Operating the Electricity Transmission Network in 2020
Response to Initial Consultation

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Executive Summary

This document presents our response to the 2020 consultation based on experience of renewable resource, risk, and power system modelling at Edinburgh and Heriot-Watt Universities. The technical content is summarised here.

0.1 Question 1: How do National Grid's observations align with your own experience or modelling of wind generation

- We believe that explicit use of historic demand and resource time series gives better results for less effort than probabilistic representations.
- For detailed local and regional resource studies, physical atmospheric modelling is likely to be required to convert meteorological records into simulated wind farm outputs.

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- Resource visualisation tools must be clearly focused on the question at hand. An example is presented of an instructive graph, showing the relationship between the quality of the wind resource and demand at high demand levels.

0.2 Question 8: What is your view of future electricity demand growth and how would you quantify any uncertainty around this?

- For high penetrations of distributed wind, it is helpful to consider the wind output as generation rather than negative load, in order to reflect better the properties of the distribution-connected wind.

0.3 Question 17: Is National Grid's current view that 'low wind' events across Great Britain need to be considered when evaluating electricity operating margins reasonable

- The variability of wind output is clearly important in determining system adequacy risk. Low wind events are relevant mainly through their effect on system risk; they are not of great importance for their own sake. Too much emphasis on investigating their frequency, independently of considerations of demand and risk levels, might be misleading.

- Our analysis suggests that a choice of half-hours spread evenly through the whole winter (e.g. all winter tea-times) is not representative of the resource at annual peak; to investigate the wind resource at peak it is necessary to focus on the hours of highest demand.

- We advocate the use of risk-based capacity credits, rather than basing the capacity credit of wind on a chosen percentile of the output distribution. This both focuses directly on the problem at hand (i.e. system adequacy risk), and avoids an arbitrary choice of percentile.

0.4 Question 18: Are our generator availability assumptions reasonable for application to analysis of future operating margins?

- Uncertainty in the assumed availabilities must be accounted for when analysing operating margins.

0.5 Suggested risk metric

- We also present a suggestion for a risk-based metric for analysing operating margins, along with an extended discussion of its implementation. This is based on the widely-used Loss Of Load Expectation (LOLE) metric.

- Such a risk-based metric gives a more complete picture of system adequacy risk than the present deterministic scenario approach; this is particularly important with high renewables penetrations, when different technologies may have very different availability properties.

- Values calculated from the last few winters may be used to calibrate the risk metric.

1 Section 5: Developments in Electricity Generation and Demand

1.1 Question 1: How do National Grid's observations align with your own experience or modelling of wind generation

1.1.1 Time series versus probability distributions

We largely agree with National Grid's approach to modelling wind generation and its relationship with system adequacy (as presented in this Consultation and the Winter Outlook), in particular with the use of wind data which is time-synchronised with demand data, and the concentration for system adequacy issues on the wind resource in hours of highest demand.

We believe that the simplest way of accounting for the relationship between demand and wind availability in a risk calculation is to perform a time series risk calculation, in which these historic time series are used directly. This is both the easiest approach technically, and automatically includes all the available statistical information on the wind-demand relationship (as well as the relationships between wind availability in different geographical areas). The data processing necessary for a probabilistic representation of the wind resource risks losing information on these key relationships.

1.1.2 Need for physical atmospheric modelling

The available historic metered wind farm output data is limited. The present transmission connected farms are all in Scotland, and even for the oldest farms only a few years' data exists.

A common approach has been to convert Met Office wind speed records directly to wind turbine load factors by passing the wind speeds at each site through a wind turbine power curve[1]. Each Met site would be regarded as representative of its local area, and a national load factor can be found using a summation weighted by the installed capacities in each region.

We expect that this approach will deliver reasonable results at a national level. However, for network modelling at a local or regional level, more detail on the geographical variation in the wind resource is required (Met stations and wind farms are usually not co-located.) In this case, we believe that interpolation from meteorological records to simulations of the wind output

[1] An example of this approach is the recent Pöyry report on *Impact of Intermittency.*

time series at specific wind farm sites using physical atmospheric modelling is required[2].

