2017

Technical Appendix

Prepared for CES-21 Grid Integration Flexibility Metrics and Standards Project:

Documentation of Input Assumptions

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Contents

I. Purpose

This Technical Appendix documents the input assumptions used for the study cases developed for the CES-21 Grid Integration Flexibility Metrics and Standards project. This document is organized as follows:

- Section II provides a high level overview of the source data used to create the CAISO and WECC systems
- Section III provides a detailed discussion on the various uncertainties modeled, including data sources and methods
- Section IV provides a more detailed description of the individual study cases
- Section V provides a discussion on the modeling changes made to the SERVM software over the course of the project

II. Source Data for CAISO & WECC

A. Source Data and Study Year

Unless otherwise noted, the input assumptions used for the project were based on the latest LTPP data for CAISO and TEPPC data for the WECC. Specifically, the project relied upon the following data sources to develop the CAISO and WECC representations:

- 2016 LTPP Scenario Tool and the data sources referenced within[1] - Generation and load data for CAISO, demand side resources based on referenced CEC data, and RPS resources based on referenced RPS Calculator data

- 2026 TEPPC Common Case Dataset[2] – Generation and load data for WECC

[1] 2016 LTPP Scenario Tool v1.2 (http://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=12332)
[2] Project used the latest TEPPC dataset available at the time of the final analysis (version 1.7), (https://www.wecc.biz/SystemAdequacyPlanning/Pages/Datasets.aspx)

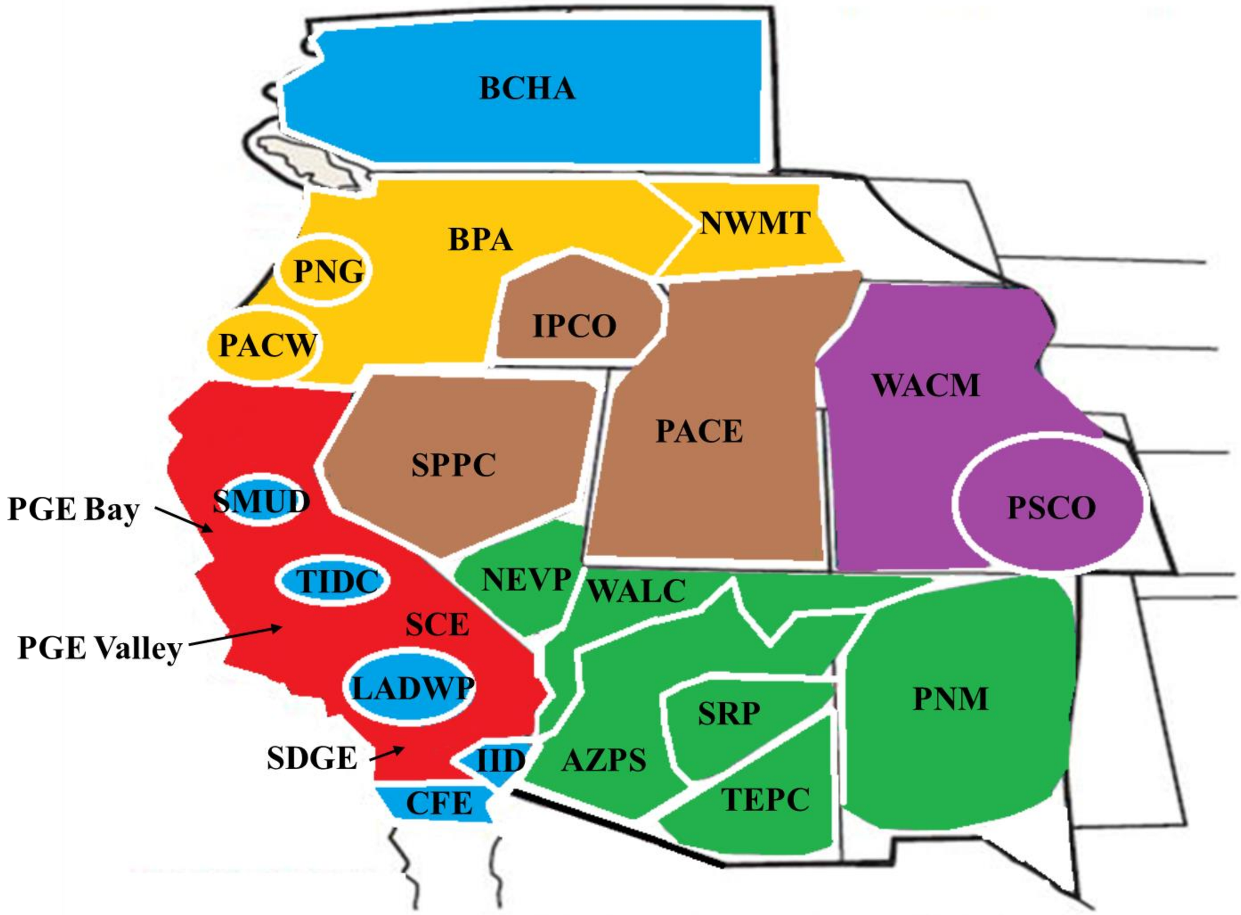
B. *Study Topology*

Figure 1 shows the study topology that was used for the study. SERVM models the regions in Figure 1 with a pipe and bubble representation, allowing for regions to share capacity based on economics and subject to physical transmission constraints. The following is a list of regions included in the study:

- Arizona Public Service Company (AZPS)
- British Columbia Hydro Authority (BCHA)
- Bonneville Power Administration – Transmission (BPAT)
- Comision Federal de Electricidad (CFE)
- Imperial Irrigation District (IID)
- Idaho Power Company (IPCO)
- Los Angeles Department of Water and Power (LADWP)
- Nevada Power Company (NEVP)
- NorthWestern Energy (NWMT)
- PacifiCorp East (PACE)
- PacifiCorp West (PACW)
- Pacific Gas and Electric Company - Bay Area (PGE Bay)
- Pacific Gas and Electric Company - Valley Area (PGE Valley)
- Public Service Company of New Mexico (PNM)
- Portland General
- Public Service Company of Colorado (PSCO)
- Southern California Edison (SCE)
- San Diego Gas and Electric (SDGE)
- Sacramento Municipal Utility District (SMUD)
- Sierra Pacific Power Company (SPPC)
- Salt River Project (SRP)
- Tucson Electric Power Company (TEPC)
- Turlock Irrigation District (TIDC)
- Western Area Power Administration – Colorado/Missouri Region (WACM)
- Western Area Power Administration - Lower Colorado Region (WALC)

CAISO was separated into 4 distinct regions in SERVM: PGE Bay, PGE Valley, SCE, and SDGE.

Figure 1. Study Topology



III. Modeling of Uncertainties

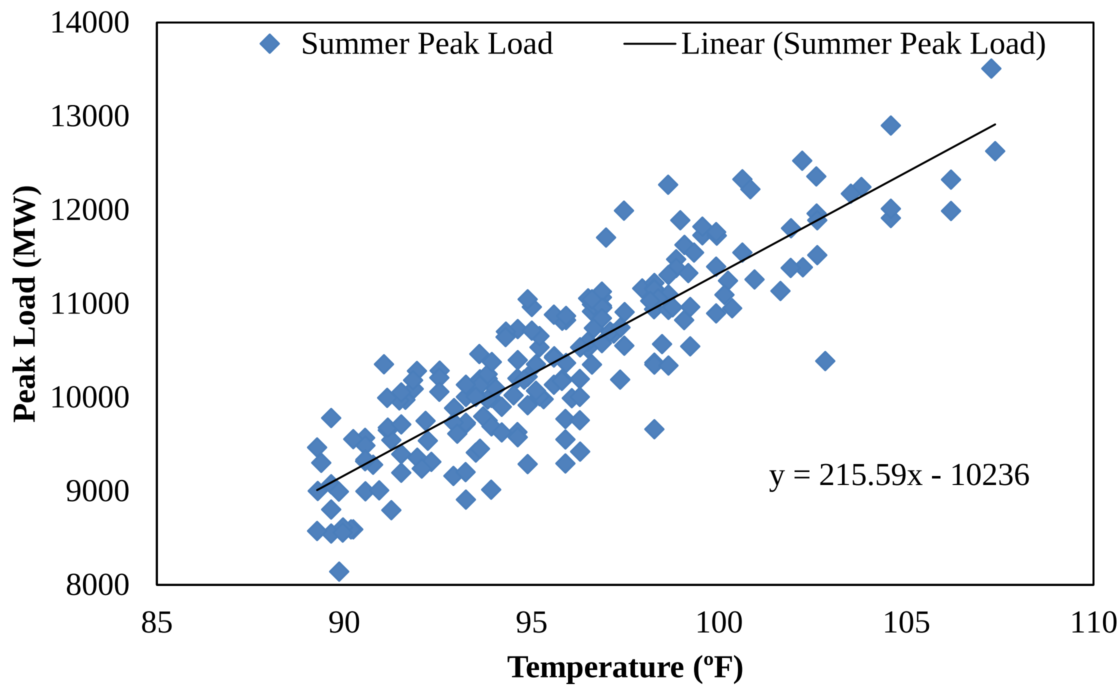
A. Load Modeling

Simulating a future year requires a forecast of not only peak load and total energy, but also the shape of load over the course of the year. Since load is a function of weather and future weather is unknown, the best representation of the shape of load is to use historical weather. To capture a wide range of possible weather conditions and the associated load, we constructed synthetic load shapes for 35 historical weather years. These shapes are our forecast of what load may look like in a future year given the expected customers and assuming we have identical weather to a historical year. For instance, the 1985 synthetic shape has an 8,760 forecast of loads for 2026 based on weather patterns from 1985.

The relationship between weather and load is derived from neural network modeling of recent historical loads and temperatures. Developing this relationship is comprised of the following steps:

- Solar production profiles were added to the 2010-2014 load shapes. Since behind-the-meter PV is treated as a generator in this study, all load shapes needed to be grossed up for historical production.
- Historical demand response calls were added back to load.
- Next, the 2010-2014 load profiles were scaled to a common base year to remove load growth.
- All load data was adjusted by a day of week factor so that all loads were representative of Wednesday weather conditions.
- Weather and timing data were collected for each year as inputs to the neural net process. Temperature data came from NOAA. The specific variables used in the training included: temperature, 24 hour prior temperature, 48 hour prior temperature, heating degree days, cooling degree days, and time of day.
- The neural net inputs and loads were then separated by month and trained with Ward System's Neuroshell Predictor. The application saves the relationship identified in the training.
- Since the neural network training process requires significant data to develop a meaningful relationship, additional modeling was required for rare extreme weather periods. A linear relationship was defined for loads in the peak hour of the day as a function of temperature. The relationship for SCE is shown in Figure 2.

