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Abstract. Having an improved awareness of the flow within a wind farm is useful for power harvesting maximization, load minimization and design of wind farm layout. Local flow information at each wind turbine location can be obtained by using the response of the wind turbines, which are consequently used as distributed sensors. This paper proposes the use of hub loads to track the position of wakes within a wind farm. Simulation experiments conducted within a high-fidelity aeroservoelastic environment demonstrate the performance of the new method.

1. Introduction

Wake interference among wind turbines in a wind power plant may generate significant power losses and increase fatigue loading. Detecting and mitigating wake interferences is a not-trivial challenge, which has gained a prominent role in wind energy control research in recent years. For example, specific techniques are being developed for checking the presence of impinging wakes [1] and optimizing the power harvested within the wind plant [2].

Irrespective of its implementation and final purpose, any wind turbine and farm control algorithm would benefit from an improved knowledge of the wind conditions, which clearly includes the position of wakes relative to affected rotors. This information is however not trivial to obtain without the use of additional sensors, such as LiDARs. On the other hand, as long as wind conditions affect the response of the turbine, one may alternatively measure the inflow at the rotor disk by interpreting the machine behavior. This turns the wind turbine into a wind sensor, providing an improved awareness of the flow conditions at its location.

The use of rotor loads and performance to infer the inflow characteristics is a rather recent idea, which generalizes the concept of wind speed estimation from rotor torque (cf. [3] and references therein). The underlying idea of wind speed estimation is to use the power balance equation, along with rotor speed, electrical torque and pitch setting, to estimate the wind speed. This concept can be extended to other wind characteristics. For example, Ref. [1] describes the detection of wake impingement on both sides of the rotor. The algorithm is based on a non-dimensional blade load static model, which describes the blade out-of-plane bending moment response as a function of tip-speed-ratio, blade setting and dynamic pressure. Another meaningful example deals with the estimation of vertical wind shear and yaw misalignment [4], where estimates are obtained from blade loads by a previously identified steady linear model.

To infer any wind parameter from rotor loads, two elements are required: a specific set of measurements that significantly dependent on those parameters, and a simplified model that

relates measurements to wind parameters.

This paper focuses on the tracking of the wake center position. Specifically, the downstream wind turbine nodding and yawing moments are related to horizontal and vertical shears by an ad-hoc identified physical steady model, which works in conjunction with a standard wind speed estimator based on the torque balance equation. Finally, tracking of the wake center is performed in two steps: first shears and rotor effective wind speed are estimated, and then a minimization algorithm is used to match a Larsen wake model [5] to the estimates.

An estimate of the lateral wake position is an important piece of information that could be exploited by algorithms for wind farm control based on wake redirection [6, 7, 8]. In fact, for example, the actual wake position could be used for suggesting a suitable misalignment angle to the upstream turbine. In a more sophisticated application, it could be employed as a feed-back measurement in a closed-loop wind farm power/fatigue optimization strategy.

The present paper is organized according to the following plan. In Sec. 2 a simple linear steady model relating nodding and yawing moments to vertical and horizontal shears is presented, along with a least-square algorithm used for identifying the model from wind turbine data. Afterwards, the proposed wake center tracking procedure is described. Section 3 reports an excerpt from the obtained results, which illustrate the performance of the proposed approach in a few different wind conditions. Finally, Sec. 4 completes the paper summarizing the results obtained so far and giving an outlook on future work.

2. Methods
2.1. Hub load model definition and identification
A wind field of speed V is parameterized using linear vertical κ_v and horizontal κ_h shears as

$$V(y, z) = V_\mathrm{H} \left(1 + \kappa_\mathrm{v} \frac{z}{R} + \kappa_\mathrm{h} \frac{y}{R} \right),\tag{1}$$

where y and z are the lateral and vertical coordinates centered at the hub, R is the rotor radius and V_H is the hub wind speed.

When κ_v and κ_h are different from zero, the fixed-frame load response of a three-bladed wind turbine is a periodic motion characterized by a constant amplitude and harmonics at multiples of 3×Rev. In this regime, as suggested in Refs. [4, 9], there is a linear relationship between the 0×Rev component of the nodding and yawing moment, denoted respectively N and Y, and the shears κ_v and κ_h. Moreover, the response of the system is supposed to be isotropic, i.e. the dependence of N and Y on the shears is the same but shifted by 90 deg.

