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How much can regional aggregation of wind farms and smart grid demand management facilitate wind energy integration?

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Abstract

As wind energy is one of the leading renewable energy sources but also the resource with the highest variability at many time scales, substantial integration into a national or local grid poses increasing challenges for balancing action as the proportion of wind energy to the overall supply increases. Here we analysed the residual load for supplying a two-year time series of national demand data with wind energy from sites across the network at an overall contribution ranging from zero to 100%. The demands on balancing and additional generation capacities was refined to address the needs for, and effectiveness of, balancing actions a set of time scales to represent short-term balancing, active generation and demand side management as possible in a smart grid environment, and support for the daily cycle. In particular the effect of aggregating spatially distributed wind power sources and of demand management actions smoothing out the residual load over a 3-hour window were investigated a possible tools to facilitate wind power integration.

Keywords: wind power production, regional aggregation, demand management, smart grid

1. Introduction

With the global drive to increase the contribution of low-carbon Renewable Energy resources to power generation, wind energy is experiencing sustained and substantial growth in almost every part of the world. Wind power in particular is one of the key technologies as it is mature, able to be installed in utility-scale installations with installed capacities of hundreds of MW, and able to compete commercially with conventional generation, e.g. [1]. However, it is also a resource associated with a significant variability at virtually all time scales, from the duration of turbulent gusts, through daily and seasonal cycles, to long-term changes associated with climate change, where each time scale poses different challenges to integrating wind energy, e.g. [2], from power quality issues to reliability issues and strategic planning.

Ultimately, the instantaneous demand and the consumption over a period must be balanced by the supply. To achieve this balance, a comprehensive portfolio of back-up generation, interconnection, demand management, and energy storage must use used. The three key factors specifying these requirements are, firstly, the actual power output at any point in time to meet the demand; this will determine the operation of alternative generation or energy storage installations. Secondly, the time-integrated electricity production specifies the utilisation of alternative generation and thereby the annual return for participation in the balancing as well as any energy storage volume required. Thirdly, the power fluctuations will determine how fast and by how much alternative generation or energy storage must respond to the balancing requirements which has imposed variability at both, the consumer and supply level. A highly idealised analysis of meeting demand by 100% wind from a single site suggested that the vast majority of energy storage volume requirement would be needed to cover time periods of less than 12 hours [3].

A recent analysis of the variability characteristics of the main renewable energy resources for the UK [4] has provided detailed insight into the characteristics associated with a small set of locations but not addressed the issue what the result is when the variability from several locations is combined into a common transmission network. For other networks, it has been shown that regional aggregation of wind farms in Texas [5] or California [6] reduce in particular the high-frequency variability and that combining power from distant wind farms across the USA leads to substantial reduction in variability at all frequencies [7]. An illustration of the distribution of the power from a wind farm power and from UK wind power fleet during the year 2012 is shown in Figure 1 a) and b), respectively. This shows that the wind power from a single wind farm exhibits a substantial part of the year extreme behaviour of either not producing power at all or producing at its rated capacity, with relatively little time producing output at intermediate levels. In contrast, the UK-wide wind power has a much more moderate profile, with the wind power for most of the time being between 10 and 40% of the time.

The UK electricity grid is an ideal case study for the

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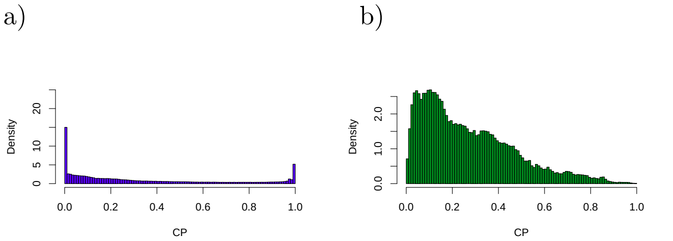

Figure 1: Illustration of the effect of the effect of aggregating power output over a wind farm and over a national transmission grid, a) Power output distribution from the total output of the wind farm, and b) Wind power contribution to the UK National Grid for 2012.

integration of variable renewable energy into the national transmission system, partly because it has a good resource in many areas and forms, from solar through wind to wave and tidal power but also because of the nature of the electricity grid. The UK is a sizeable industrialised island with a well-developed transmission and distribution network supplying a national demand of between 20 GW during summer off-peak and 60 GW during winter peak demand [8], yet with limited connection to the Irish and mainland European systems with a combined capacity of 4 GW in 2013 [9].

Standard approaches to provide residual load at the balancing stage are the use of import or export using interconnectors, the use of energy storage such as pumped hydro energy storage systems, and responsive generation from, for example from hydropower and open cycle gas turbines as those two have the fastest response time. Adding more and more wind power to the grid will pose increasing challenges to these strategies, and the emerging smart grid environment is intended to facilitate the integration of new generation, be it from large variable generators such as wind or from small distributed or embedded generation [10, 11, 12, 13].