1.1.3 Visualising the wind resource

When visualising the wind resource, we believe that it is important to base the visualisation tool used on the question at hand.

A good example of this is the ability of wind generation to support peak demand. The system adequacy-type risk[3] is usually reckoned to be dominated in GB by hours of very high demand in winter[4]. Any assessment of the wind resource in the context of meeting peak demand should therefore concentrate on such high demand hours.

In principle, a scatter plot such as that in Fig. 1 contains a great deal of information. However, because of the variability about any trend it is difficult by eye to extract information regarding that trend.

We find the graph in Fig. 2 very useful. It shows, for a given demand level x, the mean wind load factor across all hours with demand greater than x, and also the percentage of hours with demand greater than x. There is a clear trend for the wind resource to deteriorate as demand increases from typical winter hours to ACS peak. The particular strength of this representation is that it simultaneously achieves the necessary degree of aggregation to reveal trends in the data, while still focusing on the hours of highest demand.

Some previous work has not fully demonstrated this trend, either effectively basing the estimated wind resource at peak demand on the distribution of wind load factors across a category of hours assumed to be representative of peak (which results in insufficient concentration on the hours of very high demand which are most important), or concentration on answering direct questions about the prevelance of ‘no wind events’ covering the whole of GB (which in fact matter principally through their effect on system risk; more-

[2]See *Matching Renewable Electricity Generation With Demand*, a report by the Institute of Energy Systems at the University of Edinburgh for the Scottish Executive, for an example of this approach. Available for download at `http://www.scotland.gov.uk/Publications/2006/04/24110728/0`.

[3]Defining adequacy as the ability of the system to support demand in steady state, and security as the ability to respond to sudden disturbances. At present, the loss-of-load risk at transmission level is dominated by security-type events, but this situation may change going forward depending on the degree of storage and dispatchable generation/load in systems with high renewables penetrations.

[4]In a meeting at the National Grid Control Centre, we discussed the possibility that in the future there may be substantial adequacy risks during planned maintenance in autumn and spring. Due to the possibility of flexing of planned maintenance schedule, it is very hard to quantify such ‘shoulder month’ risk.

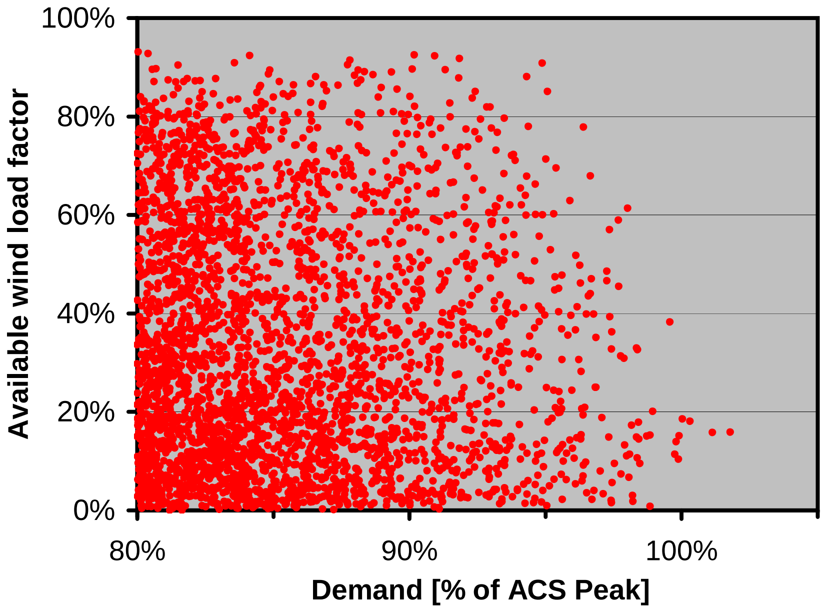

Figure 1: Scatter plot of wind availability versus demand in GB. This plot uses 3 years of metered data from transmission connected wind farms; the data therefore has limited geographical extent, but we have obtained similar results using 6 years of GB-wide simulated data.

over, the results from this type of analysis might depend strongly on the precise definition chosen for a low wind event.)

