Resource Adequacy in the Desert Southwest

Technical Appendices

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Energy+Environmental Economics

Table of Contents

List of Figures

List of Tables

A Appendix: Detailed Inputs & Assumptions

A.1 System Demand

A.1.1 Annual Energy Demand

The annual demand for energy and hourly system peak demand are developed from inputs provided by the Southwest utilities. These numbers are derived from the most recent load forecast developed in their IRPs (or comparable planning processes). Each utility's forecast reflects their projection of future loads based on expected demographic trends, changes in consumption patterns, etc. Forecasts reflect the impact of a number of load modifiers, including electric vehicle load, new large customer load, energy efficiency (EE), and behind-the-meter (BTM) solar PV. Figure A-1 illustrates the methodology used in this study to develop a complete regional demand forecast; Figure A-2 shows the annual energy forecast; and each component is further discussed in subsequent paragraphs.

Figure A-1. Overview of methodology used to develop a regional load forecast

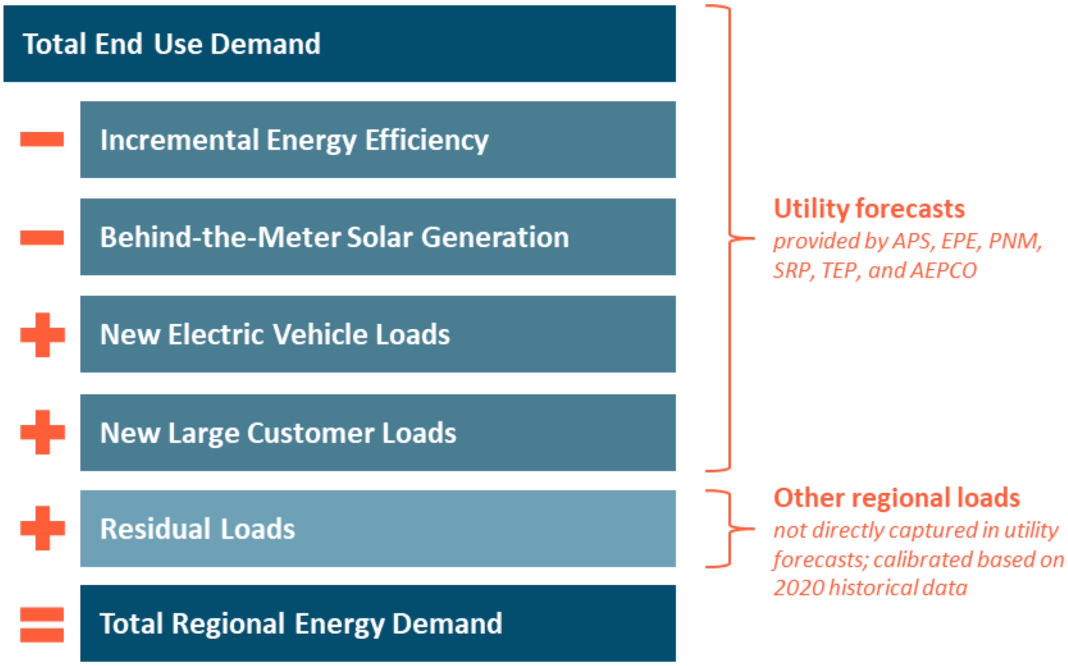
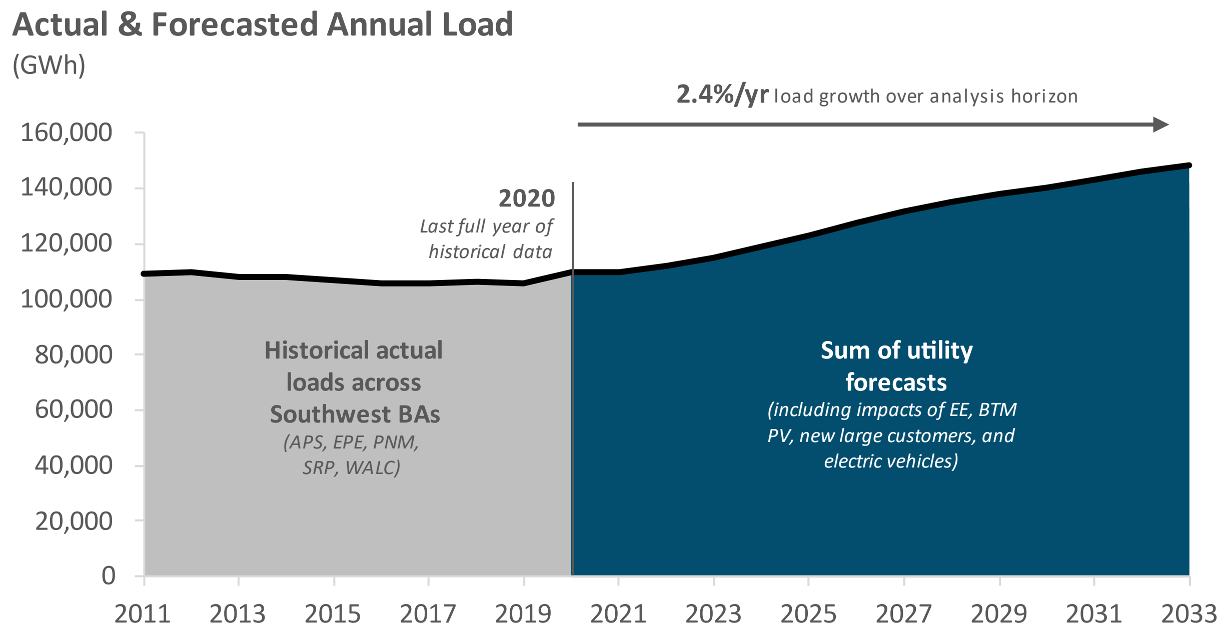


Figure A-2. Actual and forecast annual load



Total End Use Demand

Total end use demand forecast is the first step of projecting future load growth, it's the bulk metered load before re-constituting with load management adders or load drop modifiers. In 2025, total unmanaged load in Southwest is projected to be roughly 117 GWh. By 2033, the forecast is increased to 137 GWh, at a growth rate of 2.0% per year. Overall, total end use demand growth across the Southwest region is moderate over time.

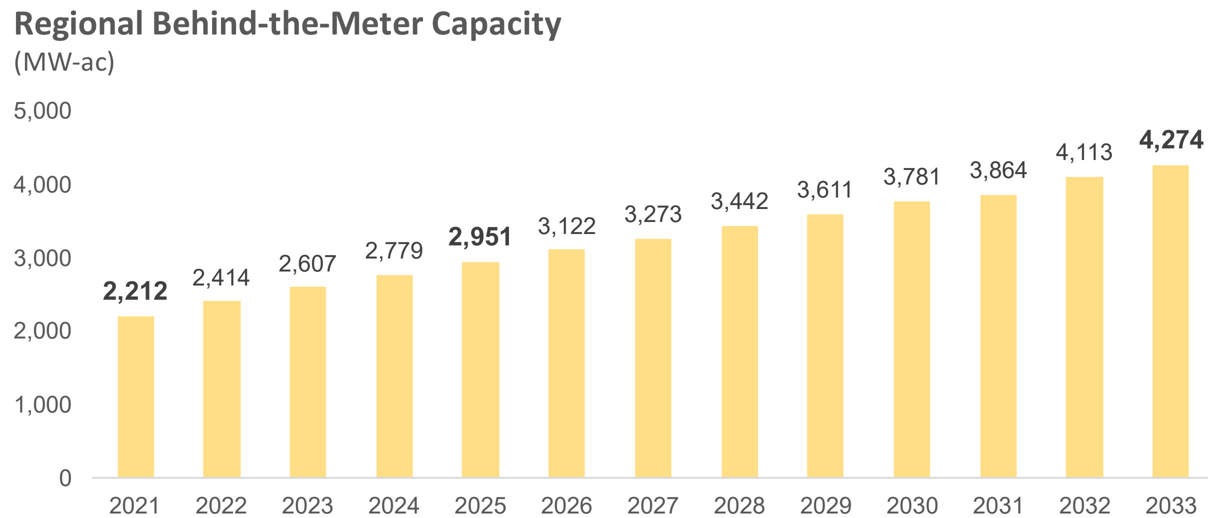
Incremental Energy Efficiency

Utilities' energy efficiency programs offset a portion of the region's load growth. By 2025, the cumulative load impact of energy efficiency (measured relative to 2020) is roughly 2,600 GWh, a 2.4% reduction in load. By 2035, the cumulative load impact of energy efficiency programs increases to 5,800 GWh, an effective 4.5% load reduction.

Behind-the-Meter Solar Generation

Distributed solar energy resource that's behind the meter is another relevant variable that offsets long-term load growth. In 2025, total customer solar generation is projected to be 5,600 GWh, equivalent to 4.6% of annual net load. By 2033, the cumulative impact from behind-the-meter solar increases to roughly 8,500 GWh, at a steady growth rate of 5.4% per year. This is an effective 5.8% load reduction. Figure A-3shows the region-wide installed capacity for behind-the-meter solar from 2021 to 2033.

Figure A-3. Projected behind-the-meter installed capacity reflected in utilites' forecasts



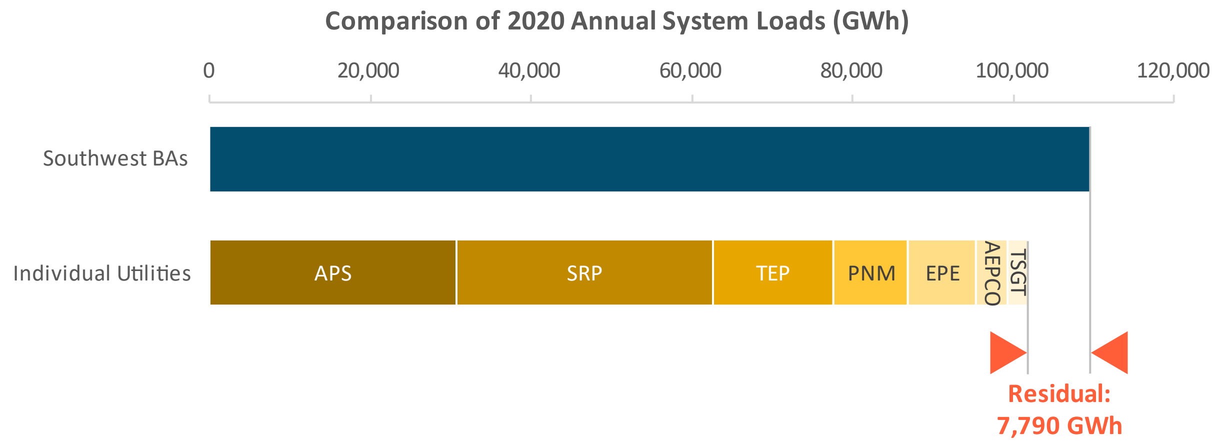
New Electric Vehicle and Large Customer Loads

The load segments associated with electric vehicle adoption and new economic development grow significantly over the forecast period. This captures the accelerated increase in the need for electricity generation as transportation electrification become more cost-competitive and more large development projects materialize.

Remaining "Residual" Loads

In addition to the utilities whose forecasts are explicitly represented in this study, a number of smaller cooperative and publicly owned utilities serve small loads within the region. To capture these loads and to ensure consistency with historic actual loads, a "residual" value is calculated on top of the utilities' aggregate load forecast. This value is calculated by comparing the 2020 loads provided by the utilities with actual total regional balancing authority load obtained from WECC (see Figure A-4). This residual is assumed to increase at the prevailing regional growth rate reflected by the utilities' forecasts from 2020-2035.

Figure A-4. Determination of the "residual" component of the load forecast



A.1.2 Hourly Demand Shapes

A.1.2.1 Historical Simulation

At the heart of RECAP's LOLP simulation is a stochastic representation of hourly load and renewable profiles that reflect the full range of potential conditions that a system may experience. Developing a robust set of hourly load profiles that is representative of a broad distribution of possible weather conditions – particularly extreme events that are often correlated with higher risk of loss of load – is a challenge for reliability modelers, as actual load shapes from recent historical years may not be representative of the long-run distribution of such extreme weather events.

[Add a paragraph that provides an overview of our neural network process, as well as a diagram summarizing the sequence of steps: obtain data, adjust weather, develop NN, simulate loads, etc.]

