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Managing Solar Photovoltaic Integration in the Western United States

Resource Adequacy Considerations

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Preface

This report is one in a series examining potential challenges related to planning future power systems with higher solar photovoltaic (PV) penetrations. In recent years, numerous renewable integration studies have examined power system operations with various wind and solar penetrations and have found it feasible to balance supply and demand. There are also examples of power systems currently operating with significant penetrations of wind or solar power in the literature. This series of reports focuses on solar PV generation specifically and delves deeper into potential integration issues that may not be so challenging at moderate penetrations but could be of more import at higher PV penetrations.

The series uses the western U.S. power system for these investigations because it is a region the authors and their colleagues have already extensively studied. We are therefore well-suited to analyze even higher PV penetrations and then examine the results in multiple models to determine whether our current approaches are missing key details that only emerge at higher PV penetrations. We also examine three regions in the western United States with significantly different existing power systems and connections to neighboring regions; this provides a more balanced picture as to how high PV penetration systems might emerge in different contexts and what the resulting issues, if any, might be.

The four publications in this series are listed and described in Table A.

Table A. Reports in the *Managing Solar Photovoltaic Integration in the Western United States* Series

Title	Description
Managing Solar Photovoltaic Integration in the Western United States: Power System Flexibility Requirements and Supply	Assessment of net load ramping needs and what resources are available to provide upward and downward ramping at different timescales
Managing Solar Photovoltaic Integration in the Western United States: Resource Adequacy Considerations	**Probabilistic resource adequacy assessment of high PV penetration scenarios and comparison to planning reserve margin approaches using capacity credit approximation methods**
Behind-the-meter Solar Accounting in Renewable Portfolio Standards	An exploration of how two renewable portfolio standard design elements can influence the interaction of behind-the-meter PV and total renewable generation
Managing Solar Photovoltaic Integration in the Western United States Appendix: Reference and High Solar Photovoltaic Scenarios for Three Regions	Resource Planning Model (RPM) inputs, scenario framework, and results for RPM-AZ, RPM-CO, and RPM-OR; two of the papers in the series use these scenarios as their starting point for analysis

This report is listed in **bold type**.

This report series was commissioned by the Western Interstate Energy Board (WIEB) as part of the Enhanced Distributed Solar Photovoltaic Deployment via Barrier Mitigation or Removal in the Western Interconnection project funded by the U.S. Department of Energy's Office of

Energy Efficiency and Renewable Energy Solar Energy Technologies Office (SETO).[1] For more information, including links to other reports, see https://www.westernenergyboard.org/western-interstate-energy-board/barrier-mitigation-to-enhanced-distributed-solar-photovoltaic/.

[1]An additional work was published as a journal article: Kenyon, Rick Wallace, Matthew Bossart, Marija Marković, Kate Doubleday, Reiko Matsuda-Dunn, Stefania Mitova, Simon A. Julien, Elaine T. Hale, and Bri-Mathias Hodge. 2020. "Stability and Control of Power Systems with High Penetrations of Inverter-Based Resources: An Accessible Review of Current Knowledge and Open Questions." Solar Energy, Special Issue on Grid Integration, 210: 149–68. https://doi.org/10.1016/j.solener.2020.05.053.

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The idea for this series of reports was developed with input from several of our colleagues at NREL and the project's technical advisory committee. Lori Bird, Kara Clark, Michael Coddington, Paul Denholm, Barry Mather, Michael Milligan, Bryan Palmintier, and Mark Ruth (NREL) provided input to an initial screening analysis of PV reliability barriers. The barriers screening analysis was then reviewed with the committee, as was a research plan developed in response to the screening results. We would like to thank committee members for their participation in those processes as well as for the review and guidance they provided throughout the execution of the research. The results and findings in this report and the broader project do not necessarily reflect their opinions or the opinions of their institutions. The committee is composed of the following individuals:

- Jim Baak, Vote Solar
- Guru Belavadi, Arizona Corporation Commission
- Ken Bolton, Western Electricity Coordinating Council
- Enoch Davies, Western Electricity Coordinating Council
- Tom Flynn, California Energy Commission
- Jennifer Gardner, Western Resource Advocates
- Daniel Haughton, Arizona Public Service Electric Company
- Carl Linvill, Regulatory Assistance Project
- Toby Little, Arizona Corporation Commission
- Clyde Loutan, California Independent System Operator
- Louise Nutter, Federal Energy Regulatory Commission
- Vijay Satyal, Western Electricity Coordinating Council
- Courtney Smith, California Energy Commission

Finally, the authors would like to acknowledge Bethany Frew, David Hurlbut, Jaquelin Cochran, Dan Bilello, Kristin Ardani, Doug Arent, Mark O'Malley, and Gian Porro (NREL) for providing

[2]SEEDS2-SES is the Solar Energy Evolution and Diffusion Studies 2 – State Energy Strategies program. For information about the program, see https://www.energy.gov/eere/solar/solar-energy-evolution-and-diffusion-studies-2-state-energy-strategies-seeds2-ses.

feedback and review on drafts of this paper, as well as Sheri Anstedt and Devonie McCamey for editorial and publication support.

Acronym List

APS	Arizona Public Service Company
ATB	Annual Technology Baseline
BA	balancing authority
CAMX	California/Mexico
DOE	U.S. Department of Energy
DPV	distributed photovoltaics
EFC	equivalent firm capacity
EIA	U.S. Energy Information Administration
ELCC	equivalent load-carrying capability
EERE	Energy Efficiency and Renewable Energy
EUE	expected unserved energy
IEEE	Institute of Electrical and Electronics Engineers
INLDC	incremental net load duration curve
LOLE	loss-of-load expectation
LOLP	loss-of-load probability
NEUE	normalized expected unserved energy
NERC	North American Electric Reliability Corporation
NEVP	Nevada Power Company
NREL	National Renewable Energy Laboratory
PACW	PacifiCorp West
PGN	Portland General Electric Company
PSC	Public Service Company of Colorado
NWPP-CA	Northwest Power Pool Canada
NWPP-US	Northwest Power Pool United States
ppm	parts per million (energy fraction)
PRAS	Probabilistic Resource Adequacy Suite
PRM	planning reserve margin
PV	photovoltaic
ReEDS	Renewable Energy Deployment System
RMRG	Rocky Mountain Reserve Group
RPM	Resource Planning Model
RPS	Renewable Portfolio Standard
SETO	Solar Energy Technologies Office
SRP	Salt River Project
SRSG	Southwest Reserve Sharing Group
TEP	Tucson Electric Power company

UPV	utility-scale photovoltaics
WACM	Western Area Power Administration, Colorado Missouri
WALC	Western Area Power Administration, Lower Colorado Region
WI	Western Interconnection
WIEB	Western Interstate Energy Board

Executive Summary

This study examines the impact of reserve margin-based reliability assessment, as commonly used in capacity expansion models, on planning resource-adequate power systems under high penetrations of solar photovoltaics (PV). As a generation resource, PV is operationally different from the conventional dispatchable resources for which most capacity expansion models were designed. The question this study attempts to answer is whether large amounts of PV on a system (in this case, the Western Interconnection of North America) would bias the results of conventional reserve margin-based capacity expansion modeling towards an over- or under-provisioning of resource adequacy.

This analysis used NREL's Resource Planning Model (RPM) for capacity expansion modeling and NREL's Probabilistic Resource Adequacy Suite (PRAS) for resource adequacy assessment. RPM uses a reserve margin requirement to enforce resource adequacy. PRAS, a collection of tools for studying the resource adequacy of power systems and the adequacy contributions of individual resources on a probabilistic basis, was used to compute multiple resource adequacy metrics across a number of simulated scenarios and system representations with differing regional detail. In all cases, including high PV penetrations (up to 33% annual generation from PV, interconnection-wide), RPM was able to produce resource-adequate systems as measured by normalized expected unserved energy and loss-of-load expectation results from PRAS.

The accuracy of reserve margin approaches depends heavily on the underlying assumptions informing the capacity credit assigned to variable and energy-limited resources, particularly when such resources are abundant in the modeled system. RPM's standard methodology for estimating variable and flexible resources' capacity contributions, which is based on the top 100 hours of net load, did not appear to systematically undervalue or overvalue variable generation relative to a more rigorous equivalent firm capacity assessment using PRAS, although both over- and undervaluations were observed in specific scenarios. In the worst cases, the top 100 hour method underestimated the equivalent firm capacity of PV by two percentage points, and overestimated the equivalent firm capacity of PV by five percentage points. Calculating capacity contributions based on the top 10 hours of net load systematically underestimated equivalent firm capacities at more modest PV penetrations, but was often a better approximation of equivalent firm capacity than the current 100-hour approach in scenarios with higher PV penetrations.

