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1.0 Motivation

"But for all its promise, wind also generates a big problem: because it is unpredictable and often fails to blow when electricity is most needed, wind is not reliable enough to assure supplies for an electric grid that must be prepared to deliver power to everybody who wants it…power plants that run on coal or gas must "be built along with every megawatt of wind capacity," said William Bojorquez, director of system planning at the Electric Reliability Council of Texas." - New York Times 2006.

1.1Overview of Energy Supply and Demand in the 21st Century

In this day and age it is widely accepted that the ways in which we have been meeting our ever-growing energy needs over the past 50 years cannot be sustained into the future (e.g. Gore, 2006 or Lovelock, 2006). This is essentially for two different reasons.

First, 77.6 % of the UK's total energy consumed in 2006 originated from oil and gas reserves (National Statistics, 2007). UK oil and gas production has already peaked (HM Government, 2007) and predictions suggest that global peak oil and gas production[1] is imminent if not occurring as we speak (Bentley, 2002) and there after production will decline as a result of the simple fact that it is not a limitless supply, hence a day will come when supply can no longer meet demand.

Second, again in 2006, the UK alone released approximately 152 million tonnes of CO_2 into the atmosphere by burning fossil fuels (National Statistics, 2007), and unless we reduce these emissions, global temperatures could rise by up to 13^{o}C (Pearce, 2006), destroying the earth and it's environments as we know them.
Predictions concerning the exact effects of this dramatic change in climate are all too well documented and are not the subject of this investigation, but needless to say change in our energy habits is absolutely inevitable and necessary, either by means of a choice in an attempt to stop/slow down global warming or our hand will be forced at a later date by non-renewable sources coming to the end of their life.

There are currently two alternative sources of energy; nuclear and renewable. Nuclear energy is produced on mass at large scale power stations by controlled nuclear fission reactions. Its primary drawback is that it produces large quantities radioactive waste which needs to be securely stored for many years[2]. As an example of the cost of dealing with nuclear power and its by-products, many of the UK's 19 nuclear power stations were built in the 60s, 70s and 80s and are now due for decommissioning at an estimated cost of £73bn (over £1000 per capita).

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[1] Peak oil production is a well debated issue and a large degree of uncertainty comes from unknown quantities of middle-eastern supplies. Peak gas will come some time after peak oil, and the middle-eastern supplies will probably last considerably longer than any other.

[2] After 10,000 years of radioactive decay, according to *United States Environmental Protection Agency* standards, the spent nuclear fuel will no longer pose a threat to public health and safety.

Renewable energy covers a range of potential power supplies that take energy out of naturally occurring dynamic systems (for example the wind, waves or tides), or natural sources of heat or radiation like the sun or geothermal energy. Of course, each of these has considerable limitations and most of them are very particular to certain site requirements. Often the technology required to implement serious renewable schemes is too expensive to compete with fossil fuels, or the primary source is inconsistent, or the supply is inconveniently distributed and hard to use.

Iceland is a prime example of a nation making the most of its natural resources as 99% of their electricity comes from hydro or geothermal power plants, however the resources that they have at their disposal are far superior to most. In contrast it seems that some counties are willing to make no effort to cut CO^2 emissions or provide economically secure energy for the future. For example China commissions a large coal fired power station at a rate of approximately two per week according to the UK foreign office, and the USA accounts for nearly a quarter of the worlds fossil fuel consumption having only 5% of its population and a fraction of its reserves.

In summary, all of today's sources of energy have associated problems examples of which have been given above, and so no single one of them will save the day. It is down to individual nations to firstly cut their energy needs to a minimum, and then asses what resources are available to meet their demands, maximising renewable potential in order to reduce CO^2 emissions.

1.2 UK Energy

Figure 1 shows how the amount of UK electricity produced by renewable sources has grown since 1990 along with targets set by the government.

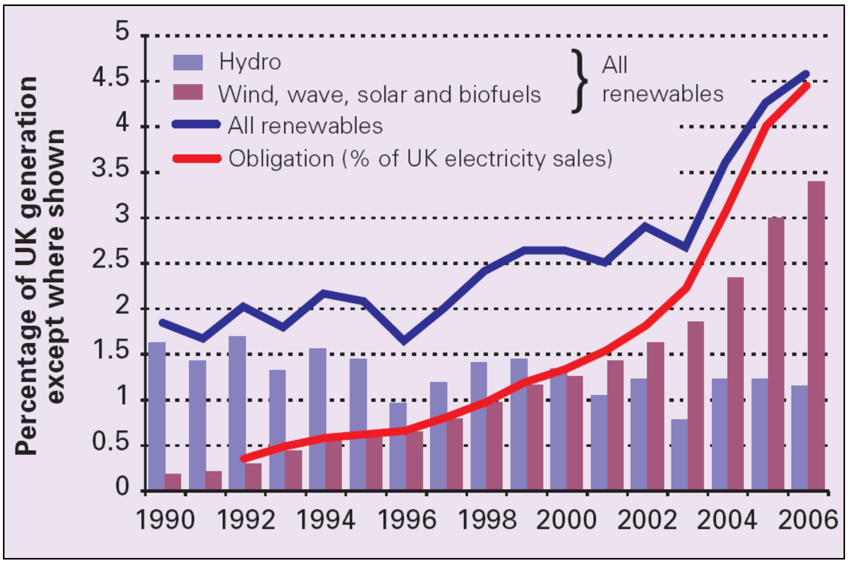


Figure 1. Growth in electricity generation from renewable sources since 1990, showing individual amounts for hydro, wind and also the target set by the government. Reproduced from "National Statistics, 2007".

The current governmental targets are to increase electricity generation from renewable sources to 10% by 2010 and 20% by 2020. They are also working towards cutting

CO^2 emissions by 60% by 2050. To put the graph above in perspective, electricity accounts for approximately 19% of overall energy consumption in the UK, so if we suppose that the 2020 target is met, then 5%[3] of the UK's total energy will originate from renewable sources.

[3] This figure is 20% of 19% plus 1.2%, the latter coming from an additional amount of renewable energy that is used directly (e.g. solar power) and there for adds to the figure for total energy consumption, but does not appear on the graph above.

2.0 Wind Power in the British Isles

Maritime islands like the UK or Iceland tend to be very favourable for exploiting natural energy sources, more so than inland continental areas for example. Being surrounded by seas means wave and tidal power are both available, and our location on the edge of the Atlantic Ocean means we tend to get stronger and steadier winds than any other areas of Europe or even the world as a whole. Also, our high rates of precipitation make hydroelectric power another reliable source. The British government is planning a large expansion of the wind power network in the UK as its foremost contributor to meeting the forthcoming energy targets.

It has been estimated that the UK is blessed with 40% of Europe's potential wind energy, which is not hard to believe looking at Figures 2 and 3.

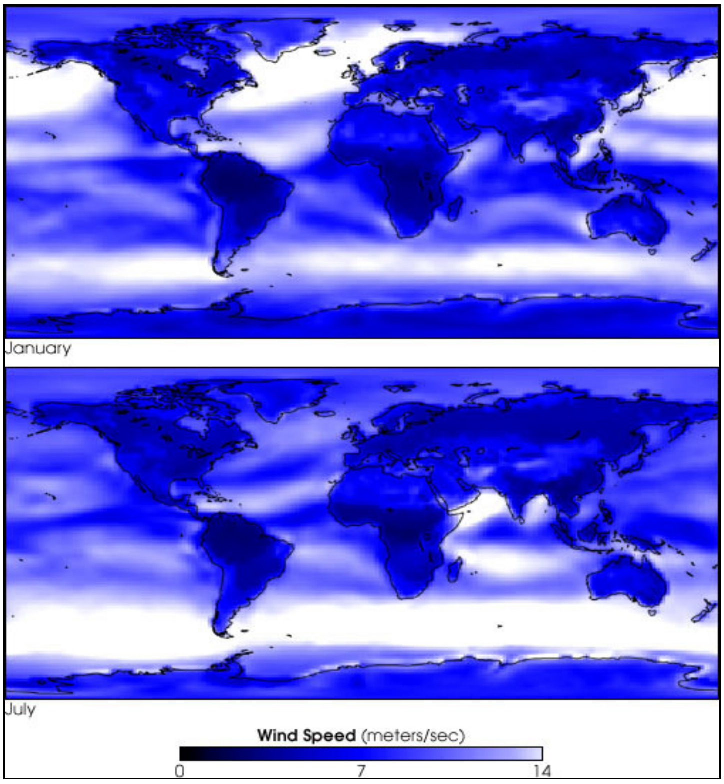


Figure 2. Maps showing global average wind speed data in mid-summer and mid-winter. Average wind speeds around the UK look favourable. Maps produced by Langley Research Centre, NASA.

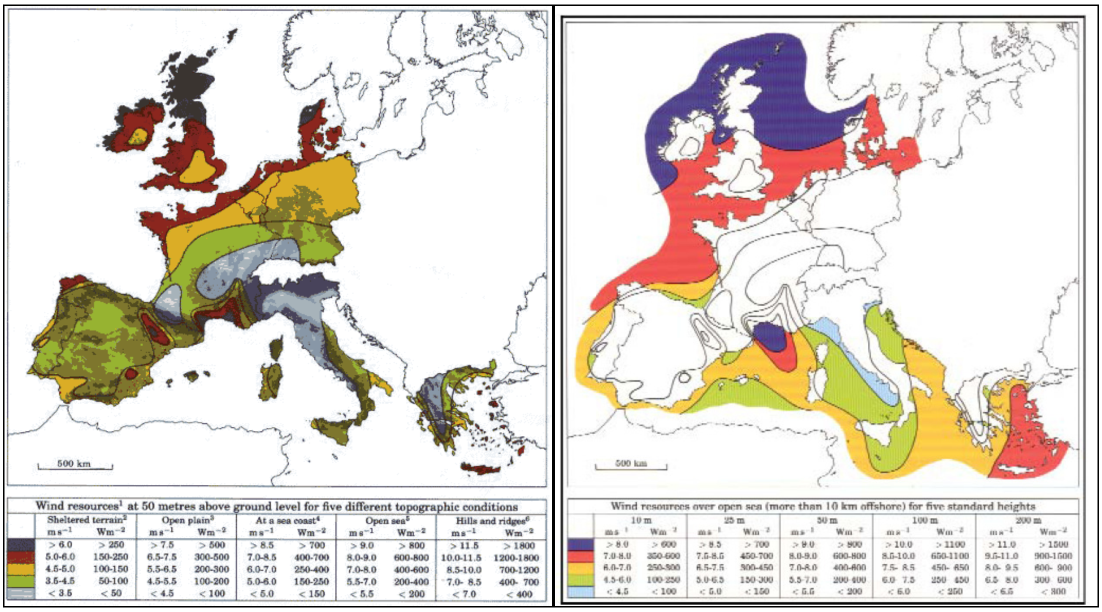


Figure 3. Maps showing distribution of average wind speeds around Europe. The British Isles and particularly Scotland are the windiest regions. Reproduced from Wind Power in the UK: a guide to the key issues surrounding onshore wind power development in the UK.

The UK wind energy network currently has an installed capacity[4] of over 2 GW (on- and offshore), which is expected to rise to over 17 GW in the future as shown by the table below.