In this paper, the main focus is to evaluate the requirements to meet the residual load after wind power at a specified level of overall contribution has been added to the basic scheduled generation. These requirements are refined to target four key time scales, the 'immediate hour' at the resolution of the available data, a short-term balancing period of ±1 hour to capture the usage of short-term energy storage, load following generation and load shifting by demand management possible through the smart grid, the daily cycle and, lastly, all longer time scales. The next section introduces the methodology and data used for this analysis. Section 3 presents the required installed capacity to meet the residual load with and without using spatial aggregating of wind power and time-shifting of demand, as well as the utilisation of that capacity and the associated ramping rates needed to provide the necessary power. The key results are then drawn together in the final section.

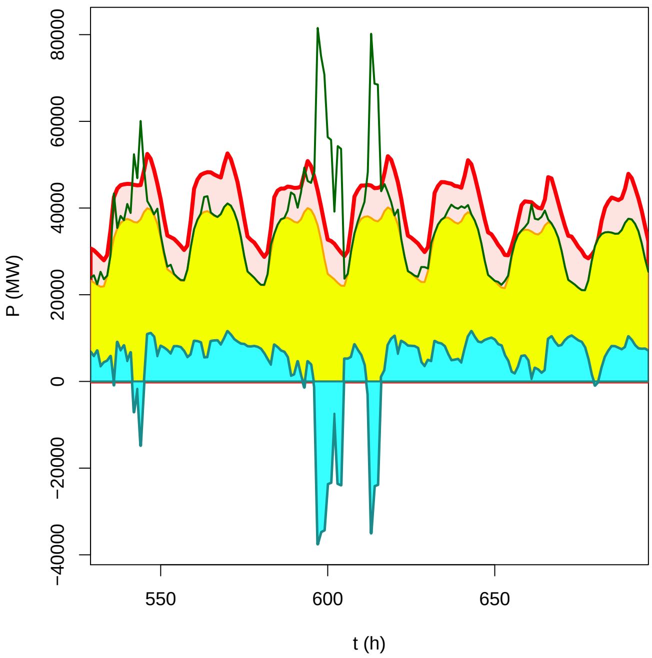

Figure 2: Illustration of (a) Demand and scheduled Generation with adjustment for mean wind power level, (b) demand and actual wind power, and (c) demand, scheduled generation plus wind power and resulting balance.

2. Methodology

The approach taken was to base the analysis of the national demand data from the National Grid [8] and wind power estimates from wind speed data from UK Meteorologial Office anemometers [14] for the two-year period from 1 January 2012 until 31 December 2013. This period includes one year with below-average wind speeds and one with above-average.

One of the main parameters was the percentage of overall electricity provided by wind power, ranging from $C_W = 0$ to 100%, and scheduled generation was constructed to provide the remainder of the consumption, $C_S = 1 - C_W$.

2.1. Demand and scheduled generation

The final UK demand for the chosen period was first averaged from the provided half-hourly resolution to hourly to align them with the wind speed data. It was assumed that the scheduling could be performed knowing the day-ahead demand data in terms of mean demand and daily cycle fairly accurately. The mean demand, $< D >$, was calculated as the 24-hour average of the demand centred at noon, and then linearly interpolated. The mean daily cycle, D', defined as the two-year average for each hour of day, and the amplitude of that daily cycle, A_D, was half the difference between maximum and minimum demand for each day. This was also linearly interpolated for each hour and then combined with the interpolated daily mean demand to set the scheduled part of the generation as as

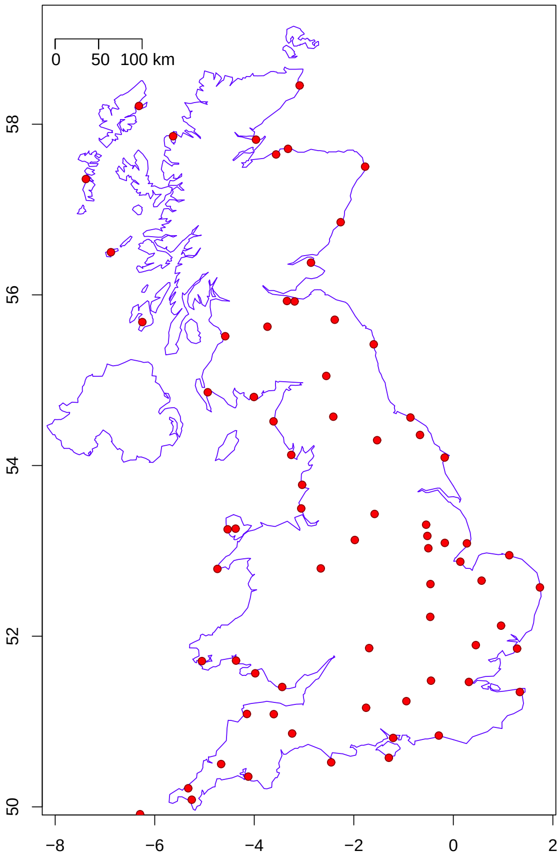

Figure 3: Map of the UK showing the location of the 72 Met. Office stations providing the wind resource data.

