BEFORE THE PUBLIC UTILITIES COMMISSION
OF THE STATE OF CALIFORNIA

Order Instituting Rulemaking to Continue Implementation and Administration, and Consider Further Development of, California Renewables Portfolio Standard Program.	Rulemaking 15-02-020 (Filed February 26, 2015)

JOINT UPDATE OF PACIFIC GAS AND ELECTRIC COMPANY (U 39 E), SOUTHERN CALIFORNIA EDISON COMPANY (U 338-E), AND SAN DIEGO GAS & ELECTRIC COMPANY (U 902 E) TO ADMINISTRATIVE LAW JUDGE'S RULING ACCEPTING INTO THE RECORD REVISED ENERGY DIVISION STAFF PAPER ON THE USE OF EFFECTIVE LOAD CARRYING CAPABILITY FOR RENEWABLES PORTFOLIO STANDARD PROCUREMENT AND SETTING SCHEDULE

JANET S. COMBS
CAROL SCHMID-FRAZEE

Southern California Edison Company
2244 Walnut Grove Avenue
Post Office Box 800
Rosemead, California 91770
Telephone: (626) 302-1337
Facsimile: (626) 302-1935
E-Mail: carol.schmidfrazee@sce.com

Attorneys for
SOUTHERN CALIFORNIA EDISON COMPANY

WILLIAM V. MANHEIM
M. GRADY MATHAI-JACKSON

Pacific Gas and Electric Company
77 Beale Street, B30A
San Francisco, CA 94105
Telephone: (415) 973-3744
Facsimile: (415) 972-5952
E-Mail: MGML@pge.com

Attorneys for
PACIFIC GAS AND ELECTRIC COMPANY

PAUL A. SZYMANSKI
SENIOR COUNSEL

8330 Century Park Ct., Cp32d
San Diego, Ca 92123
Phone: (858) 654-1732
Fax: (619) 699-5027
E-mail: Pszymanski@Semprautilities.com

Attorney for
SAN DIEGO GAS & ELECTRIC COMPANY

Dated: May 31, 2017

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Pursuant to Ordering Paragraph 2 of Administrative Law Judge ("ALJ") Simon's March 9, 2016 Ruling Accepting into the Record Revised Energy Division Staff Paper on the Use of Effective Load Carrying Capability ("ELCC") for Renewables Portfolio Standard ("RPS") Procurement and Setting Schedule (the "Ruling"), as modified by the June 6, 2016 Ruling of ALJ Simon, Pacific Gas and Electric Company ("PG&E"), Southern California Edison Company ("SCE"), and San Diego Gas & Electric Company ("SDG&E") (hereinafter referred to as "Joint Investor Owned Utilities" or "Joint IOUs") submit as Attachment 1 to this pleading, the Joint IOUs' update to their previously-filed proposal on the use of ELCC methodologies for use in RPS procurement (the "Updated Joint Proposal"). The Updated Joint Proposal contains actual ELCC calculations. Attachment 2 is a technical report ("Technical Report") documenting the input assumptions and methodology used to calculate the resulting ELCC estimates contained in

Attachment 1. Pursuant to Rulings filed in this proceeding on December 8, 2016, and March 24, 2017, ALJ Simon extended the time to submit this Updated Joint Proposal to May 31, 2017.

Respectfully Submitted on behalf of the Joint IOUs,

WILLIAM V. MANHEIM
M. GRADY MATHAI-JACKSON

By: *~~/s/ M. Grady Mathai-Jackson~~*
M. GRADY MATHAI-JACKSON

Pacific Gas and Electric Company
77 Beale Street, B30A
San Francisco, CA 94105
Telephone: (415) 973-3744
Facsimile: (415) 972-5952
E-Mail: MGML@pge.com

Attorneys for
PACIFIC GAS AND ELECTRIC COMPANY

Dated: May 31, 2017

VERIFICATION

I, Will Dong, am an employee of Pacific Gas and Electric Company, a corporation, and am authorized to make this verification on its behalf. I have read the foregoing *JOINT UPDATE OF PACIFIC GAS AND ELECTRIC COMPANY (U 39 E), SOUTHERN CALIFORNIA EDISON COMPANY (U 338-E), AND SAN DIEGO GAS & ELECTRIC COMPANY (U 902 E) TO ADMINISTRATIVE LAW JUDGE'S RULING ACCEPTING INTO THE RECORD REVISED ENERGY DIVISION STAFF PAPER ON THE USE OF EFFECTIVE LOAD CARRYING CAPABILITY FOR RENEWABLES PORTFOLIO STANDARD PROCUREMENT AND SETTING SCHEDULE, dated May 31, 2017.*

The statements in the foregoing document are true to my own knowledge, except as to matters which are therein stated on information and belief, and as to those matters I believe them to be true. I declare under penalty of perjury that the foregoing is true and correct.

Executed on this 31st day of May, 2017 at San Francisco, California.

/s/ Will Dong
WILL DONG
Principal, Renewable Integration
Pacific Gas and Electric Company

ATTACHMENT 1

ATTACHMENT 1:
UPDATED JOINT IOU PROPOSAL
TO USE EFFECTIVE LOAD CARRYING CAPABILITY METHODOLOGY FOR RPS PROCUREMENT

I. INTRODUCTION

The three investor-owned utilities ("IOUs"), Southern California Edison Company ("SCE"), San Diego Gas and Electric Company ("SDG&E"), and Pacific Gas and Electric Company ("PG&E") (collectively, the "Joint IOUs"), submitted a joint proposal ("Joint Proposal") on June 17, 2016 in response to the Administrative Law Judge's ("ALJ's") Ruling of March 9, 2016 in Rulemaking ("R.") 15-02-020 ("March 9 Ruling"), as modified by the ALJ's Ruling Granting in Part and Denying in Part Joint Motion for Extension of Time to File Effective Load Carrying Capability Proposal for Renewables Portfolio Standard ("RPS") Procurement, dated June 6, 2016 ("June 6 Ruling"). This Revised Joint Proposal utilizes the Effective Load Carrying Capability ("ELCC") methodology for procurement to meet RPS requirements identified in that June 17, 2016 Joint Proposal to calculate estimates of ELCC values. More specifically, this Revised Joint Proposal includes:

a. Standardized model inputs and assumptions for calculating ELCC values, following the guidelines in Section 6 of the Revised Staff Paper[1];

b. Draft ELCC values for two years, following the format in Section 4.2 of the Revised Staff Paper;

c. A benchmarking report that compares and contrasts the IOUs' respective ELCC values and the RPS Calculator[2] and Resource Adequacy ("RA") ELCC values, following the guidelines in Section 7 of the Revised Staff Paper;

d. A plan for benchmarking and updating ELCC values every two years;

[1] The "Revised Staff Paper" refers to the "Revised Energy Division Staff Paper on Criteria for Effective Load Carrying Capability in Least-Cost Best-Fit Analysis for RPS Procurement," filed in R.15-02-020 as Attachment A to the March 9, 2016 Ruling.

[2] The RPS Calculator can be found at: http://www.cpuc.ca.gov/RPS_Calculator/.

e. Any other elements necessary to provide a complete proposal on using ELCC values for RPS procurement purposes.

II. REVISED JOINT PROPOSAL

The original Joint Proposal covered certain topics outlined in the March 9, 2016 Ruling and further described in the Revised Staff Paper. Consistent with the June 6, 2016 Ruling, this Revised Joint Proposal provides actual draft ELCC values and a comparison of those values to the RPS Calculator and RA ELCC values.

A. Common inputs and assumptions

1. Data inputs

The IOUs propose to use the Default Scenario with Mid Additional Achievable Energy Efficiency ("AAEE") from the May 17, 2016, Assigned Commissioner's Ruling ("ACR") adopting standardized assumptions and scenarios for use in the 2016 Long-Term Procurement Planning ("LTPP") and Integrated Resources Plan ("IRP") ("May 17, 2016 ACR") as the basis for inputs to the ELCC analysis.[3] At a high level, the Default Scenario with Mid AAEE is a sensitivity to the 2016 LTPP adopted Default Scenario with lower energy efficiency based on the California Energy Commission's ("CEC's") 2015 Mid AAEE level, and therefore with higher loads and RPS generation. Given that there are alternatives to achieve the desired 40% greenhouse gas ("GHG") emission reduction goal by 2030, including energy efficiency and RPS, it is appropriate to use the Mid AAEE level to estimate the ELCCs before the IRPs are developed in the 2016 LTPP/IRP proceeding. The California Public Utilities Commission ("Commission" or "CPUC") currently plans for the IRPs for CPUC-jurisdictional entities to be filed at the end of 2017.

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[3] Assigned Commissioner's Ruling Adopting Assumptions And Scenarios For Use In The California Independent System Operator's 2016-17 Transmission Planning Process And Future Commission Proceedings, filed in R.13-012-010 on May 17, 2016, Attachment 1, pp. 54 (describing the Default Scenario with Mid AEEE).

Modeling of wind and solar generation based on region, weather, and technology type will be based on historical and forecasted data, along with other data sources provided by the California Independent System Operator ("CAISO") for the 2016 LTPP need analysis and provided by the Western Electricity Coordinating Council ("WECC") as part of its Transmission Expansion Planning Policy Committee ("TEPPC") 2026 Common Case. All inputs from the CAISO and WECC are for the 2026 operating year.

As required by the Revised Staff Paper, the Revised Joint Proposal provides a list of key input assumptions in the table below. Unless noted, the assumptions come from inputs that the Commission adopted for the 2016 LTPP Default Scenario with Mid AAEE.[4] For these inputs, the table below simply refers to the "2016 LTPP assumption". The actual numerical values for these assumptions include: energy profiles for wind and solar resources used in the Default Scenario; conventional resource inputs developed as part by the CES-21 Grid Integration Project[5] using inputs from the Energy Division's Scenario Tool; the CAISO Master Generation Capacity File; and the WECC TEPPC 2026 Common Case. The following is a list of the major assumptions used to develop the actual ELCC estimates. Attachment 2 to this filing, the Technical Report, provides a more complete documentation of assumptions and observations.