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1 Introduction

Resource adequacy, that is, ensuring a sufficiently low risk of available generation supply falling short of demand, is a key concern for all power system planners, operators, and load-serving entities. The North American Electric Reliability Corporation (NERC) produces three annual reports on this topic to document the current resource adequacy status of NERC-jurisdiction power systems: a summer assessment, a winter assessment, and an overall long-term reliability report.[3] In this way, all stakeholders can be aware of how well poised our power systems are to provide affordable electricity at peak times, both now and into the future.

The NERC reliability assessments primarily report resource adequacy in terms of planning reserve margins. A planning reserve margin is firm capacity over and above the peak load forecast, typically expressed as a percentage of the peak load forecast. Traditionally, the supply shortfall risk mitigated by this extra capacity has been driven by random outages of dispatchable generators and transmission, as well as peak load forecast error. As such, NERC recommends margins of 10% for hydro-dominated systems and 15% for thermal-dominated systems (NERC 2017).

While planning reserve margins are straightforward to compute and understand for systems dominated by fully dispatchable generators, with increasing penetrations of variable resources the key resource adequacy risks shift to phenomena not easily expressed as an extra quantity of generic capacity. These risks include correlated lulls in variable-generation output measured against (also correlated) time-varying load, as well as increasing risk related to outages of transmission links from renewable resources to load centers. It is therefore difficult to fold variable generation into planning reserve margin frameworks. However, doing so is still attractive because of the relative simplicity of those frameworks as compared to fully accounting for reliable operations at hourly or finer resolution. The translation is often made by expressing variable-generation resources' contributions to meeting peak load as a capacity credit, that is, as a fraction of nameplate capacity that can be considered firm in the sense of contributing generation at times that help the system serve more load (Ensslin et al. 2008; Madaeni, Denholm, and Sioshansi 2012; Zhou, Cole, and Frew 2018).

This study assesses the ability of a capacity expansion model that uses such a planning reserve margin methodology to ensure resource adequacy under high penetrations of distributed and utility-scale solar photovoltaics (PV). Specifically, this report summarizes how the Resource Planning Model (RPM) was used to generate high-penetration PV systems for three regions in the Western United States (Section 2), describes methods for evaluating resource adequacy and capacity credit (Section 3.1 and Section 3.2), and then applies probabilistic methods to evaluate the overall resource adequacy of those scenarios (Section 4) as well as the contribution of variable-generation resources to meeting peak load (Section 5). The report concludes by summarizing findings related to planning for resource adequacy in the case of systems with high penetrations of solar PV (Section 6).

[3]NERC is responsible for reliable operations of the power systems in the contiguous United States, Canada, and a small part of Mexico. The reliability reports are available at https://www.nerc.com/pa/RAPA/ra/Pages/default.aspx.

2 Scenario Framework

2.1 Regional Planning Model (RPM) Background

RPM is a regional capacity expansion model that projects least-cost capacity and transmission expansion through 2035 every 5 years. It represents a single interconnection; this study focuses on the Western Interconnection, which includes 36 model balancing authorities (BAs) as the primary regions in RPM. Embedded within this structure, the model has a "focus region," within which generation units, transmission lines, and loads are represented at a high level of detail, and the optimization is carried out nodally. Outside of the focus region, load and generators are aggregated and transmission is modeled zonally. The underlying data used to construct this model comes from Lew et al. (2013). Announced retirements, generators under construction, fuel costs, and technology costs are exogenous to the model and updated regularly (EIA 2018; Hale, Stoll, and Mai 2016; NREL 2018; Ventyx 2010). This analysis studies three focus models defined by different groups of BAs (Figure 1):

- Nevada Power Company (NEVP), Western Area Power Administration, Lower Colorado Region (WALC), Salt River Project (SRP), Arizona Public Service Company (APS), and Tuscon Electric Power Company (TEP) define the focus region for RPM-AZ.
- Portland General Electric Company (PGN) and PacificCorp West (PACW) define the focus region for RPM-OR
- Public Service Company of Colorado (PSC) and Western Area Power Administration, Colorado Missouri (WACM) define the focus region for RPM-CO

RPM also includes additional spatial layers to represent renewable resources. The models used here include 53-85 solar and 65-106 wind resource areas in the Western Interconnection to describe the location-specific resource potential in terms of developable area after accounting for land-use exclusions,[4] performance in terms of wind and solar generator annual and hourly capacity factors, and grid interconnection distances. Additionally, distributed PV (DPV) is added exogenously based on projections from the Distributed Generation Market Demand Model, or dGen (Sigrin et al. 2016). Resource regions are defined for each RPM focus model, with a greater density of resource regions placed within the focus region than the remainder of the interconnection. This ensures that the region of interest is represented with high spatial resolution.

As load grows and generators retire, RPM requires additional capacity to ensure reliable operation of the system during peak conditions via a planning reserve margin constraint, with resource capacity values derived via the incremental net load duration curve (INLDC) method described in Section 3.2.2 (additional details are available in Hale, Stoll, and Mai (2016)). This constraint is applied to the five NERC subregions of the Western Interconnection (Figure 2), including California/Mexico (CAMX), Northwest Power Pool Canada (NWPP-CA), Northwest Power Pool United States (NWPP-US), Rocky Mountain Reserve Group (RMRG), and Southwest Reserve

[4]For example, we assume that renewable generators cannot be placed on land that is too urban, wet, or steep; cannot be placed in National Parks; etc.

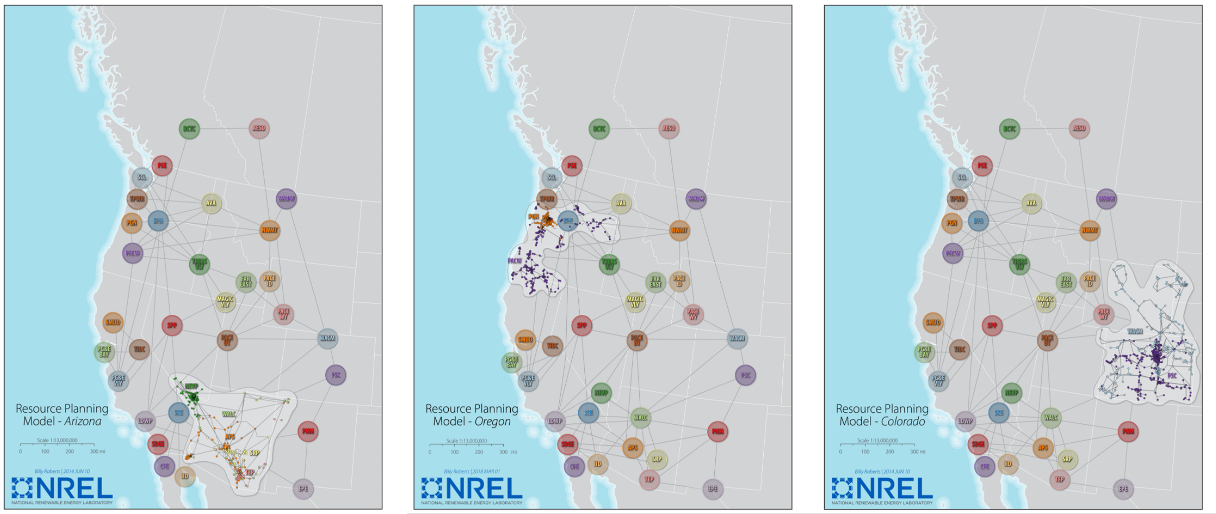

Figure 1. RPM focus models studied in this report: RPM-AZ, RPM-OR, and RPM-CO

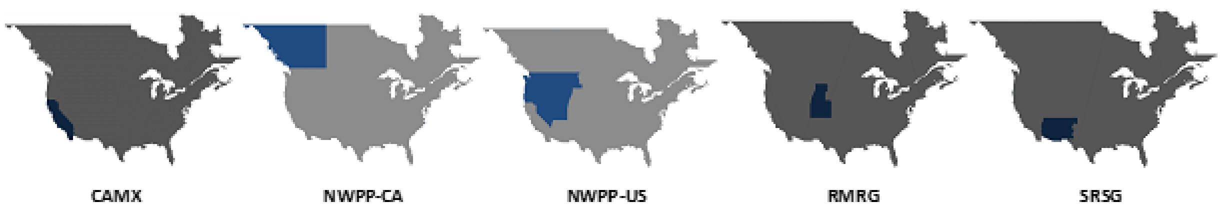

Figure 2. RPM's planning reserve constraints are defined over NERC subregions (NERC 2018a)[5]

Sharing Group (SRSG). Within the model, these planning reserve regions are required to meet or exceed the reserve margins recommended by NERC (2018a).

