2015

Study of CAISO System

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

Documentation of input assumptions for sensitivity cases presented to the Advisory Group on November 2, 2015

Prepared by
Astrape Consulting
Kevin Carden
Nick Wintermantel

November 20, 2015

Contents

I. Purpose

This report documents the input assumptions used for the sensitivity cases presented to the Advisory Group of the CES-21 Grid Integration Flexibility Metrics and Standards Project on November 2, 2015. Unless otherwise noted, the input assumptions used for Phase 3 of the project were based on the CAISO's deterministic model inputs for the 2014 LTPP 33% RPS Trajectory Scenario and the 40% RPS Scenarios. This report describes the base case assumptions (Section II), additional sensitivity cases (Section III), and the reliability and flexibility metric outputs (Section IV) of the CES-21 analysis that was presented. The Phase 3 analysis was designed to determine how much capacity and flexibility the CAISO system needed to meet the 1 day in 10 year loss of load reliability standard and the cost and CO2 emission impacts of higher and lower amounts of operating flexibility available to the system.

Furthermore, this report documents modeling changes made to the SERVM software thus far in the CES-21 project (section V); and finally, it provides a high level discussion on calibration and comparison between the CES-21 and CAISO's 2014 LTPP results (section VI).

II. Base Case Assumptions

A. Source Data and Study Year

Two SERVM analyses were developed, one for the 33% RPS Trajectory, and another for the 40% RPS scenario of the 2014 LTPP. In addition to the base case for each scenario, 10 sensitivities were studied for each scenario with varying amounts of flexibility and capacity for a total of 22 stochastic cases. With the exception of additional RPS generation, the 33% RPS Trajectory and the 40% RPS scenarios have the same load and generation.

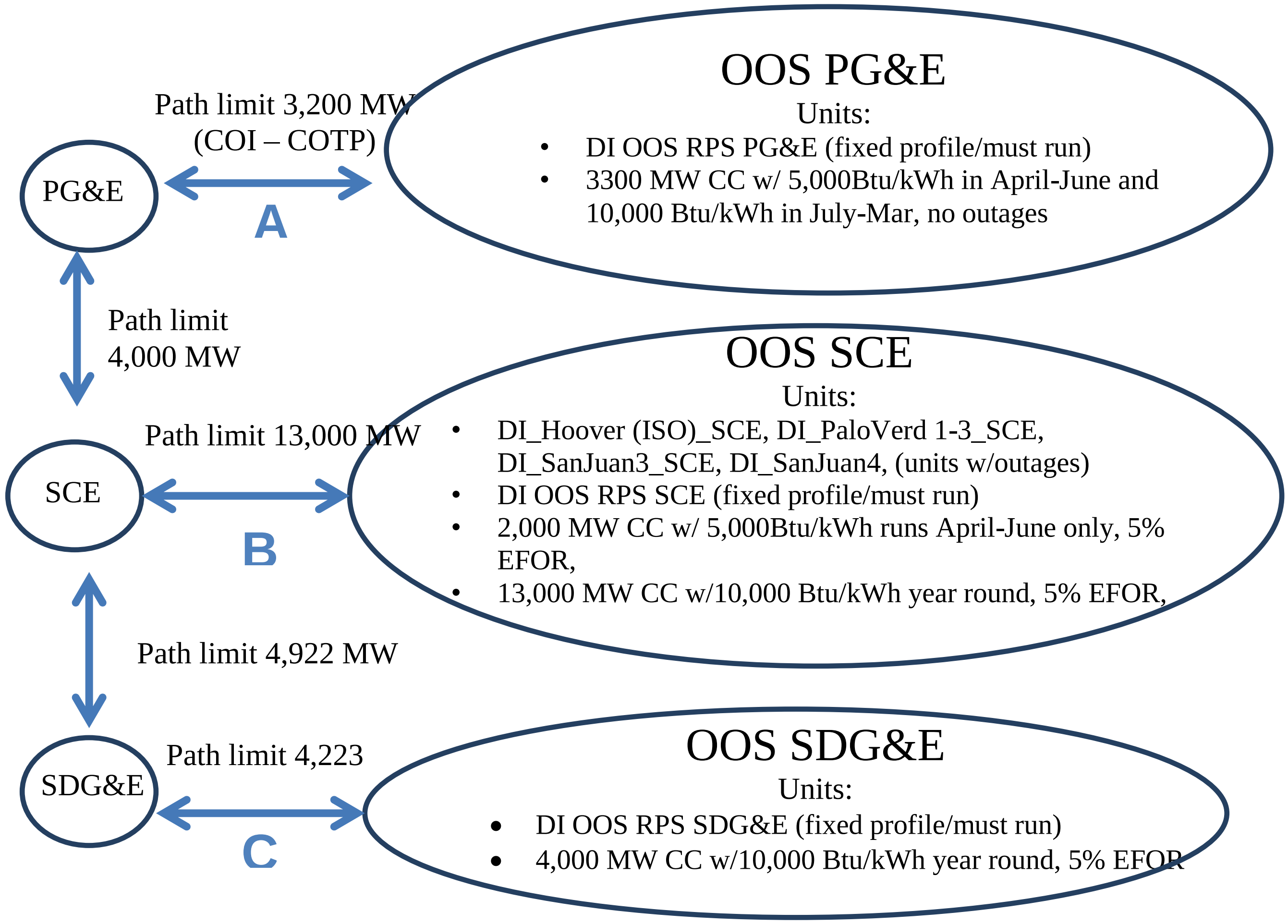
B. Study Topology

Figure 1 shows the study topology that was used for the study. While SERVM provides the capability of modeling the entire WECC Region, this preliminary study uses a simplified representation of the CAISO region and the remainder of WECC.[1] 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. Each of the external Out of State (OOS) regions is modeled with no load. All OOS RPS and Direct Imports (DI) are modeled separately and are treated as must-take on the CAISO's system bubbles except when CAISO is in an overgeneration state. All imports can be cut in hours in which CAISO would otherwise be forced to curtail generation. Additional import capacity is available for economic imports. An hourly ramp rate constraint was imposed to limit the change in net imports to about 4,000 MW per hour.[2] The maximum instantaneous import capability into CAISO was modeled as 11,300 MW, including RPS and DI resources. No minimum fossil generation requirements were used in this preliminary study.

Figure 1. Study Topology

[1] The team plans to use a detailed representation of the rest of WECC when modeling the 2016 LTPP scenarios in Phase 4 of the project.

[2] The simulation results showed that the ramp rate constraint was not binding. The maximum hourly change in net imports was approximately 3,000 MW, and 95% of all hourly schedule changes were less than 1,000 MW.



Additional Constraint: Sum of imports on Lines A, B, and C cannot exceed 11,300 MW.

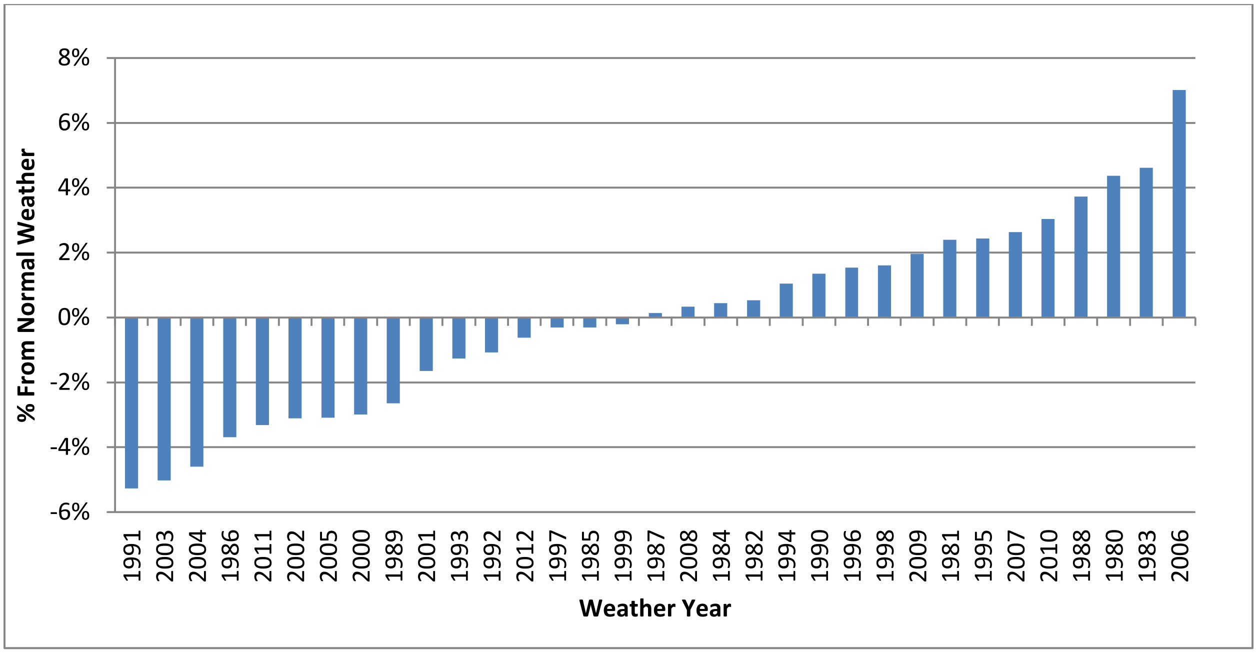
C. Load Modeling

The loads in SERVM were derived using neural nets based on the relationship between recent load and recent weather for each CAISO region. Next, the relationship was applied to historical weather to develop 33 load shapes. To match the projected 2024 summer peak, the historical weather load values for every hour for every shape are scaled by the same multiplier such that the average peak of all the weather shapes is equal to the 2024 CAISO peak load forecast. This process not only captures the variability in peak but also captures the frequency and duration of severe weather seen in actual history. The following inputs were used in the development of the load shapes: temperature, moving average temperature, 8-hour prior temperature, 24-hour prior temperature, 48-hour prior temperature, hour of day, and day of week. The temperature data for each CAISO load zone was pulled from the NOAA website[3].

Figure 2 displays the variance in summer peak load simulated based on 33 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 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.

[3]http://www7.ncdc.noaa.gov/CDO/cdopoemain.cmd?datasetabbv=DS3505&countryabbv=&georegionabbv=&resolution=40

Figure 2. CAISO (PGE, SCE, SDGE) Peak Load Variance



D. Source of weather profiles for wind and solar generation

1. Wind generation profiles

The neural net training data that was used to develop the wind shapes was based on the National Renewable Energy Laboratory (NREL) Western Wind Dataset, which provided hourly wind speed and energy production for the 2004-2006 calendar years. The 2004-2006 hourly weather data and wind output data was imported into a neural net training process. The input data into the neural net program included hour of day, wind speed, visibility, and 2-hour prior wind output.