$G_p = C_S\,(< D > + A_D D')$. This was therefore a good prediction of the day-ahead demand but without knowledge of day-specific variations around the typical demand profile.

2.2. Wind power estimation

The measurements were UK Meteorological Office land-based weather stations [14] at the 72 locations indicated as dots on the map in Figure 3 gathering hourly wind speed measurements at 10 m above ground rounded to the nearest *knot*. These 72 stations were selected from an initially larger sample to provide a good geographical distribution and, at the same time, have more than 95% of valid data available.

The conversion from the wind speed data to wind power followed a standard procedure, e.g. [15]: the wind speed measured at the anemometer height was converted to m/s, extrapolated to a nominal hub height of 80 m above ground using a logarithmic wind shear profile,

$$u_H = U_R \frac{\log z_H/z_0}{\log z_R/z_0}, \tag{1}$$

with a surface roughness of $z_0 = 30$ mm, and finally convoluted with a generic wind turbine performance curve as shown in Figure 4. The chosen roughness length of 30 mm

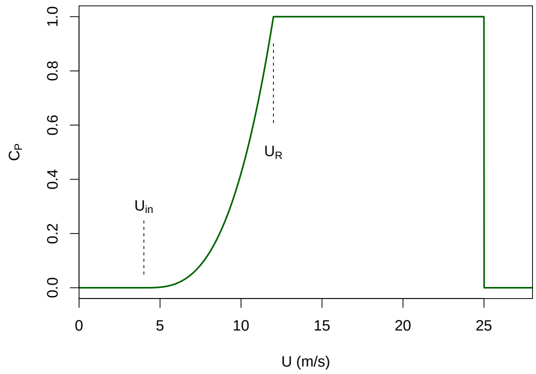

Figure 4: Performance curve of the generic wind turbine used to convert from wind speed at hub height to power output.

is appropriate for short grass, which is a typical environment for a rural meteorological station and follows the approach used by [16]. The generic turbine was characterised by a cut-in wind speed of 4 m/s, a cut-out wind speed of 25 m/s, and a rated wind speed of 12 m/s at which the turbine reached its rated output taken as unity as shown in figure 4. Using unit rated power means that the capacity factor for that turbine at a location is equal to the mean output over the analysis period. A post-hoc check with the wind power contribution to the National Grid[1] for that period confirmed that both, the mean capacity factor and the power distribution from the wind speed data was consistent with that from the National Grid.

2.3. Aggregating wind power

To create a suitably representative sample of aggregating power from N_S different sites, random samples of N_S sites were drawn from the 72 available sites which were then combined to provide a total power output. This sampling, and the successive balancing analysis was repeated up to 60 times to estimate the variability in the results. Since the statistics remained virtually constant for sample sizes of 30 or more at small N_S, the main analysis used a set of 30 samples, mainly to avoid oversampling a finite set and thereby artificially reducing the variation. The variability observed across the chosen stations is of the same order of magnitude as the inter-annual variability for each site observed by Früh [15]. As a result, the ranges of results obtained here can also be taken as indicative for expected inter-annual variation in requirements.

2.3.1. Quantifying effect of aggregation on wind power

Given that the power output profile is limited to the closed interval $[0, 1]$, the shape of the power output distribution can be approximated by the beta distribution, e.g.[17]. The probability density function of the beta distribution is

$$\phi_\beta\,(C_P) = \frac{1}{B(\beta_1, \beta_2)}\; Cp^{\beta_1 - 1}\;(1 - C_P)^{\beta_2 - 1}\,, \tag{2}$$

[1] source http://www.gridwatch.templar.co.uk

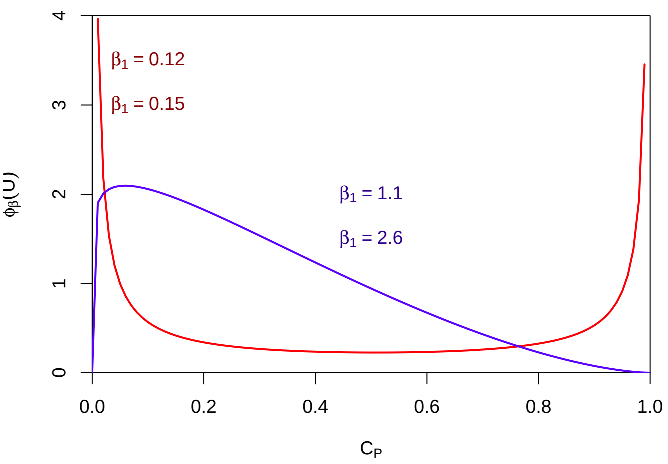

Figure 5: Example of beta functions to represent the power distributions observed in Fig. 1 b and c, respectively.

