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Capacity Value of Offshore Wind in Great Britain

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Abstract

The extent to which large volumes of offshore wind can contribute to a secure and reliable electricity supply is the subject of much debate. Central to providing credible answers is a detailed understanding of the wind resource and its variability in time and space. Here, a mesoscale atmospheric model was employed to create a ten year hindcast of British onshore and offshore wind speeds and simulate the output of a British offshore wind fleet. This enabled estimation of the capacity value of British wind fleets both on- and offshore during periods of high winter demand. It provides a credible estimate of the distinct long-term contribution of production from a future British offshore wind fleet and indicates substantial improvement over onshore wind. Further, a first level analysis demonstrated that the availability of offshore wind farms had a modest negative impact on the capacity value of wind but that conventional generation and demand levels played a more significant role.

Keywords: Capacity value, offshore wind generation, mesoscale modelling, power system risk.

Introduction

Integrating large amounts of variable renewable generation into the electricity network presents a significant challenge and is the subject of much debate. This is particularly true in Great Britain (GB) where wind generation is expected to become a significant supplier of energy. Much of this will be from wind farms located far offshore (Figure 1) with overall capacity expected to be in excess of 30GW by 2030. Debate centres on the question: 'to what extent can wind contribute to a secure and reliable electricity supply?' Key to answering this is a detailed understanding of the wind resource and its variability in time and space. Its match with demand underpins key indicators for system operation and planning including the amount of reserve required to maintain system security or, as is the focus of this paper, the capacity value of offshore wind. However, to date there have been few sources of offshore wind observations with sufficient temporal resolution or accuracy to address this issue.

Capacity value (or capacity credit) is used in power systems reliability assessments and measures the contribution of generators to meeting demand. For renewable energy it is often loosely defined as the proportion of installed renewable capacity that is able to 'displace' conventional generation or support extra demand whilst maintaining system reliability levels (a precise definition is given later). The process of calculating capacity values uses 'technical' or mechanical availability for conventional generators modelled by reliability measures such as forced outage rates, downtime and other factors. However, wind production is treated as 'negative load' and wind turbine reliability is neglected as wind availability is considered more a function of "resource availability than mechanical availability" [1]. There is currently concern over the implications of the reliability and availability of large offshore wind farms far offshore [2]. However, with only a small number of analyses for on- and near-shore farms [3],[4],[5],[6], uncertainty over future availability and a lack of a suitable framework for incorporating technical availability within capacity value assessments, this paper focuses on the resource availability. It does, however, offer a simple assessment to set the question of technical availability in context. Tavner [7] offers an excellent overview of the state-of-the-art in offshore wind turbine reliability.

There have been a number of wind capacity value assessments for different systems; Keane *et al*. [1] offer a good review. Olmos Aguirre *et al*. [8] used seven years of hourly measured wind speeds from a geographically diverse set of meteorological stations across GB to create aggregate production for assumed regional distributions of onshore wind capacity generation. The study found that with installed capacities of around 2 GW (~3% penetration), the capacity value of onshore wind exceeded 25% declining to around 15% at 10 GW and 9% at 30 GW (~30% penetration). This reduction is seen in other studies although the level depends on generation mix, wind and demand patterns, risk measures and whether transmission constraints were accounted for. For example, in an analysis of the summer-peaking western USA [9], a 10% wind penetration suggested a capacity value of around 12%.

Within the literature on capacity values several limitations are apparent. Some, such as [8], use wind data from individual meteorological stations to provide a ‘proxy’ for wind farm production across wide regions, rather than data at sites where wind farms are or would be expected to be sited. Many use relatively short periods of analysis (< 3 years) [9], [10], which does not capture the substantial inter-annual variation in wind and demand and can under or over predict capacity value; a study for Ireland suggests 8 to 10 years is sufficient to establish robust measures [11].

Few studies deal with offshore wind although [10] considered deployments off the eastern USA; unfortunately the specific contribution of offshore wind is difficult to isolate.

Taking inspiration from the GB onshore wind analysis by Olmos Aguirre *et al*. [8] this paper tackles some of the limitations in the literature. It presents a credible estimate of the contribution of British offshore wind generation in supporting demand, particularly the effect of geographical smoothing; as well as examining the similarities and differences with onshore and combined wind fleets. The analysis is underpinned by a new decade-long high resolution wind dataset created by re-analysis using a mesoscale atmospheric model across GB and surrounding waters [12]. It has been extensively validated and bias corrected and this paper substantially extends initial work presented on this topic [13]. It is understood that this is one of the first analyses of capacity value explicitly for offshore wind as well as combined on- and offshore wind fleets.

The paper is laid out as follows. The next section outlines the methodology behind the capacity value assessment and introduces the wind speed dataset and associated data that underpin it. The Analysis section reports the results, discusses the findings and their context.

