Unified Resource Adequacy and Integrated Resource Plan Inputs and Assumptions – Guidance for Production Cost Modeling and Network Reliability Studies

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1 Introduction

The California Public Utilities Commission (CPUC) staff has prepared this "Revised 2019 Unified Resource Adequacy and Integrated Resource Plan Inputs and Assumptions – Guidance for Production Cost Modeling and Network Reliability Studies" document (2019 Unified RA&IRP I&A) to serve five primary functions:

1. Describe the production cost modeling methodology, inputs, and assumptions that were used to inform the CPUC's Integrated Resource Plan (IRP) proceeding (R.16-02-007) in 2018, including the system operational and reliability studies described in Attachment B of D.18-02-018[1] and Attachment A of the November 15, 2018 ruling[2] in the proceeding.
2. Describe the production cost modeling methodology, inputs, and assumptions that were used to inform the CPUC's Resource Adequacy (RA) proceeding (R.17-09-020) in 2018, specifically Effective Load Carrying Capability (ELCC) calculations.
3. Describe the production cost modeling methodology, inputs, and assumptions that were used to inform the CPUC's Aliso Canyon Order Instituting Investigation proceeding (I.17-02-002) in 2018.
4. Describe certain inputs and assumptions to inform the production cost modeling and network reliability ("power flow") studies of the CAISO's 2019-20 Transmission Planning Process (TPP),[3] including the allocation of generic resources to transmission substations.
5. Serve as a guide for other entities conducting similar electric system modeling.

The 2019 Unified RA&IRP I&A primarily documents model inputs that were used during 2018 modeling activities. It does not include modeling improvements and updates that CPUC staff expects to undertake during the 2019 modeling activities taking place for the IRP proceeding. See the 2019-2020 IRP Events and Materials page on the CPUC website for more recent information about modeling inputs going forward.[4]

The Unified RA&IRP I&A is "unified" in the sense that it consolidates descriptions of modeling inputs and guidance for the five primary functions listed above in a single document and associated sets of data that are posted on the CPUC's website. The production cost modeling methods and data to support modeling in the IRP, RA, and Aliso Canyon proceedings are consolidated in one document because the three proceedings share a common production cost modeling platform with similar data requirements. The Unified RA&IRP I&A is also "unified" in the sense of providing for a common and consistent set of modeling conventions and input data to facilitate comparison of study results across different planning processes at the CPUC and across different agencies.

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[1] Available at: http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M209/K771/209771632.PDF.

[2] Available at: http://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M241/K155/241155600.PDF.

[3] In accordance with a May 2010 MOU between the CAISO and the CPUC, and in coordination with the CEC, the CPUC develops the new resource portfolios used by CAISO in its annual Transmission Planning Process (TPP)

[4] See: http://www.cpuc.ca.gov/General.aspx?id=6442459770

1.1 Background and Roadmap

In previous years, the "Assumptions and Scenarios" document[5] was issued annually via ruling in the CPUC's Long-Term Procurement Plan (LTPP) proceedings[6] to provide for a common set of data to guide electric system modeling activities in the LTPP proceeding and the CAISO's TPP in the same calendar year. The 2016 Order Instituting Rulemaking to Develop an Electricity Integrated Resource Planning Framework and to Coordinate and Refine Long-Term Procurement Planning Requirements (R.16-02-007) superseded the LTPP proceedings and is now commonly referred to as the IRP proceeding. As such, the historical "Assumptions and Scenarios" document is superseded by this document, the Unified RA&IRP I&A, which is designed for the new IRP process and intended for use in other proceedings requiring similar types of electric system modeling. The Unified RA&IRP I&A is expected to be updated annually and issued in February each calendar year.

The historical "Assumptions and Scenarios" document was also accompanied by two key Excel workbook deliverables, the Renewables Portfolio Standard (RPS) Calculator & Portfolios[7] and the Scenario Tool.[8] These workbooks are superseded by new deliverables designed to support the new IRP process. The new deliverables include the following:

- Workbooks containing resource portfolios to plan for long-term (typically 10 years forward) infrastructure expansion at the CAISO system level. The portfolios are based on the IRP Reference System Plan or the IRP Preferred System Plan. In general, IRP capacity expansion modeling (currently conducted using the RESOLVE model[9]) forms the basis of the Reference System Plan while the aggregation of IRPs submitted by individual load-serving entities (LSEs) forms the basis of the Preferred System Plan.[10]
- Workbooks capturing the inputs to the Strategic Energy Risk Valuation Model (SERVM)[11] production cost model being used by CPUC Energy Division staff to support the IRP, RA, and Aliso Canyon proceedings.

The historical "Assumptions and Scenarios" document was also accompanied by supplemental data and guidance from the CEC and the three large Investor Owned Utilities to allocate load and/or generic resources to transmission substations. This information will continue to be pointed to or provided with the Unified RA&IRP I&A document.

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[5] The February 2017 version: http://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M176/K948/176948479.PDF This document has also been referred to as the Standard Planning Assumptions, or SPA.

[6] The previous LTPP proceeding is R.13-12-010.

[7] See RPS Calculator v6.2 here: http://www.cpuc.ca.gov/RPS_Calculator/

[8] See Scenario Tool 2016 v1.2 here: http://www.cpuc.ca.gov/General.aspx?id=11681

[9] See RESOLVE model here: http://www.cpuc.ca.gov/General.aspx?id=6442457210

[10] The IRP Proposed Decision published March 18, 2019 chose to use a RESOLVE-based portfolio as the Preferred System Plan rather than a portfolio based on the aggregation of LSE IRPs

[11] Developed by and commercially licensed through Astrape Consulting. http://www.astrape.com/servm/

The remainder of this document is comprised of two major sections. First, it describes modeling conventions and input development for the SERVM model that was used to conduct the various types of production cost modeling studies in support of the IRP, RA, and Aliso Canyon proceedings. Resource portfolios modeled in SERVM flow from the IRP Reference System Plan or Preferred System Plan. The last section of the document describes additional guidance and data required for the network reliability studies typical of the CAISO's TPP.

1.1.1 Acronyms

Acronym	**Definition**
1-in-10	1-in-10 year weather peak demand forecast
1-in-2	1-in-2 year weather peak demand forecast
AAEE	Additional Achievable Energy Efficiency
AAPV	Additional Achievable Photovoltaics (behind-the-meter solar PV)
ADS	Anchor Data Set
BTM	Behind-the-meter
CAISO	California Independent System Operator
CARB	California Air Resources Board
CEC	California Energy Commission
CED	California Energy Demand Forecast
CHP	Combined Heat and Power
CPUC	California Public Utilities Commission
DCPP	Diablo Canyon Power Plant
DR	Demand Response
ELCC	Effective Load Carrying Capability
EO	Energy-Only (deliverability status)
EV	Electric Vehicle
FCDS	Full Capacity Deliverability Status
IEPR	Integrated Energy Policy Report
IOU	Investor Owned Utility
LCR	Local Capacity Requirement
LOLE	Loss of Load Expectation
LSE	Load Serving Entity
LTPP	Long Term Procurement Plan
NQC	Net Qualifying Capacity
OTC	Once-through-cooling
PG&E	Pacific Gas & Electric
POU	Publicly Owned Utility
PV	Photovoltaic
RPS	Renewables Portfolio Standard

SCE	Southern California Edison
SDG&E	San Diego Gas & Electric
SERVM	Strategic Energy Risk Valuation Model
TEPPC	Transmission Expansion Planning Policy Committee
TPP	Transmission Planning Process
WECC	Western Electricity Coordinating Council

2 Production Cost Modeling – Inputs, Assumptions, and Methods

2.1 Scope

This section describes the assumptions and input sources that CPUC's Energy Division staff used for Production Cost Modeling (PCM) to support the Resource Adequacy (RA) proceeding, the Integrated Resource Planning (IRP) proceeding, and the Aliso Canyon proceeding through 2018.[12] Proceeding-specific documents in each proceeding defined the higher-level modeling steps and activities to support each respective proceeding. For example, the higher-level modeling steps and activities done for the IRP proceeding in 2018 are described in Attachment B of the IRP Decision D.18-02-018[13] and Attachment A of the November 15, 2018 ruling in the proceeding.[14]

This section includes the following key components:

- Review of SERVM, software which is being used by Energy Division Staff to conduct LOLE and ELCC analysis
- Primary data sources and assumptions
- Interagency coordination
- Foundational definitions and assumptions for RA and IRP modeling
- Fundamental description of the order of studies needed to perform monthly LOLE and monthly ELCC studies
- Gathering and use of weather data for development of synthetic load shapes using weather normalization and regression analysis
- Sources of and use of weather data and weather region definitions to create hourly profiles for wind and solar production
- Description of different resource portfolios used in 2018 modeling activities
- Data related to conventional (fossil fuel) generators

[12] The previous RA proceeding is R.14-10-010. The current RA proceeding is R.17-09-020. The current IRP proceeding is R.16-02-007. The Aliso Canyon Investigation proceeding is I.17-02-002.

[13] http://docs.cpuc.ca.gov/SearchRes.aspx?docformat=ALL&DocID=209771632

[14] http://www.cpuc.ca.gov/uploadedFiles/CPUCWebsite/Content/UtilitiesIndustries/Energy/EnergyPrograms/ElectPowerProcurementGeneration/DemandModeling/R1602007_PCM%20ruling%2011-14-18%20Attachment%20A%20PDF.pdf

- Burner-tip natural gas price forecasts
- Development of data inputs and hourly profiles for hydro generators
- Data for demand response and storage resources

Study results will be separately documented and driven by the respective needs of the IRP, RA, and Aliso Canyon proceedings.

2.2 Review of SERVM Software

Energy Division staff use SERVM to calculate numerous reliability, operational, and cost metrics for a given study year in light of expected weather, overall economic growth, and unit performance. For each of these factors, variability and forecasting uncertainties are also taken into account.

As with all probabilistic models, SERVM attempts to simulate the study year many thousands of times over, with each simulation reflecting a slightly different set of weather, economic, and unit performance conditions. Iteration conditions are selected probabilistically, based on how likely they are to occur. In SERVM, a given future study year is modeled by simulating the operation of a fleet of power plants in that future year to meet hourly electric demand that reflects a wide variety of actual historical weather patterns. For each of thirty-five possible weather years, six to eight points of load forecast error can be simulated, creating roughly 210 to 280 scenarios. Each of these scenarios is in turn run with a hundred or more unit outage draws, creating thousands of iterations for the simulation. Results are expressed as the probability-weighted expected average metrics across the whole range of variability studied. The results provide a comprehensive distribution of loss-of-load events, unserved energy, and other reliability metrics. Expected values and confidence intervals are calculated based on these distributions.

2.3 Primary Data Sources and Assumptions

2.3.1 Interagency Coordination and Data Sources

Foundational to the task of coordinating the RA and IRP modeling efforts is coordination between the key California agencies that cooperatively plan for the future of electric service, including the CEC, CAISO, and CPUC. Without close integration and coordination, the complicated work described in this document would be impaired. Chief among the modeling data utilized by Energy Division are the CEC's Integrated Energy Policy Report (IEPR) and "California Energy Demand" forecast which includes electric demand and fuel price forecasts, the CAISO's datasets which catalog the generating facilities and transmission topology that operate to provide electricity to customers, and the CPUC's IRP and other resource programs datasets which lay out plans for new investment in generation and demand side alternatives.

California annual peak and energy demand forecasts including projections of demand-side resources such as energy efficiency and rooftop solar are sourced from the most recently adopted CEC IEPR California Energy Demand (CED) forecast. According to agreement between leadership at the CAISO, CEC, and the CPUC, planning processes at each agency will use the Single Forecast Set specified by the most recent IEPR CED forecast.

Energy Division staff sourced existing CAISO generating unit information from the CAISO MasterFile. In order to participate in the CAISO energy market and ensure cost effective dispatch of their plants, generator owners maintain a wide array of information in the MasterFile database. The MasterFile is used by the CAISO in order to optimize dispatch in light of an array of unit-specific characteristics such as start-up costs and start-up time, ramp rate, heat rate, and forbidden operating ranges. A number of the data fields in the MasterFile are confidential and are accessible to Energy Division staff via an annual subpoena. Definitions of all the fields in the MasterFile are public and are posted on the CAISO website.[15]

In addition to the CAISO, the Western Electric Coordinating Council (WECC) also compiles a base case dataset for the WECC and its members to use as a common basis for their modeling. Each Balancing Authority may have unique access to accurate and confidential data for generators and other market participants within its footprint, but since the WECC is so interconnected, it is difficult to accurately model reliability and economic conditions in one Balancing Authority without attention to generators and loads in the surrounding Balancing Authorities. To facilitate consistent modeling by all Balancing Authorities in WECC, every two years WECC produces a Common Case dataset containing generic information for all load and supply data across WECC.[16] Produced by a subcommittee of WECC members called the Transmission Expansion Planning Policy Committee (TEPPC), this dataset is generated for both the immediate next year and for a year ten years into the future. For modeling activities during 2018, Energy Division staff imported the TEPPC 2026 Common Case v2.0 into the SERVM dataset in order to model generating units outside of the CAISO, as well as units in most of the rest of the Western Interconnect. The peak and energy demand forecasts for regions outside of California are also sourced from the TEPPC 2026 Common Case.

The TEPPC 2026 Common Case represents the final Common Case dataset that will be produced by TEPPC. WECC is transitioning to a new organizational model and a new group called the Reliability Assurance Committee will produce a new dataset called the Anchor Data Set (ADS). It is anticipated that the ADS will take the place of the Common Case and will additionally incorporate modeling inputs for power flow modeling. Energy Division will transition to ADS data for the next IRP cycle (expected to be 2019-20).

The CAISO MasterFile and the WECC TEPPC Common Case dataset each have their advantages and disadvantages. For generators that supply information to the CAISO MasterFile, there is a larger range of information available to Energy Division for modeling purposes but some of it is confidential and/or not directly applicable to production cost modeling.

The WECC TEPPC Common Case dataset, being public data, is often generic and aggregated by class average. The 2026 TEPPC Common Case has created unit specific heat rate curves and minimum

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[15] MasterFile field definitions can be downloaded from http://www.caiso.com/Documents/GRDTandIRDTDefinitions.xls. CAISO MasterFile data are confidential, and not able to be posted; however, it may be possible to aggregate portions of these data for stakeholder review.

[16] WECC TEPPC 2026 Common Case v2.0 datasets are available for download here: https://www.wecc.biz/Reliability/Forms/AllItems.aspx

operating levels based on public data available from the Continuous Emission Monitoring System database, and this represents a significant improvement in data quality, but there are other areas where there are challenges to being as precise as possible. For this reason, it is common for particular Balancing Authorities within the WECC to substitute their own confidential, internal data for the TEPPC Common Case inputs related to their own specific balancing authority. Energy Division staff will use the TEPPC 2026 Common Case for regions external to the CAISO balancing area. For regions internal to the CAISO area, staff will use the generator-specific information obtained via subpoena from the CAISO MasterFile.

The CEC provides capacity supply forms for all LSEs within California, listing for all LSEs (including SMUD and LADWP) the unit specific sources of capacity that the LSE is relying on to meet energy needs. These Utility Capacity Supply Forms are updated annually, public, and posted to the CEC website.[17] Staff used these forms to supplement and/or cross-check with information from the CAISO Masterfile and the TEPPC 2026 Common Case.

Assumptions for new resources projected to come online by a future study year are sourced from the IRP proceeding's Reference System Plan adopted in February 2018 and developed by the RESOLVE capacity expansion model,[18] or the aggregation of individual LSE Plans that were filed in the IRP proceeding in August 2018.

All cost data (including generator operation and maintenance (O&M), startup costs, and fuel handling costs) were adjusted to 2016 dollars using a deflator series developed by the CEC in the IEPR process[19] and which equals approximately 2% inflation, year over year. This is consistent with the convention in the RESOLVE model to report all costs in 2016 dollars.

Other datasets used by Energy Division staff include the Generator Availability Data System (for generator forced and scheduled outage statistics), the National Oceanic and Atmospheric Administration (NOAA) for weather data to generate solar and wind production profiles, the National Renewable Energy Laboratory (NREL), and data specifically gathered from the utilities. These data and their use in SERVM will be described in further detail in the sections that follow.

2.3.2 Key Definitions and Reliability Metrics

Before the development of today's advanced computing, planners calculated probability of loss-of-load for the peak hour of each day, and only on weekdays, equating to about 260 data points for a study year. Today's computers perform simulations, not simple calculations, and perform simulations of each hour of the year thousands of times with multiple stochastic variables. Thus a LOLE value of 0.1, which is a direct translation of the decades old industry "one day in ten years" standard, may warrant reconsideration in light of the sophisticated hourly models and advanced computing available now.

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17 These forms are posted to the CEC website here: http://energyalmanac.ca.gov/electricity/s-1_supply_forms_2013/

18 http://www.cpuc.ca.gov/General.aspx?id=6442457210

19 The deflator series is posted here. It is derived from the April 2018 version of the CEC's NAMgas model posted here.

LOLE and ELCC studies, particularly those done to meet the needs of the IRP and RA proceedings, require a number of foundational assumptions and modeling conventions in order for the studies to proceed. Staff made assumptions about what probabilistic reliability standard at which to calibrate the CAISO system for both monthly and annual studies, and the definition of a loss-of-load event. Staff also performed a convergence analysis to evaluate the optimal number of iterations to run for each case.

In LOLE and ELCC studies for the RA and IRP proceedings, staff will use the following foundational conventions:

- The LOLE reliability target range for calibrating the CAISO system in annual studies will be 0.095 to 0.105 LOLE.
- The LOLE reliability target range for calibrating the CAISO system in monthly studies will be 0.02 to 0.03 LOLE for each month.[20]
- Multiple loss-of-load events occurring within one day shall count as one event for purposes of counting events towards a reliability target. The loss-of-load event occurs when the frequency response constraint[21] is fully relaxed and when regulation up (1.5% of hourly forecast load) and spinning reserves (3.0% of hourly forecast load) cannot be maintained, i.e. firm load is assumed to be curtailed when available capacity is less than 104.5% of load.

2.3.3 General Order of Studies in ELCC Modeling

The current scope and sequence of ELCC studies are defined by proceeding specific documents. The scope and sequence of ELCC studies that were done to support the IRP proceeding in 2018 were defined within Attachment B of the IRP Decision D.18-02-018.[22] The most recent ruling describing ELCC studies in support of the RA proceeding is February 13, 2019.[23]

Because of the complexity of the ELCC concept, the remainder of this subsection explains a generalized application of the ELCC framework to calculate monthly capacity value. As stated above, the specific scope and sequence of ELCC studies are captured in proceeding specific documents.

ELCC methods can be used to assign capacity value to particular resources or sets of resources within a larger electric system. The calibration and sequence of these studies is critical. The process is illustrated in the following chart:

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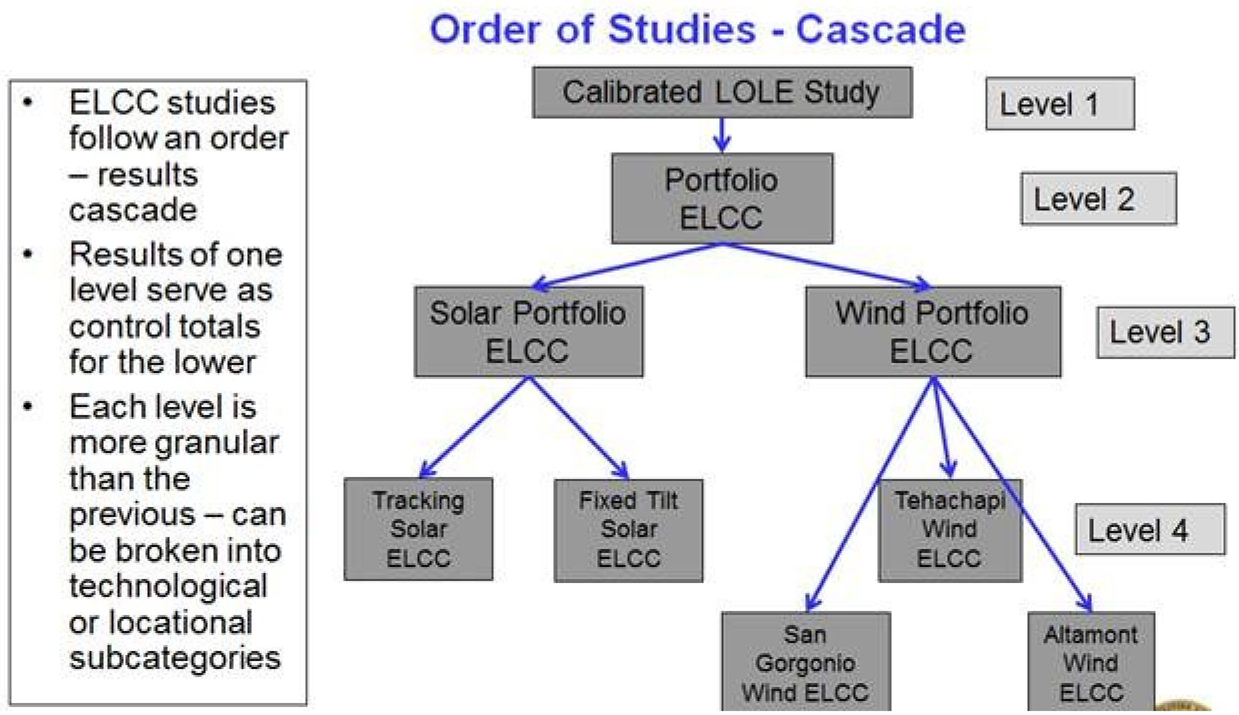
[20] Specifically, the monthly LOLE target was created by first taking the industry standard 0.1 LOLE annual target and assuming that most of those events map to the four peak months of June through September, or one third of the year. Assuming a similar target reliability for the rest of the year would mean that total LOLE over the entire year should have a target of 0.1x3=0.3. Thus, monthly LOLE studies would have a monthly target LOLE of 0.3/12=0.025, i.e. a target range of 0.02 to 0.03.

