SafeWind

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"Documentation of the severity index for wind variability and its application to wind power forecasting"

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Abstract: This deliverable of the SafeWind project presents two methods for describing the severity of wind variability. The first is based on the Hilbert-Huang transform, the second on the standard deviation of the band-pass filtered wind speed. The two metrics are compared, and are shown to be in close agreement with one another. A number of applications of the methods to the problem of characterising and forecasting wind variability are presented. A key result arising from several of the studies is that there are strong connections between parameters from the large scale weather patterns and the locally observed wind variability.

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Contents

1. Summary

To study the occurrence and predictability of severe wind variability, it is necessary to define what is meant by 'wind variability' and 'severe wind variability'. The goal of safewind task 4.7 was to develop "**A quantitative indicator (severity index) for severely variable wind energy production**". In this regard, two project partners, namely the **CSIRO Wind Energy Research Unit (Australia)** and **Risø-DTU wind energy division (Denmark)** have developed metrics for describing wind variability.

- The metrics can be applied to any time scale of interest (provided the resolution of wind speed observations is high enough), but the focus has been on fluctuations on time scales of tens of minutes to hours.
- Both metrics are successful in identifying episodes of severe wind variability.
- Both project partners have used their respective metrics to study the relationship between episodes of severe wind variability and various atmospheric explanatory factors
- The research has uncovered useful results about its predictability and climatological patterns of severe wind variability.
- Results have been described and discussed in terms of their relevance to wind power production.
- Aspects of the results have been reported (as the full or partial focus) in **4 peer reviewed journal papers**, **3 conference presentations** and **1 PhD thesis**.

2. Introduction

Large fluctuations in the wind are often observed at sites such as the Horns Rev wind farm in the Danish North Sea and the wind farms in south-eastern Australia. These fluctuations occur on all time scales, from microscale turbulent fluctuations through to diurnal, seasonal or even longer cycles. Here, we concentrate on hour-scale fluctuations, which are of special relevance to wind power forecasting for day-ahead spot market predictions. On a day-ahead basis, hour-scale fluctuations can be considered as a stochastic process (Vincent 2010), and as such we cannot forecast the precise timing of the peaks and troughs in wind speed. On the other hand, we can reasonably try to predict and describe the frequency and amplitude of the wind variability.

To predict wind variability on a day-ahead basis, it is first necessary to define metrics that describe the degree of wind variability for certain time scales of interest. The purpose of task 4.7 in the SafeWind project is to define a severity index for wind power variability and to document its application to wind power forecasting. To this end, two approaches were developed by the project partners involved in the task. At Risø-DTU, the Hilbert-Huang transform (HHT) was used to quantify the time-evolving spectral properties of wind speed time series. The application of the method to wind power forecasting was demonstrated by relating the time evolving spectra and variability time series to explanatory variables such as wind direction, precipitation rate, large scale weather patterns and mesoscale cloud patterns in visual satellite pictures. The variability metric and its applications are described in detail in Vincent et al. (2010) and Vincent et al (2011b), as well as in the PhD thesis Vincent (2011c) and conference papers Vincent (2009) and Vincent (2011a). Detailed modelling of a mesoscale phenomenon that was found to be a key driver of hour-scale wind variability at Horns Rev is described in Vincent et al. (2011a). At CSIRO, a variability metric based on the standard deviation of the band-pass filtered wind speed signal was developed, as described in Davy (2010). The metric was used to study the predictors of hour-scale wind variability in large scale weather models, and the occurrence of severe wind variability was related to factors such as boundary layer height and stability. The two metrics have been compared for a site in south-eastern Australia, and have been shown to be in excellent agreement with one another.

3. Variability metric based on the Hilbert Huang transform (Risø-DTU)

The HHT, which was first introduced by Huang et al. (1998), describes the spectral behaviour of a time series as a function of time. It consists of an empirical filter that decomposes the data into a linear combination of a set of basis functions called intrinsic mode functions (IMFs), followed by extraction of the instantaneous amplitudes and frequencies of each component using the Hilbert transform. The decomposition is called Empirical Mode Decomposition (EMD), and is adaptive and based on the data itself.

