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Simultaneous observation of wind shears and misalignments from rotor loads

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Abstract. A wind turbine is used in this paper as a sensor to measure the wind conditions at the rotor disk. In fact, as any anisotropy in the wind will lead to a specific signature in the machine response, by inverting a response model one may infer its generating cause, i.e. the wind. Control laws that exploit this knowledge can be used to enhance the performance of a wind turbine or a wind power plant.

This idea is used in the present paper to formulate a linear implicit model that relates wind states and rotor loads. Simulations are run in both uniform and turbulent winds, using a high-fidelity aeroservoelastic wind turbine model. Results demonstrate the ability of the proposed observer in detecting the horizontal and vertical wind misalignments, as well as the vertical and horizontal shears.

1. Introduction

When it comes to improving the performance of a wind turbine or of a whole wind farm, reliable and accurate information about the inflow that a wind turbine faces can be of significant help. Indeed, the presence of a horizontal misalignment decreases the harvested power and increases fatigue loading, in turn leading to vibration problems. Similarly, the correct estimation of vertical and horizontal shears can be used to improve individual pitch control or to detect the presence of a wake [1].

Unfortunately, reliable and accurate real-time information on the wind conditions at the rotor disk is still very hard to obtain via direct measurements. On-board anemometers and wind vanes can provide information about the wind speed and direction, but these measurements are local and affected by the presence of the nacelle, blade passing and wake-induced flow deformation. On the other hand, non-local measurements provided by met-masts are not co-located with the wind turbine using it. Finally, LiDARs are still not widely available.

Therefore, considering the *rotor as an anemometer* [2] could prove to be an interesting option, since it allows one to indirectly measure the wind state without additional sensors.

One recent example of this idea is given in Ref. [3], where generator speed, fore-aft nacelle acceleration and collective pitch are used along with sine and cosine components of the out-of-plane bending moments to estimate via a Kalman filter the equivalent wind speed and the vertical and horizontal shears. However, this study tested a linearized wind turbine model only in non-turbulent wind conditions that were exactly parametrized by the chosen wind states. Furthermore, the study did not account for unmodeled characteristics such as turbulence, yaw or upflow misalignments.

In this work, expanding the simple idea first proposed in Ref. [4], the wind field is described as a function of four parameters: vertical and horizontal shears and vertical and horizontal misalignments. Given that any anisotropy in the wind leads to periodic loads [5], the $1 \times \text{Rev}$ harmonic components of



the blade out-of-plane and in-plane root bending moment are used as input to infer the incoming wind field, both in uniform and turbulent conditions. This approach leads to *rotor-effective* inflow estimates. Moreover, the only hardware required for the estimation are load sensors, which are nowadays becoming standard equipment on large machines for load-reducing feedback control and monitoring.

The paper is organized in the following sections. First, the problem formulation is presented in Sec. 2, explaining how the wind field is parameterized, how blade loads are decomposed into their harmonic terms and which simulation environment has been used to perform the tests. The wind state observer formulation itself is then proposed in Sec. 2.4, explaining first what relationship can be identified between loads and wind states and then how to exploit that very relationship to estimate wind conditions. In Sec. 3, the observer is tested in both uniform and turbulent wind conditions, and the results are presented. Finally, in Sec. 4, the overall work is briefly summarized and its conclusions are presented, along with some possible outlooks for the further development and testing of the wind state observer.

2. Formulation

2.1. Wind field parametrization

In order to describe the anisotropy in the wind, the four parameters shown in Fig. 1 are defined: the yaw misalignment ϕ , the vertical shear κ_v , the upflow angle χ , and the horizontal shear κ_h , grouped together in the wind state vector $\theta = \{\phi, \kappa_v, \chi, \kappa_h\}^T$. The wind field is described as

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

where V_h and z_h are the wind speed and z -coordinate at hub height, while R is the rotor radius. The three wind components are then

$$u(y, z) = V(y, z) \cos \phi \cos \chi, \quad (2a)$$

$$v(y, z) = V(y, z) \sin \phi \cos \chi, \quad (2b)$$

$$w(y, z) = V(y, z) \sin \chi. \quad (2c)$$

2.2. Blade loads harmonics

Under a steady anisotropic wind, i.e. a wind field that is constant in time but not in space, a rotating blade will experience periodic changes in relative velocity and angle of attack. As a result, the response of a stable wind turbine system will converge to a periodic motion. Therefore a generic blade load m can be expanded in Fourier series as

$$m = m_0 + m_{1c} \cos \psi + m_{1s} \sin \psi + \dots, \quad (3)$$

with ψ the azimuth angle, m_0 the constant amplitude, subscripts $1c$ referring to the $1 \times \text{Rev}$ cosine component, whereas $1s$ refers to the sine one.

