

Simplified Methods for Renewable Generation Capacity Credit Calculation: A Critical Review

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Abstract—Capacity credits are widely used to quantify the ability of different generating technologies to support demand. Most practical capacity credit calculations are based on detailed risk modelling, however a wide range of simplified approaches are also in use. This paper presents a critical review of these simplified approaches, ranging from annual peak calculations and probabilistic representations of wind, to closed-form expressions derived for small installed wind capacities. The principal themes are that simplified methods must retain the key features of the problem at hand, and that to be of interest simplified methods must either bring substantial computational advantages, or provide additional insight beyond that from a more detailed risk calculation.

Index Terms—Wind power generation, Power system reliability, Power system modeling

I. INTRODUCTION

THE concept of capacity value is widely used to quantify the contribution of different generation technologies to supporting demand. The concept was developed many years ago in the context of all-conventional-generation systems, but has been a topic of increasing interest in recent years due to the qualitatively different contribution between the contributions of conventional and renewable technologies to supporting demand. As long as a conventional unit is mechanically available, and has sufficient fuel, then it is able to generate at full rated capacity. In contrast, renewable technologies such as wind, wave and solar generation rely on sufficient natural resource being available, and hence even a fully mechanically available unit might not be able to generate at rated capacity.

Capacity credits are variously defined in terms of the additional demand which new generation can support, by comparison with the load-carrying ability of conventional plant, or in terms of the probability distribution for available capacity at time of peak demand. As a consequence, the IEEE Power and Energy Society has set up a Task Force to survey this range of methods and report on best practice [1]. The task force has concentrated on studying capacity value approaches based on detailed risk calculations; as a complement to its work, this paper provides a critical review of the wide range of simplified approaches in use.

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These simplified approaches to capacity value calculation range from annual peak-based calculations and probabilistic representations of wind, to closed-form expressions based on linearising the mathematical models used about zero installed capacity. The key theme of the paper is that there are two principal reasons for using simplified calculations:

- They may be more transparent, and give more insight into what drives the results, than approaches based on more detailed risk calculations.
- They may require less computational resource.

It should be noted that (at least provided that network effects are not considered) the required risk calculations do not pose great computational requirements, and that the potential benefits of simplified approaches in terms of run time are therefore limited. Another key requirement of any useful simplified approach is that must capture the key features of the real-life problem; in particular some simplified approaches might not adequately account for the relationship between resource availability and demand (this is less of an issue when the simplified approach is used for greater insight, as opposed to the primary purpose being the numerical result.)

The paper begins with a brief review of the purpose of capacity credits, and detailed methods for their calculation (Section II). This section also briefly discusses simplified treatments for conventional generation. The rest of the paper reviews and evaluates the various simplified approaches:

- Section III: annual-peak-risk-based approaches.
- Section IV: the Garver approximation, based on a time series risk calculation and probabilistic wind representation.
- Section V: the z-method, based on linearisation for small additional generation capacities. This is the most detailed entirely closed-form approach to capacity credit calculation, and is therefore particularly valuable in revealing transparently what factors drive capacity value results.
- Section VI: capacity value definitions based on distributions for available generating capacity, without explicit reference to demand (and hence to system adequacy risk.)
- Section VII: simple ‘toy’ models used to explain more detailed capacity value results. An example is given based on large tidal barrages.

All examples presented except that in Section VII consider wind generation, but the ideas presented can be generalised to other renewable technologies. Finally, conclusions, including general messages from the paper, are presented in Section VIII.

II. CAPACITY VALUE DEFINITIONS

A. Definition and Purpose of Capacity Value

1) Definition:

The concept of capacity value quantifies the contribution of generating units or technologies to securing demand. There are various specific definitions in the literature, for instance:

- *Effective Load Carrying Capability (ELCC)*. The extra demand which an additional generator can support without increasing the value of a chosen risk index [2].
- *Comparison with load carrying capability of conventional plant*. This might either be in terms of the conventional capacity which can be displaced without increasing risk, or by direct comparison with the load-carrying ability of a test conventional unit, e.g. [3].
- *Percentile of peak-period availability distribution*. The capacity credit of the new generation is defined as a chosen percentile (e.g. the lower 5th percentile) of the probability distribution for its available capacity at time of peak demand [4], or alternatively in terms of the increase in a chosen percentile of the distribution for total available generating capacity when the new generation is added [5].