Table 1 – List of Input Assumptions

Input	Assumption
a. Outage rates of system resources	North American Electric Reliability Corporation's ("NERC") Generating Availability Data System power plant outages by unit class

[4] Attachment 1 to May 17, 2016 ACR, p. 54.

[5] The CES-21 (Energy Systems for the 21th Century) Program is a partnership between the Lawrence Livermore National Lab and the three IOUs. The program has two projects, a cyber security project and a grid integration project. The Commission approved the CES-21 Program on October 2, 2014 by Resolution E-4677.

Input	Assumption
b. Resource inputs and use limitations	2016 LTPP assumption
c. Contribution of hydro resources toward meeting system loads	2016 LTPP assumption; Energy Division's Scenario Tool
d. ELCC values at the appropriate level - system, local, service territory, or any other level[6]	System ELCC values for wind and solar calculated with SERVM;[7] additional comparison data was calculated using the simplified Net Load Peak ("NLP") analysis tool described below
e. Planned resource additions and resource retirement	2016 LTPP assumption; Energy Division's Scenario Tool
f. Contribution of imports toward meeting system loads	2016 LTPP assumption; Energy Division's Scenario Tool
g. Accounting for all prior procurement	2016 LTPP assumption; Energy Division's Scenario Tool
h. Data sources for weather and weather region definitions	Temperature data from the National Oceanic and Atmospheric Administration ("NOAA") (NNDC Climate Data);[8] Weather region definitions from Energy Division's ELCC modeling for the RA proceeding.

[6] The ELCC values are an output, not input, of this modeling.

[7] Strategic Energy Risk Valuation Model ("SERVM") is a unique, multi-area reliability planning tool. SERVM can perform not only Loss of Load Expectation ("LOLE") reliability analyses but also simulate production costs and flexibility requirements in a way that allows users to simulate thousands of scenarios.

[8] NCDC Climate Data may be found at this link: https://www7.ncdc.noaa.gov/CDO/cdopoemain.cmd?datasetabbv=DS3505&countryabbv=&georegionabbv=&resolution=40

Input	Assumption
i. Data sources for historical and projected load, including load shapes	Energy Division's Scenario Tool; Historical load shapes for 35 weather years adjusted to reflect incremental energy efficiency in 2026.
j. Technology and geographic combinations of resources	2016 LTPP assumption, Energy Division's Scenario Tool
k. Operating/production costs for system resources	2016 LTPP assumption with operating costs consistent with 2026 TEPPC Common Case.
l. Treatment of flexibility	Loss of load due to flexibility shortages are counted towards loss of load events, as defined by Commission decision directing modeling methodologies and approaches[9]
m. Natural gas price forecast	2016 LTPP assumption. The fuel price forecast was updated to reflect the TEPPC dataset for all regions.
n. Variable generation data for calculations of capacity value	2016 LTPP assumption consistent with 2026 TEPPC Common Case
o. Renewable penetration levels and related scenarios	2016 LTPP assumption; Energy Division's Scenario Tool
p. Common years to calculate ELCC values	2018 (~33% RPS), 2026 (~43% RPS)
q. Assumptions for years 11-20	Only 2018 and 2026 operating years modeled

[9] *See* Administrative Law Judge Ruling Directing Production Cost Modeling Requirements, filed September 23, 2016, in R.16-02-007, pp. 5-6

Input	Assumption
r. Hourly profiles for different weather years for load, wind/solar generation.	From Input section in Technical Appendix
s. Intra-hour and 5-minute forecast errors for load, wind/solar generation.	Developed from CAISO 2015 1-minute load, wind, solar historical profiles

B. ELCC Methodology

The Commission is developing two types of ELCC values for two different uses: marginal and average ELCCs. The average ELCC represents the reliability contribution that an entire existing resource class (solar or wind) brings to the system, whereas the marginal ELCC represents the *additional* system reliability that would come from adding an additional block (say 1,000 MW) of a resource to the system on top of the existing resource class. The average ELCCs are used to determine whether the system has enough dependable capacity to meet the required reliability target, presently the planning reserve margin, and are used for RA counting purposes. The marginal ELCCs are used to evaluate the cost-effectiveness of candidate resources additions when building preferred system plans and IRPs and assessing bids in the RPS procurement process.

1. Marginal ELCC Calculation

The IOUs calculated the marginal ELCC for least-cost, best-fit ("LCBF") RPS bid evaluation using 1,000 MW increments for a selection of technologies and locations. The marginal ELCC was calculated by adding the increment of each technology to the renewable portfolio in the Default Scenario with Mid AAEE after calibrating the Default Scenario with Mid AAEE to a load/resource balance point, where the Loss of Load Expectation ("LOLE") metric for the scenario equals 0.1.[10] This calibration was done by adding or subtracting conventional

[10] Generally speaking, LOLE is a measure of the number of times over a given period where generation

fossil generation in proportion to the peak demand in each IOU service area. Table 2 below categorizes the marginal ELCCs to be calculated by the study by technology and location for both the 33% and 43% cases. The study did not look at distributed photovoltaic ("PV") generators outside of California because this resource cannot actually export into the CAISO and would provide no ELCC value. Likewise, the study did not look at solar energy resources in the northwest due to the relatively lower solar resource there. Section C: Benchmarking presents the actual marginal ELCCs and compares them with in the marginal ELCC values calculates using the RPS Calculator.

Table 2: Marginal ELCC Location/Technology Combinations

Location ˜ ↓Technology	Northern Cal	Southern Cal	Northwest	Southwest
33/43% RPS Case Marginal ELCCs				
Wind	✓	✓	✓	✓
Tracking PV	✓	✓		✓
Fixed Axis PV	✓	✓		✓
Distributed PV	✓	✓		

2. Average ELCC Calculation

The IOUs also calculated the average ELCC values for wind and solar for the entire CAISO (instead of separate estimates at each location) in the Default Scenario with Mid AAEE. For this calculation, the entire CAISO wind and solar portfolio was removed to calculate aggregate ELCCs. Each technology (wind or solar) was removed both individually and together to estimate the proportional contribution to ELCC, inclusive of diversity effects. The average ELCCs were then compared with the ELCC proposals prepared by the Energy Division and

was not able to meet demand and a loss of load occurred. For this study, LOLE is defined as any day in which there is at least one hour where there is not sufficient capacity to maintain minimum regulation-up and spinning reserves.

Calpine/E3 for use in the 2018 RA compliance year.[11] Section C: Benchmarking presents this comparison.

Table 3 below shows the installed capacities in Megawatts ("MW") for wind and solar used to calculate the 2018 average ELCCs using SERVM alongside the capacities used by Calpine/E3 and Energy Division for the 2018 case. Additional data regarding load and resources used in the study can be found in the Section 1 of the Technical Report included as Attachment 2 to this filing.

Table 3: Installed Capacities (MW) Used to Calculate Average ELCC for 33% RPS (2018)

	Joint IOU Proposal ELCC ~33% RPS (2018)[12]	February 24, 2017 RA Proposal Energy Division (2018)[13]	February 24, 2017 RA Proposal Calpine/E3 (2018)[14]
Wind	5,807	6,891	5,592
All solar (Supply-side and behind-the-meter PV)	12,058	16,033	15,887

3. Models

The IOUs used SERVM to estimate both marginal and average ELCCs. The same methodology can be used to calculate ELCC values using other similar commercially available models. In addition, the IOUs developed a simplified comparison analysis tool (net load peak or

[11] Proposal for Monthly Loss of Load and Solar and Wind Effective Load Carrying Capability Values for 2018 Resource Adequacy Compliance Year filed in R.14-10-010 on Feb. 24, 2017 (Energy Division Proposal); Calpine Corporation Amended Final Phase 3 Proposal filed in R.14-10-010 on Feb. 24, 2017 (Calpine/E3 Proposal).

[12] Since some out-of-state solar resources are subject to transmission constraints that would complicate their reliability contribution, their capacity was not included in the average ELCC calculations. The out-of-state solar capacity excluded from the average calculations was approximately 1,900 MW.

[13] Energy Division Proposal, Table 3.

[14] Calpine/E3 Proposal, Figure 7.

"NLP" tool) utilizing a spreadsheet engine to provide further data for comparison. This simplified spreadsheet tool is further discussed in Section III below.

4. Key Reliability Definitions

The key definitions of desired reliability level and loss of load events reflect the Commission's direction to entities conducting modeling for purposes of analyzing system and flexibility needs utilizing stochastic models provided by Administrative Law Judge Julie A. Fitch on September 23, 2016 (Modeling Ruling).[15] Based on the Modeling Ruling, the IOUs defined loss of load event as any hour in which there is not sufficient capacity to maintain minimum regulation-up reserves plus spinning reserves.[16]

5. Developing Monthly Capacity Value Using an Annual ELCC Value

The Revised Staff Paper asks the IOUs to address how they set monthly ELCC values for resources.[17] It should be noted that the ELCC is essentially an annual approach to valuing reliability because the reliability standard it is based on, LOLE, is an annual concept. The IOUs here propose to allocate the annual capacity value (annual ELCC value of a resource times annual $/kW-year capacity cost) based on the monthly distribution of the 0.1 LOLE. For example, assume the marginal ELCC for wind is 12% of installed capacity and the annual capacity value is $100/kW-year. If 30% of the system LOLE occurs in July, the capacity value for the month of July would be $3.6/kW (i.e., 12% times $100/kW-year times 30%). Table 4 below shows the proposed monthly percentages used to allocate the study annual ELCC into monthly capacity values. Loss of load is not a significant concern outside of the traditional summer months when peak load is the highest, and most of the annual ELCC value is accordingly assigned to the months of July-September.

[15] Administrative Law Judge Ruling Directing Production Cost Modeling Requirements, filed in R.16-02-007 on Sept. 23, 2016.

