CORE Metadata, citation and similar papers at core.ac.uk
Provided by I-Revues

Scaling forecast models for wind turbulence and wind turbine power intermittency

Olmo Duran Medina[a], François G. Schmitt[a], Rudy Calif[b]

a. Univ. Lille, CNRS, Univ. Littoral Côte d'Opale, UMR 8187, LOG, Laboratoire d'Océanologie et de Géosciences, F-62930 Wimereux, France. olmo.duran@gmail.com ; francois.schmitt@cnrs.fr
b. Université des Antilles, LARGE, Laboratoire de Recherche en Géosciences et Energie, Pointe-à-Pitre, France. rudy.calif@univ-antilles.fr

Abstract :

The intermittency of the wind turbine power remains an important issue for the massive development of this renewable energy. The power variability of the produced electricity are inherent to the wind variations, thus the turbulence. The energy peaks injected in the electric grid produce a supplementary difficulty in the energy distribution management. Hence, a correct forecast of the wind power in the short and middle term is needed due to the high unpredictability of the intermittency phenomenon. We consider a statistical approach through the analysis and characterization of stochastic fluctuations. The theoretical framework is the multifractal energy cascades. The tools and methods aim to study the influence of the fully developed turbulence on a horizontal three-blade wind turbine. Here, we consider simultaneous input/output data coming from two wind turbines which have a Direct Drive technology. Those turbines are producing energy in real exploitation conditions and allow to test our forecast models of power production at a different time horizons. The spectral analysis first provide information about the scaling properties observed in the wind and the power time series. Besides, the structure functions describe the multifractal statistics by the characterization of the intermittency parameters. Finally, two forecast models were developed based on two physical principles : the scaling properties on the one hand and the intermittency in the power output increments on the other. The first tool is related to the intermittency through a multifractal log-normal fit of the power fluctuations. The second tool is based on an analogy of the power scaling properties with a fractional brownian motion. This last tool exploits an inner long-term memory contained on both time series. The encouraging results present the first steps for a unique forecast model based on a stochastic approach.

Keywords : Turbulence, forecast, intermittency, stochastic fluctuations, multifractal energy cascade

1 Introduction

The expansion of the installed wind turbine energy capacity is a result of the growing demand of power sources with carbone dioxide low-emissions. One of the long-term challenges of the massive development of wind turbines remains the wind power variability within the electric grid [1, 2]. Due to this power variability, also called intermittency, power production forecast is a challenge. An efficient prediction system may allow an adaptation of the wind turbine with the aim of stability in the power delivered. The yaw, the pitch, the cut-out, among other settings can be indeed adjusted accordingly, in order to optimize and stabilize power production for its correct distribution.

Over the last thirty years, several forecasting methods have been published [3], based on statistical methods, probabilistic learning methods or the survey of climate physical parameters. One can differentiate two different forecasting approaches. On the one hand, the approach to forecasting that considers the specific on-site conditions at the wind turbine farm emplacement. The recorded input parameters (temperature, atmospheric pression, humidity, orography, roughness, among others) are completed by the Numerical Weather Prediction (NWP) data for the refinement of the model by a downscaling method. On the other hand, an alternative is statistical modeling, that requires an important historical series which is used to build and to train the model. In many cases, a wind prediction is first commonly realized and the wind power is then deduced through a function such as the law of 1/7 [4], cubic law of the power curve [5, 6] or the combination of several models [7]. Here, we propose an statistical approach where we prefer to directly focus on the power signal. We present two prediction models based on a scale invariance approach with a particular attention to the stochastic prediction of the power output of wind turbines. We present first the theoretical framework. Besides, we show the forecasting methods that are applied to the power measurements coming from two wind turbine power time series.

2 Dataset

The dataset come from two horizontal three-blade wind turbines manufactured by Enercon. The first turbine is an on-shore turbine Enercon E-44 with a nominal power of 0.9 MW. The second turbine is an on-shore E-82 that generates a nominal power of 2 MW. The data was recorded during one year, producing energy in real exploitation conditions. Multiple simultaneous time series were recorded and here we focus on the wind velocity $V(t)$ recorded from the top of the hub and the power output $P(t)$.