Figure 2. SCE Loads in the Peak Hour of Day as a Function of Temperature



[3]

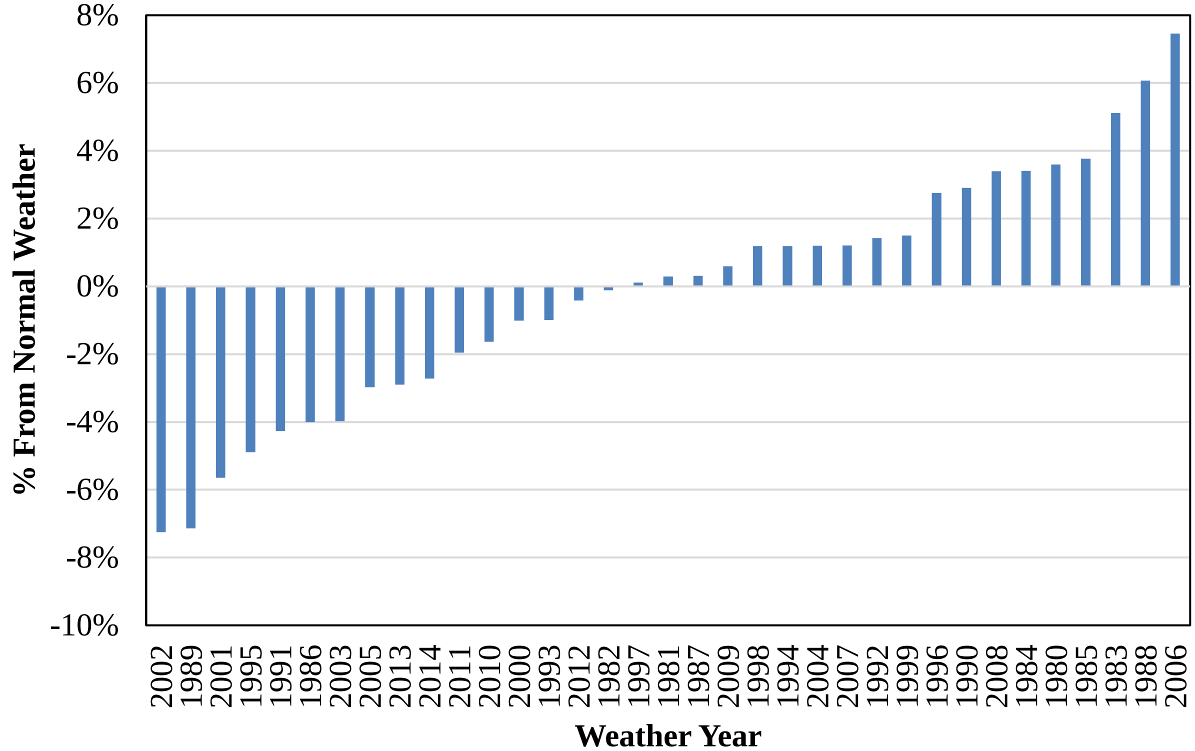
Next, the relationships were applied to historical weather to develop 35 distinct load shapes. The shapes used for the SERVM simulations are based on consumption as defined in the CEC Mid Baseline-Mid AAEE. To match the projected 2026 summer peak and annual energy, the historical weather load values for every hour for every shape are adjusted such that the average peak and energy of all the weather shapes is equal to the respective 2026 CAISO forecast (or TEPPC 2026 forecast for non-CAISO regions).

In order to meet both a peak and energy target, a load stretching algorithm in SERVM is employed. Figure 3 displays the variance in summer peak load simulated based on 35 years of historical weather (these are annual peaks as well since the annual peak occurred in a summer month in every year). In this figure, each year's value is the percentage difference from each year's peak to the average of all peaks. Compared to a normal or average weather year, peak loads across all three regions can be as high as 7% above normal and as low as 5% below normal. This variation is strictly due to weather, and does not include economic load

[3] The curve fit formula demonstrates 215 MW/F° of load response for SCE in the summer.

growth uncertainty. This load variation is not directly comparable to the variation in CEC's 1-in-5 or 1-in-10 load forecast since the CEC forecasts incorporate both economic and weather uncertainty.

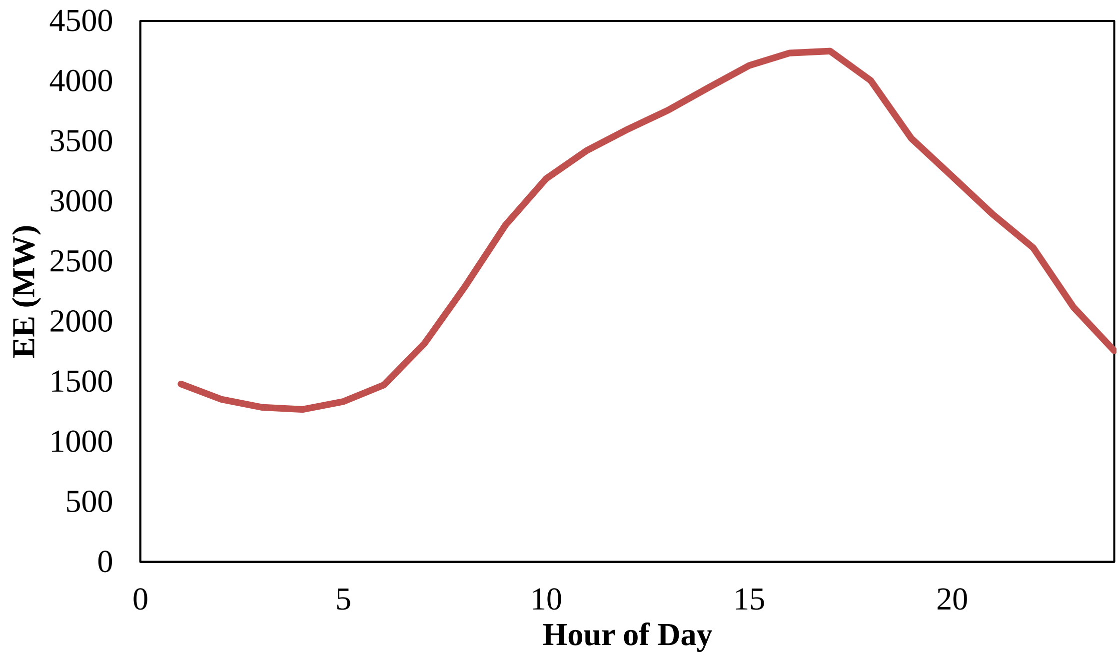
Figure 3. CAISO (PGE, SCE, SDGE) Peak Load Variance



B. Energy Efficiency Modeling

Energy efficiency was modeled as a fixed profile for every year based on the single AAEE hourly shape from the CEC. Figure 4 shows the average EE daily shape when max daily load is greater than 45,000 MW in the month of August. As the timing of the net load peak shifts to later in the day, the capacity value of AAEE drops.

Figure 4. Average EE August Daily Shape when Max Daily Load is Greater than 45,000 MW



The energy efficiency at the time of the annual peak net load for each weather year is shown below in Table 1 and demonstrates that the capacity value of AAEE is significantly variable. As discussed in the results and recommendations section of the final report, developing additional, weather based AAEE profiles represents an opportunity for future research.

Table 1. Energy Efficiency at Time of Annual Peak Net Load

Year	Peak Net Load	EE
1980	49,730.31	3,393
1981	50,119.81	4,347
1982	48,459.58	3,747
1983	51,449.94	3,681
1984	51,259.86	3,764
1985	50,024.35	3,187
1986	46,186.76	4,092
1987	48,509.23	3,947
1988	53,089.51	4,485
1989	45,724.75	2,685
1990	50,038.56	3,549
1991	49,413.28	4,152

1992	49,363.70	3,635
1993	48,276.21	3,640
1994	50,398.09	3,366
1995	46,766.40	3,787
1996	50,241.64	3,366
1997	49,562.70	3,852
1998	49,539.66	3,787
1999	49,203.13	3,547
2000	45,749.08	3,418
2001	45,648.38	3,931
2002	45,564.08	3,407
2003	46,760.45	3,856
2004	50,436.60	3,798
2005	47,237.22	3,728
2006	53,052.63	3,836
2007	50,248.71	2,837
2008	49,211.77	2,691
2009	49,712.04	3,728
2010	50,324.10	3,662
2011	48,259.33	3,006
2012	49,240.44	3,366
2013	47,646.64	3,798
2014	47,602.56	3,945

C. Source of weather profiles for wind and solar generation

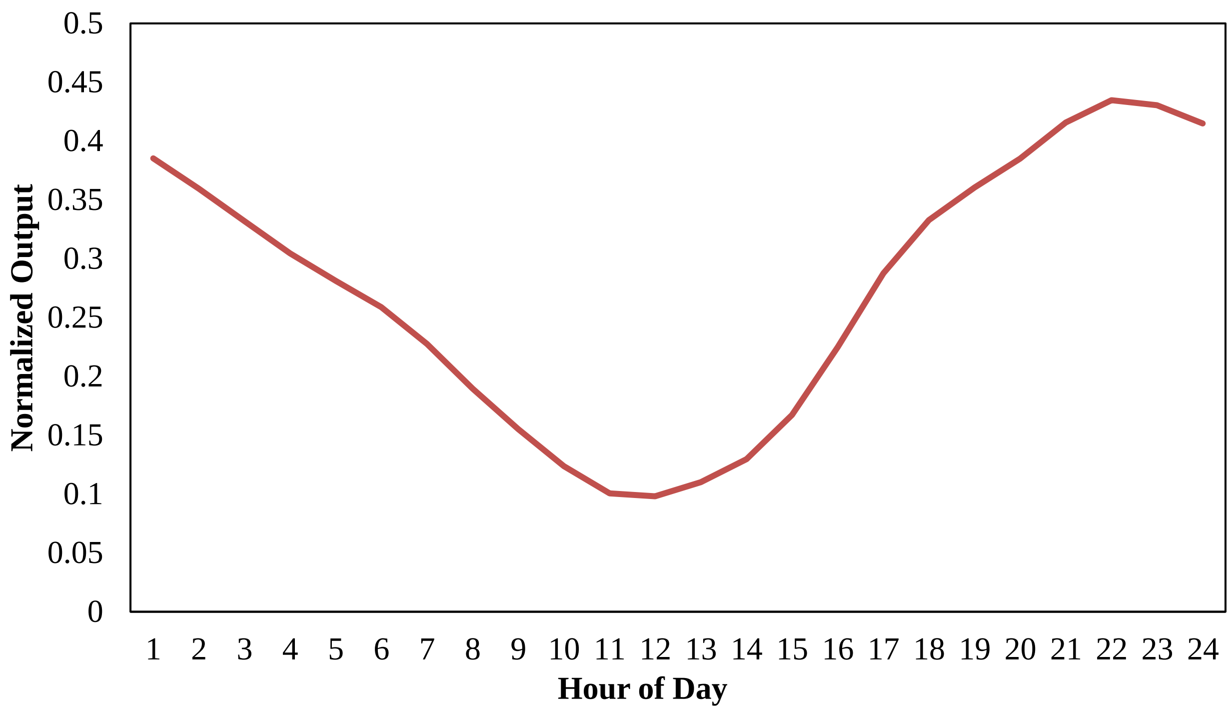
1. Wind generation profiles

Wind profiles were produced using historical metered output from 2010-2014. First, the shapes from this raw data were normalized to 100% by dividing the historical output by the appropriate annual capacity for each of the five years. Next, a correlation was created between the load and wind output for SCE and PG&E Valley. The daily wind profiles from the day that most closely matched the total load out of all the days +/- 5 days of the source day was used to create the profiles for 1980 to 2014. For example, the profile for January 1, 1980 was selected by comparing loads between December 26 and January 5 from 2010 to 2015 to the synthetically created load shape for January 1, 1980. If the closest match was from December 27, 2011, then all wind profiles in all California regions for January 1, 1980 were pulled from December 27, 2011. This method allows the historical diversity between wind projects in California to be maintained.

Hours 24 to 1 (the seams) were interpolated from hour 23 and hour 2 to avoid a drastic hourly change in output.

Figure 5 shows the average daily wind profiles for August.

Figure 5. August Average Daily Wind Profile



Wind volatility was created in the simulations based on historical one-minute data from the CAISO.[4] Hourly integrated values were calculated for the actual historical data and 5-minute shapes were calculated that minimized volatility. The 5-minute shapes with volatility removed were compared to the 5-minute actuals to develop distributions of volatility at a range of normalized output levels. Then for each simulation, Monte Carlo draws from the volatility distributions were added to wind profiles without volatility. Table 2 below demonstrates the frequency with which specific volatility values were drawn. These represent the unexpected movement in wind output in a 5-minute period.