1.2 Question 8: What is your view of future electricity demand growth and how would you quantify any uncertainty around this?

We believe that it is important to model and quantify distribution-connected renewables on a par with transmission connected generation. Being non-dispatchable, conventional distributed generation does not behave like transmission connected plant; however, as they both depend on resource availability, distributed renewables behave much more like transmission connected renewables than negative load.

One specific example of this is that it makes little sense to calculate a capacity credit for transmission-connected wind in isolation; the country's wind generation fleet as a whole should be considered, due to the decrease in capacity credit (as a percentage of rated capacity) as the installed capacity

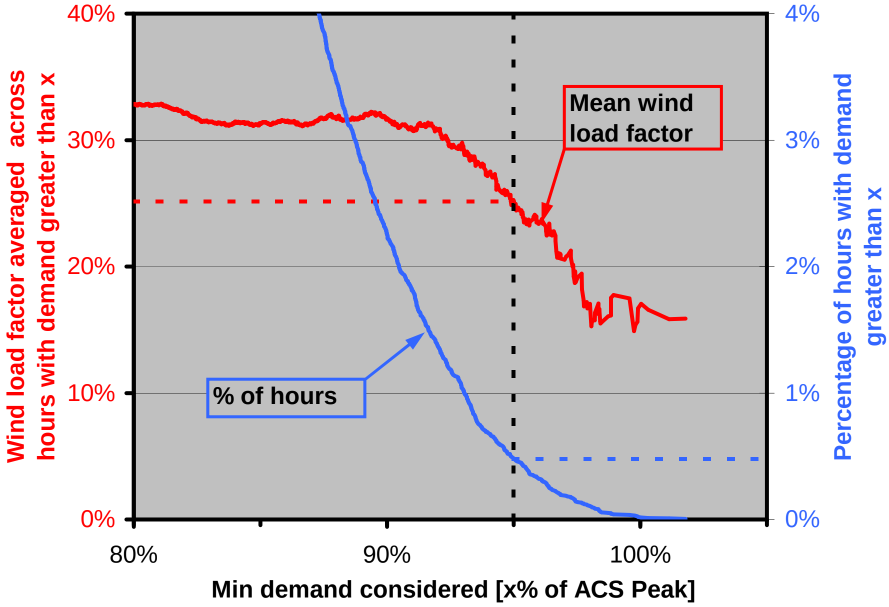

Figure 2: Trend of wind resource at high demand levels in Great Britain. For example, the demand was at least 95% of ACS peak in 0.5% of hours (blue). The average wind load factor across those 0.5% of hours was 25% (red).

increases[5].

2 Section 6: Reserve and Operating Margin

2.1 Specific Questions

2.1.1 Question 17: Is National Grid's current view that 'low wind' events across Great Britain need to be considered when evaluating electricity operating margins reasonable

The variability of wind generation clearly must be accounted for in assessing system adequacy risk. However, the existence of low wind events does not matter a great deal for its own sake; their relevance is through how they affect generation adequacy risk (in this context the relationship with demand is also important.) This is best seen through a risk calculation, which will consider all levels of wind availability on the system, in combination with

[5]See, for example, *Comparison of Whole-Winter, Winter Peak and Approximate Capacity Credit Calculations*, submitted by C.J. Dent and J.W. Bialek to IEEE Transactions on Power Systems and currently in review. Preprints are available from CJD on request.

the coincident demand levels. Too much concentration on investigating the frequency of occurrence of GB wind load factors below a particular level may be misleading, as it neglects the relationship between wind availability and demand which exists at high demand levels. As discussed in Section 1.1.3, it is however valuable to use visualisation tools such as the graph presented to show how the quality of the wind resource varies with the demand level.

