Incremental ELCC Study for Mid-Term Reliability Procurement (Updated)

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PREPARED FOR

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- 10/22/2021: Updated to provide i) incremental ELCCs for out-of-state wind for tranches 1-3 and revisions for tranche 4, and ii) direction on ELCCs for hybrids with storage durations of longer than 4-hour.
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EXECUTIVE SUMMARY

PURPOSE

The CPUC's recent 11,500 megawatts (MW) net qualifying capacity (NQC) procurement order requires standardized ELCC values so that LSEs know the compliance value of various incremental resource types and the CPUC can be confident that incremental procurement will fill their identified procurement need. This report presents the effective load carry capability (ELCC) values to be used for compliance with the CPUC's Mid-Term Reliability (MTR) Decision (D.) 21-06-035. The decision's Ordering Paragraph (OP) 15 requires CPUC staff to publish the values by no later than August 31, 2021. The values for 2025 ("Tranche 3") and 2026 ("Tranche 4") compliance dates may be updated and published by no later than December 31, 2022. E3 and Astrapé produced this report 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, dependent upon external conditions such as weather. Resources such as battery storage have limits on their ability to be dispatched, with their constraints being either total energy or time of day limitations. Consequently, the ability of these resources to serve load is not the same as a traditional, dispatchable resource. Therefore, a measure of their equivalent capacity is needed so that these resources can be properly accounted in resource adequacy assessment. The emerging industry standard for this purpose is Effective Load Carrying Capability (ELCC).

This study examined the incremental ELCC of energy storage, solar PV, and wind in the CAISO to provide ELCC assumptions to load-serving entities (LSEs) for compliance with the CPUC's Mid-Term Reliability (MTR) Decision.[1] The Decision requires that at least 11,500 MW of additional 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. ELCCs for each tranche were calculated and key observations were made concerning the interactions between those resources as well as between those resources and other conventional[2] resources as it relates to their ability to improve CAISO system reliability. All ELCCs shown in this report are annual ELCC values.[3]

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

[2] 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.

[3] 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 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

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.[4] Thus, ELCC provides a consistent metric through which renewable and energy limited resources can be directly compared based on their ability to fill the CAISO's mid-term capacity shortfall.

This study began with a "baseline" CAISO resource portfolio aligned with the baseline from which the 11.5 gigawatt (GW) capacity procurement need was measured. 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 four points in this surface, aligned with the four MTR procurement tranches. In addition, a heuristic is provided for paired or hybrid resources based on the ability to effectively charge the storage capacity in the mid-term timeframe.[5] This analysis began with the CPUC Energy Resource Modeling (ERM) team's latest SERVM version, with its existing load and resources data, and made a variety of updates including wind shapes, unspecified import shapes, forced outage rates, and operating reserve needs. 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).

RESULTS

The ELCCs by MTR Tranche are presented in Table ES1. Incremental ELCCs by MTR Tranche. Energy storage resources provide less than 100% incremental ELCC in tranche 1 due to the existing CAISO storage penetration (approximately 6 GW of batteries and pumped storage hydro) and interactions with the conventional fleet used for charging. Energy storage ELCCs decline with increasing penetration, which can be partially offset with longer duration storage additions. Solar ELCCs decline as the net peak is shifted later into the evening but then increase due to their diversity benefit with higher penetrations of energy storage on the system; by 2026, most of their incremental capacity value is from these interactive effects with other resources. In-state wind ELCCs increase as solar and storage additions move reliability need into more favorable time periods for in-state wind's typical output. Out-of-state wind and offshore wind show higher ELCCs than in-state wind due to their higher output during net peak conditions. For storage technologies other than batteries and pumped storage hydro the results here are also applicable for those, within reason.

> **"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.

[4] 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.

[5] This report refers to "Paired" resources as generation and storage resources that share the same grid interconnection and "Hybrid" resources as paired resources with constraints that require storage charging to occur using the paired generation resource rather than the grid.

Table ES1. Incremental ELCCs by MTR Tranche

	Tranche 1 2,000 MW 2023	Tranche 2 6,000 MW 2024	Tranche 3 1,500 MW 2025	Tranche 4 2,000 MW 2026
4-Hour Battery	96.3%	90.7%	74.2%	69.0%
6-Hour Battery*	98.0%	93.4%	79.6%	75.1%
8-Hour Battery*	98.2%	94.3%	82.2%	78.2%
8-Hour Pumped Storage Hydro	N/A	N/A	N/A	76.8%
12-Hour Pumped Storage Hydro	N/A	N/A	N/A	80.8%
Solar - Utility Scale and BTM PV	7.8%	6.6%	6.7%	5.7%
Wind CA	13.9%	16.5%	22.6%	21.6%
Wind WY	28.9%	28.1%	26.7%	31.6%
Wind NM	31.1%	31.0%	34.5%	34.2%
Wind Offshore	N/A	N/A	N/A	36.4%

* *The 6 and 8 hour battery rows were each simulated with one tranche of 6 or 8 hour. The underlying tranches are assumed to be comprised of only 4-hour batteries. For example, tranche 3 for the 6 hour battery row is comprised of 8 GW of incremental effective capacity from 4-hour batteries with an additional 1.5 GW of 6-hour battery capacity.*

A heuristic is recommended for paired resource ELCCs. This heuristic, presented in Table ES2, captures a calculation method for all paired resource ELCCs as well as the necessary system sizing required to ensure full charging of the storage for hybrid resources (i.e., those that are limited from charging from the grid and must charge from the paired generation resource) with 4-hr duration storage. The necessary generator system sizing ensures that hybrid resources can sufficiently charge to discharge fully during the summer evening net peak loss of load events modeled in the mid-term time horizon. For longer-duration hybrids, E3 and Astrapé recommend that minimum generation thresholds scale linearly with increasing storage duration. For example, a 5-hour solar hybrid would require 5/4 or 125% minimum generator MW as a percentage of 5-hr storage MW.

Table ES2. Paired Resource ELCC Heuristic

	ELCC Calculation Method*	Min. Generator MW (as % of 4-hr storage MW)**
Solar and Storage	solar ELCC x solar MW + storage ELCC x storage MW	100%
Wind and Storage	wind ELCC x wind MW + storage ELCC x storage MW	200%

** Subject to a cap based on interconnection sizing*

*** Applicable to hybrid resources only*

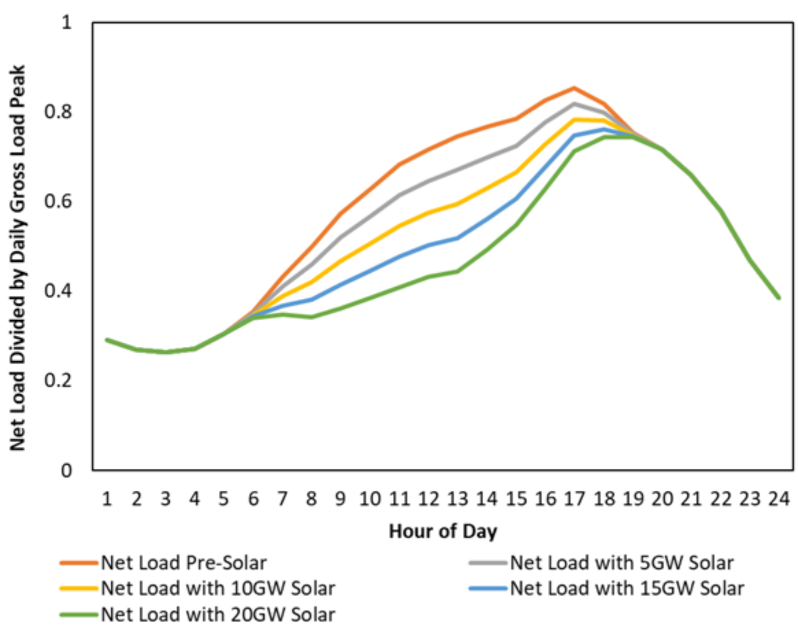
BACKGROUND AND METHODOLOGY

MTR PROCESS AND NEED FOR INCREMENTAL ELCCS

The MTR Decision requires that at least 11,500 megawatts (MW) of additional net qualifying capacity (NQC) be procured by all the load-serving entities (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. The very large amount of capacity ordered (approximately 25% 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 they 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.

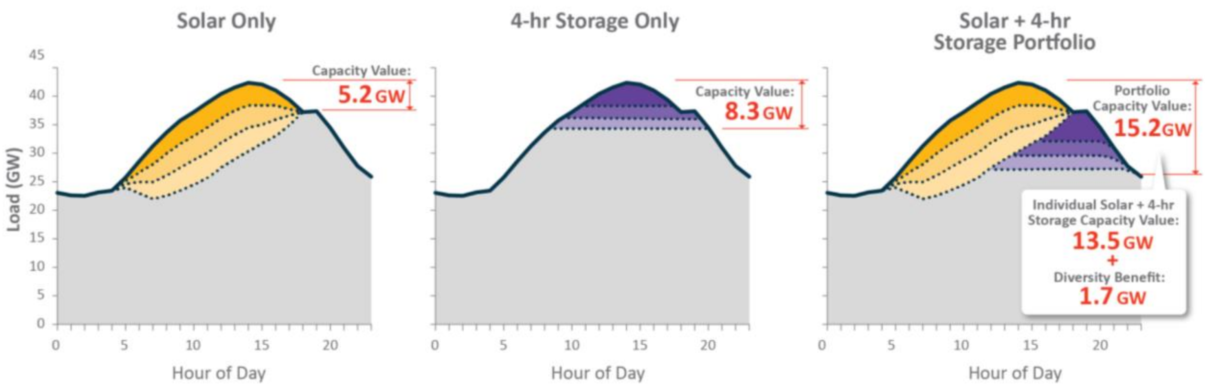
Figure 1. Illustrative Net Load Shift Due to Solar Penetration



The figure depicts the net load assuming no solar (i.e., gross load less other modifiers such as wind, energy efficiency, etc.), and then net loads at various penetrations of solar. The figure clearly depicts a time shift in the net peak load of the system. As the new net load peak approaches dusk, the contribution that the next increment of solar has to 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 dynamics within a resource type (e.g. solar), there are ELCC dynamics between resource types, which are known 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 solar hours and solar can charge energy storage as well as narrow the residual net peak storage must serve.

Figure 2. Schematic of "Diversity Impacts" between Solar and Energy Storage [6]



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 due to the saturation effects described above. 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 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.

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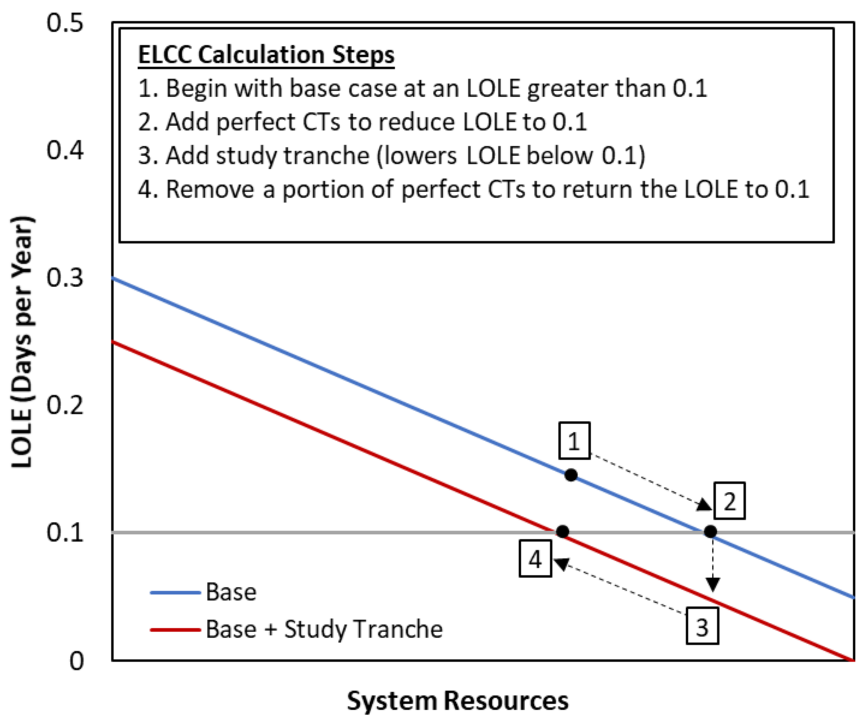
[6] N. Schlag, Z. Ming, A. Olson, L. Alagappan, B. Carron, K. Steinberger, and H. Jiang, "Capacity and Reliability Planning in the Era of Decarbonization: Practical Application of Effective Load Carrying Capability in Resource Adequacy," Energy and Environmental Economics, Inc., Aug. 2020

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 resources are modeled like Pumped Storage Hydro (PSH) facilities, with an initial generation schedule determined day-ahead based on daily load shape diversity, but which can be altered under emergency conditions. Battery resources, however, are able to 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 study system is first calibrated to a presumed target level of reliability with perfect CTs. For this study, the system was calibrated to the CPUC IRP's adopted 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 CTs. 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 CTs 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).