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[4] One-minute wind, solar, and load data, derived based on historical operations data, are provided by the CAISO publicly through its annual Flexibility Needs Assessment initiative (https://www.caiso.com/informed/Pages/StakeholderProcesses/FlexibleCapacityNeedsTechnicalStudyProcess.aspx)

Table 2. Frequency Distribution of Wind Volatility

		Normalized Output (%)									
		0	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**
Normalized Divergence (%)	**-5+**	-	.09	.42	.49	.58	.59	.68	.73	.26	-
	-4 to -3	.03	.24	.56	.63	.81	1.13	1.18	1.23	.81	.60
	-3 to -2	.16	1.08	1.69	2.45	3.38	3.89	4.01	3.54	4.15	2.08
	-2 to -1	.98	6.70	8.28	10.48	11.99	12.30	11.80	11.38	13.37	10.42
	-1 to 0	48.07	42.04	38.97	35.58	33.28	31.94	32.50	33.08	31.33	37.80
	0 to 1	49.65	41.46	38.76	36.58	33.27	32.69	32.26	32.56	34.00	37.20
	1 to 2	.99	7.15	8.53	10.25	11.60	11.94	11.83	12.05	10.70	8.33
	2 to 3	.10	1.02	1.90	2.46	3.65	3.56	3.78	3.48	3.48	3.27
	3 to 4	.02	.18	.55	.59	.99	1.13	1.21	1.05	1.19	.30
	4 to 5	-	.05	.17	.22	.30	.53	.42	.51	.48	-
	5+	-	-	.16	.25	.17	.30	.33	.38	.22	-

2. Solar generation profiles

Solar shapes were developed from data downloaded from the NREL National Solar Radiation Database (NSRDB) Data Viewer. Data was available for the years 1998 through 2014. Data was downloaded from 170 different cities. Historical solar data from the NREL NSRDB Data Viewer included variables such as temperature, cloud cover, humidity, dew point, and global solar irradiance. The data obtained from the NSRDB Data Viewer was input into NREL's System Advisory Model (SAM) for each year and city to generate the hourly solar profiles based on the solar weather data for both a fixed solar PV plant and a tracking solar PV plant. Inputs in SAM included the DC to AC ratio of the inverter module and the tilt and azimuth angle of the PV array. Data was normalized by dividing each point by the desired array size of 4,000 kWdc. Solar profiles for 1980 to 1998 were selected by using the daily solar profiles from the day that most closely matched the total load out of the corresponding data for the days that we had for the 17-year interval. The profiles for the remaining years 1998 to 2014 came directly from the normalized raw data. The previous steps for selecting a profile were completed for each of the 170 cities. The aggregated profiles for each region were calculated by averaging the cities that fell in each region.

Figure 6 show the average daily solar profiles for August.

Figure 6. August Solar Profile

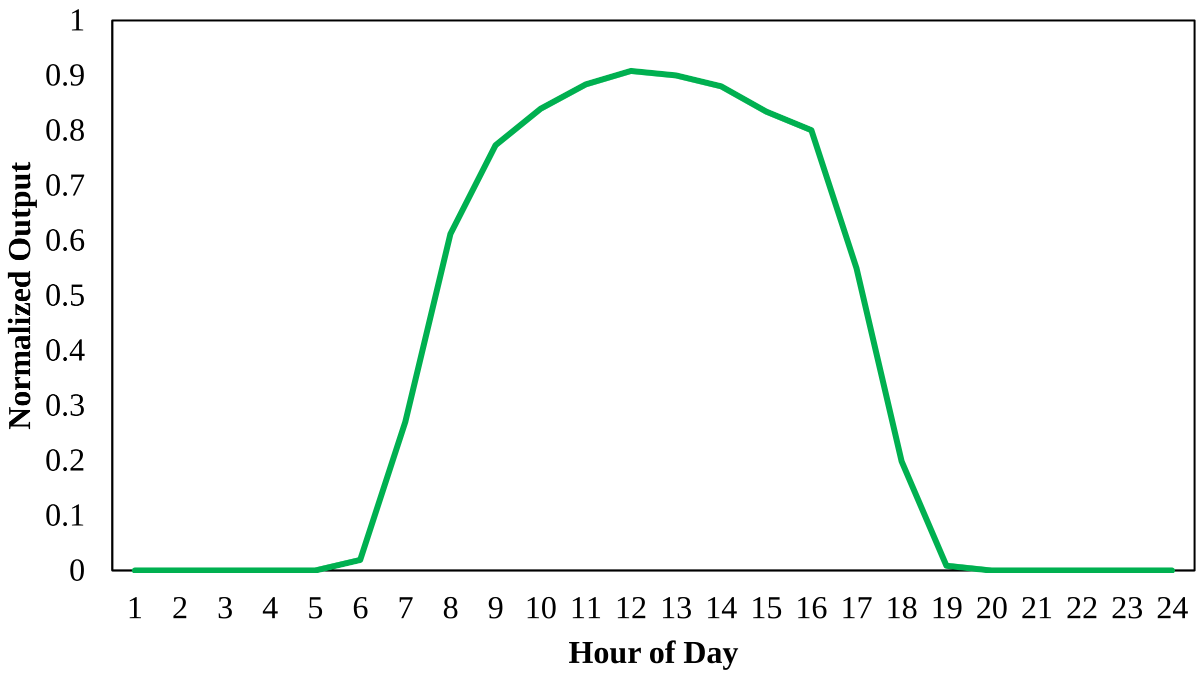


Table 3 shows similar calculations to those performed for wind were performed to create solar volatility distributions using historical solar volatility.

Table 3. Frequency Distribution of Solar Volatility

		Normalized Output (%)									
		0	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**
Normalized Divergence (%)	**-5+**	.03	2.04	3.02	1.83	2.55	2.75	1.72	1.22	.42	.24
	-4 to -3	.11	2.96	3.86	4.28	4.15	3.56	2.88	2.03	.91	.36
	-3 to -2	.83	7.41	6.48	9.38	9.67	7.54	6.88	4.72	3.02	1.07
	-2 to -1	4.65	16.8	15.28	14.96	15.42	14.21	12.36	11.74	10.44	5.23
	-1 to 0	31.24	18.45	19.32	18.89	17.7	21.42	24.8	30.62	36.64	43.09
	0 to 1	58.31	20.39	20.15	18.6	18.42	21.83	27.19	30.11	34.46	42.89
	1 to 2	4.64	19.83	17.16	17.01	15.9	15.28	13.54	11.45	8.91	5.28
	2 to 3	.18	10.01	10.68	10.07	10.2	7.67	6.73	4.33	3.37	1.36
	3 to 4	.01	1.94	3.09	3.69	3.11	3.37	2.24	2.21	1.16	.25
	4 to 5	.01	.07	.74	.83	1.63	1.57	1.02	1.02	.38	.07
	5+	-	.1	.22	.46	1.25	.79	.64	.55	.29	.17

D. Economic Load Forecast Error

Economic load forecast error multipliers were developed to isolate the economic forecast uncertainty inherent in four year-ahead[5] load forecasts. Based on reviewing Congressional Budget Office (CBO) GDP forecasts 4 years ahead, and comparing those forecasts to actual data, the standard deviation of a normal distribution of forecast deviations was calculated to develop an economic load forecast error. Because electric load grows at a slower rate than GDP, a 40% multiplier was then applied to the raw CBO forecast error. Table 4 shows the economic load forecast multipliers and associated probabilities. The table shows that 7.9% of the time, it is expected that load will be under-forecasted by 4% four years out. The SERVM model utilized each of the 33 weather years and applied each of these five load forecast error points to create 165 different load scenarios. As an example, when each of the five load forecast error points is applied to the 1980 weather year, all 8,760 hours are multiplied by the respective error. Five distinct cases then are created for 1980, each of which will be simulated independently. This process is followed for every weather year. While the economic load forecast error distribution follows a normal distribution where each point has a different weighting, each weather year was given equal probability of occurrence.

Table 4. 4 Year Ahead Economic Load Forecast Error

Load Forecast Error Multipliers	Probability (%)
0.96	7.9
0.98	24.0
1.00	36.3
1.02	24.0
1.04	7.9

[5] Four year ahead forecast uncertainty was used to represent the minimum time it takes a developer to permit and construct a new power plant.

E. Unit Outage Data

Unlike typical production cost models, SERVM does not use an Equivalent Forced Outage Rate (EFOR) for each unit as an input. Instead, historical Generating Availability Data System (GADS) data events are typically entered in for each unit and SERVM randomly draws from these events to simulate the unit outages. For this study, the mean time to repair and EFOR values from PLEXOS were utilized to calculate a mean time to repair value. Distributions around these values were then developed to be input into SERVM to represent the unit outage uncertainty. To represent unit outages in SERVM, full outages, partial outages, and planned outages were used.

The most important aspect of unit performance modeling in reliability studies is the cumulative MW offline distribution. Most service reliability problems are due to significant coincident outages. Figure 10 shows the distribution of outages for CAISO based on historical modeled outages. The figure demonstrates that in any given hour, the CAISO system can have between 0 and 3,500 MWs of its generators offline due to forced outages. Figure 7 below shows that in 10% of all hours throughout the year, CAISO has greater than 2,500 MW in a non-planned outage condition. This is typically made up of several units that are on forced outage at the same time.

Figure 7. Conventional Resources on Forced Outage as a Percentage of Time

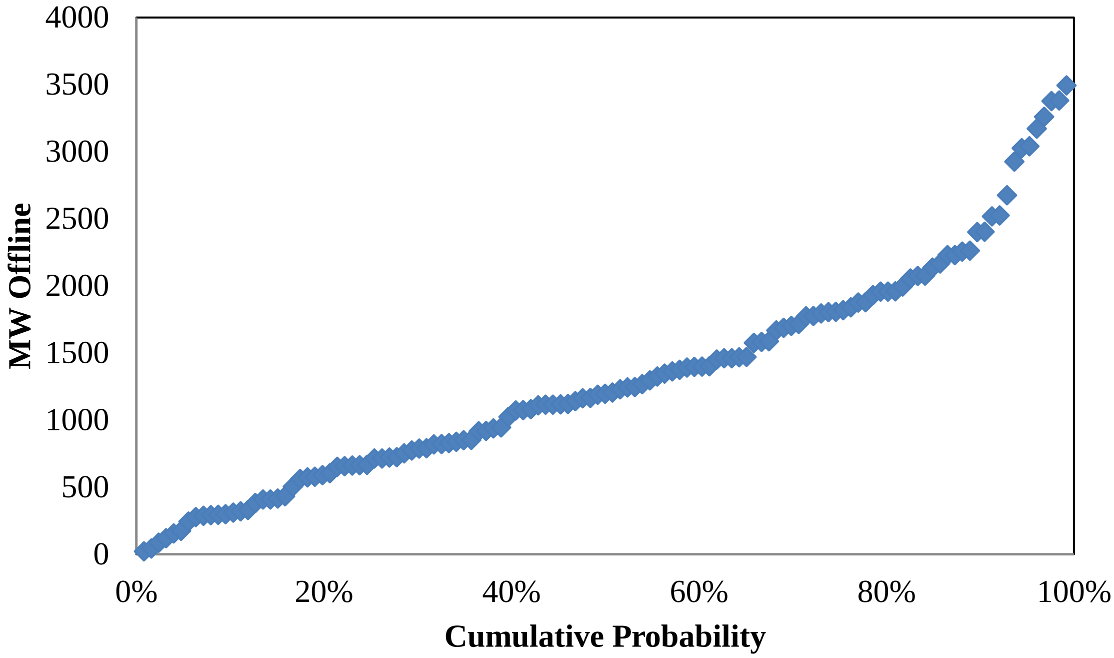
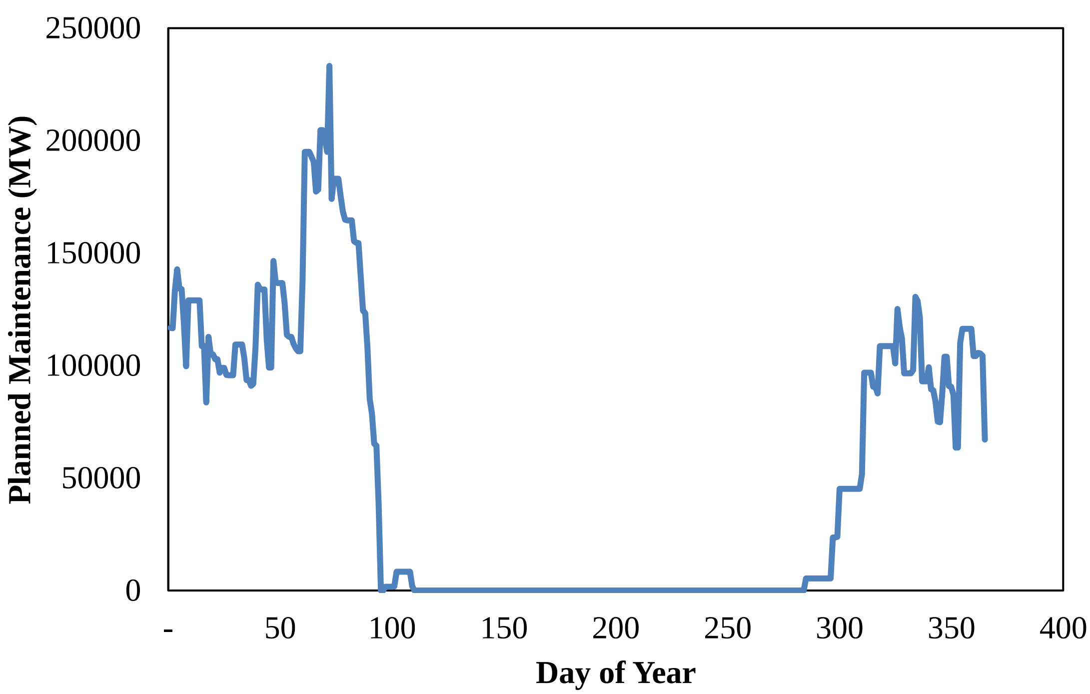