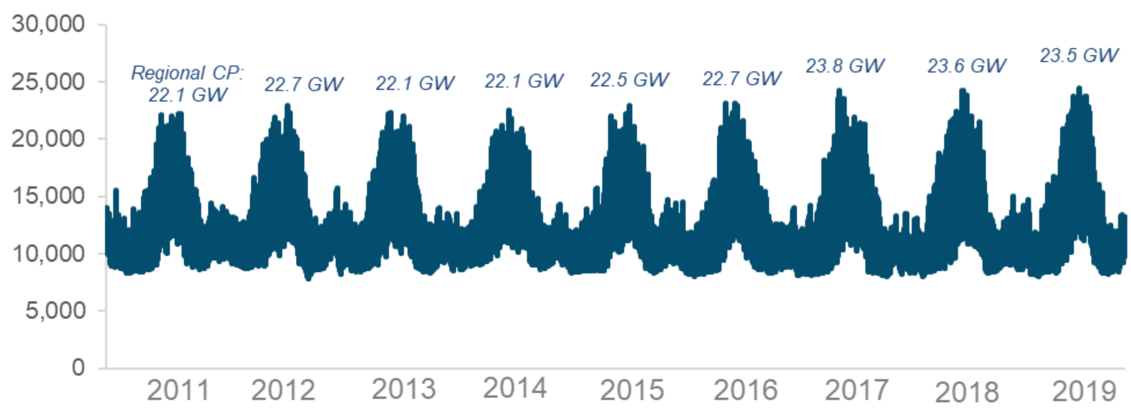
Historical Load & Weather Data

The process of developing hourly load and renewable shapes begins with the collection of recent historical hourly load data. In this study E3 uses 9 years of recent historical data (2011-2019).[1] To allow for the explicit treatment of behind-the-meter solar PV (BTM PV) resources in RECAP, historical output BTM PV is backed out of the historical load shape, such that the resulting hourly shape reflects the total demand for electricity served by behind-the-meter and wholesale power generation.

Figure A-5. Aggregate historical hourly demand in the Southwest region, 2011-2019

(MW)

[1] Load and weather data for 2020, although available, were not used in this study due to the distortionary impacts of the COVID-19 pandemic.



The neural network regression relies on historical daily maximum and minimum temperatures in Arizona, New Mexico, and El Paso published by the National Oceanic and Atmospheric Administration (NOAA) for 1950 to 2018. The historic temperature data, for the years with hourly load data (2010-2018), is used to train the model to establish the relationship between temperature and load. This trained model is then applied to a climate-adjusted weather record (1950-2019) to project hourly load under a wide range of weather conditions. Figure A-1 lists the weather stations used in this process.

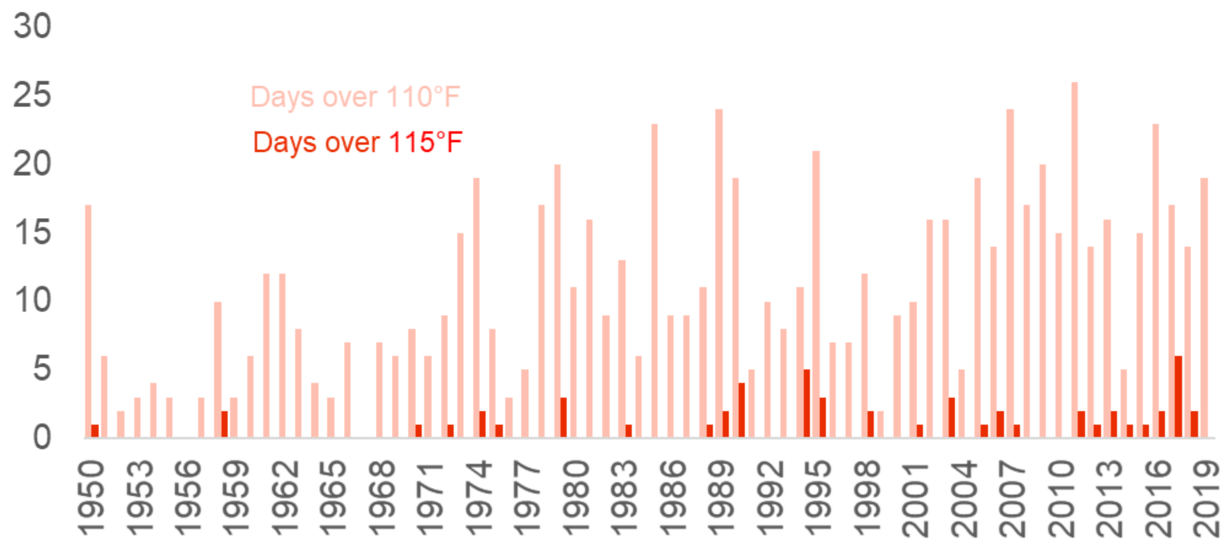
Table A-1. List of weather stations used for historical temperature data

Station Name	Location	Site ID
Albuquerque International Airport	35.0419°, -106.6155°	USW00023050
El Paso International Airport	31.81111°, -106.37583°	USW00023044
Phoenix Airport	33.4277°, -112.0038°	USW00023183
Tucson International Airport	32.1313°, -110.9552°	USW00023160

Climate Adjustments to Historical Weather Data

Incorporating a broad range of possible weather conditions is essential to robust probabilistic modeling. In the past, extensive historical weather records have been used directly to represent the distribution of possible future conditions; however, as the impacts of climate change have become more apparent in the historical record, calling this common assumption into question. The presence of a warming trend in historical data is especially clear in the Southwest, where the frequency of extreme high summer temperatures has increased dramatically since the mid-twentieth century (see Figure A-6). Should observed warming trends continue, traditional analyses which sample only from historically observed weather data risk failing to capture the even-hotter extreme temperatures and resulting reliability events.

Figure A-6. Increasing frequency of high temperature days at Phoenix Sky Harbor



To varying degrees, this warming trend is apparent across all weather stations included in this study. Table A-2 summarizes the average temperature change in the historical weather record from 1950-2019 for three values:

- Maximum daily high temperature
- Average daily high temperature
- Average daily low temperature

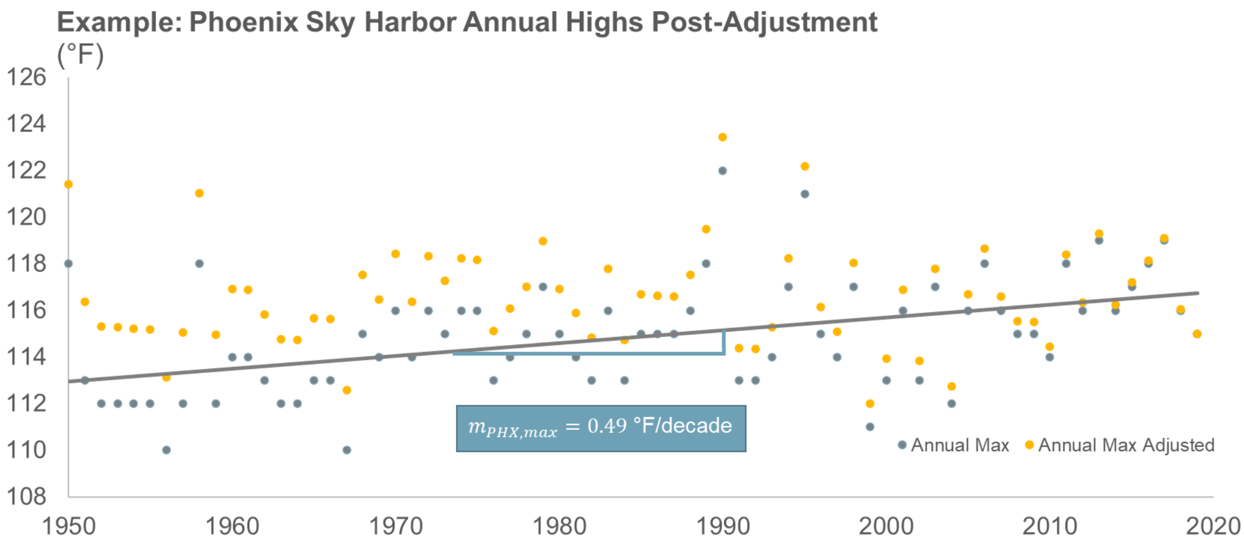
Two observations are notable in these trends. First, the annual maximum and annual average daily high temperatures have increased at relatively similar rates across the historical record. Second, in most stations, the increase in the average daily low temperature has been greater than the increase in average daily high temperature. The implication of this trend – that overnight lows have increased more than daytime highs – is that high load conditions may persist into the evening as temperatures remain higher.

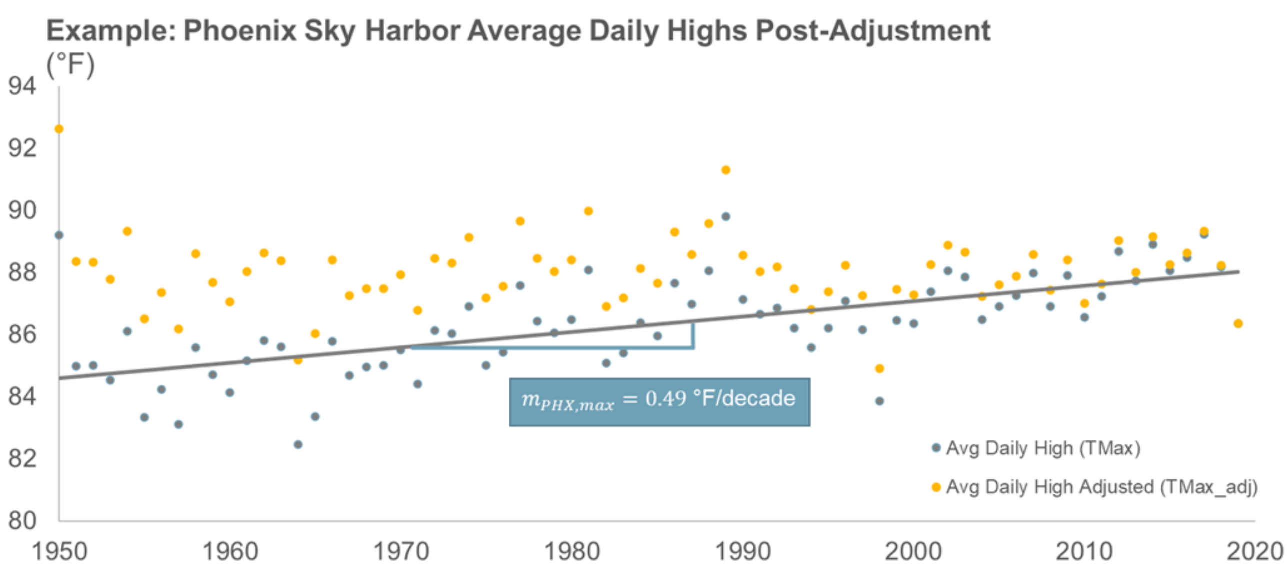
Table A-2. Average observed historical warming trends, 1950-2019

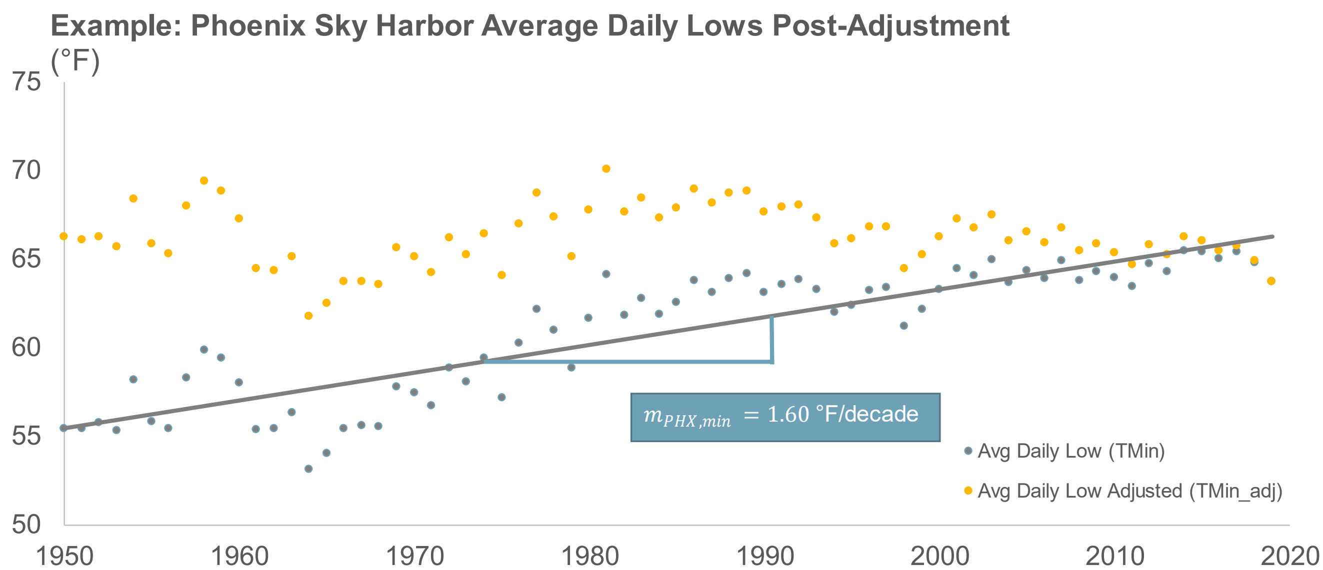
Weather Station	Average Temperature Change (Δ°F/decade)		
	Annual Maximum Daily High Temp	Annual Average Daily High Temp	Annual Average Daily Low Temp
Albuquerque International Airport	+0.08	+0.08	+0.52
El Paso International Airport	+0.43	+0.31	+0.58
Phoenix Airport	+0.55	+0.49	+1.60
Tucson International Airport	+0.57	+0.52	+0.58

To account for these warming trends, this study incorporates a linear adjustment to the historical weather record to detrend the warming impacts apparent in the historical data. A statistically adjusted weather record was produced by first generating a line of best fit on the annual average temperatures observed at each weather station (example in Figure A-7). That line of best fit was then used to create an adjusted temperature for each daily temperature at each weather station, effectively "de-trending" historical temperatures to conditions representative of 2019 climate.