Table 1. Figures for the installed capacities of UK wind farms at different stages of development.

Operating (GW)	Under Construction (GW)	Consented (GW)	Under Planning (GW)	**Total (GW)**
2.40537	0.7681	2.8602	11.336005	**17.369675**

The first wind farms in the UK were built onshore in the 1990s and their contribution to our power has grown rapidly in the last few years. This is partly as a result of ever improving technology and also changes in government policy. In December 2003 the first offshore wind farm, North Hoyle, was commissioned after permission was granted in the first round of planning applications, which also included the worlds largest off shore wind farm, the 90 MW Kentish Flats, which went online in 2005. Now a second round of applications has taken place, and the total offshore wind energy at all stages of development lies at over 7 GW.

[4] The installed capacity is the maximum amount of electricity that could theoretically be produced by a given system.

2.1 The National Grid, Capacity Factors and Consistency of Supply.

The total installed capacity for the UK national grid in 2005 was 75.5 GW and the peak demand on the system was 62.7 GW (SDC, 2005), which doesn't leave much in reserve. In other words, in mid winter at peak times of the day, over 80% of the system needs to be operational. Any method of producing electricity can be assigned a *capacity factor* which is defined as the ratio of actual electricity production over what could have been produced if the plant was working to full capacity all of the time (usually expressed as a percentage). Modern nuclear power plants have capacity factors as high as 0.9, with most of the offline time due to scheduled maintenance. However, nuclear power stations require a lot of time to start up or shut down. These factors make nuclear power plans ideal for producing base load power, but poor at dealing with short term demands which can be on time scales of several minutes, and total up to several GW of power. Large scale hydroelectric power stations operate at entirely the opposite end of the supply spectrum to Nuclear. Dinorwig for example, (the UK's largest capacity hydroelectric power plant) is used to meet the short period demands mentioned above as it can be brought up to full capacity in just 90 seconds, and when its not producing electric the turbines work in reverse to pump water back up to the top reservoir, resulting in a net electricity consumption. Systems such as Dinorwig are also essential for another reason; after sustained periods of demand mainstream power stations may be producing an excess of electricity because they cannot be shut down fast enough. This excess can be dumped and furthermore stored at the likes of Denorwig power station.

It is the job of the National Grid Company (NGC) to ensure that supply meets demand in the UK, and it is a statistical battle that has to allow for predictable daily demands and be prepared for countless possible unpredictable events.

The aim of this investigation is essentially to determine the capacity factor for large scale wind power in the British Isles and hence asses the usefulness of its contribution to the national grid.

3.0 Methods and Techniques

The computer code to carry out the numerical work was written by the author in the R programming language, and is provided as an appendix.

3.1 Wind Farm Distribution

In order to fully assess the consistency of electricity supply by wind power it is necessary to know exactly how the electricity production is distributed around the UK (because the wind speeds differ from one place to another). This information was gathered from the British Wind Energy Association (BWEA) web site.

There are currently 439 wind farm projects listed, each of which was assigned to one of 8 onshore or 4 offshore regions which were devised to represent the distribution of wind power within the British Isles. These are shown in Figure 4. The individual data for each region were then tabulated and summed (Table 2) to show the installed capacities for each zone.

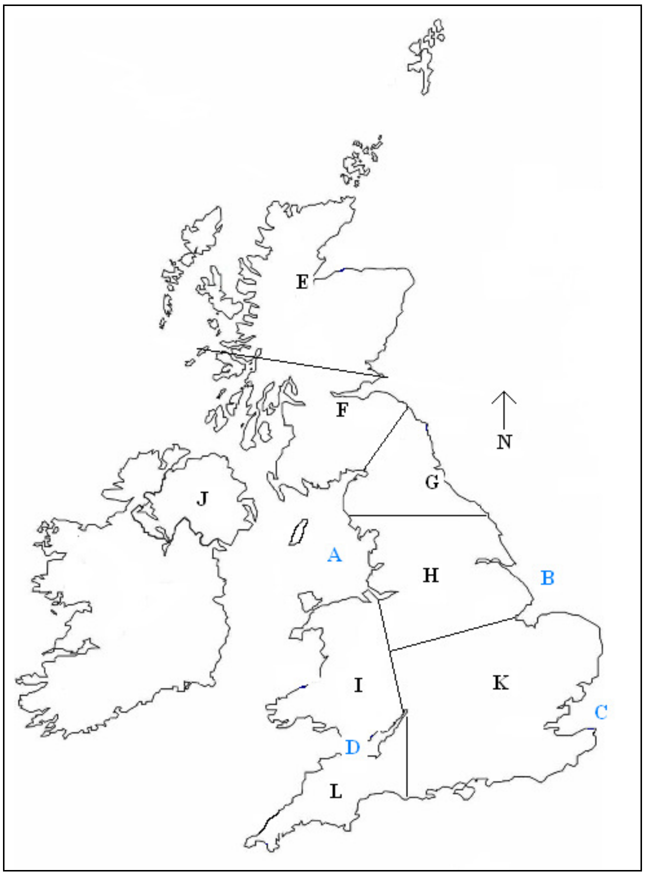


Figure 4. A map showing the British Isles split into zones. Maximum potential electricity production for each zone is shown in Table 2.

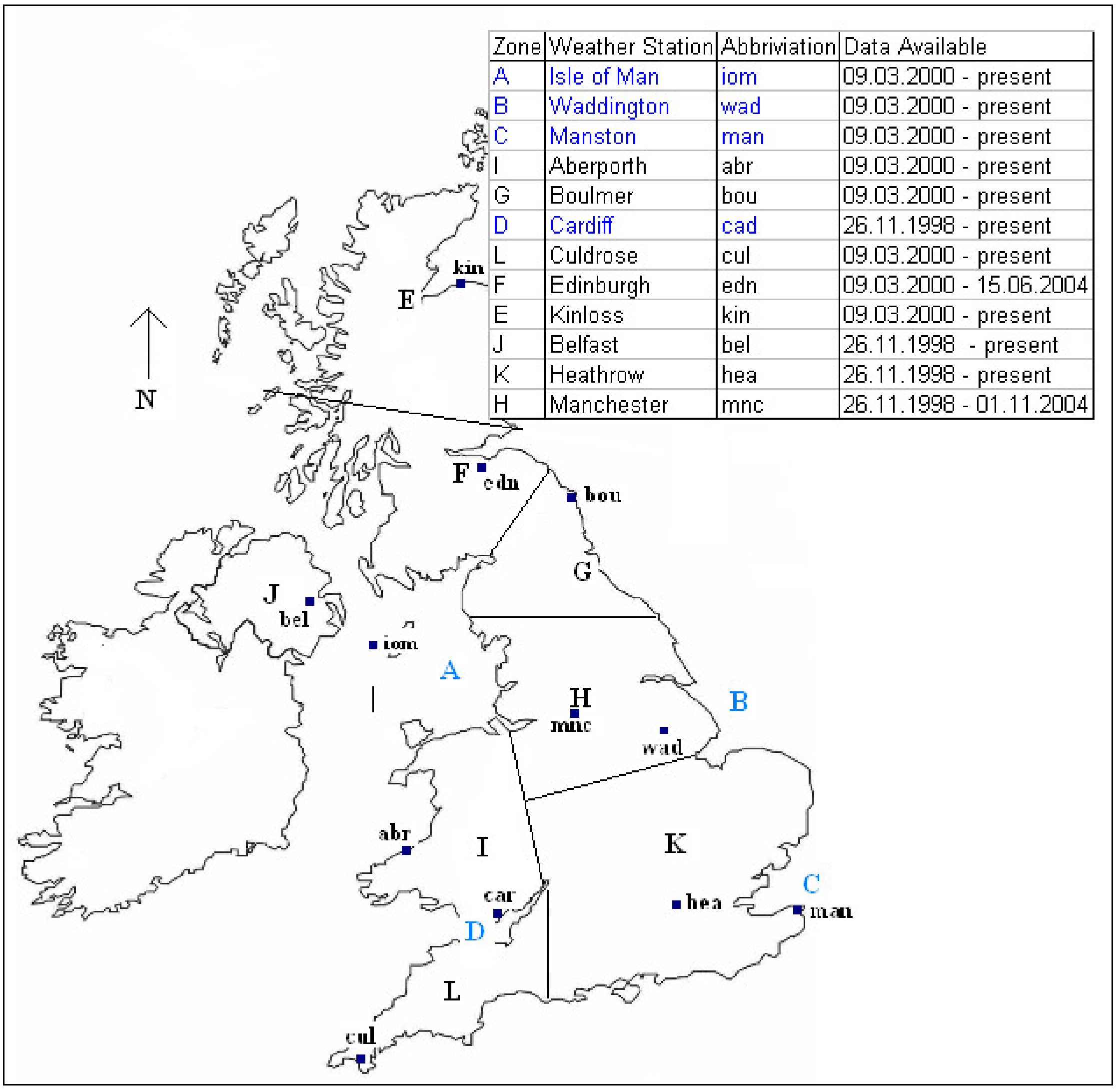
Table 2. Electricity production in Gigawatts, for each of the zones shown in Figure 4. Data are given for wind farms at 4 stages of development. Data highlighted in blue are for offshore sties.

Zone	Operating (GW)	Under Construction (GW)	Consented (GW)	Under Planning (GW)	Totals (GW)
A	0.125	0.000	0.360	1.700	**2.185**
B	0.060	0.000	0.270	3.065	**3.395**
C	0.090	0.000	0.090	1.864	**2.044**
I	0.301	0.001	0.123	0.101	**0.526**
G	0.083	0.036	0.132	0.243	**0.494**
D	0.000	0.000	0.090	0.000	**0.090**
L	0.044	0.002	0.108	0.078	**0.232**
F	0.570	0.442	0.848	2.225	**4.085**
E	0.424	0.137	0.491	1.164	**2.217**
J	0.098	0.018	0.063	0.429	**0.608**
K	0.310	0.007	0.111	0.063	**0.490**
H	0.301	0.126	0.174	0.404	**1.004**
Totals (GW)	**2.405**	**0.768**	**2.860**	**11.336**	**17.370**

3.2 Wind Speed Data

The wind speed data that were used to calculate how much power could theoretically be produced were taken from Russian meteorological archives (see references). The data originate from civilian airports or RAF air bases, and wind speeds are given in ms^{-1} at the standard recording height of 10 m above ground level.

Each of the zones shown in Figure 4 was now assigned a location for which data was available though the Russian archives. The exact station was chosen to be as central as possible to the zone in question, or else close to any areas that were particularly densely covered in wind farms. Figure 5 shows these allocations.



Zone	Weather Station	Abbriviation	Data Available
A	Isle of Man	iom	09.03.2000 - present
B	Waddington	wad	09.03.2000 - present
C	Manston	man	09.03.2000 - present
I	Aberporth	abr	09.03.2000 - present
G	Boulmer	bou	09.03.2000 - present
D	Cardiff	cad	26.11.1998 - present
L	Culdrose	cul	09.03.2000 - present
F	Edinburgh	edn	09.03.2000 - 15.06.2004
E	Kinloss	kin	09.03.2000 - present
J	Belfast	bel	26.11.1998 - present
K	Heathrow	hea	26.11.1998 - present
H	Manchester	mnc	26.11.1998 - 01.11.2004

Figure 5. Map with inset chart showing weather station allocation for wind farm zones A-H.