[21] Ancillary services and frequency response requirements are described later in this document in the System Inputs section 2.10.

[22] http://docs.cpuc.ca.gov/SearchRes.aspx?docformat=ALL&DocID=209771632

[23] http://www.cpuc.ca.gov/uploadedFiles/CPUCWebsite/Content/UtilitiesIndustries/Energy/EnergyPrograms/ElectPowerProcurementGeneration/DemandModeling/ELCC_2_13_19.PDF

Figure 1: Order of RA ELCC Studies



ELCC studies rely first on LOLE studies, and monthly ELCC studies require monthly LOLE studies. A Level 1 study is to calibrate the LOLE level of the overall electric system to the desired reliability level. Staff will add or remove electric capacity on a monthly basis in a predetermined order in order to result in a LOLE that is levelized and within the desired range, i.e. between 0.02 and 0.03.

Once LOLE level is calibrated on a month specific basis, staff will move on to Level 2. Staff will remove all wind and solar generators from the fleet of generators, in all months, then on a month specific basis, reinsert Perfect Capacity in increments until LOLE again is between 0.02 and 0.03 in each month.

Level 2 analysis in effect sets a control total meant to represent the total ELCC of the generators in question. Since there are often interaction and diversity effects between wind and solar generation in the way they contribute to reliability, this Portfolio ELCC study determines their total ELCC value.

In Level 3 analysis, staff performs individual technology specific ELCC studies, which are studies of a subset of the Portfolio ELCC studied in Level 2. All wind or all solar generators are removed from the fleet and Perfect Capacity is added back until LOLE is gain between 0.02 and 0.03 on a month specific basis. When the ELCC of wind and solar individually are determined, they are totaled and compared to the Portfolio ELCC results from Level 2. Technology specific ELCC values are adjusted either up or down so that their total is equal to the Portfolio ELCC value.

When each technology specific ELCC is determined, they become control totals for subsequent Level 4 ELCC analysis. For example, all tracking solar would then be removed, and Perfect Capacity would be added to return the system to LOLE in the desired range. Then the same with fixed tilt solar, and the resulting ELCC values of fixed and tracking solar would be totaled and compared to the solar technology ELCC values from Level 3 to see if they would be adjusted upwards or downwards to arrive at their individual ELCC values.

ELCC values are either expressed as MW equivalent of perfect capacity to a MW total of other generation, or as a percentage. The percentage ELCC represents the ratio of MWs of Perfect Capacity to MWs of generation removed. The ELCC percentage factor is applied to the nameplate MW of a particular generation type to derate its value and demonstrate the amount of "effective capacity" it provides.

The order of studies above references the steps of removing or adding units to calibrate a system to a target reliability level. Staff used the following conventions for those steps:

- Removal of generation to surface LOLE events in overbuilt systems shall be according to the following order:[24] Conventional thermal generators that have announced their retirement will be removed first. If LOLE remains below the target level, additional conventional thermal generation will be removed from CAISO areas in amounts proportional to service area load in each area. The oldest generation in each area will be removed first. No hydro generation or renewable generation will be removed.
- Addition of generation to reduce LOLE events in underbuilt systems shall use perfect capacity as additions. Perfect capacity is a modeling proxy for generation with no operating constraints, e.g. always available, starts instantly, infinite ramp rate, no minimum operating level.
- Although the calibration step alters the system under study, this is a typical way of performing ELCC calculations and is not expected to significantly affect the ELCC measurement.

2.4 Weather Data and Regions

Weather is an integral input into probabilistic reliability modeling. It is used both in the development of synthetic load shapes, which are highly correlated to temperature and humidity, and in the development of generation profiles for weather-sensitive resources such as wind and solar. In order to balance the need to model the wide range of weather across the state at any given time and the need to keep modeling times feasible, a set of representative weather stations are selected and grouped to create regions that are modeled as homogeneous areas. This section details the weather data utilized, the sources for this data, the regions modeled, and the process by which these regions were created.

2.4.1 Region Designations

Load, wind, and solar shapes are developed to correspond to regions modeled in SERVM. Staff has currently organized inputs in SERVM into eight distinct regions within California and sixteen outside of California based on utility service areas. While most utility service areas are modeled individually, some are aggregated, as specified in the table below. These regions are utilized throughout SERVM to associate groups of generation facilities with common weather, load, weather-related generation

[24] Note that the order specified here is simply a modeling convention picking one systematic way to remove capacity for the sole purpose of calibrating a system to a target reliability level in order to perform ELCC calculations. The choice and order of removing units does not imply the units are likely to retire or should retire.

profiles, transmission constraints, and utility service territories. The regions (zones) modeled are listed in Table 1, below. The regions below do not correspond to transmission-constrained Local Areas, and are not granular enough for transmission planning. In the future, higher geographic granularity could be achieved by splitting the regions into smaller areas. However, it is unlikely a production cost model will ever approach the fidelity required for network reliability (power flow) studies. Such studies are not in scope for Energy Division staff at this time.

Table 1: Assignment of WECC regions to modeled SERVM zones

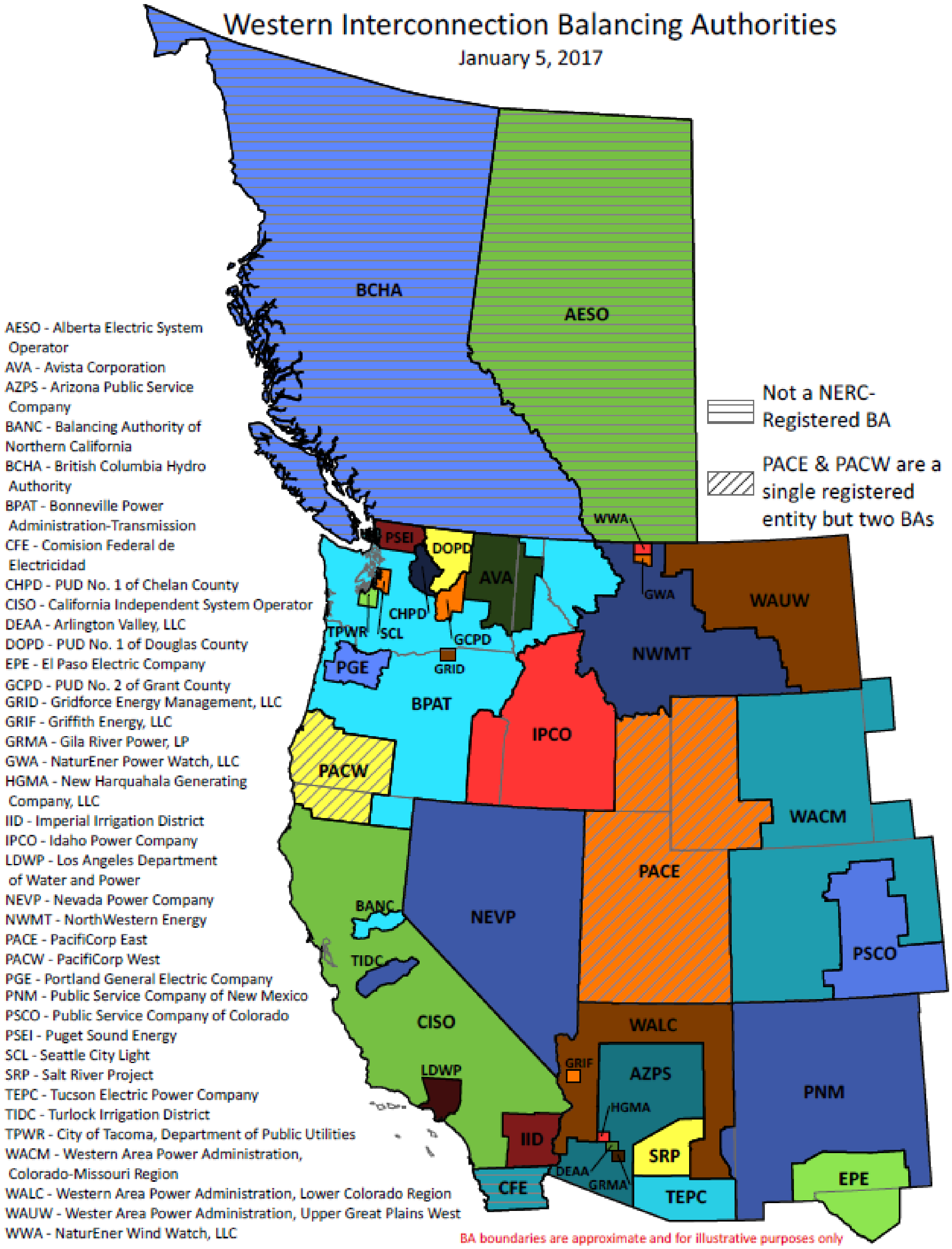
SERVM Region	Description
California Regions	
IID	Imperial Irrigation District
LADWP	Los Angeles Department of Water and Power, Burbank, Glendale
PGE_Bay	Pacific Gas & Electric (Greater Bay Area) [25]
PGE_Valley	Pacific Gas & Electric (Valley) [26]
SCE	Southern California Edison, Valley Electric Association
SDGE	San Diego Gas & Electric
SMUD	Balancing Authority of Northern California
TID	Turlock Irrigation District
Non-California Regions	
AZPS	Arizona Public Service Co
BCHA_AESO	British Columbia Hydro Authority, Alberta Electric System Operator
BPAT	Bonneville Power Adminstration, Avista Corporation, Chelan County PUD, Douglas County PUD, Grant County PUD, Puget Sound Energy, Seattle City Light, Tacoma Power
CFE	Comision Federal de Electricidad
IPCO	Idaho Power Co
NEVP	Nevada Power Co, Sierra Pacific Power
NWMT_WAUW	Northwestern Energy, WAPA Upper Wyoming
PACE	Pacificorp East
PACW	Pacificorp West
PNM_EPE	Public Service Co of New Mexico, El Paso Electric Co
PortlandGE	Portland General Electric Co
PSCO	Public Service Co of Colorado
SRP	Salt River Project
TEPC	Tuscon Electric Power Co
WACM	WAPA Colorado Missouri
WALC	WAPA Lower Colorado

Figure 2 below is an illustrative map of Western Interconnection Balancing Authorities and is generally consistent with the region definitions used in SERVM.

[25] Includes these lines from IEPR demand forecast Form 1.5a: CCSF, NCPA-Greater Bay Area, Other NP15 LSEs-Bay Area, PG&E Service Area-Greater Bay Area, Silicon Valley Power, CDWR-N, CDWR-ZP26

[26] Includes these lines from IEPR demand forecast Form 1.5a: NCPA-Non Bay Area, Other NP15 LSEs-Non Bay Area, PG&E Service Area-Non Bay Area, WAPA, PG&E Service Area-ZP26

Figure 2: Balancing Authorities in WECC



Source: WECC website, downloaded January 30, 2018
https://www.wecc.biz/Administrative/Balancing_Authorities_JAN17.pdf

2.5 Weather Normalization Process: Development of Hourly Synthetic Load Profiles

The objective of weather normalization is to create synthetic load profiles that accurately represent the relationship of hourly customer electricity demand to historical weather patterns, over as wide a range of historic weather patterns as possible. Of particular importance is the accurate preservation of both spatial and temporal correlations occurring between historical load and weather patterns. There is also the need to establish the relationship of recent weather patterns to recent electricity demand. In other words, relationships between weather and electricity demand are changing as customers use more efficient lighting and cooling equipment, and as the weather changes due to climate change, so the relationship between load and weather should be established for a set of recent, representative years.

Staff's weather normalization is informed by 35 years of historical hourly weather data across the years 1980 through 2014, and is used to develop 35 years of hourly synthetic load shapes for 24 geographical regions across the western United States. Hourly historical load profiles across the same geographical regions for the last 5 years of the time series (2010 through 2014) are used to train the model. The model is described in more detail below.

The relationship between weather and electricity demand should focus on the relationship of weather on a granular locational level to customer electricity consumption, where consumption refers to actual demand, independent of any self generation. See Table 2 for definitions of the various load types referred to in this document.

Whereas meter data is available that captures actual energy delivered, or sales, to the customer by the utility, consumption data is typically not measured directly. However, attempting to model the relationship between weather and sales, defined as consumption less any self generation, does not capture a meaningful physical relationship. This is because sales depends, for example, on the number of solar panels installed on a customer's roof, which has no relationship to the weather effects experienced by the electricity customer.

In the absence of customer self generation, consumption and sales are identical, but with increasing levels of customer self generation, consumption becomes counterfactual. Therefore customer electricity consumption must be reconstituted from the utility sales values by simulating behind the meter generation values, based on installed photovoltaic capacity and hourly insolation profiles.

Table 2: Load type definitions - consumption, sales, system and net load

Note that SERVM models behavior at the system level, and does not explicitly model both retail sales and system load. Said another way, the analysis grosses up retail sales to system level load, accounting for losses.

Load Type	Relation to Other Terms	Rationale	Measurement
Consumption	Sum of electrical energy used to operate end-use devices excluding charge/discharge of storage	Consumption is the term used in CEC forms to capture onsite energy usage.	With increased self generation, and when relying on net energy metering to apply cost responsibility to end-users, consumption becomes counterfactual.
Sales	Consumption less BTM onsite generation including storage charge/discharge	Sales is the energy term to indicate the net energy delivered through the meter to the end-use customer	Metered by the utility on a short interval basis if the utility has deployed interval metering systems for end-users; otherwise could be estimated using load research practices
System	Sales load plus T&D losses plus theft and unaccounted for	Standard electricity industry term. CEC defines "hourly system load" in its data collection regulations	Generally measured by power plant output and import flows, e.g. a top down measurement inferring loads rather than a bottom up summation of individual customer loads
Net Load	System load less system intermittent renewable generation	This is the same definition as being used by CAISO	BAA estimation of system load less measured output of wind and solar supply-side renewables

2.5.1 Data Collection and Scrubbing

Data used in this process includes hourly historical weather data (35 years), and hourly historical load data (5 years of sales data) along with any hourly self generation or demand response needed to calculate consumption from sales values. This section describes the data collection and data scrubbing process required to perform the regression analysis used in the weather normalization process.

2.5.1.1 Weather Data

Hourly historical weather data is obtained from the National Climate Data Center (NCDC) for years 1979 through 2014.[27,28] Hourly temperature and dew point data are downloaded for nearly 60 weather stations across the western United States corresponding to the western electrical grid footprint, including contiguous parts of Canada and Mexico. For California, where the finest available spatial resolution is desired, staff used over 20 weather stations to inform the model. In several cases, weather station data needs to be stitched together from geographically adjacent weather stations when a given station lacks a contiguous history across the full range of years. Note that all hourly weather station data from the NCDC ISD-Lite dataset are provided in a manner that is corrected for daylight savings, that is, all hours correspond to standard time in the local time zone.

SERVM uses 24 geographic zones, 8 of which are located in California. Weighted temperature and dew point values are determined for each of the 24 SERVM zones using the 60 NCDC weather stations. A set of normalized weighting factors mapping the NCDC weather station data to SERVM zones is developed for each zone by season. The weighting factors are determined by season from the best fit of a logarithm of consumption load versus linear temperature model.

The raw hourly weather data profiles as obtained from the NCDC contain missing data segments. Staff analyzed the distribution of missing data and found the mode length for missing temperature data is about 10 days, coincidentally roughly the length of time of a typical employee vacation. It may be that weather station data is captured by a single employee, so that when they are on vacation, missing data segments occur. Likewise, dew point data also has missing data segments. Staff filled in missing observations in both temperature and dew point data using linear interpolation to ensure complete hourly coverage across the full 35 year time span.

Additionally, hourly solar insolation, wind speed, and cloud cover data was obtained from the NCDC dataset and developed for use in calculating self generation and system renewable energy production for use by the SERVM model.

2.5.1.2 Load Data

Developing hourly consumption data requires collecting metered sales data and reconstituting consumption by adding back the hourly effects of BTM generation or demand response that was not metered separately. While some hourly BTM self generation and demand response data[29] can be obtained for some geographic regions within California and used to develop hourly consumption profiles

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[27] National Climate Data Center (NCDC): https://www1.ncdc.noaa.gov/pub/data/noaa/isd-lite/

[28] While the weather normalization spans 1980 through 2014, 1979 is used to remove boundary issues that arise when calculating lagged temperature and dew point values at the beginning of the time series, as discussed below.

[29] The hourly impacts of demand response are difficult to recreate; for areas internal to CAISO, Energy Division staff issued a data request for the actual hourly impacts from the three IOUs that manage the demand response programs from the 2010 to 2016 program years. We collected data for the years 2011 through 2016 to ensure that the trends were reasonable past 2014, but only hourly data for 2011 through 2014 was used for reconstituting consumption.

from sales,[30] it is difficult to obtain this information for all types of BTM effects and for all regions inside or outside of California. For regions outside California where BTM self generation and demand response profiles are not available, staff simply used hourly sales profiles in lieu of hourly consumption profiles. While this introduces some error into the weather normalization process, staff believes the impacts are minimal because (a) where BTM self generation and demand response is not available outside of California over the time frame we are modeling, those quantities are expected to be minimal, and (b) the focus is on the behavior of the electric grid within California, so small discrepancies between consumption and sales outside California should have minimal impact on results. As BTM self generation and demand response profiles outside California become available, staff will incorporate them into the analysis.

Hourly sales data for years 2010 through 2014 is obtained from multiple sources. For California regions within the CAISO footprint, staff used hourly CAISO Energy Management System (EMS) sales data.[31] For the remainder of the WECC footprint, staff obtained hourly sales data from FERC Form 714.[32] Hourly sales data for Pacificorp East and West regions needs to be obtained independently, since it is provided as a single region in Form 714, whereas staff has elected to model them as two separate zones.[33] Sales data for Canadian regions are also obtained independently.[34] Loads for all these regions are mapped into the zones used in SERVM.

All load data used in the weather normalization analysis is corrected for daylight savings time shifts, resulting in a consistent dataset in standard time in the local time zone. This is an important step that is required in order to accurately align hourly load profiles with hourly weather profiles. In many cases, FERC Form 714 data is not corrected for daylight savings. However, FERC Form 714 is provided in a 25-hour format that enables the user to unambiguously correct for daylight savings.[35] In contrast, CAISO EMS data does not appear to consistently and clearly indicate if and when daylight savings is in effect. Therefore, CPUC staff performed a separate daylight savings correction to the CAISO EMS data in order to consistently align it with the CPUC weather normalization process.

2.5.1.3 Behind-the-Meter Photovoltaic (BTM PV) Data

Since BTM PV generation is not individually metered or consistently accessible to CPUC staff, hourly historical BTM PV generation is simulated. This requires a tabulation of cumulative BTM PV installed

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[30] Actual hourly demand response impacts (taken from utility reports of historical demand response events) are added back into historical load figures to represent historical loads as if the demand response events had not occurred. Thus, when demand response events are modeled for the study year in SERVM, there is no double counting of demand response impacts (triggering modeled events on top of or in addition to historical events).
[31] CAISO EMS data is proprietary, and is obtained via subpoena
[32] Federal Energy Regulatory Commission (FERC) Form 714: https://www.ferc.gov/docs-filing/forms/form-714/overview.asp
[33] Pacificorp data was obtained via subpoena
[34] British Columbia (BC) hydro data: http://www.bchydro.com/energy-in-bc/our_system/transmission/transmission-system/balancing-authority-load-data/historical-transmission-data.html
[35] FERC Form 714 instructions for participating Load Serving Entities instruct that a zero load should be placed in the March skip ahead day to indicate when daylight savings goes into effect, and a 25th hour load should be provided in the November fall back day when reverting back to standard time. This unambiguously allows for adjustment to standard time in the local time zone.

capacity by month and SERVM region, and the hourly production profile of PV generators by SERVM region, from January 1, 2010 to December 31, 2014. The source of BTM PV installed MW per month for areas within the CAISO area is CaliforniaDGStats.ca.gov.[36] The source of BTM PV MW for Balancing Authorities (BAA) and utilities outside of CAISO is Energy Information Administration (EIA) form 861 Net Metering data.[37] Staff obtained EIA data for 2011-2016 and filtered the "Utility Level-States" tab to retain the BAAs within the WECC. Staff extracted data for the years 2011 through 2016 just to ensure that the trends were reasonable past 2014, but only hourly data for 2011 through 2014 was used for the weather normalization work. 2010 data was not available from EIA information, so staff had to assume that the effect could be ignored. As mentioned above, California information was available from a different source, which had data for the full 2010 to 2014 timeframe so modeling of California areas should be more accurate.

