Incremental ELCC Study for Mid-Term Reliability Procurement

(January 2023 Update)

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PREPARED FOR

The California Public Utilities Commission (CPUC)

PREPARED BY

Astrapé Consulting

Kevin Carden
Trevor Bellon

Energy + Environmental Economics

Aaron Burdick
Charles Gulian
Arne Olson

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EXECUTIVE SUMMARY

PURPOSE

The CPUC's Mid-Term Reliability (MTR), Decision (D.21-06-035), orders the procurement of 11,500 megawatts (MW) of net qualifying capacity (NQC) and requires standardized effective load carrying capability (ELCC) values. These standardized values allow for load serving entities (LSEs) to know the compliance value of various incremental resource types and allows for the CPUC to be confident that incremental procurement will fill their identified procurement need. This report presents updates to the ELCC values to be used for compliance with the CPUC's MTR Decision. The ELCC values for 2023 ("Tranche 1") and 2024 ("Tranche 2") compliance dates were finalized in a report by the CPUC in October of 2021. This report presents updates to the previously reported ELCC values for 2025 ("Tranche 3") and 2026 ("Tranche 4") compliance dates. Additionally, this report presents ELCC values for 2027 ("Tranche 5") and 2028 ("Tranche 6"), based on the January 13, 2023, Integrated Resource Planning (IRP) Proposed Decision that proposes additional MTR procurement. The study also presents a comparison to previous ELCC studies and sensitivities that consider drivers of ELCC uncertainty. E3 and Astrapé produced this study as technical consultants to the CPUC using Astrapé's Strategic Energy and Risk Valuation Model (SERVM) stochastic loss of load probability (LOLP) model.

BACKGROUND

Many renewable energy resource types, such as wind and solar resources, are non-dispatchable and variable in output, and dependent upon external conditions such as weather. Energy-limited resources such as battery storage have constraints on their ability to be discharged and are subject to charging limitations based on available excess energy from other generators. Consequently, the ability of these resources to serve load is not the same as a traditional, firm[1] dispatchable resources. Therefore, a measure of their equivalent capacity is needed so that these resources can be properly accounted for in resource adequacy (RA) assessments and procurement. The emerging industry standard for this purpose is ELCC.

This study examined the incremental ELCC of energy storage, solar photovoltaic (PV), and wind in the California Independent System Operator (CAISO) footprint to provide ELCC assumptions to LSEs for compliance with the CPUC's MTR Decision.[2] This study's primary focus was on Tranches 3 and 4: pertaining to requirements of 1,500 additional megawatts (MW) by 2025 and 2,000 additional MW by 2026. Additionally, the study reflects the proposed changes to MTR in the January 13, 2023, IRP Proposed Decision, whereby the 2,000 MW long-lead time ("LLT") resource tranche is delayed until 2028, a new 2,000 MW Tranche in 2026 replaces that LLT volume, and another 2,000 MW tranche is added in 2027.

[1] A "firm" resource can operate indefinitely when called upon.

[2] D.21-06-035, available at: https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M389/K603/389603637.PDF

METHODOLOGY

ELCCs are calculated by determining the reliability improvement contributed to the system by incremental resources in terms of the amount of additional load that can be served because of that improvement in reliability, calculated relative to a perfect capacity firm generator with no outages.[3] Thus, ELCC provides a consistent metric through which renewable and energy-limited resources can be directly compared with one another and with dispatchable generation resources based on their ability to fill the CAISO's mid-term capacity shortfall.

This study began with a resource portfolio intended to represent the expected CAISO resource portfolio in 2025, prior to the MTR procurement in 2025 and later years. This portfolio was determined by adding to the MTR baseline portfolio: 1) resources procured by LSEs in compliance with the D.19-11-016 procurement order and 2) expected cumulative LSE resource additions for compliance with MTR Tranches 1 and 2 in 2023 and 2024. The additions to the MTR baseline reflect LSE procurement data for D.19-11-016 and MTR Tranches 1 and 2 contracts, received from LSEs by CPUC staff on 8/1/2022. Recognizing that solar and energy storage resources significantly interact with each other and are likely to form the bulk of resource additions, E3 and Astrapé designed a "surface" of incremental solar and storage additions. Wind resources were studied at various points in this surface, aligned with MTR Tranches. This surface covered the existing MTR Tranches 3 and 4, as well as the additional 4,000 MW procurement volume recently proposed in the IRP proceeding and captured in Tranches 5 and 6.[4]

This analysis used the CPUC Energy Resource Modeling (ERM) team's latest SERVM version,[5] with its existing load and resources data across 1998-2020 weather years, and made a variety of updates including minor refinements of the MTR baseline, wind shape adjustments, hydro de-trending and de-coupling, and load shape adjustments consistent with 2021 Integrated Energy Policy Report (IEPR) load. For this analysis, the ELCC of incremental resource additions was determined by comparing the reliability improvement achieved with the equivalent reliability of a perfect capacity generator (represented by a combustion turbine – CT – with no forced or planned outages).[6]

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[3] In the academic literature the comparison is performed against flat blocks of load. However, in practice in the industry, the comparison is often made to generation modeled without forced or planned outages.

4 The four tranches described in this report refer to the four years of procurement ordered in the MTR decision – 2023-2026 – and are separate and distinct from the three tranches of procurement ordered in the short-term reliability decision (2021-2023), although Tranche 1 of MTR procurement coincides with Tranche 3 of the short-term reliability decision procurement.

[5] As described in "Energy Division Study for Proceeding R.21-10-002: Loss of Load Expectation and Slice of Day Tool Analysis for 2024" available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M501/K409/501409211.PDF

[6] Per the FAQ document released by CPUC staff on August 24, 2021, "for resource types for which staff publish ELCCs for by the end of August 2021, per OP 15, the ELCC is annual and should be used to determine compliance with OP 1 and OP 3. For other resource types, LSEs should use the September NQC according to RA program

RESULTS

> **"Marginal" vs. "Incremental" ELCCs**: *marginal* ELCCs refer to the ELCC benefit of adding one additional MW to a system (or another reasonably small amount). *Incremental* ELCCs refer to the ELCC benefit of a larger incremental addition or the subsequent benefits of multiple increments of additions.

The ELCCs by MTR Tranche are presented in Table 1. By Tranche 3, energy storage resources provide less than 80% incremental ELCC due to the existing CAISO storage penetration from past procurement, including Tranches 1 and 2. Energy storage ELCC decline can be partially offset with longer duration storage additions. Solar ELCCs are generally very low due to the late evening net peak but continue to provide value through their interactive effects with other resources, including providing mid-day charging energy. While solar ELCCs monotonically decline with increases in solar penetration in isolation, solar ELCCs can increase when storage penetrations increase and energy constraints become binding. This is the effect observed in the increase in solar ELCC between Tranche 3 and 4, and the continued (albeit small) incremental reliability value of solar through 2028. The assumed addition of both solar and storage helps to maintain the reliability value of both resources. In-state wind ELCCs are generally low, reflecting updated wind shapes showing lower summer afternoon output. Out-of-state wind and offshore wind show higher ELCCs than in-state wind due to their higher output during net peak conditions. The results presented in Table 1 are applicable to storage technologies other than batteries and pumped storage hydro, provided that such storage resources have comparable round-trip efficiencies and durations.

rules at the time of contract signing." The FAQ document is available at: https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/electric-power-procurement/long-term-procurement-planning/more-information-on-authorizing-procurement/irp-procurement-track

Table 1. Incremental ELCCs by MTR Tranche

	From prior study, for reference only		Updated values from this study		Additional Proposed MTR Tranches[7]	
	Tranche 1 2,000 MW 2023	Tranche 2 6,000 MW 2024	Tranche 3 1,500 MW 2025	Tranche 4 2,000 MW 2026	Tranche 5 2,000 MW 2027	Tranche 6 2,000 MW 2028
4-Hour Battery	96.3%	90.7%	75.1%	76.6%	74.0%	76.5%
6-Hour Battery	98.0%	93.4%	79.6%	80.3%	80.5%	83.3%
8-Hour Battery	98.2%	94.3%	84.0%	84.0%	87.1%	90.1%
8-Hour PSH	N/A	76.8%	82.6%	82.6%	85.7%	88.7%
12-Hour PSH	N/A	80.8%	86.6%	86.6%	89.7%	92.7%
Solar - Utility and BTM PV	7.8%	6.6%	6.6%	7.0%	7.5%	8.8%
Wind CA	13.9%	16.5%	12.0%	13.2%	14.0%	14.7%
Wind WY	28.9%	28.1%	31.0%	33.0%	31.7%	30.9%
Wind NM	31.1%	31.0%	30.0%	35.0%	33.7%	31.9%
Wind Offshore	N/A	N/A	48.0%	46.0%	44.0%	44.7%

Compared to the MTR ELCC study released in October 2021, the changes to Tranche 3 and 4 ELCC values were generally small. The largest change was to the wind ELCC values resulting from improvements to the wind shapes used in this study. These improvements led to lower in-state wind ELCCs and higher offshore wind ELCCs. The *ELCC Comparison to Past Studies* section of this report explains why and how ELCC values shift from study to study, highlighting the importance of regular updates to long-term ELCC forecasts as the load shapes, system portfolio, and weather trends evolve over time. The fact that ELCC values evolve as system portfolios change and as new weather and operational data becomes available is a key benefit of the methodology that supports continuous improvement in the CPUC's reliability planning, though it is recognized that the variable nature of ELCC values poses a challenge to multi-year forward procurement efforts.

Sensitivity analyses were conducted to consider the sensitivity of solar and storage ELCCs to key portfolio and operational parameter inputs. These analyses show that the solar and storage ELCCs presented in the table above could change by up to +/- 10 percentage points under various assumptions of future load shapes and battery operations. Further collaboration with the California Energy Commission (CEC) on multi-year weather and load datasets may reduce uncertainty in the CAISO load shape, and as batteries grow on the CAISO system, expanded operational data -- including forced outage rates/durations and ability to dispatch optimally to reduce loss of load risk -- will reduce the uncertainty in storage ELCCs.

[7] The years and volumes shown here are based on the January 13, 2022 Proposed Decision. Tranche 5 consists of 2,000 MW in 2027 and Tranche 6 consists of 2,000 MW – assumed to be 1,000 MW long duration storage and 1,000 MW firm zero carbon renewables – in 2028.

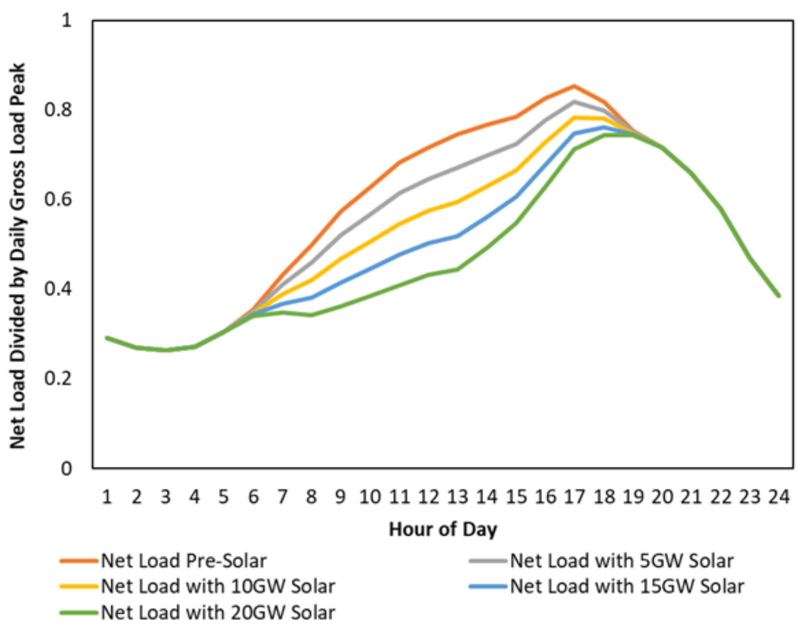
BACKGROUND AND METHODOLOGY

MTR PROCESS AND NEED FOR INCREMENTAL ELCCS

The MTR Decision requires that at least 11,500 MW of additional net qualifying capacity (NQC) be procured by all the LSEs subject to Commission jurisdiction. The capacity requirements are divided into four “tranches”: 2,000 MW by 2023, 6,000 additional MW by 2023, 1,500 additional MW by 2025, and 2,000 additional MW by 2026. Two additional procurement tranches are now proposed in the IRP proceeding for 2,000 MW in 2027 and 2,000 MW in 2028. The very large amount of capacity ordered (approximately a third of the system managed peak demand) requires a robust method for ensuring that incremental reliability contributions used by LSEs in their evaluations and compliance filings will be sufficient to completely fill the procurement need identified.

Unlike traditional resources, the system reliability contributions of renewable and energy-limited resources decline with greater penetrations of such resources. This is because energy-limited resources do not have the same dispatch flexibility that traditional resources have to meet changing system dynamics and are subject to “saturation effects.” For example, as solar is added to the system, the injections into the system from the solar resources cause a shift in the timing of the net load peak as demonstrated in Figure 1. Incremental solar produces less energy during the new net load peak period and has a corresponding lower reliability contribution.

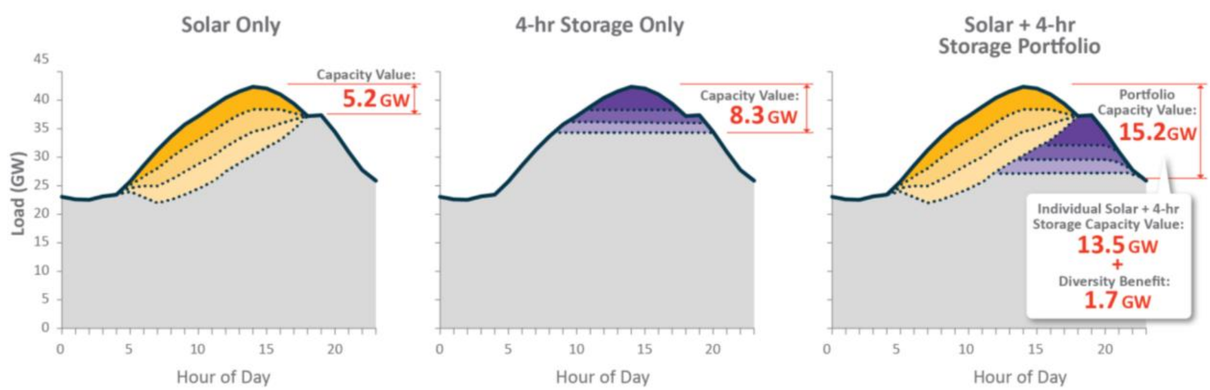
Figure 1. Illustrative Net Load Shift Due to Solar Penetration



The orange line in Figure 1. Illustrative Net Load Shift Due to Solar Penetration depicts the net load assuming no solar (i.e., gross load less other modifiers such as wind, energy efficiency, etc.), and the different colored lines below the no solar line depict net loads at various penetrations of solar. The figure clearly depicts a time shift in the “net load peak” of the system. As the new net load peak approaches dusk, the contribution that the next increment of solar provides for meeting that new peak is smaller than that of previous increment. The result is that over time, as solar is added to the system, the average ELCC – the total reliability value of all the solar resources – decreases. These dynamics are often referred to as "saturation effects."

