Capacity Value of Solar Power

Report of the IEEE PES Task Force on Capacity Value of Solar Power

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Abstract—This paper reviews methods used for adequacy risk assessment considering solar power, and for assessment of the capacity value of solar power. Topics covered are the properties of solar power as seen by the system (and how this contrasts with wind), methodology for risk calculation considering variable generation (VG), issues in incorporating VG in capacity markets, and a review of applied studies considering solar power. Finally, recommendations for further research will be presented.

Keywords—Solar power, Capacity value, Capacity credit, Resource adequacy, LOLE, ELCC, Capacity Market, Probability

I. INTRODUCTION

An important issue for power system planning is the contribution of renewable energy resources to reliably meeting demand. The ability of a generator (or other resource) to help reliably serve demand is typically measured by estimating its capacity value. Mechanical failures, planned maintenance, or lack of generating resource in real-time may leave a system with insufficient capacity to meet load—requiring load curtailment. The capacity value of a generator is estimated by examining the effect that it has on the probabilities of these load-curtailment events. The issue of real-time resource availability is particularly salient with renewables, as their output is governed by uncontrollable climactic conditions.

The literature contains a number of studies that apply capacity value-estimation techniques to wind generators. A survey of these techniques by an IEEE Task Force on Capacity Value of Wind Power provides the Task Force's view of best practices in conducting capacity value studies of wind [1]. This paper is has a similar purpose, in this case surveying methods for estimating the capacity value of solar power, updating an earlier TF conference paper on solar power [2]. In addition to issues specifically associated with solar power, material on risk calculation methodology and capacity markets which was not discussed in the earlier paper will also be presented. In particular, we will discuss issues that are similar to those affecting wind power, and to draw special attention to some of the issues that are unique to solar power (with which the power system community may be less familiar than with wind).

This paper addresses four major issues related to solar power. The first, which is discussed in Section II, has to do with the properties of solar power. Some issues that are unique to solar power include spatial and temporal correlations of solar availability and design considerations (e.g., the inclusion of a sun-tracking system, energy storage, or orientation of a photovoltaic panel) that can affect its capacity contribution.

Section III provides a more detailed discussion of the statistical methods used for adequacy index and capacity value estimation in the presence of variable generation – much of the methodology in this section applies equally to different VG technologies. An important issue is that any statistical relationship between solar radiation, demand, and (potentially) wind should be captured to produce robust estimates. Another topic of interest is using statistical models to determine what properties of the solar pattern more directly affect the capacity value of solar. These types of insights can provide useful screening tools to determine how to design solar systems and policies to maximize capacity value. Section IV discusses issues around remunerating solar plants for their capacity value. These market design issues are by no means new, but solar introduces some new complications due to seasonal and interannual variability of capacity value. Section V surveys recent capacity value studies in the industrial and research literature. Finally, Section VI concludes and provides a roadmap for future work that this task force intends to do.

II. PROPERTIES OF SOLAR POWER

The energy from the sun which is relevant to solar panels is called irradiance, with units given as energy per area, or Watts per Sq-Meter [W/m^2]. The measure of irradiance of interest in solar power calculations is the Global Horizontal Irradiance (GHI), and many models for predicting solar production have been evaluated, including models estimating plane of array (POA) irradiance based on GHI observations for tilted arrays [3].

Solar power resources differ from traditional thermal resources in that their production of energy is intermittent due to the stochastic nature of available fuel from the sun. The irradiance available to solar resources can vary considerably throughout the day according to cloud cover and haze. Temperature, humidity, and wind speed are just a few of the other weather conditions which impact solar production [4].