Figure 8 shows the distribution of planned outages across the year used in the study.

Figure 8. Planned Maintenance



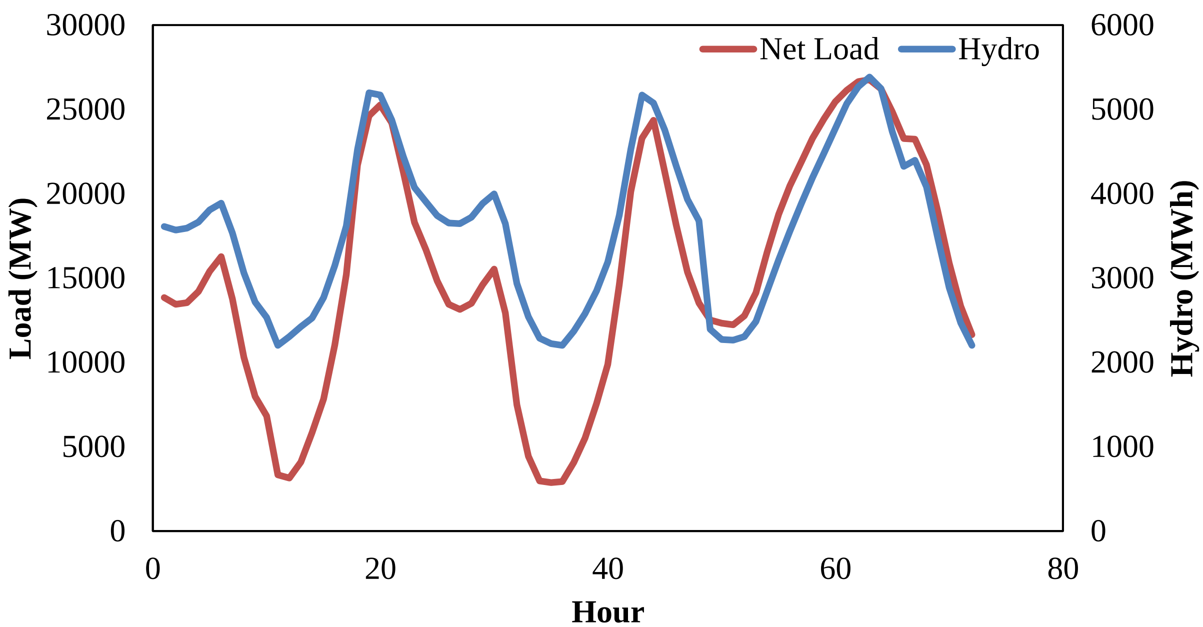
F. Hydro Modeling

Available hydro data from 1980 to 2014 was collected from the U.S. Energy Information Administration Form 923. Each project was assigned into one of the following appropriate regions for all 35 weather years. CAISO projects were assigned regions based on the definitions provided in the 2016 NQC List.

AZPS	PACW
BCHA	PGE Valley
BPAT	Portland General
IID	PSCO
IPCO	SCE
LADWP	SMUD
NEVP	TIDC
NWMT	WACM
PACE	WALC

A proportional load following algorithm for hydro was used to replicate operations. The hydro dispatch adjusts its output as demand for electricity fluctuates throughout the day. Peak net load hours have the highest hydro and low load hours have the lowest hydro dispatch. Figure 9 shows an illustration of the net load and hydro dispatch over a 3-day period.

Figure 9. CAISO Net Load and Hydro Dispatch Schedule



Using the actual hourly data from 2010 – 2014 available for SCE, PGE Valley, and BPAT, inputs were developed to be used by the proportional load following algorithm for every zone in WECC.

The average daily minimum and maximum dispatch levels, the total monthly energy, as well as the monthly maximum dispatch level was identified from the historical hourly data for PG&E Valley, SCE, and BPAT. Minimum and maximum daily dispatch levels and monthly maximum dispatch levels were defined as a function of monthly total energy as shown in the Figures 10, 11, and 12 below.

Figure 10. PGE Valley monthly maximum dispatch

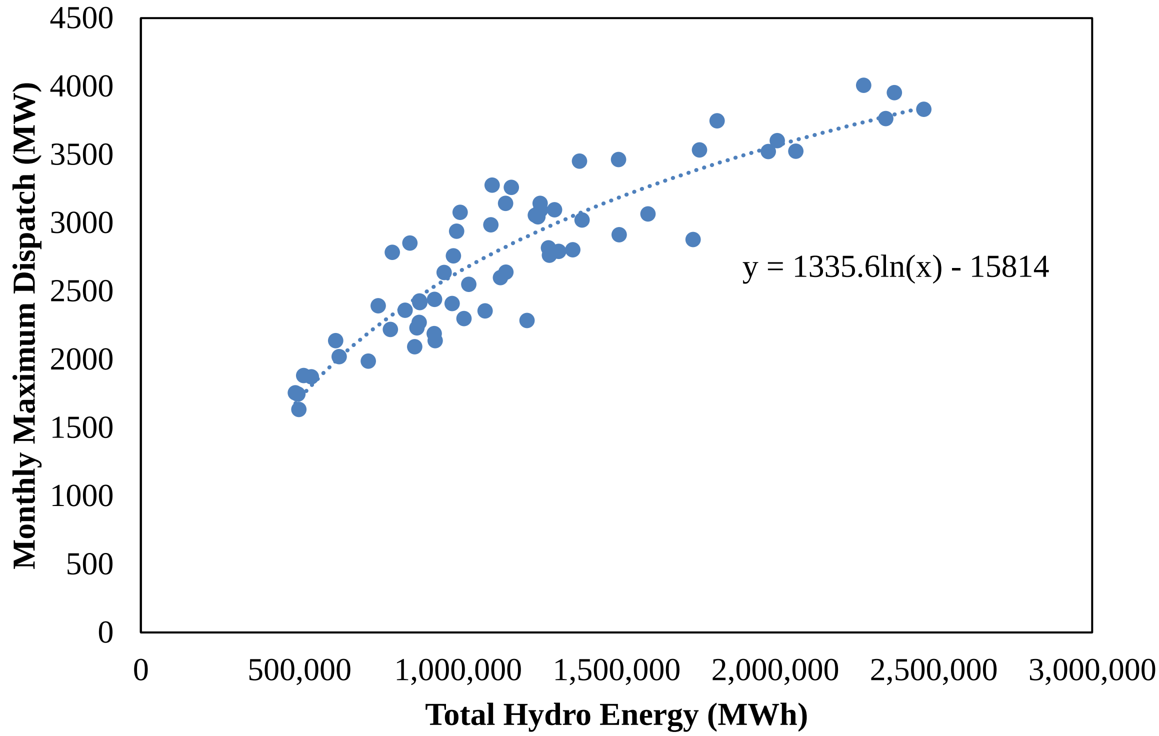


Figure 11. PGE Valley Average Maximum Daily Dispatch Levels

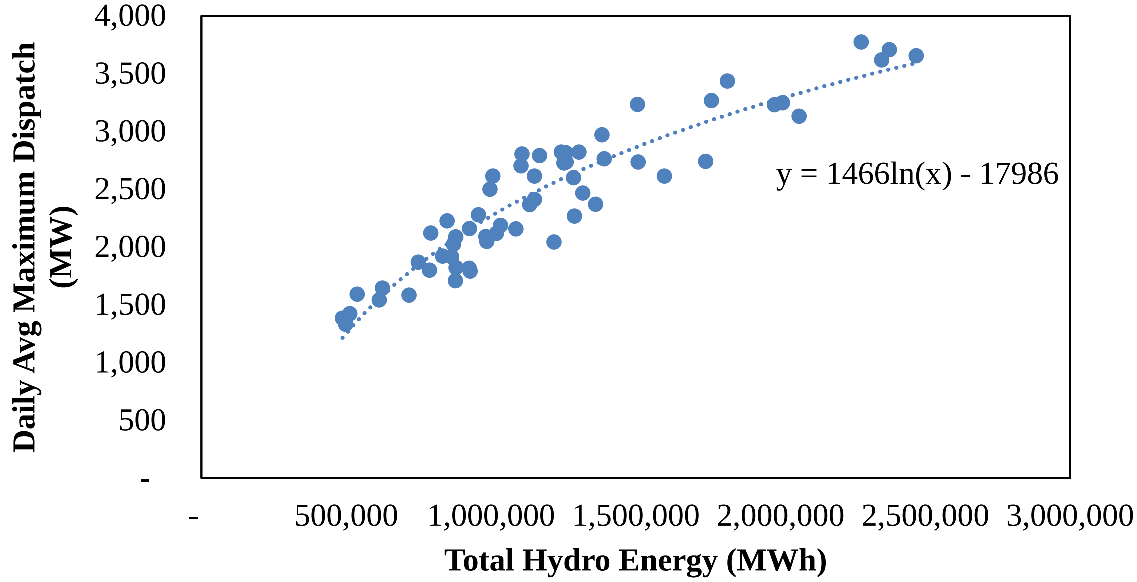
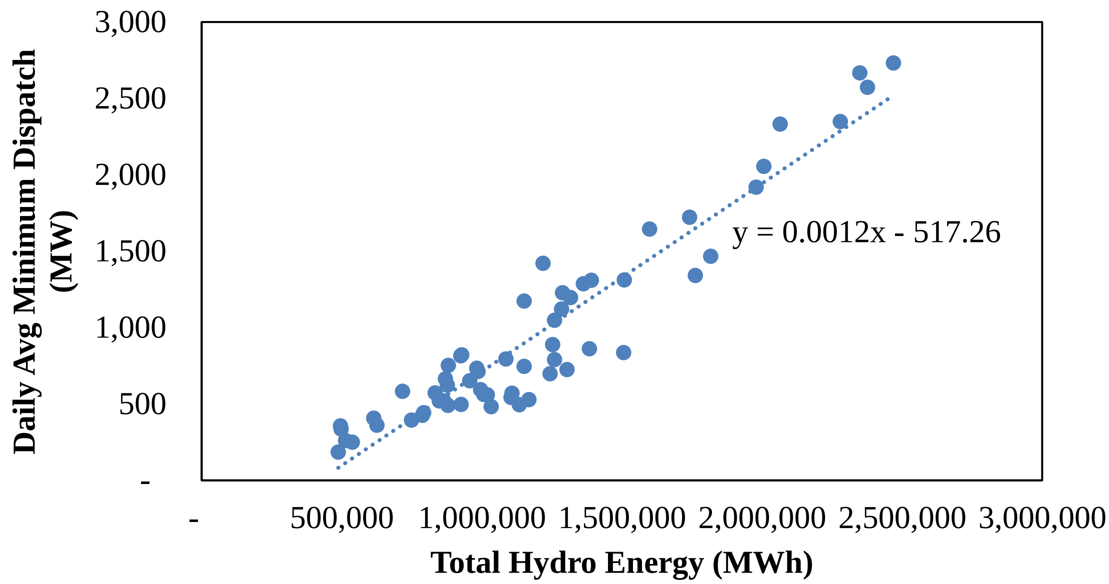


Figure 12. PGE Valley Average Minimum Daily Dispatch Levels



Based on the hydro region definitions from the 2016 NQC List, PG&E Valley energy was substantially higher in the EIA monthly data than in the historical hourly data. Some projects were apparently not included in the PG&E Valley region in the hourly hydro data that were defined in the PG&E Valley region in the 2016 NQC List. The curve fit equations were scaled up to target the higher energies in the EIA data. This means that the general relationship between energy and capacity was preserved in the scaled-up inputs.