We believe that the first of these (ELCC) provides the best capacity metric, as it requires fewer parameter choices to define the calculation, and moreover load may naturally be varied within a simulation; it is still possible to compare the results with the ELCC of conventional plant. The last (distribution percentiles) might not take full account of any relationship between resource availability and demand; this will be discussed further in Section VI. The second (direct comparison with conventional plant) requires properties of the conventional plant to be defined, which is inevitably somewhat arbitrary due to the variation in availability properties and unit sizes between technologies.

2) Purpose:

Beyond the definition above, the importance of the concept of capacity value lies in the transparency of the results. A full risk calculation (e.g. that underlying the ELCC method presented next) provides the most comprehensive view of system risks within the scope of the calculation. However, such complex algorithms generally are not very transparent in demonstrating which factors drive the results which are obtained. This is why capacity value calculations are important; they provide a means of visualising the contribution of different generating units and technologies to supporting demand.

Unlike load factor over a period (which is defined as [mean output] / [rated capacity]), the ‘capacity value’ is not a quantity which can be calculated directly from observed data. Indeed, as there are a variety of possible definitions and calculation methods, there is not (even in principle) a single definitive value for the capacity value of a given generator; as a result we refer to *simplified* rather than *approximate* calculations. The capacity value should therefore be seen as an indicative quantity used as a visualisation tool, rather than something more precise. Also, capacity value calculations usually look at each technology in isolation, and do not consider any relationship between their respective availabilities (e.g. different

technologies’ availabilities being driven by weather systems, or having diurnal cycles.) The full risk calculation result naturally considers this interaction.

As well as the straightforward matter of visualising different technologies’ load-carrying abilities, capacity values have been used for a number of applications, including:

- Calculation of an effective plant margin in systems with substantial renewable penetrations [6], [7].
- Such an effective plant margin provides a simple means of imposing a capacity requirement constraint in economic forecasting models (e.g. page 21 of [8]).
- Capacity credits are used in the all-Ireland electricity market’s capacity payment algorithm [9]

B. ELCC Methods Based on Detailed Risk Calculations

1) General Approach:

The following paragraphs describe a detailed, time-series-based method for capacity value calculation; this ELCC/Loss of Load Expectation method has been adopted by the IEEE PES Task Force on Capacity Value of Wind as its preferred approach [1]. This falls firmly into the category of detailed but non-transparent calculations, as discussed in the Introduction to this paper. The description is included here as a point of reference for the simpler approaches described later.

The informal description of ELCC described above is made more specific by the following three-point algorithm:

- 1) Calculate the value I_0 of the risk index before the additional generation is introduced.
- 2) Introduce the additional generation to the risk calculation. The risk index will then decrease.
- 3) The ELCC of the additional generation is the extra demand which returns the risk to its original value I_0 .

As there is not usually a closed form expression for the equation which must be solved (i.e. [risk index with new generation] = I_0), the bisection or secant methods provide efficient means of solving this [10].

2) Loss of Load Expectation:

The definition supplied above is independent of the risk index used. Perhaps the most common index used in capacity credit calculations is Loss of Load Expectation (LOLE), the expected (in the mathematical sense) number of periods (e.g. hours, half hours, days) in which available generation is insufficient to support demand.

There are two common approaches to including renewables in an LOLE calculation:

- Use a probabilistic model for the available renewable capacity, based on historic data (e.g. [11]).
- Use the historic time series directly in the risk calculation (e.g. [12]).

The second, time series, approach is used here, as it very naturally captures the available statistical information on relationships between resource availability in different regions, and the relationship between resource availability and demand. When forming a probabilistic model, there is a danger that information on such relationships will be lost during the data processing.

The LOLE calculation including a single renewable resource (this generalises to multiple resources in the obvious way) is then expressed as

$$I^{\text{LOLE}} = \sum_t p(X_t < d_t - r_t), \quad (1)$$

where d_t is the historic demand, and r_t is the available renewable power calculated from historic records. The historic demands might be scaled using a measure of underlying (weather corrected) peak demand level, so that the risk calculation is performed for a chosen future predicted demand level.

C. Approximate Distributions for Conventional Output

The distribution for the available conventional capacity X_t would typically be derived using a Capacity Outage Probability Table (COPT) calculation [13]. It is well known that such a random variable, which is itself the sum of a large number of random variables, may be approximated by a Normal distribution in some window about its mean [14] (the COPT calculation would usually give ‘fatter’ distribution tails than a Normal approximation.) Despite its limitations, the Normal approximation brings substantial advantages in terms of ease of use and transparency of expressions; when these factors are given priority, it is therefore worthy of consideration when it gives a reasonable fit to the COPT distribution.

