to consider the possibility of calculating a weighted average between the battery ELCCs and the DR ELCCs and applying that weighted average to both technologies.

The ELCCs for 8-hour and 100-hour long duration batteries were calculated incremental to the base case battery penetration assumptions. Therefore, to properly compare the 8-hour and 100-hour batteries to the 4-hour batteries from the ELCC matrix, a side-by-side comparison that shifts the penetration levels of the 8-hour and 100-hour batteries out by the base case penetration of 4-hour batteries is necessary. The figure below shows this side-by-side comparison.

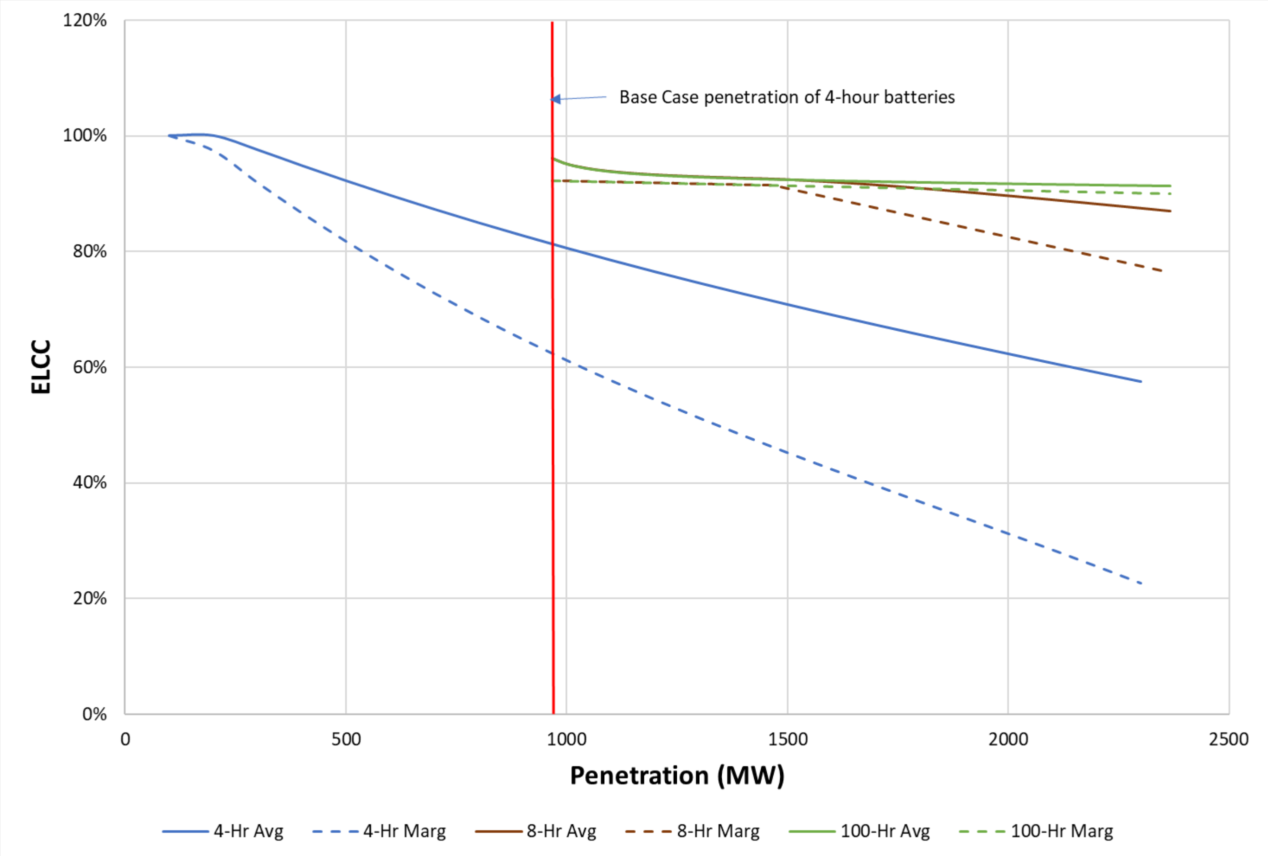

Figure ES 5. Side-By-Side Battery ELCC Comparison

APPLICATION OF AVERAGE VS MARGINAL ELCC

Average ELCCs are used to establish aggregate portfolio value. For example, the total capacity value of a portfolio of 1,000 MW of solar is the average ELCC for 1,000 MW of solar. This average solar ELCC would be used as the capacity value for all existing/embedded solar resources in the planning model. Candidate resources would not use average ELCC. Instead, candidate resources would either use a marginal ELCC or an average incremental ELCC. Marginal ELCC represents the capacity value of the next incremental MW. For example, if the average ELCC for 1,000 MW of solar was 30% and the marginal ELCC was 10%, then in aggregate, all 1,000 MW receive a 30% capacity value or 300 MW in total. However, the 1001st MW of solar would only get a 10% capacity value. For small increments of additional candidate unit capacity, the marginal ELCC is a good proxy for the capacity value. However, the most accurate approach would be to use an incremental ELCC which reflects the average contribution of a block of additions. To calculate the incremental, take the difference in average capacity value with and without the incremental block and divide by the incremental capacity. For example, if the average ELCC for 1,000 MW was 30% or 300 MW, and the average ELCC for 1,500 MW was 28% or 420 MW, then the average incremental ELCC would be (420-300)/500 = 24%.

CONCLUSIONS

Upon examination of the study results, a PRM of 20% is warranted based on the most common industry reliability standard of 0.1 LOLE. While the alternate WECC reliability standard of .0002 LOLP every hour would require a PRM of 30.3%, which we do not recommend based on the 1 day in 10 criteria. Given other factors, such as Platte River's dependence upon participation in the regional market as well as uncertainty concerning transmission import capabilities, it would be recommended that a range of PRMs be considered, with 20-25% being a primary range of consideration. A resource plan that is flexible across that range of reserve margins would be one that includes a range of potential resource additions, with the range being smaller in the near term and larger for the longer term. As final decision dates for resource decisions draw near, greater confidence in the near-term target will dictate those decisions.

Both average and marginal ELCC results for Platte River can vary greatly depending upon the timing, penetration, and mix of renewable resources that are added to the market by other market participants. However, based on the assumed base case modeling mix and penetrations, Platte River's current 2030 plan is reliable against a 20% PRM that is based on the 1 day in 10 criteria. This is true whether average or marginal ELCC assessments are applied. However, against the WECC criteria, the reliability of the plan is less certain and depends greatly upon the assumed build-out of the other market participants and the resulting ELCCs accredited to Platte River.

Regarding the ELCCs associated with the load modifications (such as EVs, BBE), because these load modifications have a different shape than the embedded load shape, these ELCCs provide an indication as to the amount of capacity needed to reliably serve these loads. This can be of importance if the growth of these load categories is disproportionately high compared to the rest of the system load. As these load categories increase relative to the business-as-usual load, it will be more accurate to determine peak load requirements as the sum of business-as-usual load plus the ELCC of these load categories rather than the sum of the coincident peak load contributions of these categories.

INTRODUCTION

The purpose of this document is to describe the analysis used to determine the Planning Reserve Margin (PRM) necessary for Platte River 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. As Platte River considers its participation in a formalized market, it is likely that a regional reserve margin requirement based on this 1 in 10 criteria will be imposed.

The state of Colorado requires all utilities in the state to reduce their carbon dioxide (CO2) emissions by 80% from the 2005 level by the year 2030. Furthermore, Platte River is working towards a 100% non-carbon supply portfolio as described by the resource diversification policy passed by its Board of Directors in 2018. These resource adequacy studies are being performed in support of those initiatives. Therefore, the study examined the reserve margin requirements for the 2030 study year.

In addition, this document will also report on the results of a study to determine the Effective Load Carrying Capability (ELCC) of a series of tranches of solar, wind, and BESS resources – as well as the ELCC of Platte River's expected 2030 Distributed Energy Resources (DER) portfolio.

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 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 historical weather years. The uncertainties that are modeled for each modeled weather year include load shapes and renewable profiles including extended periods of low or no renewable generation dubbed as Dark Calm (DC). Load shapes for each weather year are developed to represent the expected future load response to the historical weather (temperatures). For example, a 1990 weather year represents how loads would respond if 1990 weather were to repeat during the 2030 analysis year. These load shapes are then scaled so that the median of the peak demands from various weather year load shapes equals the study year weather normal peak load forecast. In the case of Platte River, since their load forecast is based on the last 10 years of history, load shapes are scaled such that the average of the last 10 years equals the study year weather normal peak load forecast. Other load shapes were scaled such that their forecast matched the median of all available weather years. Similarly, renewable profiles are developed to represent the expected future availability associated with the historical weather profile. For purposes of this study, 42 weather year scenarios were simulated representing weather conditions for the years 1980-2021.

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 probability 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 the purpose of this study, 5 LFE scenarios were chosen. These are described in the Model Development section of this document. Each of the 42 weather year scenarios are combined with each of the 5 LFE scenarios to create 210 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 210 load cases. With each outage iteration, random Monte-Carlo draws are made to determine thermal generation outage profiles associated with that scenario. With a sufficient number of iterations, the random outage for each thermal unit approaches that unit's expected Equivalent Forced Outage Rate (EFOR). For purposes of this study, convergence was achieved with 300 outage draw iterations per 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 63,000 hourly (8760-hour) production cost simulations for a single analytical run of the Platte River system and its neighbors.

42 **Weather Years** (Equal Probability)	x	5 **LFE Points** (Associated Probabilities)	=	210 **Load Scenarios** (Associated Probabilities)
210 **Load Scenarios**	x	300 **Unit Outage Draws**	=	63,000 **8760 Hour Simulations**

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 a joint dispatch of the assumed regional market and included four entities – Platte River, Public Service Colorado (PSCO), Colorado Springs Utilities (CSU), and Black Hills Corporation (BHC). The system model also included representations of the immediate first tier interconnected BAAs, including representations of Western Area-Colorado Missouri (WACM), Pacificorp East (PACE), portions of Arizona (AZ), Public Service New Mexico (PNM), and Southwest Public Service (SPS), which is in the Southwest Power Pool (SPP).[3] The figure below shows the configuration of the study model with its associated transmission interface connections using a pipe and bubble configuration.

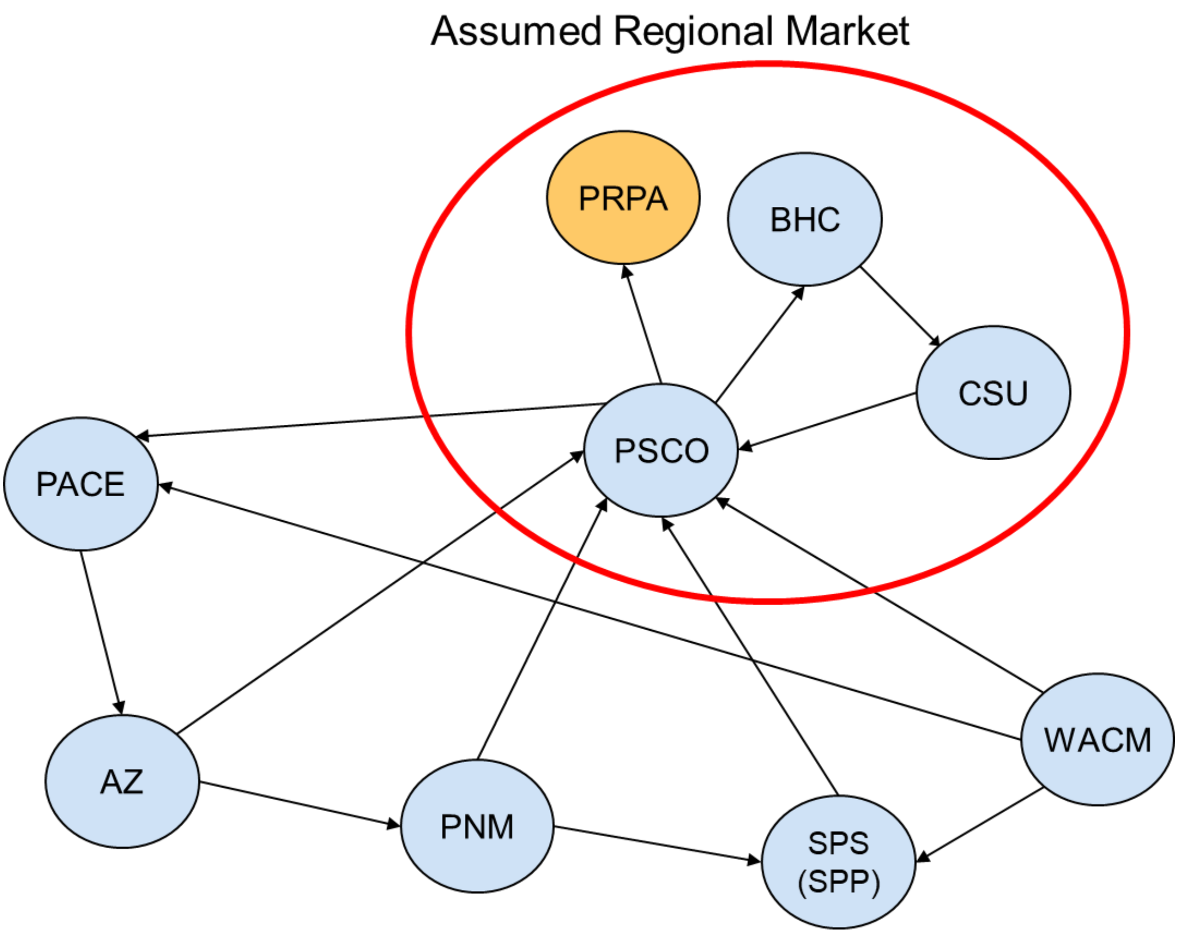

Figure 2. Study Model Configuration

[3] SPS is across the DC ties between the Eastern Interconnect and the Western Interconnect.

BASIS FOR MODEL DEVELOPMENT

For this study, the regional market was modeled as four utilities (or market entities) but dispatched jointly (i.e., as a single entity) respecting known/assumed transmission constraints between these utilities.

The basis for the SERVM model used in this study was the data available from public sources with Platte River specific data being provided directly by Platte River. The public data came from sources such as the Energy Information Authority (EIA) Form 860, available documents from the North American Reliability Corporation (NERC), various publicly available Integrated Resource Plans (IRPs), FERC Forms, and similar documents. Using this public information, load shapes, load forecasts, and resources were developed for all the neighboring utilities except for Platte River.

To ensure these neighboring entities are neither subsidizing nor being subsidized by Platte River in the reserve margin study process due to temporary surplus or deficit capacity conditions, neighboring utilities outside the market were calibrated to a 0.1 days/year LOLE reliability level. This was accomplished by either adding additional generic resources or removing existing resources as necessary. If the modeled entity had a LOLE greater than 0.1 days/year, generic resources were added until 0.1 LOLE was achieved. Conversely, if the modeled entity had a LOLE less than 0.1 days/year, existing resources were removed until 0.1 LOLE was achieved. Thus, since these regions are neither long nor short relative to the reliability criteria, the interactions between the regional market and its neighbors that impact the PRM are limited primarily to unit outage and load shape diversity.

The following provides the specifics of the Platte River data as provided by Platte River for purposes of this study.

PEAK DEMAND FORECAST

Platte River's official load forecast includes adjustments for the peak load contribution of future expectations of demand response (DR), behind the meter solar generation (DG Solar), electric vehicle (EV) charging load, and Building Beneficial Electrification (BBE)[4]. For this study, these load/resource components were all modeled as either resources or load injections as appropriate. Thus, the peak load forecast used for the PRM analysis was the base forecast prior to these adjustments. The figure below shows the official 2030 Platte River Peak Demand forecast and the adjustments made to get to the base forecast used as the base case assumptions.

[4] BBE is Platte River's electrification program.

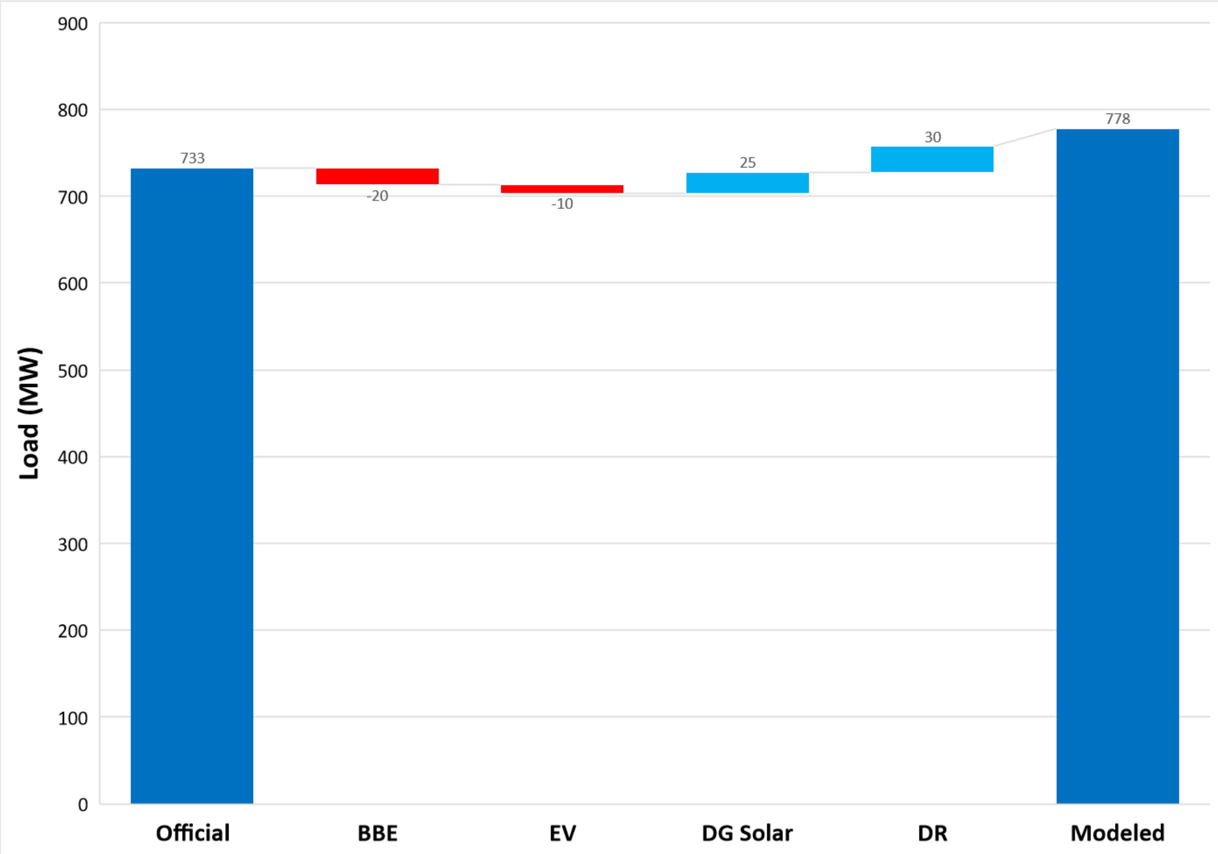

Figure 3. 2030 Peak Demand Forecast

LOAD MODELING

As described in the Study Framework subsection above, load shapes were developed for each of the 42 study years 1980-2021. These load shapes were developed based on trends and relationships between load and weather for the five historical years 2017-2021.

The five historical load shapes were trended using a neural network that was trained using hourly historical temperatures from the National Oceanic and Atmospheric Administration (NOAA) and other key variables. Temperatures from NOAA were provided by Platte River for the Ft. Collins area for the years 1997-2021. Temperatures for 1980-1997 were downloaded from NOAA using the Denver weather station.

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 1980-2021 to develop synthetic load shapes for each of the 42 weather years.

Since the 42 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 reasonable 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 42 years of synthetic data.

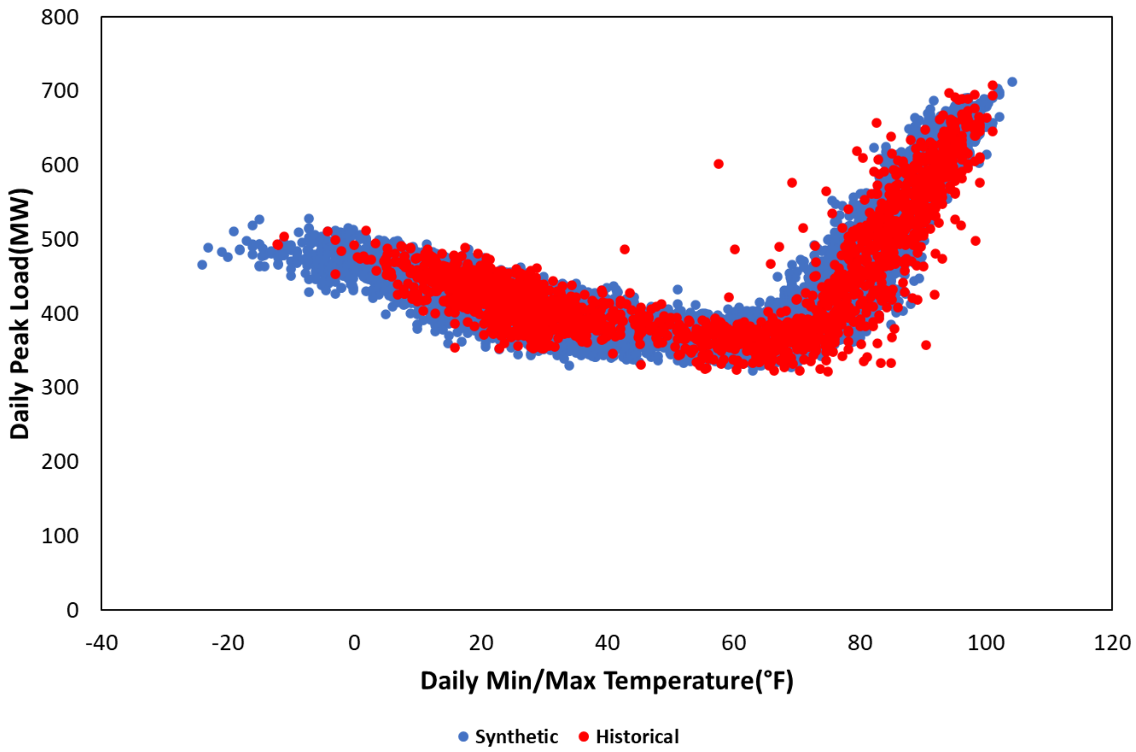

Figure 4. Synthetic vs. Historical Daily Peak Loads

The development of the 42 synthetic load shapes results in a diverse set of annual peak loads. Within SERVM, these shapes will be scaled for Platte River such that the average of the last 10 years of annual peak loads will equal the weather normal peak load. The figures below show the summer and winter peak load variance resulting from the 42 synthetic load shapes. The variance is shown in terms of its divergence from the weather normal peak load on a percentage basis, sorted from lowest to highest.