Several detailed descriptions of the HHT exist, including (Huang, 2005b), (Huang and Wu, 2008) and Vincent (2010), so it will not be repeated here. The output of the HHT is a set of instantaneous frequencies and their amplitudes that are present in the time series at any given time. The instantaneous frequencies and amplitudes for the IMFs can be collated and binned to form the *Hilbert spectrum*, which gives a useful and intuitive description of the degree of wind variability in the time series for particular time scales. This is demonstrated in Figure 1, which shows the Hilbert spectrum for a 20 day time series observed at the Horns Rev wind farm.

By integrating the Hilbert spectrum over a range of frequencies, a scalar metric of variability can be derived. In Figure 3, the scalar metric of variability calculated over five difference frequency ranges is demonstrated for a theoretically generated time series of 20 days of ten minute wind speed observations. The scalar metrics accurately capture the sudden changes in statistical properties of the time series. In Figure 2, the HHT derived variability metric is shown for a 5 day period of wind speed observations at Horns Rev, where there were sudden changes in the statistical properties of the time series.

This scalar metric is defined as our metric of wind variability for wind energy. We focus on the variability metric for time scales of 1-3 hours for several reasons: First, since our observations have a time resolution of 10 minutes, and the highest frequency resolved by the Hilbert spectrum is four times smaller than the sampling frequency, we cannot look at time scales much shorter than 1 hour anyway. Secondly, hour-scale wind fluctuations are of interest in this study because of their relevance to day-ahead spot market forecasts. Thirdly, large hour-scale wind fluctuations are often observed at Horns Rev, and can be related to fascinating meteorological phenomena such as cellular convection or gravity waves that can fall within the so-called spectral gap region of the spectrum of atmospheric motion (Vincent 2011d). These fluctuations have a strong relevance to wind energy due to their tendency to introduce regular and spatially correlated fluctuations into the wind speed field.

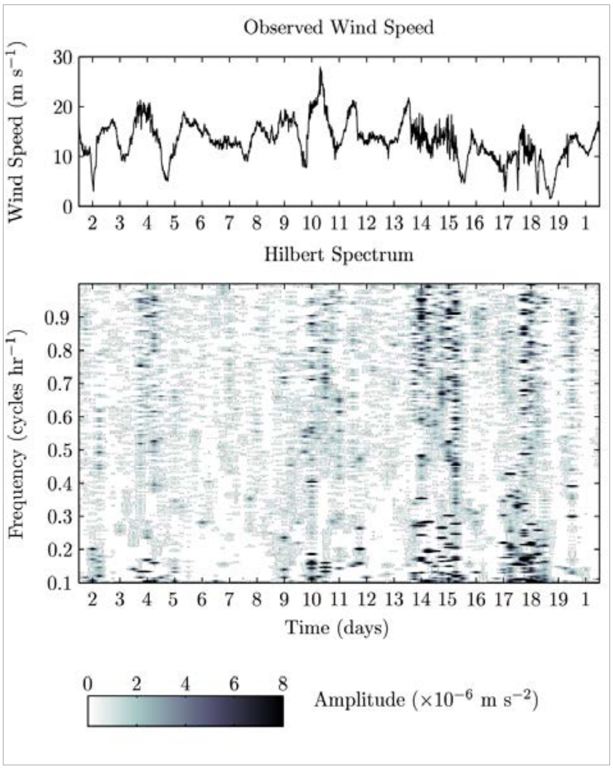

Figure 1: Hilbert spectrum for a 20 day time series observed at Horns Rev. Darker colours can be interpreted as large amplitude wind fluctuations at a given frequency.