In addition to ELCC dynamics within a resource type (e.g., solar), there are ELCC dynamics between resource types, which are referred to as "diversity impacts." This concept is illustrated in Figure 2 below, which shows that solar and energy storage added together provide more than the sum of their parts. Energy storage shifts the peak back to the higher solar production hours, during which solar can both charge energy storage and narrow the residual net peak period that storage must serve as solar production wains.

***Figure 2. Schematic of "Diversity Impacts" between Solar and Energy Storage*[8]**



Due to these saturation effects and diversity impacts, the average ELCC of the portfolio does not accurately reflect the true reliability benefit of the next increment of a resource added to the system. Therefore, for all renewable and energy-limited resources, the only way to truly capture the reliability benefit of these incremental resources is to calculate the incremental ELCC of adding new resources, which will be different than the average ELCC of the entire portfolio. Loss of load probability (LOLP) modeling is used for ELCC calculations because it accurately captures reliability contributions across a broad range (years or decades) of system conditions and because it robustly captures interactive effects between incremental resources and the existing system fleet. This study used Astrapé's stochastic LOLP reliability model SERVM for these ELCC calculations.

SERVM ELCC CALCULATION METHODOLOGY

ELCCs are calculated using SERVM by determining how much additional load can be served by the renewable/energy limited resources while maintaining a targeted reliability benchmark, expressed in

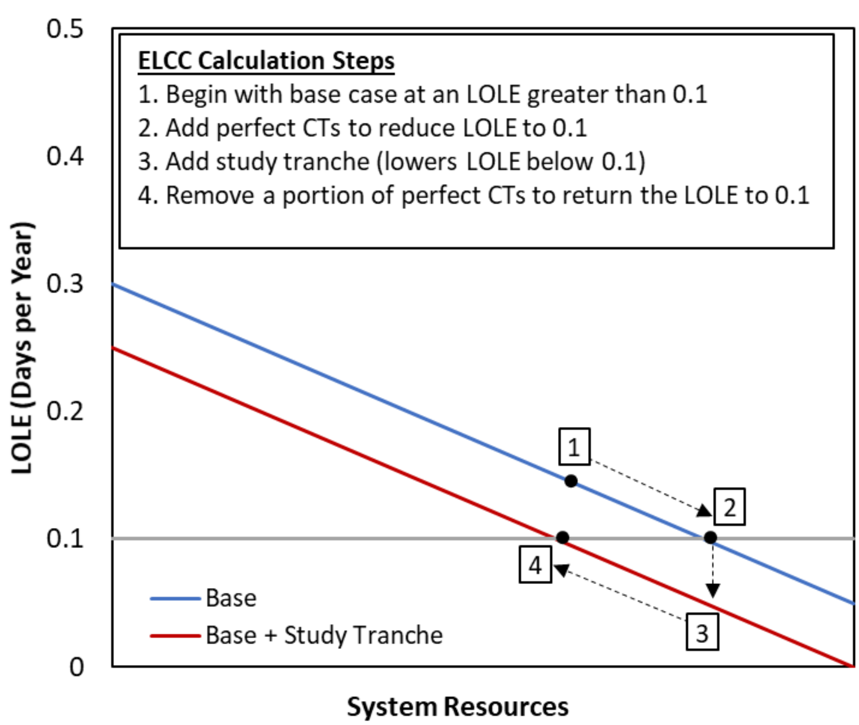
[8] N. Schlag, Z. Ming, A. Olson, L. Alagappan, B. Carron, K. Steinberger, and H. Jiang, "Capacity and Reliability Planning in the Era of Decarbonization: Practical Application of Effective Load Carrying Capability in Resource Adequacy," Energy and Environmental Economics, Inc., Aug. 2020

terms of Loss of Load Expectation (LOLE). The resource adequacy framework of SERVM ensures that the reliability impact of the renewable/energy-limited resources are evaluated across a broad range of weather patterns via historical weather years, economic growth scenarios, and outage conditions.

SERVM models renewable resources as an 8,760-hour per year injection profile into the system. A separate injection profile is modeled for each weather year considered. Battery and pumped storage hydro (PSH) resources are modeled with an initial generation schedule determined day-ahead, but which can be altered under emergency conditions. Battery resources, however, can dispatch more flexibly and serve ancillary services at a wider range of dispatch levels. These resources are modeled along with all other dispatchable resources using an 8,760-hour chronological, economic dispatch modeling approach.

To determine the reliability benefit of a portfolio of renewable/energy-limited resources, the representative 2025 starting portfolio is first calibrated to a presumed target level of reliability by adding or removing perfect capacity. For this study, the system was calibrated to the reliability standard LOLE of 0.1 days/year. The study tranche being considered (e.g., the first tranche of modeled storage additions) is then added to the system to determine the improvement in LOLE. The system is then returned to the target 0.1 days/year LOLE by removing a portion of the previously added perfect capacity. The difference in LOLE between the base case condition and the study tranche condition is the reliability benefit provided by the test portfolio. This process is illustrated in Figure 3 below.

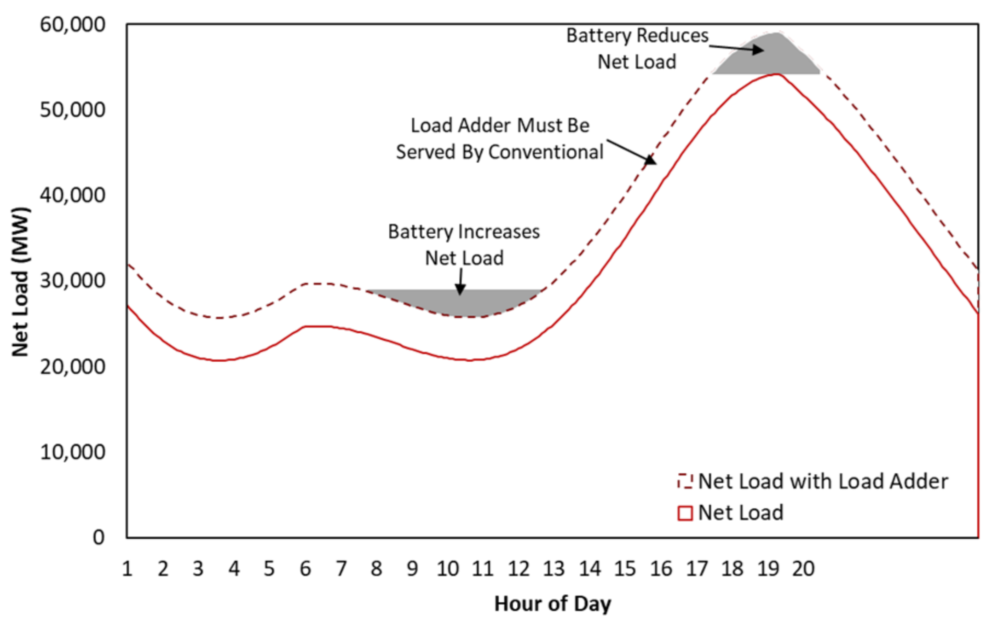
Figure 3. ELCC Calculation Process Visual



The amount of perfect capacity removed to achieve 0.1 days/year LOLE will be less than the nameplate capacity of the study tranche and represents the equivalent capacity value of the study tranche. Dividing the equivalent capacity value by the nameplate capacity of the tranche results in the incremental ELCC (expressed in percent).

When assessing ELCC, either the addition of perfect load (i.e., flat load) or the removal of perfect capacity (i.e., a dispatchable generator with no forced or planned outages) can be used. There is no industry standard approach, and both methods have been used widely in the industry; however, the method used may capture different interactive effects on energy-limited resources (such as energy storage). Prior ELCC studies performed by Astrapé for California have used the addition of perfect blocks of load to compare the reliability contributions of incremental generation.[9] That method leaves existing generation with forced outages in the fleet and tends to exacerbate negative interactions across resource classes. For instance, adding energy storage may require existing firm[10] generation to operate more mid-day to charge the storage. The additional load associated with the "perfect load" LOLE tuning method adds load in all hours, which requires dispatchable generation to operate to charge the battery and then even more dispatchable generation to operate to serve the mid-day load added. This increased operation leads to more outages and commensurately lower ELCCs for storage. Wind resources have similar effects since they have less energy prior to the peak than during the peak.

Figure 4. **Flat Load Addition Effect on Firm Generator Operations**



In contrast, the perfect capacity method typically entails a firm capacity comparison resource with no availability limits. This resource could be modeled as a "first in the stack" firm resource (i.e., a baseload resource dispatched before other dispatchable resources), or a "last in the stack" firm resource (i.e., a

[9] https://www.astrape.com/wp-content/uploads/2022/03/2021-Joint-IOU-ELCC-Study-Final-Report.pdf

[10] The term "conventional" in this report refers to resources that can be turned on and off to reflect market conditions and do not have energy/duration constraints, such as gas power plants.

peaking resource dispatched after other dispatchable resources when required to avoid loss of load). The "first in the stack" method is akin to adding load in every hour and therefore can have the same impacts on renewable and storage resources as noted above for the flat load method. The "last in the stack" method has fewer system interactions since the perfect resource being added is only operated in a manner to avoid loss of load risk versus operating in a way that changes the operations of the rest of the existing fleet. This translates into a slightly higher ELCC for storage and renewable resources, since no additional system outages are introduced in off-peak hours by the need to serve incremental load additions. The "last in the stack" perfect capacity method was chosen for this analysis because it aligns with the method used by the CPUC ERM team in their ELCC calculations, and while results are similar between both "first in the stack" and "last in the stack" methods, the selected approach most accurately reflects the reliability contribution of these resources in the system as it is projected to exist. Using the "last in stack" perfect capacity method can require removing existing firm generation from the baseline system used in this study.

STUDY DESIGN

This study was designed similarly to the previous MTR ELCC study released on 10/21/2021. The following key steps were utilized:

1. Complete SERVM methodology and input updates to the latest CPUC model version
2. Update the CAISO portfolio to reflect the MTR baseline portfolio plus projected LSE resource additions through 2024 in compliance with D.19-11-016 procurement order and MTR Tranches 1 and 2
3. Design a "surface" of incremental solar and storage additions to represent expected mid-term capacity additions in 2025, 2026, 2027, and 2028
4. Model the individual and combined additions of solar and storage capacity
5. Interpolate storage ELCCs for the resource additions needed to fill the remaining need in each MTR tranche after accounting for the ELCC of modeled solar additions
6. Allocate diversity impacts between solar and storage using the "delta method"
7. Model wind and long duration energy storage (LDES) ELCCs within each tranche of solar and 4-hour battery storage additions

The key SERVM input and methodology changes are described in the "Input Assumptions" section of this report below, which included offshore wind shapes, neighbor modeling, load shape adjustments, and hydro modeling. CAISO portfolio updates to the baseline 2022 portfolio provided by CPUC staff included the following changes:

- Add forecasted incremental utility-scale solar, energy storage, and other resource additions within the MTR baseline (resources contracted by 6/30/2020) and add any additional resources required for D.19-11-016 compliance
- Add projected MTR Tranche 1 and Tranche 2 LSE additions (i.e., forecasted additions through 2026 based on in-development contracts executed and approved by 8/1/2022 date)

- Remove planned resource retirements (OTC gas units, Diablo Canyon[11], Intermountain, etc.) and age-based retirements
- Update load forecast and load modifiers according to the 2021 IEPR forecast (including consumption, behind-the-meter (BTM) PV, additional achievable energy efficiency (AAEE), time-of-use (TOU), and electric vehicle (EV) loads)

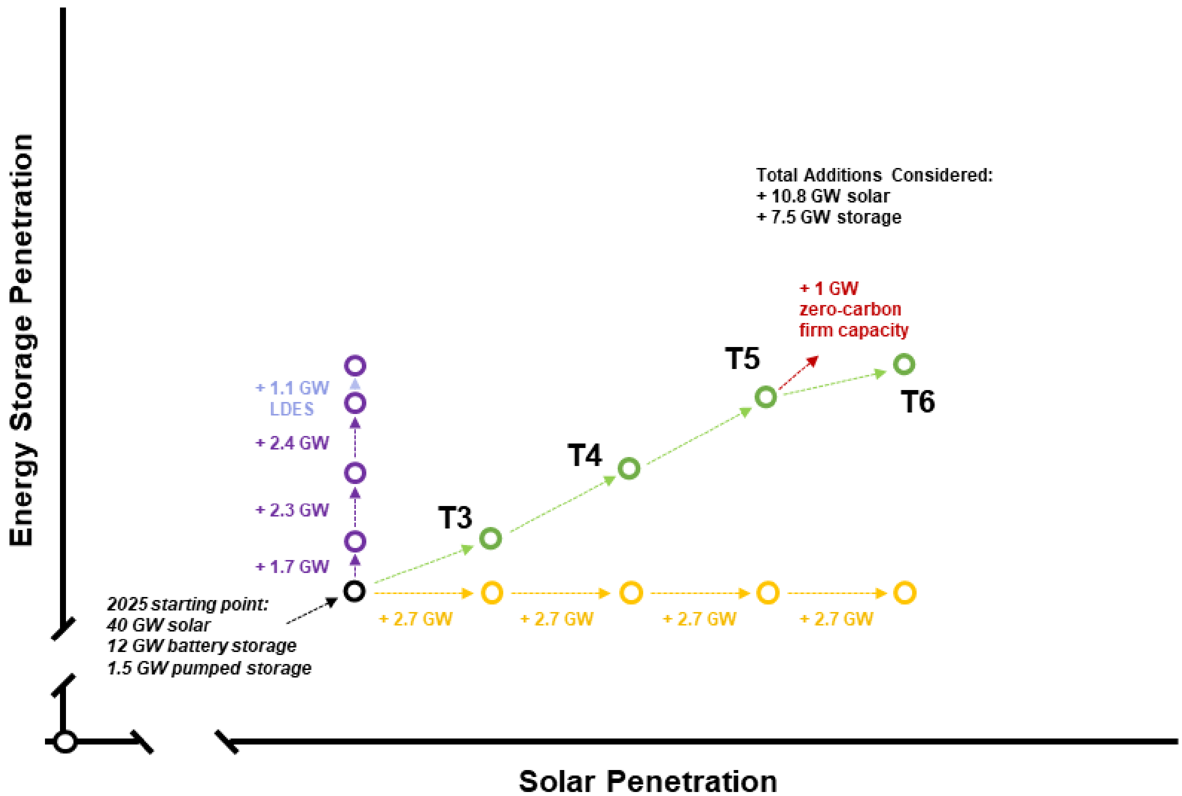
Loads were held constant at the 2030 level, because load changes between 2025 and 2030 are expected to have minimal impact on ELCCs and changing loads between study tranches would have introduced another variable to disentangle from the aggregated impact of increasing solar and storage penetration. The final CAISO portfolio onto which incremental resources were added is described in

[11] Per SB846, Diablo Canyon is excluded from this analysis. "The bill would require that the PUC not include, and disallow a load-serving entity from including in their adopted resource plan, the energy, capacity, or any attribute from the Diablo Canyon powerplant in the integrated resource plan portfolios beyond specified dates, and would require the Energy Commission not consider the energy, capacity, or any attribute from the Diablo Canyon powerplant in meeting the above state policy."

