Representation of the Solar Capacity Value in the ReEDS Capacity Expansion Model

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Representation of the Solar Capacity Value in the ReEDS Capacity Expansion Model

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***Abstract* — An important emerging issue 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, effective load-carrying capacity (ELCC), are considered to be the most robust techniques for addressing this resource variability.**

The Regional Energy Deployment System (ReEDS) capacity expansion model and other long-term electricity capacity planning models require an approach to estimating CV for generalized PV and system configurations with low computational and data requirements. In this paper we validate treatment of solar photovoltaic (PV) capacity value by ReEDS capacity expansion model by comparing model results to literature for a range of energy penetration levels. Results from the ReEDS model are found to compare well with both comparisons--despite not being resolved at an hourly scale.

***Index Terms* — power system reliability, power system simulation, solar energy, solar power generation**

I. Introduction

An important issue for electricity system operators is the estimation of renewable generating technologies' contributions to system adequacy. As supply of electricity must constantly be balanced with demand, operators procure surplus capacity to hedge against load ever exceeding available generation. A generator's ability to help reliably serve load is measured by its capacity value or effective load carrying capacity—the statistically firm capacity that a generating unit is able to provide during reliability-critical periods.

While the capacity value for conventional thermal generators is easily determined, solar and wind generation requires a more nuanced approach due to variability in the resource. Previous studies have estimated the capacity value of photovoltaic (PV) solar [1]-[2]-[3] and other renewable sources [4]-[5], finding a wide range of potential capacity values that depends on technology, resource quality, and correlation of generation and demand, among many factors.

Reliability-based methods are considered to be the most robust methods [2] of assessing capacity value. Such techniques assess how the addition of a generator affects the likelihood of adequately serving load within a planning year. Specifically, the capacity value is defined as the maximum additional load, or Effective Load-Carrying Capacity (ELCC), that the electrical system could serve while maintaining the same level of reliability or Loss of Load Probability (LOLP). A drawback of this method is that it requires extensive time series data spanning years of load and conventional and renewable generation.

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 variable resource renewable energy (VRRE) capacity value. One credible method, employed by the Regional Energy Deployment System (ReEDS) model in this paper, is the Z-method [6], which approximates LOLPs through the distribution of a system's surplus capacity. We supplement the Z-method with additional methods that weigh 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 [7]. 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 value to VRRE sources is a part of recognizing and evaluating their economic value [8]--and therefore becomes increasingly important for justifying their expanded use.

This paper describes the statistical CV calculation method within the ReEDS capacity expansion model and compares the characteristics and behavior of ReEDS CV results to reliability-based CV estimates from other models and sources. ReEDS is found to produce CV estimates useful for long-term planning purposes at a fraction of the computational and data requirements of a full ELCC accounting.

II. Factors Influencing Modeled Capacity Value

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.

A. Sensitivity of Capacity Value to Resource Quality

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 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 act as load balancing areas (BA). Note that the ReEDS 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—particularly, statistical availability during reliability-critical periods.

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.

B. Solar Energy Penetration

Solar PV capacity value is also known to be highly sensitive to increasing levels of PV deployment within the planning region [2]-[3]-[7]-[9]-[10]. 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

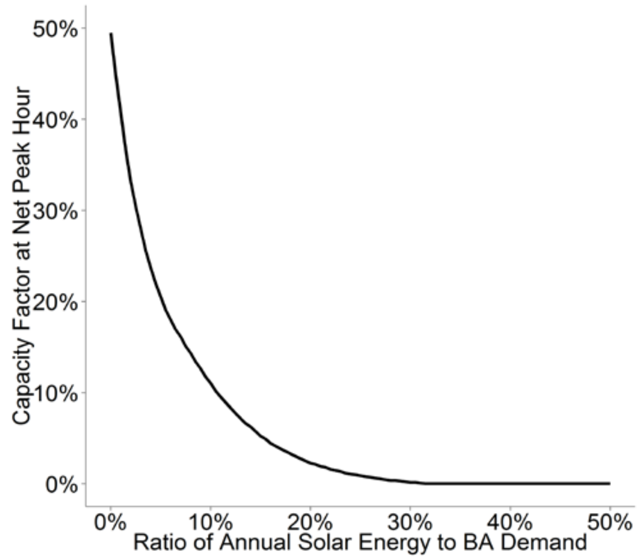

Figure 2: Representative solar capacity factor at net peak hour as a function of PV penetration for an Arizona BA in August.

