8760-Based Method for Representing Variable Generation Capacity Value in Capacity Expansion Models

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1 Introduction

Capacity expansion models (CEMs) are widely used to evaluate the least-cost portfolio of electricity generators, transmission, and storage needed to reliably serve load over many years or decades. Various forms of CEMs are used to evaluate systems ranging from local utilities and regional entities (e.g., WECC 2013; ABB 2016; Mai et al. 2015) to national systems (e.g., Eurek et al. 2016; EIA 2014; EPRI 2017). Global versions have been used in the integrated assessment model (IAM) community to evaluate optimal pathways for decarbonizing the global electricity system (e.g., Pietzcker et al. 2014, 2017; IPCC 2015; Edelenbosch et al. 2017). CEMs can be computationally complex and are often forced to estimate key parameters using simplified methods to achieve acceptable solve times or for other reasons.

In this paper, we discuss one of these parameters—capacity value (CV). We first provide a high-level motivation for and overview of CV. We next describe existing modeling simplifications and an alternate approach for estimating CV that utilizes hourly "8760" data of load and VG resources. We then apply this 8760 method to an established CEM, the National Renewable Energy Laboratory's (NREL's) Regional Energy Deployment System (ReEDS) model (Eurek et al. 2016). While this alternative approach for CV is not itself novel, it contributes to the broader CEM community by (1) demonstrating how a simplified 8760 hourly method, which can be easily implemented in other power sector models when data is available, more accurately captures CV trends than a statistical method within the ReEDS CEM, and (2) providing a flexible modeling framework from which other 8760-based system elements (e.g., demand response, storage, and transmission) can be added to further capture important dynamic interactions, such as curtailment.

1.1 Why Capacity Value Matters: Reliability

Existing grid integration analyses have shown that power systems will require greater levels of flexibility to accommodate higher levels of variable generation (VG) resources, such as wind and solar, which are variable and uncertain[1] (e.g., Mai et al. 2014; Lew et al. 2013; Palchak and Denholm 2014; Bloom and Novacheck 2017). In addition, as VG penetration levels increase, the contribution of these VG resources to reliably meeting load becomes more dependent on the evolution of and interaction with the rest of the system. For example, VG's useful capacity and energy contributions tend to decline as more VG is added to the system due to the coincident nature of the resource with other resources of the same type. Furthermore, the addition of storage or other flexibility options can mute or otherwise modify this trend. While many CEMs account for at least some aspect of this declining VG value trend, associated modeling simplifications can result in inaccurate representations, particularly at higher VG penetrations when the sensitivity and magnitude of the declining VG value trend are amplified.

CV is one key parameter that reflects the reliability attributes of VG resources.[2] Other factors that reflect the impact of VG on an evolving power system, which are outside of the scope of this

[1] Variability means that the output fluctuates over time. Uncertainty means that some of the fluctuations are unpredictable.

[2] CV is often used synonymously with capacity credit, which we assume in this paper. However, we note that at least one technical report (Mills and Wiser 2012) suggested the naming convention of "capacity credit" to represent physical capacity and "capacity value" to represent the monetary value of this capacity (units of $/MWh). Capacity credit (or capacity value as used here) is equivalent to the additional load (units of MW) that the electrical system could serve while maintaining the same level of reliability, which is the Effective Load Carrying Capability (ELCC). As described in Section 2.3, we calculate the CV as the

paper, include ramping capabilities of the thermal fleet, transient stability, system inertia, frequency response, and market rules (Miller et al. 2014; Ela et al. 2014).

1.2 Capacity Value Principles and Methods

CV is a measurement of the contribution of installed capacity to planning reserves and is typically used by power system planners in long-term reliability assessments. For example, a 100 MW generator with a 30% CV would be expected to reliably contribute 30 MW of capacity during the highest "risk" hours. These hours are by definition those with the highest loss of load probability (LOLP) and are often, but not always, the hours with the highest net load (load minus VG). Historically, system planners have ensured that sufficient capacity is built to meet peak load plus an extra planning reserve margin to account for uncertainties, such as forced outages. However, the spatial and temporal correlations between actual load and VG resources ideally require more robust and resolved "risk-based" methodologies for calculating the reliable capacity contribution of these resources as renewables' share in the power system increases (Dent et al. 2016).

Throughout literature and among leading task force groups, e.g., IEEE (Keane et al. 2011; Duignan et al. 2012), NERC (Milligan and O'Malley 2011), and IEA (Holttinen 2013), the preferred method for assessing the CV of wind and solar generation is a probabilistic approach grounded in the well-established LOLP and related reliability metrics (see Milligan et al. 2017 for an overview). Traditional probabilistic methods include convolution-based LOLP or Effective Load Carrying Capability (ELCC) [3], e.g., Keane et al. (2011) for wind and Duignan et al. (2012) for solar. ELCC can be calculated with a reliability model or by directly using historic hourly load and VG data, but some studies suggest that 8 years of data are required to account for inter-annual variability and converge on long-term values (Hasche et al. 2011; Milligan et al. 2017). Using these methods, CV can be calculated for conventional generators, VG resources, and storage.

