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Representation of Solar Capacity Value in the ReEDS Capacity Expansion Model

B. Sigrin, P. Sullivan, E. Ibanez, and R. Margolis

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Technical Report
NREL/TP-6A20-61182
March 2014

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Prepared under Task No. SS13.1020

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List of Acronyms

APS	Arizona Public Service
BA	balancing area
CSP	concentrating solar power
DOE	U.S. Department of Energy
DUPV	distributed utility-scale photovoltaics
EFOR	effective forced outage rate
ELCC	effective load-carrying capacity
ISO	Independent System Operator
IVGTF	Integration of Variable Generation Task Force
LOLE	loss of load expectation
LOLP	loss of load probability
NERC	North American Electric Reliability Corporation
NREL	National Renewable Energy Laboratory
PSCo	Public Service of Colorado
PV	photovoltaic(s)
ReEDS	Regional Energy Deployment System
REPRA	Renewable Energy Probabilistic Resource Adequacy
SAM	System Advisor Model
TEPPC	Transmission Expansion Planning Policy Committee
TriState	TriState Generation and Transmission
UPV	utility-scale photovoltaics
VRRE	variable resource renewable energy
WECC	Western Electricity Coordinating Council
WWSIS-2	Western Wind and Solar Integration Study Phase 2

Executive Summary

An important emerging issue for electricity system operators is the estimation of renewables' contributions to reliably meeting system demand, or their capacity value. While the capacity value of thermal generation can be estimated easily, assessment of wind and solar requires a more nuanced approach due to resource variability. Reliability-based methods, particularly assessment of the effective load-carrying capacity (ELCC), are considered to be the most robust and widely accepted techniques for addressing this resource variability.

This report validates treatment of solar photovoltaic (PV) capacity value by the Regional Energy Deployment System (ReEDS) capacity expansion model by comparing model results against two sources. The first comparison is against values published by utilities or other entities for known electrical systems at existing solar penetration levels. The second comparison is against a time-series ELCC simulation tool for high renewable penetration scenarios in the Western Interconnection. Results from the ReEDS model are found to compare well with both comparisons--despite not being resolved at an hourly scale.

Two results are relevant for other capacity-based models that do not use hourly calculations to model solar capacity value. First, solar capacity value should not be parameterized as a static value but must decay with increasing penetration. This is because, for an afternoon-peaking system, as solar penetration increases the system's peak net load shifts to later in the day-- when solar output is lower. Second, long-term planning models should determine how system adequacy requirements differ between time periods in order to approximate loss of load probability (LOLP) calculations. Within the ReEDS model we resolve these issues by using a capacity value estimate that varies by time-slice. Within each time-slice the net load and shadow price on ReEDS's planning reserve constraint signals the relative importance of additional firm capacity.

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1 Introduction

An important emerging issue for electricity system operators is the estimation of renewables' contribution to system adequacy. As supply of electricity must constantly be balanced with demand, system operators typically procure a 10%–20% capacity reserve margin to meet unplanned outages of existing capacity and unexpected increases in demand (NERC 2013). A generator's ability to help reliably serve load is measured by its capacity value or effective load carrying capacity (ELCC)—the firm capacity that a generating unit is able to provide during reliability-critical periods. The possibility of outages, whether planned or otherwise, therefore necessitates an accurate and dependable method of assessing each unit's firm capacity contribution to planning reserves to avoid loss of load.

The provision of variable resource renewable energy (VRRE) sources such as wind and solar presents a challenge in the assessment of their contributions to planning reserves. Whereas the effective capacity value for a conventional thermal generator is well approximated by the product of its nameplate capacity and expected forced outage rate (EFOR), variability in solar irradiance and wind speeds require a more nuanced approach. Previous studies have estimated the capacity value of photovoltaic (PV) solar (Duignan et al. 2012; Madaeni et al. 2013; Perez et al. 2006), concentrating solar power (CSP) (Madaeni et al. 2012a), and wind (NERC 2013; Keane et al. 2011; Ensslin 2008), finding a wide range of potential capacity values that depend on technology, resource quality, and correlation of generation and demand, among many factors.

Numerous techniques can be used to estimate the capacity value of renewable and conventional generators, though reliability-based methods are considered to be the most robust and widely accepted methods (Madaeni et al. 2013). Reliability-based techniques assess how the addition of a generator affects the overall reliability of the system, specifically, the likelihood of adequately serving load within a planning year. Within this framework, the capacity value of a VRRE source is defined as the maximum additional load that the electrical system could serve while maintaining the same level of reliability or loss of load expectation (LOLE). The amount of additional load that can be served with the addition of the variable generator is its ELCC and is equivalent to its capacity value. A drawback of this method, however, is that it requires extensive data, including time series spanning several years of load and conventional and renewable generation, as well as an inventory of units within a planning area and their respective maintenance schedules and forced outage rates.

ELCC-based methods have emerged as an industry-preferred means for assessing the capacity value of generating sources (Milligan and Porter 2008a; NERC 2011; Perez et al. 2008), and a common practice is to maintain an LOLE of 1 day in 10 years or less. Further discussion of the theory and practice of assessing the capacity value of solar have been performed by Duignan et al. (2012), Mills and Wiser (2012), and Madaeni et al. (2013), among others.

In contrast to reliability-based methods, approximation methods exist that require more modest amounts of system data or that can be performed on generalized systems. Availability of data can particularly be a concern for capacity expansion or capacity planning exercises, which typically are not resolved at the unit or hourly level, but nevertheless require an estimation of VRRE capacity value. One credible method, employed by the Regional Energy Deployment System (ReEDS) model in this report, is the Z-method (Dragoon and Dvortsov 2006), which approximates LOLE through the distribution of a system's surplus capacity. We supplement the Z-method with a time-period-based method that weighs the relative risk of loss of load within each time period.

Utilities and other load-serving entities have historically used a variety of methods to evaluate firm solar capacity. These range from detailed LOLP-based reliability evaluations, to time period-based estimates of solar capacity factors during top-load periods, and even rules of thumb based on engineering judgment (Mills and Wiser 2012). Many utilities do not publically disclose their valuation methodology. There is also uncertainty in characterizing changes in solar capacity value as a function of energy penetration, as there are very few electricity systems with high levels of solar energy penetration to act as case studies. Whatever their method, the assignment of capacity credits to VRRE sources is a part of recognizing and evaluating their economic value (Borenstein 2008)—and therefore becomes increasingly important for justifying their expanded use.

1.1 Report Outline

The purpose of this report is two-fold: first, to compare solar capacity values modeled by the ReEDS model to other values published in literature, both at low and high levels of penetration. Second, to understand how such factors as resource quality, energy penetration, and coincidence of generation and load profile determine the modeled capacity value of utility-scale solar. Because contributions to system adequacy increase the value of PV capacity to system operators and power producers, a predictive understanding of how capacity value evolves is an important prerequisite to understanding PV value.

The remainder of the report is as follows: Section 2 discusses the sensitivity of solar capacity value to modeling factors and the implications for other modeling efforts. Section 3 outlines the modeling assumptions and operations of the ReEDS model, and Section 4 compares capacity value outputs from the ReEDS model to those published by utilities using an ELCC methodology. Section 5 compares capacity value outputs from the ReEDS model to those of the Renewable Energy Probabilistic Resource Adequacy (REPRA) tool for simulated high levels of solar penetration in the Western Interconnection.

2 Factors Influencing Modeled Capacity Value

In this report utility-scale PV capacity value results from the ReEDS model are compared to other similar modeling efforts. In doing so, the comparison motivates a broader exploration of the nature of capacity value and its calculation, particularly within capacity expansion models. This section discusses factors that influence the capacity value calculations—and how these are implemented in ReEDS.

2.1 Sensitivity of Capacity Value to Resource Quality

While system operators maintain additional firm capacity beyond expected peak load to hedge against unexpected demand or system contingencies, in reality, there are only a few hours of the year when system adequacy is a truly pressing concern. The capacity value of a generator is assessed based on its ability to serve load during these times, when the LOLP is greatest. Most electrical systems in the United States are summer-peaking, due to cooling loads. As a result, these 'reliability-critical' periods typically occur during summer afternoons, though there are also electrical systems that experience peak demand in the winter, when electrical demand is driven by heating loads.

Physical location of a solar unit affects the capacity value of a PV unit at a very basic level. Namely, there is geographic variation in the annual quantity of solar irradiance as well as the diurnal and annual variability in irradiance. Within the ReEDS model, national solar resource is represented at the 134 areas that also serve as load balancing areas (BA). These balancing areas do not necessarily reflect the actual territories of real-world BAs, or specific reliability rules for individual balancing areas. Nevertheless, this level of geographic detail enables the model to account for geospatial differences in resource quality (Figure 1)—particularly statistical availability during reliability-critical periods.

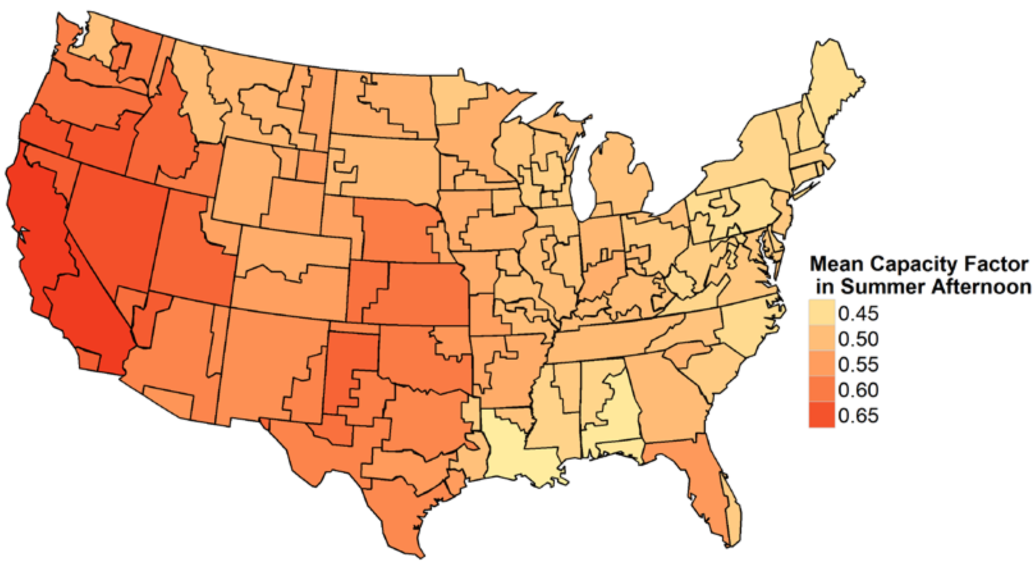


Figure 1: Mean PV solar capacity factor during summer afternoons (2 – 5pm)

2.1.1 Correlation of Load and Solar Generation

As a subtler point, geography influences the cooling and heating loads within a balancing area (BA), which thereby influences the timing of high LOLP hours. The key issue is to understand the degree of correlation between a solar unit's availability and periods of high LOLP. In general, the correlation of load and solar generation varies enough between BA to warrant detailed investigation.