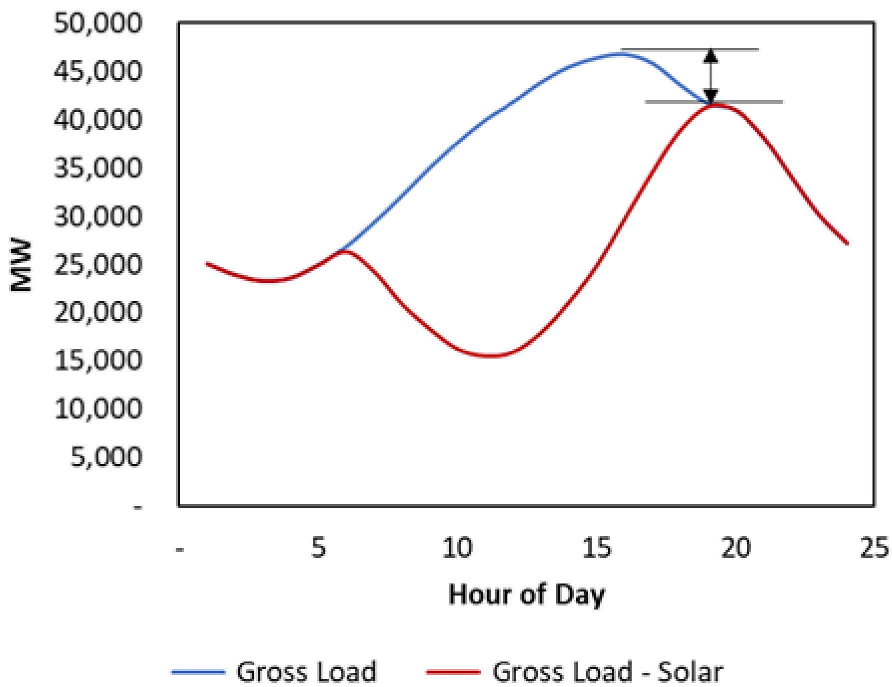
When assessing load carrying capability, either the addition of perfect load (i.e. flat load) or the removal of perfect capacity (i.e., a dispatchable generator with no forced or planned outages) can be used. There is no industry standard approach and both methods have been used widely in the industry, 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 perfect blocks of load to compare the reliability contributions of incremental generation.[7] 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 already require existing conventional generation to operate more mid-day to charge the storage and the additional load that needs to be served in all hours in the "perfect load" method requires existing generation to operate even more. This increased operation leads to more outages and commensurately lower ELCCs for storage and wind resources. The perfect capacity method was chosen for this analysis because it aligns with the method used by the CPUC Energy Resources Modeling team in their ELCC calculations. Using the perfect capacity method requires removing conventional generation from the baseline system, reducing the effect of system interactions, which tends to produce higher ELCCs for storage and wind resources. Since the difference in methods produces differences in ELCCs of only a few percentage points and baseload growth is not expected to be of the same magnitude as the capacity additions being analyzed, the perfect capacity method is reasonable for this analysis.

IMPORTANCE OF USING AN LOLP-BASED APPROACH TO CALCULATE CAPACITY VALUE

Initial approaches used in the industry to determine the reliability contribution of non-dispatchable resources were based on estimating the output of the resource during peak gross or peak net load conditions. The simplest methods, including those first used by California, entail averaging output (or using a statistical "exceedance" method) during afternoon hours when load was likely to peak. More sophisticated methods entail subtracting the net load from the gross load as shown in Figure 4. The resulting value was used to qualify capacity.

[7] https://www.astrape.com/?ddownload=9255
https://www.astrape.com/?ddownload=9137

Figure 4. Reliability Contribution of Solar Using Gross and Net Load Delta



While these methods have an intuitive foundation, they suffer from multiple flaws. First, setting the window of reliability concern - which hours and days are critical – is subjective and is unlikely to align with the periods which determine 0.1 LOLE compliance. Second, the output from energy-limited resources during critical periods cannot be accurately determined without a commitment and dispatch model since their operating schedules are determined by resource prioritization and other rules that may not match simple peak shaving strategies. Finally, these methods do not capture interactions across resource types within the system. California has since moved away from historical output-based methods to a more robust ELCC calculation methodology approach[8] and all other large RA programs in the US have adopted, are in the process of adopting, or are considering the use of ELCC methods.[9]

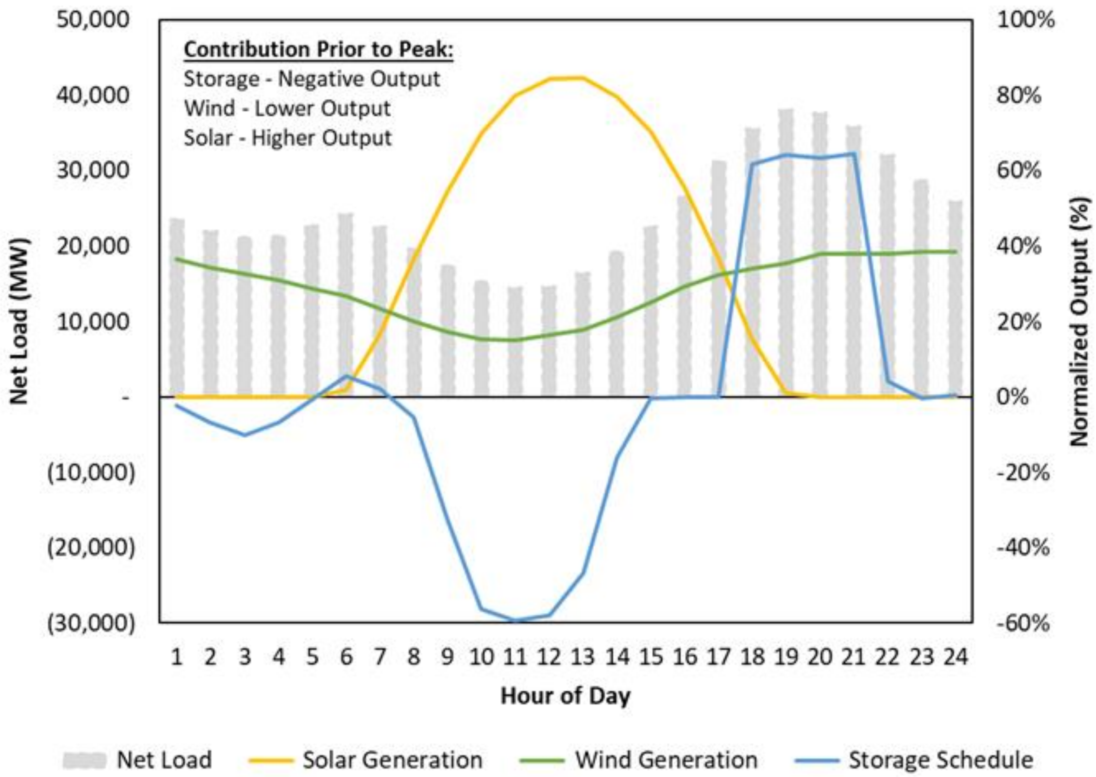
Variable and energy-limited resources have interactions amongst themselves, but also interact with the conventional generation fleet. For example, Figure 5 illustrates interactions between batteries, wind, and solar resources with conventional resources. Based on modeled dispatch, battery output is zero or negative in hours prior to the peak and then positive when discharging during higher price net load peak hours. Wind output in California is typically lower in the hours prior to peak than its output during net load peak conditions. Solar output is generally higher in the hours prior to the peak than during net load peak conditions. Resources with higher output prior to the net load peak provide a positive diversity

[8] ELCCs incorporating system operational dynamics across multiple years of load and renewable output data are used for supply-side solar and wind capacity accreditation calculations. However, behind the meter solar resources are still accredited within the IEPR forecast using a more simplified view based on single 8760 hourly shapes for load and solar generation.

[9] MISO currently uses ELCCs for wind. SPP and PJM are currently transitioning to ELCCs for solar, wind, and storage. ISO-NE and NYISO are both exploring the ELCC method.

benefit to conventional resources by reducing their operations and therefore limiting the likelihood of them facing a forced outage during the net load peak. Resources with lower output prior to the net load peak have a negative diversity impact since they require additional output from conventional resources, which then face a higher likelihood of a forced outage. This latter category includes energy storage resources if they require increased output from conventional resources to charge (storage projects that charge from paired generation would not be subject to this effect). These diversity impacts are considered within the LOLP modeling framework and result in battery and wind resources having ELCCs that are generally lower than their output during net peak conditions while solar resources have higher ELCCs than their output during peak conditions.

Figure 5. Effect of Storage, Wind, and Solar Resources on Conventional Operation



For these reasons, it is critical that ELCCs be determined through rigorous study of the reliability of the system using an LOLP model such as SERVM. LOLP models require simulating hundreds of thousands of scenarios to surface reliability problems and model the contributions of each class of resource across a broad range of weather conditions. In addition to performing quality control on the inputs required to build these scenarios, in depth review of hourly simulation outputs at the generator level is performed during initial calibration. Resulting ELCCs are validated through various means including net load validation analysis and verifying directional impacts of system changes.

STUDY DESIGN

This study utilized the following key steps:

1. Complete any SERVM methodology or input updates to the latest CPUC model version
2. Update the CAISO portfolio to reflect the MTR baseline portfolio
3. Design a "surface" of incremental solar and storage additions to represent expected mid-term capacity additions
4. Model the individual and combined additions of solar and storage capacity
5. Allocate diversity impacts between solar and storage using the "delta method"
6. 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
7. Model incremental ELCCs for 6-hr, 8-hr, and 12-hr storage assuming 4-hour storage is built to fill the previous tranches[10]
8. Model wind ELCCs within each tranche of solar and storage additions
9. Develop a heuristic for paired generation and storage resource ELCCs

The key SERVM input and methodology changes are described in the "Input Assumptions" section of this report below, which included wind shapes, unspecified import shapes, forced outage rates, and operating reserve needs. CAISO portfolio updates to the baseline 2022 portfolio provided by CPUC staff included the following changes:

- Add forecasted incremental utility-scale solar and energy storage additions within the MTR baseline (i.e., forecasted additions through 2026 based on in-development contracts executed and approved by June 30, 2020)
- Remove remaining OTC gas units
- Remove Diablo Canyon units
- Update load forecast inputs to the 2023 loads in the 2020 IEPR (including consumption, BTM PV, AAEE, TOU, and EV loads)

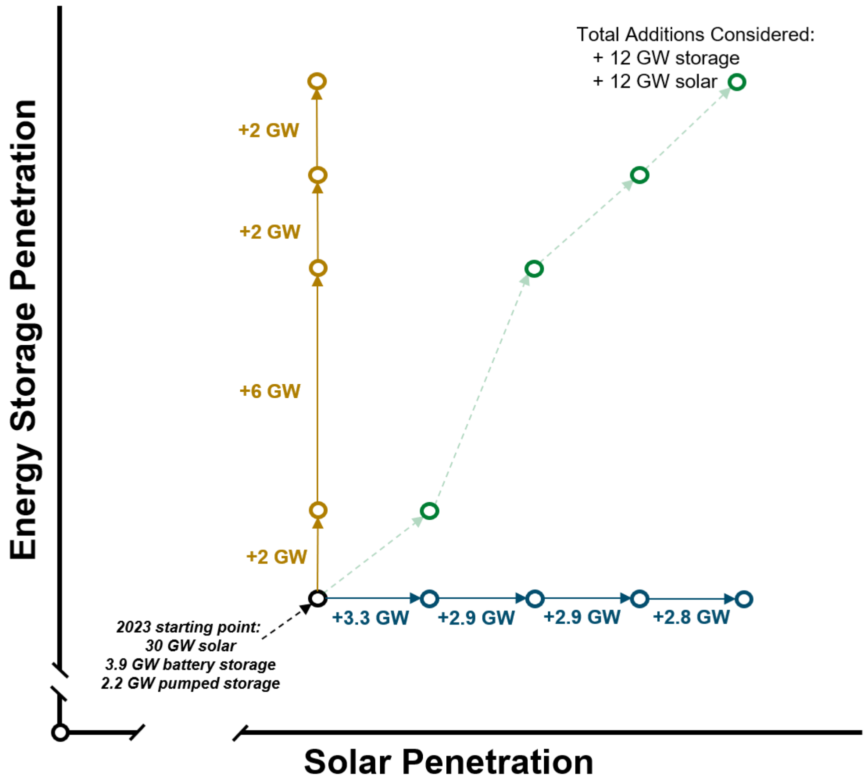
Loads were held constant at the 2023 level. Load changes between 2023-2026 are expected to have minimal impact on ELCCs and changing loads between study tranches would have introduced another variable to disentangle from the aggregated impact of increasing solar and storage penetration. The final CAISO portfolio onto which incremental resources were added is described in Table 3 below.

The solar and surface ELCC design, illustrated in Figure 6, assumed incremental utility-scale solar based on 2020 38 MMT LSE IRP planned + review resources (those above the MTR baseline that already included all online and in-development resources) while incremental BTM PV additions were based on the 2020

[10] For example, 6-hr battery ELCC in tranche 3 is calculated assuming 8 GW of incremental effective capacity from 4-hour batteries is added to fill tranches 1 and 2, with an additional 1.5 GW of 6-hour battery capacity modelled for tranche 3.

IEPR forecast.[11] Storage additions were designed to capture a range of additions 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.

