Wind Resource Visualisation at Peak Demand

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***Abstract*—We present a new approach to visualising the wind resource at times of high demand, plotting the mean capacity factor across all hours above a given demand level. This combines both aggregation of data which is necessary to see trends, with focus on the very highest demands. Examples have been presented for GB, however the same technique could be used in any other system. This approach illustrates the clarity of insight which may be obtained through data analysis, without the need for any high-tech mathematics. In particular, it shows definitively that the quality of the wind resource in GB deteriorates considerably at very high demands, and gives insights into whether the volume of data is sufficient for robust wind integration studies.**

***Index Terms*—Wind energy, Statistics**

I. Introduction

THE penetration of wind generation, and hence its importance in system planning and operation studies, is increasing in power systems worldwide; recent major studies from Great Britain are described in [1]–[3].

A key issue is the contribution which wind generation makes to supporting demand. In GB, the highest demands are driven by cold weather; there is a concern that such cold conditions usually result from high pressure weather systems, which would also imply low wind output.

Whether this concern is justified remains a matter of some controversy. The experience of National Grid (the Transmission System Operator) is that annual peak demand often coincides with very low wind output [2]. This is supported by some independent studies (e.g. [4]), but not all (e.g. [5]).

Here we introduce a new visualisation approach which answers this question definitively, combining the aggregation necessary to see trends in the data with focus of hours of highest demand. The GB wind resource does deteriorate substantially in quality from about 90% to 98% of peak demand, but the picture is much less clear at the very highest demands due to the small number of hours of direct relevance. This approach also provides interesting comparisons between the quality of the onshore and offshore resources.

At another level, this paper also demonstrates the powerful insights which can be drawn through relatively low tech data analysis (in this case, identifying the right graphical visualisation), and how such data analysis is a vital precursor to the application of higher mathematical and statistical technologies.

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II. Data

The wind output data used is based on wind speed records from 26 meteorological stations (both onshore and offshore), spread throughout Great Britain [1]. Wind speeds are transformed to wind capacity factors (CF) scaling the wind speeds to hub height and applying an aggregated wind turbine power curve; a site's wind speed time series is taken as representative of wind farms in its region. Similar approaches have been used in [5], [6].

A consistent GB demand data time series stretching back to April 2001 [7] is available; we therefore have coincident wind and demand data for calendar years 2002-08. So that all wind generation is treated on an equal basis, we add an estimate of the output from non-transmission metered embedded wind generation to each hour's demand. To allow comparison between years, demand is expressed relative to Average Cold Spell (ACS) peak demand, the standard GB measure of underlying peak demand level, corrected for the weather which occurred in a given winter.

III. Wind Resource Visualisation

Any useful visualisation of the wind resource at times of very high demand must combine the following:

- *Some degree of aggregation of data is required.* A scatter plot of CF against demand gives limited insight into trends in resource quality as demand varies, due to the variation about any trend; examples may be seen in [1].
- *Focus on the application, i.e. the highest demands.* Hours of lower demand, are not directly relevant to peak, must not be treated on an equal basis.

Our visualisation of the wind resource for 2010 and 2020 (the latter using a forecast by National Grid and Pöyry of installed wind capacity and locations) is shown in Fig. 1; the installed capacities are 5.735 GW (onshore) and 0.410 GW (offshore) in 2010, and 14.241 GW (onshore) and 18.458 GW (offshore) in 2020. In order to combine aggregation with focus on the highest demands, we plot:

- *x-axis*: Demand d as a percentage of ACS peak demand.
- *y-axis*: Mean wind CF across all hours with demand at least d.

The wind CF time series for each year (2002-08) is based on that year's wind records, and either 2010 or 2020's installed wind capacity and locations. This reveals a very substantial deterioration in the quality of the wind resource going from typical winter hours (e.g. 90% demand) to about 98% demand.

The picture of the very highest demands from Fig. 1 is less robust due to the paucity of relevant hours even with 7 years of data. Other valuable insights derived from Fig. 1 are:

- It is no surprise that the offshore CFs are higher than those onshore. The much smaller deterioration of the

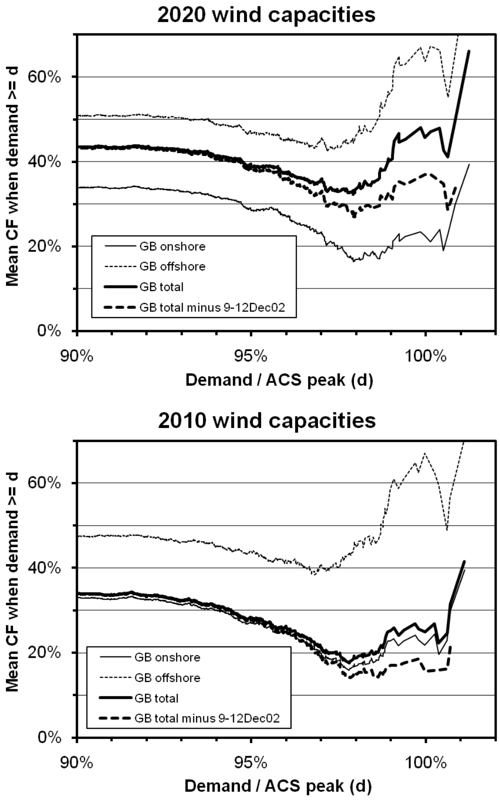

Fig. 1. Visualisations of the GB onshore, offshore, and aggregate wind resource in 2010 and 2020.

offshore resource at the highest demands has positive implications for its contribution to demand security.