Figure A-7. Adjusted Weather Record Methodology Example







The temperature adjustment methodology represents a step towards incorporate impacts of climate change into resource adequacy analysis. However, the methodology does not model the full range of potential future impacts of climate change: Temperatures are adjusted to 2019-levels (no assumptions are made about future trends), multi-day hot streaks and cold snaps are not assumed to increase in frequency, and there is not a higher incidence of generation and transmission outages resulting from extreme weather events. It will be important that future planning efforts incorporate forward-looking climate projections and resulting effects on the system.

Neural Network Regression

To generate hourly load shapes consistent with the statistically adjusted weather record, this study uses neural network regression techniques to extend the short record of historical data. Through this process, we develop a library of hourly load profiles that represent how today's electric demands would behave under a wide range of plausible weather conditions consistent with today's climate. This method allows the analysis to capture the variability of load across very long time horizons (i.e., 1-in-2, 1-in-5, 1-in-10 year events, etc.).

The following independent variables are used in the neural network regression approach:

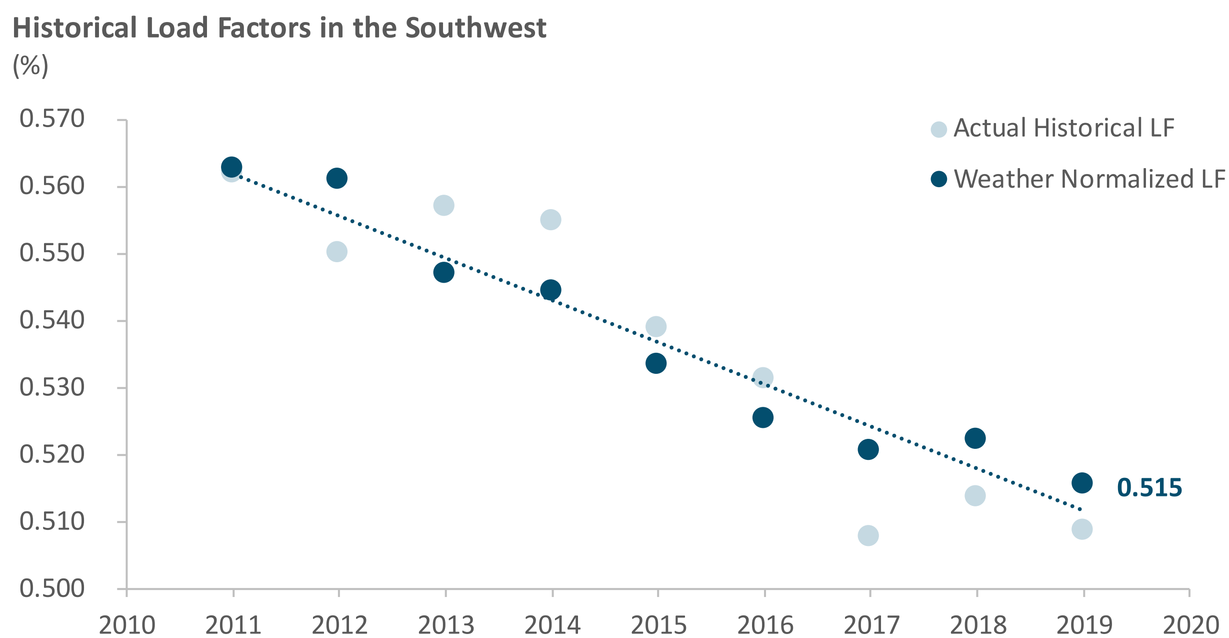
+ Max and min daily temperature (including one and two-day lag)
+ Month (+/- 15 calendar days)
+ Day-type (weekday/weekend/holiday)
+ Day index for economic growth or other linear factor over the recent set of load data

E3 performs this analysis using daily load totals by summing hourly load for each hour of the day. Once daily load totals have been predicted for historical weather days using the neural network process, E3 converts these totals back into hourly load profiles by identifying a load profile within the actual historical record that has the same day-type (weekday/weekend/holiday), is within +/- 15 calendar days, and has the closest total daily load.

Load Factor Adjustment

In a final adjustment, the hourly shape produced by the neural network is scaled to align with recent historical load factors. Over the past decade, load factors in the Southwest region have generally exhibited a declining trend – implying an increasingly "peaky" load shape (Figure A-8). For this study, the hourly shape is scaled to a load factor of 0.515 under median conditions, matching the weather-normalized load factor for the most recent historical year prior to the COVID-19 pandemic.

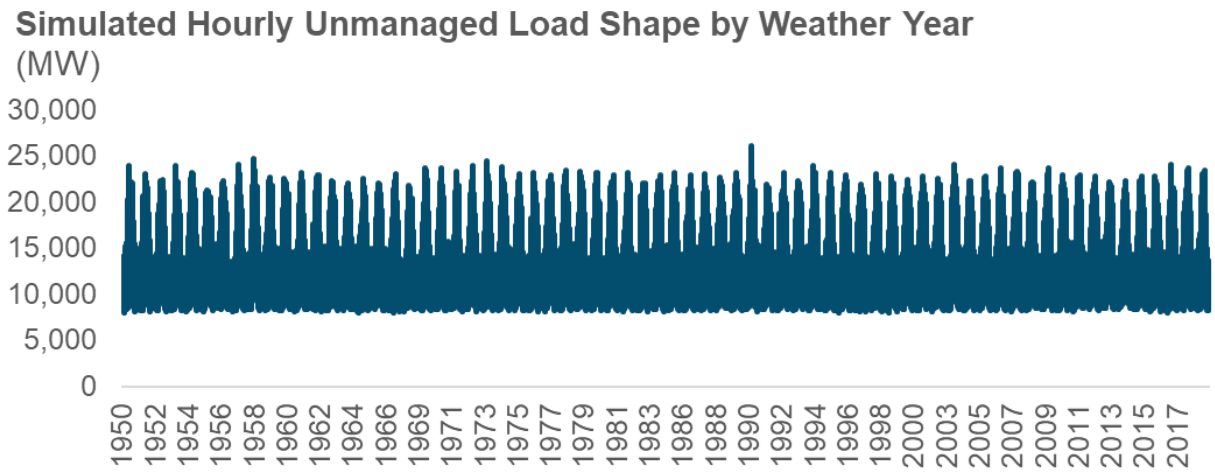
Figure A-8. Historical load factors in the Southwest



Final Simulated Shape

The neural network regression uses historic weather data to produce a simulated shape which is then scaled according to a forecast year's projected energy and peak load. This shape and the spread of its peaks loads (relative to its 1-in-2 peak) are shown in Figure A-9.

Figure A-9. Simulated load shape across 70 potential weather years



A.1.2.2 Electric Vehicle Shapes

This study leveraged the EV load profiles developed in Arizona Transportation Electrification study E3 completed in 2021.3. The single-vehicle charging profiles for each segment (including Light Duty Vehicles, School Buses, Transit Buses, and Parcel Delivery Trucks) are simulated using a Markov-Chain Mote Carlo algorithm based on historical driving behavior data and charging access data in APS and TEP service territory. The standardized profiles are then combined with statewide 2030 EV goals, i.e. targeted vehicles on the road, under medium adoption scenario established by APS and TEP to obtain BA-level EV charging profile. In this study, PNM, EPE and SRP are assumed to have a same EV load profile as APS. Since New Mexico utilize MDT (Mountain Daylight Time) in summer months, in order to align all EV shape with MST (Mountain Standard Time) time zone convention, April-to-September portion of APS profile is shifted backward by one hour to obtain EV load profile for PNM and EPE.

A.1.2.3 Other New Large Load Shapes

Other new large loads identified in utility forecasts are modeled as flat loads. These customers – typically large commercial or industrial customers – tend to have operate with high load factors throughout the year.

A.1.3 Annual Peak Demand

A.1.4 Operating Reserves

In addition to meeting load in each hour, system operators must maintain a minimum level of operating reserves in order to respond in the event of contingencies and to balance subhourly fluctuations. In general, the types of reserves held by system operators fall into three categories:

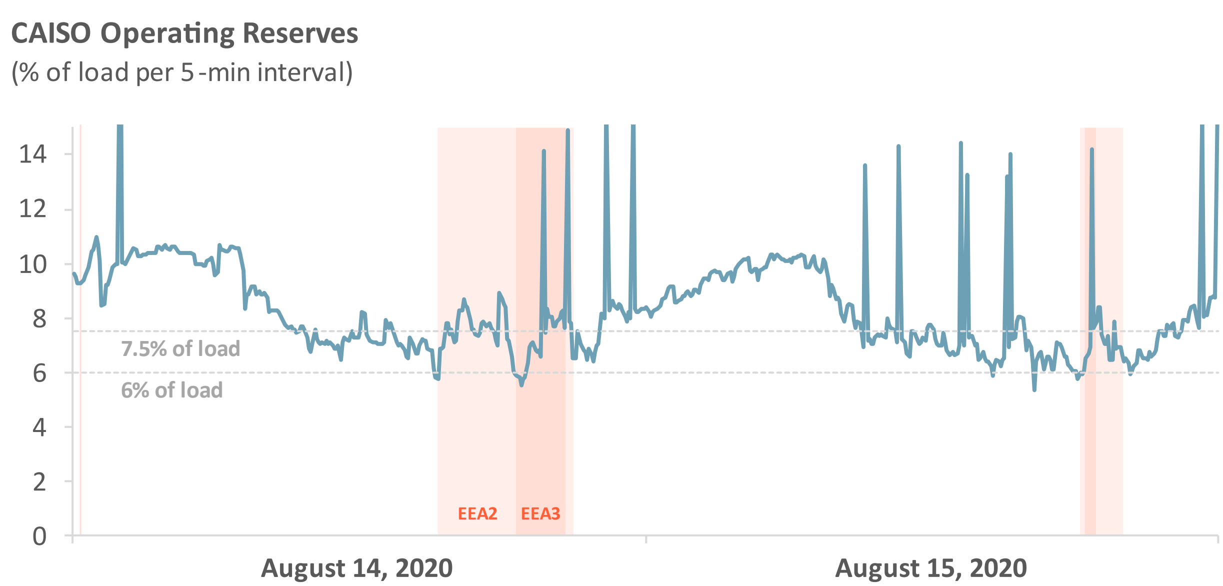
- **Contingency reserves** (including spinning and non-spinning reserves), capacity that is reserved to respond to unexpected shocks to the system – often an unexpected plant or transmission outage;

+ **Regulation reserves**, capacity that responds to changing conditions on the grid on a cycle-by-cycle basis through use of automated generator control (AGC); and
+ **"Flexibility" or "load following" reserves**, which represent capacity that is reserved at the day-ahead and/or hour-ahead time frame to allow for adjustment in response to forecast error and subhourly variability of load and variable resource output.

Typically, the minimum level of operating reserves required in LOLP modeling include contingency and regulation reserves. In contrast, flexibility reserves typically are not included; because LOLP models are intended to capture the conditions on the system in real time – when an unserved energy event would occur – reserves that are held at the day-ahead or hour-ahead time frame but can be released in real time do not increase a utility's need for capacity.