Figure 6. Solar and Surface ELCC Design



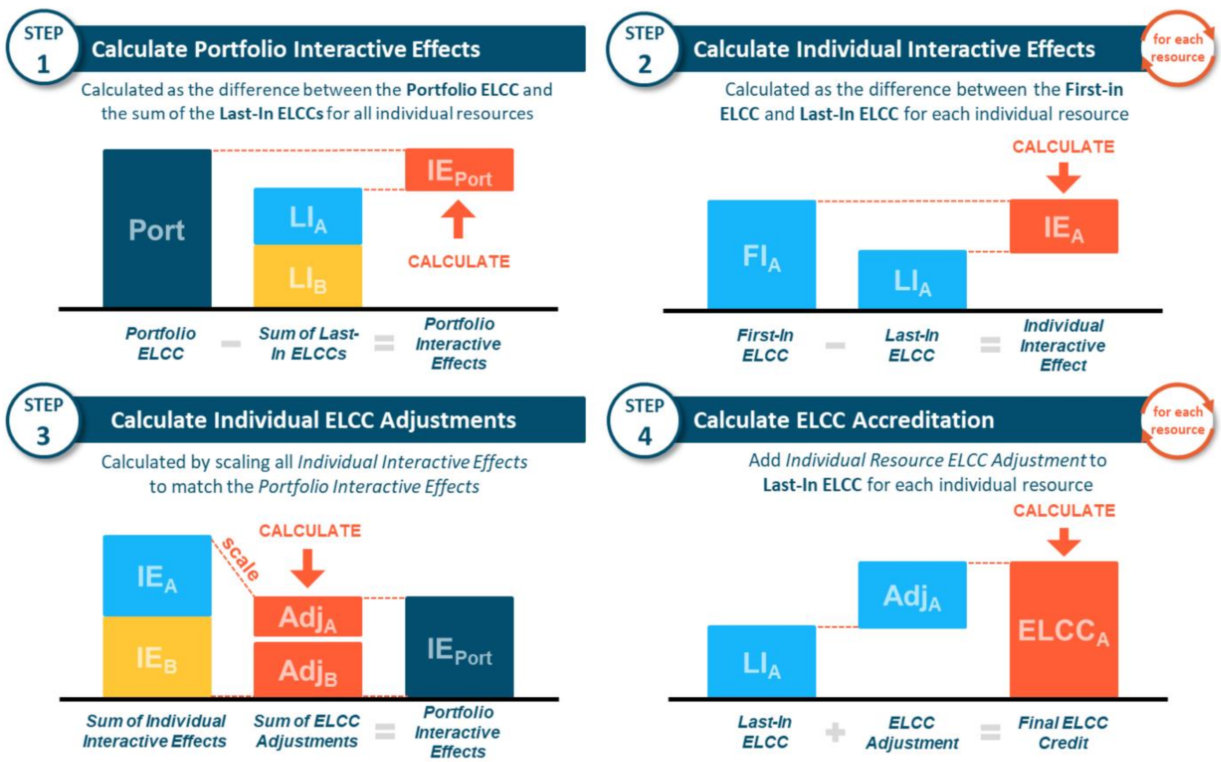
Once the solar and storage surface was designed, in-state wind was modeled as incremental to the assumed solar and storage starting points for each tranche. In other words, the tranche 2 in-state wind ELCCs were modeled as the incremental ELCC on top of a portfolio of resources that included the MTR baseline resources plus the tranche 1 solar and storage additions. This captured the interactive effects between the solar and storage additions on wind incremental ELCCs.

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

[11] The MTR baseline is aligned with the resources modelled to calculate the mid-term capacity shortfall; see the "Need Determination Model" available at: https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/integrated-resource-plan-and-long-term-procurement-plan-irp-ltpp/need-determination-model-2-22-2021-stackanalysismodel_02022021.xlsx. The aggregated LSE planned resources are contained in the CPUC's "Aggregated LSE Plan and Baseline and Dev Resources" spreadsheet, available at: ftp://ftp.cpuc.ca.gov/energy/modeling/Aggregated%20LSE%20Plans%20and%20Baseline%20and%20Dev%20Resources.xlsx.

surface. E3 developed the delta method, illustrated in Figure 7, 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 7. Delta Method ELCC Allocation Methodology[12]



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 utilized include modeled vs. actual performance of energy storage resources in the CAISO market, the assumed solar capacity additions (both BTM and utility-scale), and the impact of climate change on SERVM's CAISO load shapes and resource availability.

[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.

INPUT ASSUMPTIONS

RELIANCE ON ESTABLISHED CPUC IRP SERVM MODEL DATA

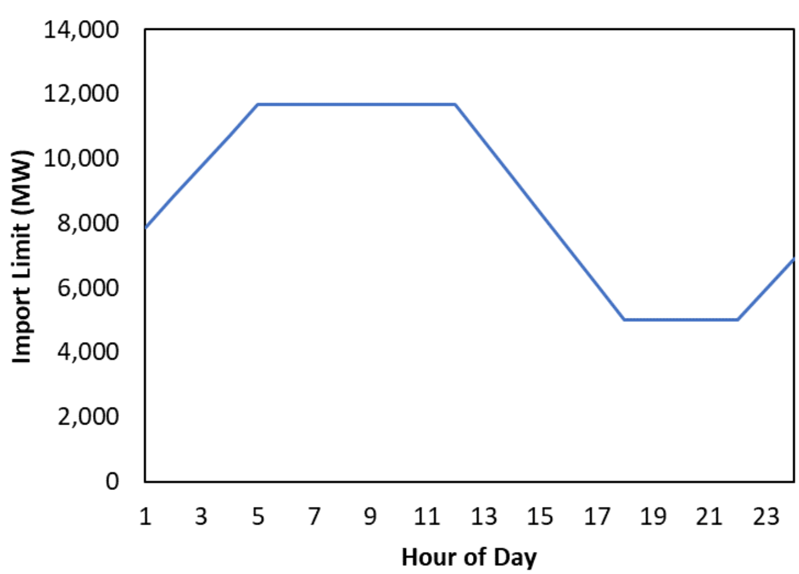
The base database was constructed using the base database created by the Energy Division in support of the Resource Adequacy (RA) and Integrated Resource Plan (IRP) proceedings.[13]

UPDATES MADE IN THE PROCESS OF THIS STUDY

IMPORT SHAPES

In the model, available on-peak imports (hours 18 to 22) are constrained from 11,665 MW in the off-peak periods to 5,000 MW. In the original dataset, the change in constraint is applied simply as a one-hour shift. This jump is unwieldy for the SERVM commitment algorithms. Instead of applying the instant shift, these simulations used a linear sloping import profile. Publicly available interchange information for CAISO was retrieved from the EIA website based on January 2020 to February 2021 actual data.[14] While historical imports often showed more than 5GW, total imports were capped as shown in Figure 8 to match the expected future transmission and generation availability constraints of 5 GW between hours 18 and 22. The historical data also showed an average of 1,000 MW/h ramping capability, leading to the use of the linear sloping import limit rather than the block shape that abruptly drops and increases 6,665 MW in one hour. Recent analyses have assumed a further reduced level of imports (e.g., only 4,000 MW unspecified imports in the MTR "High Need" scenario) which would directly affect system capacity need. However, this difference is not expected to have a significant impact on the ELCC results.

Figure 8. Modeled Maximum Import Limit



[13] https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/electric-power-procurement/long-term-procurement-planning/2019-20-irp-events-and-materials/unified-ra-and-irp-modeling-datasets-2019
[14] https://www.eia.gov/beta/electricity/gridmonitor/dashboard/electric_overview/balancing_authority/CISO

All external regions were not explicitly modeled, instead North and South neighbor assistance was modeled as a proxy. Table 1 defines which Tier 1 (one tie away) neighboring entities were classified as North and which neighbors were classified as South.

Table 1. Region Definitions for Proxy Neighbor Assistance

Region	Tier 1 Entity
North	Balancing Authority of Northern California (BANC) Bonneville Power Administration (BPA) PacifiCorp West (PACW) Turlock Irrigation District (TIDC)
South	Arizona Public Service Company (AZ APS) Comisión Federal de Electricidad (CFE) Imperial Irrigation District (IID) Los Angeles Department of Water and Power (LADWP) Nevada Power Company (NEVP) Salt River Project (SRP) Western Area Power Administration – Lower Colorado Region (WALC)

A time series of imports into CAISO was developed for North and South Tier 1 neighboring entities separately and was based on historic interchange as a function of CAISO net load by season, where net load is calculated as load minus the sum of wind, utility scale solar, and behind the meter solar. The relationship between net load and net imports was applied to all 20 weather years studied (1998 to 2017) so that each weather year included a unique profile of assistance from neighboring areas reflective of each year's renewable output and weather conditions.[15] While historical imports often showed more than 5 GW during peak net load hours, total imports were capped as shown in Figure 8 to match the expected future transmission and generation availability constraints of 5 GW between hours 18 and 22. The average hourly imports as a function of net load during hours 18 to 22 are provided in Figure 9. In most net load conditions, the 5 GW import capability is fully utilized.

[15] Net imports are exports minus imports. The study simulations do not capture periods of net export, but as a resource adequacy study, those periods are not relevant for ELCC calculations.

Figure 9. Average Hourly Imports by Zone

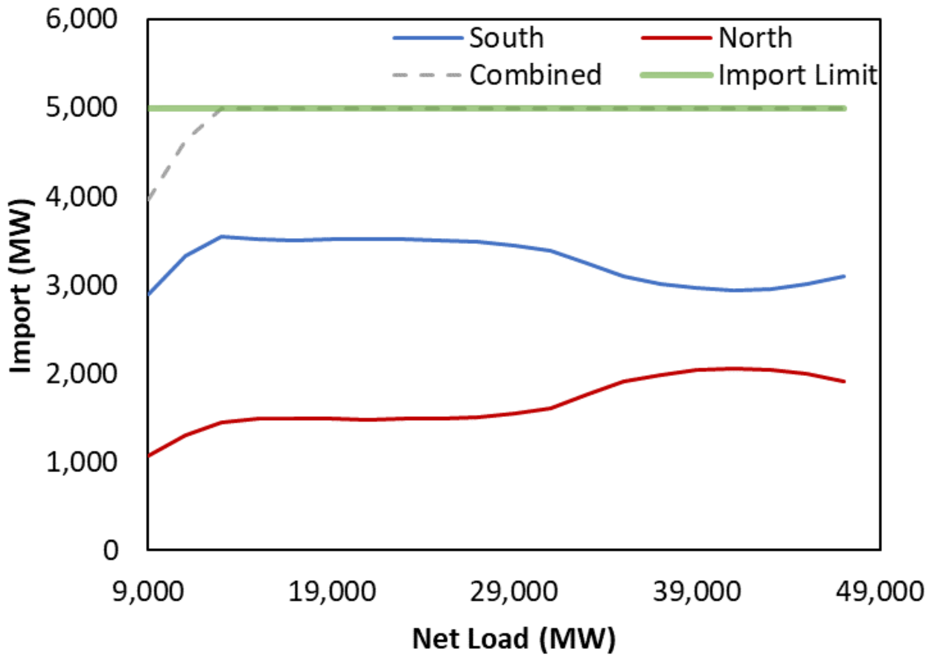
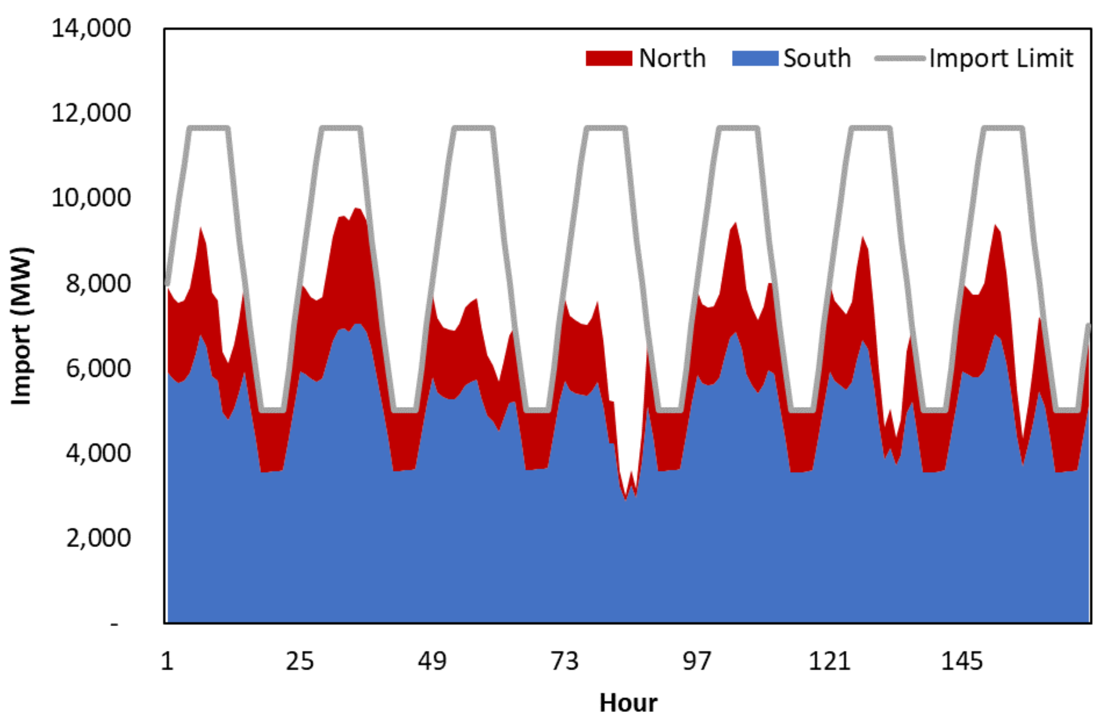


Figure 10 provides an illustrative example of a week of imports for both the North and South zones.

Figure 10. Imports – 1 Week Illustrative Example



WIND SHAPES

Astrapé created new wind shapes for land-based in-state wind resources for use in this study. The reason for creating the new wind shapes was driven by the timing of the previous wind not aligning with historical data and the large and unexpected differences in ELCCs by zone within California implied by the original shapes.[16] Astrapé constructed synthetic shapes for 1998 to 2017 using a clustered sampling method based on historical wind output data provided by CPUC staff. CPUC staff developed profiles for offshore wind and out-of-state wind resources in New Mexico and Wyoming based on the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) dataset.[17] The documentation for the wind shapes can be found in Appendix A. Prior out-of-state wind ELCCs were calculated using profiles developed by Astrapé based on historical production data. Given the limited available production data for wind projects outside California, the incremental ELCC values for out-of-state wind projects in this updated study were based on simulations using the CPUC-developed wind profiles.