The sampling frequency represents 10 minutes average following the norm IEC 2000b [9]. Thus, the statistical properties are limited to time scales larger than this data rate. However, this data rate will allow to test our forecast models of power production at different time horizons. Both turbines present a direct drive technology : it means that there is not a gear box multiplying the revolutions of the main shaft. Further specifications of both turbines are provided in table 1 below.

TABLE 1 – Technical specifications.

	E-44	E-82
Nominal power [MW]	0.9	2
Rotor diameter [m]	44	82
Hub heigh [m]	45	85
Swept area $[m^2]$	1521	5281
Rotational speed $[tr/min]$	Variable, 12-34	Variable, 6-18
Cut-out wind $[m/s]$	28-34	28-34
Wind class (IEC)	IEC/NVN IA	IEC/EN IIA
Generator	annular, Direct-Drive	annular, Direct-Drive

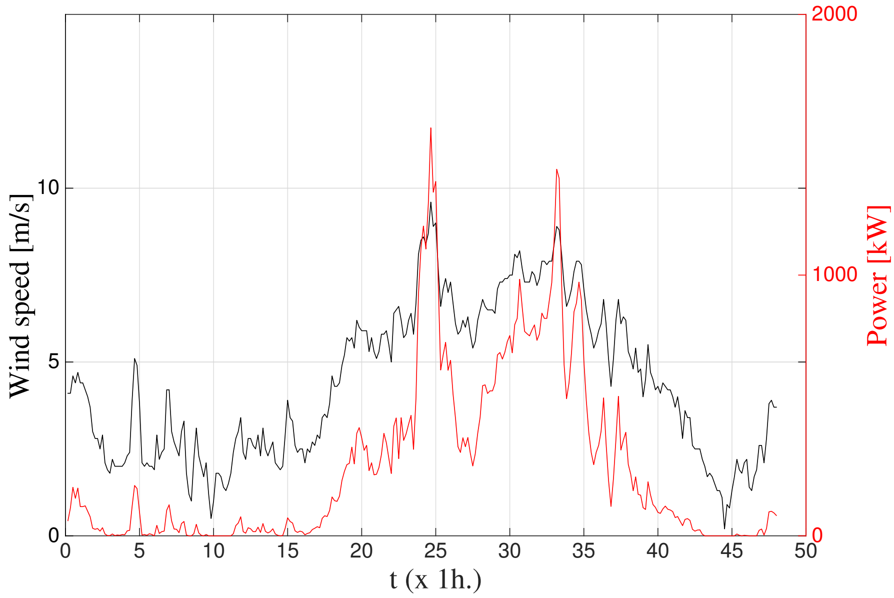

FIGURE 1 – An example of 48 hours of the recorded data coming from a wind turbine Enercon E-82. The wind and power are intermittent and seem to be related. Indeed, both curves present an analogous outline following generally an ascending and decreasing pattern.

3 Methods

3.1 Multiscale energy cascades framework

The power variability of the produced electricity is linked to the wind variations, thus the turbulence. The wind and power intermittency as seen in Fig.1 are indeed a consequence of the fully developed turbulence on a horizontal three-blade wind turbine. These sudden fluctuations are manifested at different scales and their properties are commonly studied in the framework of multifractal turbulence. We introduce the multiscale energy cascades, a classic theoretical framework in the fully developed turbulence [11, 13, 12]. The power spectral density of the velocity will follow, with the hypothesis of homogeneous and isotropic turbulence, a power law corresponding to a -5/3 power-law in the inertial range. Through the Taylor frozen hypothesis, the Fourier power density spectrum $S(f)$ is of the form [10] :

$$S\left(f\right) \sim f^{-5/3} \tag{1}$$

where f is the frequency. In figure 2, the power spectra show for both time series, a nice scaling with a -5/3 slope from the lowest time scale of 10 minutes, to a frequency of 10^{-6} Hz that represents 2 days. The wind power law scaling were already found in multiple works [17, 18, 16, 22]. Besides, the power possesses as well a 5/3 scaling exponent : the wind intermittency properties are certainly transferred, probably due to the Direct Drive technology. In [14] for example, the same power spectrum behavior has been exposed without provide an explanation of such behavior.

