An experimental analysis of wind and power fluctuations through time-resolved data of full scale wind turbines

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Abstract. Addressing short-term wind and wind turbine power fluctuations is fundamental in order to understand the nature of turbulence and of the mechanical loads to which wind turbines are subjected. This work is an experimental study of wind and power fluctuations at an onshore wind farm in Italy. Four wind turbines having 2 MW of rated power each are studied through time-resolved data. The sampling frequency is of the order of the Hz. This wind farm has been selected because there are two orders of magnitude of inter-turbine distance (3 and 7 rotor diameters) and therefore it is possible to study different levels of wake interactions recovery. The power curve at short time scales is studied and the inertia of the wind turbines, with respect to the wind fluctuations, is observed in the form of hysteresis of the power curve. Subsequently, the distribution of the wind and power variations is studied on several time scales and different features of the distributions are observed for downstream wind turbines with respect to upstream ones. The two-point statistics of power and wind-power is shown to be responsive to the wake regime to which wind turbines are subjected. This can suggest new approaches for wake control strategies.

1. Introduction
Addressing short term wind fluctuations is the keystone for characterizing the mechanical behavior and the power production of wind turbines on its adequate time scale. The Langevin approach [1] is a framework consisting of a direct method for extracting the evolution equation of a stochastic series of measurements and it has been applied for describing a vast variety of phenomena, from stock markets to wind turbulence. In the latest years, the availability of high frequency wind turbine operational data has boosted the research about the Langevin modeling of the conversion process of the wind kinetic energy into power output and of the fatigue loads distribution. In [2], the conversion process is simplified as a Langevin process for the power conditioned to fixed wind speeds. It is shown that for short time scales, where the control system of the wind conversion systems interacts dynamically with wind fluctuations, the statistical features of the power data are qualitatively similar to the wind field itself, but the magnitude of extreme events is severely higher, showing that wind turbines transfer intermittency to the grid and can amplify it. Consequently, these high frequency stability issues are gradually being integrated in the perspectives to be addressed by the industry [3]. In [4], the Langevin approach is used for reconstructing the increment statistics of the torque in single wind turbines as a
tool for estimating fatigue loads, not only of that wind turbine, but also of its neighboring ones. This in perspective can improve the accuracy of condition monitoring and decrease its cost. In [5], the Langevin approach is employed for modelling the normal behaviour of wind turbine tower acceleration for its monitoring. The results demonstrate that the Langevin model is able to better reconstruct non-Gaussian fluctuations of signals with respect to Artificial Neural Network methods. In [6], the application of stochastic models for wind energy industry practice is supported, basing on the study of load and power monitoring. In [7], operational data having 1 second of sampling time are employed for modeling the thrust load. The model is validated against aeroelastic simulations with the FAST code and against measurements of thrust load from strain gauges.

On the grounds of this discussion about the state of the art in the literature, this work is devoted to the characterization of the power curve and of the wind and power fluctuations of four full-scale wind turbines, having 2 MW of rated power each, through the analysis of time-resolved data as available from the OPC (Object Linking and Embedding for Process Control) server. This wind farm has been studied also in [8], through SCADA and time-resolved data. It was selected because there are two orders of inter-turbine distances (3 and 7 rotor diameters) and it is therefore possible to study different levels of wake recovery. While in [8], the focus was on how the power fluctuates from one turbine upstream to the next downstream, in this work the aim is studying wind and power fluctuations at each wind turbine, depending on the flow regime (free or disturbed).

The structure of the paper is as follows: in Section 2, the wind farm and the data sets are described. Subsequently, in Section 3 the methods are described; the results are reported in Section 4. The conclusions are summarized and further directions are indicated in Section 5.

### 2. The wind farm and the data set.

Four wind turbines are installed on site. The rated power is 2 MW each. In Figure 1, the layout is sketched and the inter-turbine distances are indicated in Figure 2 in units of the rotor diameter $D$.