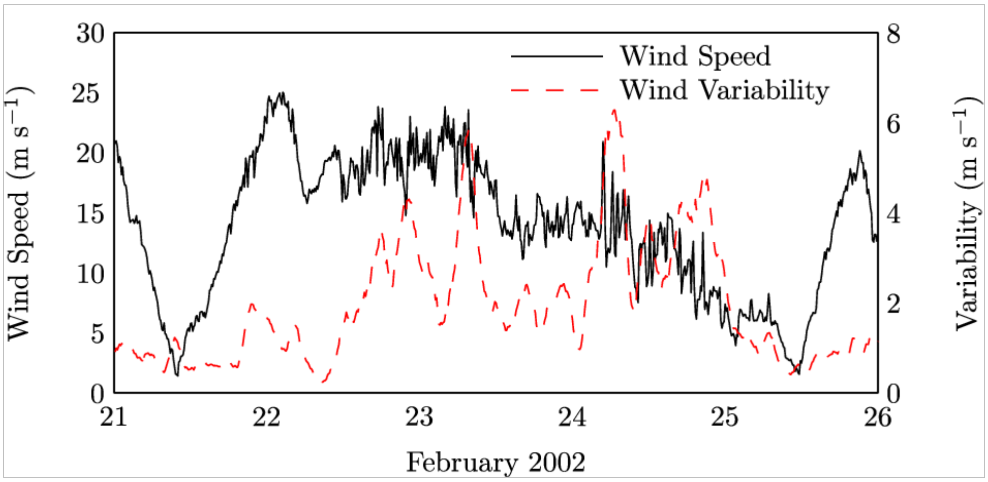

Figure 2. Time series of wind speed observed at Horns Rev over a 5 day period (black), and the variability metric for periods of 1-3 hours derived from the Hilbert-Huang Transform (Red)

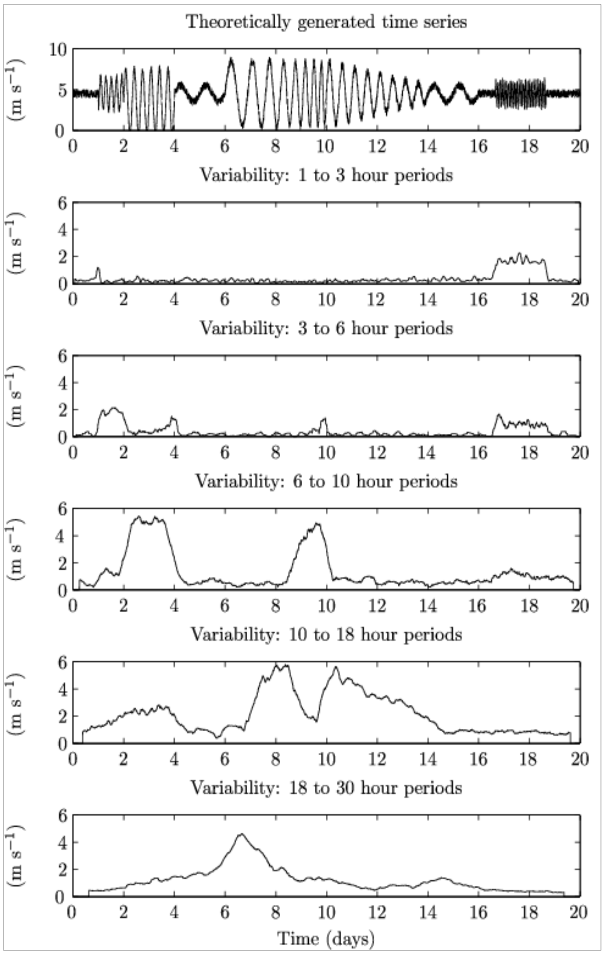

Figure 3: Variability metric for various time scales, applied to an artificially generated time series of ten minute wind speed observations.

4. Examples of usage of the HHT variability metric for quantifying and describing severe wind variability.

4.1 The conditional Hilbert Spectrum

Unlike the Fourier spectrum, the Hilbert spectrum evolves with time, and as such can be binned and averaged along the time-axis to create conditional spectra. This methodology was exploited in Vincent (2010), Vincent (2011b) and Vincent (2011c) to create a climatology of wind variability at Horns Rev that described the average variability conditions over a 4 year period with respect to wind direction, air-sea temperature difference, pressure tendency, wind speed and time of year. Only one of the results is reproduced here – further results can be accessed in the publications mentioned above. In Figure 4, the conditional Hilbert spectrum for Horns Rev for the autumn months (September, October and November 2000-2003) is shown, where the time axis has been binned and averaged according to the observed wind direction. Darker colours indicated higher average wind variability. Segments of the spectrum that are influenced by the wind farm wake, the land and the sea are indicated on the plot. The frequency axis ranges from 1 to 0.1 cycles per hour, or periods of 1 to 10 hours. The plot strongly suggests that wind variability in autumn at Horns Rev is more intense in flow with a sea fetch than in flow with a land fetch.