The turbulence is a multiscaling phenomenon where there is an interaction between the different time-space scales in the inertial range. The spectral properties of the multiscale fluctuations is known to produce multifractal statistics, classically studied by the structure functions.

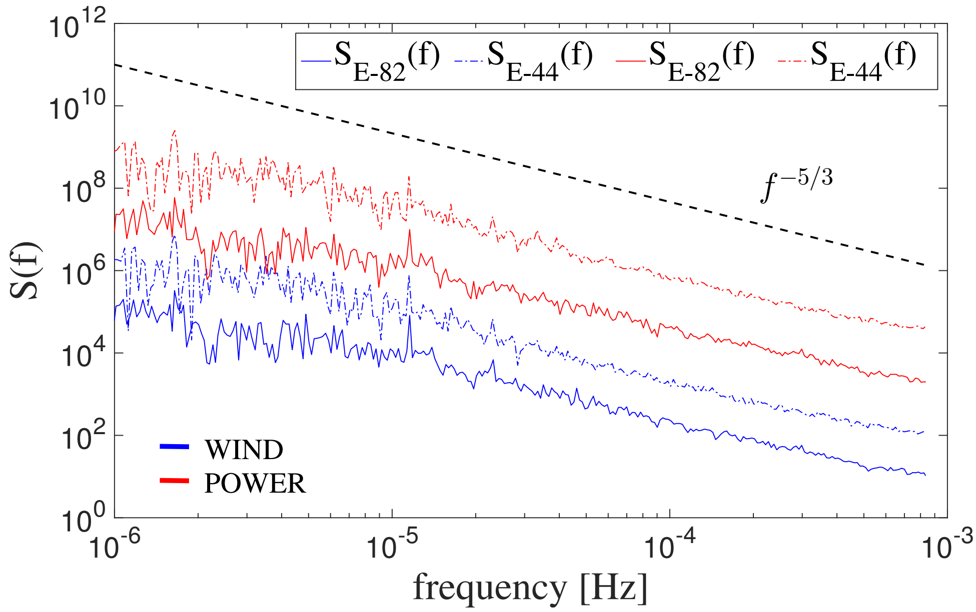

FIGURE 2 – Power Spectra of wind velocity (blue) and wind turbine power output (red). The dashed line represents a -5/3 slope as a reference. A vertical shift was applied with a plot purpose.

3.2 The structure functions

The multiscaling statistics indicates a memory in the processes due to the scale invariant cascade process for the turbulent wind. In the framework of fully developed turbulence, the application of the statistic moments on the velocity increment was first considered by Kolmogorov in 1941. If V is the wind velocity, the wind fluctuations are defined by $\Delta V_\tau = V(t+\tau) - V(t)$ for a time scale τ belonging to the inertial scale. The structure functions of order q have a scaling behavior :

$$\langle |\Delta V_\tau|^q \rangle \approx \tau^{\zeta(q)} \tag{2}$$

where $\langle . \rangle$ means statistical average. The absolute value allows to considerate non integer q moments (for $q \geq 0$). The function $\zeta(q)$ is the scale invariant moment function that indicates the multifractal behavior of the considered time series. Indeed, if $\zeta(q)$ is a linear function, the time series is considered a monofractal process. In the opposite, a non-linear and concave $\zeta(q)$ function corresponds to a multifractal process. The more $\zeta(q)$ is concave, the more the time series fluctuates.

There are several multifractal models to fit such structure function [12, 15]. The log-normal model remains a classical fit for the scale invariant moment function $\zeta(q)$. With the constraints $\zeta(0) = 0$ and $\zeta(1) = H$, the quadratic function has the following form :