For machines with at least three blades, sine and cosine components of the desired blade load $n \times \text{Rev}$ harmonics can be readily obtained by the Coleman transformation. Indeed, for the three bladed case, one can write

$$\begin{Bmatrix} m_{nc} \\ m_{ns} \end{Bmatrix} = \frac{2}{3} \begin{bmatrix} \cos(n\psi_{(1)}) & \cos(n\psi_{(2)}) & \cos(n\psi_{(3)}) \\ \sin(n\psi_{(1)}) & \sin(n\psi_{(2)}) & \sin(n\psi_{(3)}) \end{bmatrix} \begin{Bmatrix} m_{(1)} \\ m_{(2)} \\ m_{(3)} \end{Bmatrix}. \quad (4)$$

This procedure transforms $n \times \text{Rev}$ harmonics into $0 \times \text{Rev}$ components. Other harmonics are simply canceled out or transformed into multiples of the number of blades [6], which can be readily removed

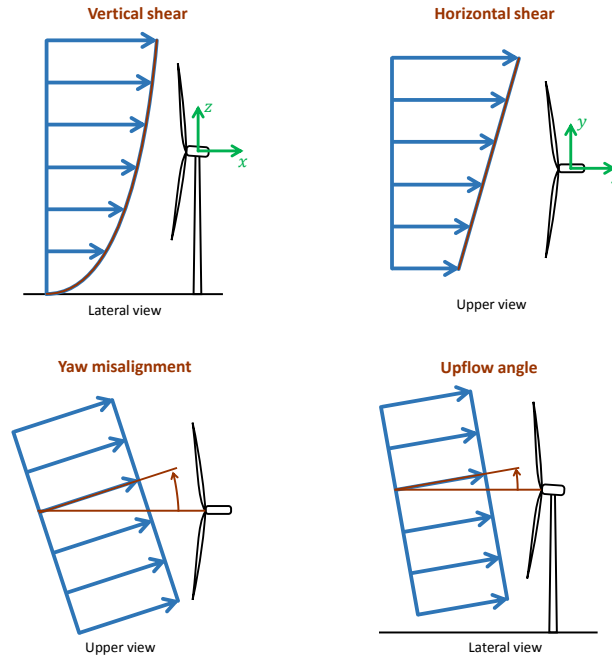


Figure 1. Wind state definition.

by a straightforward low-pass filter. Specifically, adaptive filtering should be considered to account for changes in the rotor speed.

The present formulation only considers the $1 \times \text{Rev}$ components of the out-of-plane and in-plane blade root bending moments and collects them in a vector:

$$\mathbf{m} = \{m_{1c}^{OP}, m_{1s}^{OP}, m_{1c}^{IP}, m_{1s}^{IP}\}^T. \quad (5)$$

2.3. Wind Turbine Aeroelastic Model

In this work simulations are conducted with the aeroservoelastic model of a horizontal axis machine with a rated power of 3 MW, a rotor diameter of 93 m and a hub height of 80 m. The model is simulated with the software Cp-Lambda [8], a finite element multibody code that implements flexible blades, tower and drive-train as geometrically exact nonlinear beams. The machine is controlled by a speed-scheduled pitch/torque LQR [9, 10], while pitch and torque actuators are modeled as second and first order systems, respectively. Rotor speed-dependent mechanical losses within drive-train and generator are also accounted for. The total number of degrees of freedom in the system is about 2500. The aerodynamic model is based on the blade element momentum theory (BEM), taking into account hub and tip losses, unsteady corrections and dynamic stall. Moreover, the code is interfaced with TurbSim [7], which provides turbulent wind time histories with user-defined characteristics.