[16] *Id.*, p. 2.

[17] Revised Staff Paper, p. 9.

Table 4: Proposed Monthly Capacity Value Allocation of Annual ELCC Value

Month	33% (2018)	43% (2026)
1	0.0%	0.0%
2	0.0%	0.0%
3	0.0%	0.0%
4	0.0%	0.0%
5	0.0%	0.0%
6	2.9%	2.0%
7	24.0%	23.9%
8	24.5%	20.2%
9	47.6%	53.2%
10	1.0%	0.6%
11	0.0%	0.0%
12	0.0%	0.0%
Total	100%	100%

6. Multiple Years

The Revised Staff Report asks for marginal ELCCs to be calculated for multiple years.[18] The IOUs calculated the marginal ELCCs for two years. The IOUs calculated the marginal ELCC for year 2026 with approximately 43% RPS, consistent with the Default Scenario with Mid AAEE, and for year 2018 with approximately 33% RPS using the same set of load and resource assumptions. These years were chosen to align with those currently being studied as part of the CES-21 project in order to leverage that existing work.

C. Benchmarking

The Ruling requires the Joint Proposal to include a benchmarking report that compares and contrasts the IOUs' respective ELCC values and the more recent RPS Calculator and RA ELCC values.[19]

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[18] Revised Staff Paper, p. 8-9.

[19] Ruling, p. 3; Revised Staff Paper, p. 11.

1. Average ELCC Benchmarking

The IOUs compared the average ELCC values produced by the Joint IOU proposal with the ELCC values in the E3/Calpine and Energy Division RA proposals. This is not a like-for-like comparison. The Joint IOU proposal calculates an *average annual* ELCC, and the RA proposals calculate monthly ELCCs. This does not allow for an easy direct comparison (although E3 did provide annual ELCCs upon request, which are presented below).

Table 5: Comparison of Average ELCCs from Different Studies by Technology

	Joint IOU ELCC ~33% RPS (2018)	February 24, 2017 RA Proposal Energy Division[20] (2018)	February 24, 2017 RA Proposal Calpine/E3[21] (2018)	Joint IOU ELCC ~43% RPS (2026)
Wind	21%	Aug/Sept: 27/27%	26%	22%
All-solar (Supply-side and behind-the-meter PV)	33%	Aug /Sept: 31/25%	31%	20%

Without necessarily attempting to reconcile the differences in ELCCs among the studies, the following section describes high level observations about the average ELCCs produced by each study.

Observations:

1. The Joint IOU proposal shows average ELCC values for solar decreasing with solar penetration, as expected. As solar penetration increases, the net load peak

[20] Energy Division Proposal, Tables 3 and 4. The values shown in the table correspond to August and September ELCCs for comparative purposes; the annual net load peak occurs in August for the ~33% case and in September for the ~43% case. Energy Division did not provide annual ELCC numbers in their proposal.

[21] Calpine/E3 Proposal, Figure7. In addition to their monthly ELCCs, E3 provided upon request the annual solar and wind ELCCs not included in their proposal. The annual solar ELCC provided was 4,916 MW, and the annual wind ELCC provided was 1,477 MW. Using these in conjunction with the respective solar and wind installed capacities of 15,887 and 5,592 MW from Figure 7, the annual ELCC % for each technology was calculated in Table 3 above for comparison.

(where reliability issues are more likely to occur) is pushed further into the evening when solar is generating less; thus the average contribution from solar to reliability is expected to diminish with increasing solar penetration.

2. The wind ELCC values calculated by the Joint IOU proposal increase slightly as wind penetration increases from 2018 to 2026. This is expected and due to the diversity effect that favors wind as solar penetration increases during this period as well. As solar penetration increases, the net load peak shifts further into the evening when wind tends to generate more, thus allowing wind to contribute more to reliability around net load peak hours and increasing its ELCC value.
3. The 2018 Joint IOU solar ELCC may be higher than those from Energy Division and Calpine/E3 due to the Joint IOUs using a lower installed solar capacity due to the exclusion of out-of-state solar as detailed in Table 3 above.

2. Marginal ELCC Benchmarking

Table 6 below shows the Joint IOU proposal results for marginal ELCC values.

Table 6: Marginal ELCC Values by Region and Technology

	Northern Cal	Southern Cal	Northwest	Southwest
33% RPS Case Marginal ELCC Values				
Wind	21%	14%	40%	24%
Tracking PV	21%	15%		12%
Fixed Axis PV	13%	10%		8%
Distributed PV	12%	8%		
43.3% RPS Case Marginal ELCC Values				
Wind	27%	22%	43%	20%
Tracking PV	8%	4%		3%
Fixed Axis PV	4%	4%		1%
Distributed PV	5%	2%		

The IOUs compared the marginal ELCC values in the Joint IOU proposal to the marginal ELCC values in the RPS Calculator. Table 7 presents this comparison.

Table 7: Comparison of CA Marginal ELCC Values with the RPS Calculator

	Joint IOU ELCC ~33% RPS (2018)	RPS Calculator version 6.2 for 2018 (33% RPS)[22]	Joint IOU ELCC ~43% RPS (2026)	RPS Calculator version 6.2 for 2026 (43% RPS)[23]
Wind	18%	16%	25%	17%
All solar (Supply-side and BTM PV)	13%	12%	4%	2%
Supply-Side Solar	15%	12%	5%	2%
BTM PV	10%	13%	3%	1%

Without necessarily attempting to reconcile the differences among the studies, the following section describes high level observations about the marginal ELCCs produced by each study.

Observations:

1. The Joint IOU proposal and the RPS Calculator both show marginal ELCC values for wind increasing from 2018 to 2026 as expected. This is due to the diversity benefit that favors wind when it is producing more in the hours around the net load peak, which gets pushed to later in the evening with increasing solar penetration. This increase in marginal ELCC values for wind is much greater in the Joint IOU proposal for year 2018 than in the RPS Calculator.
2. The Joint IOU proposal and the RPS Calculator also show the marginal ELCC values for solar decreasing with solar penetration by roughly the same amount across both the 2018 and 2026 RPS cases. This is expected due to the later net load peak that occurs with increasing solar penetration.
3. The marginal ELCC values from both studies across all technologies are relatively close, and differ by no more than 3% in 2018 or 2026. Based on this,

22 From information in the RPS 6.2 Calculator, ELCC_Interp worksheet.

23 From information in the RPS 6.2 Calculator, ELCC_Interp worksheet.

the Joint IOU study marginal ELCC values seem to align with those provided in the RPS Calculator.

4. Generally, the marginal ELCC values for solar in the north region are higher than for solar in the south region; similarly, the marginal ELCC values for solar in the south region are higher than for solar in the southwest region. This phenomenon is largely a function of longitudinal location and is discussed in greater detail in the Technical Report included as Attachment 2 to this filing.[24]

D. Frequency of Updating ELCC-LCBF Values

The Ruling requires the Joint Proposal to include a plan for updating the ELCC values every two years.[25] Because both average and marginal ELCC values are needed in the integrated resource planning process, the Joint IOUs recommend that in the future the Energy Division update both average and marginal ELCC values as part of the IRP cycle when preparing the system reference or preferred resource plan. The load-serving entities ("LSEs") can then use the marginal and average ELCCs to prepare their respective IRPs. The LSEs can use the average ELCCs to determine whether the system has enough dependable capacity to meet the required reliability target, presently the planning reserve margin. The LSEs can use the marginal ELCCs to evaluate the cost-effectiveness of candidate resources additions when building the preferred system plan and the LSE's IRPs. The IOUs can also use the most recently updated marginal ELCC values for purposes of their LCBF bid evaluations in the RPS program.

III. Simplified Companion Analysis Tool

The IOUs developed a simplified deterministic spreadsheet that takes hourly inputs used by SERVM to calculate the impact of renewable generation at the time of highest monthly net load peak hour. This tool is based on the Net Load Peak-Effective Load Carry Capacity ("NLP-

[24] Joint IOU ELCC Technical Report, Input Assumptions: Impact of Latitude and Longitude on Output and Reliability.

[25] March 9 Ruling, p. 3.

ELCC") tool that SCE presented at a workshop in the RA proceeding. The tool calculates an NLP-ELCC value of a resource based on the single criteria of how well that resource can reduce the peak load during the hour it occurs each month instead of the frequency of LOLEs. This NLP-ELCC analysis only requires load and production data for resources or technologies to calculate a monthly NLP-ELCC value.

Table 8 compares the monthly August/September average ELCC values for wind and solar produced by this tool with the corresponding annual ELCC values produced by the Joint Study for both the ~33% RPS and ~43% RPS scenarios.[26] The average NLP-ELCC values for the two scenarios are lower than those in the IOU study. This is due to the fact that a simple reduction in net load peak does not fully capture all the interactive effects of all system components, especially energy-limited resources (e.g. battery storage, demand response). This effect is explored in more detail in Section 3 of the Technical Appendix.

Table 8: Comparison of Average ELCC Values with the NLP-ELCC Tool

	~33% RPS Scenario (2018)		~43% RPS Scenario (2026)	
	SERVM (Annual)	NLP-ELCC Method (August)	SERVM (Annual)	NLP-ELCC Method (September)[27]
Wind	21%	17%	22%	19%
All solar (Supply-side and Behind-the-meter PV)	33%	33%	20%	18%

[26] In addition, Astrape also provided similar ELCC value approximation methods that closely mirror the NLP-ELCC tool, as discussed in Section 3 of the Technical Report. Astrape's methods extend this analysis to marginal ELCC values.

[27] In the Joint IOU study, the greatest net load peak occurred in August for the 2018 case and in September for the 2026 case. The associated monthly ELCC values from the NLP tool are used here for comparison.

