Assessing capacity value of wind power

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Abstract— **This article is a summary of a review journal article describing some of the recent research into the capacity value of wind power. With the worldwide increase in wind power during the past several years, there is increasing interest and significance regarding its capacity value. This has a direct influence on the amount of other (non-wind) capacity that is needed in future power systems. Recent work that evaluates the impact of multiple-year data sets and the impact of interconnected systems on resource adequacy. We also provide examples that explore the use of alternative reliability metrics for wind capacity value calculations. We show how multiple-year data sets significantly increase the robustness of results compared to single-year assessments. Assumptions regarding the transmission interconnections play a significant role. Results to date regarding which reliability metric to use for probabilistic capacity valuation show little sensitivity to the metric.**

Keywords-component; reliability, resource adequacy, transmission, ELCC, LOLE, LOLP, EUE, LOLH

I. INTRODUCTION

As the capacity and energy share of generation from wind and solar energy has become more significant, the question of how to take variable generation into account in resource (power) adequacy assessment has received more attention. Power system planning and investment activities include assessments of whether the installed level of generation is sufficient to meet demand at some future date. Because it is possible that some generation will be unavailable to help serve system peak demand due to forced outages, planners adopt a target level of generation that accounts for this and other uncertainties. They often refer to firm capacity that can be counted on during peak demand or other high-risk periods. The difference between the target level of generation and peak demand is often referred to as planning reserve. This has often been estimated based on previous experience, as a fixed percentage margin over peak load.

The early wind power additions to the grid were developed primarily as energy resources, providing extra capacity to the power system that was already adequate. The issue of how much of the installed capacity of wind and solar should count toward planning reserve margins was more of an academic question. However, there is more interest to the issue now as wind and solar have started to displace conventional capacity from the market. Moreover, properly valuing the firm capacity contribution from wind and solar will be critical in the future with even higher shares of renewable power. If wind and solar power can deliver a high fraction of installed capacity during high-risk time periods, then the required level of capacity from other sources would be less than if wind or solar provided little capacity value.

There is a significant difference between the installed capacity and the contribution that these variable generation resources could make toward planning reserve. The most rigorous methods that are robust against these large differences between installed capacity and the contribution to planning reserve are grounded in the well-known loss of load probability (LOLP) based probabilistic methods. This is why LOLP and related reliability metrics have been chosen as the preferred method for assessing the capacity value of wind and solar generation. This recommendation was put forward by the IEEE Wind Power Coordinating Committee Task Force paper for wind power [1], approved in The North American Electric Reliability Corporation (NERC) task force report [2], and included in the Recommended Practices for Wind Integration Studies [3]. Other standard, but less-commonly-used, reliability metrics include equivalent conventional power (ECP), equivalent firm power (EFP), and secured capacity [4][5].

In the literature, there are many other, often simplified ways to estimate capacity value, as described in [1]. One common approximation is to use the capacity factor, ideally during the highest LOLP hours, as a proxy for capacity value. Calculating the capacity factor of wind and solar over some subset of hours when the system may have the greatest risk of not meeting the load was made for PJM in the United States [6][7] using three years of wind production data, for hours ending 3:00–7:00pm. The accuracy of these capacity factor methods, however, is very sensitive to both the number of hours used and the methods used to select those hours [8]. The accuracy is also often system and technology specific. For instance, considering too many of the peak-load hours for solar photovoltaic resources [4] or too few of the peak-load hours for wind [8] can underestimate the

respective capacity value. Capacity factor approximation methods that use peak-load hours have also been shown to have decreasing accuracy with higher penetrations [9].

This paper is a summary of review journal article [9] that look at capacity value calculation questions raised in [1] and [2] regarding how many years of data is needed, what is the impact of transmission interconnections to neighbouring areas, as well as the choice of underlying reliability metric.