- There is very little difference between the 2010 and 2020 onshore plots, suggesting that the geographical diversity does not increase substantially with the higher installed capacity (due to the small 2010 offshore capacity, a similar comparison for offshore is not very relevant.)
- The picture of the resource at the highest demands changes critically if just 4 days from December 2002 are removed; these (unusually) combined very high demands with CFs around 50%; this combination was certainly not caused by a large high pressure area. Without more data, one cannot say (e.g.) whether this is a 1 in 2 year event which by chance only happened once in 7 years, or maybe a completely anomalous 1 in 100 year event.

A further illustration of how representative these 7 years are of the long-term wind resource may be obtained by creating 7 visualisation plots, each of which omits one year's data. Apart from the specific 2002 issue, this suggests that the view obtained of the wind resource is quite robust up to about 99% of ACS peak, as the other 7 data series are close together (indeed the difficulty in distinguishing the series other than '2002 missing' reinforces this point.) A conservative, pragmatic approach to analysing demand security using this data might therefore be to omit 9-12 December 02, as one might not wish to assume without further evidence that such high wind availability will recur in an extended cold spell.

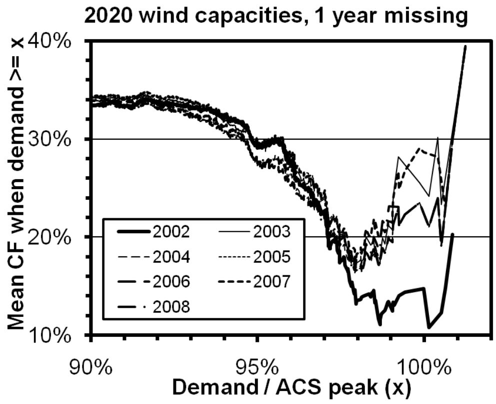

Fig. 2. Visualisation of 2020 aggregate wind resource: 7 plots, each with one year's data removed.

Our new approach is fundamentally different from conventional histograms or moving average plots, such as Fig. 9 of [5], which uses too much smoothing to allow real focus on the highest demands. Indeed, Section 5.4 defines peak demand hours as all hours above 80% of peak, most of which have little relevance to the few hours of near-absolute peak demand.

[5] also characterises the pairwise relationship between different sites' wind outputs using correlation coefficients. While this might give some information regarding the volatility of aggregate wind output over the whole year, it must not be interpreted as giving information relevant to peak demands; from different perspectives the correlation coefficient treats all hours equally, or alternatively assumes the dependence structure of a multivariate Normal distribution.

IV. Conclusions

We have presented a new approach to visualising the wind resource at times of high demand, which combines both aggregation of data to see trends, with focus on the very highest demands. Examples have been presented for GB, however the same technique could be used in any other system. This approach illustrates the clarity of insight which may be obtained through data analysis, without the need for any high-tech mathematics. In particular, it shows definitively that the quality of the wind resource in GB does deteriorate considerably at very high demands.

References

[1] Pöyry Energy Consulting, "Impact of Intermittency: Summary Report," Tech. Rep., July 2009.

[2] "Operating the Electricity Transmission Networks in 2020: Initial Consultation," National Grid, Tech. Rep., June 2009.

[3] "Our Electricity Transmission Network: A Vision for 2020," Electricity Networks Strategy Group, Tech. Rep., March 2007, available online at http://www.ensg.gov.uk/index.php?article=126.

[4] J. Oswald, M. Raine, and H. Ashraf-Ball, "Will British Weather Provide Reliable Electricity?" *Energy Policy*, vol. 36, no. 8, pp. 3212–3225, 2008.

[5] G. Sinden, "Characteristics of the UK Wind Resource: Long-term Patterns and Relationship to Electricity Demand," *Energy Policy*, vol. 35, no. 1, pp. 112–127, January 2007.

[6] P. E. Olmos Aguirre, C. J. Dent, and J. W. Bialek, "Realistic Calculation of Wind Generation Capacity Credits," in *Cigré/IEEE PES Symposium on Integration of Wide-Scale Renewable Resources*, July 2009.

[7] "National Grid: Demand Data," available at http://www.nationalgrid.com/uk/Electricity/Data/Demand+Data/.