The table shown in Figure 5 details the time window for which data are available at each weather station. A common period of three years was found to exist, and hence data were down-loaded from the 1st of December, 2000 to the 31st of November 2003 for each site.

3.3 Initial Data Processing

A command script to carry out the data processing was written in 'R' which is a programming language for statistical computing and graphics, with a command line interface. The complete script is included as an appendix (A11.1). The raw data files were firstly edited into a comma separated format (CSV) readable in R. The majority of the weather stations gave data on a 6 hourly basis, however Belfast, Manchester and Heathrow supplied information every 3 hours. After reading in the 12 files, the first thing the code does it to compile the data into one matrix extracting just the wind speeds at each site for all 1094 days. It was of vital importance that the wind speeds in any particular row of the complied matrix referred to exactly the same time and date in order to carry out a fair assessment of the results.

When the compiled matrix was initially inspected, it became apparent that there were several missing data points (<1%), so these were identified by the code and then linear interpolation using the data on either side of the missing figure, was carried out to fill the gaps.

3.4 Converting from Wind Speed to Power Output

There are several steps involved in moving from a wind speed to a power output, which will be described here.

First, the wind speed is adjusted to take it from the location at which it was measured to the location at which it is being 'used', so these two places must be identified.
As has already been mentioned, all of the wind data essentially originated from airports (albeit civilian or RAF) and measurements were taken at a height of 10 m.
The wind is being 'used' either at sea or at sites where the environment is taken to be 'average farm land', at heights of 70 m and 50 m respectively[5].
The original wind speed data has to be corrected for two things; height above ground and 'roughness' of surface. Equation 1 shows how this correction is carried out (Stull, 1999):

$$M_2 = M_1 *(\ln(z_2/r_2))/(\ln(z_1/r_1)) \qquad (1)$$

Where M_1 is the wind speed at height z_1 and roughness length r_1, and M_2 is the new wind speed at height z_2 and surface length r_2.
So the wind speed increases logarithmically with height, but the shape of the profile is dependent on the aerodynamic roughness length of the underlying surface. Some typical roughness lengths are given in Table 3.

[5] These figures are taken to be the average hub height of an offshore wind turbine (70 m) and an onshore wind turbine (50 m). Figures calculated from information on BWEA website.

Table 3. Typical roughness lengths for various landscapes. Values applicable to the sea, airports or typical onshore wind farm locations have been highlighted. Reproduced from Stull, 1999.

Roughness-Length (m)	Classification	Landscape
0.002	Sea	**Sea**, paved areas, snow covered flat plain, tidal flat, smooth desert
0.005	Smooth	Beaches, pack ice, morass, snow covered fields
0.03	Open	**Grass prairie or farm fields, tundra, airports, heather**
0.1	Roughly open	Cultivated area with low crops, occasional trees or hedge rows
0.25	Rough	High crops, scattered obstacles, vineyards
0.5	Very rough	Mixed farm fields & forest clumps, orchards, scattered buildings
1.0	Closed	Regular coverage with large size obstacles and open spaces equal to obstacle heights, suburban housing, villages, mature forests
≥ 2	Chaotic	Centres of large towns and cities, irregular forests

Using Equation 1, the hub heights and appropriate roughness lengths from Table 3, correction factors for the wind data at onshore and offshore sites have been calculated as 1.277 and 2.1975 respectively. For example a measured wind speed of 10 ms^{-1} would change to 12.77 ms^{-1} at the hub of an onshore wind turbine and 21.975 ms^{-1} at the hub of an offshore wind turbine. This emphasises the advantage of having higher turbines located offshore.

The corrected wind speeds can now be converted into a *percentage of maximum possible power output* by applying the constraints of a power curve for a typical wind turbine to the data an example of which is shown below (Figure 6).

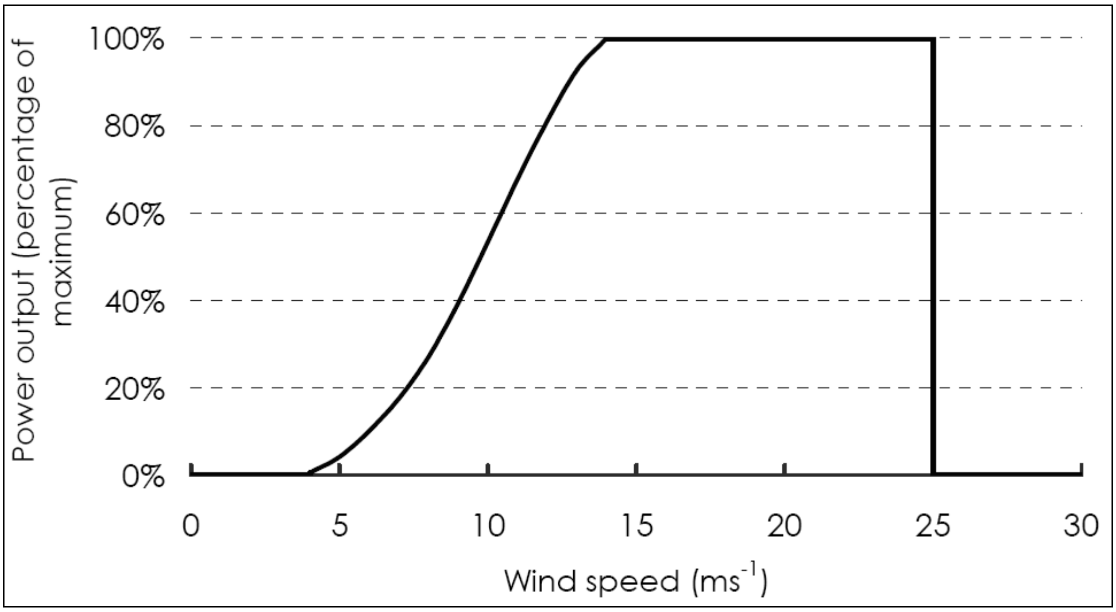


Figure 6. A typical power curve for a wind turbine. Reproduced from Sinden, 2005.

Figure 3 shows that when the wind speed is below 4 and above 25 ms^{-1} no power is produced[6] and that the amount of power increases non-linearly between 4 and 14 ms^{-1}, after which the power output remains at its maximum up to the 25 ms^{-1} cut off. All of these conditions were applied to the corrected wind data to give a matrix showing the percentage of maximum power production at each time throughout the three year period, within each of the 12 zones.
Initially, the non-linear section of the power curve was modelled with a straight line (see Figure 7 below), however this lead to unacceptable errors especially given that a high percentage of the data points fell within this band of wind speeds. As a solution, a cubic function (2) was fitted to some actual turbine data using the 'linear model' function in R. This was then applied to wind speeds between 4 and 14 ms^{-1}.

$$\text{Power} = 46.25 - 24.19w + 3.711w^2 - 0.1218w^3 \qquad (2)$$

Where w is wind speed.

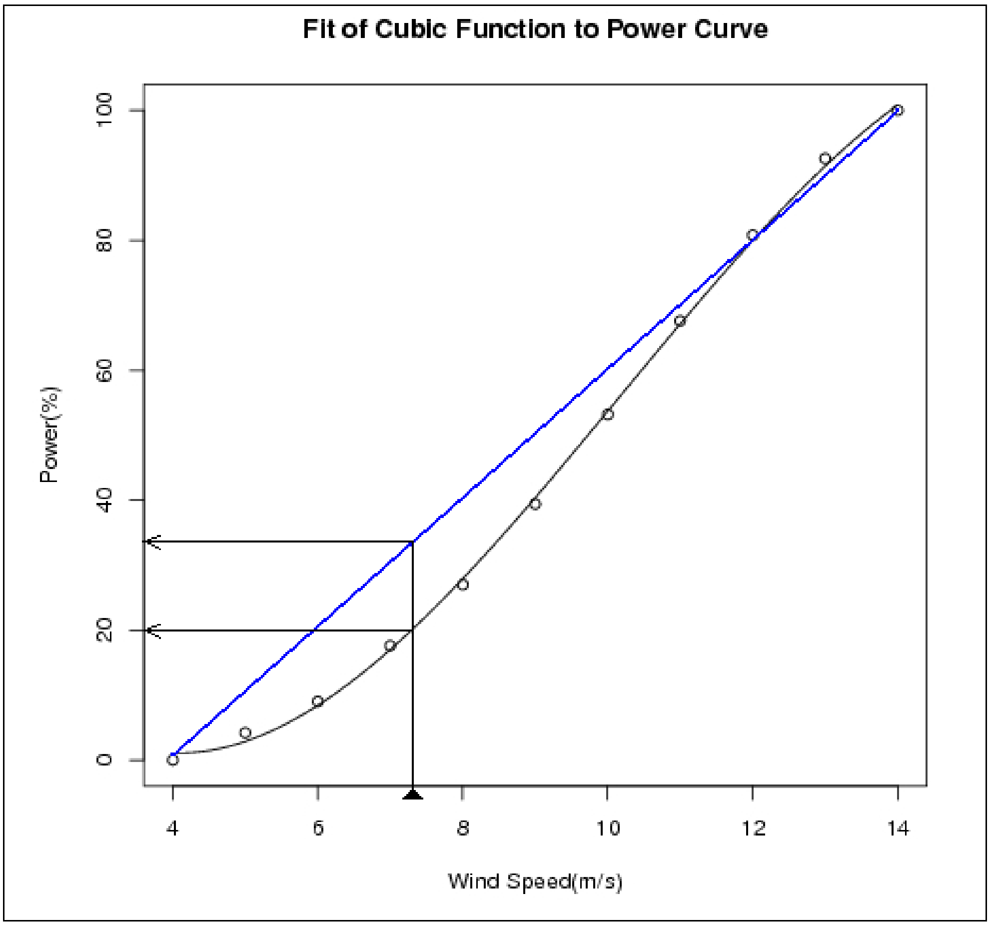


Figure 7. A plot showing the fit of the cubic function (2) shown by the black line, to some actual turbine data (circles). Also shown is the straight line (blue) initially used to model the power curve, and the difference between the two models at 7.68 ms^{-1} (the overall average wind speed). The R code written to compute the cubic co-efficients can be found in the appendix (7.2).

[6] The power production cuts off at an upper limit of 25 ms^{-1} in order to prevent damage to the turbine in gale force conditions. This figure is an approximation of the decision rules regarding turbine shut down – in reality gust amplitudes and frequencies play a larger part than the average wind speed.

The difference between using the cubic or straight line model at the average wind speed of 7.68 ms^{-1} is over 10%, as is shown by Figure 7. This emphasises the importance of having a good model to represent the power curve of the wind turbine.

Now we have a matrix which describes the power output, in terms of a percentage of possible maximum, at four times per day, in 12 zones over the three year period. By multiplying these figures by the installed capacities for each zone (shown earlier in Table 2), it is a simple task to calculate actual power output in each zone.

One final adjustment needs to be made to allow for maintenance of the wind turbines. According to the Danish Wind Industry Association, turbines require a routine service or inspection every 6 months. This results in them being unavailable for use for 2 % of the year, so assuming that the maintenance occurs entirely at random then the annual electricity production will also be reduced by 2 % which is factored in at the last stage of the data processing.

