Long term persistence in daily wind speed series using fractal dimension

Samia Harrouni*
Instrumentation Laboratory, Faculty of Electronics and Computer,
University of Science and Technology H. Boumediene (USTHB),
P.O. Box 32, El-Alia, 16111 Algiers, Algeria

ABSTRACT

In the assessment of wind turbines installations efficiency long series of wind speed data are necessary. Such data are not usually available it is then important to generate them. In this paper we examine the long-term persistence of daily wind speed data with many years of record using the fractal dimension. The persistence measures the correlation between adjacent values within the time series. Values of a time series can affect other values in the time series that are not only nearby in time but also far away in time. For this purpose, a new method to measure the fractal dimension of temporal discrete signals is presented. The fractal dimension is then used as criterion in an approach we have elaborated to detect the long term correlation in wind speed series. The results show that daily wind speed are anti-persistent.

Keywords: fractal dimension, rectangular covering method, least squares estimation, wind speed, correlation, long-term persistence

1. INTRODUCTION

Numerous natural processes described by time-series have been shown to exhibit fractal or self-affinity properties. Self-affine time series display power-law and hence characterized as having long memory. This last describes the correlation structure of a series at long lags. This correlation is also called long-range or long-term persistence.

Persistent wind energy characteristics, provides vital decision-making information for both planned and existing wind energy projects. This article's purpose, therefore, is to investigate the long-range dependence in wind speed series since our previous works have demonstrated that wind speed data are self-affine [1].

Several techniques have been developed to measure the long term persistence of time series: autocorrelation function and semivariogram, spectral analysis, wavelet analysis, rescaled-range (R/S) analysis and detrended fluctuation analysis (DFA).

This paper presents a fractal approach to measure the long term persistence in wind speed data, the approach is based on the fractal dimension as a parameter of the persistence. This new way to quantify the long-range dependence has already been used in our earlier works to examine the persistence of daily and annually global solar irradiation data [2].

*Corresponding author. E-mail: sharrouni@yahoo.fr

2. METHODOLOGY

Methods to examine long-range persistence of time series use a parameter characterizing the method itself as persistence indicator: *Ha* for the semivariogram, β for the spectral analysis, *Hw* for wavelet analysis, α for the DFA analysis and *H* for the R/S analysis [3]. For self-affine time series these parameters are also indicators of their roughness which is the role of the fractal dimension.

In this latter method, the Hurst exponent H taking values from 0 to 1 ($0 < H < 1$) allows the measure of the time series persistence as follow:

- Gaussian random walks, or, more generally, independent processes, give $H = 0.5$.
- If $0.5 < H < 1$, positive dependence is indicated, and the series is called persistent.
- If $0 < H < 0.5$, negative dependence is indicated, yielding anti-persistence.

Since the Hurst exponent H is related to D by the relation:

$$D = 2 - H \tag{1}$$

we have deduced the following persistence algorithm from the rescaled range analysis one [2]:

- $1 < D < 1.5 \rightarrow$ Persistence
- $1.5 < D < 2 \rightarrow$ Anti-persistence
- $D = 0.5 \rightarrow$ Uncorrelated

Thus, the fractal dimension indicates increasing degrees of persistence as it approaches 1 and of anti-persistence as it approaches 2.

This new way to measure the long-term persistence presents an advantage that the stationarity of the time series is not a prerequisite of the method, which is not the case in most other techniques such as the R/S analysis.

3. FRACTAL DIMENSION ESTIMATION

Several algorithms are presented in the literature for calculating fractal dimension of signals [4–6]. To improve the complexity and the precision of the fractal dimension estimation for one-dimensional discrete time series, we have elaborated a new method: "Rectangular Covering Method" [7–9] using the same basics of the Minkowsky-Bouligand dimension.

3.1. RECTANGULAR COVERING METHOD

As shown in Figure 1, the method first consists in covering the signal for which we want to estimate the fractal dimension by rectangles of length $\Delta\tau$ and of width $|f(t_n + \Delta\tau) - f(t_n)|$ or the inverse.