2.4. Wind state observer

2.4.1. Load-wind relationship modeling

In order to estimate the inflow characteristics from a given set of measured loads, a relationship between load harmonics \mathbf{m} and wind state $\boldsymbol{\theta}$ has to be defined: to this end, a black-box model is used here to express \mathbf{m} as a function of $\boldsymbol{\theta}$. Using a matrix formalism, the input-output model writes

$$\mathbf{m} = \mathbf{F}\boldsymbol{\theta} + \mathbf{m}_0 = [\mathbf{F} \ \mathbf{m}_0] \begin{bmatrix} \boldsymbol{\theta}^T \\ 1 \end{bmatrix} = \mathbf{T}\bar{\boldsymbol{\theta}}, \quad (6)$$

where \mathbf{F} and \mathbf{m}_0 are the model coefficients, identified from a set of experimentally measured \mathbf{m}_i and θ_i quantities. If we group the data of the N available experiments such that $\mathbf{M} = [\mathbf{m}_1, \dots, \mathbf{m}_N]$ and $\Theta = [\theta_1, \dots, \theta_N]$, Eq. (6) will be

$$\bar{\mathbf{M}} = \mathbf{T}\bar{\Theta}, \quad (7)$$

and \mathbf{T} can then be easily computed in a least-square sense as follows

$$\mathbf{T} = \bar{\mathbf{M}}\bar{\Theta}^T [\bar{\Theta}\bar{\Theta}^T]^{-1}. \quad (8)$$

The parameters of the load-wind model exhibit a non-negligible dependency on the operating condition of the machine. To account for this, a speed-scheduled model can be adopted. In this work we have used a piecewise linear model, defined by nodal matrices of model coefficients computed at intervals of 2 m/sec wind speeds. The identification of such a model can be performed in a way similar to the one just described, which is however not reported here for brevity.

2.4.2. Wind state estimation

Once the model has been identified, the wind state can be estimated in a least-square sense. Introducing \mathbf{r} as the measurement error with covariance $\mathbf{R} = \mathbf{E}[\mathbf{r}\mathbf{r}^T]$, the generalized least-squares estimate of the wind state, θ_E , given the measured loads \mathbf{m}_M , writes

$$\theta_E = \arg \min_{\theta} \left((\mathbf{m}_M - \mathbf{m}_0 - \mathbf{F}\theta)^T \mathbf{R}^{-1} (\mathbf{m}_M - \mathbf{m}_0 - \mathbf{F}\theta) \right). \quad (9)$$

Since the problem is linear, the solution can be worked out analytically and θ_E is found to be

$$\theta_E = (\mathbf{F}^T \mathbf{R}^{-1} \mathbf{F})^{-1} \mathbf{F}^T \mathbf{R}^{-1} (\mathbf{m}_M - \mathbf{m}_0). \quad (10)$$

Clearly, the wind state identifiability depends on the invertibility of matrix \mathbf{F} . Based on the numerous tests performed, matrix \mathbf{F} always appears to be invertible allowing therefore for the estimation of the different parameters with an error related to the matrix condition number.

2.4.3. Wind state estimation in steady conditions

To verify the performance of the proposed formulation, the turbine aeroelastic model described in Sec. 2.3 was first simulated in steady winds. For each wind condition, the wind speed is $V = 7$ m/s and the parameters θ are kept constant. The resulting wind is exactly parameterized by the wind state vector. The overall set of simulations performed considers all the combinations of the following wind states:

$$\phi = \{-16, -12, -8, -4, 0, 4, 8, 12, 16\} \text{ deg}, \quad (11a)$$

$$\kappa_v = \{0.0, 0.1, 0.2, 0.3, 0.4\}, \quad (11b)$$

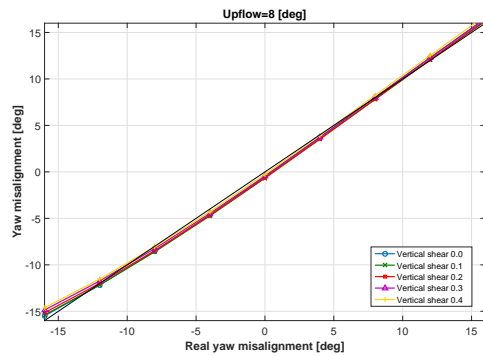
$$\chi = \{0, 4, 8, 12\} \text{ deg}, \quad (11c)$$