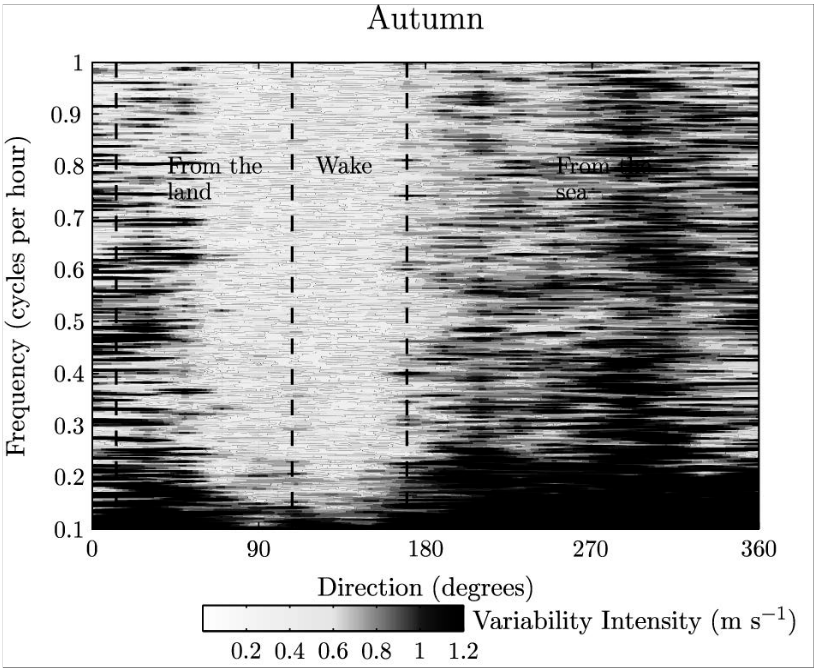

Figure 4. Conditional Hilbert spectrum showing wind variability as a function of frequency and wind direction at Horns Rev based on Autumn (September-October-November) data from 2000-2003. Darker colours indicate higher average wind variability. The wind directions that could be affected by the wake of the wind farm, and the wind directions where the flow is influenced by land or sea are indicated.

Other results from the conditional climatology can be summarized as follows: Variability tends to be higher in the winter and autumn months, when the wind is blowing from the sea, when the pressure is rising or falling rapidly, when the wind speed is very strong, when the sea temperature is warmer than the air temperature, when precipitation is occurring and when the atmospheric conditions are unstable or near-neutral (Vincent 2011b). These results demonstrate that wind variability is site dependent, and that there is good potential for predicting wind and power variability based on readily available explanatory factors.

4.2 Severe variability days analysed with respect to large scale weather patterns and satellite pictures

In Vincent (2011a) and Vincent (2011c), the index of variability based on the Hilbert Huang transform for periods of 1-3 hours was related to synoptic scale weather patterns and to visual satellite pictures. For this analysis, 'severe' variability days were defined as 24 hour periods where the average HHT derived variability metric was in the top 5^{th} percentile of all such 24 hour periods, giving 73 severe variability days in the four year period 2000-2003.

To classify the severe variability events according to large scale weather patterns, the self organising maps (SOM) clustering algorithm (Kohonen 2001) was used to create a catalogue of 36 weather types for northwest Europe and the northeast Atlantic Ocean. The catalogue was based on daily mean sea level pressure analyses of the ECMWF's ERA interim reanalysis (Simmons 2007) for the 20 year period 1990-2009.

In Figure 5, the 6 × 6 array of large scale weather patterns is shown, together with the number of severe variability days at Horns Rev during 2000-2003 in each category. There is a cluster of categories with a large number of severe variability days in the centre of the array. These categories represent transitional weather scenarios, where a low pressure centre is either directly influencing the

North Sea, or moving just to the east of the North Sea region and exposing the North Sea itself to strong, north-westerly flow. 23 out of the 36 categories contained zero or 1 severe variability days.

