

## RESEARCH ARTICLE

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# Spatial and temporal variability characteristics of offshore wind energy in the United Kingdom

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**Abstract**

The growing reliance on intermittent sources of renewable energy poses challenges for developing reliable electricity networks. This study has analysed the spatial and temporal characteristics of the UK's offshore wind energy production based on reanalysis of offshore wind speeds between 2000–2017, considering both the 2019 and future distribution of offshore wind farm capacity in UK waters. The extent and frequency of low wind power events are assessed, which are shown to vary seasonally. The correlation in output from offshore wind farm pairs reduces with increasing distance between them, albeit at a slower rate than has been observed for onshore wind farms. The conditional probability between regions of low energy production is also evaluated, which reveals that regions such as the English Channel are much more susceptible to simultaneous periods of low wind energy production if there is limited wind energy production in south-west England or in the North Sea. Nevertheless, aggregating energy production from all offshore wind farms has a positive effect in reducing the likelihood of prolonged periods of country-wide very low energy production. Comments are made on the possibilities for regional distribution of installed capacity to reduce the overall variability of wind energy and the relevance of these findings to electricity networks with increasing penetration of wind-generated electricity.

**KEYWORDS**

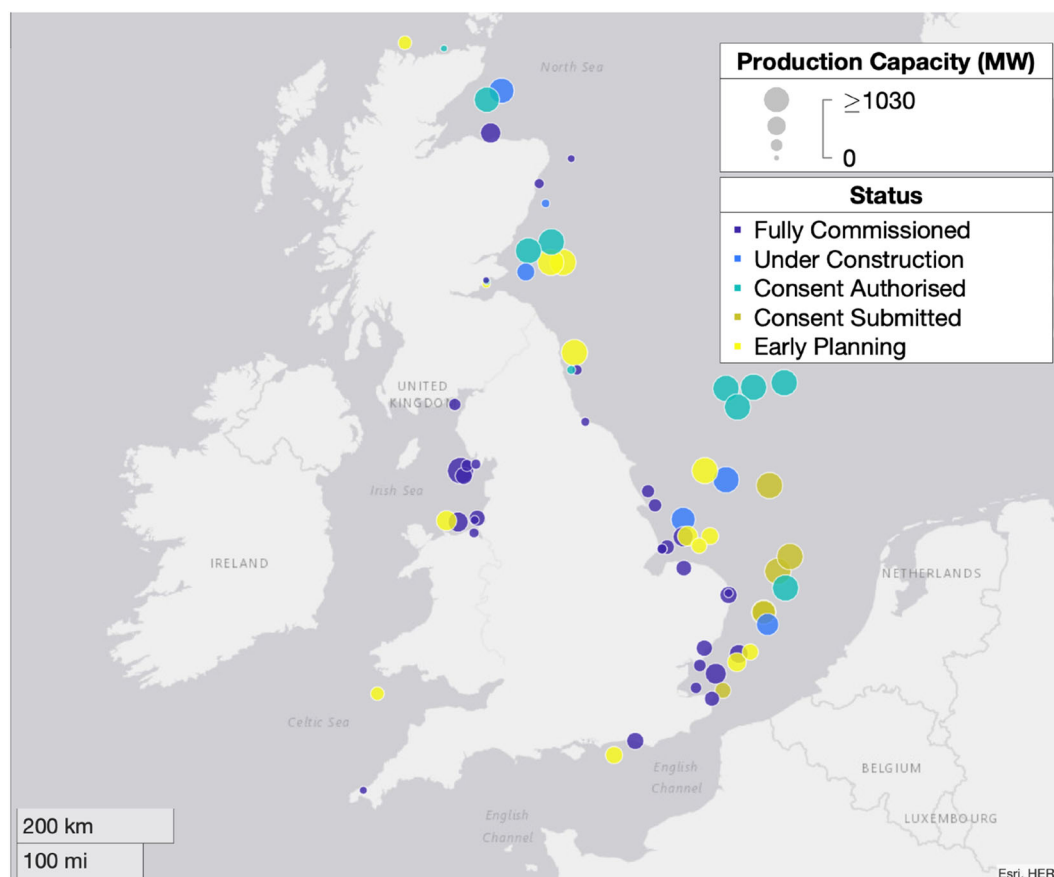
wind energy, variability, offshore wind

## 1 | INTRODUCTION

The United Kingdom has an ambitious target of reaching net-zero emissions by 2050. Meeting this target will require significant growth of the offshore wind energy from approximately 10 GW today to over 90 GW by 2050.<sup>1</sup> Wind farms consist of ever more turbines, with eight offshore wind farms in the UK now consisting over at least 100 turbines. The largest, Walney Wind Farms, has 189 turbines. Development has been generally confined to two offshore regions, with approximately 83% of the UK's installed capacity located in the Irish Sea (Region 4) or in waters around the English Channel (Regions 2/3) as shown in Figure 1. The regional weighting of installed capacity remains fairly consistent considering wind farms in planning and under construction, as the locations of the planned substantial increase in North Sea capacity (Region 1) are close to existing capacity in the English Channel. As new technologies such as floating turbines become available, there is the potential to develop other regions around the United Kingdom. One of the key challenges presented by the rapid expansion of intermittent energy sources like wind energy is how

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**FIGURE 1** Locations of UK offshore wind farms sorted by production capacity. 83% of current offshore wind farm capacity is located in Regions 1, 2, and 4

these resources can be successfully integrated into the wider electricity system. This study focuses on the characteristics of extended periods of low energy production.

The expansion of renewable energy will play a key role in reducing greenhouse gas emissions and slowing temperature rise through the 21st century.<sup>2</sup> Although there is considerable uncertainty in climate models, the natural interannual variability in wind speeds around Europe are expected to dominate any climate-driven wind speed changes.<sup>3,4</sup> Consequently, historical data have been widely used to evaluate the wind energy resource around the world. There may additionally be a slight benefit to wind turbine performance in northern Europe due to the expected reduction in icing frequency as temperatures rise.<sup>3</sup>

Wind power in the United Kingdom is typically higher in the winter months and lower during summer months, which is correlated with seasonal variations in electricity demand.<sup>5</sup> However, the interannual variations in wind power can be significant; Früh<sup>6</sup> showed that variations of 10%–15% are typical for onshore Scottish wind power. Historically, weather dependence of the British electricity network was driven by effects of near-surface temperature on energy demand. The expansion of renewable energy sources increases the sensitivity of energy supply to weather systems as well, and Bloomfield et al<sup>7</sup> suggest that the Great British electricity network's sensitivity to weather may have already transitioned from a temperature-dominated to a wind-dominated regime.

The inherent variability and limited predictability of the wind resource are often cited as a challenge for the development and operation of power grids with high penetration of wind energy sources.<sup>8,9</sup> Some of the concerns around variability can be mitigated by averaging wind energy production over a number of geographically dispersed wind farms, as the auto-correlation of wind speeds tends to decrease with distance, particularly over daily and hourly time periods.<sup>10</sup>

Previous studies have shown that variability of wind energy production can differ significantly between countries (e.g., other studies<sup>8,11,12</sup>). Kiviluoma et al<sup>11</sup> showed that variability tends to increase with capacity factor, but can be mitigated through geographical dispersion of wind farms, shown also by Fisher et al<sup>8</sup> and Shahriari and Blumsack,<sup>13</sup> albeit with diminishing returns as scale increases. This is somewhat dependent on region and the dominant weather systems, although substantial reductions in variability correlation for wind farm distances greater than 500 km have been demonstrated using both wind farm output<sup>14</sup> and meteorological reanalysis<sup>5</sup> data.

Many studies to date have focused on onshore wind farms due to the availability of data and the greater installed capacity relative to offshore farms. In the onshore environment, the effects of terrain and elevated levels of turbulence are expected to reduce output correlation more quickly over relatively small inter-farm distances compared to the offshore environment. In recent years, wind farm development in the United Kingdom has increasingly focused offshore for technical as well as social and political reasons, a trend that is expected to continue. Offshore wind farms in the United Kingdom achieved an average capacity factor of 39.6% compared to 26.2% for their onshore counterparts in 2019.<sup>15</sup> While offshore wind speeds are generally higher and less variable than onshore wind, there is still a significant degree of spatio-temporal variability caused by large-scale weather systems.<sup>16</sup> Patlakas et al<sup>17</sup> noted the potential for multiday periods of low wind speeds, particularly in the relatively near-shore regions where offshore wind farms are typically located due to water depth constraints.