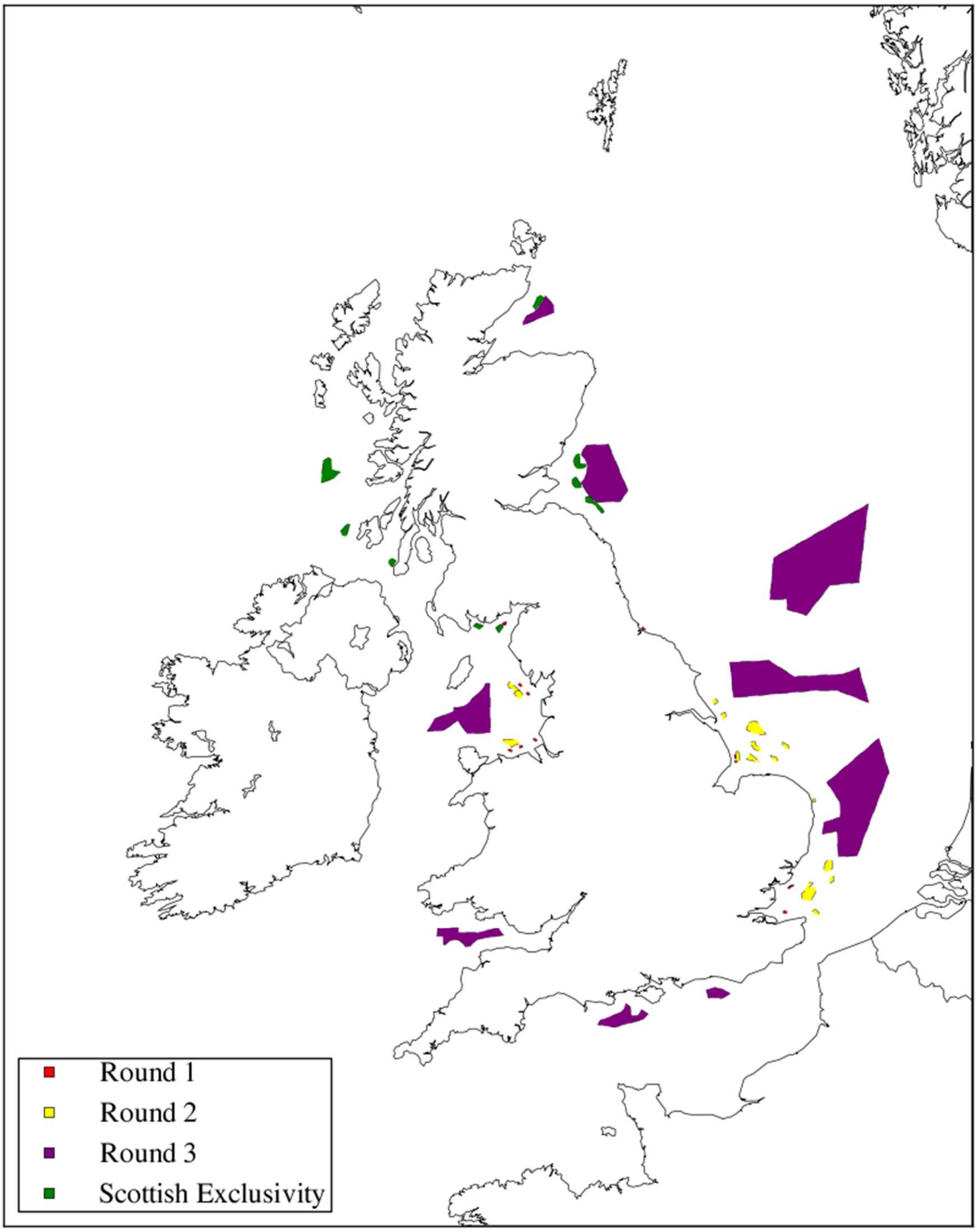

Figure 1: Location of Round 1, 2 and 3 offshore wind sites.

Capacity value assessment methodology

Assessment process

Capacity value is a key feature of the power system reliability field of generation adequacy. Generation adequacy determines the probability that a given portfolio of generation of different types and reliability characteristics can deliver sufficient power to meet demand at an instant, typically peak demand. Capacity value (or Effective Load Carrying Capability, ELCC) is defined as “the amount of additional load that can be served due to the addition of the generator, while maintaining the existing levels of reliability” [1]. This is expressed in GW but it is more common to see capacity value is expressed as a percentage of installed wind capacity.

The level of system reliability is measured by the loss-of-load probability (LOLP) and loss-of-load expectation (LOLE) [14]. The LOLP in a particular period t (hour) is defined as the probability that available generation is unable to meet demand:

$$\text{LOLP} = p(X_t < D_t) \tag{1}$$

where X_t is the available generation and D_t is the system demand (both random variables). LOLE is the expected number of periods t over a defined time horizon T (a year) in which demand is not met:

$$\text{LOLE} = \sum_{t}^{T} p(X_t < D_t) \tag{2}$$

A schematic view of the loss-of-load probability and the impact of wind energy is given in Figure 2. It shows the distribution of available conventional generation and a solid vertical line representing demand in a given hour. The shaded area to the left of their intersection is the probability that demand exceeds available generation in that hour: the LOLP. The dashed vertical line indicates that wind production reduces the 'net' demand that conventional generators must meet; consequently the LOLP decreases, all else being equal.

The capacity value is estimated using the following steps:

1. An hourly time series of demand is used together with a model of the reliability of conventional generation to estimate each hour's LOLP in the absence of wind generation. The baseline LOLE, $\mathrm{LOLE_{BASE}}$, across the time horizon is then calculated using (2).

2. Hourly wind production W_t (a random variable) is deducted from demand to provide a 'net demand' time series which, using the same process in step 1 calculates a new, lower, LOLE value, $\mathrm{LOLE_{NEW}}$ (Figure 2):

$$\mathrm{LOLE_{NEW}} = \sum_{t}^{T} p(X_t < D_t - W_t) \tag{3}$$

3. The entire demand time series data is then increased iteratively by a small amount d_{ELCC} and the $\mathrm{LOLE_{NEW}}$ recalculated each time until the original $\mathrm{LOLE_{BASE}}$ value is attained:

$$\mathrm{LOLE_{NEW}} = \mathrm{LOLE_{BASE}} = \sum_{t}^{T} p(X_t < D_t + d_{ELCC} - W_t)\,. \tag{4}$$

The resulting value of d_{ELCC} is the capacity value of the wind generation over the time horizon analysed.

Of particular interest is the availability of the wind resource during periods of high demand as these periods carry the highest adequacy risk. In GB the highest demands are driven by low temperatures occurring during winter (November-March). Accordingly, the horizon T is defined as the ten winters from 2001 to 2010 for hourly periods t. To allow the influence of the offshore wind resource on capacity value to be considered in isolation some simplifying assumptions have been made. These include:

1. a single scenario of conventional plant mix, capacity and reliability;
2. removal of inter-annual demand growth by normalising to a consistent 60 GW peak;
3. only winter production and demand is assessed as GB is currently winter-peaking;
4. transmission and distribution network constraints are ignored.

The sensitivity of the capacity value to some of these factors is considered later.

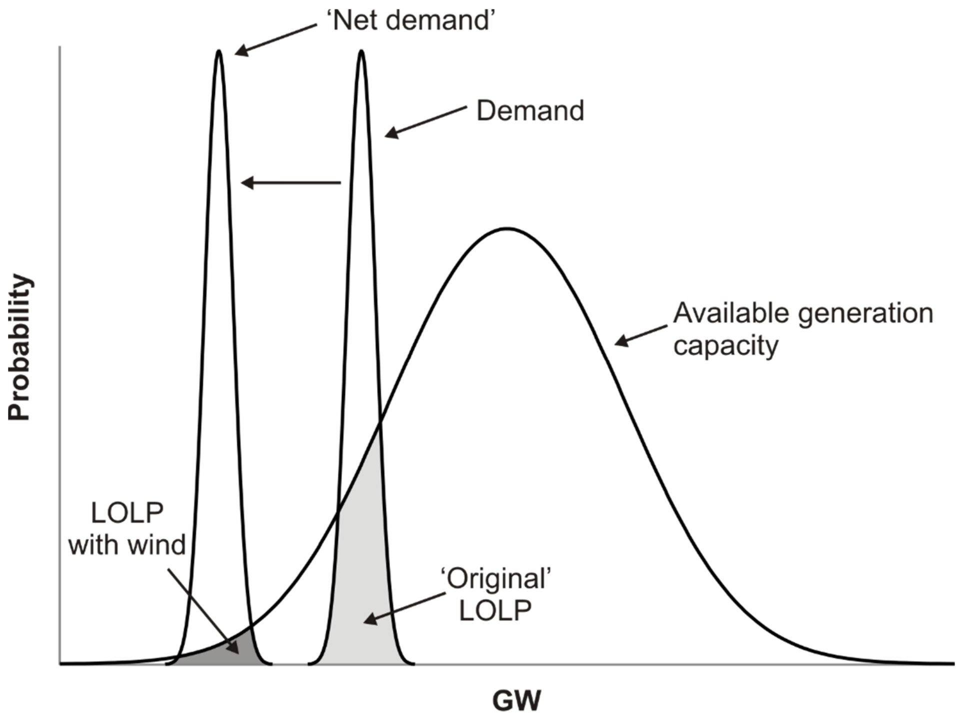

Figure 2: Schematic showing wind power reducing net demand and loss of load probability.

Reliability model of conventional generation

The calculation of LOLE requires the construction of a probability distribution for available conventional generation. This comprises all generation connected to the GB transmission system with the exception of wind. The availability of conventional generation is assumed to be independent of demand and wind capacity. Technical plant availability data is not available in GB. However, with high wholesale market prices at times of highest demand most generating companies try to make capacity available and availability is regarded as a function of the unit's forced outage rate (FOR), which are reasonably assumed independent [8].