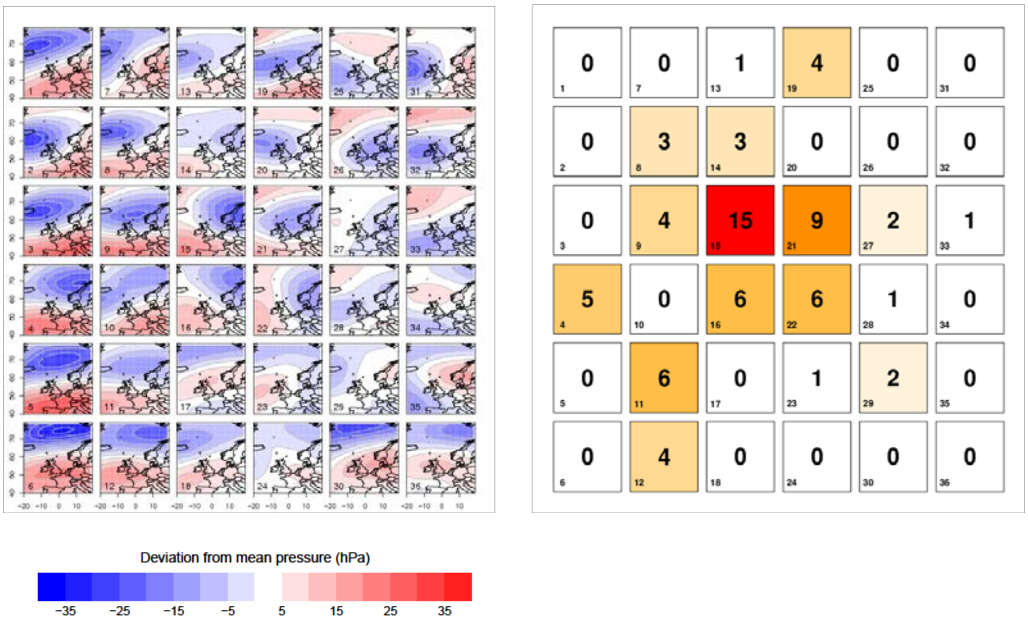

Figure 5. Left: 6 × 6 array of large scale weather patterns. Right: The number of severe variability days at Horns Rev in the period 2000-2003 in each large scale weather category, where the array has the same layout as the left hand plot.

Analysis of visual satellite pictures for the year 2003 revealed that 14 out of the 19 extreme variability days during the period occurred when open cellular convection patterns could be observed over all or part of the North Sea. An example of three such days is shown in Figure 6 together with the observed wind speed for the 24 hours centred on the image. Open cellular convection patterns consist of rings of cloudy air with clear air centres. The rings of cloud have a diameter of 10-80 km, and as such are excellent candidates for introducing hour-scale variability into the wind speed.