The relationship between weather and wind output developed by the neural network process was applied to hourly weather data from 1980 – 2012 for each region. Wind projects within WECC were matched to the closest available sites from the Western Wind Data Set. The Western Wind Dataset contains profiles assuming 100 meter hub height with 100 meter rotor diameter. The normalized shapes from the Western

Wind Dataset at those sites were multiplied by the project capacity in the Trajectory Scenario and then added together to create an aggregated shape by region.

The shapes were compared against the original NREL data and PLEXOS shapes. The capacity factor for the available historical years and the capacity factor for the neural network developed profiles was approximately 31% (the 2014 LTPP wind shapes indicated approximately 27% capacity factor). In addition, the duration curve from the neural network predicted shapes was calibrated to approximately match the duration curve from the actual data. The relationships were updated with this information gained from the calibration and applied to all years.

2. Solar generation profiles

Solar output is a function of local solar time (latitude, longitude, day of year, and other variables were used to ensure correct solar time), direct radiation, diffuse radiation, air temperature, wind speed, tilt, and azimuth. Solar output is also driven by: reference efficiency (14.94%), T(NOCT[4]) (45° C), temperature coefficient (.0045), short circuit coefficient (.000545), solar radiation coefficient (.12) , reference temperature (25°C), and inverter efficiency (97%).

All solar data came from the National Solar Radiation Database (NSRDB)[5], and includes the following:

- Solar data for 1991 – 2010 came from 225 unique Class 1 and Class 2 sites.
- Solar data for 1980 – 1990 came from 58 unique Class 1 and Class 2 sites.

Each project in a database of all WECC renewable projects in-service or planned was matched to the closest site in the NSRDB, and was assigned to the appropriate SERVM region.

[4] Nominal Operating Cell Temperature: the temperature reached by solar cells under a particular set of reference conditions.
[5] See: http://rredc.nrel.gov/solar/old_data/nsrdb/1961-1990/hourly/ and http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2010/data/hourly/

The first objective was to create a fixed-tilt profile for each region. The solar and other weather data for each project in a region was used to create a normalized profile which was then multiplied by the project capacity. An aggregated profile was created for the region by adding together each individual project's profile. The aggregated profile was then normalized. The process was then repeated to create a single-axis tracking profile.

The formulas used in the online PVWatts calculator[6] were used for calculating the solar production for all the profiles that were developed. Since all the data for predicting output was available from public sources and the formulas for calculating production are easily applied, a neural network model was not needed.

E. Economic Load Forecast Error

Economic load forecast error multipliers were developed to isolate the economic forecast uncertainty inherent in four year-ahead[7] 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 1 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 8760 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

---

[6] See: http://www.nrel.gov/docs/fy14osti/60272.pdf

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

distribution where each point has a different weighting, each weather year was given equal probability of occurrence.

Table 1. 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%

For the analysis performed using the 2014 LTPP single load shapes, the following table was developed to represent both weather and economic load growth uncertainty. The statistics around the 33 years of load shapes were used to create the weather uncertainty which was combined with the Table 1 multipliers.

Table 2. Single Shape Weather and 4 Year Ahead Economic Load Forecast Error Uncertainty

Load Forecast Error Multipliers	Probability
0.93	7.20%
0.96	12.40%
0.98	10.20%
0.99	12.40%
1.00	12.40%
1.01	11.70%
1.02	12.40%
1.03	8.00%
1.05	9.10%
1.08	4.30%

F. Unit Outage Data

Unlike typical production cost models, SERVM does not use an Equivalent Forced Outage Rate (EFOR) for each unit as an input. Instead, historical 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, only full outage and planned outages were used because partial outage data and maintenance outage data were not available from the PLEXOS inputs.

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. The following figure 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 3 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 3. Conventional Resources on Forced Outage as a Percentage of Time

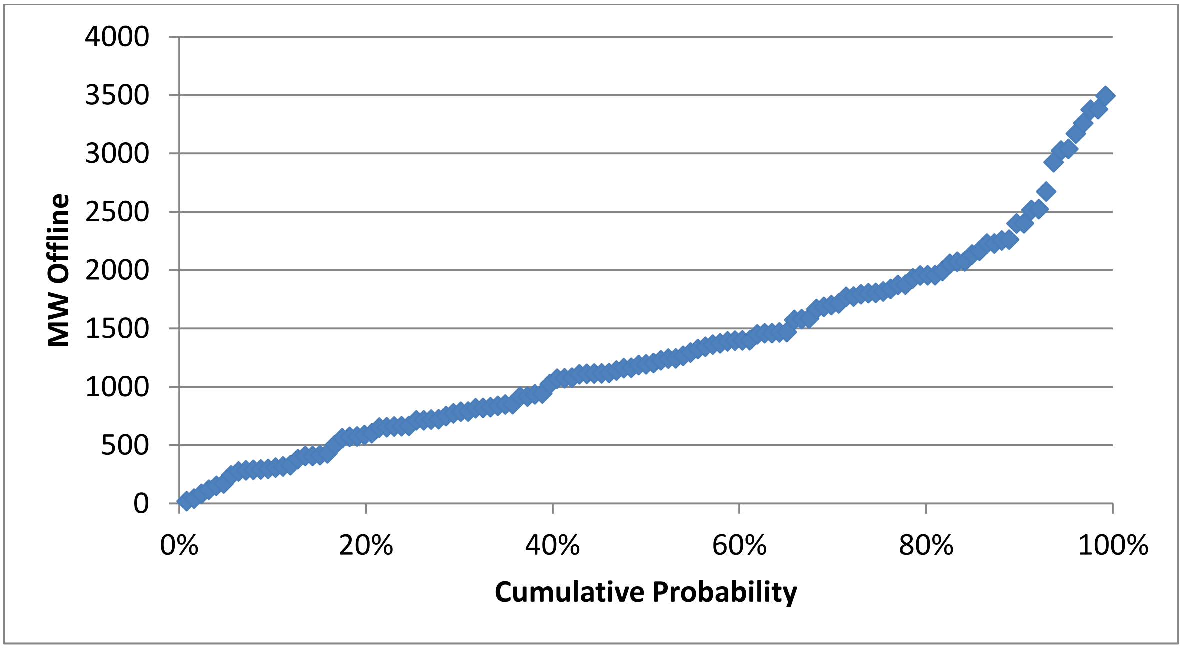
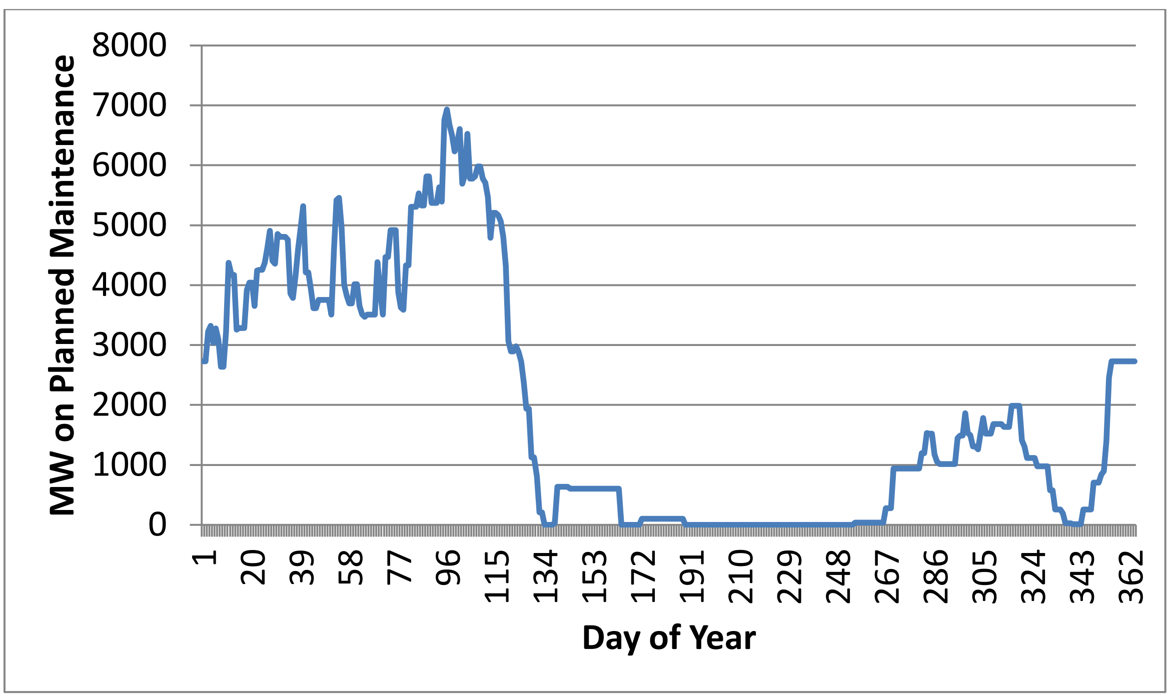


Figure 4 shows the distribution of planned outages across the year used in the study.

Figure 4. Planned Maintenance



G. Hydro Modeling

Hydro resources are split into 3 categories within SERVM:

1. Run of River Hydro: Dispatched as a fixed profile for the entire year

2. Scheduled Hydro: Dispatched to shave the peak but is forced to meet minimum gen requirements and max capacity levels. A weekly hydro generation is provided that must be fully used within the week.

3. Emergency Hydro: Dispatched only in emergency events when prices meet a specific threshold and is energy limited in that it can only be called 20 hours per year. The assumed price threshold for this study was $1,000/MWh. These resources are linked to a scheduled hydro resource. When called, energy from the scheduled hydro resource is reduced.

1. Run of River (ROR) Hydro Resources

The ROR dispatch is sourced directly from the ROR fixed dispatch profiles used in the CAISO simulations.

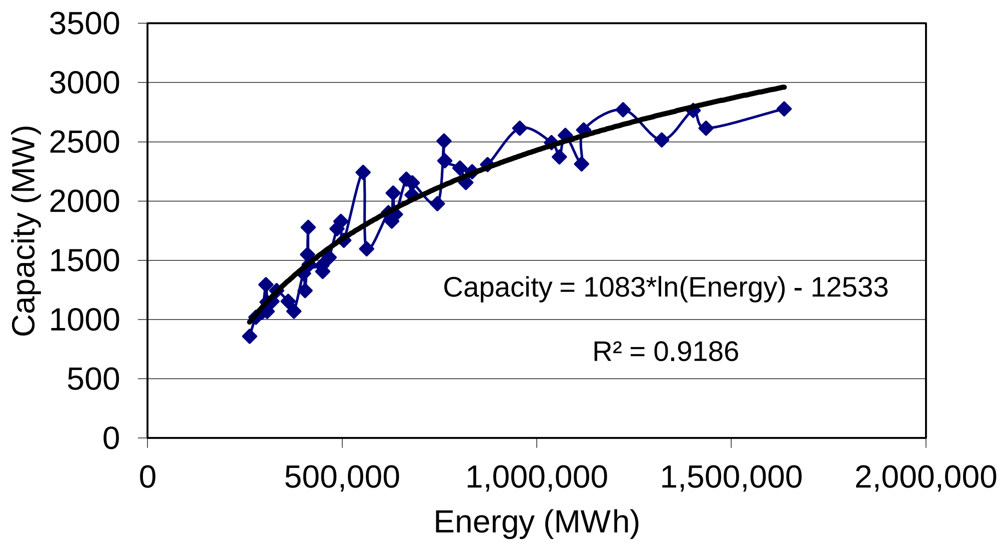
2. Scheduled Hydro Resources

Once ROR energy and capacity have been subtracted from the total energy and capacity available to a region, the remainder must be allocated across the two dispatchable hydro subtypes: scheduled and emergency hydro.

