Analysis of the time dynamics in wind records by means of multifractal detrended fluctuation analysis and the Fisher–Shannon information plane

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Abstract. The time structure of more than 10 years of hourly wind data measured at one site in northern Italy from April 1996 to December 2007 is analysed. The data were recorded by the Sodar Rass system, which measures the speed and the direction of the wind at several heights above the ground level. To investigate the wind speed time series at seven heights above the ground level we used two different approaches: (i) multifractal detrended fluctuation analysis (MF-DFA), which permits the detection of multifractality in nonstationary series, and (ii) the Fisher–Shannon (FS) information plane, which allows the discrimination of dynamical features in complex time series. Our results point to the existence of multifractal time fluctuations in wind speed and to a dependence of the results on the height of the wind sensor. Even in the FS information plane a height-dependent pattern is revealed, indicating a good agreement with the multifractality. The obtained results could contribute to a better understanding of the complex dynamics of wind phenomena.

Keywords: nonlinear dynamics

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1. Introduction

Wind energy is the fastest growing source of energy and will be used worldwide due to its competitive cost of production compared with other traditional means; furthermore, wind energy allows the well-known energy resource issues and environmental problems to be addressed [1]. Wind energy highly depends on wind speed; in fact, wind power is proportional to the cube of wind speed. Therefore, the analysis of wind speed records is very challenging not only for better design of more appropriate and more efficient wind power plants (the irregular waxing and waning of wind can lead to significant mechanical stress on the gear boxes and results in substantial voltage swings at the terminals [2]), but also for better understanding the underlying dynamical mechanisms. To this aim, it is crucial to investigate the inner dynamical structure of wind speed time series. A spatial and temporal analysis of long-range dependences in wind speed was performed by Haslett and Raftery [3]. Rehman et al [4] analysed 10 wind speed records in Saudi Arabia and found that the Weibull distribution represents a close fit. Statistical characteristics of wind speed and diurnal variation were presented by Rehman and Halawani [5].

The characterization of the temporal fluctuations of geophysical and environmental processes has always aroused great attention for the understanding of the underlying dynamical mechanisms [6]. The standard method aimed at investigating the temporal fluctuations of a process is the power spectral density \( S(f) \), which is defined in terms of the Fourier functions and describes the frequency distribution of the power. Thus, for purely random processes, which are realizations of white noise, the power spectrum is approximately flat for any frequency bands, the temporal fluctuations of the process are completely uncorrelated, any sample is completely independent of the others, and no memory phenomena exist at all. On the contrary, a power-law shape of the power spectrum, which is linear if plotted on log–log scales, indicates the presence of long-range correlated structures in the process. Such behaviour, called scaling, is typical of many geophysical and environmental processes and allows the quantification of the strength of the temporal fluctuations by estimating the value of the spectral exponent, also called the scaling exponent [7].

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Several statistical measures could be used to gain insight into the scaling dynamics of a process by means of estimation of the scaling exponent. But in the last decade a very effective tool, called detrended fluctuation analysis (DFA), invented by Peng et al [8], has been extensively used for determining the scaling behaviour of signals, even if these were affected by nonstationarities with unknown origin and cause [9]. Many applications in geophysical sciences [10]–[15], environmental research [16, 17] as well as in economics [18, 19], biology and medicine [20]–[22] have been performed using the DFA, thus revealing its universality in being used as an effective and efficient tool for time series analysis. The DFA permits the identification of scaling behaviour in monofractal series or the investigation of the monofractality of a series, because it leads to the estimation of a single scaling exponent. But one scaling exponent is sufficient to completely describe a process under the hypothesis that it is monofractal. Monofractals are homogeneous objects, in the sense that they have the same scaling properties, characterized by a single singularity exponent [23]. The need for more than one scaling exponent can derive from the existence of a crossover timescale, which separates regimes with different scaling behaviours, suggesting, e.g., different types of correlations at small and large timescales, thus leading to different types of time dynamics intrinsic to the process [24]–[27]. Different values of the same scaling exponent could be required for different segments of the same series, indicating a time variation of the scaling behaviour, relating to a time variation of the underlying dynamics [28]. Furthermore, different scaling exponents can be revealed for many interwoven fractal subsets of the signal; in this case the process is not a monofractal but multifractal. A multifractal object requires many indices to characterize its scaling properties. Multifractals can be decomposed into many—possibly infinitely many—subsets characterized by different scaling exponents. Thus multifractals are intrinsically more complex and inhomogeneous than monofractals and characterize systems featured by a spiky dynamics, with sudden and intense bursts of high frequency fluctuations [29]. Taking into account the independence of nonstationarity revealed by the DFA, its generalization into the multifractal detrended fluctuation analysis (MF-DFA) was developed by Kantelhardt et al [9]. This method is, thus, able to reliably determine the multifractal scaling behaviour of nonstationary series.