Generation unit data is taken from National Grid's Ten Year Statement [15] and the (assumed) winter peak availabilities from the 2010/11 Winter Outlook [16] are used as FORs (Table 1). The Unit Effective Capacity [15] has been used for all units, apart from transmission constrained units (limited to constrained capacity) and hydro where each cascade scheme is treated as a single unit owing to resource interdependence.

The capacity outage probability table technique [14] is used to generate the distribution of aggregate generation availability (a Bernoulli distribution, here with mean 65.3 GW and standard deviation 1.8 GW). Using this distribution the winter hourly LOLPs can be computed. For simplicity each normalised hourly demand is assumed fixed, a reasonable assumption given typically small demand forecast errors. Hourly LOLPs can then be summed to produce the baseline $LOLE_{BASE}$ for the ten winters without wind (Step 1) and the reduced $LOLE_{NEW}$ using the expected wind output at each hour (Step 2).

Power station type	*No. units*	*Capacity (GW)*	*Assumed availability*
Nuclear	22	10.1	0.75
Interconnector	1	2	1.00
Hydro	9	1.1	0.60
Coal	62	27.9	0.90
Oil	4	2.7	0.80
Pumped storage	16	2.7	1.00
OCGT	34	1.2	0.90
CCGT	124	26.7	0.90
TOTAL	272	74.4	

Table 1: Transmission connected conventional generation types [16].

Historic demand time series

There is substantial inter-annual variation in demand levels, particularly around peak demand, as Figure 3 shows. To ensure emphasis on the contribution of wind, demand was de-trended by normalising by out-turn "Average Cold Spell" (ACS) peak demand and scaling to 60 GW. ACS peak demand is a measure of underlying demand patterns and "typical" winter peak weather conditions: "a 50% chance of being exceeded as a result of weather variation alone" [17]. Out-turn ACS peak is calculated post winter [8], [15] and retains the temporal structure of demand whilst avoiding bias from high or low demand growth. A similar normalisation process was reported in [11]. Half-hourly demand data is transformed to hourly resolution by taking hourly demand as the maximum of the two half-hour periods. The time series spans ten consecutive winters from winter 2001/02 to December 2010, totalling 34,128 demand hours.

Normalisation necessitates re-statement of (4) to ensure that the capacity value is not over-predicted in lower demand hours and remains coherent with the normalised hourly demand D_t:

$$\mathrm{LOLE}_{\mathrm{NEW}} = \mathrm{LOLE}_{\mathrm{BASE}} = \sum_{t}^{T} p(X_t < D_t + s_t d_{ELCC} - W_t). \quad (5)$$

where s_t normalises the hourly capacity value using $s_t = D_t/60$ GW (at 60 GW $s_t = 1$ full capacity value is preserved, otherwise $s_t < 1$). Were demand not normalised, no adjustment of `would be required.

The assessment uses National Grid's historic aggregated half-hourly demand data dating from April 2001 [18]. The GB 'IO14_DEM' data is best suited as it is based on operational metering and includes station load and pumped storage pumping [8]. However, prior to April 2005 this relates to England and Wales only. The alternative 'INDO' demand measure, which excludes station load and pumped storage, is available for the entire period and where the 'IO14_DEM' data is not available, it is approximated by raising the 'INDO' measure by 600 MW.

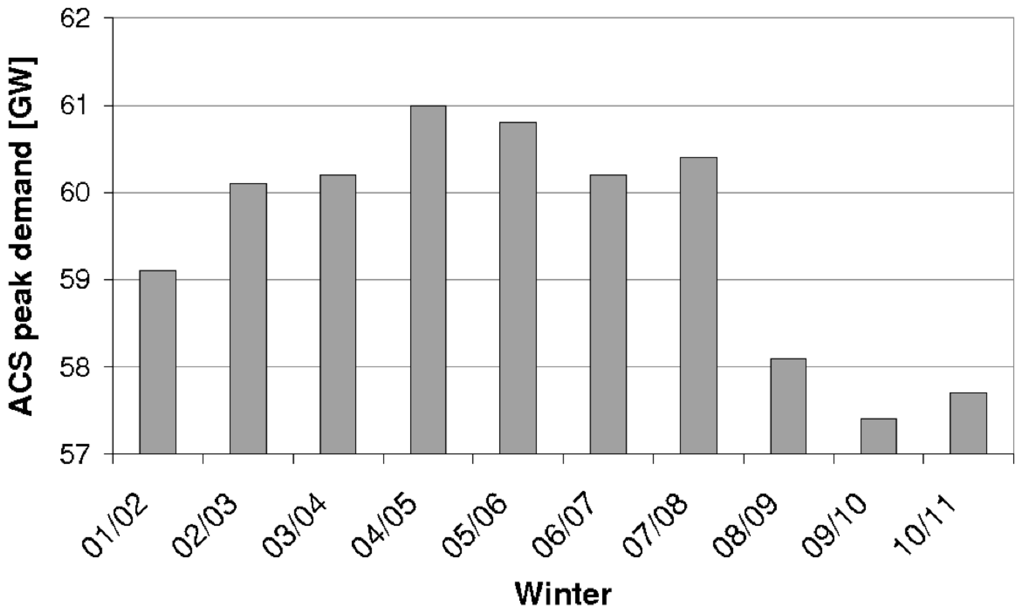

Figure 3: Winter ACS peak demand for 2001 to 2010 [8], [16].

Modelling offshore wind production

The major contribution from this work arises from the use of a state-of-the-art mesoscale atmospheric model, now becoming widely used in the wind energy field for forecasting, resource assessment [19], [20], atmospheric impact modelling [21], and as input for high resolution models including WAsP [22] and computational fluid dynamics [23]. Mesoscale models have been used for analysis of capacity values for parts of the USA [9], [10], [24]. Mesoscale models are computationally demanding, so many studies simulate short 1 to 3 year time series [9], [10] or use statistical representations of long term resource constructed from short simulations of 'typical' weather patterns [25]; random sampling to create an 'average' year [26] or the wind atlas method [22]. However, shorter term analyses do not fully capture wind speed variability while the statistical approaches do not produce continuous historic wind production time-series that can be matched with historic demand patterns, an essential requirement for capacity value assessments.

In contrast, this study uses a relatively long time series analysis delivered without recourse to statistical methods to reduce computational effort. Rather, the capabilities of a state-of-the-art high performance computing platform have been deliberately exploited to enable credible assessment of wind patterns. The study uses the well-established Weather Research and Forecast model [27]. It uses six-hourly boundary conditions at 1° resolution from the NCEP Global Forecast System Final Analysis dataset over an area covering the North Atlantic. Using progressively finer resolution domains it delivers hourly data at a resolution of 3km over the UK and Ireland. The use of enhanced model resolution near to the surface allows realistic estimates of vertical wind profiles at turbine hub heights without recourse to extrapolation using the power or log laws. Eleven years were simulated on the UK Research Council's high performance computing platform 'HECToR' using 6 million CPU hours; data from 2001-2010 inclusive has been applied here [12].

Comparisons with *in situ* wind speed observations showed very good performance onshore but a modest low bias in simulated offshore wind speeds although the temporal phasing was accurate ([13] used this data). This bias was corrected using on long term satellite measurement data [12]. Standard hourly error statistics for each class of observation (Table 2) show agreement between simulated and observed wind speeds is very good. The development of the wind dataset and other valuable insights is presented in detail in [12].