The energy allocated to the scheduled block is simply equal to the total regional monthly generation less the ROR generation. A portion of the scheduled energy is allocated to a minimum daily schedule. This minimum schedule or generation (flow) per day is a variable that is unique to each month and year. This value is set to the tenth percentile of daily MWh generation in that month and year. In some months, the minimum generation per day may be very close to zero; if selecting the tenth percentile results in more generation being dispatched than is available in a given month, SERVM will flag the issue and the value will be reduced to the amount of available energy. The minimum daily schedule is spread across the 5 hours per day surrounding the peak net load hour in equal amounts.

The remainder of the energy in the scheduled block is used to shave the peaks off net loads; in other words, higher output is scheduled in hours with higher net load. The capacity used to shave the peaks is related to the monthly generation. In the month of maximum generation, the capacity of scheduled hydro is equal to the nameplate capacity of the overall hydro fleet in the region, less the ROR capacity previously calculated. In the month of minimum generation, the capacity of scheduled hydro is near zero, with most available capacity already allocated to ROR. For the intervening months, the capacity is interpolated based on the available energy, using a formula similar to that shown in Figure , below:

Figure 5. Sample relationship between scheduled hydro energy and capacity



All scheduled hydro is dispatched one week in advance. The minimum generation quantity is scheduled to be centered on the anticipated net load peak hour of each day. The number of hours over which that minimum generation is spread is set with a monthly variable. This variable is determined by observing CAISO settlement data and estimating the typical number of hours over which hydro facilities are scheduled in a given region and time of year. Non-CAISO regions use values based on the nearest CAISO region. Scheduled hydro above the minimum is economically dispatched, up to the maximum capacity calculated for that month.

3. Emergency Hydro Resources

Because emergency hydro resources are not intended for regular dispatch, they are triggered only by high market prices (currently set to $1000/MWh) or load-shedding contingencies. These units allow a region's fleet to reach full nameplate capacity for approximately twenty hours. When emergency hydro is dispatched, the energy must be replaced by lowering scheduled hydro in some future hour. In this way, the total energy for the month never violates the input energy. If no energy is available to borrow from future schedules, the emergency hydro capacity is unavailable.

The full nameplate capacity is sourced from the TEPPC 2024 Common Case. The available energy comes from the scheduled hydro unit in the region, to which the emergency unit is linked. The emergency unit is given the ability to borrow up to 20 hours worth of energy from the scheduled unit. Beyond this linkage, however, emergency hydro and scheduled hydro units are input and viewed as separate resources in SERVM.

An important step in calibrating the hydro dispatch is ensuring that not only the total generation from the hydro fleet is comparable, but also that the frequency of dispatch at various levels is reasonable. The following figure illustrates the output duration curve for the hydro fleet in the SERVM dispatch and the PLEXOS dispatch in the 2014 LTPP 33% RPS scenario. The SERVM inputs have resulted in more hours per year with high output and fewer hours per year with low output than the PLEXOS runs. The hydro calibration will be fine-tuned in upcoming phases of this project.

Figure 6. Comparison of SERVM vs. PLEXOS hydro dispatch

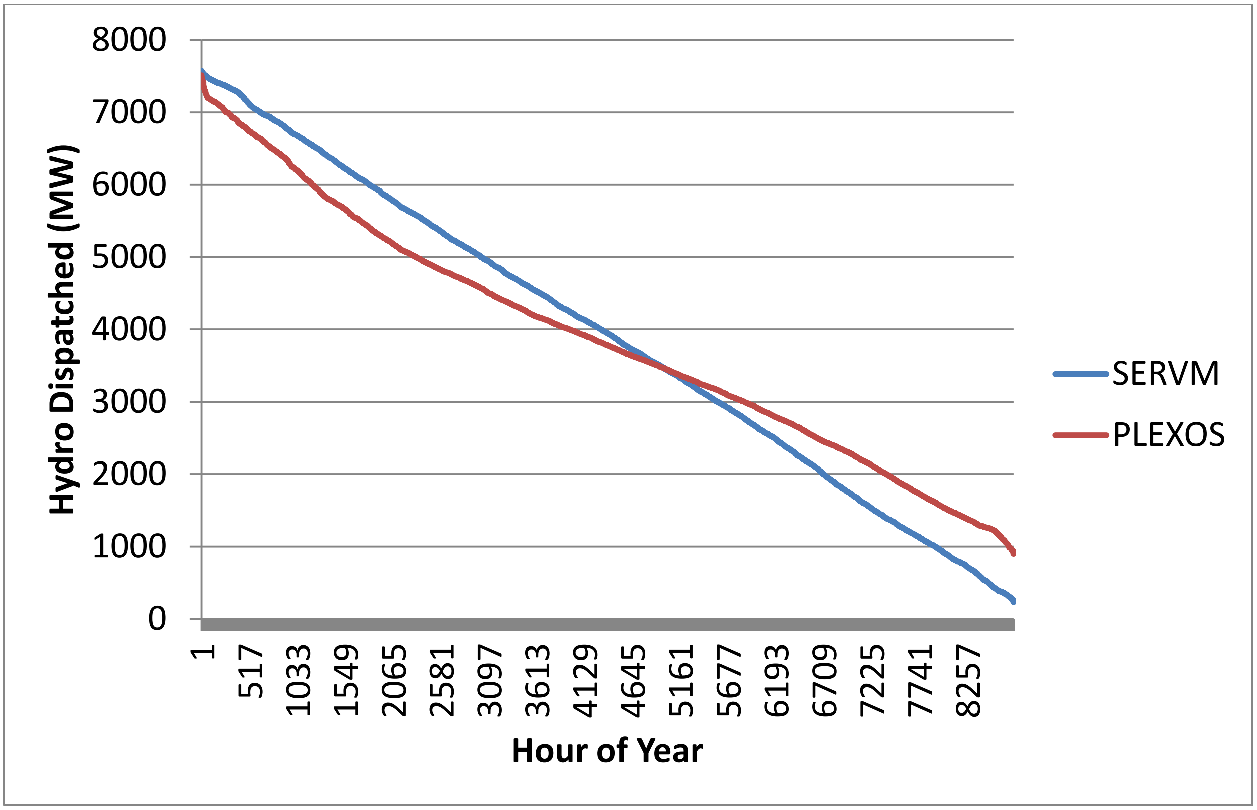


Figure 7 shows the total nameplate capacity of the hydro system in the various categories modeled.

Figure 7. Hydro Capacity

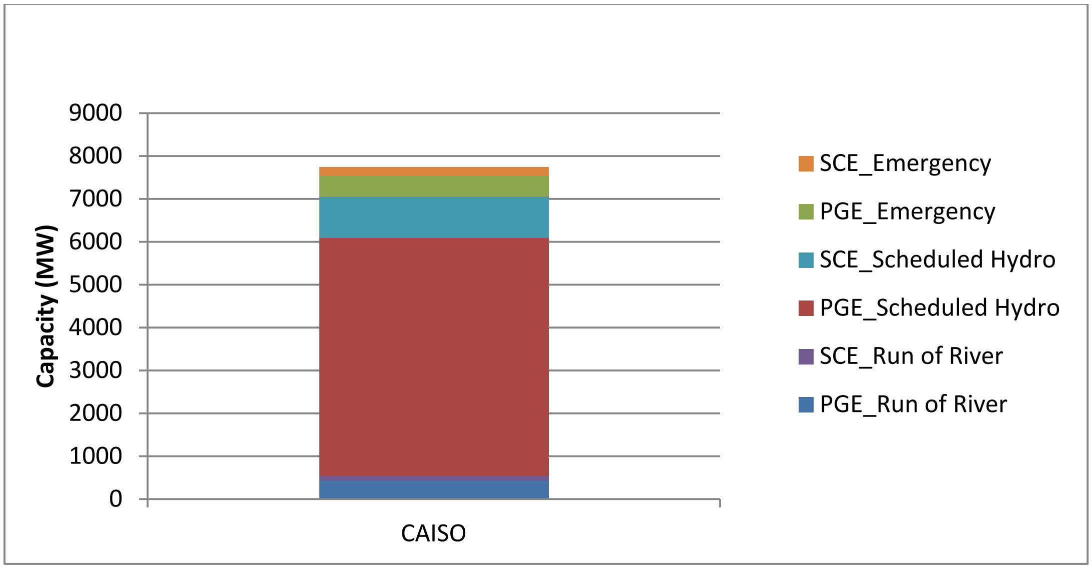
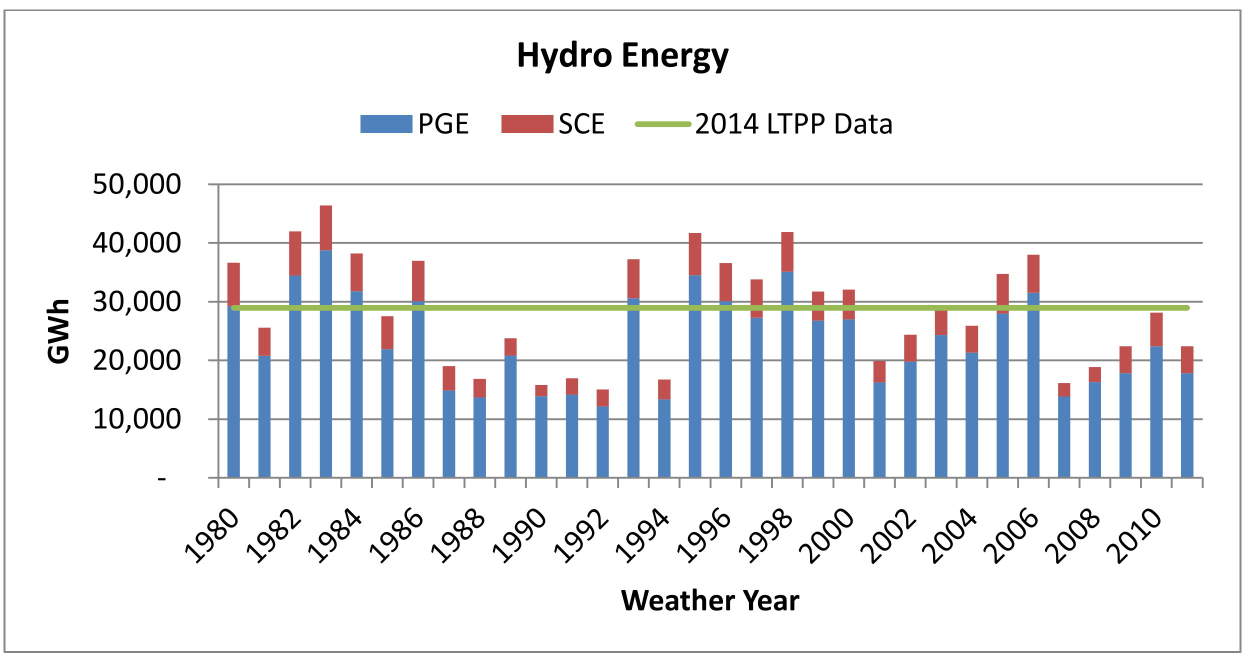


Figure 8 shows the total hydro generation by weather year. Depending on the weather year, hydro generation within the simulations varied significantly.