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 in the day, when solar irradiance is lower, thereby 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].

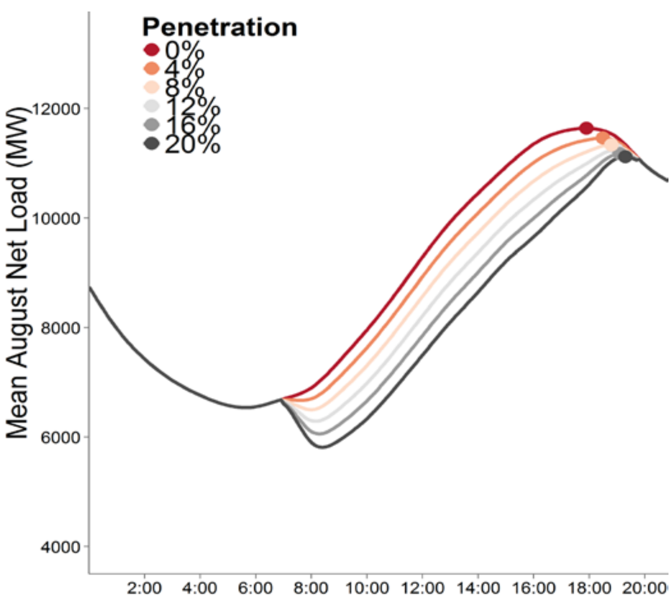

Figure 1: Representative diurnal net load curve for BA in Arizona for increasing energy fraction from PV. The dot marking the peak net load of each curve steadily shifts later into the evening as the PV fraction increases.

[1] See https://sam.nrel.gov/ for more information
[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.

Table 1
Summary of Comparison Studies

Comparison Study		ReEDS Model		
Study Region	Reported Capacity Value	PV deployment (% of annual generation)	Summer Afternoon Capacity Value	Summer Evening Capacity Value
Arizona Public Service [11]	45.9% - 48.4%	1.97%	54.9%	14.4%
Nevada Energy [12]	57.4%	4.45%	63.0%	11.7%
Nevada Power [3]	71%	4.45%	63.0%	11.7%
New York ISO [13]	44.3 – 78.3%	2.00%	47.1%	9.8%
Portland General Electric [3]	31%	1.00%	65.5%	16.4%
Public Service Colorado [14]	41 – 47%	0.60%	54.0%	12.6%
TriState [15]	20 – 57%	0.73%	59.0%	12.6%

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.

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 1 and 2). 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.

III. Background

The Regional Energy Deployment System (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 the possible evolution of the U.S. electricity system and evaluating the potential for and impact of growth in renewable energy technologies.

The ReEDS model is especially focused on representing renewable energy technologies in capacity expansion decisions. Parameters that drive variation in the siting and integration costs of solar and wind generating technologies are emphasized. These include accounting for geospatial differences in resource quality, transmission needs, electrical (grid-related) boundaries, political and jurisdictional boundaries, and demographic distributions. One limitation is that, for data reasons, the model is resolved annually over 17 time slices.

ReEDS uses a measure of a solar generator's Effective Load Carrying Capacity (ELCC) to determine its contributions to planning reserves in each of the model's 17 time periods. Specifically, the Z-method algorithm [6]-[2] is used 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.

A motivation for using the Z-method is that it permits the approximation of capacity value without conducting an hourly time-series analysis, which is infeasible given ReEDS's temporal resolution. 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. However, because the ReEDS model is resolved over 17 time-slices, these inter-hourly differences are difficult to model and modeled capacity value can vary substantially between time slices.

ReEDS mitigates the issue of low temporal resolution 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:

$$\sum_{n,m} \mathrm{CONV}_{nm} + \sum_{n,m} \mathrm{VAR}_{nm} \geq (1+r) \cdot \sum_{n,m} \mathrm{P}_{nm} \qquad (1)$$

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, such 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.