Numerous factors impact the CV of VG resources. These include broader system interactions and operating constraints, as well as assumptions regarding the quality and quantity of data used to calculate CV. Ideally, CVs account for the impact of other system components, such as transmission, storage, and flexible load resources. For example, the impact of geospatial diversity—including the spatial distribution of VG resources, intra- and inter-regional transmission interconnections, and outages of these units and lines—can impact the contribution of local generators, storage devices, and reserve requirements to meeting resource adequacy and real-time energy balancing requirements (Milligan et al. 2017; Ibanez and Milligan 2012). Similarly, thermal fleet operating constraints can limit the useful contribution from those units as well as from VG resources. In addition, the quality, quantity, and resolution of data used for calculating CV can, in some cases, significantly over- or under-estimate the resulting CV outputs, highlighting the importance of ideally using sub-hourly, error-free, measured load and VG resource data from multiple years (Gami, Sioshansi, and Denholm 2017).

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fraction of nameplate capacity that contributes to the top peak net load hours; this is done for existing wind and PV generators, as well as the "marginal" value for potential new wind and PV deployment.

[3] LOLP and related methods were first introduced by Calabrese (1947). These methods convolve together, at a minimum, load data with generator capacity and forced outage data to quantify the probability (LOLP) and expected value (LOLE) of a system outage. ELCC is the contribution (units of MW which can then be reported as a fraction of the installed capacity to represent CV) that an additional resource provides to meeting the system's load while maintaining a fixed system-wide reliability level.

In practice, such as in utility resource planning studies, a variety of methods are used to calculate VG CVs. These methods range from risk-based ELCC approaches, to using averages of historic performance for various geographic areas and/or time periods, to using a simple peak period capacity factor or other simple rules of thumb (Dent et al. 2016; Mills and Wiser 2012). Some planning entities use CEMs to design candidate portfolios, which consist of a diverse set of possible resource fleets to meet various system and regulatory requirements, for assessing capacity needs (Mills and Wiser 2012); the methods presented in this paper are of direct relevance to such efforts.

1.3 Capacity Expansion Model Capacity Value Simplifications

Within CEMs and similar planning tools, the ideal calculation of CV and other variability metrics requires an explicit co-optimized investment-dispatch treatment with many years of time-synchronous VG and load data at an hourly or subhourly resolution. Because of data and computational limitations, existing CEMs typically approximate system dispatch with simplified methods, including the use of a subset of hours from a full year, screening curves, and other duration-curve-based approaches to evaluate generator performance and select the optimal mix of units (Sullivan et al. 2014; Ueckerdt et al. 2017).

Approximation methods specifically for CV can be broadly divided into two categories. First, CV can be estimated as the ELCC by relating the addition of new capacity and LOLP, e.g., Z-method (Dragoon and Dvortsov 2006) and Garver's method (D'Annunzio and Santoso 2008; Garver 1966). The second category approximates CV as the capacity factor, either based on the hours of highest risk, e.g., Hale et al. (2016), Milligan and Parsons (1999), Madaeni et al. (2013), and Pietzcker et al. (2017), or predefined by VG resource supply bins (Sullivan et al. 2013). Across both of these categories, improvements have been suggested, including better defining supply bins or model "timeslices" to capture key, distinct periods of VG and load alignment (or misalignment) to more accurately represent CV within those bins or timeslices (IRENA 2017).

However, many of the above simplifications are prone to inaccurate estimations of the impact of VG on the broader power system, particularly when (1) only a subset of hours are included, (2) the hourly time-synchronous interactions of load and VG resources are not explicitly captured or are averaged across a larger time block, or (3) pre-defined distributions or other relationships are used to extrapolate the impact of VG to higher penetration levels and different system buildouts. For example, ReEDS formerly estimated CV using the Z-method (Dragoon and Dvortsov 2006), which assumes normal distributions for the contribution of VG to meeting load at a fixed reliability LOLP level within each model timeslice. As we show later in this paper, these underlying distributions sometimes resulted in CV trends that failed to capture the sharply declining value of PV capacity at high penetration levels. Furthermore, the use of timeslices often yielded abrupt jumps in CV between timeslices.

We contribute to this broader set of CV approximation methods by implementing an improved approach to characterizing reliable capacity contributions within the ReEDS CEM. This updated ReEDS methodology is based on the commonly used load and net load duration curves[4] to

[4] Other variants of load duration curve methods, such as "residual load duration curves" (RLDCs) to represent capacity, energy, and curtailment characteristics, have been used in IAMs (Ueckerdt et al. 2015, 2017; Collins et al. 2017). IAMs generally require more simplified temporal and spatial treatment to accommodate greater model complexity from inclusion of all energy sectors and carriers, all world regions, and the full 21st century.

estimate the contribution of VG to system capacity during high load and net load hours. This method considers time-synchronous hourly generation and load values across all hours of the year ("8760 data"), thereby capturing tail events that can be missed by simplification methods that only use a subset of hours from a year, or by statistical methods requiring load and resource distribution assumptions that may not match actual distributions. Our method also takes into account how the system evolves within each of the scenarios. Other methods, such as those based on exogenous functions or binning, lack this sort of self-consistent framework and could therefore result in erroneous extrapolations. Furthermore, our approach offers flexible application to any year and model given availability of 8760 data, as well as a flexible platform that can include additional model features (e.g., storage, demand response, and transmission). We apply this approach to the ReEDS CEM and compare annual CV outputs for wind and PV, demonstrating improved accuracy with only a modest increase in computational burden relative to the former ReEDS statistical method.