ATTACHMENT 2

Joint IOU ELCC

Technical Report

05/31/2017

PREPARED FOR

Joint IOU ELCC Report

PREPARED BY

Nick Wintermantel
Kevin Carden
Astrapé Consulting

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Report Overview

This report documents the development of average and marginal Effective Load Carrying Capability (ELCC) values for Renewable Portfolio Standard (RPS) resources at 33% and 43% renewable penetration levels. Table 1 below provides the resulting ELCC values.

Table 1: 33 and 43% ELCCs

ELCC Case and Technology	33% Study SERVM Results (%)	43% Study SERVM Results (%)
Average/-RPS	28.94	20.17
Average/-Wind	21.03	22.50
Average/-Solar	32.75	19.56
Marginal CA-N/-Wind	21.49	27.09
Marginal CA-N/-Fixed PV	13.36	4.16
Marginal CA-N/-Tracking PV	21.12	8.28
Marginal CA-N/-BTMPV	11.56	4.74
Marginal CA-S/-Wind	14.43	22.06
Marginal CA-S/-Fixed PV	9.58	3.61
Marginal CA-S/-Tracking PV	15.24	3.91
Marginal CA-S/-BTMPV	7.73	2.00
Marginal NW/Wind	40.26	43.06
Marginal SW/Wind	23.75	29.93
Marginal SW/Fixed PV	8.12	0.69
Marginal SW/Tracking PV	12.35	2.99

Section 1: Input Assumptions

Astrapé developed two SERVM analyses, one for a 33% RPS scenario and another for a 43% RPS scenario. While both scenarios utilize 2026 resource and load assumptions, the 33% RPS scenario has an RPS portfolio similar to that expected in 2018. Using the base case for each scenario, Astrapé studied multiple sensitivities for each scenario by varying amounts of capacity for different types of renewable resources. Table 2 shows that the 33 and 43% RPS scenarios have the same total gross load. The difference in the scenarios is the resource mix, which changes to accommodate the increased levels of renewable generation being studied.

Table 2: 33 and 43% RPS Scenario Comparison[1]

	33%		43%	
Load	**MWh**	**MW**	**MWh**	**MW**
Total Gross Load[2]	277,491,046		277,491,046	
Total Peak Gross Load		54,727		54,727
Total Net Load (after wind, solar, BTMPV, and EE)	216,781,862		190,151,279	
Total Peak Net Load (after wind, solar, BTMPV, and EE)		45,719		45,346
Resource Mix	**MWh**	**MW**	**MWh**	**MW**
EE	20,332,013	5,229	20,332,013	5,229
BTMPV	8,871,855	5,040	19,756,856	11,133
Biogas/Biomass	7,410,740	1,100	7,404,637	1,100
DG BTM	13,065,582	2,000	13,067,540	2,000
Geothermal	10,428,876	1,423	10,437,056	1,423
Hydro	27,676,052	488	27,676,551	488
Solar Thermal	4,229,219	1,555	4,229,979	1,555
Solar PV - Fixed	3,441,084	1,618	6,970,009	3,277
Solar PV - Tracking	10,397,788	3,845	21,455,949	7,932
Wind	13,437,225	5,807	14,594,961	6,317
CCGT	91,279,536	15,876	82,785,244	15,876
CT	10,174,403	8,260	7,767,139	8,260
CHP	31,615,261	4,095	31,267,258	4,095
Nuclear	-	-	-	-
Energy Storage	1,185,125	3,181	2,197,419	3,181
DR	1,281	630	410	630
ST	16,573	10	12,400	10
Net Imports	25,567,538	11,665	13,445,367	11,665

[1] Cells are shaded to indicate the column label does not apply.
[2] The sum of generation is greater than total gross load due to pumped storage hydro load and generation curtailment.

Regions in Study

The following is a list of regions included in the study:

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

- Salt River Project (SRP)
- Tucson Electric Power Company (TEPC)
- Turlock Irrigation District (TIDC)
- Western Area Power Administration – Colorado/Missouri Region (WACM)
- Western Area Power Administration - Lower Colorado Region (WALC)

CAISO was separated in SERVM into 4 distinct regions: PGE Bay, PGE Valley, SCE, and SDGE. SERVM models the regions with a pipe and bubble representation[3] and allows for regions to share capacity based on economics and physical transmission constraints.

Load in Study

Hourly load was modeled for each CAISO region. Load is a function of weather, so the shape of future loads was modeled using historical weather patterns. Synthetic load shapes for 35 historical weather years were constructed to capture a wide range of possible weather conditions and the associated load. The relationship between weather and load was derived from neural network modeling of recent historical loads and temperatures. The result of the load development process is a set of 8760 hourly load profiles which identify the expected load for a future year given the weather patterns from each year from 1980 to 2014[4].

Renewable Profile Development

Wind profiles were produced using historical metered output from 2010 to 2014. First, the shapes from this raw data were normalized to 100% by dividing the historical output by the appropriate annual capacity for each of the five years. Next, a correlation was created between

[3] Pipe and bubble representation is a simulation method which does not consider AC or DC transmission constraints. Each tie line between zones has a static import and export constraint which cannot be violated.

[4] The concepts of synthetic load shapes and neural network modelling are discussed in greater detail and illustrated in the *Probabilistic Reliability Modeling Inputs and Assumptions* presentation (p. 17-24) presented at the RA workshop on November 26, 2013.

the load and wind output for SCE and PG&E Valley. The daily wind profiles from the day that most closely matched the total load out of all the days +/- 5 days of the source day was used to create the profiles for 1980 to 2014. For example, the profile for January 1, 1980 was selected by comparing loads between December 26 and January 5 from 2010 to 2015 to the synthetically created load shape for January 1, 1980. If the closest match was from December 27, 2011, then all wind profiles in all California regions for January 1, 1980 were pulled from December 27, 2011. Since all output values are identical chronologically, this method allows the historical diversity between wind projects in California to be maintained. If output was highly divergent between two sites in actual history, that divergence will be present in the simulated profiles since each site's data is drawn from the same day. Since each draw was daily, the connection between hour 24 from one draw to hour 1 from the subsequent draw (the seams) was interpolated by calculating a moving average of the output from hour 23 to hour 2 to avoid a drastic hourly change in output.

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

Incremental studies were performed on Northern California, Southern California, Southwest U.S., and Northwest U.S. For Northern and Southern California, a wind, fixed PV, tracking PV, and Behind the Meter PV (BTMPV) incremental study were performed. An incremental wind study was performed on the Northwest. The Southwest incremental studies were performed on wind, tracking PV, and fixed PV technologies. (See Table 2 in the previous Joint Proposal for a summary of this). For each case, 1000 MW increments for each respective technology were added and a corresponding fossil unit amount was subtracted to bring the reliability to the desired 0.1 Loss of Load Expectation (LOLE)[5]. For the Northern California studies, PGE Valley and PGE Bay renewable units were used. For Southern California studies, SCE and SDGE renewable units were used. The Southwest studies utilized the AZPS solar units and PNM wind profiles. The Northwest study used the BPAT wind profiles.

Solar incremental studies were performed on Northern California, Southern California, and the Southwest, but not the Northwest due to the relatively low solar resource there. The solar profiles used for Northern California were from cities within the PGE Valley and PGE Bay

[5] LOLE is defined any day in which there is at least one hour in which there is not sufficient capacity to maintain minimum regulation-up and spinning reserves. A 0.1 LOLE is a widely adopted reliability standard used in planning studies.

service territories. The Southern California ELCC solar profiles came from cities within the SCE and SDGE service territory. The Southwest cases were calculated using the AZPS solar profiles. While several locations were used for each region analyzed, the average of all locations within each region is shown on Figure 1 below to illustrate the overall differences between the regions.

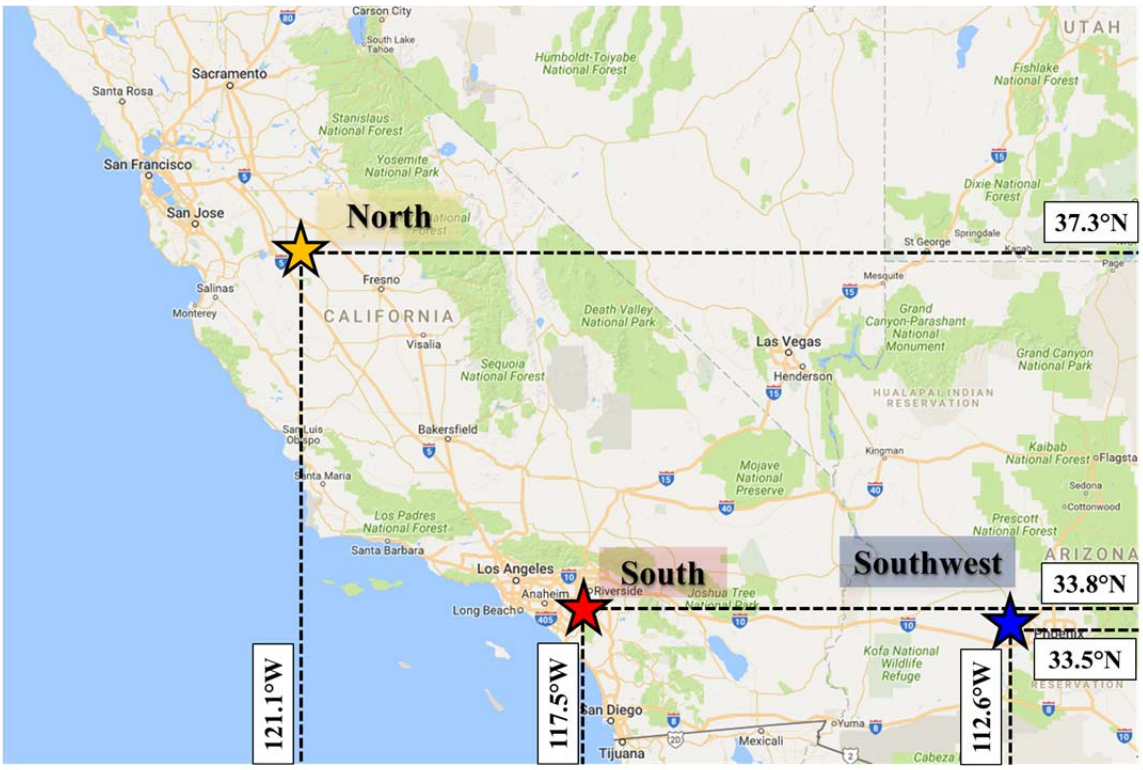

Figure 1: Weighted Average Location of all Locations Used for Each Region

Impact of Latitude and Longitude on Output and Reliability

Tests were also performed on a larger number of sites to isolate the effects of latitude and longitude on solar output during hours when a reliability issue was most likely to occur (hours 16 through 19 are critical reliability hours). These tests were performed to confirm the differences seen between the Northern and Southern California ELCC calculations. For longitude effects, solar profiles were analysed from Malibu, CA (118.8° W) to Portales, NM (103.3° W) using annual profiles from sixteen cities. For the longitude analysis, all cities were approximately located along the 34.1° N latitude line. The solar profiles were obtained for the specific cities using the method discussed above in the Renewable Profile Development Section. Once the profiles were calculated for each city, the results for hour 16 in August were plotted in Figure 2.

