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# Effects of distributing wind energy generation over Europe

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ABSTRACT:
Using data from 60 meteorological stations distributed all over Europe in conjunction with the National Grid Model (NGM) from the Rutherford Appleton Laboratory, the effects of the large-scale distribution of wind energy generation are studied. In some regions of Europe, wind energy already covers a significant proportion of the electricity demand. But the intermittence of the wind resource is always a limiting factor when penetration levels are high. Studies for single countries have shown that distributing the generation over a large area reduces the variability of the output and hence makes wind energy more appealing to utilities, since the stability requirements of the network are easier to fulfil.
The data are analysed in terms of absolute highs and lows, temporal and spatial correlations. To assess the financial benefits, the NGM is used to evaluate the match of electricity demand and generation as well as the possible savings of fossil fuel in an electricity grid incorporating various capacities of wind energy generation. To assess the value of wind energy on a trans-national scale, the European plant mix is modelled, and the NGM is used to simulate the scheduling of these plants in the presence of different penetrations of wind energy.
KEYWORDS: Cost of Energy, Dispersed Turbine Systems, Integration, National/International, Utility-Integration

## 1 Introduction

Wind energy is currently the energy source with the highest growth rate in Europe. But even considering the millions of euros spent on wind turbines in the last few years, and the tens of thousands of jobs created, wind energy only accounts for a very low percentage of the total electricity demand in the EU. The latest white paper of the EU on renewable energy proposed an indicative objective of 12% for the contribution by renewable sources of energy to the European Union's gross inland energy consumption by 2010 [1]. The growth of wind energy will ultimately be limited by the intermittence of the resource - the wind is just not blowing at all places all the time. Good sites for wind turbines have about 3000+ hours at full rated capacity or 'Full Load Hours' (FLH), and only a few exceptional sites have 4000+ hours. Even though the offshore resource is less variable, the load factor will most likely remain below 40%. But if we consider more than just one turbine, the effects of distributing them over a large area also lessen the variability. Hence it is informative to look in detail on the resource when spread out all over Europe. This work uses wind time series from all over Europe, and analyses them in terms of wind energy generation.

## 2 The National Grid Model

The assessment of the economic value of forecasting is routinely done at the Rutherford Appleton Laboratory using the National Grid Model (NGM) [2,3], which models the scheduling and dispatch of power plant to meet the demand on a large scale electricity grid. Inputs to the model are the actual power plants available for dispatch, and the prices for fossil fuel. Additionally, three time series are needed in the resolution of the time step, which typically is one hour: demand on the whole grid, wind power measurements and wind power forecasts. This tool has been used and improved continually over more than ten years.
The model runs in hourly time steps. At every step, the number of plants needed in the near future to cover the predicted demand is scheduled ahead. The predicted wind power is treated as negative load. To account for the uncertainty of the demand, the actual demand is multiplied by a Gaussian distributed random number with a distribution mean of 1 and a standard deviation of 0.015. This number is consistent with the published deviations for load prediction algorithms [4]. An assumption is made for each type of plant regarding its start-up time: a maximum of eight hours is assigned to coal- and oil-fired plant, while gas turbines are considered to start up immediately within the time frame of the model. Other plant types have start-up times in between. The eight-hour maximum also limits the time frame for looking ahead - there is no need to look beyond the maximum start-up time. Any shortfalls in load not covered by the scheduled power plant are met by either fast response plant (pumped hydro or gas turbines) or through the spinning reserve. This is thermal plant, which is not being run at full output, but at, say, 95%. The remaining 5% can be activated very fast if need be. Thermal power plants cannot be operated at less than 50% load factor, hence this is set as the minimum load factor. The spinning reserve is planned as a fraction of the predicted load (SR1) as well as a fraction of currently available wind power (SR2). Both these fractions remain fixed for a model run (typically one year), but are optimised to yield a minimum fuel cost under the condition that no loss-of-load-events (LOLE) occur. The condition that no LOLE may occur can lead to a rather high SR2 and hence a high overall spinning reserve requirement. Since power plants can only be dropped from service from one time step to the next in the model, not all of the wind power production can be accepted into the grid when all running steam plants are already at the minimum load. This means that high values of SR2 at high

penetrations of wind energy can also lead to significant wind power production being discarded.