$$\kappa_h = \{-0.1, -0.05, 0.0, 0.05, 0.1\}. \quad (11d)$$

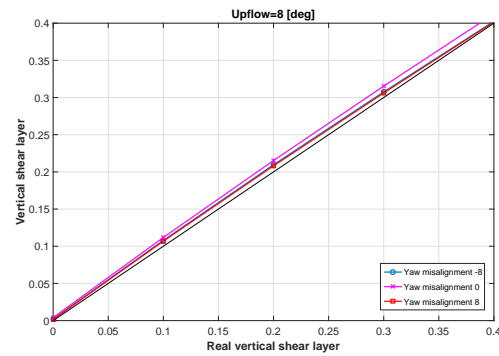
The linear model of Eq. 7 is then identified from the defined set. Finally, the estimation of θ for the same steady conditions is performed.

Figure 2 shows the matching between the real wind parameter, reported on x-axis, and the observed one, shown on y-axis, parameterized by the remaining elements of θ . The bisector of the 1st quadrant indicates the ideal match.

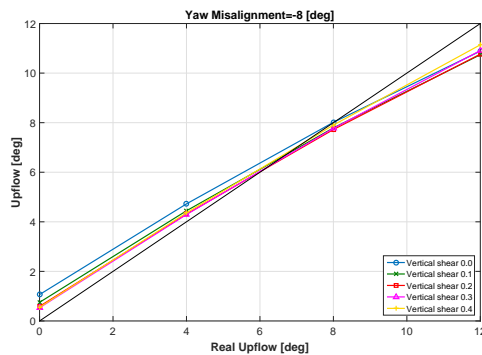
It appears that the proposed linear model is able to estimate with good accuracy all wind states, especially as far as the shears are concerned. The estimates of the angles appear to be less accurate, especially for the upflow, but their quality still remains acceptable. The errors in the estimates are most likely due to effects that are not accounted for in the present formulation, such as nonlinearities.



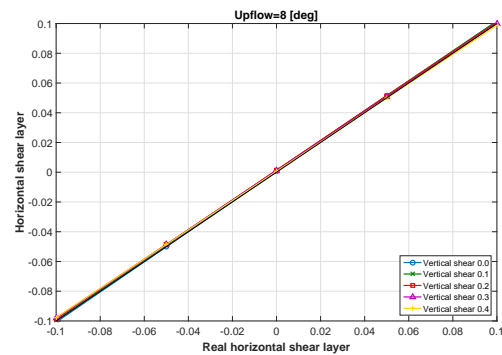
(a) Yaw misalignment ϕ at $\chi = 8$ deg and $\kappa_t = -0.1$.



(b) Vertical shear κ_v at $\chi = 8$ deg and $\kappa_t = -0.1$.



(c) Upflow angle χ at $\phi = -8$ deg and $\kappa_t = -0.1$.



(d) Horizontal shear κ_h at $\chi = 8$ deg and $\phi = -8$ deg.

Figure 2. Observed wind states for different steady inflow conditions at 7 m/s.

3. Results

3.1. Uniform wind

The proposed approach was then tested running simulations for several unsteady wind conditions. In all these cases, the inflow can still be exactly parameterized by θ , but the four components of the wind state vector vary independently in time.

The obtained load harmonics were extracted from the measured moments by the Coleman transformation, using an 8th order Butterworth filter with cut-off frequency equal to $0.35\omega_{\text{tow}} = 0.105$ Hz, where ω_{tow} is the tower frequency. Figure 3 shows the results obtained for a constant wind speed of 7 m/s. All parameters appear to be well matched, although a filter-induced delay of seven seconds is present.