2 New ReEDS CV Methodology

2.1 ReEDS Overview

ReEDS is a CEM of the contiguous United States developed in the General Algebraic Modeling System (GAMS) (Eurek et al. 2016). ReEDS optimizes the regional mix of technologies that meets physical and policy requirements of the electric sector at least cost. The model is spatially resolved into 134 load balancing regions. Load balancing, reserve requirements, and most policy and operational constraints are applied at these 134 regions. These regions are also aggregated into 18 Regional Transmission Operators (RTOs) that very roughly represent regional cooperation areas (Figure 1). ReEDS is temporally resolved into 17 timeslices to capture seasonal and diurnal variations in load and resources. The model previously estimated CV using a statistical approach that considered simple summary metrics (variance and expected value) from the underlying hourly load and resource data within each of these 17 timeslices. ReEDS optimizes investment decisions within 2-year solve periods, sequentially solving from the present day system out to the model horizon of 2050. The CV parameters are updated between each of these 2-year solve periods.

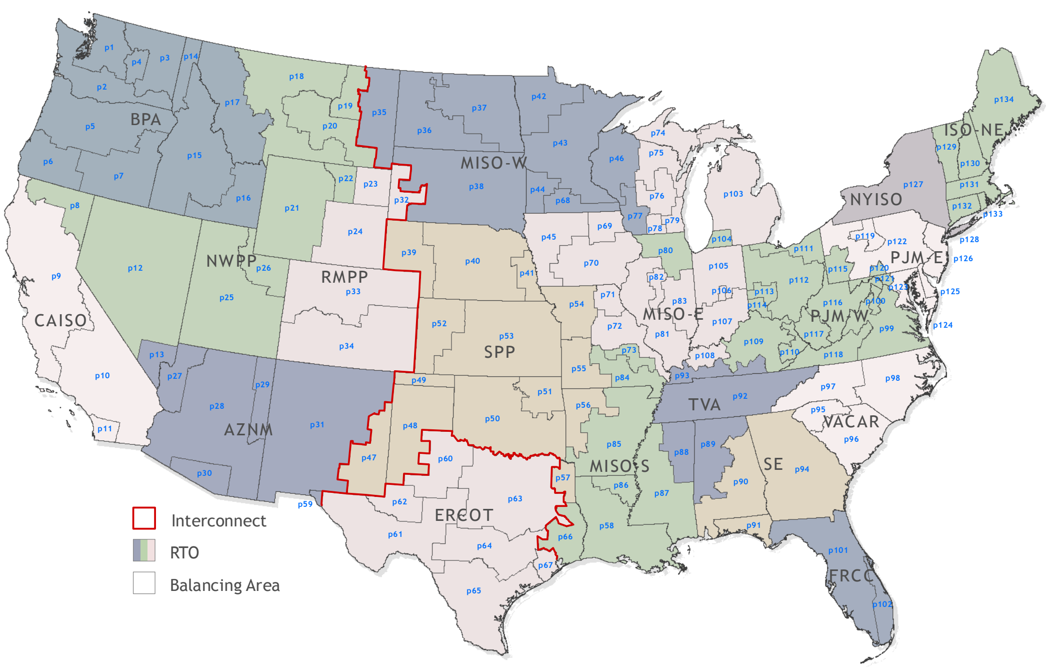

Figure 1. Map of ReEDS 134 "Balancing Area" regions and 18 “RTOs”

2.2 New ReEDS 8760-Based Method

The improved methodology for calculating CV presented here is based on explicit hourly (8760) tracking and dynamic interaction of load and VG resource, with the capability to add storage, transmission, and other operational factors in the future. The CV calculations use a capacity factor proxy that is applied to top hours in load and net load duration curves (LDCs and NLDCs).

Figure 2 shows how the current ReEDS 17-timeslice approach misses key information in the load and net load duration curve tails that are captured by an 8760 methodology, as explained previously. The solid lines show the current ReEDS methodology that uses 17 representative timeslices, which are identified by numbers above the curves. The placement of these timeslices can significantly differ between the load and net load duration curves (blue versus red) based on the VG contribution within each timeslice, as reflected by the different ordering between the blue and red numbers. The dashed lines show the new ReEDS method using the 8760 time series. The new 8760-based methodology, which estimates an annual CV, is better able to capture the highest load and net load hours on the duration curves, thereby supporting a more accurate representation of CV.