4.0 Assumptions or Limitations of the Method

Below is an outline of the assumptions made in obtaining and processing the data. The assumptions with large consequences as far as error is concerned will be discussed in more detail in the conclusions.

- It is assumed that the data from the BWEA is up to date and correct. There was some discrepancy between different pages of their web site, particularly with regard to the wind farms which are not yet operational. This is to be expected because plans are continually changing.
- The calculated wind speeds are assumed to be constant across a whole region and therefore applied to all wind farms within a particular zone. This is of course unrealistic and in fact becomes a physical impossibility at the borders between the zones.
- The corrections made to adjust the wind speeds according surface roughness were generalised for all wind farms.
- At offshore wind farms, a surface roughness of 0.002 m was applied. In reality this would change as the seas become rougher. Also, the wind direction would have some effect on the roughness of the sea, which was not taken into account.
- Wind speeds for offshore farms were calculated from corrected onshore data. This did not take into account phenomena such as sea breezes which may increase wind speeds.
- Wind speeds were corrected to average hub heights of 50 m and 70 m for onshore and offshore wind farms respectively. There is actually considerable variation in turbine hub height which, as has been shown can have a considerable effect on power output.
- Likewise a ‘typical’ turbine power curve was applied to the data and again there is some variation depending on exact type/manufacturer of turbine.
- A cut off wind speed of 25 ms^{-1} was applied to the data. This is only an approximation of the decision rules regarding turbine shut down – in reality gust amplitudes and frequencies play a larger part than the average wind speed.

5.0 Results

The results of the data analysis will be shown here in graphical form. All graphs and information given will refer to the capacity factor (CF) for wind power in the UK, which as already discussed, expresses the amount of energy produced as a percentage of the maximum possible production. Where wind power is concerned, the major factor in reducing capacity factor is that it is not normally windy enough for the turbines to work at maximum load (rather than maintenance issues as with conventional power production). Therefore there is a direct relationship between capacity factor and wind strength in the graphs shown in this section.

Unless otherwise stated, all graphs will show results from calculations that include all wind farms (not just the operational ones) and again the code to plot graphs or calculate statistical information, written in the R programming language can be found in the appendix.

5.1 The Capacity Factor for Wind Farms in the UK

The estimation for the mean average CF for wind power in the UK, including wind farms at all stages of development, was found to be 31.395% to 32.598% with an estimated standard deviation[7] of 19.95% and a standard error[8] of 0.31%. These figures represent a 95% confidence interval for the actual mean, calculated by rigorous statistical analysis which is documented in the appendix.

As stated above, the standard deviation of the CF was found to be 19.95% which is quite large considering the mean is only 32%. The overall spread of the CF data is shown below by a box plot (Figure 8).

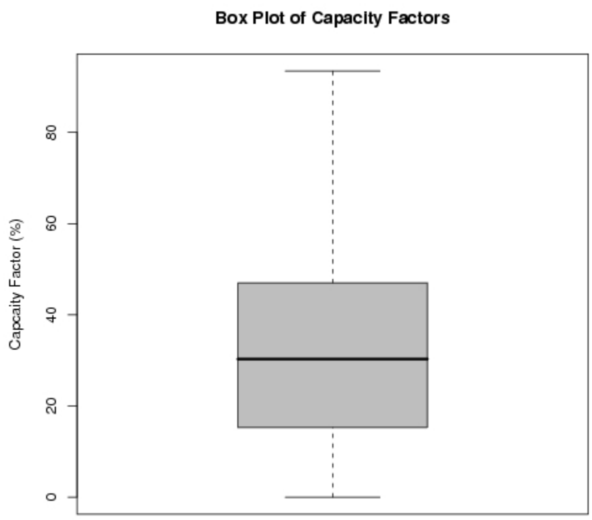


Figure 8. A box plot of the estimated, 6-hourly capacity factor data accounting for all wind power in the UK (future and present). The Black line shows the mean average, the two mid-quartiles are shown by the grey box (i.e. 50% of the time the CF lies within this range) and the maximum and minimum values are shown by the upper and lower bars.

[7] Standard deviation can be considered as the average distance away from the mean within a data set.
[8] Standard error is a measure of uncertainty in an estimate calculated by dividing the standard deviation by the sample size (~ 4000 in this case).

5.2 Annular and Monthly Variability of Capacity Factors

Figure 9 shows the CF for each month, averaged from every datum within the month over the three year period. Figure 10 shows a similar result, but for each of the three years individually.

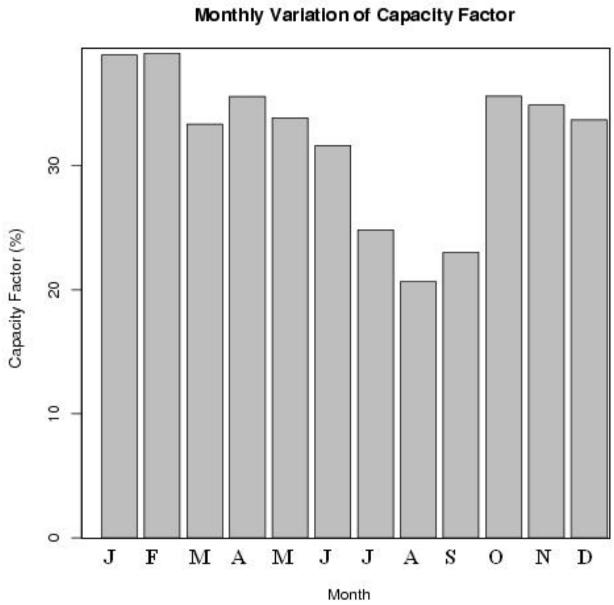


Figure 9. Average monthly CF for the British Isles wind power, averaged over a three year period.

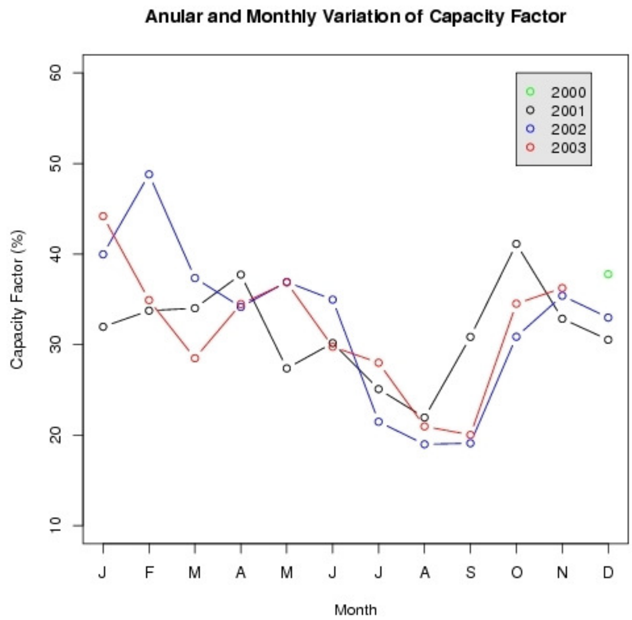


Figure 10. Monthly variation of CF shown for each of the three year periods. Standard error is within the size of the circles used to plot the data.

5.3 Diurnal Wind Patterns

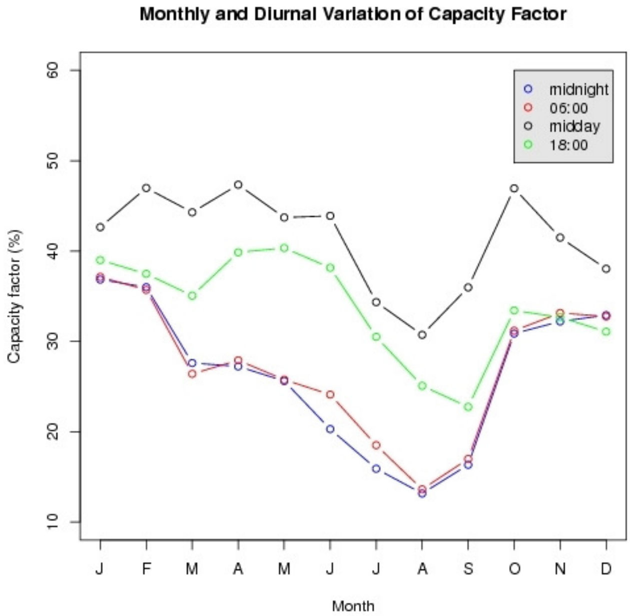


Figure 11. Diurnal fluctuations of CF for each month. Each line relates to a different time of the day according to the legend.

Out of the four possibilities, the highest CFs and hence wind speeds are on average, seen at midday, whilst the CFs at midnight and 6.00am are virtually identical and considerably lower. There is a larger difference between the wind speeds at midnight and midday, in the summer months rather than the winter which is probably a reflection of calmer summer weather systems. As in Figure 10, the variation of wind speed throughout the months of the year can also be seen very clearly in Figure 11.

5.4 Consistency of Supply

The data shown in the likes of Figure 11 are long term averages; for example the midday data point for September is an average of 90 (30 days x 3 years) pieces of information, hence the resultant smooth graph. Figure 12, shows the standard deviations of the data shown in Figure 11. As mentioned earlier the overall standard deviation is ~20%, however it is clear from Figure13 that some months of the year or times of the day tend to have much more variability than others. In summary, the wind at midnight and 6.00am is much less variable in the summer months than the winter, whereas the midday wind speeds have a high degree of variability all year round.

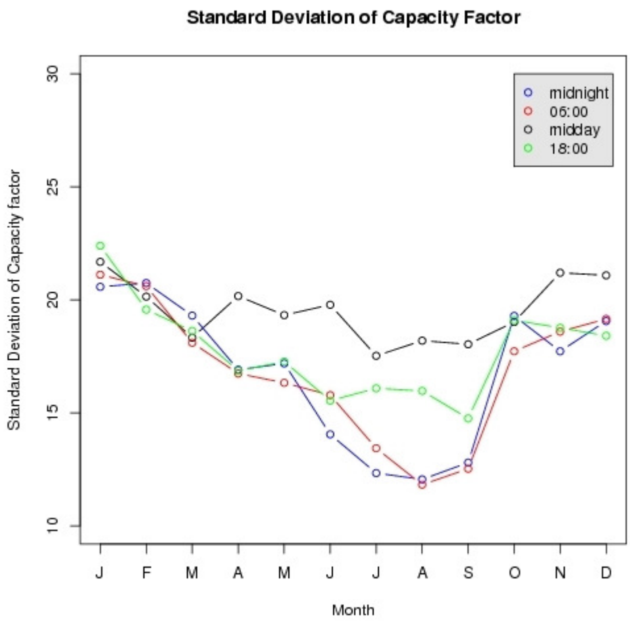


Figure13. Standard Deviation of CF shown for each time of the day in each month as per Figure 11.