![Figure 1. Layout of the wind farm under examination.](image)

|   | T01 | T02 | T03 | T04 |
|---|-----|-----|-----|-----|
| T01 | –   | 6.7 | 6.1 | 7.0 |
| T02 | 6.7 | –   | 3.3 | 6.6 |
| T03 | 6.1 | 3.3 | –   | 3.3 |
| T04 | 7.0 | 6.6 | 3.3 | –   |

*Figure 2. Inter-turbine distances in rotor diameter units.*

From Figure 2, it arises that this wind farm is characterized by two orders of inter-turbine distances: 3D between the T2-T3-T4 cluster and 7D between T1 and the rest of the wind farm. According to the classification in [9], 3D and 7D are both far wakes, but it is evident that they correspond to different levels of wake recovery that it is interesting to study and compare.
order to distinguish them clearly, in the following, 3D shall be referred to as mid wake and 7D to far wake. The data sets employed for this study are time resolved series that have been collected from the OPC server. They have been collected manually on demand because the OPC server doesn’t store them. The frequency of the time series depends on buffering issues but it is constant along each collected time series. It can be reconstructed from the data, by averaging and synchronizing against the SCADA data with 10 minutes of sampling time (as done in [8, 10]). The frequency of the time series employed for this work goes from 0.2 to 1.1 Hz. A vast number of time series has been analyzed and some have been selected, mainly on the grounds of considerations about the wake interactions between the turbines of the farm. The wind measurements come from the nacelle anemometer and the undisturbed wind speed is reconstructed by the control system through the nacelle transfer function. Crosschecks on the reliability of these measurements have been performed. As regards the wind direction, the measurements have been calibrated by computing the speed-up ratio between nearby wind turbines as a function of the wind direction measured by the nacelle anemometer. Due to the inter-turbine distance and the fact that the terrain is quite gentle, it is expected that the speed-up between two wind turbines is minimum (or maximum) at the centre of the wake sector, i.e. along the direction of the straight line between the wind turbines. If this is not the case, there likely is an offset to remove. The direction offsets have been removed and, after that, the power curve according to the IEC [11] guidelines has been crosschecked using the SCADA data and it has been observed that it is well in the limit of contractual guidelines. Therefore, the wind speed measurements have been considered fairly reliable for the objectives of the present work.

3. The methods
The analysis is developed using several methods, in order to characterize the relation between wind speed and power fluctuations by different points of view, possibly in relation with the wake regime to which the wind turbines are subjected.

A summary of the methods is the following:

(i) The short-term power curve has been studied as follows: data are grouped in wind speed intervals having 0.5 m/s of amplitude, from start-up to rated and in power intervals of 100 kW of amplitude up to rated. For each measurement in each interval, the variation of wind speed and power can be computed back or ahead:

\[ \Delta V_{\text{back}}^i = V_i - V_{i-k} \]
\[ \Delta V_{\text{ahead}}^i = V_{i+k} - V_i \]  
\[ \Delta P_{\text{back}}^i = P_i - P_{i-k} \]
\[ \Delta P_{\text{ahead}}^i = P_{i+k} - P_i \]  

(1) \hspace{1cm} (2)

\( k \) is the step and it is linked to the time shift back or ahead: \( \Delta t = \frac{k}{\nu} \), where \( \nu \) is the sampling frequency of the time series. Inside each interval, the normalized average of the above quantities can be computed and therefore a map of the power curve against wind and power variations can be constructed. Doing this, it is possible to connect, at least qualitatively, the most straightforward analysis tool of wind turbine performances (the power curve) to the wind and power variations on short time scales.

(ii) The study of the power curve using time-resolved data, as indicated above, highlights qualitatively how the control system of the wind turbines affects the phase between the wind and power signals. This motivates a quantitative analysis of the two-point statistics of wind and power measurements: for this reason, the cross-correlation between wind and speed and the autocorrelation of the power are studied. The autocorrelation of the power \( P \) with lag \( k \) is defined as

\[ c_k = \frac{1}{T\sigma_P^2} \sum_{t=1}^{T-k} (P_t - \bar{P})(P_{t+k} - \bar{P}), \]  