Other, more sophisticated ways of approximating the COPT result have also been proposed, for instance the Gram-Charlier expansion [15]. These do not have the transparency of the Normal approximation, so their use would have to be justified mainly on grounds of computational efficiency. However, as long as rounded unit capacity data is used to avoid exponential growth in the calculation size, using modern desktop computing power there is little or no difficulty in performing full COPT calculations. As a result, nowadays methods such as [15] are much less likely to bring major benefits than they were when first proposed several decades ago.

III. ANNUAL PEAK CALCULATIONS

A. ELCC Based on Peak LOLP

As discussed above, ELCC may be calculated based on any risk index. One alternative to the time-series based LOLE calculation described in the previous section is loss of load probability at time of annual peak demand. The input data requirements for the LOLE calculation are then probability distributions for available conventional capacity, available wind capacity, and demand, all at time of annual peak demand.

B. Great Britain Risk Model

In this section and for other GB examples, the initial generation capacity considered is the 75.4 GW of conventional connected to the Great Britain system, as specified in the 2008/09 Winter Outlook published by National Grid as Transmission System Operator [16]. Each unit is assumed to supply either zero or maximum capacity to the system; the ‘assumed availabilities’ from the Winter Outlook are used

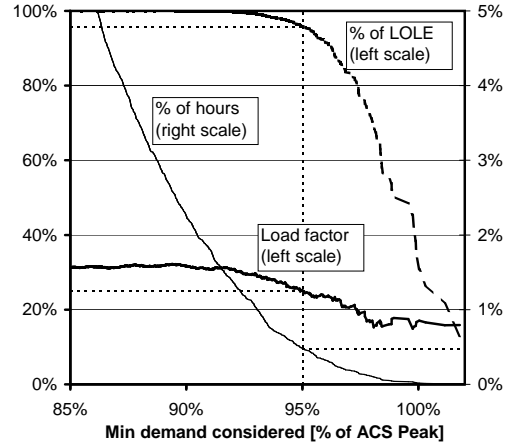


Fig. 1. Variation in the quality of the wind resource at high demands in Great Britain. Thin solid line: % of hours with demand above that on the x-axis. Thick solid line: mean load factor across hours with demand above x-axis. Dashed line: % of LOLE contained in these hours, considering conventional plant only (see Section III-B for the conventional plant model.) e.g. the 0.5% of hours with demand above 95% of peak contained 96% of the LOLE, and across those hours the mean wind LF was 24.5%.

as the unit availability probabilities. While individual unit availabilities are assumed to be independent, each generating station’s capacity contribution is capped at its Operational Realisable Capability, as determined by National Grid [17]. The resulting distribution, derived from a capacity outage probability table-like calculation [13], has mean 64.86 GW and standard deviation 1.98 GW.

C. Limitations

One limitation of annual peak calculations is that by definition they give a less complete picture of system risk than time-series based calculations. It is clear that generation shortages do not necessarily occur at times of absolute peak demand, and that an annual peak-based calculation does not explicitly recognise this.

The key limitation, however, is the available data on wind generation at time of annual peak demand; by definition, the number of data points is very small. It is therefore necessary to base the distribution on times where demand is close to peak, rather than at absolute peak. This may be problematic if the quality of the wind resource varies with demand at very high demands, in which case the resource at demands just below peak might not be representative of the resource at absolute peak; as a consequence, great care must be taken to ensure that an annual peak calculation correctly accounts for the wind-demand relationship. This issue is indeed realised in Great Britain, as shown in Fig. 1.

It is therefore difficult to give a sufficiently realistic picture of the risk in an annual peak calculation. Moreover, this approach does not meet the two key tests of a useful simplified approach stated in the Introduction. As discussed earlier, because LOLE calculations are not very computationally intensive, there is little opportunity for worthwhile improvements in run time arising from simplified calculation methods. Without further approximation, annual peak calculations are also not necessarily more transparent than LOLE approaches.

It should also be noted that if a robust annual peak calculation is required, the LOLE approach may be most appropriate. This statement may seem to be contradictory at first, as LOLE is explicitly not an annual peak index. However, the consideration of each period's LOLP focuses the LOLE index strongly on the hours of highest risk, and might therefore be regarded as an appropriate means of weighting the hours to assess the wind resource at time of peak.

