Non-deterministic wind observation from wind turbine loads

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Abstract. In this work, the wind sensing technology that exploits the turbine rotor as an anemometer is further developed into a non-deterministic formulation. First, an inflow-turbine response map is identified, which relates out and in-plane blade root bending moments to both vertical and horizontal shears and misalignments. Then, this linear model is used with and without a Kalman filter to estimate online the wind field at the rotor disk once blade loads are measured. A comprehensive simulation study, including different wind speeds and turbulence intensity levels, was performed to evaluate the accuracy of the new non-deterministic formulation. The results show that introducing a Kalman filter in the estimation process allows for a significant improvement in the angle estimates with respect to the deterministic formulation, with no considerable additional computational cost.

1. Introduction

Reliable and accurate measurements of the inflow conditions at the rotor disk are of significant importance both at the single turbine level as well as within a wind farm. To realign the rotor to the wind, decreasing in turn fatigue loads and increasing the harvested power, one must be aware of the horizontal wind direction. Such information is particularly valuable for wind farm control strategies as well, where one could also make use of the estimate of the impinging horizontal shear for wake detection. The wake recovery rate could be inferred from the level of stability of the atmosphere, which is strongly linked to the vertical shear exponent, but also information about the vertical wind direction could prove useful to characterize the flow in complex terrain.

To measure the wind inflow in the field, commonly used devices are nacelle anemometers and met-mast towers. While the first ones provide with a pointwise measurement of the wind speed and horizontal wind misalignment at the nacelle, the latter can also provide information about the vertical shear, since they are normally equipped with more measurement points over the height. Still, this information is representative of an inflow not co-located with the turbine, whereas the nacelle measurements have to be corrected for blade passing and interference with the nacelle. To characterize the free stream at the rotor disk as well as to measure also the vertical wind direction and the horizontal shear, one might use LiDARs, which are nevertheless still relatively costly and susceptible to weather conditions.

To overcome such issues and to ensure that inflow measurements are actually rotor-effective, i.e. measured at the rotor disk and over the rotor disk area, references \cite{7, 2} have proposed to turn the rotor itself into an anemometer. Indeed, in \cite{7, 2} the turbine response is linked to the spatial dis-homogeneity in the wind via a model so that, once the model itself has been
identified from either field data or simulations, it can be inverted and used to estimate the inflow conditions given measured loads. Such methodology with its different formulations has been validated with comprehensive simulations [7, 2, 3], in the wind tunnel [4] and using field measurements [1].

The wind observer formulation proposed so far is nevertheless completely deterministic, not allowing therefore for any process or measurement noise. To include such effects and improve the robustness and accuracy of the methodology, in this work a Kalman filter is used in the estimation process. Section 2 will first introduce the wind-load mapping with its deterministic and non-deterministic estimation procedure. Then, section 3 will provide a comparison of the overall performance of both methodologies.

2. Methodology

2.1. Wind field parametrization

In this work, the wind inflow is parametrized by four states: vertical and horizontal wind direction, $\chi$ and $\phi$ respectively, and vertical and horizontal linear wind shears, $\kappa_v$ and $\kappa_h$, (shown in Fig. 1). Along with the wind speed, this rotor-effective parameters represent a full first order description of the inflow at the rotor disk. Indeed, the wind field is defined as:

$$V(y, z) = V_h \left( 1 + \frac{z}{R} \kappa_v + \frac{y}{R} \kappa_h \right),$$

(1)

where $V_h$ is the wind speed at hub height and $R$ is the rotor radius. The three wind velocity components are therefore:

$$u(y, z) = V(y, z) \cos \phi \cos \chi,$$

(2a)

$$v(y, z) = V(y, z) \sin \phi \cos \chi,$$

(2b)

$$w(y, z) = V(y, z) \sin \chi,$$

(2c)

From Eq. (1), one can easily note the rotational symmetry between vertical and horizontal shear: the effect of a given horizontal shear on the inflow is the same as the one caused by an equivalent vertical shear, only shifted by $\pi/2$ [4]. To better visualize the rotational symmetry characterizing the wind directions, one can define new variables representing the non dimensional horizontal and vertical cross flow at hub height

$$\tilde{v} = \frac{v(0,0)}{V_h} = \sin \phi \cos \chi,$$

(3a)

$$\tilde{w} = \frac{w(0,0)}{V_h} = \sin \chi,$$

(3b)

and rewrite the problem in terms of the wind state vector $\theta = \{\tilde{v}, \kappa_v, \tilde{w}, \kappa_h\}$. Such reformulation can be later exploited for a simpler identification of the model.

2.2. Winds state observer

Since any spatial dis-homogeneity in the wind will cause a periodic response on a stable system, as described in [7, 2, 3, 4], one can identify a mapping relating the non-uniform inflow to the one per revolution (1P) harmonics of the blade in and out of plane bending moments, noted IP and OP respectively. The harmonic amplitudes can be readily extracted with the Coleman transformation [8] and grouped into vector $\bar{m} = \{m_{1c}^{OP}, m_{1s}^{OP}, m_{1c}^{IP}, m_{1s}^{IP}\}^T$, where subscripts $c$ and $s$ stand for the cosine and sine components, respectively.