Table 3 below.

The solar and storage ELCC surface design assumed incremental utility-scale solar based on the 2022 updated 38 MMT Preferred System Plan (PSP) portfolio, adopted in D.22-02-004, while incremental BTM PV additions were based on the 2021 IEPR forecast. Indications are that using a 30 MMT PSP portfolio would not materially change the results before 2028. Storage additions were designed to capture a range of additions of both 4-hour and 8-hour duration storage that would enable interpolating to determine the nameplate storage additions needed to fill each tranche with energy storage ELCC MW. The solar and storage capacities in each tranche are described further in tables in the *Solar and Storage Surface Inputs* section below. The solar and storage additions assumed to fill each MTR tranche are shown in Figure 5. Solar and storage additions by MTR tranche

Figure 5. Solar and storage additions by MTR tranche

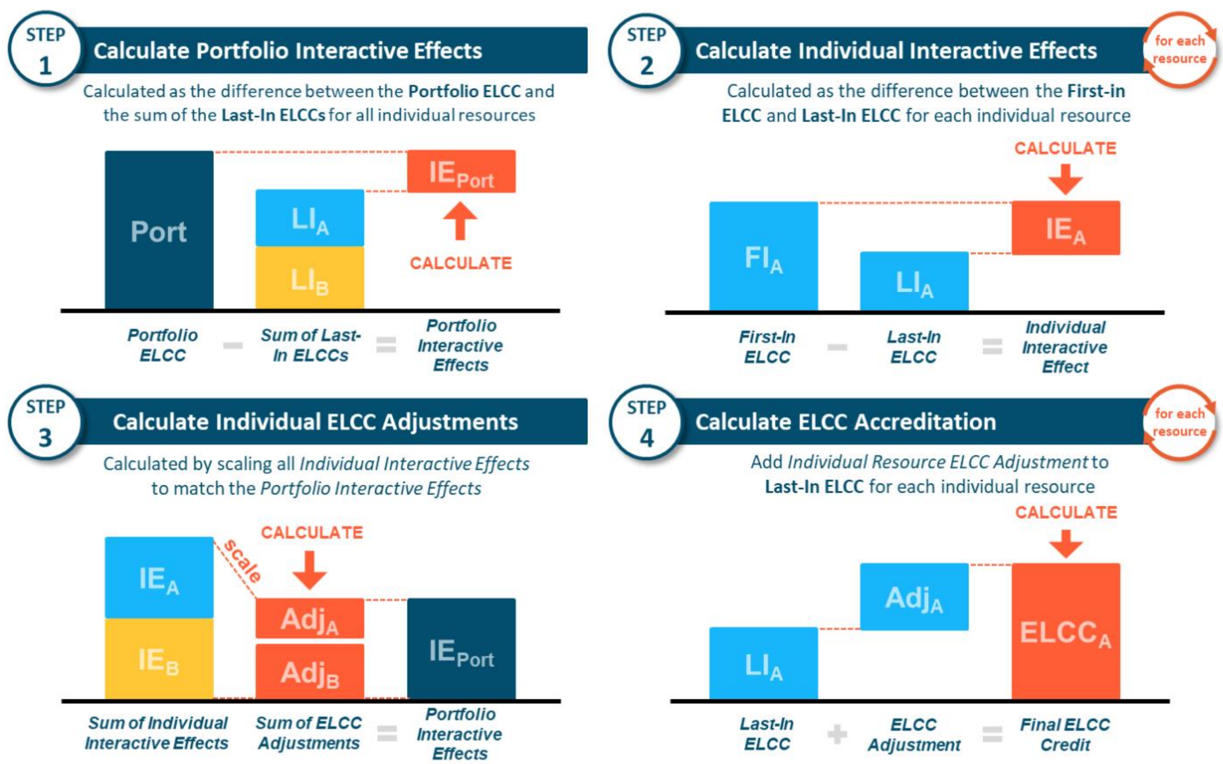


Once the solar and storage additions for each MTR tranche were interpolated from solar and storage ELCC surface points, in-state wind storage was modeled as incremental to the assumed solar and storage starting points for each tranche. In other words, the Tranche 4 in-state wind ELCCs were modeled as the incremental ELCC on top of a portfolio of resources that included the Tranche 3 solar and storage additions. This captured the interactive effects between the solar and storage additions on wind incremental ELCCs.

As noted in Figure 5. Solar and storage additions by MTR tranche, resource additions modeled to build the ELCC surface in all years except for 2028 are comprised only of solar and 4-hour batteries. Resource additions in 2028 (Tranche 6) are comprised of 1 NQC gigawatt (GW) of zero-carbon firm capacity, 1 NQC GW of long duration energy storage (LDES, modeled as 8-hour battery storage), and 2.7 GW of solar nameplate capacity.

When solar and storage are added together, they provide diversity benefits that make a portfolio of solar and storage resources contribute more to reliability than the sum of their individual ELCCs. These diversity benefits were allocated between solar and storage with the delta method, using the portfolio ELCC and the estimated first-in and last-in marginal ELCCs for solar and storage within each MTR tranche on the surface. E3 developed the delta method, illustrated in Figure 6. Delta Method ELCC Allocation Methodology, to credit each resource in a portfolio of resources in a manner that reflects the nature of their synergistic, antagonistic, or neutral interactions with the portfolio by adjusting last-in ELCC based on its difference from its first-in ELCC. The method allocates interactive effects while balancing the goals of reliability, fairness, efficiency, and acceptability. It is intended to be scalable across a portfolio of multiple resource types but can be used as well on a portfolio with two resource types (as modeled here for solar and storage).

Figure 6. Delta Method ELCC Allocation Methodology[12]



[12] For additional background information on E3's Delta Method see the following: N. Schlag, Z. Ming, A. Olson, L. Alagappan, B. Carron, K. Steinberger, and H. Jiang, "Capacity and Reliability Planning in the Era of Decarbonization: Practical Application of Effective Load Carrying Capability in Resource Adequacy," Energy and Environmental Economics, Inc., Aug. 2020.

The ELCC results are referred to as “incremental” ELCC. Marginal ELCCs refer to the ELCC benefit of adding one additional MW to a system (or another reasonably small amount). Incremental ELCCs refer to the ELCC benefit of a larger incremental addition or the subsequent benefits of multiple increments of additions. Because larger levels of additions are considered in this study, including multiple increments of solar and storage, the ELCC results are referred to as “incremental” ELCCs.

Key areas of uncertainty contained within the study design include the assumed solar capacity additions (both BTM and utility-scale), modeled vs. actual performance of energy storage resources in the CAISO market, and the impact of recent extreme weather on SERVM’s CAISO load shapes and resource availability. Sensitivity runs examined the magnitude of each of these factors.

INPUT ASSUMPTIONS

SUMMARY OF INPUT UPDATES FROM 2021 MTR ELCC STUDY

Several input updates were made to the SERVM model since the 2021 MTR ELCC study. A summary of changes is shown in the table below, with additional details on input development in the following sections.

Table 2. Summary of changes vs Previous MTR Study

Input	2021 MTR ELCC Study	2023 MTR ELCC Study
Weather Years	1998-2017	1998-2020
Solar Profiles	Aligned with 2021 database created by Energy Division in support of RA and IRP proceedings	Aligned with 2022 database created by Energy Division in support of RA and IRP proceedings[13]
CA and Out of State Wind Profiles	Astrapé developed synthetic profiles using historical CAISO settlement data	Aligned with 2022 database created by Energy Division in support of RA and IRP proceedings
Offshore Wind Profiles	Aligned with 2021 database created by Energy Division in support of RA and IRP proceedings	Aligned with 2022 database created by Energy Division in support of RA and IRP proceedings, with additional adjustments for system losses
Imports	Fixed Import Profiles	Explicit neighboring zones modeled with net peak aggregated import limit
Hydro Modeling	Aligned with 2021 database created by Energy Division in support of RA and IRP proceedings	Detrending of total hydro energy in earlier weather years and decoupling historic hydro dispatch from specific weather years
Load Profiles	Aligned with 2021 database created by Energy Division in support of RA and IRP proceedings	Aligned with 2022 database created by Energy Division in support of RA and IRP proceedings with additional shape adjustment

13 Available here: https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/electric-power-procurement/long-term-procurement-planning/2022-irp-cycle-events-and-materials/unified-ra-and-irp-modeling-datasets-2022

		to better align with IEPR 2021 managed peak forecasts

IMPORTS

Fixed import shapes from the previous MTR study were replaced with explicit modeling of external regions one transmission tie away from CAISO to capture the generator outage and load diversity benefit available to CAISO. Loads and resources were updated to reflect the most recent estimates of variable-energy resource (solar, battery, wind) penetration levels in neighboring regions as indicated in the WECC 2032 Anchor Data Set (ADS). Perfect capacity additions and load adders were applied as necessary across each individual neighboring region such that the total annual LOLE was shown to be between 0.05 and 0.15. Reliability was tuned to approximately 0.1 LOLE since the objective of including neighboring systems in this reliability study is to capture the benefits of resource diversity and generator outage diversity. If neighboring zones were above 0.1 LOLE, California would be "subsidizing" the neighbor's reliability – carrying too much capacity to meet its own needs to keep neighbors at 0.1. If neighboring zones were below 0.1 LOLE, those zones would be subsidizing California's reliability needs. This approach assumes that the Northwest and Southwest regions will in the long run trend towards load and resource balance (i.e., 0.1 LOLE), adding capacity if they are under-reliable today and retiring capacity if they are over-reliable.

Modeled regions include the following:

- Northwest
  - Bonneville Power Administration-Transmission (BPAT)
  - Portland Gas & Electric
  - PacifiCorp West
- Southwest
  - Arizona Public Service Company
  - Nevada Power Company
  - Western Area Power Administration (Lower Colorado)
  - Salt River Project
- Non-CAISO California
  - Imperial Irrigation District
  - Los Angeles Department of Water and Power
  - Turlock Irrigation District
  - Sacramento Municipal Utility District

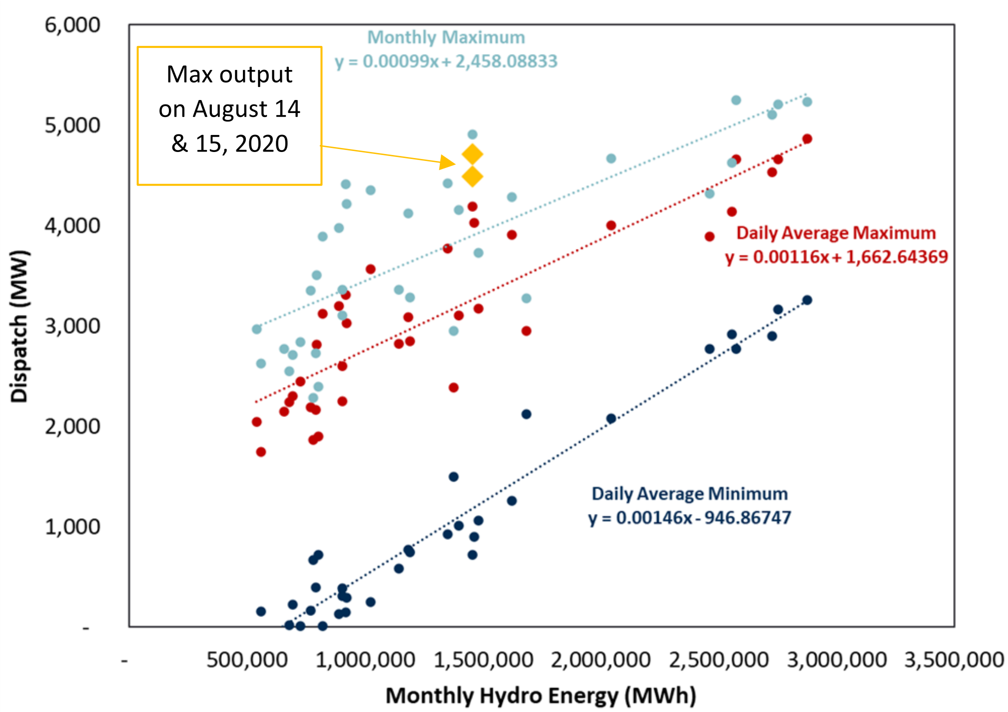
An additional transmission import constraint was applied to the hourly modeling in SERVM, which limited the total unspecified imports (aggregate value across all of CAISO) from all neighboring regions during the anticipated sales peak period. The sales peak period was defined as hour ending 17 through 22 for each day of the year. The aggregated import limit was set to 4,000MW for all ELCC simulations.

HYDRO

SERVM models hydro units by specifying operating constraints by month using historical hourly and monthly hydro generation data. Key input variables include maximum capacity values, daily scheduled flow range (minimum and maximum hydro dispatch levels based on an average load day), and total monthly hydro energy. SERVM utilizes a proportional load following algorithm to determine ideal dispatch to schedule more during high load hours and less during low load hours while still respecting monthly energy and maximum capacity value constraints.