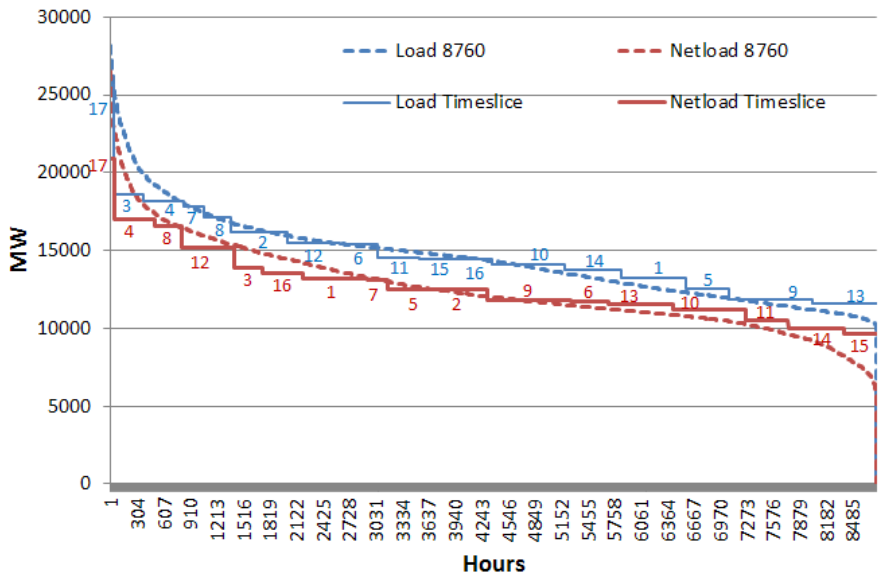

Figure 2. Representative load and net load duration curves for a single ReEDS region

Timeslice identifiers are shown above the duration curves.

To calculate CV, we use the 8760 Module that is written in R (Figure 3). The 8760 Module runs outside of the core GAMS-based ReEDS code between each 2-year solve period. The 8760 Module implements the installed VG generator capacities from the previous 2-year solve period in ReEDS, as well as 8760 VG and load time series. The raw 8760 load data is adjusted based on ReEDS inter-regional transmission flow results to account for the imports/exports between regions. This 8760 Module returns the existing and marginal CVs.[5] The 8760 Module is designed with the flexibility to incorporate additional 8760-based features, such as the capability for explicit chronological treatment to estimate curtailment and storage usage; this aspect is a key focus for future work.

[5] We refer to "existing" CV as the reliable capacity contribution from resources that have already been deployed in the model prior to the buildout of additional "marginal" resources.

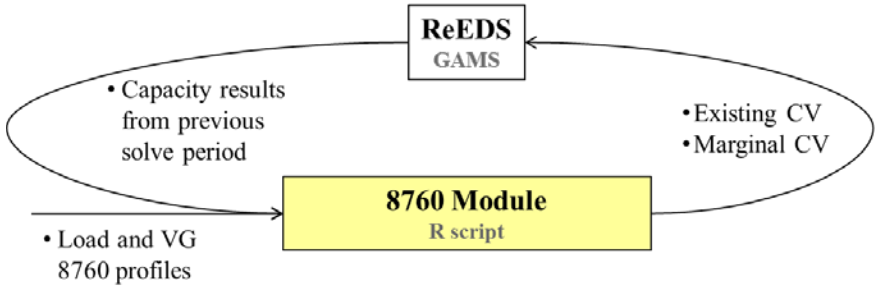

Figure 3. ReEDS data flow for new 8760-based CV methodology

2.3 New ReEDS Capacity Value Calculation

The improved ReEDS method for calculating CV uses duration curves of load and net load for the entire year. The method was developed in coordination with the CV method implemented in NREL's Resource Planning Model (RPM) (Hale, Stoll, and Mai 2016) and is similar to the approach used by the International Energy Agency's World Energy Model (IEA 2015).

Figure 4 is a graphic representation of the new ReEDS CV methodology. The LDC reflects the total load in a given modeling region, which is sorted from the hours of highest load to lowest load and is shown by the blue line. The NLDC represents the total load minus the time-synchronous contribution from VG, where the resulting net load is then sorted from highest to lowest, as shown by the solid red line.[6] The NLDC(δ), which represent further addition of VG resources, can be created by subtracting the time-synchronous generation of an incremental capacity addition from the NLDC, where the resulting time series is again sorted from highest to lowest; this is shown by the dashed red line.

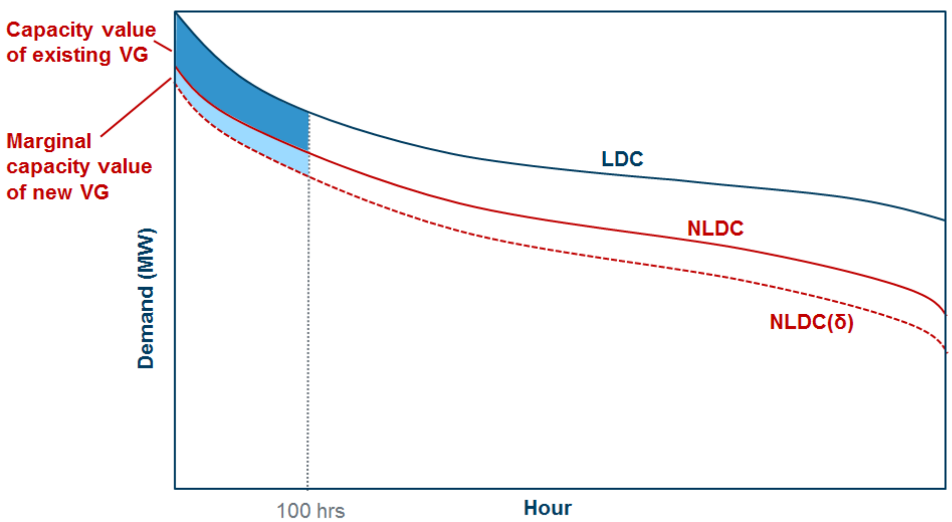

Figure 4. LDC-based approach to calculating CV

The amount of load that the existing VG capacity can meet while maintaining the same level of reliability is the ELCC. We calculate the ELCC as the difference in the areas between the LDC and NLDC during the top 100 hours of the duration curves, as shown by the dark blue shaded area in Figure 4. These 100 hours are a proxy for the hours with the highest risk for loss of load,