RPM makes investment decisions based on assumptions including the federal renewable energy investment tax credit and production tax credit, state renewable portfolio standards (RPS) as of 2017, and California's storage mandate, but not including existing demand response programs, local incentives, or California's carbon cap and trade program. Cost data for new natural-gas-fired and wind capacity are consistent with those found in NREL's 2018 Annual Technology Baseline mid case (NREL 2018). The Annual Technology Baseline mid- and low-price trajectories are used for solar technologies, particularly utility-scale PV and battery energy storage. Fuel prices are from the Energy Information Administration's Annual Energy Outlook 2018 Reference and High Oil and Gas Resource and Technology scenarios (EIA 2018).

[5]This information from the North American Electric Reliability Corporation's website is the property of the North American Electric Reliability Corporation and is available at http://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/2015_Summer_Reliability_Assessment.pdf. This content may not be reproduced in whole or any part without the prior express written permission of the North American Electric Reliability Corporation.

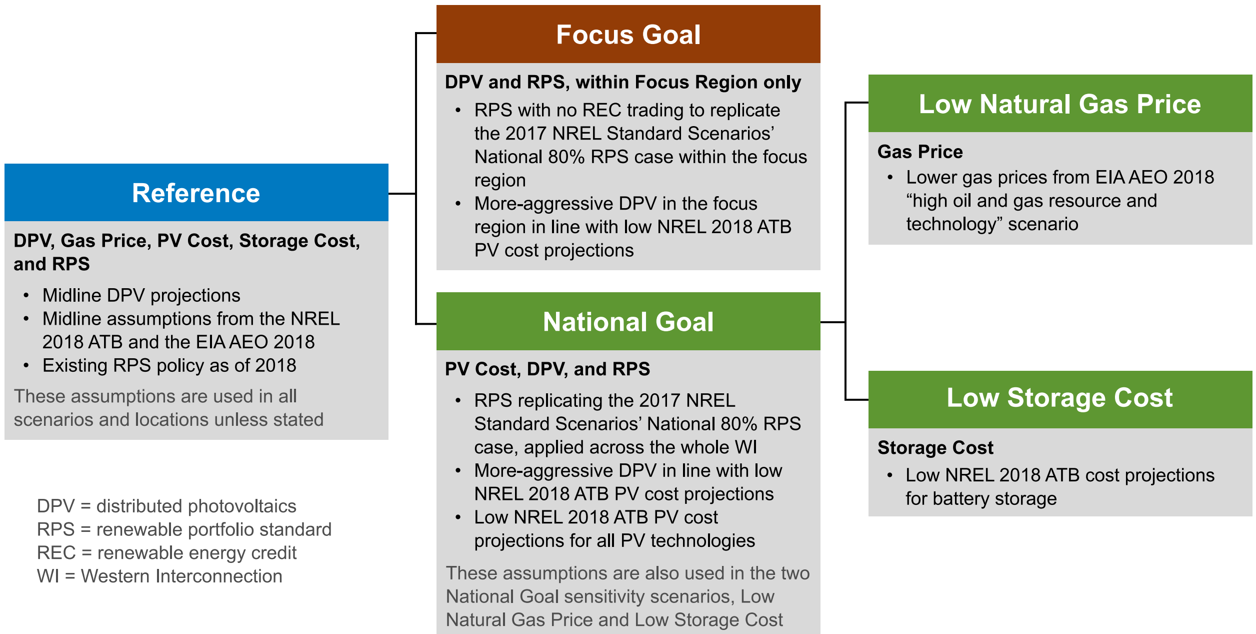

Figure 3. Hierarchical relationship between the five study scenarios. The Reference scenario uses mid-line assumptions. The study scenarios are formed by varying renewable energy goals (RPS), technology costs, and fuel prices.

2.2 High PV Scenario Creation

To study the planning and operational impacts of high solar penetrations, a set of scenarios were designed to reach high levels of solar PV generation (Figure 3) and applied as inputs to each focus model. The initial scenario is a reference case with midline gas price and technology costs, current policy requirements, and midline DPV assumptions. This scenario is then perturbed to apply an increased RPS either only in the focus region (the Focus Goal scenario) or across the entire interconnection (the National Goal scenario). To favor high PV penetrations more than high wind penetrations, the National Goal scenario also includes the assumption of low PV cost trajectories on the utility and customer (DPV) sides. Two National Goal sensitivities are included to round out the scenario framework, one with low battery energy storage costs (to potentially support additional PV deployment) and one with low natural gas prices (to reflect current trends in generation fleet composition in addition to fuel prices).

In all of the non-Reference scenarios, the RPS per state was formed artificially by leveraging the results of the 2017 NREL Standard Scenarios' National 80% RPS case (Cole et al. 2017). That is, an RPS was defined by specifying that each state should match the results seen in the Regional Energy Deployment System (ReEDS) modeling for that scenario, assuming that all hydro generation counts toward meeting the goal, in addition to the more univocally designated renewable energy technologies (wind, solar PV, concentrating solar power, geothermal, and biomass).[6]

[6]Because the goals are based on modeling outputs, we do not allow renewable energy credit trading in the model

Similarly, DPV adoption is specified using dGen results from the 2017 NREL Standard Scenarios: the National 80% RPS results for the Focus Goal scenario and Low PV Cost results for the National Goal scenarios. The resulting trajectory reaches fairly high RPS requirements across the Western Interconnection by 2035, but with a good deal of regional variation. For example, Arizona has a relatively low requirement of 50% by 2034, whereas the 2034 requirements for Idaho, Montana, Oregon, and Wyoming are over 95%.

This high variability in RPS requirements is a result of national-scale least-cost modeling out to 2050 that prioritizes state-level results and considers investment decisions in a wide variety of technologies (for a more detailed description of the ReEDS model, see Cole et al. (2017)). In contrast, the RPM modeling prioritizes balancing authorities over states and only allows investments in a subset of technologies that might be of interest in a high-renewables future. Because the primary purpose of this report and broader study is to investigate reliability and planning challenges that might arise in high PV systems, the creation of high PV systems is prioritized over highly plausible system build-outs. The results that follow should be interpreted in that light, and not taken to suggest that the particular PV penetrations modeled are appropriate for the model regions in any particular time period or perhaps ever. Rather, the range of systems is intended to provide insight into a range of possibilities, including some extremes.

These scenarios led to increased solar deployment in all focus regions, up to 77% PV within the focus region, and up to 33% PV across the entire Western Interconnection (Table 1). More information on the RPM modeling and scenario results is available in Cowiestoll, Hale, and Jorgenson (2020).

Table 1. PV Penetration (%) in 2035 for All Scenarios and Focus Models

Model	Resource	Region	Reference	Focus Region Goal	National Goal	National Goal + Low Gas Price	National Goal + Low Storage Cost
RPM-AZ	**DPV**	**Focus**	5.8	7.5	7.2	7.2	7.6
		WI	3.2	3.4	3.7	3.7	3.7
	All PV	**Focus**	30.1	49.7	48.1	49.1	49.9
		WI	15.5	19.1	30.8	31.6	32.8
RPM-CO	**DPV**	**Focus**	2.0	3.5	3.8	3.7	3.9
		WI	3.2	3.3	3.7	3.7	3.7
	All PV	**Focus**	11.5	24.1	18.7	19.5	32.8
		WI	13.7	14.6	25.0	25.6	30.6
RPM-OR	**DPV**	**Focus**	1.3	1.4	2.0	2.0	2.0
		WI	3.2	3.2	3.7	3.7	3.7
	All PV	**Focus**	10.4	75.4	75.6	73.2	77.3
		WI	15.0	17.3	27.2	27.3	32.5

WI = Western Interconnection

for these scenarios.

3 Methods

System-level resource adequacy and capacity contributions from variable-generation resources can be assessed using a variety of methods. RPM ultimately assesses resource adequacy using a planning reserve constraint that requires the sum of individual resource firm capacity contributions to meet or exceed forecasted peak load plus a reserve margin. The components and outcome of this process can be compared to methods that account for time-varying operational constraints and stochastic considerations in a more comprehensive manner. NREL's Probabilistic Resource Adequacy Suite (PRAS) provides such state-of-the-art methods, specifically addressing net-load variability, probabilistic outages, and transmission constraints.

3.1 System-Level Adequacy Assessment

Power system planning models aim to minimize costs (and thus resource investments) while keeping capacity and deliverability shortfall risks at acceptably small levels. One means of achieving this goal is to define some reserve margin above expected peak load and ensure that the total capacity provided by existing and new investments meets or exceeds this total capacity level. Another more rigorous approach involves applying probabilistic methods to explicitly quantify the risk of resource shortfall while requiring that the combination of chosen investments corresponds to a shortfall risk level that is below the threshold deemed acceptable. In this section, we discuss each of these approaches, providing details on the methods and metrics that they employ.