To our knowledge the first paper that investigated the multifractality in wind speed was by Kavasseri and Nagarajan [30]. They analysed four hourly averaged wind speed records in North Dakota at a height of 20 m above the ground level. They found that the binomial cascade multiplicative model could represent a close fit to the data, although spatial and temporal variations in wind speed are influenced by pressure gradients, turbulence, temperature and topography.

2. Wind data

We analysed the time series of the hourly speed of wind measured by a Sodar Rass system in northern Italy from April 1996 to December 2007. The data are available free of charge on the following Internet website: http://www.istitutoveneto.it/venezia/dati/atmosfera/dati_enel/234sidfg45.htm. Such a system allows the measurement of the speed of wind at different heights from the ground. We analysed the time series of wind speed at heights $H = 50, 77, 104, 131, 158, 186$ and $213$ m above the ground level. Figures 1(a)–(g) show the seven time series of wind speed; figure 1(h) shows their average and the deviation.

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3. Methods and data analysis

3.1. Multifractal detrended fluctuation analysis

The main feature of multifractals is characterized by high variability on a wide range
of temporal scales, associated with intermittent fluctuations and long-range power-law
correlations.

The data examined in this paper present clear irregular dynamics (figure 1),
characterized by sudden bursts of high frequency fluctuations, which suggests that a
multifractal analysis should be performed, thus evidencing the presence of different scaling
behaviours for different intensities of fluctuations. Furthermore, the signals appear to be
nonstationary, and, for this reason, we applied the multifractal detrended fluctuation
analysis (MF-DFA), which operates on the time series \( x(i) \), where \( i = 1, 2, \ldots, N \) and \( N \)
is the length of the series. By \( x_{\text{ave}} \) we indicate the mean value

\[
x_{\text{ave}} = \frac{1}{N} \sum_{k=1}^{N} x(k).
\]

Figure 1. Hourly wind speed time series at 50 m (a), 77 m (b), 104 m (c), 131 m
(d), 158 m (e), 186 m (f) and 213 m (g) above the ground level. (h) Average and
deviation of the wind speed time series.
We assume that $x(i)$ are increments of a random walk process around the average $x_{ave}$; thus the ‘trajectory’ or ‘profile’ is given by the integration of the signal

$$y(i) = \sum_{k=1}^{i} [x(k) - x_{ave}].$$  \hspace{1cm} (2)

Furthermore, the integration will reduce the level of measurement noise present in observational and finite records. Next, the integrated time series is divided into nonoverlapping $N_s = \text{int}(N/s)$ segments of equal length $s$. Since the length $N$ of the series is often not a multiple of the considered timescale $s$, a short part at the end of the profile $y(i)$ may remain. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end. Thereby, $2N_s$ segments are obtained altogether. Then we calculate the local trend for each of the $2N_s$ segments by a least square fit of the series. Then we determine the variance

$$F^2(s, \nu) = \frac{1}{s} \sum_{i=1}^{s} \{y((\nu - 1)s + i) - y_{\nu}(i)\}^2$$  \hspace{1cm} (3)
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for each segment $\nu$, $\nu = 1, \ldots, N_S$ and

$$F^2(s, \nu) = \frac{1}{s} \sum_{i=1}^{s} \{y[N - (\nu - N_S)s + i] - y_{\nu}(i)\}^2$$

(4)

for $\nu = N_S + 1, \ldots, 2N_S$. Here, $y_{\nu}(i)$ is the fitting polynomial in segment $\nu$. Then, after detrending the series, we average over all segments to obtain the $q$th order fluctuation function

$$F_q(s) = \left\{ \frac{1}{2N_S} \sum_{\nu=1}^{2N_S} [F^2(s, \nu)]^{q/2} \right\}^{1/q}$$

(5)

where, in general, the index variable $q$ can take any real value except zero.