2.2 Solar Energy Penetration

Solar PV capacity value is also known to be highly sensitive to increasing levels of PV deployment within the planning region (Perez *et al.* 2006; Lew et al 2010; Mills & Wiser 2012; Madaeni *et al.* 2012b; Olson & Jones 2012). PV capacity value is mainly driven by its generation level during the most critical hours of the year, when load is most likely to be dropped due to outages or available capacity. Typically, these periods of time are found during the early evenings of a few weeks of the year, especially for summer-peaking systems. When deployment of PV is at low levels of energy penetration, the additional PV generation does not significantly affect timing of reliability-critical hours. However, since the profile of solar generation is largely coincident with a summer-peaking utility's load profile, increasing levels of solar generation shifts the critical hours to later hours, when solar irradiance is lower as the sun is setting, decreasing PV capacity value. At high levels of penetration, when net load has been shifted 2 - 3 hours, the capacity factor reaches near-zero levels—as irradiance during the evening is negligible. The most critical hours are typically those with highest levels of net load, i.e., load minus variable generation.

To better illustrate the sensitivity of solar capacity value to energy penetration, the capacity factor is modeled for a representative solar unit in the ReEDS 'p28' BA, which overlaps with territory served by the Arizona Public Service utility in central Arizona. Demand in this BA is summer-peaking and the top load hours typically occur during late August afternoons. Solar capacity factors were calculated for units located in Flagstaff, Arizona, using NREL's System Advisor Model (SAM) [1] using the mean August diurnal generation profile.[2] The SAM model has a specific PV module and an hourly simulation engine. With the appropriate solar resource data, it is used to develop capacity factors by time-slice for each ReEDS region. For this illustration, wind contribution is assumed to be negligible.

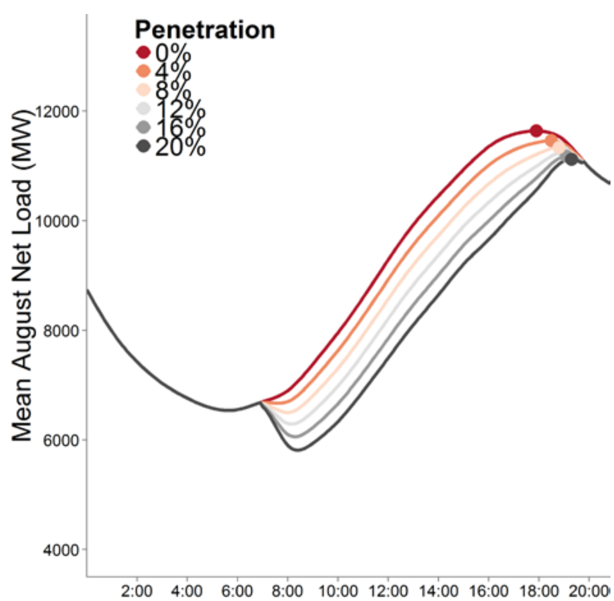


Figure 2: Representative diurnal net load curve for BA in Arizona for increasing energy fraction from PV. The dot marking the peak net load of each curve steadily shifts later into the evening as the PV fraction increases.

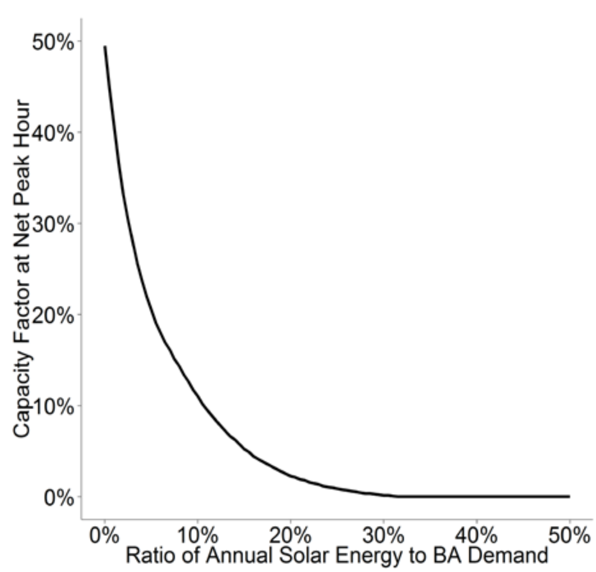


Figure 3: Representative solar capacity factor at net peak hour as a function of PV penetration for an Arizona BA in August.

[1] See https://sam.nrel.gov/ for more details
[2] Note that this result is intended only to illustrate the functional form of the relationship between capacity value and penetration and the exact quantities calculated should not be interpreted literally.

As levels of annual solar energy penetration increase from 0% to 20%, the peak load in the diurnal load profile is reduced and shifted to later in the day (Figures 2 and 3). The capacity factor at the point of peak net load erodes following an exponential form and, as predicted, becomes negligible at high levels of annual energy penetration.

3 ReEDS Background

The ReEDS model is a generation and transmission capacity expansion model of the electricity system of the contiguous United States. Developed by the National Renewable Energy Laboratory (NREL), it has been used for a number of projects exploring possible evolution of the U.S. electricity system and evaluating the potential for and impact of growth in renewable energy technologies, including the recent SunShot Vision (EERE 2012) and Renewable Electricity Futures studies (NREL 2012). ReEDS is a linear program that chooses investment and operation decisions to serve load and meet system requirements at the least overall system cost. Operating sequentially along 2-year periods, ReEDS develops scenarios of electric sector evolution from 2010 to 2050. Modeling assumptions and parameters key to this investigation are briefly described; a more thorough documentation of the ReEDS model, however, has been conducted by Short et al. (2011).

3.1 Model Structure

ReEDS uses a number of assumptions to forecast capacity expansion from 2010 to 2050. The following technology and cost assumptions were used in this analysis:

- **Load:** Ventyx Velocity Suite (2010) regional hourly load profiles, scaled annually by expected regional load growth (EIA 2013)
- **Technology Costs:** Annual Energy Outlook (EIA 2013) projections in 5-year increments
- **Existing Fleet and Retirements:** A combination of Ventyx (2010) existing fleet data and planned and announced retirements; retirements of coal units are supplemented by data from M.J. Bradley & Associates (Saha 2013)
- **Policy:** All publically announced federal and state renewable incentives, including federal investment tax credits, production tax credits, and state Renewable Portfolio Standards and solar carve outs.

The ReEDS model is especially focused on representing renewable energy technologies in capacity expansion decisions. To best represent such decisions, parameters that drive variation in the siting and integration costs of solar and wind generating technologies are emphasized. In particular, the model uses a high level of spatial resolution—where wind and CSP resources are defined at 356 resource regions and solar PV at the 134 regions that also serve as load BAs. Each resource is regionally characterized by a set of supply curves—constructed from NREL resource assessments (Lopez et al. 2012)—that distinguish resource quality and the cost of accessing the local transmission network. This level of geographic detail enables the model to account for geospatial differences in resource quality, transmission needs, electrical (grid-related) boundaries, political and jurisdictional boundaries, and demographic distributions. The 134 load regions are connected by an aggregated transmission network that gives ReEDS the ability to discern the relative value of development sites across regions.

ReEDS dispatches generation for 17 time-slices (4 time-slices for each season representing morning, afternoon, evening, and nighttime, with an additional summer-peak time-slice) (Appendix A). The temporal detail enables ReEDS to consider both seasonal and diurnal changes in demand and resource availability—but limits its ability to account for hour-on-hour variations. To account for demand and resource variability within each time-slice, ReEDS uses statistical calculations to estimate BA reliability needs and contributions from VRRE sources. In addition to the capacity value metric that is the focus of this paper, ReEDS also estimates induced operating reserve requirements and curtailment of excess production from VRRE sources.

For new investments, ReEDS can choose from a broad portfolio of conventional generation, renewable generation, storage, and demand-side technologies. Plants provide power to meet load, capacity toward adequacy requirements, and operating (spinning or non-spinning) reserves. Conventional generators contribute their nameplate capacity toward adequacy requirements and supply operating reserves while variable renewables contribute their calculated capacity value and require additional operating reserves.

Three solar PV system types are modeled—utility-scale (UPV), distributed utility-scale (DUPV), and distributed rooftop. UPV and DUPV are interconnected to the grid at the transmission level and are assumed to be utility controlled, whereas distributed rooftop is connected at the distribution network level, behind the meter. Rooftop PV projections are developed outside of ReEDS, in NREL's SolarDS model (Denholm et al. 2009) because decisions on rooftop installations are assumed to be made on a different basis (i.e., by individuals) than centralized utility or power-producer decisions. The differences in ReEDS between UPV and DUPV are primarily about size and siting freedom: DUPV systems are smaller and are assumed to be close to load, while UPV systems are wide-ranging. This report exclusively applies to UPV and does not analyze capacity value for DUPV and rooftop PV systems.

UPV represents single-axis tracking PV systems with a unit size of 100 MW. Performance characteristics for central PV were developed by the SAM PV module (NREL 2010a) using annual hourly weather files from the National Solar Radiation Database (NSRDB 2010) for 939 sites throughout the contiguous United States from 1998 to 2005. The site with the highest average annual PV capacity factor in each BA was used to represent the performance (i.e., capacity factor in each time-slice) of central PV capacity installed in that BA. For each site, generation profiles were averaged across the 8-year time period. PV capacity factors represent the average AC capacity factor after taking into account the AC-DC conversion (using an 82% derating factor). All other power metrics (e.g., nameplate capacity and capacity value) are stated in terms of their derated AC power output.