OPERATING RESERVES

Operating reserves were increased from 4.5% to 6% in SERVM for this study to be consistent with the Western Electricity Coordinating Council (WECC) contingency requirement.[18]

FORCED OUTAGE RATES

Forced outage rates for combined cycles (CCs) and combustion turbines (CTs) were updated to better reflect the actual class average outage rates. A comparison of the original and updated weighted average equivalent forced outage rates (EFORs) is shown in Table 2.

Table 2. Original and Updated Modeled Weighted Average EFORs for CCs and CTs

Unit Category	Original Weighted Average EFOR (%)	Updated Weighted Average EFOR (%)
Combined Cycle	9.3	7.2
Combustion Turbine	20.1	15.2

It was important to update these unit categories because of the significant interaction that non-dispatchable resources have with other conventional dispatchable resources that have forced outage rates, as shown in the "Importance of Using LOLP-Based Approach to Calculate ELCC" section above. The new lower forced outage rates reduce the effect from the interaction particularly for wind and storage resources, resulting in an increase in ELCCs in this study compared to Astrapé's 2021 study for the California IOUs, which used the previous forced outage rates.

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[16] This references the wind profiles used in the CPUC RA modeling efforts available at: ftp://ftp.cpuc.ca.gov/energy/modeling/wind_servm_profiles_merra.csv

[17] https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/

[18] http://www.caiso.com/Documents/Final-Root-Cause-Analysis-Mid-August-2020-Extreme-Heat-Wave.pdf

SUMMARY OF KEY INPUTS

MTR BASELINE PORTFOLIO

The Baseline Portfolio used in SERVM is provided in Table 3.

Table 3. 2023 Base Resource Mix

Unit Category	Capacity (MW)
AAEE	821
Battery Storage	3,854
Biogas	292
Biomass / Wood	527
BTM PV	15,543
CC	16,081
Coal	480
Cogen	2,294
CT	8,307
DR	1,817
EV	-1,616
Geothermal	1,469
Hydro	6,619
ICE	255
Imports	10,502
Nuclear	635
PSH	2,273
Solar 1Axis	3,307
Solar 2Axis	2
Solar Fixed	10,844
Solar Thermal	997
TOU	-2,857
Wind	7,114
Total	**89,560**

SOLAR AND STORAGE SURFACE INPUTS

The nameplate solar additions added by each tranche are provided in Table 4. The utility solar additions were assumed to be all solar single-axis tracking. The solar and surface ELCC design assumed incremental utility-scale solar additions in 2023, 2024, 2025, and 2026 based on the average annual additions of 1,658 MW between 2022 and 2026 in the 2020 38 MMT LSE IRPs planned + review resources dataset. This led to 3,317 MW of utility-scale solar being added to the MTR baseline portfolio for 2022 and 2023 LSE-planned additions and 1,658 MW being added in 2024, 2025, and 2026. This resulted in a slightly more conservative approach than the actual annual LSE planned additions, which were more front-loaded with nearly 7 GW of new additions by 2024. This conservative approach is warranted to avoid overestimating the ELCC provided by near-term solar additions (and the diversity benefit those would provide to storage additions) should LSEs not secure the very high level of near-term build contained in the LSE plans. Incremental BTM PV additions for 2024, 2025, and 2026 were taken from the 2020 IEPR forecast.

Table 4. Nameplate Solar Additions by Tranche

Tranche	BTM PV Additions (MW)	Utility Solar Additions (MW)	Incremental Solar Added by Tranche (MW)
Tranche 1 2023[19]	0	3,317	3,317
Tranche 2 2024	1,265	1,658	2,923
Tranche 3 2025	1,266	1,658	2,884
Tranche 4 2026	1,153	1,658	2,811

The incremental storage added by tranche and simulated storage levels by tranche are provided in Table 5. Recognizing that the ELCC contributions of incremental storage additions are less than 100%, the incremental simulated storage did not match the targeted procurement. The required storage capacity to meet procurement targets for tranche 4 was ultimately extrapolated from the results of these runs. 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.

Table 5. Assumed Nameplate Storage Capacity by Tranche

Tranche	Incremental Procurement Target (NQC MW)	Incremental Storage Levels Simulated by Tranche (MW)	Total System Battery Storage (MW)
Tranche 1 2023	2,000	2,000	5,854
Tranche 2 2024	6,000	6,000	11,854
Tranche 3 2025	1,500	2,000	13,854
Tranche 4 2026	2,000	2,000	15,854

[19] The first tranche of solar captures the ELCC for additional solar additions above the MTR baseline that may be added anytime between now and 2023.

RESULTS

The incremental ELCCs by MTR Tranche are presented in Table 6. For storage technologies other than batteries and pumped storage hydro the results here are also applicable for those, within reason.

Table 6. Incremental ELCCs by MTR Tranche

	Tranche 1 2,000 MW 2023	Tranche 2 6,000 MW 2024	Tranche 3 1,500 MW 2025	Tranche 4 2,000 MW 2026
4-Hour Battery	96.3%	90.7%	74.2%	69.0%
6-Hour Battery*	98.0%	93.4%	79.6%	75.1%
8-Hour Battery*	98.2%	94.3%	82.2%	78.2%
8-Hour Pumped Storage Hydro	N/A	N/A	N/A	76.8%
12-Hour Pumped Storage Hydro	N/A	N/A	N/A	80.8%
Solar - Utility Scale and BTM PV	7.8%	6.6%	6.7%	5.7%
Wind CA	13.9%	16.5%	22.6%	21.6%
Wind WY	28.9%	28.1%	26.7%	31.6%
Wind NM	31.1%	31.0%	34.5%	34.2%
Wind Offshore	N/A	N/A	N/A	36.4%

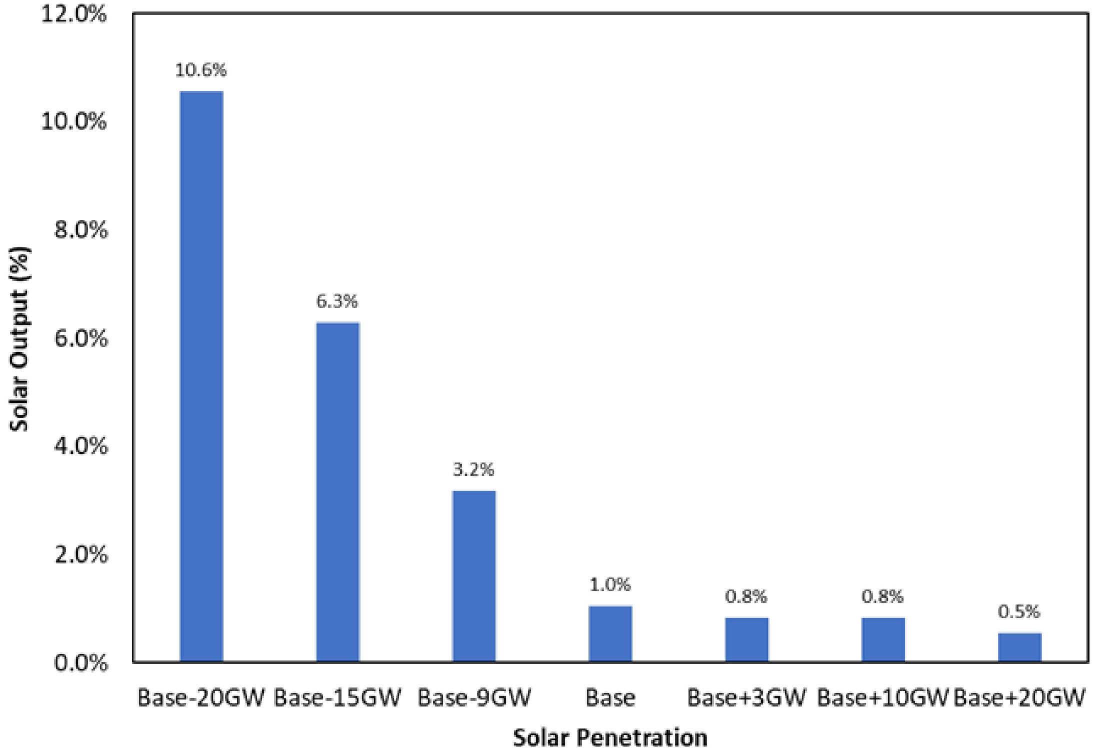
* *The 6 and 8 hour battery rows were each simulated with one tranche of 6 or 8 hour. The underlying tranches are assumed to be comprised of only 4-hour batteries. For example, tranche 3 for the 6 hour battery row is comprised of 8 GW of incremental effective capacity from 4-hour batteries with an additional 1.5 GW of 6-hour battery capacity.*

Appendix B presents a comparison of these incremental ELCCs for storage, solar, and wind resources to those from past studies, including Astrapé's 2021 Marginal ELCC study for the IOUs and the latest ELCCs from the Preferred System Plan version of RESOLVE.

SOLAR ELCC

As the penetration of solar increases, the net load peak shifts out towards the evening hours. However, there is a limit to this shift. In the extreme, the output of solar can be de minimis in the net load peak hour as demonstrated in Figure 11 below, which shows an extreme case of over 50GW of solar capacity. In a representative day where solar output is 1% of nameplate in the net load peak hour, 100 GW of solar would only reduce the net load peak by 1 GW. Figure 11 shows solar output at the timing of the net load peak as a function of solar penetration. In this figure, the "Base+3GW" values correspond to the solar included in Tranche 4. SERVM captures the net peak shift from solar across twenty years of historical load and solar modeled, whereby the extent of the net peak shift will differ from year to year based on the peak load patterns and solar output changes, driven by weather differences across those years.

Figure 11. Average Solar Output Across Top 25 Net Load Daily Peaks



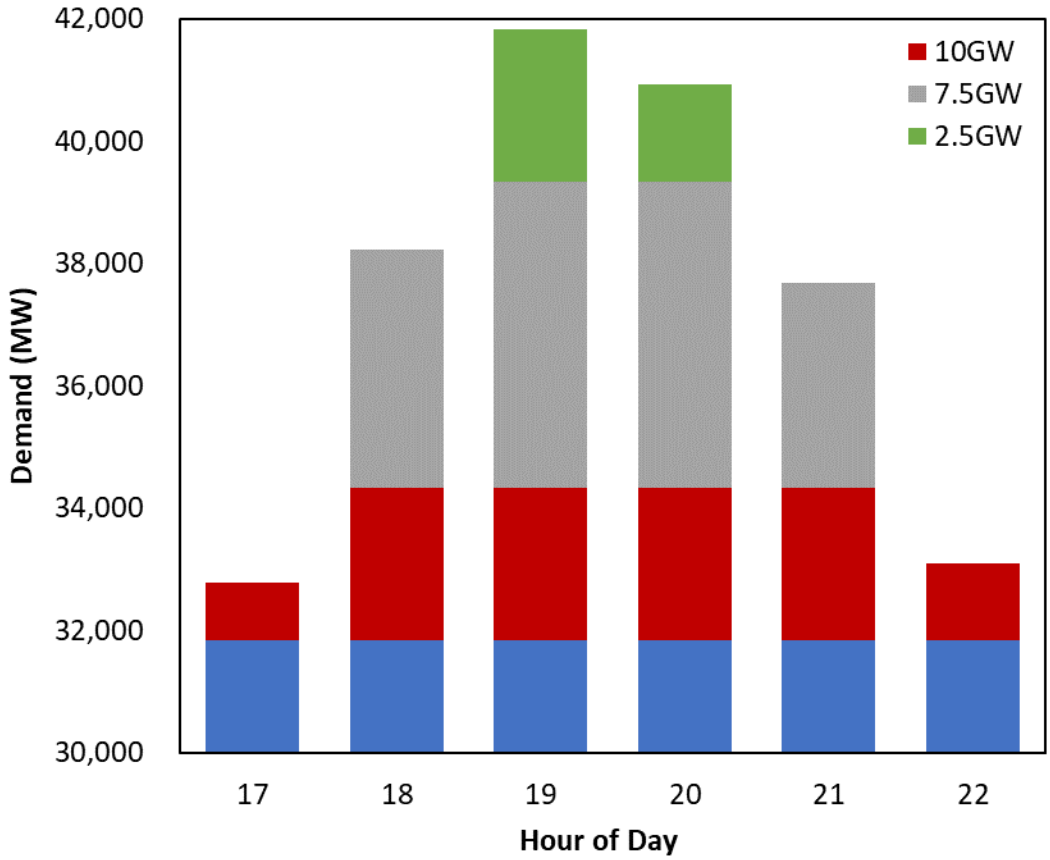
The solar ELCCs shown in Table 6 are materially higher than the values shown in Figure 11 due to the influence that solar has on the reliability contributions of other classes of resources. The interactions between solar and other resource classes will be explored in the 'Solar and Storage Interactions' section.

While solar's output during net load peak is affected by both its longitude and technology attributes (such as tracking utility 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. Astrapé's 2021 ELCC study for the CA IOUs did conduct ELCC analysis by solar type and location, which can provide an indication of which solar resources provide more or less than the resource average modeled here.

STORAGE ELCC

Storage ELCCs are predominately determined by their ability to serve load during extreme conditions without exhausting their store of energy. We will refer to this attribute as energy sufficiency. However, as described above, storage ELCCs are also affected by their interactions with other resource classes, including the charging energy served by conventional generators. This interaction results in a decline in battery ELCC prior to the level of storage penetration in which the energy sufficiency of the battery declines. The storage requirements of a battery are related to its ability to "shave the peak" of the system demand. For example, consider Figure 12 below, which illustrates hypothetical duration requirements of 2.5 GW, 7.5 GW, and 10 GW of battery storage.