Over subhourly to hourly time scales, wind variability is a concern for voltage and frequency regulation<sup>18</sup> and the capacity for the grid to manage rapid changes in supply<sup>19</sup> particularly in conditions where renewable energy production is high and demand is low, due to the low system inertia provided by wind turbines and solar photovoltaic cells.<sup>20</sup> This may lead to increased curtailment of wind farm output in future as the proportion of variable renewable energy sources in the grid increases.<sup>21</sup> Short period fluctuations in wind speed tend to be driven by atmospheric turbulence and are closely related to local topographical features, and some degree of smoothing can be achieved by aggregating production across several wind farms.<sup>22</sup> Spatially distributed wind energy production can therefore help to reduce balancing costs and increase the aggregated 'firm' generation capacity.<sup>23</sup>

At longer time scales, concerns about wind variability are related to meeting energy demand and the need for alternative energy sources during periods of low wind energy production and high demand. Of particular relevance for the United Kingdom and other North Sea countries are high-pressure systems and easterly winds which are associated with calm wind conditions and which can persist for multiple days.<sup>24</sup> In winter, these weather systems can be associated with colder weather and therefore higher energy demand, posing a particular challenge for network management and energy planning.<sup>25</sup> Li et al<sup>9</sup> found that it is possible to forecast some aspects of these so-called 'Dunkelflaute' events several days in advance; however, further work will be required to improve and generalise forecasting capabilities.

Pan-European studies show that large weather systems, particularly in the North Sea, can affect multiple countries simultaneously and that substantial investment in cross-continent interconnector capacity would be required to achieve the level of geographical dispersion required to minimise wind variability (see, for example, previous studies<sup>16,26-28</sup>). Malvaldi et al<sup>28</sup> showed that cross-correlation in wind power decreased as the distance between countries increased, finding for example a cross-correlation of 0.67 between Great Britain and Ireland. The correlation peaked when a time-shift of between 5 and 8 h was applied to British wind speeds, implying that this is approximately the time it takes for weather systems to pass between the two countries. Similarly, Foley et al.<sup>26</sup> found that 55% of periods of low mean wind speeds in Ireland coincide with low mean wind speeds in Great Britain. These dynamics arise from the prevailing east-west wind direction over the islands. In particular, Grams et al<sup>27</sup> found that peripheral regions (Iberia, Scandinavia, Balkans) had significant potential for wind energy production during severe lulls in the North Sea. However, the benefit of geographically distributing wind farms is diminished if the regions are weakly interconnected or subject to other technical and/or commercial constraints by system operators.<sup>26</sup>

The increasing importance of offshore wind energy to the United Kingdom, and the geographical changes in wind farm distribution that this brings, means that the UK grid's sensitivity to different weather systems may be changing over time. Limited interconnector capacity to neighbouring countries, and the significant likelihood that these countries will also be experiencing energy shortfalls during prolonged periods of low wind energy production (see, e.g., the literature<sup>7,28</sup>) means that it is important to understand wind variability around the United Kingdom, particularly offshore.

The objective of this research is therefore to assess how low offshore wind energy events are spatially and temporally correlated around the United Kingdom, the persistence of these events, and the times of year when these may be most significant. We also examine regions in which future wind projects could help to improve the resilience of offshore wind energy production during low energy events. This work complements and extends previous studies for the United Kingdom, in particular, other works<sup>5,6,19</sup> contribute to the growing body of literature on the spatio-temporal variability characteristics of wind energy and the benefits of wind power aggregation.

## 2 | DATA AND METHODOLOGY

This study considers the impact of spatio-temporal variability of the UK's offshore wind energy production. The available wind power is modelled using meteorological reanalysis wind speeds with a representative wind farm power model. As described in Section 2.3, a generalised wind farm power curve is derived based on the DTU 10 MW reference wind turbine, and capacity scaled to match the installed capacity of existing and planned offshore wind farms at their respective locations. This enables the study to focus on the effects of variability in wind energy production given the current and future disposition of the offshore wind fleet rather than differences associated with the different turbines installed in each farm.

## 2.1 | Data sources

Wind power output is used as the basis for the present assessment of UK offshore wind energy characteristics. As measured wind farm power output is not directly available for all wind farms, the power has been inferred from the wind speed at each respective wind farm and a representative power curve. Although wind speeds measured by Meteorological Masts (Met Masts) are preferred due to their high temporal resolution (10-min intervals) and close deployment near wind farms, these data are typically only available for limited time periods and locations.

Hence, meteorological reanalysis datasets were used as the basis of this investigation. These provide a much more comprehensive geographical and temporal coverage and have served as the data source for several previous studies of wind characteristics (see, e.g., previous studies<sup>29,30</sup>). The reanalysis model used in this study was Renewables.ninja<sup>12</sup> which is based on NASA's MERRA-2 dataset. A bias correction was developed by Staffell and Pfenninger to account for differences between observed and modelled wind farm output and was calibrated using historic data from onshore UK wind farms.

This paper investigates the spatio-temporal variability characteristics of the UK's offshore wind energy production, focusing on longer period fluctuations in the wind resource and complementing previous studies by Sinden<sup>5</sup> and Drew et al<sup>19</sup> into the variability of the UK's onshore and offshore wind energy production. The reanalysis modelling provides 18 years of wind speed data at hourly temporal resolution and a spatial resolution of  $0.500^\circ \times 0.667^\circ$  latitude-longitude. To obtain wind speeds at the wind farm of interest, wind speeds provided at reanalysis grid points must be interpolated to such location. However, comparison of bi-linearly-interpolated reanalysis with observed wind speed data obtained from MIDAS stations shows that a location's elevation and proximity to the sea-land boundary can give rise to mean wind speed errors that are significantly higher than the range of errors exhibited by nonelevated, noncoastal locations. This stems from the inability of the coarse spatial resolution in the reanalysis datasets to capture topography-dependent, short-range variations in wind speed. In the underlying model of Renewables Ninja's dataset, however, wind speeds were interpolated from the nearest twelve grid points to the location of interest by means of locally weighted polynomial regression (LOWESS).<sup>31</sup> Local-polynomial-regression-type interpolation methods like LOWESS have been found to perform well in capturing finer details in data which exhibit short-range variation.<sup>32</sup> This process was deemed to be suitable for representing the wind speeds experienced at offshore wind farm locations and in this study, the resultant wind speeds are evaluated at an altitude of 100 m, with logarithmic interpolation used where wind speed data were not directly available at this height.