The ReEDS transmission network is a 134-node system connected by roughly 300 transmission corridors representing the collection of real transmission lines that cross BA boundaries and are characterized by the carrying capacity of those lines. The transmission network is divided into three asynchronous interconnects (West, East, ERCOT) by a set of AC-DC-AC interties. Transmission flows across the system are determined by a linearized DC power flow approximation, a standard method for representing power flows in electricity system models, described and evaluated in Stott et al. (2009). The transmission network allows BAs to share power and ancillary services with each other, buffering each other's needs. It also permits long-distance transmission of remote renewable resources from high-resource areas to major loads.

ReEDS uses the net power flows within each time-slice to accurately account for sources of generation. Exporting regions are assumed to share generators' electricity proportionally across all outgoing lines. This proportional sharing assumption, introduced by Bialek (1996), links ownership between each source and load: which loads each generator has served and in what proportion. Generation is permitted to be exported and thus serve load outside the source BA. Variability parameters (e.g., capacity value and curtailments) are characterized based on the destinations of generated power, but accrue at the source. In the configuration of ReEDS used for this analysis, all generators share their output proportionally with power flows. There is no accounting for bilateral contracts in which a remote renewable resource would be dedicated to serving a particular load.

3.2 Capacity Value Calculations

ReEDS uses a measure of a VRRE generator's ELCC to determine its contributions to planning reserves in each of the 17 time periods. That is, adequacy/reliability is defined in terms of the likelihood that the system (BA, transmission zone, service territory) will have insufficient available generating capacity to meet load during a given period. We use the Z-method algorithm (Dragoon and Dvortsov 2006; Madaeni et al. 2013) to approximate a VRRE source's ELCC. This method assumes that, because of the large number of generating units in an electrical system, the distribution of hourly surplus capacity has a Gaussian form. The Z-statistic of the surplus capacity distribution, the ratio of the mean surplus to standard deviation, is a representation of the statistical likelihood of experiencing a loss of load. Keeping the Z-statistic constant between systems with PV and without approximates keeping a constant LOLP for each period—and an ELCC estimate can be derived from these assumptions. For each BA, ReEDS computes a bulk capacity value for all existing VRRE units, as well as an estimate for the marginal capacity value of potential VRRE investments in the next solve period.

The Z-method is used by ReEDS to estimate capacity value because it permits the approximation of capacity value without conducting an hourly time-series analysis, which is infeasible given ReEDS's temporal resolution. However, the Z-method assumption of a Gaussian form can be violated under high-renewable scenarios if the real time-slice probability distribution of VRRE output does not follow a Gaussian distribution.

3.2.1 Capacity Value Point Estimates

System planners typically determine the capacity value of a generator as a point value that represents the unit's ability to reliably serve load over the course of a planning year. This point value is the result, however, of analyzing hourly-level LOLPs. Hourly-level analysis is important because of differences in the availability of a solar unit. However, because the ReEDS model is resolved over 17 time-slices, these inter-hourly differences are difficult to model.

Figure 4, which shows the mean summer (June–August) diurnal capacity factor for a representative solar unit in Flagstaff, Arizona, illustrates the temporal discreteness in the ReEDS model. Overlaid in the figure are the average capacity factors for the Flagstaff solar unit discussed earlier during three select ReEDS time periods (summer morning, summer afternoon, and summer evening). Collectively, these three periods span the most critical load hours for the BA. As solar penetration increases, the peak net load period shifts from afternoon to evening, and the corresponding capacity factor in the residual peak time-slice—the most important factor in estimating capacity value—drops as a step function.

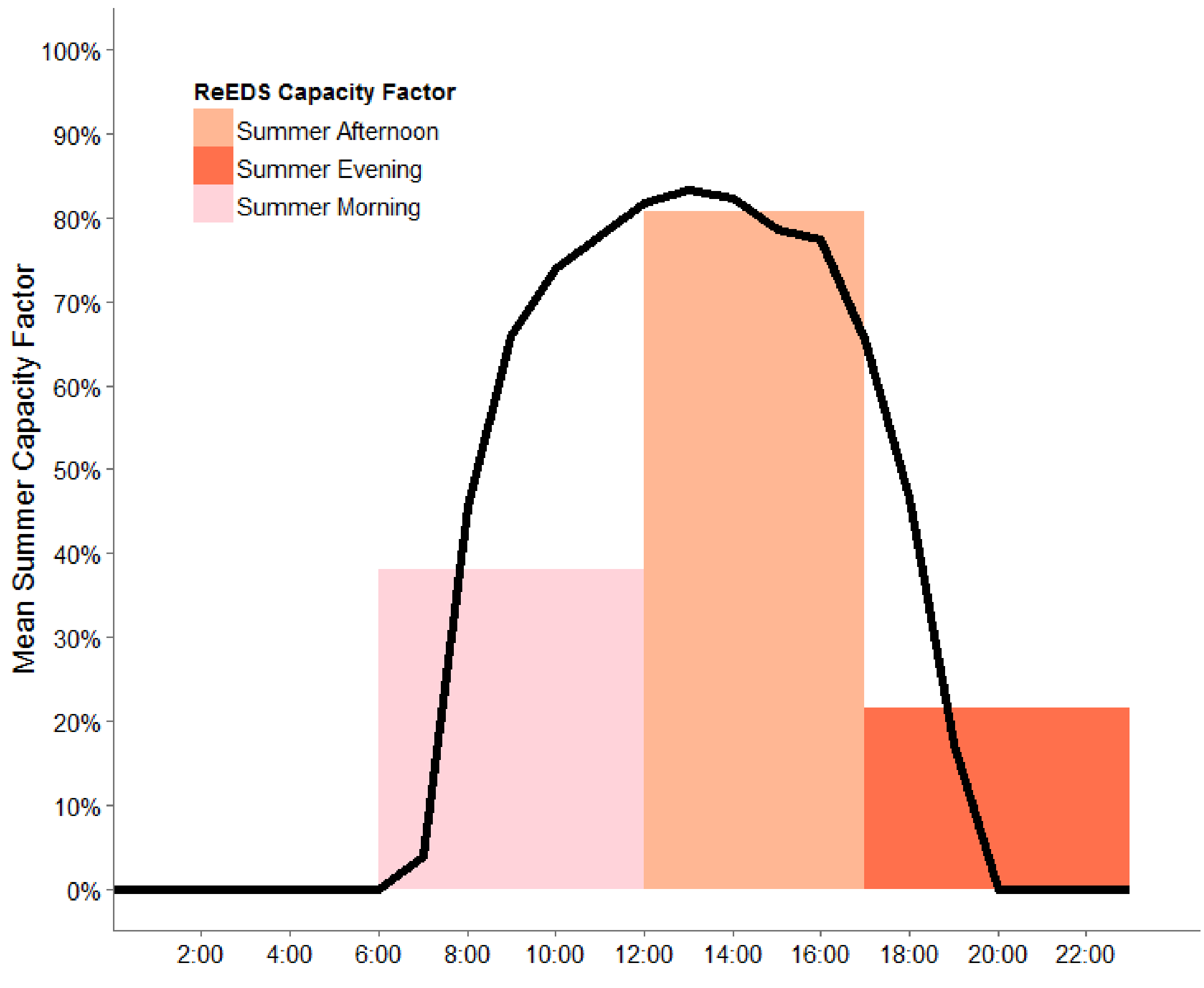


Figure 4. Discrete temporal representation of solar capacity factor in the ReEDS model

ReEDS mitigates the issue of steep time-slice gradients via two strategies. Internally, the ReEDS model does not employ a single point estimate of capacity value across time periods, but rather uses a capacity value for each time period that is based on the average capacity factor for hours spanning that time period. By varying the value of capacity available during each ReEDS time periods, this mimics the time-varying availability of actual solar units.

Second, a planning reserve constraint (1) inherently provides the optimization with information about the relative difficulty of serving load in each ReEDS time period as solar penetration increases. For each time-slice (m) and BA (n), available capacity must exceed the planning reserve target:

$$\sum_{n,m} CONV_{nm} + \sum_{n,m} VAR_{nm} \geq (1+r) \cdot \sum_{n,m} P_{nm} \tag{1}$$

Where $CONV_{nm}$ is the available conventional capacity (including forced outage rates) in period m and BA n, VAR_{nm} is the available variable capacity—that is, the product of nameplate capacity (MW) and capacity credit (fraction), r is the planning reserve margin (fraction), and P is the expected peak time-slice load. When variable capacity is low, the planning reserve constraint is most binding for the peak load hour—likely, the summer afternoon when solar capacity value is high. As solar capacity increases, however, the relative difficulty of meeting the planning reserve target shifts from summer afternoon, when there is already sufficient available solar capacity, to evening when capacity factors are lower. In other words, when making future capacity expansion decisions at high solar penetration, ReEDS recognizes the decreased value of solar capacity services and makes optimal investment decisions relative to other expansion options.

One more feature is needed to quantify the relative difficulty of meeting planning reserve targets, as well as scenarios in which the planning reserve constraint is binding in more than one period. When available capacity is scarce enough that the planning reserve constraint is binding, the marginal price (shadow price) on the constraint represents the additional cost the system would incur to increase reserve capacity by a single unit. That is, the marginal price on the planning reserve constraint signals the relative difficulty of serving load in each period and can be used to appropriately weight the capacity value in that period. As solar penetration increases, the ReEDS planning reserve constraint will be increasingly binding in evening periods.

3.2.2 Benefits of Power Diversification

Power flow assumptions in ReEDS affect capacity value calculations, where the diversification of power flow across multiple BAs tends to increase solar PV capacity value. By sourcing PV from multiple, diverse locations, a load region can narrow its PV production probability distribution and reduce the integration burden of those resources. This encourages investment in areas that will raise the level of diversification seen at each local load and thereby helps to slow the erosion of capacity value as penetration levels increase.