Observation class	Number of stations	Bias (m/s)	Root Mean Square Difference (m/s)	Coefficient of Determination, R^2
Met stations	222	0.15	2.03	0.64
Wind farm masts	6	0.27	2.27	0.71
Offshore buoys	9	0.47	1.92	0.74
Lightships	4	-0.05	1.83	0.82

Table 2. Summary of wind speed error statistics by observation type

Power production was simulated at all existing on- and offshore wind farms as well as those planned and under construction. For existing farms on- and offshore, the location and turbine type specified in the RenewableUK Wind Energy Database [28] was used to define the relevant power curve. The location of future offshore wind farms was based on the Crown Estate Round 1, 2 and 3 sites shown in Figure 1. The scale of the sites has increased with each round and the turbine technology deployed is assumed to evolve: here a generic 3MW turbine was assumed for Round 2 sites and a generic 5MW turbine for Round 3 (based on commercially available turbines). The final installed capacity in each future offshore site was assumed to be its maximum lease capacity.

Hourly wind speeds at each wind farm location were extracted from the mesoscale model output and converted to power output. Power curves are commonly used to convert wind speed into production and many studies simply apply these to a single turbine and 'scale up' to the right number of turbines. Unfortunately, it is unlikely to deliver realistic estimates of farm production, as variations in wind speed across the farm, wakes, storm control actions, losses and turbine reliability, and potentially curtailment combine to reduce 'headline' production and introduce substantial scatter. Detailed farm level modelling can capture many of these effects, but is not practical across the hundreds of farms simulated here. Instead, 'aggregate power curves' [29] modify the shape of specific power curves to smooth the ramp up and ramp down areas of the curve (Figure 4). This serves to capture wake and other 'within farm' losses that lower aggregate yields (~10%) but does not explicitly account for the availability of individual turbines. While hourly farm level production is modelled in megawatts the overall hourly aggregate production has been presented as capacity factor (CF), computed by weighting wind farms by installed capacity. Aggregate offshore and onshore CFs are calculated separately.

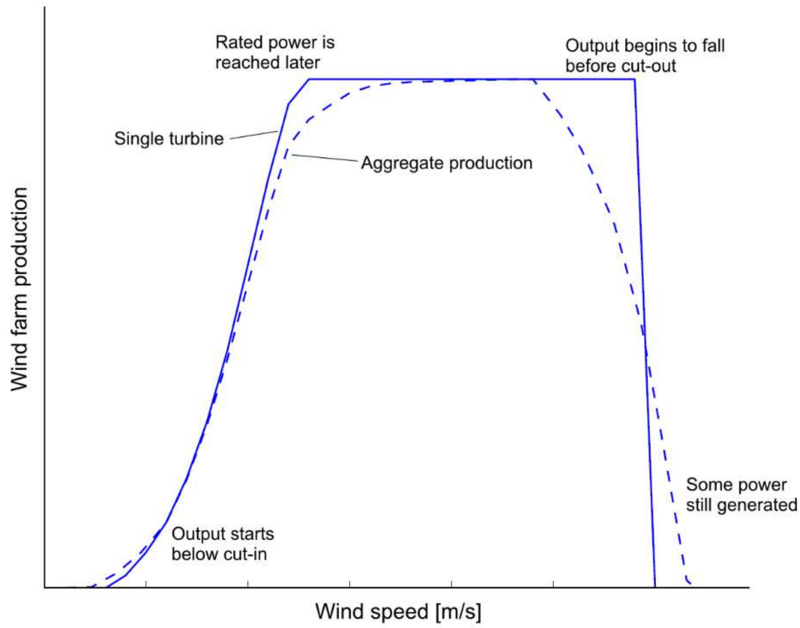

Figure 4: Schematic of 'farm' power curves derived from individual turbine power curves, after [29].

With metered production data from individual wind farms not publically available production estimates were validated using a range of publicly available information:

1. Aggregate annual production data from on and offshore wind from the DECC Directory of Energy Statistics (DUKES) [30] for 2001 to 2010;
2. Monthly capacity factors for individual on- and offshore wind farms using data from Ofgem's Renewable Obligation Certificate (ROC) Register [31] for April 2006 to December 2010;
3. Half-hourly aggregate metered wind production for the GB system from Elexon for October 2008 to December 2010 [32].

Figure 5 shows the simulated and actual annual capacity factors. The simulated annual capacity factors were very similar to the DUKES statistics for onshore wind over the 10 year period. Overall, the model under-predicts CF by 1.6%, with the model tending to over-predict slightly in the first half of the decade and under-predict slightly in the second. In line with the development of offshore farms, DUKES only contains statistics for the second half of the decade, and for the first two of these years, there is significant over-prediction. However, for the last three years, the match is close (~1.2%) which fits well with the documented experience for Round 1 farms where initial operational difficulties was followed by improvements in availability and production [3]. Comparisons with the ROC Register show that for the 2.7 GW of capacity at over 200 onshore wind farms the simulated production is biased around 3% high, with systematic differences at some individual wind farms arising from the modelled terrain at 3km resolution not adequately capturing all sites. For the 8 offshore farms representing total capacity of 1 GW, the bias is 2%.

In principle the Elexon aggregate half-hourly metered generation represents an excellent data source for comparison but in practice its use is challenging. Firstly, metered data is itself subject to errors and omissions. Secondly, metered data inherently includes farm operational characteristics and discrete events including the influence of curtailment, planned and un-planned maintenance and commissioning. Thirdly, simulations in each year are based on the full capacities available at the end of the year but in practice farms connect throughout the year, meaning that the production potential changes continuously. Finally, the metered generation includes all transmission-connected wind farms, wind farms larger than 50 MW embedded in distribution networks and other farms that opt for metering by National Grid; this does not therefore include all wind farms captured by the simulations.

Taken together, these effects suggest that the simulations will overestimate production. To aid comparison with the Elexon data, simulated production from wind farms with a capacity of less than 50MW was omitted, although this was not a precise one-to-one match with metered wind farms. Given the extensive changes in installed capacity during the period, comparison is on the basis of MW production, rather than capacity factor. A sample of the resulting time series for the simulated aggregate production and metered data is shown in Figure 6 for the three months at the end of 2010. While the simulated production does not precisely match at all times, the pattern and shape of production is very well captured. Importantly the metered on and offshore production sits within an envelope of simulated production, and only rarely and marginally exceeds that suggested by simulation. The correlation coefficient is very high (0.82) suggesting that much of the mismatch is due to non-weather factors. This is supported by the 2 to 3% high bias in the annual and monthly values, which fits with reported 97% availability for onshore wind farms [4].

Overall, the high correlation between the observed and simulated production supports the decision to focus on the wind resource as the main determinant of aggregate wind production. It creates confidence that a capacity value assessment based on a much larger set of on- and far-offshore farms will be reliable. However, while the validation indicates high levels of availability for existing on- and near-shore farms, it is not currently possible to make the same assertion with regards to the availability of wind farms that have yet been built far offshore. With that caveat the wind production dataset was used for determining capacity value.