To detect anomalies in the data, staff created filled line charts showing total installed BTM PV MW by BAA and utility, by year and month for the 6 year period. The EIA Form 861 data consists of total installed BTM PV MW, so the curves are expected to increase and include some flat sections when BTM PV installations slow. The charts created with EIA Form 861 data revealed some dips and steep increases, indicating incomplete data. For months in which the dips or steep increases were more than 4 MW, staff calculated reasonability adjustments. Staff made adjustments to less than 1% of the data lines, for nine utilities in five states outside of California. Using the installed MW values by month and SERVM region with the hourly production profiles for solar generation, staff simulated hourly BTM PV effects which were added back to hourly sales data to reconstitute consumption.

2.5.2 Weather Normalization Model

Staff's weather normalization approach is based on the Monash Electricity Forecasting Model,[38] and is consistent with the approach taken by the California Energy Commission's weather normalization process.[39] In this approach, each hour of the day is modeled separately, and reconstituted at the end of the process. This allows development of different regression relationships between hourly load and the driver variables (e.g. temperature and dew point) for different hours of the day. For example, during peak load hours, the relationship between the weather driver variables and consumption is more tightly constrained than during off peak hours, and one would expect a better fit to the regression relationship for these model hours. Furthermore, the model also separates out the impacts of the average annual load, a scalar quantity defined by year, from the corresponding normalized hourly load profile shape. This feature of staff's approach essentially separates the scalar magnitude from a normalized load shape.

In production cost modeling (PCM), staff relied on the CEC IEPR forecasts as the basis for the magnitude of the average annual and peak load characterizing load profiles in the target year. Both average annual

[36] These data are available for download at https://www.californiadgstats.ca.gov/

[37] These data are available for download at https://www.eia.gov/electricity/data/eia861/

[38] Monash Electricity Forecasting Model, see: https://robjhyndman.com/papers/MEFMR1.pdf

[39] CEC Demand Analysis Working Group, Friday, March 17, 2017, Forecasting Hourly Loads, see: http://www.dawg.info/sites/default/files/meetings/2.2017%2003-17%20DAWG%20Long%20Term%20Hourly%20Elec%20Model%20Vaid.pdf

and peak load are scalar quantities defined for each target year in the CEC's 10 year IEPR forecast. Staff linearly scaled the normalized load profiles generated by the regression analysis in a manner that preserves the average annual and peak load for each target year modeled in the PCM (see Section 2.6.3 for more information on the load stretching algorithm). This approach separates impacts of the magnitude of the (CEC IEPR-based) average annual and peak load from the corresponding normalized load profile development process. In other words, the weather normalization process is only concerned with developing a regression relationship between weather and normalized hourly load profiles, for each geographic region in question.

In this weather normalization approach, p denotes the model hour, where p ranges from 1 to 24. If t denotes the hour in our time series data corresponding to the most recent 5 years over which the regression relationship is derived, then t ranges from 1 to approximately $t_{max} \sim 24 \times 365.25 \ \times 5$, where the approximation depends on where the leap year falls. p can be written as $p = [(t - 1) mod 24] + 1$.

As mentioned above, the model used to create a relationship between hourly load and the driver variables separates average annual load from a normalized peak load profile, and for each region can be written as:[40]

$$\mathbf{log}(\boldsymbol{y_{t,p}}) = \ \mathbf{log}(\boldsymbol{y^*_{t,p}}) + \mathbf{log}(\boldsymbol{\bar{y}_i}) \qquad (1)$$

Where:

- $y_{t,p}$ is the hourly load for model p and hour t
- $y^*_{t,p}$ is the normalized load profile
- $\bar{y}_i$ is the average annual load corresponding to year *i*

Then the Monash approach can be used to model the normalized peak load profile as:

$$\mathbf{log}(\boldsymbol{y^*_{t,p}}) = \boldsymbol{f_p}(\boldsymbol{WT_t}) + \boldsymbol{g_p}(\boldsymbol{DP_t}) \ + \boldsymbol{h_p}(\boldsymbol{t}) + \mathbf{ResRate}_{\boldsymbol{t,p}} + \boldsymbol{\epsilon_t} \qquad (2)$$

Where:

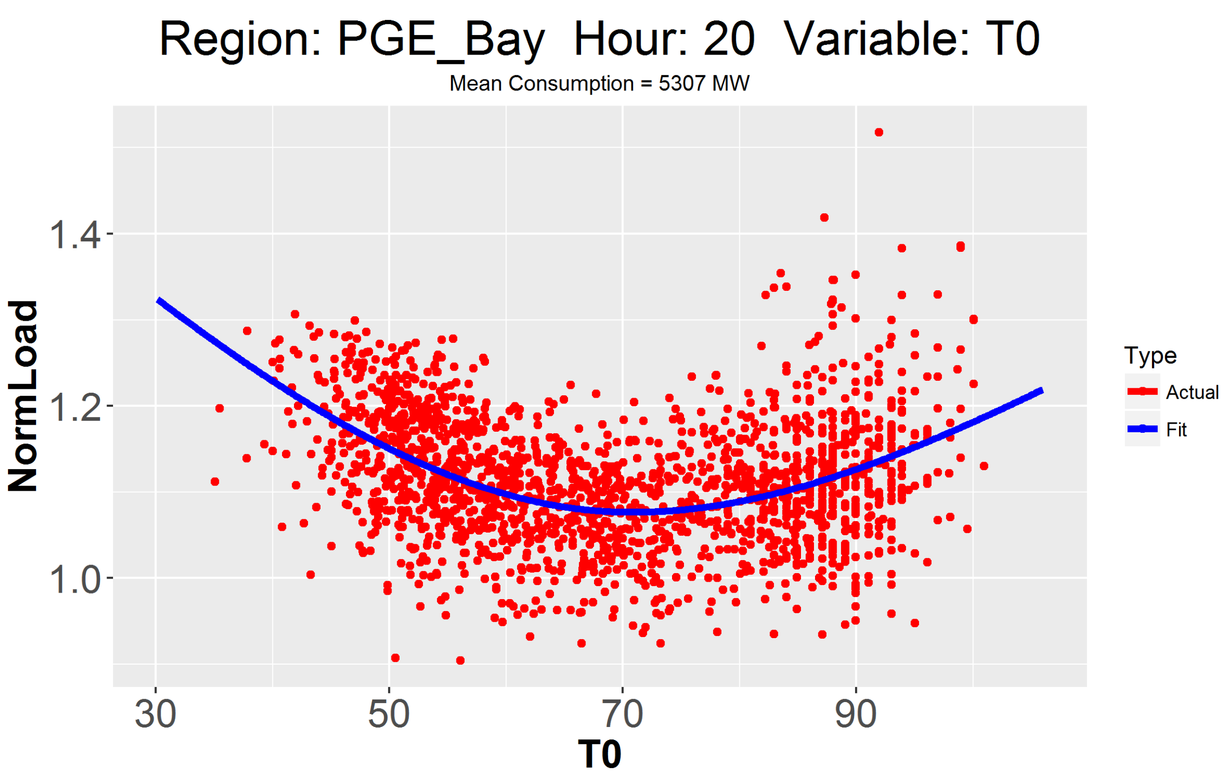
- $f_p(WT_t)$ models the effects of the weighted temperature WT
- $g_p(DP_t)$ models the effects of the weighted dew points DP
- $h_p(t)$ models all calendar effects, including dummy variables for month, day of week, and holidays
- $h_p(t)$ models all calendar effects, including dummy variables for month, day of week, and holidays
- $\mathrm{ResRate}_{t,p}$ models the effects of the residential retail rate, which serves to balance energy consumption across the model regions, in which a relatively higher retail rate should lead to lower consumption

[40] Recall log(ab) = log(a) + log(b)

- ϵ_t is an error term which is serially correlated, reflecting the fact that there are other environmental conditions not captured by this model.

Apart from the logarithm of the normalized load term, the regression model is essentially linear. However both the temperature and the dew point terms are able to capture the nonlinearity embedded within these physical parameters. The nonlinearity in the load-temperature relationship can most easily be understood by realizing that the load versus temperature relationship tends to have a 'U' shape, with the minimum of the 'U' at about 70° F, the temperature at which most people do not require heating or cooling. Below this temperature, load increases due to heating loads, and above this temperature, loads increase due to cooling loads. Figure 3 illustrates this relationship corresponding to Hour 20 (8pm) for the Pacific Gas and Electric service region in the bay area. The relationship in this figure is for temperature (T0, where the 0 represent 0 lag, see below). Similar nonlinear relationships exist for dew point, as well as for all lagged variables, discussed below. The nonlinear relationship is most easily observed during peak hours, which is when the relationship between load and temperature, or dew point and temperature, is most well defined.

Figure 3: Example of the nonlinear relationship between normalized load and temperature for a particular region used in the CPUC PCM model. Historical normalized load (red points) versus temperature for PGE_Bay (corresponding to Pacific Gas and Electric, bay area) for the 5 year model training period. Only data for the model with hour ending 20 are shown. Temperatures are in Fahrenheit.



Temperature effects are modeled in such a way as to incorporate previous day effects, and additional lagged terms, which correspond to the same hour of the model (i.e. same value of p), as well as cross model terms (i.e. different values of p). An identical approach is taken to modeling dew point effects, so the equation below for temperature effects can be used for dew point effects also. The temperature effects term can be represented as:

$$\boldsymbol{f_p(WT_t) = \sum_{k=0}^{6} F_{k,p}\,(WT_{t-k}) + \sum_{j=1}^{6} G_{j,p}\left(WT_{t-24j}\right) + H_p^{avg}(x_t^{avg}) + H_p^{min}(x_t^{min}) + H_p^{max}(x_t^{max})}$$

(3)

Where the functions below represents the nonlinear relationship between load and temperature:

- $F_{k,p}(WT_{t-k})$ for the primary term (k = 0, corresponding to no lag) as well as cross model terms (k = 1 to 6) corresponding to different hourly models
- $G_{j,p}\left(WT_{t-24j}\right)$ for the within model lagged terms (j = 1 to 6) corresponding to the same hourly model, but lagged from one to six days prior
- $H_p^{type}(x_t^{type})$ representing additional cross model terms for, respectively, the average values across the past 7 days, the minimum value across the past 24 hours, and the maximum value across the past 24 hours

Nonlinear relationships for temperature and dew point are fit using cubic splines. Staff has empirically found that nonlinear cubic splines with 2 degrees of freedom, corresponding to a single knot, best fit historical data for temperature and dew point, and for all lag, average, minima and maxima terms. This is consistent with staff's understanding of the 'U' shape relationship, since a single knot positioned at or near the minima of the 'U' will allow for a reasonable fit to the nonlinear relationship. All cubic spline terms, including the location of the knot, are determined from least squares fits.

This quasi log-linear relationship is then used to determine linear coefficients for each term in the model, including dummy variables. As discussed previously, the most recent 5 years, for which both load and weather data is available, is used to train the model. The results of the training is the complete determination of this quasi nonlinear relationship between load and weather variables, which is then used to create a set of 35 yearly load profiles from the 35 years of weather data available. The final result of this analysis is 35 synthetic yearly normalized load (consumption) profiles for each geographic region in the SERVM model.

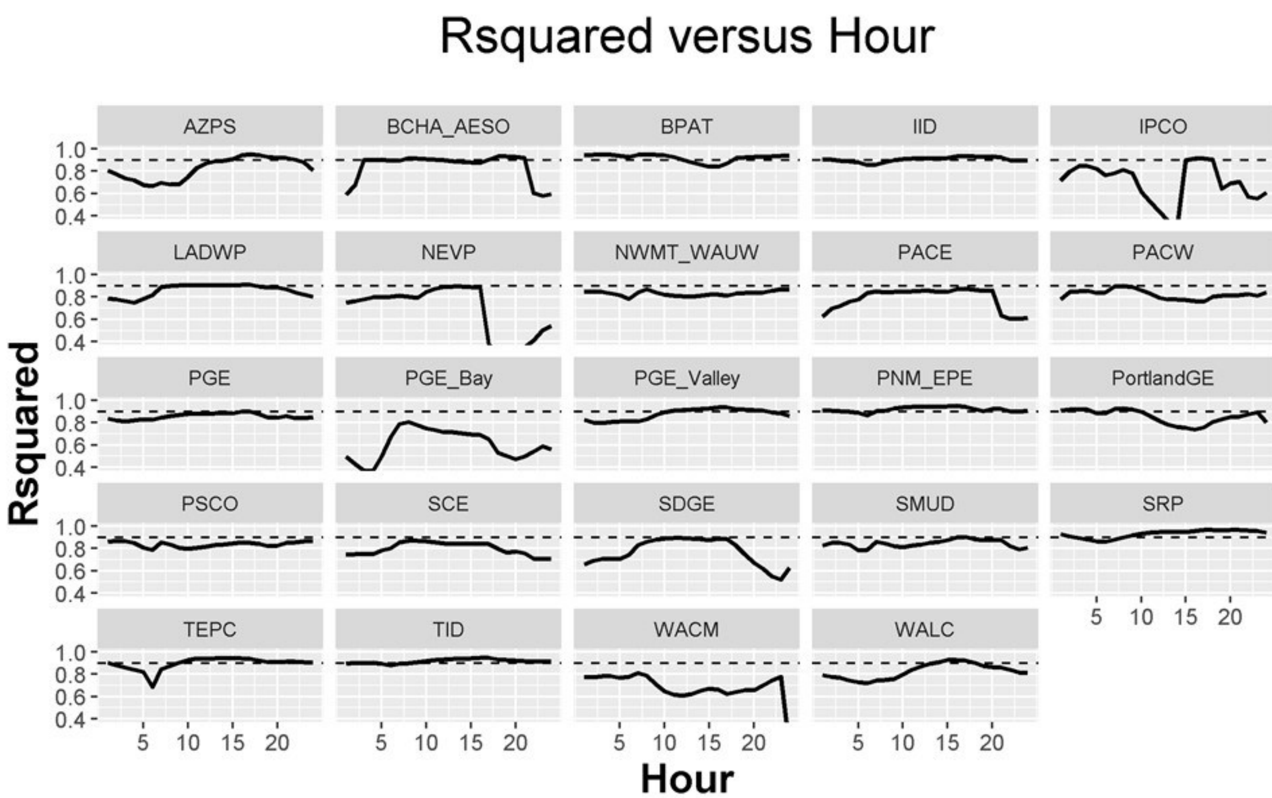
Goodness of fit is determined by examining how well the synthetic load profiles fit the historical load profiles during the 5 year period comprising the training data. Staff calculated R squared[41] for each hour of the model, for each geographic zone, as shown in Figure 4. Most values for R squared lie around 0.9, a reasonable value.[42] For some regions, like Pacific Gas and Electric, bay area, for which there is relatively small load, the regression is not well defined, and values of R squared are significantly less than one. Generally, values for R squared tend to be closer to one for daylight hours, when loads are significantly

[41] R squared: See https://en.wikipedia.org/wiki/Coefficient_of_determination

[42] Recall a value of R squared equal to one corresponds to a perfect fit.

greater than during night time. Staff also considered whether potential bias exists in this approach by examining the distribution of residuals by geographic region, as well as by month and time of day (day or night). No significant systematic bias was found.

Figure 4: R squared versus hour from weather normalization regression analysis for all geographical zones used in the CPUC production cost model. A dashed line at 0.9 is drawn for clarity.



2.6 Forecasts of Total Electricity Peak and Total Energy throughout Study Years

2.6.1 Use of IEPR Forecasts and Hourly Shapes

As stated in the 2017 IEPR final report adopted by the CEC in February 2018,[43] the managed Single Forecast Set specifies that the California Energy Demand (CED) 2017 adopted baseline "mid demand" case with 1 in 2 weather conditions shall be used for system-wide studies along with the mid-mid Additional Achievable Energy Efficiency (AAEE) and Additional Achievable Photo-Voltaics (AAPV) forecast scenarios. CPUC staff has used this managed Single Forecast Set along with corresponding supplemental data provided by the CEC that supplies the necessary temporal and geographic granularity required for the modeling of load and demand-side resources in SERVM.

[43] https://efiling.energy.ca.gov/getdocument.aspx?tn=223205

The 2017 IEPR CED forecast for the first time also includes hourly forecasts for both load and demand-side resources.[44] This is a major improvement in the fidelity of the IEPR forecast. CPUC staff has used the IEPR CED forecast's hourly shapes for the demand-side resources that SERVM represents as non-dispatchable and non-weather-dependent resources.

For modeling activities in 2019, including Reference System Plan development for the 2019-20 IRP cycle, staff expects to use the 2018 IEPR Update CED forecast, recently adopted by the CEC in January 2019. As discussed later in Section 3 of this document, staff also expects the CAISO's 2019-20 TPP to use the 2018 IEPR Update CED forecast.

In summary, the IEPR CED forecast is used to:

- Linearly scale up the 35 weather years of system level synthetic hourly load shapes described in the previous section to match the annual peak demand and energy of the IEPR forecast baseline with baseline (committed) BTM PV reductions backed out. (The IEPR baseline is already without AAEE and AAPV.)
- Create non-dispatchable resources in SERVM to represent each of the following: sum of baseline (committed) BTM PV and AAPV, AAEE, electric vehicles (EV) load, and Time-Of-Use (TOU) rate impacts.

The following table itemizes key forms and workbooks that CPUC analytical work relies on.

[44] For each forecast year, hourly data were developed for load and demand-side resources for the three large IOU TAC areas, i.e. the CAISO control area. Hourly data were not developed for areas outside the CAISO control area.

Table 3: IEPR Forms and Workbooks and Uses

IEPR Form or Workbook	Geography	Data component	How used
Form 1.1c: Electricity Deliveries to End Users by Agency (Retail Sales)	LSE	Sales load by LSE	IRP load and emissions accounting
Form 1.5a: Total Energy to Serve Load by Agency and BA (Sales plus Line Losses)	Agency/BA	System load without AAEE & AAPV (committed BTM PV must be removed)	Scale energy of synthetic shapes
Form 1.5b: 1 in 2 Net Electricity Peak Demand by Agency and BA	Agency/BA	System peak without AAEE & AAPV (committed BTM PV must be removed)	Scale peak of synthetic shapes
Form 1.2: Total Energy to Serve Load (equals sales plus line losses)	Planning Areas	Individual load and load modifier components	Cross-checking totals
Form 1.4: Net Peak Demand (equals total end use load plus losses minus self-generation)	Planning Areas	Individual load, load modifier components, and peak shift factor	Remove committed BTM PV reductions and peak shift from system load
CAISO Hourly Loads and Modifiers	IOU TAC areas	Individual load and load modifier components hourly and annually	Build EV, TOU, and AAEE hourly shapes
All AAEE Savings by Utility and Sector End Use	Large IOUs & POUs	AAEE including SB350 savings by IOU and POU	Use AAEE totals by area to scale AAEE hourly shapes
All Committed PV and AAPV by Agency and BA	Agency/BA	Installed capacity, energy, and peak impacts	Remove committed BTM PV reductions from system load; Build total BTM PV hourly shapes
CAISO Load and Modifiers Mid Baseline-Mid AAEE-Mid AAPV	IOU TAC areas	Individual load and load modifier components and underlying assumptions (T&D factors, coincidence factors, EV and other electrification)	Remove EV additions from system load and cross-checking totals

2.6.2 Reconstituting forecasts of peak and total consumption

The system level synthetic hourly load shapes were developed based on historical consumption load, specifically, metered sales load but with load reductions from historical BTM PV self generation and demand response events removed, including accounting for T&D losses since all SERVM modeling is at the system level.[45] As such, staff must use the same type of annual peak demand and energy value from the IEPR CED forecast in order to correctly scale up the synthetic load shapes. Specifically, staff used the IEPR Form 1.5b "1 in 2 net peak demand (non-coincident) no AAEE AAPV" and Form 1.5a "net energy for load no AAEE AAPV"[46] but added back the respective peak and energy reduction from BTM PV self generation including avoided losses for both sets of data.[47] Staff "backed out" the BTM PV load reduction using raw self-generation forecast data (includes installed capacity, energy, and peak impact, by agency/BA and year) provided by CEC Demand Analysis staff. Staff also backed out future impacts from Electric Vehicles and TOU rates from the IEPR CED forecast since those effects are modeled as separate shapes from the load shapes in SERVM. In the case of peak demand data, staff also backed out the IEPR's peak shift adjustment for IOU planning areas since essentially the consumption peak was needed. The resulting IEPR peak and energy values after the adjustments described above were then used to scale up the synthetic load shapes to produce a final system level consumption shape for a future study year.

2.6.3 Linear Stretching of Consumption Shapes to Forecast Years

The mathematical process for scaling the 35 normalized synthetic hourly load shapes to match a target IEPR study year forecast peak and energy is explained in this subsection. Peak loads in each synthetic load shape varied based on the relevant historical weather patterns. The peak loads can range from around 7% higher than normal peak in hot years to around 10% below normal peak in mild years. A single scaling factor was calculated by dividing the target peak for the study year by the average of the peak loads from the raw 35 synthetic load shapes. The synthetic load shapes must also be scaled such that total energy matches the study year forecast total energy, by SERVM zone, using an algorithm that maintains the peak values.