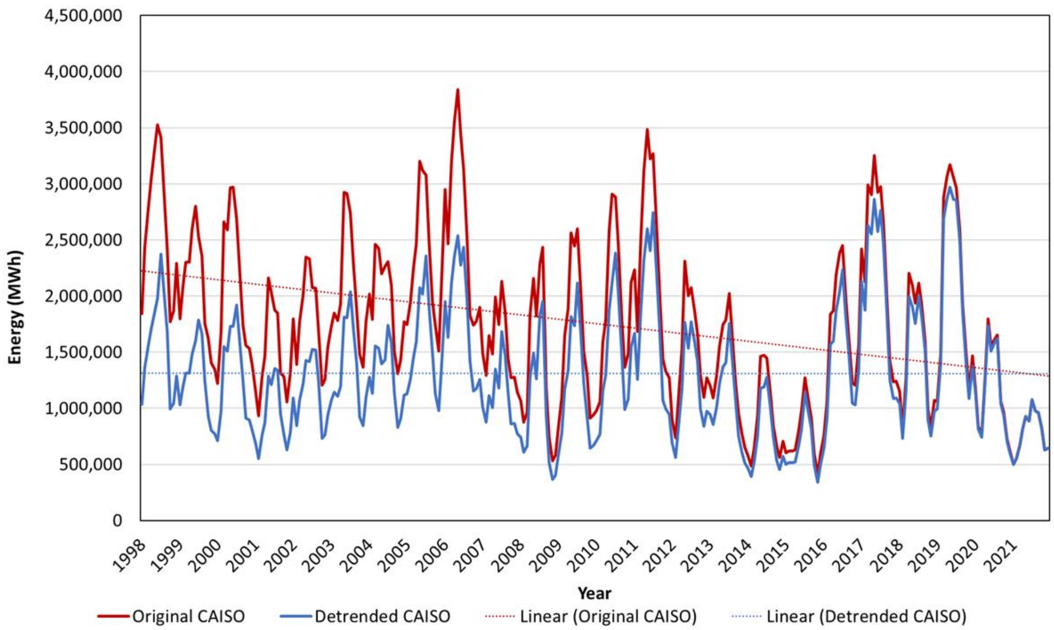
All hydro input variables for CAISO and the modeled neighboring regions were updated using the most recent historical hourly hydro generation data from CAISO, BPAT, and the United States Energy Information Administration (EIA) between 2018-2021. In addition, 23 years of historical total monthly hydro energy production (1998-2020) from EIA was analyzed. Using the 2018-2021 hourly data, relationships were established between monthly hydro energy production and the following variables: daily maximum dispatch, daily minimum dispatch, and monthly maximum capacity. These relationships based on recent hourly data provide a realistic understanding of how hydro resources are currently being dispatched within CAISO and its neighbors. Historical monthly energy data from historical weather years further in the past can then be used to determine the associated monthly maximum, daily average maximum, and daily average minimum by month for those weather years. The relationships for CAISO hydro resources are shown in the figure below as an example.

Figure 7. Historical CAISO Hydro Data



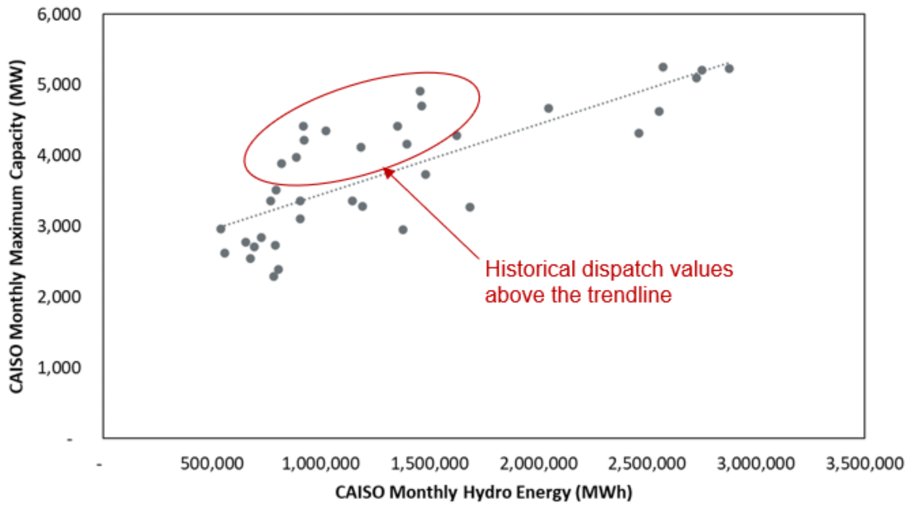
Before applying the relationships above to the historical monthly hydro energy data from EIA between 1998-2020, the monthly hydro energy values were detrended to reflect the declining total energy available from hydro resources in recent years. This decreased the total monthly hydro energy for weather years in the more distant past to avoid overestimating the expected availability from hydro in the future. Figure 8 below shows the original monthly energy values and the "detrended" values that were utilized in the updated SERVM input parameters.

Figure 8. Original and Updated "Detrended" CAISO Hydro Energy Availability



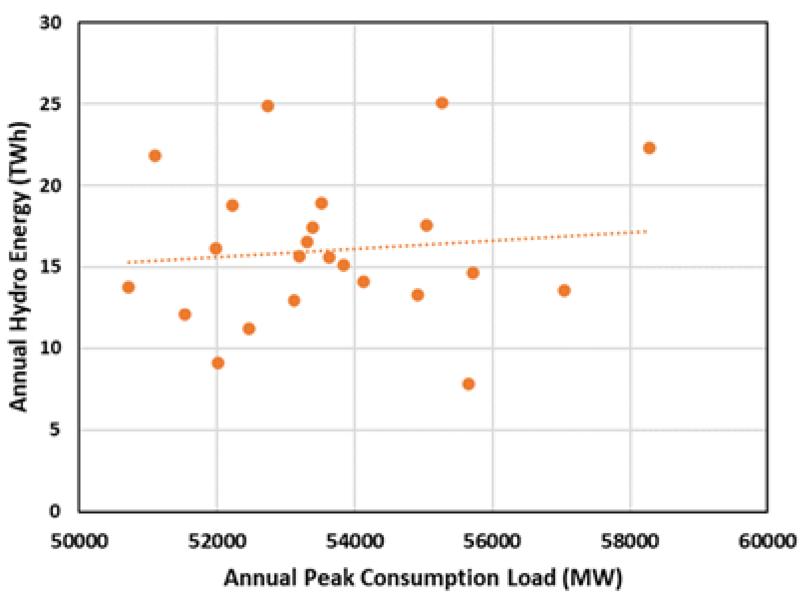
Emergency hydro units were also modeled as an improvement to the MTR ELCC analysis. These units reflect the additional maximum dispatch capability of existing hydro resources that would be expected to be utilized during emergency conditions. The difference between actual monthly maximum hydro dispatched and the trended dispatch values were compared to determine the availability of additional emergency hydro capacity. Historical months below 1.5 terawatt-hour (TWh) of total hydro energy production were modeled with 817 MW of emergency hydro capacity (677 MW for Pacific Gas and Electric (PGE) and 140 MW for Southern California Edison (SCE). Above 1.5 TWh of total hydro energy, the total capacity of emergency hydro decreased linearly as total hydro energy increased. Emergency hydro availability is limited to 20 hours of dispatch. Emergency hydro capacity was not considered to be available for historical months where the total hydro energy exceeded 2.48 TWh. The figure below demonstrates the observed historical dispatch values that were seen to be greater than the trendline for CAISO hydro resources.

Figure 9. Historical CAISO Hydro Maximum Output



Lastly, to get a better statistical sampling of hydro resource performance across all modeled weather year and load forecast error combinations, hydro performance was decoupled from the historical weather year in SERVM simulations. Instead of modeling 1998 hydro performance alongside the load and renewable profiles associated with the 1998 weather year, the 1998 hydro conditions were modeled across all weather years (and so on for each hydro performance year). The chart below shows the correlation between historical hydro energy production and the CAISO annual gross load peak. This low correlation implies that a high load weather year is just as likely to experience a high amount of hydro energy production as it is to experience a low amount of energy production.

Figure 10. CAISO Annual Hydro Production vs. Annual CAISO Peak



The resulting combination of weather years (load), hydro performance year, and load forecast errors that were applied to each ELCC scenario is summarized in the formula below.

$$23\ weather\ years \cdot 23\ hydro\ years \cdot 5\ load\ foreacst\ errors$$
$$= 2{,}645\ unique\ cases\ simulated\ per\ scenanario$$

CALIFORNIA AND OUT-OF-STATE WIND PROFILES

Creation of wind production profiles requires a production curve that translates wind speed data into hourly generation (MWh) from wind turbines. For onshore and out of state wind production curves, staff created a curve based on historical MWh wind generation data sourced from CAISO and other sources based on historic availability.

For the 2021 MTR ELCC study, wind speed data was sourced from the National Climate Data Center ISD-Lite database. For the 2023 MTR ELCC study, wind speed data was updated using the NASA MERRA2 dataset which consists of greater availability and granularity of weather data. Due to the growing diversity of wind generator locations and the very specific locational differences between wind speeds, the more granular data set was needed. In addition, due to the need for creation of 23 years of weather history, it was critical to use a dataset that covers the entire set of simulated weather years. In this case, staff used weather data from 1998 through 2020 to create sufficient weather variability.

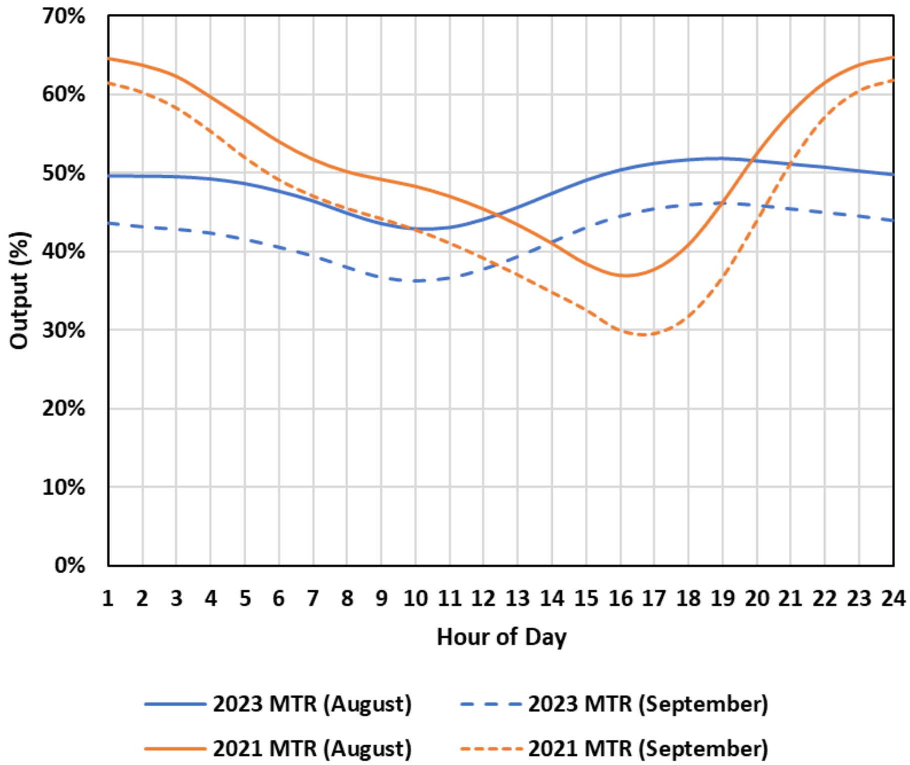
Astrapé provided support in this development to calibrate wind production on peak load days with historical production data. The updated wind profiles reflect slightly lower output on average during summer afternoons for in-state wind, which is the primary contributor to slightly lower ELCCs.

OFFSHORE WIND PROFILES

The offshore wind profiles were updated by the Energy Division using available weather data and applying the NREL offshore wind output response curve. For the 2021 MTR ELCC study, wind production curves were sourced from NREL data, due to the lack of existing wind generation (MWh) data from offshore wind generators. Wind speed data was sourced from the National Climate Data Center ISD-Lite database.

For the 2023 MTR ELCC study, wind profiles were updated using the NASA MERRA2 dataset. This change in source for historical wind speed data was due to the need for greater availability and granularity of weather data. Due to the growing diversity of locations which will be sites for wind generators, and the very specific locational differences between wind speeds, the more granular data set was needed. In addition, due to the need for creation of 23 years of weather history, it was critical to use a dataset that covers the entire set of weather years needed. In this case, staff used weather data from 1998 through 2020 to create sufficient weather variability. Astrapé applied an additional derating factor across all hours of the year by approximately 12% to account for environmental, technical, electrical, and availability losses as defined by the National Renewable Energy Laboratory (NREL)[14].

Figure 11. Daily Average Wind Output Comparison (2023 MTR ELCC Study vs. 2021 MTR ELCC Study)

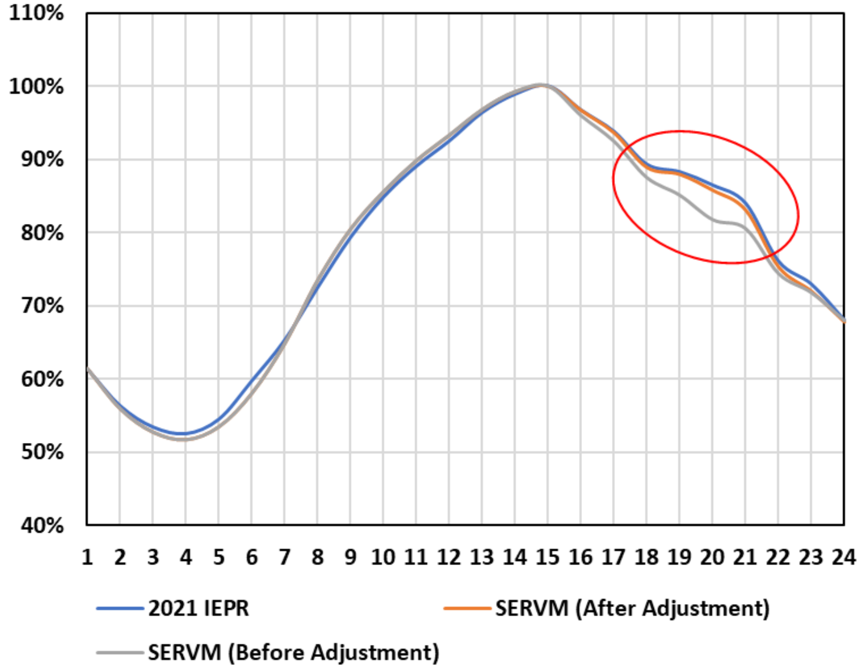


LOAD PROFILES

The load shapes utilized in this analysis were based on the synthetic load shapes for weather years 1998-2020 developed as part of the IRP and RA proceedings using 2021 IEPR 2021 forecast data. An additional adjustment to the load shapes was applied to align with the 2021 IEPR managed peak load forecast by adjusting afternoon hours (HE16-24) for high load days in summer months (June through September). The normalized load shapes before and after the adjustment are shown in the figure below. A sensitivity was performed to understand the impact this load adjustment had on the ELCC values for Tranche 3.

[14] https://www.nrel.gov/docs/fy22osti/82341.pdf

Figure 12. Average Normalized September Load (> 45 GW Daily Peak)



SUMMARY OF KEY INPUTS

MTR BASELINE PORTFOLIO

The Baseline Portfolio used in SERVM is provided in

Table 3. Base Resource Mix. This portfolio reflects the baseline portfolio used to determine the MTR Decision's 11.5 GW capacity need and procurement target, as well as projected LSE resource additions through 2024 for compliance with the D.19-11-016 procurement order and MTR Tranches 1 and 2. The study year of 2030 was selected for developing the solar and storage ELCC matrix with the necessary amount of perfect capacity added to calibrate the base case to 0.1 LOLE. To ensure all ELCC values within the matrix were calculated using the method described in the methodology section above (i.e., adding incremental resources and removing perfect capacity), a small amount of thermal resources were replaced with perfect capacity. This avoided the potential for modeling an incremental resource addition in later tranches with a reliability value that exceeded the amount of perfect capacity available in the system to remove. The selection of the 2030 study year did not impact the established presumed penetration for key resources such as solar, wind, and battery storage.