Repeating the procedure described above, for several timescales $s$, $F_q(s)$ will increase with increasing $s$. Then analysing log–log plots of $F_q(s)$ versus $s$ for each value of $q$ we determine the scaling behaviour of the fluctuation functions. If the series $x_i$ is long-range power-law correlated, $F_q(s)$ increases for large values of $s$ as a power law

$$F_q(s) \propto s^{h(q)}.$$  

(6)

Monofractal time series are characterized by $h(q)$ independent of $q$. The different scalings of small and large fluctuations will yield a significant dependence of $h(q)$ on $q$. For positive $q$, the segments $\nu$ with large variance (i.e. large deviation from the corresponding fit) will dominate the average $F_q(s)$. Therefore, if $q$ is positive, $h(q)$ describes the scaling behaviour of the segments with large fluctuations; and, generally, large fluctuations are characterized by a smaller scaling exponent $h(q)$ for multifractal time series. For negative $q$, the segments $\nu$ with small variance will dominate the average $F_q(s)$. Thus, for negative $q$ values, the scaling exponent $h(q)$ describes the scaling behaviour of segments with small fluctuations, usually characterized by larger scaling exponents.

The value $h(0)$ corresponds to the limit $h(q)$ for $q \to 0$, and cannot be determined directly using the averaging procedure of equation (5) because of the diverging exponent. Instead, a logarithmic averaging procedure has to be employed:

$$F_0(s) \equiv \exp\left\{ \frac{1}{4N_S} \sum_{\nu=1}^{2N_S} \ln[F^2(s, \nu)] \right\} \approx s^{h(0)}.$$  

(7)

In general the exponent $h(q)$ will depend on $q$. For stationary time series, $h(2)$ is the well defined Hurst exponent $H_u$ [31]. Thus, we call $h(q)$ the generalized Hurst exponent. In order to select the adequate order of the polynomial fitting function, we applied the MF-DFA, varying the order of the fitting polynomial from 1 to 5. Figure 2(a) shows, as an example, just the results for the wind series at height $h = 213$ m and for $q = 2$. The fluctuation curves are just slightly vertically shifted from each other, but the slopes remain almost unchanged. Therefore, hereafter the results are obtained using detrending polynomial fitting functions of order 1 in the MF-DFA. Figure 2(b) shows the fluctuation functions $F_2(s)$ for the seven wind speed time series. It is striking that whatever the height of measurement, the fluctuation functions increase as a power law up to the crossover $s_c \sim 4–6$ months, after which the fluctuation functions tend to flatten, thus indicating the presence of two different dynamics. It may be very likely that the origin of such a crossover is seasonal and linked with meteo-climatic phenomena. Even changing the
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Figure 2. (a) $F_2(s) \sim s$ curves for the order of the detrending polynomial fitting functions varying from 1 to 5 for the wind series at height $= 213$ m. (b) $F_2(s) \sim s$ curves for the wind speed time series plotted in figure 1.

order of the moment $q$, the crossover still remains, as shown in figure 3, which shows, as an example, the fluctuation functions for $q = -10, 0, +10$ for the height $H = 104$ m. This indicates that the seasonal crossover, which approximately separates two scaling regions, and, thus, discriminates two different dynamics for timescales respectively lower and higher than $s_c$, is a characteristic parameter of the wind data, and does not depend on the range of variability of the data, because it is present for large ($q > 0$) as well as small ($q < 0$) fluctuations. Furthermore, the different slopes of the fluctuation curves ($\sim$0.69
Figure 3. Fluctuation functions for $q = -10, 0, +10$ for the height $H = 104$ m.

for $q = +10$, $\sim 0.83$ for $q = 0$ and $\sim 0.95$ for $q = -10$) indicate that small and large wind fluctuations scale differently, indicating the presence of multifractal dynamics.

