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Valuing variable renewable energy for peak demand requirements

Ella Zhou*, Wesley Cole, Bethany Frew

National Renewable Energy Laboratory, United States

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ABSTRACT

The capacity credit for a generator is the fraction of its nameplate capacity that can contribute to meeting the system's resource adequacy. However, estimating the capacity credit of variable renewable energy is challenging due to the variability, uncertainty, and spatial diversity of the renewable resources. This study uses the Regional Energy Deployment System to quantify the impacts on the U.S. power sector through 2050 from misestimations of renewable capacity credit. Results show that small underestimates of the renewable capacity credit have little impact on system buildout, but that large underestimates (>50%) can reduce solar photovoltaic deployment by nearly 100 GW (50%) and wind by up to 43 GW (22.8%) in 2030s. Such large differences are possible because the capacity credit for variable renewable energy can substantially impact the overall costs and value of variable renewable energy relative to other technologies. Such effects are most strongly felt in the mid-term but are less relevant over the long-term due to the declining value of variable resources. Underestimating the capacity credit of variable renewable energy leads to increased system costs and emissions. Conversely, overvaluing the capacity credit of variable renewable energy reduces system costs at the risk of lower reliability. Keywords: Wind, Solar, Renewable Energy, Capacity Value, Capacity Credit, Resource Adequacy.

1. Introduction

With the recent rapid increase in variable renewable energy (VRE) deployment—primarily wind and solar photovoltaics (PV)—in power systems across the world, there is a need to understand how VRE generators contribute to resource adequacy. Resource adequacy ensures that there is sufficient generating capacity to support the demand for a target level of reliability [1]. Historically, resource adequacy focused on the peak demand times for a given region. Each generator can contribute up to its nameplate capacity toward the resource adequacy requirement. The monetary value of a given generator's capacity contribution to the overall system adequacy is known as capacity value, and the capacity contribution as a fraction of the generator's nameplate capacity is referred to as capacity credit [2]. In this paper, the acronym "CV," rather than "CC," is used to refer to the average capacity credit of a generator in order to avoid confusion with the commonly used acronym "CC" for combined cycle plants.

While the concept of VRE CV is generally understood, there is no consensus on its treatment or estimation method. As this paper discusses later, the ideal calculation of CV is with reliability-based probabilistic methods. However, in practice (i.e., actual system planning activities and research-based modeling analyses) estimation methods are often used. Some use simple rules of thumb to using averages of historic capacity factors (CFs) during periods of highest system risk [2]. Some use statistical-based methods that aim to link the capacity contribution of a given resource to a desired reliability target [3]. Full probability models are often used in academic studies [4]. Methods used by real system operators tend to be simplistic. For example, MISO does a two-step calculation by first calculating the capacity factor for each wind farm for the top 8 peak load hours of the previous year, then multiply a scalar of $K = 0.65$, which is MISO's ratio of effective load carrying capacity, to the weighted average of the wind farm capacity factors [5]. PJM uses the hourly output data during the prior three summers of operation to calculate the CF to be used in the current year [6]. The resulting CVs can vary widely between these estimation methods, highlighting the importance of ensuring proper method selection when applying CV approaches to long-term planning.

Understanding the contribution of VRE to resource adequacy is increasingly important because VRE is projected to comprise a significant portion of the overall U.S. generator fleet in the next several decades [7], with technology cost reductions driving much of that growth in VRE [8]. Overvaluing VRE could lead to system

* Corresponding author.
E-mail address: ella.zhou@nrel.gov (E. Zhou).

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List of acronyms

CC	combined cycle
CF	capacity factor
CT	combustion turbine
CV	capacity credit; used to avoid confusion with combined cycle (CC)
ECP	equivalent conventional power
EFP	equivalent firm power
ELCC	effective load carry capability
abrIEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
LOLE	loss-of-load expectation
LOLP	loss-of-load probability
NERC	North American Electric Reliability Corporation
PV	photovoltaic
RE	renewable energy, including wind, solar photovoltaic, concentration solar power, geothermal, biomass, and marine and hydrokinetic technologies
ReEDS	Regional Energy Deployment System
VRE	variable renewable energy, including wind and solar photovoltaic

capacity shortages or more-expensive stopgap measures to ensure adequacy, while undervaluing VRE could lead to suboptimal deployment of VRE and a more expensive, overbuilt system. In addition, other elements of the power system such as storage, electric vehicle charging, and demand response are evolving in ways that could change the highest risk hours, which are often used for calculating the CVs of VRE. As a result, it is important that VRE CV calculation methods account for the dynamic interactions of VRE with the broader system.