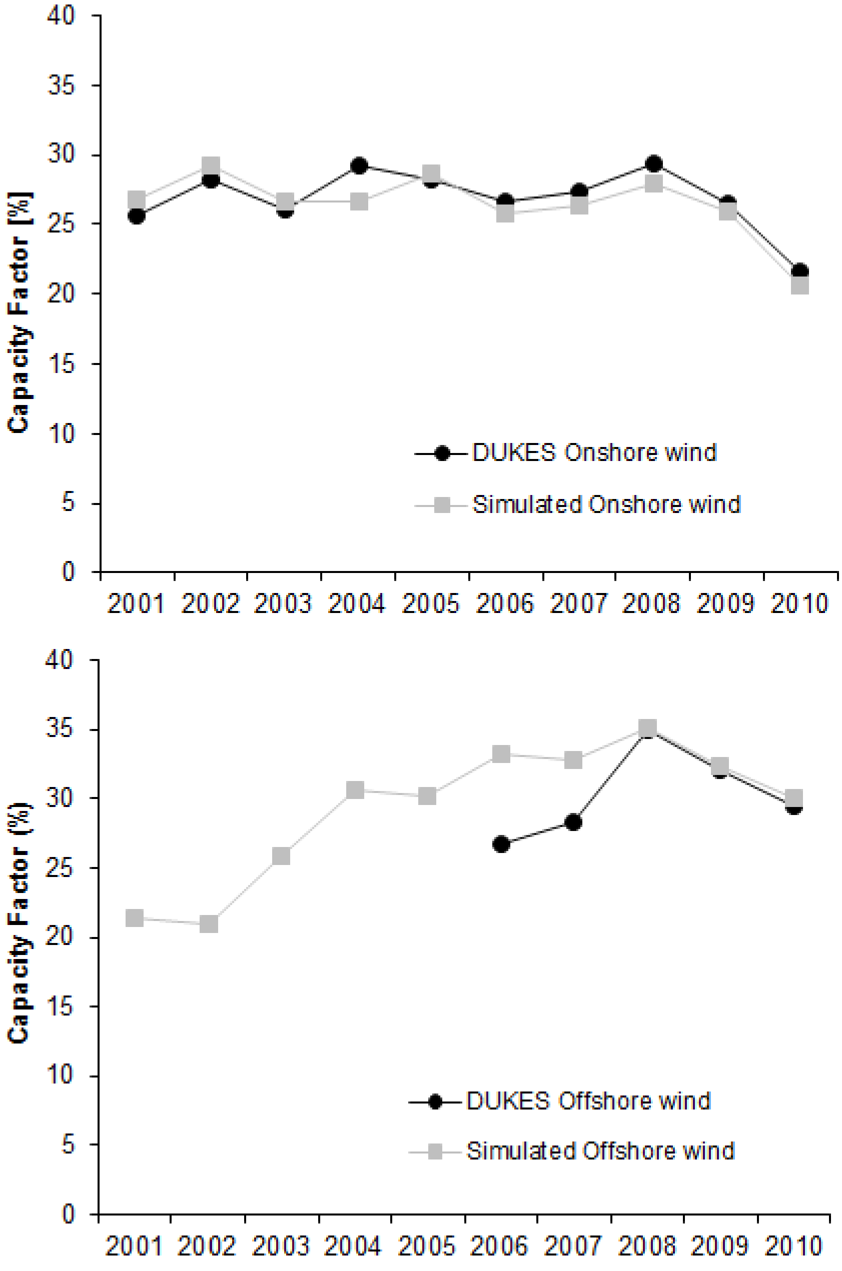

Figure 5: Simulated and observed annual CF for entire GB wind fleet (top) onshore and (bottom) offshore.

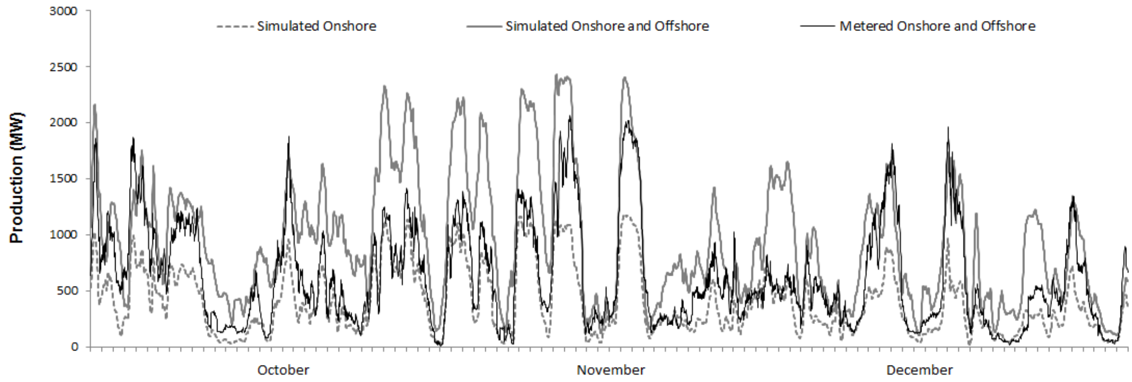

Figure 6: Simulated and observed aggregate hourly production.

Analysis

Wind and demand match

Prior to the calculation of capacity value it is valuable to examine the underlying match between wind production and demand. With a fixed scenario of demand, the precise match will depend on which specific portfolio of existing and future wind farms are included as this will affect the extent of geographic smoothing and installed capacity. As the analysis presented later is for different combinations of wind farms, an example of the matching process is given for what could be considered a 'long term' scenario where a geographically diverse on- and offshore wind fleet has been constructed; here this amounts to an installed capacity of 35 GW with all on- and offshore sites developed to capacity.

For this long term scenario, Figure 7 shows the normalised hourly demand time-series for the first 10 days of December 2010 (containing that winter's highest demand), and aggregate wind production and capacity factor. The demand pattern is clearly evident as is the inter-day variation. It is also clear that wind production is variable with periods close to 30 GW and instances nearer to 10 GW. It should be noted that not all periods in each winter period have these levels of output with some substantially lower; it is important to consider much longer periods to ensure representative measures.

Figure 8 shows the simulated average aggregate long-term CFs for wind generation during the highest demand hours across the ten winters where demand exceeds the 90^{th} percentile (2143 hours). The demand hours are categorised into 1% bins and the label indicates cumulative hours at each demand level. Demand levels above 100% of peak are possible as ACS peak is exceeded in some years. The pattern of average CFs shows a good agreement with the analyses of transmission metered onshore wind farms presented by Zachary and Dent [33]. However, absolute levels of CF are higher at 55 to 60% for the 90 to 95% demand levels compared to 20% onshore [33], reflecting higher capacity factors offshore. The extent to which average production appears to decline at extreme demand levels is less severe than onshore [33] largely due to higher geographic diversity. However, it is difficult to be definitive as there are very few hours of data in either study on which to base firm conclusions. The impact of differences between on- and offshore wind production is examined in the following subsections.

A simple assessment of how reduced wind farm availability affects the match with demand is also given. Figure 8 also shows wind farm availability reduced to 90% by uniform scaling of production, equivalent to 10% of turbines out-of-service. The effect is to reduce the average CF at the high demand levels by around 5 percentage points, albeit with a smaller absolute reduction at the highest demand levels. While this is evidently a significant simplification it will have an impact on capacity value and this will be considered later in the sensitivity analysis.