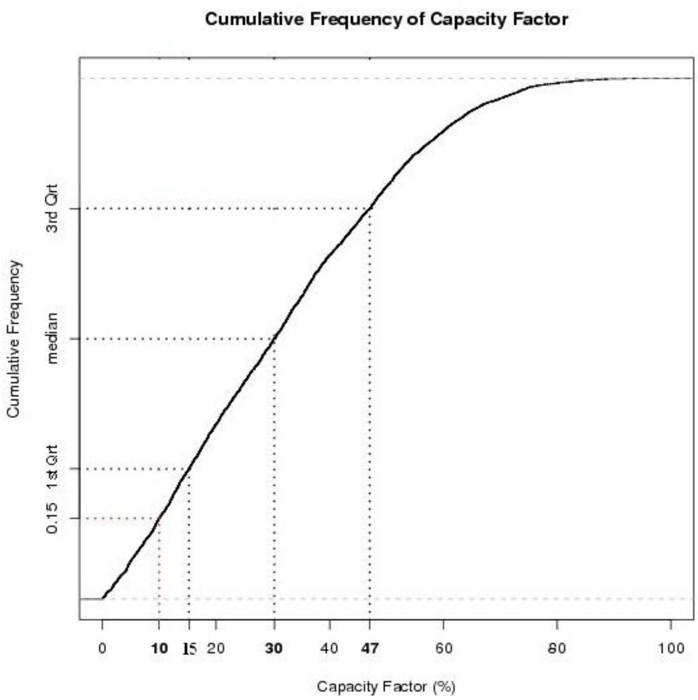


Figure14. Cumulative frequency of the capacity factor for UK wind power.

The quartiles labeled on Figure14 show that; 25% of the time the CF is below 15%, half the time it is 15-47% and the remaining 25% of the time it is above 47%. CFs of over 80 occur for less than 1% of the time.

5.5 Geographical Diversity

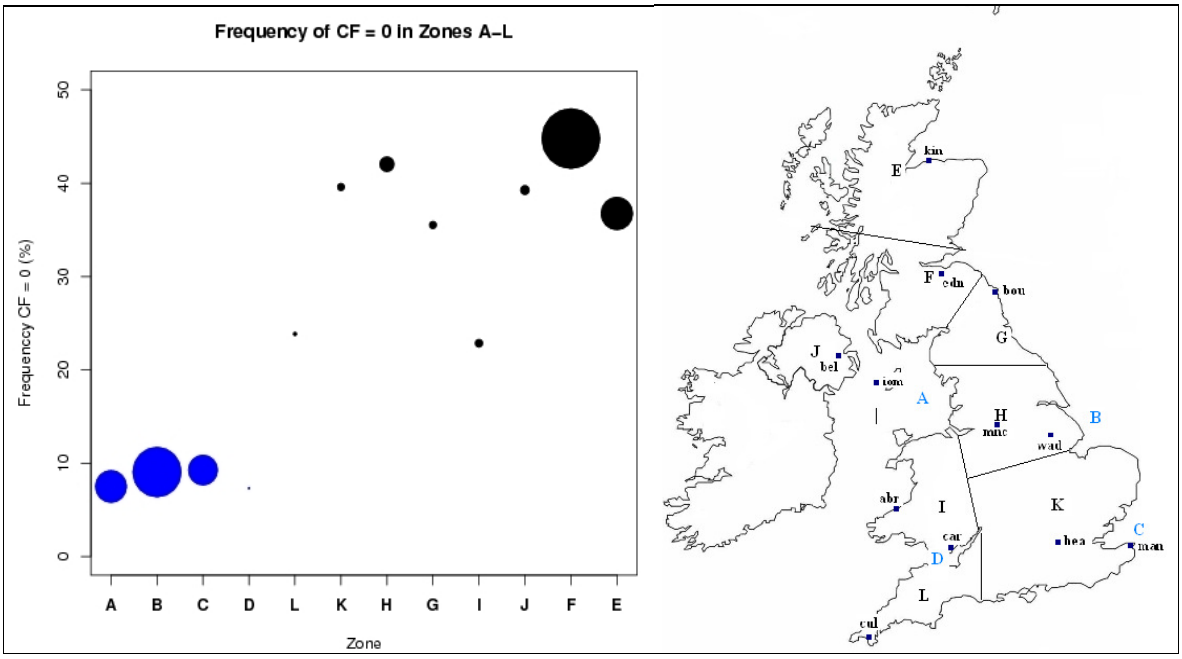


Figure15. Percentage of time when power production is zero, for each of the 12 zones around the UK (shown on the right). The markers, sized proportionally to the amount of electricity being produced in that zone, are ordered with the offshore sites first (in blue), followed by the most southerly zone, moving north there after. For reference, the circle representing southern Scotland (zone F) equals 4 GW of electricity production.

Figure 15 shows that zero power productions is common when individual regions are considered (particularly onshore), despite the fact that nationally such events occur less than 0.05% of the time (only twice in over 4000 measurement times was no power being produced anywhere in the UK).

The dates corresponding to the pair of wide-spread zero power production were found to be the 22nd of September 2001 and the 3rd of September 2003, both at midnight. Out of interest and to check that this seemed reasonable, the barometric charts[9] corresponding to these dates were sourced (Figures 16a & 16b), note however, that they show data at midday rather than midnight. In the first case the weather systems surrounding the UK were such that there was no air-pressure gradient[10] across it, and in the second case the UK was amidst a widespread high-pressure system. The date of maximum power production was also found (93.4% capacity factor at midday on the 26th of April, 2002) along with the corresponding barometric chart (Figure 16c), which shows a low-pressure system creating a consistently high gradient of air-pressure across the UK. Figure 16d shows similarly predictable results for an hour when the capacity factor was ~30%.

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[9] A barometric chart is a map that shows contours of air pressure across a region – they form the basis of weather forecasting.

[10] A gradient of air pressure (i.e a difference in pressure from one place to another) is what creates wind by the action of the air moving from the area of higher pressure to the area of lower pressure.

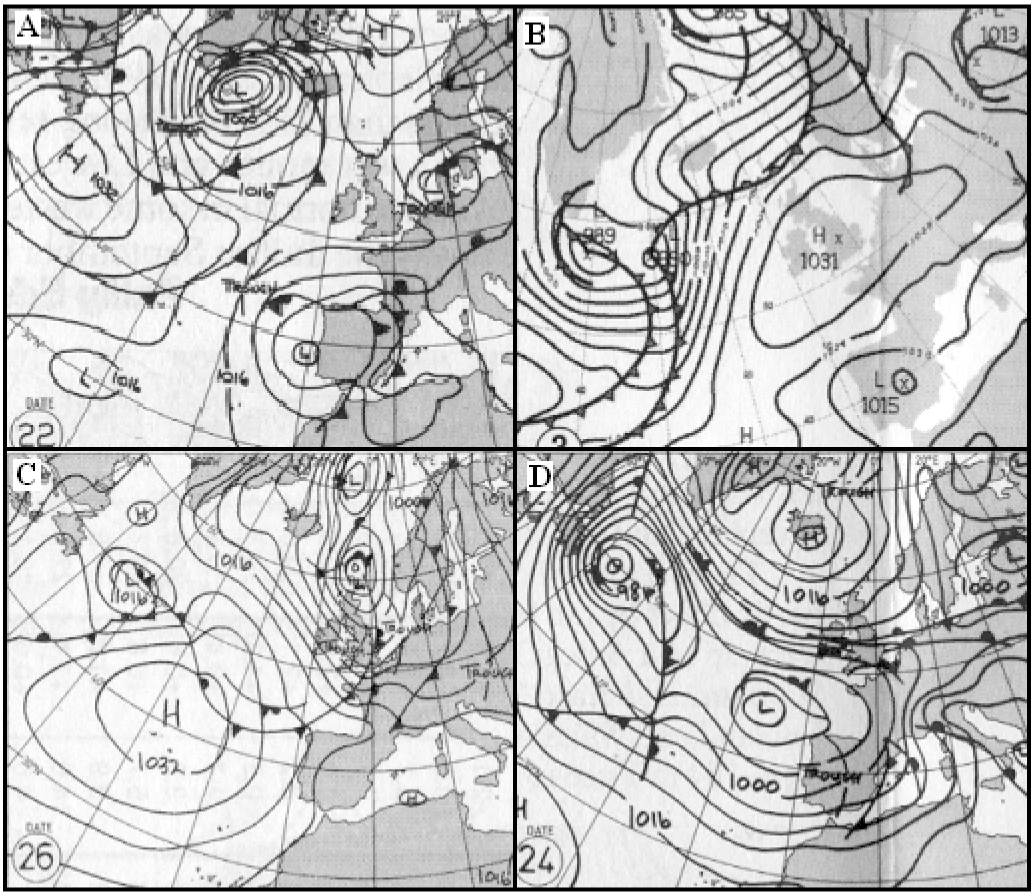

Figure 16 a-d. Barometric charts corresponding to: a & b – days of zero power production, c – the hour of maximum power production where UK wind farms would have theoretically been producing 93% of their potential, and d – an hour of 30 % power production. Charts are taken from the Royal Met Soc Journal called Weather, which is produced monthly.

6.0 Discussion

6.1 The Capacity Factor for Wind Farms in the UK

As stated in Section 5.1, the capacity factor for wind farms in the UK was found to be 31.395% to 32.598%. This may seem very low, and indeed it is when compared to other methods of electricity production (nuclear power ~ 74-76%, gas fired power station ~ 60-65%, coal fired power station ~ 40-50%, NEF, 2007), however it is higher than reported figures for wind power in the UK which vary from 24% to 31% (DUKES, 1998 & 2004). The CF calculated here is very much at the high end of the spectrum of reported figures; this is because it is a projection into the future, taking into account offshore wind farms, with higher wind speeds, that have not yet been built, and a larger geographical spread of wind farms which reflects future development plans. The CF calculated using just the operational wind farms (see Table 2) is only 22.27%, which seems like a slight underestimation according to reported figures, however it does show that the move towards offshore wind power with larger turbines, and the highest geographical diversity possible is going to have a considerable impact on the national capacity factor for electricity production by wind.

The variation of the capacity factor is in many respects more important than its actual value. Imagine the two following scenarios;

a) The capacity factor is consistently 33% - the country's needs could feasibly be met solely by wind power with a total installed capacity of three times the maximum demand.

b) The capacity factor is considerably higher at 50% but half the time maximum power is being produced whilst the rest of the time none is being produced Despite the fact that the CF is higher in case b, no amount of installed capacity would suffice because half the time there is simply no wind. Hence a detailed look at the variation of the CF on different timescales is very important. These variations can then be compared to the fluctuations of electricity demand on similar timescales to see if they complement or conflict with one another.

The result shown by Figure 9 is, on the whole, fairly intuitive; the summer months are least windy whilst the winter months the windiest. However it seems odd that from October to December there is a steady fall in the capacity factor. Figure 10 is similar to Figure 9, however it shows data for each year individually, and it seems that in all three years the average capacity factors for November and December are relatively low. On closer inspection of Figure 10, it seems that the 2001 data are particularly anomalous, especially with regard to the winter/spring months.

6.2 The North Atlantic Oscillation

Much of Europe's climate and especially the wind in winter, is very well correlated to the North Atlantic Oscillation (NAO). The NAO is a climatic phenomenon similar to El Niño but relating to the Atlantic Ocean rather than the Pacific, and its state (the NAO index) is defined by the normalised difference in sea level air pressure between the Iceland Low and Azores High (Figure 17). Wanner at al., 2001.