(3)
where $\sigma_P^2$ is the variance of the power and $\bar{P}$ is the average of the sample time series. The definition is similar when dealing with the cross-correlation. In order to compare different turbines, possibly subjected to different wake regimes, the correlation have been normalized to their maximum. These quantities have been further elaborated, with the objective of following quantitatively the evolution in time of the wake regime (depending on the wind direction), for the different wind turbines in the farm. This has been done as follows: the wind and power signals have been cut in slices of fixed amplitude, whose center moves with time, and the discrete integral (with the trapezoidal method) of the cross-correlation and autocorrelation is computed and normalized to the length of the subsample for each selected subsample. This results in a function of the center of the subsample, having values between 0 and 1: it can be considered as a Wake Index because, as argued in Section 4, it is responsive to the fluctuations and therefore to the wake regime to which the wind turbines are subjected. The notation is the following: the Wake Index computed from the autocorrelation of the power is indicated as $\tilde{\Lambda}$ (Equation 4), the Wake Index computed from the wind-power cross-correlation is indicated as $\hat{\Lambda}$.

$$\tilde{\Lambda} = \frac{1}{N_p} \sum_{k=1}^{N_p} \frac{c_k}{\text{max}(c_k)}.$$  

Equation 4

(iii) Finally, the variations of wind and power are computed on several time scales and analyzed statistically: their distribution in units of standard deviation is analyzed. This technique is useful for several objectives: for example, the deviations of the distribution from the Gaussian, depending on the time scale, can be studied.

4. Results

In Figure 3, a sample power curve is reported for the T1 wind turbine. The scale of colors refers to the values of $\bar{V}_{\text{back}}$, where $k = 1$: in other words, the wind speed fluctuations at the shortest observable time scale are put in relation to the power curve. In red, the theoretical power curve is plotted.
The first thing to notice is that, as expected, the power curve observed through high frequency data shows much more variability with respect to the theoretical power curve based on 10 minutes sampling time. In particular, the hysteresis phenomenon is observable: when the wind increases (colors towards the yellow), the production is lower than the theoretical: the wind turbine must run after the wind. On the other way round, when the wind intensity decreases (colors towards the blue), the wind turbine is producing more than the theoretical production: this is due to the wind turbine inertia. These observations stimulate a deeper and more quantitative comprehension of the phase shift between wind and power signals.

In Figure 4, the distributions of the normalized wind and power output fluctuations are reported as a function of the standard deviation, considering a time interval of 25 seconds. A time series has been selected, during which the wind was blowing from around 300° of direction and with an intensity associated to medium-high thrust regime: T2 and T3 are therefore under the wake of T4. From Figure 4, it is possible to distinguish between the upstream isolated wind turbine (T1), the upstream wind turbine in the cluster (T4) and the downstream wind turbines in the cluster (T2 and T3). The lesson is that the distributions of wind speed and power fluctuations are more populated at the tails for the downstream wind turbines. Further, by comparing T1 against T4, some qualitative differences arise that can be probably explained by the fact that wake interactions produce a sort of retro-feedback also at the upstream wind turbine of a cluster.
Figure 4. Sample distributions of the fluctuations of power output and wind speed normalized versus the standard deviation considering a time interval of 25 seconds.

The above observations about Figure 4 inspire the further developments of this work, that are obtained through the analysis of the wind-power cross-correlation and of the autocorrelation of the power, elaborated through the Wake Index formulated in Section 3.