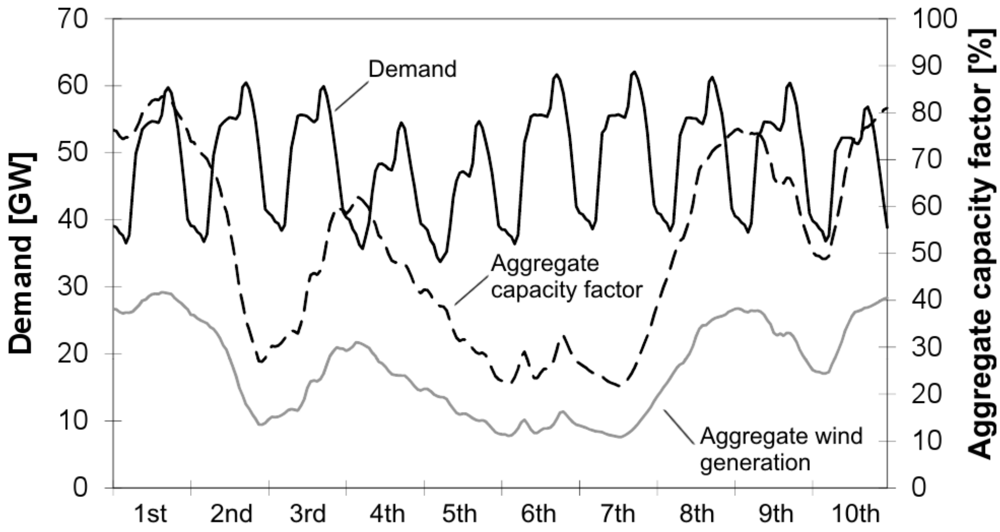

Figure 7: Hourly normalised demand profile for 10 days in December 2010 alongside simulated aggregate long-term CFs and wind generation from a 35 GW installed capacity.

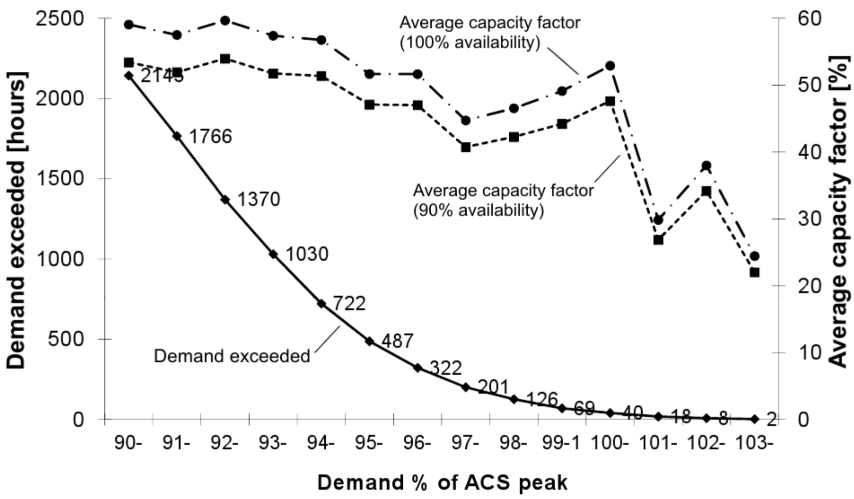

Figure 8: Average long-term CFs for highest demand levels (right y-axis): base-case and scaled by 0.9 (upper and lower dashed lines). The demand hours exceeded are shown on the left y-axis.

Offshore wind capacity value

The offshore wind resource is initially considered in isolation with particular interest in the relationship between the spatial distribution of generation capacity and capacity value. Two distinct approaches can be applied to this calculation: *long-term* and *build-based* capacity.

The vast majority of capacity value studies apply the first method where the capacity is distributed according to its eventual long-term locations. The weighting and hence contribution of individual locations is then fixed and the analysis performed across a range of installed wind capacities. The result is a characteristic monotonically-decreasing relationship where capacity value falls as capacity rises [8] (see Figure 11, later). Here the *long-term* capacity value is calculated for offshore wind using CFs distributed according to the final capacities in the Crown Estate lease agreements (Figure 1).

In reality, construction will proceed sequentially, with the larger offshore sites being developed later. The *build-based* capacity value approach captures this. They are calculated using a projected offshore wind build schedule constructed from the three Crown Estate auctions that define the locations (Figure 1) and expected capacities of the offshore farms in a given year. The aggregate CFs are then derived using the geographically weighted average of CFs at each location. The build schedule and the results of both analyses are illustrated in Figure 9. The dashed line shows capacity values calculated using *long-term* aggregate CFs and the solid line shows the capacity values calculated using the *build-based* aggregate CFs weighted over just the wind farm sites online at the start of each year. The total installed capacity expected to be online by the stated year is the same in both cases, however the *build-based* CFs are weighted across a less diverse resource. This demonstrates that considering sites by build schedule leads to lower estimated capacity values than those defined by long-term capacity, largely as a result of diversity.

The effect of the diversity can be seen in Figure 10. This uses the information from the build-based analysis and shows probability mass functions for the start, middle and end of the build schedule (2011, 2015 and 2020). In each case it also shows the mean and coefficient of variation (CV) of offshore wind production during demand hours within 5% of peak (a sample size of 655 hours over the ten winters). These demonstrate how the distribution of aggregate CFs for the sampled hours changes with capacity and location of offshore farms. Moving from the 2011 build assumptions through to the more diverse 2020 build, there is a clear reduction in frequency of low CF hours and an increase in high CF hours. In all cases the probability of high CF operation remains above those typically simulated onshore, such as [8]. This sort of insight is not available from analyses that feature a single probability distribution applied to all levels of capacity.

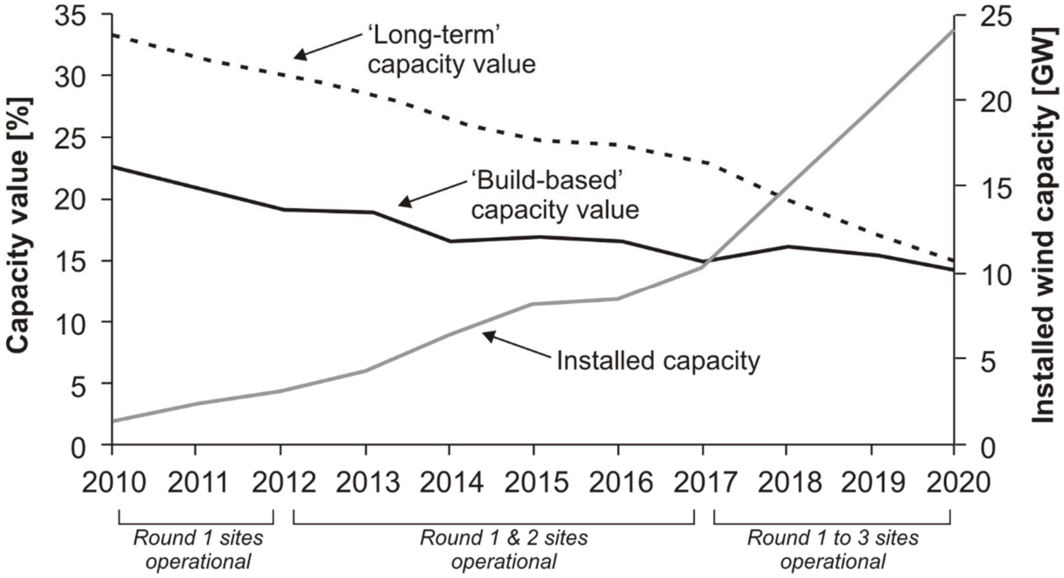

Figure 9: Capacity value and installed capacity for GB offshore wind using long-term and build-based CFs.