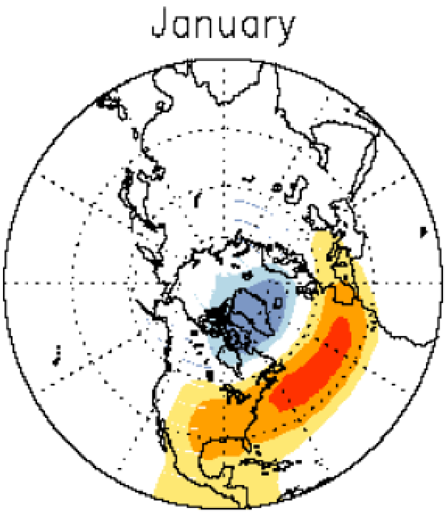

Figure 17. The Iceland Low pressure system and the Azores High pressure system; the driving forces of the NAO.

A large difference in air pressure gives rise to a positive NAO index which is well correlated to unusually strong westerly winds in Europe and vice versa. Wanner at al., 2001.

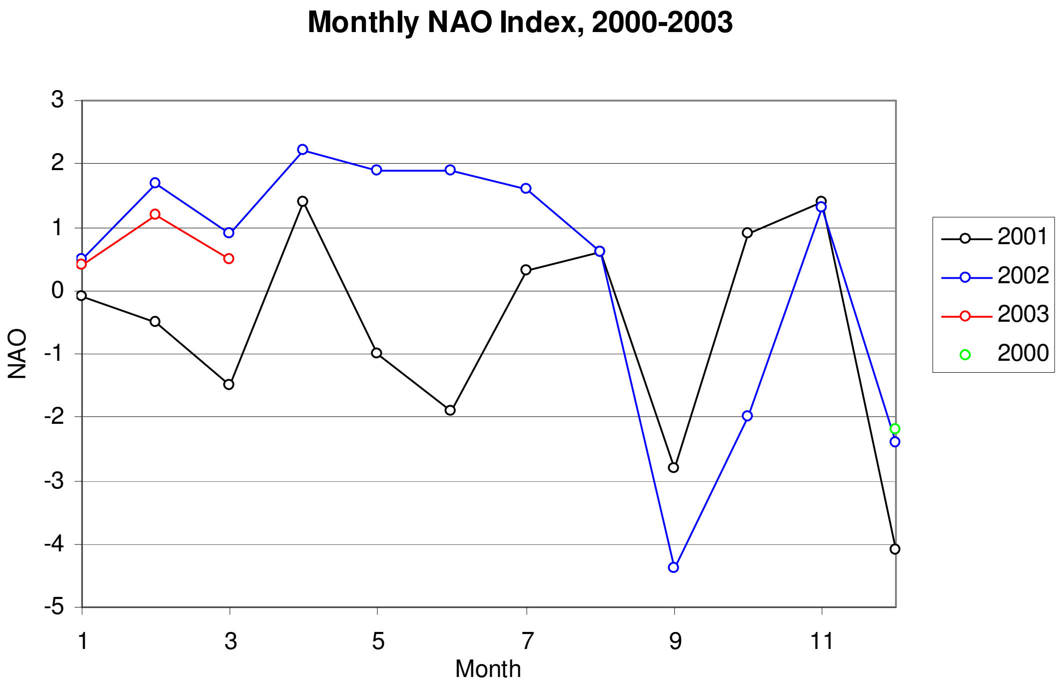

Figure 18. Monthly variation of NAO index for the time span relating to Figure 10. No data were available after March 2003. Data courtesy of J.W. Hurrell (Climate Analysis Section, National Center for Atmospheric Research, Boulder, Colorado, USA) - http://www.cgd.ucar.html.

The NAO index for the winter of 2001 was anomalously low at -1.89: this gives reason to the low wind speeds and hence CFs seen in Figure 11 for that year. The data shown in figure 18, can be compared month for month with that of Figure 10 and the correlations are again very good, particularly the lows seen in the months of September and December.

6.3 Annular Wind Patterns

The average capacity factors for 2001, 2002 and 2003 were 31.44, 32.58 and 32.178 percent respectively. The variation among these figures is very small when compared to other published results (e.g. Sinden, 2008) however a time period of decades rather than years would need to be analyzed to properly asses the long period behavior of wind patterns in the UK.

6.4 Diurnal Wind Patterns

"In many places, wind tends to blow best on winter nights, when demand is low" – New York Times 2006.

Amounts of wind generally change systematically throughout the day (diurnal variations) as a result of the sun warming the Earth's surface. This effect can be seen in the data (Figure 11), although it is only constrained at four times of the day (00.00, 06.00, 12.00, &18.00) so it is difficult to ascertain at exactly what time of day it tends to be most windy for example. Out of the four times of the day at which data were available, midday was consistently most windy.

6.5 Consistency of Supply

One of the largest concerns whenever wind power is mentioned is *"what about when the entire UK is experiencing low wind…"*, or indeed high wind because this also causes wind turbines to produce no electricity. The frequency of such events can be assessed by looking at Figure14. If a national low wind event is defined as being when the CF drops below 10%, then from Figure14 this situation occurs 15 % of the time. Interestingly, the capacity factor for the whole of the UK was zero only twice out of the 4000+ times analyzed despite the fact that at any one particular site the CF would go to zero quite often (>25% of the time in some places), this supports the statement that: *because there is no wind in one area of the UK does not necessarily mean there is none else where* – see section 6.7.

6.6 Correlation between Wind Strength and Demand for Electricity

As already mentioned in section two, there are very well established diurnal and annual patterns of electricity demand (Figure 19), which can be compared to the corresponding fluctuations of wind power shown by Figures 10 and 12 to see if there is any correlation.

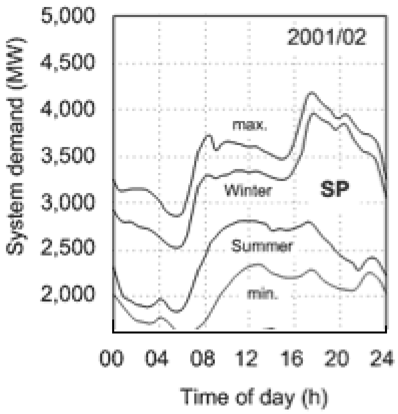

Figure 19. Daily and annular variation of demand for electricity in Scotland. www.scotland.gov.uk

Assuming that the variation of demand in Scotland is more or less the same as that of the UK as a whole, then there are clearly some broad similarities between this and what is shown in Figure 11; electricity demand and wind power are higher a) in winter than summer, and b) during the day rather than at night.
These two dynamic systems have been rigorously correlated using numerical methods by Sinden, 2008.

6.7 The Importance of Geographical Diversity

Figure15 shows that the amount of time when zero power is produced at some sites is as high as nearly 50%, with an average of about 30%. However as previously mentioned, only twice in over 4000 occasions measured, is there no power being produced anywhere in the UK. This is a reflection of the very wide variety of weather systems that are experienced by different areas of the UK, which ultimately lead to a low correlation between the power being produced in Scotland and Southern England for example.

The advantage of offshore wind power is highlighted by Figure 15; the frequency of zero power days is below 10% for all of them – a considerable improvement over the land based wind farms. The reason for this is the increased wind speeds as a result of a) a lower roughness length over the sea, and b) a general increase in the size (hence hub height) of the turbines themselves.

Figure 15 highlights what is probably the biggest flaw with the methodology used, which is essentially a question of how well the wind data from the airport chosen to exemplify a particular zone, actually represents the wind at the farms within that zone. Looking back to Figure 3, it would be reasonable to expect the frequency of zero power days in onshore zones would be lowest in Scotland and N. Ireland, with a gradual upward trend as the zones become more south-westerly, however this is not the case as is shown by Figure 15. This may be due to local effects upon the wind at the airport in question (e.g is Edinburgh Airport sheltered by the Pentland Hills?), or it could be an effect of the location of the airport within the zone as a whole. There is some support for the second hypothesis according to the following evidence;

i) Zones L & I, represented by *west coast* airports, have capacity factors equal to zero for about 25% of the time,
ii) Zones K, H, G, J, F & E have CFs = 0 considerably more often; about 36-44% of the time, and they are represented by *inland* or *east coast* airpots.

In summary, wind speed data from west coast airports are generally higher than that of inland or east coast airports, thus not giving a true representation of the wind speeds at the inland locations of the wind farms within that zone. This conclusion seems logical, given that the prevailing wind direction in the UK is from the west. The influence of this problem on the overall conclusions drawn from this investigation will probably be minimal because it only affects two zones where little energy is produced anyway (L and I).

6.8 Predicting Low Power Output

The European Centre for Medium-Range Weather Forecasts (ECMWF) does a particularly good job of predicting the occurrence of high pressure weather systems (personal communication, R. Thompson), which are most likely cause of mass power outage from wind in the UK, thus giving time to put back up supplies into action. A Medium-Range forecast predicts conditions 10 days in advance, and their success has improved by a factor of about 1.5 since the eighties.

Contracts detailing where electricity supply will come from are agreed one hour in advance in the UK (SDC, 2005), and on this time scale wind power predictions are very accurate indeed as shown by Figure 20.

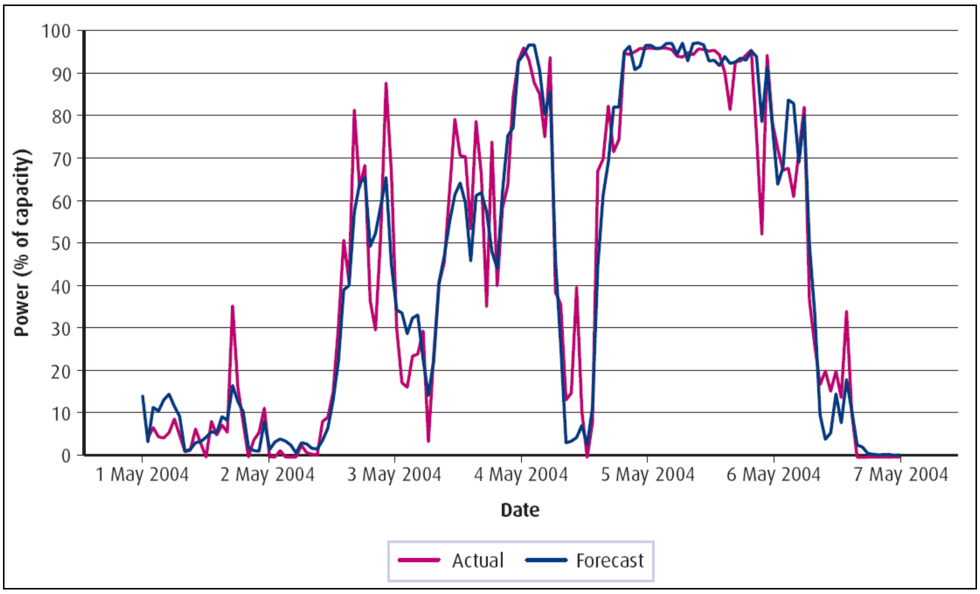

Figure 20. The forecast of power output from one wind farm given 1 hour in advance vs the actual power output, Ireland 2004. Reproduced from SDC, 2005.

So in summary, with forecasts available on timescales ranging from one hour to in excess of a week there is no reason why, with the right supplementary power supply options (see below), the potentially massive power source that the wind represents could not be fully integrated into the national grid. This view has been confirmed by the National Grid Company (NGC).