A. Solar System Designs

Solar panels can be arranged in fixed array configurations at a constant mounting angle or in array-tracking systems with movement allowed in 1 axis or 2 axes. As shown in Fig. 1, axis tracking systems tend to produce more energy throughout a given day since it is constantly following the angle of the sun and maximizing the amount of direct normal irradiance (DNI) at all times. Not only does this allow for higher energy production value, but will afford the maximum value as a capacity resource, elevating power production during peak afternoon demand hours common in summer-peaking regions.
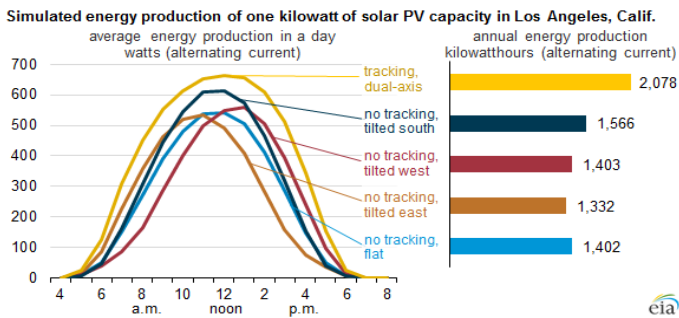
Figure 1: Simulated solar energy production with different tracking technologies and mounting angles [5].

Photovoltaic (PV) solar technology has no inherent storage capability unless coupled with battery technology, thus has availability as a capacity resource only during daylight hours. Contrary to PV technology, concentrated solar power (CSP) uses an array of solar reflectors to heat water to produce steam which drives a turbine. There is inherent thermal storage in the heated water which allows CSP to produce power during the day or night depending on the capacity of the storage [6].

B. Aspects different from wind

The intermittent nature of solar energy production differs in many ways from wind energy production.

1) Geographic Intermittent Resolution: Weather patterns can be very localized within a power system, with some regions in full sun while others have full cloud cover. Partly cloudy days can have sparse cloud cover, and even closely-spaced solar plants can experience different intermittent power production. Hence the geographic correlation is lower since the solar energy interruptions across a region occur at a very fine geographic resolution. This differs from wind power, where wind speed has the characteristic of having stronger geographic relationships and the wind power intermittent behavior has a more coarse resolution across a region [1]. Nonetheless, geographic diversity of solar plant siting remains important for less power fluctuations, where a growing fleet of solar plants would have less intermittent generation as a whole if they are geographically diverse.

2) Available fuel patterns: Wind energy production has a probability of occurring at any time over a 24-hour period, though there is typically some variability of availability statistics with time of day and year [7]. However solar power will only be produced during daylight hours when the sun is shining, producing none during the night – this time window of possible generation has a predictable start and end time from sunrise to sunset as in Figure 2. The daily hours of availability change throughout the year based on the predictable seasonal angle of the sun, and more hours of solar fuel availability are possible during the summer months with fewer hours available during the winter months. This diurnal pattern also has predictable dependence on geography and latitude position, e.g. increased seasonal dependence of resource at higher latitudes. Figure 3 illustrates based on resource data from Spain how pronounced these daily and seasonal cycles in solar resource can be.
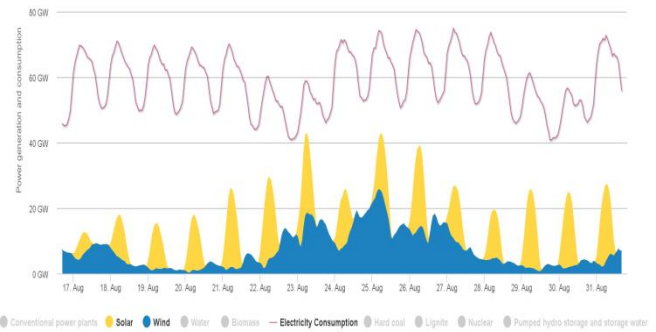

Figure 2: Solar and Wind production over a two week time period in Germany. Shows how daily solar production, though still variable, falls within a predictable time window as compared to wind [8].
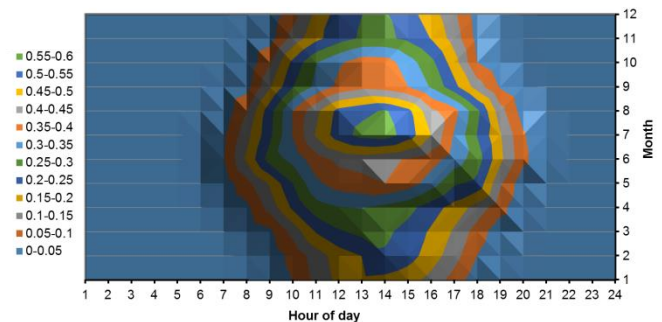

Figure 3: Monthly mean load factor for different times of day in Spain (based on resource data from 2010-13 [9]).