# 3 Input preparation

In order to simulate the European grid, the details of every power station in Europe, the fuel prices, a full demand time series of the selected countries and the corresponding wind speed/power time series would be needed. Unfortunately, not all of this was available. The installed capacity in the selected countries (Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, The Netherlands, Portugal, Spain, Switzerland, and the United Kingdom) was available [5], broken down by plant type. Additionally, the full individual power unit details for England/Wales, Ireland and Portugal were known, as were the details of all European nuclear power stations [6]. In order to estimate the distribution of the individual power units for the remaining countries, the known power units were divided into 8 categories. For each category, the number of units was scaled up to the appropriate total capacity for the European countries selected. The overall capacity for all categories is 461.42 GW [5].
The wind data came from 60 meteorological stations in the selected countries and is detailed elsewhere [7,8]. The simulation period was December 1990 to December 1991. In order to calculate the total European wind power generation from these sites, a European average wind turbine distribution was used. The distribution can be found in Table 1. Since the time series is only three-hourly, the wind was linearly interpolated at every station before applying the power curve. The wind was scaled to a height of 50m above ground level. The total power curve incorporating all the turbines in Table 1 corresponds to a 6.1 MW unit and is a superposition of the power curves of:

| | | |
|---|---|---|
| 1 | Vestas V66 | 1650 kW |
| 1 | Avedøre test turbine | 1000 kW |
| 2 | Micon | 750 kW |
| 1 | Wind World W-3700 | 500 kW |
| 1 | Windane 34 | 400 kW |
| 2 | Vestas V27 | 225 kW |
| 2 | Danwin 27 | 225 kW |
| 1 | Nordtank | 150 kW |

**Table 1: Overview of wind turbines used to model the European wind turbine distribution.**

The sum is 6100 kW, the average is 554.5 kW. This is adequate since the average among newly installed turbines in Germany up until October1998 was 764 kW, while the installed base rated capacity was 444 kW/unit [9]. Extrapolating these trends, this turbine distribution should be representative for late 1999. Using the superposed power curve for each site, the power output time series was aggregated over Europe. A data point was only used if at least 25 sites had a non-missing wind speed value - otherwise, linear interpolation of the resulting time series was used. This was necessary in 76 cases. This time series is referred to as 'EU-Averaged'. In order to measure the effects of time series with higher load factors, but also higher variability, two additional series were created: the one called 'Selection' is averaged over the 25 farms with more than 2000 FLH, while the series called 'Malin Head' is the single site time series with the most FLH, which came from Malin Head in the Republic of Ireland, with 3865 FLH.
The demand time series were available from France, the UK and Portugal. These were scaled in order to fit the overall European load, which was 1603 TWh. Every time series had a weight of 1/3, as determined by the cumulative load in that period.

# 4 Results

### 4.1 Wind Time Series Properties

Here are some properties of the European average wind profile: Maximum power generated was 4085.6 kW on December 26 1990 at 1100 hours, minimum was 93.8 kW on October 22, 0100 hours. (In fact, maximum generation was 4414.7 kW at 1200 hours on December 19, 1991, but since the NGM only takes one year as an input, the last December was omitted.) It is also worth noting that neither the full rated capacity nor zero rated output occur during the year in question. The mean generation is 1346.9 kW, while the standard deviation is 772.7 kW. This corresponds to 1934 FLH, which reflects the fact that the data come from all over Europe, including a large number of inland sites. The smoothness of the wind power generation is important for large-scale integration. Therefore, the distance dependency of the wind time series was analysed in terms of cross- and autocorrelations of the combined time series.

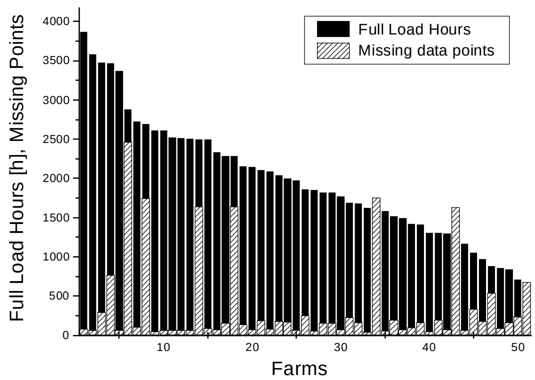


**Figure 1: Number of full load hours in the single station time series.** Here many stations are inland and in practice would only see development where local topographical effects enhance the resource.