The algorithm takes the normalized hourly load forecast shape for a given year, X_t, (developed in the weather normalization process described in section 2.5.2), and creates a linear transformation $aX_t + b = Y_t$ such that $\max_t Y_t = q$ and $\mathrm{mean_t}\, Y_t = p$. That is, one can transform all 35 shapes such that the average peak and total energy of the load shapes matches the annual average (mean) and peak load (max) corresponding to the target year forecast.

The justification for this linear transformation is as follows: If you take the peak for the original load forecast to be $\max_t X_t = s$ and the energy to be $\mathrm{mean_t}\, X_t = r$, then

$$a = \frac{q-p}{s-r} \text{ and } b = \frac{ps-qr}{s-r}$$

This comes from some basic substitution:

[45] Note that historical non-PV self generation was left embedded during the development of synthetic load shapes. Staff felt that this simplifying convention was fine since non-PV self generation generally has a flat profile and is not weather-dependent.

[46] http://energy.ca.gov/2017_energypolicy/documents/#02212018

[47] Note that we are backing out the "committed PV self generation" impacts only and leaving non-PV self generation impacts embedded in the baseline. The AAPV is already removed from the load forecast by virtue of using the IEPR Form 1.5 version with "NO AAEE AAPV."

$$\max_t Y_t = q \Longrightarrow \max_t (aX_t + b) = q \Rightarrow a = \frac{q-b}{\max_t X_t} = \frac{q-b}{s}$$

And

$$\mathrm{mean_t}\, Y_t = p \Rightarrow \mathrm{mean_t}(aX_t + b) = p \Longrightarrow b = p - a(\mathrm{mean_t} X_t) \Longrightarrow b = p - ar$$

Substituting for a in the second equation gives the result for b:

$$b = p - \left(\frac{q-b}{s}\right) r \Rightarrow b - \frac{br}{s} = b\left(1 - \frac{r}{s}\right) = b\left(\frac{s-r}{s}\right) = \frac{ps - qr}{s} \Rightarrow b = \frac{ps-qr}{s}\left(\frac{s}{s-r}\right) = \boldsymbol{\frac{ps-qr}{s-r}}$$

Substituting for b in the first equation gives the result for a:

$$a = \frac{q - \frac{ps-qr}{s-r}}{s} = \frac{\frac{qs-qr-ps+qr}{s-r}}{s} = \frac{qs-ps}{s(s-r)} = \frac{q-p}{s-r}$$

This approach is the basis for a linear transformation that takes the original load shape, characterized by a mean and peak energy, to a transformed load shape, characterized by the mean and peak energy of the target year.[48] Adjusted scaled load shapes are posted to the CPUC website.[49] Each of the 35 normalized synthetic hourly load shapes uses the 1990 calendar, meaning the first day of the year is a Monday, and all holidays and weekends correspond to 1990 dates. 1990 is not a leap year, so all synthetic load shapes are uniformly 365 days, or 8760 hours, in length.

The SERVM model can be configured to apply probabilities to each of the 35 weather years used as input. Currently, Energy Division's model is setup with the 35 weather years 1980-2014 and each year has equal weight, i.e. probability of 1/35. If data becomes available that indicate more recent years' weather patterns should be more heavily weighted, e.g. due to climate change projections, Energy Division could consider updating the weighting of SERVM's weather years.

2.6.4 Economic and Demographic Forecasting Uncertainty

Load uncertainty is driven not only by year-to-year volatility in weather patterns, but also by long-term uncertainty in economic and demographic growth forecasts. Unanticipated economic growth or downturns can result in peak loads that are substantially higher or lower than forecast.

SERVM accounts for this potential error by incorporating a "load forecast multiplier" into each model run. A range of load multipliers can be entered into the model, along with the probability of selecting each value. Collectively, they intend to represent the distribution of load forecasting error due to non-weather causes (economics, demographics, etc.). At the beginning of each case, a particular weather year and its corresponding load shapes are selected. A load forecast multiplier is selected independently, and all hourly load values are adjusted upwards or downwards by that same value. For

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[48] The load stretching algorithm comes from Ben Kujala of the Northwest Power and Conservation Council (http://www.nwcouncil.org/)

[49] http://www.cpuc.ca.gov/General.aspx?id=6442451973

example, if a load forecast multiplier of 0.95 is selected (simulating an unexpected economic downturn), then a region with a peak load of 1000 MW in the given weather year would be adjusted to have a peak load of 950 MW. A new weather year and a new load forecast multiplier would be selected for the next case. Number of weather years multiplied by number of load forecast multipliers equals the number of total cases that are run as part of a study.

The load forecast multipliers used in Energy Division modeling are based on analysis of near term forecasting that was available from the OECD Journal.[50] Staff evaluated projections of 1 year ahead and 2 year ahead GDP growth, noting the magnitudes of GDP uncertainty and their probabilities. These figures were entered as a basis for the load forecast uncertainty variables in SERVM. The values are summarized in the table below.

Table 4: Economic/Demographic Forecast Error Probabilities

Magnitude of forecast error (percentage)	Probability of error occurring (percentage)
2.5% error	6.68% probability
1.5% error	24.17% probability
0% error	38.29% probability
-1.5% error	24.17% probability
-2.5% error	6.68% probability

Source: OECD Journal: Journal of Business Cycle Measurement and Analysis, Volume 2010 Issue 2. "An Evaluation of the Growth and Unemployment Forecasts in the ECB Survey of Professional Forecasters"

2.6.5 Hourly Shapes for BTM PV, AAEE, EV, TOU Rate Impacts

The sum of baseline (committed) BTM PV and AAPV, AAEE, electric vehicles (EV) load, and Time-Of-Use (TOU) rate impacts were each modeled as non-dispatchable resources in SERVM. As explained above, their effects were removed from the load forecasts used to develop the hourly load shapes used by SERVM. The installed capacity and annual energy of total BTM PV, by year and agency/BA, was sourced from the 2017 IEPR CED forecast, mid "committed PV self generation" plus mid "AAPV" scenarios. The explanation of how this data was used to create solar generation profiles is provided later in this document under the section describing how renewable resource units are modeled in SERVM (i.e. type R resources in SERVM nomenclature).

The 2017 IEPR CED forecast included annual hourly shapes for AAEE, EV load, and TOU rate impacts. The hourly data were sourced directly from the CEC Demand Analysis staff. The hourly data by large IOU TAC area and by forecast year, was matched to the corresponding SERVM zone and target study year.

[50] Link here: http://www.keepeek.com/Digital-Asset-Management/oecd/economics/an-evaluation-of-the-growth-and-unemployment-forecasts-in-the-ecb-survey-of-professional-forecasters_jbcma-2010-5km33sg210kk#page9

The AAEE and TOU shapes were directly used to build non-dispatchable resources in the SERVM model. For EV shapes, two options were available: IEPR-provided EV hourly shapes vs. month-hour normalized EV shapes in the RESOLVE model. Staff elected to directly use the IEPR-provided EV hourly shapes. Each of the SERVM annual shapes for AAEE, TOU, and EV load do not vary based on which of the 35 weather years is being used as the basis for the load shape in a given SERVM model study year. In other words, staff assumed AAEE, TOU, and EV charging patterns are generally weather independent.

2.7 Existing and New Resource Portfolios

As described earlier in this document, Energy Division staff sourced data on the existing fleet of generating units dispatched within the CAISO control area from the CAISO MasterFile. For existing non-CAISO generating units (includes most of the rest of the Western Interconnect), staff sourced data from the TEPPC 2026 Common Case v2.0.

To support the RA and IRP proceedings, SERVM was used to study the years 2020, 2022, 2026, and 2030. Studying these years required a projection of the mix of generating units that will come online or retire by the target study year. The projected generation mix coming online or retiring can be broadly categorized as follows:

- Contracted Additions: Projects not yet online that have an ownership or contractual relationship with a LSE and have or are undergoing regulatory approval or LSE-board approval, as applicable (e.g. projects in the CPUC's RPS database and projects undergoing approval in a CPUC Application)
- Planned Retirements: Units that have announced retirement (e.g. Diablo Canyon Power Plant and units subject to Once Through Cooling (OTC) phase-out policy[51])
- New Additions: New (generic) resources selected or assumed by an exogenous analysis, usually a capacity expansion model (e.g. the RPS Calculator or the RESOLVE model)
- New Retirements: Retirements of existing units assumed by an exogenous analysis, usually a capacity expansion model (e.g. the RPS Calculator or the RESOLVE model)

SERVM unit-level inputs for contracted additions and planned retirements were drawn directly from the sources described above. Assumptions for new additions and new retirements were drawn from the RESOLVE capacity expansion model used in the IRP proceeding to develop the Reference System Plan that was adopted in February 2018. SERVM results using these assumptions were published in September 2018. During the latter half of 2018, the assumptions for new additions and new retirements were updated to reflect the aggregation of individual LSE Plans that were filed in the IRP proceeding in August 2018. SERVM results using these assumptions were published in January 2019.

2.7.1 Baseline Units and IRP Reference System Plan Units Tables

The aggregated by class baseline (baseline represents existing and contracted, as defined above) and new resources for the CAISO balancing area as represented by the RESOLVE model are shown in the tables below. The complete workbooks translating aggregate capacities in the RESOLVE model to

[51] http://www.energy.ca.gov/renewables/tracking_progress/documents/once_through_cooling.pdf

available unit level data are posted to the Data section of CPUC Energy Division's Energy Resource Modeling landing page.[52] This identifies units and locations for baseline (i.e. existing and contracted) resources assumed in the 50% RPS Default Core Case and the 42 MMT Core Case that are part of the IRP Reference System Plan adopted in February 2018.

One important amendment to the contracted units assumed by the RESOLVE model is that the Puente Power Project[53] should no longer be included. SERVM modeling in 2018 did not include this power plant and Table 5 reflects that amendment (to the CAISO_Peaker1 line item).

Table 5: Baseline Non-Renewables in RESOLVE (MW)

Resource Class	2018	2022	2026	2030
CAISO_CHP	1,685	1,685	1,685	1,685
CAISO_Nuclear	2,922	2,922	622	622
CAISO_CCGT1	12,419	13,703	13,703	13,703
CAISO_CCGT2	2,974	2,974	2,974	2,974
CAISO_Peaker1	5,195	5,293	5,293	5,293
CAISO_Peaker2	2,859	2,729	2,729	2,729
CAISO_Reciprocating_Engine	263	263	263	263
CAISO_ST	6,416	652	652	652
CAISO_Hydro	7,064	7,064	7,064	7,064
CAISO_PS	1,833	1,833	1,833	1,833
CAISO_Storage_Mandate	690	1,113	1,325	1,325
CAISO_Shed_DR_Existing	1,752	1,752	1,752	1,752

[52] http://www.cpuc.ca.gov/energy_modeling/

[53] http://www.energy.ca.gov/sitingcases/puente/

Table 6: Baseline Renewables in RESOLVE (MW)

Zone[54]	Contract[55]	Technology	2018	2022	2026	2030
BANC	CAISO	Small_Hydro	6	6	6	6
CAISO	CAISO	Biomass	1,046	1,046	1,046	1,046
CAISO	CAISO	Geothermal	1,182	1,232	1,232	1,232
CAISO	CAISO	Small_Hydro	1,040	1,039	1,039	1,039
CAISO	CAISO	Solar	10,927	13,318	13,318	13,318
CAISO	CAISO	Wind	6,082	6,215	6,215	6,215
IID	CAISO	Geothermal	455	271	235	235
IID	CAISO	Solar	20	70	70	70
LDWP	CAISO	Wind	5	5	5	5
NW	CAISO	Biomass	32	32	32	32
NW	CAISO	Geothermal	15	15	15	15
NW	CAISO	Small_Hydro	29	29	29	29
NW	CAISO	Wind	1,646	1,646	1,646	1,646
SW	CAISO	Solar	127	127	127	127
SW	CAISO	Wind	622	622	622	622
Other	CAISO	Wind	849	849	849	849

[54] In RESOLVE, "zone" designates where a resource's energy is balanced and delivered to meet load. A resource's zone does not necessarily have to be the same as its physical location.

[55] In RESOLVE, "contract" designates which "zone" has contracted for the resource and thus "owns" its energy production and, if applicable, its renewable attribute (REC). If a resource's zone and contract match, it means the resource will deliver energy and RECs (if applicable) to that zone. However, a resource's contract does not necessarily have to match its zone. For instance, a solar resource in the SW (zone = SW) with a contract to CAISO (contract = CAISO) will deliver its energy to meet SW loads, but will provide RECs that count towards the CAISO RPS target. These resources are typically referred to as out-of-state RECs (bucket 3). The table above does not include units that are tagged as zone = CAISO and contract = other area.

Table 7: New Build in RESOLVE for 50% RPS Default Core Case

Renewable Resource Build by Location (MW)					
RESOLVE Resource	Tx Zone	2018	2022	2026	2030
Tehachapi_Solar	Tehachapi	-	1,013	1,013	1,013
Kramer_Inyokern_Solar	Kramer_Inyokern	-	978	978	978
Mountain_Pass_El_Dorado_Solar	Mountain_Pass_El_Dorado	-	62	62	62
Southern_Nevada_Solar	Mountain_Pass_El_Dorado	-	1,024	1,024	1,024
Central_Valley_North_Los_Banos_Wind	Central_Valley_North_Los_Banos	146	146	146	146
Tehachapi_Wind	Tehachapi	153	153	153	153
In-State		299	2,353	2,353	2,353
Out-Of-State		-	1,024	1,024	1,024
New Energy Storage	Unit	2018	2022	2026	2030
Li_Battery	MW	-	-	-	807
Li_Battery	MWh	-	-	-	807
Li_Battery Duration	hr	-	-	-	1

Table 8: New Build in RESOLVE for 42 MMT Core Case

Renewable Resource Build by Location (MW)					
RESOLVE Resource	Tx Zone	2018	2022	2026	2030
Tehachapi_Solar	Tehachapi	-	1,013	1,013	1,013
Kramer_Inyokern_Solar	Kramer_Inyokern	-	978	978	978
Riverside_East_Palm_Springs_Solar	Riverside_East_Palm_Springs	-	3,831	3,831	3,831
Southern_Nevada_Solar	Mountain_Pass_El_Dorado	-	3,006	3,006	3,006
Solano_Wind	Solano	643	643	643	643
Central_Valley_North_Los_Banos_Wind	Central_Valley_North_Los_Banos	146	146	146	146
Greater_Carrizo_Wind	Greater_Carrizo	160	160	160	160
Tehachapi_Wind	Tehachapi	153	153	153	153
Riverside_East_Palm_Springs_Wind	Riverside_East_Palm_Springs	42	42	42	42
Northern_California_Geothermal	Northern_California	-	-	-	202
In-State		1,145	6,967	6,967	7,169
Out-Of-State		-	3,006	3,006	3,006
New Energy Storage	Unit	2018	2022	2026	2030
Li_Battery	MW	-	-	162	1,992
Li_Battery	MWh	-	-	162	2,243
Li_Battery Duration	hr	-	-	1	1

The PCM calibration and vetting activities described in Attachment B to D.18-02-018 state that SERVM studies will be done based on a version of RESOLVE updated to use the 2017 IEPR demand forecast. This version of RESOLVE using the 2017 IEPR, along with results from rerunning the 42 MMT core case, is posted on the CPUC website.[56] The baseline resources in RESOLVE remain the same but the new resources selected by RESOLVE changed due to updated assumptions based on the 2017 IEPR. A summary of the new resources selected is presented in the table below. The workbook translating

[56] http://cpuc.ca.gov/General.aspx?id=6442457210

aggregate capacities in [RESOLVE using the 2017 IEPR to available unit level data] for the 42 MMT core case is also posted to the CPUC website.

Table 9: New Build in 2017 IEPR version of RESOLVE for 42 MMT Core Case

Renewable Resource Build by Location (MW)					
RESOLVE Resource	Tx Zone	2018	2022	2026	2030
Tehachapi_Solar	Tehachapi	-	1,013	1,013	1,013
Kramer_Inyokern_Solar	Kramer_Inyokern	-	978	978	978
Riverside_East_Palm_Springs_Solar	Riverside_East_Palm_Springs	-	854	854	918
Southern_Nevada_Solar	Mountain_Pass_El_Dorado	-	3,006	3,006	3,006
Solano_Wind	Solano	643	643	643	643
Central_Valley_North_Los_Banos_Wind	Central_Valley_North_Los_Banos	146	146	146	146
Greater_Carrizo_Wind	Greater_Carrizo	160	160	160	160
Tehachapi_Wind	Tehachapi	153	153	153	153
Riverside_East_Palm_Springs_Wind	Riverside_East_Palm_Springs	42	42	42	42
NW_Ext_Tx_Wind	Northern_California	-	-	-	601
SW_Ext_Tx_Wind	Riverside_East_Palm_Springs	-	-	-	500
Greater_Imperial_Geothermal	Greater_Imperial	-	-	-	1,276
Northern_California_Geothermal	Northern_California	-	-	-	424
In-State		1,145	3,990	3,990	5,754
Out-Of-State		-	3,006	3,006	4,107
New Energy Storage	Unit	2018	2022	2026	2030
Li_Battery	MW	-	-	187	2,104
Li_Battery	MWh	-	-	187	2,734
Li_Battery Duration	hr	-	-	1.0	1.3

SERVM modeling was also conducted to reflect the aggregation of individual LSE Plans that were filed in the IRP proceeding in August 2018. This means a different mix of new resources than Table 9 was modeled in SERVM. This portfolio was termed the "Hybrid Conforming Portfolio," defined in the November 15, 2018 IRP ruling. For details see SERVM Model Input Data for Hybrid Conforming Aggregated LSE Portfolio 2030 Studies and Attachment A: IRP Proposed Preferred System Portfolio of the January 11, 2019 IRP ruling.

2.7.2 Aligning the modeled generation fleets in RESOLVE and SERVM

Both SERVM and RESOLVE model the commitment and dispatch of resources to balance load and generation across most of the Western Interconnect. As such, certain outputs from the two models can be compared, e.g. emissions, operating cost, and capacity factors by unit class. To make the comparison valid, it is important to align the inputs of both models as much as possible. However, SERVM models at the unit-level with finer representation of the transmission system (24 zones), while RESOLVE models with aggregated unit classes and coarse representation of the transmission system (6 zones). These differences plus a number of other differences in modeling conventions and design make it challenging to completely align the generation fleets modeled in RESOLVE and SERVM. For example, the SERVM database is regularly updated and was built up from multiple sources over time, including the CAISO Masterfile, the TEPPC Common Case, the RPS contracts database, and individual data requests to utilities. In contrast, RESOLVE primarily draws from the preliminary 2017 CAISO NQC List posted August 2016, supplemented with additional information from the CAISO Master Generating Capability List posted November 2016, the TEPPC 2026 Common Case, and the CARB Scoping Plan.

Energy Division staff attempted to reconcile and align the generation mix of existing units, contracted additions, and planned retirements from both models. For new additions and new retirements, the assumptions from RESOLVE were directly translated into the SERVM model, so the differences primarily lie within the assumed baseline of each model. A comparison of the total baseline and new resources in the RESOLVE model and the SERVM model was presented to the IRP Modeling Advisory Group process on July 13, 2018,[57] and updated in Attachment B of the September 24, 2018 Ruling Seeking Comment on Production Cost Modeling[58] in the IRP proceeding. The summary comparison table of generation nameplate capacity for the CAISO area that was in Attachment B is repeated in the table below. See Attachment B for further details describing this table.

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57 http://cpuc.ca.gov/uploadedFiles/CPUCWebsite/Content/UtilitiesIndustries/Energy/EnergyPrograms/ElectPowerProcurementGeneration/irp/2018/IRP_MAG_webinar_2018-07-13_SERVM_2017IEPR_RSP_posted.pdf

58 September 24, 2018 Ruling: http://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M229/K725/229725945.PDF
Attachment B:
http://www.cpuc.ca.gov/uploadedFiles/CPUCWebsite/Content/UtilitiesIndustries/Energy/EnergyPrograms/ElectPowerProcurementGeneration/DemandModeling/IRP_RSP_2017IEPR_SERVM_results_20180913.pdf

Table 10: Comparison of CAISO nameplate capacity in RESOLVE and SERVM model datasets

	TOTAL SERVM RESOURCES, MW			TOTAL RESOLVE RESOURCES, MW			SERVM minus RESOLVE, MW		
Resource Type	**2022**	**2026**	**2030**	**2022**	**2026**	**2030**	**2022**	**2026**	**2030**
Battery Storage	1,115	1,514	3,431	1,113	1,512	3,429	2	2	2
Biomass	676	676	676	1,107	1,107	1,107	-431	-431	-431
Geothermal	1,728	1,728	3,428	1,487	1,487	3,187	241	241	242
Nuclear	2,923	623	623	2,922	622	622	1	1	1
Utility-scale Solar PV	19,637	19,637	19,701	19,211	19,211	19,276	426	426	425
Thermal	26,539	26,539	26,539	27,561	27,561	27,561	-1,023	-1,023	-1,023
Wind	10,522	10,522	11,325	7,816	7,816	8,917	2,707	2,707	2,409
BTMPV	12,301	16,727	20,759	12,758	17,454	21,573	-457	-727	-814
DR	1,754	1,754	1,754	1,752	1,752	1,752	1	1	1
Hydro	7,402	7,402	7,402	9,163	9,163	9,163	-1,761	-1,761	-1,761

The comparison above is between the 2017 IEPR version of RESOLVE results from the 42 MMT core case, and the SERVM dataset. The capacity totals for SERVM include all units serving CAISO load including must-take but not dynamically-scheduled specified imports. The capacity totals for RESOLVE include all units modeled as within the CAISO footprint, whether contracted to a CAISO LSE or not. The "thermal" category includes CHP, CCGT, CT, reciprocating engine, and steam. Capacity from existing renewables are based on the contracted capacity reported in the RPS Contracts Database maintained by CPUC staff and the three major IOUs. The SERVM BTMPV value is based directly on the installed capacity in the 2017 IEPR (mid case with mid-mid AAPV). The RESOLVE BTMPV value is based on a calculated capacity from the 2017 IEPR BTMPV annual energy (mid case with mid-mid AAPV) and RESOLVE's assumed BTMPV capacity factor (which is slightly lower than the capacity factor assumed in the 2017 IEPR). Both model's BTMPV values are grossed up for T&D losses. The "hydro" category comparison excludes Hoover and includes pumped storage hydro. Hoover is modeled in both models but was left out of this input comparison in order to simplify the hydro comparison.