This mapping, which can be considered as a black box, is formulated as follows
Figure 1. Wind state definition.

\[
m = F(V)\theta + m_0(V) = \left[ F(V)m_0(V) \right] \begin{bmatrix} \theta^T \\ 1 \end{bmatrix} = T(V)\bar{\theta}, \tag{4}
\]

with \( F(V) \) and \( m_0(V) \) the model coefficients scheduled with respect to the wind speed. This scheduling parameter is known in simulations, but can also be easily measured or even estimated in the field [14]. In details, \( m_0(V) \) represents the gravity-induced 1P loading, due for instance to coning or uptilt, whereas \( F(V) \) represents the derivative of the machine response with respect to the wind parameters.

The model can be readily identified just by collecting enough measurements of loads \( m_i \) and the respective wind inflow parameters \( \theta_i \), with \( i = 1, \ldots, N \), \( N \) being the number of available datapoints. Defining \( M = [m_1, \ldots, m_N] \) and \( \Theta = [\bar{\theta}_1, \ldots, \bar{\theta}_N] \), focusing here for brevity on one wind speed \( \bar{V} \), the system

\[
M = T(\bar{V})\Theta, \tag{5}
\]

is inverted so that \( T \) can be computed in a least-square sense as

\[
T(\bar{V}) = M\Theta^T[\Theta\Theta^T]^{-1}. \tag{6}
\]

An alternative identification strategy was described in [4] to face the possibility of an incomplete dataset, i.e. a dataset where not all required wind states are measured. In a nutshell, by exploiting the rotational symmetry of the rotor one can correlate the model coefficients depending on the horizontal wind direction to the ones depending on the vertical one, the same
holding for the shears. Therefore, first the coefficients of the measurable parameters are directly identified from Eq. (6), and then the missing ones are simply derived exploiting the rotor symmetry. This procedure can be particularly useful in a field test campaign, where usually only measurements of the horizontal wind direction and vertical shear are provided.

Once the coefficients have been identified, the wind states can be deterministically estimated in a least-squares sense from the measured response of the machine \( m_M \), leading to the solution of the following simple problem

\[
\theta_E = \arg \min_\theta \left( (m_M - F\theta - m_0)^T (m_M - F\theta - m_0) \right). \tag{7}
\]

2.3. Non-deterministic observation
In order to increase the robustness of the estimation process, a Kalman filter is introduced allowing therefore for both a process and a measurement noise \([11, 12]\). At any time \( k \), the estimate of the wind state vector is defined as

\[
\theta_k = \theta_{k-1} + w_{k-1}, \tag{8}
\]

with \( w \) the process noise with covariance \( Q \), whereas the output equation of the filter writes

\[
z_k = m_M - m_{obs} + v_k = m_M - (F\theta_k - m_0) + v_k, \tag{9}
\]

where \( m_{obs} \) represents the observed machine response and \( v_k \) the measurement noise, with covariance \( R \). Note that the filter output \( z_k \) is set to zero to enforce Eq. (4).

3. Results
To quantify the potential benefits of the Kalman-based formulation, several tests were run at different turbulence intensities (TI) with different mean wind speeds and mean inflows, i.e. setting the wind directions and shears to constant mean values but with a TI-dependent standard deviation.

In this work, a three-bladed, 3 MW machine, with cut in and cut out speeds of 3 and 25 ms\(^{-1}\) respectively and region II\( \frac{1}{2} \) between 9 and 12.5 ms\(^{-1}\), was considered as reference model. Its aeroservoelastic behavior was simulated with \texttt{Cp-Lambda} [5], a modelling tool representing tower and blades as geometrically exact non-linear beams and including mechanical losses and a torsionally elastic drive train. The aerodynamic model is based on the Blade Element Momentum theory along with unsteady corrections, dynamic stall and tip and hub losses, and a collective LQR pitch and torque controller is used to regulate the machine [6, 13]. In addition, \texttt{TurbSim} [10] was used to provide as input to \texttt{Cp-Lambda} turbulent wind grids, computed according to the Kaimal model.

For each simulation performed, both a deterministic and non-deterministic wind observer were used to estimate the rotor effective wind parameters. Figure 2 shows an excerpt of the results obtained at 17 ms\(^{-1}\) and 12% TI with a linear wind-response model, i.e. a model that was identified with a dataset where measurements of all four wind parameters were available.

In each subplot, one per parameter, one can compare the reference wind condition (black) with the observed one with (red) or without (blue) a Kalman filter. The reference wind states, considered here as ground truth, were obtained fitting Eq. (1) and (2) on the rotor-swept area of the \texttt{TurbSim} generated turbulent grid, and therefore also represent a rotor-equivalent measurement.
Figure 2. Wind parameters vs. time at 17 ms\(^{-1}\) and 12\% TI for the linear model: reference condition (black), deterministic estimation (blue), non-deterministic estimation (red) for yaw misalignment, vertical shear, upflow angle, horizontal shear (top to bottom).