Table 3. Base Resource Mix

Unit Category	Nameplate Capacity (MW)
Battery Storage	12,093
Biogas	223
Biomass/Wood	442
CC	14,771
Coal	0
Cogen	335
CT	7,329
DR	2,392
Geothermal	1,376
Hydro[15]	4,568
ICE	259
Nuclear	635
PSH	1,483
Utility Solar + BTMPV	40,305
Wind	7,286

SOLAR AND STORAGE SURFACE INPUTS

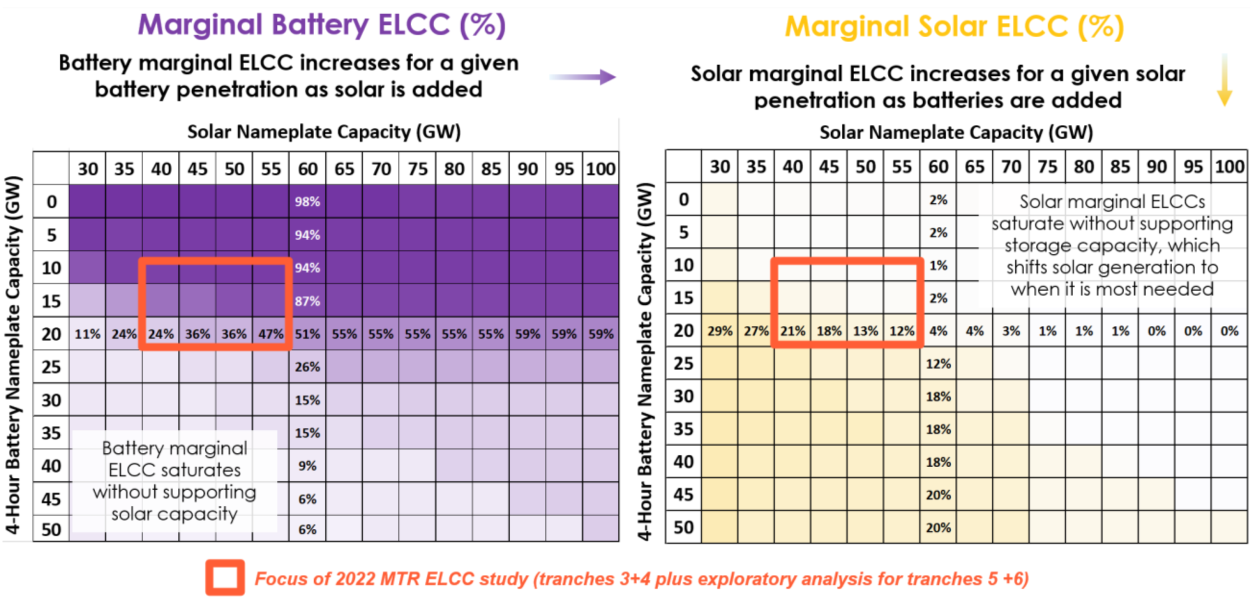
The proposed solar and storage surface for use in 2022-23 IRP inputs and assumptions is shown in **Error! Reference source not found.**, which provides a heatmap indicating the marginal/incremental storage ELCCs and the marginal/incremental solar ELCCs for various penetrations of solar and storage. This large surface was generated from SERVM for use in RESOLVE capacity expansion, whereby the optimization is granted wide freedom to test the reliability and economics of traversing in multiple directions across the surface.

The battery ELCC and solar ELCC heatmaps are nearly a perfect inverse of one another, clearly displaying the fact that the diversity benefits associated with adding solar and storage in tandem are critical to supporting the ELCC of the other resource as penetrations increase. RESOLVE is likely to find that – for

[15] 2020 Weather Year value

solar and storage as reliability assets – the least-cost solution to meeting long-term reliability needs is to add a combination of solar and storage such that the incremental storage ELCC is maintained as much as possible. This involves straddling the diagonal line that bifurcates each table between the zones where incremental ELCC is maintained (e.g., where solar can support batteries to be sufficiently charged). Eventually, even these diversity impacts become saturated as the net load peak may shift outside of the traditional days or seasons when solar energy is abundant. At this point, the economic solution to long-term reliability needs is to diversify the portfolio by adding other resources, most critically adding or maintaining firm capacity – that can operate on demand through low solar periods – but also adding anti-correlated renewables to solar such as onshore, out-of-state, and offshore wind.

Figure 13. Proposed RESOLVE Solar and Storage Surface + the Subsection Studied in this Report



From this larger solar and storage surface used for long-term planning, a smaller solar and storage surface was developed to drill down with greater precision on the specific MTR tranches ordered by the CPUC. Notably this is a key region of the surface where solar and storage interactive effects become pronounced and storage ELCCs decline dramatically without additional concurrent solar additions.

The nameplate solar and storage additions added by each tranche are provided in Table 4. The utility solar additions were assumed to be all single-axis tracking. The solar and surface ELCC design assumed incremental utility-scale and BTM solar additions in 2025, 2026, 2027, and 2028 based on the average annual additions of 2,700 MW between 2025 and 2030 in the 2022 updated 38 MMT PSP and 2021 IEPR forecast. This led to 2,700 MW of utility-scale and BTM solar being added to the MTR baseline portfolio each year for each year of the analysis period (2025-2028). Storage additions were added to allow interpolation such that the combined solar and storage ELCC added was sufficient to fill the tranche. Recognizing that the ELCC contributions of incremental storage additions are less than 100%, the incremental storage nameplate simulated to fill each tranche was higher than the tranche size in NQC.

Table 4. Cumulative Nameplate Solar and Storage Additions by Tranche

Tranche	Incremental Solar (MW)	Incremental 4 hour Storage (MW)	Incremental 8 hour Storage (MW)
Tranche 3 (2025)	2,700	1,500 | 3,500 | 5,000	750 | 1,500
Tranche 4 (2026)	5,400	1,500 | 3,500 | 5,000	750 | 1,500
Tranche 5 (2027)	8,100	3,500 | 5,000 | 7,000	750 | 1,500
Tranche 6 (2028)	10,800	3,500 | 5,000 | 7,000 | 10,000	750 | 1,500

Table 5 shows the post interpolation storage nameplate required to fill each tranche. The portfolio ELCCs for the levels simulated were curve fitted to a second order polynomial, which was then used to forecast the required 4-hour storage resources needed to meet the procurement targets, after accounting for the solar added and interactive benefits between solar additions and storage additions.

Table 5. Assumed Cumulative Nameplate Storage Additions by Tranche

Tranche	Cumulative Procurement Target (NQC MW)[16]	Cumulative 4 Hour Storage (MW)	Cumulative 8 Hour Storage (MW)
Tranche 3 (2025)	1,500	1,759	0
Tranche 4 (2026)	3,500	4,123	0
Tranche 5 (2027)	5,500	6,553	0
Tranche 6 (2028)	7,500[17]	6,553	1,110

[16] MTR procurement volumes incremental to the 8,000 MW ordered in Tranches 1 and 2.

[17] Tranche 6 includes 1,000 NQC MW of zero-carbon firm capacity additions.

RESULTS

The incremental ELCCs by MTR Tranche are presented in Table 6.

Table 6. Incremental ELCCs by MTR Tranche

	From prior study, for reference only		Updated values from this study		Additional Proposed MTR Tranches[18]	
	Tranche 1 2,000 MW 2023	Tranche 2 6,000 MW 2024	Tranche 3 1,500 MW 2025	Tranche 4 2,000 MW 2026	Tranche 5 2,000 MW 2027	Tranche 6 2,000 MW 2028
4-Hour Battery	96.3%	90.7%	75.1%	76.6%	74.0%	76.5%
6-Hour Battery	98.0%	93.4%	79.6%	80.3%	80.5%	83.3%
8-Hour Battery	98.2%	94.3%	84.0%	84.0%	87.1%	90.1%
8-Hour PSH	N/A	76.8%	82.6%	82.6%	85.7%	88.7%
12-Hour PSH	N/A	80.8%	86.6%	86.6%	89.7%	92.7%
Solar - Utility and BTM PV	7.8%	6.6%	6.6%	7.0%	7.5%	8.8%
Wind CA	13.9%	16.5%	12.0%	13.2%	14.0%	14.7%
Wind WY	28.9%	28.1%	31.0%	33.0%	31.7%	30.9%
Wind NM	31.1%	31.0%	30.0%	35.0%	33.7%	31.9%
Wind Offshore	N/A	N/A	48.0%	46.0%	44.0%	44.7%

SOLAR ELCC

As the penetration of solar increases, the net load peak shifts towards evening hours when solar output is generally a small fraction of its nameplate capacity due to low solar angles. With continued solar growth, the net peak can shift to nighttime hours when solar output is zero. Even in this extreme case when the net peak after solar and wind output is after sunset, solar achieves positive ELCC by allowing energy-limited resources such as storage, hydro, or demand response programs to charge or conserve energy before the net peak. The positive ELCC which solar derives from its interactions with other resources on the system is termed “diversity benefit,” and contributes significantly to the increasing ELCC values for solar from 2025 to 2028 in Table 6.

The interactions of solar with the other resource classes modeled are complex and change with the penetration of each resource class (i.e., the ELCC of each resource class is highly dependent on where the portfolio lies on the broader solar and storage surface).[19] For example, the solar ELCC increases slightly between Tranche 3 and Tranche 4. Despite adding 2.7 GW of solar in Tranche 3, the concurrent additions

[18] The years and volumes shown here are based on the January 13, 2022 Proposed Decision. Tranche 5 consists of 2,000 MW in 2027 and Tranche 6 consists of 2,000 MW – assumed to be 1,000 MW long duration storage and 1,000 MW firm zero carbon renewables – in 2028.

[19] Solar interactive effects are also secondarily dependent on the penetrations of wind, the types and outage rates of thermal plants, hydro modeling, and other factors.

of 1,759 MW of batteries drives the solar energy value to become slightly more important for battery charging in Tranche 4 than Tranche 3. This trend continues into later study years as continued solar additions do not result in a steep decline in incremental solar ELCCs due to the addition of a sufficient amount of battery storage.

(Note that while solar output during net load peak is affected by both its longitude and technology attributes (such as tracking utility-scale PV vs. BTM PV), interactive effects in the system mute some of these differences. This study did not calculate distinct ELCCs by solar category or by location. The 2022 LSE Plan ELCC analysis[20] conducted an ELCC analysis by solar category which can provide an indication of which solar resources provide more or less than the resource average modeled here).

STORAGE ELCC

Storage ELCC values are predominately determined by storage resources' ability to serve load during extreme conditions without exhausting their store of energy. Storage ELCCs are therefore a function of both storage resources' maximum store of energy (relative to their maximum discharging capacity; in short, by their *maximum discharge duration*) and by their ability to charge from energy provided by both firm generators and renewables prior to net load peak hours. Diversity benefits with solar therefore also contribute significantly to the storage ELCC values reported in Table 6.

As a result of increasing penetration of solar relative to storage and the associated diversity benefit, storage ELCC values increase slightly over the 2025-2028 study period despite continued battery additions. However, it should be noted that this increase in battery storage ELCC values throughout the study period does not indicate an expected trend in ELCC values beyond 2028. Through the development of related analyses, it has been shown that storage ELCC values can have a significant decline as penetration increases depending upon the system's position within the solar+storage ELCC surface.

Storage with longer maximum discharge duration, for instance 8-hour duration battery storage, has consistently higher ELCC than 4- hour duration storage. The ELCC of 8-hour duration pumped hydro storage is lower than the ELCC of 8-hour battery storage due to its lower round trip (charging and discharging) efficiency.

The incremental value of long duration storage is not simply driven by differences in energy duration. Long duration storage is modeled with forced outage risk during both charging and discharging periods. An 8-hour battery storage resource that must charge for over 8 hours a day to be able to discharge for 8 hours a day carries considerably more outage risk than a firm generator with the same EFOR[21] that only operates for 8 hours a day. Also, at very high storage penetrations, long duration storage can become

[20] https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/integrated-resource-plan-and-long-term-procurement-plan-irp-ltpp/2022-irp-cycle-events-and-materials/20220729-updated-fr-and-reliability-mag-slides.pdf

[21] Equivalent Forced Outage Rate (EFOR) is defined by operating hours, not by all hours.

charging constrained when excess dispatchable capacity is not available for the full period required to fully charge; in this analysis the primary constraining effect was the forced outage risk and not the charging constraint.

WIND ELCC

Wind output is generally negatively correlated with hot weather and the associated higher loads and this is generally reflected in ELCC values that are materially lower than wind resources' annual or seasonal capacity factors. Locational diversity provides some reliability value for wind resources -- although at the existing wind penetrations in California, incremental additions within the state likely bring limited diversity value. Projects located outside the state or offshore are subject to different climatological conditions, which provides additional diversity in output and result in higher incremental ELCCs. The ELCCs change only slightly between 2025 and 2028 as the solar+storage portfolio grows, indicating that there are minimal interactive effects for wind and solar+storage. The greater driver of wind ELCC reductions would be if more wind is added over the MTR timeframe in place of the modeled solar+storage additions.

APPROACH FOR OTHER RESOURCES NOT MODELED

The CPUC's MTR decision requires the following method for determining incremental capacity value for resources not covered in this or next year's study:

> "For all other resource types, counting will be in accordance with the system resource adequacy NQC counting rules at the time the contract for the new resource or capacity added to an existing resource is executed." (D.21-06-035, p. 71).

If new resources have project-specific constraints that might impair their ability to meet the NQC counting rules (such as the resource type specific "technology factors" published in the CPUC's NQC List), these resources may require additional analysis to determine their capacity value. As an example, a new geothermal resource may have project specific characteristics (such as working fluid temperatures, cooling system types, or certain project locations) that make them susceptible to temperature based de-rates during the summer net peak conditions.

These project-specific characteristics may cause a resource to deviate from the RA program NQC counting rules and, if so, the CPUC could utilize a process to evaluate that project's expected performance. For instance, if LSEs submitting new resources using the RA NQC counting rules can provide their forecasted output (or potential maximum output) during summer net-peak conditions (5-10pm in June through September), that output can be compared against the RA technology factors to determine their reasonableness for that specific project. Since the Commission has suggested using the September NQC value specifically, this assessment could even be limited to the month of September.