II. SUMMARY OF RESULTS FOR CAPACITY VALUE OF WIND POWER

An example of results for capacity value for wind power is presented in Figure 1 [10]. There are two main findings. First, the capacity value is often close to the average power produced by wind power (25%–40%) when the share of wind power in the system is small, but adding a larger share of wind power results in a decreasing capacity value. This decrease of capacity value can be seen more dramatically with a smaller system size and more concentrated wind (Norway examples). Second, the results can be very different if there is a systematic correlation of wind with climatic conditions causing peak demand. For example, the New York results show that onshore wind resource is often poor when low temperatures cause the highest loads to occur, and thus the capacity value is only 10%. However, the wind resource offshore is strong even in low temperatures, so the capacity value for offshore wind is as high as 40%. The Minnesota 2006 study calculated capacity value for 3 years and found a significant difference in the annual capacity value of wind among those years.
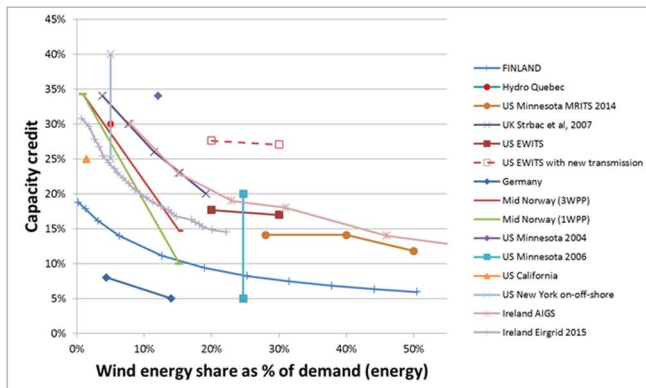

Figure 1. Summary of results for capacity value of wind power for several regions as a function of the share of wind power installed in the system [10].

The results presented in Figure 1 for capacity value of wind power are from the following studies: Germany [11]; Finland [12]; Ireland [13][14]; Canada Quebec [15]; Norway [16]; UK [17]; US New York [18]; US Eastern Wind Integration and Transmission EWITS study [19]; US Minnesota [20][21]; US California [22].

III. IMPACT OF NUMBER OF YEARS OF DATA

Many capacity value studies have used a single year of data; however as there is considerable inter-annual variation in many of the inputs for capacity value evaluation, multi-year data sets are required for robust results.

When conventional resource data is input into LOLP models, one of the relevant variables is the unit's forced outage rate. These are typically determined by size and type of unit and take into account many years of data. Solving the

resource adequacy assessment is determining the level of installed generation needed for a time period that may cover many years in the future.

The key question here is: how many years of wind production data are necessary to produce a reasonable long-term result that is consistent with what is already done for conventional generators?

A. Examples of multi-year analyses

Wind turbine forced outage rates are very low (approximately 1% to 2%) and statistically independent of each other. The primary influence on wind production is wind speed. The question of how many years of wind data are necessary for stable capacity value has begun to be explored. Below, we highlight several studies examining this question.

Zachary et al. claim that the 25 years of data they analyzed for Great Britain is not enough and they present an analysis of prevalent weather patterns during high demand situations to demonstrate the statistical difficulties [23].

Hasche et al. analyzed the question of how many years of data should be used for capacity value in the Irish power system [24]. Using a 10-year data set of demand and wind power production data, they calculated the effective load-carrying capability (ELCC) for various subsets of the data and then compared them to the 10-year ELCC. The objective was to estimate the number of consecutive years of data needed to approximate the long-term average. Therefore, each single year of data was run separately with 1,000 MW of installed wind capacity, and the capacity value (in MW) is calculated and plotted in the first column of Figure 2. Next, all possible consecutive two-year sequences were used to calculate the two-year capacity values, which are plotted in the same graph in Column 2. This process was repeated for 3, 4, … , 10 years. The results show that increasing the number of consecutive years of data improves the results, which tend to converge to the long-term value. Using 8 years of data, the range of capacity value is within approximately 2% of the 10-year value whereas using a single year has a wide spread of results and can under- or over-estimate the result by 10-20%.
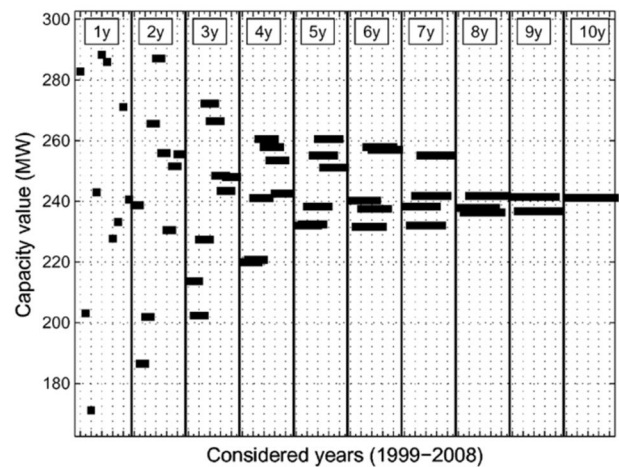