$$\zeta_{LN}(q) = qH - \frac{\mu}{2}\left(q^2 - q\right) \tag{3}$$

where H is the Hust exponent ($0 < H < 1$) and μ is chosen here to verify $\mu = 2H - \zeta(2)$. H defines the degree of roughness or smoothness of the considered time series and μ ($0 \leq \mu \leq 1$) is the intermittency exponent. Figure 3 shows the scale invariant moment function for the wind and power output time series coming from the E-82 turbine. A similar behavior is as well observed for the E-44 turbine (not shown). The concavity and non linearity of both $\zeta(q)$ functions indicate that theirs fluctuations obey multifractal statistics. Table 2 provides the different log-normal model parameters (H, μ) estimated for each series. In the present case, we obtain $\mu(P(t)) > \mu(V(t))$ for both turbines, hence the power time series show a more fluctuating behavior in comparison to the wind time series. This is verified by the concavity of the $\zeta(q)$ curve corresponding to the power output, the wind turbine seems to amplify the wind fluctuations for which $\zeta(q)$ is less concave.

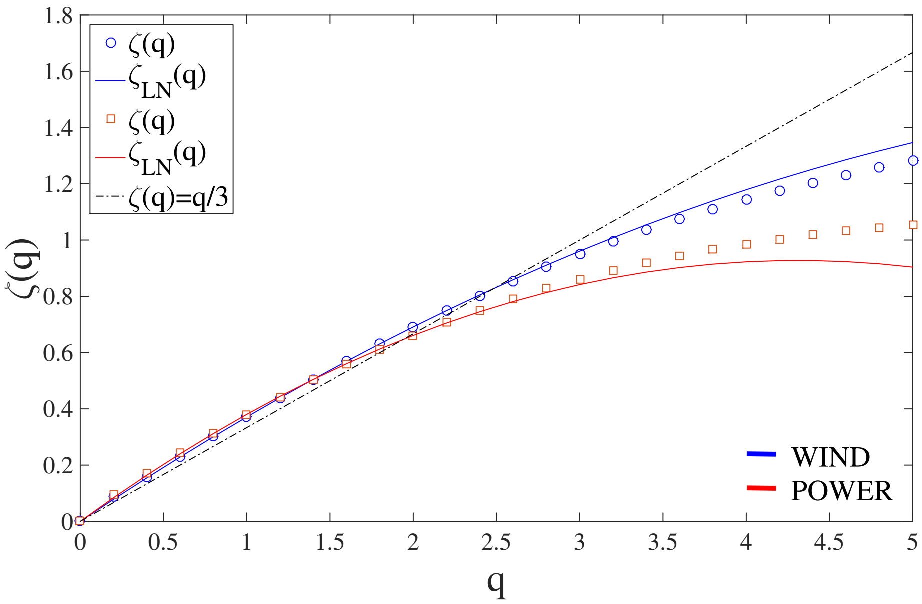

FIGURE 3 – The scale invariant moment function $\zeta(q)$ estimated for wind and power output series coming from the turbine E-82. The log-normal models $\zeta_{LN}(q)$ are superposed for each curve : the fit is respected for the lowest orders. The $\zeta(q)$ functions are concave and compared to the linear function $q/3$ (dashed line) which indicate the multifractal properties.

TABLE 2 – Multifractal parameters.

Turbine	Data	$H = \zeta(1)$	$\zeta(2)$	μ
E-44	Wind velocity	0.41	0.78	0.046
	Power output	0.41	0.76	0.094
E-82	Wind velocity	0.35	0.66	0.048
	Power output	0.36	0.62	0.098

4 Forecasting Tools

4.1 1st forecasting model : Scaling memory

The forecasting model presented in this section is based on the intrinsic scale memory of the fractional Brownian motion (fBm) process. Indeed, there is a long-range memory coming from the scale invariant properties [19] observed in both turbine's power output spectra. The fBm process is a Gaussian model at the stationary increments of covariance function $Cov(B_t, B_s) = min(s,t)$, a standard model for a stochastic process with a self-similarity property. The forecast approach is based in an analogy of the power output $P(t)$ with a fBm process of order H, with a Hurst index $H < 1/2$ (cf. table 2). The long-range memory property of the power output time series can be exploited to realize a forecast. In the mathematical literature, such forecast expression is written by expressing a conditional expectation [20, 21] :

$$E\left[B_H\left(T\right)|\sigma\left(B_H(s):-\infty < s \le t_1\right)\right] = C\int_{-\infty}^{t_1}\left(\frac{T-t_1}{t_1-s}\right)^{\alpha}\frac{1}{T-s}B_H(s)ds \tag{4}$$