4 Comparison of Capacity Value at Low Penetration

Between planning areas, there exists considerable variation in the capacity credit assigned to a UPV unit based on its geographic location, the utility's load profile, existing level of PV deployment, and the method used to assess capacity value. In this section the ReEDS model's estimates of capacity value are compared to those published by utilities or other research teams at low levels of solar energy penetration—that is, for actual electrical systems with specified levels of PV deployment or with low (simulated) levels of PV penetration. Comparison is restricted to studies conducted using an ELCC-based methodology.

4.1 Estimates of Solar Capacity Credit in Planning Studies and Similar Literature

The particular method used by electricity system planners to estimate solar capacity value substantially affects the calculation of capacity value, and thus the value awarded. Use of an ELCC-based method is preferable because of the acknowledgment of inter-hour variability in the unit's generation, particularly during hours when the electrical system is expected to have a higher LOLP (Perez et al. 2008a). To benchmark the ReEDS model, we compiled a set of solar capacity value studies conducted for known systems based only on ELCC methods (Table 1).

Though an ELCC-based method has not been fully adopted by all utilities in their planning studies, three utilities, Arizona Public Service (APS), Public Service of Colorado (PSCo), and TriState Generation and Transmission (TriState), were identified to employ an ELCC/LOLP framework in their reliability and planning studies (APS 2013; PSCo 2013; TriState 2010). Other researchers not explicitly associated with a utility have also assessed solar capacity value for known non-test electrical systems (Lu et al 2012; Perez et al. 2008a; Perez et al. 2008b). These studies correspond, respectively, to the Nevada Energy, Nevada Power, Portland General Electric utilities, and territory served by the New York Independent System Operator (ISO). While many of the studies report a single point estimate of capacity values, others report a range of values. The range in reported capacity value could be due to assessing the capacity value for a variety of sites within the planning area as well as variation in their scenario parameters.

Table 1. Description of Comparison Studies and Results

Utility District Studied (Authors)	Summary of Methodology	Reported Capacity value
Arizona Public Service (APS 2013)	Performance data from installed system in service territory, load profiles from 2003 to 2007; single-axis tracking; deployment projections for 2015; ELCC simulations for existing capacity and next 100 MW built	45.9%–48.4%
Nevada Energy (Lu et al. 2012)	Nevada Energy southern system generation fleet in the 2007 study year; ELCC calculation using LOLE of 1 day in 10 years	57.4%
Nevada Power (Perez et al. 2008a)	Satellite-derived resource data to simulate output; simulated 2% PV deployment; 30° SW-facing fixed systems; ELCC calculation	71%
New York ISO (Perez et al. 2009b)	South-facing fixed slope; ELCC calculation for simulated 2% PV grid penetration using 2007 generation and load data	44.3–78.3%
Portland General Electric (Perez et al. 2008a)	Satellite-derived resource data to simulate output; simulated 1% PV deployment; 30° SW-facing fixed systems; ELCC calculation	31%
Public Service Colorado (Xcel 2013)	2009-2010 historic load and solar generation; single-axis tracking; ELCC calculation using LOLE of 1 day in 10 years	41%–47%
TriState (TriState 2010)	LOLP method, with expected capacity availability during peak load hour; unclear assumptions for generation and load data	20%–57%

4.2 ReEDS Scenario Parameters

ReEDS calculations of solar capacity value were compared to the studies in Table 1 in order to benchmark performance of the model. To facilitate an equitable comparison, scenarios were constructed to match each utility region's geographic location, existing generation fleet, and PV deployment levels as closely as possible. By default, ReEDS uses historic capacity expansion from 2010 to 2013 and business-as-usual assumptions for capacity expansion projections thereafter. Operation of the fleet is made in a least-cost optimization framework. For studies based on a specific forecasted level of PV penetration, the ReEDS model is required to exactly attain the specified level of PV deployment at the least-cost solution.

Because ReEDS balancing area service territories do not exactly match the service territory of each of the comparison studies, capacity value is geographically compared using the smallest set of ReEDS BAs that wholly encapsulates each study's service territory (Figure 5). If the study territory encapsulates several ReEDS BAs, the range of capacity values among BAs within the study territory are reported. See B-1 for a map of the BA regions.

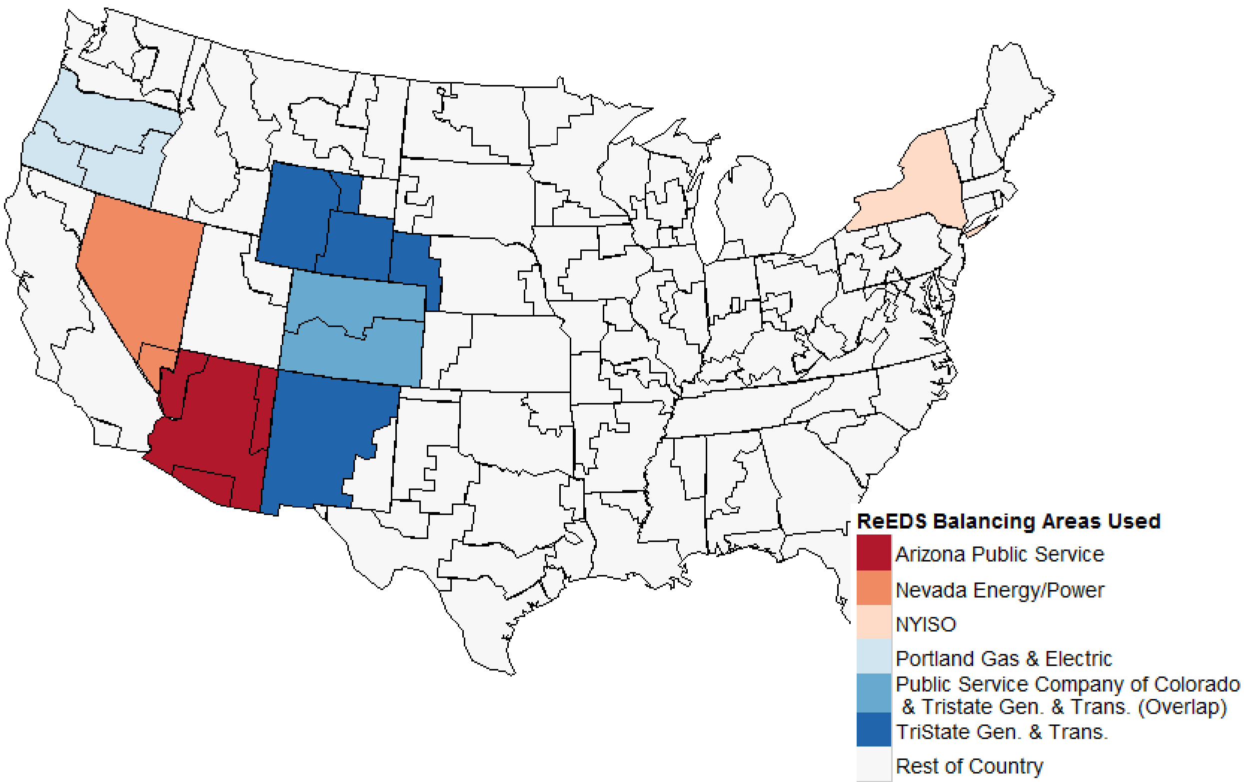


Figure 5. Map of ReEDS balancing areas spanning service territory of comparison studies

The ReEDS model does not report annual point estimates of capacity value but rather a capacity value for each of the model's 17 time periods (Appendix A)—and thus transitions between time periods are abrupt. Solar capacity value in each time period is primarily determined by the mean capacity factor for hours in that time period. In practice this means that while an hourly ELCC evaluation would be expected to see a smooth transition from afternoon to evening, ReEDS observes two distinct regimes—afternoon and evening—and an abrupt shift between them. While ReEDS reports capacity values in this stepwise manner, the information loss at the time-slice interface is mitigated by ReEDS' simultaneous consideration of adequacy in all time-slices. In particular, as the reliability-critical period shifts from afternoon to evening, ReEDS can be thought of as blending the two capacity values for the afternoon and evening time-slices. Because planning reserves are required to be met in all time periods with a time-varying capacity value, this simulates a utility's requirement of minimizing the LOLE over all service hours.

Figure 5 compares the capacity values reported by utilities to results from the ReEDS model. For each utility, we use capacity value for the set of ReEDS time periods spanning that utility's reliability-critical periods. Comparisons might include more than one BA if the utility has territory spanning more than one ReEDS BA. For the areas considered, these time periods are mostly the "summer afternoon" and "summer evening" periods, although there are some regions considered that are winter-peaking. This method assumes that LOLP is well-correlated with net system load. In particular, Madaeni et al. (2013) showed that weighing a solar generation unit's capacity factor by the LOLP for the 10 highest net load hours provided an accurate estimate of the ELCC. That is, due to strong correlation between load and generation, the capacity value is well-estimated by these few, most reliability-critical hours of the year.

For example, ReEDS models the APS utility with four BAs (p27–30). For 3 of the APS BAs, their 10 highest load hours occur in both the summer afternoon period as well as the summer evening; the fourth highest load hours solely occur during the summer evening time period (Figure 5). The APS study reports bulk capacity values of 45.9%–48.4% for 242–166 MW of (modeled) capacity in 2015. In contrast, results from ReEDS reports an average bulk capacity value of 54.9% in summer afternoon and 14.4% in summer evening for the same levels of penetration in 2015.