Figure 2. Multiple-year ELCC results for 1000 MW wind power in Ireland [23].

Wind power capacity value for Finland was calculated using 9 years of measured wind power production data [12].

The same data set was employed for [9] to replicate and extend the work by [24]. Similar to the results shown in Figure 2, Figure 3 shows how the capacity value of wind power evolves with increasing number of years. However, the figure uses 35 years of data from National Aeronautics and Space Administration MERRA ReAnalysis. The data set has been trained using real wind power and electricity demand time series with 9 year overlap (see more in Milligan et al 2016). The last (rightmost) set has only two temporally independent 17-year periods (left gray lines). They are still approximately 1.2% from each other. Therefore, even with 17 years of data, there is still considerable uncertainty surrounding the capacity value of wind power. This gives only a lower bound, because using more decades of data could show more variation. Using ReAnalysis wind data for wind power has significant shortcomings, even when the data is scaled to match average historical wind power generation. Consequently, the resulting capacity values are not reliable. However, ReAnalysis data should still give a relevant demonstration for using multiple years in the capacity value calculation. The spread in the ReAnalysis-based capacity value is somewhat higher than it is in the real data, but it shows similar decrease as more years are added.
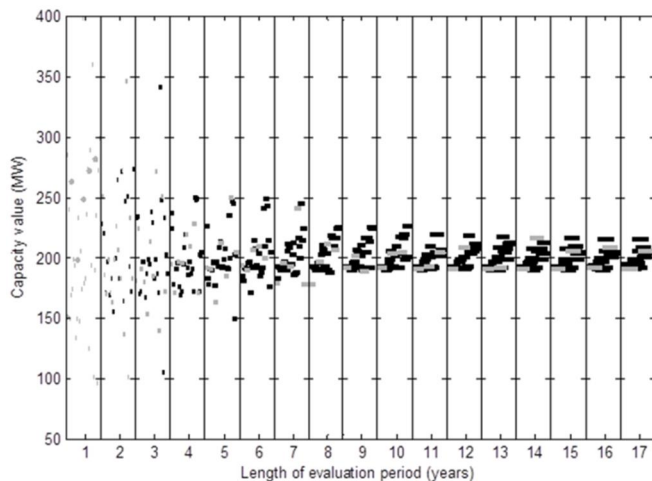

Figure 3. Capacity value of wind power using different number of years for evaluation and based on 35 years of NASA/MERRA data. Grey markers signify independent time series and black markers have partial overlap with some of the other time series.

B. Other data recommendations

Another important recommendation of calculating capacity value of wind power is that hourly demand data and wind data should be paired chronologically [1], to create net demand time series. This is motivated by the concern that there is an underlying weather driver that influences both demand and wind (and solar) energy. For systems with significant hydropower, it is also important to ensure that the underlying weather—and thus its combined influence on demand, wind power and hydro power—is preserved. This may be especially important if the system is energy restricted more than capacity restricted.