Figure 13 shows a comparison of the monthly hydro energy between the EIA Data and the CPUC Energy Division Data.

Figure 13. Monthly Hydro Energy by Source

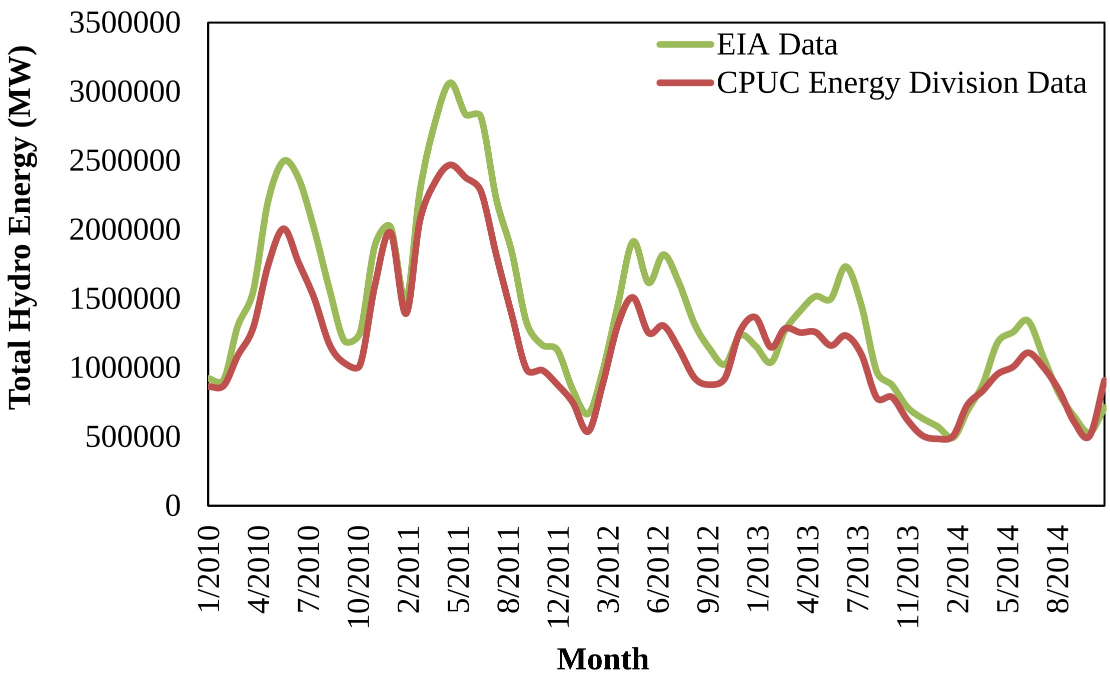
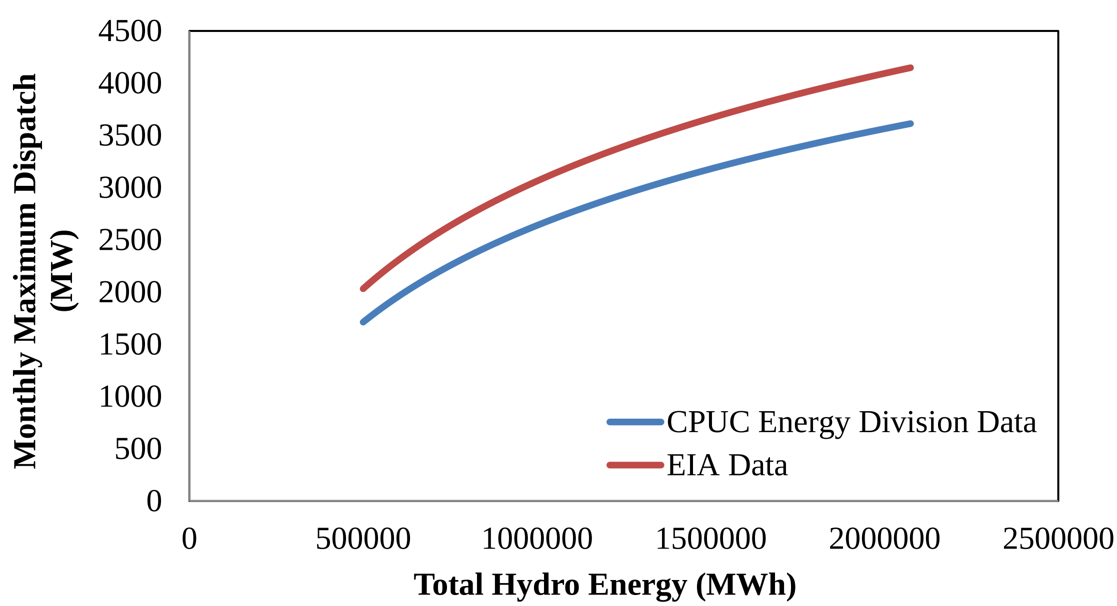


Figure 14 shows the monthly maximum dispatch for EIA and CPUC Energy Division Data for PGE Valley.

Figure 14. PGE Valley Monthly Max Dispatch by Data Source



For PGE Valley, SCE, and BPAT, the curve fit equations were then used to apply to historical energy from the monthly energies provided in the EIA data forms going back to 1980. Figure 15 shows the total hydro generation for CAISO by weather year that was used in the SERVM modeling runs.

Figure 15. Hydro Energy

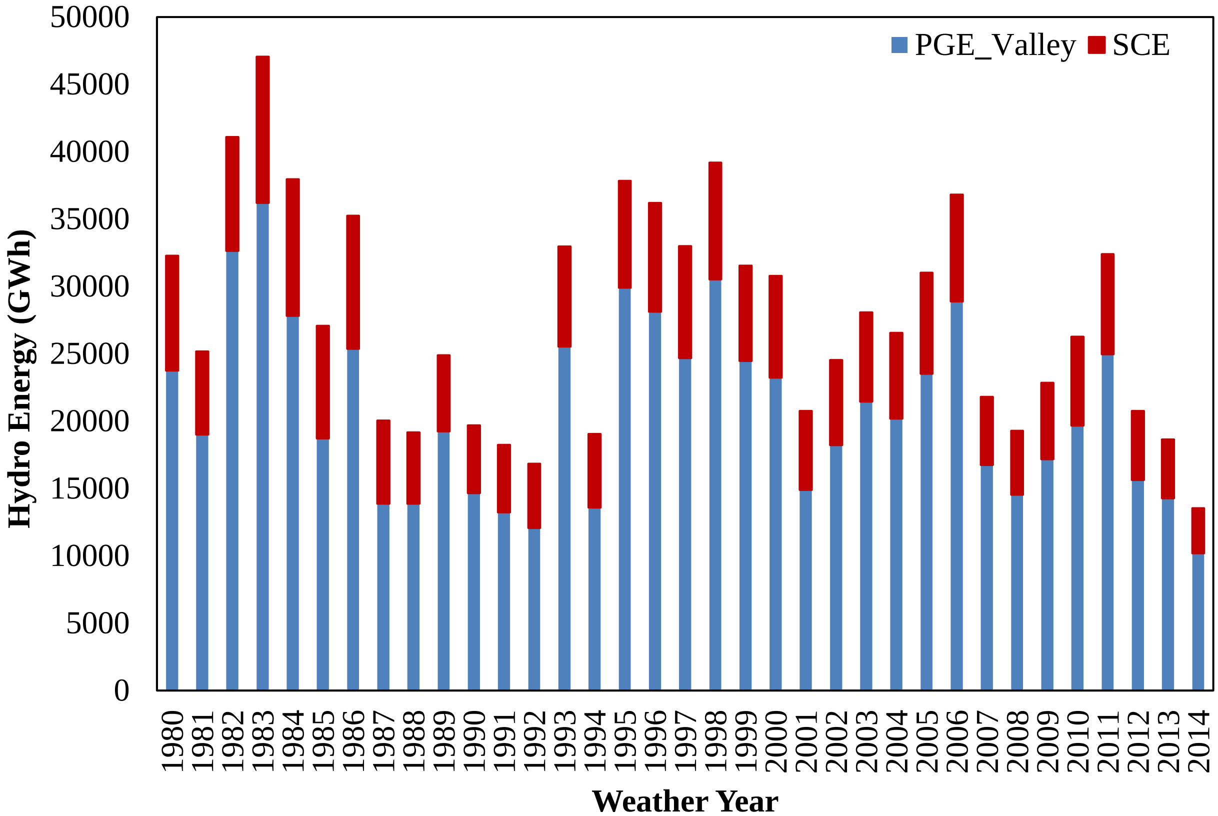
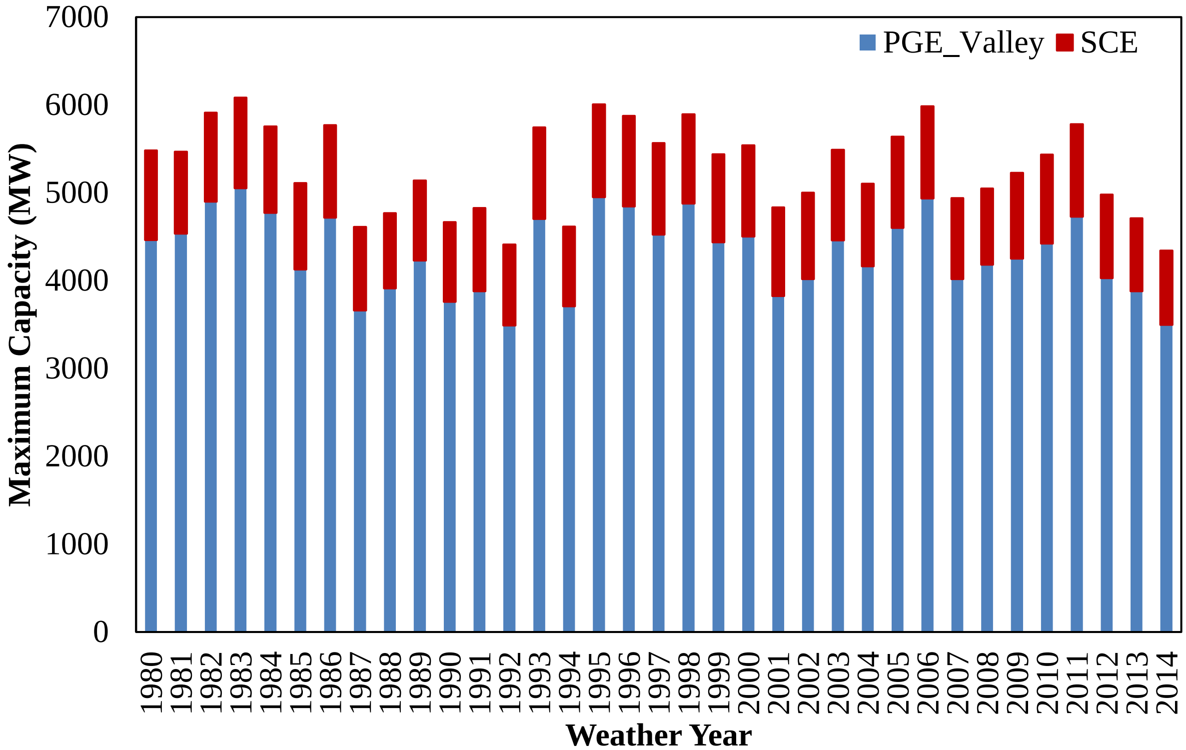


Figure 16 shows the maximum capacity for the hydroelectric fleet for CAISO by weather year that was used in the SERVM modeling runs.