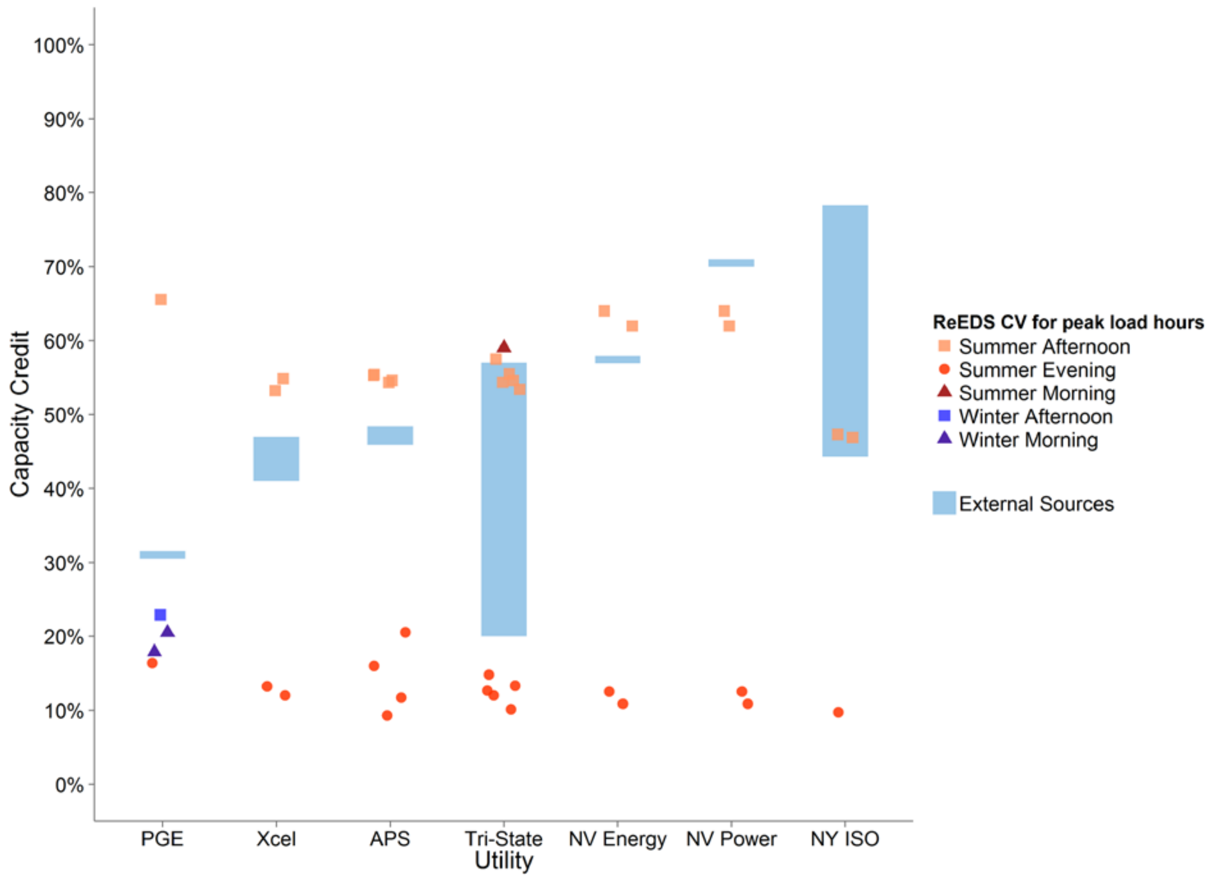


Figure 6. Comparison of solar capacity values in reliability-critical time periods to published values

Results from the comparison show that the ReEDS modeled capacity values for reliability-critical time periods mostly bound the reported capacity values. Two exceptions are for the Nevada Power and New York ISO studies, which report somewhat greater capacity values than those calculated by ReEDS. Notice among the ReEDS reporting that time-slices produce clusters of estimates and that summer afternoon capacity value clusters are substantially higher than summer evening clusters as predicted by the capacity factor analysis above. Interpreted in that light, the external sources are undergoing a transition from afternoon importance to evening importance, and, in fact—in particular Xcel, APS, and NV Energy, being close to the summer afternoon cluster—are early in that transition. For the majority of studies compared (Xcel, APS, Tri-State, NV Energy), capacity value in the summer afternoon period slightly over-predicts the reported capacity value. This bias is explained when considering the load hours represented by each time period. The APS grid, for example, has historically achieved its annual peak load between 4 pm and 5 pm on summer weekdays (R.W. Beck 2009). Capacity values for the APS system, then, should be intermediate to those of the summer afternoon and summer evening time periods but closer to the summer afternoon capacity value—the result observed. A similar logic applies to the remaining study regions.

5 Comparison of Capacity Value at High Penetration

Several researchers have conducted modeling efforts to quantify the operational value of solar and other VRRE generation at high (10%+) levels of penetration (Perez et al. 2006; Lew et al. 2010; Mills and Wiser 2012; Madaeni et al. 2012b; Olson and Jones 2012). These studies find that the capacity credit assigned to solar generation declines significantly at high level of energy penetration for the reasons outlined in Section 1.2. As penetration increases, the marginal economic value of PV drops considerably, primarily because of changes in capacity value, but also in energy value (Mills and Wiser 2012). Clearly, this decrease in value decreases the overall economics of future solar units (Olson and Jones 2012) and could suppress additional investment.

Unfortunately, there are very few actual electrical systems operating at high levels of solar penetration, and so there is scarce available literature on the capacity value of solar on real electrical systems. Therefore, the ReEDS model's treatment of solar capacity value at high levels of energy penetration is compared with results derived from Phase 2 of the Western Wind and Solar Integration Study (WWSIS-2) (Lew et al. 2013). The WWSIS-2 sought to simulate grid operation in the U.S. Western Interconnection for four hypothetical high-renewable deployment scenarios in 2020. Capacity values for the WWSIS-2 scenarios are calculated using NREL's Renewable Energy Probability Resource Adequacy tool (REPRA) (Ibanez and Milligan 2012), which estimates the capacity value of VRRE sources using a time series ELCC algorithm.

5.1 Data Sources

Representation of the generation fleet for the REPRA tool is based on Phase 2 of NREL's WWSIS (Lew et al. 2013). This data is consistent with studies performed by the Western Electricity Coordinating Council's (WECC's) TEPPC. The WWSIS-2 studied the performance of the power system in the Western Interconnection under high levels of wind and solar energy penetration. A reference scenario was created based on WECC's TEPPC (WECC 2009) with wind and solar (PV and CSP) penetration at 9.5% and 3.5%, respectively. Three high penetration scenarios were also defined: *high wind* (25% wind, 8% solar), *high solar* (25% solar, 8% wind), and *high mix* (16.5% of wind, 16.5% solar). The ReEDS model was used to inform capacity expansion for the WWSIS-2 scenarios, and the commercial production simulation tool PLEXOS is used to model unit commitment (Lew et al. 2013).

Load time series data from 2006 was chosen from the Ventyx Velocity Suite (Ventyx 2010) and was forecasted based on load growth projections to represent load in 2020. The wind dataset was derived from the large wind speed and power database developed by 3TIER using a numerical weather prediction (NWP) model applied to the West (3TIER 2010). Because the model allows for the simulation of the weather, at any time and space, wind speed data was sampled at representative hub heights for modern wind turbines every 10 minutes for a 3-year period on a 2-km spatial resolution. The resulting dataset was then used to construct the 2006 time series, which was paired with the 2006 load data time series to preserve the consistency of common weather impacts. Solar data was produced by NREL (Orwig et al. 2011) based on the satellite-derived irradiance generated by the State University of New York/Clean Power Research (Wilcox et al. 2007), which is available on a 10-km grid at an hourly resolution.

5.2 ReEDS Modeling Assumptions and Parameters

As in Section 3, to facilitate equitable comparison of the REPRA and ReEDS models, scenario parameters for the ReEDS model were chosen to parallel those of the WWSIS-2 scenarios. These include levels of solar PV and wind deployment and geographic region of comparison. Two differences remain:

- **Capacity Expansion:** The ReEDS scenario is prescribed to match the gross WECC-wide PV deployment levels for the four WWSIS-2 scenarios by 2020, and the ReEDS model was used to inform capacity expansion decisions for both analyses. However, because each analysis uses different model versions and assumptions, the geographic distribution of renewable and conventional capacity deployment within the ReEDS and WWSIS-2 analyses may differ. For similar reasons, generation is not harmonized between the models.

- **Balancing Area Regions:** Both the ReEDS model and REPRA tool use slightly different BA definitions for the Western Interconnection. Appendix B and Appendix C show boundaries for each model's BAs. For geographic equity, results from the two models are compared at a state level; when a BA overlies multiple states it is allocated to whichever state contains the majority of its area.

5.3 Comparison Results

As in Section 3.3 the ReEDS solar capacity value is reported as the range of capacity values during the BA's reliability-critical time-slices. Figure 7 shows the range of ReEDS capacity values for the ReEDS time periods that contain each BA's 10 highest net load hours. For the areas considered for comparison[3], these time periods are the summer afternoon, summer evening, and winter afternoon time-slices. For the majority of ReEDS BAs, summer afternoon and summer evening are the most reliability-critical time-slices. An exception is Montana, a winter-peaking system, and so adequacy concerns are greatest during the winter afternoon. Each point within Figure 7 represents the capacity value for the ReEDS or REPRA model within a single BA for a given time period and WWSIS-2 scenario. That is, the variation within a subplot at a given penetration level reflects variation in capacity value between different BAs in the same state. All four WWSIS-2 scenarios are shown in the plot to demonstrate the relationship between capacity value and penetration.

[3] Note that the states of Idaho and Washington as well as the El Paso area of Texas are regions within the Western Interconnection. However, because an insubstantial amount of solar capacity was built for these regions in each model, results for those regions were excluded from this analysis.