Figure 4 shows the $q$-dependence of the generalized Hurst exponent $h(q)$ determined by fits in the regime $30 \ h < s < 10^{3.5} \ h$ for the seven wind time series (the upper limit was chosen to be less than the crossover $s_c$). Although the $h(q) \sim q$ relationships are quite similar, slight differences in the multifractal degree can be evaluated. To this aim, a computation of the multifractal spectrum by means of the Legendre transform was performed. The multifractal scaling exponents $h(q)$ defined in equation (6) are directly related to the scaling exponents $\tau(q)$ defined by the standard partition function multifractal formalism [9, 56, 57]. Suppose that the series $x_k$ is a stationary and normalized sequence. Then the detrending procedure of the MF-DFA is not required. Thus the DFA can be replaced by the fluctuation analysis (FA), for which the variance is defined as

$$F_{FA}^2(s, \nu) = [y(\nu s) - y((\nu - 1)s)]^2.$$  

Inserting this definition in equation (5) and using equation (7), we obtain

$$\left\{ \frac{1}{2N_S} \sum_{\nu=1}^{2N_S} [F_{FA}^2(s, \nu)]^q \right\}^{1/q} \approx s^h(q).$$  

For the sake of simplicity, we assume that the length $N$ of the sequence is an integer multiple of the scale $s$, obtaining $N_S = N/s$ and therefore

$$\sum_{\nu=1}^{N_S} [F_{FA}^2(s, \nu)]^q \approx s^{qh(q)-1}.$$  

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Figure 4. $h(q)$–$q$ relationships for the wind speed time series, calculated on the range scales $30 \text{ h} < s < 10^{3.5} \text{ h}$.

The term $[y(\nu s) - y((\nu - 1)s)]$ is the sum of the numbers $x_k$ within each segment $\nu$ of size $s$. This sum is known as the box probability $p_s(\nu)$ in the standard multifractal formalism for normalized series $x_k$. The scaling exponent $\tau(q)$ is usually defined via the partition function $Z_q(s)$,

$$Z_q(s) = \sum_{\nu=1}^{N_S} |p_s(\nu)|^q \approx s^{\tau(q)},$$

where $q$ is a real parameter as in the MF-DFA. Equation (11) is identical to equation (10), therefore

$$\tau(q) = q h(q) - 1.$$  

In this equation $h(q)$ is different from the generalized multifractal dimensions $D(q) = \tau(q)/(q - 1)$; in fact, while $h(q)$ is independent of $q$ for a monofractal series, $D(q)$ depends on $q$ in that case [19], [53]–[55]. Therefore, monofractal series with long-range correlations are characterized by linearly dependent $q$-order exponents $\tau(q)$, i.e. the exponents $\tau(q)$ of different moments $q$ are linearly dependent on $q$,

$$\tau(q) = Hq - 1,$$

with a single Hurst exponent,

$$H = d\tau/dq = \text{const.}$$
Long-range correlated multifractal signals have a multiple Hurst exponent, i.e. the generalized Hurst exponent \( h(q) \),

\[
h(q) = \frac{d\tau}{dq} \neq \text{const},
\]

where \( \tau(q) \) depends nonlinearly on \( q \) [32].

The singularity spectrum \( f(\alpha) \) is related to \( \tau(q) \) by means of the Legendre transform,

\[
\alpha = \frac{d\tau}{dq},
\]

\[
f(\alpha) = q\alpha - \tau(q),
\]

where \( \alpha \) is the Hölder exponent and \( f(\alpha) \) indicates the dimension of the subset of the series that is characterized by \( \alpha \). The singularity spectrum quantifies in detail the long-range correlation properties of a time series. Figure 5 shows the multifractal spectrum \( f(\alpha) \) for the seven wind time series. The multifractal spectrum gives information about the relative importance of various fractal exponents present in the series. In particular the width of the spectrum indicates the range of the present exponents. In particular the values of the multifractal width are in very good agreement with those obtained by Kavasseri and Nagarajan applying the binomial multiplicative cascade model [30].

