Method for Designing a High Capacity Factor Wide Area Virtual Wind Farm

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Abstract

Moving towards a future power system dominated by renewable energy, it is vital that the siting of spatial-dependent technologies such as wind maximises the power generation while minimising the variability associated with wind power. This study develops a novel methodology for wind farm diversification by identifying pairs and triplets of locations across Western Europe which together form 'virtual' wind farms with a better guarantee of a minimum power generation level, providing capacity planners with tools to design a network of connected wind farms working together on a continental scale. These locations were found using hourly wind speed data spanning 10 years by examining time periods of local low wind availability at each grid point and identifying the best complementary wind resource locations. The best links are identified and presented in this paper. From an idealised capacity factor (CF) of 0.70 for a single site, the method found the potential for virtual CFs of 0.64 for grid point pairs and 0.68 for grid point triplets. This suggests that this approach can model virtual wind farms with virtual CFs comparable to conventional generation technologies and drastically reduce the amount of time during which farms are producing no power.

1 Introduction

The quest for a clean, sustainable energy supply is a key challenge we must tackle this century in order to secure our future on this planet. To continue to burn fossil fuels at the current rate would lead to a runaway global warming effect with severe consequences for the environment and the global economy [1]. Additionally, fossil fuels are a finite resource, with oil and gas set to run out by 2050 [2], therefore an alternative energy source is needed to guarantee energy security.

Todays global power demand is in the region of 13TW but the generation capacity potential of renewable technologies far outstrips our demand for energy. Wind alone could supply about 96PWh/year of energy, yet currently we only generate a fraction of that [3]. In the present climate wind power is the most economical form of renewable energy [4], and is currently seeing an exponential growth across the globe as the cost of generation allows it to compete with traditional power sources such as coal, gas and nuclear.

Europe is home to about a third of global wind power capacity, which in 2016 totalled 153.7GW (10.4% of EU electricity consumption), a net growth of 142.6GW since 2000 [5] and the European Wind Energy Association (now WindEurope) forecasts a central scenario of 320GW of installed capacity in 2030 (24.4% of EU electricity consumption) [6]. This still only represents a fraction of the economically competitive potential of onshore and offshore wind in Europe [7], which estimates the energy generation potential to be 7 times more than the total demand in 2030. There is plenty of evidence to show that a 100% renewable future is possible [3, 8]. However, with large shares of renewable technologies come new challenges. By its very nature renewable energy is an intermittent source of energy due to the stochastic nature of wind availability, and this greater energy variability requires better capacity planning and grid flexibility to ensure the demand is always adequately matched by the supply.

Historically, energy planners and policymakers had a simple approach to generation expansion, opting to invest in utilities which produced energy at the lowest rate [9]. This was suitable as most of these plants ran on fossil fuels and therefore their outputs could be controlled to match the electricity demand. A diverse portfolio of plants was selected based on how quickly energy generation would need to be switched on and off. As the penetration of variable technologies increases, the complexity associated with maintaining grid stability increases. As well as this, capacity planners nowadays must broaden the criteria for energy planning by taking into account factors such as reducing dependency on fossil fuels, improving demand response and mitigating climate change [9].

The requirement for better planning methods for siting wind farms becomes ever more important, since the location of sites is the largest contributing factor to the output characteristics of the farm. As the field of wind farm diversification has matured, several different methodologies have emerged to formulate optimisation problems to tackle the challenges of smoothing out power fluctuations [10], maximising grid penetration and transmission [11, 12], minimizing the static reserve capacity [13, 14], increasing grid stability [15, 16] and balancing supply and demand [17, 8, 18]. All these approaches agree on the benefits in closer coordination between countries on renewable energy policies, as the spread of wind farms across a larger geographical area leads to less correlation between sites and a greater potential for efficiency gains. This study proposes a new methodology for wind farm diversification that identifies pairs and triplets with wind profile characteristics which complement the generation of wind power with one another in a way which smoothes the combined power output of the farms. The scope of this study will primarily focus on wind resource availability. The economic factors of farm construction and operation will not be considered. Transmission aspects will be simplified to prefering solutions that are geographically less dispersed, using distance as a proxy for transmission losses.

2 Wind Energy and Transmission Background

2.1 Wind Power

A wind turbine generates power by extracting kinetic energy from the wind and converting it into electrical energy. As wind passes through a turbine, it slows down and spreads out, which reduces its kinetic energy, some of which is exploited by the turbine. If a turbine were to extract all the kinetic energy, the outlet wind speed would drop to zero, which would prevent more air from passing through the turbine. In order to keep the wind moving there must be an outlet velocity at the exit of the wind turbine, therefore not all the wind energy can be extracted. This theoretical limit is described by Betz's law, which states that the maximum power that can be extracted by the wind is 59.3% [19]. Modern wind turbines can reach 75–80% of this limit under the right conditions [20].

The amount of power produced by a wind turbine is determined by its diameter and the wind speed. The larger the swept area of a wind turbine, the more energy it can extract. Figure 1 presents a simplified capacity factor profile for a wind turbine, and the one used for this study. A minimum cut-in wind speed of 4 ms^{-1} is required to begin to generate power, achieving maximum power at $13ms^{-1}$ to a maximum cut-out speed of $25ms^{-1}$, above which the turbines shut down to prevent damage to the blades due to the high stresses induced. The Capacity Factor is a measure of the ratio of maximum power to actual power generated.

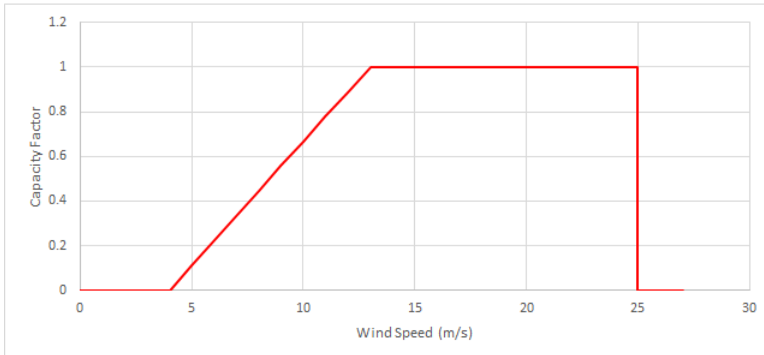

Figure 1: A typical idealised wind turbine capacity factor profile.