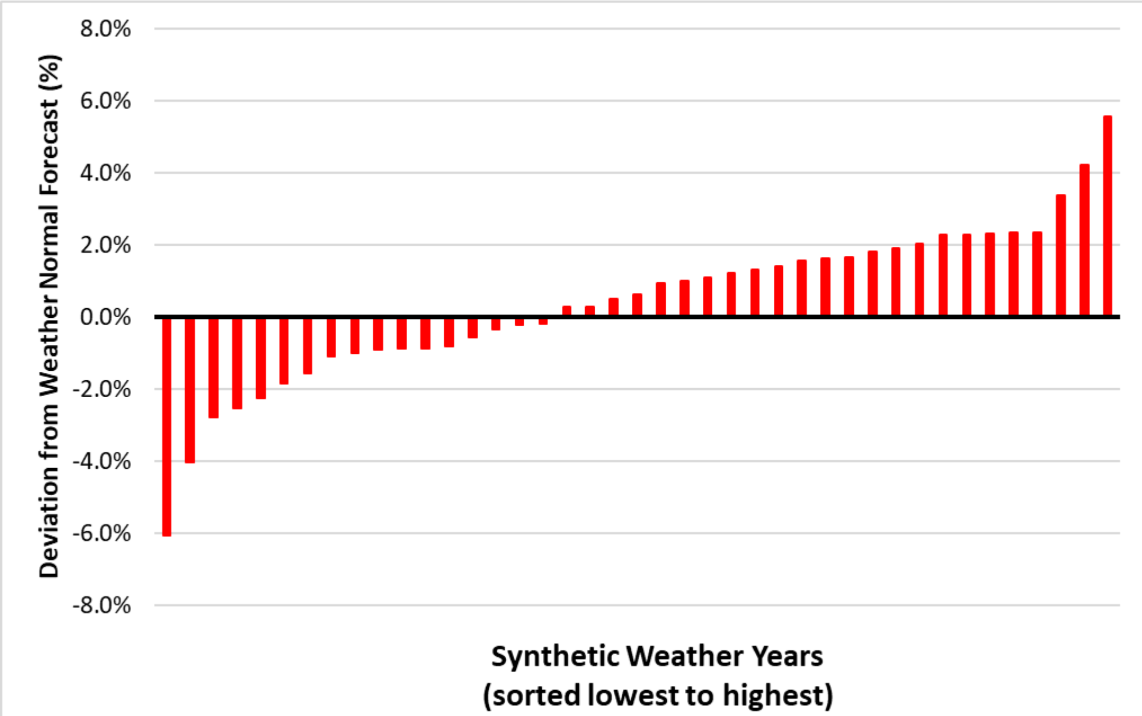

Figure 5. Summer Peak Load Variance

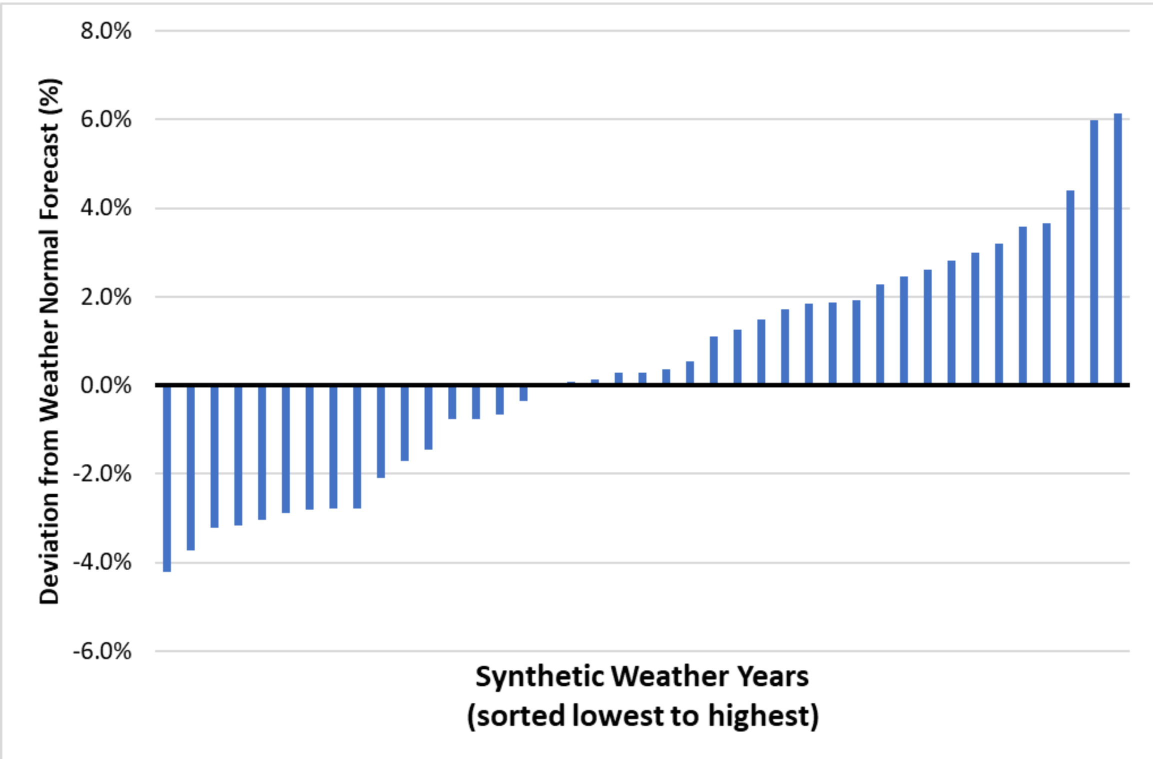

Figure 6. Winter Peak Load Variance

Because the neural network predictor can only produce reliable results in the range of temperatures for which it was trained, an extreme temperature analysis was performed to develop a set of regressions for summer afternoon, winter afternoon, and winter morning extreme temperatures.

These regressions were used to predict the load during those extreme conditions. The figures below show the regressions performed for each of those three periods.

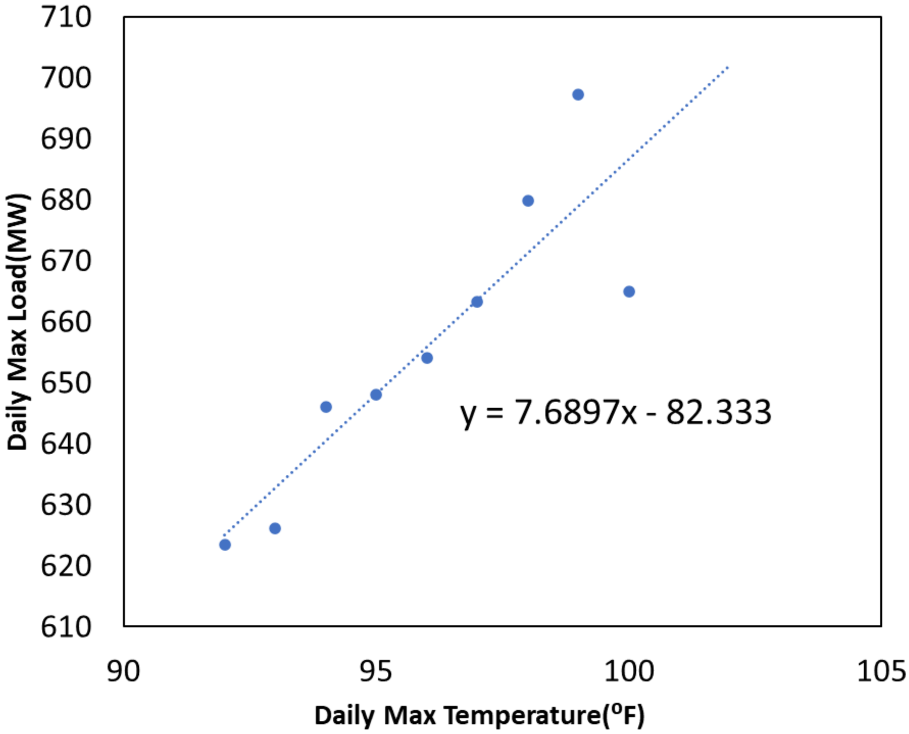

Figure 7. Summer Afternoon Extreme Temperature Regression

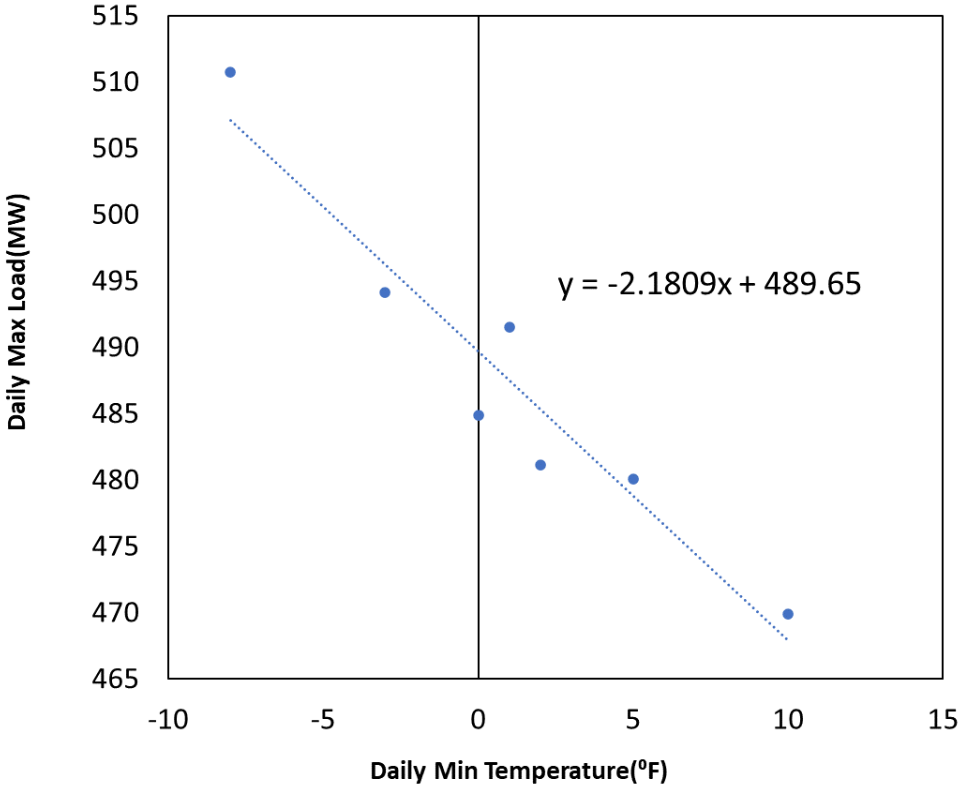

Figure 8. Winter Afternoon Extreme Temperature Regression

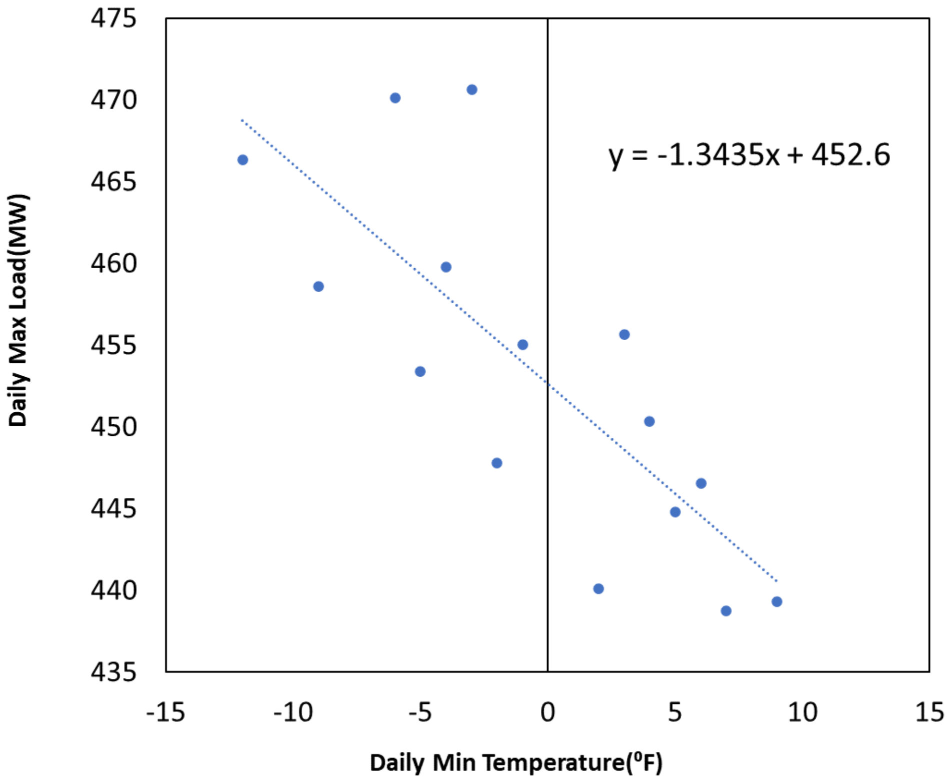

Figure 9. Winter Morning Extreme Temperature Regression

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 42 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 economic growth. 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 1. LFE Model

LFE	Probability
-4%	7.26%
-2%	24.10%
0%	37.28%
2%	24.10%
4%	7.26%

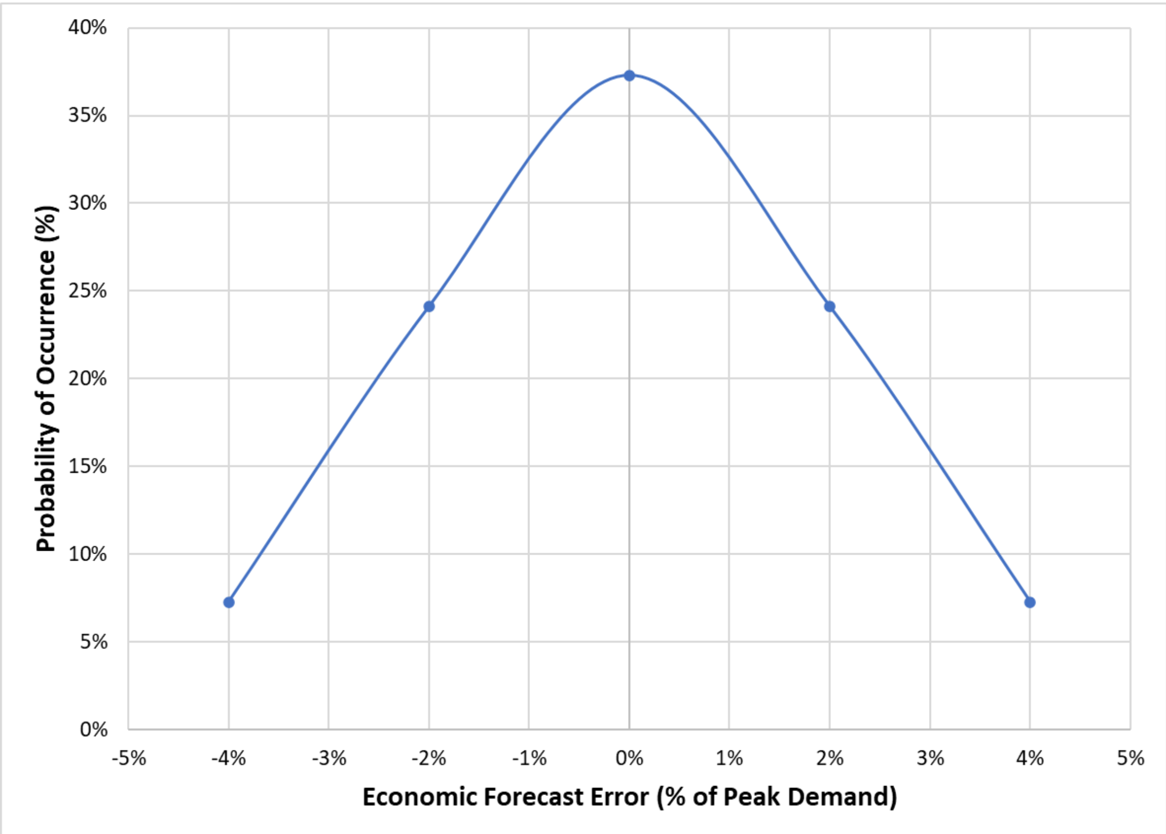

Figure 10. LFE Model

CONVENTIONAL RESOURCE MODELING

Resources for neighboring entities were developed using publicly available information. Resources for Platte River were developed using data provided by Platte River as outlined in the subsections below.

GENERATING CAPACITY

The following table shows a summary of all the resources assumed to be available to Platte River in 2029 along with their corresponding summer capabilities.

Table 2. Platte River Resource Capacities

Unit Name	Unit Category	Summer Capacity MW
PRP Battery 1	Battery Storage	50
PRP Battery 2	Battery Storage	50
PRP Battery 3	Battery Storage	50
PRP Battery 4	Battery Storage	50
LMS100 A	CT	87.44
Rawhide A (EA 1)	CT	65
Rawhide B (EA 2)	CT	65
Rawhide C (EA 3)	CT	65
Rawhide D (EA 4)	CT	65
Rawhide E (FA 1)	CT	128
PRP DR	DR	30
RICE 1	ICE	18
RICE 2	ICE	18
RICE 3	ICE	18
RICE 4	ICE	18
Future Solar	Solar	300
NTRFP Solar	Solar	150
PRP DG Solar	Solar	87
Rawhide Flats Solar	Solar	28
Rawhide Prairie Solar	Solar	21
WAPA-LAP	WAPA Purchase	30
WAPA-CRSP	WAPA Purchase	54
Future Wind	Wind	300
Medicine Bow	Wind	6
Roundhouse	Wind	225
Spring Canyon 2& 3	Wind	60

To model the transition from summer ratings to winter ratings, technology curves were developed for each CT that adjusted the maximum capacity of the resource based on ambient temperature.[5] Reciprocating Internal Combustion Engine (ICE) units were assumed to have the same summer and winter capabilities.

OUTAGE MODELING

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

Planned Maintenance. SERVM can model planned maintenance, often called planned outages (PO), as either discrete schedules or an annual rate in percentage 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.

Based on examination of historical planned maintenance events and discussions with Platte River, the planned maintenance rates for the Platte River CT and ICE units were assumed to be 5%.

SERVM models 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 generator. The 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 it reaches the TTR threshold, at which point it is once again made available and a new TTF variable is chosen for the resource. With sufficient Monte-Carlo iterations, the EFOR of the resource converges to its expected value.

Platte River provided EFOR targets for their resources. A distribution of TTR and TTF values were then developed such that the resulting EFOR values matched those provided by Platte River. The figure below shows those resulting EFOR values.

[5] Details concerning these curves can be found in the appendix.

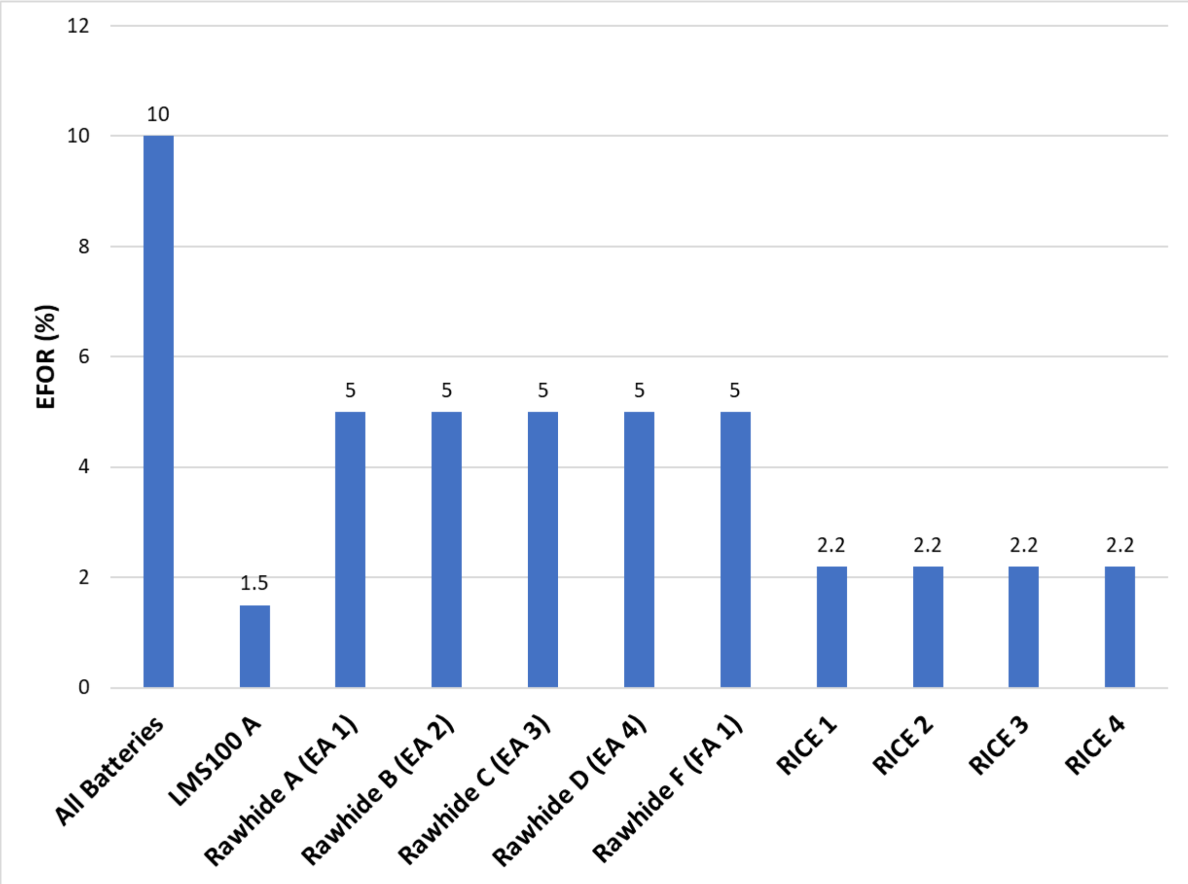

Figure 11. Plate River EFOR Rates

HEAT RATES

While heat rates do not have a direct impact on the reliability of the system, it is important to accurately represent the relative dispatch of resources on the system so that outages (which are affected by hours of operation and thus do affect reliability) can be accurately modeled. Heat input requirements are modeled within SERVM using binomial (a.k.a., A-B-C) heat rate coefficients. Total heat input, average heat rates, and incremental heat rates, therefore, would be determined using the following formulas:

Total Heat Input = $A + B*X + C*X^2$
Average Heat Rate = $A/X + B + C*X$ and
Incremental Heat Rate = $B + 2*C*X$

Where X = the output of the resource in MW.

Average and/or incremental heat rates at various loading points were provided by Platte River for the CT and ICE units. These were converted into A-B-C heat input coefficients resulting in summer, full load average heat rates as shown in the figure below. Modeled heat rates would obviously vary depending upon the specific output of the resource in each hour.

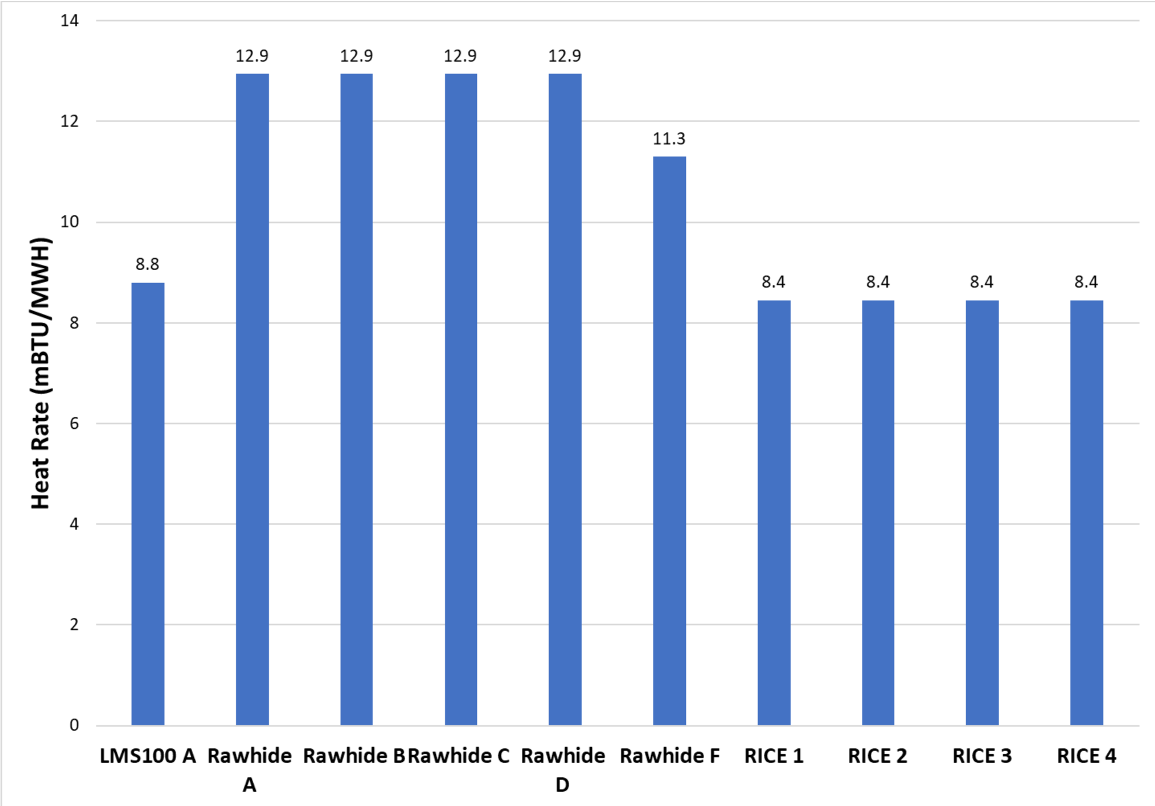

Figure 12. Platte River Heat Rates

FUEL COSTS

As with heat rates, precise accuracy in fuel costs does not directly impact reliability. However, the relative cost of one fuel source to another can affect unit operations, which in turn can affect unit outage modeling. Platte River monthly fuel costs were provided by Platte River as shown in the figure below for the 2030 study year. Fuel prices for other regions and technologies were determined from publicly available sources.

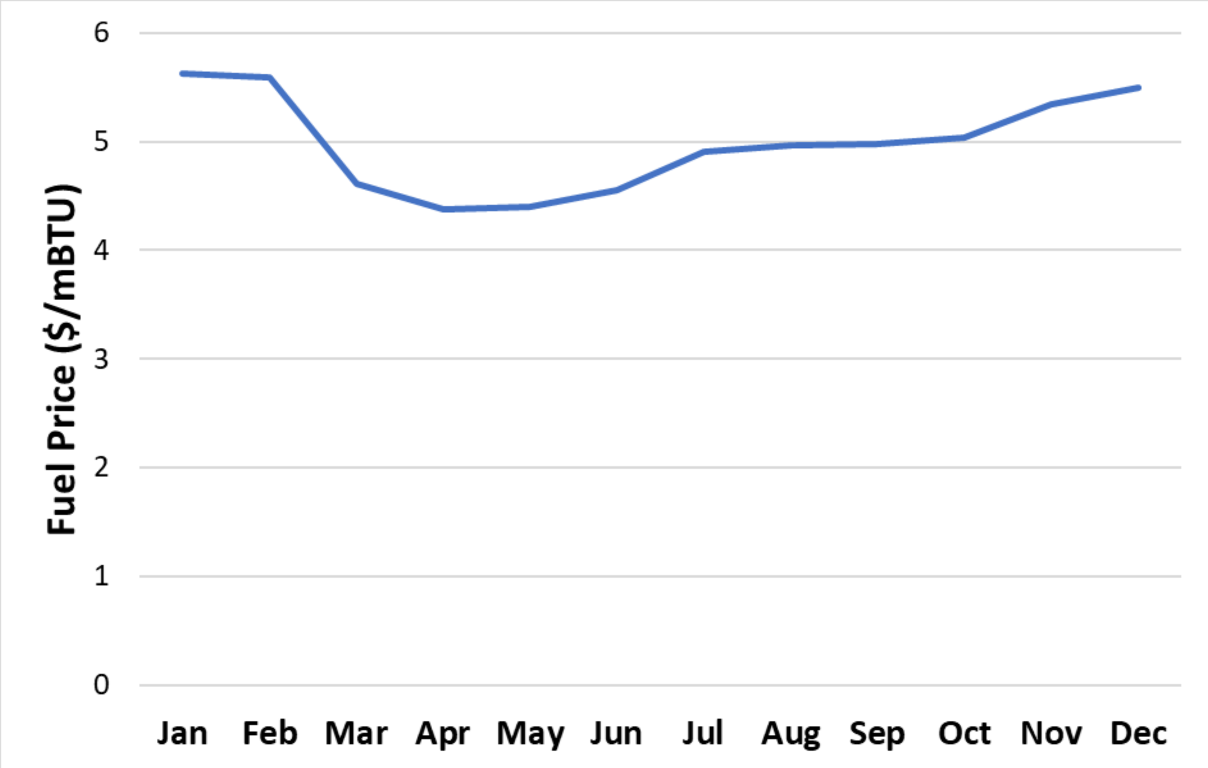

Figure 13. Platte River Monthly Fuel Costs

OTHER CONVENTIONAL DATA

Other conventional resources data provided by Platte River included variable O&M, 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 except to the extent they may have affected hours of operation and thus (ultimately) outage profiles.