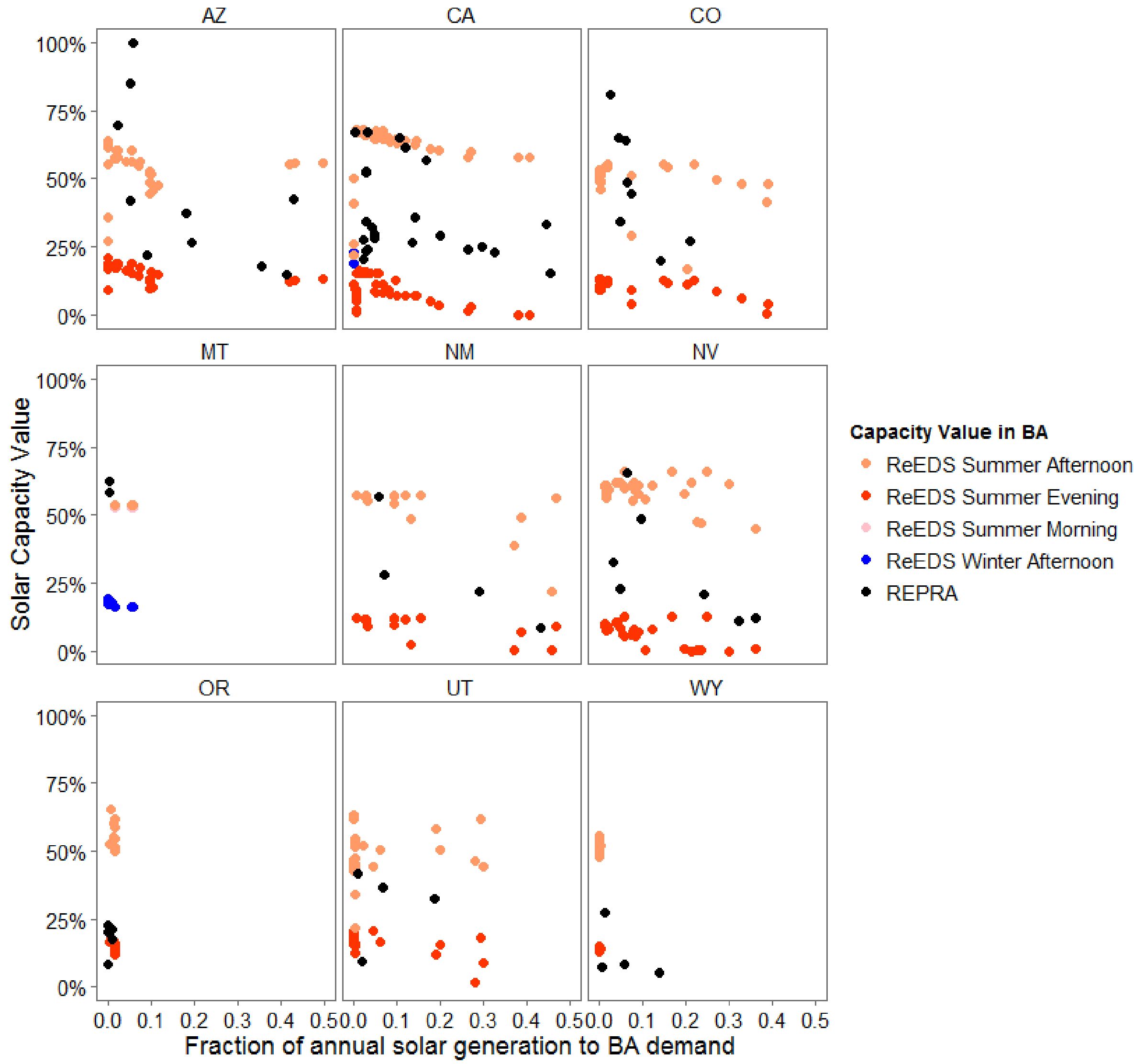


Figure 7. State-based solar PV capacity values for reliability-critical time periods for WWSIS-2 scenarios in 2020

The range of ReEDS capacity values bounds the REPRA values in most states (Arizona, California, Colorado, New Mexico, Nevada, Utah) but is a poor fit in states with few data points for comparison. While there is disagreement between ReEDS and REPRA at low penetration levels in Arizona, Colorado, and New Mexico, agreement improves at high penetrations. Erosion within a ReEDS time slice is generally shallower than that of the REPRA results, which is consistent again with the set of reliability-critical hours shifting into the evening as penetration increases. The within-time-slice ReEDS results, of course, do not include that transition, but recall that ReEDS itself does so implicitly by requiring all systems to meet adequacy needs in all time-slices.

Notice, also, that there is some erosion of capacity value within a time-slice as penetration increases. This is consistent with the hypothesis that within any set region adding more PV increases its self-correlation. As does a system operator, ReEDS has the capability to diversify its resource base somewhat, but not fully, and the intra-time-slice erosion represents the limit of that ability.

Figure 8 shows the bulk capacity credit from the WWSIS-2 results for all ReEDS daytime time-slices, not just reliability-critical periods. That is, each subplot aggregates results from the four WWSIS-2 scenarios (3.5%, 8%, 16.5%, and 25% solar penetration WECC-wide) and for the 33 ReEDS balancing areas used to represent WECC. Results suggest that a large source of capacity value variation within the ReEDS model is between time-slices. We suggest that capacity value erosion within a time period is explained through increased self-correlation of energy production, as well as decreases in available high-quality resource sites within the region. This is because shifts in peak net load are not explicitly considered *within* a time period. Variation in modeled capacity value *holding penetration constant* can be explained through geographic variation in resource quality in Western BAs—though this is not formally shown.

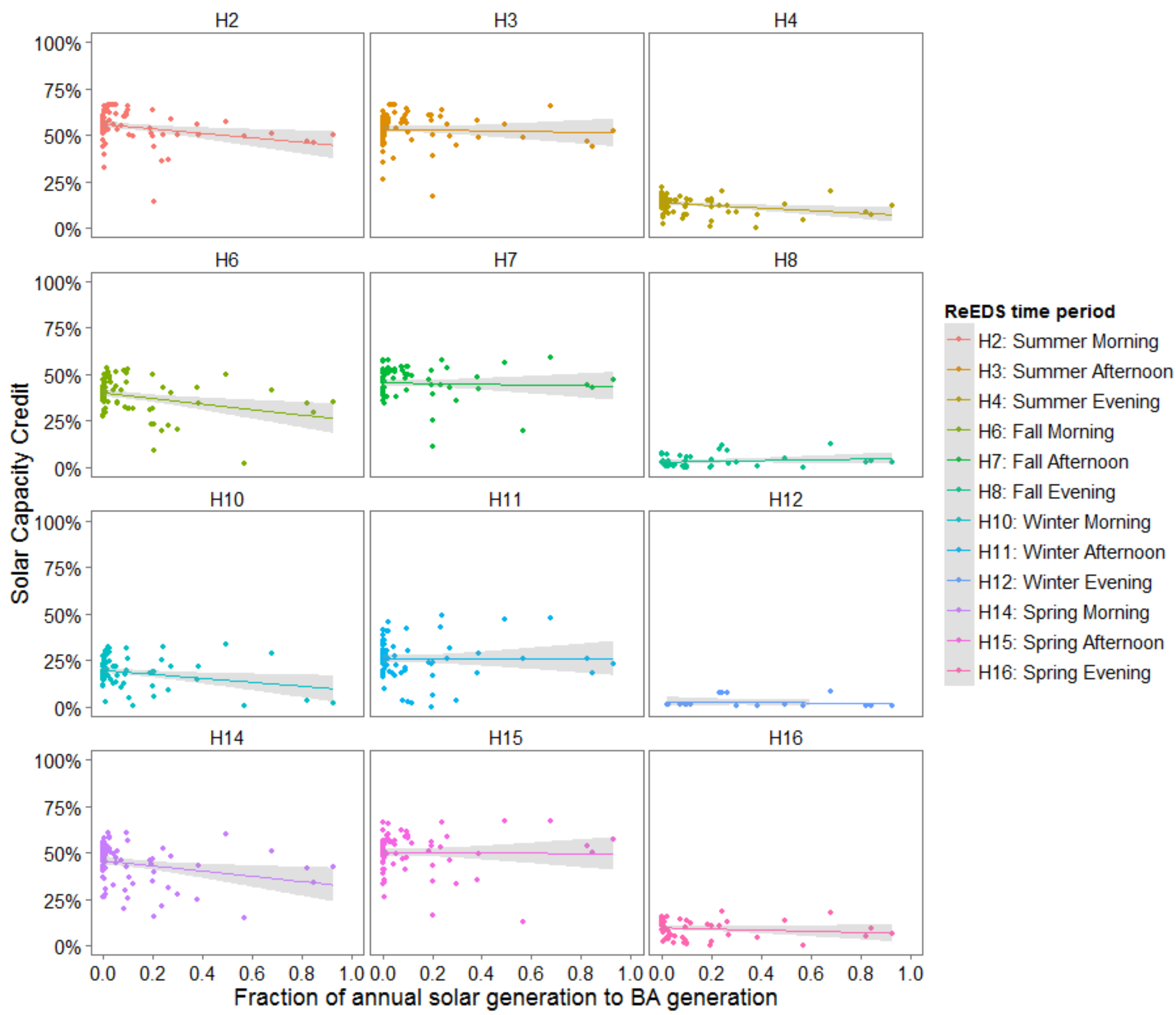


Figure 8. Sensitivity of ReEDS PV capacity value to time period and solar energy penetration.

6 Conclusion

ReEDS was designed to represent characteristics that drive variation in investment and operation costs of renewable energy technologies, including geospatial resource assessment and integration of variable resources into a reliable electricity grid. Because these characteristics give the model accurate information about the economic value of, for instance, an additional unit of solar capacity, ReEDS is able to make well-informed investment decisions. Capacity value, as discussed here, is one of the economic components ReEDS includes in its decision making—one that can change dramatically with system configuration and is important to model dynamically.

To accurately reflect solar capacity value in capacity expansion decisions, ReEDS models a number of factors that determine its ELCC. These include representation of the statistical availability of a solar unit, a high level of geographic resolution in resource quality and grid conditions, and correlation of residual load and solar generation. Additionally, ReEDS simultaneously considers adequacy issues in all time-slices. Because the value of capacity services is highest during reliability-critical periods, and increased solar generation shifts those periods away from peak solar output, this accounts for the diminishing capacity value of solar at high levels of penetration. We find that capacity value outcomes from the ReEDS model compare favorably with results from hourly resolution ELCC-based analyses for a range of real and modeled levels of solar energy penetration.

References

Amelin, M. (May 2009). “Comparison of Capacity Credit Calculation Methods for Conventional Power Plants and Wind Power.” *IEEE Transactions on Power Systems* (24:2); pp. 685–691.

Borenstein, S. (January 2008). “The Market Value and Cost of Solar Photovoltaic Electricity Production.” UC Berkeley: Center for the Study of Energy Markets. Berkeley, CA: UC Berkeley

Bialek, J. (1996). “Tracing the Flow of Electricity in Generation, Transmission and Distribution.” *IEEE Proceedings* (143: 4); pp. 313-320).