3.1.1 Planning Reserve Margins

Traditionally, system planners have used planning reserve margins (PRMs) as a means to determine appropriate generation resource investment levels and avoid capacity shortfalls. This reserve margin is added onto projected peak load, typically resulting in a total capacity requirement in the range of 15% above peak load, with the reserve component intended to ensure supply adequacy in the event of generator outages, weather uncertainties, and peak load forecast errors (NERC 2017).

Reserve-margin-based planning has been popular historically because of its transparency and conceptual simplicity. PRMs are also straightforward to implement as constraints in mathematical-programming-based power system planning models (Mai et al. 2013; Eurek et al. 2016). However, this approach fails to explicitly consider the composition of the generator fleet in terms of unit size and reliability. Even when calculating PRMs in terms of unforced capacity (where unit nameplate capacities are derated based on their average forced outage rate), two systems meeting identical PRMs can have very different individual generator characteristics and thus very different capacity shortfall risks (Billinton 1970).

As a simple example, a system comprised of a single 200-MW generator with a 10% forced outage would have a nameplate capacity of 200 MW and an unforced capacity of 180 MW. A second system comprised of two 100-MW dispatchable generators, each having a forced outage rate of 10%, would have identical nameplate and unforced capacities, providing seemingly identical levels of reliability relative to a shared PRM. In fact, in the former system random outages would leave the system with no available generation capacity 10% of the time, whereas in the latter system this would only occur 1% of the time (assuming unit-level random outages occur independently), reducing shortfall risk considerably.

PRM-based resource adequacy assessment becomes increasingly problematic when considering systems not strictly limited to dispatchable, capacity-based resources, such as those incorporating variable-renewable and energy-limited resources. Clearly, the "firm" capacity of such resources is less than their nameplate capacity. The problem of determining what fraction of nameplate capacity such resources should be credited with has come to be known as "capacity valuation" and is discussed in more detail in Section 3.2.

Although a variable or energy-limited resource's derated capacity value is preferable to nameplate capacity when considering resource adequacy contributions, the process of reducing the resource's potentially nontrivial operating availability down to a static capacity metric will always oversimplify the relation between that resource and the system's overall resource adequacy. These additional considerations can be better captured through probabilistic assessment and Monte Carlo analysis, discussed in Section 3.1.2.3.

3.1.2 Probabilistic Assessment

While planning reserve margins are concerned primarily with individual unit capacities and ensuring that the total surpasses some threshold, probabilistic metrics can take a broader view to include other considerations, most importantly the likelihood of concurrent outages resulting from unit-level forced outage probabilities. Certain methods allow other operational considerations as well. Although there are multiple ways to perform probabilistic analyses, most probabilistic assessments ultimately express their results in terms of common probabilistic risk metrics. We describe these metrics, as well as exhaustive enumeration and Monte Carlo methods for obtaining them, in the following subsections.

3.1.2.1 Probabilistic Resource Adequacy Metrics

Probabilistic resource adequacy metrics quantify the risk of load dropping in a system, generally in terms of probabilities (e.g., loss-of-load probability [LOLP]) or probabilistic expectation (e.g., loss-of-load expectation [LOLE], expected unserved energy [EUE]). NERC (2018b) provides a useful overview of commonly used metrics among power system planners in industry, of which the most relevant for this study are:

- **Loss-of-Load Probability.** The probability of not being able to serve all load given a particular system state at some point in time (e.g., load and variable-generation levels). This metric only considers the likelihood of dropping load, not the potential magnitude of that shortfall.
- **Loss-of-Load Expectation.** For a collection of individual points in time, LOLE quantifies the expected (average) number of time periods in which load will be dropped. This is

mathematically equivalent to the sum of LOLPs for each hour in the considered time span if the LOLPs are independent (i.e., not serially correlated). Like LOLP, LOLE only considers the number of periods in which load could be dropped, not the magnitude of any of those shortfalls. In North America, this metric is also commonly referred to as Loss-of-Load Hours when the individual periods considered correspond to all hours of the year.

- **Expected Unserved Energy.** EUE is the expected value (or average) of the probability distribution of unserved energy over some time span. It quantifies both the probability and magnitude of a shortfall occurrence, but as a result is unable to distinguish between a small, likely shortfall and large, unlikely one. EUE can also be reported as normalized expected unserved energy (NEUE) by expressing the expected energy shortfall as a fraction (usually parts per million, or ppm) of total energy demand in the time period studied; this is convenient for comparing reliability levels across different systems.

3.1.2.2 Exhaustive Enumeration Methods

Exhaustive enumeration considers all possible combinations of system component (e.g., generator and transmission line) outage states to derive exact probability distributions of outcomes of interest (such as unserved energy). The number of unique system states is generally intractable for large systems (2^n for systems with n components that are either available or forced offline, before considering load or variable-generation uncertainty). However, if transmission constraints are ignored and available capacity is quantized (e.g., rounded to the nearest megawatt), closed-form discrete convolution methods can leverage the resulting degeneracy to very quickly calculate a one-dimensional probability distribution for systemwide available dispatchable capacity.

System capacity shortfall risk for each time period of interest can be calculated directly by combining this available dispatchable capacity distribution with time-varying load and variable-generation capacity levels. This is the resource adequacy assessment approach recommended by the Institute of Electrical and Electronics Engineers (IEEE) Task Forces on the Capacity Value of Wind and Solar (Keane et al. 2011; Dent et al. 2016).

NREL's PRAS implements this single-region convolution functionality as the `NonSequentialCopperplate` simulation method. This was the method used in this study for any resource adequacy assessments that neglected transmission (i.e., Section 4.2).

Once transmission constraints or intertemporal dependencies (e.g., storage charging and discharging) are considered, the increased dimensionality of the problem causes the number of system states needing to be considered to increase exponentially, and the problem quickly becomes intractable for all but the smallest of systems and shortest of time horizons. In these cases, resource adequacy metrics can be estimated via Monte Carlo sampling techniques instead.

3.1.2.3 Monte Carlo Sampling Methods

Monte Carlo simulation involves repeatedly drawing from predetermined input probability distributions and simulating some process to estimate the probability distributions of output variables of interest. In resource adequacy assessment, this generally involves generating random unit outages (generation and potentially transmission) and simulating a simplified, constrained grid operations model while recording the distribution of observed energy shortfall events (if any). Uncertainties in variable generation and load are incorporated by drawing their realized values from appropriate distributions.

Unlike analytical probabilistic methods that are restricted to a small set of mathematical operations over random variables (e.g., addition) to remain tractable, in a Monte Carlo framework the level of detail in operational considerations (e.g., transmission and flexibility constraints, unit commitment, AC power flow, and so on) is limited only by required simulation runtime and computational resources.

Most simulation methods implemented in PRAS are based on Monte Carlo simulation. Transmission-constrained analysis in this study (i.e., Sections 4.3, 4.4, and 5) used the `NonSequentialNetworkFlow` method, a hybrid approach that analytically convolves time-varying probability distributions for regional supply (as described in the previous section) but then samples those distributions in a Monte Carlo network flow simulation to calculate risk metrics with transport model[7] transmission constraints considered.

3.2 Adequacy Contributions of Individual Resources

In spite of the challenges of reserve-margin-based planning discussed earlier, the technique remains a popular approach in industry, as well as in research-oriented capacity expansion models. Using a PRM to determine adequate investment levels requires mapping each individual resource in the system to a capacity contribution ("capacity value" or "capacity credit"). "Firm" dispatchable resources are generally credited their seasonal net capacity or are derated based on their average outage rate (unforced capacity), whereas variable or energy-limited resources (e.g., storage) require more sophisticated valuation approaches.

Three capacity valuation methods for nonfirm resources are described here: static capacity factor approximations; incremental net load duration curve approximations; and probabilistically derived metrics, specifically equivalent firm capacity.

3.2.1 Static-Hour Capacity Factor Approximation

The simplest approach to capacity valuation is to calculate the capacity factor of variable resources during certain predetermined high load or net load (load minus variable generation) time periods, approximating capacity value with capacity factor during times of highest expected system risk. This is a common approach among U.S. regional transmission operators and independent system operators such as NYISO (2018). While easy to explain and highly transparent, this method requires presupposing the system's high-risk periods and can therefore neglect the impacts of newly added resources on shifting the system's high net load (high risk) hours. The

[7] A transport or "pipe and bubble" power flow model constrains active power injections, withdrawals, imports and exports to balance within each region and enforces limits on interregional flow magnitudes, but does not consider transmission losses or other electrical network properties.

technique also neglects transmission constraints that may impact the deliverability of the resource's energy supply, and is problematic for valuing nongeneration resources, such as storage.