6.9 Requirement for Backup – Accommodating Wind

There is of course a need for back up systems to deal with times of low (or even zero) power production, the exact nature of which becomes ever more crucial as the percentage of the UKs electricity is produced by wind farms increases. However this requirement is nothing new for the National Grid Company, who are prepared for sudden outages of large scale single power stations which are far less predictable than how windy it may be on a given day. This highlights a significant advantage of wind farms over conventional power stations; if one wind turbine fails it has no significant effect because it is one of many that are making a contribution, however the failure of a single nuclear power station could potentially cause a “black out”.

Firms such as the NGC fight a statistical battle to ensure that electricity demand is always met. They do this by looking at the system as a whole, with each contributing power station (or wind farm) having been assigned a “capacity value” which is a statistical probability that the plant can contribute firm capacity to the network (SDC,

2005). For the most reliable gas power stations this is around 90%, i.e. a 10 GW power station would be counted upon for 9 GW of supply. As long as peak demand can be met by the total amount of *firm* capacity, then statistics say that demand will always be met. Nevertheless, even without wind there would always theoretically be a chance that several large contributors would not be able to meet their firm capacity such that the demand could not be met, but the point is that the capacity values are set such that this is a statistically acceptable risk.
The capacity value of wind varies inversely with its installed capacity, because as more is installed the risk that it poses to demand not being met increases. The NGC figures for the capacity value of wind are as follows;

- 8 GW of installed capacity would replace 3 GW of conventional plant; or a 6% contribution to the grid equates to a 35% capacity value.
- 25 GW of installed capacity would replace 5 GW of conventional plant; or a 20% contribution to the grid equates to a 20% capacity value.

6.10 Will the Government Targets be met?

To recap, the targets set by the UK government for electricity production from renewable sources are 10% by 2010 and 20% by 2020. The total electricity production in 2006 was 350 TWh[11] (HM Government, 2007). Taking the installed capacity of wind power to be 17.37 GW (total capacity for all wind farms inc. those that are still at the elementary planning stage (see Table 2)), and using a capacity factor of 32 % this alone represents 48.7 TWh of electricity – nearly 14 % of demand if the above value for 2006 is assumed. This is calculated using Equation 3;

$$C_i * CF * Hrs = P_t \qquad (3)$$

Where C_i is the installed capacity and P_t is the total electricity produced.

In 2006 the contribution to UK electricity production was 1.15% from hydro and 2.25% from wave, solar & bio-fuel with the latter being the largest contributor (HM Government, 2007). So assuming a total contribution of 3.4% from renewables other than wind, then wind needs to supply 6.6 % (or 23 TWh) to meet the 2010 target. Using a rearrangement of Equation 3, this equates to a required installed capacity of 8.24 GW. Is this likely? Considering there are only 21 months left until 2010 and looking at the figures in Table 1 (sourced in January 2008), then *no* would be the instinctive answer. However, Table 4 shows how figures have changed in just over 2 months since this project began; this increases confidence to a certain degree, nonetheless if the target were to be met then all farms that are either under construction or that have consent would need to be operational by 2010.

Table 4. Changes in the capacities of UK wind farms, at different stages of development, in just over 2 months since the project began.

Date	Operating (GW)	Under Construction (GW)	Consented (GW)	Under Planning (GW)	Totals (GW)
Jan-08	2.41	0.77	2.86	11.34	**17.37**
Mar-08	2.43	1.39	5.14	9.43	**18.39**

[11] One terawatt hour (TWh) would be the amount of energy produced by a 42 GW power station (very hypothetical) or approximately 14,000 3 MW wind turbines, running at capacity for one day.

In order for the 2020 target to be met the installed capacity of wind that would be required is 25 GW, assuming that there is no expansion of the other renewable sources. This target seems very achievable when the rapid development over the last 10 years is considered.

At the moment there is a limit to the contribution that wind can feasibly make, not due to a shortage of wind itself but due to its variable nature. Some estimations of the UK wind resource (SDC, 2005) suggest that it could theoretically meet UK needs several times over; the answer to bringing this to fruition lies in being able to store energy that is produced when there is an excess of wind, suggestions for which include more pumped storage facilities such as Dinorwig or the production and storage of hydrogen or even compressed air. Storage techniques are of course inefficient - 50% according to Wald 2006, but this compares favourably to the efficiency of a fossil fuel burning power station where the coal or gas has to be bought in the first place, and remember that a coal burning power station produces approximately one ton of CO_2 per MWh of electricity produced.

7.0 Further Work

To further validate the results of this investigation, it needs to be repeated using wind data that better represent the actual wind speeds at individual wind farms. The potential inaccuracy resulting from dividing the UK up into just 12 zones, and then using airport data that have to be corrected, were shown and discussed in section 5.7. In the ideal world, each wind farm would store wind data collected on site which could then be applied to the turbines at that farm.

A more representative data set may be available from the ECMWF and alike, which uses geostrophic calculations from barometric data to calculate wind speed. Using this, the UK could probably be divided into a much smaller grid and a much wider time window with more frequent measurements of data would be available, allowing long period (decadal) wind variations to be assessed, as well better establishing the daily variation of power output which was poorly constrained here with only four measurements per day.

The method of wind speed correction could be improved by finding a roughness length for each wind farm individually and also checking for any special circumstances relating to their locations. The offshore wind data should be corrected for sea-breezes, which do not exist at the inland sites (airports) where the data originate from, and also the roughness length is variable according to wind direction and wind speed – a more complex model could be designed to take these factors into account.

More work could also be done to carry out numerical analysis of the correlation between wind speed and electricity demand, and between the distance between wind farms and the amount of power produced (as in Sinden,2008).

8.0 Conclusions

In many respects the development of offshore wind farms, which are currently in their infancy, has several advantages over conventional onshore projects, not least that they tend to produce much more power with greater consistency, but they also potentially have fewer environmental impacts and less objection from the general public. According to calculations carried out here, their introduction will increase the capacity factor from low 20s to 32%.

The assessment of the geographical diversity of wind farms within the UK has highlighted the acute importance of this matter; the amount of time of zero power production due to low wind, for a single region of the UK can be as high as 45%, however when the UK as a whole is considered this figure drops to well below 1%. So future expansions of the wind-power network should be planned with this in mind.

Finally, it should always be remembered that using less energy in the first place is probably the easiest, cheapest and most environmentally friendly way in which any one can help reduce CO_2 emissions.

9.0 Acknowledgements

Many thanks to Prof. R. Thompson for his help during this investigation, particularly where sourcing information was concerned, and introducing me to the R-programming language.

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www.windpower.org/en/tour/econ/oandm.htm Information on turbine maintenance.
www.nmcco.com/ Nuclear Management Company, US.
www.scotland.gov.uk Statistics for electricity demand.
www.theoildrum.com Oil debating website.
www.ecmwf.int European centre for medium-range weather forecasting.

11.0 Appendix

11.1 R-Code to Calculate UK Capacity Factors

```
#==============================================================
# Assessment of Consistency of Supply for UK  Wind Energy
#Author: N. Johnson
#==============================================================
# Read data from txt files
iom<-read.csv('IOM.txt',skip=45,header=FALSE)
wad<-read.csv('WAD.txt',skip=45,header=FALSE)
man<-read.csv('MAN.txt',skip=45,header=FALSE)
abr<-read.csv('ABR.txt',skip=45,header=FALSE)
bel<-read.csv('BEL.txt',skip=45,header=FALSE)
bou<-read.csv('BOU.txt',skip=45,header=FALSE)
cad<-read.csv('CAD.txt',skip=45,header=FALSE)
cul<-read.csv('CUL.txt',skip=45,header=FALSE)
edn<-read.csv('EDN.txt',skip=45,header=FALSE)
hea<-read.csv('HEA.txt',skip=45,header=FALSE)
kin<-read.csv('KIN.txt',skip=45,header=FALSE)
mnc<-read.csv('MNC.txt',skip=45,header=FALSE)
# Create matrix combining relavent parts from above to give wind data hea, bel and mnc not included yet because
#they do not use the same time inetervals  headers= y,m,d,t,wind_iom,wind_wad,wind_man etc etc

nr<-nrow(iom)
mat2<-matrix(c(iom[,1],iom[,2],iom[,3],iom[,4],iom[,13],wad[,13],man[,13],abr[,13],bou[,13],cad[,13],cul[,13],
edn[,13],kin[,13],rep(NA,nr*3)),nr,16)
#Insert hea, bel and mnc data into new matrix
nr<-nrow(mat2)
nr2<-nrow(bel)
for (i in 1:nr2){
loc<-bel[i,1]==mat2[,1]& bel[i,2]==mat2[,2] & bel[i,3]==mat2[,3] & bel[i,4]==mat2[,4]
nn<-(1:nr)[loc]
mat2[nn,14]<-bel[i,13]
}
nr2<-nrow(hea)
for (i in 1:nr2){
loc<-hea[i,1]==mat2[,1]& hea[i,2]==mat2[,2] & hea[i,3]==mat2[,3] & hea[i,4]==mat2[,4]
nn<-(1:nr)[loc]
mat2[nn,15]<-hea[i,13]
}
nr2<-nrow(mnc)
for (i in 1:nr2){
loc<-mnc[i,1]==mat2[,1]& mnc[i,2]==mat2[,2] & mnc[i,3]==mat2[,3] & mnc[i,4]==mat2[,4]
nn<-(1:nr)[loc]
mat2[nn,16]<-mnc[i,13]
}
#remove "NA" rows
loc<-is.na(mat2[,4])
nn<-(1:nrow(mat2))[loc]
mat3<-mat2[-nn,]
# Interpolate each row for fill in any remaining gaps.
for(i in 5:16){
nr<-nrow(mat3)
x<-(1:nr)[!is.na(mat3[,i])]
y<-mat3[x,i]
xnew<-(1:nr)[is.na(mat3[,i])]
a1<-approx(x,y,xnew)
mat3[a1$x,i]<-a1$y
}
```

```
# look at data.
image(as.matrix(mat3[,5:16]))
# Plot data
r1<-range(mat3[,5:16],na.rm=T)
r2<-range(1:nr)
plot(r2,r1,type='n',xlab='Time',ylab='speed (m/s)')
for(i in 5:16){
lines(1:nr,mat3[,i],col=i)
}
# Create matricies of adjusted wind speeds and power output at sites
# Column 13 of power matrix shows % of max possible power being produced and column 14 factors in 2%
#maintenance time
power_dat<-read.csv('power_dat.csv',header=FALSE) # file containing power data for each geographical zone
power_mat<-matrix(t(power_dat),5,13)                    #transpose matrix
nr<-nrow(mat3)
wind<-matrix(c(mat3[,5]*2.1975 ,mat3[,6]*2.1975,mat3[,7]*2.1975,mat3[,8]*1.277,mat3[,9]*1.277,
mat3[,10]*2.1975,mat3[,11]*1.277,mat3[,12]*1.277,mat3[,13]*1.277,mat3[,14]*1.277,mat3[,15]*1.277,mat3[,16]*1.2
77),nr,12,dimnames=list(c(1:nr),c("iom","wad","man","abr","bou","cad","cul","edn","kin","bel","hea","mnc")))
loc<-wind[,1:12]<4 | wind[,1:12]>25
power<-matrix(NA,nr,14,dimnames=list(c(1:nr),c("iom","wad","man","abr","bou","cad","cul","edn","kin","bel","hea",
"mnc","%max power","maint")))
power[loc]<-0                              #zero power produced due to too much/little wind available
loc<-wind[,1:12]<=25 & wind[,1:12]>14          #max power produced when wind > 14 but < 25 m/s
for (i in 1:12){
power[loc[,i],i]<-power_mat[5,i] #change the row number of power_mat to see results for windfarms opperating,
                                  #under constuction, consented, in planning or all of the above (1-5 respectively)
}
loc<-wind[,1:12]<=14 & wind[,1:12]>=4            # power curve modeled as cubic function between 4 & 14 m/s
for (i in 1:12){
power[loc[,i],i]<-((46.2597-24.1904*(wind[loc[,i],i])+3.7117*((wind[loc[,i],i])^2)-
0.1218*((wind[loc[,i],i])^3))/100)*power_mat[5,i] # change row number again here
}
# Calulate % of max power being produced
for (i in 1: nrow(power)){
power[i,13]<-(sum(power[i,1:12])/power_mat[5,13])*100 # change row number again here
}
power[,14]<-((power[,13])-2)
# Plot to check consistency between power output and wind speed at iom
 r1<-range(wind[,1],na.rm=T)
r2<-range(1:100)
plot(r2,r1,type='n',xlab='Time',ylab='speed (m/s) & power')
lines(1:100,power[1:100,1])
lines(1:100,wind[1:100,1])
# add time date etc.
power<-matrix(c(mat3[,1],mat3[,2],mat3[,3],mat3[,4],power[,1],power[,2],power[,3],power[,4],power[,5],power[,6],
power[,7],power[,8],power[,9],power[,10],power[,11],power[,12],power[,13]),nr,17,dimnames=list(c(1:nr),c("year","
month","day","time","iom","wad","man","abr","bou","cad","cul","edn","kin","bel","hea","mnc","%max power")))
# Average % of max power being produced
mean(power[,17])
 # Create matrix of capacity factors
capfacs<-power
for(i in 1:12){
capfacs[,(i+4)]<-((capfacs[,(i+4)])/(power_mat[5,i]))*100
}
#============================================================
# End of Code
#============================================================
```