SOLAR RESOURCE MODELING

Platte River has six solar facilities that were modeled in this study. Their facility names, location, nameplate capacity, and technology are shown in the table below.

Table 3. UTILITIES Solar Facilities

Facility	Location	MW	Technology
Rawhide Flats	Rawhide, CO	28	Tracking
Rawhide Prairie	Rawhide, CO	21	Bi-Facial[6]
NTFRP Solar	Ft. Collins, CO	150	Bi-Facial
Future Solar	Ft. Collins, CO	300	Bi-Facial
DG Solar	Various (Ft. Collins, CO)	87	Fixed Axis

[6] Bi-Facial also assumes single-axis tracking in addition to the bi-facial.

SERVM models renewable resources as an hourly profile for each weather year. To model the above solar facilities as well as the solar facilities of the other Colorado Joint Dispatch entities, eight locations were modeled. These eight locations were selected as being representative of the actual location of all the existing and planned solar projects in Colorado. All solar resources in Colorado were mapped into one of those locations. The figure below[7] shows these eight locations.[8] All of Platte River solar facilities were mapped into the technology-appropriate profile for the North Central Colorado (i.e., near Ft. Collins) location.

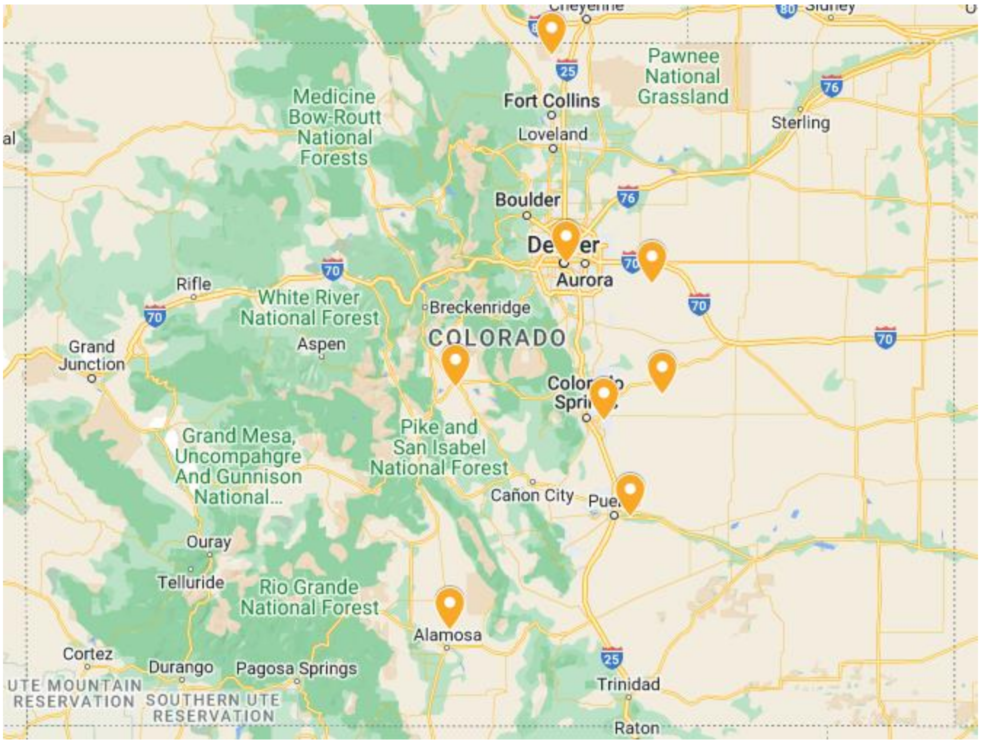

Figure 14. Solar Model Locations

To create the weather year profiles for each of these locations, irradiance data for these eight locations were downloaded from the National Renewable Energy Laboratory (NREL) National Solar Radiation Database (NSRDB) Data Viewer for the years 1998 to 2020.[9] The data obtained from the NSRDB Data Viewer was input into NREL's System Advisor Model (SAM) [10] for each year and location to generate the hourly solar profiles based on the solar weather data for fixed, tracking, and bi-facial[11] with 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 Platte River load out of all the days +/- 2 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.

[7] Map created courtesy of Google maps (maps.google.com).
[8] The precise GPS locations for the sites modeled can be found in the Appendix.
[9] https://maps.nrel.gov/nsrdb-viewer/
[10] https://sam.nrel.gov/
[11] Bi-facial profiles were only created for the North Central Colorado location.

To ensure appropriate capacity and energy contributions, the resulting profiles were then adjusted using the inverter loading ratio to achieve the desired capacity factor.

The figures below show respectively the resulting summer[12] daily output profiles for tracking and fixed[13] technologies for each of the eight sites modeled as well as the bi-facial[14] technology for the North Central Colorado site.

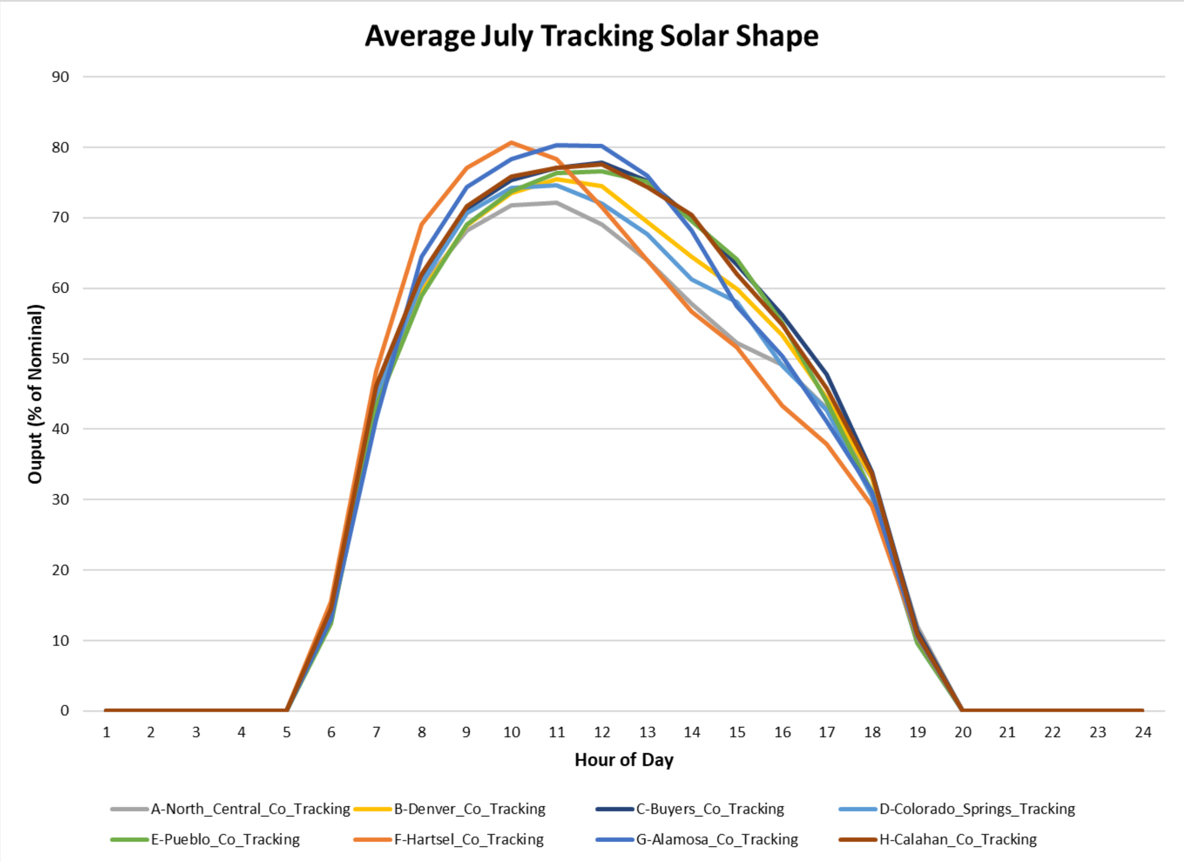

Figure 15. Average Summer Tracking Solar Profiles

[12] i.e., the average of all July days including all weather years. Similar figures for winter can be found in the appendix.

[13] Fixed and Tracking shapes shown in figures assume a 1.17 inverter loading ratio. Actual inverter loading ratios for Platte River were selected to achieve desired capacity factor as shown in appendix.

[14] Bifacial shape assumes a 1.3 inverter loading ratio. Actual inverter loading ratios for Platte River were selected to achieve desired capacity factor as shown in appendix.

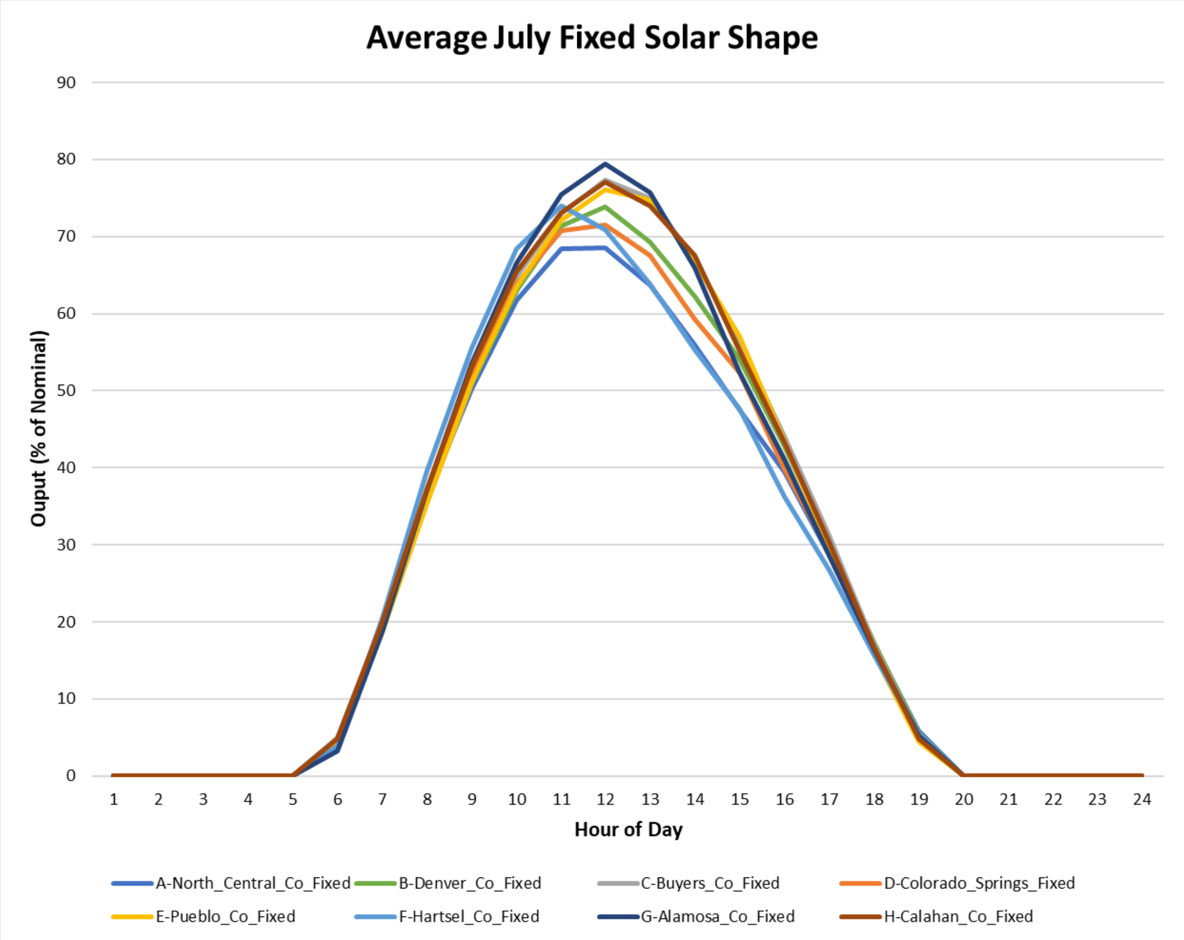

Figure 16. Average Summer Fixed Axis Solar Profiles

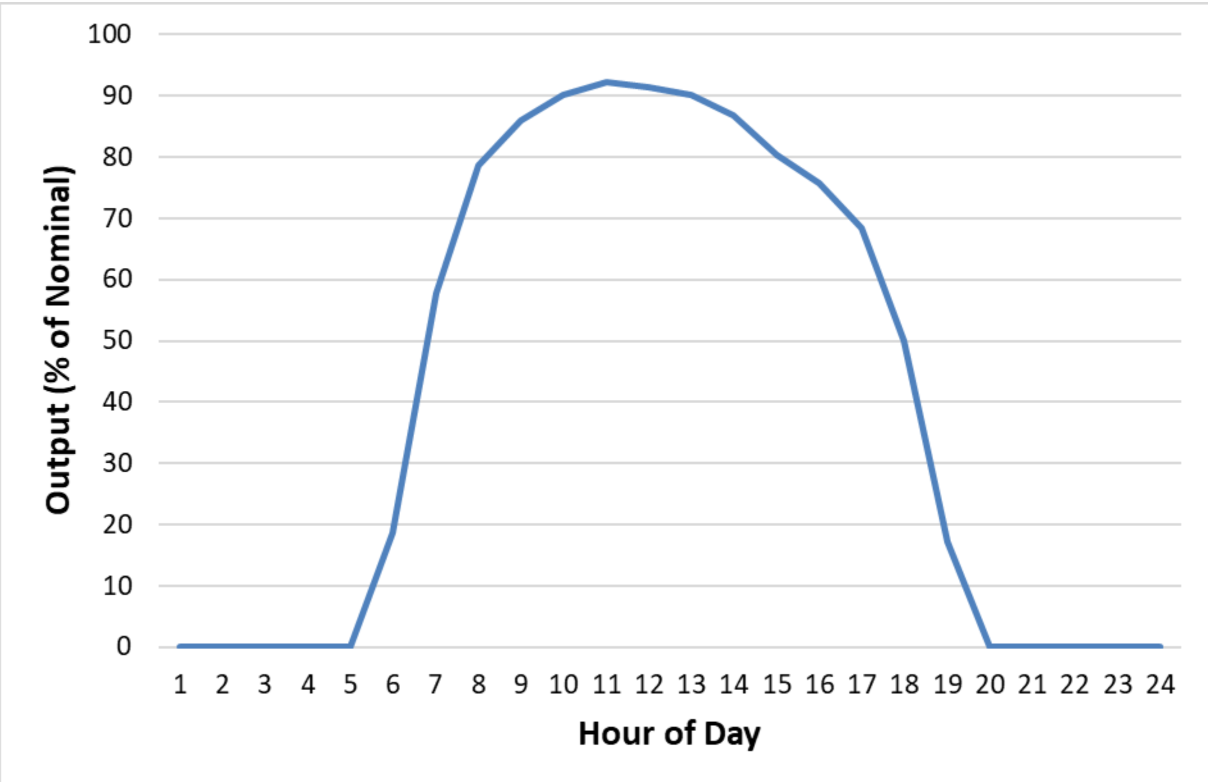

Figure 17. Average Summer Bi-Facial Solar Profile

Future solar for ELCC purposes was all modeled at the North Central location using bi-facial technology.

WIND RESOURCE MODELING

Platte River had four[15] wind resources assumed for the 2030 study year as indicated in the table below.

Facility	Location	Capacity
Medicine Bow	Medicine Bow, WY	6.3
Spring Canyon 2 & 3	Peetz, CO	60
Roundhouse	Southeast, WY	225
Future Wind	NE Colorado	300

Wind modeling for these resources, as well as the wind resources of the other market entities, was based upon profile data developed using the SAM Model, with wind data downloaded from NREL's wind toolkit. The SAM model was able to download wind data for years 2007-2014. The profiles for the remaining weather years were determined by a process similar to that used for the solar profiles, except that the matching was done based on +/- 5 days instead of +/- 2 days.

Based on the location of the base case wind projects in Colorado, a total of six (6) sites were chosen for which all the wind projects would be mapped. The figure below[16] shows the location of those sites.[17]

[15] Spring Canyon 2 & 3 were modeled as a single resource.
[16] Map created courtesy of Google maps (maps.google.com).
[17] The precise GPS locations for these sites can be found in the appendix.

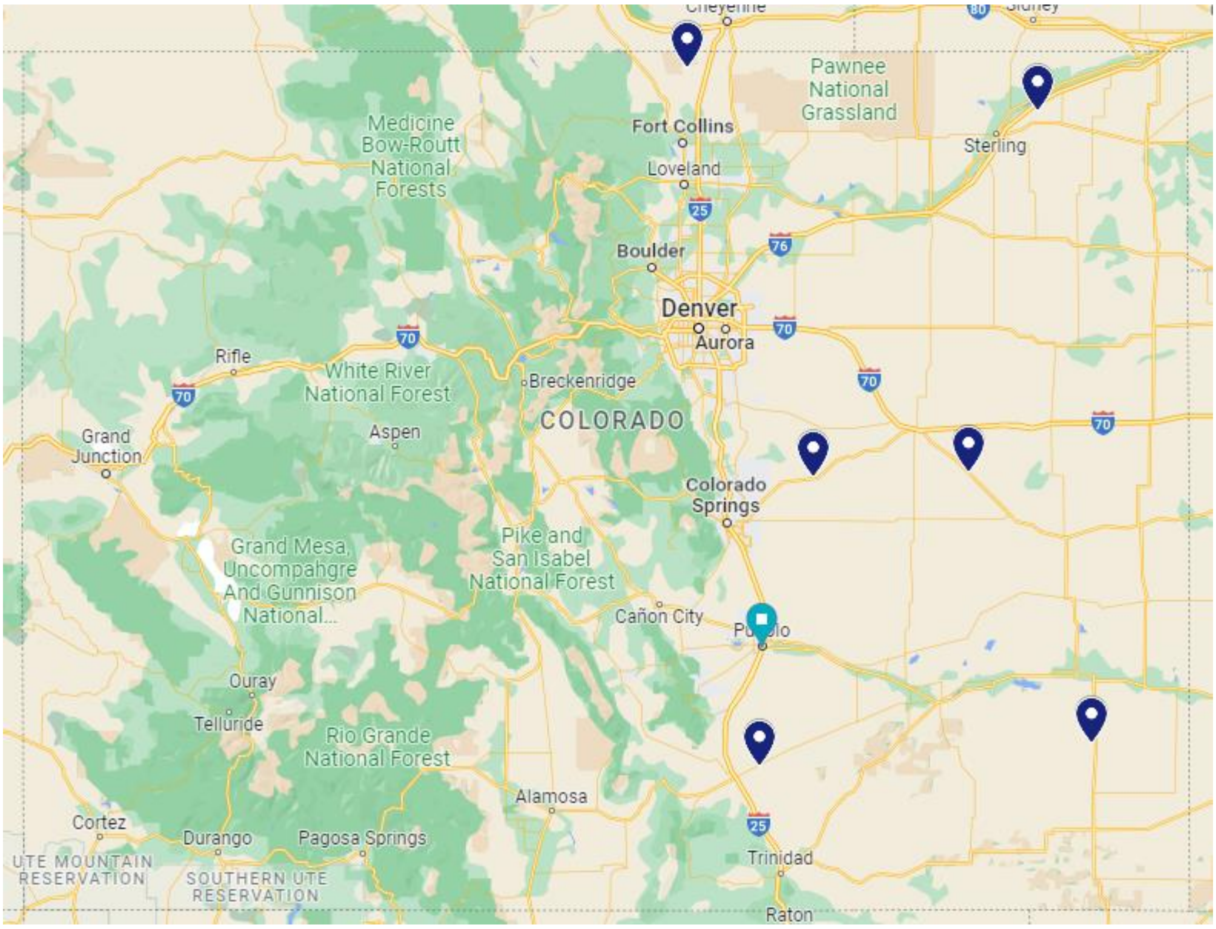

Figure 18. Wind Model Locations

The Spring Canyon facility was mapped to the northeastern, Colorado location while the rest of the Platte River wind projects were mapped to the north central Colorado location. Other wind projects were mapped to one of the six projects based on their specific location.

To ensure consistency with previously experienced wind output, several adjustments were made to the NREL profiles. First, capacity factors and output shapes were modified to match an output duration curve that achieves roughly 44% capacity factor. To accomplish this, an output duration curve of the historical data was created. This was done by unitizing an available historical profile and then sorting all hours from highest output to lowest output. Similar output duration curves were developed for the NREL wind profiles. The output duration curves for the NREL data set were then scaled so that over the 2007-2014 period they would, on average, match the historical data set.

Next, the profiles were further adjusted to create a more realistic profile of wind output vs. load. Based on prior modeling experience in other regions as compared to available historical profiles, NREL wind profiles tend to show greater output in periods of high load than historical data has demonstrated. To properly adjust for this output bias requires a significant amount of available historical data. Ideally, historical Colorado profile data would be used for this process, but such data was not publicly available. For this project, the closest publicly available data was from the panhandle of ERCOT. Therefore, that data was used as a proxy for making the output bias adjustments. ERCOT wind data should be of sufficient representation as to not introduce significant error into the analysis.

Making these adjustments first requires mapping per unit wind output as a function of per unit load for both the Colorado profiles and the ERCOT profiles. These are then compared to see where adjustments need to be made. Making these adjustments without impacting output duration curve profiles or capacity factor requires a painstaking and meticulous process of swapping output in higher load periods with output in lower load periods until the output vs. load profiles for Colorado are more consistent with expectations (i.e., those demonstrated historically in ERCOT). This process was done on an aggregate basis for all six of the Colorado sites, but the adjustments were applied to individual profiles so that locational diversity was maintained while aggregate output approached expected values. The table below shows the resulting aggregate comparison of the original NREL data, ERCOT data, and NREL adjusted data during high per unit load periods.

Table 4. Wind Output as a Function of Load

	Load	Wind Output (% of Nominal)									
Data Source	(% of Pk)	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
NREL	80-90	9.6%	19.6%	17.1%	16.3%	12.4%	9.6%	8.0%	5.2%	2.0%	0.3%
	90-100	10.5%	19.4%	20.7%	14.9%	13.7%	8.8%	6.9%	4.0%	0.9%	0.0%
ERCOT Panhandle	80-90	21.9%	17.3%	14.1%	11.5%	10.3%	9.7%	7.9%	5.8%	1.4%	0.0%
	90-100	20.8%	21.7%	16.3%	12.9%	10.4%	7.9%	6.0%	3.3%	0.7%	0.0%
NREL Adjusted	80-90	21.6%	18.2%	15.3%	11.4%	10.9%	9.1%	7.3%	5.1%	0.9%	0.0%
	90-100	21.1%	22.6%	13.2%	13.7%	10.0%	9.2%	6.6%	3.3%	0.2%	0.0%

The figure below shows the summer average wind profile by modeled location.[18]

[18] A similar figure for winter along with resulting capacity factors can be found in the appendix.