Figure 8. Hydro Energy



H. Operating and Flexibility Reserve Requirements and Operating Reserve Demand Curve

Table 3 shows the assumptions that were used by SERVM for regulation, spin, non-spin, and load following requirements for the 33% RPS and 40% RPS base cases.[8] 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 3. 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	On average totals approximately 4% - 5% Calculate as the hourly net load change plus 2% of load (for the 33% RPS scenario) and 3% of load (for the 40% RPS scenario)	No
Load Following Down	Load Following down is targeted at 1.5% of load	No
Non Spin	3%	No

[8] The major distinction between SERVM and the approach used by CAISO is that the load following requirement in SERVM is calculated based on the variability of net load across the hour rather than a set value for a given hour and month. A comparison is provided in Figure 9 below.

Figure 9. Average July Load Following Requirement Comparison

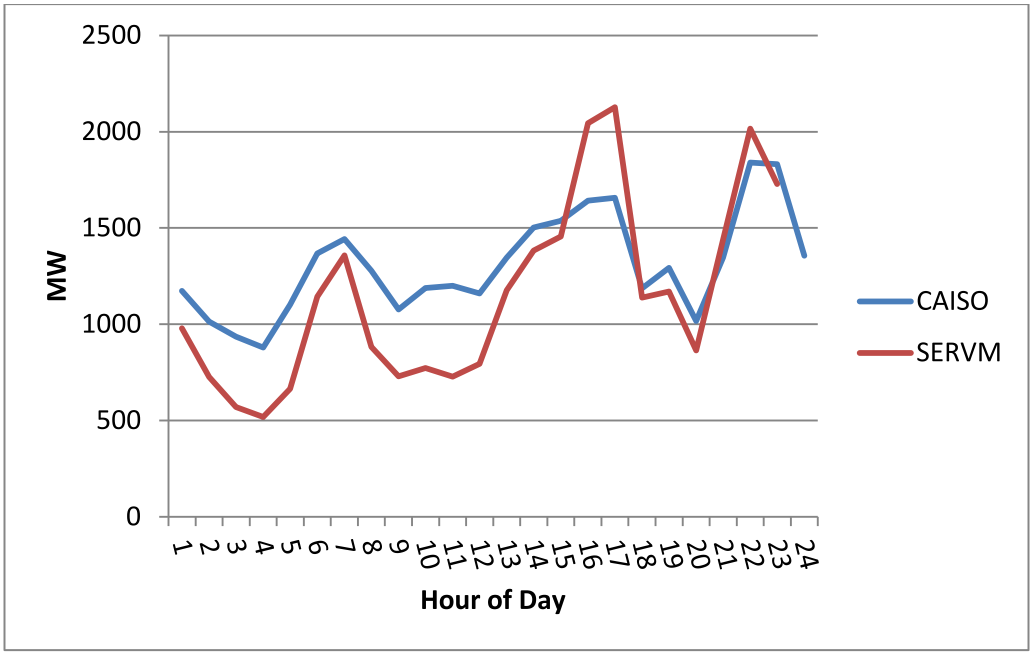
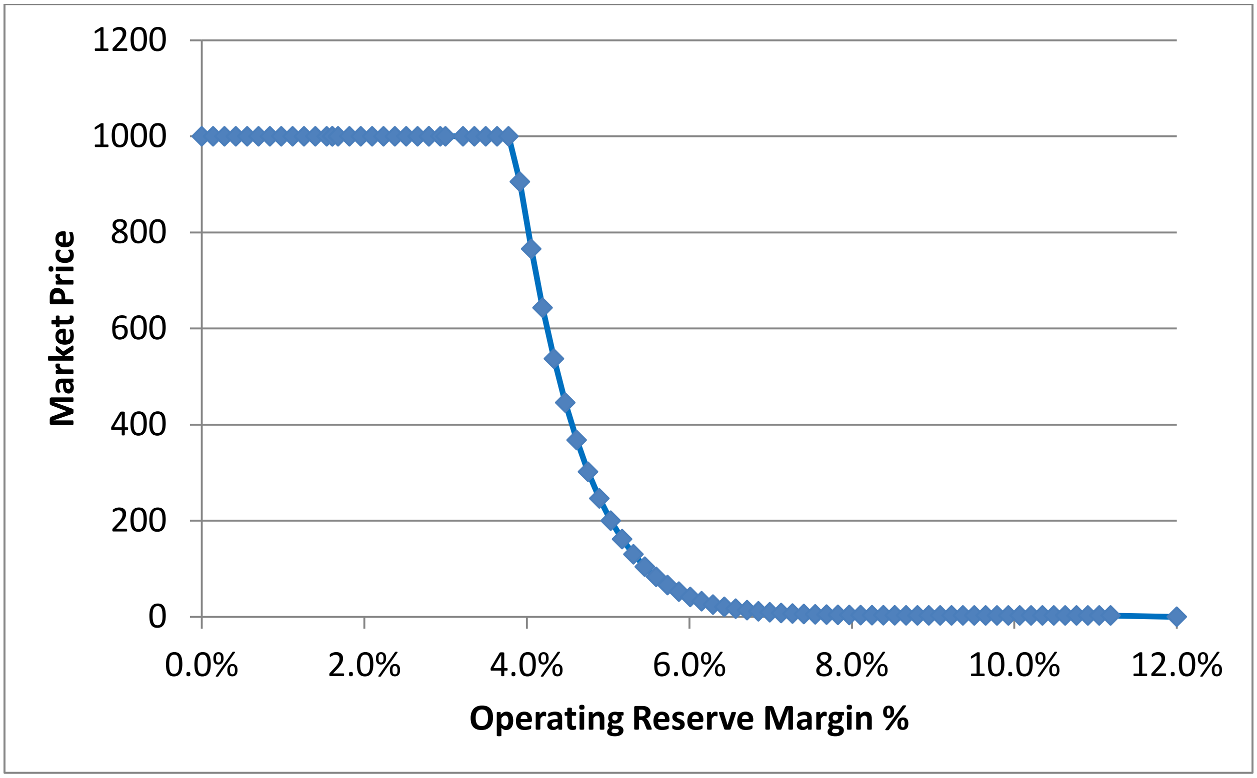


Figure 10 displays the operating reserve demand curve that was used to determine the price of scarcity in any given hour. The prices in the curve represent incremental scarcity pricing above the marginal cost resource that is committed to serve load. The curve is assumed to be flat for the first 4% at a value representing the Value of Lost Load (VOLL). Therefore, if only enough resources were available to meet load plus 3% 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.

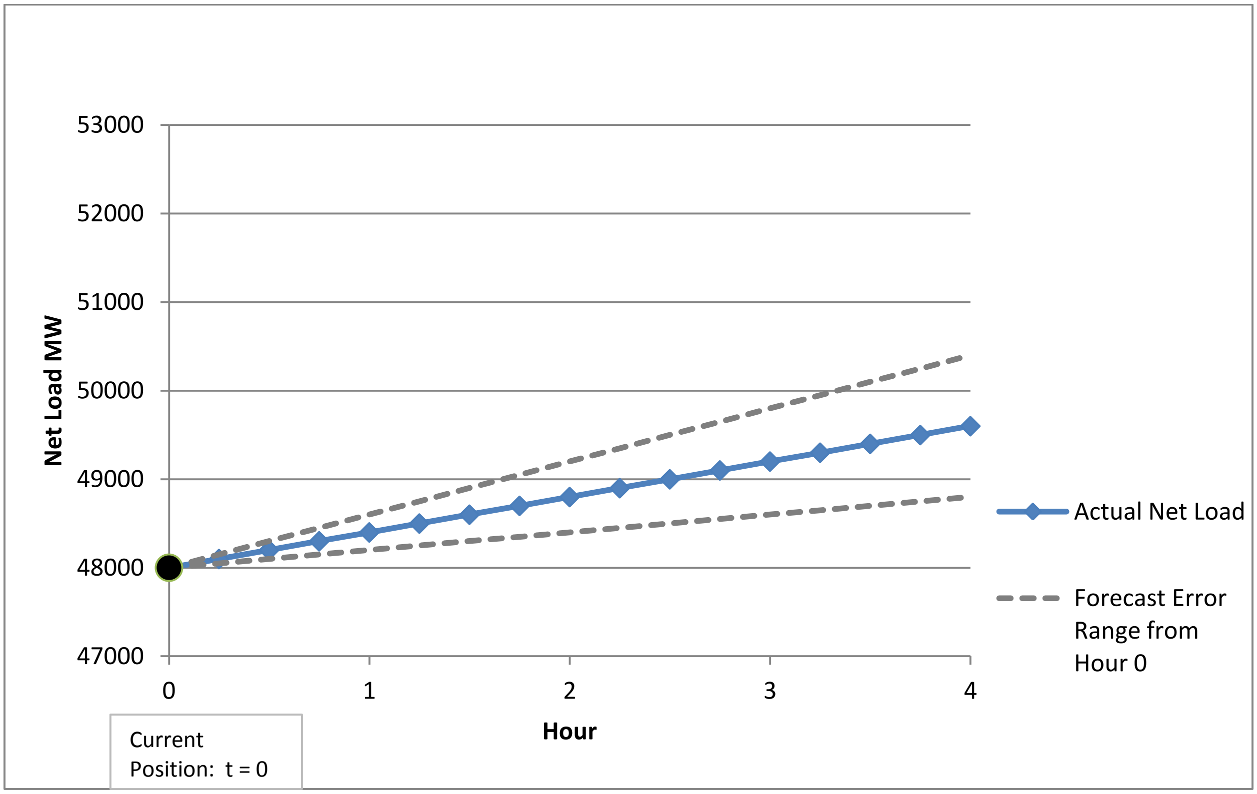
Figure 10. Operating Reserve Demand Curve



I. 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 11 provides an example of how the model adjusts its commitment each hour and how the uncertainty expands for long time intervals. At hour 0, 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 11. 1-4 Hour Ahead Forecast Error



In addition to longer-scale weather variation, load, wind, and solar instantaneous values are significantly volatile intra-hour. Figure 12 illustrates the instantaneous volatility used in the simulations from a perfectly smooth shape for the given hour. As an example, in an hour in which SERVM expects solar to ramp from 3,000 MW at the start of the hour to 4,000 MW at the end of the hour in a straight line, this distribution introduces volatility such that the actual solar will deviate from the straight line. To continue the example, there is approximately a 1% chance that solar will deviate by 1% from its straight line expected output.