3.2. Turbulent wind

Additional simulations were performed to test the wind observer behavior in turbulent wind conditions. Ten-minute-long turbulent winds were generated by TurbSim [7] and for each simulated case six different turbulent seeds were tested in order to obtain statistically accurate results. Since the real wind is now characterized by turbulent structures, it is not possible to perfectly describe it by means of vector θ : a least-squares fitting of Eq. (1) and (2) on the turbulent wind grid was therefore performed, and the obtained parametrization was used as a reference to check the observer behaviour.

Different turbulent intensity levels (TI) were considered: Fig. 4 shows the results at $TI = 2\%$ and 12% with a mean wind speed of 7 m/s while Tab. 1 and . 2 the standard deviation and absolute mean error of the estimated wind states.

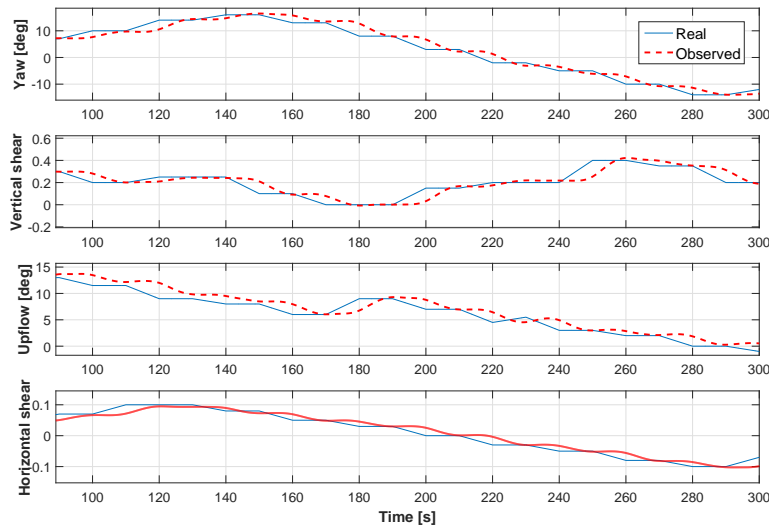


Figure 3. Observed inflow conditions in uniform wind at 7 m/s.

Table 1. Wind state estimate standard deviation.

Standard deviations	2% TI	12% TI
σ_{ϕ} [deg]	0.3	2.6
σ_{κ_v}	5e-3	2.8e-02
σ_{χ} [deg]	0.3	2.1
σ_{κ_h}	2.5e-3	1.2e-2

Table 2. Wind state estimate absolute mean error.

Mean absolute error	
ϵ_{ϕ} [deg]	0.8
ϵ_{κ_v}	1.1e-2
ϵ_{χ} [deg]	0.3
ϵ_{κ_h}	2.4e-3

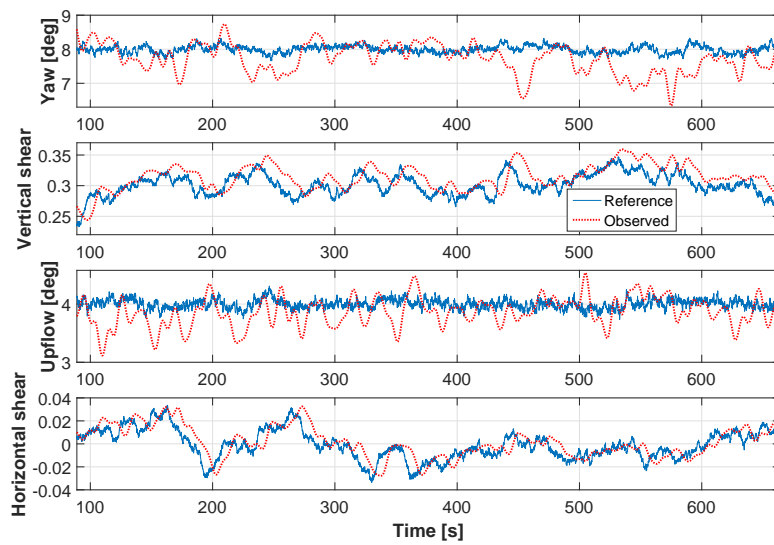
The accuracy in the estimates of both shears κ_v and κ_h appears to be particularly good. Both the mean value and the instantaneous oscillations are matched well by the model, although a seven second delay induced by the filter is present. The same behaviour is observed for low and relatively high turbulence intensities, suggesting that a good instantaneous shear estimation is possible despite the disturbances caused by turbulent wind fluctuations.