IV. THE GARVER APPROXIMATION AND PROBABILISTIC REPRESENTATIONS OF WIND AVAILABILITY

A. The Garver Approximation

1) Description:

In 1966, Garver published a simplified approach to ELCC calculation, in which the calculation method could be expressed graphically [2]. In the 1960s such simplified techniques had great value in terms of reduced computational requirements, but this value has diminished in recent years as full time series calculations have become feasible using reasonably-priced desktop PCs.

Garver's original paper considered a two-state model for conventional units only; it has been extended in [11] to consider multi-state units. It relies on two key approximations:

- The wind generation is represented probabilistically; the probability distribution for wind availability is the same at all times, and is thus independent of demand.
- The LOLE before addition of the wind may be approximated as Be^{md_0} , where d_0 is the peak demand, and m and B are fitting parameters.

The ELCC (\bar{d}) of the wind generation is then calculated as

$$\bar{d} = -\frac{1}{m} \ln \left[\sum_i p_i e^{-mw_i} \right], \quad (2)$$

where p_i is the probability that the available wind capacity is w_i .

2) Garver: 'Peak Season' or 'Annual Peak' Approach?:

Great Britain ELCC results using the Garver approximation, with a peak demand of 60 GW, are compared with an annual peak-based ELCC calculation with a fixed demand of 60 GW in Fig. 2 (the conventional plant model is described in Section III-B.) These two approaches are also compared with a full time-series/LOLE based ELCC calculation. The probability distributions for wind availability in the peak and Garver calculations are the same, and results are shown basing this distribution on hours between 10%, 5% and 3% of annual peak demand.

It is clear that, in this example system, the Garver results are much more similar to those from the annual peak calculation than to the LOLE-based results. This is a consequence of the Garver approximation's neglect of the dependence between the wind availability distribution and the demand level, despite its use of LOLE as the underlying risk index. Detailed examination of the proof in [11] shows that the Garver approximation's risk calculation effectively combines the results from fixed demand peak calculations with a range of demand levels, weighting them according to risk. This explains the similarity

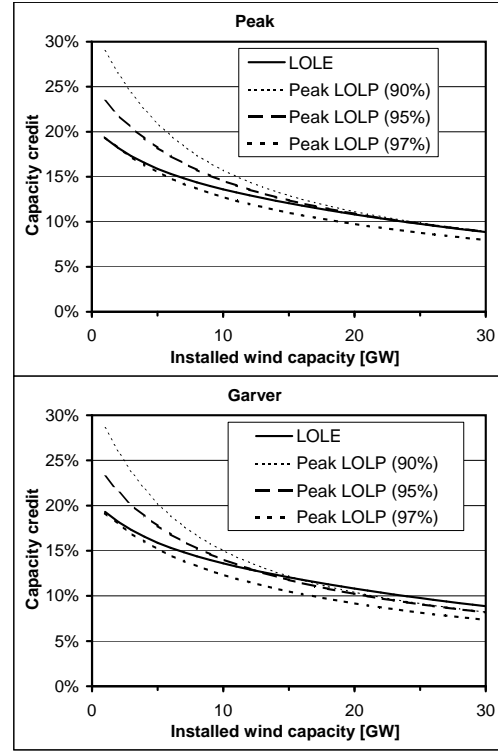


Fig. 2. Garver approximation results compared with an annual peak calculation.

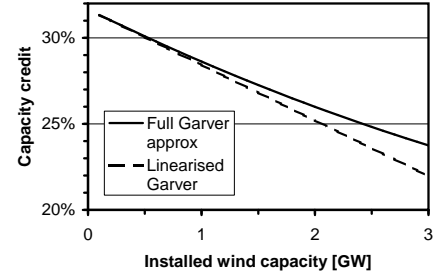


Fig. 3. Comparison of results between the full (2) and linearised (3) approximations. The ACS peak demand is 60 GW, and the wind distribution based on hours where demand is within 10% of ACS peak.

between the Garver and peak results for GB in Fig. 2, and implies that the same will be observed in Garver-based results for any system.

3) Linearised Garver approximation:

For small installed wind capacities, (2) may be linearised to give the more transparent expression (presented for the first time here)

$$\bar{d} \simeq \bar{\mu} - \frac{mc}{2} \bar{\sigma}^2, \quad (3)$$

where $\bar{\mu}$ and $\bar{\sigma}$ are the mean and SD of the probability distribution for available wind capacity. Results using this are compared with those from the full expression (2) in Fig. 3; the underlying risk calculation is the same as in Section IV-A2.