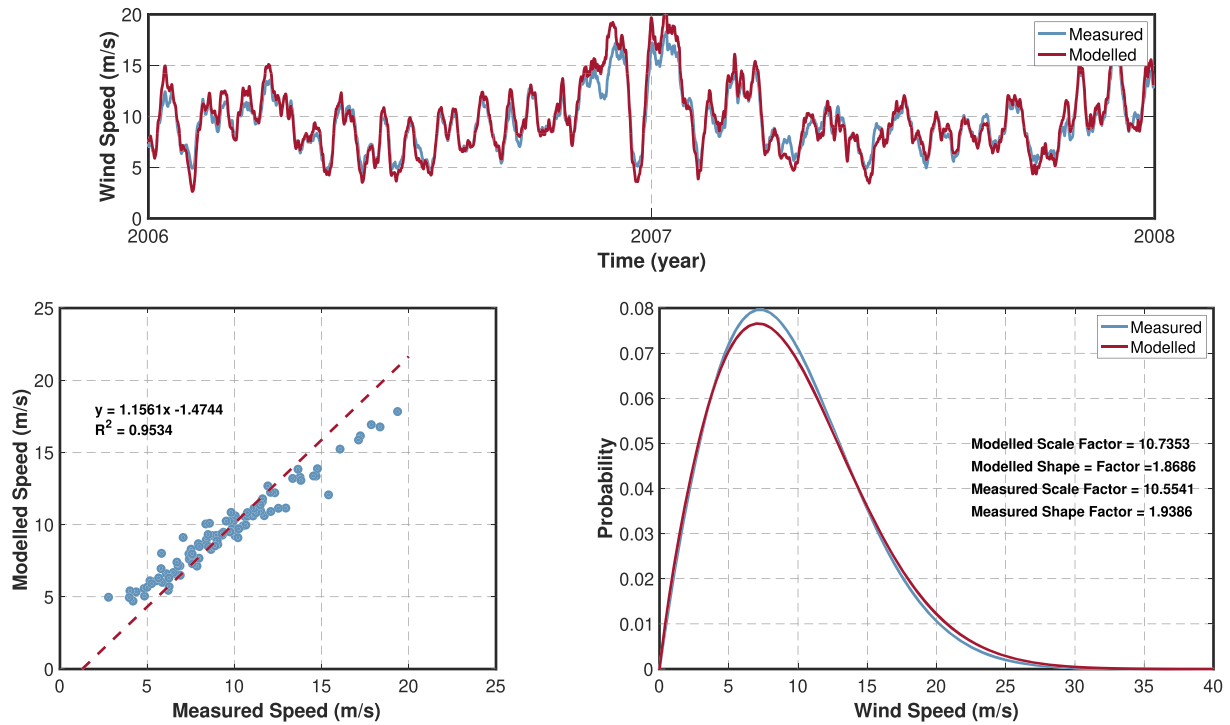
## 2.2 | Wind speed validation

Validation of the reanalysis wind speed modelling was carried out for four of the key offshore wind regions identified in Section 1 to investigate potential spatial variation in agreement with respect to Met Mast observations. Validation was only performed with reference to Regions 1 to 4 due to the availability of Met Mast data. A representative wind farm was selected in each region for further analysis.

Details of the validation of hourly wind speeds are summarised in Table 1 and key metrics are illustrated in Figure 2. The strongest correlation between modelled and measured datasets is found for Region 4, with a Pearson correlation value of 0.9764 and  $R^2$  value of 0.9534. The root mean square error (RMSE) and mean absolute error (MAE) in predicted wind speed were  $0.8508 \text{ ms}^{-1}$  and  $0.6363 \text{ ms}^{-1}$ , respectively. Similarly good

**TABLE 1** Summary of data validation statistics for Regions 1–4

	Region1	Region 2	Region 3	Region 4
Wind Farm	Westermost	Greater Gabbard	Rampion	Gwynt y Mor
Latitude (°)	53.81	51.88	50.81	53.45
Longitude (°)	0.15	1.94	−0.1	−3.58
Met Mast Height (m)	100	88	107	69
Period	2005	2008–2011	2012–2014	2006–2007
Pearson's R	0.9493	0.9367	0.8	0.9764
$R^2$	0.9013	0.8773	0.7568	0.9534
Mean Bias (m/s)	0.5305	0.3996	−0.6725	0.0056
RMSE (m/s)	1.1714	1.195	1.3602	0.8508
MAE (m/s)	0.8894	0.9116	1.1966	0.6363
50th Percentile Error (%)	4.85	1.89	−11.32	−1.41
90th Percentile Error (%)	7.68	9.5	−12.36	3.84
95th Percentile Error (%)	11.74	12.97	−19.28	5.66



**FIGURE 2** Data validation for Region 4, represented by Gwynt y Mor wind farm. Hourly modelled wind speed time series plotted along with measured wind speed (top). Hourly modelled wind speed plotted against measured wind speed (bottom left). Weibull distribution of the modelled wind speed distribution and the measured wind speed distribution (bottom right)

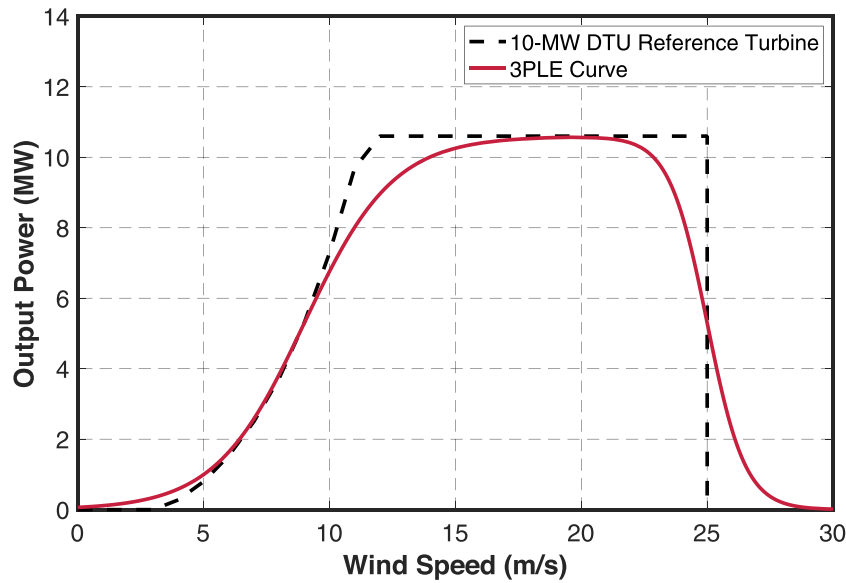
agreement was found in Regions 1 and 2, with RMSE and MAE in predicted wind speed less than  $1.2 \text{ ms}^{-1}$  and  $1.0 \text{ ms}^{-1}$  for both regions. A higher RMSE,  $1.3602 \text{ ms}^{-1}$  and MAE,  $1.1966 \text{ ms}^{-1}$ , were found in Region 3. The probability of wind speeds over  $15 \text{ ms}^{-1}$  are overestimated in the reanalysis data in Regions 1, 2 and 4, whereas wind speeds above  $10 \text{ ms}^{-1}$  are underestimated in Region 3. Percentile errors refer to the percentage difference in modelled and observed wind speed at a certain percentile. At higher percentiles (90th and 95th), all regions except Region 4 exhibit wind speed error magnitudes higher than 10%. On the contrary, Regions 1, 2, and 4 show relatively smaller errors of 4.85%, 1.89%, and  $-1.41\%$  respectively at the 50th percentile. This is a favourable result given that wind speeds at these high percentiles are beyond the rated wind-speed of most wind turbines and so will have minimal impacts on the power output.

On the whole, although Regions 1, 2, and 4 show good agreement between the reanalysis model and observed wind speeds, the model's performance in Region 3 is significantly poorer. This result is expected given that Region 3 is located in the English Channel, a narrow body of water surrounded by two major land masses, which adds even more uncertainty to reanalysis models' performance in the sea-land boundary that sophisticated interpolation methods struggle to resolve. However, the region consists of only two relatively small wind farms and therefore will have a limited impact on the present analysis. Furthermore, while the highest wind speeds appear to be overestimated in the reanalysis data, the periods of low wind production which are the focus of the present study are largely associated with lower wind speeds.

### 2.3 | Conversion of wind speed to power output

Wind speeds were translated into power output using the DTU 10 MW reference wind turbine power curve.<sup>33</sup> Although larger than the off-shore wind turbines installed around the UK to date, the 10 MW reference turbine is representative of turbines being deployed in the near future. The reference power curve was modified to account for the effects of operation within a wind farm using a three-parameter logistic function.<sup>34</sup> A comparison between the resultant aggregate power curve and the underlying DTU 10 MW reference turbine power curve is shown in Figure 3. Farm power is normalised by the rated power to define the capacity factor  $CF$ , the ratio of output power  $P$  to the rated power  $P_r$ :

$$CF = \frac{P}{P_r} \quad (1)$$



**FIGURE 3** The 3 parameter logistic function (3PLE) power curve (red) accounting for the effects of in-farm operation compared against the DTU 10 MW reference turbine power curve (dashed) as a function of wind speed

This allows the analysis to be performed independently of the magnitude of the power of the reference wind turbine and can be scaled by installed farm capacity where required. The use of a single reference wind turbine allows the spatio-temporal variations in wind energy production of interest in the present study to be identified without the added complexity of different turbine characteristics at different locations.

Wind turbine performance degrades over time due to erosion of the aerodynamic surfaces of the turbine blades and reduced reliability due to wear and tear over time. Staffell and Green found that the wind turbine power output degrades at a rate of 1.57% per year, factoring in long-term changes in wind conditions and improvements in technology.<sup>31</sup> This rate of performance degradation was applied to all wind farms in the present study, using the average time that each wind farm has been in operation.

Whilst the wind speed is the main determinant of energy production, shutdown periods and a lack of electricity demand can also contribute to turbines operating below their maximum capacity.<sup>5</sup> We have not considered these additional factors in the present paper, although it is noted in particular that curtailing of wind production may become increasingly significant during periods of high wind speeds and low energy demand as more wind farms are commissioned.