As far as the angle estimation is concerned, the accuracy of the results appears to be considerably affected by TI. Indeed, the instantaneous values exhibit significant fluctuations, although mean values seem to be more accurately identified. This suggests that, even though a good instantaneous matching is not achieved, the proposed wind state observer can be used to detect mean misalignments over a time window. To this aim, additional filtering, such as a moving average, can be implemented to improve the results, especially for higher turbulence levels.

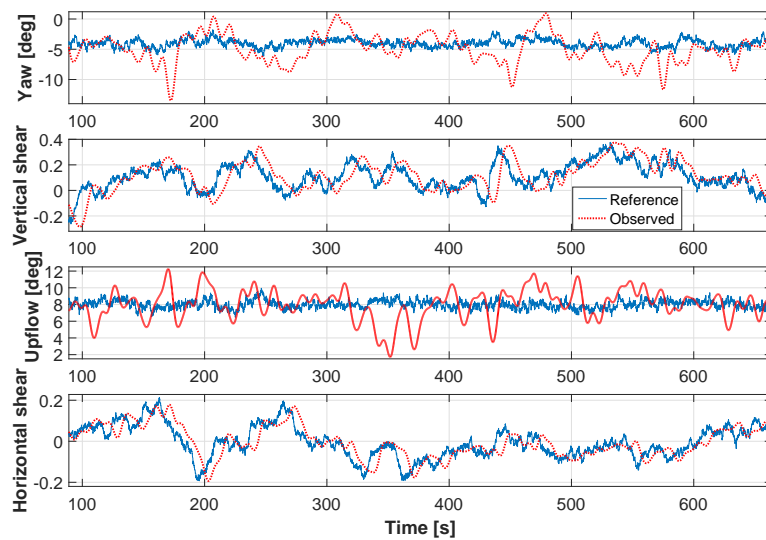
4. Conclusions

The proposed observer exploits the relationship between wind and the loads it generates, to ultimately identify the inflow characteristics.

The input-output model presented here is able to provide significantly accurate least-square estimates of both misalignments, upflow and yaw angle, and both shears, vertical and horizontal, in uniform wind conditions. In turbulent winds, the observer is still able to correctly estimate both the instantaneous and the mean values of the vertical and horizontal shears, even though a small filter-induced delay is always present. As far as the angles are concerned, in turbulent conditions the model is not able to



(a) TI of 2%



(b) TI of 12%

Figure 4. Wind state observations in turbulent wind conditions at 7 m/s for a TI equal to 2% (left) and 12% (right). Solid thick blue lines: reference wind parameters; dotted thick red lines: observations by the linear model.

provide time accurate estimates, although their mean values can be correctly detected. These promising results and the simplicity of this approach compared to higher order models suggest that the proposed wind state observer could be used to estimate wind inflow characteristics, with several different possible applications.

For instance, an accurate estimate of the mean vertical shear can be used to improve IPC control laws, i.e. changing the controller gains, and to infer the stability of the atmosphere, which in turn determines the recovery of wakes. Moreover, wakes could be detected if information about the horizontal shear is available, thus improving wind farm control. All the mentioned applications will not be negatively affected by the delay present in the estimates, since to perform this kind of controls time windows bigger than tens of seconds are usually considered. The same holds even for yaw control strategies, that could of course benefit from the accurate estimation of the mean yaw misalignment angle that can be obtained with this observer.

Work is in progress to improve the methodology and the understanding of its capabilities. Further developments are possible for the filtering process, by using a faster filter for the estimation of the shears and a moving average for the angles. Moreover, the model has been tested in a wider range of operating conditions, considering the effects of various sources of uncertainty and disturbances. The non-linear formulation of the observer has also been studied and compared with the linear one here proposed. In addition, a theoretical analysis has been developed that explains the different behavior of shears and angles. All these developments will be duly reported in a forthcoming publication. Finally, the method should be tested in the field, as already partially demonstrated in Ref. [11].

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