For this GB example, the linearised Garver expression is only a good approximation to the full Garver result for installed wind capacities somewhat below 2 GW; it is therefore not a useful approach for practical capacity credit calculation.

Its utility thus depends on whether it can bring additional insights. The dependence of \bar{d} on the parameters on the right hand side of (3) is certainly very transparent. m , however, is not a simple parameter of any of the distributions involved, which complicates the interpretation of (3). A more transparent linearised expression (the z -method) will be discussed in Section V.

B. Probabilistic Representations of Wind Availability

1) Simple Probabilistic Representations:

It is clear that if a single probability distribution for the available wind capacity at each time is used in an LOLE calculation, without taking proper account of any dependence between wind availability and demand, the ELCC results will resemble quite closely those from an annual peak calculation with the same distribution (as observed for the Garver approximation in Section IV-A).

A probabilistic approach which did model sufficiently the relationship between wind and demand would not show this same effect. However, such a multivariate probabilistic approach would lose at least some of the benefits in terms of simplicity which this class of methods possesses; indeed, the necessary data processing may be more complex than that required in a historic-time-series based LOLE calculation, and it is uncertain whether there would be any compensating benefits in terms of quality of results.

2) Synthetic Time Series:

An alternative probabilistic approach is to use synthetic time series, which are designed to have similar statistical properties to the real historic time series, e.g. [18], [19]. Where limited historic data is available, this allows generation of a longer time series for use in Monte-Carlo simulation. If they model in sufficient detail temporal correlations in resource availability, diurnal effects, the relationship with demand etc., synthetic time series can certainly provide more realistic results than the simple probabilistic approaches discussed previously. However, they will not be considered in detail here, as they do not fit in the category of ‘simplified approaches’.

V. Z-METHOD

The z -method is an approximate peak-demand-LOLP-based ELCC calculation. It is of particular importance, as it is the most detailed completely closed-form capacity credit approach available. As a result, it transparently confirms various intuitive points about what drives capacity credit results. As it based on a linearisation in the installed capacity of the new generation, it is not of great use for practical computation of the ELCC of entire wind portfolios; it may however give a reasonable result for the ELCC of individual wind farms or conventional units provided the assumptions made are reasonable. These assumptions are explored here using an example based on the Great Britain system.

A. Theory

1) General Theory:

The z -method for peak-period capacity credit calculations was introduced in [20]; this section clarifies the assumptions

involved and the method’s derivation. It is based on an assumption that, when the new generation is added in the ELCC calculation, the shape of the probability distribution for available capacity does not change. Defining the random variable S (mean μ_s , standard deviation, SD, σ_s) as the surplus of supply over demand, this assumption implies that the normalised variable $Z = (S - \mu_s)/\sigma_s$ has the same distribution before and after addition of the new generation. Its value at zero surplus, $z_0 = -\mu_s/\sigma_s$, may then be used as a proxy for LOLP in the ELCC calculation.

Defining

- μ_0 and σ_0 to be respectively the mean and SD of the surplus S before addition of the new generation,
- $\bar{\mu}$ and SD $\bar{\sigma}$ to be the mean and SD of the available capacity from the new generation,
- \bar{d} to be the ELCC of the new generation,

then by definition once the new generation is introduced to the distribution for surplus margin, and \bar{d} to the demand, the risk remains constant. Equivalently z_0 remains constant:

$$z_0 = \frac{-\mu_0}{\sigma_0} = \frac{\bar{d} - \mu_0 - \bar{\mu}}{\sqrt{\sigma_0^2 + \bar{\sigma}^2}}, \quad (4)$$

giving via a leading-order Taylor expansion in $\bar{\sigma}/\sigma_0$:

$$\bar{d} = \bar{\mu} + z_0 \left(\sqrt{\sigma_0^2 + \bar{\sigma}^2} - \sigma_0 \right) \simeq \bar{\mu} + \frac{z_0 \bar{\sigma}^2}{2\sigma_0}. \quad (5)$$

This is the most general completely closed form formula available for the ELCC of additional generation. It transparently confirms the intuitive understanding that the benefit of adding new generation should increase as system reliability decreases (i.e. z_0 becomes less negative), and decrease as the new generation’s mean availability decreases ($\bar{\mu}$ decreases) or its output becomes more volatile ($\bar{\sigma}$ increases).