[6] Residual LDC (RLDC) is an equivalent term to NLDC used in the literature.

i.e., LOLP.[7] Similarly, the contribution of an additional unit of capacity to meeting peak load is the difference in the areas between the NLDC and the NLDC(δ), as shown by the light blue shaded area in Figure 4. We assume 100 MW for the incremental capacity size of new solar and wind builds in ReEDS; see Section 3.1 for a discussion on the sensitivity of this incremental value. These areas are then divided by the corresponding installed capacity and number of top hours (100 in this case, but this can be flexible) to obtain a fractional annual-based CV.

The resulting CV values then feed into ReEDS (right side flow arrow in Figure 3) to quantify each VG resource's capacity contribution to the planning reserve requirement, which is based on North American Electric Reliability Corporation planning reserve margin assessments and the peak load by region. This use of CV within a planning reserve constraint is consistent with many other CEMs and IAMs (IRENA 2017). Thus, these CV metric inform the investment decision of new VG by impacting the *capacity*-based value of those new VG additions.

In the ReEDS 8760 Module, these calculations are done by region and technology for the existing CV, and by region, technology, and resource class[8] for the marginal CV. For existing VG units, the user can define the regional level to either the 134 ReEDS regions or the 18 broader RTO regions. All marginal calculations are performed at the 134 region level. Future work will refine the intra- and inter-regional transmission impacts.

[7] We currently use only a single year of wind, solar, and load data to calculate CV. Expansion of this method to use multiple years of data would increase the robustness of this calculation.

[8] In addition to VG regions and technology types, ReEDS further categorizes VG resources into resource quality classes with corresponding resource supply curves.

3 Verification of New ReEDS Capacity Value Method

Because the CV is an explicit calculation based on the load and net load profiles, the CV outputs from the 8760 Module were verified against a manual calculation of the difference between the load and net load in each of the top 100 hours. Figure 5 shows existing and marginal PV and wind CV outputs from the 8760 Module, which matched the manual verification calculations. In this figure, the wind generation level was held constant while PV capacity alone was increased to achieve higher VG penetration levels. Thus, the marginal PV CV values diminish at higher VG penetration levels due to the coincident nature of the solar resource, while the existing and marginal CV of wind slightly increases in response to the shifting peak net load period to more windy (and less sunny) hours. This reduction in marginal PV CV is consistent with the literature, which shows rapid decrease in capacity contribution beyond 20% penetration levels (Mills and Wiser 2012).

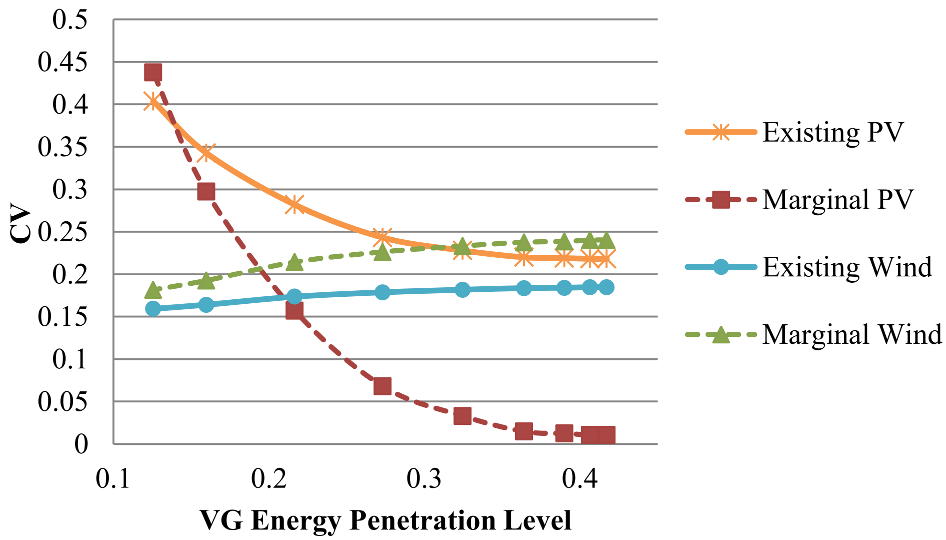

Figure 5. Existing and marginal CV outputs from ReEDS and manual calculation

3.1 Sensitivity of Incremental Capacity Size

The new ReEDS CV methodology assumes a static 100 MW increment size ("incCap") for new wind and solar builds. This means that the marginal CV calculated with this additional 100 MW of new capacity is assumed to scale linearly for any buildout quantity in the following 2-year ReEDS solve period. Consequently, this 100 MW selection may not represent actual capacity deployment increments. For example, if the marginal CV based on the 100 MW increment is 50%, and ReEDS builds 2000 MW of this high quality resource, then the model may be over-valuing some portion of this 2000 MW capacity addition.