ELCC COMPARISON TO PAST STUDIES

WHY RESOURCE INCREMENTAL ELCC VALUES CHANGE

The CPUC frequently conducts ELCC studies for various use cases associated with reliability planning. To aid stakeholder understanding about why changes occur between study vintages, this section describes drivers of change generally and then examines this study's results as compared to prior studies' results.

Table 7 shows the reasons why ELCCs change between studies and their general magnitude, informed by the authors' past experience as well as the sensitivity analysis performed for this report. To be clear, the dynamic nature of ELCC values is an expected part of the ELCC methodology and does not necessarily represent a failure in method or process. Reflecting the varying contribution of resources as the forecasted portfolio or other assumptions change allows for ELCC values to adapt as new weather and operational data become available.

This dynamic nature of ELCCs is best utilized within the context of an ELCC-based need definition (i.e., a perfect capacity planning reserve margin based on the total ELCC MW needed to reach 0.1 LOLE). This need definition remains quite stable over time even as the portfolio mix evolves and resource ELCCs change. It is also important to note that recent IRP ELCC studies typically report marginal or incremental ELCC values that tend to be more sensitive to change, while the underlying total capacity contribution of all resources is more stable.

Table 7. Why ELCC Values Change Between Studies

Change	Reason for ELCC Impact	Examples	General Magnitude
Portfolio Changes	Due to interactive effects within and between resources, the resource portfolio is the primary input into ELCC calculations	Changing marginal ELCCs used for LSE IRPs based on the changing CAISO resource portfolio	High
Resource shape changes	Resource shapes are the most direct factor impacting solar and wind ELCCs	Updated wind shapes	Medium-High
Load shape changes	Load shape changes impact the load shape to which resources are dispatched when ELCCs are calculated	Re-calibration of SERVM load shapes when updating IEPR vintage	Medium
New weather years added	New weather years can impact the periods of extreme weather that drive reliability events, and therefore ELCCs	Addition in this study of the August 2020 extreme weather event	Medium

Changes to other input parameters	Due to interactive effects between resources, other input parameters may impact resource ELCCs	Hydro modeling, neighbor modeling, forced outage rates	Low-Medium
Methodological Changes	ELCC study methods may change slightly between different studies	Type of LOLE tuning method used (perfect capacity vs. firm load)	Low

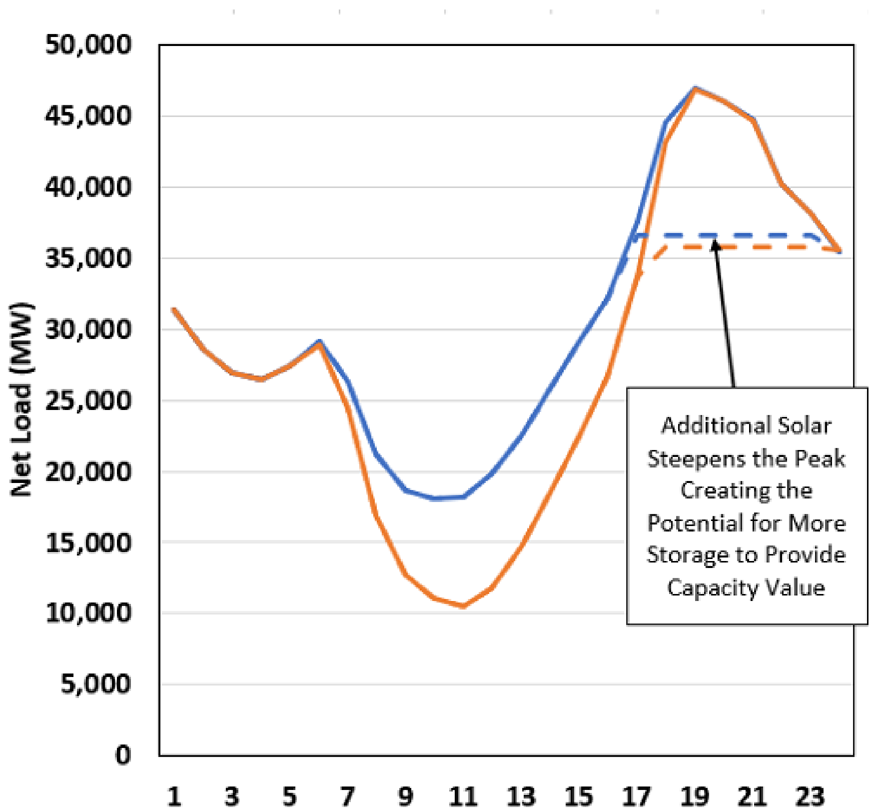
CHANGES TO STORAGE ELCC

Figure 15. 4-hour Duration Battery Storage ELCC Comparison shows a comparison of incremental 4-hour duration battery storage ELCC values from this 2023 MTR ELCC study (covering a 2025-2035 study period), the 2021 MTR ELCC study (covering a 2023-2026 study period), and the 2022 LSE plan ELCC forecast study (covering a 2024-2035 study period). Each of these studies used SERVM to calculate ELCC values, however each study made different assumptions about CAISO loads and resources. Table 2 provides a detailed description of the various inputs and assumptions that differ between these ELCC studies and which account for the differences in their core ELCC results, primarily updated resources using preliminary MTR procurement data.

For battery storage, the ELCC values published in this study are close but slightly higher than those published in the 2021 MTR ELCC study for 2025-2026 (MTR Tranches 3 and 4), which is likely driven by the higher levels of solar penetration relative to storage that were modeled in this study for those years. The total solar penetration modeled in the 2025-2026 timeframe in this study was approximately 4 GW higher than in the 2021 MTR ELCC study. The 2022 LSE ELCC forecast results exhibit a higher starting ELCC and a declining ELCC trend, while this study demonstrates a lower starting ELCC and generally stable ELCC trend. Several inputs are different between the two studies. Input differences in this study that correspond with lower storage value include: a smaller proportion of tracking solar, higher storage penetration, and lower wind penetration. Input differences in this study that correspond with higher storage value include: higher afternoon gross loads to calibrate with IEPR shape and higher solar penetration. Since the magnitude of these impacts vary across the study years, the composite impact is a difference in both the starting magnitude and the trend in ELCCs. The increasing storage ELCC in this study was validated through net load analysis which showed incremental solar providing the requisite energy in critical hours to restore some lost capacity value for incremental storage additions.

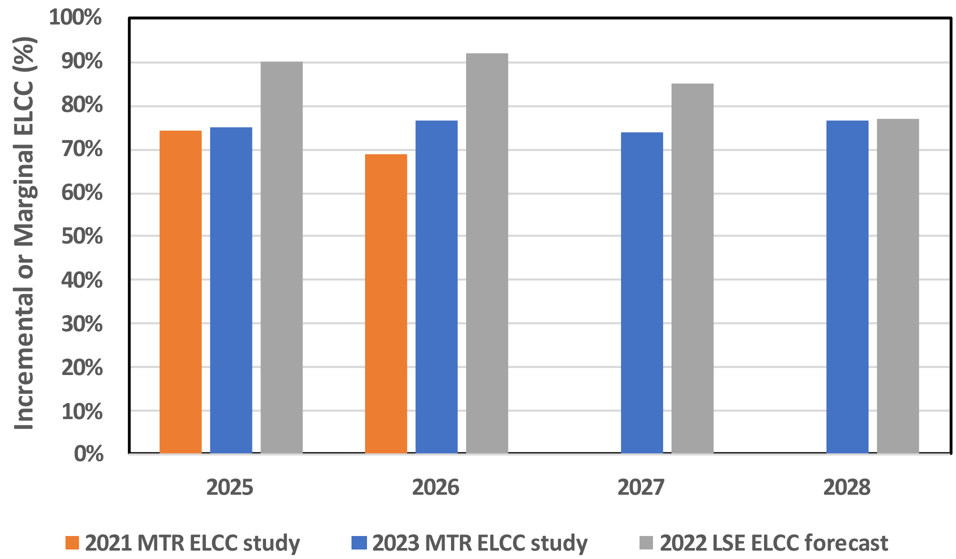
Through the various scenarios analyzed, the ratio of storage capacity value created to solar capacity added was between 7-13%. Figure 14 illustrates this effect showing that with 10,000 MW of additional solar, the steepening effect on net load creates the potential for approximately 700 MW of additional capacity value from the storage fleet. The lower mid-day net load also allows for greater charging energy sufficiency. Proposed RESOLVE updates to incorporate a solar and storage ELCC surface will allow RESOLVE to economically optimize the additions of solar and storage based on the diversity benefits captured within that ELCC surface.[22]

Figure 14. Solar Additions Effect on Storage Potential



[22] See Sept 2022 IRP I&A MAG: https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/integrated-resource-plan-and-long-term-procurement-plan-irp-ltpp/2022-irp-cycle-events-and-materials/iamag09222022.pdf

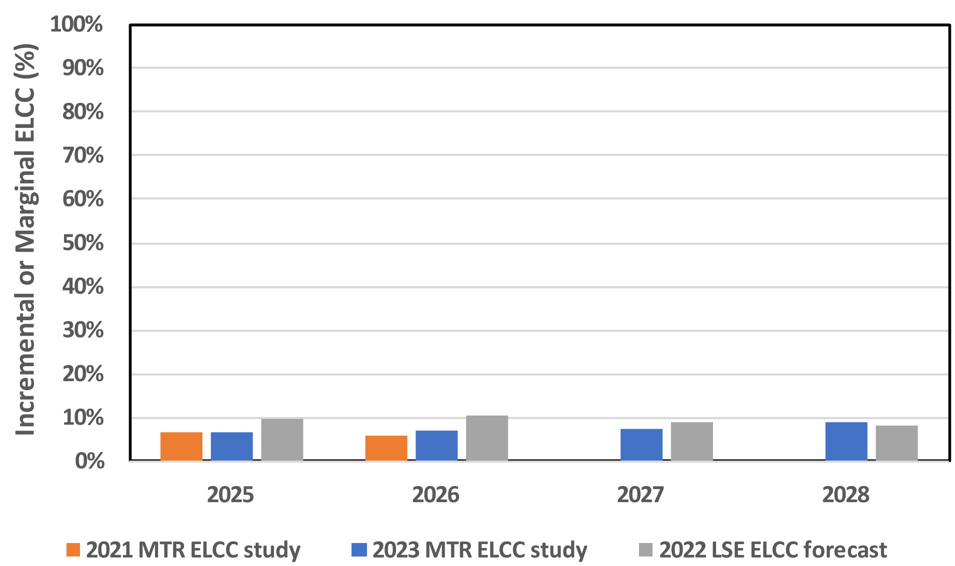
Figure 15. 4-hour Duration Battery Storage ELCC Comparison



CHANGES TO SOLAR ELCC

The solar ELCC values published in this study are very similar to those published in 2021's report. Solar ELCC values generally remain between ~5-7% in the 2025-2026 timeframe. The 2022 LSE ELCC forecast results have slightly higher solar ELCC values than those published in this report.[23] Solar ELCC results follow similar trends over time: starting around 6-9% in 2025, declining to ~3-5% by 2030, but not falling to zero.

Figure 16. Solar ELCC Comparison



[23] The LSE plan solar marginal ELCC values shown here are an average of the utility-scale and BTM marginal ELCCs provided for LSE plans.

CHANGES TO WIND ELCC

For Tranche 3 and 4, wind ELCC values for California land-based wind projects have decreased relative to the values published in the 2021 MTR ELCC Study. This change is driven by differences in the wind profile inputs used to model wind in SERVM, as discussed in the “Input Assumptions” section. Wind ELCC values are well aligned between this study and the 2022 LSE ELCC forecast in the 2025-2027 timeframe, but begin to diverge in later study years. This is likely due to the LSE ELCC forecast including significant growth in wind by 2030 per the updated PSP portfolio, leading to saturation effects in the wind ELCC. This study assumed greater growth of solar and storage resources, which is consistent with preliminary MTR procurement data from LSEs. This further emphasizes the portfolio dependency of ELCC calculations and the need to maintain forecasts that continue to reflect the best data available from LSEs and the market on the technologies most likely to be added in the CAISO.

Offshore wind ELCCs have increased relative to values published in 2021’s MTR ELCC Study. This is driven by higher production shown in updated offshore wind profiles during critical net load periods in the late afternoon. The summer average capacity factors are similar between the vintages of offshore wind profiles, but the current profiles demonstrate a more consistent output across the day, resulting in higher ELCCs.

Out-of-state (Wyoming and New Mexico) wind ELCC values are close to or slightly greater than those published in 2021’s MTR ELCC Study. The out-of-state wind ELCC declines in later years, and generally follows a trend similar to that observed in ELCC values published in the Reliability Filing Requirements for Load Serving Entities’ 2022 Integrated Resource Plans - Results of PRM and ELCC Studies (2022 LSE plan ELCC forecast study).[24]

Offshore wind ELCC values are close to those published in the 2022 LSE plan ELCC forecast study, and are greater than those published in the 2021 MTR ELCC study in part due to the aforementioned changes to the modeling approach taken for offshore wind.