2.8 Resource Inputs and Use Limitations

2.8.1 Generic Resource Information

There are a number of inputs that are common to all supply side resources (including demand response, intermittent renewables, thermal facilities, and storage) in order to identify and characterize their capabilities for the model. For example, the model requires each resource to be identified with a unique ID number, a region in which the resource is located, and the first and last year of expected service. Additionally, there are numerous input fields that are specific to particular unit types. The following table summarizes the resource categories in the SERVM database.

Table 11: Resource types modeled in SERVM

Resource Type	Description of Category
(T)hermal	Combustion turbine
(F)ossil	Fossil steam generators
(N)uclear	Nuclear generators
(R)enewable	Renewable generators whose output is dependent on weather patterns – non-dispatchable and not economically triggered
(C)urtailable	Demand response with constraints such as hours per day or month
(P)umped Storage (used to model all storage facilities)	Storage resources that can either consume or generate electricity; available energy and round-trip efficiency are essential modeling inputs for this resource type
(H)ydropower	Hydropower facilities that are not pumped storage; they are modeled as one of three subtypes – emergency, scheduled, or run of river

For modeling activities in 2018, data sources used for generic facility inputs are summarized in Table 12, below. The table does not list specific variable names in SERVM, but instead gives a less specialized narrative name. These data fields are common to all types of resources. For some data fields, it is easy to process existing data into SERVM data formats, but data reconciliation is difficult. For example, some plants with more than one unit are modeled as a single combined unit in one source dataset, but as two separate units in another dataset. Combined cycle plant configurations are often challenging, and judgment calls are needed. Energy Division staff will evaluate all judgment calls with other parties to ensure the accuracy and reasonableness of decisions. It is also important to note that these values can vary by month and by year – meaning a generator can have a heat rate, ramp rate, maximum capacity, or any other variable that changes across different months and different years in the model.

Table 12: Generic data inputs common to most resource types (T, F, N, R, C, P, and H)

Variable	Applicable Gen Types	Sources/Comments
Resource name	All	CAISO MasterFile for resources located in CAISO; TEPPC 2026 Common Case dataset for resources outside of CAISO (including resources in LADWP or SMUD territories)
In service and retirement dates	All	CAISO MasterFile for resources located in CAISO; TEPPC 2026 Common Case dataset for resources outside of CAISO (including resources in LADWP or SMUD territories)
Region location	All	CAISO MasterFile for resources located in CAISO; TEPPC 2026 Common Case dataset for resources outside of CAISO (including resources in LADWP or SMUD territories)
Minimum and maximum MW production level (P_{min} and P_{max})	All	CAISO MasterFile for resources located in CAISO; TEPPC 2026 Common Case dataset for resources outside of CAISO (including resources in LADWP or SMUD territories). Values can be month-specific.
Fuel type (i.e., natural gas, biogas, nuclear, etc.)	T, F, N, R	CAISO MasterFile for resources located in CAISO; TEPPC 2026 Common Case dataset for resources outside of CAISO (including resources in LADWP or SMUD territories). Price curves for natural gas are discussed in the thermal resources section, below.

Each type of resource has some inputs that are unique to it. The following sections give more detail regarding specific resource types in SERVM and the data sources used to populate the database for modeling.

2.8.1.1 Disaggregating Aggregate Units Into Child Units

Staff generated unit inputs from CAISO MasterFile data and the TEPPC 2026 Common Case as specified above. Staff did some amount of disaggregation on the two data sources, however, when it was apparent that between databases a combination of units were listed as one aggregated unit. Staff believed that in the case of peakers and combustion turbines, the model would produce more accurate results when aggregated units were modeled individually. This presented the challenge of generating unit inputs for individual "child" units derived from one "parent" aggregate unit. Table 13 summarizes how individual unit inputs were generated.

Table 13: Generation of Inputs for Child Units from Aggregate Units

Input Field	Disaggregation Process
Inservice date	List same inservice date for each child unit as the aggregate unit – in effect all child units came online at same time and will retire at same time
capmax	Assume capmax of aggregate unit is total of all child units and divide capmax equally among child units unless there is a reason to do otherwise
capmin	Assume capmin is the capmin of one child unit and use that value for all child units, assuming each child unit has the same capmin
Minimum on time and minimum down time	Assume value is equal for all child units
Fuel type	Assume all child units consume same fuel as aggregate – use same value for all child units
Ramp rate	Assume ramp rate is total of all ramp rates of all child units, and divide equally among child units
Start up time	Assume start up time is the same for all child units, and use the value for the aggregate unit as the value for all child units
Start up costs	Assume value is equal for all child units

2.8.2 Thermal Resources – Types T, F, and N

The following discussion covers several types of information that are specific to thermal resources and are not common across other types of generators. They include heat rate, ramp rate, and forced and planned outage information. Because Energy Division staff conducted its reliability modeling utilizing a blend of both aggregate heat rate and ramp rate data from the TEPPC Common Case (consistent with similar production cost modeling work done by the CAISO and SCE) and unit-specific heat rate and ramp rate values based on the CAISO MasterFile, there are some inputs that can be posted publicly and some that cannot.

2.8.2.1 Heat Rates

SERVM can model the heat rate of a given generator over its operating range in one of two ways. It can either:

- Calculate an average heat rate curve based on a quadratic equation. To create this curve, staff takes data on the unit's operation at different levels of MW output (known as "segments"), and fits a quadratic curve to these segments. This quadratic curve is defined by three coefficients, which are then input into SERVM.
- Use a constant average heat rate (i.e. a single value across the generator's entire operating range).

There are tradeoffs between these two approaches. Although the first method is more precise, the segment data required to implement it is not always available. In addition, segment data is confidential and cannot be available to the public. The second is simple and transparent, and avoids the confidentiality concerns associated with using plant-specific heat rate segment information. However, this approach does not fully reflect the nuances of economic dispatch. Thus, it would be impossible to accurately project the actual dispatch of the facility in a real economic dispatch scenario (where the heat rate of an individual unit is essential for determining its position in the supply stack). As a result, the generator might be dispatched unrealistically throughout its operating range.

Because of the crucial importance of accuracy in calculating heat rates, staff decided to use the first method as much as possible. Staff used CAISO segment data (for units in the CAISO) and TEPPC 2026 segment data (for units outside the CAISO) to calculate quadratic average heat rate curves, where this data was available. Where this data was not available, staff assumed constant average heat rates.

The table below summarizes average heat rates by dispatchable thermal resource type in the CAISO area. The averages include units within the CAISO and certain units located outside CAISO that have the ability to be dynamically scheduled in the CAISO market. Data for years 2022 and 2030 are shown because the thermal fleet that is online differs slightly between the two years. These average heat rates are calculated from SERVM model results completed in July, 2018, as total fuel burn divided by total MWh generated by unit type for the selected study year.

Table 14: Average output heatrate by resource type in CAISO area

Unit Type	Average heat rate MMBtu/MWh (2022)	Average heat rate MMBtu/MWh (2030)
CCGT	7.54	7.57
CT	10.98	10.71
CHP (dispatchable)	9.13	9.21

In the SERVM model, CHP heat rates were derived from the CAISO Masterfile which does not separate fuel for useful heat vs. electricity production. This results in higher heat rates as some of the fuel goes towards useful heat. Other models such as RESOLVE used a lower heat rate based on only the portion of fuel used for electricity production. Energy Division staff will work with the CEC and CHP stakeholders to improve the heat rate assumption in SERVM for future modeling activities.

2.8.2.2 Ramp Rates

SERVM allows for the entry of a set of ramp rate segments for each facility, both in the upwards and downwards direction. Similar to its approach on heat rates, staff used the following "loading order" logic to assign each generating unit a ramp rate (or multiple ramp rates, where data on multiple segments across the plant's operating range was available):

- If the unit had segment data from the CAISO, use that data as-is, as it is the most precise.
- If that dataset was not available for the unit, use ramp rates from the 2026 TEPPC Common Case.
- If neither of the above datasets were available, use class average ramp rates from the 2022 TEPPC Common Case (the class average ramp rates have not been updated since 2022).

2.8.2.3 Minimum Up and Down Times

The table below summarizes capacity-weighted average minimum up and down hours parameters by dispatchable thermal resource type in the CAISO area. This does not include units located outside CAISO but with the ability to be dynamically scheduled in the CAISO market, as minimum up and downtime data is unavailable for these units. Data for years 2022 and 2030 are shown because the thermal fleet that is online differs slightly between the two years.

Table 15: Average minimum up and down times by resource type in CAISO area

Unit Type	Average minimum up hours (2022)	Average minimum down hours (2022)	Average minimum up hours (2030)	Average minimum down hours (2030)
CCGT	7.2	4.8	7.2	4.8
CT	1.8	1.6	1.8	1.6
CHP (dispatchable)	1.9	1.8	1.9	1.8

2.8.2.4 Generator Forced Outage and Planned Maintenance

To model generators properly, some data regarding the chances of outages on those generators are needed. SERVM makes use of outage data by modeling generators with a distribution of time to fail, time to repair, and partial outage states. Table 16 lists the variables in SERVM that relate to forced or maintenance outages on generating units. The table does not list specific variable names in SERVM, but instead gives a less specialized narrative name.

Table 16: Inputs related to forced and planned outage hours and statistics for SERVM

Variable description	Comments	Sources/Comments
Availability	Percentage factor (1- percent of time unit is unavailable)	At this time, Energy Division staff will source all of these inputs from GADS data, using class averages.
Time to fail	User can specify a distribution of hourly values for how long a resource will run before it fails. SERVM draws a value from this distribution to draw outages on resources - user can specify either high values (making generators more reliable) or low values (making generators less reliable).	
Time to repair	Given in hours, this variable is how long a resource is out when it is on outage. Users can specify a number of hours for planned and forced outages separately.	
Partial outage derate	User can specify partial outage states	
Maintenance periods	Unit specific variable users can use to specify more than one maintenance period for each year	
Start up probability	Users can specify what the probability is for resources to fail upon startup	

Since 2010, generator owners operating in North America have been required to electronically submit outage data that describes each event that occurs at their generator to the North American Electric Reliability Council (NERC) in a standard format. Before that, the data submission was voluntary and non-electronic. Generator Availability Data Systems or (GADS) data is commonly used for purposes of modeling generator outages in production cost models. This data is available to CPUC staff via license from NERC. GADS data is reported to NERC by individual generators. Thus unit specific data is available, although unit specific data would be confidential. For the RA and IRP modeling, Energy Division staff has generated class averages for these variables, using the following categories to differentiate generators:

- Steam Turbines in California
- All Steam Turbines including those in California
- Combustion turbines within California
- All Combustion Turbines including those in California
- Combined Cycle plants within California
- All Combined Cycle plants including those in California
- All cogeneration facilities including those in California (there were insufficient facilities to generate averages solely for California plants)

CPUC staff use of GADS data is in contrast with the modeling that the CAISO completed in support of the CPUC's Long Term Procurement Plan (LTPP) during 2012; for that modeling, the CAISO generated outage statistics based on its internal outage logging system. The CAISO uses data it gathers from generators via the Scheduling and Logging Interface for California (SLIC) database to generate class average summary statistics. The SLIC system however is due to be retired in December 2014, and the new Outage Management System (OMS) will replace it.[59] While having the advantage of being public, class average values fail to meaningfully differentiate between generators that in reality perform quite differently.

Considering the retirement of the San Onofre Nuclear Generating Station (SONGS) and other units that use OTC technology, there is a particularly significant need to accurately differentiate between individual generators (some of which are scheduled to come into compliance with OTC requirements) in order to measure how reliability will be affected by forthcoming retirements and retrofits. Moreover, as the generating fleet moves from fossil-based resources that largely operate in baseload orientation to fewer fossil generators seeking to balance an ever increasing ratio of energy generated by intermittent resources, differentiating between generators with regards to outage rates is important to gauge the reliability effects of this transition. This level of granularity is needed to accurately assess how much reliability and flexibility is served by those generators that retire (even differentiating between individual OTC generators) and how the new generators recently brought online and those in planning provide more, less, or equivalent reliability and flexibility.

2.8.2.5 Startup Information

SERVM requires that the user specify each generator's startup time, startup cost, and startup fuel, for three types of starts: hot, warm, and cold. Staff used segment data from the CAISO Masterfile to calculate this startup information for generators in the CAISO. For generators outside of the CAISO, staff

[59] The CAISO OMS project page is linked here: http://www.caiso.com/informed/Pages/StakeholderProcesses/OutageManagementSystemProject.aspx

used the TEPPC 2026 Common Case dataset, although this data only had cost, and not startup time or fuel information. To fill in data gaps such as these, staff derived class averages from the CAISO data and used this to fill in the missing data for both inside and outside CAISO.

The table below summarizes capacity-weighted average startup parameters by dispatchable thermal resource type in the CAISO area. Data for years 2022 and 2030 are shown because the thermal fleet that is online differs slightly between the two years. The start cost does not include the cost of burning fuel during the start. Fuel burn from starts is separately calculated for each unit based on the unit's startup profile obtained from the CAISO Masterfile.

Table 17: Average hours per start by resource type in CAISO area

Unit Type	Average start cost $ (2022)	Average hours per start (2022)	Average start cost $ (2030)	Average hours per start (2030)
CCGT	11,191	2.48	11,162	2.47
CT	3,178	0.96	3,174	0.96
CHP (dispatchable)	421.0	1.02	421.1	1.02

2.8.2.6 Attributes of "Perfect Capacity" used for ELCC studies

Effective Load Carrying Capability (ELCC) studies require a relative comparison to a perfectly dispatchable unit. SERVM models this construct with "perfect capacity." This subsection describes the attributes of "perfect capacity" as modeled in SERVM.

ELCC is calculated by measuring the reliability of the system (staff chooses to use the LOLE metric to measure reliability), and achieving the desired LOLE. Then, the target generator is removed, a substitute generator is added in, and LOLE is recalculated. The LOLE results are calibrated such that the right amount of substitute capacity is added to achieve the same LOLE as the system with the target generator included. The ratio of the substitute capacity MW to the target generator MW is referred to as the ELCC of the target generator (relative to the substitute capacity).

It is important to specify exactly what the substitute capacity is in terms of performance, outage rate, and other characteristics. One could choose an existing plant to compare against, or one could compare against "perfect capacity". A perfect generator is one with operational and performance characteristics that ensure optimal ability of that generator to contribute to reliability. In essence, a "perfect" generator contributes reliability to the system equivalent to the size of the generator – there is no derate for performance. It is an impossible standard of course, since no generator operates perfectly, without any equipment failures or with no time to start up. No generators are "perfect" and it is just a theoretical modeling convention, but comparison against "perfect capacity" allows all generators to be rated against each other. Even new peaker plants will not have an ELCC of 100%.

Staff created generic "perfect capacity" peaker generators in the SERVM database such that they would be available for use in ELCC studies. Table 18 lists the characteristics of the "perfect capacity."

Table 18: Resource Characteristics of Perfect Capacity

Variable description	Description	Value of Variable
Capmax	Maximum generation level	200 or 100 MW
CapMin	Minimum capacity level (PMin)	1 MW
Availability	Percentage factor (1- percent of time unit is unavailable)	1 (indicating perfect availability)
Time to fail	User can specify a distribution hourly values for how long a resource will run before it fails. SERVM draws a value from this distribution to draw outages on resources - user can specify either high values (making generators more reliable) or low values (making generators less reliable).	90000 (never fail)
Time to repair	Given in hours, this variable is how long a resource is out when it is on outage. Users can specify a number of hours for planned and forced outages separately.	0 (Repairs instantly)
Startminutes	How long in minutes for the plant to start up	2 minutes
Maintenance periods	Unit specific variable users can use to specify more than one maintenance period for each year	None
Start up probability	Users can specify what the probability is for resources to fail upon startup	1 (Never fails on startup)

2.8.2.7 Natural Gas Price Forecasts

The natural gas price forecasts utilized by SERVM were developed by the CEC, consistent with the 2017 Integrated Energy Policy Report (IEPR).[60] CEC staff ran the NAMGas model to produce a forecast of burner tip prices composed of prices at the natural gas hub and transportation prices to delivery point. Staff deflated nominal prices to 2016 dollars using a series of deflators also produced by the CEC as part of the NAMGas model. NAMGas results were also provided to WECC for use in the WECC-wide Anchor Data Set.

Energy Division staff used the CEC NAMGas data to create both annual fuel price projections for each hub, but also fuel handling inputs (the "csthnd" variable in SERVM). Each individual generating unit was linked to a particular fuel price curve as well as given a fuel handling variable. These values are in addition to other economic variables that SERVM uses to simulate economic operation of a particular unit. In addition to fuel price and fuel handling charge, a unit would also have cost variables for startup cost and variable operations and maintenance ("strtup" and "cstvar" variables in SERVM respectively) as well as a profile of fuel used during startup.

2.8.2.8 Carbon Price Forecasts

The carbon allowance price forecasts utilized by SERVM were developed by the CEC, consistent with the 2017 Integrated Energy Policy Report (IEPR).[61] The carbon allowance price was used in SERVM as a carbon adder on fuel burn of in-state generation and thus affected dispatch decisions for in-state gas generation. The carbon allowance price was also used in SERVM as a carbon adder on California import hurdle rates and thus affected the decision to import energy into California. In 2030, the carbon allowance price is $27.37 per metric ton of CO2. This equates to $11.71 per MWh as a California unspecified import hurdle rate adder, assuming the unspecified import emissions factor 0.428 metric tons per MWh (same as assumed in the RESOLVE model). Costs are in 2016 dollars.

2.8.2.9 Variable Operating and Maintenance Cost

In addition to fuel costs, variable operating and maintenance (O&M) costs add to the cost to a particular generator of generating electricity. Variable O&M costs are expressed in $/MWh and factor into dispatch order. Facilities with higher variable O&M costs are less likely to be dispatched than those with lower costs, all else being equal.

The actual variable O&M costs of each facility are both confidential and difficult to arrive at. Analysis of each individual contract would determine the cost values for each particular facility, and this value is likely impossible to publish. It is important to note that this value, though generally reflective of technical specifications of generating equipment, is also influenced by subjective contracting realities, such as labor costs. Staff used the values in Table 19 below in all SERVM studies conducted in 2018. In the future staff will collaborate with the CAISO to refine these values. Possible values can be drawn from the CAISO Generator Resource Data Template for resource modeling, posted to the CAISO website.

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[60] The April 2018 version of the NAMGas model posted here: http://www.energy.ca.gov/assessments/ng_burner_tip.html

[61] http://docketpublic.energy.ca.gov/PublicDocuments/17-IEPR-03/TN222145_20180116T123231_2017_IEPR_Revised_Carbon_Allowance_Price_Projections.xlsx

Table 19: Variable Operations and Maintenance Costs

Type of resource	Weighted average VOM for CAISO, $/MWh
Battery Storage	$0.31
Biogas and Landfill Gas	$3.28
Biomass and Wood	$2.86
CC	$2.65
Coal	$2.84
Cogen	$3.50
CT	$4.08
DR	$0.86
Geothermal	$2.78
ICE	$3.44
Nuclear	$1.00
PSH	$2.00
Solar PV	$0.00
Steam	$3.01
Wind	$1.96

2.8.2.10 Specified Imports, Dynamically scheduled resources, and Direct Purchases

The WECC interconnect is a very complicated region, with power flowing over numerous transmission interfaces. Several large plants provide energy to multiple regions, and provide valuable reliability service across WECC. Some regions are more dependent on direct purchases from outside the region than others, and it is very important to link regions with the generating plants that supply them with power. For example, Southern California Edison relies on specified imported power from among other facilities, the Palo Verde Nuclear Station in Arizona and Hoover Dam in Nevada. LSEs within the CAISO also directly purchase specified power from certain out-of-state renewable generators. Certain out-of-state dispatchable generators can also be dynamically-scheduled into the CAISO day-ahead market. Each of these cases must be modeled in SERVM.