This capacity factor profile is a simplified case, using a linear segment from cut-in to rated speed. In reality the gradient of the increasing slope tends to decrease with higher wind speeds, and above the cut-out speed the capacity factor drops with a steep gradient. Additionally wind turbines tend to be built as part of a larger wind farm, which leads to losses caused by upstream turbines slowing down the wind and reducing the amount of power which can be extracted further. These losses vary depending on wind farm design and direction of the prevailing wind [21], and as a result wind farms have a slightly altered capacity factor profile.

2.2 Grid Integration and Transmission Losses

Before the electrical energy produced is sent to the grid, it needs to be converted in order to match the frequency of the grid. Wind turbines produce AC power with a variable frequency depending on the wind speed, therefore it is first converted into DC and subsequently back into AC at the correct frequency. A transformer then steps up the voltage to several hundred kV and the power is fed into the grid. Offshore wind farms transmit power to the onshore grid via high voltage AC (HVAC) cables, normally at 132 kV or lower. Electricity is transmitted at high voltages in order to reduce the losses in the cables, as according to Joule's Law heating losses in the conductors are directly proportional to the square of the current for a given power. Voltage is inversely proportional to current therefore doubling the voltage reduces these losses by a factor of 4.

The grid is a network of generators and consumers with variable load patterns of supply and demand. A control system ensures electrical energy is generated at the same rate as it is consumed. Imbalances in the grid can cause generators or transformers to shut down to prevent damage which can lead to blackouts. As the variability of generation increases with the growth of renewable technologies it becomes more difficult to guarantee this balance. When demand exceeds supply, gas-fired plants or stored hydro plants on standby are switched on, or industrial customers consuming large amounts of energy are curtailed until sufficient generation is available again [22]. Conversely, when supply outstrips demand stored hydro can also pump water back into its reservoirs storing energy, or thermal power plants are switched off until their energy is required again. Interconnectors joining countries together help to balance the grid by supplying or demanding excess power to avoid options such as shutting down plants, expensive energy storage options or negative energy pricing [23].

For the purposes of this study, tranmission losses are not explicitly computed. Distance between locations is used as a simple proxy to prefer compact solutions over disperse solutions. In practice, the energy generated would be fed into the European transmission grid. Currently, the overall transmission losses for the European grid are reported at 6.44% [24]. This could be compensated by installing a 7% larger wind farm to ensure the same end point delivery. An alternative, more conservative, estimate at transmission losses is to consider the combined losses of the European countries crossed. Based on the key result from this paper, the countries (with transmission efficiencies from [24]) are: Sweden (95.2%), Germany (96.1%), France (93.6%), and Spain (90.4%); leading to a combined efficiency of 77.5%, or equivalently a total line loss of 22.5% requiring a 29% larger wind farm to compensate for this loss.

3 Conceptual Framework

A 'virtual' wind farm will be created by connecting a set of geographically separate wind farms. A few assumptions and simplifications will be made in this analysis. The capacity of each of the constituent (physical) farms in the virtual farm will be equal. While the total potential capacity of the virtual wind farm will be the sum of the individual farms, this analysis focuses on the ability to guarantee a high capacity factor of a single constituent farm. As a result of this assumption, there are no calculations on the levelised cost of energy, as this would add complexity to the design that is beyond the scope of this study. That is, the focus of this work is to maximise availability and security of wind power. The fundamental idea is to identify 'complementary' wind sites: these are sites where when there is low wind availability at one site, there will be sufficient wind availability at the complementary site with high probability.

3.1 Virtual Wind Farm Concept

A virtual wind farm combines a set of 2 or more wind farm sites which are geographically separated but treats them as one single farm. In this study the resultant transmission losses which would occur when transmitting the power from one site to another are neglected, forming this virtual wind farm which can take advantage of the complementary wind relationship between sites to reduce variability in power output. Sites are selected with complementary wind profiles where power at one site tends to be produced at times when the alternate site is not producing power, and vice versa. The process of finding these sites is explained in Section 4. As a result the capacity factor of the virtual wind farm is improved, however a new definition of 'virtual' capacity factor is required to understand the difference. A virtual wind farm with a 1GW capacity consisting of 2 complementary sites requires a total installed capacity of 2GW, 1GW at each site. The modified capacity factor measures the proportion of time that at least 1GW of power is being generated by the combination of both sites, which could be producing upto 2GW at any moment in time. The capacity factor no longer relates to the maximum rated power, but to the virtual wind farm rated power.

3.2 Pareto Optimality Criterion

The wind farm site pairs were evaluated on the basis of two objectives: the virtual capacity factor and the distance between the two sites. In order to identify the best pairs within groups of links from a geographical cluster, Pareto Optimality conditions were applied. Pareto Efficiency is where one objective can only be improved at the cost of the other, which in this case was maximising virtual capacity factor and minimising the distance. Using this technique it was possible to find the best unique sets of pairs within a sample.

3.3 Atmospheric Data Assimilation

The wind speed data used in this investigation originates from the MERRA-2 database [25], a reanalysis data product based on the GMAO/GEOS-5 Data Assimilation System (Global Modelling and Assimilation Office/ Goddard Earth Observing System [26]). It combines an atmospheric model, land surface model and ocean model to simulate climate variability on several time scales, from hourly to multi-century climate change. It is based on measured data from weather stations and satellites, coupled with climate models to generate several of climate data parameters, developed to support earth science research into climate and weather prediction, system modelling and design, and basic research, such as this study. The data was supplied in NetCDF Format, which supports array-oriented scientific data, and the two required parameters were wind speeds at 10m height and the surface roughness coefficient. It was necessary to use the surface roughness data in order to calculate wind speeds at hub height. Surface roughness is a measure of the friction generated by the land on wind which slows it down as it gets closer to sea level. The following logarithmic wind shear equation was used:

$$v = v_{ref} \frac{\ln \frac{z}{z_0}}{\ln \frac{z_{ref}}{z_0}} \tag{1}$$

where v represents the wind speed at hub height, v_{ref} is the wind speed at reference height, z is the hub height (set to 50m), z_{ref} is the reference height (set to 10m), and z_0 represents the surface roughness.

4 Methodology

The data acquired from NASA's MERRA-2 reanalysis database covered Western Europe and some of Central Europe, between the latitudes of 36°N–65°N and longitudes of 11.25°W–20.00°E. The spatial resolution of these data points is 0.5°× 0.625°respectively, producing 2950 grid points. The temporal resolution is hourly and spans 10 years between 2005–2015, leading to over a quarter of a billion data points in total. For most of the analysis, only the first two years of data (2005 & 2006) were used to produce results, with the other 8 years used to analyse their reliability. The surface roughness values were used to calculate actual wind speed at an assumed hub height of 50m. This is a good approximation for onshore turbines however offshore turbines tend to be larger and this hub height is an underestimation.