Figure 3. Wind parameters vs. time at 17 ms\(^{-1}\) and 12\% TI for the symmetric model: reference condition (black), deterministic estimation (blue), non-deterministic estimation (red) for yaw misalignment, vertical shear, upflow angle, horizontal shear (top to bottom).

While the deterministic instantaneous estimation of both shears appears to be very accurate, the observation of both angles can only follow the mean value of the parameters, though with some fluctuations. The use of a Kalman filter appears to significantly reduce such fluctuations, especially for the vertical direction, thus improving the model performance. Such considerations apply also to the results obtained with a rotationally symmetric model, i.e. a model identified exploiting the symmetry of the rotor, as shown in Fig. 3. Here as well, the Kalman filter reduces the fluctuations in the angle estimation, whereas no margin of improvement can be noticed as far as the shears are concerned.

A statistical overview of the performance is presented next. For each chosen wind speed in the range \(V \in [7, 17] \text{ ms}^{-1}\), given a TI level, three different mean inflows were considered, including
therefore different values of wind misalignments and shears. Moreover, for each mean inflow 4 different turbulent seeds were used: each marker in figures from 4 to 7 represents therefore a total of 12 10-minute long turbulent simulations.

**Figure 4.** Standard deviation $\sigma$ of the four wind states vs. wind speed for 5% and 12% TI levels for the linear model. Deterministic formulation: solid lines; non-deterministic formulation: dashed lines.

**Figure 5.** Mean absolute error $\epsilon$ of the four wind states vs. wind speed for 5% and 12% TI levels for the linear model. Deterministic formulation: solid lines; non-deterministic formulation: dashed lines.

Figure 4 and 5 show, respectively, for two different TI levels (5 and 12%), the standard deviation and the mean absolute error in the estimates of all parameters for both a deterministic
Figure 6. Standard deviation $\sigma$ of the four wind states vs. wind speed for 5% and 12% TI levels for the symmetric model. Deterministic formulation: solid lines; non-deterministic formulation: dashed lines.

Figure 7. Mean absolute error $\epsilon$ of the four wind states vs. wind speed for 5% and 12% TI levels for the symmetric model. Deterministic formulation: solid lines; non-deterministic formulation: dashed lines.
(solid line) and non-deterministic (dashed line) linear model. Coherently to what seen in the exemplary time history, while no improvement in the accuracy can be seen in the shear estimates, a significant improvement can be noticed for the angles. A possible explanation for this behaviour lies in the physics behind the model. As thoroughly discussed in [2], vertical and horizontal shears leave a clearer fingerprint on the machine response than upflow and yaw misalignment. In fact, to generate the same change in angle of attack, and in turn in blade loading, one needs a higher variation in wind directions than in shears. Similar results were confirmed by a singular value decomposition analysis [9, 2], which also showed that, while both shears are linearly independent parameters, a coupling is present between upflow and yaw misalignment: an error in the yaw estimate will also propagate in the upflow observation, and vice versa. The Kalman filter seems to be able to compensate for these issues, reducing the propagation of the error. Indeed, for higher wind speeds and turbulence levels, when the Kalman filter is employed the angle standard deviation decreases of almost two degrees, while the mean error of 1.5 deg, leading to a maximum absolute error in the estimation of 2.3 and 2.1 deg for yaw and upflow angle, respectively. Similar considerations can be drawn for Fig. 6 and 7, which show standard deviation and mean error for a deterministic and non-deterministic rotationally symmetric model. No improvement in the shear estimation can be noticed, whereas higher accuracy can be obtained for the angles. Again, the most significant improvements can be noticed for higher wind speeds and higher turbulence, leading to a maximum estimation error of 2.4 and 1.8 deg for yaw and upflow angle respectively.

4. Conclusions and Outlooks

In this work, the wind sensing technology described in [2, 4] was further developed in order to include non-deterministic effects. A linear and rotor symmetrical model relating wind conditions and blade loads were identified; during operation, the inflow at the rotor disk was inferred from the machine measured loads. A Kalman filter was included in the estimation process in order to increase the robustness of the observations and, with it, their accuracy.

Based on a simulation study including several variations of mean inflow, wind speed and turbulence intensity, the following conclusions can be drawn:

- The non-deterministic wind observer is capable of capturing the instantaneous variations of both vertical and horizontal shear very accurately. Additionally, no significant improvement in the estimation can be noted with respect to the deterministic formulation.
- As far as the wind directions are concerned, the non-deterministic observer is capable of reducing the fluctuation in the estimates of the angle mean values, leading to significant higher accuracy. This is particularly the case when considering higher wind speeds and TI, where the mean absolute error can decrease up to almost 2 deg.
- While both the non-deterministic linear and symmetric observer prove better than their deterministic counterparts, no significant difference can be noted comparing their performance. This proves once again that one may simplify the model identification exploiting the symmetry of the rotor without decreasing the quality of the results. This is very valuable particularly for field test applications, where usually only information about the vertical shear and about the horizontal wind direction are available.
- Finally, the implementation of the described Kalman filter does not imply any significant addition to the computational cost of the observer. Indeed, considering that this methodology relies on simple linear models using as input blade load measurements, the observer still remains an easy-to-implement solution for wind inflow estimation.
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