In order to understand what the type of multifractality underlying the \( q \)-dependence of the generalized Hurst exponent is, we applied the random shuffle method to generate 100 surrogate series for each wind speed time series. Generally, two different types of multifractality in the time series can be discriminated: (i) due to a broad probability density function, and (ii) due to different long-range correlations for small and large
fluctuations. In the shuffling procedure the values are put into random order and, although all correlations are destroyed, the probability density function remains unchanged. Hence the shuffled series coming from multifractals of type (ii) will exhibit simple random behaviour with $h_{\text{shuf}}(q) = 0.5$, while those coming from multifractals of type (i) will show $h(q) = h_{\text{shuf}}(q)$, since the multifractality depends on the probability density [9]. If both types of multifractality characterize the time series, then the shuffled series will show weaker multifractality than the original one. Figure 6 shows the results of the generalized Hurst exponents versus $q$, averaged over 100 randomly shuffled versions of the original time series. The error bars delimit the $1 - \sigma$ range around the mean values. The mean $h_{\text{shuf}}(q)$-values range around 0.5 for any height, but with a slight $q$-dependence; this indicates that most of the multifractality of the wind speed data is due to different long-range correlations for small and large fluctuations. Figure 7 shows the multifractal spectra, through the Legendre transform, of the shuffles. For comparison the multifractal spectrum of the original wind speed series at $H = 50$ m is also shown. It is clearly evident that the shuffled series are characterized by lower multifractality degrees. And this confirms that most of the multifractality of the wind series depends on the different long-range correlation properties for small and large fluctuations.

3.2. The Fisher–Shannon method

A further approach used to investigate the dynamics of the wind speed records is the Fisher–Shannon (FS) information plane. The Fisher information measure (FIM) is a powerful tool to investigate complex and nonstationary signals, quantifying the degree of order or organization; the Shannon entropy is the well-known magnitude to quantify the degree of disorder in dynamical systems. The FIM was introduced by Fisher in 1925 in the
context of statistical estimation [33]. In a seminal paper Frieden [34] has shown that the FIM is a versatile tool to describe the evolution laws of physical systems. The FIM allows one to accurately describe the behaviour of dynamic systems, and to characterize the complex signals generated by these systems [35]. This approach has been used by Martin et al. to characterize the dynamics of EEG signals [36]. Martin et al. [37] have shown the informative content of the FIM in detecting significant changes in the behaviour of nonlinear dynamical systems disclosing, thus, the FIM is an important quantity involved in many aspects of the theoretical and observational description of natural phenomena. The FIM has been used in studying several geophysical and environmental phenomena, revealing its ability in describing the complexity of a system [38,39] and suggesting its use to reveal reliable precursors of critical events [40,41].

The Shannon entropy can be used to define the degree of uncertainty involved in predicting the output of a probabilistic event [42,43]. For discrete distributions, this means that if one predicts the outcome exactly before it happens, the probability will be a maximum value and, as a result, the Shannon entropy will be a minimum. If one is absolutely able to predict the outcome of an event, the Shannon entropy will be zero. Such is not the case for distributions (probability densities) on a continuous variable, ranging, e.g., over the real line. In this case, the Shannon entropy can reach any arbitrary value, positive or negative. Therefore, the use of the power entropy (that is defined below) avoids the difficulty of dealing with negative information measures. The Shannon entropy provides a scientific method to understand the essential state of things [44,45].

Let us introduce the relevant Fisher- and Shannon-associated quantities [37]. Let $f \equiv q^2$ be a probability density in $\mathbb{R}^d$ ($d \geq 1$). Fisher’s quantity of information associated to $f$ (or to the probability amplitude $q$) is defined as the (possibly infinite) non-negative
number $I$

$$I(f) = \int_{\mathbb{R}^d} dx \frac{\vert \nabla f \vert^2}{f}$$

(18)

or in terms of the amplitudes

$$I(q) = \int_{\mathbb{R}^d} dx (\nabla q \cdot \nabla q),$$

(19)

where $\nabla$ is the differential operator. This formula defines a convex, isotropic functional $I$, which was first used by Fisher [33] for statistical purposes. It is clear from equation (19) that the integrand, being the scalar product of two vectors, is independent of the reference frame [37].