Figure 16. Maximum Capacity for CAISO Hydroelectricity Plants



Inputs for regions without historical hourly hydro dispatch data were developed using the energy-to-capacity relationships from either PGE, SCE, BPAT, or other proprietary relationships to which Astrapé has access. Each region was tested using the relationship of all the source regions available. The region used for sourcing the relationship was determined by the reasonableness of the capacity factor and load duration curves produced by the respective region.

G. Operating and Flexibility Reserve Requirements & Operating Reserve Demand Curve

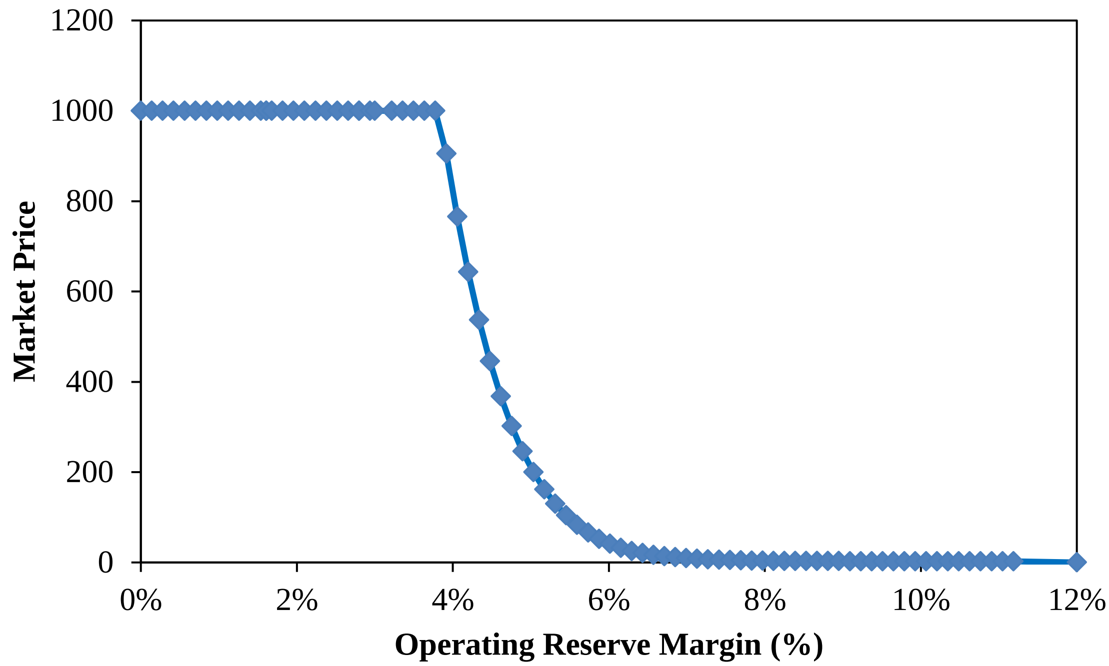
Table 5 shows the assumptions that were used by SERVM for regulation, spin, non-spin, and load following requirements for the 33% RPS, 43% RPS, and 50% RPS base cases. These are target volumes which SERVM will provide if available from its own resources or from the market. The one exception is that external market purchases will not be made solely to cover non-spin requirements. In addition to these base case assumptions, sensitivities were run with low load following reserves, and with lower load shedding levels, as explained in Section III.

Table 5. Operating Reserve Requirements

	% of Load	Shed Firm Load to Maintain Reserves
Regulation Up/Regulation Down	1.50%	Yes
Spin	3.00%	Yes for 1.5% of the 3%
Load Following Up	5% for 33% RPS; 7% for 43% RPS; 9% for 50% RPS	No
Load Following Down	Load Following down is targeted at 1.5% of load	No
Non Spin	3%	No

Figure 17 displays the operating reserve demand curve (ORDC) that was used to determine the price of scarcity in any given hour. The prices in the curve represent incremental scarcity pricing above the marginal cost resource that is committed to serve load. The ORDC only affects system costs to the extent purchases were made during scarcity situations such that the clearing price was affected by the ORDC. The curve is assumed to be flat for the first 4% at a value representing the Value of Lost Load (VOLL). Therefore, if only enough resources were available to meet load plus 4% of operating reserves, the incremental scarcity pricing would be $1,000/MWh. From a physical reliability perspective, however, this curve does not impact results as all available resources will be committed to prevent a loss of load event.

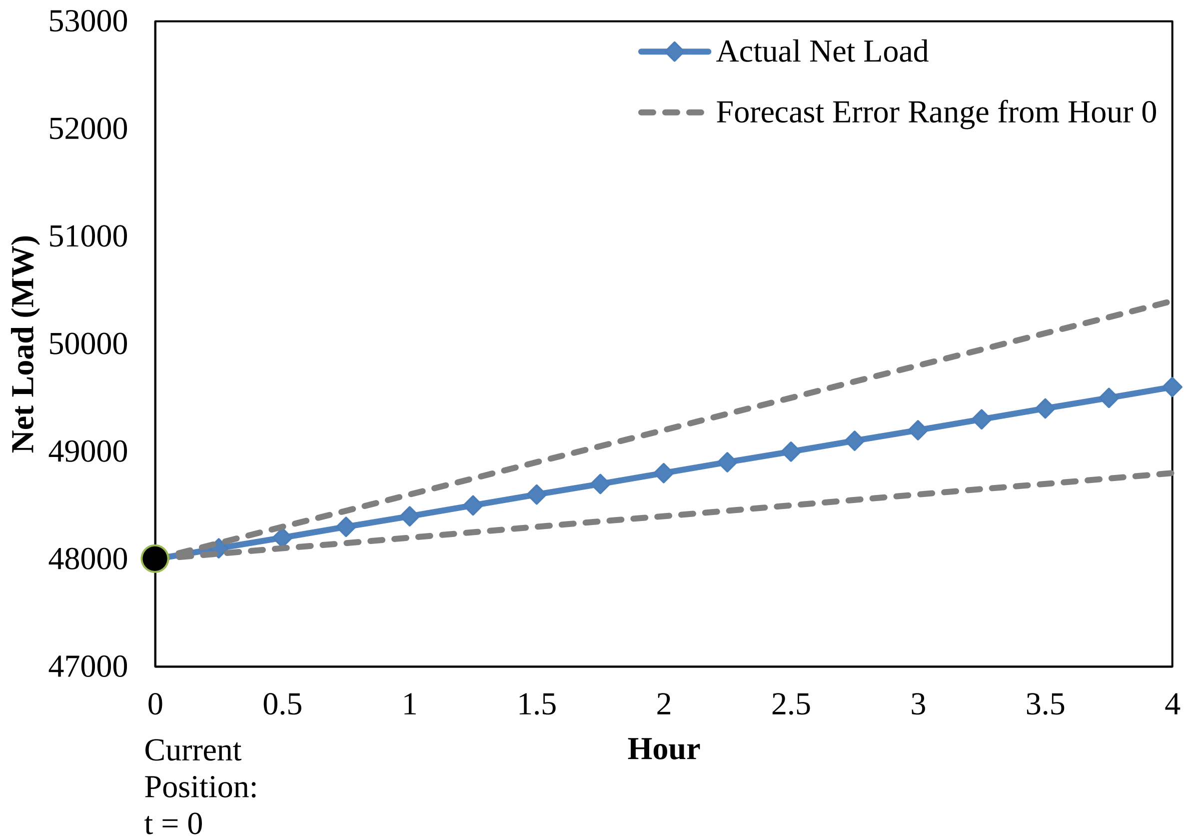
Figure 17. Operating Reserve Demand Curve



H. Unit Commitment Uncertainty & Recourse

SERVM's full economic unit commitment occurs over several time intervals. Each unit commitment is based on a forecasted net load that is calculated based on the uncertainty distributions at each time interval. First, a weekly commitment is done for the entire week. Then each day, a day-ahead commitment is performed making adjustments to the original commitment as net load forecasts become more certain. Subsequent unit commitment decisions may be made 4 hours ahead, 3 hours ahead, 2 hours ahead, and 1 hour ahead if the net load forecast has changed and units with adequate flexibility are available. Finally, intra-hour commitment of quick start resources is allowed as the intra-hour load varies subject to notification periods. Figure 18 provides an example of how the model adjusts its commitment each hour and how the uncertainty expands for long time intervals. At hour zero, SERVM draws from correlated load, wind, and solar forecast error distributions for intra-hour, 1 hour ahead, 2 hours ahead, 3 hours ahead, and 4 hours ahead uncertainties. SERVM then makes commitment and dispatch adjustments based on the uncertain forecast, but ultimately must meet the net load shape that materializes.

Figure 18. 1-4 Hour Ahead Forecast Error



In addition to longer-scale weather variation, load, wind, and solar profiles have significant intra-hour volatility.

Figure 19 shows the solar volatility on an average day, and Figure 20 shows the solar volatility on an extreme day.