Figure 12. Intra-Hour Solar Uncertainty Distribution

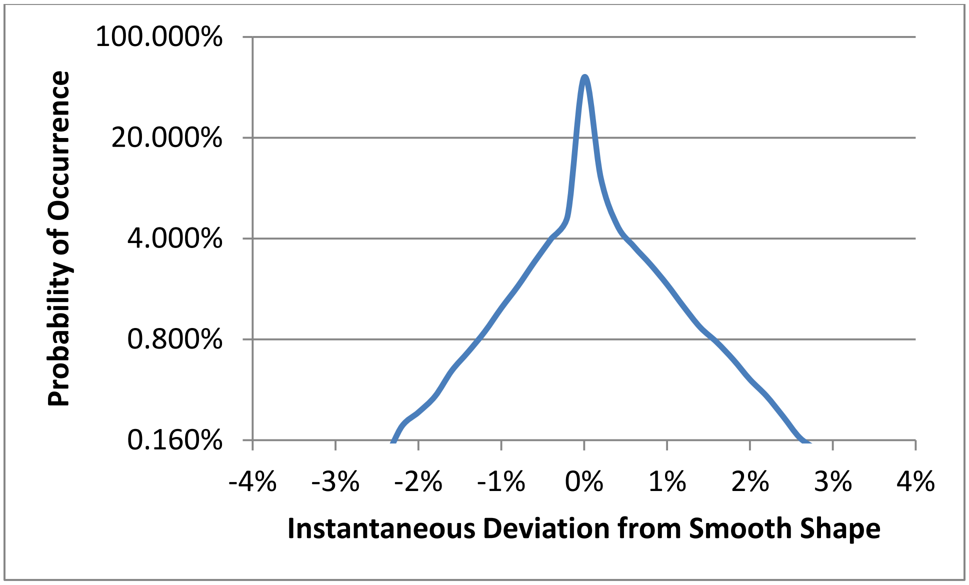
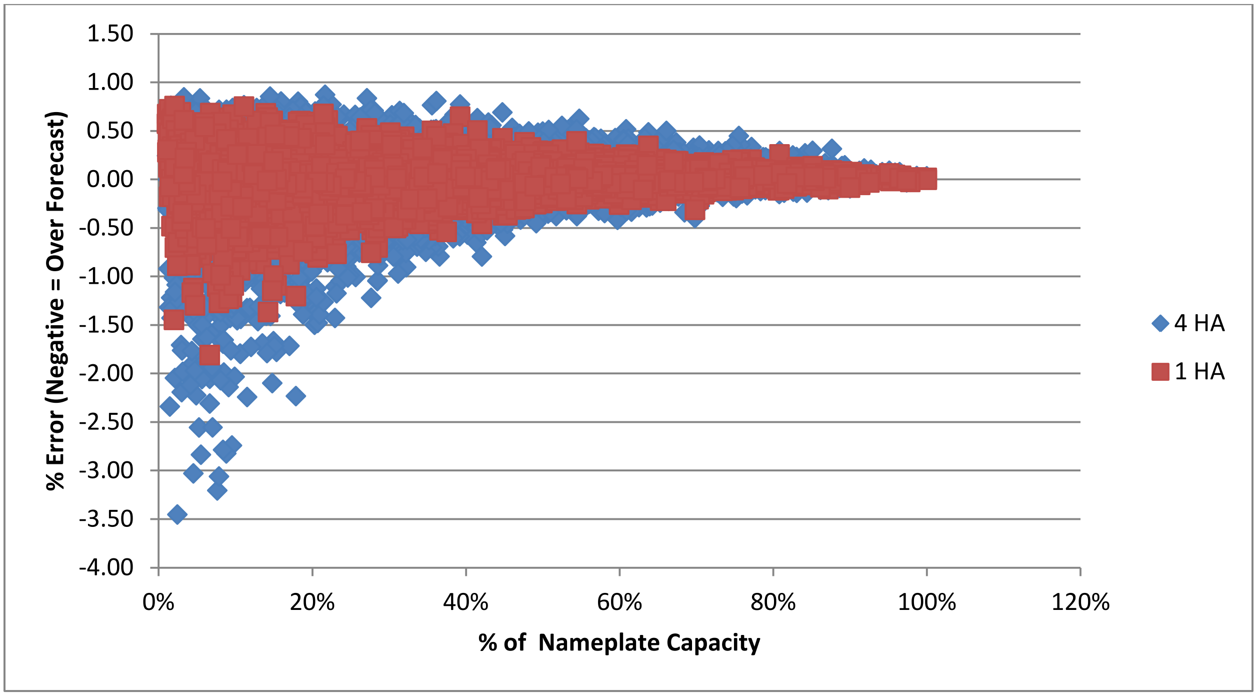


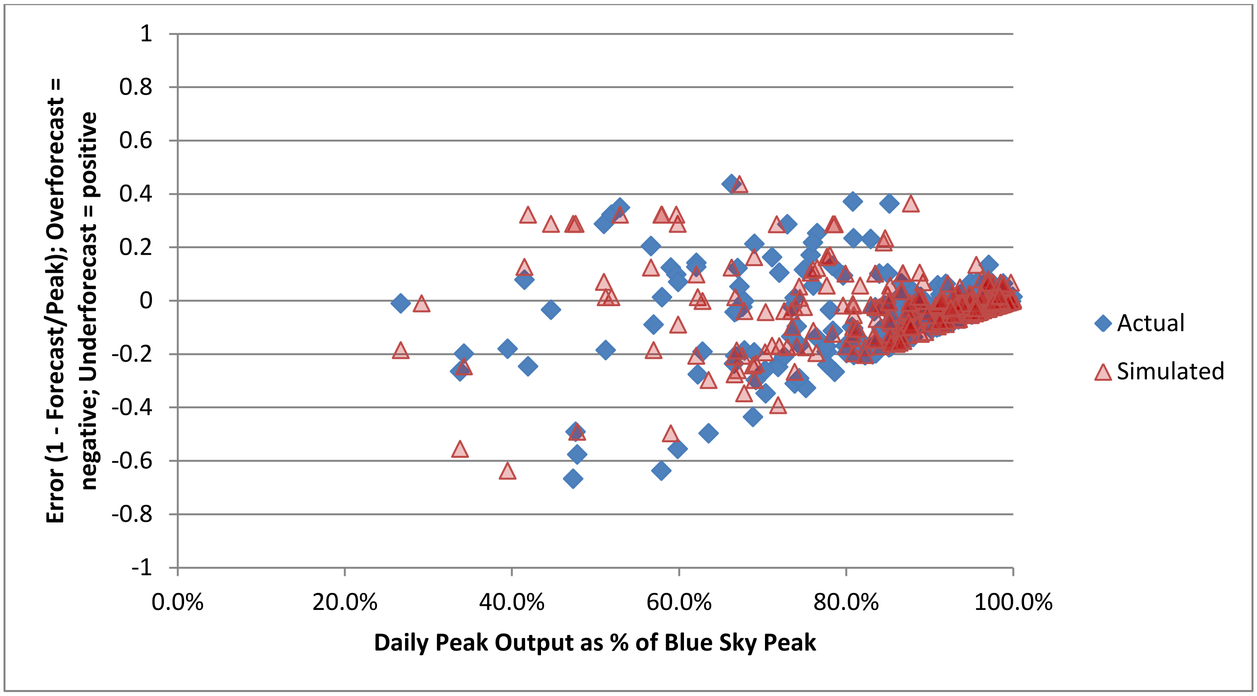
Figure 13 illustrates the multi-hour forecast error that SERVM uses during the commitment process. As expected, the 4-hour ahead error has wider error bands than the 1-hour ahead error. This also illustrates that the forecast error is not simply random draws, but is based on the actual wind conditions. For instance, in periods where wind is close to its full nameplate output, there is little forecast error.

Figure 13. Multi-Hour Wind Uncertainty



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 14. Day Ahead Solar Uncertainty



J. CT Startup Times Intra-Hour

For this study, 10 minute startup times 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.

K. Overgen Penalty

Within the unit commitment, the cost of renewable curtailment is an input. Depending on economics, the commitment will determine whether or not to commit more or less resources based on this assumption. For this study, $300/MWh was used consistent with the assumption used in CAISO's prior evaluations of the 2014 LTPP scenarios.

III. Sensitivity Cases

Table 4 below is a high level summary of the 22 cases presented at the November 2nd, 2015 advisory group meeting.

Table 4. Sensitivity Cases

Sensitivity Case #	Flexibility - Pmin	Installed Capacity	Flexibility - LFR[1]	Load Shed Threshold
		Base Case (**33%** RPS)[2]		
Sa-01	Base Case	Base Case	2%[3]	4.5% of Load[4]
Sa-02	Base - 4k MW			
Sa-03	Base - 2k MW			
Sa-04	Base + 2k MW			
Sa-05	Base + 4k MW			
Sa-06	Base + 6k MW			
Sa-07		Base - 1k MW		
Sa-08			1%[3]	
Sa-09				3.0% of Load
Sa-10				1.5% of Load
Sa-11				0.0% of Load

Sensitivity Case #	Flexibility - Pmin	Installed Capacity	Flexibility - LFR[1]	Load Shed Threshold
		Base Case (**40%** RPS)[2]		
Sb-01	Base Case[2]	Base Case	3%[3]	4.5% of Load[4]
Sb-02	Base - 4k MW			
Sb-03	Base - 2k MW			
Sb-04	Base + 2k MW			
Sb-05	Base + 4k MW			
Sb-06	Base + 6k MW			
Sb-07		Base - 1k MW		
Sb-08			1.5%[3]	
Sb-09				3.0% of Load
Sb-10				1.5% of Load
Sb-11				0.0% of Load

1. Loaf Following Reserves; 2. 2014 LTPP Trajectory or 40% RPS Scenario; 3. Target modeled as 1%, 2%, or 3% of load + expected intra-hour net load ramp
4. Represents the minimum level of regulation and operating reserves that must be maintained

A. Renewable Penetration

Simulations were performed at 33% and 40% renewable penetration. The previous phase (phase 2) only simulated at 33% renewable penetration. The assumptions used to develop the 40% renewable penetration were based on the CAISO 2014 LTPP dataset. However, since the capacity factors were slightly different over the 33 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 was the same as the CAISO total energy for each category. This resulted in differences in capacity in some of the renewable resources. The following table compares the capacity and energy in the 33% and 40% scenarios for the CAISO RPS resources[9].