3.2.2 Incremental Net Load Duration Curve Approximation

Incremental net load duration curve (INLDC) methods present a refinement of the static-hour capacity factor approach, considering the impact of new resources on system risk periods by calculating the average difference in the system's net load duration curves before and after the addition of a new energy-limited resource. Although no specific time periods need to be chosen, users of this technique still need to choose the number of top net load hours to consider in the difference calculation, and deliverability constraints within the region of interest are still neglected. RPM uses this approach internally with 100 top net load hours: more details are available in Hale, Stoll, and Mai (2016).

3.2.3 Probabilistically Derived Metrics

A more rigorous approach is to assess overall system risk probabilistically (in terms of LOLE or EUE, as described in Section 3.1.2), determine the incremental change in risk associated with some new resource, and express that change in terms of capacity. Equivalent firm capacity (EFC) is one example of a metric based on this technique. Zachary and Dent (2012) and Milligan et al. (2017) provide more details on EFC and other probabilistically derived metrics, such as effective load-carrying capability (ELCC).

EFC determines the amount of 100%-available capacity that would be required to reproduce the incremental reliability benefit provided by the study resource, providing a capacity value that can be counted toward a system planning reserve margin. Unlike alternative load-based capacity value metrics such as ELCC, EFC provides a spatially and temporally unambiguous means of comparison, particularly when considering interregional transmission constraints.

While probabilistically derived metrics such as EFC can overcome limitations of simpler metrics, they can also require more care in their implementation to ensure that the results of this kind of analysis are meaningful. One common challenge arises in multiregion systems with transmission constraints, where the overall system may be very reliable, but with risk highly concentrated in transmission-limited load pockets. When assessing EFC of resources outside those load pockets, neither variable resources nor theoretical firm capacity will provide significant incremental reliability benefits, thereby limiting the usefulness of expressing one in terms of the other, and requiring careful system adjustment in preparation for a capacity value analysis.

4 System Resource Adequacy Assessment

Probabilistic resource adequacy metrics were calculated for the Western Interconnection as a whole for each RPM model (i.e., RPM-AZ, RPM-CO, RPM-OR) and scenario to understand the model's ability to generate a reliable system buildout under high penetrations of solar PV. To quantify the separate contributions of capacity availability and deliverability (i.e., transmission) toward shortfall risk, each system configuration was assessed twice: once assuming a "copper plate" system without inter-regional transmission constraints, and again with those constraints added in. The difference in results under these two models can be taken as the contribution of transmission constraints toward unserved energy risk.

4.1 System Representation

In preparation for the probabilistic assessment, RPM results for each model (differentiated by focus region), scenario, and model year were mapped into PLEXOS production cost model inputs according to the techniques first developed in Gagnon et al. (2018). The system was then imported into PRAS: dispatchable units (e.g., coal, natural gas, geothermal, biomass) were characterized by their maximum capacity and forced outage rate, and time-varying wind and solar PV generation profiles were aggregated into regional variable-generation profiles. Hydro resources with fixed load profiles were treated as variable-generation resources, whereas energy-limited hydro resources were treated as firm capacity (with seasonal deratings as specified in the PLEXOS model). Pumped hydro and battery storage resources were both treated as firm capacity with 100% capacity value, as the version of PRAS used in the study did not support chronological state-of-charge modeling (a newer version supporting this functionality has subsequently been developed).

It should be noted that the probabilistic assessments carried out for this study used just a single year of wind, solar, and load data. While this is not unusual for this kind of analysis, it raises the issue that the weather conditions against which the system is tested are far from an exhaustive set and may not be representative of the system's long-term "typical" operating conditions, potentially over or understating variable-generation capacity value and system-level adequacy. Furthermore, the weather conditions used in the probabilistic assessment are identical to those considered during the planning process, raising the possibility that while the system may perform well under the specific conditions that it was designed against, a different choice of weather year or the introduction of forecast errors in the probabilistic assessment could yield markedly different results.

This lack of weather diversity becomes increasingly problematic at higher penetrations of weather-dependent resources (i.e., wind and solar). Future probabilistic assessment work should attempt to consider longer time horizons with more potential weather conditions (droughts versus high-rainfall years, mild versus harsh winters, hot versus cool summers, and so on), which could affect supply availability as well as demand.

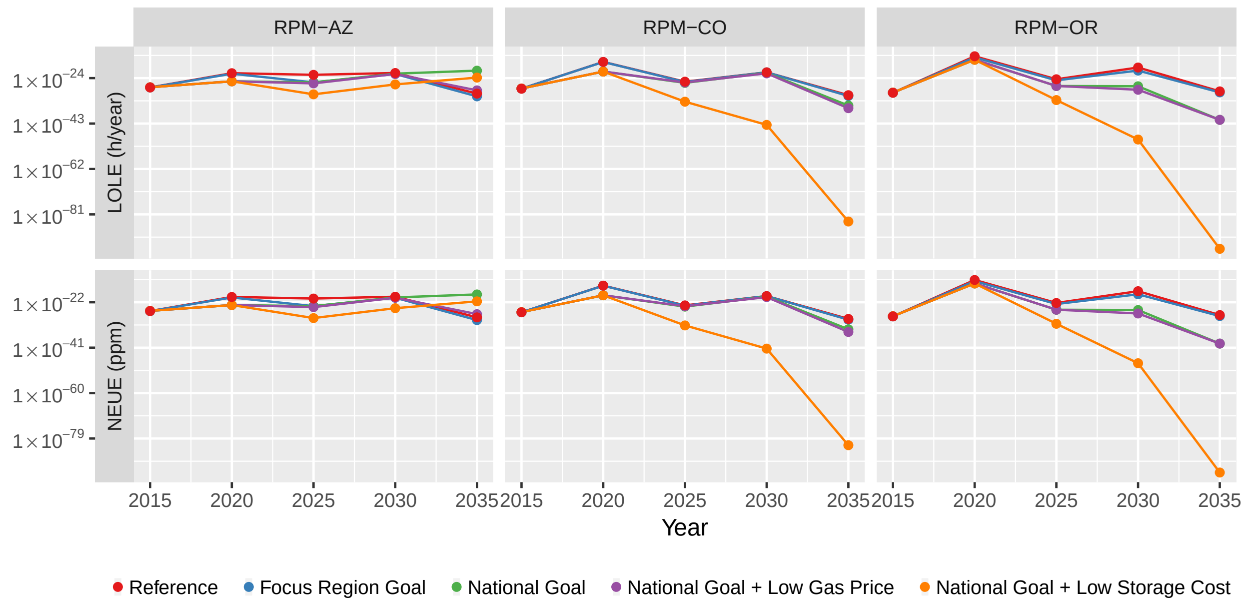

Figure 4. Western Interconnection resource adequacy (log scale) without transmission considered

4.2 Copper Plate Analysis

Ignoring interregional transmission constraints to focus strictly on capacity availability reveals a significant capacity surplus in the system. As shown in Figure 4, systemwide LOLE and EUE are several dozen orders of magnitude below levels generally considered "acceptable" (in this study, 2.4 hours/year for LOLE and 10 ppm for NEUE), indicating extremely high levels of capacity adequacy.

Resource adequacy considerations are represented in RPM through planning reserve margin constraints for each of the five NERC regions in the Western Interconnection. Figure 5 merges these five regions to report the ratio of assessed capacity value of resources systemwide relative to the sum of expected peak load in each region (note that this aggregation is a significant simplification as it neglects the potential for nonconcurrent peaks and interregional synergies of variable resources).

Interestingly, the increasing reliability in the RPM-CO and RPM-OR cases (particularly the low-cost storage case) occurs at the same time that planning reserve margins tighten to the prescribed minimum levels (corresponding approximately to a 17% systemwide PRM). This is counterintuitive to the general assumption that higher planning reserve margins correspond to higher resource adequacy, particularly when ignoring transmission. While this is likely partly attributable to the treatment of storage devices as firm capacity in the probabilistic resource adequacy analysis (but not in RPM's reserve margin calculations), it also reinforces the point that the relationship between PRMs and probabilistic resource adequacy is not trivial and that fleet composition and variable-generation capacity value assumptions are important factors to consider.