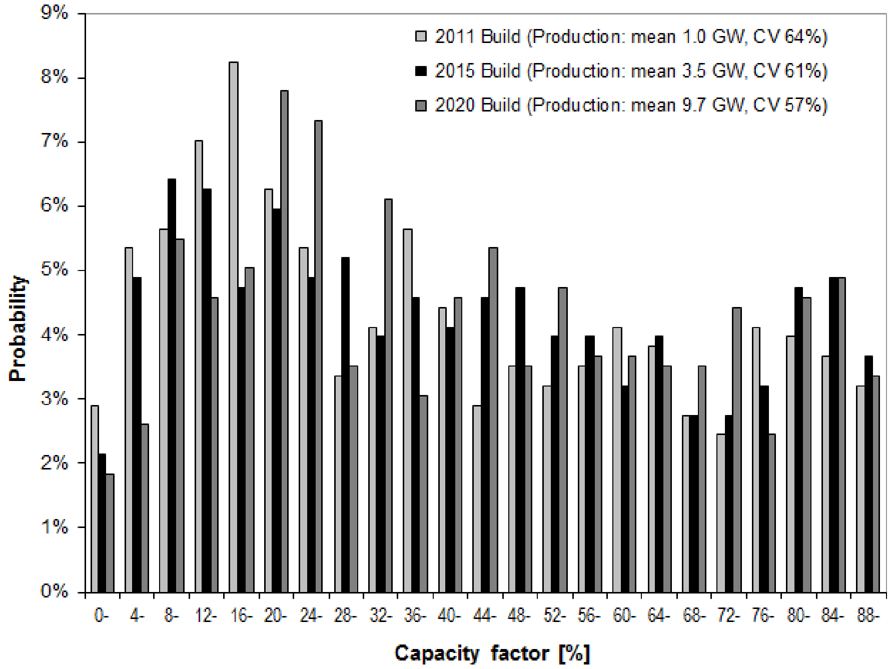

Figure 10: Probability mass function for GB offshore wind CFs for demand hours within 5% of annual peak for installed capacity corresponding to specific years.

Aggregate GB wind capacity value

Attention now turns to the combined GB wind resource and the distinction between on- and offshore wind. Figure 11 shows the capacity value for the *long-term* aggregate CFs for onshore, offshore and combined wind fleets. Although based on the same information, the traces are much smoother than those in Figure 9 which featured more 'lumpy' capacity additions governed by installation rates.

Figure 11 shows that the capacity value of a geographically diverse offshore wind fleet is much higher than an equal capacity of diverse onshore wind. This is particularly apparent at lower installed capacities where at 5 GW, the offshore capacity value was 28% against 14% for onshore. The enhanced performance offshore extends to very high installed capacities (12.5% vs. 8.5% at 30 GW), which are key values where the long-term values are being considered.

The third curve is for a combined on- and offshore wind fleet derived by weighting the on- and offshore sites based on their long term capacities. With 78% of total capacity accounted for by offshore sites (especially Round 3), the capacity value is driven largely by offshore wind. It is notable that the joint capacity value is *below* that for offshore wind alone. This perhaps surprising result occurs despite an expectation of additional geographic diversity from the onshore sites and arises as the GB onshore sites lie within a spatial envelope bounded by the large offshore sites. Together with smaller onshore capacity the aggregate level of diversity is lower. These results suggest that for very high levels of highly geographically diverse wind capacity, the joint capacity value converges to that of offshore wind; a value of 10-12% appears credible.

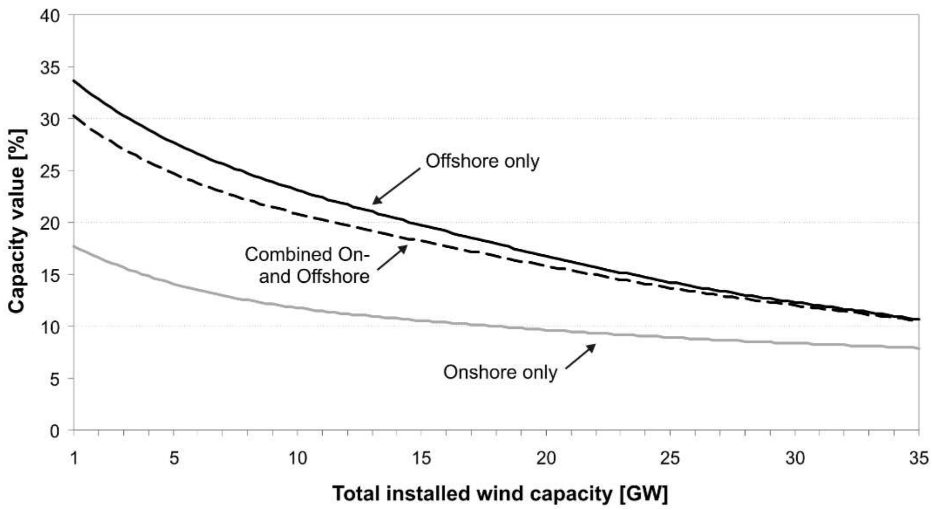

Figure 11: Long term capacity value results for several GB wind fleets: onshore only, offshore only and combined on- and offshore.

Sensitivity analysis

As mentioned previously, isolating the influence of the offshore wind resource on capacity value required simplifications including fixing the conventional generation mix and eliminating inter-annual demand growth. To illustrate the impact of these factors and to make a first level estimate of how wind turbine availability might affect capacity values, four sample cases were examined for the combined on- and offshore fleet across the same range of installed capacity:

1. Normalised peak demand reduced from 60 to 57 GW (reducing baseline $LOLE_{BASE}$ by 99%);
2. Total available conventional generation reduced by 4 GW to a distribution with mean 62.2 GW, and standard deviation 1.7 GW (increasing baseline $LOLE_{BASE}$ by 3000%);
3. Wind availability uniformly reduced to 90% (no change in baseline $LOLE_{BASE}$);
4. Wind availability uniformly reduced to 80% (no change in baseline $LOLE_{BASE}$).

Figure 12 shows the resulting capacity values. The reductions in capacity value are most apparent at lower installed wind capacities largely as a result of the higher impact that wind has in small volumes. Lowering peak demand reduces risk, so the capacity value falls by just under 3 percentage points at 5 GW wind capacity and 1 percentage point at 30 GW. Broadly similar increases in capacity value would be expected for the case of increasing demand. Reducing available conventional generation by 4 GW leads to increasing risk and consequently the capacity value of wind rises by 5 and 1.5 percentage points at 5 and 30 GW, respectively. This demonstrates the impact of underlying system risk on the results obtained. Further, the results show that for GB where substantial amounts of conventional generation is expected to retire and demand to grow, the capacity value of wind generation will tend to increase.