Table 5. Renewable Energy and Capacity Comparison

33% Renewable Penetration

	CAISO			Astrape		
	Capacity (MW)	Energy (MWh)	Capacity Factor	Capacity (MW)	Energy (MWh)	Capacity Factor
PGE Solar	3,910	7,817,529	22.8%	3,847	7,817,529	23.2%
SCE Solar	7,295	15,482,261	24.2%	7,121	15,482,261	24.8%
SDGE Solar	857	1,628,348	21.7%	833	1,628,348	22.3%
PGE_Wind	1,798	3,660,397	23.2%	1,516	3,660,397	27.6%
SCE_Wind	3,393	8,885,649	29.9%	2,905	8,885,649	34.9%
SDGE_Wind	877	2,225,156	29.0%	690	2,225,156	36.8%

40% Renewable Penetration

	CAISO			Astrape		
	Capacity (MW)	Energy (MWh)	Capacity Factor	Capacity (MW)	Energy (MWh)	Capacity Factor
PGE Solar	7,335	14,281,833	22.2%	6,864	14,281,833	23.8%
SCE Solar	11,223	23,253,767	23.7%	9,766	23,253,767	27.2%
SDGE Solar	1,165	2,231,133	21.9%	1,005	2,231,133	25.3%
PGE_Wind	2,149	4,211,048	22.4%	1,764	4,211,048	27.2%
SCE_Wind	3,751	10,195,950	31.0%	3,343	10,195,950	34.8%
SDGE_Wind	1,268	3,309,546	29.8%	1,031	3,309,546	36.7%

Compared to the 33% RPS base case, more $LOLE_{FLEX}$ events initially occurred in the higher 40% renewable penetration level 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 of 1% of load were added to the 40% RPS base case.

[9] Does not include SCE solar thermal resources

B. Pmin Scenarios

In the prior phase, sensitivities were performed around resource Pmins by adjusting all minimum operating levels by the same percentage. In this Phase 3, 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[10]. Some other small units with low heat rates were also used[11]. The total nameplate of all resources used in at least one Pmin scenario was approximately 17,000 MW with a starting minimum dispatch level of about 7,500 MW.

The following Pmin sensitivities were performed for both the 33% and the 40% scenarios:

- -4000 MW
- -2000 MW
- Base Case
- +2000 MW
- +4000 MW
- +6000 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.

C. Load Following Reserves Sensitivities

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

[10] As an example, Blythe CC has a max capacity of 490 MW in all scenarios. In the Base Scenario, its minimum capacity level was modeled as 208 MW. In the -4000 capmin scenario, its minimum capacity level was modeled as 98 MW. In the +6000 MW scenario, its minimum capacity level was modeled as 365 MW.
[11] Specifically, all gas units with heat rates below 8.4

following reserves allows the system to absorb larger intra-hour net load volatility events. For this phase, a sensitivity of 50% of the incremental component of the base case load following assumption was made for both the 33% renewable scenario and the 40% scenario. This resulted in a 1% load following target plus expected load ramp for the 33% scenario and 1.5% load following target plus expected load ramp for the 40% scenario.

D. Firm Load Shed Definition Sensitivities

At the request of the advisory group, additional sensitivities were run in this Phase 3 of the Project on both the 33% RPS and 40% RPS base scenarios to show the effect of lower firm load shedding level. As indicated in Section H (Table 3), the base case for each scenario protected a 4.5% minimum reserve level (3% operating reserves and 1.5% regulation) by shedding firm load consistent with CAISO's current operating procedures. The sensitivities were run at the following alternative firm load shedding levels:

- At 3% reserves
- At 1.5% reserves
- At 0% reserves

E. Installed Capacity Sensitivities

Additional sensitivities were also run on both the 33% RPS and 40% RPS base scenarios to show the effect of reduced capacity being available to the CAISO system. Reduced capacity sensitivities were run at approximately 1,000 MW less of capacity than the base case for the 33% RPS and 40% RPS scenarios. Specifically, the following resources were removed from the base case for the low capacity sensitivities:

Table 6. Resources used to adjust installed reserve margin

Unit Name	Capacity (MW)	Region
OrangeGroveP2	48.5	SDGE
Panoche EC_1	100	PGE_Valley
Panoche EC_2	100	PGE_Valley

Panoche EC_3	100	PGE_Valley
Panoche EC_4	100	PGE_Valley
Pio Pico LCR LMS100-1	100	SDGE
Walnut Crk_1	100	SCE
Walnut Crk_2	100	SCE
Walnut Crk_3	100	SCE
Walnut Crk_4	100	SCE
Walnut Crk_5	100	SCE
Total	**1048.5**	**CAISO**

IV. Modeling Changes

The following describes the modeling changes incorporated in this phase or planned for in the next phase of the project. With one exception[12], the changes are intended to bring the commitment and dispatch decisions in SERVM more in line with CAISO's current practices.

A. Downward Ramp Capability

An error was identified in SERVM which was giving resources more downward flexibility than their inputs specified. Specifically, when AGC-capable units were dispatched in the downward direction they were allowed to move at twice their downward ramping speed. All else equal, this error resulted in slightly fewer reliability events and lower curtailment. This correction for this issue was implemented for all the simulations described in this report.

B. Timing of Unit Starts and Shutdowns

Since SERVM was originally designed as an hourly model, a number of 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 a number of 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.

[12] 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. Intra-Hour CAISO Clearing

Similar to Item B, intra-hour decisions improve the optimality of the commitment and dispatch. Previously, transfers were scheduled once per hour between SCE, SDG&E and PG&E. 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 PG&E and increases the output of units in SCE or SDG&E to balance load and still respect the import/export constraints.

D. Pre-emptive Market Ramping

Ramping constraints were imposed on the interties for this phase of between 3,000 MW and 4,000 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. With the 3,000 - 4,000 MW of hourly market purchase ramping, this was not a significant driver of prior results. However, with higher penetrations of renewable resources (primarily solar) in future scenarios, the net load ramps may become steeper, which elevates the impact of this enhancement.

E. 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 .5% and 1% of the total hourly solar output depending on the current hour's output. This floor and cap results in a maximum swing from the expected 5-minute solar output of 2% of the total installed capacity. While the effect of this input seemed intuitive, the volatility parameters for subsequent phases of this project will be refined.

F. 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:

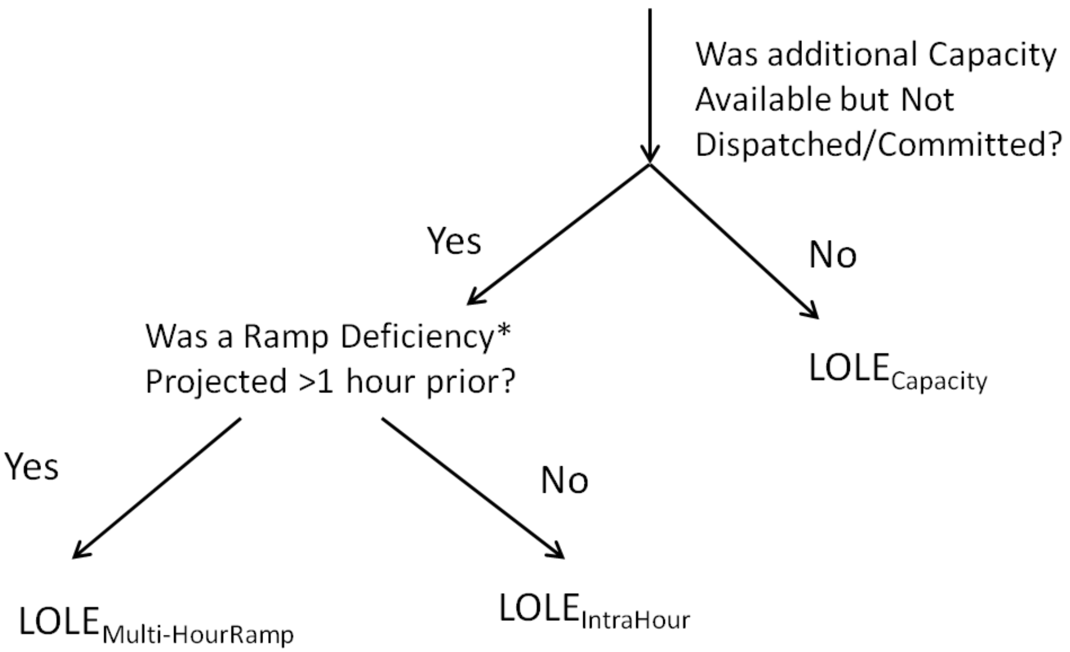
- Loss of Load Expectation Generic ($LOLE_{GEN}$) – Events per year and only represents outage events that occur due to capacity shortfalls in peak conditions. If a resource is available but was not committed and cannot meet load due to ramp rates or startup times, then the event is not counted.

- Loss of Load Expectation Intra-Hour ($LOLE_{INTRA\text{-}HOUR}$) – Events per year and events caused from system ramping deficiencies inside a single hour

- Loss of Load Expectation Multi-Hour ($LOLE_{MULTI\text{-}HOUR}$) – Events per year and events caused from system ramping deficiencies of longer than one hour in duration

The following diagram explains the process used to estimate different sources of loss of load events

Figure 15. Flexibility vs capacity shortages



[13]

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 15.

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. The beta version of reports will be further tested and made available in the next phase of the project.

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

V. Simulation Calibration and Comparison

At the November 2, 2015 advisory committee meeting the topic of validation of SERVM relative to other models and convergence of SERVM results was discussed. This report documenting the analysis presented at that meeting provides additional information about calibration and comparisons of SERVM results done before and as part of the CES-21 Grid Integration project.

The CES-21 project did not anticipate the need for simulating a historical year with SERVM to compare model results against past CAISO operation. However, SERVM results have been compared against the results of other planning models modeling similar scenarios. Prior to the start of the CES-21 project, a collaborative review of planning models was conducted in 2014 comparing five models or modeling approaches, including SERVM. A report was prepared documenting the various features of the models and comparing the model results (April 2014 Collaborative Report).[14]

April 2014 Collaborative Report compared the methodologies and inputs used by the models, and sample results for the 2012 LTPP Base Scenario without San Onofre Nuclear Generating Station. A comparison of the models, including inputs and results can be found in Section 3 of the April 2014 Collaborative Report.