The first analysis conducted was to calculate the capacity factor between 2005–2006 for each grid point. This was to filter out the locations with low average wind speed which were points of little interest for this study. Calculating the potential ideal capacity factor (CF) instead of mean wind speed gave a better indication of the value of that point, as mean wind speed does not account for very high wind speeds at which wind turbines would be shut down, or for turbine power profile against wind speed. The ideal capacity factor is calculated every hour and a mean over the 2 years is found for each location. The minimum CF was set to 0.65 (see Table 1) following some a simple parameter analysis to determine a suitable minimum which will be discussed in the results section.

The main experiment was designed to find pairs of locations whose low wind profiles complemented one another, so that whenever there was no wind at one location, there would be a high probability of good wind at the other site. For each grid location, the timestamps at which there was insufficient wind were recorded. The Low Wind Threshold (LWT) was initially set at 4ms^{-1}, the same speed as the turbine cut-in speed below which the wind turbines would not produce power. Each grid location had a unique set of timestamps for low wind conditions, which were used to calculate the capacity factors of all the other grids at these times. The top 10 locations with the highest CF for each point was found. Using this list, the best overall locations were found based on how often these locations occurred in the top 10 locations of other grid points, and their corresponding top 10 locations formed a matrix of the top grid points.

The next step was to find complementary links between the locations. In order for a pair to be considered they must both feature the other in their top 10 locations. Once the pairs were established, the next step was to calculate their combined virtual capacity factor. The pairs were modelled as a virtual wind farm, taking the highest capacity factor for every hour of either of the two sites to produce a new combined virtual capacity factor for the pair. As a proxy for transmission losses, the Euclidean distance between the two points was also calculated. Shorter links are more desirable due to lower transmission losses. Using these two objectives, the Pareto Optimal front was identified to the groups of pairings which had similar coordinates to find the best unique spatial links across Europe.

As well as finding pairs, a further analysis was conducted to find the best triplets which could further increase the capacity factor. It was possible to use the same methodology to find an additional point by treating the original pairs found as a single wind farm, and then iterating the search process again. This was applied to all the top pairs found in the first experiment, using the same LWT to find the third point. Due to the complexity of calculating proportionate distances between 3 points a distance value was not calculated, however this will be explored in the discussion section.

A key parameter in the analysis was the Low Wind Threshold. This determined the timestamps which were to be involved in finding suitable pairs. By increasing this threshold the amount of data being analysed increases. Increasing the threshold to the maximum wind speed, all timestamps would be used, essentially reducing to the brute force technique. The brute force method involves computing every possible combination of sites to find the best result. The threshold value was varied between 4–11ms^{-1} in 1ms^{-1} steps, and the results were compared to the brute force results to evaluate the effectiveness of the method. Both the pairs and the triplets were compared. Compared to the pairs $O(n^2)$ level of complexity, finding the additional point using the method was $O(2n^2)$ while the brute force triplets search was $O(n^3)$, significantly more computationally intensive.

A separate study applied the methodology to the area surrounding the United Kingdom, to establish its own geographical links and suggest locations to potentially develop. In order to evaluate the reliability of these results, the best pairs and triplets were evaluated for a further 8 years from 2007–2015. These results are presented in the next section.

5 Results and Discussion

5.1 Capacity Factors

Figure 2 shows a map presenting the geographical limits of the study and the mean potential capacity factors calculated at each gridpoint. The number of gridpoints in each band is shown below in Table 1. The results found in this analysis are idealised values based on multiple assumptions and in reality it is not possible for a wind farm to acheive a 0.7 capacity factor. The capacity factors of two actual UK offshore wind farms can be compared to the calculated values; The Greater Gabbard farm, located North East of London has a reported capacity factor of 0.422, and the farm West of Duddon Sands near the Isle of Man has a reported capacity factor of 0.442 [27]. This methodology calculated these sites to have a 0.634 and 0.592 ideal capacity factor respectively.

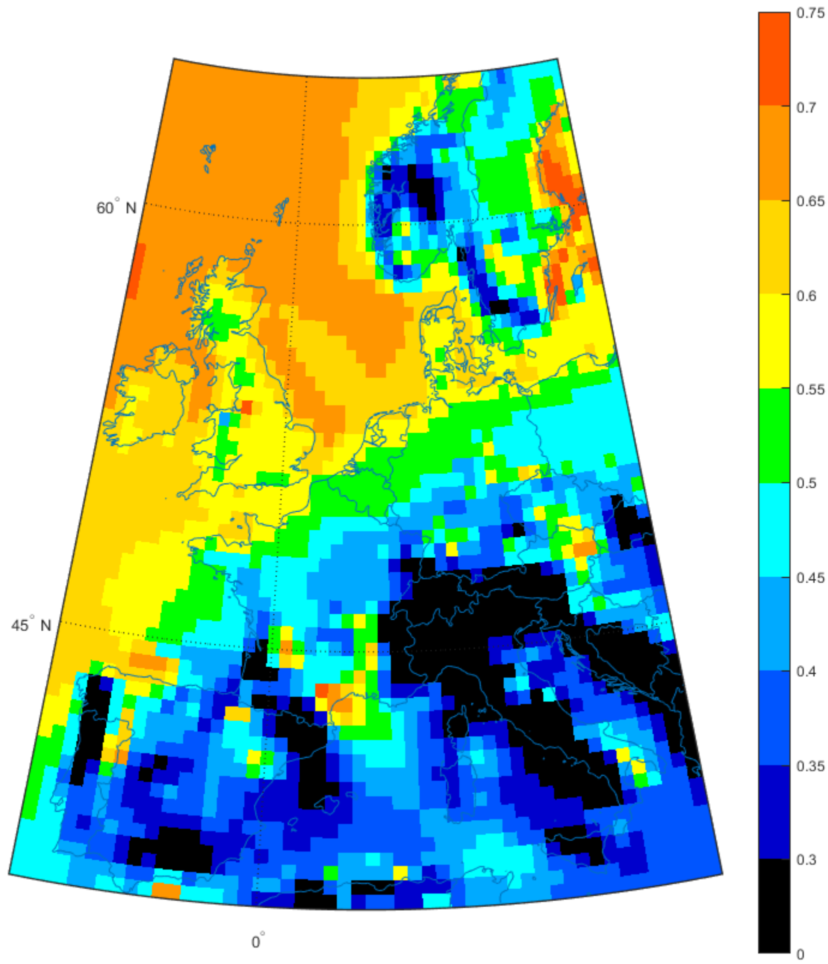

Figure 2: Potential Capacity factors across 2005-2006.