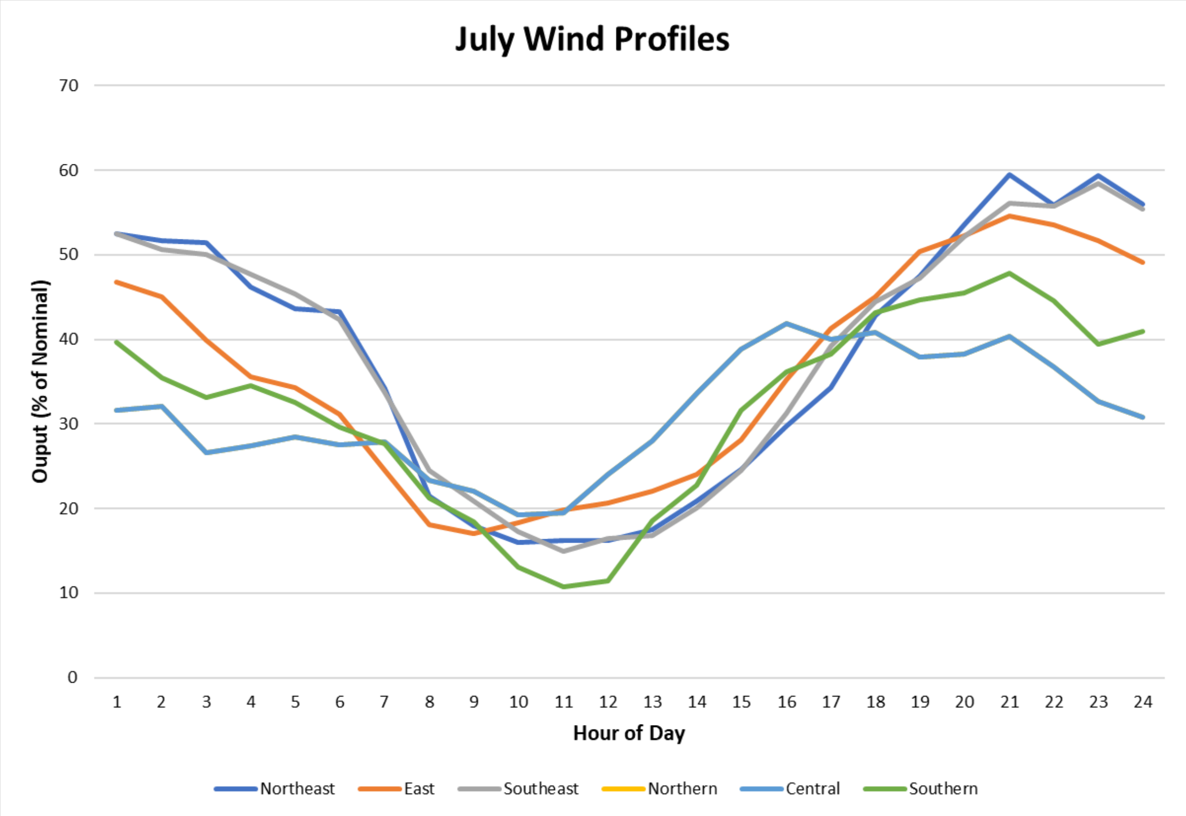

Figure 19. July Wind Output Profiles

Finally, the profiles were adjusted one more time using the SERVM inverter loading ratio to achieve the desired project specific capacity factors as provided by Platte River.[19]

Future wind projects for ELCC modeling purposes were split between the Central and Northeast locations.

DARK CALM EVENTS

Dark calm events are extended periods of time in which both wind and solar output is severely restricted. Many of these events are inherent in the irradiance and wind climate data used to develop the solar and wind profiles. However, certain winter storms can create dark calm events that are not evident as part of the climate data. For example, a snowstorm may blanket a solar farm such that – until such time as the snow melts or can be otherwise removed – prevents significant solar output even on a bright, sunny day. Similarly, ice buildup on wind turbines may significantly decrease the efficiency of the turbine or extremely cold weather may adversely affect the gear oil so that even with significant wind present, turbine output is greatly restricted. Although combined dark and calm (i.e., solar + wind) events rarely last more than two days because of maintenance efforts are typically able to clear off snow from a solar farm within 48 hours of a snowstorm, the wind portion of a dark calm event may last much longer – up to 60 hours or longer.

[19] These capacity factors can be found in the appendix.

An examination of publicly available aggregate wind and solar data from EIA for period July 2018-December 2022 for the state of Colorado was performed to examine the number of events in which solar and wind output was reduced to below 20%[20] of nominal aggregate capacity for extended periods of time. The tables below show the frequency of dark calm events that occurred during the winter months and the incremental (i.e., over and above the combined wind and solar dark calm events) that occurred either in summer or winter.

Table 5. Historical Dark Calm Events

EIA Dark Calm Event Data			
Duration of Event (hours)	1 Day	2 Day	3 Day
Total Events	9	1	0
Est Events/Year	2.0	0.2	0.0

Table 6. Incremental Wind Lull Events

EIA Incremental Wind Lull Events								
Duration of Event (hours)	18	24	30	36	42	48	54	60
Total Events	44	25	7	4	5	0	2	2
Est Events/Year	9.7	5.5	1.5	0.9	1.1	0.0	0.4	0.4

Dark Calm Events were modeled within SERVM by creating a partial outage of wind and solar resources on a random basis to simulate a significant reduction in solar and/or wind output for a period of time. Combined solar and wind outages were confined to winter months while incremental events could occur throughout the year. While some events already existed organically in the underlying climate data, the frequency and duration of incremental events were tuned such that the combined organic and outage-imposed events approximated that in the historical data. The three figures below show, respectively, a modeled 24-hour dark calm event, a modeled 48-hour dark calm event, and an extended wind event.

[20] Due to the effects of geographic diversity, consideration of output thresholds lower than 20% resulted in a very small sample of historical events. Conversely, due to normal ebbs and flows of wind and cloud cover patterns, consideration of output thresholds above 20% makes it difficult to distinguish between a dark calm event and normal output patterns.

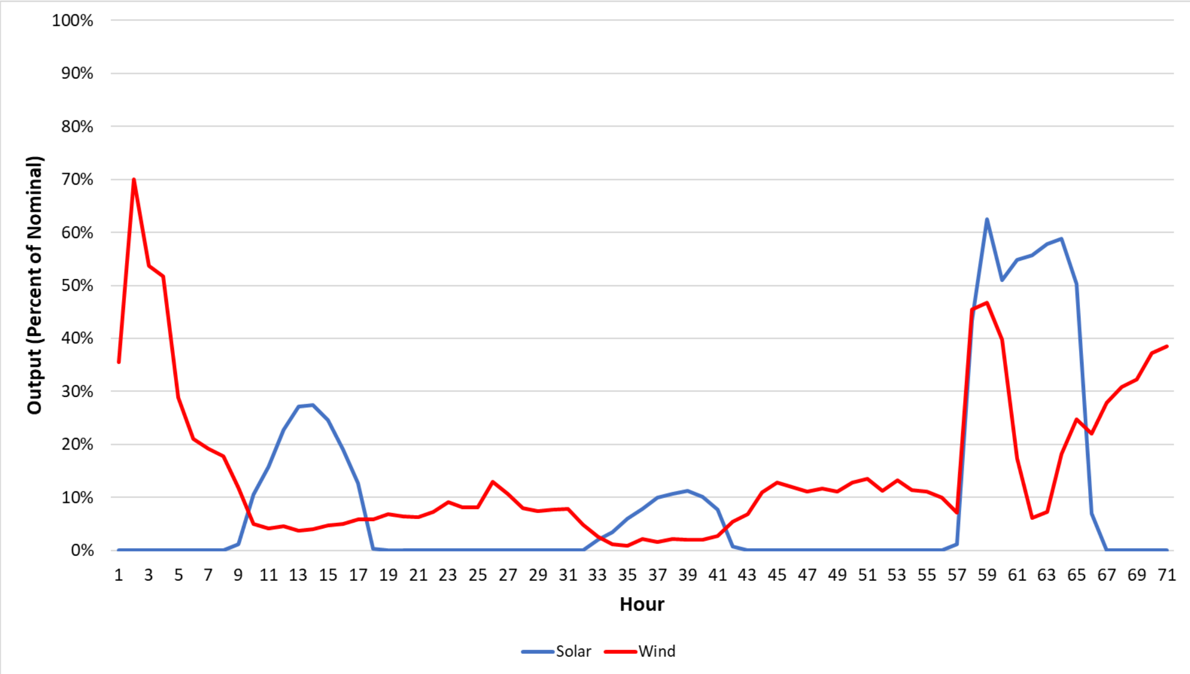

Figure 20. 24-Hour Correlated Dark Calm Event

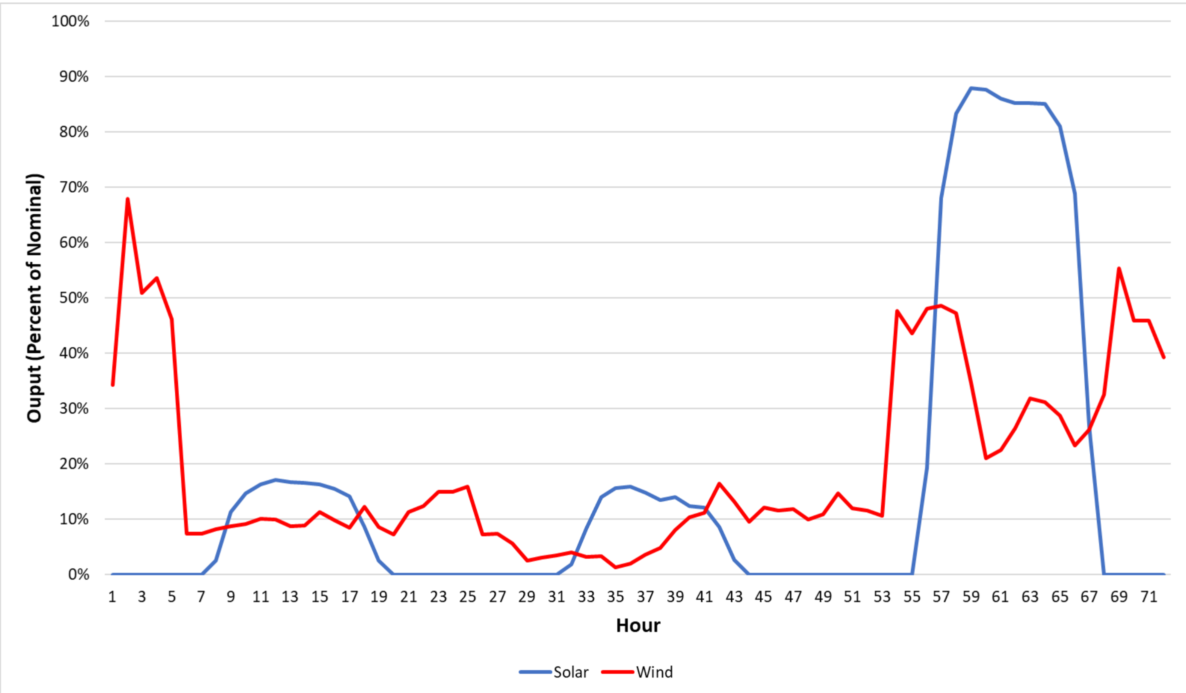

Figure 21. 48-Hour Correlated Dark Calm Event

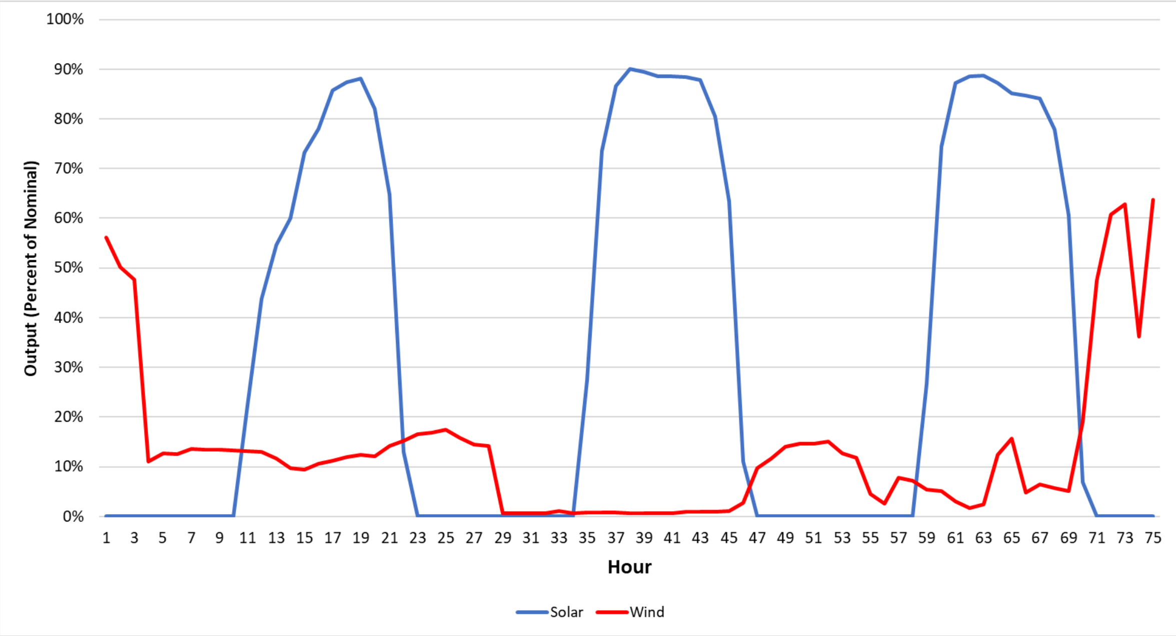

Figure 22. Extended Uncorrelated Wind Event

STORAGE RESOURCE MODELING

Platte River was modeled with four 50 MW battery storage resources for a total of 200 MW of battery storage. The modeled characteristics of battery resources are shown in the table below.

Table 7. Battery Storage Characteristics

Characteristic	Value
Maximum Discharge Capacity (MW)	50
Minimum Discharge Capacity (MW)	0
Storage Capacity (MWh)	200
Charging Capacity (MW)	50
Able to Provide Ancillary Services	Yes
Cycle Efficiency (%)	85

These battery storage resources were modeled as being available for economic arbitrage. However, during times of reliability risk, the economic arbitrage schedule was allowed to deviate so that the batteries would be discharged to avoid loss of load if storage capacity was available.

Furthermore, based on recent industry experiences,[21] grid-scale battery storage resources are expected to have outage rates of up to 15%, with improvements expected as operational experience

[21] See https://www.aps.com/-/media/APS/APSCOM-PDFs/About/Our-Company/Doing-business-with-us/Resource-Planning-and-Management/APS-RPAC-Meeting-Presentation-102622.ashx?la=en&hash=9AE20E699D178AFCF8AB30BF9C64FFED, slides 41-46, with emphasis on slide 46, “Specific lessons for battery storage”.

improves. Therefore, these (and all other) battery storage resources were modeled with a 10% forced outage rate.

HYDRO RESOURCE MODELING

The only hydro facilities available to Platte River are two hydro purchase contracts from the Western Area Power Administration (WAPA). These purchases were modeled in accordance with data provided by Platte River regarding the monthly minimum and maximum scheduled flows. The summer capacities for the two purchases are shown below.

Table 8. UTILITIES WAPA Hydro Purchases

Unit Name	Capacity (MW)
WAPA-LAP	30.2
WAPA-CRSP	54.4

DEMAND RESPONSE MODELING

Platte River has one 30 MW active Demand Response (DR) program that was modeled in this study as being available to respond to reliability conditions and with the characteristics shown in the table below.

Table 9. Platte River DR Characteristics

Characteristic	Value
Hours Per Day	4
Max calls per week	3
Max calls per year	24

FINAL COMPOSITION OF MARKET

Based on the resources modeled from publicly available data for PSCO, CSU, and BHC as well as the Platte River resources modeled as described in the preceding sections, the final resource mix showing 2030 installed capacity in MW by resource category for the regional market is shown in the figure below. A detailed listing of the resources can be found in the appendix.

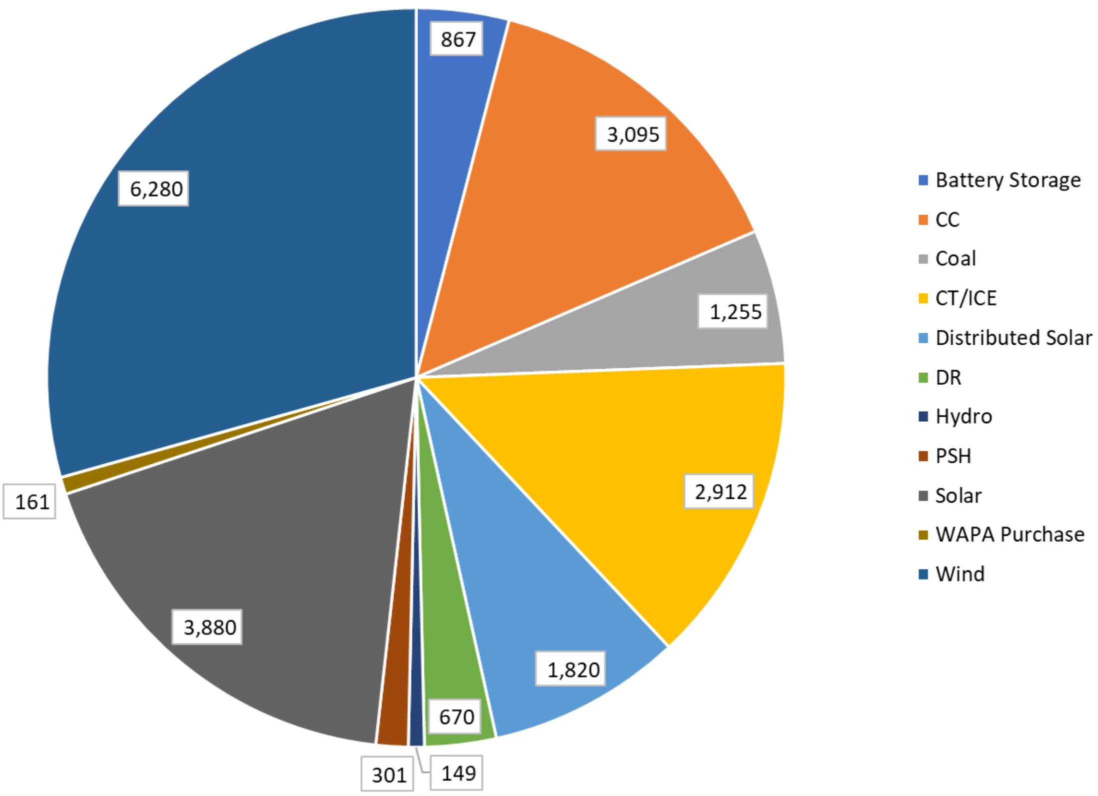

Figure 23. Regional Market Capacity Mix (MW)

The table below shows the non-coincident forecasted peak loads as modeled for each of the entities in the market as well as the coincident peak load[22] of the market.

Table 10. Regional Market Peak Demands

Region	Peak Load (MW)
Platte River	778
PSCO	8,339
CSU	1,047
BHC	686
Regional Market	10,619

ANCILLARY SERVICES MODEL

The ancillary services model in this study included the modeling of regulating reserves, contingency reserves spinning (spinning reserves), contingency reserve supplemental (non-spinning reserves), and

[22] The regional market coincident peak load was calculated as the median of the coincident peak loads of all four entities in the market for weather years 2012-2021 (i.e., the last 10 years – consistent with Platte River forecasting norms).

a load following reserves target. SERVM will commit the system to maintain all ancillary services requirements.[23] However, load following reserves and non-spinning reserves would be allowed to deplete to zero to avoid a load shedding event. Regulating reserves and spinning reserves would be maintained during load shedding events. While there is no industry standard for setting the reserves level during load shed assumption, many entities utilize a similar level to those used in this study. California for instance, not only includes 6% reserves during load shed in their planning models, but they also protected that level of reserves during the reliability load shed events of 2020.[24] The following baseline set of operating reserves was modeled.

Table 11. Base Ancillary Services Requirements

Reserve Component	Requirement (% of Load)
Regulating Reserves	1.5
Spinning Reserves	3
Non-Spinning Reserves	3
Load Following Reserves	3

TRANSMISSION MODEL

Note: some of the information contained within this section of the report is confidential and subject to Critical Energy/Electric Infrastructure (CEII) restrictions.

Due to the nature in which the western interconnection transmission grid is scheduled combined with the intricate nature of the interconnections within the assumed market, establishing a pipe-and-bubble representation of the market and its immediate neighbors can be complex. For purposes of this analysis, the Platte River import and export capabilities were provided by Platte River. Other import/export values were determined based on an examination of several publicly available documents, including the following:

- The EIA Balancing Area Authority Hourly Historical Interchange Reports,[25]
- The 2021 PSCO Resource Adequacy Study,[26]
- Tri-State Utilities ATC Path Postings,[27,28]
- PSCO Oasis Postings,[29] and

[23] The load following reserve component is a target, not a requirement. SERVM will attempt to commit to the targeted level of load following reserves but will not shed load if such reserves are not available to be committed.
[24] http://www.caiso.com/Documents/Final-Root-Cause-Analysis-Mid-August-2020-Extreme-Heat-Wave.pdf
[25] https://www.eia.gov/electricity/gridmonitor/dashboard/electric_overview/US48/US48
[26] https://www.xcelenergy.com/staticfiles/xe-responsive/Company/Rates & Regulations/Resource Plans/Clean Energy Plan/HE_115-KDC-1-Planning_Reserve_Margin_Study.pdf
[27] http://www.oatioasis.com/TSGT/TSGTdocs/ATCID_Combined_Posting_10-14-2011.pdf
[28] https://qa.waac.oasis.oati.com/TSGT/TSGTdocs/Springelville-TOT2A-Scheduling-Limit-V4.pdf
[29] https://www.rmao.com/public/wtpp/PSCO_Operating_Studies.html

- The WECC Path Ratings Catalogue.[30]

From these sources, the transmission import and export values for the model topology used in this analysis is shown in the figure below.

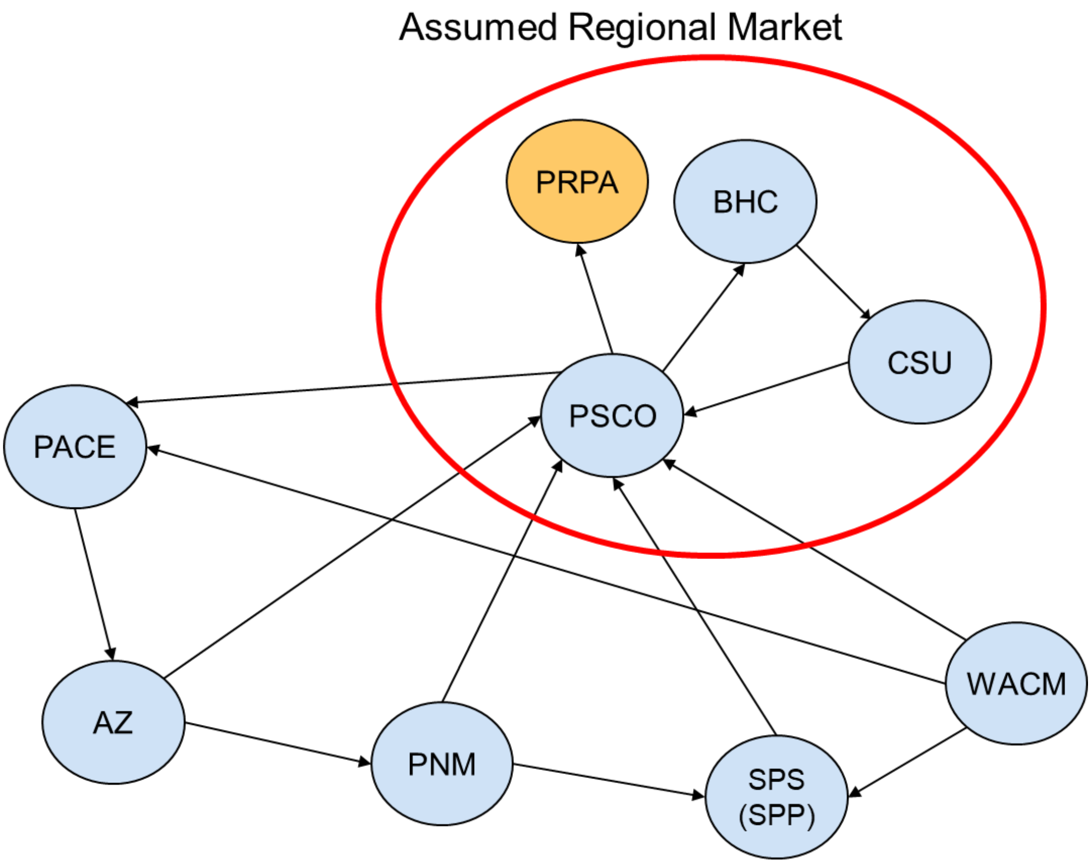

Figure 24. Transmission Import/Export Limits

Each path shows two numbers, with the first number being the flow limitation in the direction of the arrow and the second number being the flow limitation in the opposite direction of the arrow.

In addition to the above constraints and in order to limit imports into the regional market to a reasonable level, a simultaneous import limit of 750 MW was placed in the combined market. Furthermore, each region was limited so that its most expensive, reliability only resources (e.g., demand response, oil CTs, etc.) could not be sold to other regions. However, within the market, which is jointly dispatched, the market members would not have these restrictions and would only be restricted by the transmission constraints shown above. Thus, all members of the market would take all actions possible to prevent a loss of load event and would share in any loss of load event on a pro-rata basis.

[30] https://www.yumpu.com/en/document/read/29758369/path-rating-catalog-2013-western-electricity-coordinating-council

MARKET ASSUMPTIONS

As SERVM performs its 8760-hour production cost simulation, it decides each hour as to the availability and price of potential market transactions between entities. For purposes of this analysis, the regional market is assumed to have a single joint dispatch. Therefore, for the market, these transactions are made based on marginal cost economic dispatch decisions as constrained by the transmission limitations and other operational considerations. For transactions between the regional market and external entities, economic and reliability transactions are determined through the development of both a day ahead and an hourly market price for each region. Those prices are determined using a combination of energy price and a scarcity price adder 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 is a scarcity price established based on the amount of remaining un-dispatched operating reserves.[31] SERVM allows economic transactions based on each region's resulting market price subject to transmission constraints.

[31] Details on the ORDC curve can be found in the appendix.