Generally speaking, SERVM accounts for the production, exports, and emissions of a given generation unit in the area in which that unit serves load (which does not necessarily match the area where the generator is physically located, e.g. Hoover). There are two different ways that the user of SERVM can specify this load area: through the normal **Region** variable, and through the **Remote Generator** tab of the model. The use of these two concepts is explained below.

- All units in SERVM must have a Region. A Region roughly corresponds to a balancing authority.[62] Optionally, in addition to its Region, the user can declare a unit as a Remote Generator. If a unit is declared as a Remote Generator**,** it has a **"Source Region"** and one or more **"Remote Regions."**
- If a unit has only a Region declared, but is not declared a remote generator, the model treats the unit as having ALL of the following characteristics:
  - The unit is <u>considered</u> physically located in that Region (usually a balancing authority).[63]
  - The unit primarily serves the load of that Region (usually a balancing authority).
  - If at any point this unit exports to another region, its production counts as <u>unspecified</u> exports (which the model calls "Energy Sales"). This is because the unit is not dedicated to serving any particular region except its home region, and is exporting "opportunistically" because that is an economically better option than ramping down.
- If a unit is declared as a Remote Generator, the following applies:
  - The unit is physically located in the "Source Region," but primarily serves the load in the Remote Region(s). This information supersedes the unit's "Region."
  - The unit's costs, generation, and carbon emissions, if any, accrue to the "Remote Region(s)" because it is serving that region's load.
  - The unit's production is counted as <u>specified</u> gross imports (to the Remote Region) or gross exports (from the Source Region), which the model calls Direct Purchases or Direct Sales, respectively. A later section explains these terms in more detail.
  - Remote generators in SERVM are modeled as "must run" and are NOT economically dispatched.

A drawback with the Remote Generator designation is that the specified import generator is dispatched as a must run facility, without economic dispatch considerations. Thus there is the possibility of unrealistic dispatch patterns. For those external facilities that are specified imports into a region <u>and</u> are dispatched economically, i.e. dynamically scheduled in the CAISO day-ahead market, those facilities were listed as being <u>within</u> the regions they are imported into. This preserved the economic dispatch function.

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[62] The CAISO balancing area is an exception to this rule. It is broken out into four regions: PGE_Bay, PGE_Valley, SCE, and SDGE. However, these are "co-regions" with zero transmission costs between co-regions but transmission constraints between them to reflect possible congestion.

[63] Even though in reality some units are not physically in that Region, e.g. Hoover and certain CAISO market dynamically-scheduled OOS dispatchable units. Such OOS units are "modeled" as within the CAISO region so that the model can economically dispatch them in CAISO. They cannot be modeled as "Remote Generator" because in SERVM such remote generators are restricted to being modeled as must-run only.

The table below summarizes how SERVM modeled different types of specified imports into the region where it serves load. Note there was an input update between the IRP Reference System Plan with 2017 IEPR studies and the IRP Hybrid Conforming Portfolio studies due to better information on whether a generator primarily serves load where it is located or exports to a remote region. See Attachment B to the September 24, 2018 IRP ruling for a presentation of inputs and results for Reference System Plan with 2017 IEPR studies and see Attachment A to the January 11, 2019 IRP ruling for a presentation of inputs and results for Hybrid Conforming Portfolio studies.

Table 20: How SERVM modeled different types of specified imports

Unit	Modeled as remote generator?	Reference System Plan w/ 2017 IEPR model: Capacity to load "Region" mapping in 2030	Hybrid Conforming Portfolio model: Capacity to load "Region" mapping in 2030
Palo Verde	Yes	SRP (3180 MW), LADWP (407 MW), SCE (623 MW)	SRP (3180 MW), LADWP (407 MW), SCE (623 MW)
Out-of-CAISO renewables that serve CAISO load, including RESOLVE selected resources	Yes	CAISO, (7553 MW) LADWP, (301 MW) SMUD (260 MW)	CAISO, (2247 MW) SMUD (230 MW)
Out-of-CAISO thermal resources that dynamically schedule into CAISO market (tagged "DYN"): Arlington, Griffith, Mesquite, Yuma	No	SCE (1799 MW)	None
Hoover	No	LADWP (393 MW), SCE (764 MW)	LADWP (393 MW), SCE (764 MW)
Intermountain CC Repower	No	SCE (322 MW), LADWP (878 MW)	SCE (322 MW), LADWP (878 MW)

Because Palo Verde and the out-of-CAISO renewables are must-run (first two rows of the table), they can be modeled as remote generators. However, certain out-of-CAISO dynamically-scheduled resources, for example Hoover and Intermountain, are economically dispatched by the CAISO in reality. Thus, these units are "moved into" CAISO and LADWP for modeling purposes, with no remote generator variables specified.

To account for the remote generators' usage of the transmission system, transmission path capacities from outside CAISO are decremented by the resources' usage of that path.

2.8.3 Energy Storage Resources - Type P

While there are numerous different energy storage technologies, most can be described according to several key variables such as available energy, maximum output, maximum draw, and efficiency. This section describes these modeling inputs. However, because very little energy storage has been deployed to date, the testing protocols and sources that would normally determine how storage operations should be modeled will need to be developed over time. The table below shows the available inputs to model a storage device in the SERVM model. Below, staff further identifies specific numerical assumptions for energy storage the SERVM model used to align with assumptions used in the IRP Reference System Plan.

Table 21: Input parameters for storage in the SERVM model

Input	Units	Source
Maximum rated discharge	MW	CAISO MasterFile
Total usable storage volume (given allowable depth of discharge)	MWh	Calculated based on testing: Maximum rated discharge * (discharge test duration)
Maximum rated charge	MW	CAISO MasterFile
Round trip efficiency	% efficiency	Calculated based on testing submitted to the CAISO: (discharge MW*duration) ÷ (charge MW*duration)
Capable of supplying non-spinning reserves	Y/N	Start time testing submitted to the CAISO demonstrating < 10 minute startup
Facility in-service dates	mm/dd/yyyy – mm/dd/yyyy	CAISO MasterFile, unless utilities have more current information
Scheduled maintenance and maintenance outage periods	% of month/year, date range, and/or hours to repair	Historical data from the CAISO, to be collected over time for new facilities
Able to provide regulation	Y/N	Ability to provide regulation, from CAISO MF

2.8.3.1 Numerical Assumptions for Committed and New Energy Storage

SERVM was used to model future study years and must therefore make assumptions about the future amounts and operational attributes of storage despite the lack of current operational history.

CPUC Decision (D).13-10-040 established a 2020 procurement target[64] of 1,325 MW of newly installed energy storage capacity within the CAISO planning area. Of that amount, 700 MW needs to be transmission-connected, 425 MW needs to be distribution-connected, and 200 MW needs to be customer-side-connected. D.13-10-040 allocated a portion of the 1,325 MW energy storage procurement target to each of the three major IOUs.[65] Energy storage resources that are procured to satisfy a local capacity requirement are assumed to count towards satisfying the 1,325 MW energy storage target. Since procurement directives specify this amount of energy storage, the storage can be described as "committed," in order to distinguish it from candidate "new" storage selected in the IRP process.

CPUC staff assumed that the full 1,325 MW is online by 2024 and has an average duration of 4 hours, meaning the full 1,325 MW counts towards RA obligations, is dispatchable, and can be used to provide ancillary services, regardless of interconnection domain (transmission-connected, distribution-connected, BTM). This was consistent with the assumptions used in the RESOLVE model and the IRP Reference System Plan. Staff used the same round-trip efficiency assumptions as used in the RESOLVE model, 85% for lithium-ion battery storage and 81% for pumped hydro storage, in the absence of historical operational data.

For new storage beyond the 1,325 MW target, SERVM used the assumptions specified by the RESOLVE model and the IRP Reference System Plan. Refer to section 2.7.1 and the referenced workbooks for the amounts of new storage. Refer to section 3.2.3 for guidance on locating new storage to transmission substations.

Note that the CEC's IEPR demand forecast includes a projection of peak demand reduction due to BTM energy storage impacts. This projection does not overlap with the assumed energy storage procurement due to the 1,325 MW target.

CPUC staff is aware that the IOUs have recently procured battery storage that in aggregate exceeds the 1,325 MW target. However, that amount is still far less than the candidate "new" battery storage selected in the IRP process. Thus, it is reasonable to assume that the sum of 1,325 MW and the "new" battery storage selected in the IRP process is inclusive of the existing online and recently procured (but not yet online) battery storage.

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[64] The Decision specifies that resources must be online by 2024 so in the planning assumptions, target amounts are reached in 2024.

[65] The CPUC also established an additional procurement target of 1% of load for ESPs and CCAs. Staff did not assume this amount of ESP or CCA storage procurement as part of the baseline in the RESOLVE model. Instead, staff let the RESOLVE model optimize the amount of new storage to build and assumed that this amount of storage more than covers the 1% of load procurement target for ESPs and CCAs.

For modeling how storage contributes towards RA obligations, staff used the RESOLVE model convention: "To align with resource adequacy accounting protocols, RESOLVE assumes a resource with four hours of duration may count its full capacity towards the planning reserve margin. For resources with durations under four hours, the capacity contribution is derated in proportion to the duration relative to a four-hour storage device (e.g. a 2-hour energy storage resource receives half the capacity credit of a 4-hour resource). This logic is applied to all committed and candidate storage resources."[66]

2.8.4 Renewable Resources – Type R

The major distinction in SERVM between Type R resources and other types (such as F, T, or N) is in how resources are dispatched. Type R facilities (whether renewable or not) are modeled with production that is dependent on weather, and not dependent on economic dispatch logic. Type R facilities (loosely here called renewable) include wind and solar photovoltaic (PV) facilities. Other renewable resources, such as geothermal, biomass, and biogas generation facilities, are more accurately modeled economically via production cost dispatch; thus, the term "renewable" is really shorthand for weather-dependent intermittent must-take resources. Thus facilities that are going to be modeled with prices and startup costs, including solar thermal facilities, will be modeled as Type F or T units.

This section details the inputs and assumptions utilized in modeling type R resources, including the methodology for creating weather-based wind and solar photovoltaic generation profiles.

For work to support the IRP proceeding SERVM used the renewables portfolios specified by the RESOLVE-based IRP Reference System Plan with the 2017 IEPR. Refer to section 2.7.1 and the referenced workbooks for the amounts of new renewables. Refer to section 3.1.4 for guidance on locating new renewables to transmission substations.

2.8.4.1 Wind and Solar Generation Profiles

Wind and solar facilities have significant dependence on ambient weather conditions, which must be taken into account to correctly predict their output. Their output is a function not just of wind speed and solar irradiance, respectively, but also of other weather parameters such as cloud cover and temperature. Complicating this correlation is the fact that publicly available weather data is restricted to standardized locations (generally airports), and is not specific to the exact location (including altitude/height and orientation) of individual renewable energy facilities.

Additionally, renewable energy projects employ a multitude of different technologies, each of which may have a different response to the same weather conditions. For example, tracking and non-tracking PV will generate different amounts of electricity under the same weather conditions. Panel orientation also contributes to significant differences between non-tracking facilities. Solar thermal technology has an even more divergent weather response, relative to solar photovoltaic technologies.

To accurately reflect the variability in wind and solar production profiles, modeling of solar and wind facilities requires mapping of the power output of existing and new facilities utilizing various technology

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[66] See section 6.1.5 of Attachment B to the Proposed Reference System Plan Ruling, September 2017, RESOLVE Documentation: CPUC 2017 IRP Inputs and Assumptions, found here: http://cpuc.ca.gov/irp/proposedrsp/

types to the 35 years of historical weather that are modeled in SERVM. This mapping results in hourly performance profiles for each year of weather data, representing the overall variability of wind and solar production related to weather.

There are multiple possible approaches to developing such hourly performance profiles. One approach is to utilize generation profiles created by key stakeholders who are already conducting similar facility performance modeling. For example, developers need to forecast the generation profiles of their facilities in order to predict potential energy revenues and inform bids into RFOs or energy markets. Thus they could be helpful in developing similar production profiles for use in SERVM. Utilities also have an interest in predicting potential generation for resources that they are considering for contracting, operation, or management. Both developers and utilities may be able to create annual synthetic production profiles based on the same publicly available NOAA weather data utilized in SERVM synthetic load profile generation. Thus, there are several potential sources of wind and solar generation profiles that could be used.

However, there could be drawbacks to utilizing manufacturer, developer, or utility-supplied data for reliability modeling. It might be difficult to match potential production to load profiles or weather profiles, as the manufacturer curves or utility information may predict performance based on other factors, or may be based on single-year weather projections that cannot be extrapolated to the entire 35 years of weather history required for consistency with other weather-based SERVM inputs and algorithms. Data for performance of wind and solar facilities external to California may also be much more difficult to access, complicated by different utility service areas, regulatory jurisdictions, and information access guidelines.

For 2018 modeling activities, staff pursued an approach of mapping standard, publicly available weather information to the power output of wind and solar facilities using either normalized profiles based on output from the NREL PVWatts[67] calculator (for PV facilities) or off-the-shelf neural network modeling software (for wind facilities). Neural network modeling software can be used to determine relationships between weather/facility input variables and wind facility production, and produce a predictor file. With this predictor file, Energy Division staff, together with Astrape Consulting, constructed synthetic wind production profiles for existing and new facilities that correspond to the 35 years of weather history and associated synthetic load shapes utilized by SERVM. The large sample of weather years will enable SERVM to capture realistic variability in generation from wind and solar facilities. However, creating these wind and solar facility profiles required extensive performance, technology, and weather data.

It is expected that the synthetic production profiles (and the predictor file, for wind facilities) will be reconstructed at least every two years to reflect the evolving relationships between weather and production (considering such issues as technology improvement and locational clustering of installed capacity). The section below describes:

1. the sources for performance data,

[67] http://pvwatts.nrel.gov/

2. the weather data and regions modeled,

3. the development of technology categories to group similar responses to weather inputs,

4. neural network modeling or PVWatts-based calculation to be utilized to create weather response predictions for each technology category, and

5. how these predictions are input into and used by the SERVM software.

6. staff expects variability in production of wind and solar facilities to be one of the more important drivers of reliability risk in the future, as wind and solar resources continue to account for an increasing share of the California generation mix. Thus, while this area of data development has required significant effort, the current generation profiles and any future refinements will also pay off in greater modeling accuracy.

2.8.4.2 Performance Data Sources and Assumptions

Energy Division staff receives hourly settlement data (in hour-ending or "HE" format, representing average output over the hour) from all facilities represented by scheduling resource IDs on the CAISO Master Generating Capability Data List. These data have been supplied for facilities since 2008 for use in Qualifying Capacity calculations, and were used to validate the synthetic shapes that were developed.

For the construction of synthetic wind profiles for facilities both inside and outside of the CAISO service territory, 2004-2006 hourly wind speed and generation profiles were taken from the NREL Western Wind Resources Dataset.[68] The dataset includes over 30,000 potential wind sites nationwide, with generation profiles for each site assuming a 100-meter hub height and 100-meter rotor diameter. In modeling facility performance, wind facilities within each SERVM region were assumed to have the same geographic distribution as RPS-certified wind facilities in that region, as reported by the CEC.[69]

Solar PV profiles were calculated based on several performance assumptions, as shown in Table 22, below.

Table 22: Solar PV Facility Performance Inputs

Performance Input	Assumption
Reference Efficiency	14.94%
Nominal Operating Cell Temperature (NOCT)	45°C

[68] http://wind.nrel.gov/Web_nrel/

[69] http://www.energy.ca.gov/portfolio/documents/List_RPS_CERT.xls

Temperature Coefficient	0.0045
Short Circuit Coefficient	0.000545
Solar Radiation Coefficient	0.12
Reference Temperature	25°C
Inverter Efficiency	97%

2.8.4.3 Technology and Locational Granularity

All solar PV weather data are sourced from the NREL National Solar Radiation Database (NSRDB).[70] Solar data is a combination of three data streams, the 1980-1991 information for 237 sites in the United States, the 1991-1997 information from 1,454 sites in the United States, and the 1998 to 2014 information from rom 1980-1990 come from 58 unique sites, while 1991-2010 data come from 225 unique sites. These are referred to as the TMY2 and TMY3 datasets. These data are comprised of the following inputs:

- Local solar time (calculated based on latitude, longitude, day of year, and other variables)
- Direct radiation
- Diffuse radiation
- Air temperature
- Wind speed

Because NSRDB data extends only to 2010, previous years' weather is used to determine the 2011 and 2012 generation profiles. The modeled solar profile for 2011 is identical to the pattern seen in 2008 and the modeled solar profile for 2012 is identical to the pattern seen in 2009 for all regions. A more rigorous approach to developing solar profiles for 2011 and 2012 may be used in the future.

Wind weather inputs are sourced from 33 years of NOAA data. Specific weather inputs are: hour of day, wind speed, temperature, dew point, and cloud cover.

Because weather data are available at limited locations, and because modeling time increases dramatically as granularity increases, one weather profile was compiled per wind or solar technology for each modeling region, for each historical weather year being modeled. To create each region's weather

[70] http://rredc.nrel.gov/solar/old_data/nsrdb/

profile, staff calculates a weighted average hourly weather profile based on one to three weather stations that are selected as indicative of a given renewable technology's generation capacity in the region. In other words, if capacity of a particular technology type is primarily located in the northern part of a region, the weather modeled for that region in SERVM will be more heavily weighted towards the northern weather station(s) selected for that region. The location of each facility is sourced from it's the CEC RPS Certification Report.[71] Alternative approaches to weather station weightings may be considered if SERVM is utilized for longer-term modeling in the future; sensitivity to weather station selection will also be tested.

An important exception to the above methodology is the treatment of wind in the SCE TAC Area modeling region. Because most wind resources are in either the San Gorgonio or the Tehachapi areas, and because these areas have very distinct weather, wind in the SCE TAC Area is modeled with two separate weather profiles, one for each of these two sub-regions. Individual wind facilities in the SCE region are also separated into San Gorgonio and Tehachapi sub-regions, with facilities located in the Big Creek/Ventura Local Area assumed to be in Tehachapi and all others assumed to be in San Gorgonio. Wind and solar resources outside of the United States are treated differently, due to data limitations. Neural network modeling and PVWatts calculations are not being conducted for Canadian and Mexican wind and solar resources. Rather, the results from similar US regions – the Pacific Northwest and the average of IID and New Mexico, respectively – are applied to the Canadian and Mexican weather shapes in order to develop weather-based wind and solar production profiles for these regions. In addition, Wyoming wind was ascribed weather from Colorado, as there were no production profiles developed for Wyoming.

In developing wind technology and weather response relationships in the neural network software, the representative regional weather was input. In the future, the model performance will be tested using more local weather for individual facility locations, where available; however, neural networks generally yield better predictive capability when developed with a more limited set of parameters. Too many variables involved in the creation of the predictor file can create muddied correlations that lead to bad predictions of weather and generation relationships.

2.8.4.4 Technology Categories

Solar resources are differentiated by fixed or tracking categories, inverter loading ratio, and utility-scale vs. BTM. All wind facilities are considered equivalent technologies. Solar facilities are assigned to one of three categories: utility-scale fixed tilt PV, utility-scale tracking (single axis) PV, or BTM PV. The inverter loading ration is assumed to be 1.3 for utility-scale solar and 1.1 for BTM PV. This is consistent with assumptions used in the RESOLVE model and the IRP Reference System Plan. Although better modeling methods will be developed for solar thermal facilities in the next phase of the modeling project, for the time being they are included in the category of tracking solar facilities. Additional possible categories that could be explored in the future include PV with storage, wind with storage, or south facing versus west facing PV.

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[71] http://www.energy.ca.gov/portfolio/documents/List_RPS_CERT.xls

Each technology category and region (or sub-region, in the case of wind in the SCE region) is evaluated separately to develop weather response predictions within that region, and across that category type. SERVM models each facility's generation based on both its technology category (indicative of response to weather) and weather region (the relevant weather input).

However, data are limited. The CAISO Generating Capability Data List places units in Local Areas, which are translatable to regions in the SERVM database, while for facilities outside of the CAISO area, the WECC TEPPC database provides the primary reference for location, generation type (solar, wind, tracking, fixed, etc.), and date of commercial operation.[72]

Regardless, direct category assignment (rather than imputing technology category based on vintage) will be possible for facilities in California either from the monthly RPS Project Development Status Reports (PDSRs) or via data gathered from the CEC Wind Performance Reporting System. Information for facilities outside of California will continue to be derived from TEPPC 2026 Common Case information.

Existing and contracted utility-scale solar facilities were assigned to either fixed or tracking PV generation profiles. For facilities with CAISO settlement data, this was determined by analyzing late-afternoon generation on a sunny day and assessing whether generation levels (normalized for facility capacity) were indicative of fixed PV (lower generation in the late afternoon) or tracking PV (higher generation in the late afternoon). To ensure accuracy, facilities with known technology types (as submitted by the CPUC-jurisdictional IOUs) were analyzed to develop an appropriate cut-off point in assigning those facilities with unknown technology to one of the two possible categories. For facilities outside of the CAISO service territory, the TEPPC 2026 common case specified which of the two categories is more appropriate for modeling individual PV facilities.