where $C = 1/\pi \sin\pi(1/2-H)$ and $\alpha = 1/2+H$. The discretization of the equation 4 is written as follows :

$$\hat{P}\left(t+T_0\right) = C\sum_{i=t-T1}^{t-1}\left(\frac{T_0}{T_1-i}\right)^{\alpha}\frac{P(t-T_1+i)}{T_0+T_1-i} \tag{5}$$

where $\hat{P}$ is the power prevision, t is the present time, T_0 is the forecast horizon, T_1 replace $-\infty$ and $s = t - T_1 + i$. Indeed, the range $[T_1, t]$ correspond to the learning window necessary in the statistical approach (cf. section 1). The index H is chosen from the whole measured power data for better statistics (cf. table 2).

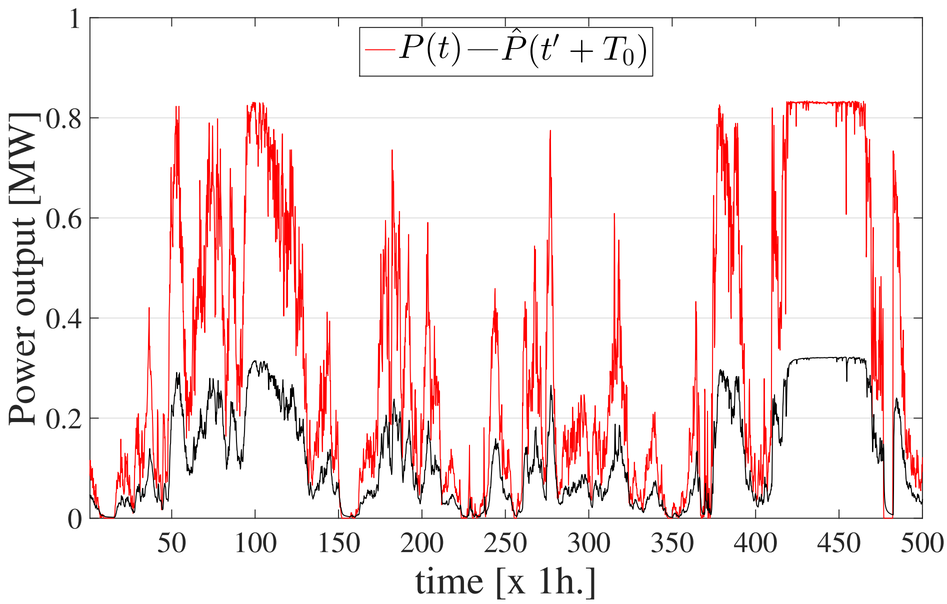

Figure 4 – Example of the forecast model applied to the E-44 turbine. This is a running forecast, with time t going from 0 to 500 and T_0 fixed. The method is based on the long-range properties of invariant scale processes. The method has been applied during a period of 500 hours where the forecast horizon is $T_0 = 10$ minutes and the learning window is $T_1 = 166$ hours.

The application of such methodology is illustrated in the figure 4. The model runs during a period of 500 hours with a forecast horizon $T_0 = 10$ minutes. The learning window $T_1 = 166$ hours has been chosen as approximative 1/3 of the considered period. The estimated power $\hat{P}\left(t+T_0\right)$ follows the global tendency of the real power output. One can remark that the forecast follows the upward and downward variations without capturing however, the peaks and sudden power changes. Besides, the power prevision presents clear underestimation. This is a consequence of the mono-fractal character of the forecast model since the equation 4 has been formulated for a fractional Brownian motion, a mono-fractal process. This model does not take into account the multiscale fluctuations of the wind power that is characteristic of a multifractal process.

The principal advantage of this method is the ability to estimate power with missing values since the scalar memory depends on the learning window, hence T_1. In the case of a dysfunction of the data recording, this model is able to provide an information of the upward and downward power variations if the missing values are negligible with respect to the considered window. One can increase the learning window with an impact on the calculation time that remains below the data rate of 10 min.