Figures 5 to 8 refer to a time series characterized by the the wake of turbine T4 on turbines T2 and T3: this corresponds to what in Section 2 is labeled as mid wake. The Wake Index, defined in Section 3, is reported for the wind-power cross-correlation and for the power auto-correlation. Contextually, the wind direction measured by the upstream T4 wind turbine and the powers of all the wind turbines are reported in Figures 7 and 8. The Wake Index reported in Figures 5 and 6 is computed using a basis of 600 measurements rigidly moving along the time series. The rationale for this choice is that 600 measurements from the time series at disposal roughly correspond to one SCADA measurement with 10 minutes of sampling time: the time evolution of the Wake Index therefore provides a picture of the complex underworld of fluctuations that the SCADA averaging smears out. Ar regards the time series selected as instructive, notice that the more the wind direction approaches the center of the wake sector [12] between T4 and T2-T3 (indicated by the horizontal line in Figure 7) the more the Wake Index diminishes. Actually, because of its definition (Equation 4), a low value of the Wake Index means severe fluctuations. Therefore, the basic lesson is that the Wake Index is responsive to the level of wake fluctuations. This is a first recognition of the fact that the proposed Wake Index could be used for exploring fluctuations in more challenging regimes: for example, in complex terrain, where wake interaction mix with terrain effects. Furthermore, the Wake Index could be of interest for understanding the response of the wind turbine according to the control system and therefore for possibly customizing it as a function of the wake regime. Finally, it is interesting to notice a slight retro-feedback at the T4 wind turbine, especially as regards the power-power correlation (this is consistent with what arises from Figure 4).
In order to better understand the procedure and the results, in the following Figures 9 and 10, the autocorrelation of the power and the wind-power cross-correlation are reported for two sensible intervals: the one starting from the first point of the time series (because it corresponds to the maximum in Figure 5) and the one starting from the time stamp of minimum in Figure 5. The selected wind turbine is T3, because it is under the wake of T4. The Wake Index $\tilde{\Lambda}$ and $\hat{\Lambda}$ at the two afore mentioned points in Figures 5 and 6 are the discrete integral of the curves in Figures 9 and 10.
Figure 9. Autocorrelation of the power for T3 for two sample intervals of maximum and minimum wake.

Figure 10. Wind-speed cross-correlation for T3 for two sample intervals of maximum and minimum wake.

In the following Figures 11 to 14, results are reported for a time series during which wake interactions have been mostly absent, except for a small duration of far wake. Actually, at the beginning of the time series, the wind blows from around 245° and this corresponds to the far wake of turbine T1 on T2 (horizontal line plotted in Figure 13): correspondingly, the Wake Index in Figures 11 and 12 diminishes for turbine T2.

Figure 11. Wake Index $\tilde{\Lambda}$ of the autocorrelation of the power. Far-wake time series.

Figure 12. Wake Index $\hat{\Lambda}$ of the autocorrelation of the power. Far-wake time series.
5. Conclusions
The practice of wind farm managing has been based on operational SCADA data having 10 minutes of sampling time. This is practical for a vast number of reasons, but on the other hand the industry commonly doesn’t exploit all the possibilities of data analysis at short sampling times and the academia often lacks a widespread disposal of this kind of data for validating scientific studies. It is therefore valuable to stimulate the dialogue between industry and academia as regards the use of high frequency data of wind turbines and this work has been a contribution to this perspective. The objective has been formulating some methods for elaborating high frequency data in light of the operational conditions of wind turbines. Data time series of an onshore wind farm sited in Italy in a gentle terrain have been analyzed: they have been selected basing on the fact that it has been possible to distinguish between wind turbines under wake (with different level of recovery) and wind turbines catching free wind. The different high frequency behavior of upstream and downstream wind turbines is observable in the distribution of wind and power fluctuations (Figure 4) and especially through the analysis of two-point statistics. A Wake Index has been formulated for observing the time evolution of the features of the wind and power two-point statistics: the Wake Index has been interpreted in light of the high frequency data giving information about the wind conditions (and therefore the wake regime). It arises that the proposed index is responsive to the onset of wake interactions and the responsiveness is related to the wake recovery level. Further, the analysis of the Wake Index also highlights a retro-feedback effect on the upstream wind turbine, whose wake affects the downstream ones. This can be considered an interesting element for studying wind farm blockage effects, induced by wakes, using high frequency operational data. Summarizing, the lesson from this work is that the two-point statistics is particularly adequate for investigating the role of the control system in responding to them with a certain constitutive inertia. This can be instructive for understanding turbulence and for connecting theoretical modeling of fatigue loads on wind turbine blades to measurements, for upstream and downstream wind turbines. This could also possibly highlight the different role of the control system in acting as a further source or sink of loads, depending on the wake regime. Several are the possible further directions of this work: it would be interesting to study the impact of the control system by comparing against aeroelastic simulations. The availability of high-frequency data could be empowered by the measurement of mechanical loads for the comprehension and the modeling of the control system. This is particularly useful in the perspective of customized control system algorithms [13] for mitigating wake losses and fatigue damage of the wind turbines.
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