3) Solar Plant variations in capacity factor

A recent study analyzed what drives performance variation among solar PV plants using multivariate regression analysis to explain variance in capacity factors as seen by the AC system [10]. The three independent variables which explained much of the variance included GHI on site - analogous to wind capacity factors improving with favorable wind speeds on site - and two technology-specific features: the tracking capability, and the Inverter Loading Ratio (ILR) or DC-to-AC ratio of the system. The tracking capability will boost the GHI falling on the plane of array throughout the day as seen in Figure 1, while increasing ILR saturation can cause the inverter to operate closer to full AC capacity more of the day particularly in the morning and afternoon shoulder periods. Wind power has different technology-specific design elements to consider for improvements in its reliability contribution during peak, such as cut-in wind speed and tower hub height [11].

III. RISK CALCULATION METHODOLOGY

This section will outline the general framework used for risk-based adequacy and capacity value assessment in systems with substantial variable generation (VG) penetration. Most of the material is equally applicable to solar, wind and other variable renewables, and so unlike other sections of this paper it seldom makes specific reference to solar power.

A. Probability Background

In adequacy assessment, we are interested in the values of conventional generation X_t, variable generation Y_t and demand

D_t at more than one point t in time. Let the (random) vector $S_t = (X_t, Y_t, D_t)$ denote the system state at $t = 1 \dots n$ within the period under study. The system margin, $Z_t = X_t + Y_t - D_t$, is then a function of S_t. A full probability model for the system would be sequential, describing S_t as a stochastic process over the entire time period – this is needed to calculate some risk metrics, e.g. frequency and duration indices, or the distribution of total energy unserved within the period under study.

However, some quantities such as Loss of Load Expectation, $\text{LOLE} = \sum_{t=1}^{n} \mathbf{P}(Z_t < 0)$ are defined in terms of the marginal distributions of the S_t, and may be specified in terms of a simpler time-collapsed model with a time-independent state vector $S = (X, Y, D)$ whose distribution is specified by $\mathbf{P}(S \in A) = \frac{1}{n}\sum_{t=1}^{n} \mathbf{P}(S_t \in A)$ for any event A. LOLE is then specified in terms of a snapshot Loss of Load Probability (LOLP) as $\Delta t \mathbf{P}(Z < 0)$, and Expected Energy Unserved (EEU) as $\Delta t \mathbf{E}(\max(-Z, 0))$ where $Z = X + Y - D$ and Δt is the length of the period under study. The distribution of S may often be estimated from the empirical distribution of observations of the S_t – the time-collapsed model is thus almost always, albeit implicitly, used in adequacy studies which measure risk using quantities such as LOLE which do not require a full sequential model.

In the use of probabilistic and statistical concepts such as independence or correlation, it is essential to be clear as to which of the sequential and time collapsed models this refers. For example, suppose Y_t is available solar power, that at any given time t the random variables Y_t and D_t are independent (neither being informative about the other), and $\{Y_t\}$ and $\{D_t\}$ are independent (but clearly not time-homogeneous) processes. Then daily minimum demand usually occurs overnight when it is dark, so the lowest D are associated with zero Y – the variation with time of the marginal distributions of both processes has introduced probabilistic dependence between their time-collapsed counterparts Y and D.

B. Statistical Estimation

Most studies using the sequential picture assume that VG and demand are independent processes conditional on being in the season under study, e.g. [12, 13]. However this is usually too strong an assumption without good supporting evidence, as VG availability is driven by the weather which in most systems also influences on demand. There is little research on joint stochastic process modelling of VG and demand for adequacy assessment – see [14, 15] for existing early stage work.