11.2 R-Code to Fit a Cubic Function to Turbine Power Curve

```
#===========================================
# Code to calculate power curve equation
#Author: N. Johnson
#===========================================
power<-read.csv('power.csv',skip=1,header=FALSE)
power<-matrix(c(power[,1],power[,3]),nrow(power),2)
plot(power[,1],power[,2],xlab='Wind Speed(m/s)',ylab='Power(%)',main='Fit of Cubic Function to Power Curve')
x1<-power[,1]
x2<-x1^2
x3<-x1^3
y1<-power[,2]
lm1<-lm(y1~x1+x2+x3)
lm1                                                     #displays coefficients for cubic function.
xx<-seq(4,14,by=0.1)
yy<-46.2597-24.1904*xx+3.7117*(xx^2)-0.1218*(xx^3)
lines(xx,yy)
postscript("cubic_curve.ps")
dev.off()
  dev.print(postscript,file='cubic_curve.ps')
#===========================================
#end of code
#===========================================
```

11.3 R-Code to Plot & Analyse Results

```
#==============================================================
# Code to produce graphs and carry out statistical annalysis
#Author: N. Johnson
#==============================================================
summary(power[,17]) #power[,17] is the column of data showing UK CF for all times measured
boxplot(power[,17],col="grey",main="Box Plot of Capacity Factors", ylab="Cumulative Frequency (%)")
qqnorm(power[,17])
postscript("bx_plt.ps")
dev.off()
  dev.print(postscript,file="bx_plt.ps")
#how often is CF = 0 at each site?
cf_zero<-matrix(rep(NA,12),1,13)
for (i in 5:17){
loc<-power[,i]==0
xx<-0
for (j in 1:nrow(power)){
if(loc[j]==TRUE) xx <- xx+1
}
cf_zero[1,i-4]<-xx*100/nrow(power)
}
plot(c(5:12),cf_zero[1,c(7,11,12,5,4,10,8,9)],cex=c(0.232*2,0.49*2,1.004*2,0.494*2,0.526*2,0.608*2,4.085*2,2.217
*2),main="Frequency of CF = 0 in Zones A-L",xaxt="n",ylab="Frequenccy CF = 0
(%)",xlab="Zone",ylim=c(0,50),xlim=c(1,12),pch=16)
points(c(1,2,3,4),cf_zero[1,c(1,2,3,6)],cex=c(2.185*2,3.395*2,2.044*2,0.20),pch=16,col="blue")
axis(1,at=1:12,labels=c("A","B","C","D","L","K","H","G","I","J","F","E"),font=2)
postscript("cf_zero.ps")
dev.off()
  dev.print(postscript,file="cf_zero.ps")
# Find the dates of the zero power days and the max power day
loc<-power[,17]==0
zero_date<-power[loc,c(1:4,17)]
loc<-power[,17]==max(power[,17])
max_power_date<-power[loc,c(1:4,17)]
#calculating 95 % confidence interval for the mean CF
```

```
s<-sd(power[,17])
nr<-nrow(power)
se<-s/sqrt(nr)
qt<-qt(0.975,df=nr-1)
conf<-qt*se
mean(power[,17])+conf
mean(power[,17])-conf
#cumulative freq plot
plot(ecdf(power[,17]),xlab="Capacity Factor (%)",xlim=c(0,100),yaxt="n",ylab="Cumulative
Frequency",main="Cumulative Frequency of Capacity Factor",pch=".")
axis(2,at=c(0.155,0.25,0.5,0.75),labels=c("0.15","1st Qrt","median","3rd Qrt"))
axis(1,at=c(10,15.25,30.26,47.03),labels=c("10","15","30","47"),font=2)
abline(h=c(0.25,0.5,0.75),v=c(15.25,30.26,47.03),lty=3,lwd=2)
abline(h=.155,v=10,col="red",lty=3,lwd=2)
postscript("cu_freq.ps")
dev.off()
  dev.print(postscript,file="cu_freq.ps")
#diurnal & monthly patterns
mean_month<-matrix(NA,12,2)
for (j in 1:12){
loc<-power[,2]==j
mean_month[j,1]<-mean(power[loc,17])
mean_month[j,2]<-sd(power[loc,17])
}
barplot(mean_month[,1],main="Monthly Variation of Capacity Factor",xlab="Month",ylab="Capacity Factor (%)")
postscript("monthly.ps")
dev.off()
  dev.print(postscript,file="monthly.ps")
# Calculate and plot Monthly variation in capacity factor for each time of the day
mean_month12<-matrix(NA,12,3)
for(i in (1:12)){
loc<-power[,2]==i & power[,4]==12
mean_month12[i,1]<-mean(power[loc,17])
mean_month12[i,2]<-sd(power[loc,17])
}
mean_month12[,3]<-c("J","F","M","A","M","J","J","A","S","O","N","D")
plot(mean_month12[,1],type="b",xaxt="n",ylim=c(10,60),xlab="Month",ylab="Capacity factor (%)",main="Monthly
and Diurnal Variation of Capacity Factor",bg="grey90")
axis={axis(1,at=c("1","2","3","4","5","6","7","8","9","10","11","12"),labels=c("J","F","M","A","M","J","J","A","S","O","N",
"D"))}
mean_month00<-matrix(NA,12,2)
for(i in (1:12)){
loc<-power[,2]==i & power[,4]==0
mean_month00[i,1]<-mean(power[loc,17])
mean_month00[i,2]<-sd(power[loc,17])
}
lines(mean_month00[,1],type="b",col="blue",bg="grey90")
mean_month06<-matrix(NA,12,2)
for(i in (1:12)){
loc<-power[,2]==i & power[,4]==6
mean_month06[i,1]<-mean(power[loc,17])
mean_month06[i,2]<-sd(power[loc,17])
}
lines(mean_month06[,1],type="b",col="red",bg="grey90")
mean_month18<-matrix(NA,12,2)
for(i in (1:12)){
loc<-power[,2]==i & power[,4]==18
mean_month18[i,1]<-mean(power[loc,17])
mean_month18[i,2]<-sd(power[loc,17])
}
```

```
lines(mean_month18[,1],type="b",col="green",bg="grey90")
legend(10,60,c("midnight","06:00","midday","18:00"),pch=1,col=c("blue","red","black","green"),bg="grey90")
postscript("diurnal.ps")
dev.off()
  dev.print(postscript,file="diurnal.ps")
# Plot standard deviations of diurnal and monthly variations.
plot(mean_month12[,2],type="b",xaxt="n",ylim=c(10,30),xlab="Month",ylab="Standard Deviation of Capacity
factor",main="Standard Deviation of Capacity Factor",bg="grey90")
axis={axis(1,at=c("1","2","3","4","5","6","7","8","9","10","11","12"),labels=c("J","F","M","A","M","J","J","A","S","O","N",
"D"))}
lines(mean_month00[,2],type="b",col="blue",bg="grey90")
lines(mean_month06[,2],type="b",col="red",bg="grey90")
lines(mean_month18[,2],type="b",col="green",bg="grey90")
legend(10,30,c("midnight","06:00","midday","18:00"),pch=1,col=c("blue","red","black","green"),bg="grey90")
postscript("sd_diurnal.ps")
dev.off()
  dev.print(postscript,file="sd_diurnal.ps")
# Calculate and plot variation in CF over three years for each month
mean_month2001<-matrix(NA,12,3)
for(i in (1:12)){
loc<-power[,2]==i & power[,1]==2001
mean_month2001[i,1]<-mean(power[loc,17])
mean_month2001[i,2]<-sd(power[loc,17])
}
mean_month12[,3]<-c("J","F","M","A","M","J","J","A","S","O","N","D")
plot(mean_month2001[,1],type="b",ylim=c(10,60),xaxt="n",xlab="Month",ylab="Capacity Factor (%)",main="Anular
and Monthly Variation of Capacity Factor",bg="grey90")
axis={axis(1,at=c("1","2","3","4","5","6","7","8","9","10","11","12"),labels=c("J","F","M","A","M","J","J","A","S","O","N",
"D"))}
mean_month2002<-matrix(NA,12,2)
for(i in (1:12)){
loc<-power[,2]==i & power[,1]==2002
mean_month2002[i,1]<-mean(power[loc,17])
mean_month2002[i,2]<-sd(power[loc,17])
}
lines(mean_month2002[,1],type="b",col="blue",bg="grey90")
mean_month2003<-matrix(NA,12,2)
for(i in (1:11)){
loc<-power[,2]==i & power[,1]==2003
mean_month2003[i,1]<-mean(power[loc,17])
mean_month2003[i,2]<-sd(power[loc,17])
}
lines(mean_month2003[,1],type="b",col="red",bg="grey90")
loc<-power[,2]==12 & power[,1]==2000
mean_dec2000<-mean(power[loc,17])
points(12,mean_dec2000,type="b",col="green")
legend(10,60,c("2000","2001","2002","2003"),pch=1,col=c("green","black","blue","red"),bg="grey90")
postscript("annular.ps")
dev.off()
  dev.print(postscript,file="annular.ps")
#========================================================================
#end of code
#========================================================================
```