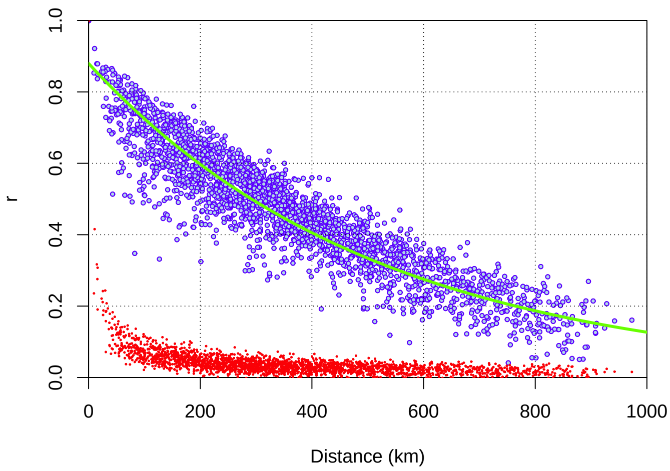

Figure 6: Correlation coefficient between stations against their respective distance: blue circles: wind speed correlation for the 72 stations shown in Figure 3 during 2012-2013 after applying a 3-hour running window averaging filter; small red dots: correlation of wind speed fluctuations.

where

$$B(\beta_1, \beta_2) = \frac{\Gamma(\beta_1)\Gamma(\beta_2)}{\Gamma(\beta_1 + \beta_2)} = \int_0^1 t^{\beta_1 - 1} \ (1-t)^{\beta_2 - 1} \, dt$$

is the Beta function required here to normalise the distribution. The two parameters β_1 and β_2 determine the shape of this distribution such that it has a single maximum within the interval if both parameters are larger than 1, while it diverges to infinity at one or both ends if one or both parameters are less than 1. If $\beta_1 = \beta_2$, the distribution is symmetric around the centre value, $C_P = 0.5$, whereas the maximum is shifted to lower values if $\beta_2 > \beta_1 > 1$ and *vice versa*. An example of two beta distributions for a wind farm and the UK wind contribution are shown in 5, where the individual wind farm is best described by the beta distribution with $\beta_1 = 0.12$ and $\beta_2 = 0.15$ while the national wind power corresponds to $\beta_1 = 1.1$ and $\beta_2 = 2.65$.

2.4. Representation of active demand management

As this study is intended to consider the balancing at different time scales through various generation and demand management actions, rather than assess a particular technology or strategy, only the desired outcome of active demand management made possible in a smart grid environment is considered. From a purely demand side point of view, these are load shifting, in particular peak shaving and valley filling. However, with significant variable and not load following generation, the task would be more appropriately quantified as reducing balancing operation between generation and demand. In terms of demand management, this could be bringing forward anticipated flexible demand in the case of excess available power or delaying it in the case of residual load (power deficit). Moving demand forward and backward in time requires both, some predictive ability and good control of demand as well as control of responsive generation which encapsulates the main function of the smart grid environment.

While much research is progressing on predicting demand and generation, as well as optimum strategy and implementation of the smart grid environment, we simply parametrised the effect of this as an averaging action in time which can smooth out rapid variations in residual load over a time scale specified by a window length T_W. Applying a moving window averaging to the time series of the residual load, the residual load is decomposed into two components, the averaged, low-pass filtered part, and the residual high-pass filtered part. The high-pass filtered part describes the short-term balancing including demand management actions, use of short-term energy storage, import or export to other grids, and fast responding balancing generation. The low-pass filter represents the power required through scheduled and planned generation which might also include some large-scale energy storage. For the purpose of this paper, two scenarios were investigated, minor 'DM' balancing with a smoothing operation over $\pm$1h and extreme demand management and utilisation of large-scale energy storage to cover the cycle, with a smoothing operation over $\pm$12h.

3. Results

3.1. Regional aggregation of wind power

3.1.1. Wind speed coherence and variability

Figure 6 compares the pairwise correlation of the hourly wind speeds and of the hourly wind speed changes against the distance between the stations. There is a clear link between the wind speed and the distance, decreasing rapidly from $r \approx 0.9$ for the closest station pair to around $r = 0.5$

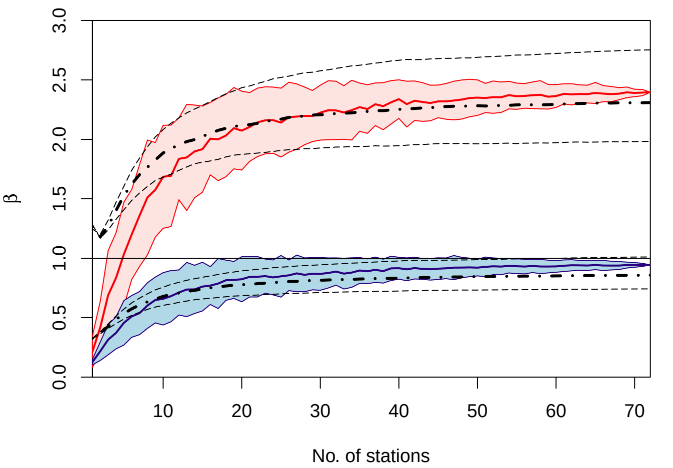

Figure 7: Change of best-fit beta distribution parameters for power output as the number of stations used for aggregation increases; lower blue area for β_1 and upper red area for β_2.