For new solar units selected as part of the IRP Reference System Plan, staff will use the same assumption as used in the RESOLVE model, 25% fixed tilt and 75% single axis tracking.

2.8.4.5 PV Production Profile Development

Energy Division calculated hourly generating profiles for each of the 24 regions in the model, for three generation categories – utility-scale fixed tilt, utility-scale single axis tracking, and BTM PV types. These profiles were generated from weather data spanning 1980 through 2014. PV production profiles were developed by inputting the weather and facility data discussed above into the NREL PVWatts[73] calculator. The calculator output a facility-specific hourly generation factor ranging from 0 to 1, which are then multiplied by the total facility's capacity (sized in MW) in each study year. Different sites were available for 1980 - 1990 and 1991 - 2014, so some calibration of the datasets was required to ensure continuity. To ensure consistency, the range in output duration curves of the 1980 - 1990 was shaped to match the range in duration curves seen in 1991 - 2014 data. This entailed calibrating the number of hours at max output, moderate output, low output and every point in between.

[72] More information on TEPPC, see https://www.wecc.biz/committees/BOD/TEPPC/Pages/TEPPC_Home.aspx
[73] http://pvwatts.nrel.gov/ and http://www.nrel.gov/docs/fy14osti/60272.pdf

The result of the above exercise is 35 years of regional generation profiles for the three solar PV technology types. With 24 regions modeled in SERVM, this yields 2520 hourly generation profiles for solar PV facilities.

2.8.4.6 Wind Production Profile Development

2.8.4.6.1 Neural Network Modeling

Staff has updated the wind generation profiles since previous studies were performed in 2015. Data is now available through 2014, and Energy Division used the recent data to revise all profiles generated from 1980 now through 2014. Generation depends on many aspects of weather. The fact that SERVM weather region inputs are not specific to the precise resource location further obscures the relationship between weather and generation output. To create a reasonably accurate prediction of generation output in response to weather, a neural network can be used to map weather to output and create a relationship file that can be used for new facilities and weather years. This process is similar to the use of a neural network to create synthetic load shapes, which are used elsewhere in the SERVM model.

First, the regional weather data are placed into a spreadsheet for a given technology category.[74] One variable is chosen as the primary predictor of generation output, and is placed in the left-hand column. In the case of wind technologies this is the region's wind speed (from NOAA). The other key weather inputs (from NOAA, as discussed previously) are included as additional columns. These data are paired with actual facility and potential generation data from facilities of the given technology type, sourced from the Western Wind Resources Dataset, as previously discussed. The hourly generation data from the Western Wind Resources Dataset (WWRD) were first scaled by a ratio of each facility's nameplate capacity in MW to the facilities modeled in the WWRD, and then summed to create a single aggregate generation profile for a given region and year. It was this aggregate profile that was utilized in neural network modeling.

This neural network model trained itself to see the underlying relationships between the hourly generation data and the other columns of input data (much like a dynamic iterative regression model). It developed predictive relationships between the columns of data (the variables mentioned previously such as temperature and humidity), and produced an algorithm that was able to predict relationships between regional wind speed, secondary weather variables, and generation facility output.[75] Once that was completed, the algorithm predictor model could then produce a generation forecast from any set of NOAA weather data, for any facility that falls under the given technology category (including new facilities).

However, because of significant volatility and randomness in wind data, neural network models tend to predict average values more frequently than they actually occur. For this reason, there was some adjustment to the distribution of wind predictions after the initial neural network modeling. Staff

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[74] As previously mentioned, wind resources in the SCE TAC Area region are modeled separately, by San Gorgonio/Tehachapi sub-region.

[75] The algorithm was trained until the distribution of peaks and valleys was adequate. Further calibration was performed in a later step.

performed validation on the resulting performance shapes to ensure accuracy, by comparing the resulting shapes for the CAISO regions to actual historical generation patterns and normalizing to ensure that the predictor files output similar generation magnitudes and duration curves, compared to historical generation. Staff also checked that the capacity factors output by the predictor files were reasonable. Once the predictor files and additional processing were finalized, regional production profiles were created for all wind facilities in each weather year, using hourly NOAA weather data from 1980 to 2014.

After the wind profiles were created and validated to history, they were sent to Energy Division for input into the model. Unlike previous work performed by Energy Division, at this time no distinction was made based on hub height. All wind facilities were given one production profile only distinguished by location.

2.8.4.6.2 Category Normalization

In order to compare across wind facilities of varying sizes, output was normalized relative to sum of all the capacity in a particular category currently installed in the region prior to neural net "training". Additionally, because the neural network develops aggregate production profiles for a given technology category in a given region, differences in installed capacity over the training years must also be accounted for and normalized. One option is to assume that the smaller capacity installed in earlier years is representative on average of the larger total capacity in future years regardless of facility location or technology installed. However, this may be imprecise due to differences in the generation profile shape and volatility as more capacity is installed in new locations. To mitigate this problem, new facilities are instead assigned an hourly production profile from one representative existing facility determined to be "similar" in location and technology, and scaled to the MW size of the facility being modeled.

2.8.5 Demand Response – Type C

Demand response (DR) is modeled as a type "C" for "curtailable load" in SERVM. For work to support the IRP proceeding, SERVM used the total DR amounts specified by the IRP Reference System Plan and the RESOLVE model. RESOLVE's baseline shed DR capacity in 2030 is 1,617 MW (1,752 MW at the system-level after accounting for losses). The IRP Reference System Plan did not include any shed DR beyond this baseline amount.

The following subsection provides a narrative description of how shed DR was modeled in SERVM. Section 3.2.4 discusses DR modeling that is specific to network reliability studies, including the methods to allocate load impacts to transmission substations for the purposes of power-flow type studies.

2.8.5.1 Demand Response Parameters in SERVM

Key inputs available in the SERVM model are listed in Table 23, below.

Table 23: Demand Response parameters available in SERVM

Input (as applicable to the program)[76]	Units	Source
Maximum capacity	MW	LIR portfolio-adjusted load impacts, 1 in 2 weather
Maximum dispatch days per week	days	Program tariff
Maximum consecutive dispatch days	days	Program tariff
Maximum dispatch hours per day	hours	Program tariff
Minimum minutes per dispatch	minutes	Program tariff
Maximum number of dispatches per day	dispatches	Program tariff
Maximum dispatch hours per month	hours	Program tariff
Maximum number of dispatches per month	dispatches	Program tariff
Maximum dispatch hours per year	hours	Program tariff
Maximum number of dispatches per year	dispatches	Program tariff
Minimum number of dispatches per year	dispatches	Program tariff
Look-Ahead	hours	Not implemented

[76] Different DR programs have different design constraints; as a result, different inputs will apply to different programs. If a program lacks a certain constraint (for example, no maximum number of dispatches per week), then the associated input will not be included in the specification of that program in SERVM.

Notification period	Hours/minutes	Either DA (10am), HA,
First month available each year	month	Program tariff
Last month available each year	month	Program tariff
Period Availability (i.e., weekdays from 2-6 pm)	days and hours	Program tariff
Curtail (Dispatch) price	$/MWh	CAISO Plexos assumptions or program tariff[77]
Emergency-only dispatch	Yes/No	Program tariff
Region[78]	Region name	Program tariff
Program in-service dates	mm/dd/yyyy – mm/dd/yyyy	Program tariff
Ramp Rate	MW/min	Program tariff
Program performance degradation (customer fatigue)	Percent degradation factor per day	Not implemented

2.8.5.1.1 Resource Capacity

Currently, the maximum capacity for a given DR resource is set to its Load Impact Report[79] (LIR) portfolio-adjusted monthly system peak values for 1-in-2 weather conditions. However, under more extreme weather conditions, performance for weather-dependent resources may exceed the 1-in-2

[77] Most DR programs do not have a set price trigger. The assumptions adopted by the CAISO for its Plexos modeling are an approximation of a price trigger that corresponds to the actual dispatch criteria.

[78] These regions are used throughout the SERVM model, and are described further in the Weather Data and Regions section of this document.

[79] The Load Impact Protocols followed in developing Load Impact Reports were specified by Decision 08-04-050, and modified by Decision 10-04-006. Load Impact Reports are filed by each IOU for the programs they run, annually in April.

value, potentially reaching the LIR 1-in-10 capacity values. Apart from weather impacts, a DR resource may underperform or overperform relative to expectations due to variation in customer load and response.

To address the possibility of DR resources performing beyond the 1-in-2 value, staff plans to ultimately incorporate 1-in-10 values into the model as well. This can be accomplished by creating a "technology response curve" that maps regional temperature to changes in DR capacity. For 90th percentile temperatures (the conditions under which the 1-in-10 LIR is calculated) and above, the LIR portfolio-adjusted monthly system peak values for 1-in-10 weather conditions can be used. For 50th percentile temperatures (the conditions under which the 1-in-2 LIR is calculated) and below, the 1-in-2 LIR capacity values can be used. Linear interpolation can be used to approximate DR response between these two temperature bounds.

To address the possibility of over- or underperformance relative to expectations, three years of program history could be used to create a likely distribution of responses. The difference relative to expectation for a given dispatch can be defined as the percentage difference between the ex-post load impact found in the LIR and the daily forecast capacity predicted day-ahead. Each historical dispatch can be weighted according to the magnitude of the daily forecast capacity, so that larger dispatches are more heavily weighted. When a DR program is dispatched by SERVM, its response magnitude would then be adjusted upwards or downwards by selecting one of the historical performance data points. The performance point selected would be random, but weighted as previously discussed. While the necessary data for such adjustments have not yet been input into the model, the modeling functionality is in place, and staff plans to incorporate this performance uncertainty in the future. This could be accomplished with a variable that allows for randomly drawn output. For instance, if a DR resource has three performance levels of 90%, 100%, and 110%, and each is entered into the database, then one third of the time when it is dispatched it will operate at 90% of maximum, one third at 100% of maximum, and one third at 110% of maximum capacity.

2.8.5.1.2 Dispatch Notice and Response Time

DR programs have different dispatch notice requirements (day-ahead, 30-minute-ahead, etc.), which are described in their tariffs. Once dispatched, they also have varying response times. These requirements, whether a time-of-day cut-off or a minimum advance notice period, could be incorporated into the model in the future.

2.8.5.1.3 Triggers

Most existing DR programs do not have a set price trigger. The model used approximate price triggers that generally correspond to actual dispatch criteria. A number of DR programs are triggered via heat rate or emergency stage triggers, which are difficult to translate to price points. Energy Division staff continues to explore alternative approaches to fit the current portfolio of DR programs into the economic dispatch model in SERVM.

2.8.5.1.4 Customer Fatigue

The SERVM simulations did not currently consider the impacts of customer fatigue on long-duration or consecutive dispatches. With appropriate data, such impacts could be incorporated in the future.

2.8.5.1.5 Look-Ahead

For DR programs with dispatch limitations, demand response providers may occasionally refrain from dispatching if they believe that the resource could be better dispatched at a later time. For example, if a week is expected to have steadily increasing temperatures, a DR resource may not be dispatched earlier in the week, even if the price trigger has been reached, in order to preserve the possibility of operating later in the week. This "look-ahead" dispatch decision is not incorporated into the SERVM model, but could be in the future.

2.8.6 Hydropower Resources – Type H

All hydropower (hydro) resources that are not pumped storage[80] were modeled as Type H units. SERVM classified these hydropower resources according to three subtypes: run of river (ROR), scheduled, and emergency hydro. Each of these resources can have capacity and energy levels that vary by month and year, in order to reflect the seasonal variability of this resource type.

Run of river hydro represents the minimum output that is expected to occur regardless of electricity system needs or economic dispatch. Scheduled hydro represents the portion of the hydropower fleet that can be economically dispatched, in light of monthly resource availability. Emergency hydro represents the capacity and energy that can be "borrowed" from scheduled hydro to address occasional, short-term electricity system emergencies. Table 24 lists sources for particular data inputs.

Table 24: Data Sources for Hydropower Inputs

Data	Source
Facility generation per month (MWh/month), 1980-2012	Form EIA-923: Power Plant Operations Report[81]
Facility locations (model region)	TEPPC 2026 Common Case, Form EIA-923, CEC Energy Almanac,[82] and miscellaneous other sources such as the US Bureau of Reclamation[83]

[80] Pumped storage is modeled as Type P, as discussed in the energy storage section of this document, above.

[81] These data are available for download at http://www.eia.gov/electricity/data/eia923/.

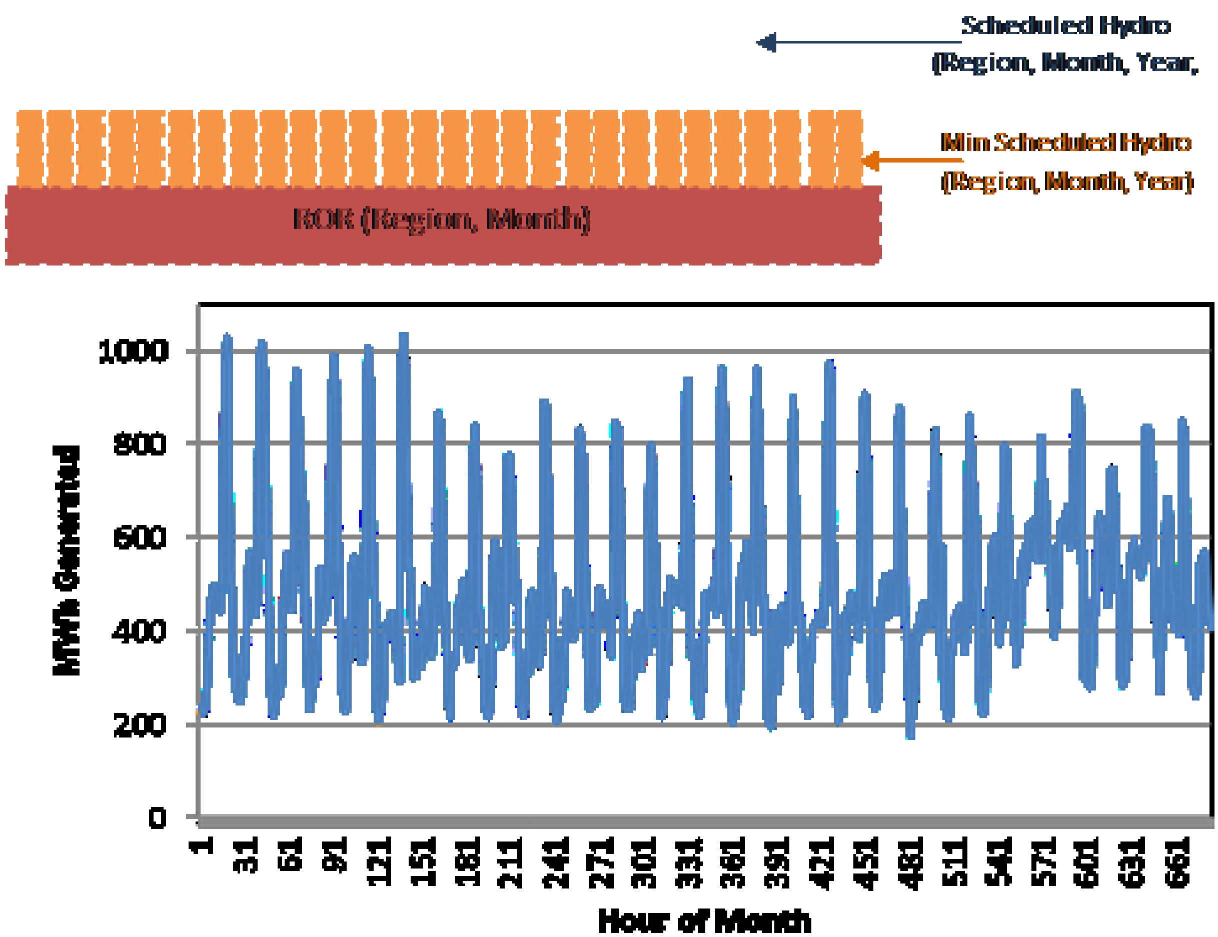
[82] Data can be downloaded from http://energyalmanac.ca.gov/renewables/hydro/hydro.xls and http://energyalmanac.ca.gov/powerplants/Statewide_PP_8.5X11_hydro.pdf.

[83] Searchable database at: http://www.usbr.gov/projects/.

Regional maximum capacity (MW)	TEPPC 2026 Common Case
Monthly hydro dispatch	Form EIA-923
Hourly hydro flows within California	Historical monitoring data aggregated to mask confidential information

Hydro resources were modeled in aggregate, by subtype and modeling region. For example, all ROR hydro facilities in SCE service territory were modeled as one “unit” in SERVM. Before these “units” were input into the model, the aggregated energy and capacity for each region was calculated and then allocated across the three subtypes. An intuitive visualization of the resulting allocation can be seen in the randomized sample hydro generation shape below. The methodology used will be described in more detail in the following sections.

Figure 5: Sample hydro generation shape and sub-type allocation (based on randomized historical data)



For facilities in Canada and Mexico, hydropower generation shapes were based on the closest neighboring US region (the Pacific Northwest and Arizona, respectively), and simply scaled to the region's maximum capacity.

2.8.6.1 Regional Aggregation of Energy

Monthly hydro generation (MWh/month) for all existing hydro resources in WECC is listed in Form EIA-923 for the years 1980-2012. This actual historic generation by month is used to determine the energy available from ROR, scheduled, and emergency-only hydro profiles generated for each region. However, because it is reported to EIA on a facility-specific basis, each facility must first be assigned to its region in SERVM based on the particular facility's location in the TEPPC Common case. The generation from all facilities within a given region is then summed to yield the total energy generated in that region, in each historical month and year.

2.8.6.2 Run of River (ROR) Hydro Resources

The energy generation and capacity for ROR resources within a region are unique to each month, but uniform across all weather years. This is because the ROR unit represents a minimum output that is always present, regardless of weather variability and dispatch choices, and because there have been very few new hydro facilities developed in WECC over the last 33 years. The available energy is set to be the fifth percentile of MWh generated by all hydro resources for a given month and region. In other words, the value is set such that in 19 out of 20 years, hydro facilities in that region in that month produce more than that number of MWh.

The capacity of ROR units is calculated as the available energy value in MWh divided by the total number of hours in that month. ROR units are assumed to operate at this calculated capacity for all hours of the month, meaning there is no hourly or daily variation in output within a given month. In other words, ROR production is flat across all hours of a given month, across all years modeled.

2.8.6.3 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 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, and is sourced from CEC historical generation data. Regions outside of California for which data is lacking are modeled data generated for the most similar region for which we have sufficient data. 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, SERVM will flag the issue and the value will be reduced. The minimum daily schedule for each scheduled hydro profile is spread across a specified number of hours each day 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. Available hydro capacity is allocated between emergency, scheduled, and run or river hydro based on higher or lower levels of hydro available generation and typical historical usage in each month. Scheduled, run of river and emergency hydro capacity always sums to total month specific capmax of the hydro fleet.

All scheduled hydro is dispatched one week in advance. The minimum generation quantity is scheduled to be centered on the anticipated peak load 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.

2.8.6.4 Emergency Hydro Resources

Because emergency hydro resources are not intended for regular dispatch, they are triggered only by high market prices (currently set to $2,500) 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 sum of total capacity of emergency, scheduled, and run of river hydro is equal to the total capacity of the hydro fleet in each area.

The full nameplate capacity is sourced from the TEPPC 2026 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 a MWh amount equivalent to a specified number of hours of full operation from the scheduled hydro unit.

2.9 Transmission Inputs

SERVM uses a transportation representation of the transmission system instead of an AC or DC representation. For a given region and a given connected region, the capacity limits in and out of the region (with respect to the connected region) are specified. These limits can vary by study year, by month, and by percent of peak load. Energy Division staff sourced transmission limit values from Maximum Available Import Capability in the Import Allocation Process. The Maximum Available Import Capability levels are updated annually and available at the CAISO website.[84] For areas not represented in the CAISO Import Allocation process, TEPPC Common Case 2026 v2.0 information was used. The transfer limits by region and hurdle rates between regions that were modeled in SERVM are posted to the Data section of CPUC Energy Division's Energy Resource Modeling landing page.[85]

2.10 System Inputs

2.10.1 System Periods

SERVM allows for resources to be available in specific periods of the day or week but not others. DR programs are given specific system periods when they are available. The system periods are defined according to the days of the week and hours of each day that are assigned to each period. Interested parties are invited to comment on these periods and suggest additional or alternative periods.

Table 25: System Periods

System Period	Day	Hours (*Hour Ending*, or HE)

[84] http://www.caiso.com/Pages/documentsbygroup.aspx?GroupID=3025C28C-1B60-4262-BEF9-66CF403FF107

[85] http://www.cpuc.ca.gov/energy_modeling/

OffPeak	Friday	23-24
	Saturday-Sunday	1-24
	Monday	1-6
Weekday	Monday-Friday	7-22
WeekdayOffPeak	Monday-Thursday	23-24
	Tuesday-Friday	1-6

2.10.2 Operating Reserves, Ancillary Services, and Frequency Response

Operating reserves and ancillary service requirements and targets are input as a percentage of hourly forecast load, and are assumed to be consistent across all regions, months of the year, and hours of the day. Interested parties are invited to suggest alternative or more differentiated reserve requirements, along with documentation. Current staff assumptions are shown in Table 26, below.