Billinton, R.; Allan, R.N. (1996). *Reliability Evaluation of Power Systems*. New York, NY: Plenum Press.

Denholm, P.; Drury, E.; Margolis, R. (September 2009). *The Solar Deployment System (SolarDS) Model: Documentation and Sample Results.* NREL/TP-6A2-45832. Golden, CO: National Renewable Energy Laboratory, 52 pp.

Dragoon, K.; Dvortsov, V. (2006). “Z-Method for Power System Resource Adequacy Applications.” *IEEE Transactions on Power Systems* (21:2); pp. 982-988.

Duignan, R.; Dent, C.; Mills, A.; Samaan, N.; Milligan, M.; Keane, A.; O’Malley, M. (2012). “Capacity Value of Solar Power.” *Power and Energy Society, IEEE General Meeting;* 6 pp.

EIA. (2013). *Annual Energy Outlook 2013*. DOE/EIA-0383. Washington, DC: EIA.

Ibanez, E.; Milligan, M. (September 2012). “A Probabilistic Approach to Quantifying the Contribution of Variable Generation and Transmission to System Reliability.” NREL/CP-5500-56219. Golden, CO: National Renewable Energy Laboratory.

Integration of Variable Generation Task Force. (2011). “Methods to Model and Calculate Capacity Contributions of Variable Generation for Resource Adequacy Planning.” Princeton, NJ: North American Electric Reliability Corporation. Accessed January 27, 2014: http://www.nerc.com/docs/pc/ivgtf/IVGTF1-2.pdf.

Keane, A.; Milligan, M; Dent, C; Hasche, B.; D’Annunzio, C; Dragoon, K.; Holttinen, H.; Samaan, N.; S¨oder, L.; O’Malley, M. (May 2011). “Capacity Value of Wind Power.” *IEEE Transactions on Power Systems* (26:2); pp. 564–572.

Lew, D.; Brinkman, G.; Ibanez, E.; Florita, A.; Heaney, M.; Hodge, B.; Hummon, M.; Stark, G.; King, J.; Lefton, S.; Kumar, N.; Agan, D.; Jordan, G.; Venkataraman, S. (2013). *Western Wind and Solar Integration Study: Phase 2*. TP-5500-55588. Golden, CO: National Renewable Energy Laboratory, 244 pp. Accessed January 27, 2014: http://www.nrel.gov/docs/fy13osti/55588.pdf.

Lopez, A.; Roberts, B.; Heimiller, D.; Blair, N.; Porro, G. (2012). *U.S. Renewable Energy Technical Potentials: A GIS-Based Analysis*. TP-6A20-51946. Golden, CO: National Renewable Energy Laboratory, 40 pp. Accessed January 27, 2014: http://www.nrel.gov/docs/fy12osti/51946.pdf.

Lu, S.; Diao, R.; Samaan, N.; Etinov, P. (2012). "Capacity Value of PV and Wind Generation in the NV Energy System." PNNL-22117. Richland, WA: Pacific Northwest National Laboratory, 35 pp.

Madaeni, S.H.; Sioshansi, R.; Denholm, P. (July 2012a) "The Capacity Value of Solar Generation in the Western United States." *Power and Energy Society General Meeting*. IEEE, pp.1-8, 22-26 July 2012. doi: 10.1109/PESGM.2012.6345521.

Madaeni, S.H.; Sioshansi, R.; Denholm, P. (May 2012b). "Estimating the Capacity Value of Concentrating Solar Power Plants: A Case Study of the Southwestern United States." *IEEE Transactions on Power Systems* (27:2); pp. 1116–1124.

Madaeni, S. H.; Sioshansi, R.; Denholm, P. (2013). "Comparison of Capacity Value Estimation Techniques for Photovoltaic Solar Power." *IEEE Journal of Photovoltaics* (3:1); pp. 407-415.

Milligan, M.; Porter, K. (2008a) "Determining the Capacity Value of Wind: An Updated Survey of Methods and Implementation". NREL/CP-500-43433. Golden, CO: National Renewable Energy Laboratory, June 2008. http://www.nrel.gov/docs/fy08osti/43433.pdf.

Milligan, M.; Porter, K. (2008b). "Wind Capacity Credit in the United States." In Proc. IEEE Power and Energy Society Gral. Meeting, pp. 1-5.

Milligan, M. (2002). "A Chronological Reliability Model Incorporating Wind Forecasts to Assess Wind Plant Reserve Allocation." Golden, CO: National Renewable Energy Laboratory. Accessed January 27, 2014: http://www.nrel.gov/docs/fy02osti/32210.pdf.

Mills, A.; Wiser, R. (2012). "An Evaluation of Solar Valuation Methods Used in Utility Planning and Procurement Processes." LBNL-5933E. Berkeley, CA: Lawrence Berkeley National Laboratory.

NERC. (December 2013). "2013 Long-Tern Reliability Assessment." Princeton, NJ: North American Electric Reliability Corp.

NERC. (March 2011). "Methods to Model and Calculate Capacity Contributions of Variable Generation for Resource Adequacy Planning." Princeton, NJ: North American Electric Reliability Corp.

National Renewable Energy Laboratory (NREL). (2010a). "System Advisor Model (SAM) Version 2010.4.12." Accessed April 12, 2010: https://www.nrel.gov/analysis/sam/.

(NREL). (2012). *Renewable Electricity Futures Study*. Hand, M.M.; Baldwin, S.; DeMeo, E.; Reilly, J.M.; Mai, T.; Arent, D.; Porro, G.; Meshek, M.; Sandor, D. eds. 4 vols. NREL/TP-6A20-52409. Golden, CO: National Renewable Energy Laboratory.

National Solar Radiation Database. (2010). "National Solar Radiation Data Base 1991 – 2010 Update." Accessed November 11, 2013: http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2010/.

Orwig, K.; Hummon, M.; Hodge, B.-M.; Lew, D. (2011). "Solar Data Inputs for Integration and Transmission Planning Studies." Proc. 1st Int. Workshop on Integration of Solar Power into Power Systems, Aarhu, Denmark, October 2011.

Perez, R.; Taylor, M.; Hoff, T.; Ross, J.P. (2008). "Reaching Consensus in the Definition of Photovoltaics Capacity Credit in the USA: A Practical Application of Satellite-Derived Solar Resource Data." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* (1:1); pp 28–33.

Perez, R.; Hoff, T.E. (2008). "Energy and Capacity Valuation of Photovoltaic Power Generation in New York." Solar Alliance and the New York Solar Energy Industry Association, March 2008. Accessed January 27, 2014: http://asrc.albany.edu/people/faculty/perez/publications/Utility%20Peak%20Shaving%20and%20Capacity%20Credit/Papers%20on%20PV%20Load%20Matching%20and%20Economic%20Evaluation/Energy%20Capacity%20Valuation-08.pdf.

Perez, R; Margolis, R.; Kmiecik, M; Schwab, M.; Perez, M. (June 2006). *Update: Effective Load-Carrying Capability of Photovoltaics in the United States.* NREL/CP-620-40068. Golden, CO: National Renewable Energy Laboratory.

Public Service Company of New Mexico. (July 2011). "Electric Integrated Resource Plan: 2011-2030." Accessed January 27, 2014: http://www.pnm.com/regulatory/pdf_electricity/irp_2011-2030.pdf.

Renewable Electricity Futures Study. (2012). Golden, CO: National Renewable Energy Laboratory; NREL Report No. TP-6A20-52409.

R.W. Beck, Inc. (January 2009). "Distributed Renewable Energy Operating Impacts and Valuation Study: Prepare for Arizona Public Service." 424 pp.

Saha, A. (12 April 2013). "Review of Coal Plant Retirements." M.J. Bradley & Associates.

SAIC Energy, Environment, & Infrastructure LLC. (May 2013). "2013 Updated Solar PV Value Report." Arizona Public Service. Accessed January 27, 2014: http://www.solarfuturearizona.com/2013SolarValueStudy.pdf.

Short, W.; Sullivan, P.; Mai, T.; Mowers, M.; Uriate, C.; Blair, N.; Heimiller, D.; Martinez, A. (2011). "Regional Energy Deployment System (ReEDS)." TP-6A20-46534. Golden, CO: National Renewable Energy Laboratory, 94 pp.

Stott, B.; Jardim, J.; Alsac, O. (August 2009). "DC Power Flow Revisited." *IEEE Transactions on Power Systems* (24:3). Accessed January 27, 2014: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=4956966&tag=1.

EERE. (February 2012). *SunShot Vision Study*. Energy Efficiency & Renewable Energy (EERE), BK-5200-47927; DOE/GO-102012-3037. 320 pp.; 3TIER. (2010). "Development of Regional Wind Resource and Wind Plant Output Datasets." NREL/SR-550-47676. Golden, CO: National Renewable Energy Laboratory. Accessed January 27, 2014: http://www.nrel.gov/docs/fy10osti/47676.pdf.

Tri-State Generation and Transmission Association, Inc. (November 2010). "Integrated Resource Plan/ Electric Resource Plan for Tri-State Generation and Transmission Association Inc." Accessed January 27, 2014: http://www.tristategt.org/ResourcePlanning/documents/Tri-State_IRP-ERP_Final.pdf.

Ventyx. (2010). "Energy Market Data." Accessed January 27, 2014: http://www.ventyx.com/velocity/energy-market-data.asp.

Western Electricity Coordinating Council. (2009). "Transmission Expansion Planning Policy Committee 2009 Study Program Results Report." Accessed January 27, 2014: www.wecc.biz/committees/ BOD/TEPPC/Shared Documents/TEPPC Annual Reports.

Wilcox, S; Anderberg, M; George, R; Marion, W; Myers, D; Renne, D; Lott, N; Whitehurst, T; Beckman, W; Gueymard, C; Perez, R; Stackhouse, P.; Vignola, F. (July 2007). "Completing Production of the Updated National Solar Radiation Database for the United States." CP-581-41511. Golden, CO: National Renewable Energy Laboratory.