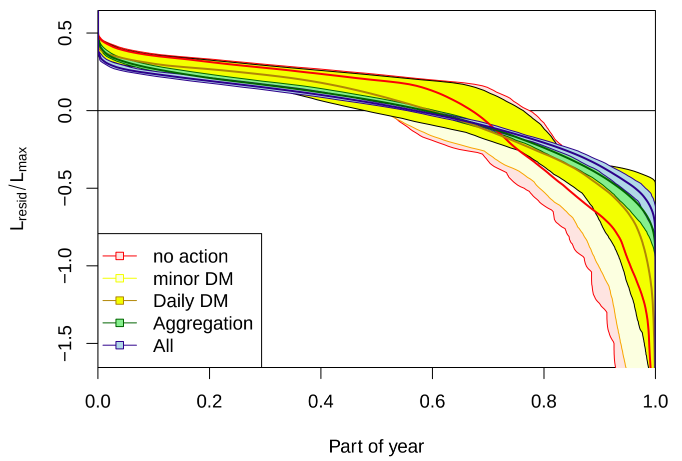

Figure 8: Load duration curves for a wind contribution of C_W = 50%.

at a distance of 200 - 300 km, followed by a more gradual decay to $r \approx 0.2$ at around 700 km. The wind speed fluctuations, on the other hand appear to be largely uncorrelated except for the four closest pairs with distances less than 20 km. This is clear evidence that the wind speeds over the entire UK reflect the synoptic weather patterns with spatial coherence of length scales of hundreds of kilometres. The pattern formed by the blue circles for the wind speed is entirely consistent with the analysis by Sinden [18] for estimated power output at a very large number of sites across the UK as well as the correlation between sites across Germany [19]. However, it also shows that the hourly variation is not significantly affected by the large-scale teleconnection but by much more localised events. This suggests on one hand that variations of the wind over a typical weather regime change will affect the nationally available wind power, with implications for scheduling of other forms of generation. On the other hand it suggests, that it might be possible to smooth out short-term power fluctuations from individual wind farms by aggregating them with other wind farms across the country. The result is that implications of power quality and short-term energy storage might not be too severe an issue when integrating substantial amount of wind power into the transmission system.

3.1.2. Effectiveness of aggregation

Figure 7 demonstrates how effective aggregation of wind power from different regions is as the β parameters from fitting the beta distribution to the sample of aggregated power sources against the number of sites contributing to the overall power. The shaded regions indicate the range of results due to the sampling while the solid lines are the mean values. The reduction of the range at higher number of contributing stations is due to the sample size approaching the population leading to repeatedly sampling the same stations. This effect becomes noticeable once the sample size exceeds a third of the population size. Superimposed are the expected ranges for the beta parameter from combining random samples of power output from partially correlated Weibull distributions with a pair-wise correlation of the mean correlation of the full set of stations. As the sample size increases, this simple random model converges well to the actual observations.

One can see that both, the random model and the station samples start with low values of the β parameters, which rapidly increase as the number of stations increases until saturation sets in between 20 to 30 contributing sites. For the given wind resource, the value at which β_2 saturates is significantly larger than one, indicating that full output from all wind farms is rarely observed, while β_1 converges to a value around unity, indicating that periods of zero output from the entire wind fleet is still possibly though not very frequent. The key general result is that aggregation of spatially distributed wind farms is highly effective but saturates quickly and virtually all transmission grids will have exploited this smoothing effect already. However, developing and remote grids - such as those found on some islands - could still benefit from judicious planning of new wind farms.

3.2. Effect of active demand management

Since the effect of aggregation is virtually fully exploited from a little over 20 sites, this section compares a single site with the aggregation of 25 sites to retain a realistic variation from sampling different stations. Figure 8 shows a set of residual load duration curves overlaid for the example of 50% of electricity provided by wind power, where the shaded regions give the range observed from the sampling, and the solid lines denote the mean curves. The lowest layer, shaded in light red, shows the residual load duration from a single wind power site without any further action. The next layer, in pale yellow represents the residual load after minor demand management actions

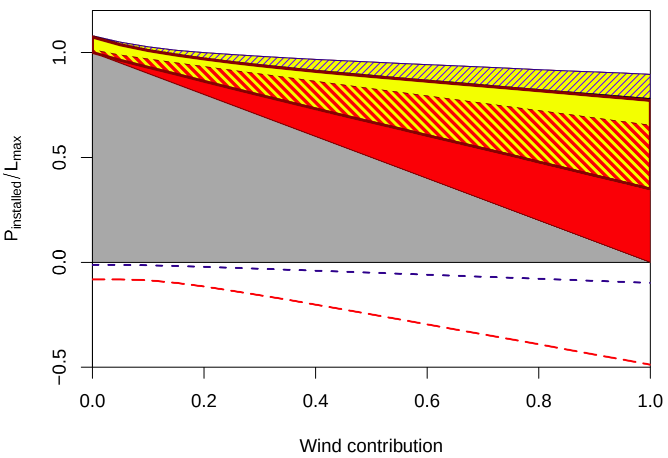

Figure 9: Required capacity to supply the residual load for 99% of the time.