Figure 19. Solar Volatility on an Average Day

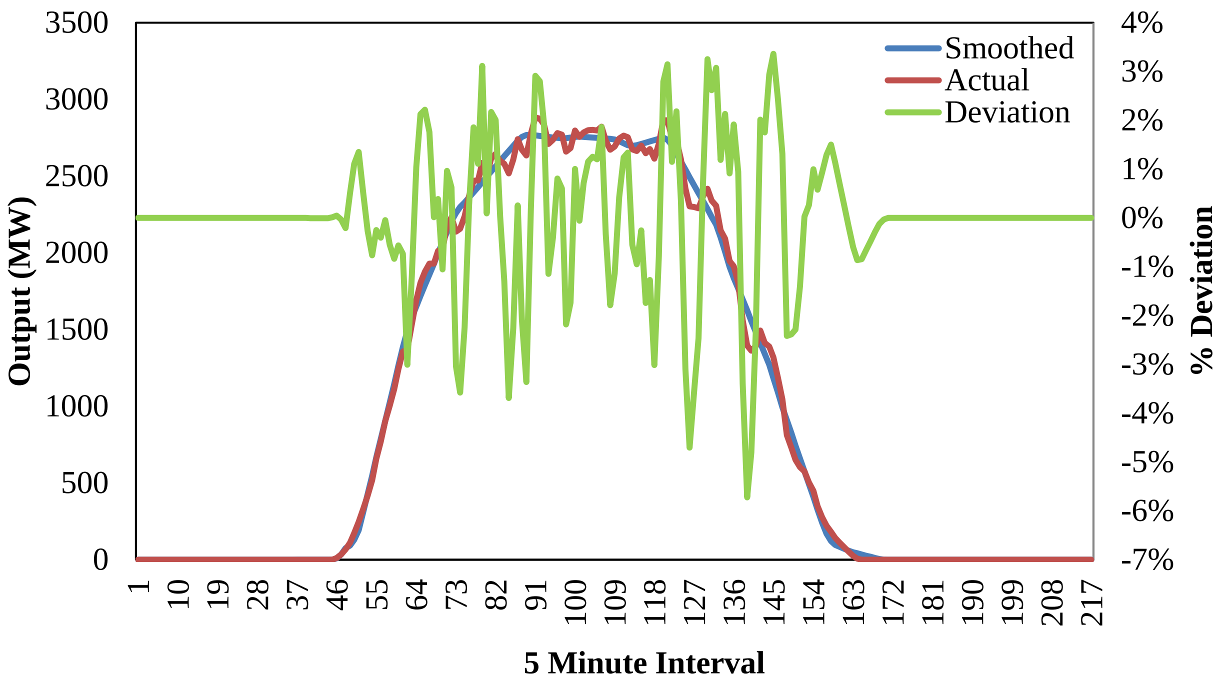


Figure 20. Solar Volatility on an Extreme Day

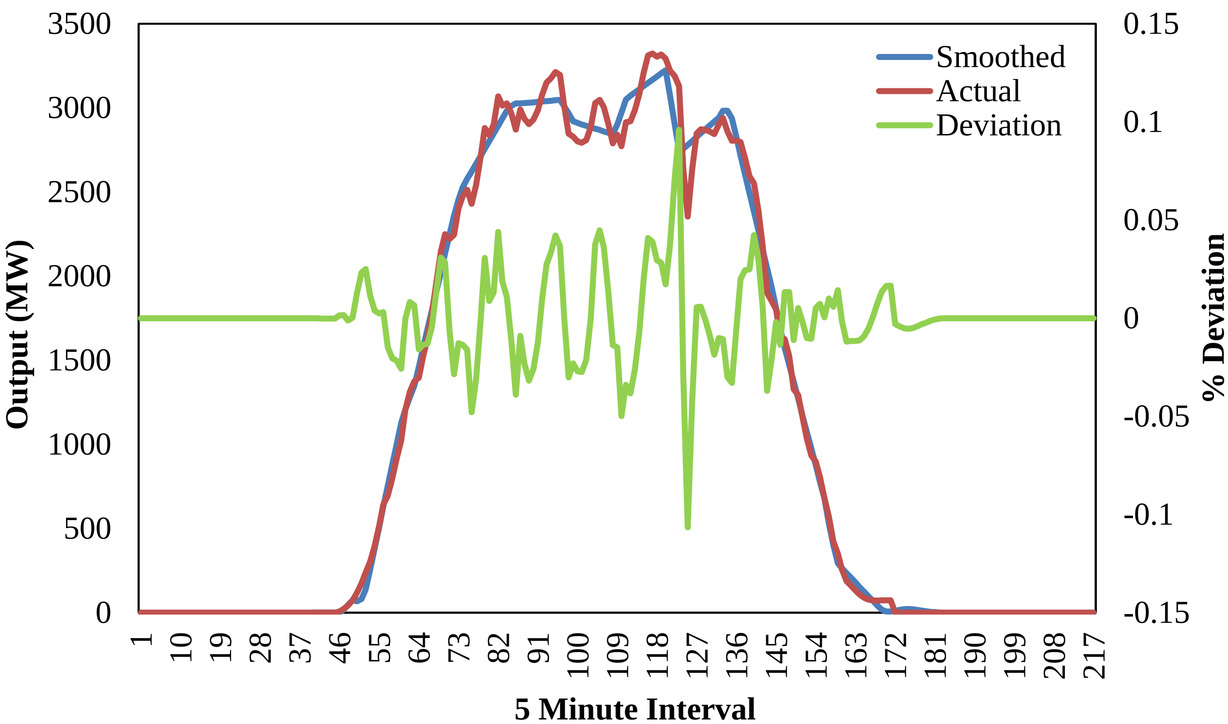


Figure 21 shows the multi-hour wind uncertainty for the 1 and 4 hour ahead uncertainties.

Figure 21. Multi-Hour Wind Uncertainty

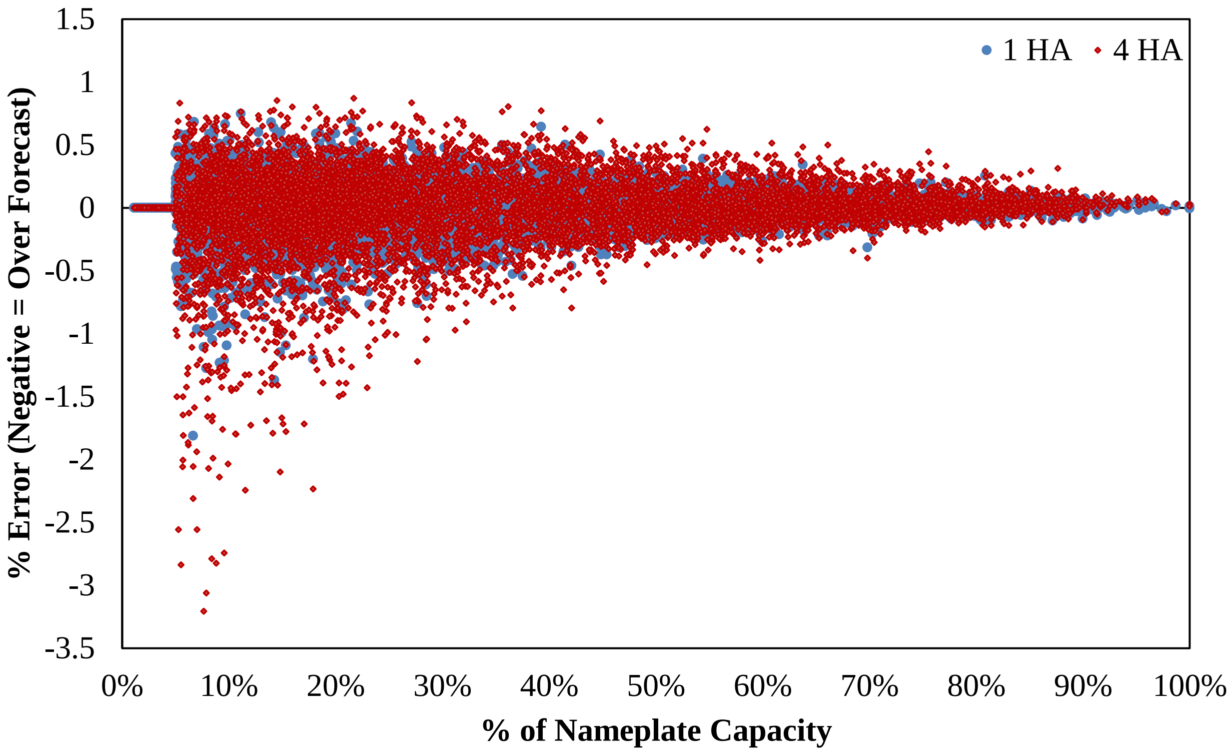
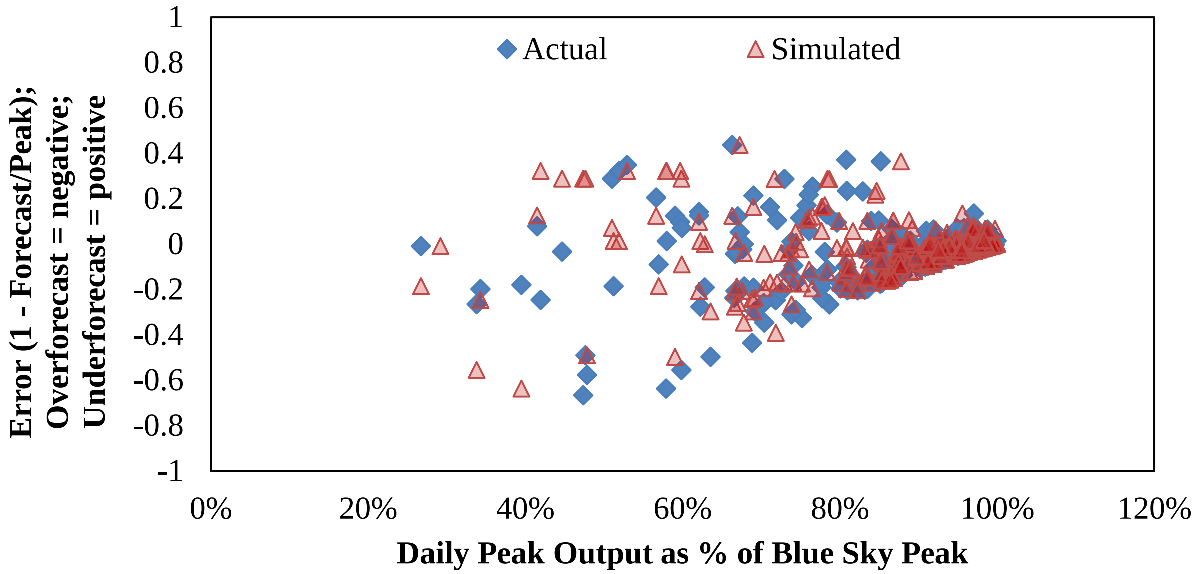


Figure 22 shows the relationship between normalized divergence and probability for the 2017 wind group. Solar forecast uncertainty is also correlated to the max potential output of the resources. In days with high output levels relative to the max output capability (or Blue Sky Day Output), the forecast error is smaller than in days when the output level is low relative to max output capability.

Figure 22. Day Ahead Solar Uncertainty



I. CT Startup Times Intra-Hour

For this study, a range of start times between 8 and 20 minutes were assumed for quick start resources to be utilized intra-hour. The assumption can be a significant driver in the intra-hour flexibility deficiency results. SERVM was modified to allow for decisions to be made intra-hour for these quick start resources.

IV. Modeling of Study Cases

Table 6 below is a summary of the study cases simulated.

Table 6. Sensitivity Cases

Case #	Type of Case	RPS % by 2026	Load Following	System Pmin	Interchange 3-Hr Ramp	Net Exports Limit
BC_01	PRM Base Cases	33%	5% of Load	LTPP Default	Unlimited	2,000 MW
BC_02		43%	7% of Load			
BC_03		50%	9% of Load			
SC_01	**Reference Case**	**50%**	**9% of Load**	**LTPP Default**	**Unlimited**	**2,000 MW**
SC_02	Load Following (% of Load)		5% of Load			
SC_03			7% of Load			
SC_04			11% of Load			
SC_05	Load Following (Net Load Observed)		95th Pct			
SC_06			99th Pct			
SC_07			100th Pct			
SC_08	System Pmin(+/- MW)			(-4,000)		
SC_09				(-2,000)		
SC_10				(+2,000)		
SC_11				(+4,000)		
SC_12	Interchange 3-Hour Ramp Limit				3,000 MW	
SC_13					6,000 MW	
SC_14					9,000 MW	
SC_15	Net Exports					3,500 MW
SC_16						5,000 MW
SC_17						8,000 MW

A. Planning Reserve Margin (PRM) Base Cases

Simulations were performed at 33%, 43%, and 50% renewable penetration. The assumptions used to develop the energy for the renewable penetration scenarios were based on projected load provided in the 2016 LTPP Scenario Tool. With the exception of additional RPS and BTM generation, the 33% RPS, 43% RPS and the 50% RPS scenarios have the same load and generation.

However, since the capacity factors were slightly different over the 35 weather year scenarios used in the SERVM simulations from the single shape scenarios used in the CAISO runs, the cases were calibrated so that on average, considering all weather profiles, the total renewable energy by category in SERVM matched closely the total energy for each category.[6] This resulted in differences in capacity in some of the renewable resources. Table 7 compares the capacity and energy in the 33%, 43%, and 50% scenarios for the CAISO RPS resources[7].