With specific reference to Paragraph 6.41 of the Consultation, we disagree with the assessment of the wind resource at peak in the SKM report referenced. This work assumed that all winter half hours between 1700 and 1830 in the evening are representative of peak demand conditions. Our analysis (Section 1.1.3) suggests strongly that any such 'whole winter' selection of hours cannot be taken as representative of annual peak demand, and that the wind resource deteriorates very substantially at the hours of very highest demand. While we have observed a very similar trend to that in Fig. 2 using GB-wide onshore wind outputs simulated from Met Office data, we have not included offshore wind, and therefore cannot compare directly with the distribution plotted in Fig. 4.8 of the SKM report.

We advocate the use of risk-based capacity credits, rather than basing the capacity credit of wind on a chosen percentile of the output distribution. This both focuses directly on the problem at hand (i.e. system adequacy risk), and avoids an arbitrary choice of percentile (see the reference in Footnote 5 for details). A capacity credit may then be based on the quantity of additional demand which can be supported by the new wind generation without increasing system risk; this may be compared with the load-carrying ability of conventional plant.

2.1.2 Question 18: Are our generator availability assumptions reasonable for application to analysis of future operating margins?

We do not have the expertise to comment on whether the availability levels assumed are appropriate. We do however note that as the availability levels are necessarily approximate, the sensitivity of the operating margin to the values assumed should be considered. For instance, a decrease of 1 percentage point in all the availabilities would correspond to a decrease of almost 1 GW in the net operating margin (based on a total installed capacity of 75-100 GW); this is a substantial proportion of the original estimate for operating margin.

2.2 Suggested risk metric

2.2.1 Motivation

We also have a general suggestion for generation adequacy assessment in the context of both future requirements and the annual Winter Outlook[6].

In the context of an all-conventional system, the present approach of presenting a deterministic plant margin metric is both highly transparent and reasonably robust. It may reasonably be extended (as at present with wind) to a system with a single variable-output renewable technology, via scaling the renewable capacity by an appropriate capacity credit. This deterministic method however gives a limited picture of the risk structure; moreover, it will in any case be less satisfactory with multiple renewable technologies, as capacity credits generally consider each technology in isolation (ignoring the interactions of different technologies' variability patterns).

2.2.2 Loss of load expectation

We suggest using Loss Of Load Expectation (LOLE)[7] as a measure of the generation adequacy risk in a given winter (or year). LOLE is defined as the expected (in the mathematical sense) number of periods (e.g. hours, half-hours) in which generation is insufficient to meet demand. It may equivalently be defined as the sum over periods of the Loss Of Load Probabilities (LOLP)[8].

Other risk indices are also available. In particular Loss Of Energy Expectation (LOEE) may reflect more directly than LOLE the cost of loss-of-load risk; however, LOLE is harder to work with mathematically as for each hour it requires summation over all generation states which do not support 100% of demand.

In the LOLP calculation, 'failure' can be defined in various ways, e.g. in terms insufficient generation to meet demand, or erosion of reserve margins. For devising an adequacy metric, the precise choice of risk index might not matter; if one index increases it is likely that others will also increase, and in any case the goal of calculating an absolute level of risk (as opposed to

[6]We have already discussed this matter with the Energy Requirements team at the National Grid Control Centre in the context of the Winter Outlook.

[7]Paragraph 6.40, on page 36 of the Consultation, makes reference to 'Loss of Load Expectation'. This is clearly a different quantity from the one described in the present document. Our understanding is that our definition of LOLE is most common in the literature; that in the consultation might be described as a probability of insufficient reserve.

[8]A more technical description of the suggested calculation may be found in the paper by C.J. Dent and J.W. Bialek referenced in Footnote 5.

comparing risk levels under different circumstances) is unrealistic. There is therefore value in working with the simplest to evaluate, namely LOLE, particularly as this makes the calculations accessible to a wider range of engineers.

2.2.3 Inclusion of renewables

Renewable generation may be included in this LOLE calculation by requiring that at each time conventional plant must meet net demand once the available renewable capacity has been subtracted.

For instance, if time series for demand d_t and available wind capacity w_t in period t are available, then the LOLE may be calculated as

$$I^{\mathrm{LOLE}} = \sum_t p(X_t < d_t - w_t) \tag{1}$$

where X_t, a random variable[9], is the available conventional capacity at time t. This calculation takes into account all available statistical information on any relationship between demand and wind availability.