Table 1: Cumulative number of Grid Points for each Capacity Factor

Capacty Factor	Number of Points
>0.70	24
>0.65	528
>0.60	904
>0.55	1227
>0.50	1518
>0.45	1862
>0.40	2157
>0.35	2457
>0.30	2654

The discrepancy between ideal and actual CFs may be due to the following:

- The data acquired from the MERRA-2 database consists of hourly time-averaged values. While this temporal resolution may be high and provides a decent representation of the wind profile, the power output of a turbine will change instantaneously with the wind speed, and the variability in the wind across this hour leads to some error in the power generated, generally overestimating it.

- The capacity factor was calculated using the simplified wind turbine power profile shown in Figure 1. As mentioned in Section 2, in reality different sizes and models have different power profiles and the majority of wind turbines are built as part of a larger wind farm, leading to array losses that occur due to upwind turbines sapping some of the energy out of the wind.

- Routine downtime for maintenance and repair is necessary to keep turbines operating efficiently. Typically an individual wind turbine is available 97–98% of the time [28], and wind farms will attempt to limit the number of turbines which are offline at any given time.

- Demand for wind power is assumed to be always 100%. This is not always the case as there are times when wind speeds are high but energy demand is low, leading to a surplus of energy in the grid. In extreme cases this leads to a shutdown of wind farms if the surplus energy cannot be stored or used elsewhere.

To compensate for the ideal Capacity Factor overestimation, a correction factor is calculated. By taking the arithmetic mean of the correction factor for both the Greater Gabbard and the West Duddon Sands wind farms, an estimate correction factor of 0.7061 is obtained. This will be used to scale computed ideal Capacity Factors into an estimated Capacity Factor.

It was desirable to reduce the number of grid points analysed to improve computational efficiency. After running the initial experiment at different capacity factors it was established that the minimum capacity factor should be set to 0.65, reducing the number of points to 528 in the European grid. All the top pairs found consisted of locations with capacity factors above this value, and the interaction with other points did not affect the results. A three-fold decrease in points between 0.5 and 0.65 resulted in a $3^2 = 9$-fold decrease in computational time when calculating the pairings, since the code manipulates this number twice; The first is when comparing one grid point to all the other grid points, and second when it does this for every other grid. When calculating triplets, this reduces the computational time by a further three-fold decrease to a total of $3^3 = 27$-fold decrease, due to the extra step of comparing the pairs with an additional point. This reduction applies to both the experimental methodology and the brute force method.

5.2 Effect of Low Wind Threshold

The LWT was varied between 4–11ms^{-1} and the results were compared to the brute force method. In the case of the triplets, the LWT was kept constant for both finding the first pair and then the additional location. The results are illustrated in Figure 3. The first point to note is the values of the virtual capacity factors were found to be around 0.90 for the pairs and 0.96 for the triplets, a significant increase in comparison to the individual locations of around 0.70. The graph presents the highest CF value found as well as the average CF for the best 10 pairs/triplets found in each method.

When finding the pairs, we can see that a LWT of only 6ms^{-1} is necessary to achieve the same result as the brute force method (where all windspeed data is considered). This threshold finds on average 2500 timestamps for each gridpoint, which compared to the brute force method which uses 17520 timestamps it gives a 7-fold decrease, justifying the use of this method. Even when using 4ms^{-1} the maximum pair and mean of the top 10 found is only 0.24% and 0.83% lower respectively, using just 1000 timestamps per grid.

With respect to the triplets, a slightly higher LWT was required to achieve similar results to the brute force approach, however using 6ms^{-1} again only lead to a 0.37% and 0.60% reduction in maximum and mean vir-

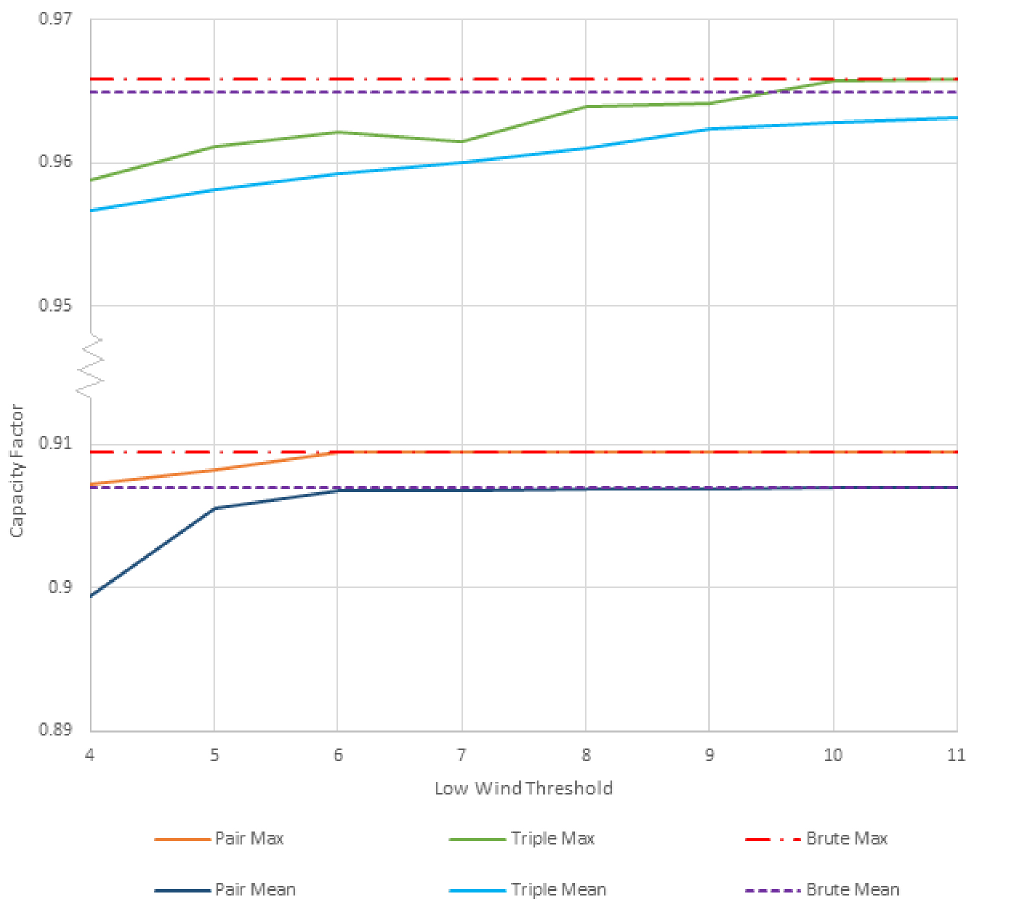

Figure 3: Comparing Low Wind Threshold to the maximum possible values and the average value of the top 10 results.

tual capacity factor in the triplets as compared to the brute force approach. Overall these are promising results, proving that the proposed methodology is effective at finding pairs and triplets of points.