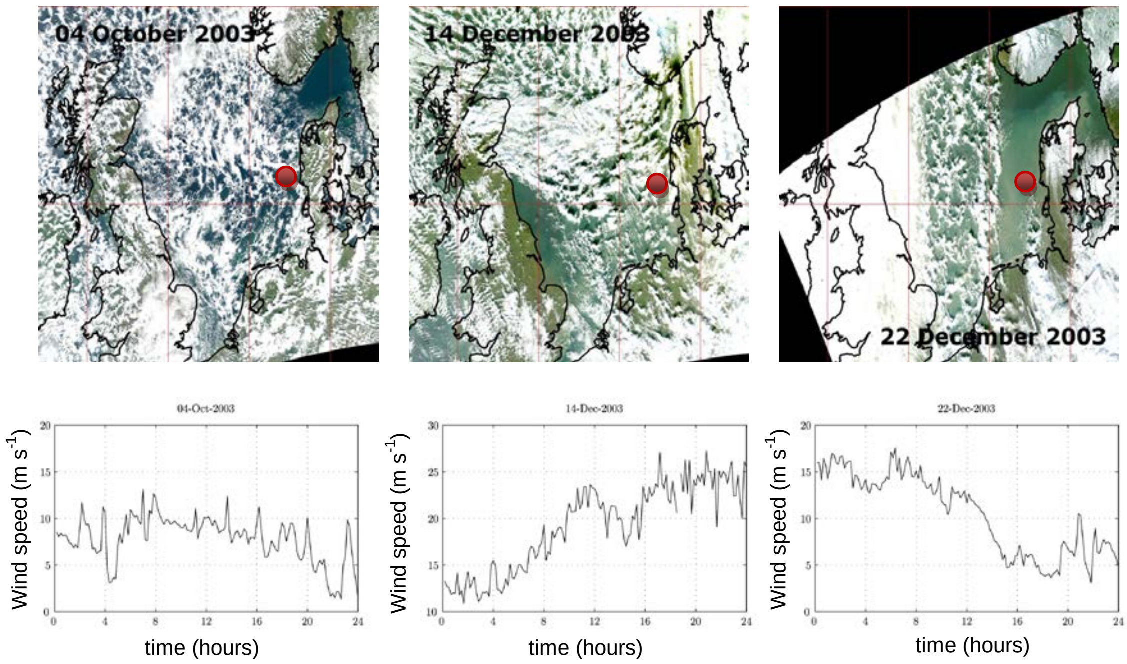

Figure 6. Examples of open cellular convection over the North Sea (top panels), when severe wind variability (lower panels) was observed at Horns Rev. The position of the Horns Rev wind farm is indicated by the red dot on the satellite pictures.

4.3 Modelling of severe wind variability associated with open cellular convection

One of the cases of severe wind variability that was identified using the Hilbert-Huang variability metric was modelled in some detail using the WRF mesoscale model, as described in Vincent (2011d). The mesoscale model was shown to capture the basic features of the open cellular convection that could bring about hour-scale wind fluctuations. In Figure 7, the vertical velocity for an idealized WRF simulation of open cellular convection is shown. The simulation was run with a horizontal grid spacing of 1 km, periodic boundary conditions and explicit cumulus convection. It was initialized using vertical profiles of wind speed, temperature and water vapour mixing ratio that were taken from the actual conditions on a day when severe variability was observed at Horns Rev. The right hand plot of Figure 7 shows a cross section through 30 composited and averaged cells from the idealized simulation. The result is important to the use of mesoscale models for wind speed and wind power forecasting, because it shows that the model can capture the mesoscale structure of the cells. The vectors show the cell-scale vertical and cross wind velocity components, and it is clear that large fluctuations at the surface arise due to the strong divergence and convergence around the cell walls.

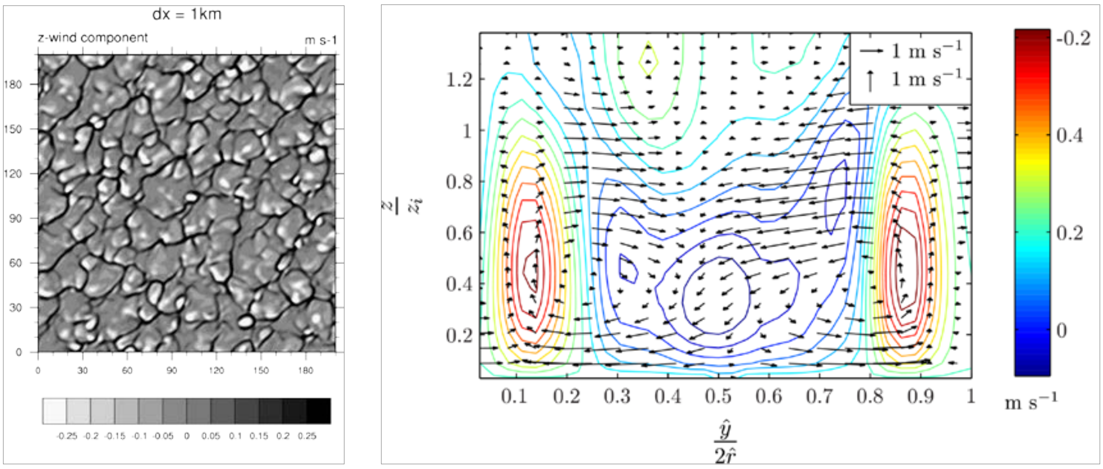

Figure 7. Left: Vertical velocity for a simulated field of open cellular convection from the WRF model, using a horizontal grid spacing of 1 km. Right: Cross section, perpendicular to the mean wind, through 30 aggregated cells from the WRF simulation. The horizontal axis shows the horizontal extent of the cell, scaled by the average cell diameter, 2r. and the vectical axis shows height, scaled by the boundary layer height. Contours show the vertical velocity and vectors show vertical and cross-wind components of the wind speed.