by redistributing power over ±1h. The darker yellow represents the residual load after the daily cycle has been taken care of. The blue represents the results of aggregating wind power sources across the region but without any active demand management, while the green area represents the final residual load after both, aggregation and the daily cycle have taken up the short-term residual load fluctuations. While the range of the residual load increases substantially with higher wind penetration, the relative shape of the duration curves remain very similar from a wind power contribution of 20% up to 100%. The duration curves show a strong asymmetry between residual load (positive values) and excess power (negative) with excess power occurring more frequently and reaching higher values, due to the capacity factor of wind being less than 50% and therefore requiring an installed wind capacity exceeding the maximum demand.

Adding moderate balancing operation by smoothing across preceding and following hour does shift the duration curve closer the axis, i.e., reduces times of high residual load or excess power but does little to reduce the variability across different samples. Not surprisingly, taking the full daily cycle out of the requirements shifts the mean duration curve much closer to the axes, but a substantial range of variation across the samples remains as indicated by the darker yellow area. In contrast to this, the effect of spatial aggregation alone without any further Demand Management actions reduces both, the times of high residual load and excess power, as well as the variation across the samples. Applying both, strong demand management and spatial aggregation leads to the final curve (in green).

3.3. Effect of wind energy contribution

To summarise the residual load duration curves, the residual load values which cover 98% of the year are determined, where $L_{\mathrm{resid}}/L_{\max} = 0.01$ quantifies the level of available generation required to meet the residual load for 99% of the time, while $L_{\mathrm{resid}}/L_{\max} = 0.99$) quantifies the corresponding level of power to be absorbed, be it through interconnection, energy storage, or demand shifting. Figure 9 shows the required generation capacity against wind energy contribution. The grey triangle represents the installed capacity of the schedule generation, decreasing directly with the wind contribution from 100% to 0%, the combination of the other shaded regions indicates the total required generation capacity in addition to the schedule generation and wind power if the wind power source is from a single site. As the wind contribution increases, and the scheduled contribution decreases, the additional capacity increases steadily, though not quite as fast as the scheduled generation decreases.

The savings made through aggregating wind farms to a national wind fleet is shown by the upper hatched and shaded regions in Figure 9, while short-term demand management over a few hours does not reduce the remaining capacity requirement noticeably. Separating the daily cycle from the longer term requirements leads to the remainder being separated into three regions, where the yellow area indicates the requirement for daily cycle cover which would reduce the longer term requirement. The central shaded region covers the requirements which have to cover both, the daily cycle and the longer term needs, while the red region is to supply only the electricity beyond the day ahead. This separation can be interpreted such that most energy storage technologies, operating at the daily time scale at most, and extensive demand management strategies can only effectively address a restricted part of the balancing requirements and that the remainder splits relatively evenly into, secondly, those types of generation which has to provide power at all time scales and, thirdly, those who are only needed for the slower response beyond the day-ahead scheduling. Those longer time scales are mostly associated with the synoptic weather time scale of two to three weeks and the seasonal cycle in both demand and wind resource.

The level of power to be absorbed, either be short-term demand management or by action to absorb the daily cycle are indicated by the two dashed lines in Figure 9.

The installed capacity is only one aspect of the electricity supply system with both, the utilisation of that capacity and its response rate as two further, complementary characteristics. The utilisation is a measure of the income generated, or costs avoided in the case of demand shifting, while the response rate characterises the technology needed to provide the required generation in time. The utilisation, measured as the energy provided can be quantified as the load factor using the installed capacity from Figure 9, is shown in Figure 10 a) and b) for a small grid with a single wind farm and for a large grid with aggregated wind power, respectively. Both indicate that the additional generation, beyond scheduled and wind, is increasingly used as the wind contribution increases to somewhat over 20% but that this then levels out at a load factor of around $C_L = 27\%$ for the national grid with an aggregated wind fleet, and at around $C_L = 40\%$ for the small

