Multi-scale correlations between synchronized power and wind measurements: a way to characterize turbulent effect in a scale invariant way.

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1. Introduction

The growing global demand of energy provides an impulse to a sustainable energetic model more attentive of the environment. In this way, the wind energy is playing a major role; the global wind market grows rapidly and continuously. The ongoing effort to develop more efficient wind turbines faces the discontinuity problem of the electric power in different scales, including large fluctuations also called intermittency. The high fluctuations of power production are inherent to the turbulent wind nature.

2. Approach

From earlier studies, we know that wind speed and the aggregate power output are intermittent and multifractal over a wide range of scales [1]. Here, we consider the relation between velocity and power output with synchronous wind turbine database. The database is a wind turbine situated in Denmark with a 36.5 Hz sampling frequency.

In a framework of fully developed turbulence with high Reynolds number in the atmospheric boundary layer (as large as 10^8), there exist a development of an energy cascade also called the Richardson-Kolmogorov energy cascade. On the inertial range between the large injection scale (several tens of hundreds of meters) and the dissipative scale (of the order of millimeters), wind speed fluctuations are scaling. The fluctuations of wind speed produces large fluctuations at all scales, this property is defined as intermittency. Those multi-scale fluctuations can be studied through the moment of order q called "structure functions of order q". For certain conditions, the intermittency properties are transferred to the power output possessing as well, very large fluctuations. These fluctuations can lead mechanical stress and result in substantial voltage swings at the terminals. We aim to characterize the intermittency on both times series, wind speed and power output, in order to obtain the scaling properties for this renewable energy.

3. Abstract

The wind-power relationship, at smaller scales, is of random nature. It is important to be able to model such relation. Here, we use several methods to grasp such relation and to characterize it in a multi-scale way: classic Fourier spectral analysis and co-spectral analysis. We employ in particular, two methods for quantify scaling properties in a multi-scale way and to look for multi-scale correlations:

- Empirical Mode Decomposition (EMD)

Empirical Mode Decomposition (EMD) and Hilbert-Huang transform [2] belong to a same method that has been introduced 17 years ago by Norden Huang. The method decomposes nonlinear, non-stationary time series into a sum of different time series called modes, each one being narrow-banded and having a characteristic frequency [3]. After the decomposition, the Hilbert-Huang transform is then introduced to each mode time series separately. This way, Hilbert space power spectra are estimated that are similar to Fourier power spectra. The method is much less perturbated by the periodic forcing than the structure functions approach.

- Time-dependent intrinsic correlation (TDIC)

When a classic correlation is applied to a non-stationary time series, the obtained cross correlation information can be misleading [4]. An alternative way, consistent with the possible non-stationarity of the time series, is to estimate the cross correlation coefficient by using a sliding window or a scale dependent correlation technique. The estimation of the cross correlation between time series, in a multi-scale framework, may use a window based on the local characteristic

scale given by the data itself. With this adaptive window, we estimate a so-called time-dependent intrinsic correlation (TDIC). The efficiency of this approach to characterize the relation between two time series for several problems has been shown in [4] and applied recently in Huang and Schmitt [5]. Here we use this recent method to estimate cross correlations between nonlinear and non-stationary data time series.

4. Conclusion

This paper aim to have a better understanding between the relationship of wind input and power output of a wind turbine. The local correlations obtained through high frequency data will put some light in a multi-scale way presented on the complex dynamics of wind power.

5. Learning objectives

- Better understanding of collective effects: the difference between an isolated turbine and a wind farm.
- Better understanding of multi-scale fluctuations in wind speed and the effect on the power output.
- Better description and understanding of the correlations between wind and power time series.