4.2 2nd forecasting model : Log-normal fluctuations

This second model runs using directly the hypothesis of lognormal multifractal fluctuations. In the log-normal framework, we consider the fluctuation $\Delta P_{T_0} = |P(t+T_0) - P(t)|$, obeying a lognormal law written as :

$$p(z) = \frac{1}{z\sigma\sqrt{2\pi}} \left[-\frac{(\log(x) - m)^2}{2\sigma^2} \right] \tag{6}$$

where $m = \langle \log X \rangle$ and σ is the standard deviation of $\log X$. The method consists first into adjusting the probability density function (PDF) of the fluctuations ΔP of the power time series with a forecast horizon of T_0. Through this PDF fit, the power estimation is then estimated as follows :

$$\hat{P}(t+T_0) = P(t) \pm \Delta P_{T_0} \tag{7}$$

where ΔP_{T_0} is a random variable obeying the PDF given in (6). Figure 5 illustrates the PDF of $z = \Delta P_{T_0}$ for a forecast horizon of $T_0 = 10$ min applied to the turbine E-82. The dashed line correspond to the log-normal fit (cf. equation 6) where $m = \langle \log z \rangle$ and $\sigma^2 = \left\langle (\log z - m)^2 \right\rangle$. Indeed, the values (m, σ^2) were estimated during the learning phase. Although this adjustment have a nice correspondence on the interval $x \in [20; 300]$, the fit is not representative for the extreme values.

Through this adjustment , the power prediction $\hat{P}$ at the horizon T_0 is written as follows :

$$\hat{P}(t+T_0) = P(t) + sZ \tag{8}$$

where s is a sign, taking the value +1 or -1 according to a binomial distribution with a parameter 1/2. Z is a log-normal random variable generated within the log-normal PDF adjustment. This is simply written $Z = \exp(m + \sigma g)$ where g is a normal random variable with a zero mean and a variance equal to 1.

The application of this forecast model is shown in figure 6. There is a superposition of the measured data $P(t)$ and the stochastic predictions $\hat{P}$ where the forecast horizon is $T_0 = 10$ min. and $t' = t - T_0$. We consider a learning window of 6 months and a 200 hours forecast period.

The general tendency is well followed, but the power energy pikes are not well predicted in general. Indeed, one of the weakness of such statistical approach is the difficulty to well determine the sign (cf.

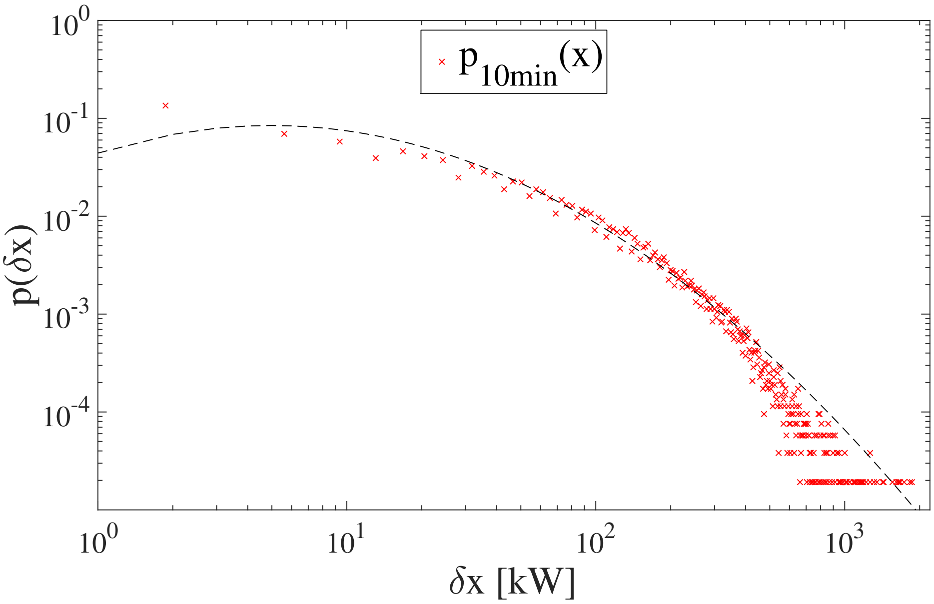

FIGURE 5 – Probability density function $p(x)$ applied to the power output increments of the E-82 turbine at a time interval of 10 min. The log-normal fit (dashed line) is globally correct. Nevertheless, this adjustment does not capture power increments less than 20 kW and higher than 300 kW. The extremes are overestimated.