5. Variability index based on standard deviation of the 2 hour band-pass filtered wind speed signal (CSIRO)

At CSIRO, a variability index based on the standard deviation of the band-pass filtered wind speed signal was developed. The CSIRO index and the Risø-DTU index were both applied to dataset supplied by CSIRO for a site in south-eastern Australia for comparison purposes. This analysis usefully showed that the two variability indices gave very similar results. In Figure 8, the two indices are shown for a sample 4 day period, and in Figure 9 the two indices are compared for a three year period. The main difference was that due to its local formulation, the Hilbert-Huang based analysis tended to emphasize the peaks in variability, leading to a positive bias when compared to the CSIRO method. However, both methods are satisfactory in identifying major wind variability events.

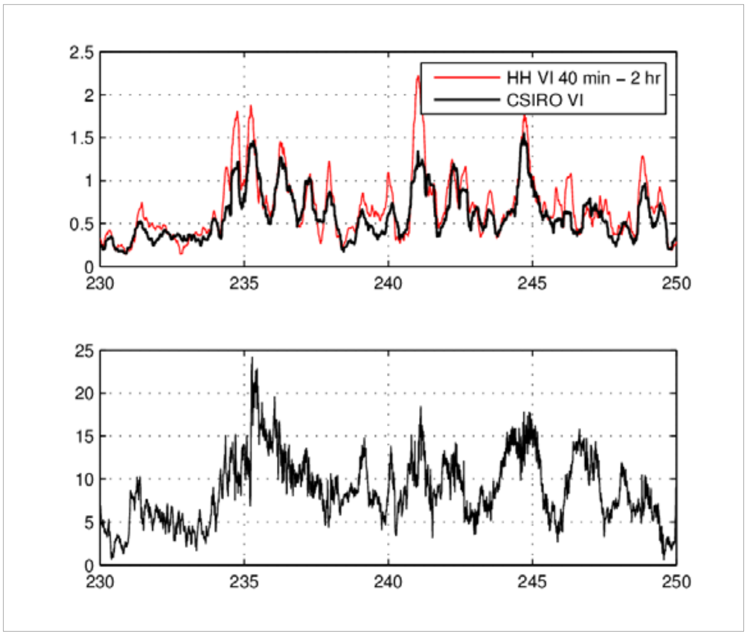

Figure 8. Sample 4 day time series for site in south-eastern Australia (lower panel) and the CSIRO and Risø-DTU variability index.

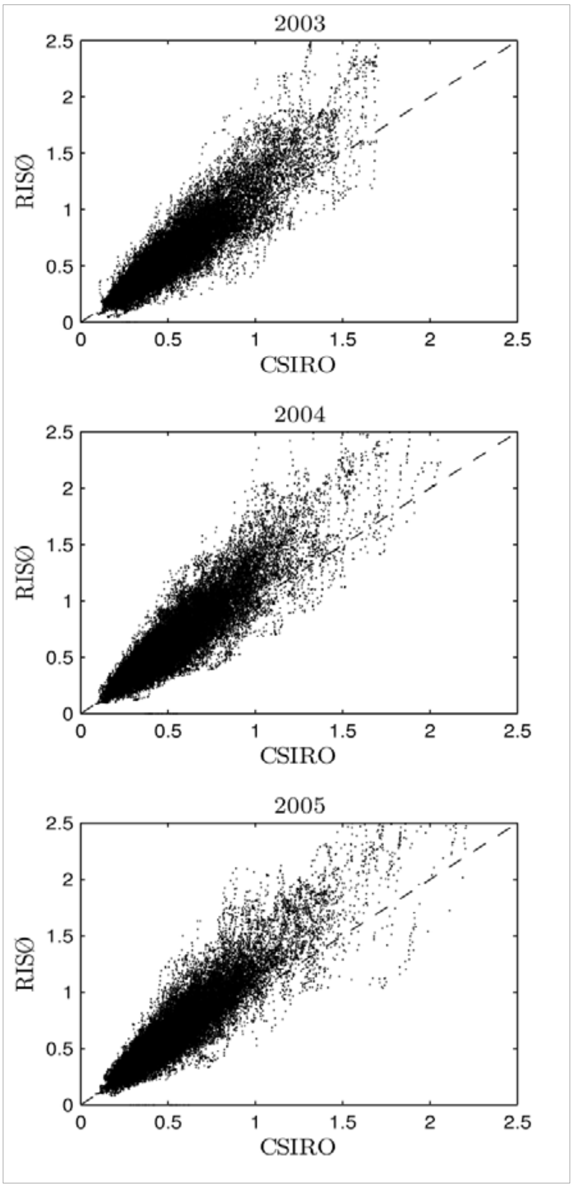

Figure 9. The Risø-DTU and CSIRO variability indices for three years of data.