The collaborative review of planning models was intended to improve understanding of planning models rather than recommend or select a particular model. Thus, the collaborative effort reviewed and evaluated the various capabilities and features of the models under consideration (one of them being the SERVM model). Based on this evaluation, the CES-21 Project found SERVM to be better suited for the CES-21 work because SERVM was able to:

- Run multiple scenarios to capture the range of potential conditions

[14] Aa copy of the report can be found at http://www.cpuc.ca.gov/NR/rdonlyres/ECE43E97-26E4-45B7-AAF9-1F17B7B77BCE/0/CombinedLongTermProcure2014OIR_Report_CollaborativeReview.pdf

- Modeling uncertainty affecting operating decisions
- Produce reliability, operating flexibility metrics in additions to cost and emission
- Consider transmission constraints within the CAISO
- Model interactions between the CAISO and the rest of WECC

As part of the CES-21 project, SERVM results have been periodically compared to the 2014 LTPP deterministic simulations performed by the CAISO for the 33% RPS and 40 % RPS scenarios. Those comparisons have been part of the information presented to the advisory group in prior meetings.

During the construction and debugging of the scenarios, a number of calibration steps were performed in addition to those discussed in the input sections above.

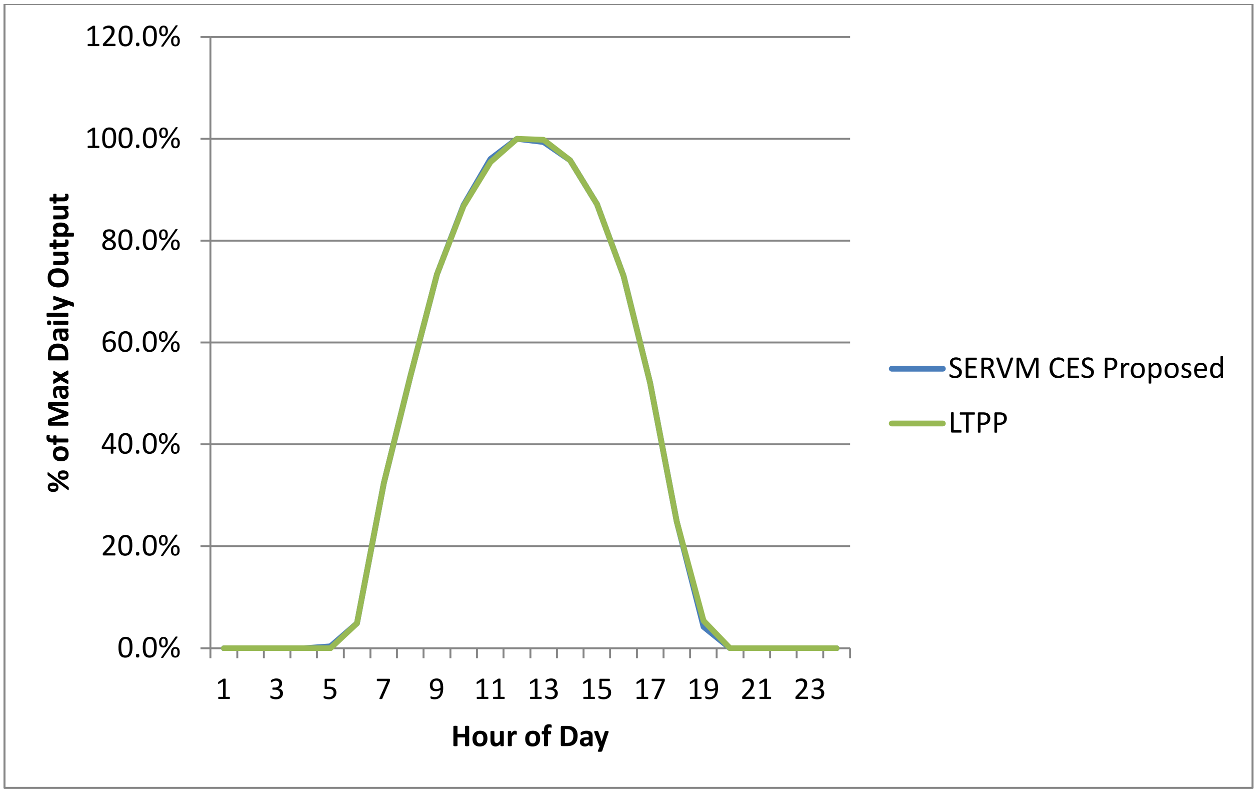
A. Fixed Dispatch Calibration

A significant component of the energy produced in both the 33% renewable scenario and the 40% renewable scenario comes from resources with fixed or must-run dispatch. This includes the wind and solar resources obviously, but also some hydro, biomass, geothermal, nuclear, and CHP resources. Since the simulations in SERVM are using multiple weather years, most resources whose output is contingent on weather were converted into shapes consistent with the historical weather pattern. Some exceptions to this procedure include the CAISO run-of-river hydro profile (most of the hydro energy was converted into weather-based datasets), and out-of-state RPS projects. Biomass, geothermal, nuclear and CHP resources were set to must-run in SERVM since the CAISO profiles had these resources running at maximum output. For the wind, solar, and hydro resources which were converted to the appropriate historical weather shape, attempts were made to calibrate the energies and shapes and volatility parameters to information from the CAISO dataset as much as possible. However the SERVM weather year wind shapes showed higher capacity factors and higher afternoon profiles than the CAISO dataset on average. The wind all-weather year profiles will be redeveloped and calibrated for the final phase of CES-21.

With respect to the solar daily shapes, capacity factors and volatility parameters were calibrated to match the average shapes in the single year CAISO data by technology based on the profiles in the 33% renewable dataset.

The following chart illustrates the shaping done on the daily solar profiles. The shaping was performed by scaling the raw hourly SERVM shape by the ratio of the SERVM shape to the CAISO LTPP shape for each hour. For future phases, we intend to calibrate the solar shapes to actual profiles as well.

Figure 16. Solar Daily Profile Shape Comparison



The resources in the 40% set used the same shapes as in the 33% set just scaled up to the total energy. The different mix of solar technologies in the 40% case (higher tracking solar penetration relative to that in the 33% case) resulted in an increased capacity factor for solar in the SERVM dataset; however this effect was not seen in the CAISO dataset.

B. Load Calibration

As part of the CES-21 project, the SERVM load shapes were calibrated to produce an overall load factor that matches the load factor from the 2014 LTPP Trajectory Scenario.

The initial SERVM load shapes were developed based on historical load information from 2010 – 2014, which indicated a consistent 58% load factor as opposed to the 53.5% load factor present in the LTPP load shapes.

To remain consistent with the LTPP shapes, the scaling methodology discussed below was employed:

I. The Astrape 2005 weather year load shape was scaled so that its peak load matched the LTPP peak load, which also used 2005 weather. Both shapes were sorted to create a declining load duration curve.

II. The LTPP shape was subtracted from the Astrape shape to create an 8760 hourly curve of hourly differences (delta curve).

III. The delta curve was scaled using a single scalar so that the average load factor of all 33 Astrape weather year load curves equaled the LTPP load factor.

IV. The end result is a set of 33 weather year profiles, each with different peaks and load factors, which on average have a 53.5% load factor.

V. This adjustment was done to the aggregate LTPP CAISO load shapes (consisting of the PGE, SCE, and SDGE regions). The individual region shapes were then re-calculated using the same percentage that the region had of the original Astrape load shape.

This preserved the peak variability, but lowered the minimum load levels significantly. To validate and calibrate results, the exact LTPP load shape for 2024 based on 2005 weather conditions was simulated in SERVM.

C. Conventional Resource Dispatch and Market Calibration

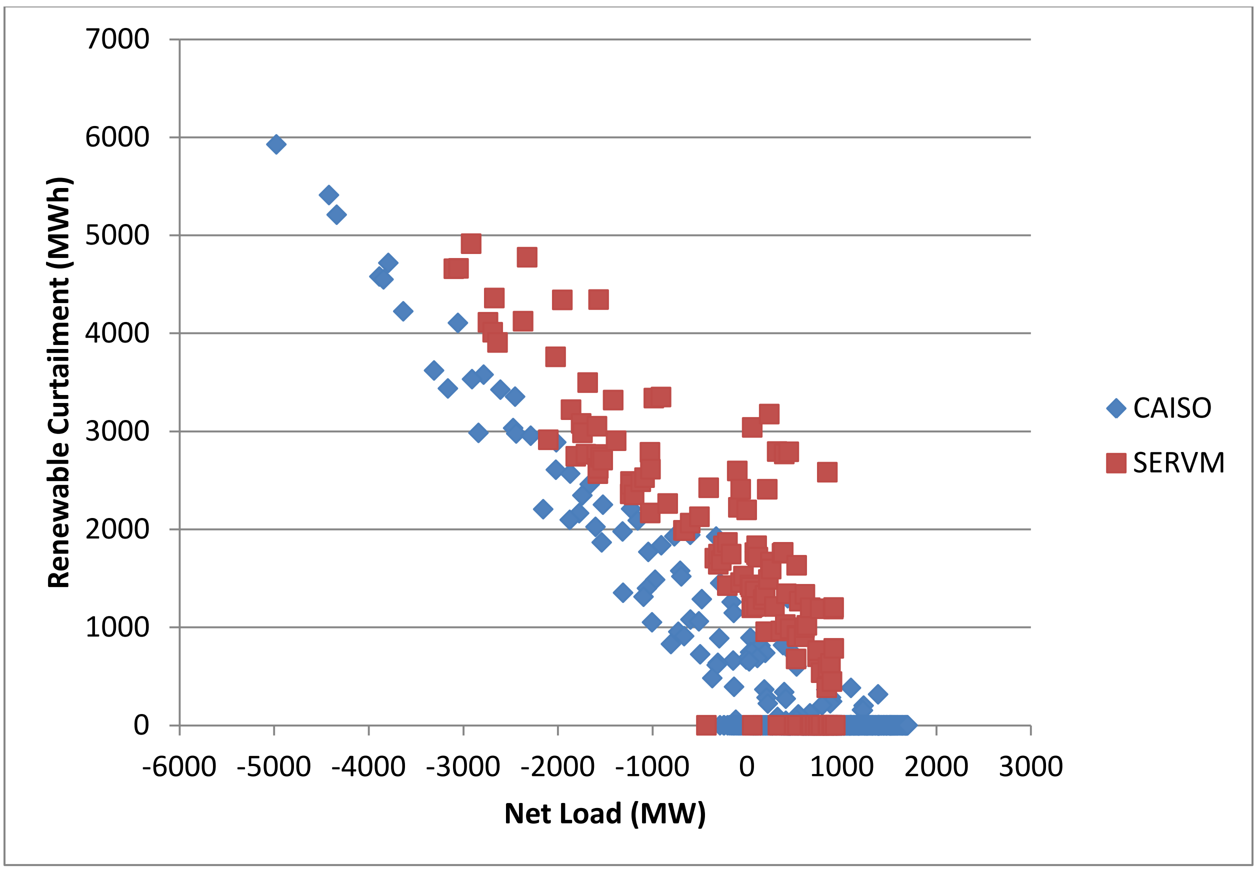
Since the accuracy of commitment and dispatch of conventional resources inside California is dependent on the level of support available from the external markets, this step was performed simultaneously. Primary objectives of the external modeling were to ensure robust support during high load hours in CAISO, and to provide some ramping support during high CAISO net load ramps.