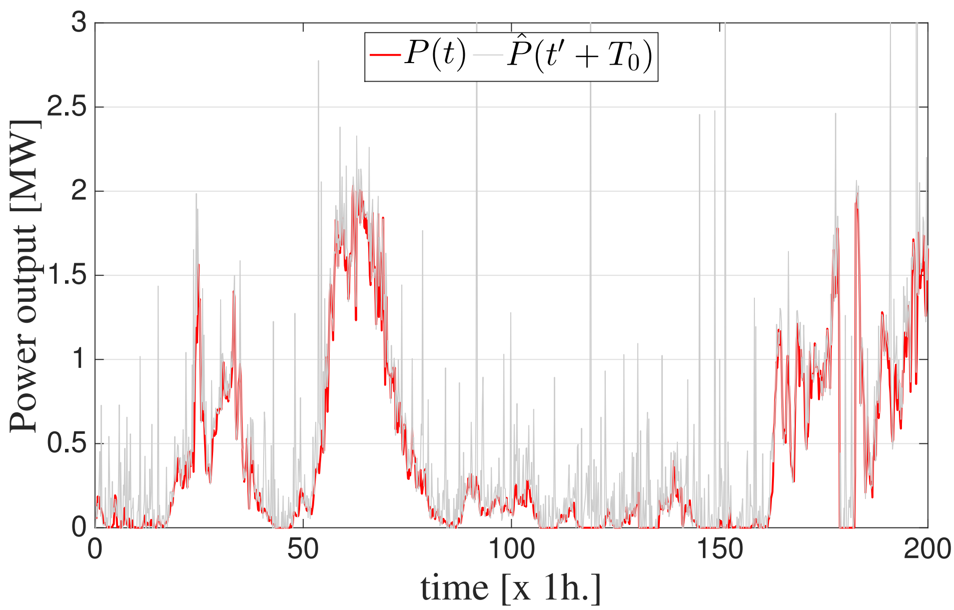

FIGURE 6 – Example of the forecast model based on a log-normal distribution of the power increments during a period of 200 hours. The method was applied to the power output coming from the E-82 turbine with a forecast horizon $T_0 = 10$ min.

s eq. 8) for a correct estimation of the value $P(t)$. The information of the sign is lost by the application of the method and the binomial distribution is not adapted for the fluctuations complexity. On the other hand, the pikes represent overestimated values of $\hat{P}$ due to the inadequate adjustment of the PDF extremes. One possible futur improvement of this approach is the fusion of the lognormal multifractal properties with the long-range properties of invariant scale processes as seen in section 4.1.

5 Conclusion

We have consider two time series from two wind turbines. The data was recorded during one year at a sampling frequency of 10 minutes which provides good statistics for the application of two forecasting tools. In the framework of the multifractal energy cascades, the wind velocity and power output time series possess scaling fluctuations since both spectra follow a -5/3 power law for scales from 10 minutes to 2 days. This could be possibly due to the Direct Drive technology that allows the intermittency properties transfert.

The structure functions have allowed the analysis of the multifractal statistics through the observed multiscaling properties. The estimation of the scaling moment functions $\zeta(q)$ reveals the fluctuating behavior of wind and power time series. Larger fluctuating degree μ are is observed for the power output for the two considered wind turbines. The privileged hypothesis of this phenomenon is an amplification of the wind fluctuations by the wind turbine.

Two forecast models were developed based on the memory generating principles : the first forecasting tool is based on an analogy of the power scaling properties with a fractional Brownian motion. The second is related to the intermittency through a multifractal lognormal fit of the power fluctuations. These are the first steps to a search of efficient forecasting approaches for grid adaptation facing the wind energy fluctuations. Such methods are, to our knowledge, the first attempt to provide a forecast stochastic model exploiting the inner data physical properties. Although both models show encouraging results since a correct tendency of the signal is respected, multiple difficulties are to be managed before a correct application in the field. Some obstacles could be solved through a combinaison of both forecast methods, which will be considered in further works.