To understand the impact of this assumption on marginal CV values and capacity deployment, we compared five sensitivity cases with various incremental capacity sizes: 50, 100, 250, 500, and 1,000 MW. The 1000 MW case captures at least the 75th percentile of all wind and PV regional and resource class level buildouts across all model solve years. As shown in the left pane of Figure 6 for PV, the marginal CV generally decreases with increasing incremental capacity size. The marginal CV also declines over time as the penetration level increases. However, as shown in the right pane of Figure 6, corresponding deployment is very insensitive to the choice of incremental capacity size. Similar results were observed for wind. The insensitivity of these results suggests that any capacity increment in this range (50-1000 MW) would have a limited effect on deployment and, thus, supports our use of 100 MW for the marginal CV calculations. In other words, as long as VG installations for any given region/technology/resource class do not significantly exceed 1000 MW, then the choice of the incremental capacity size for the marginal CV calculations is inconsequential.

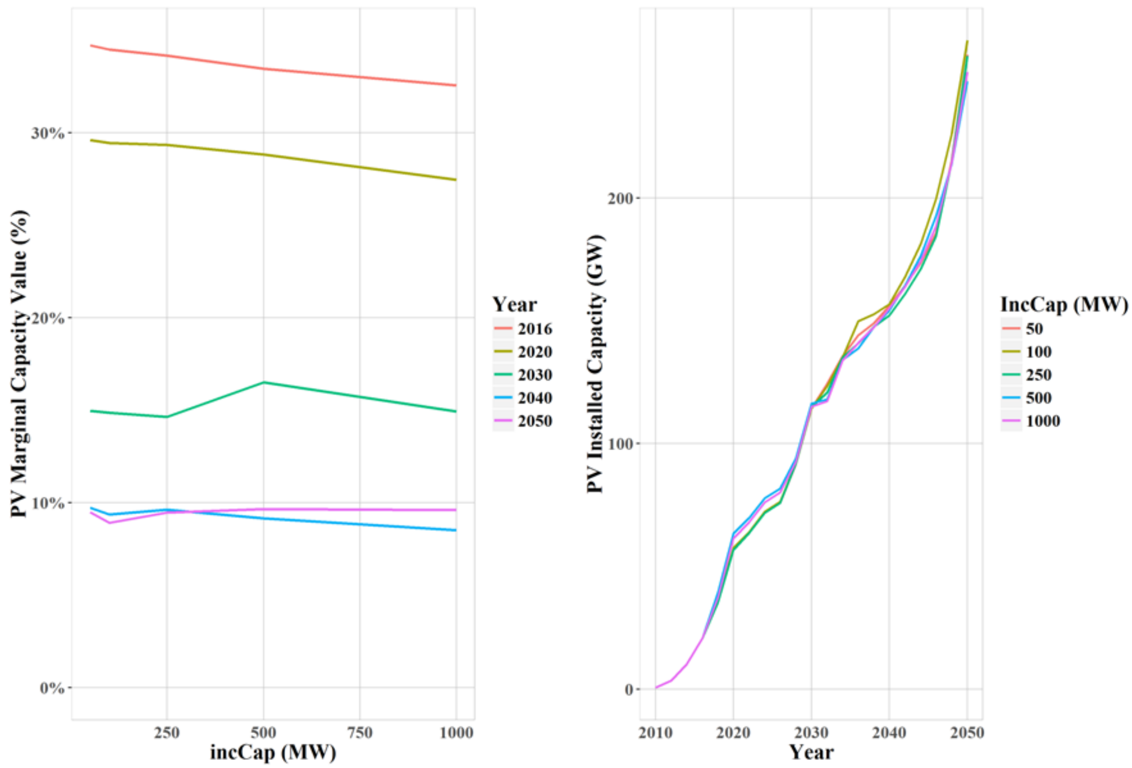

Figure 6. (Left) National PV marginal capacity value (median value across resource regions) by incremental capacity value at 2016, 2020, 2030, 2040 and 2050, respectively; (Right) National installed PV capacity by year for different incremental capacity value selections

4 Comparison of Former and New ReEDS Capacity Value Methods

Results to date suggest that the new 8760 Module offers a more accurate representation of VG CV in ReEDS than the former statistical approximation method with less than a 10% increase in solve time. The marginal PV CV outputs derived by the former ReEDS statistical method and the new 8760 method are shown in Figure 7 for two regions with high quality solar resource: Austin, Texas (left pane) and Southern California (right pane). Note that the former ReEDS method calculates CV at the timeslice level, while our new method reports annual CV outputs. To provide a more equal comparison, we show the former method CV outputs from the timeslice with the largest marginal value ("binding timeslice") in the planning reserve constraint. This is often, but not always, the summer afternoon or evening timeslices.