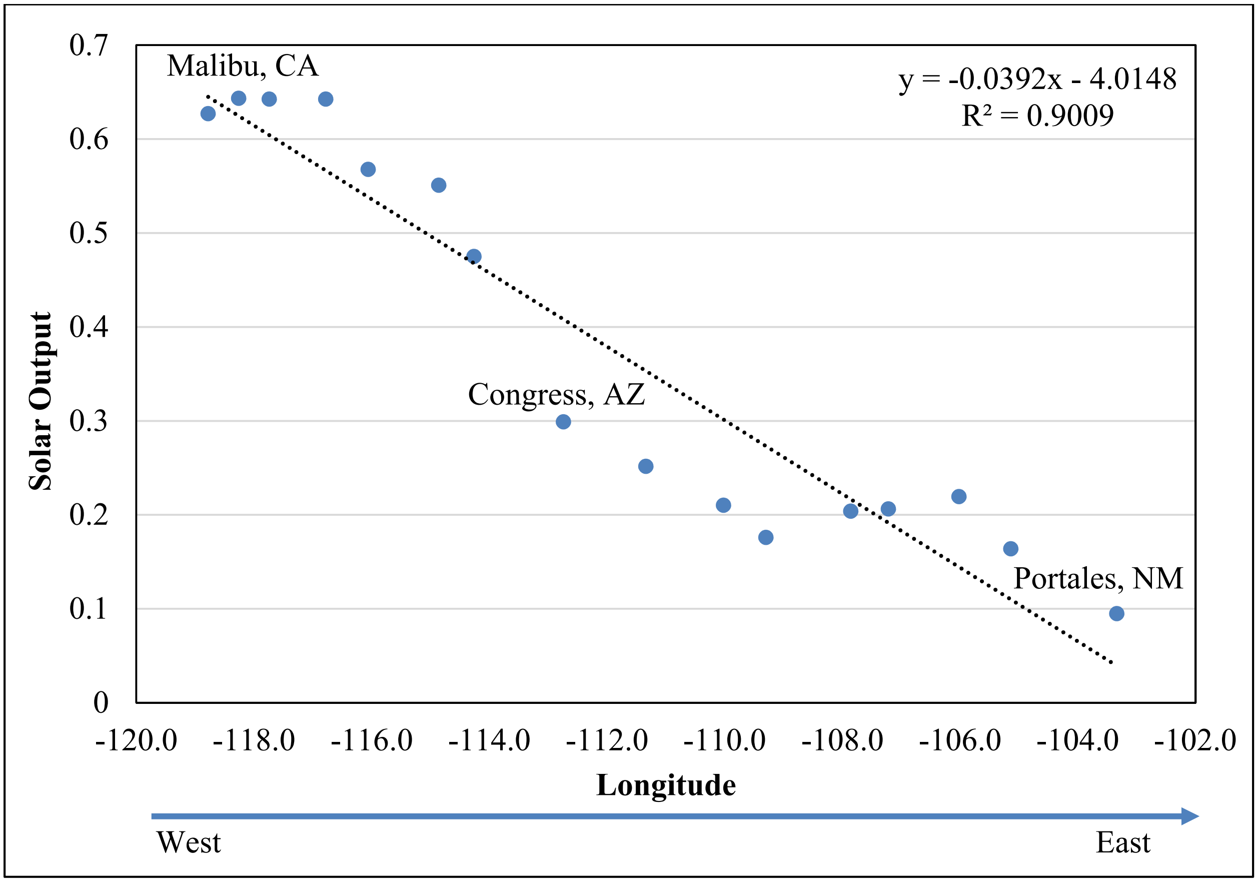

Figure 2: Average August Solar Output as a Function of Longitude for Hour 16

This demonstrates that for every degree of longitude further east from Malibu, the output in hour 16 is expected to be 3.92% lower in hour 16. This corroborates the results of the ELCC analysis which showed that projects further east have lower capacity value due to lower output in the reliability-critical late afternoon hours. Solar projects further west have higher output late in the day and provide output during the hours when reliability issues are likely to occur, all else equal. While the profiles are categorized by Northern and Southern California in this particular study, the Northern California sites are significantly further west than the Southern California sites and thus provide somewhat greater reliability than further east solar sites in the south. The annual capacity factors are higher in Southern California, but the ELCCs are higher in Northern California due to this characteristic.

The effects of latitude on solar output are not as distinctive on the reliability contribution of solar projects. For latitude effects, solar profiles were analysed from Long Beach, CA (33.8° N) to Plethora, Nevada (41.7° N) using profiles from fifteen cities. For the latitude analysis, all profiles were from cities approximately at 118° W longitude. The average hour 16 August output for all cities is plotted in Figure 3 below.

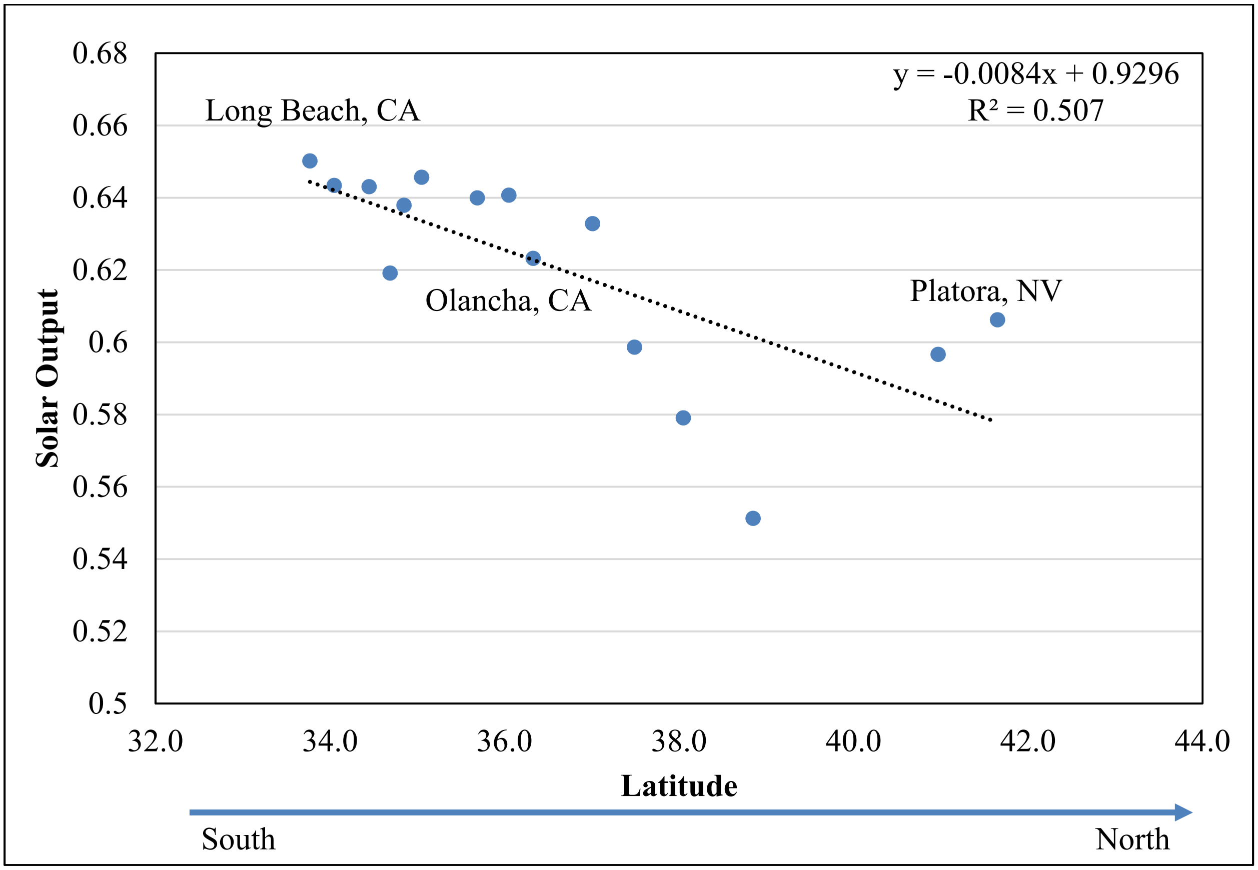

Figure 3: Average August Solar Output as a Function of Latitude for Hour 16

This demonstrates that for every degree north of Long Beach, CA, the solar output in hour 16 in August is expected to be 0.84% lower. This effect is only 20% of the magnitude of the longitude effect discussed previously.