STUDY APPROACH AND RESULTS

The two objectives of this study were to (a) establish the PRM for the Platte River system and (b) determine the ELCC for various penetrations of solar, wind, battery energy storage system (BESS) and DER resources. However, due to the joint dispatch nature of the assumed regional market, the required reserve margin for Platte River is ultimately contingent on the reliability planning of all entities in the market area. When multiple utilities are combined into a joint dispatch situation, such as with a newly formed market, there are often outage and load diversity benefits that result in improved overall system reliability. The result is that the resulting reserve margin of the overall market is lower than what most of the entities would have achieved independently. Attempting to calculate the reserve margin of a single entity within a jointly dispatched market has the effect of inappropriately assigning all of these benefits to that single entity. This would result in a reserve margin that is lower than the rest of the system, shifting all the cost associated with maintaining reliability to the other entities. Thus, to ensure that all entities are contributing equitably to reliability, both the PRM and the ELCCs were determined on a market-wide basis as described below.

ESTABLISHING MW ADJUSTMENT

The PRM for the regional market was determined for the 2030 study year. To determine the PRM, the external (non-market) regions were calibrated to a 0.1 days/year LOLE. This calibration was done by either retiring capacity or adding new expansion capacity[32] as necessary. With the external system calibrated, CT expansion capacity was then added to the market until it reached 0.1 days/year LOLE. This required making multiple runs with differing amounts of expansion CTs and then trending the resulting LOLE values so that the 0.1 LOLE point could be interpolated from the results.

Before the PRM could be determined, however, it was necessary to determine the effective capacity value of the renewable and storage portfolio of the base case system as described in the subsection below.

EXISTING PORTFOLIO ELCC AND RESULTING PRM

Determining the portfolio ELCC required the following steps:

1. Remove the full portfolio of solar, wind, storage, and DR resources,
2. Iteratively add back perfect capacity until system returns to 0.1 days/year LOLE, and
3. Calculate portfolio ELCC by dividing the perfect added capacity by the nameplate capacity removed.

[32] Any new capacity added was modeled as a reliability only resource that did not significantly affect either the capacity factors of other, existing resources or transactions between regions.

For purposes of this and all subsequent ELCC calculations, the ELCC simulations were performed assuming a "copper sheet" system (i.e., no internal transmission limitations). While taking transmission constraints into account is appropriate for calculating the PRM, transmission limitations should not adversely impact the ELCC calculations. Otherwise, the ELCC may be improperly influenced by transmission limitations and therefore would not be applicable universally across the system. It is more appropriate to calculate an ELCC that is not influenced by transmission limitations but then use that appropriately within the transmission constraints of the system. Similarly, so that shifts in sales and purchases to external entities did not adversely impact the ELCC calculations, the ELCC simulations were performed excluding all non-market regions.[33]

For the 2030 study, the portfolio evaluated included 1,168 MW of battery and pumped storage hydro; 1,820 MW of DG solar; 3,880 MW of utility scale solar; 6,280 MW of wind; and 670 MW of DR. The analysis described above resulted in a portfolio ELCC value of 28.3%.

Applying these ELCC values to the nameplate capacities for those resources allows for the final determination of the PRM (in %) determined as follows:

PRM = [(Existing Capacity[34] + Adjustment Capacity) / Peak Load – 1] * 100.

Those calculations are shown in the table below:

Table 12. PRM Calculation

Component	Value
Coincident Peak Load (MW)	10,653
Existing Effective Capacity (MW)	11,197
MW Adjustment (MW)	1,580
Total Capacity Requirement (MW)	12,777
Reserve Requirement (MW)	2,124
Reserve Requirement (%)	19.9

To demonstrate the relationship between reserve margin and LOLE visually, Figure 25 below shows the LOLE as a function of reserve margin and clearly indicates that the 0.1 days/year LOLE occurs at 19.9%.

[33] This required recalibrating the regional market to 0.1 LOLE without purchases from or sales to these external entities.

[34] For PRM calculation purposes, demand response, hydro, and DG Solar are all treated as a resource, and all renewable, DR, and storage resources are applied at the appropriate portfolio ELCC value.

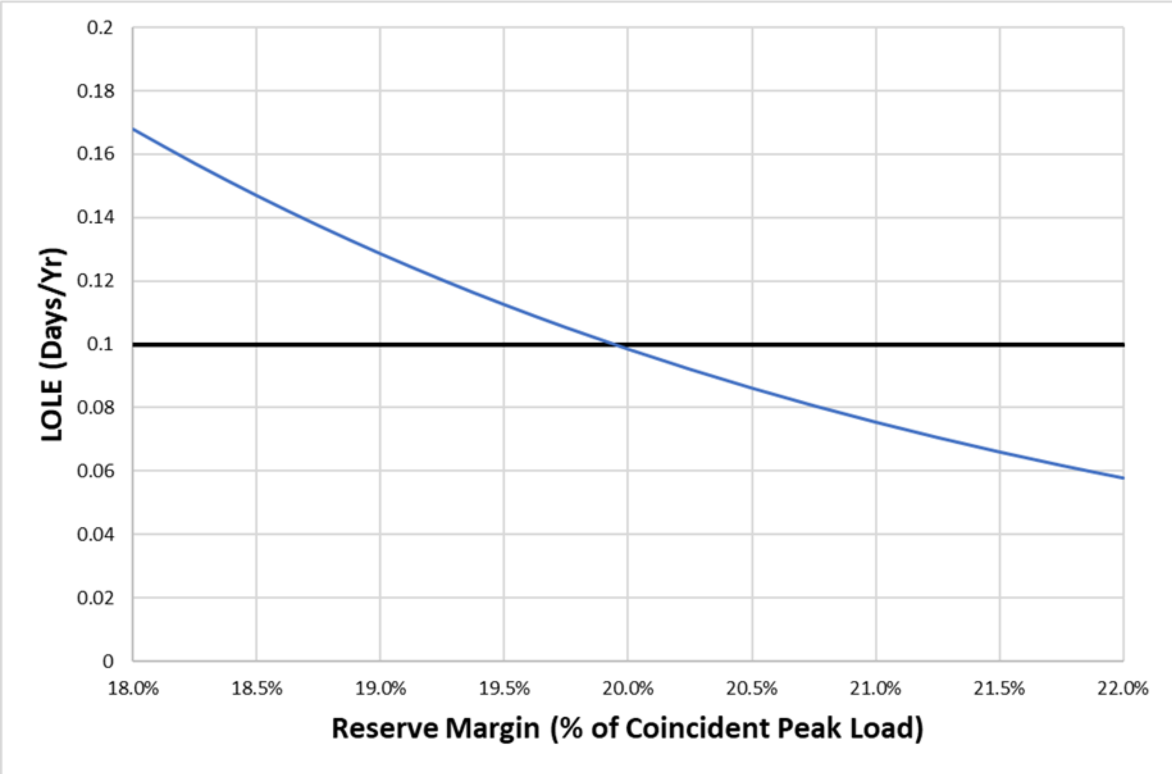

Figure 25. LOLE Analysis

To demonstrate the risk of loss of load with respect to the weather, the figure below shows the breakdown of loss of load expectation across each of the 42 weather years.

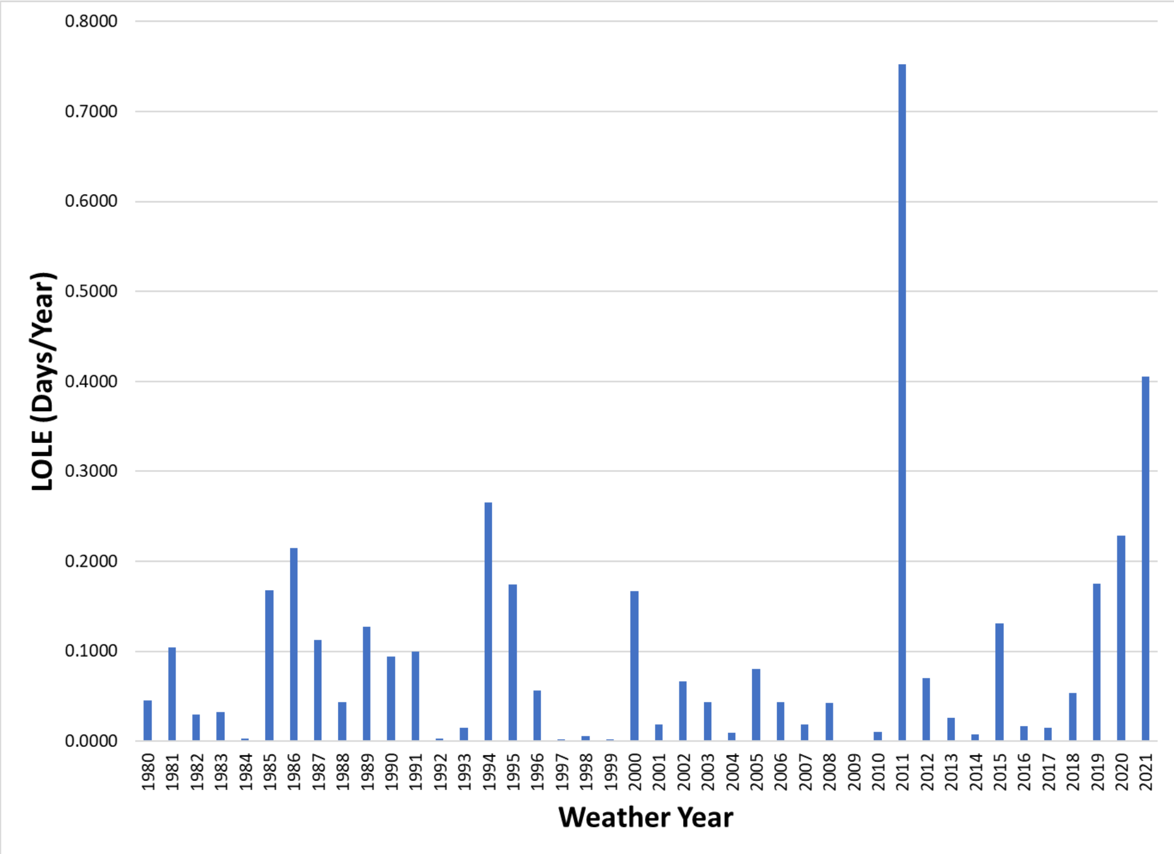

Figure 26. LOLE by Weather Year at PRM

As the figure shows, the worst weather year risk occurred in 2011. However, this does not correspond to the year with the most extreme temperatures. Rather, it corresponds to the year with the highest net load. In a high renewable penetration environment, it is net load rather than gross load that drives reliability need. This is demonstrated Figure 27 below. The weather year with the highest gross peak load is 2005. However, the year with the highest net peak load is 2011. A calculation was performed to determine the volume of reserves necessary to bring the 2011 weather year to 0.1 days/year LOLE. The result was the need for 30.3% planning reserves.

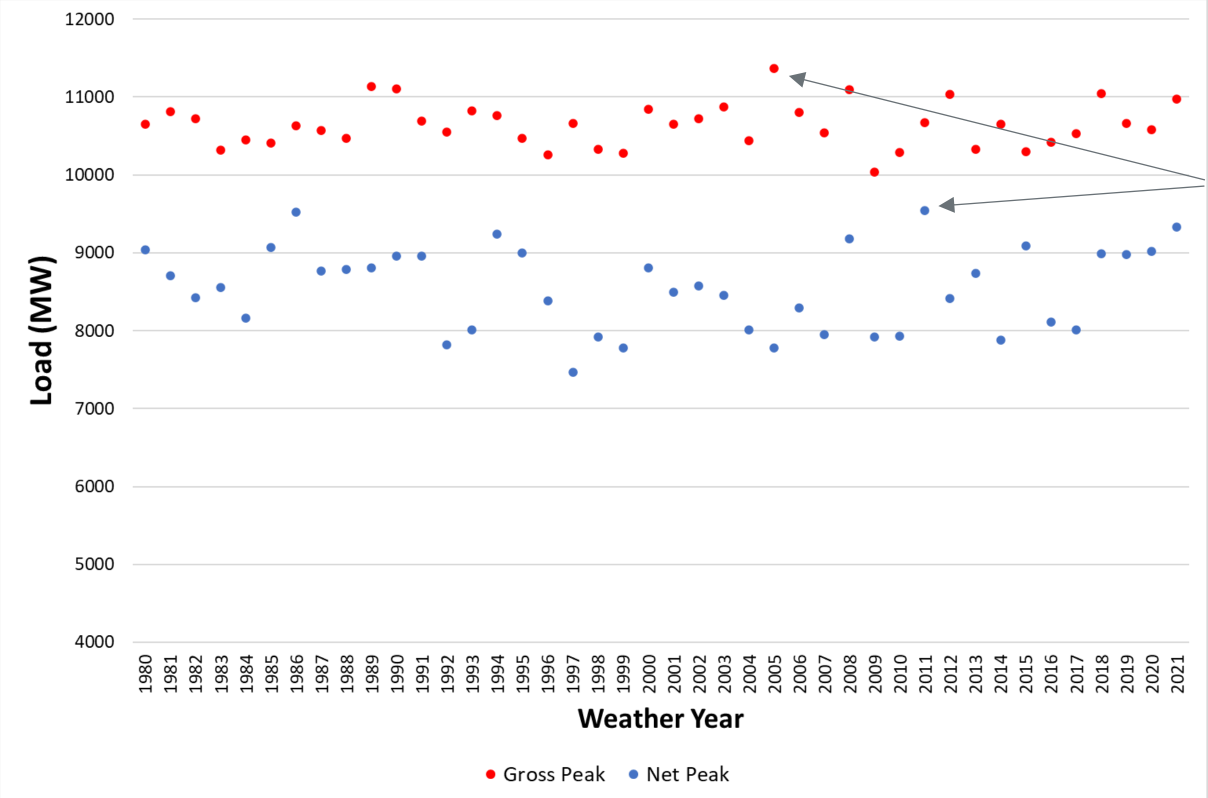

Figure 27. Net Peaks vs. Gross Peaks

To demonstrate the risk of loss of load by season, the Figure 28 below shows the breakdown of loss of load expectation by month. As the figure shows, most of the reliability risk occurs in the summer months, although there is some minimal risk of loss of load in almost every month. As electric heating load is expected to grow over time, the monthly distribution of risk will shift. With reliability risk spread across more months, a higher seasonal PRM will be required since each season will need to meet a more stringent standard than 0.1 LOLE for the annual LOLE to not exceed 0.1.

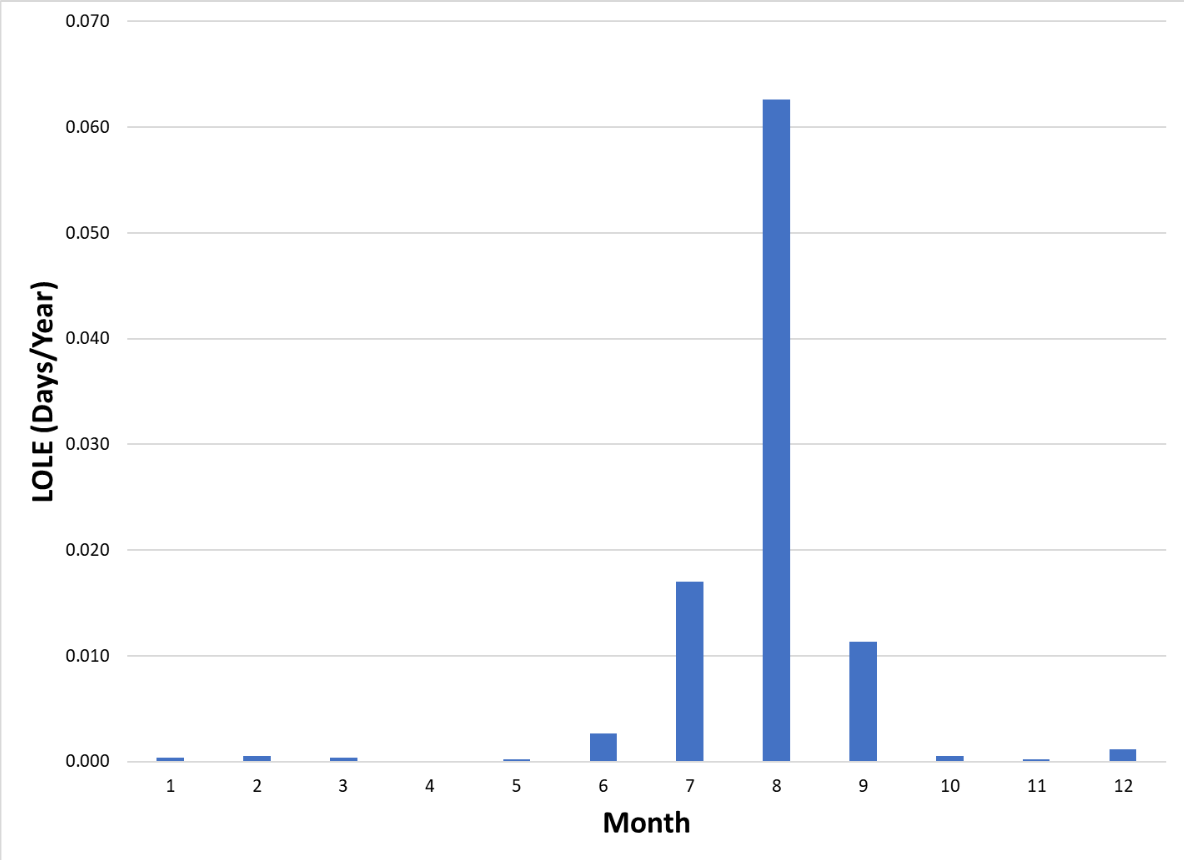

Figure 28. LOLE by Month at PRM

To establish the PRM based on the WECC recommendation of 0.0002 days/year LOLE in every hour, additional runs were made whereby a 12x24 assessment of the hourly LOLE was calculated for each run. Based on those runs, a PRM of 30.3% would be required. The table below shows the resulting 12x24 representation of the LOLE.

Table 13. 12x24 Representation of LOLE Using WECC Criteria

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
2	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
3	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
4	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
5	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
6	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
7	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
8	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
9	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
10	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
11	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
12	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
13	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
14	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
16	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
17	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.001%	0.000%	0.000%	0.000%	0.000%
18	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.001%	0.005%	0.000%	0.000%	0.000%	0.000%
19	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.003%	0.021%	0.005%	0.000%	0.000%	0.000%
20	0.000%	0.000%	0.000%	0.000%	0.000%	0.001%	0.006%	0.002%	0.001%	0.000%	0.000%	0.000%
21	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.001%	0.000%	0.001%	0.000%	0.000%	0.000%
22	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.001%	0.000%	0.000%	0.000%
23	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
24	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%

The table below shows Platte River's anticipated LOLE, Loss of Load Hours (LOLH), Loss of Load Probability (LOLP) and Expected Unserved Energy (EUE) in MWh at the recommended 19.9% PRM.

Table ES 6. Key Reliability Indices at PRM

LOLE	0.10 Days/Year
LOLH	0.14 Hours/Year
LOLP	0.0011
EUE	12.2 MWh

At 0.1 Days/Year LOLE, the LOLH of 0.14 Hours/Year translates to 1.4 Hours/Event.[35]

DIVERSITY CONSIDERATIONS

Because the PRM was calculated based on the entire regional market, it was necessarily calculated based on the coincident peak of all market participants. Because there is diversity between Platte River and the other participants in the market, consideration of the impacts of that diversity should be taken when planning the system to a non-coincident peak load forecast. Across the 42 weather years evaluated in this study, Platte River experienced a median diversity value of 2.2%. Because the PRM was calculated on a coincident peak load basis, this diversity would have the effect of lowering the forecasted peak load against which the PRM is applied by 2.2%. Thus, the resources required for maintaining a reliable system would be reduced by 2.2%.

[35] Event duration = LOLH/LOLE.

ACCOUNTING CONSIDERATIONS

The SERVM analysis performed for this study calculated the total number of effective megawatts required to maintain 0.1 days/year LOLE. Reserve margin is an accounting exercise premised on that determination and there are several ways in which that accounting may be derived. For example, traditional resources may be accounted for based on either their installed capacity or a value reduced by their EFORd. Some entities also variously treat resources such as DR, hydro, and purchased capacity on either the resource side (like was done for this study) or as a peak load adjustment. This accounting is not particularly critical so long as it is always treated consistently with how it was determined.

PRM RECOMMENDATION

Based on this analysis, a PRM in the 20% range is appropriate. However, even small changes in assumptions can have drastic impacts on PRM results. For example, Platte River's participation in the regional market makes its PRM highly dependent upon the support it gets from the market. Without that support, Platte River's PRM would be considerably higher. Any change in Platte River's ability to import capacity from the market from the assumptions used in this analysis would cause an increase in PRM. The PRM required to satisfy the WECC reliability criteria of 0.0002 hourly LOLP is 30.3%. While we do not recommend the WECC criteria, a reserve margin target range between 20-25% would provide some contingency to address potential risks not included in the base case assumptions.

TECHNOLOGY SPECIFIC ELCC

In addition to the portfolio wide ELCCs developed for purposes of calculating the PRM, technology specific ELCCs were developed for a series of 83 total scenarios. Phase I consisted of 47 scenarios that included a combination of solar and battery resources at the base case wind penetration of 6,280 MW of wind. The matrix in the table below shows the solar and battery combinations that were evaluated. These were all evaluated assuming the base case wind penetration of 6,280 MW.

Table 14. Solar and Battery ELCC Combination Scenarios

	4-Hr Battery Penetration						
Solar Penetration	0	500	1000	1500	2000	2500	3000
0	X	X	X	X	X	X	X
250	X						
500	X	X					
750	X	X	X				
1000	X		X				
1500	X		X	X			
2000	X		X	X			X
3000	X			X	X		

4000	X			X	X		
5000	X			X	X	X	
6000	X				X	X	X
7000	X			X	X	X	X
8000	X					X	X
9000	X		X			X	X

From these scenarios, marginal ELCCs for the full spectrum of solar and battery combinations were calculated (see results below).

Due to the large number of scenarios required and the fact that wind ELCC is generally more stable across penetrations of solar and battery, the number of wind-based scenarios was limited to three wind penetrations and three different solar and battery combinations (for a total of nine wind scenarios). The wind penetrations evaluated were 3,000 MW, 6,000 MW, and 9,000 MW and were calculated for the following solar and battery combinations:

a. the base case assumptions (5,700 MW of solar and 867 MW of battery),
b. 7,000 MW of solar and 2,000 MW of battery, and
c. 90,00 MW of solar and 1,000 MW of battery.

These results were trended and average and marginal ELCCs were calculated using the trend for a broad range of wind penetrations (see results below).[36]

In addition to the solar, 4-hour battery, and wind scenarios, several additional scenarios were evaluated as follows.

1. Three 8-hour battery scenarios plus a reference using base case modeling assumptions as the underlying system (*i.e.*, incremental to the base case battery penetration), including:
    a. 500 MW,
    b. 1,000 MW, and
    c. 1,500 MW.
2. Three 100-hour battery scenarios using the same reference as the 8-hour batteries, including:
    a. 500 MW,
    b. 1,000 MW, and
    c. 1,500 MW.
3. Four distributed solar scenarios plus a reference using the base case without distributed solar as the underlying system, including:
    a. 500 MW,

[36] ELCCs tend to follow reasonably predictable trends across increasing penetrations. Thus, fewer scenarios can be evaluated, reducing project cost while still providing results across a meaningful range of penetrations. Smoothing and trending a series of discrete ELCC calculations, therefore, allows for the ability to accurately interpolate results at penetrations not specifically studies. In addition, it dampens/removes some of the noise that exists naturally within stochastic evaluations like these.

    b. 1,000 MW,
    c. 2,000 MW, and
    d. 4,000 MW.
4. Three BBE scenarios plus a reference using the base case without BBE as the underlying system, including:
    a. 100 MW,
    b. 200 MW, and
    c. 300 MW.
5. Three EV scenarios plus a reference using the base case without EV as the underlying system, including:
    a. 100 MW,
    b. 200 MW, and
    c. 300 MW.
6. Three DR scenarios plus a reference using the base case without DR as the underlying system, including:
    a. 100 MW,
    b. 200 MW, and
    c. 300 MW.

The market-wide base case modeling assumptions for solar, wind, and 4-hour batteries for these scenarios were as follows:

- Solar – 5,700 MW
- Wind – 6,204 MW
- Battery – 867 MW

For purposes of ELCC calculations, the demand response scenarios were calculated for a summer only program that may be called four hours per day, 3 days per week, with a maximum of 12 calls per year.

For all scenarios, the results were trended. Using the trend, average and marginal ELCCs were calculated for a broad range of penetrations.

ELCC METHODOLOGY

To determine the average ELCC for each of these scenarios, each scenario was evaluated in accordance with the following steps.

1. Develop a reference case for the scenario set (i.e., all the phase 1 solar/battery scenarios used the same reference case)
    a. Remove the technology class(es) being evaluated (e.g., remove all existing solar and battery resources).
    b. Iteratively add back perfect capacity until system returns to 0.1 days/year LOLE.
2. For each scenario, add back the penetration of the technology class(es) being evaluated (e.g., for the 0 battery/250 solar scenario, add back 250 MW of solar).

3. Iteratively add load until the system returns to 0.1 days/year LOLE.
4. Divide the total amount of capacity added by the total amount of load added to get the average ELCC for the scenario.

SOLAR AND BATTERY ELCC SCENARIO RESLUTS

The table below shows the average scenario ELCC for each of the 47 solar/battery combination scenarios. All of these scenarios, along with the expanded dense matrix results that follow, were calculated assuming base case market-wide wind penetration assumptions of 6,204 MW.