24 Available here: https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/integrated-resource-plan-and-long-term-procurement-plan-irp-ltpp/2022-irp-cycle-events-and-materials/20220729-updated-fr-and-reliability-mag-slides.pdf

Figure 17. In-state Wind ELCC Comparison

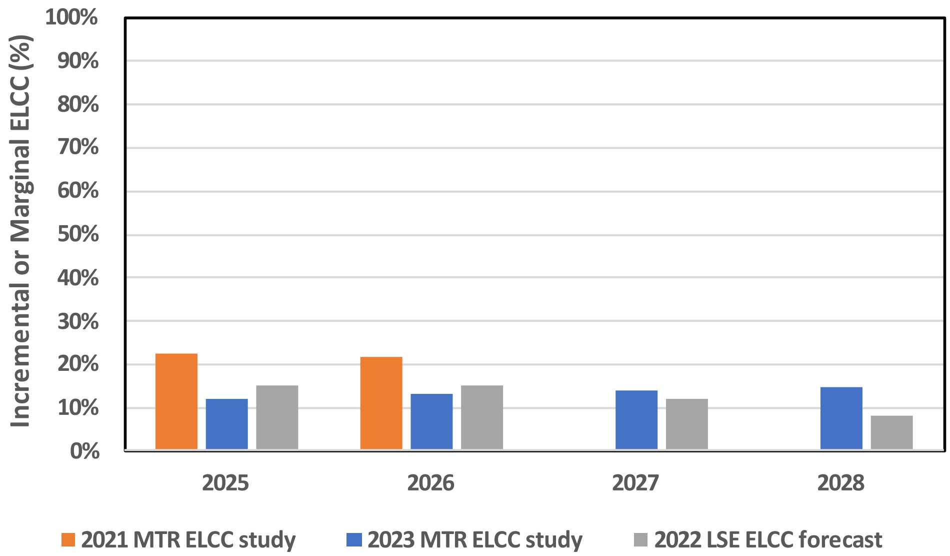


Figure 18. Wyoming Out-of-State Wind ELCC Comparison

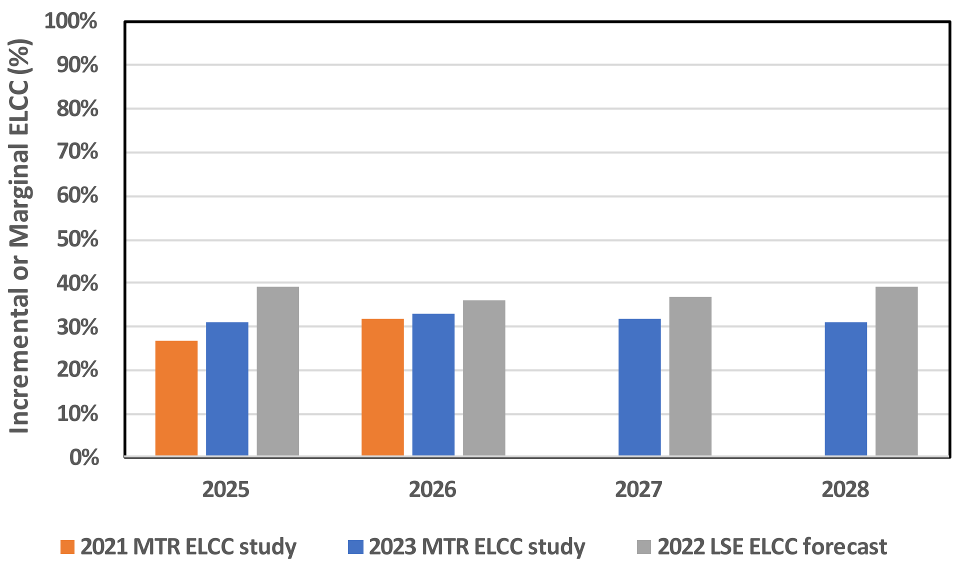


Figure 19. New Mexico Out-of-State Wind ELCC Comparison

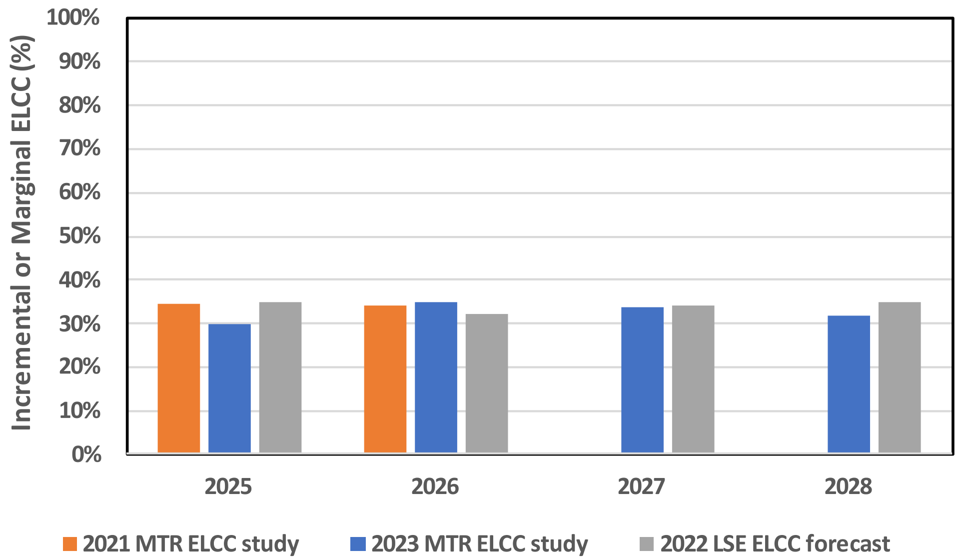
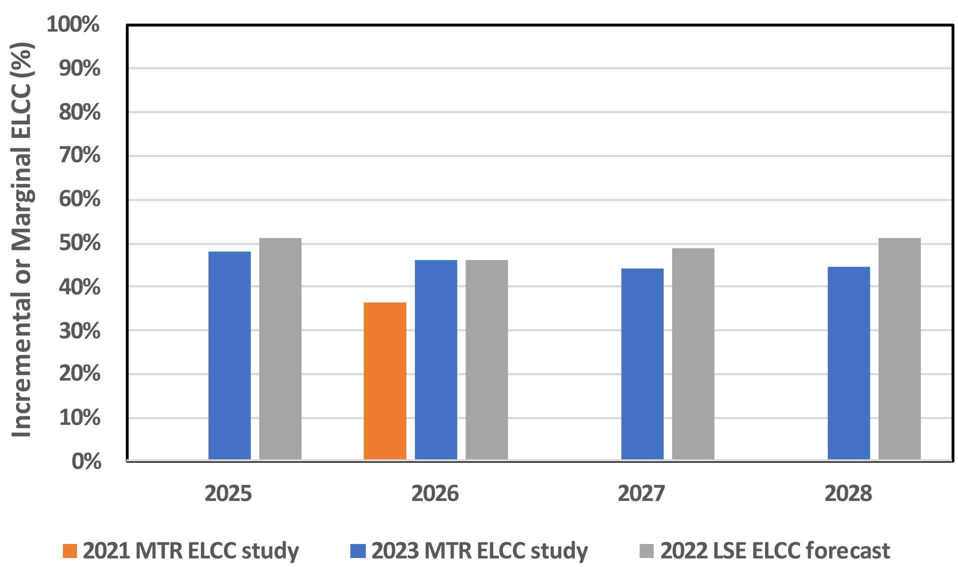


Figure 20. Offshore Wind ELCC Comparison



SENSITIVITIES

Several sensitivities were performed to understand how the following might impact the reliability contribution of solar and battery storage[25]:

- No new solar growth
- Low BTM PV IEPR forecast
- Alternate afternoon load shape
- Weather year re-weighting
- Pessimistic battery operation assumption

As demonstrated by variable battery and solar ELCCs produced across several studies over the past several years, the reliability contribution of these resource classes is highly contingent on input assumptions that are evolving in real-time as new extreme weather data and new operational data becomes available. The sensitivities described here are designed to provide insight into the relative impact that specific uncertainties have on the value of these resources. Recognition of the impact of different input assumptions should encourage some conservatism in procurement volumes and flexibility to update ELCC values over time rather than rigid implementation of one study vintage.

Reliability planning entails rigorous study of many variables, using robust simulations based on historical weather correlations. It provides actionable insights into reliability risk but should not be construed as analysis without uncertainty. Unfortunately, some uncertainty in resource performance, such as the correlation of renewables with new emerging extreme weather events and the uncertain operations of new technologies like battery storage, are an inherent challenge of the energy transition. ELCC methods are no less subject to these uncertainties than other capacity accreditation methods. Compared to the use of average or exceedance-based output over historical periods, ELCC methods are likely less susceptible to uncertainties due to their use of more precise historical correlations in large datasets considering a broad range of weather conditions instead of averaged values that may obscure historical correlations (e.g., how windy it is in the evening on extreme heat days).

The following sections provide a qualitative and quantitative exploration of the various risks associated with different input assumptions. The results indicate that load shapes, battery operating heuristics, weather year weighting, and different resource portfolios can impact the incremental ELCC of solar and storage by +/- 10 percentage points, while other input assumptions do not have a significant impact on ELCCs.[26]

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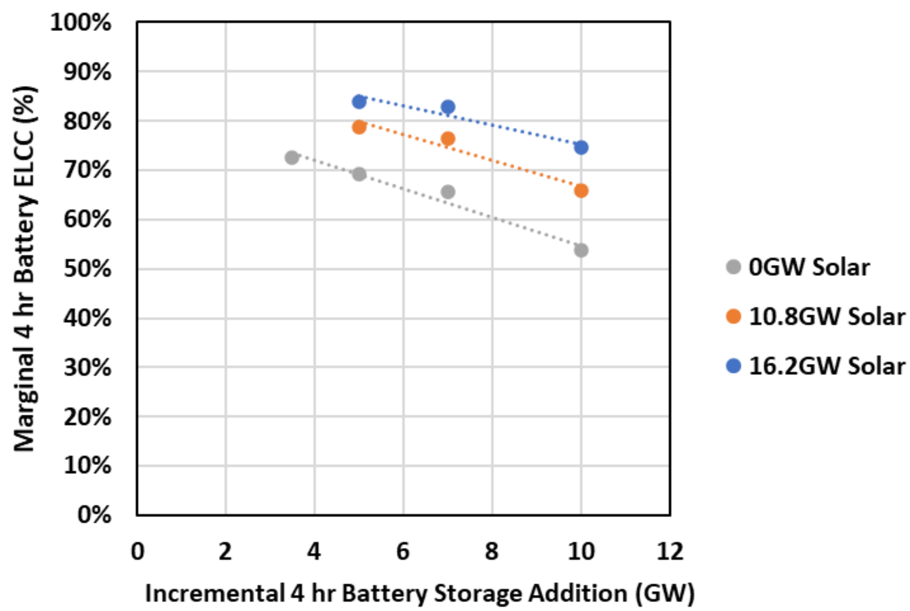
[25] Wind ELCC sensitivities were not performed as the changes to the wind shapes described in the sections above are the main driver for wind ELCC changes between this study and the 2021 MTR ELCC Study. Additionally, the calculation of the incremental wind ELCC for each tranche at different levels of solar and battery demonstrates the minor impact on wind ELCC values for the portfolios studied.

[26] Note that compared to total portfolio ELCC value, incremental ELCCs can be more sensitive to input assumptions as a function of how saturated variable and use-limited resources are on critical load days. The level of uncertainty

NO NEW SOLAR GROWTH

To demonstrate the declining incremental ELCC value of 4-hour battery storage that occurs when solar resources are not procured in tandem, the battery storage incremental ELCCs were calculated assuming the 2025 level of solar penetration. This analysis was meant to be indicative and not necessarily aligned with specific MTR tranches. As shown in the figure below, battery storage ELCC values decline rapidly from approximately 75% to 50% if there are no solar additions beyond the 2025 level of solar capacity (~40 GW of utility-scale and BTM solar), whereas additional solar procurement, indicated in Figure 21 by both the 10.8 and 16.2 GW, respectively, results in a positive interactive effect that maintains ELCCs between 70-80% even at high levels of battery penetration.

Figure 21. Incremental 4 Hour Battery Storage ELCC at Multiple Levels of Solar Additions above the 40 GW 2025 Baseline



LOWER BTM SOLAR GROWTH

The impact of assuming low BTM PV growth per the 2021 IEPR forecast on solar and battery storage ELCC was calculated for Tranche 3, in which the solar addition was reduced from 2.7G W to 2.1 GW. The overall impact was found to be minor and is summarized in the table below. The values in Table 8 represent the "Last In" ELCC values and do not account for diversity impacts. This decrease in battery ELCC and the slight increase in solar ELCC shown in the 3.5 GW level below would grow over time if less BTM PV is added to the system than the 2021 IEPR forecasted (e.g., if less rapid growth in BTM results by recent net energy metering changes).

stated here is not necessarily expected when considering the total ELCC of a portfolio of resources, instead of incremental ELCCs based on a specific point on the portfolio ELCC surface.

Table 8. Low BTM PV Incremental ELCC Sensitivity Results

	Incremental 4-Hour Battery ELCC (%)		Incremental Solar ELCC (%)	
4-Hour Battery Penetration (GW)	**Base Case**	**Low BTM PV**	**Base Case**	**Low BTM PV**
1.5	79%	76%	7%	6%
3.5	77%	73%	9%	10%

IEPR AFTERNOON LOAD SHAPE ADJUSTMENT

In the 2023 MTR ELCC Analysis, the base case ELCC values were simulated with an adjusted load profile (see SERVM with Load Adjustment in the figure below). The pre-adjusted load profiles were sourced from the 2022 RA and IRP SERVM analyses (see SERVM without Load Adjustment in the figure below). A sensitivity was performed with the pre-adjusted load profiles to understand how this load adjustment impacted the battery storage ELCC values. As described in the input assumptions section of this report, this adjustment was made to reflect the IEPR load shapes and to calibrate the historical weather based SERVM load shapes with the median IEPR load demand from its single year 8760 hourly forecast.

The increase in loads during critical reliability hours and an increase in the gross peak load duration suggests that the Load Adjustment would have had a detrimental impact on storage ELCC values. However, additional analysis showed that the duration of the net load peak was decreased due to high solar performance in weather years with a dominating impact on LOLE results (e.g., 2020). This reduction in the net load duration resulted in an increased ability for batteries to shave the peak and an increase in their ELCC by ~10%. Commensurately, solar ELCCs drop slightly with the small shift in the timing of the net load peak. The net load shape impact is shown in Figure 22 below.

Figure 22. Average Daily Net Load Profile Comparison (September, Daily Peak > 40 GW)

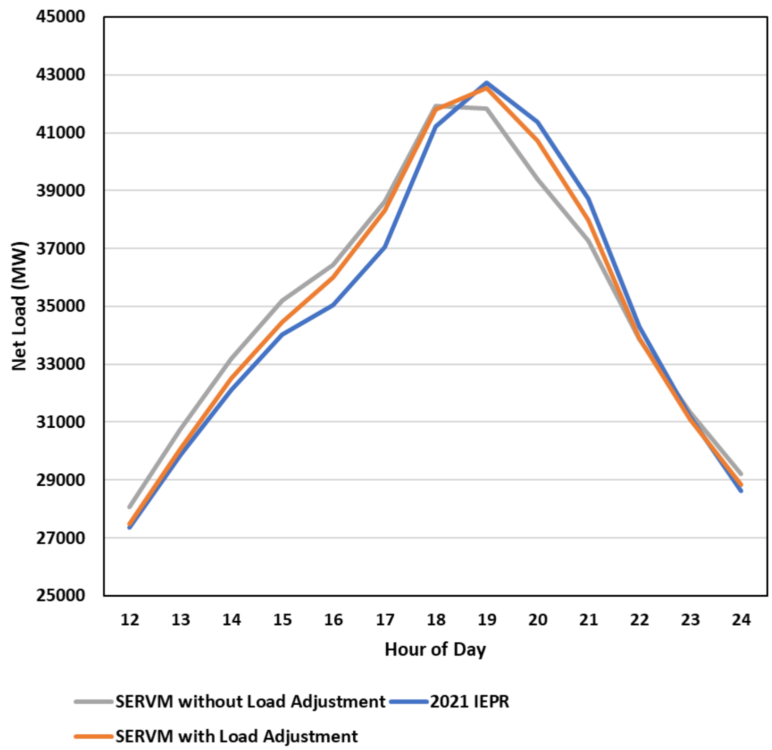


Table 9. IEPR Afternoon Load Shape Adjustment ELCC Sensitivity Results

	Incremental 4-Hour Battery ELCC (%)		Incremental Solar ELCC (%)	
4-Hour Battery Penetration (GW)	**Base Case**	**Without IEPR Adjustment**	**Base Case**	**Without IEPR Adjustment**
1.5	79%	69%	7%	8%
3.5	77%	69%	9%	10%

WEATHER YEAR RE-WEIGHTING

An exploratory analysis was conducted to estimate the potential impact of increased frequency of extreme weather events on the overall reliability value of solar and storage. This was accomplished by eliminating weather years prior to 2011 and only utilizing the most recent ten historical weather years (2011-2020) for determining the weighted average LOLE. All weather years were given an equal probability weighting except for 2020, which was given a higher weighting of 20%. The roughly doubling of the probability weighting for 2020 acknowledges the fact that in the recent history not currently incorporated into the SERVM analysis (i.e., September 2022 heat wave event), CAISO has experienced gross peak load deviations higher than those anticipated in the 23-year distribution of weather scenarios currently modeled. The 2022 weather event was 12.5% higher than the IEPR median peak forecast. This compares to the highest value of ~10% above the 23 year median managed peak load modeled in the current SERVM weather dataset for 2020 weather.