$f(t_n)$ is the global irradiance at the time t_n.$\Delta\tau$ and $|f(t_n + \Delta\tau) - f(t_n)|$ is the irradiance variation related to the interval $\Delta\tau$. Then, it would be necessary to calculate the area $S(\Delta\tau)$ of this covered curve by using the following relation:

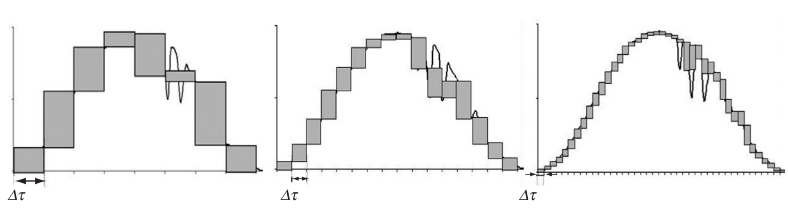

Figure 1 An example of a curve covered by rectangles at different scales $\Delta\tau$.

$$S(\Delta\tau) = \sum_{n=0}^{N-1} \Delta\tau \left| f(t_n + \Delta\tau) - f(t_n) \right| \quad (2)$$

N represents the size of the studied signal.

Bouligand defined the fractal dimension D as follows [10]

$$D = 2 - \lambda(S) \quad (3)$$

where $\lambda(S)$ is the similitude factor and it represents the infinitesimal order of $S(\Delta\tau)$. It is defined by:

$$\lambda(S) = \lim_{\Delta\tau \to 0} \left[\ln\left(S(\Delta\tau)\right) / \ln(\Delta\tau) \right] \quad (4)$$

Replacing $\lambda(S)$ by its value in the relation (3) we obtain:

$$D = \lim_{\Delta\tau \to 0} \left[2 - \left(\ln\left(S(\Delta\tau)\right) / \ln(\Delta\tau) \right) \right] \quad (5)$$

The properties of the logarithm permit us to put the relation (5) under the following shape:

$$D = \lim_{\Delta\tau \to 0} \left[\ln\left(S(\Delta\tau) / \Delta\tau^2\right) / \ln(1/\Delta\tau) \right] \quad (6)$$

The fractal dimension is then deduced from the following relation by using the least-squares estimation:

$$\ln\left(S(\Delta\tau) / \Delta\tau^2\right) = D \cdot \ln(1/\Delta\tau) + \textit{constant, as } \Delta\tau \to 0 \quad (7)$$

To determine the fractal dimension D which represents the slope of the line (7), it would be necessary to use different time scales $\Delta\tau$ and to measure the corresponding area $S(\Delta\tau)$.

Let's recall that in the usual fractal analysis, signals are covered by disks centered at the same point. However in our case, we chose the rectangle as the structuring element to cover the irradiance signal. In this manner, this makes it possible to join every point in the time axis to the corresponding point in the irradiance axis, thus achieving the covering of the signal without information loss.

A good estimation of the fractal dimension D requires a good fitting of the log-log plot defined by (7). Therefore, the number of points constituting the plot is important. This number is fixed by $\Delta\tau_{max}$ which is the maximum scale over which we attempt to fit the log-log plot.

To estimate the fractal dimension most of methods determine $\Delta\tau_{max}$ experimentally. This procedure requires much time and suffers from precision. Also, we developed an optimization technique to estimate $\Delta\tau_{max}$.

Figure 2-a represents an example of log-log plot. Our optimization technique consists first in taking a $\Delta\tau_{max}$ minimal about 10, because the number of points constituting the plot should not be very small then; $\Delta\tau_{max}$ is incremented progressively as far as reaching $N/2$. We hence obtain several straight log-log lines which are fitted using the least squares estimation. The $\Delta\tau_{max}$ optimal is the one corresponding to the log-log straight line with the minimum quadratic error. This error is defined by the following formula:

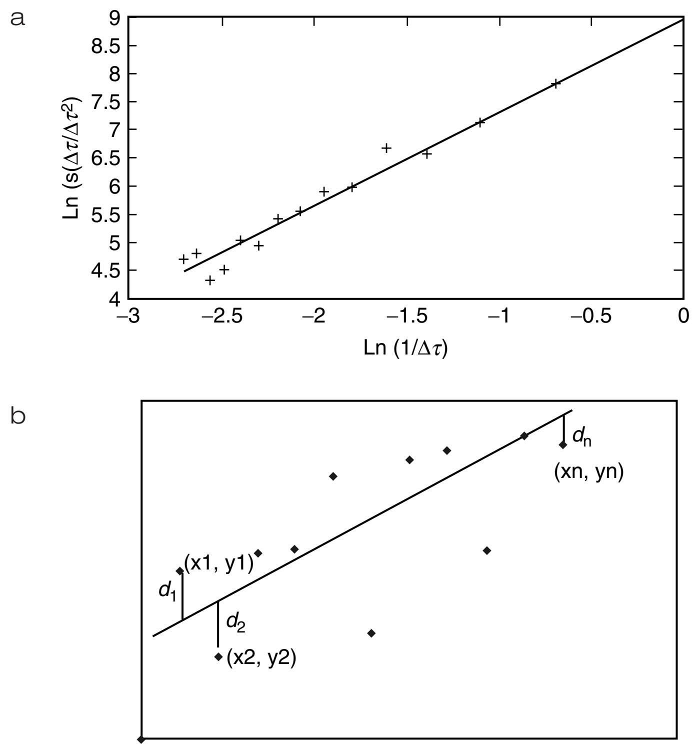

Figure 2 Illustration of the optimisation technique a) An example of log-log plots drawn from the points ($\ln(1/\Delta\tau)$, $\ln(S(\Delta\tau)/\Delta\tau^2)$) and fitted by the least squares estimation b) Calculation of the distance d_i between the points ($\ln(1/\Delta\tau_i)$, $\ln(S(\Delta\tau)/\Delta\tau_i^2)$) denoted here ($Xi$, Yi) and the fitted straight log-log line.

$$E_{quad} = \sum_{i=1}^{n} d_i / n \tag{8}$$

In this relation n denotes the number of points used for the straight log-log line fitting, d_i represents the distance between the points ($\ln(1/\Delta\tau)$, $\ln(S(\Delta\tau)/\Delta\tau^2)$) and the fitted straight log-log line. This distance is calculated as showed in Figure 2-b. In this figure $\ln(1/\Delta\tau)$ is denoted X and $\ln(S(\Delta\tau)/\Delta\tau^2)$denoted Y. The distance d_i is calculated from the difference between the co-ordinates Y of these points.

4. DATA BANK

The data used in this study consist of daily wind speeds recorded at the station of Paris (2°20'11"E - 48°51'06"N - alt. 60 m) from 17/01/2006 to 20/04/2012. These data have been extracted from the weather station history of "Météo-paris" site [11].

Figure 3 shows the variability in wind speed frequency distribution for the studied period. As can be seen from the figure the distribution can be approximated as many other wind speed distribution by the Weibull function.

Figure 4 shows the daily wind speed evolution over one year (example of the year 2011) and over all the studied period.