With this last consideration, the hub load model can be written with a specific structure as

$$\left\{ \begin{array}{c} N \\ Y \end{array} \right\} = \left[\begin{array}{cc} \alpha & -\beta \\ \beta & \alpha \end{array} \right] \left\{ \begin{array}{c} \kappa_\mathrm{v} \\ \kappa_\mathrm{h} \end{array} \right\} + \left\{ \begin{array}{c} N_0 \\ Y_0 \end{array} \right\},\tag{2}$$

where N_0 and Y_0 are the constant nodding and yawing moments not due to aerodynamics (i.e. induced by gravity), whereas α and β are the model parameters. Such parameters are scheduled as functions of a low-pass filtered wind speed, to account for the different behavior of the wind turbine in different operating conditions. In addition, they should be corrected for air density. Because of the isotropic rotor response, one has that $\partial N/\partial \kappa_\mathrm{v} = \partial Y/\partial \kappa_\mathrm{h} = \alpha$ and $\partial Y/\partial \kappa_\mathrm{v} = -\partial N/\partial \kappa_\mathrm{h} = \beta$.

From model (2), given nodding and yawing measurements N_M and Y_M, the horizontal shear κ_E can be readily estimated as

$$\kappa_\mathrm{h,E} = \frac{(Y_\mathrm{M} - Y_0) - \xi(N_\mathrm{M} - N_0)}{1 + \xi^2} \frac{1}{\alpha},\tag{3}$$

where variable $\xi = \beta/\alpha$ can be interpreted as the delay which characterizes the steady periodic response of the rotor.

In order to identify the model, multiple observations of hub loads N_M and Y_M and vertical shear measurements $\kappa_{v,M}$ should be collected under different wind conditions. After filtering and organizing the various measurements, a linear fitting between N_M and $\kappa_{v,M}$ readily yields the unknown parameters α and N_0. Similarly, by fitting Y_M to $\kappa_{v,M}$, one obtains parameters β and Y_0.

Were the rotor response not isotropic, the identification of the model from field test data could be complicated by the fact that significant horizontal shears are seldom experienced in standard operating conditions. Indeed, taking advantage of rotor isotropy, only the variation of vertical shear is required, making it easier to identify the model using field measurements in conjunction with inflow data provided, for example, by a nearby met-mast. If the model identification is performed in a simulation environment, it is on the other hand quite simple to generate wind conditions that also include horizontal shear.

2.2. Wake position tracking

A wake impinging on a rotor will have, among others, two important effects: a longitudinal wind speed non-uniformity, which can be approximately viewed as a horizontal shear, and a deficit in the mean wind speed experienced by the downstream wind turbine with respect to an unwaked case. The simplified Larsen wake model [5] provides a simple description of such effects:

$$\left\{ \begin{array}{c} \kappa_{h,W} \\ \Delta V_W \end{array} \right\} = \boldsymbol{f}(\tau, V, d, l), \qquad (4)$$

being $\kappa_{h,W}$ the wake-induced horizontal shear, ΔV_W the mean wind speed deficit, τ and V the ambient turbulence intensity and wind speed, whereas d and l are the lateral and longitudinal distance between wake and wind turbine centers. Figure 1, on the left, shows a schematic plot of two interacting wind turbines. The right part of the same figure shows the wake-induced horizontal shear (upper plot) and the mean wind speed deficit (lower plot), as functions of d for $d > 0$, for an ambient wind speed of 8 m/s, a turbulence intensity of 5%, and a streamwise rotor distance of 4 diameters ($l/D = 4$).
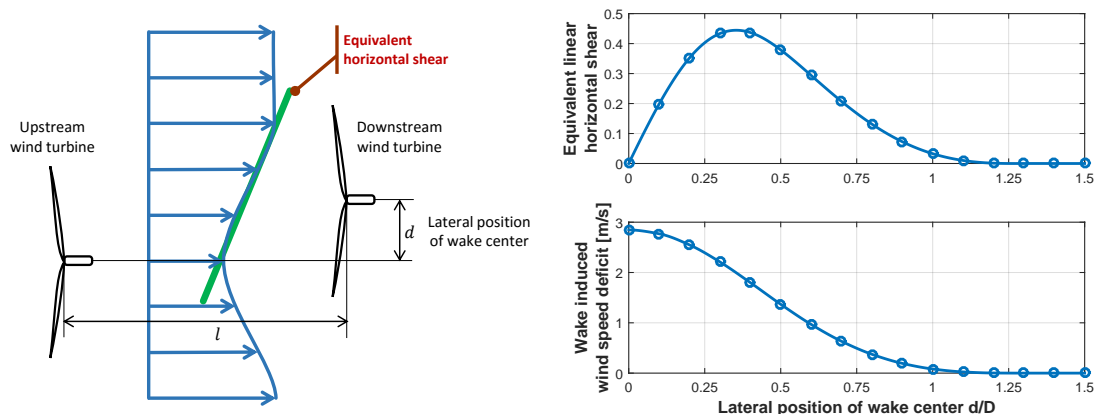

Figure 1. Equivalent horizontal shear and wind speed deficit, $V_E = 8$ m/s and $\tau = 5\%$.