### 3 | UK OFFSHORE WIND ENERGY PRODUCTION CHARACTERISTICS

The characteristics of the aggregated offshore wind energy production are presented in this section. The aggregated wind speed  $v_{agg}$  and capacity factor  $CF_{agg}$  are defined based on weighted averages of the wind speed and capacity factor respectively, where the weightings correspond to the 2019 distribution of installed capacity of the UK's offshore wind farms

$$\begin{aligned} v_{agg} &= \frac{1}{C} \sum_{i=1}^n c_i v_i \\ CF_{agg} &= \frac{1}{C} \sum_{i=1}^n c_i CF_i, \end{aligned} \quad (2)$$

in which  $c_i$  is the capacity of the  $i^{th}$  wind farm,  $C$  is the total UK offshore wind farm capacity (8,568 MW), and  $n$  is the number of wind farms. The general characteristics of the UK offshore wind energy production are presented in this section, namely its temporal and spatial variability, and the persistence of low generation events.

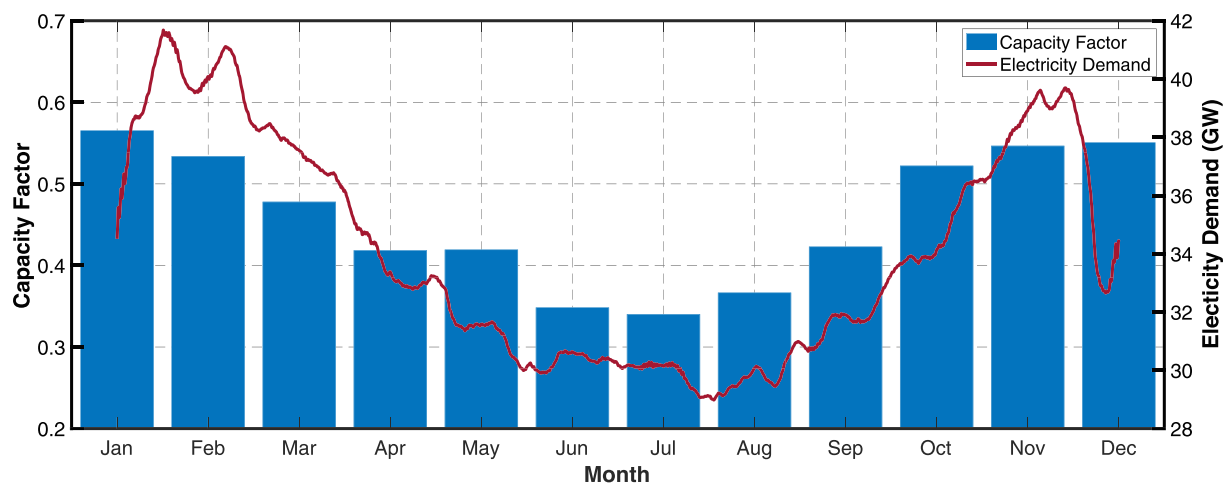
#### 3.1 | Temporal variability

The interannual variability of wind energy production represents a significant source of uncertainty in the prediction of annual energy yield.<sup>35</sup> Over the 18 years between 2000 and 2017, the mean capacity factor of 0.459 has a normally distributed interannual variability of 4%.

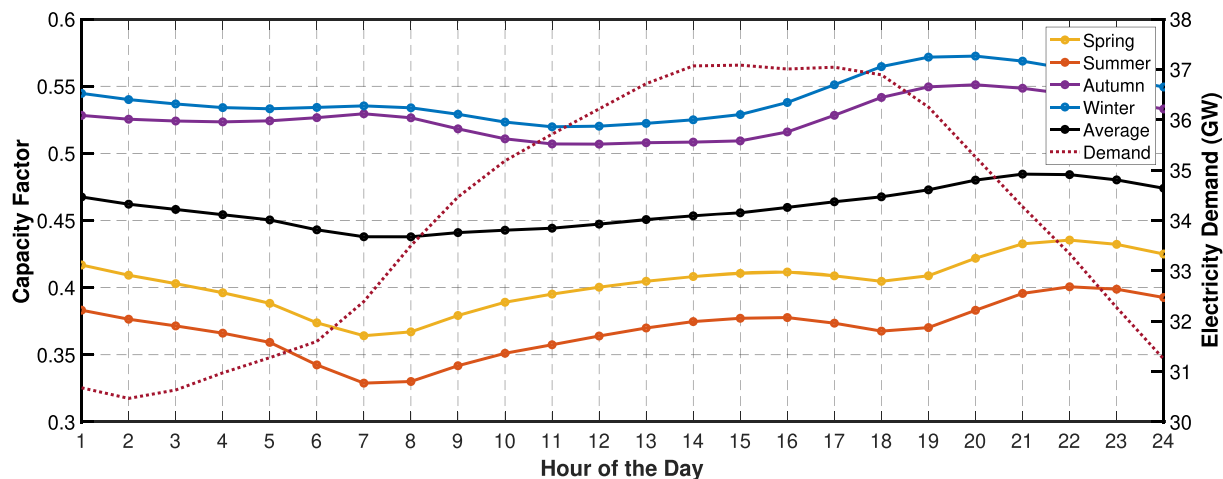
Significant seasonal variation is observed in offshore wind energy production, as shown in Figure 4. During the winter months (December, January, February), the mean monthly capacity factor is 0.5415, which is 47% higher than that of the summer months (June, July, August) which stands at 0.3690. The mean capacity factor is 0.4037 and 0.5261 in spring and autumn respectively. Consequently, the summer months represent only 20% of annual energy production, compared to 39% for the winter months. In the United Kingdom, the trend of greater wind energy in the winter is positively correlated with seasonal trends in electricity demand.

Diurnal variability of offshore wind energy production varies on a seasonal basis, as shown in Figure 5. In spring and summer, the capacity factor is greatest during the nighttime around 2100–2200 hours before decreasing by around 19% to its minimum in the morning at 0700–0800 hours. Diurnal variation in wind speed is less pronounced in autumn and winter, and is roughly half that of the spring and summer months. Peak power output occurs slightly earlier in the evening, around 1800–2100 hours during the autumn and winter months, and minimum capacity factor around midday.

Averaged over the year, offshore wind power generation is higher at night than during the day, with the highest capacity factor at 2100 hours and the lowest capacity factor at 0700 hours. This is a reversal of the onshore generation pattern, due to the land breezes which develop in the evening and cause cooler air to move offshore. While this generation profile may not closely correlate to the overall UK electricity demand profile, it complements the generation profiles of onshore wind farms and solar farms (see, e.g., Sinden<sup>5</sup>), which produce higher power during the day, and thus may be desirable for the electricity grid as a whole.



**FIGURE 4** Annual variation of power output, presented in terms of monthly capacity factors (blue). Average annual UK electricity demand between 2011 and 2017 is shown in red



**FIGURE 5** Diurnal variation of capacity factor by season. Average daily UK electricity demand from 2011 to 2017 is shown in red