Based on guidance from utilities, this study assumes a minimum operating reserve requirement of 7.5% of load in each hour. This assumption includes both contingency (6% of load) and regulation (1.5% of load) reserves. This level of reserves is generally consistent with the level of operating reserves maintained by the California Independent System Operator during California's August 2020 blackouts. Figure A-10 shows the real-time operating reserves during the two days in which load was shed in California.

Figure A-10. Operating reserves held by California ISO during August 2020 blackout

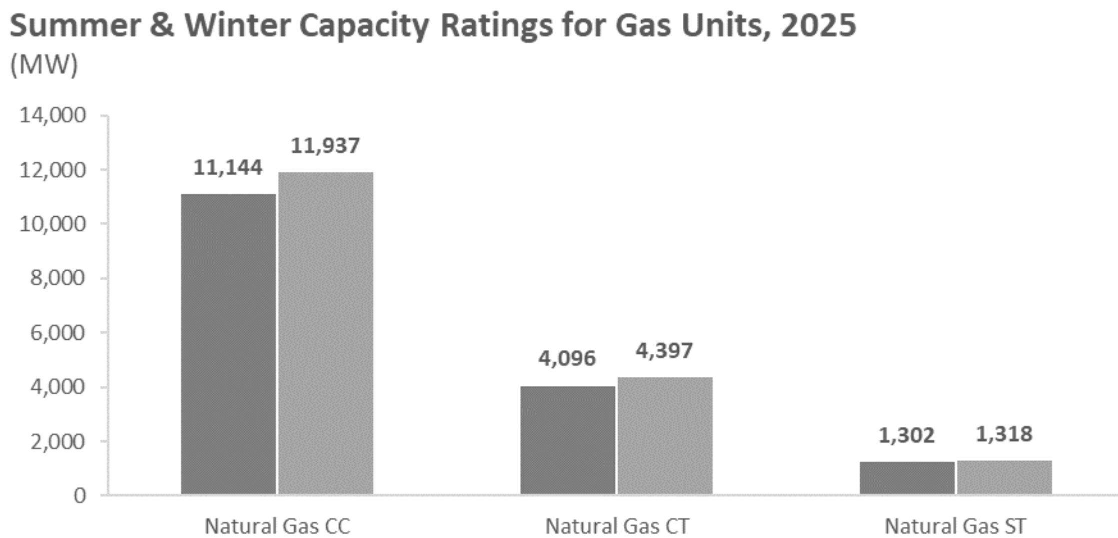


A.2 Firm Resource Characteristics

A.2.1 Seasonal Capacity Ratings

Thermal plant ratings are specified on a seasonal basis, allowing the simulation to capture the reduction in efficiency and output of gas generators under extreme high temperatures. Summer and winter ratings were developed from ABB Velocity Suite, with plant-specific adjustments to align with assumptions used in utility IRPs. The specific summer ratings – intended to capture each plant's potential performance under an extreme high temperature condition – are typically 5-10% below their winter ratings for natural gas combined cycles and combustion turbines; in aggregate, these derates reduce the capability of the region's natural gas fleet by over 1,000 MW relative to its winter rating.

Figure A-11. Differences in seasonal capacity ratings for natural gas generators in the Southwest



While the use of seasonal and/or monthly plant ratings is common practice in reliability and economic analysis, actual plant capabilities will vary on a day-by-day basis with local ambient weather conditions. While these variations are likely small in comparison to plant size, continuing efforts to understand how natural gas plants will perform in the region under increasingly extreme temperatures will be important to maintaining a balanced perspective on resource adequacy..

A.2.2 Outage Rates

Assumptions for plant outage rates of thermal resources were provided by participating utilities based on historical operating experience. Summary statistics for the outage rates assumed in this study are summarized in Table A-3.

Table A-3. Summary of forced outage rates assumed by technology

	Average (%)	Minimum (%)	Maximum (%)
Nuclear	1.5%	1.5%	1.5%
Coal	8.3%	1.7%	18.3%
Natural Gas CC	3.0%	2.5%	6.6%
Natural Gas CT	3.4%	2.1%	9.6%

Natural Gas ST	3.8%	0.9%	7.7%

Thermal plant outages are simulated independently, reflecting an assumption that they are uncorrelated. Experts in the field of resource adequacy modeling have raised concerns that failure to capture an underlying correlation in outage patterns where one exists will lead to an overstatement of reliability and the value of generators subject to correlated outages. However, this quantitative nature of this risk may vary significantly from region to region; factors that might lead to correlated outage risk in one region may not be applicable in another. A recent analysis of historical outage data conducted by researchers at Carnegie Mellon University[2] provides some indication of both the range and importance of correlated outage risk. Based on NERC GADS data from 2011-2014, this study presents strong evidence of correlated outage risk in six North American regions[3] but could not reach a definitive conclusion that such a risk was present in WECC (though the study cautions that the four years of data used may not be sufficient to validate that finding and warns that the region is likely not immune to correlated outage risk).

While there is not strong historical evidence to suggest that a risk of correlated outages is as significant as in other parts of the country, this study nonetheless recognizes it as a possible risk worthy of additional exploration. While this study does not model correlated outages directly, it includes a high outage sensitivity to understand the extent to which this assumption – and outage rates in general – will impact the region's reliability. In this study, outage rates are doubled related to the base case.

A.3 Variable Resources

A.3.1 Utility-Scale Solar Profiles

Hourly profiles for utility-scale solar resources are simulated using NREL's System Advisor Model (SAM) for the historical period 1998-2019. Individual profiles are simulated based on plant-specific characteristics (location, tracking type, tilt, azimuth and inverter loading ratio) based on plant characteristics reported in EIA Form 860. When data were not available, a generic representative single-axis tracking plant with an inverter loading ratio of 1.3 was assumed based on industry trends as captured in LBNL's Tracking the Sun.[4]

Simulated profiles from existing solar plants were benchmarked against BA-level historical production data gathered from EIA for the period 2019-2020. The simulated profiles capture the diurnal and seasonal production patterns with sufficient accuracy for use in the ELCC calculation. Figure A-12 shows how simulated profile compares to actual solar generation in Southwest in 2019.

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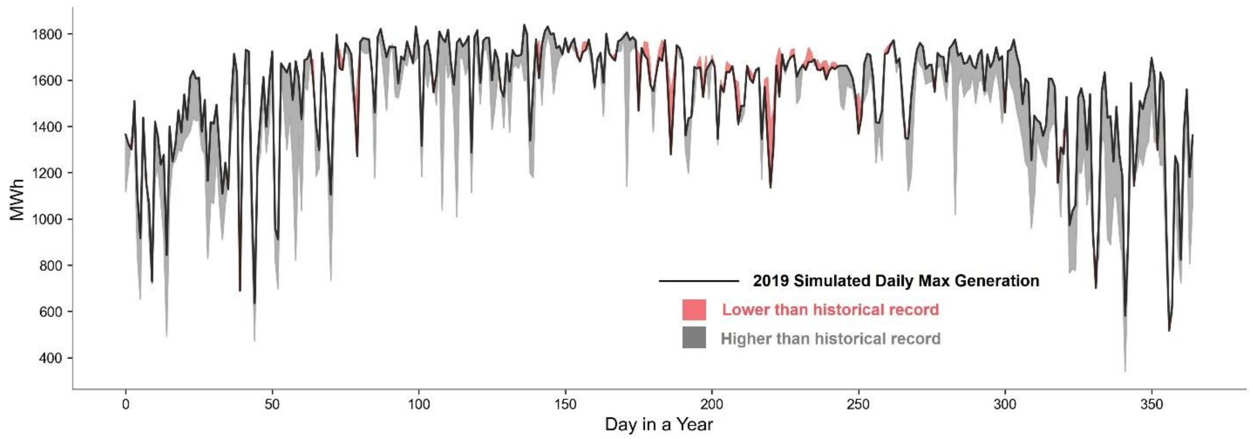
[2] Murphy, S., J. Apt, J. Moura, & F. Sowell/ "Resource adequacy risks to the bulk power system in North America." *Applied Energy*, Volume 212, 2018, Pages 1360-1376. ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2017.12.097.

[3] Midwest Reliability Organization, Northeast Power Coordinating Council, ReliabilityFirst Corporation, Southeast Reliability Corporation, Southwest Power Pool, Texas Reliability Entity

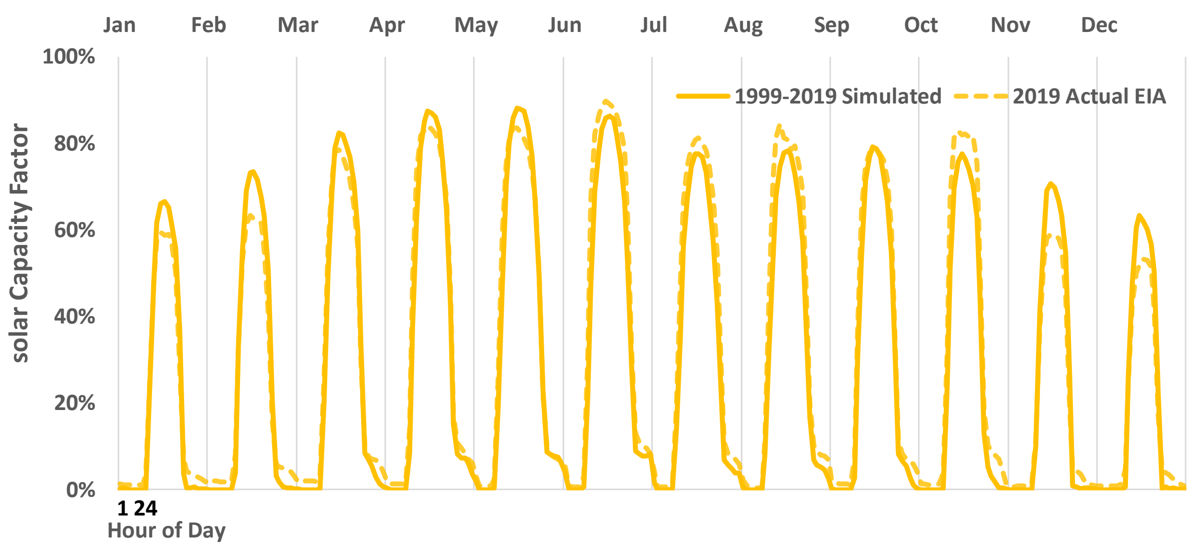
[4] A small number of plants constructed prior to 2011 were simulated based on a generic fixed tilt plant with inverter loading ratio of 1.2 and a 25° tilt angle based on the most common configuration at the time.

Figure A-12. Historical daily max generation compared to simulated profile



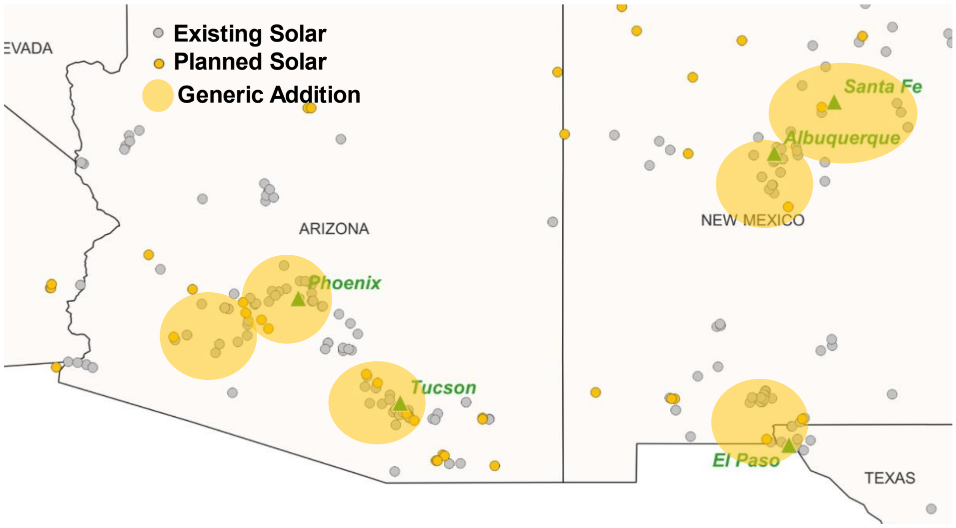
Averaging generation by month of year and hour of day is illustrated in Figure A-13. An evening bump in summer months are caused by the 250-MW Solana concentrating solar power (CSP) plant in APS service territory. Generally, simulated solar shape shows similar behavior and capacity factor in most months of a year. Average production profiles and levels track particularly well in the summer months (June through September) when electric demand is highest.