2) Conventional Units:

If the new generation consists of n conventional units, each of which has capacity c and availability probability a , then $\bar{\mu} = nca$, and $\bar{\sigma}^2 = nc^2a(1 - a)$. This leads to a closed form expression for the capacity credit of conventional plant κ , derived here for the first time:

$$\kappa = \frac{\bar{d}}{nc} \simeq a \left(1 + \frac{z_0(1 - a)c}{2\sigma} \right). \quad (6)$$

Similar linearised expressions could be derived for alternative capacity credit definitions, such as comparison of load carrying capability with that of a test conventional unit.

B. Great Britain Example

1) Risk Model:

The probability distribution for available conventional capacity is as described in Section III-B. The risk index used in the calculation of ELCC in this section is winter peak Loss of Load Probability (LOLP). A fixed demand is assumed, equal to the underlying, weather-corrected annual peak demand as published by National Grid (termed ‘Average Cold Spell’, or ACS, peak demand [16].) In the following, capacity credit results calculated using an explicit COPT-based risk calculation are compared with the z -method approximation.

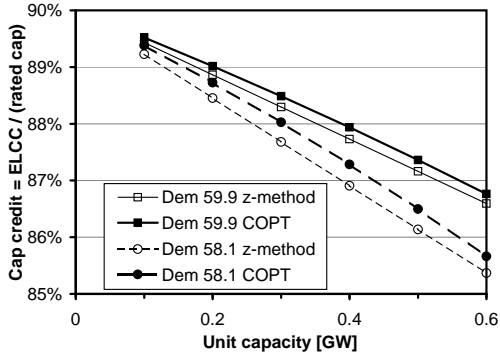


Fig. 4. Comparison between z-method approximation and COPT calculation for capacity credit of a single additional conventional unit.

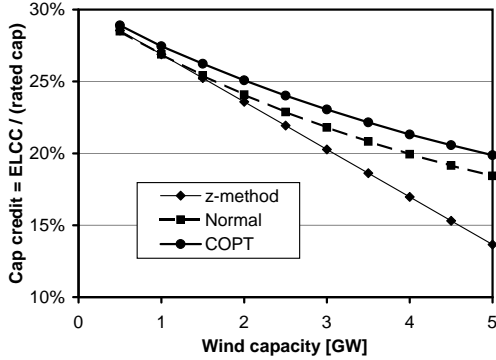


Fig. 5. Comparison between z-method approximation and 'exact' calculation for capacity credit of a portfolio of wind generation in Great Britain.

2) ELCC of Thermal Units:

Capacity credit results using (6) are compared in Fig. 4 with the 'exact' calculation for two different fixed demand levels:

- 59.9 GW: the ACS peak demand forecast for winter 2008/09 [16] (published in October 2008).
- 58.1 GW: the actual ACS peak demand for winter 2009/09. The drop is partly explained by the economic downturn and by demand response to high prices [17].

The results are for new units with availability $a = 0.9$. The linearised expression (6), as well as being a good approximation to the COPT calculation, transparently explains the trends in the capacity credit as the unit capacity and demand are varied. Moreover, the z-method is useful for practical calculations of the ELCC of individual conventional units, as the linearisation required in the method's derivation is then valid (i.e. the SD of the available capacity from a single conventional unit is very small compared to the SD of the distribution for total available capacity, $\bar{\sigma} \ll \sigma_0$.)

3) ELCC of Small Wind Portfolio:

Results for the capacity credit of a wind portfolio are presented in Fig. 5. The probability distribution for the available wind load factor is based on the wind data published in [16], considering only hours where demand was within 10% of peak. This wind load factor distribution has mean 30.2%, and standard deviation 22.9%. The three calculations use:

- 'z-method': the z-method expression in (5); the only information on the wind availability distribution is thus

its mean and SD.

- 'COPT': COPT distribution for conventional plant, and the full wind distribution, are used in the ELCC calculation.
- 'Normal': as COPT, except a Normal distribution is used for conventional plant; the full wind distribution is still considered.

The approximation is only good at small wind penetrations, when the linearisation required is valid (for large wind penetrations the SD of the distribution for available wind capacity becomes comparable with the SD of the distribution for conventional capacity.)