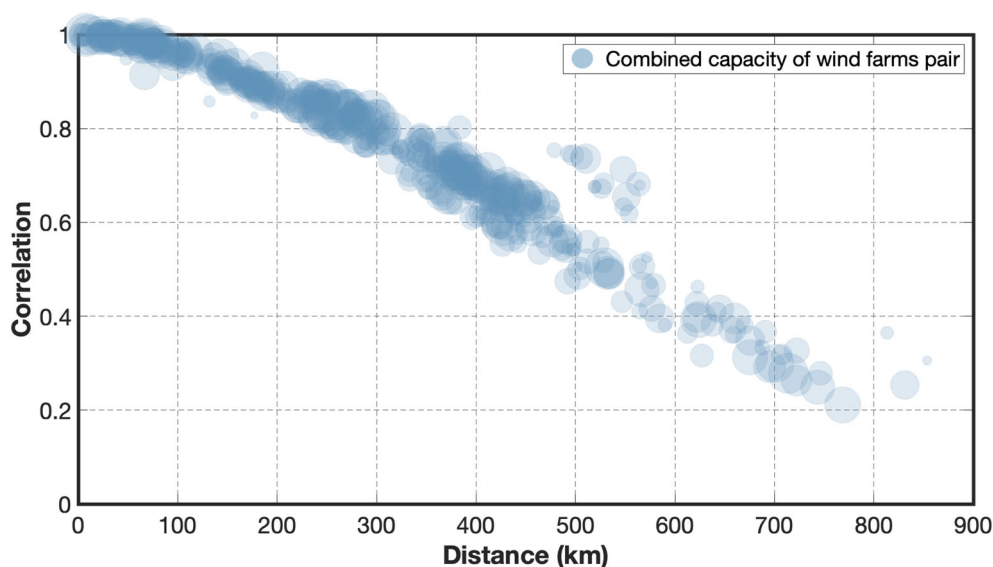


### 3.2 | Spatial variability

The examination of the wind's spatial variability focuses on the effects of geographic diversity on wind power output. Previous studies of the wind resource (see, e.g., previous works<sup>5,14</sup>) have predominantly used Pearson ( $r$ ) correlation or cross-correlation metrics to quantify the spatial correlation of output between two wind farms. While the analysis of long-term wind characteristics is based on a stationary wind model, where wind speed is assumed as an ergodic random process of a constant mean with fluctuating components, at certain time scales, wind speed exhibits nonstationary characteristics, and using Pearson ( $r$ ) correlation would therefore be inappropriate.<sup>36,37</sup> To validate this nonstationary assumption, the augmented Dicker-Fuller test, which tests the null hypothesis that there is a unit root in the time series, and hence, is nonstationary, was implemented.<sup>38</sup> By using data from all 32 wind farms in the study and segmenting each farm's wind speed data by different time scales, it was found that at time scales longer than one year, augmented Dicker-Fuller test successfully rejected the null hypothesis in 97.7% of all the segments. On the contrary, augmented Dicker-Fuller test successfully rejects the null hypothesis 0.1% and 1.3% of all the quarterly and monthly wind speed segments, thus confirming the nonstationary assumption for these shorter time scales. Given that wind variability at shorter time scales is also the focus of this study, it is necessary to address the drawbacks of Pearson's correlation coefficient with non-stationary data. Therefore, the detrended cross-correlation analysis cross-correlation coefficient (DCCACC), first proposed by Podobnik,<sup>39</sup> is employed in this paper.

A DCCACC was calculated using the wind speed time series over the 2000–2017 period for each pair of wind farms and is shown as a function of the distance between the farm pairs in Figure 6. The size of the dots in the figure correspond to the combined capacity of each farm-pair to illustrate the spatial distribution of the offshore fleet. As indicated by the intensity of the colouring, most wind farm pairs are less than 450 km apart, with a correlation in output greater than 0.6. The correlation in their wind speeds decreases as the distance between farm sites increases. This reduction occurs at the greatest rate over distances of 300 to 700 km, with the correlation coefficient reducing below 0.3 at distances greater than c. 700 km. The groupings of data above the predominant distance-correlation trend at 500–600 km and 800–900 km represent the correlations between Regions 6 and 2 and Regions 6 and 5, respectively. It should be noted that only one site lies within Region 6 (WaveHub) in the present analysis.

Low correlations between wind farms are desirable as the combination of their outputs reduces the effects of short-medium term variability in the temporal domain, smoothing the aggregate generation profile. Figure 6 highlights the importance of a geographically diverse fleet of wind farms. At present, 87% of the UK's offshore wind farms are within 500 km of each other, for which the average correlation coefficient is greater 0.5. Reducing the correlation of the offshore fleet will rely on developing more geographically diverse regions, in particular Region 6 (South-West England) and Region 5 (Scotland). Whilst the deeper waters in these locations may limit opportunities for fixed-foundation turbine deployment, floating wind turbine technologies have the potential to expand the positive benefits that these regions may have for aggregate offshore wind production.



**FIGURE 6** Distance-correlation scatter plot for the 32 × 32 offshore wind farm location pairs in Regions 1 to 6. The size of each circle represents the combined capacity of a wind farm pair



### 3.3 | Low generation events

Periods of low energy generation are associated with extreme wind speed events, defined here as prolonged periods of low or high wind speed where turbines do not operate. In the case of low wind speed events, these are periods where the wind speed falls below the cut-in speed of  $4 \text{ ms}^{-1}$  and for high wind speed events, where the wind speed exceeds the cut-out limit of  $25 \text{ ms}^{-1}$ .<sup>5</sup> Turbine shutdown at these wind speeds lead to periods of low or zero power generation and pose a problem for the reliable integration of wind power into the wider electricity network. Hence, quantification of these low generation events is an integral part of the assessment of the UK's offshore wind energy production as it has important implications for wider energy strategic planning as well as for the development and deployment of energy storage technologies.

In the United Kingdom, low wind speeds are responsible for the majority of low generation events. Across the UK's offshore wind farm locations, low wind speed events occurred on average of 7% of the time in the 18-year period between 2000 and 2017 as compared to the incidence of high speed events of 0.3%. Low wind speed events were therefore responsible for 96% of all low generation events.

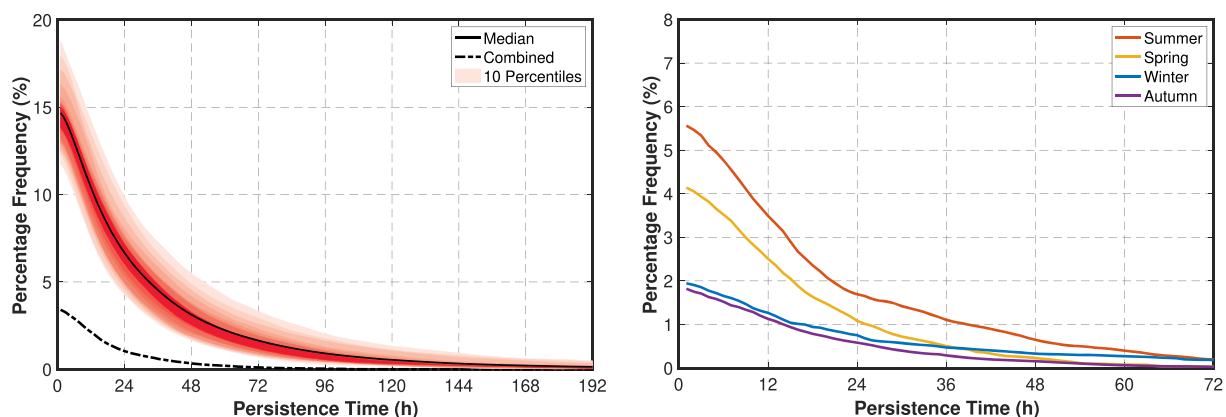
Figure 7 presents the percentage frequency that the capacity factor was below 5.67% for a given period. The 5.67% capacity factor threshold corresponds to a mean velocity of  $4 \text{ ms}^{-1}$ , the turbine's cut-in velocity, over the period. It should be noted that wind speed fluctuations around this speed and the smoothing of the power curve due to the 3PLE method (Section 2.3) allow for a small amount of power generation below the reference wind turbine's cut-in threshold, which may mean that the frequency of low generation events is slightly underestimated in the present study. The frequency of low generation events mimics an exponential decay with respect to the persistence time. Figure 7A shows that there is an appreciable spread of between 4% and 12%, with a median of 6.66%, in the probability of at least 24 h where the capacity factor is less than 5.67% at any one site. The probability of at least 24 h below this level is significantly reduced to 1.04% when offshore production is considered in aggregate.

The frequency of low generations events has substantial seasonal variability; the probability of those corresponding to the 5.67% CF threshold is shown in Figure 7B. For any given persistence time window, the frequency of low generation events is significantly higher in spring and summer than in autumn and winter. This reflects the seasonal variations discussed Section 3.1 where the average diurnal capacity factor is higher in autumn and winter than in spring and summer.