Figure A-13. Benchmarking month-hour average solar capacity factor (%)



To develop profiles for future generic solar resources, this study simulated generic plants in several general locations throughout the Southwest. Locations for generic profiles are chosen for general proximity to major load centers and are consistent with current development trends. For each location, the performance of a benchmark single-axis tracking plant with an inverter loading ratio of 1.3 is simulated using NREL SAM.. A total of 145 sites were simulated and aggregated to capture likely geospatial diversity within the regions identified; these individual profiles were aggregated to create aggregated to 6 generic profiles – Western Phoenix, Metro Phoenix, Tucson, Albuquerque, Santa Fe, and El Paso (see yellow shadow area in Figure A-14). The generic solar resources in each utility's portfolio were mapped to these profiles based on proximity to the utility's major load centers.

Figure A-14. Map of existing, clanned and generic solar PV resources



A.3.2 Behind-the-Meter Solar Profiles

A similar approach was used to generate hourly profiles for behind-the-meter solar. Ten to fifteen specific sites throughout each major load center in in the Southwest represent generic rooftop PV sites across five balancing authority areas. In order to capture customer diversity, residential and non-residential sector are simulated individually in the model.

Other input parameters including location, orientation, and ILR are based on generic assumptions supported by design trends for distributed PV systems in the country in 2021. A range of different rooftop configurations are modeled to reflect the trend toward more diverse panel orientations, especially in residential sector. **Error! Reference source not found.** shows the capacity distribution of these configurations.

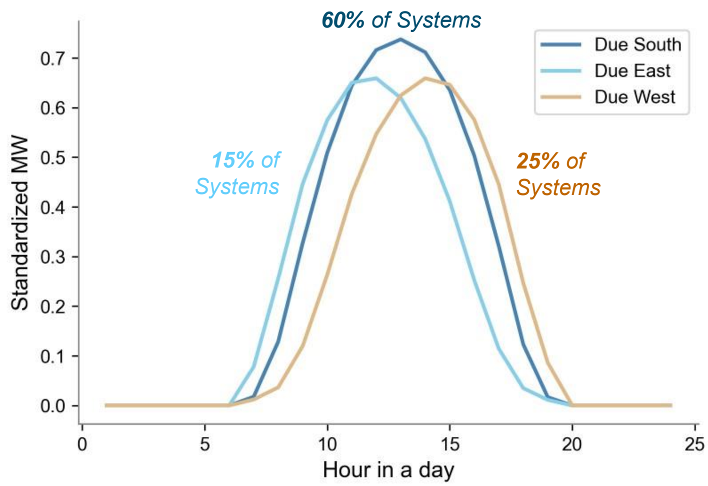
Table A-4. Assumptions for BTM PV

Segment	LIR	Tilt	Azimuth (Orientation)	Capacity distribution
Residential	1.15	20°	180° (Southward)	60%
			90° (Eastward)	15%
			270° (Westward)	25%
Non-residential	1.15	10°	180° (Southward)	80%
			90° (Eastward)	5%

	270° (Westward)	15%

Figure A-15 shows an average BTM daily shape around Phoenix area. Generally, greatest energy production for fixed-tilt systems occurred when panels are oriented due south, but more prevalent west-facing and east-facing systems can shift max generation to off-peak times.

Figure A-15. Illustrative impact of configuration on BTM PV shape at different panel orientation in Phoenix, AZ

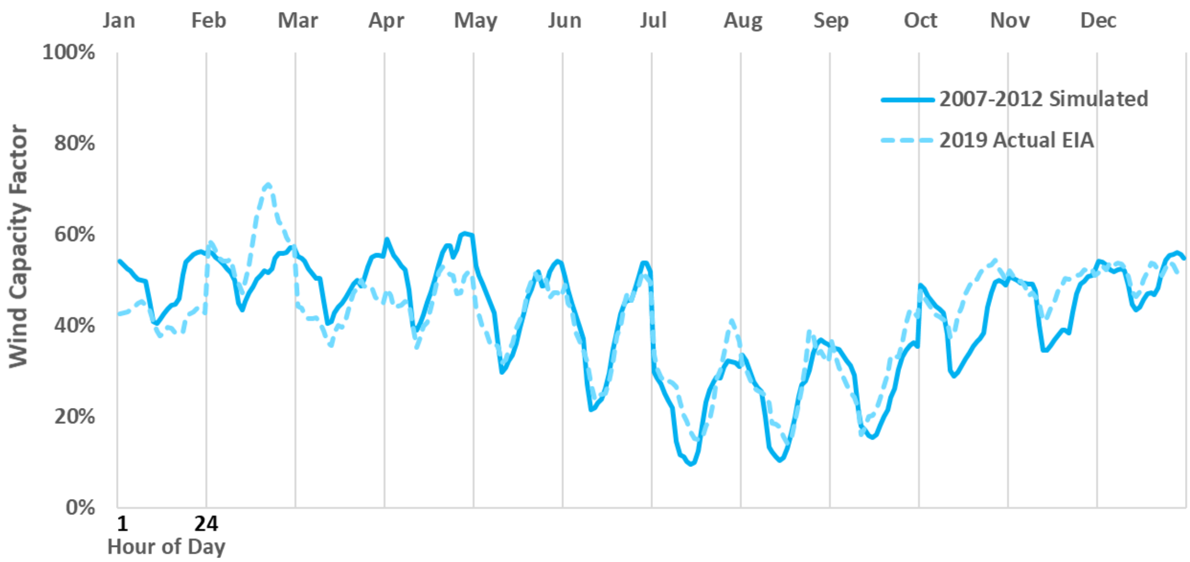


A.3.3 Wind Profiles

Hourly profiles for existing & committed wind plants are simulated from meteorological and turbine power data gathered from NREL's WIND Toolkit for the historical period 2007-2012. Each plant's profile depends upon plant-specific design characteristics, including the hub height and power curve for the turbines installed.

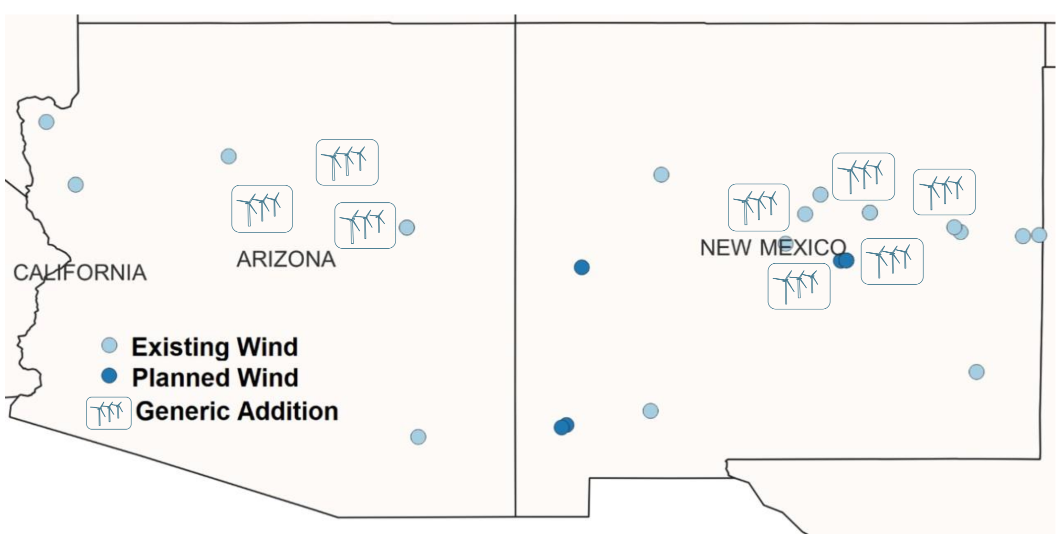
These profiles are then benchmarked against actual hourly production data from wind resources in the region in 2019. Because the WIND Toolkit does not produce simulations for a historical period during which actual historical data for wind production is readily available, benchmarking of wind profiles focuses on seasonal and diurnal patterns through a comparison of month-hour capacity factors in the simulations (2007-2012 weather) and in historical data (2019) available from EIA. The benchmark results are illustrated in Figure A-16. Generally, hourly wind output is higher during winter months and lower during summer months. However, while overall capacity factors tend to be lower in the summer months, the times of day when wind capacity factors are the highest – typically later in the day and evening – complement the diurnal production patterns of solar resources well.,

Figure A-16. Month-hour average wind capacity factor (%)



New generic wind sites are identified based on the highest average wind speed locations across the Southwest region, notably Eastern New Mexico area. To incorporate geographical diversity, some candidate wind resources are also assumed to be added in Northern Arizona. An NREL generic power curve is applied to each generic resource depending on level of wind speed. For instance, mid wind-quality sites in Northern Arizona are assumed to have a generic NREL-2 turbine with 100-meter hub height and a power curve that achieves maximum output at a wind speed of 14 m/s and has a cut- out speed of 25 m/s. The simulation yields an annual average capacity factor of approximately 31% in North Arizona, and 51% in Eastern New Mexico. Figure A-17 illustrates the location of new candidate wind sites in the region.

Figure A-17. Map of existing, planned and generic wind resources



A.4 Hydro Resources

A.4.1 Federally Owned Hydro Resources

A number of federally owned hydroelectric projects along the Colorado River play a role in meeting the energy and capacity needs of the Southwest region; these include the Hoover Dam near Las Vegas; the Parker and Davis Dams along the California-Arizona border, and the Colorado River Storage Project (CRSP), which includes the Glen Canyon Dam and a number of smaller upstream facilities in the state of Utah. These facilities are operated by the United States Bureau of Reclamation, and their output is sold to offtakers in Arizona, California, and Nevada by the Western Area Power Administration (WAPA). The shares of these resources that are contracted with Southwest entities are summarized in Table A-5. As of today, more than 1.2 GW of hydro resources can be dispatched to meet load, accounts for roughly 5% of Southwest's power generation capacity.

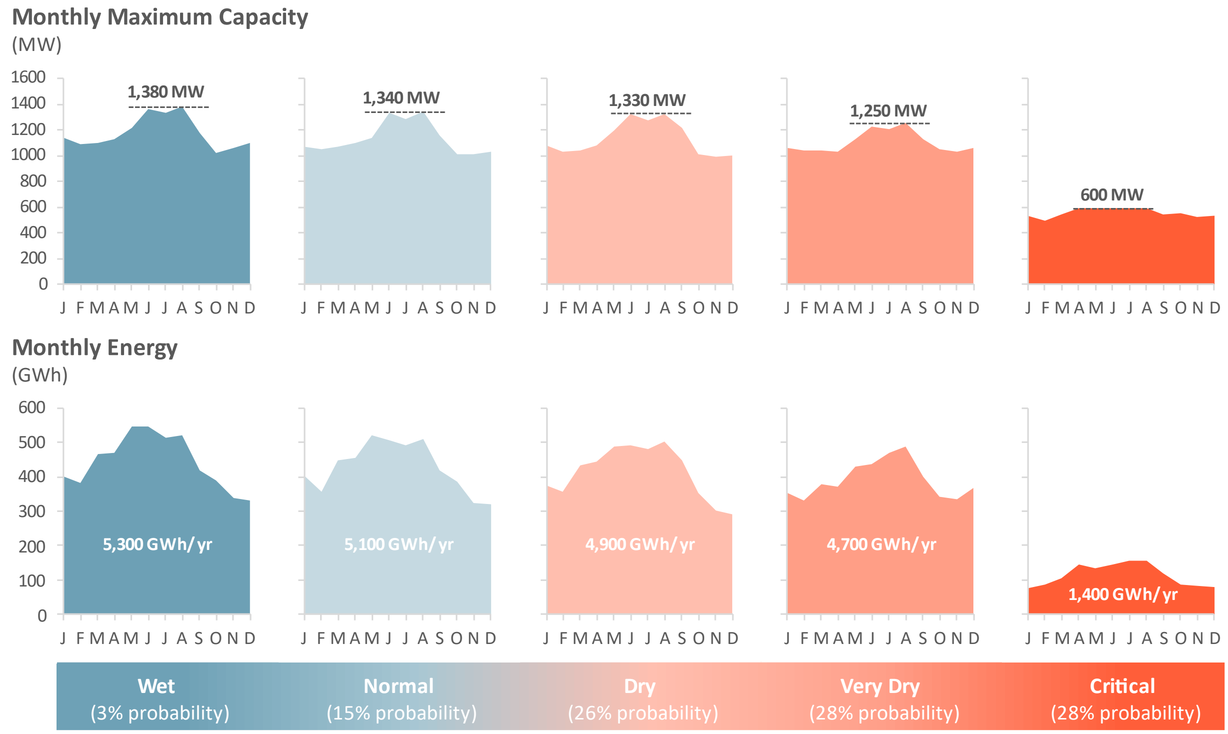
Table A-5. Shares of total project energy and capacity under contract to Southwest utilities

	Shares of Output Allocated to Southwest Utilities (%)		
Project	**Energy**	**Summer Capacity**	**Winter Capacity**
Hoover	24%	23%	23%
Parker-Davis	58%	58%	58%
CRSP	80%	81%	78%

Output from these projects is dispatchable – that is, it can be shaped according to the needs of the utilities served – but the resource is fundamentally "energy-limited" and cannot be operated at maximum capacity at all times due to hydrological conditions. Further, the capabilities of these resources will vary based on prevailing hydrological conditions within the region. In particular, the risk of continued drought conditions in the Colorado River basin could severely diminish the capabilities of the system should reservoir storage drop below critical levels.