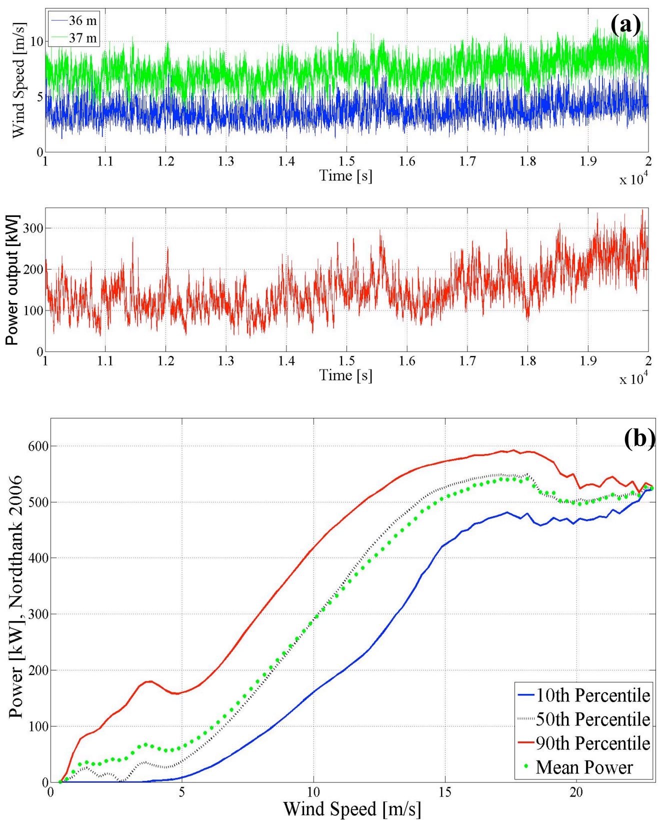

Figure 1: (a) Nordthank Wind turbine dataset for 3 hours measurements. Wind data were measured at 2 different heights, 36 and 37 m. (b) Nordthank power curve for measurements acquired during the year 2006.

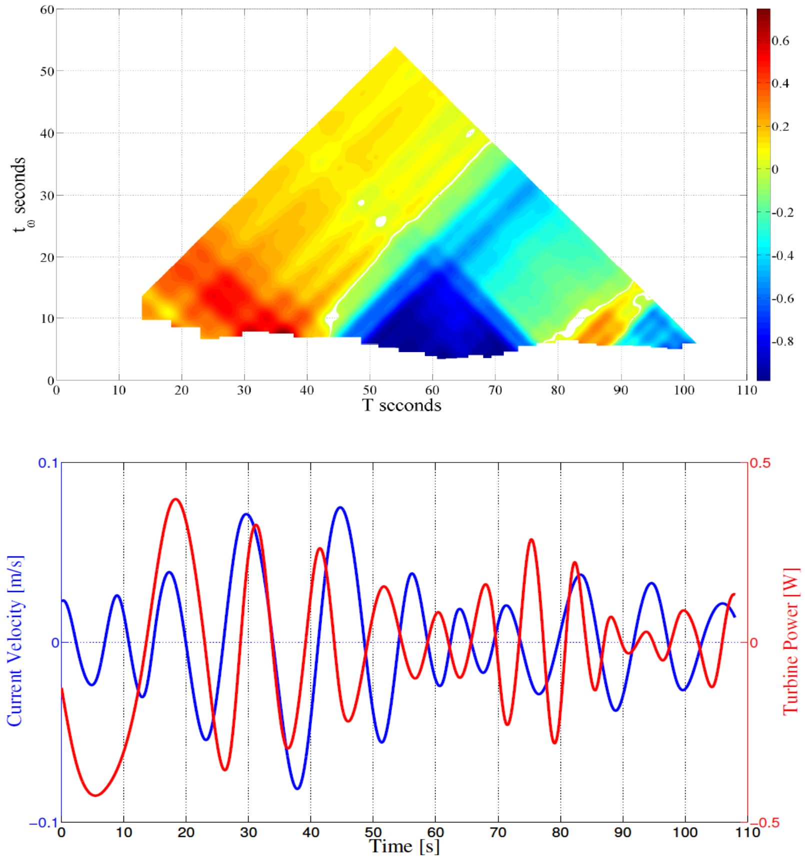

Figure 2: Example of TDIC method applied on a marine current turbine. The color bar indicates information about correlation: positively correlated (R = 1) is in red color meanwhile a negatively correlated (R = -1) is shown by the blue color. Here, we observe a direct observation of two curves corresponding to current velocity and current marine turbine modes. When the maxima value turbine is in phase with the minima value of current velocity it results in a blue color surface. When both maxima values occurs at the same time, we obtain red color surfaces.

References

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