Extrapolating this methodology to finding more than three points could lead to greater errors in the final result. A further experiment could improve this by using varying LWT values at each stage of the method. For example using a LWT greater than 6ms^{-1} to find the first pairs has been shown to be unnecessary. There is also the issue that the search is delivering virtual wind farms with a virtual capacity factor close to the limit of 1, and further reiterations would not yield significantly different results. Finally, the calcalated ideal CFs are scaled to provide an estimate of what would be expected in the real world.

5.3 European Pairs

Figure 4 shows the best unique pairs of locations in Europe based on a LWT of 6ms^{-1}. The first part of the methodology, before applying optimality conditions produced a total of 96 pairs. From these, 3 unique groups of links were identified visually. These groups are represented by the green line, and the optimal links are shown by the black line. It is evident that there is a strong link between South-West Europe and the Baltic Sea, with 80 of the 96 pairs found here. This link spans a distance of roughly 2,500km.

Comparing the results to actual wind farm locations in Europe, the largest proportion of onshore and offshore wind farms are located in Denmark, Germany and the surrounding North Sea, yet none of the pairs found have coordinates in this region. Since wind is spatially-correlated, the links with the highest capacity factors favour the sites furthest away from another, hence the absence of points in this area. This is a limitation of the methodology, which will be discussed fully in the next section.

When the actual wind farms in the Baltic Sea and in the Gulf of Bothnia are compared to the cluster of points found here using the Global Offshore Wind Farms Database [29], this region is highly underdeveloped compared to the North Sea, despite its high wind potential and shallow seas. This region was found to be of great importance to the overall reliability of a European-wide network of wind power. The wind industry in this area is less mature and presents a key region of growth for European Wind. A 2012 report commissioned by the Intergovernmental Baltic Sea Region Energy Co-operation [30] provides a strategy for the promotion of wind power throughout the Baltic Sea Region (BSR), estimating its total constrained potential to exceed 130GW of installed capacity, with over half of this potential found in

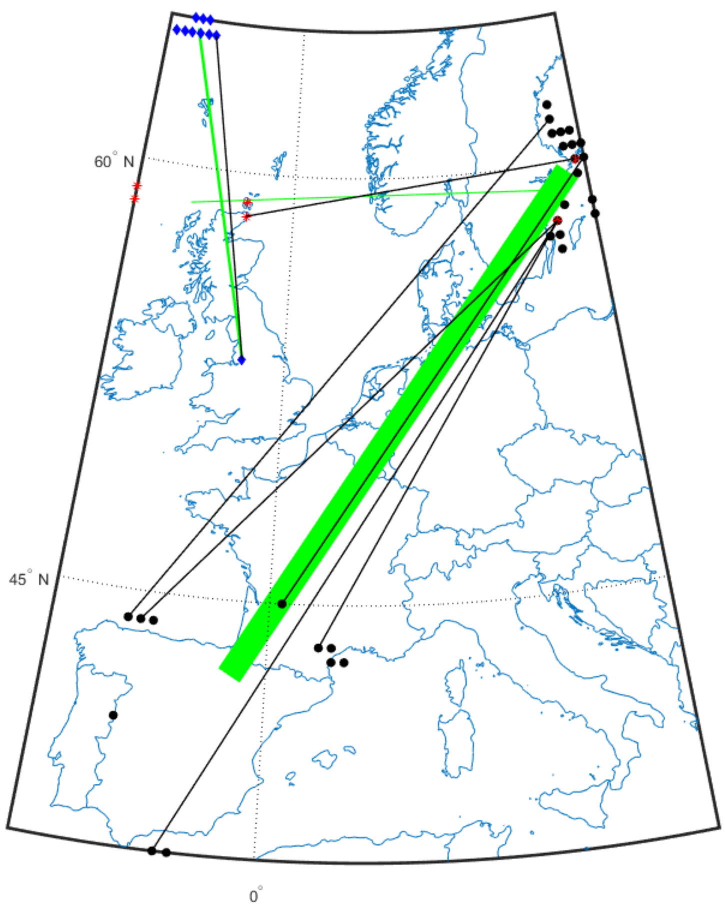

Figure 4: Map presenting the results of the experiment to find the best pairs of points across Europe. The 3 types of point markers indicate the 3 main links found when using an LWT of 6ms^{-1}. The green line represents the average of each group of points, and the thickness of the line is proportional to the number of individual pairs. The black lines are the best pairs found by applying Pareto Optimality on links with similar coordinates.

Finnish waters. Estimates predict that by 2020 the BSR will be home to 4.3GW of capacity, so the potential for growth in this region is enormous.

Looking at the European South-West region, the Offshore Database can be used in conjunction with inland databases to assess the current situation. The 5 points in Spain have good potential for expansion and yet have very few current or proposed wind farms. Wind farms had been proposed in the past in the Northern region by seAsturlab [31] to test new technologies but have faced difficulties leading to cancellations. The cluster of points in the South of France correlate to a high density of wind farms in this area, including further proposed offshore wind farms. If built up in conjunction with the Baltic Sea, these regions can compliment one another very well, with idealised virtual capacity factors in the region of 0.90 (scaled CF of 0.64).

The North of Scotland is another location with favourable links to the Baltic Sea, with the added benefit of being significantly closer geographically. Despite this the ideal virtual capacity factors found are still high at 0.89 (scaled CF of 0.63). Some of these points are located in deep waters not yet suitable for offshore developments, however as offshore wind technology matures locations such as these may become feasible in the near future.