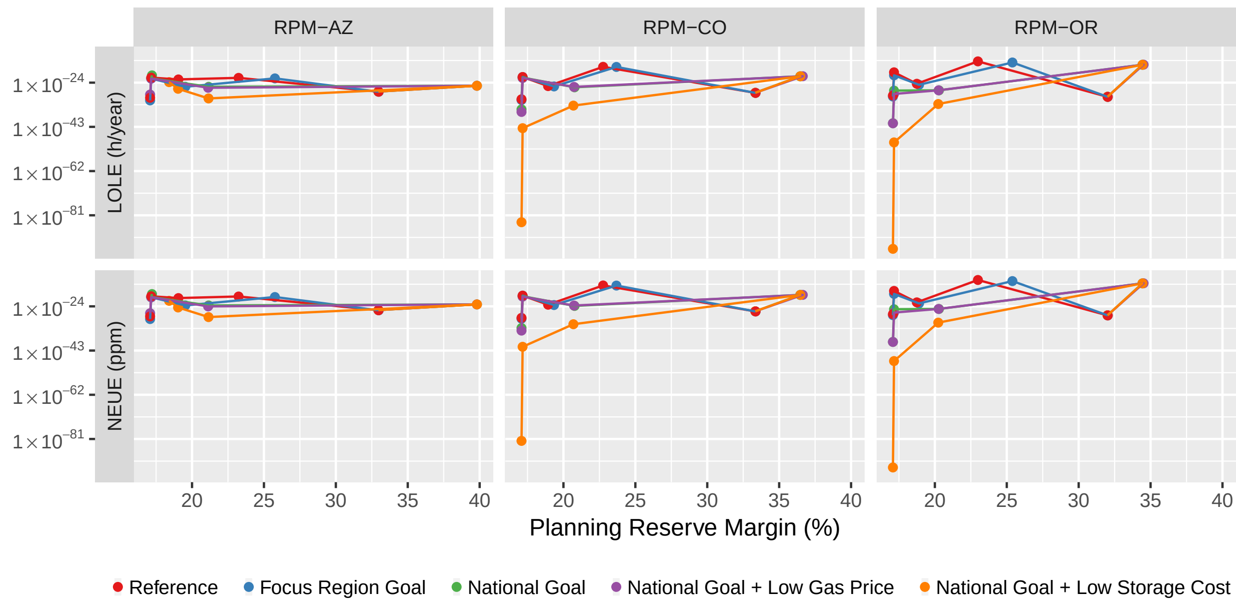

Figure 5. Copper plate metrics versus planning reserve margin

Taken in isolation, this analysis would suggest that RPM's high-PV penetration Western Interconnection model starts overbuilt and becomes more so over time, in spite of tightening reserve margins. While this may be true on a strict capacity basis, the deliverability of that capacity is an important contributor to shortfall risk, particularly in a system of this geographic scale. The next section will capture the impact of this important factor.

4.3 Transmission-Constrained Analysis

Transmission is a key driver of resource adequacy in a system as large as the Western Interconnection. Running the resource adequacy assessment with transmission limits enforced among the 36 BAs in the RPM Western Interconnection model shows that transmission constraints have a significant impact on the risk of unserved energy in the system, even when assuming 100% transmission availability. As shown in Figure 6, imposing interregional transmission limits increases both LOLE and EUE estimates by many orders of magnitude (as simulated by 40,000 Monte Carlo simulations), indicating that while there may be a significant surplus of capacity in the prescribed buildouts, geographic distance and interconnection limits constrain the ability of that capacity to serve load across the system.

Not only are LOLE and EUE significantly larger in the transmission-constrained case, they also increase over time. This is more consistent with what would be expected from tightening planning reserve margins (Figure 7), although the observed concurrent increase in capacity-only resource adequacy (Figures 4 and 5) may suggest that this decrease in transmission-aware resource adequacy is driven by load growth outpacing transmission expansion in RPM's investment decisions.

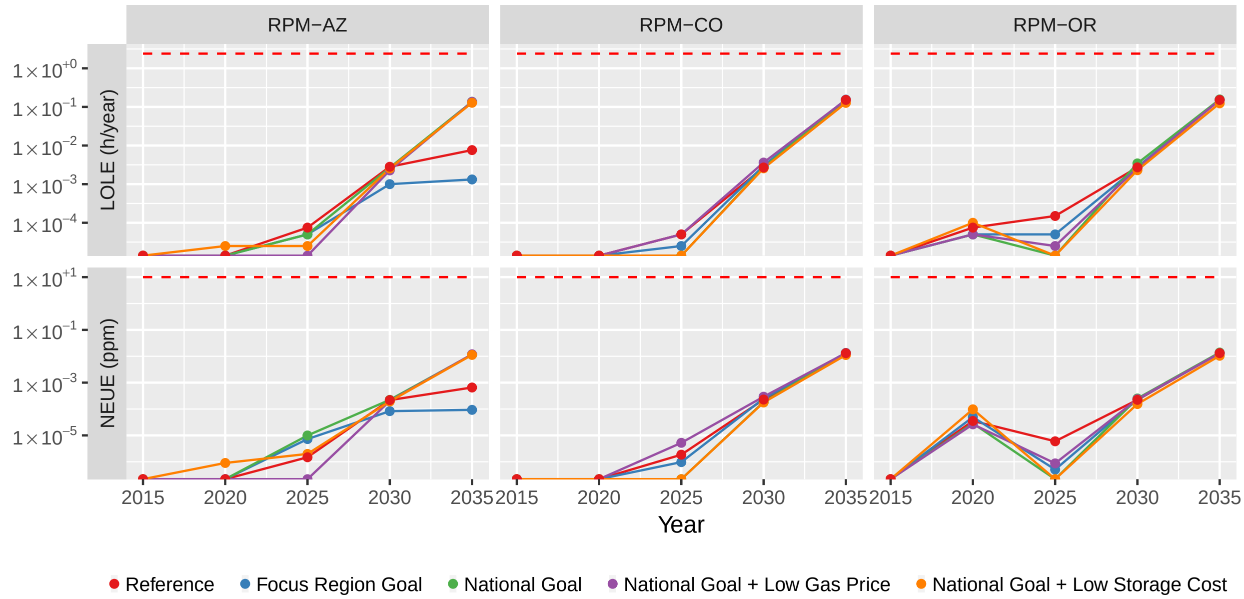

Figure 6. WI resource adequacy (log scale) with transmission considered. The red line indicates a general threshold above which a system could be considered resource-inadequate (2.4 h/year LOLE, 10 ppm NEUE).

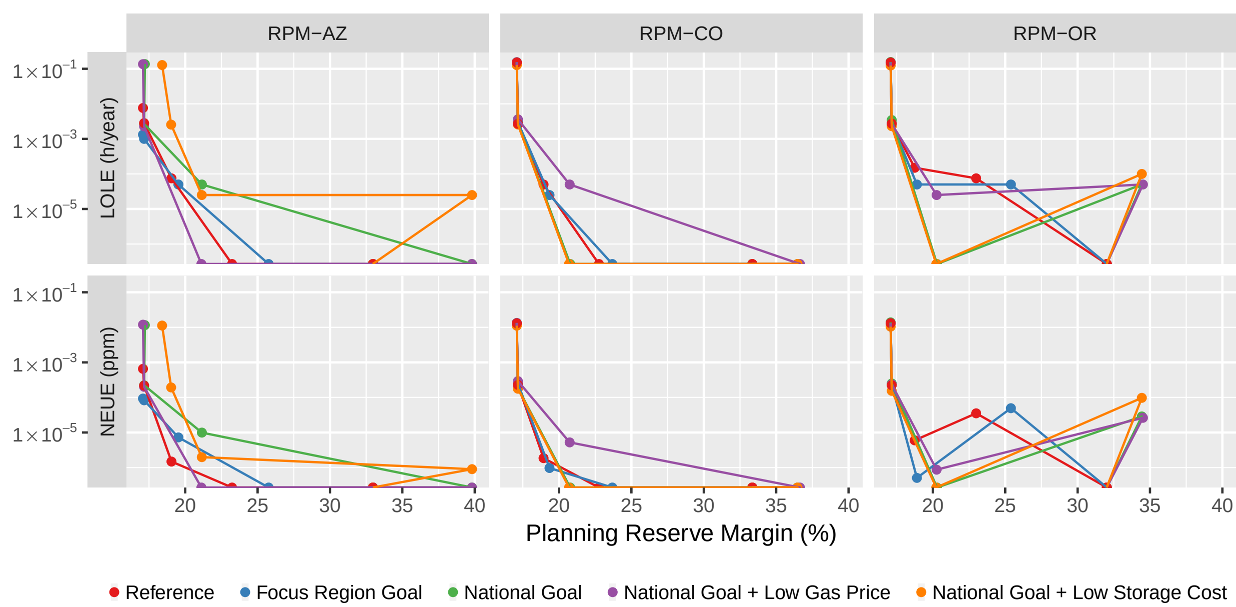

Figure 7. Transmission-constrained probabilistic resource adequacy metrics versus planning reserve margin

It should be stressed that while the addition of transmission considerations significantly decreases resource adequacy both overall and over time, system-level reliability remains well above levels that are consistent with the common “1 day in 10 years” rule of thumb (commonly approximated as an LOLE of 2.4 hours per year). With system LOLE peaking across scenarios at around 0.1 hours per year, the modeled system is arguably still overbuilt.