Finally, the lateral distance d is computed based on the estimated lateral shear and speed

deficit. This wake center tracking problem is formulated as the minimization of the cost function

$$J = \left\{ \begin{array}{c} \kappa_{\mathrm{W}} - \kappa_{\mathrm{E}} \\ \Delta V_{\mathrm{W}} - \Delta V_{\mathrm{E}} \end{array} \right\}^{T} \left[\begin{array}{cc} w_1 & 0 \\ 0 & w_2 \end{array} \right] \left\{ \begin{array}{c} \kappa_{\mathrm{W}} - \kappa_{\mathrm{E}} \\ \Delta V_{\mathrm{W}} - \Delta V_{\mathrm{E}} \end{array} \right\}, \tag{5}$$

being w_1 and w_2 two tuning weights. The rotor effective wind speed V_{E} is estimated by a standard observer based on the torque balance equation [3].

This formulation is based on the fact that the wake induced speed deficit and lateral shear are strictly related to the lateral wake position. Hence, assuming that the Larsen model can reasonably approximate the behavior of the wake, the wake center can be tracked by fitting the model to estimated values of speed and lateral shear. The shape of κ_{W} and ΔV_{W} as function of d, as shown in Fig. 1, suggests that local minima can be expected and that the global one should consequently be found by using global optimization tools like a genetic algorithm [10].

3. Results

The performance of the observer was tested using a high-fidelity multibody model of a 3 MW wind turbine with a diameter of 92 m, implemented in `Cp-Lambda` [11]. A simple one-to-one wake interference condition between two wind turbines, shown in Fig. 1, was recreated by superimposing the Larsen wake deficit onto turbulent wind grids provided by TurbSim [12]. This way, only the downstream wind turbine has been simulated.

For different wake center lateral positions $d/D \in [-1.2, 1.2]$, wind speeds and turbulence intensities, several 10-minute simulations were performed. First, the equivalent horizontal shear $\kappa_{h,\mathrm{E}}$ was computed from Eq. (3), along with the effective wind speed extracted using the standard torque balance based estimator. Afterwards, the estimated mean shear $\kappa_{h,\mathrm{E}}$ and mean speed deficit ΔV_{E} were averaged over a time window of 10 minutes and fed to the wake position tracking algorithm.

Figure 2 shows a comparison between effective and estimated wake induced speed deficits, on the left, and between effective and estimated horizontal shears, on the right, for a turbulent wind with intensity of 5% and mean speed of 8 m/s. It appears that both quantities can be captured well by the proposed estimation technique. The error in the speed deficit is quite modest for all overlap levels, whereas the horizontal shear estimation is of a good quality especially in the range $|d/D| > 0.4$. The performance degradation in the range $|d/D| < 0.4$ is principally due to the fact that, in full waked conditions, a linear shear cannot precisely match the effective lateral wind profile felt by the downstream machine. On the other hand, a linear shear offers a reasonable approximation in a partial wake overlap situation.

Figure 3 on the left reports the estimated wake position as a function of the real one, showing that all estimates lay close to the ideal matching, which is represented by the solid line bisecting the first and third quadrants. A close look at the results shows that the tracking algorithm is able to estimate very precisely the position of the wake in the range $|d/D| > 0.4$. On the other hand, the range $|d/D| < 0.4$ is characterized by higher but still acceptable errors, as expected from the comparison shown in Fig. 2.

In order to test the performance of the observer at higher turbulence intensity levels, a different condition characterized by a wind speed of 5 m/s and a turbulence intensity of 10% was analyzed. The results are displayed in the right part of Fig. 3. The matching is satisfactory also in this case as a proof of the robustness of the procedure.