The variability index developed by CSIRO is further described in Davy (2010), where it is applied to the problem of modeling wind variability based on reanalysis models. It was shown that for the colder months of the year (June-September), model fields that were important in describing wind variability were (in order of importance): height of the planetary boundary layer, vertical velocity, U wind-speed component, geopotential height, V wind-speed component and absolute vorticity. In the warmer months of the year (December-February), model fields that were important in describing wind variability were (in order of importance): U wind-speed component, geopotential height, cloud water, geopotential height, v wind-speed component and surface lifted index.

6. Conclusions

The goal of this task was to produce a "quantitative indicator (severity index) for severely variable energy production". This task has been achieved successfully. Two different methodologies have been proposed and applied to the problems of characterizing the predictability and climatology of severely variable wind speeds, which are implicitly linked to severely variable power production.

Both methods have been applied to the challenge of relating wind variability to large scale and local meteorological conditions, and these have been described peer-reviewed journal papers, conference papers and a PhD thesis.

The analysis of hour-scale wind variability will take on increasing importance with the development of very large wind farms where a high concentration of turbines are situated within a limited geographical area. The well-defined patterns between wind variability and the local and large scale weather conditions indicate that there is great potential for forecasting wind variability using statistical modelling. Furthermore, the mesoscale modelling results indicate that there is potential for explicitly forecasting wind variability using numerical models.

7. Publications relating to task 4.7

C L Vincent, A N Hahmann and M C Kelly (2011d). Idealised numerical simulations of open cellular convection over the sea. *Boundary Layer Meteorology. In Press.*

C L Vincent (2011c). Mesoscale wind fluctuations over Danish waters. PhD Thesis. *Technical University of Denmark, Risø National Laboratory for Sustainable Energy*

C L Vincent, P Pinson and G Giebel (2011b). Wind fluctuations over the North Sea. *International Journal of Climatology* **31**(5), DOI: 10.1002/joc.2175

C L Vincent and A N Hahmann (2011a). Hour-scale wind fluctuations over the North Sea. EWEA 2011, European Wind Energy Association Annual Event - Scientific Proceedings, Brussels, Belgium, March 2011

R J Davy, M J Woods, C J Russell and P A Coppin (2010). Statistical downscaling of wind variability from meteorological fields. Boundary Layer Meteorology 135, pp. 161-175.

C L Vincent, G Giebel, P Pinson and H Madsen (2010). Resolving non-stationary spectral signals in wind speed time-series using the Hilbert-Huang transform. *Journal of Applied Meteorology and Climatology* **49**(2), pp. 253-267

C L Vincent, G Giebel and P Pinson (2009). Characterisation of wind variability at the Horns Rev wind farm. In proceedings: EWEC'09, European Wind Energy Conference, Marseille, France, 2009 ¨

R J Davy, M J Woods, C J Russell and P A Coppin (2009). Forecasting Wind Energy Variability using Statistical Downscaling Techniques. In proceedings: EWEC'09, European Wind Energy Conference, Marseille, France, 2009

8. Other references

T Kohonen (2001). Self-organizing maps. Springer series in information sciences. Springer-Verlag, Berlin, 3rd edition, 2001.

N E Huang, Z Shen, S R Long, M C Wu, H H Shih, Q Zheng, N-C Yen, C C Tung, and H H Liu (1998). The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis. Proc. Roy. Soc. A., **454,** pp 903–995.

N Huang, (2005b). Hilbert-Huang Transform and its applications. World Scientific Publishing Company, 1-26 pp.

N Huang and Z Wu (2008). A review on Hilbert-Huang transform: Method and its applications to geophysical studies. Rev. Geophys., **46**, RG2006.

A Simmons, S Uppala, D Dee, and S Kobayashi (Winter 2006/2007). Era-interim: New ECMWF reanalysis products from 1989 onwards. ECMWF Newsletter, **110**, pp 25–35.

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