Table 26: Operating Reserves and Ancillary Service Requirements and Targets

Operating Reserve Type	Requirement or Target	Value (Percent of Load)
Regulation Up	Requirement	1.5%
Regulation Down	Requirement	1.5%
Spinning Reserves	Requirement	3.0%
Non-Spinning Reserves	Target	3.0%
Load Following Up	Target	2.5%
Load Following Down	Target	1.5%

2.10.2.1 Frequency Response Requirements

A frequency response constraint refers to a model constraint to have committed headroom from certain types of generation within the CAISO balancing area at all times to ensure the CAISO can meet its obligations under the NERC BAL-003-1 standard. The RESOLVE model used for the IRP proceeding assumed a total constraint of 770 MW, that is, 770 MW of certain resources types (those operated through governor response) must have committed headroom at all times. Staff implemented the frequency response constraint in SERVM as follows:

- 50% of the headroom requirement (385 MW) is assumed to be met by hydro resources (excluding pumped hydro storage) and is not explicitly modeled. This is based on CAISO's operational experience that hydro can respond to under-frequency at any time without imposing explicit constraints on hydro operations.
- 50% of the headroom requirement (the remaining 385 MW) is assumed to be met by storage (excluding pumped hydro storage) and/or online combined cycle resources.
    - Storage units can satisfy the headroom requirement on a MW-for-MW basis, up to available storage headroom.
    - Combined cycle units can provide 0.08 MW toward the headroom requirement for each MW of online capacity, up to available combined cycle unit head room.
- The headroom requirement applies for all 8760 hours of the typical one-year production cost simulation model.

Staff will collaborate with CAISO staff to update this constraint as needed to be consistent with CAISO's projected frequency response obligations. Staff also intends to seek stakeholder feedback via the IRP's Modeling Advisory Group process on appropriate ways to project and model the ability of other resource types to provide frequency response.

2.10.2.2 Operating Reserve Demand Curves (Scarcity Pricing)

Regulation up, regulation down, spin, and non-spin scarcity prices are input into SERVM, specified according to the applicable remaining hourly reserve margin percentage. While values can vary by region, month, and hour, staff is not currently utilizing this feature. Data for reserve demand curves are in development.

2.11 Other Production Cost Models

Other entities may wish to use other production cost models to conduct studies for comparison to CPUC studies or other related analyses. In this section, staff documents known major differences between SERVM and the PLEXOS model used by the CAISO and the CEC.

The PLEXOS model as generally used by the CAISO and the CEC is used as a deterministic model, that is the model simulates commitment and dispatch of a single study year at a time, with a deterministic set of inputs. This is in contrast to the SERVM model which simulates hundreds of years of a target study year based on stochastic variation of key inputs such as weather and unit outages.

The CAISO's PLEXOS model uses 2009 historical shapes for load, solar, wind and hydro, scaled up to match the annualized forecast values of a target study year. 2009 was selected to be consistent with the TEPPC 2026 Common Case. For modeling intended for comparison with SERVM, the CPUC expects the PLEXOS 2009-based shapes to match with the corresponding 2009 weather-year-based shapes in SERVM.

On January 7, 2019 CPUC staff held an IRP workshop where production costs modeling results were presented by different parties. The workshop materials provide further information comparing different models that will be used to improve modeling efforts going forward.

2.12 Next Steps

Energy Division staff will continue to refine this document, post additional data sets, and work to update the datasets used for production cost modeling. Parties are encouraged to contact Energy Division staff with suggestions of better data sources, help in developing and formatting data, or checking for errors in datasets.

3 Network Reliability Modeling – Transmission Planning Study Inputs and Assumptions

The previous section of this document described the detailed inputs and assumptions that were used in production cost modeling performed by CPUC staff in 2018 with the SERVM model. This section provides additional inputs, assumptions, and guidance intended to inform the network reliability ("power flow") and production cost modeling studies planned for the CAISO's 2019-20 Transmission Planning Process (TPP). This additional information includes:

- Specification of new resource portfolios to be studied in the 2019-20 TPP as the:
    - Reliability Base Case
    - Policy-Driven Base Case
    - Policy-Driven Sensitivity Cases
- Description of key inputs and assumptions that should be used in the 2019-20 TPP studies to leverage the latest available information and maintain alignment and consistency with the CPUC's IRP process
- Guidance on allocating geographically coarse load and resource data from the IRP process to transmission substations in order to facilitate network reliability studies.

3.1 New Resource Portfolios

In accordance with a May 2010 MOU between the CAISO and the CPUC, and in coordination with the CEC, the CPUC develops the new resource portfolios used by CAISO in its annual Transmission Planning Process (TPP). The CPUC typically transmits to the CAISO multiple distinct portfolios developed in its IRP process:

- The "Reliability Base Case" portfolio is used to assess transmission grid reliability and ensure NERC, WECC, and CAISO planning standards are met over a 10-year planning horizon
    - CAISO also uses this portfolio for economic planning studies

- The "Policy-Driven" portfolio(s) may include a base case and one or more sensitivity cases and are used to plan for new renewables deliverability, grid integration, and policy goals that may drive the need for new transmission over a 10-year planning horizon

The following subsections describe the portfolios intended for study in the 2019-20 TPP.

3.1.1 Reliability Base Case

The Reliability Base Case new resource portfolio is based on the IRP Reference System Plan 42 MMT core case developed with the RESOLVE model updated to the 2017 IEPR demand forecast. This case was designed to achieve a 42 MMT GHG emissions target by 2030 statewide. Staff made minor manual adjustments to the RESOLVE-selected new resource portfolio to:

- Accommodate the most recent available information about available transmission and upgrades in different transmission planning areas[86]
- Maximize the deliverability of new geothermal and wind resources to the extent possible.[87]

Table 27 summarizes the Reliability Base Case new resource portfolio. See section 3.1.4 for details on how these resources are allocated to transmission substations to facilitate network reliability studies.

Table 27: Reliability Base Case 2030 New Resources, Deliverable and Energy-Only Nameplate Capacity

Resource Types	**FCDS+EO MW**	**FCDS MW**	**EO MW**
Li Battery, about 1 hour	2,104	2,104	-
Solar	5,916	2,709	3,207
In-State Wind	1,145	341	803
OOS Wind	1,101	1,101	-
Total Wind	2,246	1,443	803
Geothermal	1,700	1,048	652
Total New Renewables	9,862	5,200	4,662
Total New Renewables and Storage	11,966	7,304	4,662

This case also assumes retirement of existing fossil units older than 40-years age and without an existing contract in the year being studied. Staff did not include the retirement assumption as part of the RESOLVE optimization to build the new resource portfolio. Refer to section 3.2.2 for further details on this retirement assumption and how to apply it to the 2019-20 TPP.

86 In January 2019, CAISO transmission planning engineers provided CPUC staff with updated transmission availability and upgrade size and cost data.

87 New geothermal and wind are higher capacity value resources that would likely bid into resource solicitations as fully deliverable and providing RA capacity. Under current assumptions RESOLVE did not need new system RA capacity and thus sometimes selected new geothermal and wind as energy-only resources.

3.1.2 Policy-Driven Base Case

The Policy-Driven Base Case new resource portfolio is identical to the Reliability Base Case new resource portfolio.

3.1.3 Policy-Driven Sensitivity Cases

Two Policy-Driven Sensitivity Case new resource portfolios are described here, one that focuses on in-state new resource development and one that allows selection of moderate amounts of out-of-state (OOS) wind on new transmission when economic. Staff designed these two portfolios using the RESOLVE model updated to the 2017 IEPR demand forecast, but with input assumptions updated to:

- Achieve a 32 MMT[88] GHG emissions target by 2030 statewide
- Achieve at least a 60% RPS
- Include moderately higher demand from light-duty vehicle electrification
- Include a 40-year age-based fossil retirement assumption as part of the RESOLVE optimization
- Include the option of selecting up to 4,250 MW of New Mexico and Wyoming wind potential on new transmission when economic
- Include the most recent available information about available transmission and upgrades in different transmission planning areas

In addition, the portfolios selected by RESOLVE were manually adjusted to maximize the deliverability of new geothermal and wind resources to the extent possible, and to fit the portfolio within the "nested" transmission availability constraints specified by CAISO engineers.[89]

Both recommended portfolios include substantially larger amounts of new resources than have been previously studied by the CAISO. Both portfolios trigger in-state transmission upgrades in order to access greater amounts of renewables potential. The in-state focused case required up to 1,570 MW of upgrade in the Westlands area and up to 654 MW of upgrade in the Greater Carrizo area. The case allowing OOS wind only required the up to 654 MW of upgrade in the Greater Carrizo area. These upgrades also imply a necessary similar sized upgrade to the Southern PG&E area that encompasses both Westlands and Greater Carrizo.

Table 28 summarizes the two Policy-Driven Sensitivity Case new resource portfolios. See section 3.1.4 for details on how these resources are allocated to transmission substations to facilitate network reliability studies.

[88] 32 MMT according to the 2017-18 IRP proceeding version of RESOLVE which does not include BTM CHP emissions of about 4 MMT.

[89] "Nested" refers to the fact that certain groups of transmission planning areas have individual transmission availability constraints and a whole group of areas also has a total transmission availability constraint. The sum of individual area constraints is often greater than the total constraint over a group of areas. At this time, RESOLVE can only handle "flat" transmission availability constraints and does not handle "nested" constraints, hence the need to make some manual adjustments either to RESOLVE inputs, outputs, or both to ensure fit within the actual "nested" constraints.

Table 28: Policy-Driven Sensitivity Cases 2030 New Resources, Deliverable and Energy-Only Nameplate Capacity

	Sensitivity #1: In-state focus with OOS wind on existing transmission only			Sensitivity #2: Allow up to 4,250 MW OOS wind on new transmission		
Resource Types	**FCDS+EO MW**	**FCDS MW**	**EO MW**	**FCDS+EO MW**	**FCDS MW**	**EO MW**
Li Battery, about 2 hour	-	-	-	2,602	2,602	-
Li Battery, about 4 hour	4,347	4,347	-	-	-	-
Pumped Storage Hydro	1,342	1,342	-	-	-	-
Solar	11,588	3,952	7,636	6,220	2,004	4,216
In-State Wind	2,775	2,512	262	2,333	2,070	262
OOS Wind	2,000	1,466	534	6,250	2,273	3,977
Total Wind	4,775	3,978	797	8,583	4,344	4,239
Geothermal	2,020	1,368	652	2,020	1,368	652
Total New Renewables	18,383	9,298	9,085	16,823	7,716	9,107
Total New Renewables and Storage	24,071	14,987	9,085	19,425	10,318	9,107

This case also assumes retirement of existing fossil units older than 40-years age and without an existing contract in the year being studied. Staff approximated and included the 40-year age-based fossil retirement assumption as part of the RESOLVE optimization to build the new resource portfolios. However, the amount retired in RESOLVE is not the same as the amount that should be assumed retired to be consistent with the Reliability Base Case (less total existing capacity was assumed retired in the Reliability Base Case because some units were assumed to stay online until end of contract if the contract was still in place at age 40). Refer to section 3.2.2 for further details on this retirement assumption and how to apply it to the 2019-20 TPP. When studied in the TPP, the two Policy-Driven Sensitivity Cases should implement the 40-year retirement assumption in the same manner as the Reliability Base Case, in other words assuming units stay online until end of contract if the contract is still in place at age 40.

3.1.4 Allocation to Transmission Substations

Each of these TPP study cases must have all resources mapped to transmission substations in order to facilitate power flow analysis. This includes renewable projects under development with approved contracts as well as new generic projects. The CPUC has worked with the CAISO and CEC to identify each project and map it to an appropriate substation if it does not already have one assigned. At the request of CPUC staff, CEC staff have allocated each of the new generic resources in the portfolios described above to substations. The workbooks providing details on resource mix by transmission areas and deliverability status are posted to the CPUC website.[90] The workbook with substation allocations is posted to the CEC website.[91]

3.2 Other Key Inputs and Assumptions and Allocations to Substations

Besides studying the new resource portfolios from the CPUC, the CAISO's TPP should also align a number of its other key inputs and assumptions with those used in the CPUC's IRP process and other resource program areas, and the CEC's IEPR demand forecast. These include:

- Load and load-modifiers
- Fossil retirement assumptions
- Energy storage
- Demand response

3.2.1 Load and Load-modifiers

As stated in the 2018 IEPR Update report adopted by the CEC in February 2019,[92] the managed Single Forecast Set specifies that the California Energy Demand (CED) 2018 adopted baseline "mid demand" case paired with the mid-mid Additional Achievable Energy Efficiency (AAEE) and Additional Achievable Photo-Voltaics (AAPV)[93] forecast scenarios shall be used for bulk system studies, while the mid-low AAEE and AAPV scenarios shall be paired with the baseline mid demand case for local reliability studies. Accordingly, the 2019-20 TPP should use the managed Single Forecast Set from the 2018 IEPR Update California Energy Demand Updated Forecast 2018-2030 as fundamental input.

Note that the IRP process relied on the previous IEPR vintage (the 2017 IEPR and corresponding CED forecast) to develop portfolios for eventual study in the CAISO's TPP. The CPUC recognizes that the CAISO's TPP may be based on an IEPR vintage that differs from that which was used to develop the IRP proceeding's Reference or Preferred System Plan portfolios to be studied in the CAISO's TPP. This mismatch is acknowledged and considered necessary and acceptable.

The aggregate load and load modifier assumptions from the IEPR CED forecast must be assigned to CAISO-controlled transmission substations to facilitate network reliability studies.

- For load (including committed energy efficiency, committed BTM PV, load-modifying demand response (e.g. non-event based or price responsive), and other non-PV self-generation) there exists a mature process for the CAISO to work with Participating Transmission Owners (PTOs) to allocate IEPR CED forecast load to substations.
- For the incremental load modifier AAEE, the CEC provides substation allocations of the mid-low AAEE forecast scenario directly to the CAISO. The allocation is generally based on the mix of load by economic sector currently at each substation, matched with the energy efficiency

[90] http://www.cpuc.ca.gov/General.aspx?id=6442460548

[91] https://efiling.energy.ca.gov/Lists/DocketLog.aspx?docketnumber=17-MISC-03

[92] https://efiling.energy.ca.gov/getdocument.aspx?tn=226392

[93] Incremental BTM PV adoption to reflect 2019 Title 24 residential building standards update in support of Zero Net Energy goals for new residential homes, starting in 2020.

programs targeting those sectors. The mid-low AAEE forecast is used in power flow studies to assess local reliability due to locational uncertainty on which specific locations the energy efficiency savings will materialize.

- For the incremental load modifier AAPV, the CAISO works with staff at the CEC and CPUC to leverage analysis such as that developed by the CPUC's consultant, DNV-GL,[94] and with the three large IOUs in their capacity as CAISO PTOs, to allocate the forecast AAPV amounts to substations.

3.2.2 Fossil Retirement Assumptions

All portfolios that the CPUC recommends for study in the 2019-20 TPP include planned or announced retirements from existing units (such as Diablo Canyon Power Plant and other once-through-cooled units), plus an incremental 40-year age retirement assumption to approximate additional potential for existing fossil units to retire within the IRP planning horizon. Specifically, existing fossil units older than 40-years age and without an existing contract in the year being studied are assumed retired. The CAISO's TPP should study the transmission implications of up to this level of retirement to inform the question of how much existing generation may need to be retained to cost-effectively maintain not just system but also local reliability standards. The table below shows the additional capacity that could be retired by 2030 with the 40-year age-based assumption. This is incremental to planned or announced retirements. More detailed data itemizing specific existing units and assumed retirement years is posted to the CPUC's website.[95]

Table 29: Additional Capacity Assumed Retired by 2030 Due to 40-year Assumption, Nameplate MW

	CCGT	CT	Cogeneration	Steam	ICE	Total
PGE Bay	0	384	131	0	0	514
PGE Valley	78	25	787	0	0	890
SCE	0	143	1,064	49	0	1,255
SDGE	0	0	109	0	0	109
CAISO	78	552	2,090	49	0	2,768

3.2.3 Energy Storage

The total energy storage resources that should be considered in the TPP studies include existing pumped hydro storage, existing battery storage, contracted and/or committed battery storage to ensure achievement of the CPUC 1,325 MW storage target by 2024, and finally new battery storage by 2030 that is beyond the 1,325 MW target and new pumped hydro storage (i.e. selected by RESOLVE). In the RESOLVE model, existing battery storage (119.5 MW as of early 2018) is subsumed within either the

[94] California Public Utilities Commission, *Customer Distributed Energy Resources Grid Integration Study: Residential Zero Net Energy Building Integration Cost Analysis*, October 18, 2017.

[95] Available here: http://www.cpuc.ca.gov/General.aspx?id=6442460548

1,325 MW target or the amounts of new battery storage selected by RESOLVE. Thus, the summary table below does not include a line item for existing battery storage.

Table 30: Total Energy Storage Associated with each TPP Portfolio

All values are for 2030	Reliability and Policy-Driven Base Case		Sensitivity #1: In-state focus with OOS wind on existing transmission only		Sensitivity #2: Allow up to 4,250 MW OOS wind on new transmission	
	MW	Hours	MW	Hours	MW	Hours
Existing pumped hydro storage	1,832	na	1,832	na	1,832	na
Battery storage to achieve the 1,325 MW target	1,325	4	1,325	4	1,325	4
New battery storage selected by RESOLVE	2,104	1.3	4,347	4	2,602	2
New pumped hydro storage selected by RESOLVE	-	na	1,342	na	-	na

Note that the CEC's IEPR demand forecast includes a projection of peak demand reduction due to BTM energy storage impacts. This projection does not overlap with the assumed energy storage procurement due to the 1,325 MW target.

CPUC staff is aware that the IOUs have recently procured battery storage that in aggregate exceeds the 1,325 MW target. However, that amount is still far less than the candidate "new" battery storage selected in the IRP process. Thus, it is reasonable to assume that the sum of 1,325 MW and the "new" battery storage selected in the IRP process is inclusive of the existing online and recently procured (but not yet online) battery storage.

To be modeled in the TPP base study cases, the CAISO needs to know the locations and operational attributes of energy storage resources. This information is obtainable for all existing online units and contracted but not yet online projects. CPUC staff is in the process of collecting the most recent information about procured storage resources. CPUC staff will provide that information to the CAISO when it is finished compiling that data. The CAISO will then use that information to map storage resources to specific locations and model operations, all of which is expected to be documented in the CAISO's study results. As an example of the data that CPUC staff will be updating, the list of procured storage resources that was provided to the CAISO in early 2018 is posted to the CPUC website.[96]

[96] Available here:
http://www.cpuc.ca.gov/uploadedFiles/CPUCWebsite/Content/UtilitiesIndustries/Energy/EnergyPrograms/ElectPowerProcurementGeneration/irp/2018/Combined_IOU_Storage_2017update_public.xlsx

The TPP portfolios also include "generic" storage resources that are beyond what is existing and/or under contract. Generic storage resources are any residual amounts yet to be procured to satisfy the requirements of the 1,325 MW target, or the candidate "new" storage selected in the IRP process (in the Reliability Base Case this is 2,104 MW of battery storage).

These generic storage resources have unknown locations and operational attributes and the CAISO will not include them in the TPP base study cases. Instead, generic storage will form a pool of resources available to mitigate any issues revealed in the TPP base case studies, for example, renewables integration or local capacity reliability issues. The CPUC in coordination with the CAISO and its 2019-20 TPP study process will jointly develop a framework for siting generic storage to locations that provide the highest value to resolving renewables integration and/or local capacity reliability issues that will not be apparent until draft TPP base case results become available in early fall, 2019. This process can reveal more valuable locations and use cases for storage that can inform market participants where projects should be interconnected and how they should be used.

3.2.4 Demand Response

This subsection provides guidance on modeling treatment of demand response (DR) programs in network reliability studies including allocating capacity from those programs to transmission substations.

The CPUC's RA proceeding (R.17-09-020 or its successor) determines what resources can provide system and local resource adequacy capacity. Current RA accounting rules indicate that all existing DR programs count to the extent those programs impacts are located within the relevant geographic areas being studied for system and local reliability.

By nature, impacts from DR programs are distributed across large geographies. To be applied in network reliability studies, capacity from DR programs must be allocated to transmission substations in order to facilitate power flow analysis. [97] The CPUC requested the IOUs to allocate their existing DR programs[98] to substations, with the expectation that the IOUs would submit that information to CAISO through the CAISO's annual TPP Study Plan stakeholder process that solicits input on DR assumptions.[99] The data contains confidential information so the CPUC expects the CAISO and the IOUs in their capacity as PTOs to exchange the data using their own NDAs.

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[97] The CAISO noted that DR eligible for inclusion in the TPP must be allocated to CAISO-controlled substations and must be a CAISO integrated resource, meaning that resource is mapped to specific "PNodes"

[98] Based on the April 2018 annual Load Impact Reports, using the August portfolio-adjusted 1-in-2 weather year condition ex-ante forecast of load impact coincident with CAISO system peak

[99] http://www.caiso.com/Documents/StakeholderInput-2019-2020UnifiedPlanningAssumptions.html