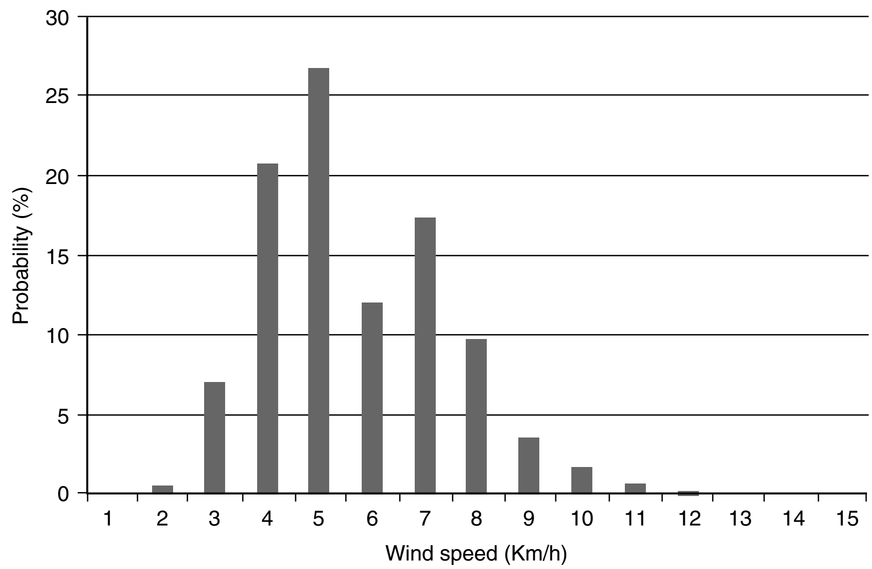

Figure 3 Daily Wind Speed Distribution for the period: 17/01/2006 to 20/04/2012.

5. RESULTS AND DISCUSSION

Using the "Rectangular Covering Method" we have estimated the fractal dimension of the wind speed series described previously, first for each year then for the whole period.

Figure 5 presents two examples of the log–log lines permitting the estimation of the fractal dimension of wind speed curves. From this last we note clearly that the studied wind speed series exhibit fractal behavior since log-log plots lie on straight lines.

Table 1 gathers fractal dimensions of daily wind speed series. We note that fractal dimension of these data for one year is in average equal to 1.92. To explore the long range persistence of daily wind speed we have estimated its fractal dimension over the entire time period considered (17/01/2006-20/04/2012), it was then found equal to 1.91. These results show that daily wind speed series present high degrees of anti-persistence. On the other hand, an increasing trend of the wind speed (decreasing trend) in the past implies its decreasing trend (increasing trend) in the future. These results are similar with those presented in [12].

6. CONCLUSION

The long-range dependence nature of daily wind speed was confirmed by this study. By using the fractal approach we conducted an investigation on the long-term persistence of the daily wind speed over two scales: One year and more than six years.

All data series studied show strong anti-persistence, exemplified by fractal dimension values superior than 1.90. This means that values of wind speed series are negatively correlated, the increase of the variable tends to be followed by its decrease and vice-versa.

These results suggest that the wind speed data are predictable at long-term. This is very important in meteorology since it allows establishing typical meteorological days and in energetic area in view of the fact that it is the source of wind turbines.

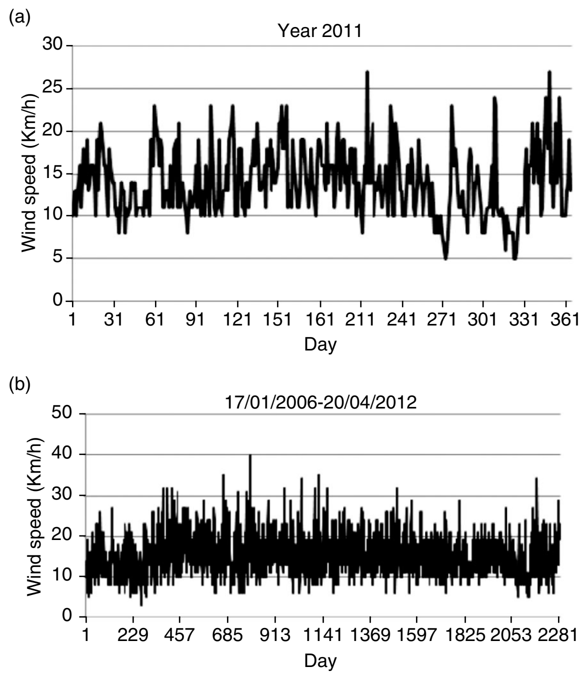

Figure 4 Daily wind speed evolution (a) over one year (2011) (b) over all the studied period (17/01/2006 to 20/04/2012).