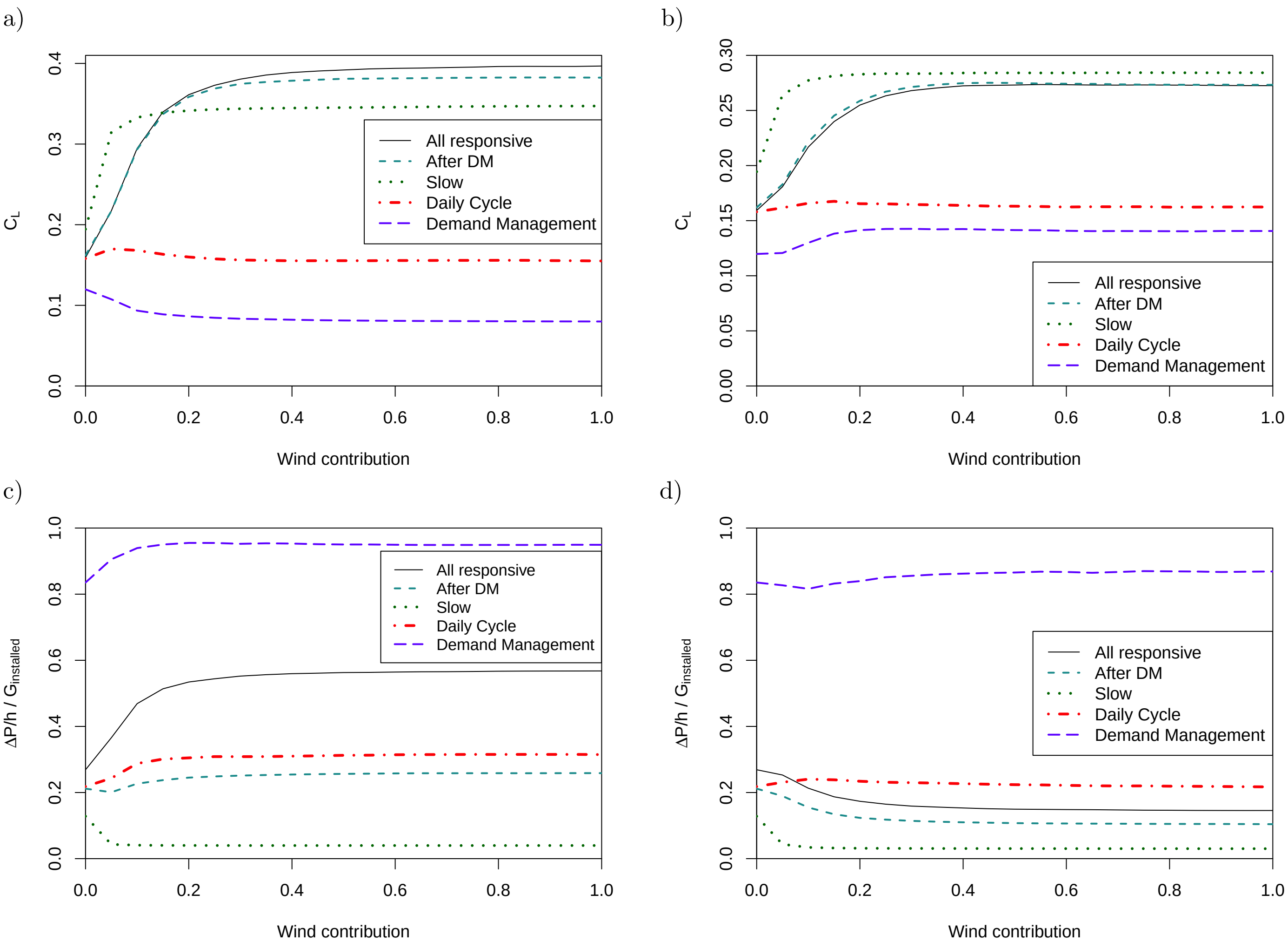

Figure 10: Utilisation of generation and ramping requirements against wind energy contribution; a) Utilisation in a small grid with a single wind farm, b) Utilisation of generation with aggregated wind power fleet, c) ramping requirements in a small grid, and d) ramping requirements in a large grid.

grid with a single wind farm. Smoothing out the hour-to-hour variation through moderate demand management actions has very little effect on the utilisation of the generation required to supply the residual load. The daily balancing requirement to meet the residual load increases directly in line with the wind contribution, and the daily cycle utilisation remains virtually constant in both types of grids (red dash-dotted lines).

The other characteristic is the ramp rate required to meet the residual load within the time specified. In Figures 10 c) and d) the required ramp rate to meet the residual demand at the right time is expressed as the change in power output per hour, normalised by the installed capacity for that time scale of generation as shown in Figure 9. For the demand management actions and the daily cycle balancing, the installed capacity include the pumping requirement to deal with excess power, whereas the slower generation only considers the output. Similar to the utilisation, the required ramping capability settles to a constant level once the wind contribution has reached around 20%. The black line representing the balancing ramping needs without further intervention shows that this increases rapidly from around 27% to 57% of the installed responsive capacity in the case of a small grid with a single wind turbine or farm, but decreases from 27% to around 15% in the case of a national grid with an aggregated wind fleet. This can be interpreted through the fact that the volatility of the wind power from a single source is larger than the slower variation at the daily, synoptic and seasonal variation. The former requires a fast response or higher ramping rate whereas the latter only requires a significant change in the power output but at a very low ramping rate. In contrast, the volatility of the aggregated wind power is reduced to a degree where it is less than the daily or slower variability. In line with this argument, even a moderate demand management scheme smoothing the residual load over ±1h, reduces the response requirement from 57% to 20% in the small-grid situation but has only a minor effect in the national grid case (the cyan dashed line). However, also dealing with the daily cycle shown by the greed dotted line reduces the response rate requirement to between 3 and 4% for both grids. The requirements on the balancing actions are that the hourly response requirement requires the ability to change the output by over 80% of its capacity in both grids to meet the balancing power for the 99% of the time as identified in Figure 9, whereas the daily cycle balancing has to respond at between 20 and 30% of its capacity per hour.