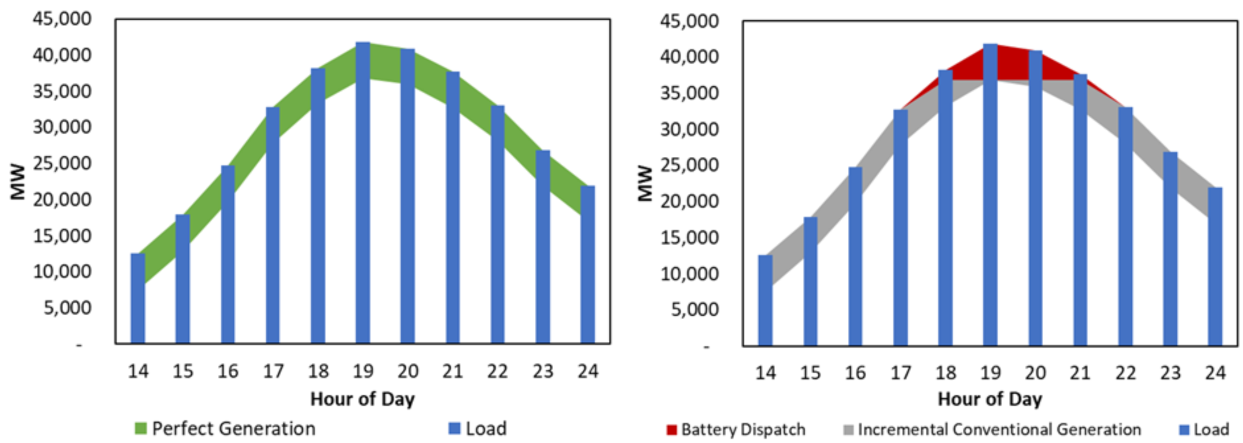
Figure 12. Battery Storage Duration Requirement (illustrative)



The illustrative figure indicates that the first 2.5 GW of batteries on the system only need to have a storage duration of 2 hours. At 7.5 GW of capacity, the incremental battery resources would need 4 hours of storage, while at 10 GW of capacity, the incremental battery resources would need 6 hours of storage. (In the figure the blue areas represent load not served by batteries.)

Because of the previously discussed interactions between resource classes, the ELCC of the batteries may not fully achieve 100% even if their duration is sufficient to serve the required portion of the net load. Because of the increased utilization of the conventional resources associated with serving additional load in other hours, there is probability that one of these resources could experience a previously unexpected outage that impacts the ability of the battery to meet the system peak. Figure 13 shows a comparison of adding a perfect generation resource with adding a battery resource to the system. Because the battery can only operate for a limited period, generation that was supplied by a perfect generator in the comparison case must come from existing conventional generators which have forced outage rates. So even if batteries have a very low forced outage rate, their contribution to reliability more closely mimics the reliability contribution of a generator with system average outage characteristics. This is the reason for the ELCC of less than 100% in the first tranche. Even though the battery has sufficient energy, system interactions reduce its contribution to reliability. A conventional resource with system average EFOR would be expected to show a similar ELCC since the comparison is against a perfect resource. As solar penetration increases, excess mid-day energy is able to serve as charging energy for incremental batteries on the system, which reduces the interactive effects described here.

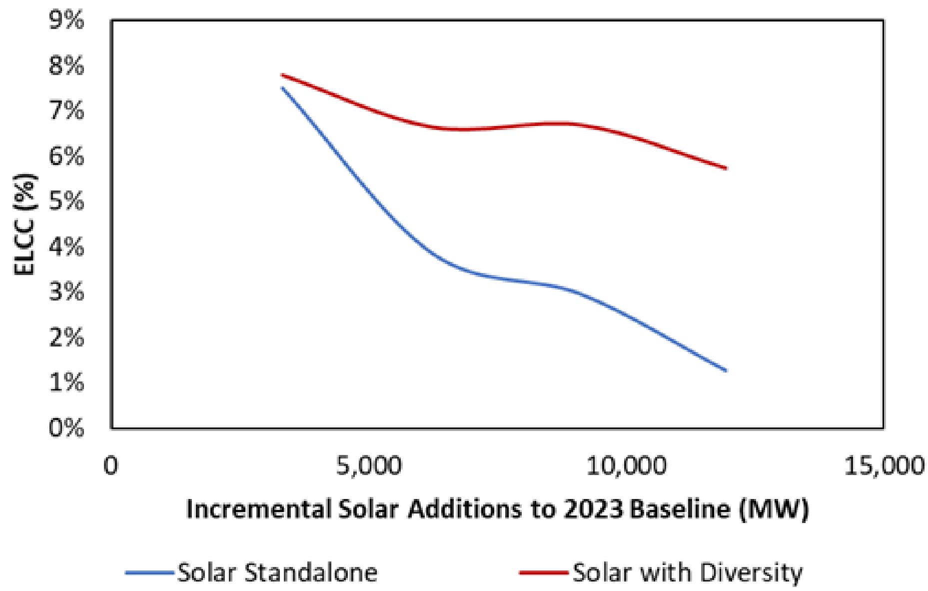
Figure 13. Incremental Battery Additions Compared to Incremental Perfect Generation



SOLAR AND STORAGE INTERACTIONS

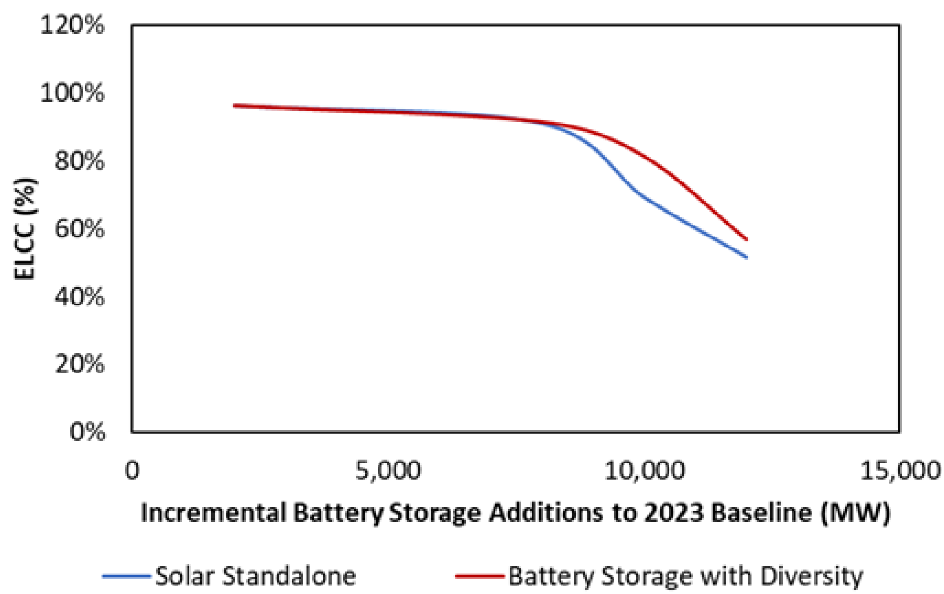
While ELCCs for both solar and storage resources follow declining marginal curves as penetration increases, the resource classes exhibit synergistic effects. Increasing solar penetration steepens the net load shape, allowing for more storage capacity to provide reliability value. To isolate this synergy and determine appropriate allocations for each technology, simulations were performed for both standalone solar, standalone storage, and combined solar and storage. The difference in the sum of the standalone values and the portfolio value is the diversity benefit, which was then split between the technologies, using the delta method. For solar, as shown in Figure 14, the standalone ELCC approaches 0% as the total penetration by 2026 exceeds 40 GW. There is very little solar output at the time of the net load peak at this solar penetration. However, as demonstrated by the post-diversity calculations, the steepening effect on the net load results in a net reliability contribution that is meaningfully higher. Importantly, the diversity benefit is only material when the battery fleet is not energy sufficient. In cases where the battery energy is exhausted, the additional energy from solar can delay the start of battery discharge.

Figure 14. Solar ELCC Comparison



The diversity impact contribution to storage ELCCs is of similar magnitude, as shown in Figure 15, though the storage ELCCs are at a higher starting point so the effect appears less pronounced.

Figure 15. Battery Storage ELCC Comparison



PAIRED GENERATION AND STORAGE

A heuristic is recommended for paired resource ELCCs. This heuristic, presented in Table 7, captures a calculation method for all paired resource ELCCs as well as the necessary system sizing required to ensure full charging of the storage for hybrid resources that are limited from charging from the grid and must charge from the paired generation resource. The necessary generator system sizing ensures that hybrid resources can sufficiently charge to discharge fully during the summer evening net peak loss of load events modeled in the mid-term time horizon.

Table 7. Paired Resource ELCC Heuristic

	ELCC Calculation Method*	Min. Generator MW (as % of 4-hr storage MW)**
Solar and Storage	solar ELCC x solar MW + storage ELCC x storage MW	100%
Wind and Storage	wind ELCC x wind MW + storage ELCC x storage MW	200%

** Subject to a cap based on interconnection sizing*

*** Applicable to hybrid resources only*

The additional constraints that a paired resource faces with respect to its ability to contribute to system reliability are the limitation of charging the battery from onsite renewable generation (in the case of hybrids), and the size of the inverter or interconnection. As shown in prior assessments of the reliability contributions of hybrid resources,[20] this constraint is unlikely to bind as long as the minimum generation thresholds are satisfied. As shown in Figure 16, a solar resource in California in a hybrid configuration with battery capacity at a 1:1 ratio will be able to charge a 4-hour battery at 95% confidence from its renewable energy output[21]. The chart illustrates the distribution of daily solar energy available to charge the battery. The 5th percentile series represents days with low solar energy and therefore low charging potential. When the CAISO daily net load peak is low, it is often cloudy, and solar production is low, so there is risk in being able to fully charge 4-hour batteries. However, on high load days, when reliability is of concern, the 5th percentile solar output represents more than enough energy to charge a 4-hour battery. The trend is different with wind as wind output has a slight negative correlation with summer peak loads. In the highest net load days, the wind energy is less dependable and less likely to be able to charge a 4-hour battery. As shown in Figure 17, a wind resource in California would be expected to be able to charge a 2-hour battery at a 1:1 capacity ratio at 95% confidence from its renewable energy output.[22] These thresholds are used to set the minimum generation requirement shown in Table 7. For hybrids with longer storage durations than 4-hour, E3 and Astrapé recommend that minimum generation

[20] https://www.astrape.com/?ddownload=9255

[21] The energy from paired solar exceeds that required to charge a 4-hour battery in at least 95% of all high net load days.

[22] The energy from paired wind is approximately equal to that required to charge a 2-hour battery in 95% of all high net load days.

thresholds scale linearly with increasing storage duration. For example, a 5-hour solar hybrid would require 5/4 or 125% minimum generator MW as a percentage of 5-hr storage MW.

Figure 16. Charging Potential of PGE Bay 1Axis PV and Storage Paired Resource

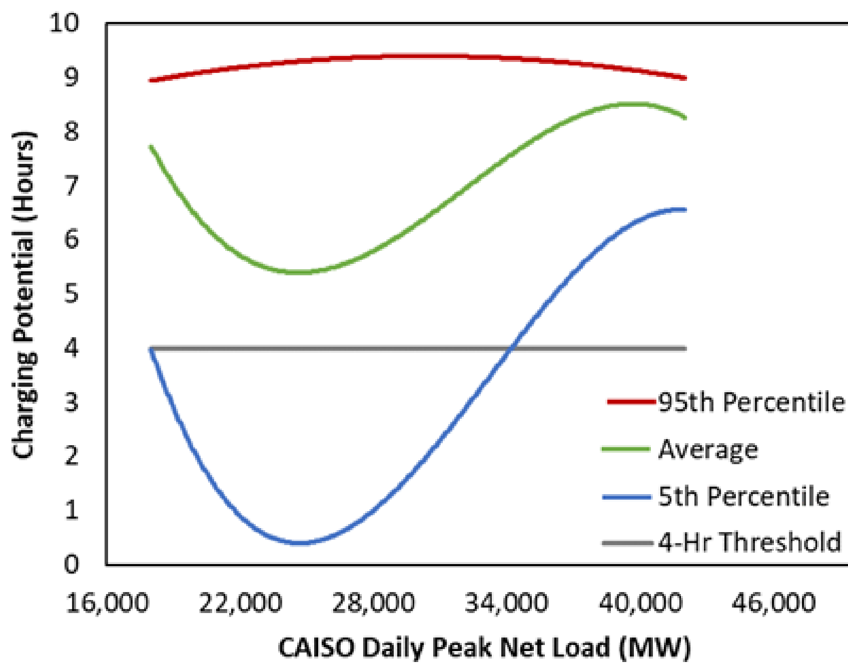
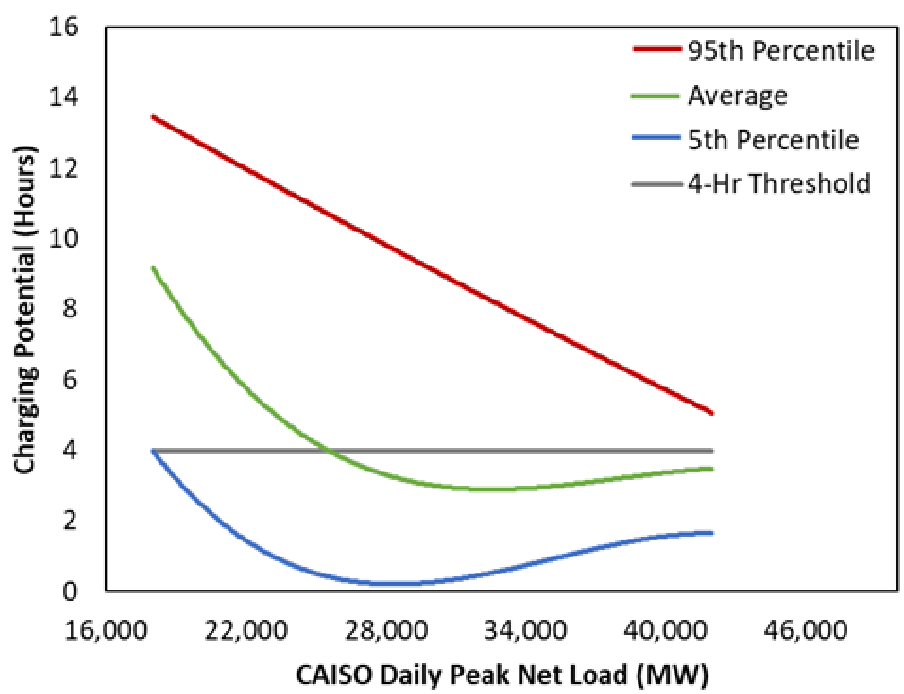


Figure 17. Charging Potential of PGE Bay Wind and Storage Paired Resource



WIND

Wind output is generally negatively correlated with hot weather and this is generally reflected in ELCC values that are materially lower than their annual or seasonal capacity factors (see the Appendix of this report for more information about these dynamics). 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 likely subject to different climatological conditions, which provides additional diversity and results in higher ELCCs even if their annual capacity factors are similar to those in California.