While the resource adequacy contribution from the external markets was reasonable, several simplifying assumptions in the external market modeling resulted in lower than expected energy over the course of the year. The CAISO 2014 LTPP simulations showed approximately 50,000 GWh of net imports compared to 19,000 GWh of net imports in the SERVM single shape simulations. This is explained by the simplified representation of modeled imports as combined cycles or resources without load obligation which did not need to be used unless they were economic compared to the CAISO's marginal unit cost or needed for reliability reasons.

D. Curtailment Comparison

To validate the magnitude and frequency of curtailment an initial comparison was performed between the CAISO 2014 LTPP runs and the SERVM single shape runs. The following chart illustrates the curtailment as a function of net load[15].

Figure 17. Renewable Curtailment by Net Load Level

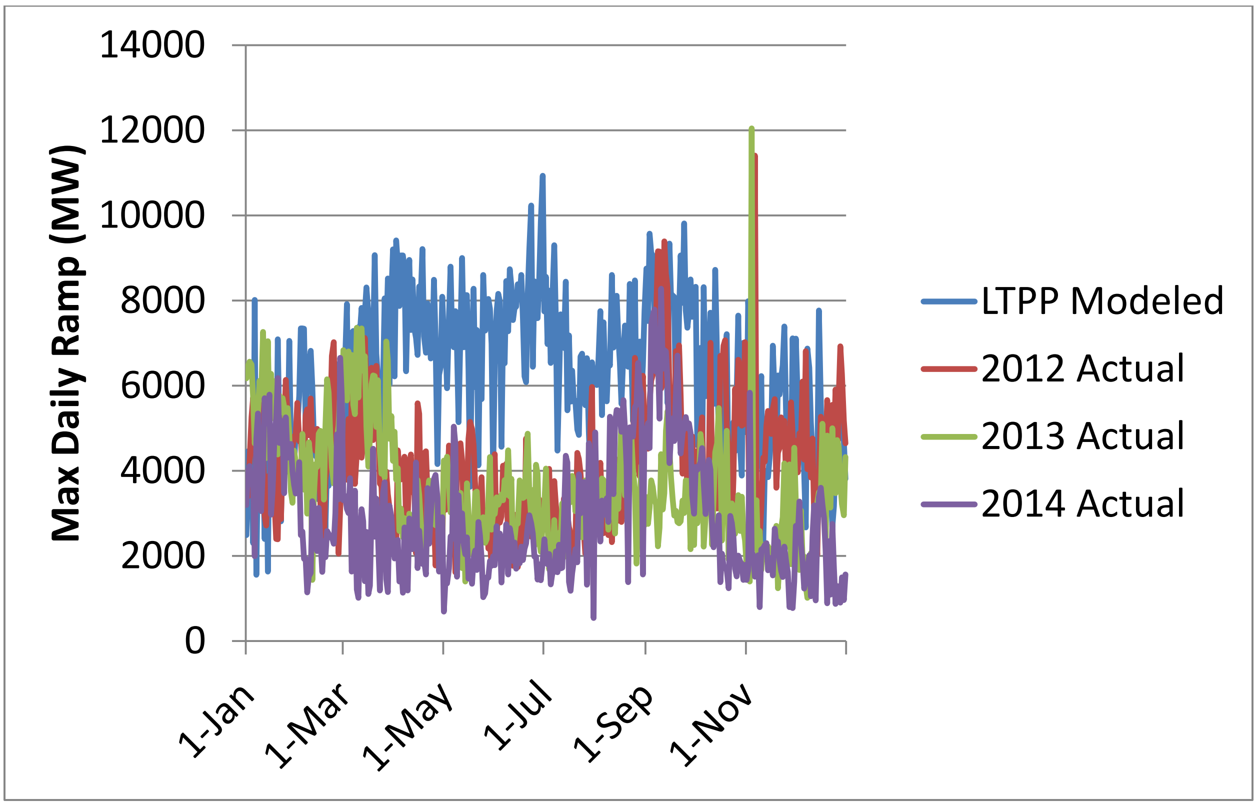


After some investigation, the lower SERVM curtailment was at least partially due to lower reliance on purchase ramping to manage curtailment. The ability of the system to use market interaction to manage curtailment will be explored further when full WECC modeling is explored in the next phase. During low

[15] Net load is defined here as load minus the sum of Renewable, Hydro, CHP, and Nuclear generation.

net load hours in SERVM, more conventional resources were required to be online in order to be able to handle the net load ramp. While further investigation is necessary, a review of historical purchases indicates that using imports to manage net load ramps during days with very low minimum net loads may not be entirely feasible. For instance, in CAISO, the maximum difference between minimum daily imports and maximum daily imports was relatively limited in the spring months when most curtailment is occurring. This effect is shown in the following figure.

Figure 18. CAISO Intra-Day Max Change in Net Interchange



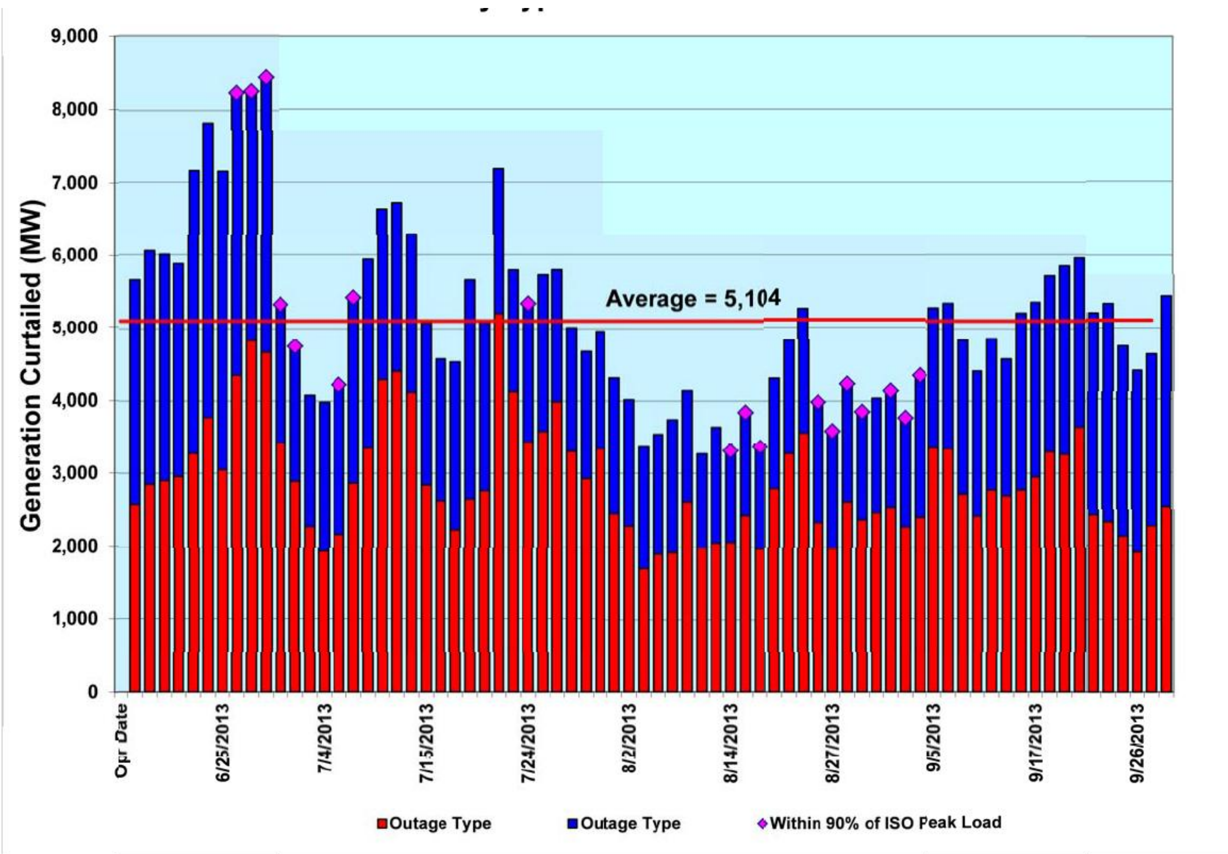
E. Reliability Calibration

Calibration of reliability events is challenging because historical events are relatively rare. The most recent significant reliability events occurred in the early 2000s and a number of system conditions have changed significantly enough that benefit of reconstructing those conditions would be limited. To calibrate the results of reliability models, the primary method employed is to compare distributions of cumulative generator outages, weather related load deviation, and economic-related load deviation.

For this effort, historical outages from the CAISO 2014 Summer Assessment[16] were compared to outages in SERVM. The chart below shows the actual 2013 Weekday Generation Outages. The red bars are planned outages and the blue bars are forced outages. This demonstrates an average of over 5,000 MW of outages including over 2,000 MW of forced outages. Since planned maintenance events are typically scheduled in off-peak seasons, the SERVM model did not attempt to replicate the summer peak season planned maintenance events. The high level of planned maintenance events was assumed to be due to high installed reserve margins during recent history which allowed planned maintenance to have little effect on reliability. The size of the conventional fleet historically is different than the expected size of the conventional fleet in 2024. Therefore the outages had to be compared as a percentage of the conventional fleet. Both the historical review and the SERVM runs demonstrated approximately 5% of the nameplate of conventional resources being in an unplanned outage event during the peak season. The conventional resources totaled approximately 28,000 MW of capacity. The 5% forced outages correspond to approximately 1,400 MW on outage during the peak season. The outage modeling in SERVM is further described in detail in section II.F above.

Figure 19. CAISO actual summer 2013 outages

16



Generation Curtailed (MW)
9,000
8,000
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
Average = 5,104
Opr Date
6/25/2013
7/4/2013
7/15/2013
7/24/2013
8/2/2013
8/14/2013
8/27/2013
9/5/2013
9/17/2013
9/26/2013
Outage Type
Outage Type
Within 90% of ISO Peak Load