The resource surplus on the system in earlier years of the solution reflects the already-overbuilt nature of the Western Interconnection: RPM’s planning reserve margin constraints, based on current prescribed values in NERC regions, tend not to be binding in the earlier years of the simulation. As units retire, RPM chooses new investments that just meet the PRM requirements (approximately 17% systemwide), but the fact that the system remains overbuilt even with PRM constraints binding suggests the possibility that the PRM values themselves could be decreased to achieve capital cost savings. If this trend were to persist under further study using a larger sample of wind, solar, and load data (for the reasons discussed in Section 4.1), one option would be to apply an iterative feedback process between RPM and PRAS to determine the PRM levels that result in desirable LOLE and EUE values, as discussed in Frew et al. (2019).

An alternative explanation for the overbuilt nature of the systems is that RPM’s capacity valuation method for variable resources systematically undervalues the capacity contribution of variable generation toward the PRM. This is unlikely given that system reliability in a given year remains very similar across scenarios with differing variable-generation penetration levels. Differences in adequacy contributions of variable generation as assessed by PRAS and RPM are explored further in Section 5.

4.4 Regional Expected Unserved Energy Occurrences

The system-level resource adequacy assessment provides a broad view of the reliability of the system as a whole, but overlooks potential regional variation resulting from transmission constraints. A successful set of investment decisions should not only result in a desirable level of system-level resource adequacy, but also ensure that EUE is distributed appropriately across regions.

Figure 8 quantifies the fraction of BAs (out of 36 total) with nonzero EUE in 2035 across all model versions and scenarios, as observed after 40,000 sample Monte Carlo simulations. It indicates that, with no load scaling applied, EUE is always concentrated in a small-but-nonzero number of BAs. This may suggest that, in addition to RPM systems being somewhat overbuilt (“too reliable”), most regions are actually significantly overbuilt to the point that no shortfall events are observed in those regions over the 40,000 simulated operation years, while a small number of regions are less reliable than the systemwide NEUE average would suggest.

One option for addressing this in RPM’s existing PRM-based adequacy paradigm would be to define PRMs for each BA, rather than for the larger NERC regions (which may overlook internal transmission constraints). Of course, this increased consideration of transmission constraints would likely exacerbate the system overbuilding issue, and so ideally would be paired with a reduction in PRM targets as discussed in the previous section.

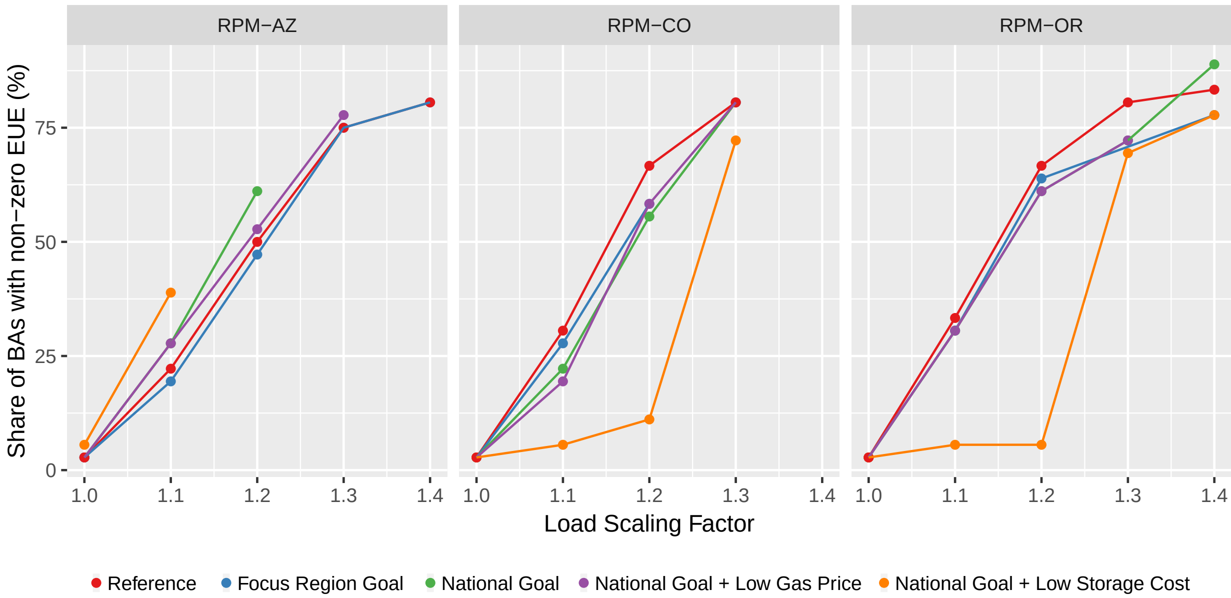

Figure 8. Percent of BAs with expected dropped load as a function of load scaling

The dominance of zero-EUE BAs also presents a challenge for the capacity valuation analysis in Section 5, as probabilistically derived capacity value measures depend on observing differences in nonzero EUE values. With unserved energy concentrated in load pockets, adding resources systemwide can have a disproportionately small impact on reducing load dropping events, regardless of the nature of the resource added. Since neither firm nor intermittent generation has an impact, the expression of the resource's contribution in terms of a firm capacity value is meaningless. Distributional issues aside, highly reliable systems also require large numbers of Monte Carlo samples to quantify resource adequacy metrics with sufficient precision to resolve differences resulting from the addition or removal of specific resources.

A relatively simple approach to address these issues is to scale up load, artificially introducing load dropping in a larger number of BAs. Figure 8 indicates how the number of nonzero EUE BAs increases with increasing load for the 2035 model year.

While most scenarios start showing nonzero expected unserved energy in a larger number of BAs after a 10%-20% increase in load, the Low Storage Cost scenario when run with RPM-CO and RPM-OR focus regions continues to serve load in almost all BAs until 30% load scaling is applied. This may be attributable to the treatment of storage as a firm capacity resource in this analysis, which generally overstates the contribution of storage assets to resource adequacy.

5 Variable Generation Contributions to Resource Adequacy

A key research objective of this work is to understand RPM's ability to approximate the contribution of variable-generation resources to capacity adequacy in a reserve-margin-based planning framework under scenarios with high penetrations of utility-scale and distributed solar PV. RPM's internal decision process uses an incremental net load duration curve (INLDC) method to accomplish this. Ideally, the results of this approximation method would closely match the results obtained through a more rigorous probabilistic approach, such as equivalent firm capacity (EFC). Section 3.2 provides details on each of these approaches.

To understand the relationship between these approaches under high PV penetrations, the interconnection-wide average capacity values of wind, DPV, and utility-scale PV (UPV) were calculated via both the EFC and INLDC methods for each RPM scenario and focus region case in the 2035 solve year. RPM's internal capacity valuation uses the top 100 net load hours, although other numbers of hours could be used if that were expected to better match a probabilistic approach. To that end, the 100-hour variant of the INLDC method was compared with the use of 10, 50, and 200 hours, for a total of five different capacity value results per buildout case.

Load in each region was scaled up to avoid the shortfall sparsity issues discussed in Section 4.4. A scaling factor of 30% was selected to ensure that the majority of regions were experiencing non-zero EUE across all scenarios and system models, based on the results depicted in Figure 8. Figure 9 presents the firm capacity valuation results for wind, DPV, and UPV as a function of total systemwide solar penetration under the different scenarios.

5.1 Distributed and Utility-scale Solar PV

As expected, the systemwide capacity value of the PV resources generally decreases as solar penetration in the scenarios increases (as net load peaks are shifted out of daylight hours), although complexities in the relationship between resource mixes and transmission investments across the scenarios can still result in deviations from this general trend.

Among the INLDC methods, the top 50-, 100-, and 200-hour results are generally very close to each other, whereas the top 10-hour results are somewhat distinct and provide more conservative valuations. At lower solar penetrations, the top 10 hours tend to undervalue capacity relative to EFC while the 50/100/200 results are close, but at higher penetrations this relationship is somewhat reversed. In the RPM-AZ focus region cases and most of the RPM-CO focus region cases, INLDC with top 100 load hours mirrors EFC very well, but in RPM-OR the INLDC results tend to undervalue the capacity value of DPV relative to the EFC results.