The third main link found was between a location near Manchester and several points near the coast of Iceland, also located in waters too deep for current wind farm technologies. Under closer inspection, this result seemed anomalous and may be the result of errors in the data. The capacity factor for the UK gridpoint is significantly higher than that of the adjacent points, which can be seen in Figure 2. The raw wind speeds obtained from the MERRA dataset where compared to wind speeds from NOABL, an alternative database which is regularly used by the wind industry to provide estimates of wind speed, and the results were largely similar. However, the surface roughness of this grid is significantly higher than the surrounding areas, which leads to the method erroneously calculating that at higher altitude the wind speed increases faster due to the greater wind shear, explaining why this outcome is consistent even when looking at different times throughout the 10 years of data. Through this inspection it was revealed that the Surface Roughness coefficients were incorrectly calibrated to the wind speed data, with the surface roughness of this grid near Manchester supposed to be representing North Wales, which in Figure 2 is represented by a blue square. However, correcting for this error was outside of the scope of this study, and therefore the extent of its effect on the results is unknown.

5.4 European Triplets

Figure 5 shows the best 3 unique triplets that together have the highest capacity factor. Once again locations in the Baltic Sea Region dominate the results, with similar links to Southern France, Spain and the seas to the East of England. The 3 best results were selected based on the highest capacity factor and not distance. It is difficult to objectively measure the relative distance between the triplets. There are numerous ways to quantify this distance, such as measuring the perimeter of the triangle, the average distance to the midpoint of the triangle or even the area. Furthermore, the distance is not the only factor to consider when assessing the proximity of the points, as the locations and sizes of existing interconnects is a key contributor to the capability of distributing this energy evenly throughout the grid. Additional studies would require an assessment of distance, briefly discussed in the next section.

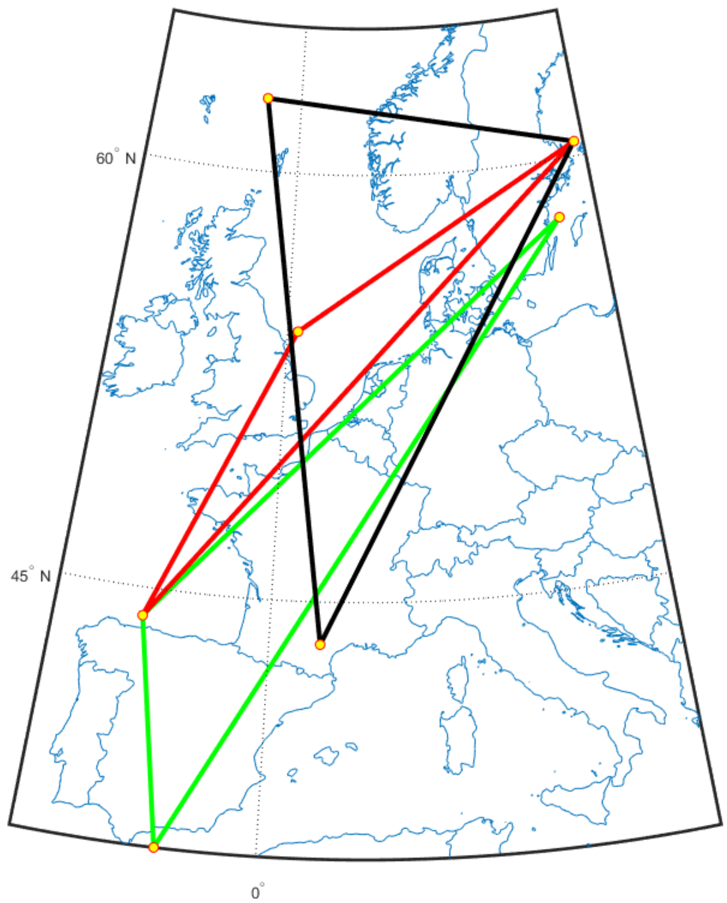

Figure 5: Map presenting the best three unique triplets found using LWT of 6ms^{-1} for both finding the pair and the additional point, resulting in ideal capacity factors of 0.96 (scaled CF 0.68).

The performance of these triplets was compared to the performance of the constituent individual sites. The Red Triplet was selected for analysis, and a time series graph of individual capacity factors for each of the 3 sites was compared to the virtual capacity factor as well as the average power, shown in Figure 6.

As can be seen from the graph, the virtual CF (green line) provides a consistent high output as expected, maintaining approximately maximum virtual CF for the majority of the time. While the virtual CF tracks the highest output of any of the farms, the blue line is the average power output of the 3 farms combined. Since this measure is reflective of the actual power output it fluctuates about an average of 0.70, just as the single sites do, however the variability of the generation is greatly decreased. As more sites are added to form an extended network, this variation should continue decreasing until forming an optimal smooth power generation. It is also worth noting that the total time spent producing no power due to low wind conditions amounts to only 8hrs a year for the virtual triplet, whereas in comparison the individual sites had on average 43 days (1,032 hours) of zero output, a significant improvement.

In order to construct virtual wind farms from these triplets, a large investment in interconnectors is required. The interconnectors across Europe are currently not extensive enough to support the exchange of large amounts of energy across the continent, therefore a high level of coordination between countries is required. In light of this a final experiment was conducted looking at the UK and its surrounding waters to assess the potential of the method on a smaller scale.

5.5 UK Analysis

A rectangular grid of 420 points spanning a latitude of 49.5°–59.5°N and a longtitude of 10.625°W –1.875°E was selected, covering the British Isles and its surrounding seas. All the points were involved in the analysis instead of filtering by capacity factor since the number of points was still smaller than the EU experiment. Based on the previous experiments, a LWT of 6ms^{-1} was selected, and only the pairs were found. Figure 7 presents the 3 main groups of links found in this experiment, as well as the best performing pairs within these groups established using the Pareto Optimality curve. The average virtual CF for these pairs comes to 0.86 (scaled CF of 0.61).