The first test was to investigate the cross correlation between two stations. The correlation function of two time series $p_t$ and $q_t$ is as follows [10]:

$$a_k = \frac{1}{N}\sum_{t=1}^{N-k} \hat{p}_t \hat{q}_{t+k} \Big/ \sigma_p \sigma_q$$

with

$$\hat{p}_t = p_t - \mu_p \text{ and } \hat{q}_t = q_t - \mu_q .$$

$\mu_{p/q}$ is the mean of the corresponding time series, $\sigma_{p/q}$ is their standard deviation. $k$ refers to the time lag between the two series.

A value of 1 means that the time series are completely correlated, while a value of 0 means that the data is completely uncorrelated.

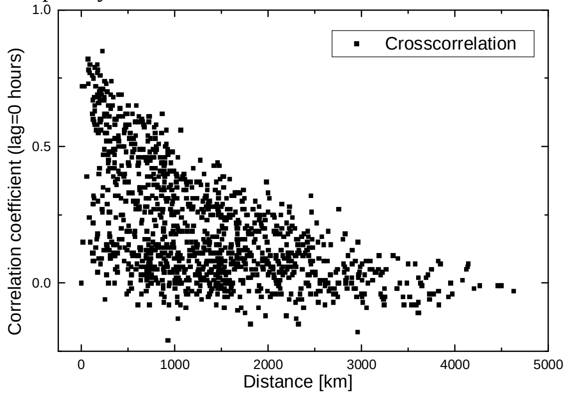


**Figure 2: Correlation coefficient for every pair of stations at lag=0 hours.**

Figure 2 shows the correlations for all pairs of farms with their respective distances. While short distances give the highest correlations, a short distance does not necessarily mean that the time series are correlated. Local effects can actually lead to a significant decoupling of the time series[11]. For longer distances the result is as expected: the correlation is very small. Interestingly, in some cases the time series are even somewhat anticorrelated, meaning that a wind speed increase at one station often coincides with a wind speed decrease at the other station. (The two pairs with the most negative correlation are Roches Point/IE-Lisboa/PT with -0.21 and Zaragoza/ES-Naxos/GR with -0.18.) It is also easy to see that the average correlation decreases with distance. Hence spreading out the wind power generators should give a less variable resource.

### 4.2 Averaged Time Series Properties

But this is for two farms only. How does this behave if one combines the time series of all farms within a certain radius and calculates the standard deviation of this resultant time series? The answer is to be found in figure 3.

At every station, an averaged time series was calculated, which included the time series of every other station within a circle with radius R. The radius R was then varied in steps of 100 km around the station. Care was taken to only include unique combinations of stations for the final plot. For every unique combination, if there was the possibility to reach the same combination from various stations, the smallest radius R was chosen as the radius for inclusion in the plot. Note that at the outside borders of the domain, less farms are included in the same circle, since the circles were centered around each station.

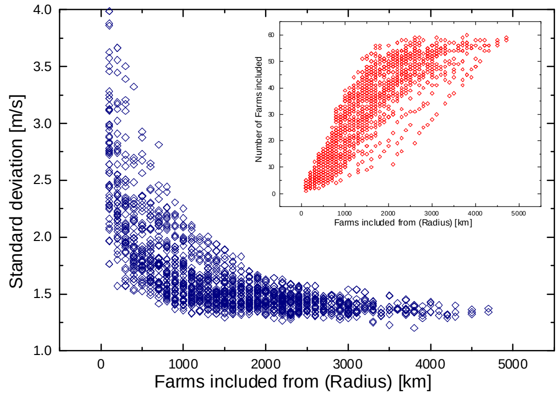


**Figure 3: Standard deviation of the time series resulting from combining all available stations within a circle of radius R around any one station, and number of included farms for a given radius.**

This also shows that the time series resulting from combining many farms in a large area is considerably smoother than a single time series. Another explanation for this behaviour could be that the higher the radius chosen, the more time series were averaged. Naturally, for a larger radius more of the met stations are within the circle, hence the averaging is done including more stations, as can be seen in the inset in Figure 3. To cover for this effect, in Figure 4 only averaged time series from a combination of between 15 and 20 stations was taken into account. Here, no real trends are noticeable, hence the reduction of standard deviation in Figure 3 must be an effect of the distance.