Within the VG integration community, where VG-demand dependence is accounted for in the time-collapsed picture this is usually through a 'hindcast' approach, in which the empirical historical distribution of VG-demand pairs (y_t, d_t) is used as the predictive joint distribution in the risk calculation. Then for instance $\text{LOLE} \propto \sum_t \mathbf{P}(X_t + y_t < d_t)$, where the sum is now over historic measurements at times t. To the best of our knowledge, the only work looking at more sophisticated modelling of VG-demand relationship in the time collapsed picture is [16], which additionally uses temperature as an explanatory variable for both wind and demand, and then invokes independence of wind and demand conditional on temperature, and on time of day/week/year.

C. Capacity Values and Analytical Results for Special Cases

It is often useful, either in visualizing the contribution of VG within adequacy calculations or, in specific application such as capacity markets, to define capacity value metrics [17]. Within the time-collapsed picture we can define margin of conventional supply over demand $M = X - D$. Then commonly used capacity value metrics include Effective Load Carrying Capability (ELCC) defined with respect to LOLP by $\mathbf{P}(M < 0) = P(M + Y < v_{Y,M}^{\text{ELCC}})$, and Equivalent Firm Capacity (EFC) defined with respect to LOLP by $\mathbf{P}(M + Y < 0) = P(M + v_{Y,M}^{\text{EFC}} < 0)$. Note that ELCC and EFC are determined by both Y and M; they depend on both the VG capacity Y and on the background M to which it is added.

Outputs of adequacy models must be evaluated numerically unless the input probability distributions have very specific forms. On the assumption of independence between M and Y, there are two significant special cases for which analytical results for EFC and ELCC exist – while these are not usually necessary for tractability, they are valuable in explaining what aspects of model inputs determine the results of calculations.

Suppose that in the relevant region the left tail of the distribution of M is exponential with decay constant λ, and Y is continuous with probability density function (pdf) $f_Y(y)$. Then adding independent Y shifts the distribution of M by an amount $-\frac{1}{\lambda}\ln\left(\int \mathrm{d}y\, f_Y(y) e^{-\lambda y}\right)$ which is also the EFC and ELCC of Y [17]. Less general results were previously published for ELCC of a 2-state Y [18] and multistate discrete Y [19].

The second special case occurs where the variance of Y is small relative to the scale over which the distribution of M decays in its left tail. If M has a pdf $f_M(m)$, then ELCC and EFC may be approximated as $\mu_Y - [f'_M(0)/2f_M(0)]\sigma_Y^2$ [17, 20] where μ_Y and σ_Y^2 are the mean and variance of Y. This confirms some intuitive observations, e.g. ELCC increases with the mean of Y and decreases when variability of Y increases. Notably, if the distribution of M shifts so as to increase risk, then any increase in the capacity value is due to the form of the distribution of M, not due to any intuitive explanation of additional capacity necessarily being of more value when the risk level is higher. The special case of small Y and Gaussian M had previously been published as the 'z-method' [21], however it is unclear whether this is realistic in practical situations, particularly as where a distribution is approximated as Gaussian this approximation is usually poorer in the tails which are of primary interest here.

If M and Y are not independent, the same small Y result applies replacing the mean and SD of Y by the mean and SD conditional on being in the critical region $M = 0$. Then in the 'hindcast' approach described in III-B, for very small Y the EFC and ELCC are $(\sum_t y_t f_X(d_t))/(\sum_t f_X(d_t))$, i.e. the mean of the historic VG records y_t, weighted by the pdf of X at the corresponding demand record, $f_X(d_t)$. This specifies how, if weighted mean available VG capacity is used to approximate a full capacity value calculation, this should be done – this is in contrast to the more common approach of using the cumulative distribution function (or equivalently the LOLP) as the weighting function as in e.g. [22] for solar power. More

broadly, these 'small Y' results provide a basis for identifying when output means might be expected to provide a suitable proxy for risk-based methods of assessing capacity values, e.g. that the capacity value of Y may exceed Y's unconditional mean if demand is driven by the need for air conditioning on days and at times of the day when solar power is abundant.