Overall, utility-scale PV reports larger systemwide average capacity values than distributed PV. While a part of this result is no doubt caused by a more strategic selection of high-resource-quality utility-scale sites, the difference in resource class capacity values can be explained primarily as a modeling artifact driven by differences in the total installed capacity levels. As there is significantly more UPV than DPV on the system across buildout scenarios (see Section 2), the UPV capacity value is measured in the context of a much smaller preexisting solar penetration

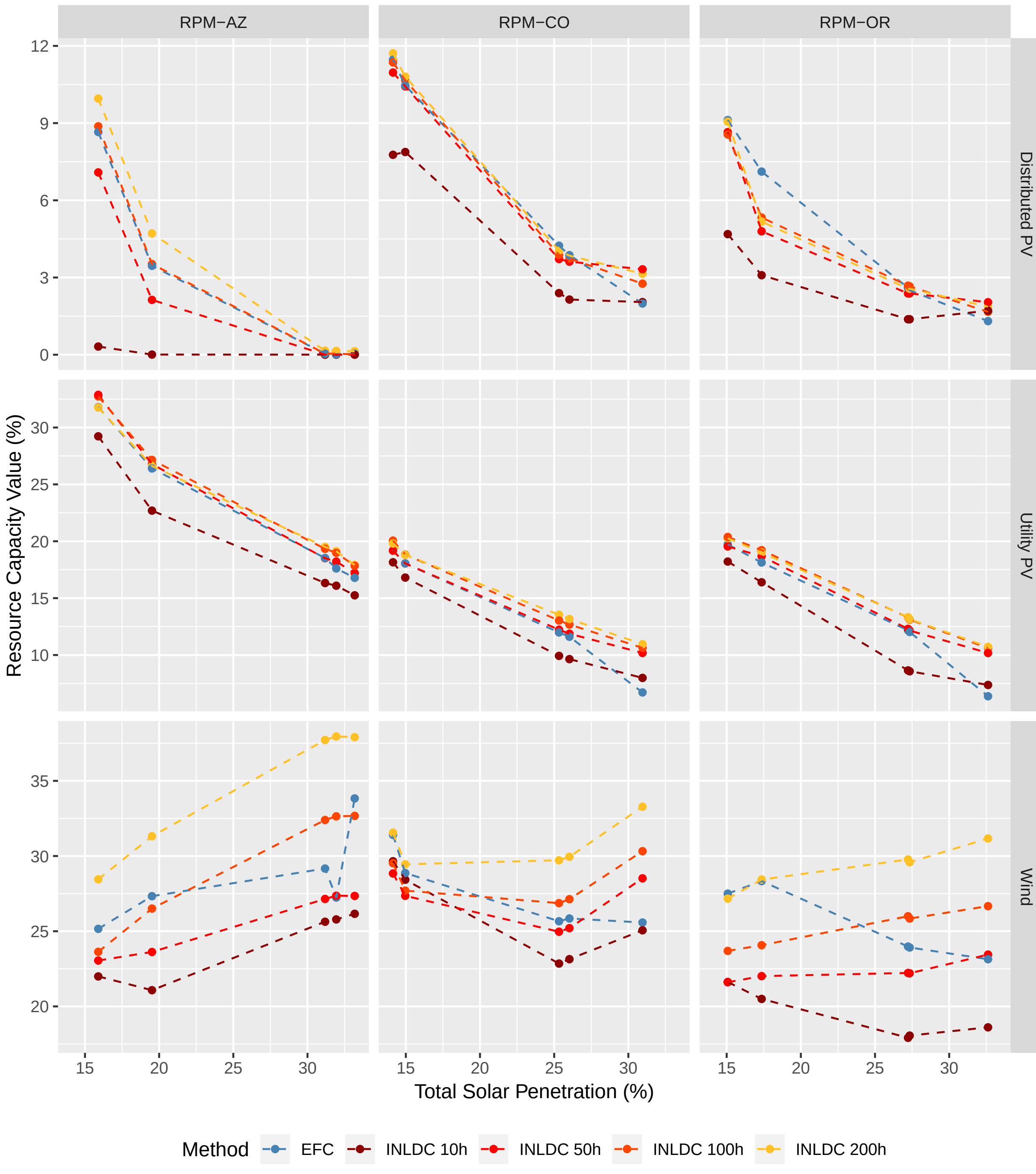

Figure 9. Capacity value results for the Western Interconnection as a function of scenario solar penetration, grouped by focus region case and resource type, after 30% load increase

than the DPV case. When valuing DPV, the larger UPV generation has already shifted peak net load hours away from peak solar production hours, reducing the apparent benefit of the DPV resource because the UPV was "counted first" in the DPV capacity valuation.

5.2 Wind

As is to be expected from a fundamentally different resource type, the systemwide average capacity value of wind shows very different trends with respect to both valuation methods and overall solar penetrations. There is significantly more variation in wind capacity value estimates both across INLDC methods and between INLDC and EFC results. While for any given scenario and focus region model there is usually an INLDC method that provides a similar capacity value to the EFC, no single choice of INLDC method tracks EFC consistently.

INLDC results generally show an increasing relationship between solar penetrations and the systemwide capacity value of wind (somewhat intuitive, as solar generation will tend to shift peak net load into the night and winter, which are generally periods of higher wind generation). Although the EFC values for the RPM-AZ focus case match this trend, the EFC of wind actually decreases in the higher-PV RPM-CO and RPM-OR cases. This may be the result of considering transmission constraints that are neglected in the INLDC method, although further study would be required to understand this phenomenon more thoroughly.

5.3 Method Comparison

Overall, there is no clear "best" option for choice of top net load hours to approximate EFC with an INLDC method. For estimating the capacity value of solar PV, RPM's current choice of 100 hours seems reasonable, particularly at lower penetrations, while at higher penetrations 10 hours might become more preferable. For wind, the situation is less clear. While RPM's choice of 100 hours is arguably the best option across the RPM-AZ focus region cases, this relationship does not seem to hold in cases with different focus regions.

At the highest solar penetrations, RPM's top 100 net-load-hour INLDC method seems to overestimate capacity value relative to EFC. However, RPM's systems remain sufficiently (if not overly) reliable in spite of this overestimation (see Figure 6), supporting the notion that the model's reserve margins may be able to be decreased somewhat, particularly if capacity value estimates could be improved or made more conservative at higher variable-generation penetrations.

6 Conclusion

This work assessed the ability of the Regional Planning Model (RPM) to generate least-cost capacity expansion plans under high penetrations of distributed and utility photovoltaics while maintaining acceptable levels of resource adequacy. Five future scenarios (varying policy and technology cost assumptions) across three Western Interconnection network representations (emphasizing nodal detail in different regions) were considered, resulting in system buildouts with systemwide PV penetrations ranging from 15% to 33%.

Across these scenarios, RPM's reserve margin-based planning approach tends to consistently deliver systems that are highly resource-adequate in terms of normalized expected unserved energy (NEUE) and loss-of-load expectation (LOLE), to the point of being overbuilt. This finding is subject to key caveats, however. Energy-limited resources (predominantly pumped hydro and battery storage) were modeled as firm capacity: while likely reasonable for longer-duration resources, this is an optimistic assumption for certain assets and could overstate the system's resource adequacy. Transmission was also modeled as fully firm, only captured as links between BAs, and even for inter-BA transmission did not describe individual real-world lines. Furthermore, the analysis only considered a single year of wind, solar, and load conditions, potentially overlooking less-frequent weather-driven resource adequacy events for which effective mitigation would require higher planning reserve margins. Future work could address these shortcomings to deliver a more authoritative result.

The analysis also assessed RPM's internal representation of the capacity contribution of variable resources, comparing the top-100 hours of various load duration curves to more rigorous probabilistically derived metrics, as well as to identically formulated load duration curve methods that simply vary the number of top hours that are compared. RPM's top-100 net load hour capacity value approximation was not seen to systematically over- or undervalue the contributions of resource adequacy across all penetration levels, relative to the probabilistically derived equivalent firm capacity metric. Other numbers of top net load hours (10, 50, and 200) were considered as well, and although no single alternate choice consistently outperformed the existing 100-hour method in tracking the calculated EFC, the 10-hour option was frequently more accurate when valuing distributed or utility PV in the highest-penetration PV scenarios.

Overall, while there remains room for improvement, RPM's reserve margin-based resource adequacy constraints and capacity value estimations appear sufficient to ensure the system's ability to serve peak net load under solar PV penetrations of up to 33% across the Western Interconnection. The reserve constraints may be conservative, resulting in higher-than-necessary investment levels, although this result should be tested further with more accurate representations of energy limited resources and transmission under a wider range of system operating conditions (multiple years of sub-hourly wind and solar resource data).

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