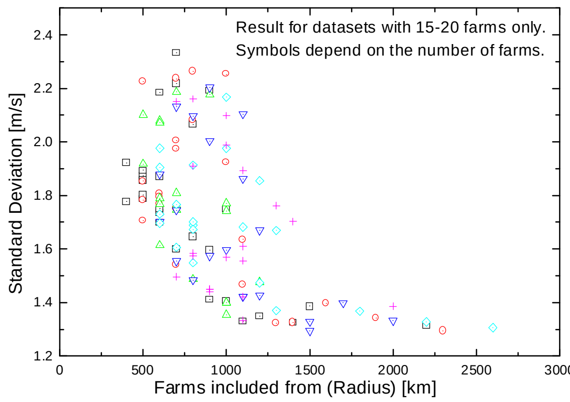


**Figure 4: Standard Deviation as in Figure 33,** but this time only for data sets containing between 15 and 20 stations. Different symbols refer to different numbers of stations included for the averaging.

## 5 Financial assessment

Below is a table with the main parameters for the three wind power data sets used:

| Units: [kW] | Mean | SDev |
|---|---|---|
| Average: | 1347 | 773 |
| Selection: | 1850 | 1055 |
| Malin Head: | 2646 | 2202 |

Note here that Malin Head has by far the highest standard deviation, but also the highest mean.

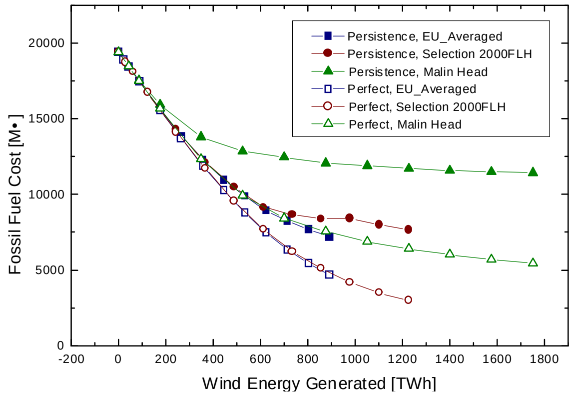


**Figure 5: Fossil fuel cost for different wind energy production.** The x-axis denotes wind energy produced by the simulated turbines. For comparison note that the European overall demand was 1603 TWh that year.

In figure 5 we see that for small penetrations the possible savings correlate with the amount of wind energy which is fed into the network. The shape of the graphs in figure 5 are determined by the ability of the grid to accomodate all of the produced wind energy without compromising the stability of the supply. This can be seen from figure 6, where the fraction of the produced wind energy that is accepted into the grid is shown as a function of the produced wind energy. Actually, at high penetrations the fuel savings correlate with low variability of the time series and high forecast accuracy - the highest savings for very high penetrations are attainable with a medium of perfect forecasting and high wind energy generation. All the data points of the different graphs are equidistant in installed wind capacity. The saturation effects for high variability of the input, coupled with bad forecasting, are clearly visible, even though in no case it reaches full saturation. Note that the spread between the forecasting methods is bigger for more variable wind time series.

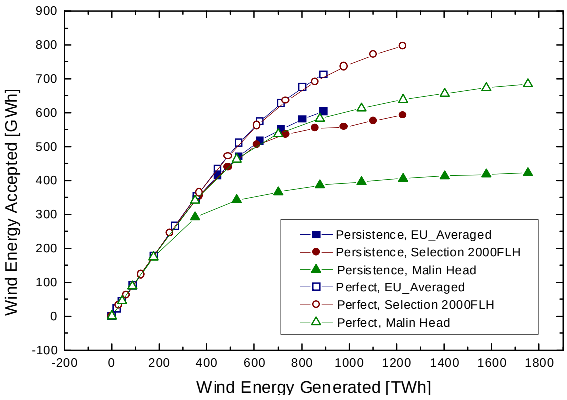


**Figure 6: Accepted wind energy production.** This figure shows, how much wind energy is accepted into the grid, for how much energy generated.

Figure 6 tells us that good forecasting combined with a low variance wind production leads to a better integrable resource, while high variability and bad forecasting leads to much wasted wind energy, since the grid cannot accept all the wind energy due to security of supply reasons.

# 6 Conclusions

Spreading out the wind energy production over all of Europe leads to a significantly less variable resource. This is both an effect of the inclusion of many turbines in the generation and of the geographical spread of the generation. This is also beneficial in a financial analysis, where it could be shown that a low variability in the generated wind production coupled with good forecasting can lead to higher fossil fuel savings for the grid than without, especially for high penetrations of wind energy.

# 7 Acknowledgements

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