IV. CAPACITY MARKETS

Many energy markets are considering, or have implemented, remuneration mechanisms that compensate generators for the capacity they provide to the market, over and above energy supplied. The arguments behind capacity markets are discussed in the literature [23-25]. Particular challenges arise when considering variable generation e.g., solar and wind.

Independence: The first major difference between VG and conventional generation is that available capacity from a VG unit may not be independent of that from other units or load. The risk calculations that underpin most capacity mechanisms use a standard model of thermal generation in which each unit's available capacity is independent of other units – this is in contrast to solar units for which available capacity is dependent on weather patterns that correlate units locally and regionally. Weather patterns also influence load, resulting in possible correlation with VG availability. Capacity market designs must properly account for any load-solar relationship and also any wind-solar relationship on a regional and system aggregate basis.

Design: Solar panel design can optimize either annual energy or peak demand. There are many design options when constructing solar panels, including the direction the panel is facing, the angle relative to vertical, and whether tracking is included as detailed in Section II. Table 1 [26] shows data for Los Angeles with several fixed panel design options, each resulting in very different production levels. If market incentives only reward energy production, maximizing total system benefits is not likely optimized. Additionally, if market incentives are provided based on all system solar installations (e.g. ERCOT and IESO) instead of recognizing individual unit contributions then individual producers are not appropriately incentivized to maximize system benefits. Solar design options should be accounted for in deciding the relative rewards to facilities with different tradeoffs between regional and system capacity and energy optimum (e.g. as in MISO [27] for wind and CAISO [28] for solar).

Los Angeles - Average Solar Insolation (kWh/m2/day) with panel facing south				
	June	July	August	September
Flat Surface (90° angle)	7.83	7.54	6.87	5.70
Optimal Year Round (56° angle)	6.80	6.69	6.67	6.40
Summer Performance (71° angle)	7.50	7.31	6.99	6.31

Table 1. CAISO solar performance data.

Temporal: Capacity contributions for solar can vary greatly from year to year, especially when the highest demand is in the summer. High electricity demand is strongly correlated with temperature in summer months. High temperatures can reduce solar panel performance and output [29]. Additionally, depending on the month and time of day that the high demand occurs, the solar resource can vary significantly. For CAISO it can be over 30% of installed solar capacity[30]. In 2013, CAISO had its peak demand in June while in 2014 it was in September [31]. History for the last 20 years shows this variation of peak loads from June to September, and from hour 14:30 to 16:53. Markets that rely on singular seasonal capacity valuations miss the monthly variation and can over or under value the capacity contribution. Improvements can be achieved by utilizing a monthly rating approach or a risk based seasonal method.

Diminishing Returns: Similar to wind [17, 32], as more solar capacity is installed on a system its calculated capacity value as a percentage of nameplate decreases very substantially, in contrast to thermal generation – this arises from the lack of independence discussed in Section III, and the consequent possibility of very low output across a whole system. As marginal capacity benefits decrease with new solar additions, a market design must decide whether the capacity payment to existing solar installations is diminished as a result of the new installation (equal value to all), or if the capacity payment should be lower for new installations based on the marginal system capacity benefit that they provide. Equal capacity payments can result in new facilities being over-paid with respect to the system benefits provided, which may overstimulate new development.

Subsidies: Subsidies for renewable generation, whereby renewable generators receive extra revenue (or tax credits) and/or preferential market treatment by virtue of the fact that they are renewable generators (such as through renewable standards), interfere with market design as is the case when any externality is not internalized to the market. Regardless of whether a renewable subsidy is offered based on investment or production, it can distort incentives contrary to the requirements of a market. For example, a production tax credit incentivizes maximum production without consideration of peak demand requirements. One approach that is used in the UK is to disallow subsidized technologies from participating directly in capacity markets, although the impacts of renewable generation should be reflected in lower established capacity requirements. This prevents subsidized technologies from earning excess profits but may not result in optimally designed solar facilities according to the rationale stated above. Improvements to markets can be achieved by setting clear rules and values on required market products to minimize development risk and then modifying subsidies if they are necessary to meet other policy goals, such as carbon reduction and/or security of supply. The effects of pre-existing subsidies will still remain a challenge.