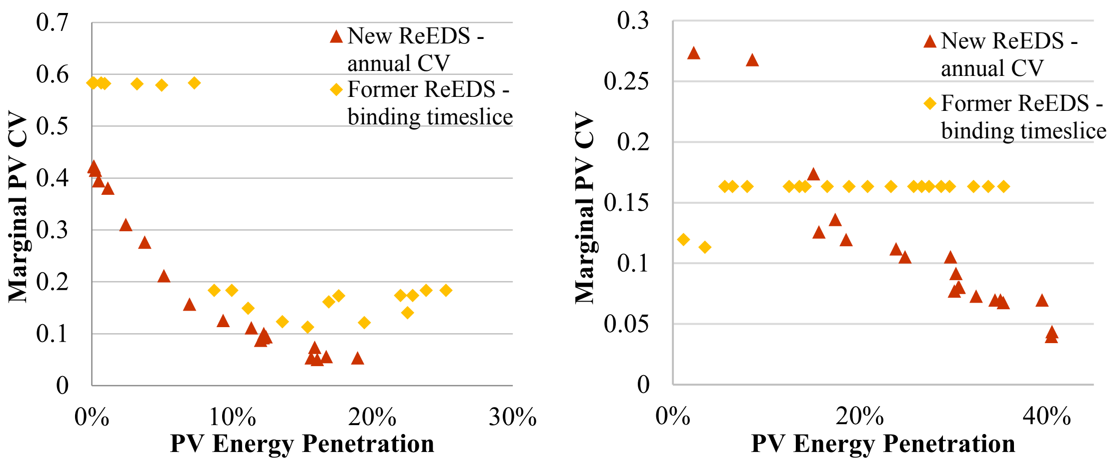

Figure 7. Incremental PV CV using the former and new ReEDS CV method in the Austin, Texas region (left) and Southern California region (right)

The new ReEDS method better captures the declining value of capacity with increasing VG penetration levels. Previous work has shown, and Figure 7 supports, that the former ReEDS CV method yields abrupt changes in CV between the different timeslices, particularly between summer afternoon and evening (Sigrin et al. 2014). These results can be seen in Figure 7's left pane by the sharp drop in the former ReEDS method marginal CV around the 7% PV penetration level, where the planning reserve constraint binding timeslice shifts from summer afternoon to evening (yellow diamonds). Furthermore, as the right pane shows, the coarse timeslice-based values in the former ReEDS method often estimate persistently high CVs for PV even at relatively high penetration levels. The new 8760-based method (red triangles), which looks across the top 100 net load hours to calculate an annual CV, results in a smoother and more rapid decline in CV.

For PV, the new 8760-based ReEDS method also often yields larger CVs at lower penetration levels, as shown in the right pane of Figure 7, where the marginal PV CV with the new ReEDS method is nearly twice as large as the CV calculated by the former ReEDS method at penetration levels below about 18%. As we will see later, this drives greater PV deployment in early ReEDS years with the new CV method.

At the national level, the new ReEDS CV method tends to produce more consistent CVs across wind penetration levels as compared to PV. Figure 8 shows the national median marginal CV for wind and PV, each as a function of their respective technology energy penetration levels. PV CVs tend to decline more rapidly than wind with increasing energy penetration levels. This is driven by the stronger correlation of solar with load than wind, resulting in larger PV CV values at low penetration levels when the solar resource is coincident with both peak load and net load hours. Solar's strong correlation with load occurs in most of the United States, which typically experiences summer afternoon peaking load. However, as the penetration level increases, this strong PV-load correlation pushes out high solar-producing hours from the top 100 *net load* hours included in the CV estimation. This shift in high-risk periods from summer afternoon to the early evening, which causes the deterioration in the capacity value of solar PV at higher penetration levels, has been noted in the literature, e.g., (Munoz and Mills 2015). Similar to Figure 5, this PV CV trend aligns well with the results in Mills and Wiser (2012), where the marginal CVs rapidly decline as the PV penetration level nears 20%. In contrast, wind-producing hours maintain a more consistent presence in these top net load hours to yield more constant marginal CVs on a national median basis across the penetration levels included in Figure 8. We note, however, that at the regional level, these CV results vary depending on the existing fleet and resource profiles. This is particularly true for wind which is more spatially diverse than PV. For the limited penetration levels observed in Figure 8, wind CVs fall within the values observed in other grid integration studies (Holttinen et al. 2016), though the values vary significantly across the different regions reflected by those studies, typically declining to near 5% above ~30% wind penetration levels.

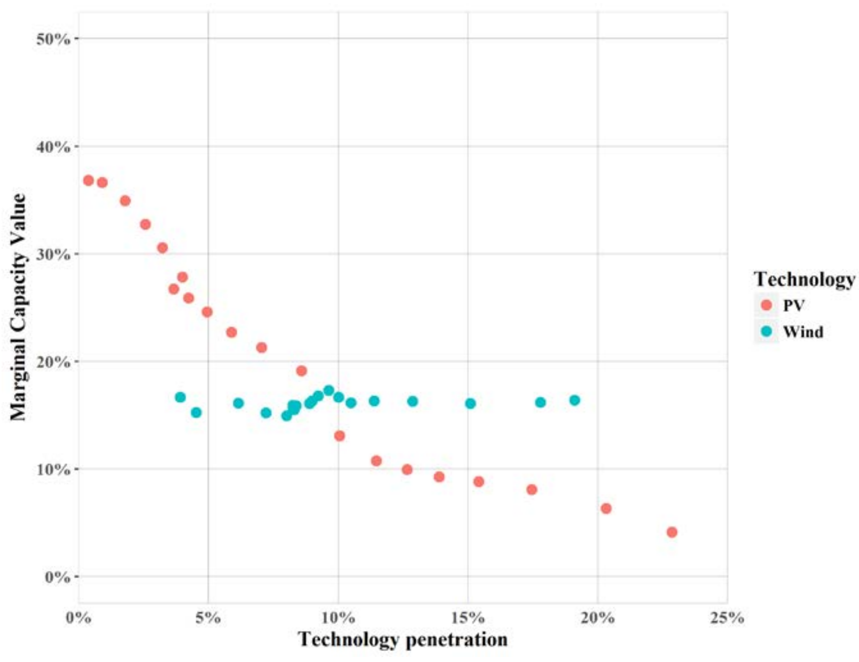

Figure 8. National median marginal CV for PV and wind as a function of their respective energy penetration level with the new ReEDS CV method