Table 8. Wind Incremental ELCCs by MTR Tranche

	Tranche 1 2023	Tranche 2 2024	Tranche 3 2025	Tranche 4 2026
Wind CA	13.9%	16.5%	22.6%	21.6%
Wind WY	28.9%	28.1%	26.7%	31.6%
Wind NM	31.1%	31.0%	34.5%	34.2%
Wind Offshore	N/A	N/A	N/A	36.4%

APPROACH FOR OTHER RESOURCES NOT MODELED

The Commission 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).

E3 and Astrapé agree that this is a reasonable approach. 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.

CONCLUSIONS AND LESSONS LEARNED

CONCLUSIONS

Based on the analysis presented in this report, E3 and Astrapé conclude the following:

- Energy storage resources provide less than 100% incremental ELCC in tranche 1 due to the existing CAISO storage penetration (approximately 6 GW of batteries and pumped hydro) and interactions with the dispatchable fleet used for charging.
- Energy storage ELCCs decline with increasing penetration, which can be partially offset with longer duration storage additions.
- Solar ELCCs decline as the system net peak is shifted later into the evening but then increase due to their diversity benefit with higher penetrations of energy storage on the system; by 2026, the majority of their incremental capacity value is from interactive effects with other resources.
- In-state wind ELCCs increase as solar and storage additions move reliability need into more favorable time periods for in-state wind's typical output. Out-of-state wind and offshore wind show higher ELCCs than in-state wind due to their higher output during net peak conditions.

RECOMMENDATIONS FOR FURTHER RESEARCH

- **Consider updating incremental ELCCs for tranche 3 (2025) and 4 (2026)**: while this analysis examined a surface of solar and storage additions to calculate incremental ELCCs through tranche 4 (2026), this analysis could be refreshed for later MTR tranches if more information is available that would materially impact the CAISO resource changes between now and 2025-2026. Potential differences versus the assumptions made for this analysis include the level of utility solar additions, behind-the-meter solar additions, or wind capacity additions. More or less solar will have impacts on the incremental storage ELCCs (and vice versa). A refresh may be warranted given the extremely large size of the capacity shortfall being filled.
- **Refresh of forced outage data in SERVM to reflect the latest data on resource performance**: while updates were made to CCGT and CT forced outage rates, other resources have relatively low class average EFOR values that should be validated with the latest NERC GADS data. Additionally, forced outage rates for battery storage were not incorporated into this analysis due to lack of operational data for CAISO storage resources. Battery storage outage rates should be updated as further data becomes available based on their performance in 2020, 2021, and 2022. Monitoring other aspects of real-world battery operations, such as their ability to be fully utilized within CAISO market operations, can inform whether additional updates are needed in SERVM to reflect their performance.
- **Review effects of uncertainty on the reliability contributions of energy limited resources:** The uncertainty in load, wind, solar, and generator performance leads to uncertainty in the availability of energy limited resources. The simulations in this study assumed that net load was known with high precision at the time of resource commitment. While operating procedures should mitigate

most of the reliability effects of uncertainty, analysis which includes distributions of net load uncertainty would be beneficial in validating estimates of energy limited resource reliability value.

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

APPENDIX A: UPDATED WIND SHAPE METHODOLOGY DOCUMENTATION

The following has been prepared for the California Public Utilities Commission "CPUC" to document the onshore wind profile development efforts made by Astrapé Consulting using a clustered sampling method.

HISTORICAL DATA

Astrapé began with hourly project level wind data from 2014 to 2020 for 119 different projects provided by CPUC staff. Astrapé assigned each project to one of the four regions to aggregate the data into larger profiles. Projects with incomplete or bad data were excluded. The number of projects included and excluded from each project are shown in Table A1. Capacities, shown in Table A2, were calculated from the hourly net dependable capacity profiles to achieve normalized hourly profiles for each of the seven regions.

Table A1. Project Designations

Region	# of Projects Excluded	# of Projects Included	Total # of Projects
PGE Bay	12	17	29
PGE Valley	1	0	1
San Gorgonio	7	47	54
Tehachapi	10	25	35
Total	**30**	**89**	**119**

Table A2. Project Capacities Assigned by Region

Region	MW Excluded	MW Included	Total MW
PGE Bay	89	1389	1,478
PGE Valley	13	0	13
San Gorgonio	135	3,696	3,830
Tehachapi	324	762	1,087
Total	**561**	**5,847**	**6,408**

Figure A1 - Figure A3 are the summarized normalized shapes by region for the annual, summer, and winter periods. Table A3 provides the annual capacity factors for the source data.

Figure A1. Annual Wind Shapes by Hour of Day

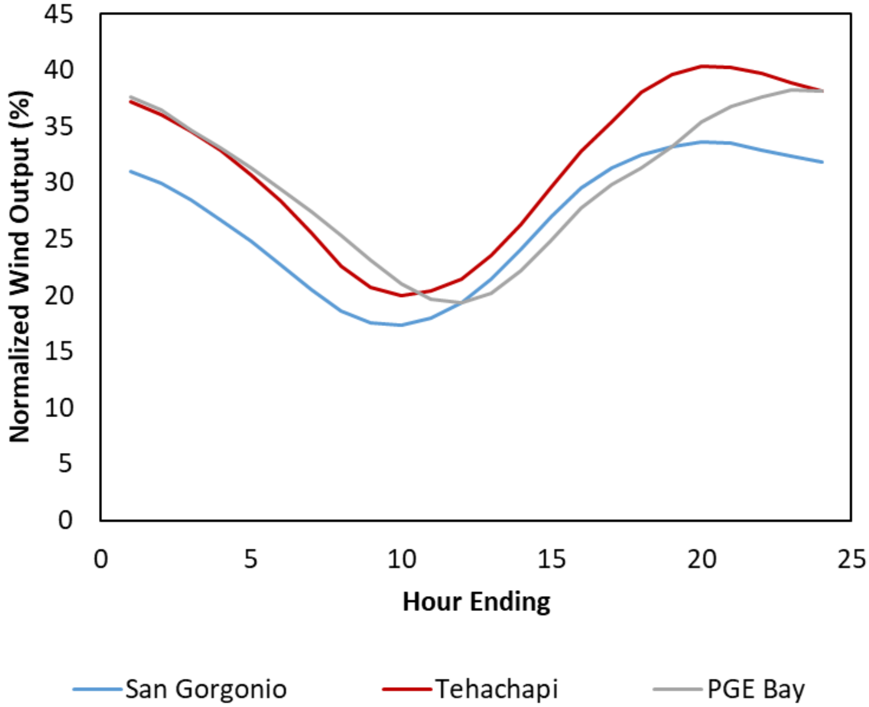


Figure A2. Summer Wind Shapes by Hour of Day

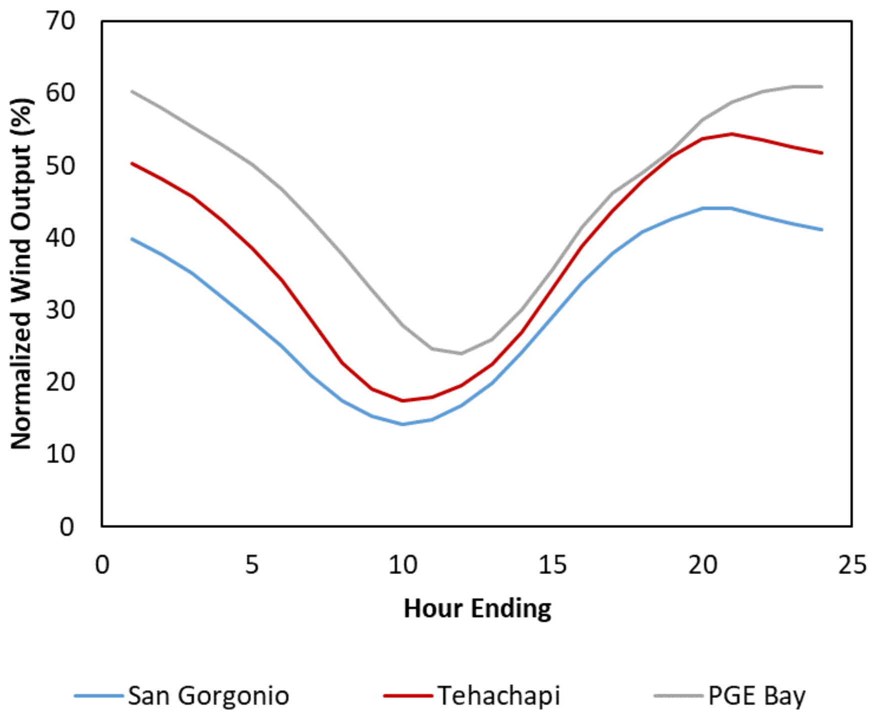


Figure A3. Winter Wind Shapes by Hour of Day

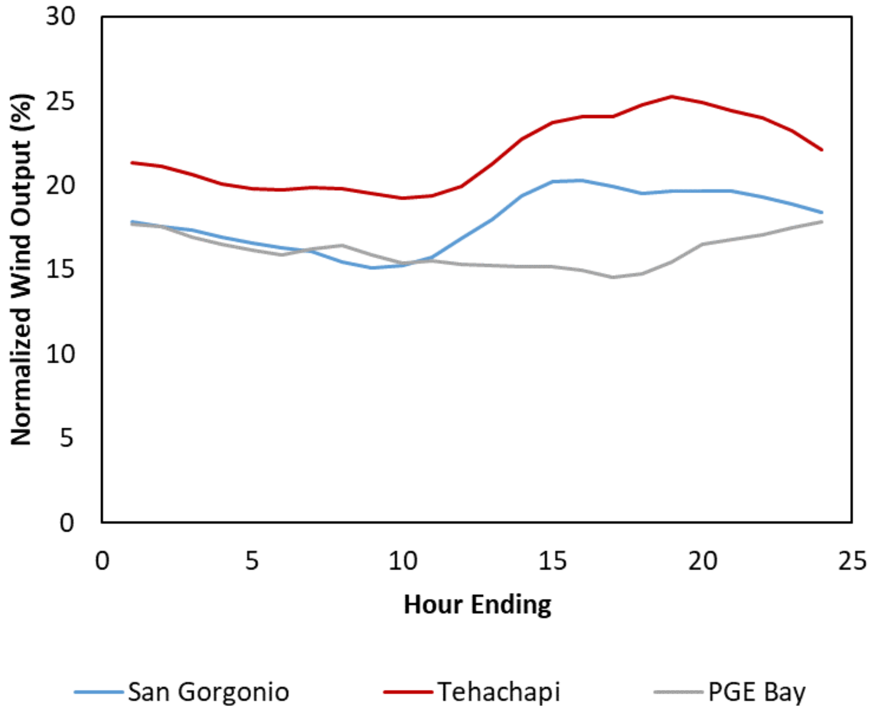


Table A3. Annual Capacity Factors

	San Gorgonio	Tehachapi	PGE Bay
2014	27.3	26.1	29.8
2015	24.0	28.6	30.3
2016	28.3	33.5	29.4
2017	26.2	33.0	28.5
2018	27.8	33.5	31.4
2019	26.3	32.4	29.2
2020	26.3	32.5	29.8
Average	**26.6**	**31.4**	**29.8**

Table A4 shows the capacities by year for each aggregate wind profile.

Table A4. Installed Wind Capacity (MW) by Year

Year	San Gorgonio	Tehachapi	PGE Bay
2014	3,254	106	1,246
2015	3,432	360	1,332
2016	3,558	390	1,332
2017	3,558	390	1,332
2018	3,686	445	1,378
2019	3,686	617	1,369
2020	3,435	746	1,369

Table A5 shows the correlation seen in the historical profiles. With these regions covering such a large geographical area, the correlation is not extremely high. There is a reasonable amount of correlation for the two California profiles that are in close proximity to each other. For example, San Gorgonio and Tehachapi have a 0.92 correlation. Astrapé maintains these correlations across zones in developing the final set of zonal shapes.