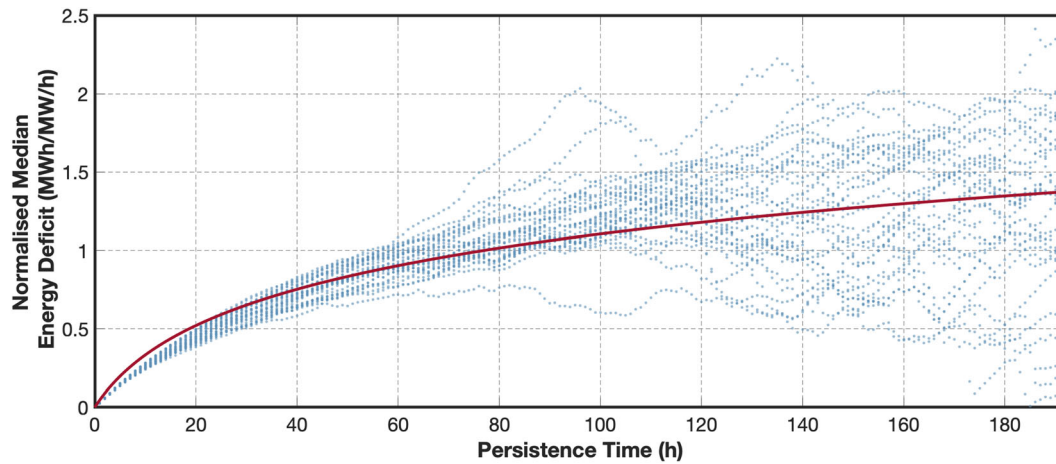
The likelihood of prolonged periods of reduced wind energy production depends on the selected capacity factor threshold. Low energy events defined by a higher capacity factor threshold of 20% occur at a substantially higher frequency than those defined by the 5.67% CF case. Combined offshore wind output was below the 20% CF limit for 16.57% of all 24 hour periods in 2000–2017, with the probability decreasing to less than 1% only when the persistence period exceeded 16 days. The challenge of persistently low, but nonzero, offshore wind energy production may therefore be a significant factor when considering requirement for alternative generation and energy storage systems.

It is useful to characterise periods of low generation in terms of the energy deficit relative to baseline production levels. The capacity of storage systems is a major constraint on how well they are able to mitigate variable energy sources like wind power, and it is also important to understand the timescales over which the storage systems are required to act.<sup>40</sup>

Figure 8 shows the mean energy deficit per hour  $E_d$  below the 5.67% CF threshold and normalised on installed wind farm capacity as a function of the deficit persistence period  $T$ . This is shown for each farm in blue, and the best-fit trend line is shown in red. The mean deficit was



**FIGURE 7** Frequency of low generation events as a function of persistence time expressed as percentages of time for (left) all wind offshore farms and aggregate production (dashed line) and (right) aggregate production across different seasons



**FIGURE 8** Normalised median energy deficit below 5.67% CF per hour as a function of persistence time of low energy events. Each offshore wind farm is shown in blue, and the trend for all farms is shown in red

determined by calculating and grouping each energy deficit below the 5.67% CF threshold  $E_i$  for every wind farm into persistence windows based on the deficit period:

$$E_d = \frac{\sum_{i=1}^n E_i}{nT} \quad (3)$$

where  $n$  is the number of low generation periods of period  $T$  that were recorded.

Normalisation of the mean deficit with respect to persistence period and farm capacity aids in cross-comparison between different deficit periods and installed capacities, as shown in Figure 8. The mean deficit is small for short persistence periods because it measures how much, on average, the energy production was below the 5.67% CF threshold, and there are many brief periods where energy production is only slightly below the CF threshold. There are fewer instances of longer periods of low energy production, but these are associated with persistently low wind speeds, hence the general increase in the normalised mean deficit with persistence time. The rate of increase in the normalised mean deficit slows as persistence time increases due to the averaging effect over long time periods on the wind speeds encountered within the wind farm. Naturally, the normalised deficit increases more quickly and tends towards a greater value when a higher CF threshold, for example, 20%, is employed.

The present analysis demonstrates that the mean deficit exceeds the installed turbine/farm rated energy production when the deficit period exceeds 70 h. The volume of energy storage required to compensate for extended periods of low energy production in large offshore wind farms may therefore be quite large. The Walney wind farm cluster has a capacity of 1,030 MW. Based on the average energy storage system capacity in the United Kingdom of 27 MWh,<sup>41</sup> this corresponds to approximately 12 h of production below the 5.67% CF threshold. The need for storage can be mitigated by diversifying sources of energy production, but this needs to be available during periods of low wind generation.

## 4 | REGIONAL ANALYSIS

While the previous section considers the general characteristics of the UK's current offshore wind energy production, this section focuses on the spatial distribution of power production considering both the 2019 distribution of wind farm capacity as well as the contribution of farms proposed and under development. This introduces an additional 35 wind farms to the 32 considered above. This study aims to identify regions which may have the potential to bolster the overall resilience of generation capacity.

### 4.1 | Regional characteristics

The key statistics of each region, for both current (2019) and projected capacity, are presented in Table 2. Two further metrics are introduced to quantify the reliability of each region's wind power production: the coefficient of variation  $CV = \sigma/\mu$ , the ratio of the standard

**TABLE 2** Key metrics describing regional capacity factor and variability for six offshore regions considering current (2019) and proposed UK offshore wind farms

Variables	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
Current Capacity (MW)	871.1	3126.7	727.2	1886.4	1747.2	210.0
Additional Capacity (MW)	11244.0	10763.0	400.0	576.0	8910.0	224.0
Projected Capacity (MW)	12115.1	13889.7	1127.2	2462.4	10657.2	434.0
Mean Intra-Dist (km)	120.0	104.1	120.3	63.3	111.4	-
Projected Mean Intra-Dist (km)	155.3	114.2	103.5	63.3	140.1	134.5
Max Intra-Dist (km)	198.1	202.6	120.3	165.2	177.2	-
Projected Max Intra-Dist (km)	297.3	233.9	155.2	165.2	316.7	134.5
Min Intra-Dist (km)	20.3	2.4	120.3	3.9	48.2	-
Projected Min Intra-Dist (km)	7.4	2.4	35.0	3.9	3.9	134.5
Mean CF	0.447	0.477	0.420	0.462	0.430	0.535
Projected Mean CF	0.541	0.508	0.443	0.465	0.511	0.524
Median CF	0.437	0.495	0.383	0.465	0.402	0.629
Projected Median CF	0.630	0.560	0.426	0.469	0.572	0.604
SD of CF	0.313	0.315	0.313	0.326	0.310	0.329
Projected SD of CF	0.321	0.321	0.317	0.326	0.326	0.330
Variability Coefficient	0.504	0.498	0.525	0.544	0.513	0.535
Projected Var. Coef.	0.500	0.509	0.524	0.545	0.520	0.536
Availability	0.862	0.881	0.840	0.847	0.852	0.882
Projected Availability	0.904	0.888	0.851	0.849	0.882	0.877

Note: Region 6 currently consists of only one wind farm.

Abbreviations: CF, capacity factor; SD, standard deviation.

deviation to the long-run mean,<sup>42</sup> and the availability, defined as the percentage of time the winds are strong enough for the wind farm to generate electricity:

$$\text{Availability} = \frac{\text{No. of hours } CF \geq CF_{\text{threshold}}}{\text{Total no. of hours}} \quad (4)$$

The capacity factor threshold  $CF_{\text{threshold}}$  used to compute the availability described herein was 5.67%.

Region 2's low variability ( $CV = 0.498$ ) and high availability (88.1%) make it an attractive region for offshore wind power generation, helped by relatively shallow water depths, with 3,127 MW deployed to date, representing more than one third of total installed capacity. The characteristics of Region 3 (English Channel) are less favourable for energy production with higher variability ( $CV = 0.525$ ) and lower availability (84.0%) resulting in the lowest mean and median regional capacity factors.

Region 4, the Irish Sea, has an installed capacity of 1,886 MW and exhibits comparatively high variability ( $CV = 0.544$ ) and lower availability (84.7%). The region is small, having the smallest mean inter-farm distance of any region, which has a tendency to make regionally aggregated production more variable as the wind farms see similar conditions more of the time.

Region 6 has significant wind potential, being the region most exposed to strong Southwesterly winds coming from the Atlantic Ocean. The variability of production is slightly higher than most other regions, and the higher water depths encountered in this region is also a challenge for potential developments.

Table 2 also indicates how the additional capacity of the 35 farms proposed and under development is distributed across the six regions identified in this paper. The total additional capacity is 32 GW, the majority of which is to be deployed in Regions 1, 2, and 5. Regions 3, 4, and 6 have only relatively small capacity increases planned at present. The regional coefficient of variations are projected to remain roughly the same under the planned developments, although regional capacity factors are generally expected to rise, with particularly significant increases in Regions 1 and 5 of 21% and 19% respectively from their current values. This is partly due to the increased dispersion of farms within these regions, as seen in the increased mean inter-farm distance, which provides a degree of geographical smoothing of power output. Availability is also forecast to rise slightly for most regions.