To characterize variations in potential future generation available to Southwest utilities from these federal projects, this study considers five different future hydrological scenarios ranging from "Wet" to "Critical" based on data provided by WAPA. Monthly limits for energy and capacity, as well as associated estimates of the probability of each scenario, are shown in Figure A-18. Under most scenarios, the impact of hydrological conditions is limited to a relatively narrow range, but under a "Critical" scenario, the capability of the system is severely reduced; under this scenario (estimated at 28% likelihood), severe drought is assumed to prompt a shutdown of operations at the Glen Canyon Dam. These inputs enable a probabilistic treatment of hydro availability in this study.

Figure A-18. Total WAPA hydro resource monthly capacity & energy available to Southwest utilities under different hydrological conditions



These scenarios and their associated probabilities were provided by WAPA based upon inputs from the Upper and Lower Basin Bureau of Reclamation 24 Month Studies, which forecast capacity and energy at each of the plants. Since the Bureau of Reclamation uses slightly different hydrologic scenarios in its 24 Month Study as compared to the scenarios provided and prepared by WAPA, the assumptions and results are considered provisional and only for the purposes of the Resource Adequacy study in this project.

A.4.2 Other Hydro Resources

The portfolios studied in this analysis also include some run-of-river hydro units. These are smaller water facilities with limited flexibility of operation, mostly located in SRP's service territory. By 2025, there are roughly 200 MW of small hydro units in the portfolio. They are modeled as firm resources with a varying monthly capacity to reflect expected differences in seasonal capacity factors.

A.5 Storage Resources

The portfolios studied in this analysis include a mix of storage resources of different durations; the duration of the storage resources will impact their relative effectiveness in meeting the region's reliability needs. The duration associated with each resource is based on assumptions provided by each utility. The distribution of capacity across different durations is summarized in Table A-6.

Table A-6. Storage resource capacity by rated duration in each portfolio

	Installed Capacity (MW)				
Duration	2021 Existing	2025 Existing & Committed	2025 IRP	2033 Existing & Committed	2033 IRP
1 hour	20	144	144	144	144
2 hour	-	66	665	66	665
3 hour	-	50	50	50	50
4 hour	52	852	2,665	852	8,987
5 hour	-	-	-	-	1,925
8 hour	-	-	7	-	262
10+ hour	187	187	187	187	1,187
Total	**259**	**1,299**	**3,718**	**1,299**	**13,220**

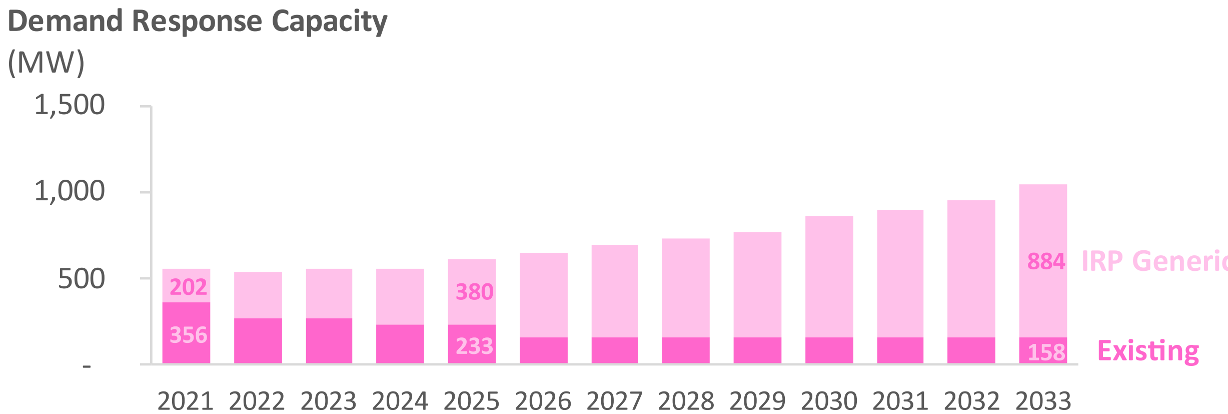
An increasing quantity of the region's storage capacity in these portfolios is assumed to be hybridized with solar PV capacity. Based on utility input, 2,465 MW of storage is modeled as a part of a solar-storage hybrid in the 2025 IRP portfolio; by 2033, this value increases to 8,040 MW. Constraints on hybrid resources are imposed such that (a) charging of hybrid storage resources is limited to periods when the associated solar resource is generating; and (b) the combined output of the solar and storage resources to the grid cannot exceed an assumed interconnection limit.

All battery storage resources are modeled with a 2% outage rate except in sensitivities that test alternative outage probabilities.

A.6 Demand Response

Demand response programs allow utilities to meet a portion of their resource adequacy needs through customer responsive loads. These may include both programs that allow direct control of customer devices (for example, smart thermostats or water heaters) as well as large customers served on an interruptible tariff. Figure A-19 summarizes the projected capacity of both existing demand response programs and future plans for expansion of demand resources as reflected by the utilities' IRPs.

Figure A-19. Projected capacity of demand response resources in the Southwest region



Much like energy storage and hydroelectric generation, demand response resources are "energy-limited": while they can generally be dispatched to capacity on demand, they are limited by the number and length of calls with which each program is designed. Utilities' existing demand response programs are modeled based on current program characteristics, which generally define three relevant parameters for resource adequacy analysis: (1) the program's size, in MW, reflecting the expected load reduction during a call; (2) the limit on calls, typically specified as an annual limitation on the frequency of calls;[5] (3) the duration of each call, which defines the length of the period over which the load reduction will occur. For parameters not specified by utilities, generic assumptions include a limit of twelve calls per year and a call duration of four hours are assigned. Table A-7 summarizes the specific characteristics assumed for utilities' existing programs.

Table A-7. Characteristics of existing demand response programs

Utility	Program	Capacity (MW)	Limit on Calls (#/yr)	Call Duration (hrs)
APS	CPower 2021	60	18	5
APS	Residential Thermostats	67	20	2
APS	C&I DR	25	18	5
EPE	Interruptible DR	56	12*	4*
PNM	PeakSaver	11	12*	4*
PNM	PowerSaver	22	12*	4*
SRP	Residential DR	60	15	4
SRP	C&I DR	45	10	3

[5] In some instances, a program may have limits on the number of calls per month; these constraints were translated to limits on the annual number of calls for the purposes of this study.

TEP	SmartDR	4.7	6	4
TEP	DLC	5.3	6	8

*Generic assumptions

Future demand response resources included in the IRP scenarios are also assigned generic characteristics of twelve calls per year and maximum four hours per call.

A.7 Regional Market Support

The primary purpose of this study is to assess whether the resources of the Southwest region will be sufficient to meet future resource adequacy needs; as such, under Base Case assumptions, this study does not consider the availability of surplus market power from other regions as contributing to the resource adequacy needs of the Southwest. In the absence of a formalized market structure for sharing capacity among regions, assuming certain quantities of market support may be available in the future represents a risk, especially considering that neighboring regions (particularly California) have long relied on imports *from the Southwest* to ensure their resource adequacy. Further, quantifying the available surplus in neighboring markets – especially as they transition to more variable and energy-limited resources themselves – is a challenging and imprecise exercise, and most estimates are subject to risk of false precision.

Nonetheless, the diversity of the broader Western grid does unequivocally play an important role in supporting utilities' ability to serve loads reliably. To illustrate the impacts that neighboring electricity markets could have on reliability in the Southwest, this study also investigates a sensitivity in which potential imports from neighboring regions that are well-connected to the Southwest via transmission (California and Nevada) are characterized on an hourly basis. The hourly shape for import availability is derived through a sequence of several steps:

- Use actual operating data from 2019 to estimate the availability of surplus capacity in each neighboring system in each hour of the year under historical conditions;
- Scale up loads to reflect growth between 2019 and 2025;
- Adjust generation portfolios to account for expected changes in resource mix in each area by 2025 (derived from the CPUC's Preferred System Plan and NV Energy's latest IRP filing);
- Reevaluate estimated available surplus on an hourly basis based on changes to loads and resources of neighboring regions under weather conditions from 2019;
- Use day-matching algorithm to extend hourly surplus estimates for weather year 2019 to other weather years considered in analysis (1950-2019).

While this method provides a useful indication of the possible nature of market interactions between regions, it is admittedly imprecise and relies on assumptions that may overstate its impact (for instance, that California's energy storage resources may be shared with the Southwest when not needed).

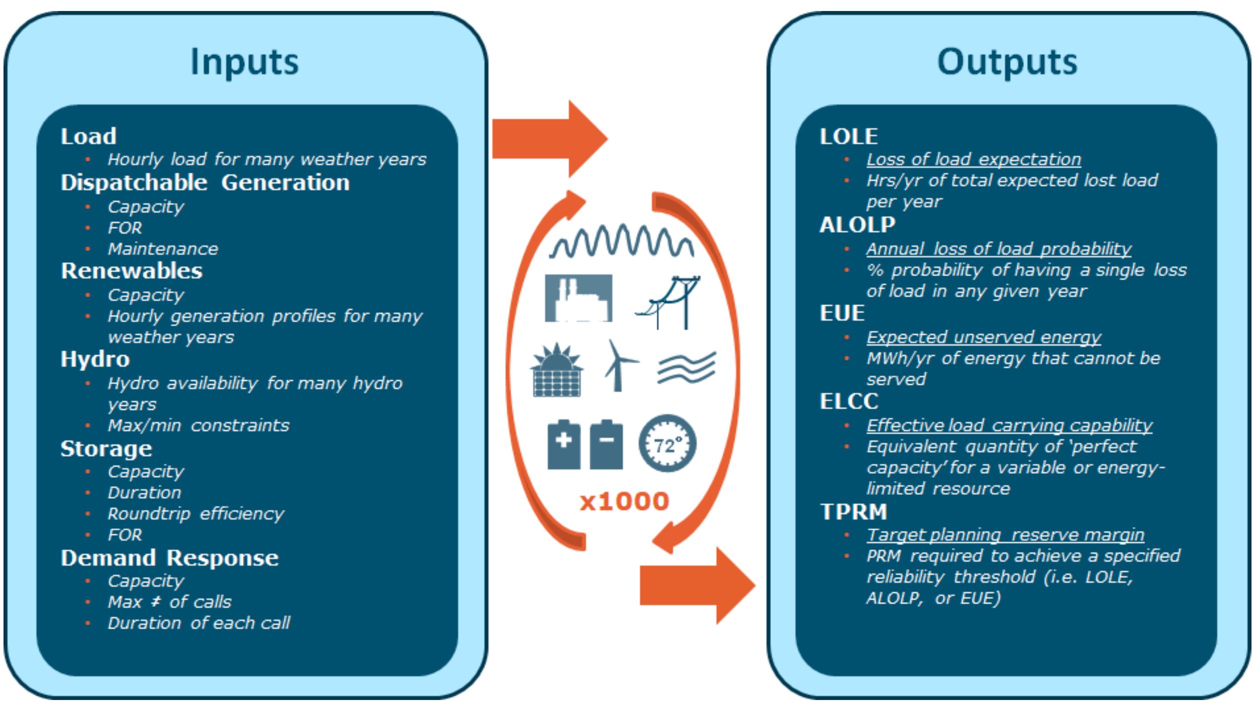
B Appendix: RECAP Methodology

E3's **Renewable Energy Capacity Planning Model (RECAP)** is a loss-of-load-probability model designed to evaluate the resource adequacy of electric power systems, including systems with high penetrations of renewable energy and other dispatch-limited resources such as hydropower, energy storage, and demand response. RECAP was initially developed for the California Independent System Operator (CAISO) in 2011 to facilitate studies of renewable integration and has since been adapted for use in many jurisdictions across North America.