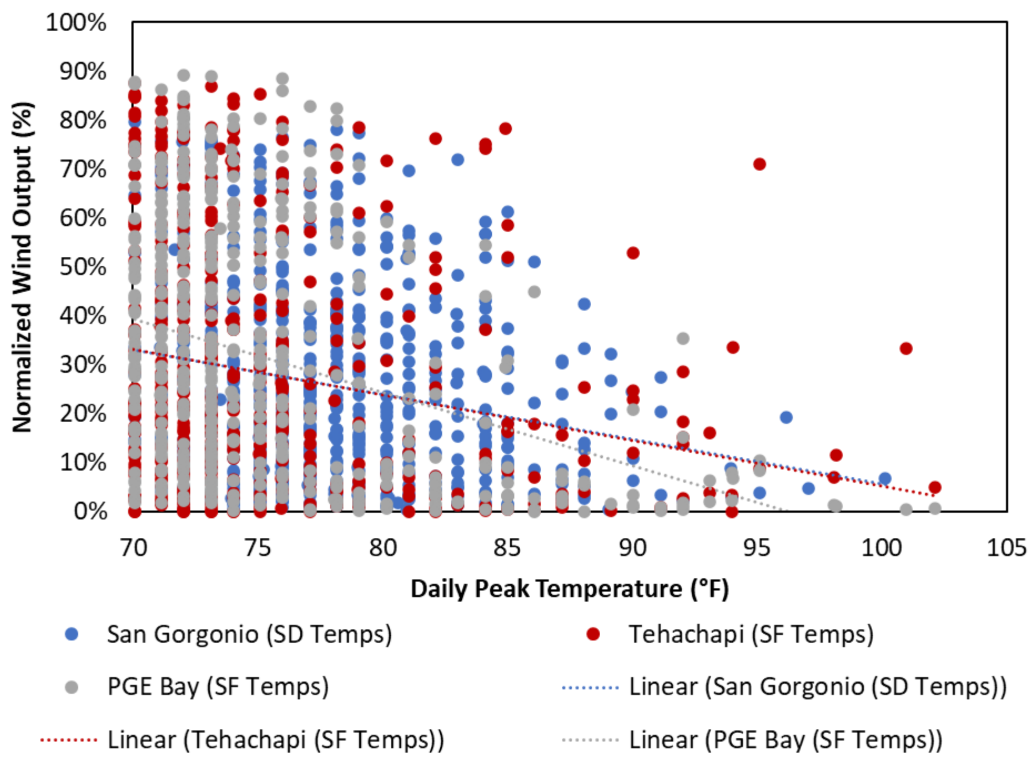
Table A5. Correlations Across Profiles

	San Gorgonio	**Tehachapi**	**PGE Bay**
San Gorgonio		92%	41%
Tehachapi			41%
PGE Bay			

SYNTHETIC WIND PROFILE DEVELOPMENT USING CLUSTERED SAMPLING

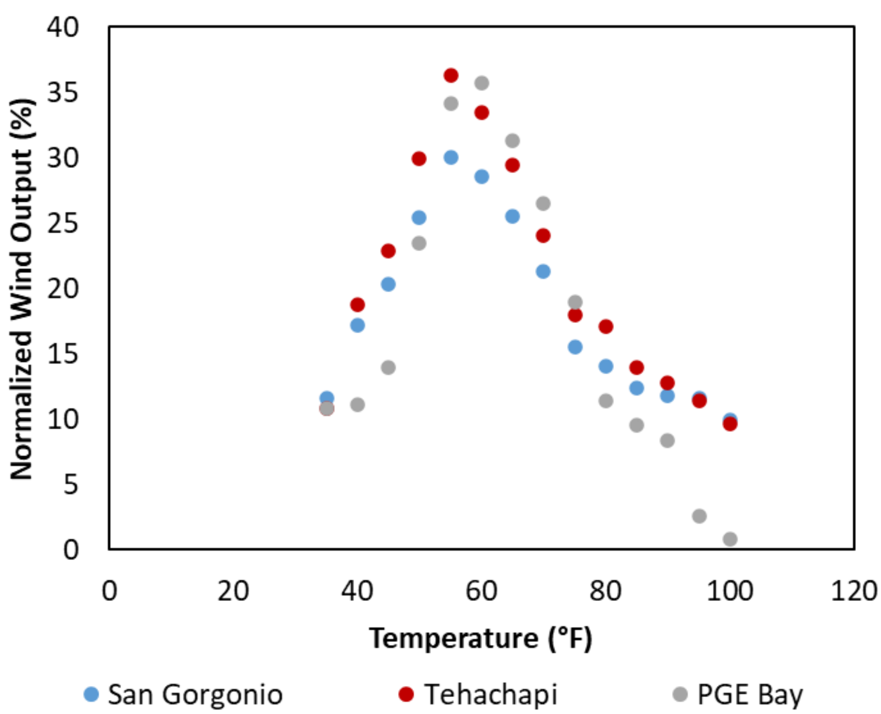
Because CPUC's analysis is based on a framework analyzing 1998 – 2017 weather years, it is important to develop synthetic shapes for these years. In resource adequacy modeling it is important to include actual daily shapes to mimic the distribution of historical wind output. In Astrapé's experience, modeled wind output data developed using mesoscale models has resulted in shapes that resemble an accurate average 12 x 24 capacity factor but tend to miss significant volatility or correlations that are seen in actual historical data. This is often due to inclusion of too much diversity between individual sites. For this reason, the 2014 to 2020 shapes are used to develop shapes for the 1998 to 2014 period based on San Francisco peak temperatures using a clustered sampling technique. A plot of historical afternoon wind output as a function of daily peak temperature is shown in Figure A4.

Figure A4. Historical Wind as a Function of San Francisco Daily Peak Temperature



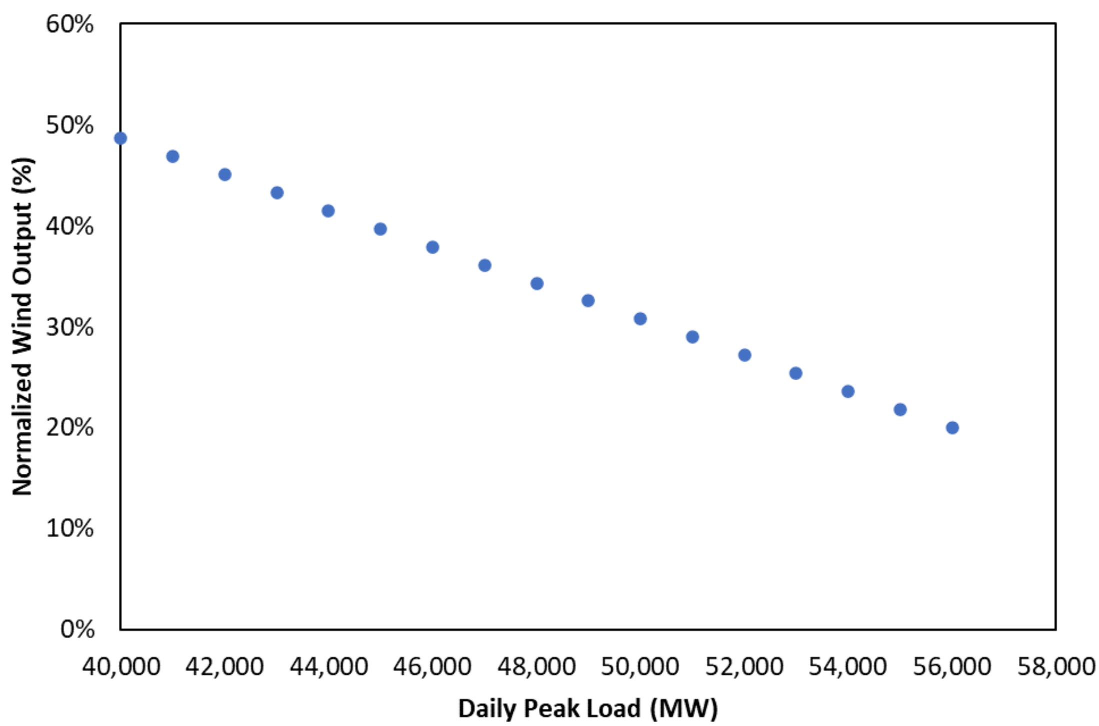
The average historical wind output as a function of San Francisco temperatures is provided in Figure A5. The correlations across California wind sites are visually apparent.

Figure A5. Average Historical Wind Output as a Function of San Francisco Temperature



Given the relationship of wind output to temperatures, historical data is clustered based on daily max temperatures and month of the year. Daily wind output is chosen based on the sum of the top 4 maximum hourly San Francisco temperatures for each day. The matching day is restricted to choose within the same month of the source data. For example, January 10, 1998 will use the closest matching temperature profile within the January time frame of the 2014 and 2020 historical wind data. Because the matching method for the existing profiles held the correlations constant by using the same seed day for all profiles, additional work was not needed to ensure correlations. A final resampling, which involved switching daily profiles, was done to match the load and wind output relationship present in the historical profiles. The wind output in the synthetic profiles on days with peak loads > 40GW was compared to the trend of wind output in historical data as a function of peak load. If the synthetic profile was higher than trend, its profile (for all synthetic wind sites to maintain correlations) was swapped with the profile from another day with lower wind output and with lower load. The resampling was performed to conform California wind with the trend in Figure A6.

Figure A6. California Afternoon Wind Output Trend as a Function of Daily Peak Load



The correlations for the 1998-2017 shapes are provided in Table A6. To smooth the transition between days (since days selected were not consecutive), the modeled output in hours 23 to 2 was averaged (hour 23 was the average of the profile in hour 22, 23, and 24; hour 24 was the average of hours 23, 24, and 1, etc.). The average final summer wind shapes are shown in Figure A7.

Table A6. Correlations Across Synthetic Profiles for 1998 to 2017

	San Gorgonio	Tehachapi	PGE Bay
San Gorgonio		89%	40%
Tehachapi			40%
PGE Bay			

Figure A7. Average Summer Wind Shapes for 1998 to 2017 Synthetic Wind Profiles

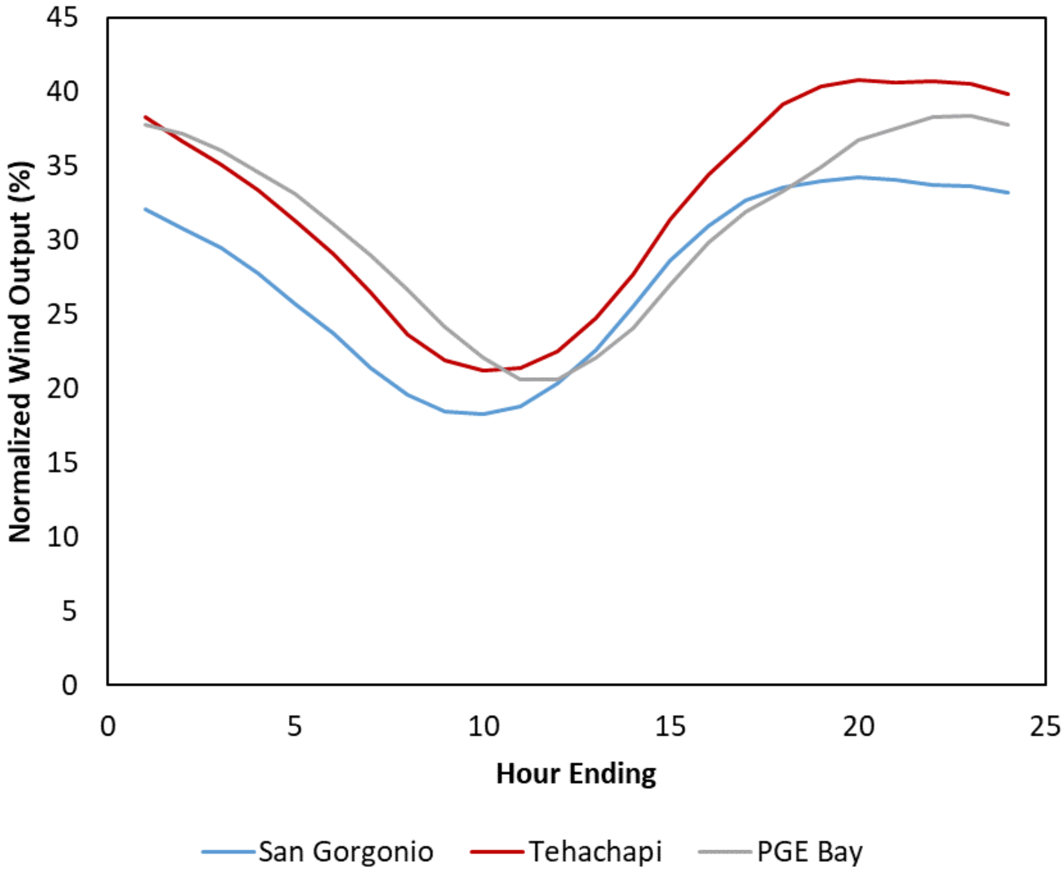


Table A7 provides the annual capacity factors for the synthetic wind profiles.