Let us focus our attention on the one-dimensional case. Let us consider a measurement $x$ whose probability density function is denoted as $f(x)$. Its FIM is defined as

$$I = \int_{-\infty}^{+\infty} \left( \frac{\partial}{\partial x} f(x) \right)^2 \frac{dx}{f(x)}.$$  

(20)

The Shannon entropy is given by the following formula [35]:

$$H_X = -\int_{-\infty}^{+\infty} f_X(x) \log f_X(x) dx.$$  

(21)

For convenience the alternative notion of entropy power [46]

$$N_X = \frac{1}{2\pi e} e^{2H_X}$$  

(22)

will be used rather than the entropy $H_X$. The use of the power entropy $N_X$ instead of the Shannon one $H_X$ arises from the so-called ‘isoperimetric inequality’ [46]–[49], a lower bound to the Fisher–Shannon product which reads as $IN_X \geq d$, where $d$ is the dimension of the space. The ‘isoperimetric inequality’ suggests that the FIM and the Shannon entropy are intrinsically linked, so that the dynamical characterization of signals should be improved when analysing them in the so-called Fisher–Shannon (FS) information plane [35], in which the $y$- and $x$-axes are the FIM and the Shannon entropy (as outlined above, instead of the Shannon entropy we will use the entropy power $N_X$). Vignat and Bercher [35] showed that the simultaneous examination of both the Shannon entropy and the FIM through the FS plane could improve the characterization of the nonstationary behaviour of complex signals. The product $IN_X$ can be considered as a statistical measure of complexity [47]. The line $IN_X = 1$ separates the FS plane into two parts: one allowed ($IN_X > 1$) and one not allowed ($IN_X < 1$), and the distance of a signal point from the ‘isocomplexity line’ $IN_X = 1$ can measure the degree of complexity of the signal.

Equations (20) and (21) involve the calculation of the probability density function (pdf) $f(x)$.

An estimation of the pdf $f(x)$ may be obtained by means of the kernel density estimator technique [50, 51]. The kernel density estimator provides an approximate value

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Figure 8. The Fisher–Shannon information plane for the wind speed time series plotted in figure 1.

of the density in the form

\[
\hat{f}_M(x) = \frac{1}{Mb} \sum_{i=1}^{M} K\left(\frac{x-x_i}{b}\right),
\]

where \(M\) is the number of data and \(K(u)\) is the kernel function, which is a continuous non-negative and symmetric function satisfying

\[
K(u) \geq 0 \quad \text{and} \quad \int_{-\infty}^{+\infty} K(u) \, du = 1,
\]

while \(b\) is the bandwidth. In our estimation procedure the kernel used is the Gaussian of zero mean and unit variance. In this case

\[
\hat{f}_M(x) = \frac{1}{M\sqrt{2\pi}b^2} \sum_{i=1}^{M} e^{-((x-x_i)^2/2b^2)}.
\]

The Gaussian kernel allows one to evaluate the kernel density estimator and the bandwidth with a low computational complexity [52].

Figure 8 shows the Fisher–Shannon information plane for wind speed data measured in northern Italy. Each symbol represents a record of the wind speed at a certain height above the ground level. A pattern with the height is clearly visible, revealing that the FIM of the wind speed (and correspondingly the Shannon entropy) decreases (increases) with the height. From these results it can be deduced that the degree of disorder is higher at greater heights above the ground level.

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4. Conclusions

The mechanisms underlying wind dynamics are complex. The multifractal analysis and Fisher–Shannon approach performed in the present study have led to a better description of this complexity. Although the physical interpretation of such results is not a simple task, it is noteworthy that the both the analyses (MF-DFA and FS) have furnished very consistent results, indicating a height-dependent behavioral trend in wind speed. Further similar analysis performed over different wind speed time series, measured at different sites and for different periods could give insight into a better understanding of the complexity of wind phenomena.

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