Finally, further studies will be realized in order to compare those methodologies with the existent ones, specially with the persistance forecasting method, an elementary forecast method from which many methods are classically compared. Actually, the error estimate over different forecast horizons will indicate the performance of our models.

Références

[1] G. Van Kuik, J. Peinke (ed.), Long-term Research Challenges in Wind Energy-A Research Agenda by the European Academy of Wind Energy, Springer (2016).

[2] R. Calif, F. G. Schmitt, O. Duran Medina, -5/3 Kolmogorov Turbulent Behaviour and Intermittent Sustainable Energies, In Sustainable Energy, Intech (2016), edited by A. Zobaa, S. A. Aleem and S. N. Afifi, pages 95-107.

[3] A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, E. Feitosa, A review on the young history of the wind power short-term prediction. Renewable and Sustainable Energy Reviews (2008), 12(6) :1725–1744.

[4] W. D. Lubitz, Power law extrapolation of wind measurements for predicting wind energy production. Wind Engineering (2009), 33(3) :259–271.

[5] B. G. Brown, R. W. Katz, A.H. Murphy, Time series models to simulate and forecast wind speed and wind power. Journal of Climate and Applied Meteorology (1984), 23(8) :1184–1195.

[6] G. D'Amico, F. Petroni, and F. Prattico, Wind speed and energy forecasting at different time scales : A nonparametric approach. Physica A (2014), 406 :59–66.

[7] Sanchez, I, Short-term prediction of wind energy production. International Journal of Forecasting (2006), 22(1) :43–56.

[8] J. Jung, R. P. Broadwater, Current status and future advances for wind speed and power forecasting. Renewable and Sustainable Energy Reviews (2014), 31, 762-777.

[9] J. F. Manwell, J. G. McGowan, A. L. Rogers, Wind energy explained : theory, design and application, John Wiley & Sons (2010).

[10] A. S. Monin, A. M. Yaglom, Statistical fluid dynamics Vol. I and II, MIT Press (1971).

[11] U. Frisch, Turbulence : The legacy of AN Kolmogorov, Cambridge University Press (1995).

[12] Schmitt, F. G. and Huang, Y. Stochastic analysis of scaling time series : from turbulence theory to applications, Cambridge University Press (2016).

[13] S. Pope, Turbulent flows, Cambridge University Press (2000).

[14] J. Apt, The spectrum of power from wind turbines, Journal of Power Sources (2007), 169(2) :369-374.

[15] D. Schertzer, S. Lovejoy, F. G. Schmitt, Y. Chigirinskaya, D. Marsan, Multifractal cascade dynamics and turbulent intermittency, Fractals (1997), 5(03) :427-471.

[16] R. Calif, F.G. Schmitt, Multiscaling and joint multiscaling description of the atmospheric wind speed and the aggregate power output from a wind farm, Nonlinear Processes in Geophysics (2014), 21(2) :379-392.

[17] F. G. Schmitt, Gusts in intermittent wind turbulence and the dynamics of their recurrent times, In Wind Energy, Proceedings of the Euromech Colloquium, edited by J. Peinke, P. Schaumann and S. Barth, Springer (2007b), pages 73-79.

[18] J. F. Muzy, R. Baile, P. Poggi, Intermittency of surface-layer wind velocity series in the mesoscale range, Physical Review E (2010), 81(5).

[19] J. Beran, Statistics for long-memory processes, CRC Press (1994), volume 61.

[20] A. M. Yaglom, Correlation theory of processes with random stationary nth increments, Amer. Math. Soc. Transl. (1958) (2), 8 :87-141.

[21] V. V. Anh, A. Inoue, Prediction of fractional brownian motion with hurst index less than 1/2. Bulletin of the Australian Mathematical Society (2004), 70(02), 321-328.

[22] O. Duran Medina, F.G. Schmitt, R. Calif, Multiscale analysis of wind velocity, power output and rotation of a windmill, Energy Procedia (2015), 76 :193-199.