To further illustrate this, the August average daily solar profiles for the Northern and Southern California regions in the ELCC studies along with their delta are shown below in Figure 4. The time shift between the Northern California profile and Southern California profile is highlighted by the delta calculation (output in Northern California minus output in Southern California) shown on the secondary Y-axis. In hour 8, the Southern California normalized output is 16.3% higher than the respective Northern California output. In hour 17, the Northern

California output is 8.2% higher than the Southern California output. This highlights the fact mentioned earlier that "northern" solar facilities are typically located further west than "southern" solar facilities and thus contribute more to reliability.

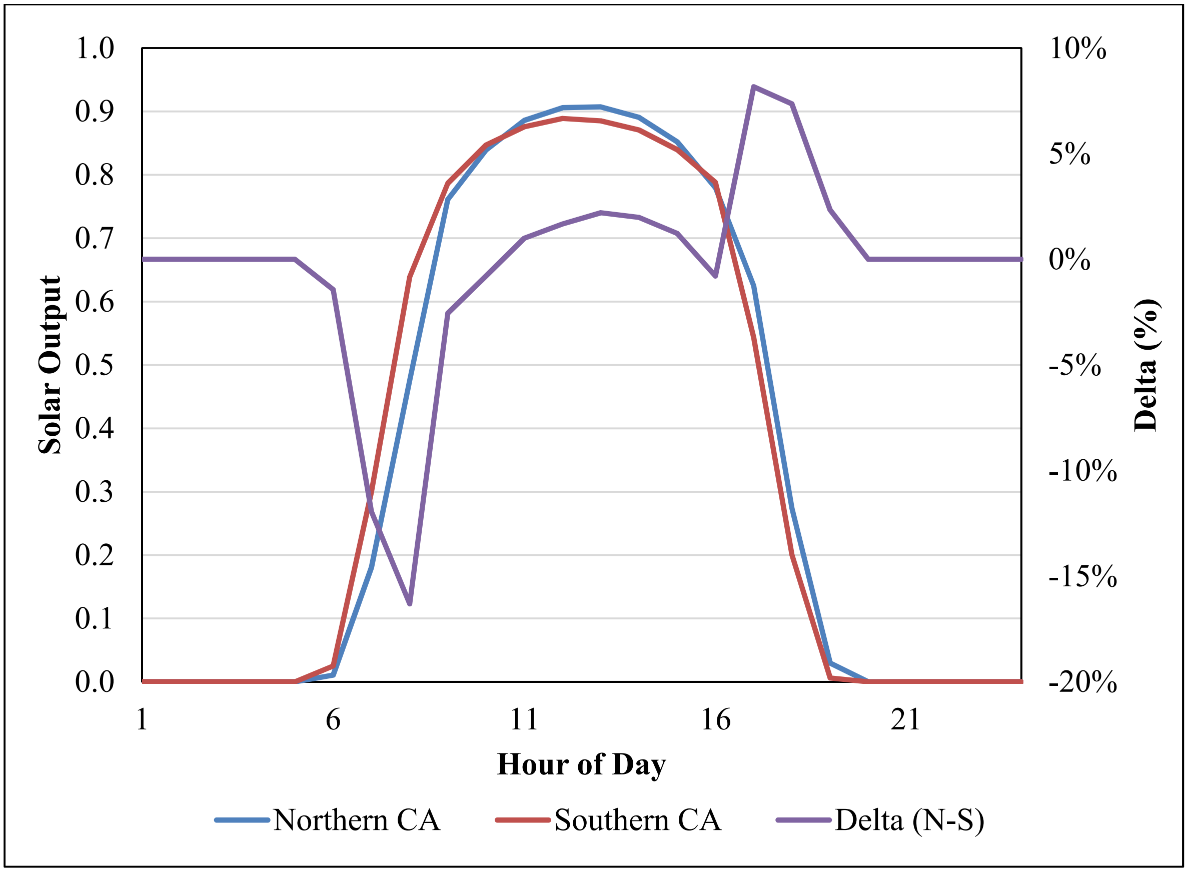

Figure 4: 33% Northern and Southern California Average August Day Comparison

This decrease in output during reliability hours is even more pronounced when comparing Southern California and Southwest. The August average daily solar profiles for the Southern California and Southwest regions in the ELCC studies along with their deltas are shown below in Figure 5. The delta calculation shows that the output in Southern California is 31.6% higher in hour 17 than in the Southwest.

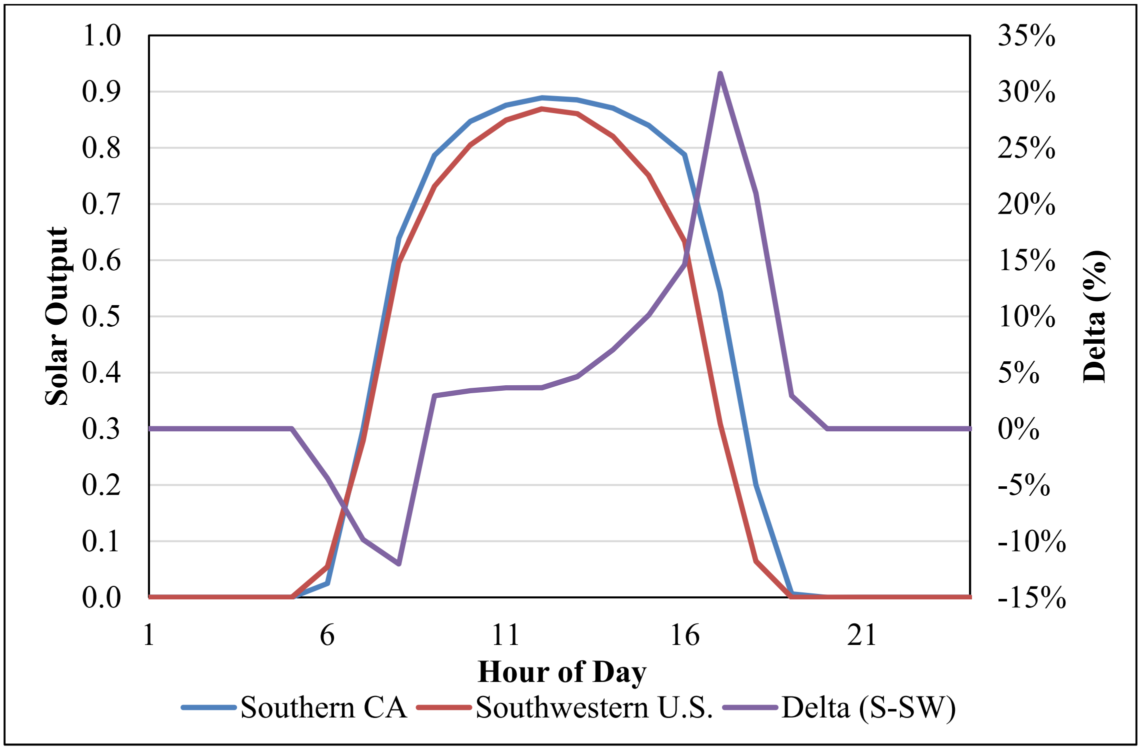

Figure 5: 33% Southern California and Southwest Average August Day Comparison

Figures 4 and 5 show that, during afternoon and early evening hours, Northern California solar facilities are producing moderately more output and contribute more to system reliability; similarly Southern California solar facilities are producing more than Southwestern facilities and contribute more to system reliability.

Section 2: Hourly vs. Intra-hourly ELCC Determination

Simulations were performed using both hourly and 5-minute intra-hour time steps. Simulations using an hourly time step average all 12 of the 5-minute intra-hour time intervals within the hour. So even though the instantaneous peak load that falls at some point within the hour may be significantly higher than the average of all load values throughout the hour, simulations in hourly mode are only obligated to serve the average load. Intra-hour simulations were expected to show that the instantaneous net load peak has an asymmetric effect on reliability. For example, the obligation of meeting the higher instantaneous peak load (from intra-hour time steps) is more challenging than meeting the average peak load (from hourly time steps). In the last hour of daily solar output, the average output may be several thousand MW, but the output at the end of the hour will be 0 MW. When output is 0 MW, reliability is harmed more than reliability is helped by the high solar output at the beginning of the hour. This intuition suggests that intra-hour simulations would show lower ELCC values for solar. However, after performing the ELCC simulations and calculations using intra-hour simulations, the effect was found to be minimal. Other system effects mute the impact of the instantaneous peak. While running intra-hour simulations does show higher capacity need than the results of hourly simulations because of the instantaneous peak, this is present in systems both with and without significant renewable penetration.

To illustrate the fact that solar ELCCs can be well approximated using hourly time steps, the peak hour is analysed in two scenarios: "without solar" and "with solar". The "without solar" peak hour typically occurs in hour 16. As shown in Figure 6, the instantaneous peak load occurs 25 minutes past the start of hour. The instantaneous peak load is 130 MW higher than the average load across the hour. In the "with solar" cases, load is analysed after removing solar output. The net load peak in the "with solar" scenario occurs in hour 19. The instantaneous peak also occurs 25 minutes past the start of the hour. In this case, the instantaneous peak is 200 MW above the average load for the hour. The introduction of solar has made the instantaneous peak more challenging to meet, but only slightly. The "with solar" case includes 24,000 MW of solar and only increased the impact of instantaneous load by 70 MW. Figure 6 represents these values visually to highlight the relatively small difference that the addition of solar has on the impact of intra-hour simulations.