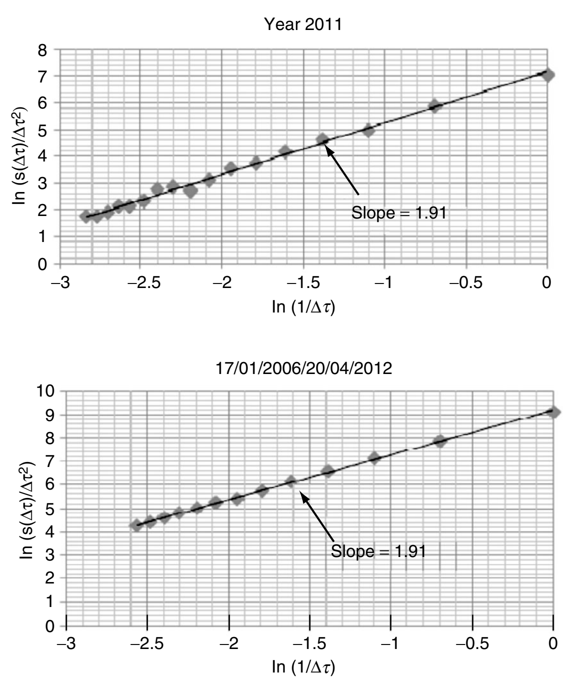

Figure 5 Two examples of log-log plots fitted by the least squares estimation with their slopes which represent an estimated fractal dimension *D*. Left column: year of 2011. Right column: all the studied period (17/01/2006-20/04/2012).

Table 1 Fractal dimension of daily wind speed series for each year studied.

Year	Fractal dimension *D*
2006	1.92
2007	1.94
2008	1.94
2009	1.91
2010	1.93
2011	1.91

REFERENCES

[1] S. Harrouni. Fractal analysis to quantify wind speed fluctuations. *3rd Conference on Nonlinear Science and Complexity (NSC 3rd)*, Ankara, Turkey, 28–31 July 2010.

[2] S. Harrouni, and A. Guessoum. Using fractal dimension to quantify long-range persistence in global solar radiation. *Chaos. Soliton. Fract*. 2009, **41** (3): 1520–1530.

[3] B. D. Malamud, and D. l. Turcotte. Self-affine time series: measures of weak and strong persistence. *J. Stat. Plan. Infer*. 1999, **80** (1):173–196.

[4] P. Maragos, and FK. Sun. Measuring the fractal dimension of signals: morphological covers and iterative optimization. *IEEE. T. Signal. Process*. 1993, **41** (1): 108–121.

[5] C. Tricot, JF. Quiniou, D. Wehbi, C. Roques-Carmes, and B. Dubuc. Evaluation de la dimension fractale d'un graphe. *Rev. Phys*. 1988, **23**: 111–124.

[6] B. Dubuc, F. Quiniou, C. Roques-Carmes, C. Tricot, and S.W. Zucker. Evaluating the fractal dimension of profiles. *Phys Rev A*. 1989, **39** (3): 1500–1512.

[7] S. Harrouni, A. Guessoum, and A. Maafi. Classification of daily solar irradiation by fractional analysis of 10–min–means of solar irradiance. *Theor. Appl. Climatol*. 2005, **80** (1): 27–36.

[8] S. Harrouni, and A. Guessoum. New method for estimating the time series fractal dimension: Application to solar irradiances signals. In: *Solar Energy: New research*, (Tom P. Hough. (Ed)). Nova Science Publishers, New York, 2006, 277–307.

[9] S. Harrouni. Fractal classification of typical meteorological days from global solar irradiance: Application to five sites of different climates. In: *Modeling solar irradiance at earth surface*, (Viorel Badescue. (Ed)). Springer Verlag Berlin Heidelberg, Germany, 2008, 29–54.

[10] G. Bouligand. Ensembles impropres et nombre dimensionnel. *Bull Sci Math*. 1928, **52** (2): 320–344, 361–376.

[11] *http://www.meteo-paris.com/ile-de-france/station-meteo-paris/pro/*

[12] T.P Chang, H-H Ko, F-J Liu, P-H Chen, Y-P Chang, H-Y Liang, H-Y Jang, T-C Lin and Y-H Chen. Fractal dimension of wind speed time series. *Appl. Energ*. 2012, **93**: 742–749.