In practice, an actual historic time series for demand would be used. For wind, there is the option of using a coincident time series for metered availability where appropriate. Alternatively, time series for any renewable resource could be simulated using historic meteorological or oceanographic data.

2.2.4 Interpretation

It is widely accepted in the engineering literature that calculating an absolute level of risk is challenging. Due to data uncertainties and the extreme scarcity of relevant events (we understand that the last loss of load in GB due to absolute system adequacy at time of very high demand was in the mid-1960s) we believe that calculating an absolute level of loss-of-load risk within the scope of an LOLE calculation is an unrealistic goal. In addition, the true loss-of-load risk may be dominated by security-type events (i.e. sudden disturbances), rather than the adequacy-type events which are in scope for a typical LOLE calculation.

Comparing relative levels of risk between years is a much more robust process. In this case, when looking towards 2020, it would be possible to

[9] In the most general formulation, the demand and wind at each time would be random variables also. The formulation given here is for deterministic time series, assuming that these will always be based on real historic time series data.

compare the adequacy risk metric under different scenarios with typical values from the last few winters; the current generation fleet appears to provide an appropriate level of demand security at present demand levels, so this provides a baseline for the risk metric.

2.2.5 Conventional Plant Availability

The simplest reasonable model for availability of conventional generating capacity treats the available capacity from each unit as a two-state random variable (i.e. either full rated, or no capacity available), with a specified availability probability. Three options are available for deriving a distribution for available capacity from the entire conventional fleet (in increasing order of computational time required):

- Normal approximation
- Direct convolution of the individual two-state units
- Monte-Carlo (MC) simulation[10]

In our experience, for GB the Normal approximation works well down to hourly LOLPs of about 3%; as only the mean and standard deviation need to be derived, it is clearly the quickest approach, and also the easiest to implement. Direct convolution is probably the hardest to code, as it requires programming skills (whether in VB or a more traditional language)[11]; comparison with the Normal approximation shows that the tails of this 'direct convolution' distribution are rather fatter than a Gaussian. Given enough trials, a Monte Carlo simulation can achieve any degree of accuracy; our experience[12] is an MC simulation with n trials give good results down to LOLPs of about $100/n$.

In one sense, for the present purpose the choice of technique for the conventional plant does not matter much; if a change of circumstances increases the 'Normal distribution' version of the LOLE index, it is very likely that

[10] Hybrid approaches, where a Normal approximation is used for small units and a more detailed approach is taken for larger ones, are also possible.

[11] For computational tractibility it is necessary to round the unit capacities; using unrounded data and n units, the size of the calculation scales as 2^n, whereas using rounded data it scales as [Number of units] * [Total installed capacity] / [Width of rounding 'bins'].

[12] This experience is supported by the following 'back of the envelope' analysis. Essentially each simulation trial is the outcome of a two-state (Bernouilli) random variable, with 'success' probability p the LOLP which is required. If you perform n trials then the estimator is $\hat{p} = [\text{no. successes}]/n$. This has variance $p(1-p)/n$ which to a good approximation can be approximated by $\hat{p}(1-\hat{p})/n$. So to get the sd of the estimator to 10% of the value of p, it is necessary to solve for n: $0.01p^2 = p(1-p)/n$.

the ‘direct convolution’ version will increase also, and comparisons between scenarios can still be made. The Normal approximation certainly brings huge benefits in terms of the range of people who could apply the risk metric (particularly among third parties outside National Grid; it can be implemented easily in a spreadsheet). If very low risks are relevant, however, the limitations of the Normal approximation in describing distribution tails may be considered too great. The MC simulation might provide a middle ground between realism and ease of implementation (particularly if a specialist risk modelling package is used).

The limitations of using a two-state model for plant availability must not be forgotten. In particular, an assumption of independence between units neglects station faults, broader type faults, and fuel shortages, all of which will tend to fatten the low availability tail of the distribution. Quantification of these effects is an interesting modelling challenge.