## 4.2 | Temporal correlation of low generation events

The temporal correlation of low generation events between the different offshore regions was investigated using a Bayesian probability framework. The probability of low power in region A given the observation of low power in region B,  $P(A|B)$ , is defined as

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad (5)$$

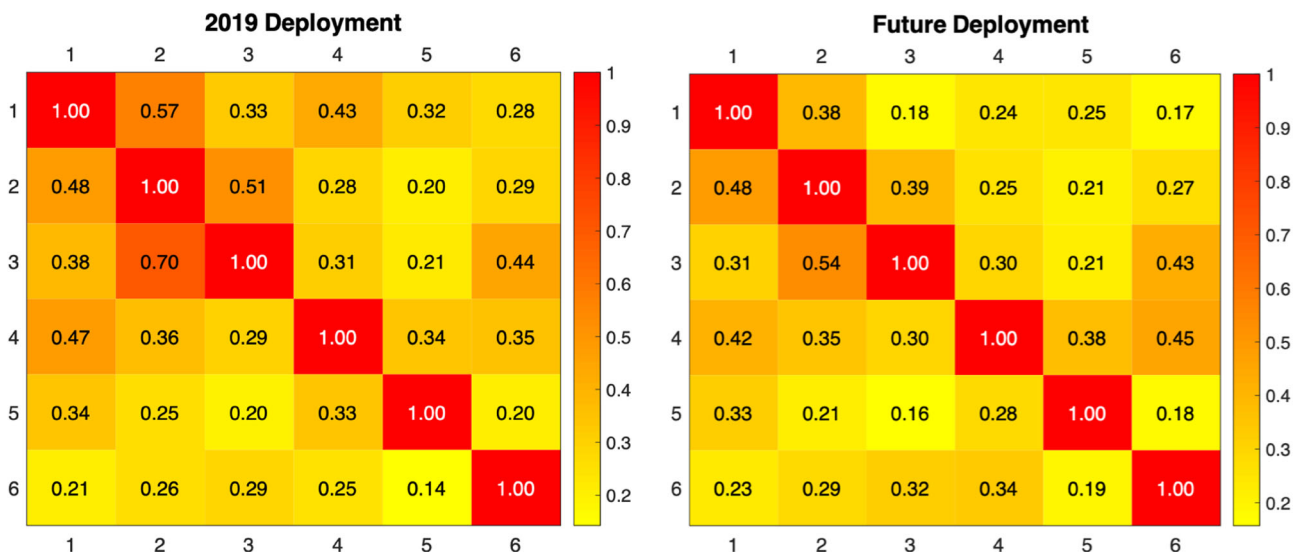
where  $P(A)$  and  $P(B)$  represent the probability of low generation events in regions A and B respectively, and  $P(A \cap B)$  is the probability of both regions experiencing low generation events at the same time. The probabilities were approximated from the 18 years of wind speed data for 2000–2017.

The matrix of conditional probabilities for the current and projected UK offshore wind fleets is shown in Figure 9, where the diagonal is necessarily  $P(A|A) = 1.00$ . Pairs of regions in close proximity, such as Regions 1 and 2, or 2 and 3, demonstrate a higher probability of simultaneous low generation events due to the increased likelihood of experiencing similar wind conditions, whereas the probability of simultaneous low generation is much lower for regions further apart, such as Regions 5 (Scotland) and 6 (south-west England). Further insight is gained by comparing  $P(A|B)$  and  $P(B|A)$ . For example, given a low generation event in Region 6, the probability of a simultaneous low wind energy event in Region 3  $P(3|6) = 0.44$ , whereas the converse probability  $P(6|3) = 0.29$ . The funnelling of south-westerly weather systems from Region 6 into Region 3 contributes to increased likelihood of simultaneous periods of low wind, whereas this effect is less prominent when the winds come from the opposite direction [SEA].

Figure 9 also shows that there is a general decrease in the temporal correlation of low generation events between regions based on the distribution of the projected future UK offshore wind fleet. The most significant decrease, given low generation in other offshore regions, occurs for Region 1 (north-east England). This is because the planned developments in the region will result in a much greater diversity of wind farm locations compared to present and that wind availability is expected to increase as developments move further offshore. Greater correlation in output between Regions 4 (Irish Sea) and 6 (south-west England) arises as a result of the locations of proposed farms in Region 6 being close to Wales, significantly reducing the mean distance between the two regions, increasing the likelihood of farms in the two regions being affected by the same low energy events. Nevertheless, there is an overall reduction in the level of temporal correlation of low generation events if all proposed offshore wind farms are developed.

## 4.3 | Fleet optimisation approach

The combined wind farm capacity of a country can be considered to be a portfolio of wind farms, to which an objective of identifying the optimal regional allocation of generating capacity can be applied, inspired by the work of Roques et al.<sup>43</sup> In the present study, we utilise Markowitz's



**FIGURE 9** Comparison of Bayesian conditional probability matrices between the current (left) and the projected (right) UK offshore wind farm fleets

Mean-Variance Portfolio Theory,<sup>44</sup> which was originally developed to optimise the efficiency of a portfolio of financial assets, i.e., to minimise the portfolio risk for a given target of expected return or vice versa. Applied to wind generation, this approach can be used to minimise variability across the network subject to certain capacity factor targets.

Previous sections have demonstrated that spatial diversification of capacity around the UK lowers the overall risk of prolonged low energy events in a similar way to the basis of Mean-Variance Portfolio theory that diversification of resources into varied assets lowers the risk of the overall investment. The UK's offshore wind portfolio can be considered to be comprised of six assets, representing the offshore regions identified in Figure 1, weighted according to the generating capacity deployed in each region. The less correlated the assets in the portfolio are, the lower the overall portfolio risk. The expected return  $E(r_p)$  of a portfolio  $P$  containing  $n$  assets  $i$  is given by:

$$E(r_p) = \sum_{i=1}^n w_i E(r_i) \quad (6)$$

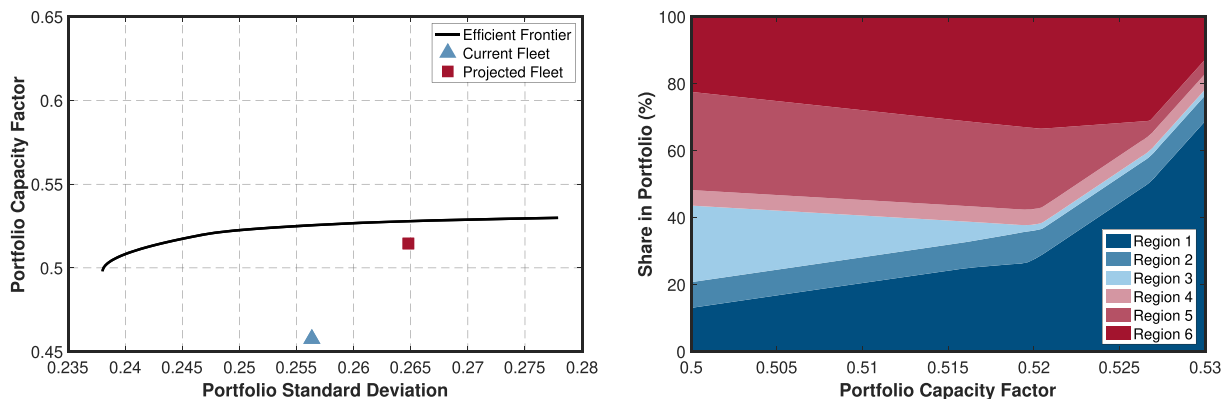
where  $w_i$  is the proportion of the portfolio allocated to asset (region)  $i$  and  $E(r_i)$  is the individual return of the asset (CF variability in each region). The “risk” in this case, is how well correlated the assets' volatilities are to one another and hence, is the standard deviation of the portfolio  $\sigma_p = \sqrt{wCw^T}$  where  $w$  is a vector of the asset (installed capacity) weights, and  $C$  is a matrix of sample covariance between each wind farm pair.