Wind turbine availability affects levels of capacity value with uniform 10 and 20% reductions in availability equivalent to cutting production levels or capacity by the same amount: at 80% availability this is a 6 GW loss of capacity from a 30 GW fleet. Inherently this lowers the capacity value of wind. A 10% reduction in availability lowers capacity value by 1.6 percentage points to 23% at 5 GW wind capacity levels and 0.5 percentage points to 11.5% at 30 GW levels. The impact of a 20% reduction in availability is approximately double this. To put these in context, removing a fifth of the wind capacity has a substantially lower impact on the capacity value of wind generation than a much smaller change in levels of demand or conventional generation.

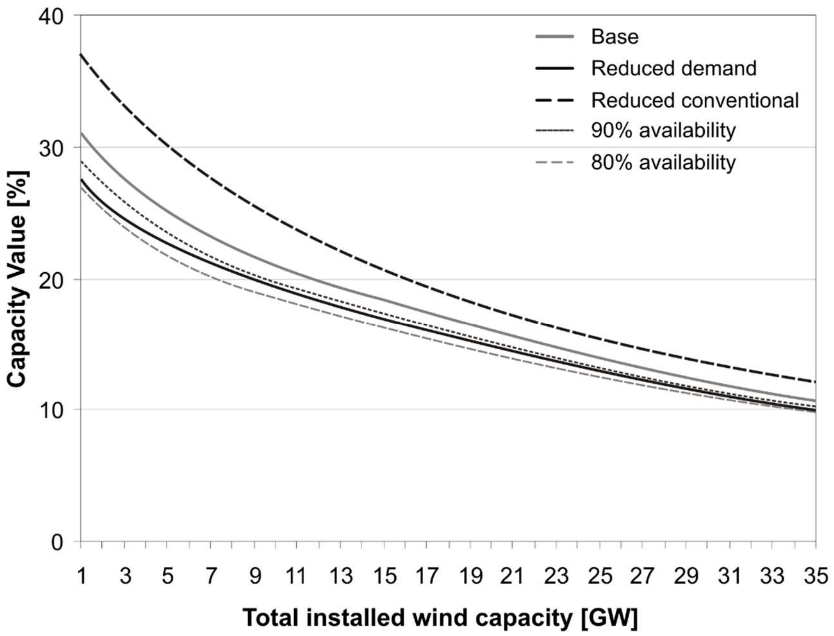

Figure 12: Sensitivity of capacity value to reductions in demand and conventional generation levels and wind turbine availability levels.

Discussion

The methodology applied here is robust and offers a valid contribution to defining current approximations for on- and offshore wind capacity values in Great Britain for application in system operator security analyses and for policy analysis[16], [34].

The work is based on a very substantial effort to accurately model wind speeds on- and offshore. A key benefit is that the major differences between on- and offshore wind capacity values are distinguished, indicating that 'extrapolation' of onshore wind patterns to represent those offshore is not advisable. Although there are differences in detail, the greater spatial resolution used here delivers markedly lower onshore capacity credits than the 'regional' wind modelling approach by Olmos Aguirre *et al.* [8]: 17% versus 25% at 2GW, 12% versus 15% at 10 GW and 8.5% versus 9% for a 30GW onshore fleet. Cradden *et al*. [35] demonstrate that the level of spatial aggregation has a substantial impact on the level and variability of aggregate production onshore; this is one of the reasons for the lower capacity value. Interestingly, [35] finds much greater homogeneity offshore suggesting that lower resolution wind data may be acceptable offshore. Finally, the build-based analysis illustrates clearly that capacity value studies that neglect the changes in spatial distribution of wind capacity over time will tend to over-estimate capacity values.

Simplifications allowed the influence of the offshore wind resource to be clarified. The use of a single scenario of conventional plant mix, capacity and reliability and no inter-annual demand change is not fully realistic as there will be substantial changes in GB up to 2020. As the sensitivity study shows, these affect the levels but not the overall 'shape' of wind capacity values. Modelling winter conditions alone is reasonable and captures current risk well. In summer, underlying levels of risk would be much smaller due to low demand and together with reduced average wind production suggest a relatively low summer capacity value. The picture is complicated by planned maintenance of conventional generation occurring during summer periods which would tend to raise risk. As such, a whole year analysis would be valuable particularly given the potential for increased summer demand from climate change. Adopting an approach similar to the *build-based* assessment allows explicit representation of scenarios of wind, conventional generation and demand within system reliability and capacity value assessments. It has been assumed that the network capacity is sufficient to deliver all power from the wind fleet but active management of network constraints and curtailment of wind will be required as the wind fleet increases. To handle this detailed power flow analysis would need to be incorporated; the high resolution of the wind dataset makes such analysis feasible and is an area for further work.

Although noting concerns over the reliability of wind farms far offshore, the work did not fully consider the reliability of wind turbines within the standard framework of the capacity value assessment. However, the work goes some way to identifying the influence that availability levels have on capacity value and system reliability. The approximately 0.5 percentage point reduction in capacity value for a uniform 10% reduction in availability suggests a modest impact and supports the view that the capacity values obtained are robust within the limits of existing analytical techniques. With relationships between weather conditions and turbine availability becoming better understood [7], [36] and with limited offshore weather windows for repairs, it is conceivable that greater localised reductions in offshore wind availability may occur, affecting the underlying geographic diversity that boosts capacity values. New approaches that explicitly incorporate turbine, farm and network reliability within system reliability methods would be valuable but examples in the literature [37] offer simple analysis of wind resource dependency and are not aimed at offshore environments. The authors speculate that methods would involve a more detailed representation of specific wind farms and their network infrastructure. A composite resource and forced outage/ repair model may fit with the current method of representing conventional generation. However, it will require information on evolving offshore turbine reliability and extensive simulation.

Ten years data does not represent a full wind climatology for GB (30 years is standard), particularly with (limited) evidence of climate change affecting wind speeds [38], [39]. However, ten years allowed sampling of a wide range of synoptic conditions and the analysis is a substantial improvement on comparable studies. The inter-annual variability of wind production at times of peak demand varies considerably between years. For example, in January 2010 a blocking high pressure over northern Europe led to very cold temperatures and high demand, yet low wind speeds over GB. It supports the earlier assertion that short term analyses [9], [10] may misrepresent the capacity value. Ultimately, while capacity value is a valuable indicator of long term security contribution it does not guarantee that wind power will be available in any one instance. The issue of ‘what happens when the wind doesn’t blow’ remains challenging. However, well informed, independent commentary [40] does not regard this as a problem for the GB system up to around 20% wind penetration; beyond that, flexible generation, demand side response, storage and interconnection will be necessary to manage variability.

Conclusion

Capacity value assessments are a popular way of estimating the contribution of wind power to the reliability of power systems but require a detailed understanding of the wind resource and its variability in time and space. A mesoscale atmospheric model was employed to create a ten year hindcast of offshore wind speeds and simulated production in Great Britain. A capacity value assessment has provided new insight into the influence on system reliability of production from offshore wind farms at periods of high demand in Great Britain. It is shown that for Great Britain capacity values for offshore wind are greater than onshore particularly at lower installed capacities being approximately 34% at 1 GW installed capacity offshore (18% onshore), 30% at 5 GW (14%), 23 at 10 GW (11%) falling to 12% at 30 GW (8%). Further the capacity value of combined on- and offshore fleets are dominated by those offshore. The sensitivities of these estimates to the underlying level of system risk have been discussed and the availability of wind turbines is shown to have a modest impact on capacity value.

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