When using multiple years of synchronized time series, it should be taken into account that electricity demand does not stay constant throughout the years. Historical time series data for demand contains the impact of economic activity, changes in energy efficiency, and other drivers of demand for electricity—for example, increased use of air source heat pumps for heating instead of direct electric heating. If these changes are not removed, the LOLP is not comparable throughout the years and the capacity value calculation may be mainly based on those years that have had highest non-weather induced consumption. To distinguish the economic or technical changes, it is necessary to have a proxy for their impact. This can be some measure of economic activity like GDP, industrial output for energy-intensive sectors, number of installed new devices, etc. The data can then be used to perform a statistical operation such as regression analysis to estimate how different factors influence consumption along with non-changing signals such as time of day, day of week, temperature, and possibly wind and solar irradiation (e.g. [25][12]). The correlation coefficients can then be used to normalize the changes that should not influence the capacity value evaluation. Finally, expected future changes in electricity demand and wind power can be overlaid on the processed historical data when analyzing future years.

IV. IMPACT OF TRANSMISSION INTERCONNECTION

Modern power systems are generally combinations of networks that are interconnected. This means that if one balancing region experiences shortfalls in generation, this may not result in disconnecting load but could induce an unplanned import from a neighboring system as inertial and governor response increase output from units responding to frequency drops. In other cases, a given system may be short on capacity but has made plans to import capacity from a neighboring system. A situation such as this would likely be handled by including the import in the LOLP calculation. Generally LOLP may not necessarily refer to disconnecting load but may mean that some combination of the following occur: (1) operating reserve margins are not maintained, (2) neighboring capacity is planned to alleviate shortfalls, or (3) unanticipated imports may occur.

Numerous studies have demonstrated the interconnection benefit of reducing LOLP. Interconnecting two non-identical systems will increase reliability (decrease LOLP) in both systems. This is because of the principle of diversity—demand in different areas is only partially correlated. However, the degree of this benefit for a given area depends on its location in the system, the system load level, and the transmission limitations [26].

Multi-area generation reliability analyses can consider tie line and/or transmission line constraints and inter-regional cooperation in addition to the regular reliability considerations. Proposed methods for calculating the multi-area reliability include the "system failure mode" approach that accounts for each failure mode probability and expected capacity [27], Monte Carlo simulations to account for uncertainty (e.g., [28]), modifications to the capacity outage probability table to account for uncertainties and capacity limitations of both the generators and transmission lines [29], and more advanced algorithms that explicitly consider individual components in the network (e.g., minimal cuts method in [30]). This multi-area issue is widely known, and in NERC [2] one of the key recommendations for adequacy studies is to clarify the assumptions regarding transmission interconnections to neighboring system.

Ibanez and Milligan [32] undertook an analysis in the Western Interconnection in the United States to analyze the upper-bound role that transmission could play in resource adequacy assessments. They analyzed alternative wind/solar

build-outs in the West that were taken from the Western Wind and Solar Integration Study Phase 2 (WWSIS-2) [31]. A reference case had 8% annual energy from wind and 3% from solar (29 GW of installed wind and 14 GW of solar). Alternative cases had 33% of annual demand supplied by wind and solar, split evenly, and high wind/ low solar and high solar/low wind combinations.

The analysis compared the ELCC of the full transmission system with three different levels of geographic aggregation that represent alternative levels of interconnectedness: (a) business as usual, in which each balancing authority area operator is constrained by transmission to the neighboring system, (b) regional transmission is a copper sheet but each region is isolated from the remaining system, and (c) perfect transmission exists throughout the interconnection (full copper sheet). The objective of the study was to determine how much effective installed capacity could be replaced by transmission using loss of load expectation (LOLE) analysis. Key results are presented in Figure 4. The graph shows the reduction in required ELCC made possible by perfect transmission within each sub region and by perfect transmission across the interconnection—with Balkanized system planning the total required ELCC needed to achieve 1 day/10 years LOLE is 244 GW, whereas with copper-sheet planning the levels of ELCC needed for 1 day/10 years is 184 GW. Although copper sheet transmission is unlikely to ever be built, the example does show the trade-off between transmission and generation and the impact that transmission can potentially have on the need for new resource additions.