The variance of the offshore wind farm portfolio  $\sigma_p(w)$  can be minimised as a function of how installed capacity is distributed regionally for a given level of expected overall capacity factor to determine the *optimal portfolios*. Optimising across a range of portfolio capacity factors establishes a locus, the *efficient frontier*, corresponding to the lowest risk combination of regional capacities for each respective expected national capacity factor. Allocation portfolios below the efficient frontier are considered to be sub-optimal, and those beyond the frontier are unattainable.

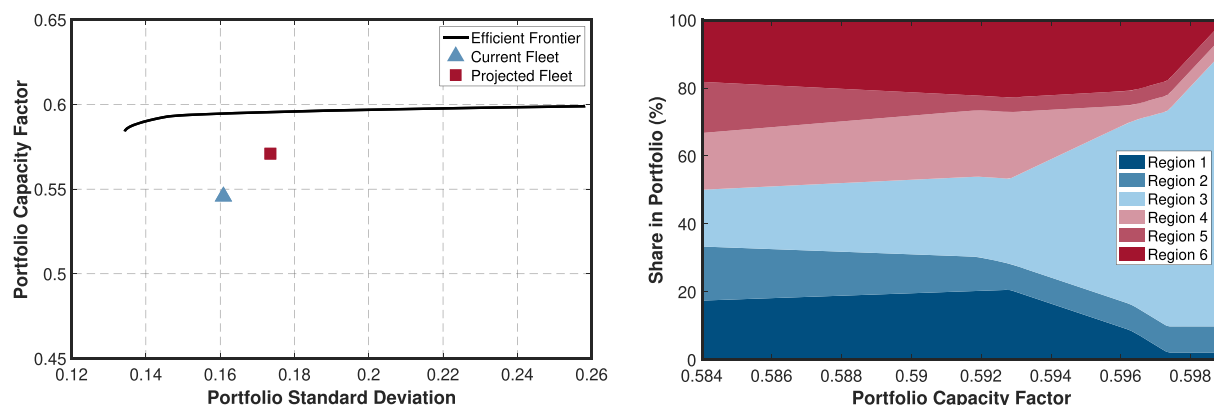
Optimisation of two objective functions was considered: maximisation of total wind power output (objective 1), and maximisation of wind power output during peak demand periods (objective 2). We evaluate portfolios with a total capacity of 40,686 MW, which incorporates the additional capacity for all proposed farms identified in Figure 1 and Table 2. This was constrained by requirement that the minimum capacity allocated to each region corresponds to no less than its current installed capacity. Inter-regional correlation was assessed using the DCCACC in place of the Pearson's correlation more commonly used in mean-variance portfolio theory following the advantages for the spatio-temporal variability of wind presented in Section 3.2.

As shown in Figure 10, the efficient frontier for the objective of maximising total wind power output (objective 1) demonstrates that higher portfolio capacity factors are achieved by increasing the standard deviation of output. The distribution of the current wind farm fleet results in higher than optimal variability in overall production, hence it is some way off the efficient frontier. Accounting for proposed wind farms, the portfolio capacity factor is expected to increase by about 14% increase in overall capacity factor from the current 45.5%, achieved at the cost of a slightly increased level of variability. The future wind fleet is closer to the efficient frontier, indicating that is closer to what is expected to be the optimal regional allocation given the level of variability.

On the efficient frontier, risk-averse portfolios (seeking to minimise variability) more evenly distribute capacity across the six offshore regions, with a slight weighting towards Regions 3, 5, and 6 (English Channel, Scottish North Sea, and south-west England respectively). These regions are further apart and therefore the interregional correlation is relatively lower. Portfolios on the efficient frontier that tolerate higher levels of



**FIGURE 10** (Left) The efficient frontier as a function of capacity factor and variability for objective function 1 (power maximisation) with the position of the current (triangle) and the projected (square) portfolios indicated. (Right) The regional portfolio allocation on the efficient frontier as a function of capacity factor



**FIGURE 11** The efficient frontier as a function of capacity factor and variability for objective function 2 (power maximisation during periods of high demand) with the position of the current (triangle) and the projected (square) portfolios indicated. (Right) The regional portfolio allocation on the efficient frontier as a function of capacity factor

variability allocate production primarily to Region 1 (North Sea) due to the relatively high capacity factor that can be achieved in this region. The distribution of capacity to other regions is largely dictated by the existing capacity in those regions.

The second objective function seeks to maximise power output during periods of peak demand, identified as those where electricity demand was equal to or greater than the 90th demand percentile during the period 2000–2017. The portfolio capacity factor is higher in Figure 11 because demand tends to be higher in winter, which also tends to be associated with stronger, more consistent winds and thus a higher capacity factor as discussed in Section 3.1. The efficient frontier is therefore at higher portfolio capacity factors and lower variability. The current offshore wind fleet is also proportionally closer to the efficient frontier, given the level of variability, than it was for objective 1. The projected wind fleet will be slightly more productive during periods of high demand, although variability during these periods will also increase slightly.

A low variability wind fleet that maximises wind production during periods of high demand entails a fairly even distribution of wind capacity across all regions, as shown in Figure 11B. However, as the targeted capacity factor increases, the balance of production shifts dramatically towards Region 3, in the English Channel, has strong winds here have been historically highly correlated with periods of high electricity demand. The proportion of capacity allocated to other regions is largely dictated by the constraints of existing capacity. However, the authors recognise that it may not be plausible to deploy allocate almost 36 GW of wind farm capacity in English Channel, and note that the optimal deployment in the English Channel considering overall power maximisation, not just in periods of high demand, is much smaller as shown in Figure 10.

## 5 | CONCLUSIONS

The rapid growth of intermittent renewable energy supplies makes electricity networks more susceptible to problems arising from prolonged periods of no or low levels of generation. Previous studies, for example, Foley et al<sup>26</sup> and Malvaldi et al,<sup>28</sup> have highlighted the relatively high correlation in wind production between closely neighbouring countries such as the UK and Ireland, which means there may be limited opportunities to rely on electricity imports during extended periods of low wind generation. Consequently, it is important to understand the scope for within-country mitigation of wind energy variability, particularly during periods likely to cause stress to the grid. This work has considered the distribution and capacity of current (2019) and proposed offshore wind farms around the UK to examine the likelihood of prolonged periods of low offshore wind capacity using historical wind speeds from 2000 to 2017. This complements previous studies of the UK's onshore wind, such as, the literature.<sup>5,6,19</sup>

Seasonal variations were identified in the UK's offshore wind, with the mean monthly capacity factor in the winter months being approximately 47% higher than those in the summer months. This is correlated with seasonal trends in electricity demand.

Correlation in offshore wind farm output decreases with increasing distance between farm pairs, although remains significant over the distances (<500 km) that encompass the majority of the UK's offshore wind farms. Correlation reduces at a slower rate offshore, compared to onshore, due to the lack of topographical features that typically vary over much shorter distances and play an important role in the winds seen by onshore wind farms.

Aggregated offshore wind energy production has a much lower likelihood of prolonged periods of low energy production compared to that for individual wind farms. This study focused on low wind speeds as the cause of these periods, as it was found that low wind speeds (<4ms<sup>-1</sup>) were responsible for approximately 96% of all low generation events in the 2000–17 period studied. This is slightly lower than that



reported by Sinden<sup>5</sup> which found that 99% of the periods of low onshore wind energy production were due to low wind speeds. Our study also found that the likelihood of prolonged periods of low wind energy varied seasonally, with autumn and winter being less common than spring and summer.

Persistent low energy production for periods in excess of a week were observed in the data set, and may potentially require significant volumes of energy storage or alternative energy supplies to compensate for the deficit in production. This can also be mitigated to some extent by considering production in aggregate rather than for individual wind farms. This is best achieved by wind farms in regions far apart, whereas those with a higher likelihood of experiencing similar wind conditions provide less balancing. We also used portfolio optimisation techniques to consider the trade-off in maximising mean aggregate capacity factor compared to minimising production variability. In general, a relatively even distribution of wind capacity is preferred for minimising variability of aggregate energy production, whereas maximising overall energy production favours a deployment strategy focused on regions with particularly strong winds.

## CONFLICT OF INTEREST

The authors declare no conflicts of interest.

## PEER REVIEW

The peer review history for this article is available at <https://publons.com/publon/10.1002/we.2685>.

## DATA AVAILABILITY STATEMENT

The wind speed data that support the findings of this study are openly available from the Renewables.ninja website, <http://www.renewables.ninja>, reference.<sup>12</sup>

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