RECAP evaluates resource adequacy through time-sequential simulations of thousands of years of plausible system conditions to calculate a statistically significant measure of system reliability metrics as well as individual resource contributions to system reliability. The modeling framework is built around capturing correlations among weather, load, and renewable generation. RECAP also introduces stochastic forced outages of thermal plants and transmission assets and time-sequentially tracks hydro, demand response, and storage state of charge.

Figure B-1 provides a high-level overview of RECAP including key inputs, Monte Carlo simulation process, and key outputs.

Figure B-1. RECAP model overview



B.1 Model Inputs

RECAP is designed to allow loss of load probability simulation on a wide range of electricity systems that may comprise a diverse mix of generating resources, each with different constraints and characteristics that affect their availability to serve load at different times. The input data for RECAP, summarized in **Error! Reference source not found.**, enables a robust evaluation of loss-of-load-probability that can account for a broad variety of technologies and resource types, including:

+ **Firm resources** capable of producing at their full rated capacity when called upon by operators (except during periods of maintenance and unforced outages);
+ **Variable resources**, typically wind and solar, whose availability will vary on an hourly basis as a result of weather and solar irradiance patterns;
+ **Hydroelectric resources** that can be dispatched relatively flexibly but have constraints related to streamflow and underlying hydrological conditions;
+ **Storage resources** that can be dispatched flexibly but have limited durations across which they are available due to limits on state of charge; and
+ **Demand response programs** that can be called upon as a last resort by operators to maintain reliability but typically have limits on the frequency and duration of calls that vary depending on the type of program.

Table B-1. Key inputs to RECAP model

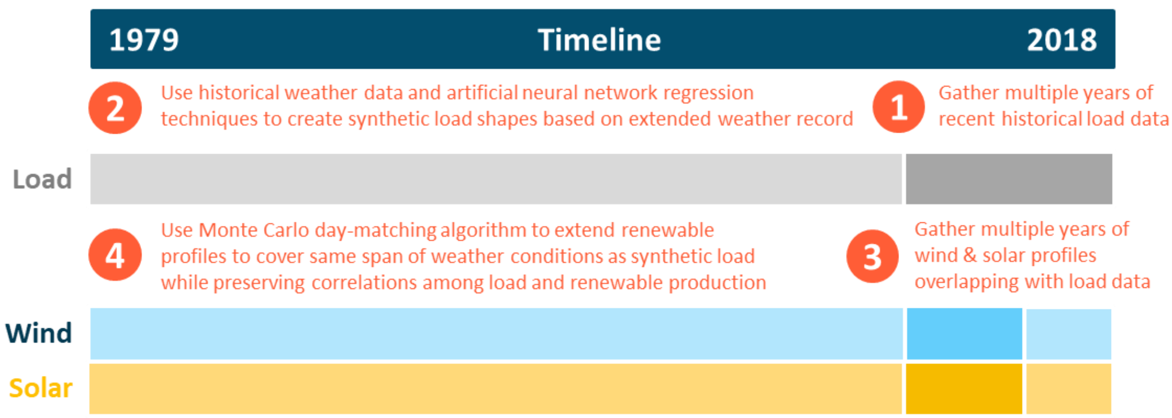
Module	Inputs Needed
System Demand	• Annual energy demand • Annual 1-in-2 peak demand • Hourly profiles corresponding to a wide range of weather conditions (20+ years) • Minimum operating reserve requirements
Firm Resources *(e.g. nuclear, coal, gas, biomass, geothermal)*	• Monthly capacity rating by resource • Forced outage rate by resource • Maintenance profile by resource
Variable Resources *(e.g. wind, solar)*	• Installed capacity by resource • Hourly profiles for multiple years, ideally including multiple years of overlap with hourly load profile data
Hydroelectric Resources	• Installed capacity by resource • Monthly/daily energy budgets across a range of plausible hydro conditions • Minimum output levels by month/day • Sustained peaking limitations by month/day
Storage Resources *(e.g. batteries, pumped storage)*	• Installed capacity by resource • Duration by resource • Charging & discharging efficiency by resourceerr • Paired variable resource (for hybrids) • Interconnection configuration & rating (for hybrids)
Demand Response Resources	• Expected load impact by program • Limits on number of program calls (per year or per month) • Duration of calls

B.2 Model Methodology

B.2.1 Load & Renewable Simulation

Generating an extensive record of load and renewable profiles that capture both the range of variability of each as well as the key correlations between them is a necessary but challenging step in reliability modeling. To generate such a record, RECAP relies upon historical time-synchronous load and renewable profiles but also uses statistical approaches to extend what is typically a limited historical record. The four-step process used in RECAP is shown in Figure B-2.

Figure B-2. Illustration of typical processes used to generate load & renewable profiles for RECAP



A long record of load, wind, and solar profiles is a crucial input to loss of load probability models. Because actual historical data is not available over a long enough record to use, RECAP inputs are typically derived from simulated hourly profiles.

Typically, the availability of historical hourly load data that can be practically incorporated into RECAP is limited—both by data availability and by the fact that historic load shapes from previous years may not appropriately reflect the composition of end uses and customers that make up today's system (an issue that becomes increasingly pronounced farther back in time). At the same time, a rigorous approach to measuring reliability requires consideration of a breadth of potential weather conditions.

To allow consideration of a broad range of potential weather conditions observed across multiple decades in spite of the lack of useful historical load data during most of that period, RECAP uses a neural network regression algorithm to extend a relatively shorter sample of actual historical load data across a longer period based on key weather indicators and drivers across that longer period. The neural network algorithm is trained with a set of historical loads and associated underlying weather data and then used to simulate load levels that reflect the composition of end uses and the underlying economic conditions that reflect today's electricity demands while also capturing the underlying weather conditions across a much broader record.

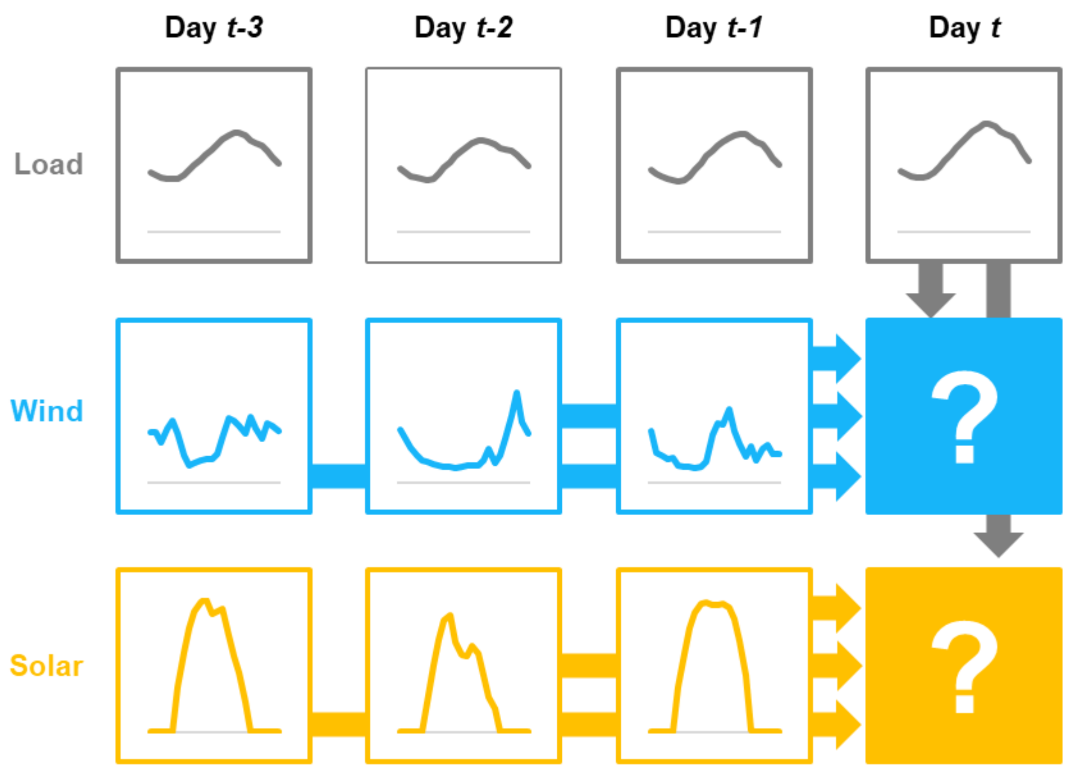
Similarly, Multiple years of actual and/or simulated hourly profiles for wind and solar resources are a key input to RECAP. Whenever possible, actual historical metered data is preferred, but in its absence (given the relatively small amount of renewable generation existing today), simulated hourly profiles from sources like NREL's WIND Toolkit and NREL's System Advisor Model provide coverage across multiple historical years (2007-'12 and 1998-'18, respectively). Several considerations are important in developing these data sets:

- Hourly profiles should capture multiple years. The potential variability of renewable generation, particularly during periods of extreme load, is high enough that a single year may not appropriately capture its expected production during those periods. Therefore, multiple years (typically at least four) are needed.
- Hourly profiles should correspond to a period for which load data is also available. Developing a dataset of load and renewables that is weather-matched based on actual historical conditions allows the modeling to account for the actual observed correlations between load and renewables.
- Hourly profiles for wind and solar should (ideally) cover the same historical period. Like above, this allows the model to preserve actual observed correlations between wind and solar—not just between load and each renewable technology independently.

A stochastic rolling day-matching algorithm is used to match the limited sample of renewable profiles with the extended record of simulated load data using the observed relationship for years with overlapping data i.e., years with available renewable data. The day matching algorithm, illustrated in Figure B-3, selects a renewable profile for each day of the simulation based the corresponding level of load in that day and the level of renewable generation in the prior day(s).[6] The potential sample of renewable profiles from the historical record that are considered as potential matches for each day in the extended record is also restricted to days within +/- 15 calendar days of that day to ensure that seasonal factors (e.g. variations in patterns of insolation, which affects solar production on a seasonal basis) are also accounted for in the process. Ideally, this day matching algorithm can be run on both wind and solar profiles simultaneously—this is possible when the historical records for wind and solar profiles are contiguous—but the algorithm can also be run independently on wind and solar if overlapping records are not available.

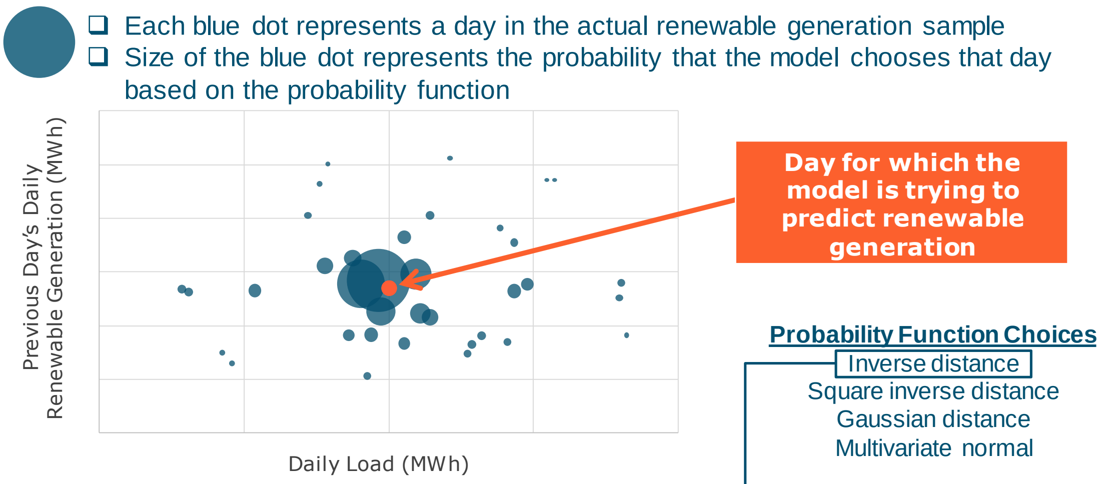
[6] The number of prior days' renewable generation included in the matching algorithm can be varied as needed to ensure that extended weather events observed in the historical record (e.g. multi-day storm systems) occur within the stochastic simulation.