All 3 links represent a similar amount of pairings, and the majority of the sites are located offshore. As before the method favoured sites with large distance between them, increasing the likelihood of a high CF. The East Coast of England has a shallow sea, and the blue points found here correspond to an extensive network of offshore wind farms. From these results it is clear that building farms in off the West Coast of Scotland could help balance the power output produced in these locations, however these locations are situated in waters with depths ranging from 200–2000m [32], currently unfeasible for farm construction. Similarly, sites highlighted in red East of Scotland, some of which correlate to actual wind farm locations, would also benefit strongly from turbines being constructed here. The pairs

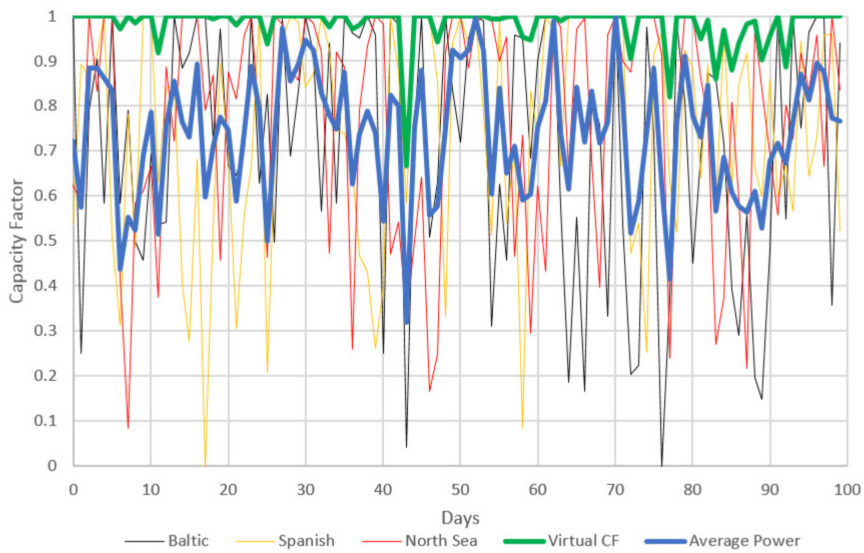

Figure 6: A Time Series Graph of the Red triplets daily response over the first 100 days of 2005. The Green Line is the Virtual Capacity Factor, the blue line shows the average combined power of the 3 sites, and the other three thin lines represent the individual sites. The daily points represent the mean of the last 24 hourly timesteps.

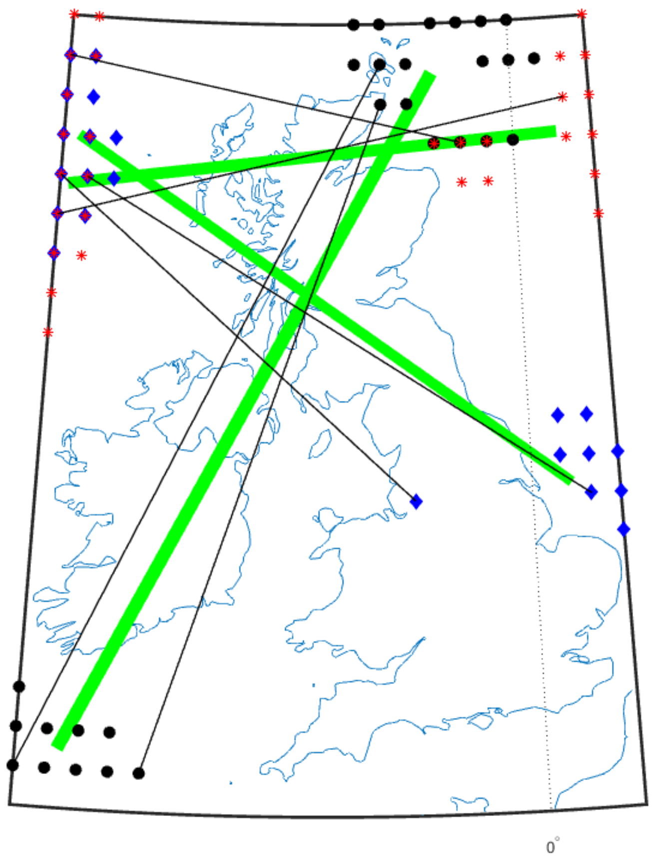

Figure 7: The 3 main links are represented by the green lines, whose thickness is proportional to the number of pairs it represents. The point markers indicate which grid locations are involved in the results, with the black lines displaying the best unique pairs found for each link.

represented by black circles highlight a strong link between the North East of Scotland and the Celtic Sea South of Ireland. These points are found in much shallower waters, with depths at either side ranging between 60–150m. Sea depth in excess of 60m is considered deep water with respect to wind farm construction, however the water is still significantly shallower than the sites in the North-West and demonstrate a large area of untapped potential which could in the near future offer excellent conditions for offshore wind development. There are no current or proposed farms in the Celtic Sea, a vast area of sea with high wind conditions, little oil or gas exploration [33] and relatively low shipping traffic. A drawback of this is the lack of deep sea power cables crossing the region, with only one interconnector joining the South of Ireland to the French Coast, increasing the cost of installations of wind farms in this region.

5.6 Ten Year Comparison

For decisions on wind farm locations to be based on the work above, it was necessary to investigate how stable the wind conditions were and how this affected the results. The best 9 unique pairs found across Europe were tested for a period of ten years, from 2005–2015. Table 2 presents the results of this, comparing the original 2 years of data to 10 years, as well as the best and worst 2 year capacity factor.

Table 2: Table comparing the original 2 year data to an extended period of 10 years for European Pairs

Pair number	Original CF	10 Year CF	Best 2 Years	Worst 2 Years
1	0.9072	0.9018	0.9099	0.8865
2	0.9070	0.8933	0.9070	0.8735
3	0.9056	0.9036	0.9157	0.8940
4	0.9045	0.8950	0.9056	0.8809
5	0.8971	0.8950	0.9076	0.8832
6	0.8967	0.8835	0.9025	0.8670
7	0.8949	0.8823	0.8961	0.8611
8	0.8871	0.8806	0.8934	0.8670
9	0.8745	0.8702	0.8802	0.8585

From this table, it can be seen that the 10 year capacity factor value is consistently lower than the Original CF, however the reduction is very small, with an average decrease of 0.86%. All the pairs except one experience a higher CF at an alternate 2 year period within the 10 years, suggesting that performance of the pairs is not at a maximum between 2005–2006. Overall these results indicate that the pairs output is reasonably reliable across the 10 years, with no drastic reductions in ideal CF and therefore it is expected that they will continue to perform well over several decades.

6 Discussion and Limitations

The methodology and results were critically analysed, with the aim of highlighting the acheivement of the study, assessing the reliability of the results, the limitations of the method and how these could be addressed in subsequent investigations. Overall this research highlights some interesting correlations between points across both Europe and the UK. These links indicate that greater investments in interconnectors across the continent are necessary, in particular joining the UK to the mainland and the Baltic Sea to the rest of the Europe, which corroborates the work conducted by Speicker [12] evaluating interconnector investments in Northern Europe considering wind power penetration. Combining his study with the results found here and with the further work discussed in this section, one could produce results which could actively contribute to the field of capacity planning and wind farm diversification.