Table 15. Solar and Battery Scenario Average ELCC Results

	4-Hr Battery Penetration						
Solar Penetration	**0**	**500**	**1000**	**1500**	**2000**	**2500**	**3000**
0		90.4%	82.6%	75.7%	64.4%	56.7%	47.5%
250	77.3%						
500	72.2%	84.3%					
750	69.4%	80.7%	79.3%				
1000	66.2%		76.7%				
1500	58.7%		70.1%	67.1%			
2000	55.0%		65.9%	64.4%			52.3%
3000	45.0%			56.9%	55.2%		
4000	37.6%			48.8%	49.0%		
5000	31.9%			43.1%	44.1%	43.8%	
6000	28.3%				39.8%	40.0%	39.4%
7000	24.8%			35.1%	36.3%	36.8%	36.7%
8000	22.0%					34.4%	34.1%
9000	20.2%		26.7%			31.8%	32.4%

Using a process called pyramid smoothing, the sparse matrix above was expanded into a dense matrix of average ELCCs for solar and wind combinations. The resulting dense matrices of marginal solar and marginal battery ELCCs are too large to be included in this report. The figure below shows a surface plot of the total capacity value for solar penetrations up to 9,000 MW combined with battery penetrations up to 3,000 MW. To determine the combined solar plus battery capacity for any combination of solar and battery penetrations on the system, find the point on the surface associated with that combination of penetrations. The table following the surface plot shows a subset of the actual capacity values as taken from the surface.

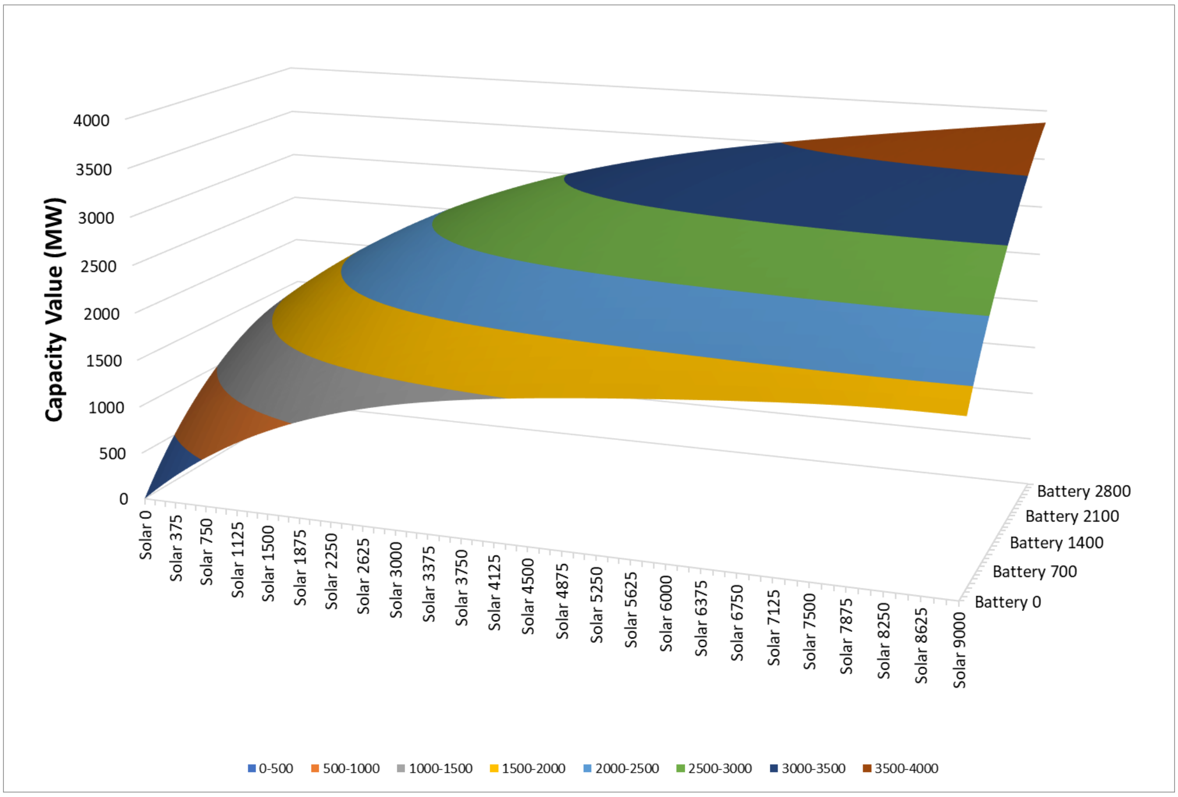

Figure 29. Surface Plot of Solar/BESS Capacity Values

Table 16. Subset of Solar/Wind Capacity Values

Solar Penetration	Battery Penetration: 0	500	1,000	1,500	2,000	2,500	3,000
0	0	461	806	1,062	1,246	1,358	1,390
1,000	648	1,111	1,456	1,709	1,888	1,993	2,016
2,000	1,057	1,535	1,893	2,158	2,347	2,460	2,490
3,000	1,308	1,804	2,179	2,463	2,669	2,801	2,846
4,000	1,464	1,974	2,366	2,668	2,894	3,048	3,117
5,000	1,571	2,088	2,490	2,807	3,052	3,229	3,325
6,000	1,655	2,171	2,578	2,905	3,167	3,366	3,491
7,000	1,727	2,235	2,642	2,977	3,254	3,476	3,631
8,000	1,776	2,276	2,683	3,027	3,321	3,569	3,758
9,000	1,785	2,283	2,693	3,049	3,368	3,649	3,880

From that dense matrix of capacity values marginal solar ELCCs as a function of battery were calculated. Because the dense matrix is too large to be included in this report, the surface plot in the figure below is a visual representation of the resulting marginal solar ELCC results.

From the full matrix of capacity values, marginal solar and marginal battery ELCCs were calculated. The figure below shows the surface plot of the marginal solar ELCC as a function of battery penetration. To determine the marginal solar ELCC for any combination of solar and battery penetrations on the system, find the point on the surface associated with that combination of penetrations. The table following the surface plot shows a subset of actual marginal solar ELCCs as taken from the surface.

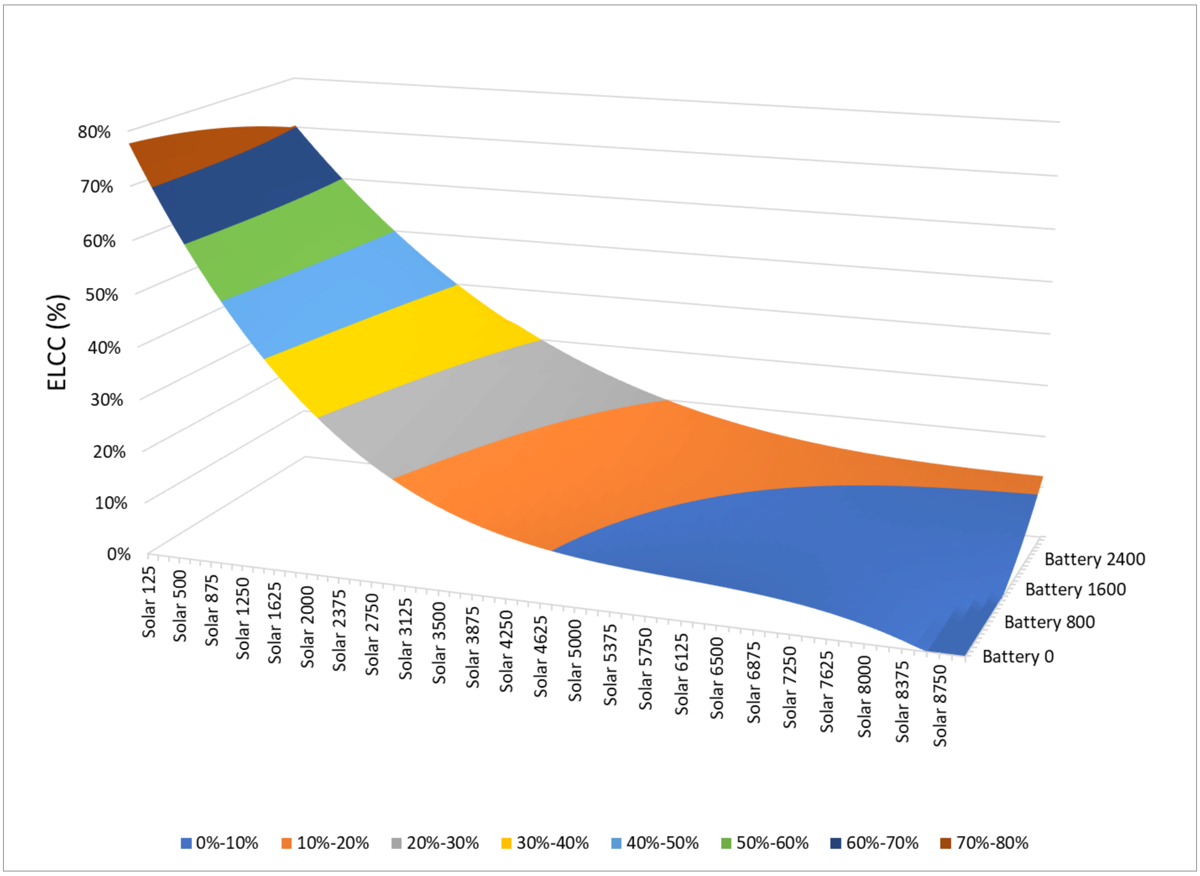

Figure 30. Marginal Solar ELCC

Table 17. Subset of Marginal Solar ELCCs

Solar Penetration \ Battery Penetration	-	500	1,000	1,500	2,000	2,500	3,000
1,000	52.8%	53.8%	54.5%	55.1%	55.4%	55.5%	55.4%
2,000	32.8%	34.5%	36.2%	37.8%	39.2%	40.6%	41.6%
3,000	20.1%	21.8%	23.6%	25.4%	27.4%	29.4%	31.6%
4,000	12.9%	14.0%	15.4%	17.1%	19.1%	21.4%	24.0%
5,000	9.4%	9.7%	10.5%	11.8%	13.6%	15.9%	18.6%
6,000	7.8%	7.4%	7.6%	8.5%	10.1%	12.3%	15.2%
7,000	6.4%	5.6%	5.5%	6.2%	7.8%	10.1%	13.3%
8,000	3.4%	2.7%	2.9%	3.9%	5.9%	8.7%	12.4%
9,000	0.0%	0.0%	0.0%	0.7%	3.7%	7.5%	12.2%

The marginal solar ELCC values decline with increased penetrations of solar because the incremental solar additions move the system "net peak" further out into the evening until such time that the net peak occurs after the sun has set. At that point, the marginal solar ELCC approaches zero. However, the synergies associated with adding battery resources to the solar resources cause an increase in marginal solar ELCC with increasing battery penetration. Both effects are evident on the surface plot as the slope decreases with increasing solar penetration and increases with increasing battery penetration. This demonstrates the complex nature of the synergistic (or sometimes antagonistic) relationship between solar and storage ELCCs. Various combinations of solar and storage may either flatten the load shape or sharpen (make the peak steeper) the load shape. These changes in net load shape can either cause increases or decreases in the ELCC. For example, small penetrations of solar may flatten the net load shape, causing a decrease in the battery ELCC (antagonistic relationship). On the other hand, larger penetrations of solar will create sharper, more peaky net load shapes, causing an increase in the battery ELCC (synergistic relationship).

Figure 31 below shows the surface plot of the marginal 4-hour battery ELCC as a function of solar penetration. To determine the marginal battery ELCC for any combination of solar and battery penetrations on the system, find the point on the surface associated with that combination of penetrations. The table following the surface plot shows a subset of actual marginal solar ELCCs as taken from the surface.

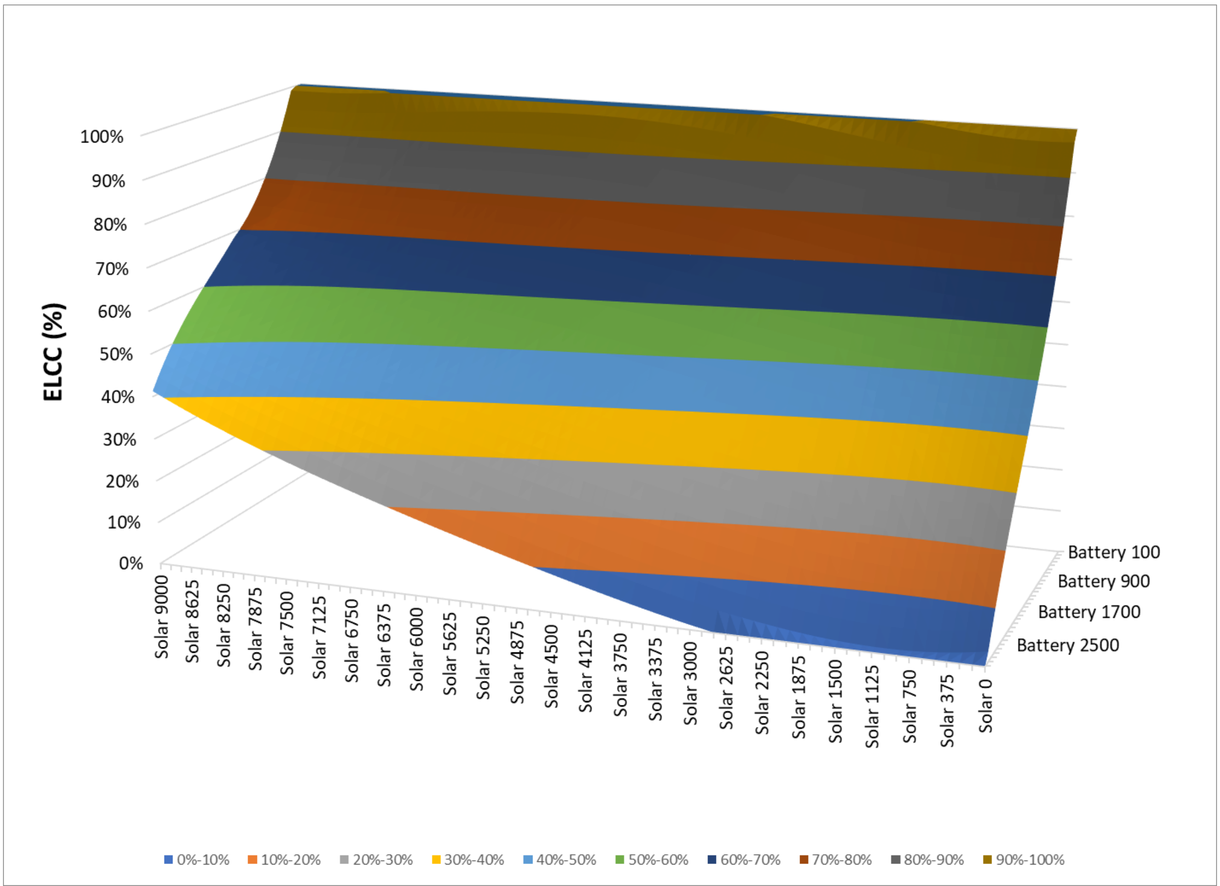

Figure 31. Marginal Battery ELCC

Table 18. Subset of Marginal Battery ELCCs

Battery Penetration	Solar Penetration: 1,000	2,000	3,000	4,000	5,000	6,000	7,000	8,000	9,000
100	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
500	82.0%	84.9%	88.4%	91.4%	93.1%	93.3%	92.4%	91.4%	91.3%
1,000	60.9%	63.5%	67.0%	70.4%	72.9%	74.3%	74.9%	75.6%	76.7%
1,500	44.4%	46.7%	50.2%	54.0%	57.3%	59.9%	62.1%	64.5%	68.3%
2,000	29.9%	31.8%	35.4%	39.6%	43.7%	47.5%	51.1%	55.3%	60.9%
2,500	14.7%	16.3%	19.9%	24.5%	29.4%	34.4%	39.6%	45.4%	52.7%
3,000	0.0%	0.0%	1.1%	6.1%	11.8%	18.0%	24.6%	32.2%	41.3%

As with marginal solar ELCC, marginal battery ELCC declines with increased penetrations of battery. For batteries, this decline is the result of a flattening of the overall net peak, making incremental additions of battery resources less effective. This decline decreases until a 4-hour battery can no longer contribute to improving reliability. However, the synergies associated with adding solar resources to the battery resources cause an increase in marginal battery ELCC with increasing solar penetration. Both effects are evident on the surface plot as the slope decreases with increasing battery penetration and increases with increasing solar penetration. Note: The orientation of the surface plot has been arranged so that the slope is visually evident.

WIND ELCC SCENARIO RESULTS

The table below shows the average scenario ELCC for each of the 9 wind scenarios.

Table 19. Wind Scenario Average ELCC Results

Wind Penetration	Base Case 5700 Solar 867 Battery	7000 Solar 2000 Battery	9000 Solar 1000 Battery
3000	23.8%	21.9%	22.6%
6000	16.6%	16.0%	15.9%
9000	13.1%	13.1%	12.9%

These results were trended and marginal wind ELCCs were calculated as shown in the figure below.

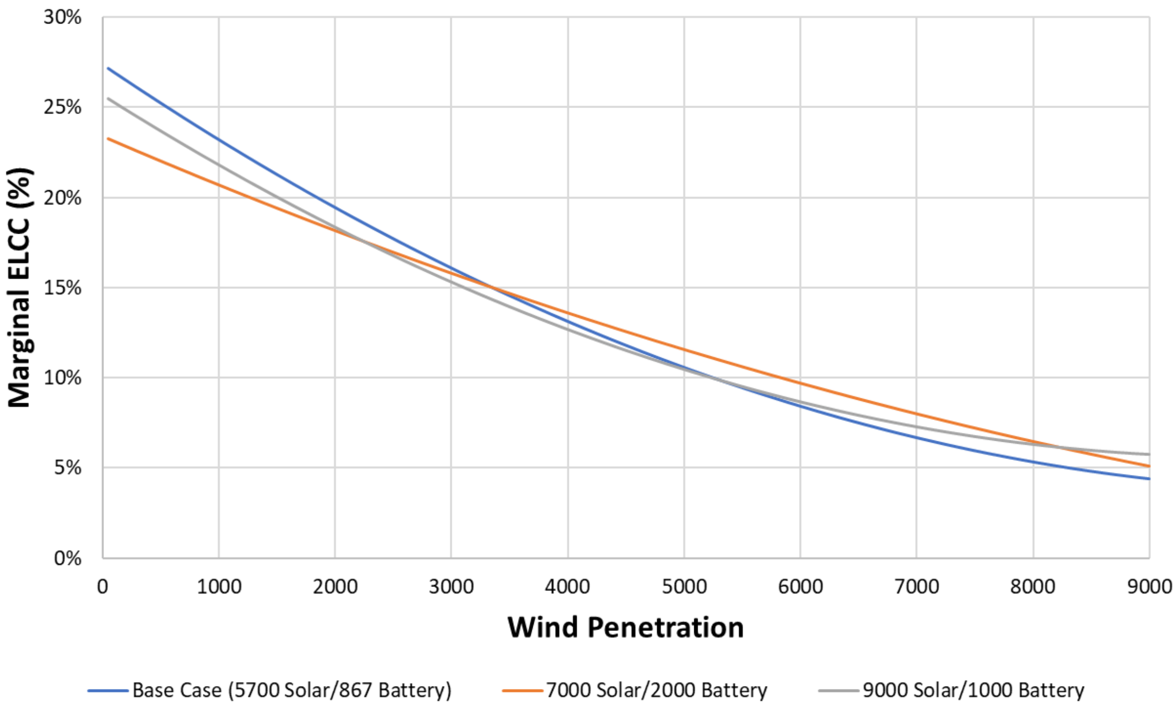

Figure 32. Marginal Wind ELCC Results

ADDITIONAL ELCC SCENARIO RESULTS

For the additional sets of scenarios, each set of scenarios were evaluated then trended. The market-wide base case modeling assumptions for solar, wind, and 4-hour batteries for these scenarios were as follows:

- Solar – 5,700 MW
- Wind – 6,204 MW
- Battery – 867 MW

The table below shows the trended average and marginal ELCCs for each scenario.

Table 20. Additional ELCC Scenarios

Technology	Penetration (MW)	Average ELCC (%)	Marginal ELCC (%)
8-hour batteries	500	92.7%	91.6%
8-hour batteries	1000	90.5%	84.4%
8-hour batteries	1500	87.0%	75.6%
100-hour batteries	500	92.7%	91.6%
100-hour batteries	1000	91.9%	90.8%
100-hour batteries	1500	91.4%	90.0%
DG Solar	500	8.5%	7.9%
DG Solar	1000	8.0%	7.2%

DG Solar	2000	7.2%	5.8%
DG Solar	4000	5.8%	2.9%
BBE	100	6.9%	7.4%
BBE	200	7.3%	8.2%
BBE	300	7.8%	9.0%
EV	100	32.0%	33.6%
EV	200	33.8%	37.3%
EV	300	35.7%	41.0%
DR	100	92.3%	87.3%
DR	200	87.1%	77.8%
DR	300	82.6%	70.4%

The following two graphs show the trended ELCC results for the 8-hour and 100-hour batteries, respectively.

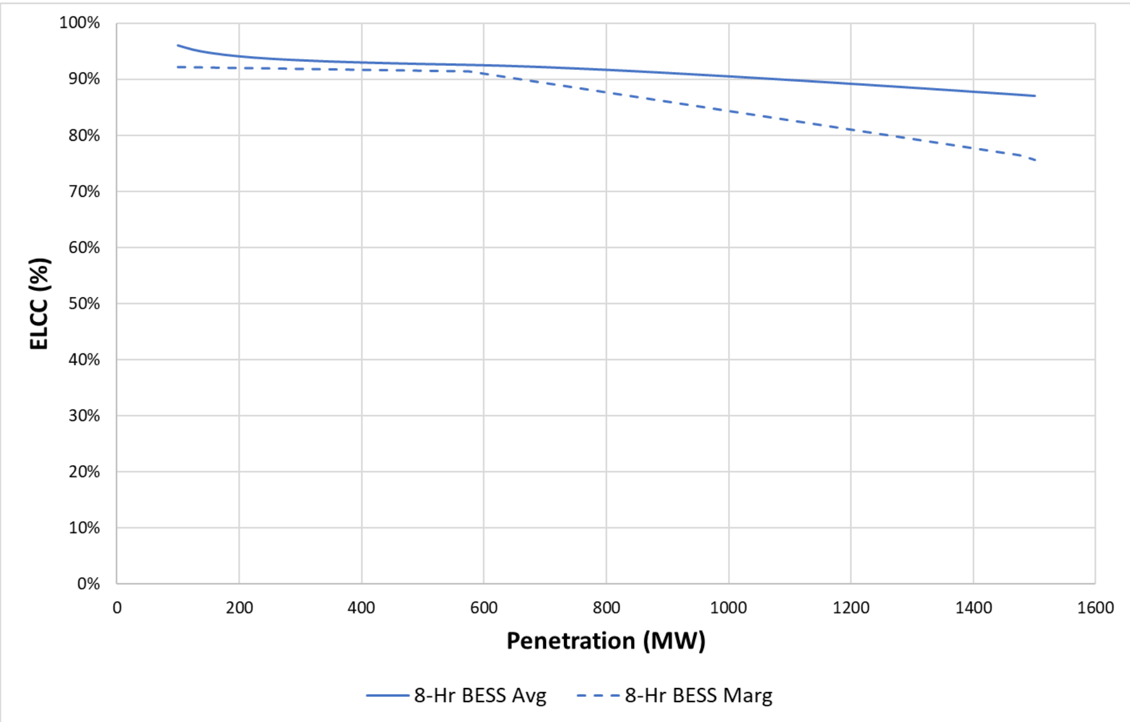

Figure 33. 8-Hour BESS ELCC Results

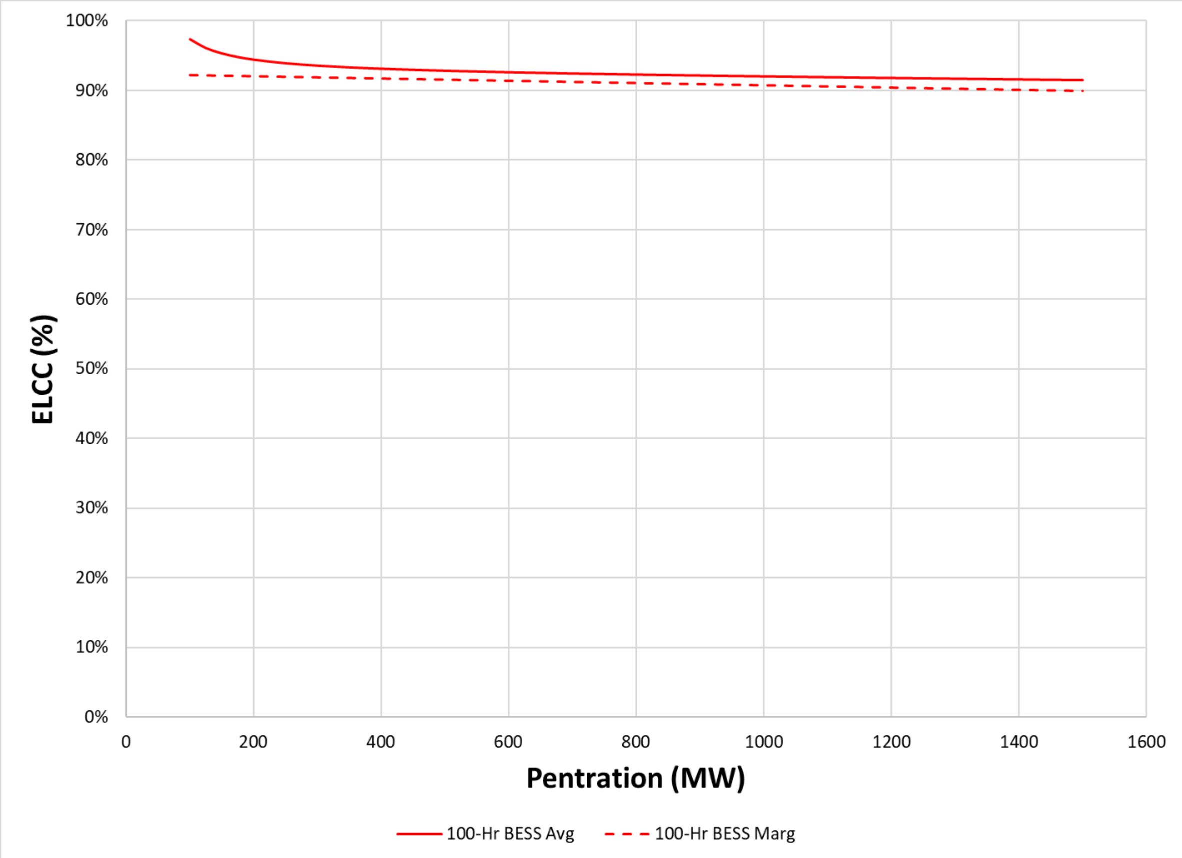

Figure 34. 100-Hour BESS ELCC Results

However, given the underlying penetration of batteries (867 MW), it would be more appropriate to show these ELCC values with an 867 MW shift in penetration. The figure below shows this shift and compares the results of the 8-hour and 100-hour batteries with the results of the 4-hour batteries assuming no solar penetration.