Figure B-3. Illustration of day-matching algorithm used to extend record of renewable profiles to match loads



The algorithm used to select renewable profiles is a probabilistic one that allows for stochastic pairings of load and renewable shapes—in other words, multiple plausible combinations of load and corresponding renewable profiles are generated for the extended weather record. In order to choose a renewable profile for a specific day of interest (day *t*), the model searches through the actual record of time-synchronous historical load and renewable profiles to find days similar to day *t*. For each day *i* in the true historical record, RECAP evaluates a similarity rating based on multiple criteria, including the load on that day and renewable generation on preceding days. Figure B-4 illustrates the assignment of probabilities for a specific individual day; the days in the historical record that are "closest" to that day (in terms of that day's load and the previous day's renewable generation) are assigned the highest probability.

Figure B-4. Renewable profile selection process



$$\text{Probability of sample i being selected} = \frac{\frac{1}{Distance_i}}{\sum_{j=1}^{n} \frac{1}{Distance_j}}$$

$$\text{Where distance}_i = \text{abs}[\text{load}_{\text{Aug 12}} - \text{load}_i]/\text{stderr}_{\text{load}} + \text{abs}[\text{renew}_{\text{Aug 12}} - \text{renew}_i]/\text{stderr}_{\text{renew}}$$

The similarity rating is calculated as shown below, where w indicates weights, L indicates daily load, R indicates daily renewable production, and σ indicates standard deviation. If both load and renewable production are normalized, weights should be equal.

$$Similarity\ Rating_i = w_L \frac{|L_t - L_i|}{\sigma_L} + w_{R1} \frac{|R_{t-1} - R_{i-1}|}{\sigma_R} + \cdots + w_{Rn} \frac{|R_{t-n} - R_{i-n}|}{\sigma_R}$$

Once the similarity has been determined between each day, a daily renewable profile for each class of renewable resources is stochastically selected based on the similarity rating, with higher similarity days having a higher chance of being selected. There are multiple probability functions that the model can use in this step, and the function that E3 used in this analysis is shown below.

$$\Pr(target = i) = \frac{e^{-\left(\frac{similarity_i}{\sigma}\right)^2}}{\sum_{j=1}^{n} e^{-\left(\frac{similarity_j}{\sigma}\right)^2}}$$

This day-matching algorithm produces a more extensive record of synthetic weather-matched load and renewable shapes that also captures the autocorrelation of the renewable generation profile itself. For example, winter storms tend to last for multiple days which means that a windy or still day is more likely to be followed by a windy or still day which is captured in this approach. Other correlations are also captured that are dependent upon the specific system in question.

B.2.2 Loss of Load Probability Simulation

Based on the inputs described above, RECAP simulates the loss of load probability for an electric system using a Monte Carlo time-sequential simulation to capture plausible combinations of load, variable renewables, and outages across hundreds of potential years. For each broad class of resource enumerated above, RECAP includes a module that evaluates the ability of each resource in that class to contribute to load in each hour of the simulation. The elements of the time-sequential simulation are shown in Figure B-5, and the methodology used in each module is discussed in further detail in Table B-2.

Figure B-5. Steps of RECAP simulation methodology

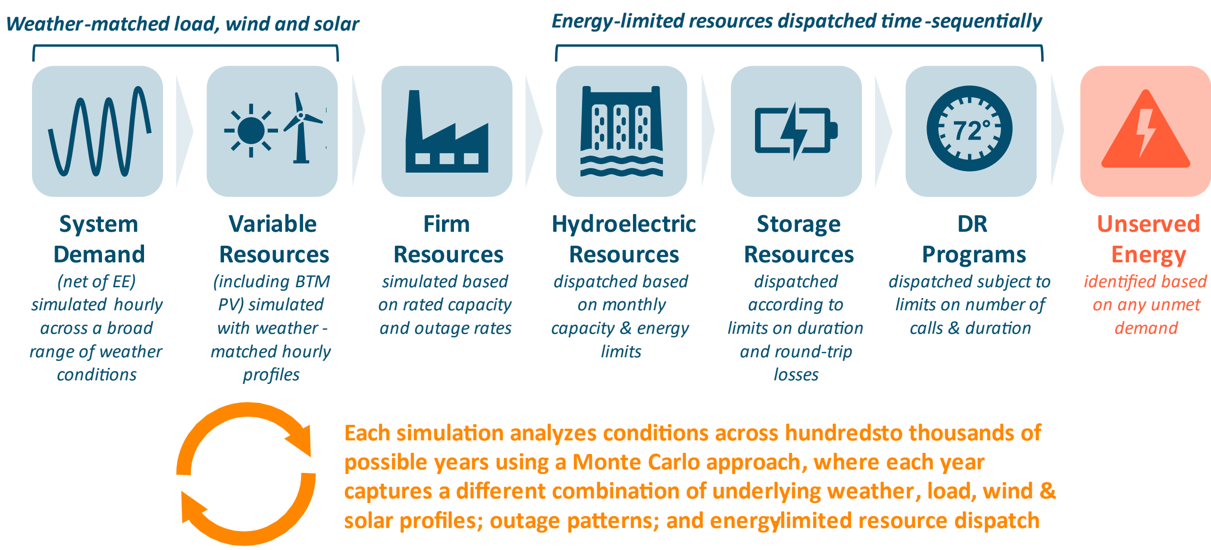


Table B-2. Overview of methodology used to compare load and resource availability

Module	Methodology
Load	The hourly profile of electricity demand is determined based on an hourly load shape that covers a broad range of historical weather conditions (multiple decades) that is scaled to the desired level of annual and peak demand. The underlying load shape itself is a result of a pre-processing neural network regression that simulates hourly load shapes for the full available weather record based on recent historical loads and a longer record of weather data.
Firm Resources *(e.g. nuclear, coal, gas, biomass, geothermal)*	Available dispatchable generation is calculated stochastically in RECAP using forced outage rates (FOR) and mean time to repair (MTTR) for each individual generator. These outages are either partial or full plant outages based on a distribution of possible outage states. Over many simulated days, the model will generate outages such that the average generating availability of the plant will yield a value of (1-FOR).

Module	Methodology
Variable Resources *(e.g. wind, solar, run-of-river hydro)*	Availability of variable renewable resources is simulated stochastically based on the rolling probabilistic day-matching algorithm described above. This results in an hourly timeseries profile for all variable resources that aligns with the hourly load profile.
Imports/Market Purchases	Availability of generic resources from external areas (i.e. assumed wholesale market purchases) can be specified at an hourly, monthly, or annual level. This is an input to RECAP.
Hydroelectric Resources	To determine hydro availability, the model uses a monthly historical record of hydro production. For every simulated load year, a hydro year is chosen stochastically from the historical database. Associated hydro budgets are typically assigned on either a weekly or daily basis and then "dispatched" to minimize net load (load less variable resources and hydro) during that period while accounting for a number of constraints, including: • Minimum output levels that capture the lower limit on the level of generation that a system may produce when considering hydrological and other physical constraints on the system • Sustained peaking limits, which limit the output of the hydro system across a range of rolling time windows (e.g. 1-hour, 2-hour, 4-hour, and 10-hour) to capture how hydrological factors may limit the ability to discharge water through a dam for sustained periods of time.
Storage Resources *(e.g. batteries, pumped storage)*	The model dispatches storage if there is insufficient generating capacity to meet load net of renewables and hydro. Storage is reserved specifically for reliability events where load exceeds available generation. It is important to note that storage is not dispatched for economics in RECAP which in many cases is how storage would be dispatched in the real world. However, it is reasonable to assume that the types of reliability events that storage is being dispatched for (low wind and solar events), are reasonably foreseeable such that the system operator would ensure that storage is charged to the extent possible in advance of these events. (Further, presumably prices would be high during these types of reliability events so that the dispatch of storage for economics also would satisfy reliability objectives).
Demand Response Resources	The model dispatches demand response if there is still insufficient generating capacity to meet load even after storage. Demand response is the resource of last resort since demand response programs often have a limitation on the number of times they can be called upon over a set period of time. For this study, demand response was modeled using a maximum of 10 calls per year, with each call lasting for a maximum of 4 hours.

To the extent the portfolio of resources whose availability is determined through the steps above is insufficient to meet demand in any hour, a loss of load event is recorded. After simulating hundreds of years of possible Monte Carlo outcomes, RECAP calculates the system's LOLE and a variety of other reliability statistics.

B.2.3 Effective Load Carrying Capability Calculation

The simulation of LOLE for a given electric system enables the calculation of "effective load carrying capability" (ELCC) for individual resources, or, in more colloquial terms, their capacity value: a measure of the equivalent amount of "perfect capacity" that could be replaced with the addition of a specified resource while maintaining the same level of reliability. ELCC for individual resources (or combinations of resources) is calculated through iterative simulations of an electric system:

1. The LOLE for the electric system without the specified resource is simulated. If the resulting LOLE does not match the specified reliability target, the system "adjusted" to meet a target reliability standard (most commonly, one day in ten years). This adjustment occurs through the addition (or removal) of perfect capacity resources to achieve the desired reliability standard.
2. The specified resource is added to the system and LOLE is recalculated. This will result in a reduction in the system's LOLE, as the amount of available generation has increased.
3. Perfect capacity resources are removed from the system until the LOLE returns to the specified reliability target. The amount of perfect capacity removed from the system represents the ELCC of the specified resource (measured in MW); this metric can also be translated to percentage terms by dividing by the installed capacity of the specified resource.

This approach can be used to determine the ELCC of any specific resource type evaluated within the model. In general, ELCC is not widely used to measure capacity value for firm resources (which are generally rated either at their full or unforced capacity) but provides a useful metric for characterizing the capacity value of renewable, storage, and demand response resources.

The ELCC of a resource depends not only on the characteristics of load in a specific area (i.e. how coincident its production is with load) but also upon the resource mix of the existing system (i.e. how it interacts with other resources). For instance, ELCCs for variable renewable resources are generally found to be higher on systems with large amounts of inherent storage capability (e.g. large hydro systems) than on systems that rely predominantly on thermal resources and have limited storage capability. ELCCs for a specific type of resource are also a function of the penetration of that resource type; in general, most resources exhibit declining capacity value with increasing scale. This is generally a result of the fact that continued addition of a single resource or technology will lead to saturation when that resource is available and will shift reliability events towards periods when that resource is not available. The diminishing impact of increasing solar generation as the net peak shifts to the evening illustrates this effect.

B.2.4 Planning Reserve Margin Calculation

The results of RECAP can also be translated into a simpler and more widely used planning reserve margin requirement (PRM), a target for system reliability expressed as a percentage requirement above expected peak demand. PRM requirements are used by many utilities and RTOs in their administration of resource adequacy requirements. Thus, RECAP also expresses its outputs in terms of the PRM:

+ The "actual" PRM of a system is calculated based on the summation of capacity provided by all resources; firm resources are rated at nameplate capacity, while hydro, variable, and use-limited resources are rated based on ELCC endogenously calculated as described above. This total amount of capacity is divided by the expected peak to provide a planning reserve margin.
+ The "target" PRM of a system (i.e. the PRM needed to achieve a corresponding specified LOLE target) is calculated by adjusting the starting system as needed with perfect capacity resources

to achieve the desired LOLE. The PRM for this adjusted system then represents the reserve margin needed to meet the comparable LOLE standard.

B.3 Key Model Outputs

A primary benefit of the RECAP model is the ability to produce an array of summary results that give insight into system reliability and the nature of frequency, magnitude, and duration of loss of load events on an electric system. The summary reliability statistics produced include:

+ **Loss of load expectation (LOLE, measured in days per year),** the expected number of days in which loss-of-load events occur in each year;
+ **Loss of load hours (LOLH, measured in hours per year),** the expected number of hours of lost load in each year;
+ **Loss of load events (LOLEV, measured in events per year),** the expected number of reliability events that occur within each year;
+ **Annual loss of load probability (ALOLP, measured in %),** the probability that at least one loss-of-load event will occur within a year; and
+ **Expected unserved energy (EUE, measured in MWh per year),** the expected amount of unserved load within each year.

RECAP also produces a number of metrics that help translate these detailed reliability statistics into a more typical planning reserve margin framework. If the user specifies a specific reliability target (for example 0.1 days/yr LOLE, or "one day in ten years"), the model calculates the required quantity of capacity necessary to achieve that level of reliability through an internal search algorithm. Comparing the required quantity of capacity to the median (1-in-2) peak load yields the target planning reserve margin while comparing it to the quantity of existing firm capacity on the system yields a net capacity shortage. Included in this measure of firm capacity is the effective load carrying capability (ELCC) of all non-firm resources including wind, solar, hydro, demand response, and battery storage.