Figure 9 summarizes the impact of the new ReEDS CV method on overall model deployment results. As previously discussed, PV capacity value is higher in the earlier years, driving greater PV deployment with the new CV method, while the opposite trend is observed in later years. This PV deployment trend is primarily a tradeoff with wind. As shown in the example in Figure 9, the end result in 2050 is 120 GW less cumulative PV capacity and 44 GW more wind capacity as compared to the capacity buildout with the former ReEDS CV method.

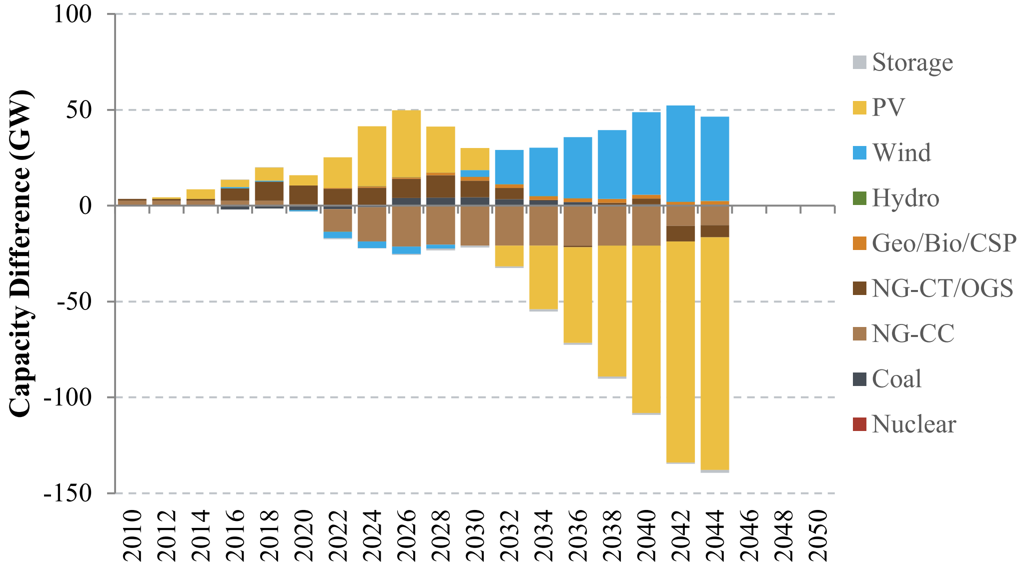

Figure 9. Difference in nationwide cumulative installed capacity between new and former ReEDS CV methods (new minus former).

With the new 8760-based CV method, ReEDS has 44 GW more wind capacity and 120 GW less PV in 2050.

5 Summary and Future Work

Accurately reflecting the impact of VG on system reliability and flexibility in CEMs is increasingly important as VG penetration levels grow. CV is a key parameter that reflects the reliability attributes of system generators. The ideal calculation of CV requires capturing the interaction of the entire generator fleet, storage, and transmission on both existing and potential new VG installations. Various methods exist for approximating CV in CEMs, though many are based on a representative subset of hours that can miss important tail events and/or time synchronicity issues.

In this paper we have demonstrated that our approach provides an improved representation of CV trends in the ReEDS CEM by explicitly capturing these load and VG interactions across all 8760 hours of the year, with a specific focus on the top 100 net load hours as a proxy for the highest LOLP hours. This method improves upon the former statistical method that assumes normal distribution for the contribution of VG to reliably meeting load. These assumed distributions may not match actual distributions, especially at higher VG penetration levels. Results revealed that this statistical method sometimes yielded CVs that failed to capture the declining contribution of PV capacity at high penetration levels. Additionally, by calculating an annual CV, the new 8760 method avoids abrupt jumps in CV between timeslices that was previously observed with the former ReEDS CV method. The 8760 approach implemented in ReEDS could be applied more broadly to CEMs at many different scales where hourly resource and load data are available, greatly improving the representation of challenges associated with the integration of variable generation resources.

Our initial results verified our CV calculations and justified our incremental capacity size assumption. Future work will continue to improve the CV estimation and application within ReEDS by applying multiple years of underlying 8760 data to capture inter-annual variability; validating the choice of 100 top hours for our CV calculations; investigating the appropriate values to use for reserve margins within the planning reserve constraint; and developing methods for calculating CV for non-VG technologies including storage.

While this improved CV approach is based on the widely used load and net load duration curves, the modeling framework under which this method is built provides a flexible platform to incorporate additional 8760-based features, including chronological operation (e.g., storage, minimum generation constraints, demand response, and transmission). This capability allows our 8760 approach to further capture important system interactions, such as curtailment, without the computationally costly economic dispatch optimization of a more detailed operational model. Future work will incorporate such a capability to estimate curtailment and potential reduction in curtailment enabled through deployment of storage and more flexible operation of select thermal generators.

6 Acknowledgements

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