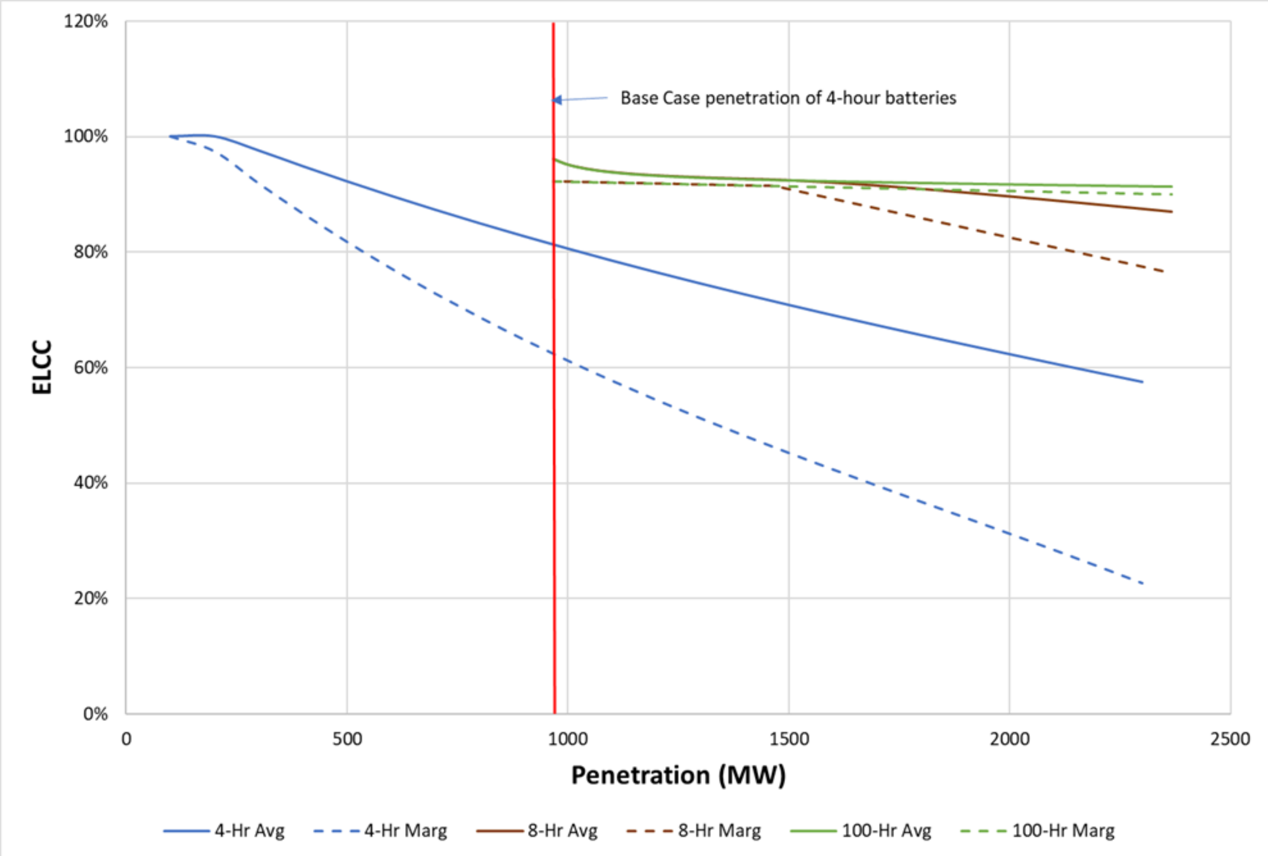

Figure 35. Comparison of Battery ELCC Results

As the graph indicates, 8-hour and 100-hour batteries decline in value at a significantly slower rate than 4-hour batteries. This is primarily a function of the net load shape at the penetrations of assumed solar and wind. High solar penetrations create a net load shape with a sharper (i.e., more needle-nosed) peak, which causes batteries to decline in value at a slower rate. Wind penetrations can flatten net load shapes, which create an antagonistic affect that causes batteries to decline in value at a higher rate. At the base case assumptions for wind and solar, 4-hour batteries decline rapidly, while 8-hour batteries maintain their value much longer.

The figure below shows the trended ELCC results for distributed generation solar.

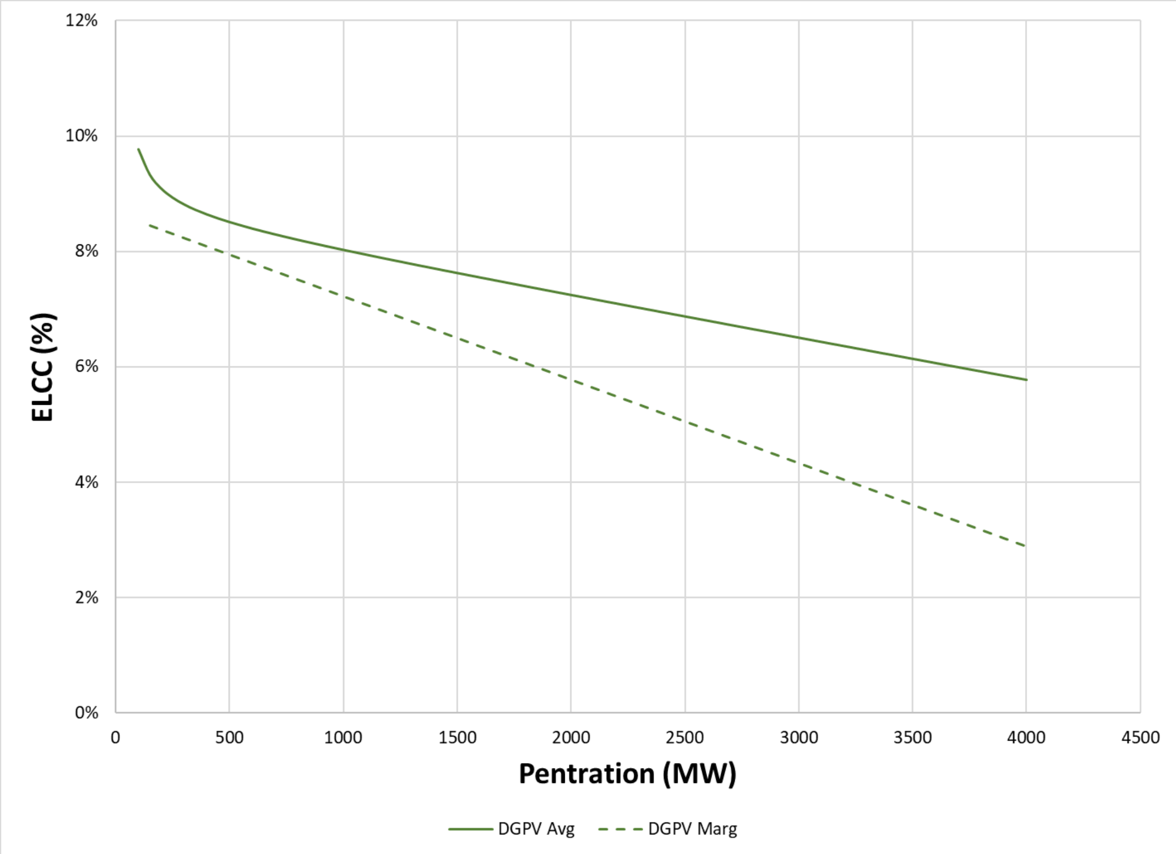

Figure 36. DG Solar ELCC Results

The following figure shows the trended ELCC results for demand response.

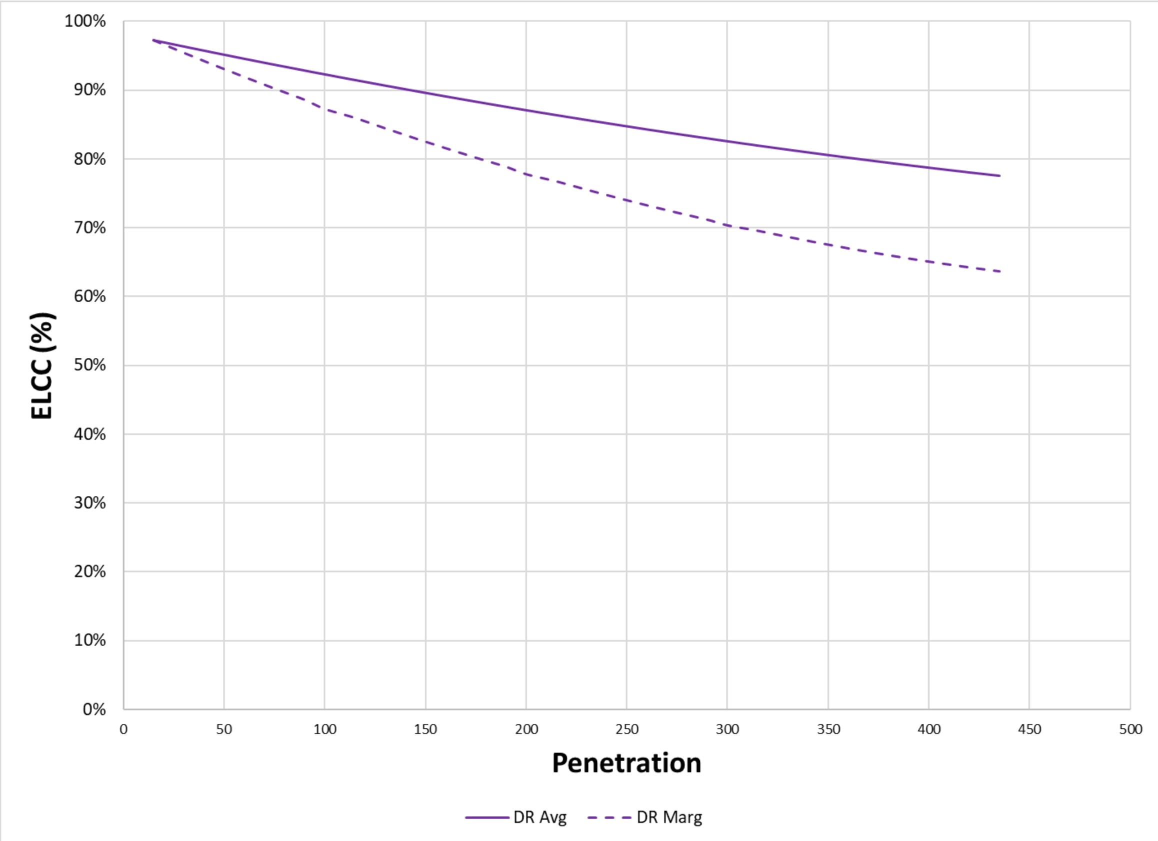

Figure 37. Demand Response ELCC Results

The high DR ELCCs relative to 4-hour batteries are due primarily to the fact that the model calls storage before it calls DR. For energy limited resources such as DR and storage, the longer the resource is held in reserve before being called, the greater its overall capacity value will be. Having 4-hour batteries called prior to 4-hour DRs will preserve the DR and thus increase its relative capacity value. This ordering is appropriate given that storage can be recharged but DR cannot be recharged. Thus, it is likely that this curtailment order is such that the frequency of DR calls is not exceeding its calls per year limit, which further boosts its value. A reversing of the curtailment order between storage and DR would result in DRs being called first, resulting in its exhaustion of yearly calls. This scenario, while not recommended, would have the effect of storage having a higher capacity value than DR. While the reported ELCCs are not wrong as modeled, it may be prudent to consider the possibility of calculating a weighted average between the battery ELCCs and the DR ELCCs and applying that weighted average to both technologies.

The following two graphs show the trended ELCC results for the two incremental load categories, Building Better Electrification and Electric Vehicle Charging, respectively.

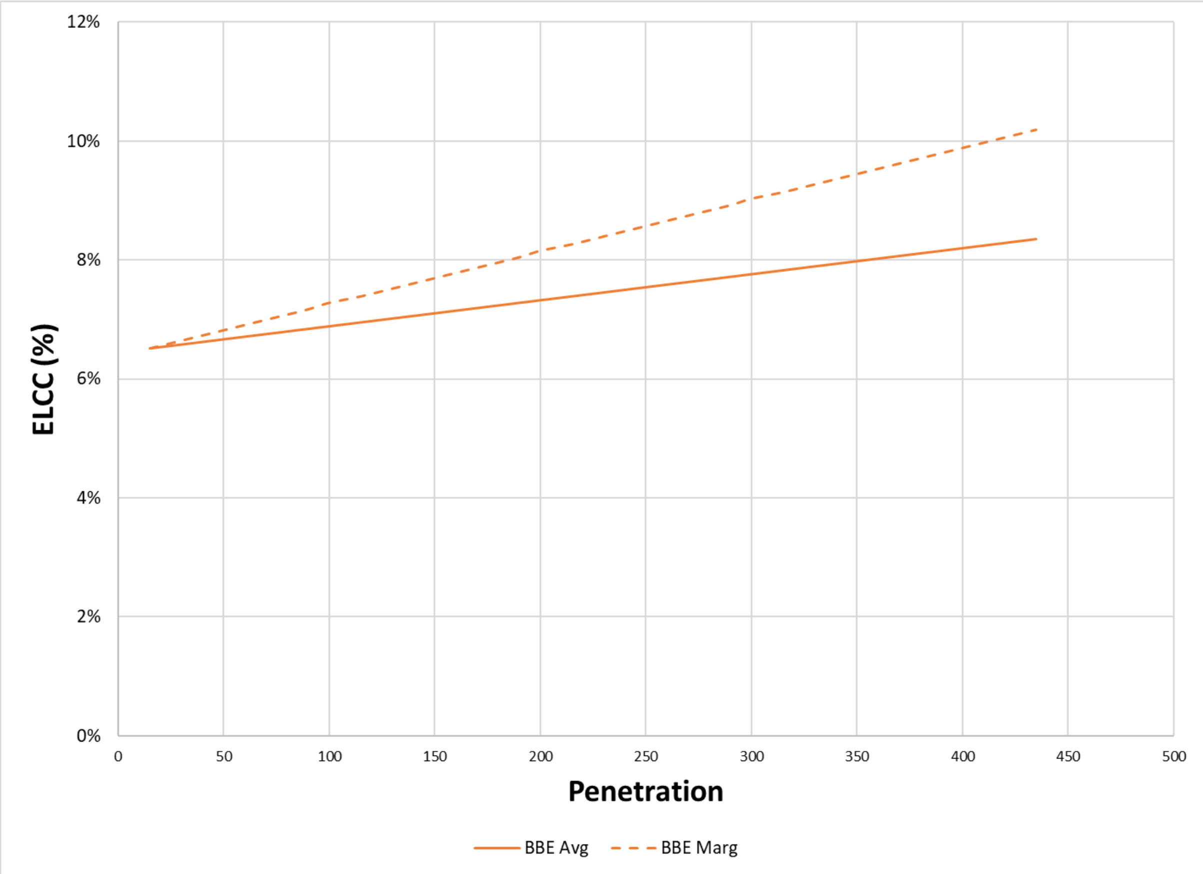

Figure 38. BBE ELCC Results

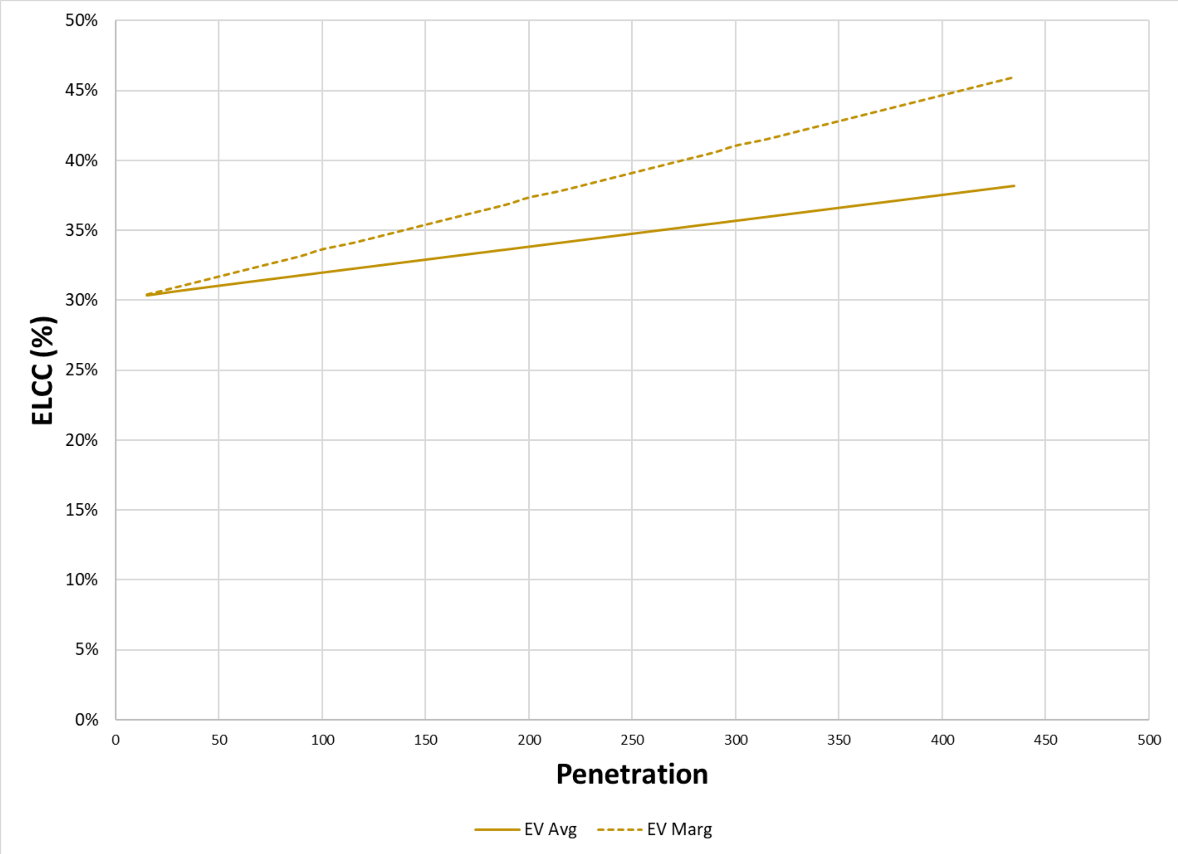

Figure 39. EV Charging ELCC Results

Unlike the ELCCs for renewable or demand response resources, the ELCCs for incremental load categories like BBE and EV are monotonically increasing. These ELCCs represent the amount of capacity necessary to reliably serve the incremental load. Because its load shape is so distinct from the aggregate load shape of the system, the requirement to serve these loads does not conform to the PRM established in this analysis. Thus, when determining the amount of capacity that is needed to reliably serve load, these requirements should be determined independently from the "business as usual" load.

CONCLUSIONS

Upon examination of the study analysis, a PRM in the range of 20-25% is warranted. While alternate standards proposed by WECC suggest a PRM as high as 30.3%, we believe a 20-25% PRM range adequately balances reliability needs and economic considerations.

Both average and marginal ELCC results for Platte River can vary greatly depending upon the timing, penetration, and mix of renewable resources added by the neighboring utilities. However, based on the assumed base case modeling mix and penetrations, Platte River's current 2030 plan is reliable against a 20% PRM that is based on the 1 day in 10 standard. This is true whether average or marginal ELCC assessments are applied. However, against the WECC criteria, the reliability of the plan is less certain and depends greatly upon the assumed build-out of the other market participants and the resulting ELCCs accredited to Platte River.

Regarding the ELCCs associated with the load modifications, it is recommended that these ELCCs be used when establishing the forecasted peak load against which the PRM will be applied. Using a peak-hour only adjustment to the forecasted peak load may not adequately establish the reliability requirements for these load classifications. Using the ELCC of these loads rather than the peak contribution will ensure that the proper number of resources are being added to the system to reliably serve these additions.

APPENDIX

The following contains additional detail regarding various input parameters used in this analysis.

Technology Curves

The technology curve used for the existing Rawhide CTs was based on generic information from the industry and is shown in the figure below.

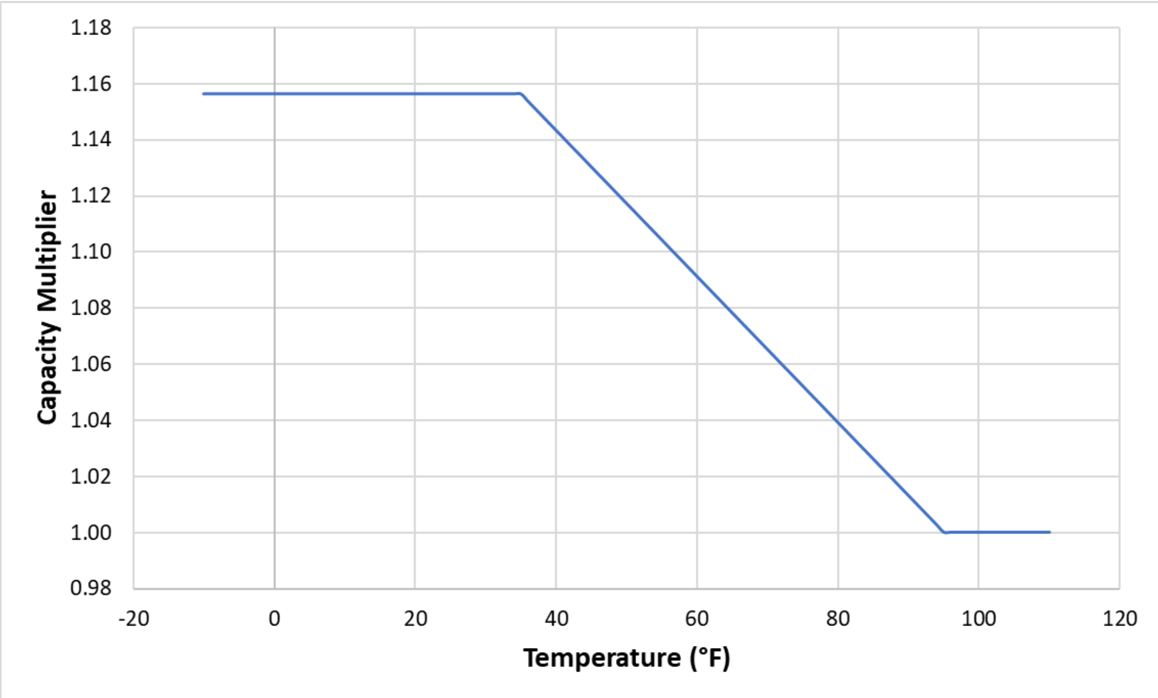

Figure 40. Rawhide CT Ambient Temperature Multipliers

The ambient temperature multiplier curve for the new LMS 100 CT was provided by Platte River and is shown in the figure below.