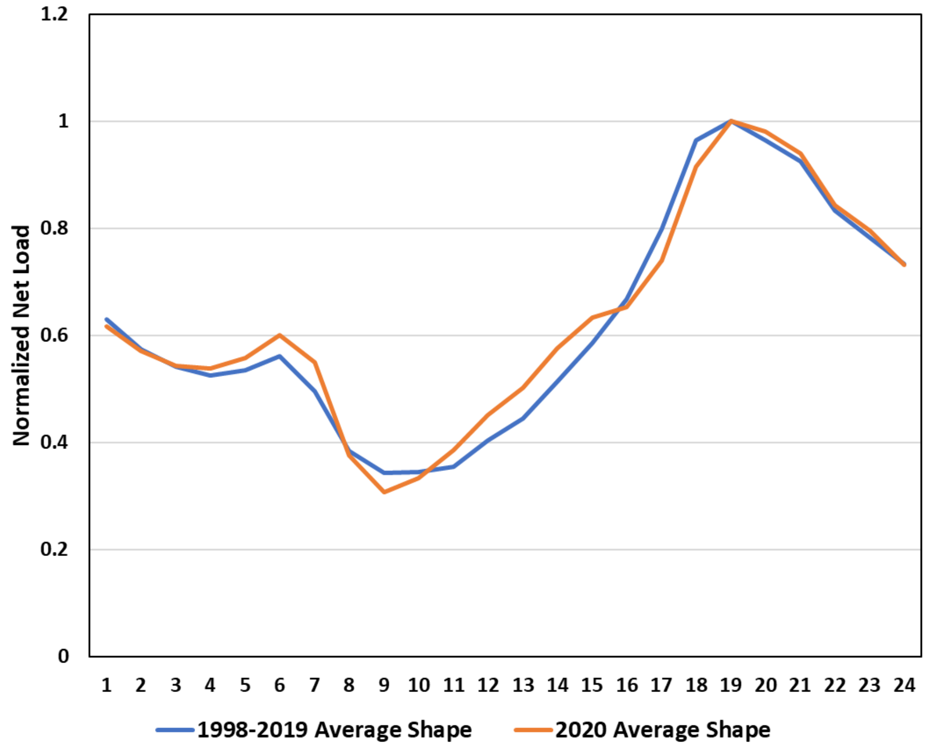
Once included in the SERVM model, the 2022 weather year may drive a higher total reliability need to minimize outages to less than 1 day in 10 years. The probability re-weighting assumes that a 2020-like year will happen more often in part to account for the 2022 event, which occurred only two years after the extreme weather of 2020. The final probability weighting values are shown in Table 10 below.

Table 10. SERVM Weather Year Probability Weighting

Weather Year	Base Case	Weather Year Re-Weighting Sensitivity
1998	4.35%	0%
1999	4.35%	0%
2000	4.35%	0%
2001	4.35%	0%
2002	4.35%	0%
2003	4.35%	0%
2004	4.35%	0%
2005	4.35%	0%
2006	4.35%	0%
2007	4.35%	0%
2008	4.35%	0%
2009	4.35%	0%
2010	4.35%	0%
2011	4.35%	8.9%
2012	4.35%	8.9%
2013	4.35%	8.9%
2014	4.35%	8.9%
2015	4.35%	8.9%
2016	4.35%	8.9%
2017	4.35%	8.9%
2018	4.35%	8.9%
2019	4.35%	8.9%
2020	4.35%	20%

While the magnitude of the load variability is significant, the shape of the net load profile in 2020 on high load days is similar to the net load profile that in other extreme weather years.

Figure 23. Normalized Net Load Shapes on Extreme Days



Because the shape (i.e., duration) of the net load peak period is expected to be a primary driver in a battery storage resource's contribution to ELCC, the similarity of the net load shapes between 2020 and prior weather years implies that the reliability contribution of energy-limited resources would be similar to base case results. However, the distribution of LOLE days also changes with this sensitivity. Essentially all LOLE is concentrated in 2020 in this sensitivity, and a single day from the 2020 weather year has LOLE in almost every iteration. In other words, this day is so extreme that the addition of any type of capacity (energy constrained or not constrained) has little effect on LOLE.

The large gap in reliability between the most extreme day and subsequent days means that energy constraints on incremental units are unlikely to surface new reliability events, resulting in higher incremental ELCCs (6-7 percentage points higher than base case results). Ideally, instead of shortening the historical weather dataset used, adjustments could be made to a longer dataset to account for climate impacts. This approach would lead to less concentration of LOLE (and therefore the dynamics that drive ELCC values) in fewer modeled extreme weather days. For these reasons, these sensitivity results should be viewed as indicative of ELCCs under August 2020 conditions, rather than a comprehensive indication of ELCCs under climate impacts.

Table 11. Weather Year Re-Weight ELCC Sensitivity Results

	Incremental 4-Hour Battery ELCC (%)		Incremental Solar ELCC (%)	
4-Hour Battery Penetration (GW)	**Base Case**	**Weather Year Re-Weight**	**Base Case**	**Weather Year Re-Weight**
1.5	79%	85%	7%	12%
3.5	77%	84%	9%	16%

In addition to analyzing the effect of batteries on LOLE, we also analyzed their effect on Expected Unserved Energy (EUE[27]). Since the extreme day in 2020 nearly always has EUE, the effect of adding storage on the volume of EUE may provide additional insight into the capacity value of storage in a more extreme weather environment. On this extreme day, while adding storage and removing perfect capacity does not substantially change LOLE, 4-hour batteries are not as effective at reducing EUE as perfect capacity is. The EUE-based analysis showed that 3.5GW of 4-hour batteries have an incremental ELCC of 61%[28] - a reduction of approximately 5% from the base case.

PESSIMISTIC BATTERY OPERATION

The way in which battery storage resources are dispatched in the SERVM model can impact the final reliability contribution of the resource class. While uncertainty of system conditions can influence the value of certain resource classes, batteries are generally flexible enough to change their schedule to mostly mitigate this impact. Consequently, the primary concern around the impact of battery operation on its reliability value is its operating flexibility, not the magnitude of uncertainty in system conditions.

Battery storage resources are scheduled in SERVM using an algorithm that considers available resources and the day ahead net load profile. However, random generator outages may occur that are not accounted for in the day ahead schedule. Also, the availability of energy to purchase from the market is not known with certainty in the model at the time of setting the original schedule. Additionally, real time market signals can cause batteries to discharge earlier in the day (as was seen on September 6, 2022), although CAISO is actively seeking to resolve its market optimization to avoid this situation (the issue seen on September 6 was resolved by September 7 and 8, 2022).

In the base case, batteries are able to adjust their charging and discharging schedule in order to resolve reliability issues caused by random generator outages or changes to market availability. In the pessimistic battery operation sensitivity, batteries were not allowed to reschedule their dispatch, leading to dispatch inefficiencies that may occur during actual grid operation if operators are not allowed — or battery owners

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[27] Average total quantity of unserved energy (MWh) over a year due to system demand plus reserves exceeding available generating capacity

[28] ELCC calculated by removing perfect capacity until the EUE level before the incremental addition of battery storage is reached.

are not given proper signals — to change operating schedules (e.g., a battery may discharge fully earlier in the day assuming ample supply from thermal resources later in the day, which did not actually materialize due to random generator outages). The results from this sensitivity are shown in the table below. The last-in battery ELCC values decreased by approximately 10% from the base case at higher 4-hour battery penetration levels, suggesting an earlier declining ELCC curve for battery storage resources. Solar ELCCs are higher since the additional energy can resolve some of the effects of the imperfect foresight on the battery value, by reducing the total energy the storage must discharge to avoid a loss of load event.

Table 12. Pessimistic Battery ELCC Sensitivity Results

	Incremental 4-Hour Battery ELCC (%)		Incremental Solar ELCC (%)	
4-Hour Battery Penetration (GW)	**Base Case**	**Pessimistic Battery**	**Base Case**	**Pessimistic Battery**
1.5	79%	77%	7%	10%
3.5	77%	66%	9%	14%

CONCLUSIONS AND LESSONS LEARNED

CONCLUSIONS

- The updated MTR ELCCs are shown in Table 1.
- Incremental ELCCs for mid-term reliability procurement require mapping a specific part of the multi-dimensional ELCC surface that changes as a function of solar, wind, storage, and demand response penetrations. This study focuses on mapping the interactive effects of adding solar and storage resources to fill the MTR need, based on their prevalence in RESOLVE modeling results and the preliminary MTR compliance data received by the CPUC.
- ELCCs for Tranches 3 and 4 are generally close to last year's MTR study except for wind ELCCs, which used updated wind shapes that lead to lower ELCCs for in-state wind and higher ELCCs for offshore wind.
- Between 2025 and 2028, solar and storage ELCCs tend to stabilize at ~75% incremental ELCC for 4-hr storage and ~6-8% incremental ELCC for solar. This is due to the diversity benefits of adding the two resources in parallel. Critically, the maintenance of this storage ELCC is dependent on the continued growth of solar modeled in this study (utility-scale and/or BTM). Sensitivities showed that 4-hr storage incremental ELCCs drop quickly to as low as ~50% without the concurrent growth of solar. Storage, in turn, is responsible for the continued, albeit small, incremental ELCC value of solar.
- Longer duration storage provides additional reliability value over 4-hr batteries. This additional value tends to be ~8-14 percentage points incremental ELCC for 8-12hr storage. Long-duration pumped storage and battery storage provide very similar value, though pumped storage's higher round trip losses and operating constraints cause a small decrement at the same duration.
- Sensitivities show that resource portfolio, extreme weather frequency, and operational assumptions can each drive +/- ~10 percentage point impacts to incremental ELCCs. This is in part due to the sensitivity of incremental ELCCs in the section of the solar and storage ELCC surface considered in this study. This uncertainty is inherent in rapidly changing extreme weather patterns and limited data for new resources, such as battery storage. ELCCs are no more uncertain than other capacity accreditation methods in this regard – in fact, they are probably less uncertain, since they are probabilistic and rely on longer historical records of correlations than deterministic planning approaches.

RECOMMENDATIONS FOR FURTHER RESEARCH

- **Refresh of ELCC forecasts as CAISO portfolio evolves**: A static forecast of incremental ELCCs is necessary for procurement processes like MTR. ELCCs were calculated in this study using the updated PSP, the 2021 IEPR, and preliminary MTR procurement resource mixes. This was done assuming a CAISO system at 0.1 days/yr LOLE. If either the mix of resources or the state's effective reliability standard changes, ELCCs will change accordingly. Just as a marginal ELCC forecast was provided in the current IRP cycle for LSE planning, future IRP cycles can benefit from regularly updating ELCC forecasts when the view of the long-term system portfolio evolves as market dynamics and resource costs change over time.

- **Incorporate 2021 and 2022 weather into SERVM**: September 2022 saw the highest ever peak load in the CAISO, so incorporating the extreme weather and load from that year will be critical to studying reliability going forward. Hourly CAISO sales data and hourly demand response dispatch data needed to incorporate some of these weather years will likely be available in late 2023.
- **Continue coordinating with the CEC on weather and load modeling, including climate impacts**: an exploratory scenario of weather year re-weighting was presented in this study. CPUC staff are also undertaking more scientific approaches to perform Climate Informed Forecasting that links future Global Warming Levels to downscaled climate model outputs. Further coordination with the CEC IEPR load development process is necessary to align the weather years, climate impacts, and load shapes between SERVM's weather year and load dataset and the IEPR. Past comparisons indicate a disconnect between the current IEPR shapes, load variability across the IEPR's 30-year weather dataset, and SERVM's 1998-2020 weather year dataset.
- **Continue making updates to battery operational data as more storage is added to the system**: understanding how optimally batteries operate in real-world conditions compared to their modeled behavior will be critical for modeling reliability as batteries grow to become a major part of the CAISO's reliability stack. Specifically, data updates for forced outage rates and mean time to repair of lithium-ion batteries should be updated as the sample size of past outages increases and operators learn how to manage outage risk.

LIST OF ACRONYMS

AAEE	Additional Achievable Energy Efficiency
AZ APS	Arizona Public Service Company
BANC	Balancing Authority of Northern California
BPA	Bonneville Power Administration
BTM PV	Behind the Meter Photovoltaic
CAISO	California Independent System Operator
CC	Combined Cycle
CFE	Comisión Federal de Electricidad
CPUC	California Public Utilities Commission
CT	Combustion Turbine
DR	Demand Response
EFOR	Equivalent Forced Outage Rates
EIA	Energy Information Administration
ELCC	Effective Load Carrying Capability
ERM	Enterprise Risk Management
EV	Electric Vehicle
GW	Gigawatts
ICE	Internal Combustion Engine
IEPR	Integrated Energy Policy Report
IID	Imperial Irrigation District
IRP	Integrated Resource Plan
LADWP	Los Angeles Department of Water and Power
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
LSEs	Load-Serving Entities
MMT	Million Metric Ton
MTR	Mid-Term Reliability
MW	Megawatts

NERC GADS	North American Electric Reliability Corporation Generator Availability Data System
NEVP	Nevada Power Company
NQC	Net Qualifying Capacity
PACW	PacifiCorp West
PRM	Planning Reserve Margin
PSH	Pumped Storage Hydro
PV	Photovoltaic
RA	Resource Adequacy
RSP	Reference System Portfolio
SERVM	Strategic Energy and Risk Valuation Model
SRP	Salt River Project
TIDC	Turlock Irrigation District
TOU	Time-of-Use
WALC	Western Area Power Administration - Lower Colorado Region
WECC	Western Electricity Coordinating Council
Wind CA	California Wind
Wind NM	New Mexico Wind
Wind WY	Wyoming Wind