As more VRE resource is added to the system, the marginal CV of the resource declines due to its coincidental nature with other resources of the same type. The gradual declining CV trend for wind and the benefit from geographic aggregation is documented in wind [9]. The marginal CV for solar PV has a steeper decline than wind CV, even though solar PV's initial CV is much higher [10]. The exact shape of this CV versus penetration curve can vary significantly by region and by resource type, but the shape generally slopes downward. CV levels for PV start higher than those for wind and sharply drops to about 0% CV around 20% penetration levels; wind CV levels start lower than those for PV and slowly approach under 20% CV beyond 20% penetration.

Previous work has established that capturing the downward sloping shape for PV CV is critical for properly valuing the capacity contribution of VREs in long-term planning models [11]. However, it is unclear how accurate that shape must be, as the impact of misestimations of CVs have not been quantified. This study assesses the sensitivity of the VRE CV estimation within a long-term capacity expansion model. This study shifts the CV curve down (and up as a sensitivity) by scaling the wind and PV CVs by certain fixed percentage factors to represent the misestimation of VRE CV. As shown in Fig. 1, this is similar, but not equivalent to, uniformly shifting the curve to the left. The impact on VRE deployment and overall system cost is then evaluated. Furthermore, the results show that VRE deployment is insensitive to the placement of the CV curve as long as CV estimates deviate by no more than about 10% from the actual value.

The purpose of this work is to help system planners, regulators, and other electric system stakeholders understand the consequences of inaccuracy in their CV methods, assuming the underlying CV curve is adequately shaped and other system interactions are properly considered. This paper consists of four parts:

- Literature review of CV assessment methods and the challenges in obtaining accurate CVs,
- Methods for using a capacity expansion model to evaluate the impact of misestimating CV,
- Modeling results including installed capacity, generation, system cost, and emissions, and
- Conclusions.

2. Literature review

A review of the existing literature shows that 1) a wide range of CV assessment methods with different merits are available; 2) VRE brings additional challenges to producing robust CV results; and 3) simplified CV estimation methods are used in planning and analytical models, resulting in inaccurate CV results. These three issues combined makes misestimations of VRE CVs possible in real life. The impact of such misestimations at the U.S. national level has not been quantified. Therefore this paper's contribution to the literature is to quantify the potential impact of misestimations in VRE CVs on the contiguous U.S. power system.

2.1. Capacity credit assessment methods

Abundant literature has covered a variety of VRE CV methods. Milligan and Porter [12] review U.S. wind CV methods and how wind is defined as a capacity resource in different regions. Zhang et al. [14] review solar CV methods and examines the difference between solar CV and wind CV. And Dent et al. [4] review applied studies considering solar power, particularly incorporating VRE in capacity markets. The VRE CV methods can be divided into two broad groups: reliability-based methods and approximation-based methods. Reliability-based approaches use probabilistic methods that are rooted in the loss-of-load-probability (LOLP) and the loss-of-load expectation (LOLE) metrics, which are used to calculate the effective load carry capability (ELCC) of generators [15]. The probabilistic methods are the preferred method for calculating CV, recommended by NERC [16], IEEE Wind Power Coordinating Committee [17], and the International Energy Agency Wind Task 25 [9].

Other similar metrics used in LOLP-based methods include equivalent firm power (EFP) and equivalent conventional power (ECP). EFP of a generator is the capacity of a fully reliable generator (i.e., with a forced outrage rate of 0%) that can be replaced while maintaining the same LOLE. Similarly, ECP is the capacity of a conventional generator (with a positive forced outrage rate) that can be replaced while maintaining the same LOLE. ECP helps to benchmark variable generation CV against that of a conventional dispatchable resource [18]. The CV results based on the ELCC, EFP, and ECP methods are usually consistent [19].

The LOLP-based metric is robust but has a drawback. It only considers the number of days or hours during which the system may experience a capacity shortage, but is not concerned with the magnitude or duration of the shortfall [16]. As a result, other metrics such as expected unserved energy and loss of load hours are also been used. Expected unserved energy is used in a virtual demand curtailment model to endogenously represent the capacity contribution of VRE, in which generator capacities are decision variables, not pre-determined [10]. Loss of load hours is used in a building energy model coupled with a power system model to