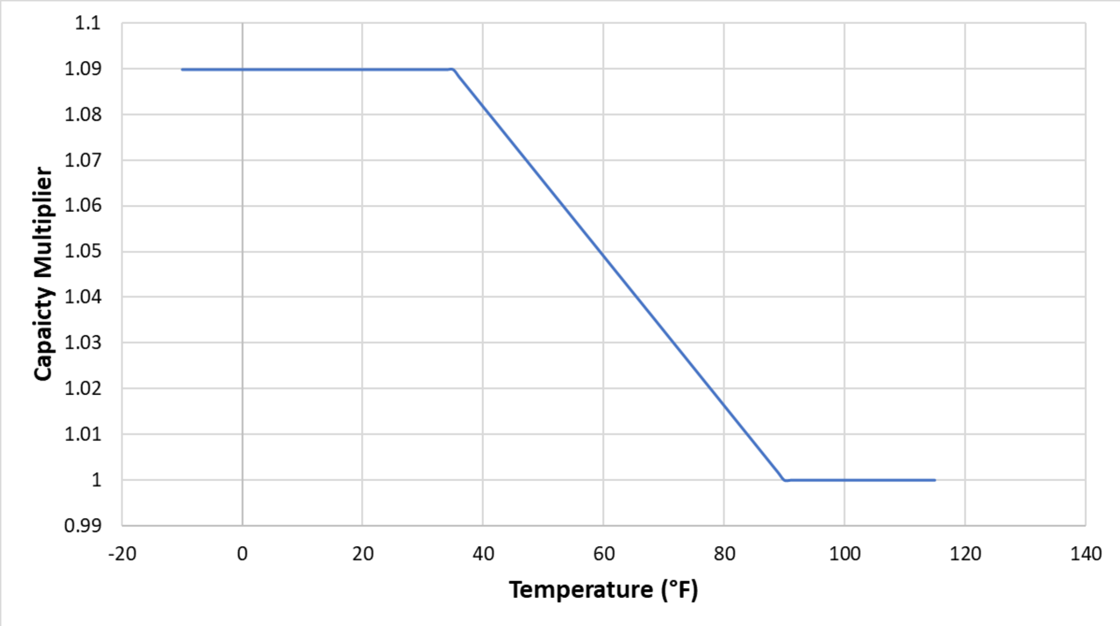

Figure 41. LMS 100 CT Ambient Temperature Multipliers

Solar Modeling

The table below shows the GPC coordinates for each of the eight sites used to model solar facilities in Colorado.

Table 21. Solar Model Coordinates

Location	GPS Coordinates	
North Central Colorado	40.93	-105.1
Denver, Colorado	39.73	-104.98
Buyers, Colorado	39.61	-104.34
Colorado Springs, Colorado	38.81	-104.7
Pueblo, Colorado	38.25	-104.5
Hartsel, Colorado	39.01	-105.82
Alamosa, Colorado	37.57	-105.86
Calhan, Colorado	38.97	-104.26

The figures below show the winter average solar profiles for tracking and fixed axis solar technologies.

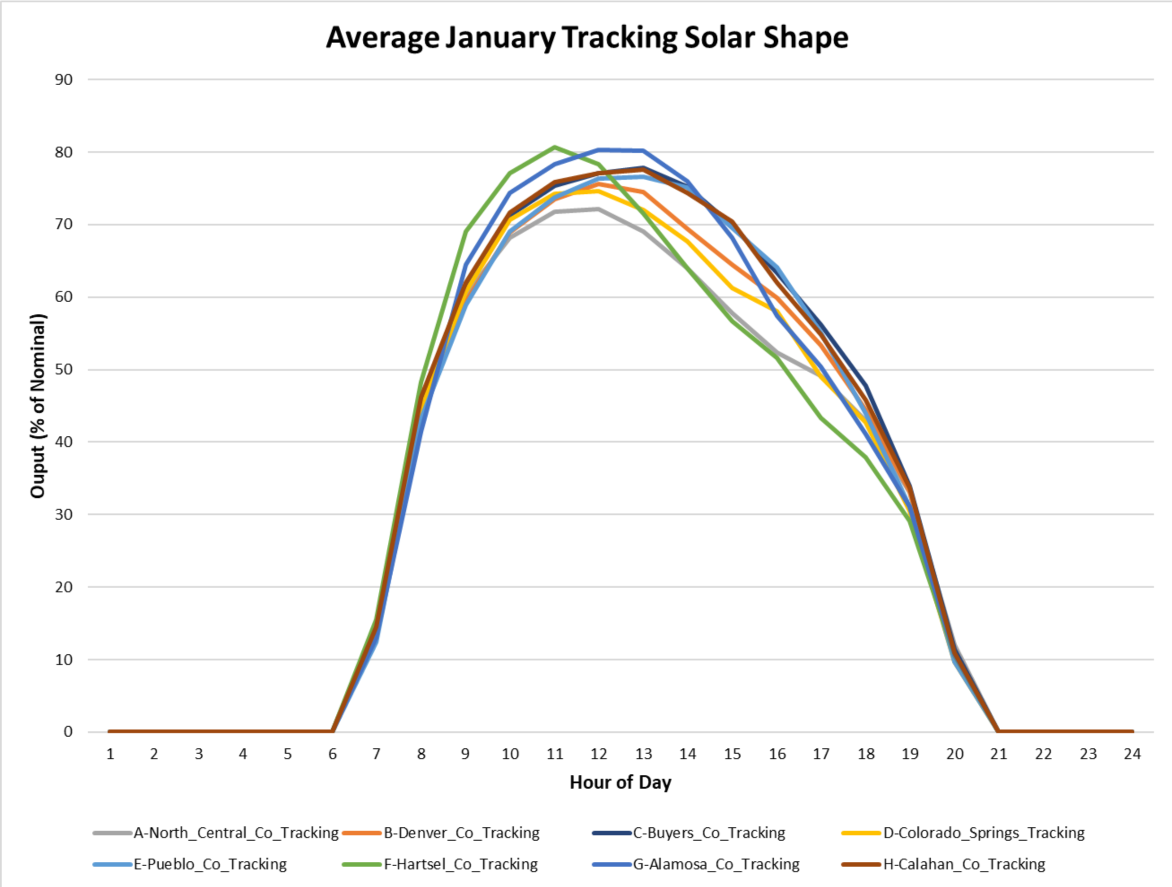

Figure 42. Average Winter Tracking Solar Profile

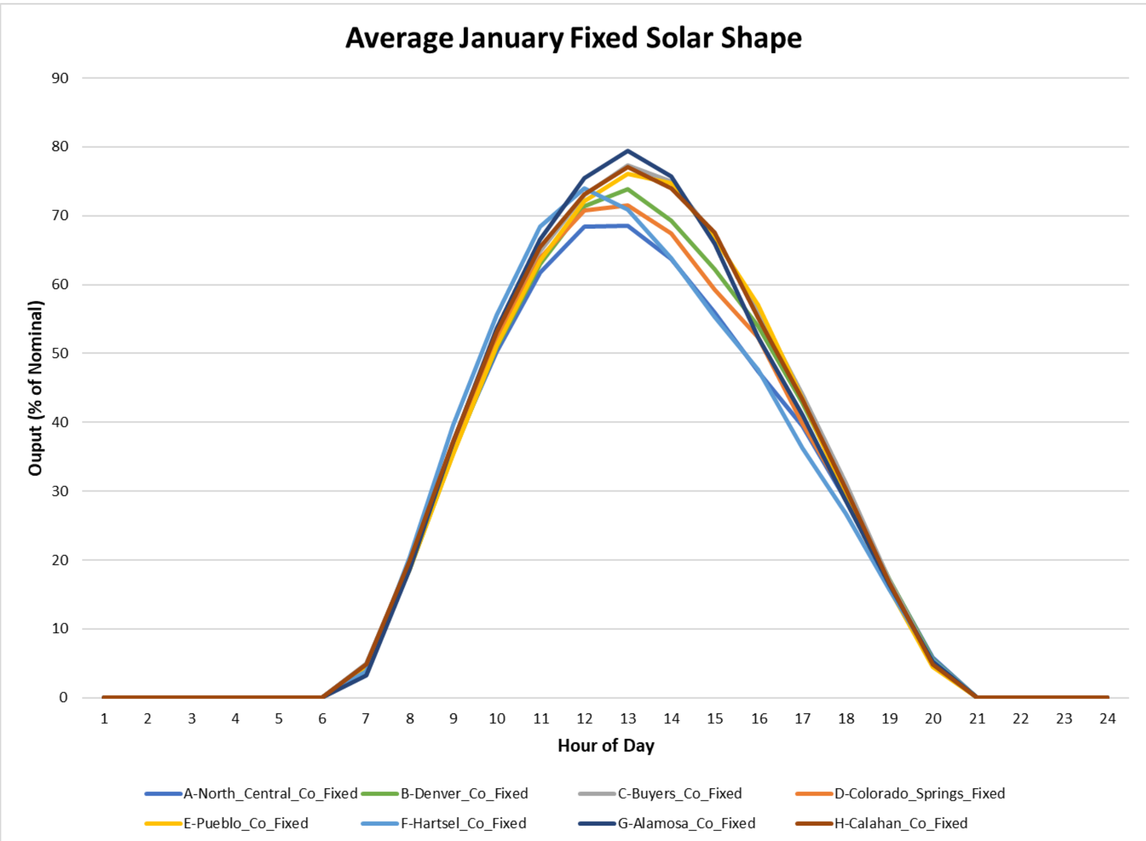

Figure 43. Average Winter Fixed Axis Solar Profile

The resulting average capacity factors (in %) for each site across all weather years are shown in the table below.

Table 22. Solar Site Average Capacity Factors

Solar Site	Fixed	Tracking
A-North_Central_Co	17.6	22.2
B-Denver_Co	18.4	23.1
C-Buyers_Co	18.8	23.7
D-Colorado_Springs	18.9	23.8
E-Pueblo_Co	19.1	24.0
F-Hartsel_Co	19.7	25.0
G-Alamosa_Co	20.5	26.0
H-Calhan_Co	19.4	24.4

Inverter loading Ratio-adjusted capacity factors for Platte River specific solar projects are shown in the table below.

Table 23. Platte River Solar Project Capacity Factors

Solar Project	Capacity Factor (%)
Rawhide Flats	23
Rawhide Prairie	28
NTRFP Solar	28
Future Solar	28
DG Solar	14

Wind Modeling

The table below shows the GPC coordinates for each of the six sites used to model wind facilities in Colorado.

Table 24. Wind Model Coordinates

Location	LONG	LAT
Northeast Colorado	40.73	-102.95
East Colorado	39.06	-103.37
Southeast Colorado	37.79	-102.63
Northern Colorado	40.92	-105.06
Central Colorado	39.04	-104.3
Southern Colorado	37.68	-104.63

The figure below shows the winter average wind profile for each location.

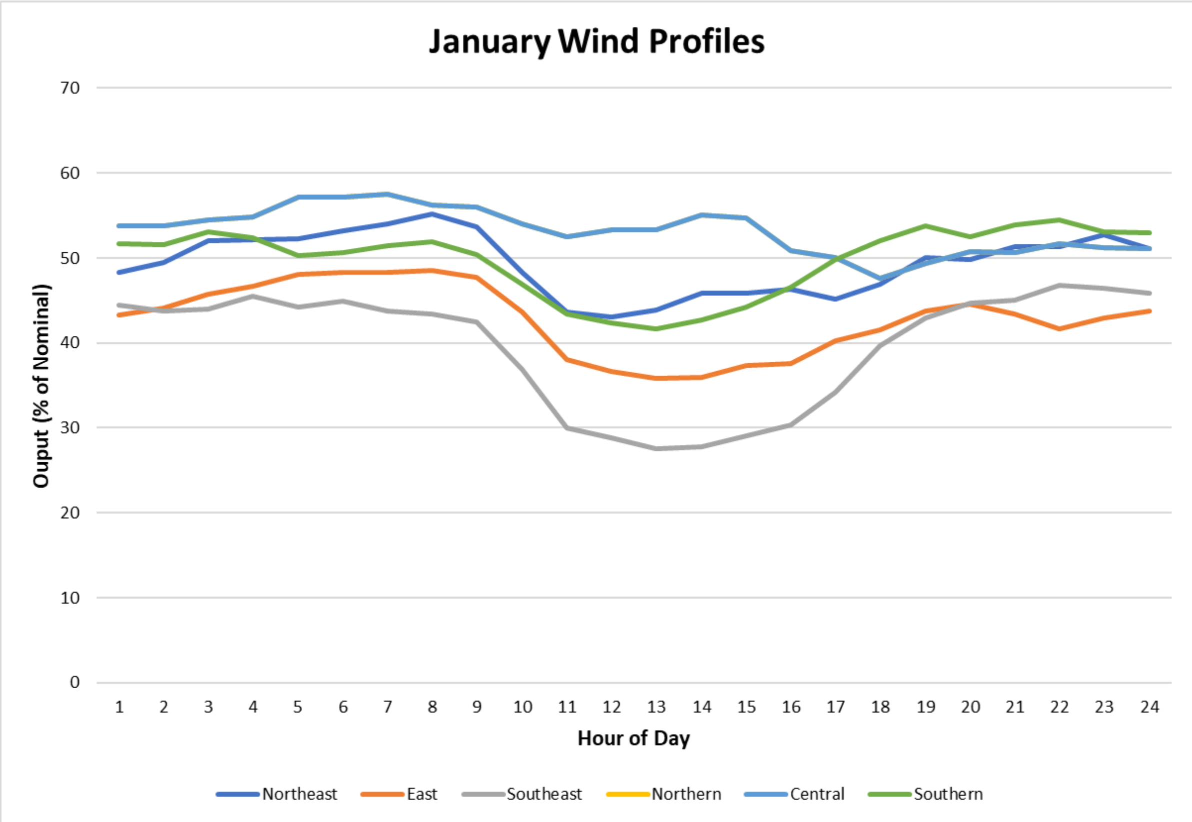

Figure 44. January Wind Output Profiles

The table below shows the final resulting capacity factors for each of the six modeled wind locations.

Table 25. Wind Profile Capacity Factors

Location	Capacity Factor (%)
Northeast	44.3
East	44.1
Southeast	43.6
Northern	43.6
Central	43.6
Southern	43.7

The table below shows the final resulting capacity factors for the Platte River wind projects after applying final inverter loading ratio adjustments.

Table 26. Platte River Wind Project Capacity Factors

Resource	Capacity Factor (%)
Medicine Bow	33.0
Spring Canyon	43.5
Roundhouse	42.5
Future Wind	40.0

Regional Market Resource List

The following table contains the full list of resources included in the regional market. The list is shown "as assumed" prior to inclusion of any generic reliability resources necessary to achieve PRM.

Table 27. Regional Market Resource List

Unit Name	Unit Category	Capmax	Region
AC Rewards	DR	68	PSCO
Airport Industrial IC1	CT	2.5	BHC
Airport Industrial IC2	CT	2.5	BHC
Airport Industrial IC3	CT	2.5	BHC
Airport Industrial IC4	CT	2.5	BHC
Alamosa CT1	CT	12.82	PSCO
Alamosa CT2	CT	13.5	PSCO
BHC Future Battery	Battery Storage	50	BHC
BHC Future Solar 1	Solar	129	BHC
BHC Future Solar 2	Solar	129	BHC
BHC Future wind	Wind	149	BHC
BlueSpruce CT1	CT	130	PSCO
BlueSpruce CT2	CT	134	PSCO
Brighton 1	CT	70	PSCO
Brighton 2	CT	35	PSCO
Brush13 CC1x1	CC	76.8	PSCO
Brush4 CC2x1	CC	132.1306	PSCO
Busch Ranch Wind Energy Farm 2	Wind	59.4	BHC
Busch Ranch Wind Energy Farm WTG	Wind	29	BHC
CabinCreek 1	PSH	150.45	PSCO
CabinCreek 2	PSH	150.45	PSCO
Cherokee CC	CC	576	PSCO
Clear Springs Ranch	Solar	10	CSU
Comanche 3	Coal	750	PSCO
Critical Peak Pricing	DR	49.6	PSCO
CSU 17MW Battery 5	Battery Storage	17	CSU
CSU Battery 1	Battery Storage	50	CSU
CSU Battery 2	Battery Storage	50	CSU
CSU Battery 3	Battery Storage	50	CSU
CSU Battery 4	Battery Storage	50	CSU
CSU Future Solar	Solar	175	CSU
CSU Hydro	Hydro	28	CSU
CSU_Commercial	DR	25	CSU
CSU_Thermostat	DR	9.6	CSU
DarkCalmSolar	Dark Calm Unit	1	PSCO
DarkCalmWind	Dark Calm Unit	1	PSCO

ERZ 1-Cedar Creek	Wind	80	PSCO
ERZ 1-CedarCreek II	Wind	80	PSCO
ERZ 1-SpringCanyon	Wind	90	PSCO
ERZ 2-CheyRidge	Wind	124	PSCO
ERZ 2-Rush Creek	Wind	126	PSCO
ERZ 3-ColoGreen	Wind	250	PSCO
ERZ 3-TwinButtes	Wind	250	PSCO
ExpansionBattery1	Battery Storage	100	PSCO
Fleming	Wind	91	PSCO
FortLupton CT1	CT	44	PSCO
FortLupton CT2	CT	44	PSCO
Front Range Power Plant	CC	460	CSU
Fruita CT1	CT	14	PSCO
FSV CC	CC	680	PSCO
FSV CT5	CT	144	PSCO
FSV CT6	CT	144	PSCO
Ft. Lupton	CC	272	PSCO
Future Solar	Solar	300	PRP
Future Wind	Wind	300	PRP
Grazing Yak	Solar	35	CSU
Holy Cross_Arriba Wind	Wind	100	PSCO
Holy Cross_Hunter Solar	Solar	30	PSCO
IREA_Hunter Solar	Solar	45	PSCO
IREA_Kiowa Solar	Solar	54.5	PSCO
IREA_Pioneer Solar	Solar	80	PSCO
IREA_Victory Solar	Solar	12.8	PSCO
ISOC160 Hour Customers	DR	116.0564	PSCO
ISOC40 Hour Customers	DR	12.00421	PSCO
ISOC80 Hour Customers	DR	60.63942	PSCO
LM6000	CT	40	BHC
LMS100 1	CT	90	BHC
LMS100 2	CT	90	BHC
LMS100 A	CT	87.44	PRP
Manchief CT11	CT	127.45	PSCO
Manchief CT12	CT	127.45	PSCO
Manitou Springs 1	Hydro	2.5	CSU
Manitou Springs 2	Hydro	2.6	CSU
Manitou Springs 3	Hydro	0.5	CSU
Medicine Bow	Wind	6.3	PRP
NFR-Titan	Solar	400	PSCO
Nixon 2	CT	27	CSU
Nixon 3	CT	27	CSU
NTRFP Solar	Solar	150	PRP
Palmer	Solar	60	CSU
Pawnee 1	Coal	505	PSCO

Peak Day Partners	DR	10	PSCO
Peak Partner Rewards	DR	57.8	PSCO
Peak View Wind Farm WTG	Wind	60.8	BHC
PlainsEnd	CT	111.8774	PSCO
PlainsEnd II	CT	109.8334	PSCO
PRP Battery 1	Battery Storage	50	PRP
PRP Battery 2	Battery Storage	50	PRP
PRP Battery 3	Battery Storage	50	PRP
PRP Battery 4	Battery Storage	50	PRP
PRP DG Solar	Solar	87	PRP
PRP DR	DR	30	PRP
PRP_WAPA-LAP	WAPA Purchase	30.234	PRP
PSCO_East Hydro	Hydro	36.75	PSCO
PSCO_West Hydro	Hydro	4.9	PSCO
Pueblo Airport Generating Station	CC	200	BHC
Rawhide A (EA 1)	CT	65	PRP
Rawhide B (EA 2)	CT	65	PRP
Rawhide C (EA 3)	CT	65	PRP
Rawhide D (EA 4)	CT	65	PRP
Rawhide E (FA 1)	CT	128	PRP
Rawhide Flats Solar	Solar	28	PRP
Rawhide Prairie Solar	Solar	21	PRP
RICE 1	ICE	18	PRP
RICE 2	ICE	18	PRP
RICE 3	ICE	18	PRP
RICE 4	ICE	18	PRP
RMEC CC	CC	580	PSCO
Roundhouse	Wind	225	PRP
Ruxton Park 1	Hydro	1	CSU
San Luis Valley-Hooper	Solar	300	PSCO
Savers Switch Residential	DR	231	PSCO
SFR-Neptune	Solar	200	PSCO
SFR-Thunderwolf	Solar	200	PSCO
Solar Bighorn	Solar	240	PSCO
Solar Boone	Solar	113	PSCO
Solar Cogentrix	Solar	30	PSCO
Solar CommunityEnergy	Solar	120	PSCO
Solar Connect	Distributed Solar	50	PSCO
Solar Front Range	Solar	100	PSCO
Solar Garden	Solar	4	CSU
Solar Gardens	Distributed Solar	545	PSCO
Solar Hartsel	Solar	72	PSCO
Solar Hooper	Solar	50	PSCO

Solar Iberdrola	Solar	30	PSCO
Solar Neptune	Solar	250	PSCO
Solar On-Site	Distributed Solar	1225	PSCO
Solar Sandhill	Solar	19	PSCO
Solar ThunderWolf	Solar	200	PSCO
Spindle CT1	CT	137.1358	PSCO
Spindle CT2	CT	137.1358	PSCO
Spring Canyon 2& 3	Wind	60	PRP
Storage Front Range	Battery Storage	50	PSCO
Storage Neptune	Battery Storage	150	PSCO
Storage Thunderwolf	Battery Storage	100	PSCO
SWGArapahoe CC2x1	CC	118.3292	PSCO
SWGFountainValley CT1	CT	39.6146	PSCO
SWGFountainValley CT2	CT	39.6146	PSCO
SWGFountainValley CT3	CT	39.6146	PSCO
SWGFountainValley CT4	CT	39.6146	PSCO
SWGFountainValley CT5	CT	39.6146	PSCO
SWGFountainValley CT6	CT	39.6146	PSCO
Tesla 1	Hydro	28	CSU
TM2500 1	CT	26	CSU
TM2500 2	CT	26	CSU
TM2500 3	CT	26	CSU
TM2500 4	CT	26	CSU
TM2500 5	CT	26	CSU
TM2500 6	CT	26	CSU
TM2500 7	CT	26	CSU
USAFA	Solar	5.25	CSU
Valmont CT6	CT	43	PSCO
Valmont CT7	CT	41	PSCO
Valmont CT8	CT	41	PSCO
WAPA_Allocation_East	Hydro	29	PSCO
WAPA_Allocation_West	Hydro	16	PSCO
WAPA-CRSP	WAPA Purchase	54.441	PRP
WAPA-LAP	WAPA Purchase	61	CSU
WAPA-SLC	WAPA Purchase	15	CSU
Western Slope-Hooper	Solar	200	PSCO
Wind Bronco	Wind	300.2	PSCO
Wind CedarCreek	Wind	300.5	PSCO
Wind CedarCreek II	Wind	250.8	PSCO
Wind CedarPoint	Wind	252	PSCO
Wind CheyRidge	Wind	500	PSCO
Wind ColoGreen_PSCo	Wind	162	PSCO
Wind GoldenWest	Wind	249.4	PSCO
Wind Limon	Wind	200	PSCO

Wind Limon II	Wind	200	PSCO
Wind Limon III	Wind	200.6	PSCO
Wind Logan	Wind	201	PSCO
Wind MtnBreeze	Wind	169	PSCO
Wind NorthernColorado	Wind	151.8	PSCO
Wind NorthernColorado II	Wind	22.5	PSCO
Wind PeetzTable	Wind	199.5	PSCO
Wind Ridgecrest	Wind	29.7	PSCO
Wind RushCreek	Wind	600	PSCO
Wind SpringCanyon	Wind	60	PSCO
Wind TwinButtes_PSCo	Wind	75	PSCO

Operating Reserve Demand Curve

The following figure shows the ORDC utilized in this study. It was developed by Astrapé based upon pre-2022 ERCOT scarcity pricing data and is generally representative of scarcity pricing across a broad range of markets.

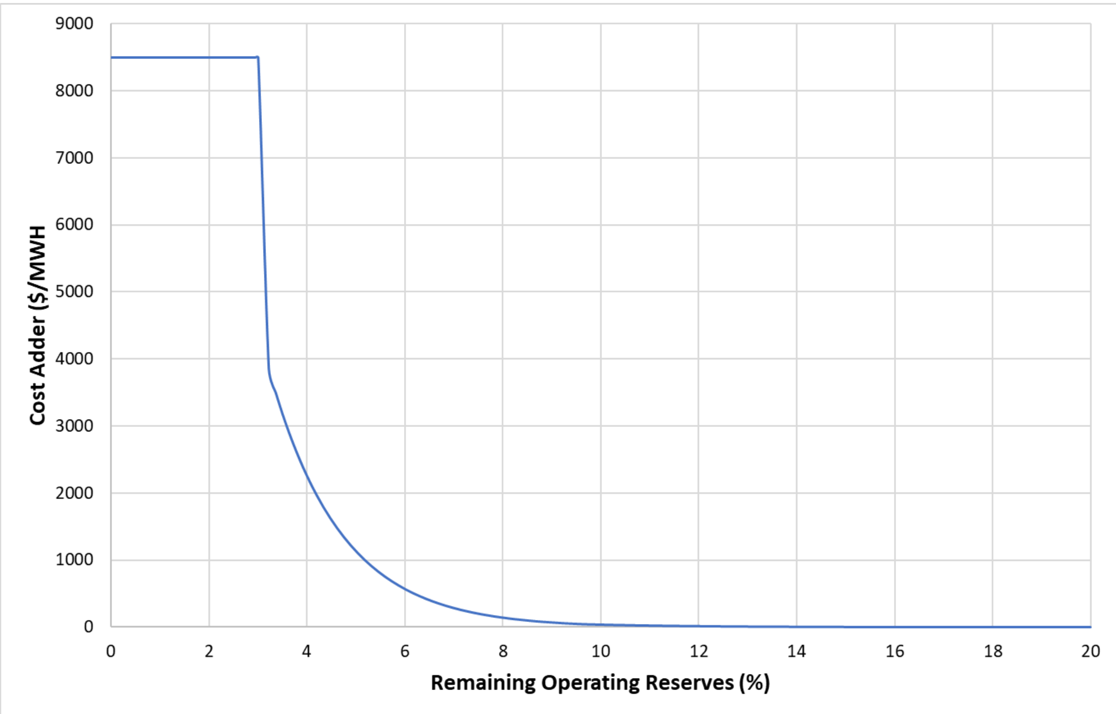

Figure 45. Operating Reserve Demand Curve