IV. Low Penetration Comparison

Next, the ReEDS models' estimates of capacity value are compared to seven studies published by utilities or other research teams at low levels of solar energy penetration (Table 1). Comparison is restricted to studies conducted using an ELCC-based methodology. To ensure equitable comparison, ReEDS model scenarios were constructed to match each study's geographic region of analysis, existing generation fleet, and PV deployment levels as closely as possible.

Figure 3 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. [2] 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

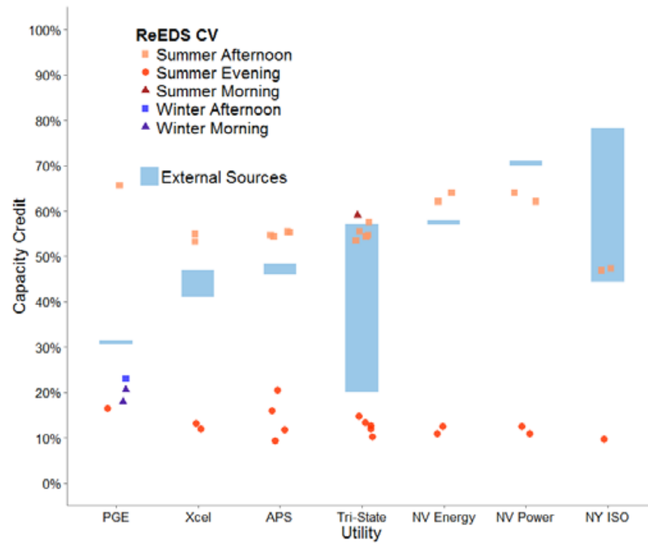

Fig. 3. Comparison of solar capacity values in reliability-critical time periods to published values.

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. 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 [11]. 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.

V. High Penetration Comparison

Analysis of the operational value of solar and other variable generation at high (10%+) levels of penetration has been performed on many simulated systems [3]-[4]-[7]. These studies find that the capacity value of solar generation declines significantly as penetration increases since peak net load shifts to later in the day—when there is less solar output. Clearly, this decrease in value decreases the overall economics of future solar units 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) [9]. The WWSIS-2 sought to simulate grid operation in the U.S. Western Interconnection for four hypothetical high-renewable deployment scenarios (3.5%, 8%, 16.5%, and 25%) by 2020 in the Western Interconnection. Capacity values for the WWSIS-2 scenarios are calculated using NREL's Renewable Energy Probability Resource Adequacy tool (REPRA) [16], which estimates the capacity value of VRRE sources using a time series ELCC algorithm.

As in the low penetration results, ReEDS solar capacity value is reported as the range of capacity values during the balancing area's peak net load time periods. 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 4 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.

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.

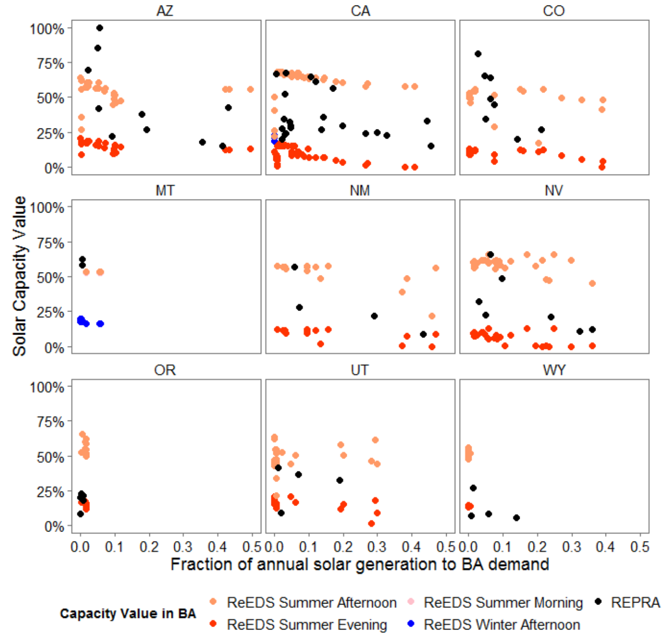

Fig. 4. WECC solar PV capacity values for reliability-critical time periods in 2020.

V. Conclusion

ReEDS was designed to represent variation in the 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.

Acknowledgements

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