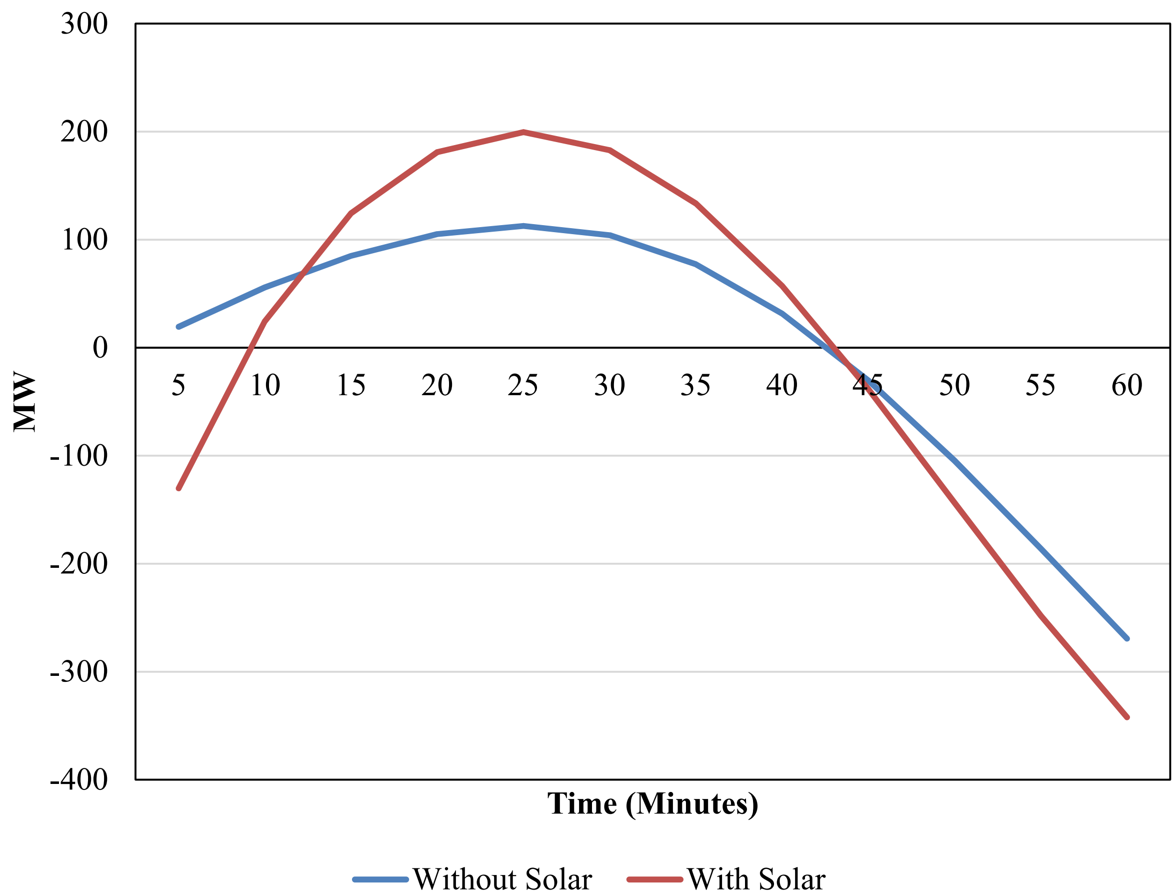

Figure 6:
Instantaneous Load Compared to Hourly Integrated Load

This small increase in the impact of intra-hour modeling is reflected in the slightly lower ELCC values produced by the intra-hour simulations. The average portfolio ELCCs were 0.3% to 0.5% lower from the intra-hour simulations than the hourly simulations. Because the effect is so small, and simulations are significantly more time consuming to setup and perform on intra-hour time steps, our recommendation is to use hourly modeling when performing ELCC calculations in the future. All of the results shown in this report are based on hourly simulations.

Section 3: ELCC Approximation Methods (Net Load Peak Impacts)

The reliability contribution of renewable resources can be approximated by simply analysing the difference in peak load with and without renewable resources using the net load peak-ELCC (NLP-ELCC) method. The NLP-ELCC method is much simpler than the SERVM analysis in that is only calculates an ELCC value of a resource based on the single criteria of how well a renewable resource can reduce the highest single hour of gross load (delta between gross and net load) over a given time. The results from a version of this method to determine monthly average ELCC values were presented Table 8 in the proposal using a spreadsheet NLP tool that calculates the monthly maximum reduction in net load peak due to wind and solar. To extend this analysis to an equivalent annual basis, the Joint IOUs here provide a similar method (IOU NLP method). The results of this annual method are different from the values in Table 8 in the proposal because the annual gross load and net load peaks can fall in different months in some weather years. The IOU NLP method determines the annual marginal ELCCs as well as the annual average ELCCs by calculating the difference between the maximum annual gross load and the maximum annual net load. Since the SERVM simulations were performed for 35 weather years, the IOU NLP method is performed for all 35 weather years by comparing the max peak and max net load peak in each individual weather year and averaging all of these values.

The NLP method values for the average wind and solar portfolio were grossed up to reflect diversity benefits[6]. The starting load for this method was the gross load net of energy efficiency.

Table 3 compares the ELCCs using this annual IOU NLP method to those derived from the SERVM simulations in the 33% RPS penetration scenario. While the average portfolio ELCC is similar, many of the marginal simulations show significant differences. Namely, the marginal solar values are significantly lower in the approximation method. The approximation method yields lower values in this instance primarily because the effects on other system resources are not considered. Depending on the resource mix being analysed however, the simulation approach can produce either higher or lower ELCCs than an approximation method. At low solar penetrations, incremental solar flattens the load shape resulting in more hours per day near the peak load. This higher frequency of reliability constrained hours yields a lower ELCC for simulation methods than for approximation methods which do not consider frequency. The differences between simulation methods and approximation methods are discussed in more detail later in this section.

[6] The ratios of the technology specific ELCCs to the sum were multiplied by the RPS portfolio ELCC in MWs. This yielded the technology specific ELCCs with diversity benefits in MW terms.

Table 3: IOU NLP Method Comparison to SERVM Results – 33% RPS Case

ELCC Case and Technology	NLP Method (Average Annual) (%)	SERVM Results (%)
Average/-RPS	29.08	28.94
Average/-Wind	20.83	21.03
Average/-Solar	32.61	32.75
Marginal CA-N/-Wind	26.25	21.49
Marginal CA-N/-Fixed PV	4.08	13.36
Marginal CA-N/-Tracking PV	8.74	21.12
Marginal CA-N/-BTMPV	3.78	11.56
Marginal CA-S/-Wind	22.25	14.43
Marginal CA-S/-Fixed PV	1.80	9.58
Marginal CA-S/-Tracking PV	4.00	15.24
Marginal CA-S/-BTMPV	1.29	7.73
Marginal NW/Wind	42.89	40.26
Marginal SW/Wind	17.57	23.75
Marginal SW/Fixed PV	0.64	8.12
Marginal SW/Tracking PV	1.93	12.35

Performing the same comparisons with the 43% RPS penetration identifies other differences between the methods, as shown in Table 4.

Table 4. IOU NLP Method Comparison to SERVM Results– 43% RPS Case

ELCC Case and Technology	NLP Method (Average Annual) (%)	SERVM Results (%)
Average/-RPS_43	17.97	20.17
Average/-Wind_43	20.88	22.50
Average/-Solar_43	17.20	19.56
Marginal CA-N/-Wind_43	18.44	27.09
Marginal CA-N/-FixedPV_43	0.15	4.16
Marginal CA-N/-TrackingPV_43	0.85	8.28
Marginal CA-N/-BTMPV_43	0.33	4.74
Marginal CA-S/-Wind_43	20.69	22.06
Marginal CA-S/-FixedPV_43	0.02	3.61
Marginal CA-S/-TrackingPV_43	0.16	3.91
Marginal CA-S/-BTMPV_43	0.02	2.00
Marginal NW/-Wind_43	43.27	43.06
Marginal SW/-Wind_43	21.41	29.93
Marginal SW/-FixedPV_43	0.00	0.69
Marginal SW/-TrackingPV_43	0.00	2.99

The SERVM-produced values in the 43% RPS penetration scenario are consistently higher, except for NW/-Wind. The difference is due to a number of factors. First, the approximation method only analyses a single pair of hours – the peak load and peak net load hours. This ignores the fact that reliability can be a problem in a number of other hours in the year. The simulations performed in SERVM demonstrate that expected unserved energy (EUE) can occur in dozens of different hours across a large set of renewable profiles, load profiles, and generator outage draws. If the NLP method were applied for all pairs of hours in which EUE could possibly occur, the resulting ELCCs would be much closer to the ELCC values produced by SERVM. As an example, using the top 100 hours of peak load minus net load peak results in a marginal ELCC of 3.2% for the northern California tracking PV vs 0.85% using only the top value for each year. While using a more accurate set of hours to perform the ELCC approximations can improve its accuracy, additional modeling is still required to identify that set of hours.

Second, the inclusion of energy limited resources can affect the reliability contribution of renewable resources. Take for instance the northern California tracking PV case again. The additional solar energy provided prior to the peak net load hour serves to preserve energy limited resources in extremely hot days. Before the addition of the marginal solar, some of the 2, 4, and 6 hour battery storage products were being exhausted prior to the net load peak. So even though the output of the solar is de minimis in the hours with EUE, it improves the reliability of the system by providing a support role to energy storage. This translates to higher ELCC values for solar in the SERVM runs. This effect is possible for any type of energy limited resource including pumped storage hydro, dispatchable hydro, battery storage, and demand response resources with contract constraints.

These two effects – the challenges of identification of the critical reliability hours and the changing nature of interactions with energy limited resources – are evident in analysis of the shape of the system net load as renewable penetration increases. Figure 7 below shows the daily shape of peak load days as the system moves from no renewables to a 43% RPS penetration. Initially as the addition of renewables shifts the net load peak to later in the day, the overall shape is flattened. As renewables continue to be added, the net load shape begins to steepen. With the flat load shape in the 33% RPS scenario, more hours close to peak load stress the system, particularly on energy limited resources. The extra energy from renewables in sub-peak hours in the 43% RPS scenario allows for the preservation of energy limited resources, and thus allows them to increase the ability of renewables to provide reliability.