Table 7. Renewable Energy and Capacity Comparison for 33, 43, and 50% Renewable Penetrations

(7a) 33% Renewable Penetration

Resource	Capacity (MW)	Energy (MWh)	Capacity Factor (%)
PGE_Bay Solar	24	56,484	26.9
PGE_Valley Solar	1,249	2,999,376	27.4
SCE Solar	5,636	14,864,614	30.1
SDGE Solar	109	272,094	28.5
PGE_Bay Wind	902	2,207,670	27.9
PGE_Valley Wind	562	1,375,123	27.9
SCE Wind	4,109	9,253,979	25.7
SDGE Wind	234	559,517	27.3

(7b) 43% Renewable Penetration

Resource	Capacity (MW)	Energy (MWh)	Capacity Factor (%)
PGE_Bay Solar	24	56,452	26.9
PGE_Valley Solar	2,189	5,258,002	27.4
SCE Solar	10,442	27,366,224	29.9
SDGE Solar	109	271,541	28.4
PGE_Bay Wind	1,148	2,809,197	27.9
PGE_Valley Wind	400	978,675	27.9
SCE Wind	4,373	9,846,365	25.7
SDGE Wind	234	559,527	27.3

[6] This data was obtained from the RPS Calculator scenarios referenced by the 2016 LTPP Scenario Tool
[7] Does not include SCE solar thermal resources

(7c) 50% Renewable Penetration

Resource	Capacity (MW)	Energy (MWh)	Capacity Factor (%)
PGE_Bay Solar	25	58,972	26.9
PGE_Valley Solar	2361	5,657,822	27.4
SCE Solar	13864	36,231,008	29.8
SDGE Solar	112	280,903	28.6
PGE_Bay Wind	1192	2,916,851	27.9
PGE_Valley Wind	1072	2,622,817	27.9
SCE Wind	4510	10,153,497	25.7
SDGE Wind	234	559,532	27.3

Compared to the lower RPS base cases, more $LOLE_{FLEX}$ events initially occurred in the higher renewable penetration levels because the added volatility in the incremental renewable projects was not covered by additional ancillary service requirements. To get the $LOLE_{FLEX}$ back to a reasonable number, additional load following reserves were added to the higher RPS base cases, as explained in the "Operating and Flexibility Reserve Requirements" section earlier.

B. Load Following Reserves Cases

The frequency and magnitude of $LOLE_{FLEX}$ events is largely driven by the input load following reserve target. While the load following reserves are not protected through the use of firm load shed, they will be procured when available from the external market or internally available resources. Carrying more load following reserves allows the system to absorb larger intra-hour net load volatility events.

For this project, Load Following reserves were calculated using two different methods:

- As a % of the hourly load – four cases were studied on 5, 7, 9, and 11% load following levels.
- Based on Net Load observed in the previous 60 days –load following reserves target were set as a function of observed volatility in load, wind, and solar profiles (i.e., load net of wind and solar)

over the past 60 days.[8] Three cases were studied based on max volatility level (100th percentile) in the past 60 days or the 99th or the 95th percent highest volatility value

C. System Pmin Cases

Sensitivities were performed around resource Pmins by adjusting all minimum operating levels by the same percentage. The Pmin sensitivity modeling was performed by making larger changes to a smaller set of resources. The changes were primarily applied to the combined cycle fleet[9]. Some other small units with low heat rates were also used[10]. The total nameplate of all resources used in at least one Pmin scenario was approximately 16,939 MW with a starting minimum dispatch level of about 7,192 MW.

The following Pmin sensitivities were performed for the 50% scenario:

- -4000 MW
- -2000 MW
- Base Case
- +2000 MW
- +4000 MW

When adjusting the Pmins, several other variables also had to be adjusted in concert. Since startup time measures the time required to achieve minimum output, new startup times were input to correlate lower Pmins with faster startups and higher Pmins with slower startups. Longer startup times also produced more energy, so fuel burn during start and the associated costs and emissions had to be adjusted as well.

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[8] This method attempts to mimic the persistence forecasting method used in certain ISO/RTO markets where forecast is based on actuals observed in the recent past.

[9] As an example, Blythe CC has a max capacity of 490 MW in all cases. In the Reference Case, its minimum capacity level was modeled as 264 MW. In the -4000 capmin case, its minimum capacity level was modeled as 92 MW. In the +4000 MW case, its minimum capacity level was modeled as 324 MW.

[10] Specifically, all gas units with heat rates below 8.4

D. Interchange 3-Hour Ramp Limit Cases

The reference case (SC_01) did not include any constraints on the import ramp limit other than the implicit constraint of neighboring zones being able to ramp their units fast enough to match the desired purchases in CAISO. Sensitivities were completed on the 50% RPS reference case to show the effect of aggregated 3-hour ramp limits on the system. The ramp limits tested were 3,000, 6,000, and 9,000 MW. The ramp limits were only imposed on increases in imports so imports could drop by more than the limit in a 3-hour period.

E. Net Export Sensitivities

Studies were completed to test the effects of net exports on the system. The base case simulations allow CAISO to be net exporters of up to 2,000 MW if the neighboring regions were able to economically absorb the energy. This limit considers all imports (including dedicated imports) and exports. Sensitivities included 3,500 MW, 5,000 MW, 8,000 MW, and unlimited exports. To test these effects, transmission constraints were modified to match the desired export capacity.

F. Additional Energy Storage Sensitivities

Two sets of sensitivity cases were modeled to understand 1) Reliability contribution; and 2) Economic and curtailment benefits of storage devices.

To study reliability contributions, three cases were modeled by adding 3,000 MW, 6,000 MW, and 10,000 MW of 4 hour duration battery storage to the reference study case.

To study economic and curtailment benefits, four cases were modeled by adding a different 1,000 MW storage product to the reference study case:

- 2-Hour
- 4-Hour
- 6-Hour
- 8-Hour

V. Modeling Changes

Over the course of the project, several modeling changes were incorporated in the SERVM modeling tool. With one exception[11], all of the changes are intended to allow the project to better explore the flexibility needs of the system and to bring the commitment and dispatch decisions in SERVM more in line with CAISO's system operations.

A. Timing of Unit Starts and Shutdowns

Since SERVM was originally designed as an hourly model, several modeling procedures still had practices consistent with an hourly model instead of an intra-hour model. One of those components was the timing of unit starts and shutdowns. Previously all unit starts and shutdowns were implemented at the top of the hour. The effects of this commitment procedure included significant unnecessary curtailment as well as a small amount of incremental LOLE. When many units are brought online simultaneously, some efficiency in dispatch is lost due to most units operating at well below their rating.

For this phase of CES-21, unit commitment decisions take place throughout the hour in an attempt to optimize production costs and minimize the potential for LOLE.

B. Intra-Hour CAISO Clearing

Similar to Item A, intra-hour decisions improve the optimality of the commitment and dispatch. Previously, transfers were scheduled once per hour between SCE, SDGE and PGE. In this phase, enhancements were made to allow the three CAISO regions to clear economically at each 5-minute interval. This results in the identification of more hours and partial hours when Path 26 is constrained. When the path is constrained, SERVM ramps down the output of units in PGE and increases the output of units in SCE or SDGE to balance load and still respect the import/export constraints.

[11] Section IV.A refers to a modeling error in SERVM, not an enhancement to reconcile differences in modeling practices between SERVM and those employed by CAISO.

C. Pre-Emptive Market Ramping

Ramping constraints were imposed on the interties for this phase of between 3,000 MW and 9,000 MW per hour. In the previous version, ramp rates were imposed on the OOS regions' units instead. The change in this phase allowed for more precise control of market purchase ramping. One issue that this raised was that in days with high net load peaks and significant ramps up to those peaks, the market may not schedule adequate purchases in advance of the need. Since SERVM performs market clearing on an hourly basis, signals may not always be received in the hours preceding the peak because of the lack of need in those prior hours. An enhancement was made to SERVM to recognize this need in advance and schedule market purchases accordingly. This was only imposed for the ramping constraint sensitivities as the base cases had unconstrained ramping capability.

D. Intra-Hour Solar Uncertainty Cap

Data from CAISO at 5-minute granularity was used for load, wind, and solar intra-hour volatility in all of the simulations. A cap and floor were placed on the intra-hour solar volatility of between -6.4% and 6.4% of the total hourly solar output depending on the current hour's output. This floor and cap were imposed because some of the intra-hour data which produced higher values appeared to be anomalous.

E. Calculation of reliability metrics that account for operating flexibility shortages

A series of flags were added in SERVM to calculate loss of load events due to shortages of flexibility rather than generic, non-flexible capacity, and to distinguish between hourly or multi-hour ramping shortages from intra-hour flexibility shortages. After the simulation is completed, the model estimates:

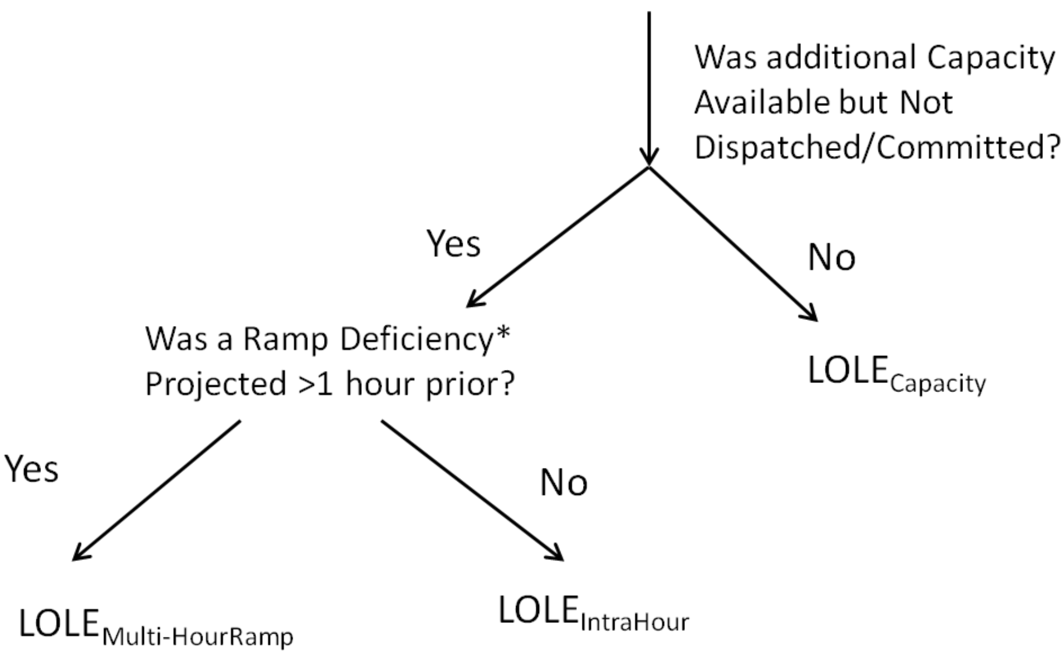
- Loss of Load Expectation Generic ($LOLE_{GEN}$) – Events per year and only represents outage events that occur due to capacity shortfalls in peak conditions. If a resource is available but was not committed and cannot meet load due to ramp rates or startup times, then the event is not counted.

- Loss of Load Expectation FLEX ($LOLE_{FLEX}$) – Events per year and events caused from system ramping deficiencies when a multi-hour ramping shortage was not identified.

- Loss of Load Expectation Multi-Hour ($LOLE_{MULTI-HOUR}$) – Events per year and events caused from system ramping deficiencies identified more than one hour in advance.

Figure 23 explains the process used to estimate different sources of loss of load events.

Figure 23. Flexibility Versus Capacity Shortages



[12]

The allocation to the three categories of LOLE is performed after a shortage has occurred. The logic in the model follows the steps in Figure 23.

[12] Ramp Deficiency Projection is calculated by comparing the ramping capability over a multi-hour period to the actual net load ramp.

F. Reporting Template

New reporting templates have been developed to provide additional annual and monthly reports of loads and resources for individual cases and sensitivities allowing the user to compare expected output and individual weather year or load growth scenario outputs. The reports are being designed to have the same look and feel of reports made available by the CAISO in past LTPP studies.

G. Physical Curtailment Prevention

The commitment logic in SERVM was updated to allow users to prevent the selection of commitment decisions which would result in curtailment, even if the decision was necessary to prevent firm load shed at another time in the day.