Xcel Energy Services, Inc. (May 2013). "Costs and Benefits of Distributed Solar Generation on the Public Service Company of Colorado System."

Appendix A. ReEDS Temporal Resolution

The ReEDS model dispatches generation for 17 time-slices (4 time-slices for each season representing morning, afternoon, evening, and nighttime, with an additional summer-peak time-slice). This level of temporal detail enables ReEDS to consider seasonal and diurnal changes in demand and resource availability but limits its resolution at inter-hour analysis. The planning reserve constraint that maintains system adequacy is held at each of the 16 standard time-slices. For adequacy purposes, the superpeak is assumed to be a subset of the summer afternoon (H3) time-slice.

Table A-1. ReEDS Time Period Definitions

Name	Hours Per Year	Season	Time of Day	Time Period
H1	736	Summer	Night	10 p.m. to 6 a.m.
H2	644	Summer	Morning	6 a.m. to 1 p.m.
H3	328	Summer	Afternoon	1 p.m. to 5 p.m.
H4	460	Summer	Evening	5 p.m. to 10 p.m.
H5	488	Fall	Night	10 p.m. to 6 a.m.
H6	427	Fall	Morning	6 a.m. to 1 p.m.
H7	244	Fall	Afternoon	1 p.m. to 5 p.m.
H8	305	Fall	Evening	5 p.m. to 10 p.m.
H9	960	Winter	Night	10 p.m. to 6 a.m.
H10	840	Winter	Morning	6 a.m. to 1 p.m.
H11	480	Winter	Afternoon	1 p.m. to 5 p.m.
H12	600	Winter	Evening	5 p.m. to 10 p.m.
H13	736	Spring	Night	10 p.m. to 6 a.m.
H14	644	Spring	Morning	6 a.m. to 1 p.m.
H15	368	Spring	Afternoon	1 p.m. to 5 p.m.
H16	460	Spring	Evening	5 p.m. to 10 p.m.
H17	40	Summer	Peak	40 highest demand hours of summer

Appendix B. ReEDS Geographic Resolution

ReEDS represents the continental United States using 134 BAs, the regional level at which demand requirements must be satisfied and all non-wind/CSP technology expansion occurs. Portions of this report's analysis only pertain to the Western Interconnection, which has 35 BAs. Because BA service territories do not exactly match the service territory of the comparison studies in Section 3 or the WWSIS-2 balancing areas, for the purpose of comparison, we use the smallest set of ReEDS BAs that wholly encapsulates each study's service territory. If the study territory encapsulates several ReEDS BAs, we report the range of capacity values for each BA within the study territory.

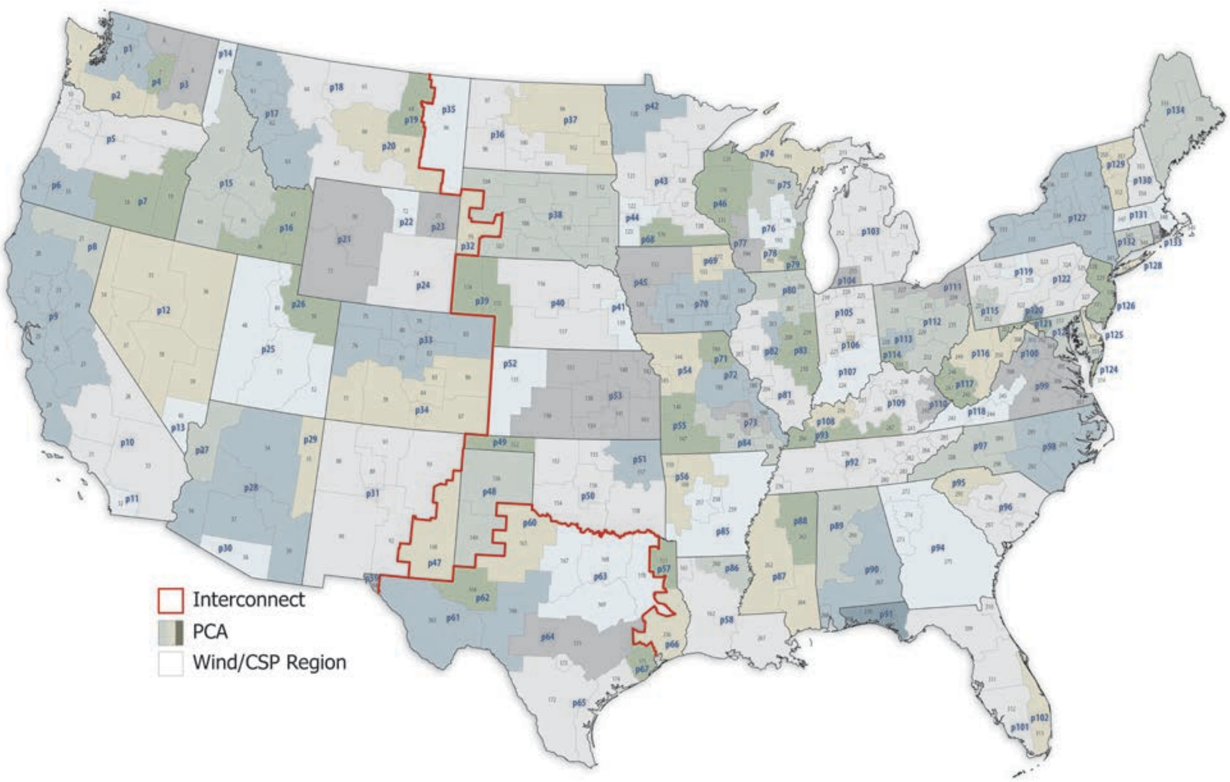
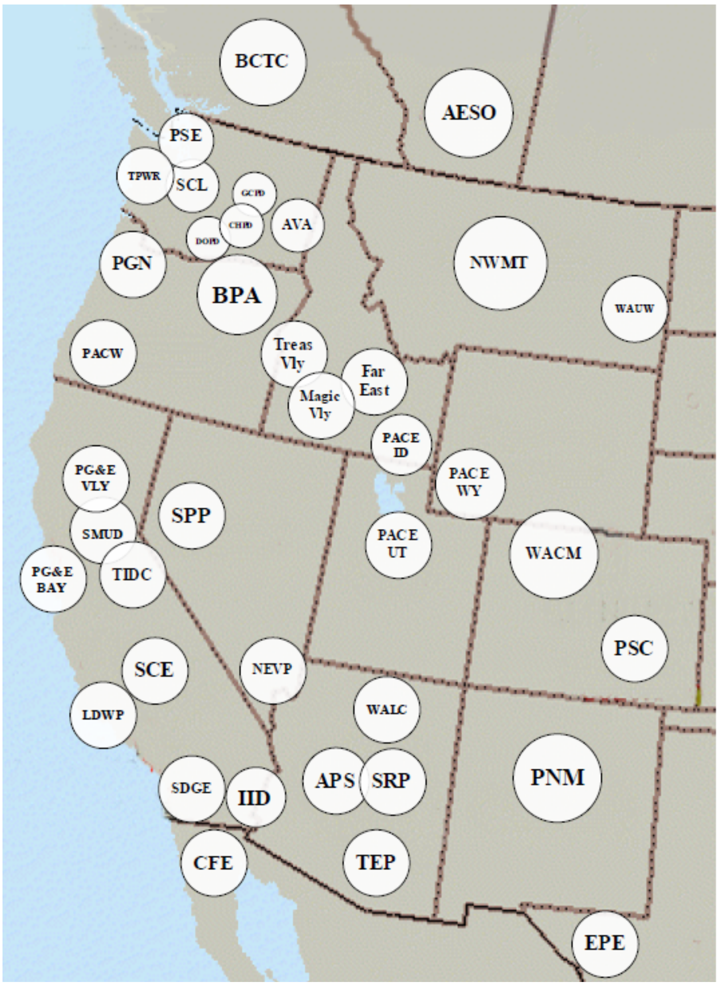


Figure B-1. Map of ReEDS balancing areas and resource regions (Short 2011)

Appendix C. WWSIS-2 Balancing Areas

The WWSIS-2 represents the U.S. Western Interconnection using 36 BAs (Figure C-1) designated by the WECC's TEPPC (TEPPC 2009). This data is consistent with other TEPPC studies except that WECC-2 BAs in Canada and Mexico are excluded. Because WWSIS-2 BA service territories do not exactly match the service territories of BAs used in ReEDS, for the purpose of comparison we compare the two models at a state-level; when a BA overlies multiple states it is allocated to whichever state contains the majority of its area.



Legend

AESO	Alberta Electric System Operator
APS	Arizona Public Service
AVA	Avista
BCTC	British Columbia Transmission Corp
BPA	Bonneville Power Administration
CFE	Comision Federal de Electricidad
CHPD	Chelan Co PUD
DCPD	Douglas Co PUD
EPE	El Paso Electric
Far East	Far East (Idaho Power)
GCPD	Grant Co PUD
IID	Imperial Irrigation District
LDWP	Los Angeles Dept of Water & Power
Magic Vly	Magic Valley (Idaho Power)
NEVP	Nevada Power
NWMT	Northwestern Montana
PACW	PacifiCorp West
PACE ID	PacifiCorp East – Idaho
PACE UT	PacifiCorp East – Utah
PACE WY	PacifiCorp East -- Wyoming
PG&E Bay	Pacific Gas & Electric Bay Area
PG&E VLY	Pacific Gas & Electric Valley Area
PGN	Portland Gen Electric
PNM	Public Service New Mexico
PSC	Public Service Colorado (Xcel)
PSE	Puget Sound Energy
SCE	Southern California Edison
SCL	Seattle City Light
SDGE	San Diego Gas & Electric
SMUD	Sacramento Municipal District
SPP	Sierra Pacific Power
SRP	Salt River Project
TEP	Tucson Electric Power
TIDC	Turlock Irrigation District
TPWR	Tacoma Power
TreasVly	Treasure Valley (Idaho Power)
WACM	Western Area Power Admin Colorado/Missouri
WALC	Western Area Power Admin Lower Colorado
WAUW	Western Area Power Admin Upper Missouri

Figure C-1. Map of TEPPC/WWSIS-2 balancing areas