As it essentially linearises the risk calculation about zero wind capacity, the z-method approximation might be expected to be best at small wind capacities. This is indeed realised in Fig. 5, but it is tangent to the result using a Normal distribution for available conventional capacity, not the COPT-based calculation. This observation will be discussed next.

This method would be equally valid for calculating the ELCC of individual wind farms, when added to a large portfolio of conventional plant. There is little prospect of extending the method to higher wind penetrations, as the shape of the distribution for available capacity would certainly then change on adding the new generation, and the linearisation required would not be valid.

4) z-Method and Normal Approximation:

An *explicit* assumption in the z-method's derivation is that the shape of the distribution for available capacity does not change on adding the new generation; no explicit assumption about the shape of this distribution is used.

The observation that the z-method is a better approximation to the Normal distribution than the COPT-based one, made for the first time in Section V-B3 of this paper, suggests that the above explicit assumption carries an *implicit* assumption that the unchanged distribution shape is actually Normal;

The Central Limit Theorem implies that the sum of a large number of independent random variables will be approximately Normally distributed, as long as no one variable dominates the sum¹. If the wind capacity is small enough, these conditions remain satisfied for the available capacity distribution even after the wind is added (a Normal approximation for the wind distribution itself is not required.) Therefore, following the addition of a small wind capacity, the Normal approximation for the total capacity remains reasonable, implying that (5) is a valid approximation to the capacity credit.

VI. CAPACITY CREDIT DEFINITIONS BASED ON AVAILABILITY DISTRIBUTIONS ALONE

A. Probabilistic Approaches

A number of publications have presented capacity credit calculations based on percentiles of distributions for available capacity alone (whether considering wind in isolation, or the conventional fleet also). This section discusses these approaches; one (guaranteed capacity) is closely related to ELCC, whereas others do not directly consider system risk.

¹More strictly, the CLT states that as the number of variables tends to infinity, the cumulative distribution function tends pointwise to that of a Normal distribution [14]

1) Guaranteed Capacity:

The concept of ‘Guaranteed Capacity’ is commonly used in German studies, e.g. [5], [21], [22]. For a given generation fleet the statistically guaranteed available capacity, at a level of security of supply of $100\alpha\%$, is defined as the level of available capacity which is exceeded with probability α (or equivalently the demand which gives an LOLP of $1 - \alpha$). The capacity credit of new generation is then defined as the increase in statistically guaranteed available capacity when the new generation is added. The results do not depend strongly on the risk level chosen (Fig. 12-6 of [21]).

This is approximately equivalent to an annual peak-based ELCC calculation, where the demand level has been adjusted so that the risk measure meets a pre-defined target. Such a practice is quite common in capacity credit calculations, as it can improve comparability of results between studies [1], or ensure that the capacity credit result reflects a long-term sustainable adequacy risk level rather than short term fluctuations about this. An example of the latter in Great Britain is that at present the margin of installed conventional capacity over demand is very comfortable [6], but that a number of older nuclear and coal stations are expected to close shortly, due either to age alone, or new emission restrictions [23].

2) Wind Availability Distribution Percentile:

Another approach to assigning wind a capacity value is to define the capacity value as a certain percentile of the probability distribution for available wind capacity at time of peak demand. For example, in [4] the capacity credit is defined as the available wind capacity which is exceeded with probability 95%. This approach makes no direct reference to the effect of wind generation on system adequacy risk, and hence gives a much less comprehensive picture of wind’s contribution to supporting demand than ELCC. Moreover, the capacity value assigned will clearly depend strongly on the arbitrary choice of percentile; this is in contrast to the weak dependence on the chosen risk level in the guaranteed capacity approach.

B. Load Factor-Based Approaches

Peak-period load factors have sometimes been used as capacity credits. For instance, [24] discussed PJM’s use of the mean load factor across the hours between 1500 and 1800 in June, July and August to assign a capacity value to wind generation.

It is a truism that load factor is essentially an energy metric; it is defined as the actual energy generated as a percentage of theoretical maximum. It therefore gives very limited information on generation adequacy risk, which is a matter of capacity rather than energy. In particular, system risk levels are generally determined by probability of either very low generation availability or very high demand, whereas load factor by definition considers typical conditions only. Load-factor-based approaches are therefore unlikely to deliver a sufficiently comprehensive picture of wind’s contribution to securing demand.