V. IMPACT OF RELIABILITY METRIC CHOSEN

Alternative metrics that are based on LOLE analysis but represent different ways of capturing the risk of inadequacy include loss of load hours (LOLH) and expected unserved energy (EUE). LOLH improves upon the daily LOLE metric, because it evaluates LOLP at every hour of the year, discarding those hours during which there is zero LOLP. In contrast to this hourly treatment, daily LOLE is based on the single peak hour of the day.

A. Comparison of reliabiltiy metrics

Ibanez and Milligan [33][34] undertook some analysis to shed light on the use of LOLH and EUE using models of the U.S. Western Interconnection. These analyses were based on either the WWSIS-2 reference case with 8% wind and 3% solar energy penetration (2014b) or the WECC's Transmission Expansion Planning Policy Committee (TEPPC) 2024 data set with roughly 9% wind and 5% solar capacity penetration [34]. For alternative values of LOLE, the reliability model was run, and a trace was developed to show how LOLH or EUE varied as a function of LOLE. This was performed for several balancing authority areas, subregions, and the entire interconnection. In all cases, the relationship between LOLH or EUE and LOLE is log-linear, with parallel curves for all regions [34]. The differences among the regions depends both on the number and size of the generators (smaller areas tend to have larger slopes), as well as the net load shape (profiles that show higher relative peaks tend to have larger slopes) [33].

Ibanez and Milligan [33] also calculated the impact of these same reliability metrics on capacity value, using equivalent levels of reliability for each metric. The resulting curves had similar shapes, which further confirmed that the various reliability metrics are capturing the same phenomena. The results of this work indicate that the capacity value of wind and solar is relatively robust against the underlying reliability metric, if LOLE, LOLH or EUE are used.

B. Impact of reliability level

LOLE of 0.1 days/year is a common use of the 1 day/10 year standard, but these are not necessarily equivalent since an average annual reliability performance does not capture inter-annual variability among individual years. There has been little if any development of similar LOLH targets or characterizations of the relationship between these metrics for systems with significant wind and solar energy.

Amelin et al. [35] show that the capacity value of a resource is dependent upon the initial system reliability level. It is important to note that if a system is extremely reliable with LOLE $\sim= 0$, then virtually no generator will have any meaningful capacity value. This is because there is essentially no LOLE, and thus there is no way that any generator could meaningfully contribute to lowering LOLE. In many systems, LOLH is 0 for most hours of the year, becoming significantly greater than 0 for a relatively small number of days or hours. The specific days/hours of potential reliability shortfall is dependent on the reliability target that is chosen. It is therefore common to adjust demand or other system parameters so that the LOLE represents a desired target level. An example of this type of adjustment can be found in [32].

VI. CONCLUSIONS AND DISCUSSION

This paper summarizes results and methodology from recent work on the capacity value of wind, based on a WIREs journal article [9]. Areas of analysis and research have continued to show differences in capacity value by location.

Single-year estimates of wind ELCC are not likely to represent the long-term value, and thus decisions regarding overall resource needs will not be well informed. Two studies have shown that eight to nine years of data are needed to provide a robust estimate of wind capacity value.

The contribution of transmission to resource adequacy and the related impact on wind capacity value is critical. It is clear that assumptions concerning interconnections with neighboring systems will be critical to assessing overall resource adequacy and also the contribution that can be made by wind energy.

Alternative LOLE-related metrics appear to make little difference whether daily LOLE, hourly LOLH, or EUE are used as the basis of wind ELCC calculations.

Multi-area methods as well as simplified methods are a research topic that is timely, as wind and solar power start to impact the adequacy of the power systems. At present, there is ongoing work to develop capacity value methods for larger interconnected systems in Europe by ENTSO-E. There is also considerable interest in evaluating new capacity market structures and questions about how this type of market can incorporate the reliability component of capacity value.

Anticipation of large quantities of wind and solar energy on the future grid drives an interest in developing methods to assess flexibility. Work from [36] points toward the development of flexibility-adequacy metrics and, by implication, metrics that can quantify the contribution of different resources to the flexibility target.

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