Most markets use some form of historical renewable performance data in defining the capacity value for subsequent years. Although basing renewable capacity values on historical average performance stabilizes revenues to renewable facilities, it does not address system security impacts from year-to-year performance variability unless reserves are increased to account for the increased risk. Several markets (e.g. PJM) have developed capacity performance standards for non-renewable generators that

include penalties for underperformance. Similar standards that hold renewable facilities accountable for declared capacity are appropriate to shift performance risk to the generator from load and motivate improved design and facility maintenance. Additionally, risk studies should be conducted to adjust reserves based on increased system variability.

Any market mechanism should ideally be technologically-neutral, i.e. would apply to all generators on the same terms yet there are differing risk and uncertainties related to each technology. Due to differences introduced by VG, it is necessary to consider a broader range of factors and conduct additional analysis to more accurately determine the system benefits that the VG technology provides. Placing performance risk on each technology may be the most equal determination that a capacity market can provide.

V. ADEQUACY STUDIES CONSIDERING SOLAR POWER

A. Summary of Previous Task Force Paper

While the risk calculation structure is essentially the same for solar as for other renewable technologies, the previous review [2] found that a wider range of capacity value metrics beyond risk-based ELCC or EFC have been used for solar compared to wind. In addition to peak-period capacity factor approaches, these included reduction of peak net demand (i.e. demand minus solar) in a historic series, and metrics representing the amount of storage or demand response which mitigates the variability of the solar power.

B. Methods Underpinning Capacity Mechanisms

Mills and Wiser in a 2012 LBNL report [33] survey solar capacity value approaches in a number of different utility resource planning studies. They note that only Arizona Public Service (APS) and Public Service of Colorado (PSCo) use risk based capacity values in evaluating solar's contribution. More recent utility studies using risk-based approaches include XCEL Minnesota [34] (using risk-based ELCC), XCEL Colorado [35] (which compares ELCC results with a peak-period capacity factor calculation, without giving details of methodology for the former), and the California Public Utilities Commission [36] (which is considering using ELCC as the basis for VG's participation in the capacity market).

PJM [37], MISO [38] (see presentations in the August and December 2015 meetings of MISO's LOLE Working Group) and ISO-NE [39] currently use an average of historic performance for some capacity planning purposes, and Pacificorp (Appendix N on p675 of [40]) use an LOLP-weighted mean capacity factor rather than a simple peak period capacity factor, following [22]. While in principle crediting VG with its mean available capacity may overstate its contribution, this approach is reasonable as long as the installed capacity is small. PJM [41] and ISO-NE [39],[42] both discuss how they incorporate embedded solar in their long term load forecasts, and MISO express an intention to explore ELCC when sufficient data are available.

C. Other Studies Considering Solar Power

In addition to those published by utilities, a number of other recent studies have appeared in the research literature. [43] and [44] investigate realistic embedding of solar's contribution within generation expansion models. [45] describes a large scale study of resource adequacy in the Western Interconnection, including investigation of the effect of choice of adequacy metric on calculated capacity values. [46] presents a calculation of solar capacity value considering both mechanical and resource availability. [47] (and other papers by the same authors) and [48] investigate the capacity value of concentrated solar power.

VI. CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER WORK

This paper has reviewed methods for incorporating solar power in resource adequacy studies. The Task Force regards the following areas as priorities for further research:

- Inclusion of both solar and wind power in the same study, and whether capacity value metrics such as ELCC and EFC may then meaningfully be defined.
- Interaction of VG with operation of storage and demand response.
- Incorporating VG in capacity mechanisms in a way which both reflects its contribution to risk mitigation, and provides correct incentives for capacity investment.
- Joint statistical modelling of VG resource and demand, so as to provide confidence bounds on risk model outputs such as LOLE and ELCC, and also sequential modelling to allow exploration of variability of out-turn about expected values.

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