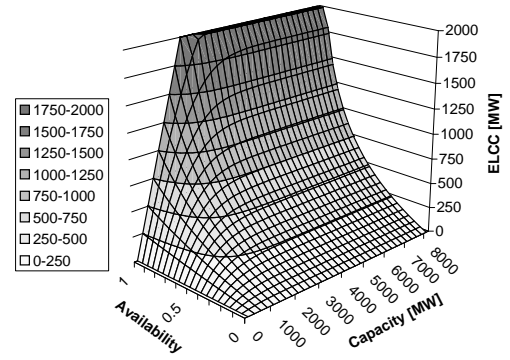


Fig. 6. Dependence of ELCC of two-state tidal barrage on capacity and availability.

VII. ‘TOY’ MODELS OF INDIVIDUAL TECHNOLOGIES

A simple ‘toy’ models might be of great help in explaining what drives the capacity value of an individual technology, without any intention that the model should be used for practical capacity value evaluation. This will be illustrated here using a simplified model of tidal barrage generation, which has not previously been published.

A. Tidal Barrage Generation

Tidal barrage schemes harness the potential energy gained by sea water as the tide rises and falls to generate electrical energy [25]. The proposed Severn Barrage scheme in Great Britain is an ebb generation scheme [26]; water would enter a tidal basin behind the barrage through sluices as the tide rises, the sluices would be closed at high tide, and power would be generated in a similar manner to a hydro plant once the tide has fallen sufficiently to give a large enough head.

Detailed simulations of barrage output reveal its ELCC (in a system with no other tidal generation) to be surprisingly low, at less than 10% of rated capacity [27]. This phenomenon may be explained using a simple two-state model of the barrage.

B. Simplified Severn Barrage Model

1) Description:

The simplified model assumes:

- Fixed demand d of 61 GW.
- Normal distribution for available conventional capacity X , with mean 64.88 GW and SD 1.92 GW.
- Barrage modelled as a single two-state conventional unit, with available capacity c available with probability a at peak, and zero capacity available with probability $1 - a$.

The ELCC \bar{d} is then given by solving:

$$F_X(d) = aF_X(d + \bar{d} - c) + (1 - a)F_X(d + \bar{d}) \quad (7)$$

2) Results and Discussion:

The dependence of the ELCC on the capacity c and availability probability a in the simple barrage model are shown in Fig. 6. As expected, for any installed capacity the ELCC increases as the availability probability increases. The ELCC increases with installed capacity up to capacities of about 2

GW, but above that is almost constant as the capacity increases further. This is because, for large capacities, when the barrage is available the half-hourly LOLP risk is reduced to almost zero; almost the same effect occurs independently of the precise installed capacity. Because the availability probability is quite small (indeed for an ebb-only scheme in realistic operational modes it must be less than 0.5), the resulting ELCC is very small as a percentage of rated capacity. This simple model thus transparently reveals the consequences of tidal barrage generation being truly intermittent (having a substantial probability of zero output), as opposed to a wind generation fleet which will quite often produce very little output, but very rarely produce none at all.

VIII. CONCLUSIONS

This paper has reviewed and evaluated simplified methods for capacity value calculation. The common theme running through the analysis is that a simplified method should be used in preference to a more detailed one if it gives a useful reduction in run-time, or if it provides greater insights. As (at least as long as a network model is not used) a time-series based calculation is not computationally challenging with modern computing power, it is unlikely that great run time benefits can be achieved in practice. Simplified methods must also clearly achieve a minimum level of realism; in particular they must model adequately any relationship between resource availability and demand.

Of particular interest is the z-method, which is the most detailed completely closed form expression for capacity value available; it linearises the mathematical model used about zero capacity of the new generation. This transparent closed form result therefore provides valuable insights, even if it is not valid for large renewables fleets. Simplified ‘toy’ models for individual technologies can also provide valuable insights (a model for tidal barrage generation is outlined here.)

Other approaches might not pass the transparency or realism tests. Annual peak-based calculations require a probability distribution for available renewable capacity, which might be hard to obtain if there is strong variation with demand in the quality of the wind resource. They are certainly easier to perform than time-series calculations, but are not necessarily more transparent. Another well-known method is the Garver approximation; this can handle large renewable capacities, but does not fully account for the relationship between resource availability and demand, and is not particularly transparent as the formulae involved are not completely closed form. Among approaches which do not explicitly consider the demand level, the ‘guaranteed capacity’ approach is roughly equivalent to an peak-based ELCC calculation using a target demand level; other approaches based purely on the distribution for available capacity from the new generation may not consider the generation adequacy risk in sufficient detail.

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