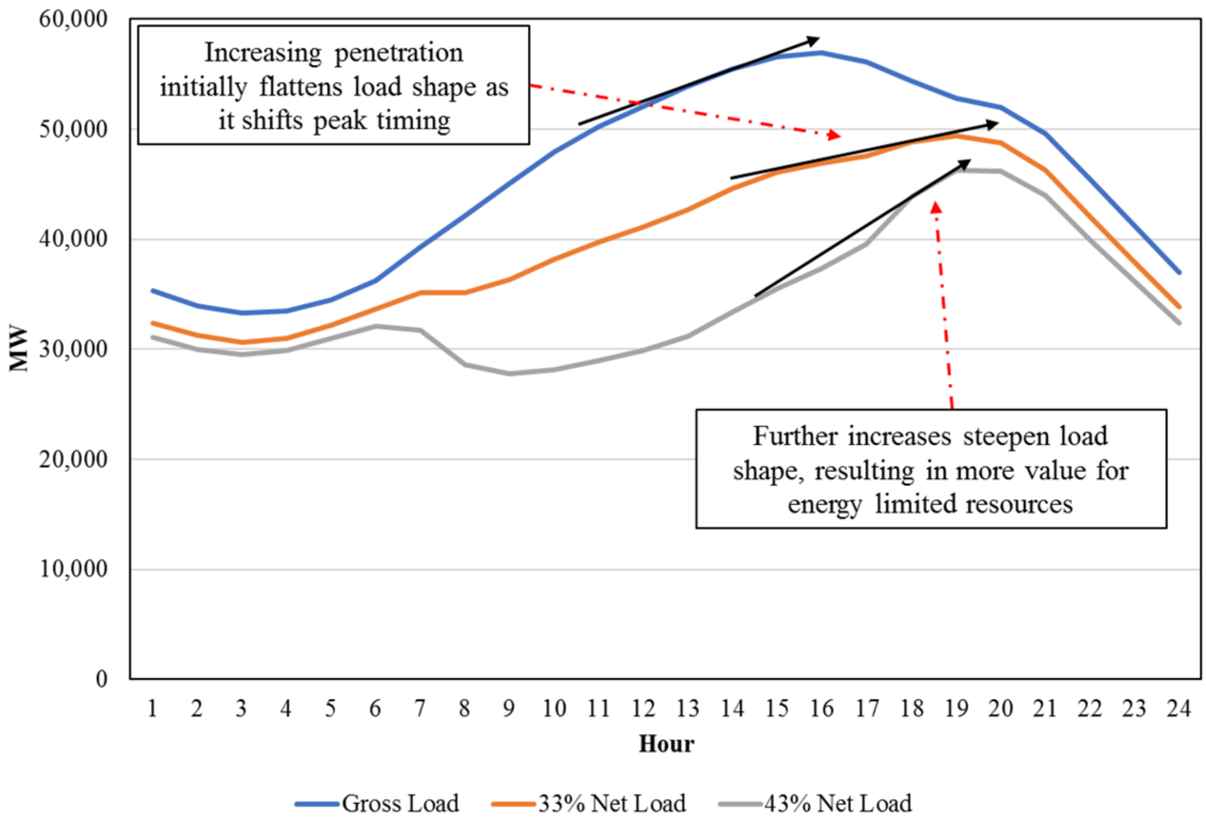

Figure 7: Shifting Load Shape as More Renewable Are Added

To more fully explain the relationship of sub-peak hours to system reliability, consider the following examples in Figures 8 and 9 below. Using the same data from Figure 7, a dispatch is created which limits conventional output by its potential capacity (the 43% conventional capacity is lower than that in the 33% scenario). In the 33% scenario dispatch shown in Figure 9, the Battery/pumped storage hydro (PSH) resources are needed for 7 hours and the Demand response is needed for 4 hours. Since some of the Battery/PSH capacity only has energy for 2, 4, or 6 hours of dispatch, some of its capacity would have become unavailable for the final peak load hours.

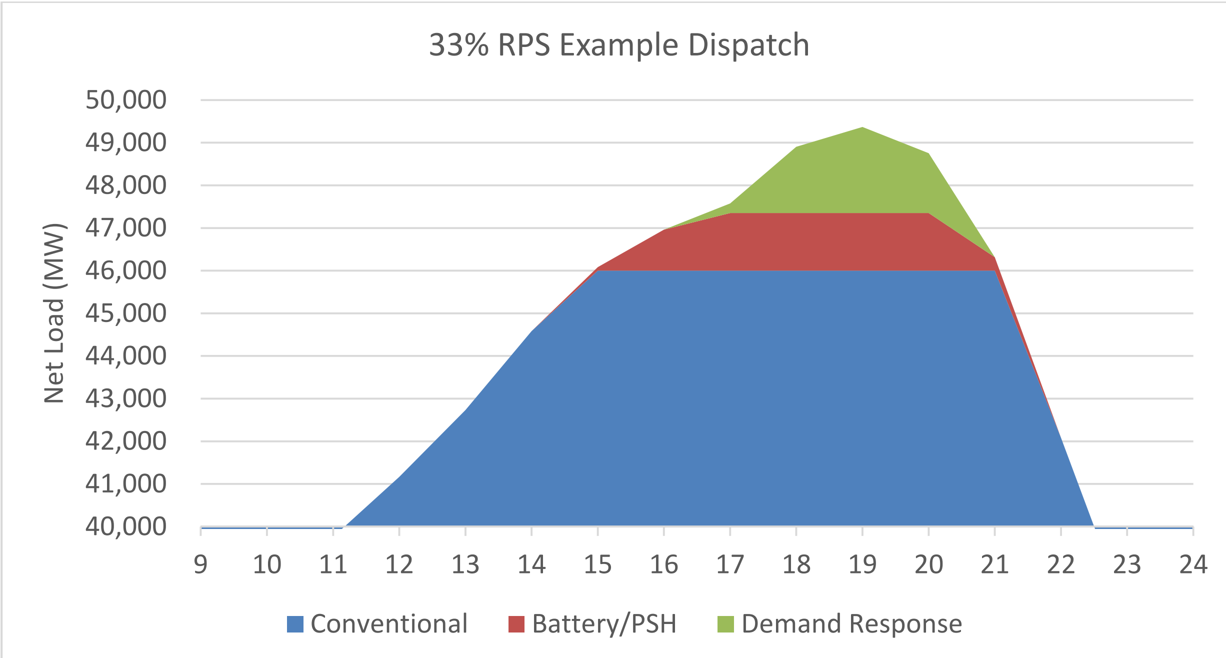

Figure 8: 33% RPS Example Dispatch

The corresponding 43% RPS dispatch has a steeper net load shape resulting in fewer hours of need for the energy limited resources. The Battery/PSH are only needed for 4 hours and the Demand Response is only needed for 2 hours. This lighter demand on the energy-limited resources was due to the additional renewable energy in the hours prior to the peak and helped to preserve reliability in the 43% scenario.

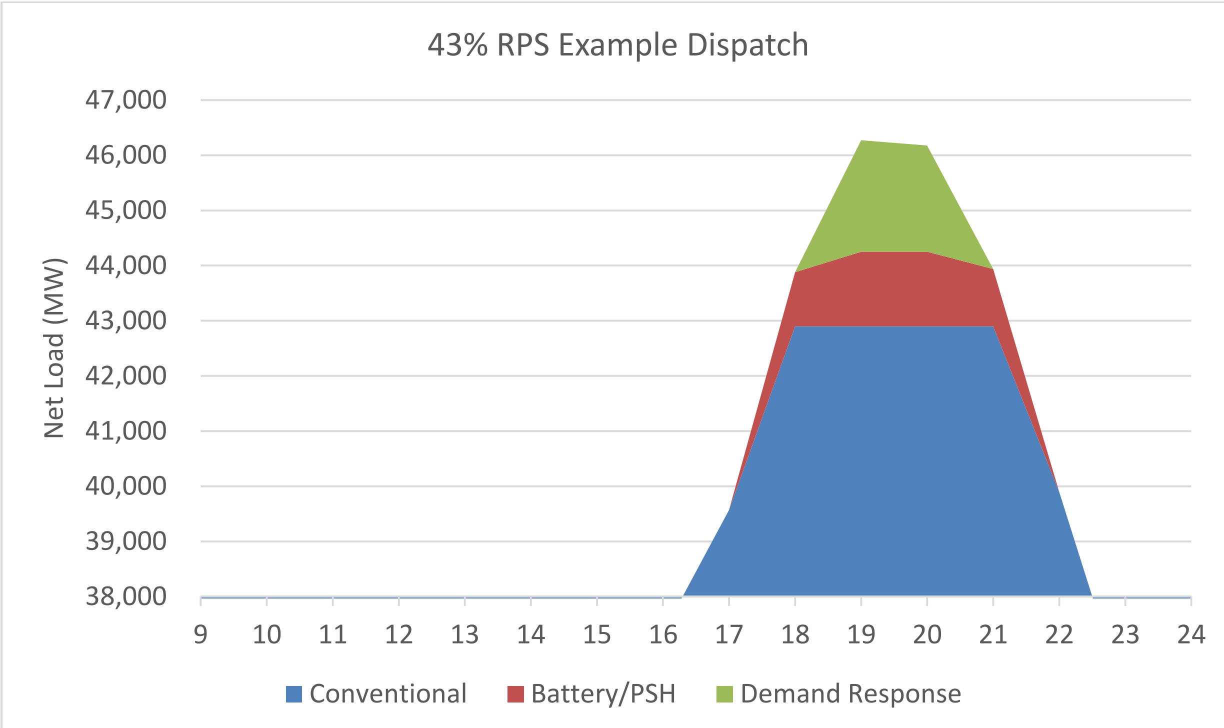

Figure 9: 33% RPS Example Dispatch

Conclusion

This document describes a robust methodology for the calculation of ELCC values for renewable resources using SERVM. This methodology fully considers the reliability contribution of renewable resources in that the hourly simulations reflect the renewable resources' impact on the system for all hours of the year. While peak hours are most critical, the interactions between renewable resources and other system resources in sub-peak hours can also have an effect on the reliability contribution of renewable resources. This comprehensive approach provides a framework for considering the reliability contribution of any class of resource.