Table A7. Annual Capacity Factors for Synthetic Wind Profiles

Year	San Gorgonio	Tehachapi	PGE Bay
1998	29.9	34.9	31.6
1999	28.5	33.9	30.8
2000	28.6	33.8	34.0
2001	26.6	31.2	30.3
2002	27.9	32.7	32.1
2003	28.2	33.4	30.7
2004	26.4	31.5	31.0
2005	28.4	33.4	30.9
2006	27.4	31.6	29.9
2007	27.0	32.0	31.7
2008	26.9	32.3	30.5
2009	27.9	32.9	28.8
2010	28.0	33.0	33.4
2011	28.1	33.2	32.4
2012	28.6	34.4	34.2
2013	28.3	33.0	30.2
2014	27.3	26.2	29.8
2015	24.0	28.6	30.3
2016	28.3	33.5	29.4
2017	26.2	33.0	28.5
Average	**27.6**	**32.4**	**31.0**

The profiles used to calculate Wind ELCCs for projects outside California were developed by CPUC Staff based on the MERRA-2 dataset.[23] A comparison of average annual daily profiles and average daily profiles during the top 20 highest net load days between California land-based wind, Wyoming wind, and New Mexico wind is provided in Figure A8 and Figure A9.

[23] https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/

Figure A8. Average Annual Wind Shape Comparison

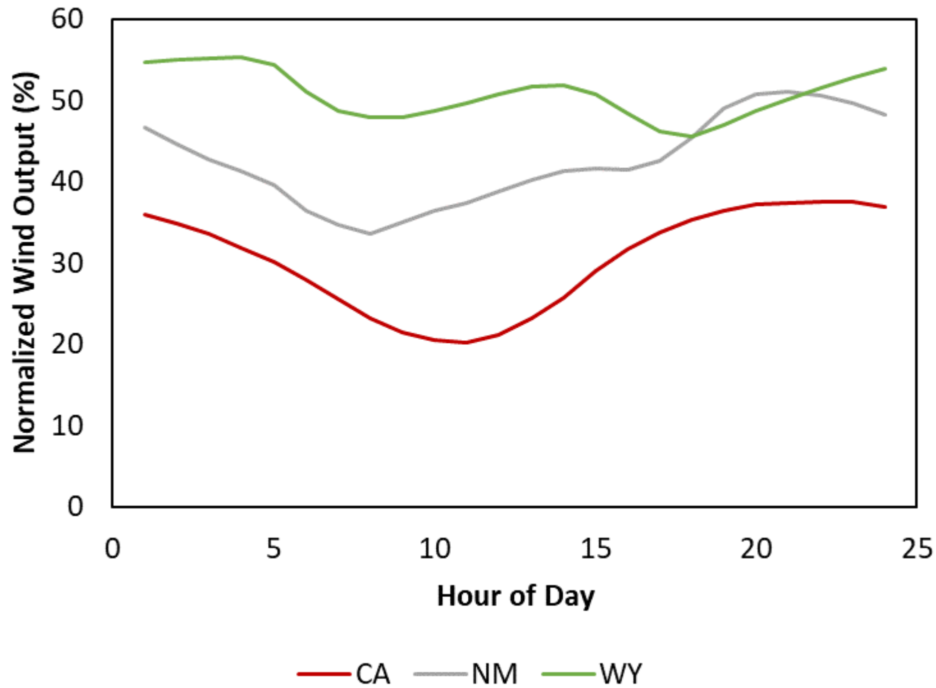
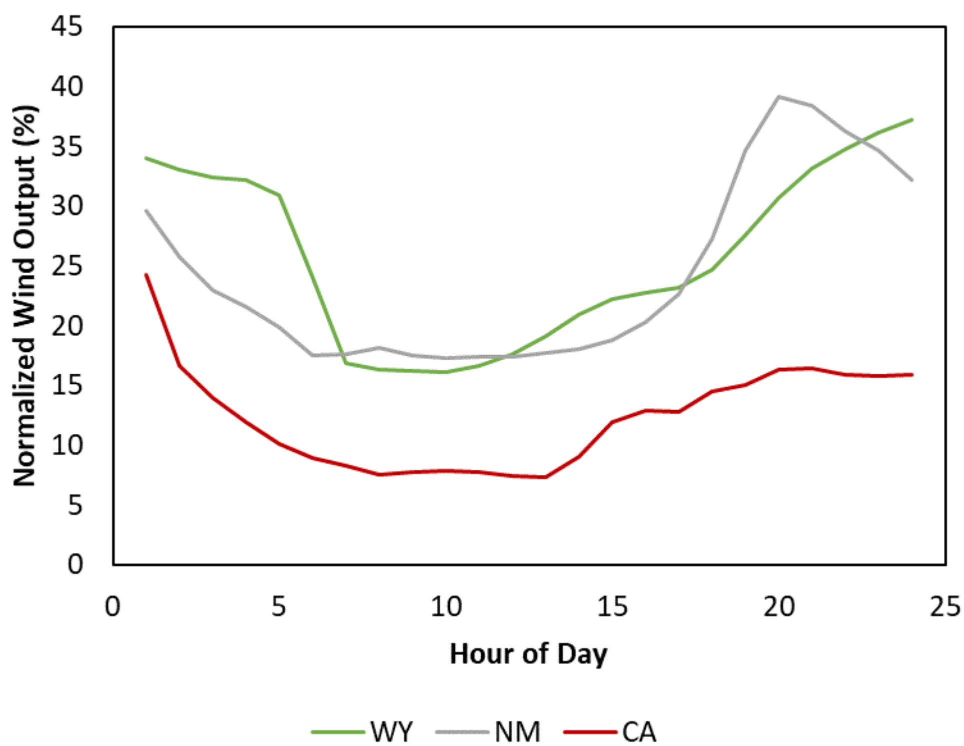


Figure A9. Average Wind Shape Comparison During Top 20 Net Load Days



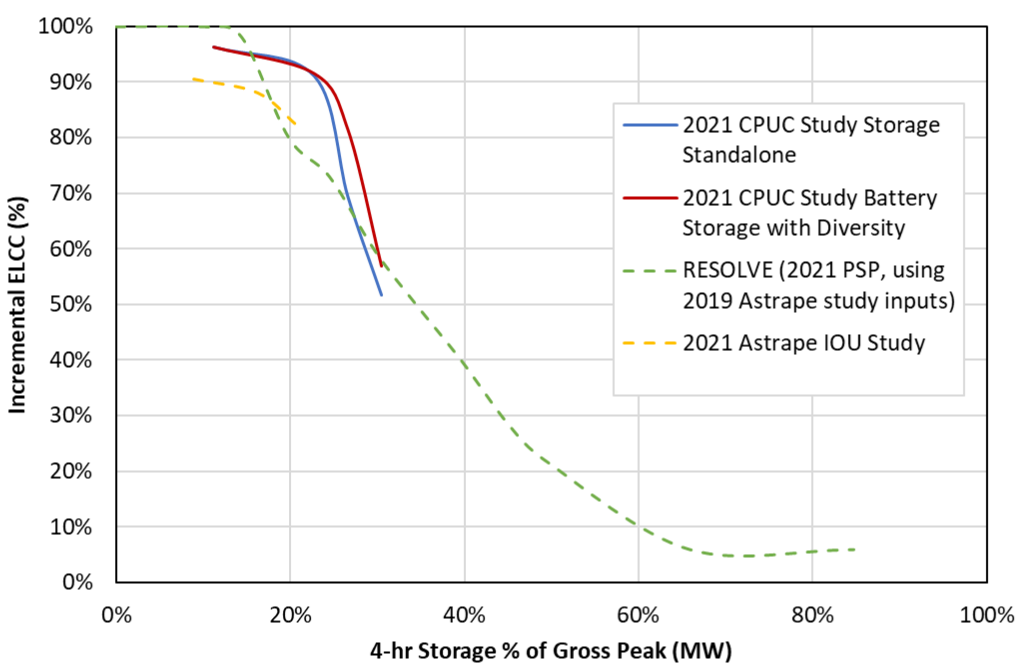
APPENDIX B: ELCC COMPARISON

This Appendix compares the incremental ELCC results of this study (2021 CPUC study) to Astrapé's 2021 Marginal ELCC study for the IOUs and the ELCC assumptions in the 2021 Preferred System Plan version of RESOLVE.

ENERGY STORAGE ELCCS

The graph below shows a comparison of incremental 4-hour battery storage ELCCs across the three studies. They are generally well aligned at 90-100% ELCC for the first 10% of peak, followed by a decline after that penetration, converging around 60% incremental ELCC by 30% of peak penetration. The differences between results are caused by this study using higher forced outage rates than the 2021 IOU study but lower forced outage rates than the 2019 Astrapé study that generated the inputs into RESOLVE's energy storage ELCC curve. This study also used the perfect capacity replacement ELCC calculation method, whereas the 2021 IOU study used the perfect flat block of load ELCC calculation method, which resulted in lower initial storage ELCCs in that study. There are also other differences in the study years, loads, and resource portfolios modeled.

Figure B1. 4-hr Energy Storage ELCC Comparison

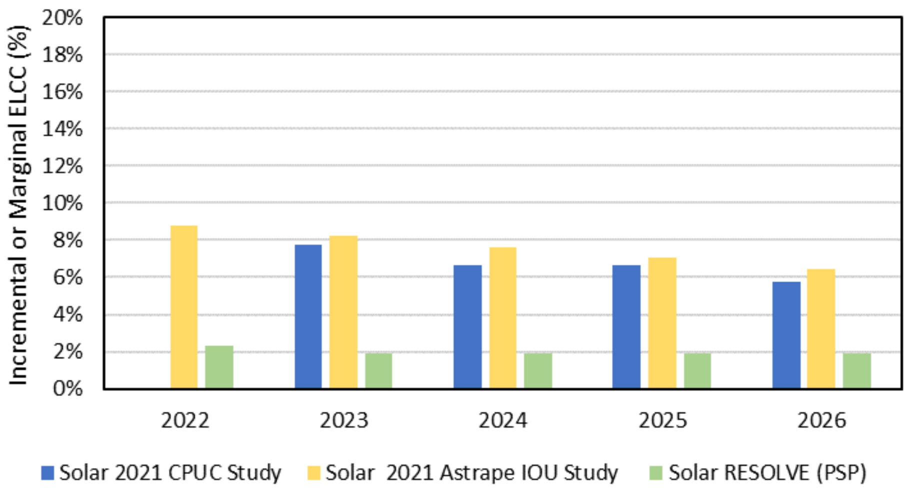


SOLAR ELCCS

Solar ELCCs are well aligned between the two studies using SERVM (the 2021 CPUC study and the 2021 Astrapé IOU study). Incremental/marginal ELCCs remain between ~6-8% in the 2023-2026 timeframe, driven in part by interactive effects captured in SERVM. RESOLVE shows lower marginal ELCCs for solar. This is driven by the fact that RESOLVE captures the solar/storage diversity benefits within its storage

ELCCs, not the solar ELCC values on its ELCC surface. There are also differences in the underlying dataset of load and solar output between the latest SERVM vintage and the older data vintage used in E3's RECAP model for RESOLVE's ELCC surface. For the next IRP cycle, E3 and Astrapé recommend updating the RESOLVE ELCC surface to reflect the latest IRP dataset and further studying methods to capture solar and storage ELCC interactions within RESOLVE.

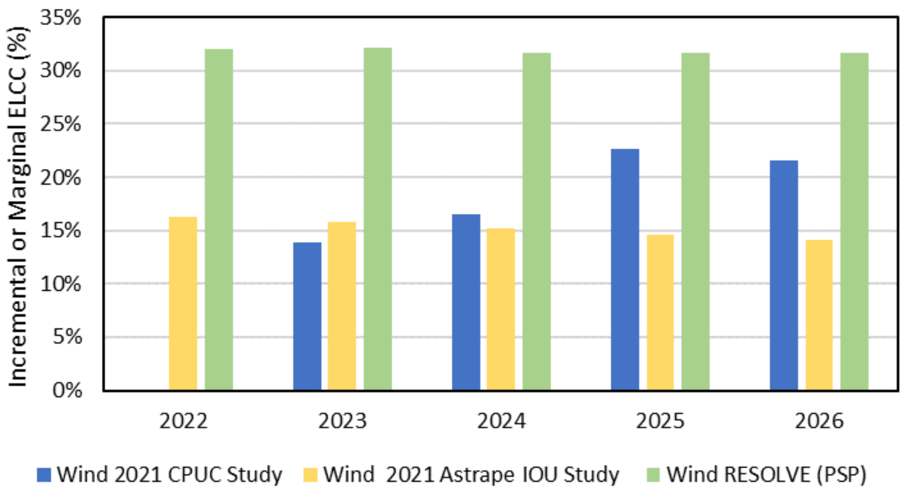
Figure B2. Solar ELCC Comparison



WIND ELCCS

Wind ELCCs for California on-shore wind projects are well aligned between the two studies using SERVM (the 2021 CPUC study and the 2021 Astrapé IOU study), at least in the near-term where they remain around 15%. Thereafter they diverge slightly, with the CPUC study increasing and the IOU study slightly decreasing. The 2021 CPUC study design did not model further saturation of in-state wind but did model diversity benefits from high solar + storage additions. The higher solar additions modeled provide a diversity benefit to new wind. RESOLVE marginal ELCCs include diversity benefit of solar only and no interactive effects with energy storage as well as using older and different wind shapes vs. those developed for the 2021 CPUC ELCC study. E3 and Astrapé recommend updating the RESOLVE ELCC inputs for wind to update underlying data to align with the latest IRP dataset.

Figure B3. Wind ELCC Comparison



Regarding out-of-state wind, the 2021 Astrapé IOU study included New Mexico wind at a much lower ELCC than modeled in the latest 2021 CPUC study. This difference is driven by the use of older CPUC wind shapes (with a time shift added) in the IOU study versus the wind shapes newly constructed by CPUC Staff.

Table B1. Out-of-state Wind ELCC Comparison

Wyoming Wind (2026)		New Mexico Wind (2026)	
2021 CPUC Study	**2021 Astrapé IOU Study**	**2021 CPUC Study**	**2021 Astrapé IOU Study**
31.6%	N/A	34.2%	8.6%