There are some considerations which need to be acknowledged in order to develop the results from idealised values to realistic scenarios. The capacity factors found must account for the constraints and losses in the real-world discussed in Section 5.1. It is suggested that further work should primarily focus on tackling this issue, in particular the transmission losses associated with transporting power over large distances. For now, the estimated CF values are approximated using a scaling factor of 0.7061, found when comparing the calculated ideal capacity factor of two operational wind farms in Section 5.1 against the reported values in [27]. Table 3 compares the capacity factors of other generation technologies against the estimated virtual wind farm solutions identified in this work.

This table demonstrates how poorly wind and solar are currently performing with regards to CF. Many wind farms such as The Greater Gabbard farm boast of capacity factors above 0.40 and yet the average CF is just 0.22. There are many reasons for this, but the main problem can be attributed to sub-optimal siting. It is often the case that the optimal siting for a wind farm from a capacity factor point of view is not the same as the optimal location for an investor, the government or the local population. Sites near densely populated areas or places that rely heavily on tourism, in particular on coastal areas where wind speeds are higher, receive a lot of opposition, whereas sites in rural areas are favoured, leading to more farms being built at sub-optimal locations [34]. Additionally, many of the sites found to have the highest capacity factors in this study are situated in deep waters which are a largely untapped resource due to technological barriers.

While by no means an accurate estimate, the scaled CF values provide a good idea of the potential for virtual wind farms to compete with traditional generation technologies on capacity factor (see Table 3). It is important to consider that, where possible, renewable technologies are given priority on the grid, therefore in times of abundant energy the coal and gas plants are switched off first, reducing their capacity factor. Even so, wind is traditionally considered to have a low capacity factor with an unpredictable power output and this study presents an alternate view that it can have high capacity factors if diversified correctly and using the modified capacity factor. This suggests that wind is capable of performing far better within the grid than it currently is performing.

With regards to the reliability of the results, the length of time over which the data represents should be considered. Although 10 years may seem a long time on an economical and technological level, it is a relatively short time when measuring atmospheric oscillations and thus wind speeds [34]. The longer the temporal range is, the more reliable the results, and

Table 3: Comparison of Capacity Factors of various generation technologies in Europe [27]

Generator Type	Average Capacity Factor
Nuclear	0.77
Coal	0.51
Natural Gas	0.39
Hydro	0.40
Wind	0.22
Solar PV	0.13
Greater Gabbard WF	0.42
West Duddon WF	0.44
European Virtual Pair	0.64 (corrected)
European Virtual Triplet	0.68 (corrected)
UK Virtual Pair	0.61 (corrected)

the pairs were found using only 2 years of wind speed data. With more time and computational power it would be beneficial to use data spanning several decades to determine the prime locations. The error identified in Section 5.3 in the calibration of the surface roughness will have reduced the reliability of the results, however it is a simple fix and an error which subsequent investigations should not make.

Additionally, while increasing the LWT level above $6ms^{-1}$ did not improve the maximum capacity factor by much, it did lead to alternative groups of pairs being found not featured in the presented results. The effect of this threshold was not fully investigated and had a greater influence on the results than originally thought. It does suggest that there are many more links to be found throughout Europe, typically connecting the regions of high capacity factor identified in Figure 2. The results presented are just an example of the type of links that could be found and do not demonstrate all of them, however it is a promising start which with further work could provide a key tool to capacity planners in building a European wide network of wind power.

From the results found, it is clear that the method tends to favour points that are furthest away from one another due to their stronger complementary correlation. Currently the pairs are found based on the virtual capacity factor, and then the distance is considered afterwards to find the best ones. In order to improve this, further revisions should incorporate a technique which accounts for the distance between the points during the initial analysis. This should lead to local phenomena being better represented in the final results.

Another limitation of the methodology is that the only pairs found are those which feature in the top 10 locations of their complementary location and vice versa. This fails to capture those pairs of sites who feature first for one of the grids but 11th for the other, therefore a revised method would analyse all the complementary locations and instead use their overall rank to rate their suitability.

7 Conclusions

As we look towards a future EU power system dominated by wind and solar, the tools required to design a reliable yet flexible international grid become ever more complex as generation variability increases. The results produced by this research suggest that better coordination in capacity planning across the continent can lead to improved forecasting in total wind power generation. If countries fail to adequately diversify the locations of wind farms, instead choosing to concentrate them in sub-optimal locations then the grid will be unable to cope with the large gradient change in demand caused by changes in the wind. In this scenario the need for large energy storage capacity will outstrip the technological feasibility of such projects [13] leading to reduced grid reliability and increased chances of blackouts, which disrupt the economy and reduce confidence in renewable energy.

The concept of a virtual CF should be used in conjunction with traditional CF values when assessing the suitability of a site. During the proposals of new wind farms neighbouring countries with shared interconnectors could collaborate to maximise the virtual CF for mutual gains. Alternatively with some modification of the method it would be possible to map out the locations of current wind farms and evaluate which new locations provide the best output characteristics to stabilise the overall power output.

This research could be taken further by conducting a similar analysis of Europe's solar potential and combining it with the wind data to produce a network of solar and wind sites that together can further stabilize the total power output. Solar output is also dependent on the atmospheric conditions that produce clouds and therefore there may be patterns and links not previously found hidden in irradiance data. Additionally solar produces the most energy at times that wind power generates the least [8] i.e. during the day peaking in the summer months, therefore it is important to develop methodologies that look to optimise the geographical distribution of these technologies. Ummel [17] takes a different approach to this problem by finding the sites for wind and solar in South Africa that run at the highest capacity factor during times of peak load demand, which are the periods of time most likely to suffer from blackouts. By tailoring the diversification of sites to maximise outputs during these times, it is possible to increase the grid stability. A combination of the two approaches, with the additional work suggested in the discussion section has great potential to identify strategies for renewable energy deployment.

Another application of this study could be to determine whether areas of high wind speed variability such as mountain ranges could contain a network of locations which together can produce a stable enough output to make it economically viable to build turbines in these regions. The summits of mountains can have very high wind speeds at times and an assessment of the region using a higher spatial resolution could produce some interesting results. Specially designed wind turbines which can take better advantage of the turbulent environment could become feasible in these regions if an effective network of turbines is designed.

The wind is always blowing somewhere across Europe. Between 2005–2006 the lowest average hourly wind speed recorded was $13ms^{-1}$. Technologically we are at a stage where we can state with confidence that a 100% renewable future for Europe is possible.

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