Mild differences were experienced for a different choices of the tuning weights w_1 and w_2. This result is however expected, as the estimated wind speed deficit and horizontal shear match well their respective reference quantities (cf. Fig. 2). Hence, assigning more importance to one variable or to the other does not entail significant differences in terms of the final wake position estimate.
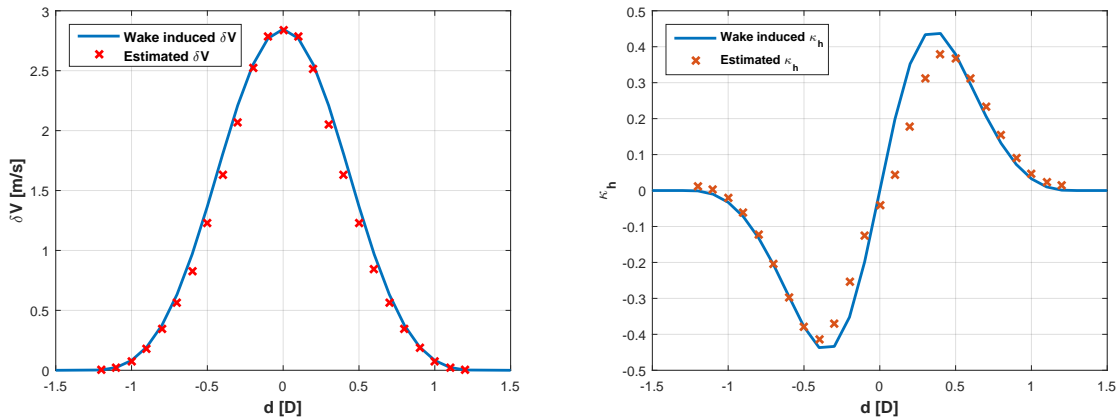
Figure 2. Comparison between reference and estimated wind speed deficit (left) and equivalent horizontal shear (right), $V = 8$ m/s and $\tau = 5\%$.
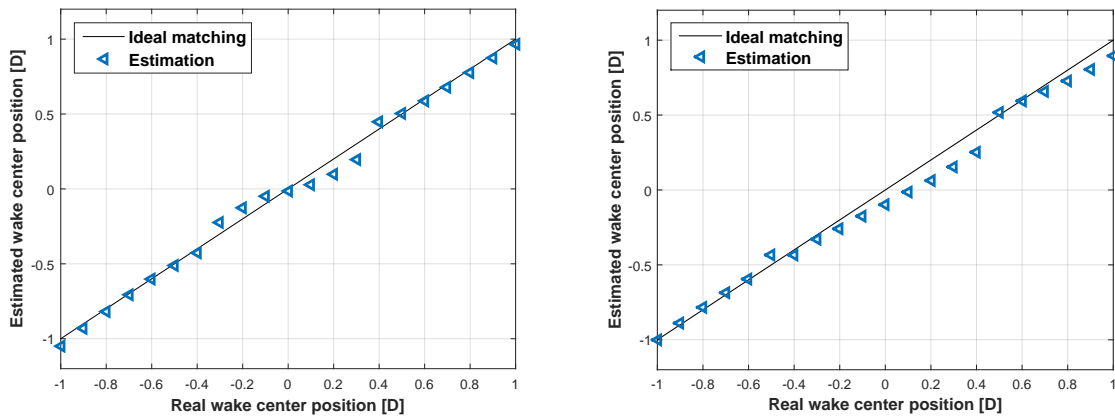

Figure 3. Wake tracking algorithm performance. Left: $V_{\mathrm{E}} = 8$ m/s and $\tau = 5\%$. Right: $V_{\mathrm{E}} = 5$ m/s and $\tau = 10\%$.

4. Conclusions and outlook

This work has developed an estimator of the position of a wake impinging on a downstream wind turbine. The method is based on a simplified linear model, which correlates hub loads to inflow characteristics. Wake position tracking is performed by coupling in a minimization algorithm the estimated wind speed deficit and the horizontal shear induced by the wake. These two pieces of information allow one to track the wake center position with a good level of accuracy. The resulting position can be used in wind farm control algorithms based on a wake redirection strategy, or whenever knowledge of the wake position is useful.

Improvements and extensions of the present algorithm can be pursued on multiple fronts. A possible limitation of the algorithm may be due to Larsen's model, and a more accurate and detailed wake modeling should be considered. Specifically, one should include the effects due to yaw misalignment on both speed deficit and induced shear. Moreover, a validation by wind tunnel testing [13] is necessary to improve confidence on this new method, in preparation for a possible real field demonstration.

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