As all the analysis is technology-independent and does not specify explicitly how any excess power is used or what supplies the residual load, the analysis can be extended to a scenario where the wind contribution exceeds the specified demand substantially. Such a case could be realised if some of the excess power were to be used to decarbonise transport by electric vehicles or for production of hydrogen. In that case, one could expect that the conventional electricity demand used in this analysis would be met more frequently by wind energy than if the installed capacity were just matching that demand. This effect on the overall balancing requirement to make up any wind power shortfall, is shown in Figure 11 for installed capacities to generate in a year up to 300% of the conventional demand, with the surplus possibly used for meeting losses from energy storage, charging electric vehicles or producing hydrogen. As can be seen, over-supplying a small network has virtually no effect on the balancing requirements, as the percentage of time when the wind speed is below the cut-in wind speed does not change whatever the installed capacity. In contrast, over-supplying a national grid has a clear beneficial effect for all demand management approaches, as the livelihood of zero wind power is extremely small.

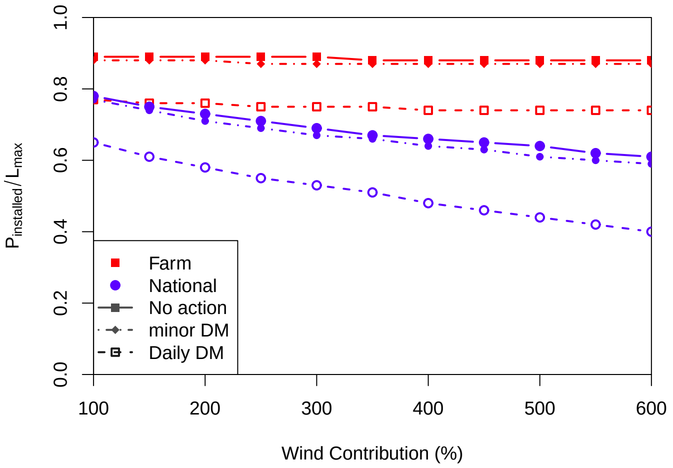

Figure 11: Required capacity to supply the residual load for 99% of the time if the installed wind capacity exceeds the requirements for meeting electricity consumption.

4. Conclusions

This paper aimed to identify the effect of the volatility of the wind energy resource on its integration into the grid, how the aggregation of spatially distributed wind power reduces that volatility and how active demand and generation management as envisaged by a smart grid can absorb that volatility. Combining hourly national demand data and regionally distributed wind speed data, this analysis has quantified complementary generation requirements to supplement electricity from wind, where the key parameter was the contribution of wind energy to the current demand profile, ranging from zero to 100%. Rather than directly specifying individual technologies, the different requirements were characterised by the time-scale over which they had to operate. For the purpose of this paper, the time scales chosen were the hour-by-hour variation, 3h-averaging, the daily cycle, and 'slow' response capturing the synoptic weather and seasonal time scales. The 3-hour averaging was to represent a moderate amount of active demand management in addition import/export to other grids and the use of short-term energy storage technology, while the daily cycle, averaging over $\pm$12h was to represent most of the large-scale energy storage technology and extensive demand management actions.

Three measures were used to quantify this requirement, namely the capacity needed to meet the residual demand for 99% of the time, the load factor for that capacity over the chosen two-year period analysed, and the ramping rate needed to provide the power when was needed. One of key results were that aggregating spatially separated wind power sources reduces the volatility of wind power substantially and that the full benefit is realised with only a moderate number of sources combined. Once more than 20 to 30 wind farms covering a maximum distance of 800km, the full benefit of that effect has been exploited. In contrast to this, managing demand and generation across the 3-hourly window has little effect on the required complementary capacity and its utilisation, although it reduces the required ramping capability. This reduction is relatively minor in the case of a large grid where wind power is spatially aggregated but it results in a substantial reduction in a small grid with few wind farms over a restricted area.

Overall, the complementary capacity increases steadily with the expected wind energy contribution, where the full spatial aggregation reduces that capacity by around 15%, around 25% are needed to cover the daily cycle only, around 15% to provide power at the slow time scale beyond the day ahead only, and the remaining 45% are needed to cover both, the daily and longer time scales. These relative contributions are fairly constant for any wind contribution over 25%. Over-supplying a network with excessive installed wind capacity, where excess power could be used for other purposes, does not have any further affect on the requirements in small grid but it does reduce the required capacity in a large grid.

The logical next step in this approach is to use technology-specific or strategy-specific solutions to meet the calculated residual load. This analysis would initially assign typical efficiencies or losses, ramping rates, costs, and carbon emission factors to identify optimum portfolios of different strategies, and the demands to be met by a particular technology or strategy.

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