Field testing of a local wind inflow estimator and wake detector

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Abstract.

This paper presents the field validation of a method to estimate the local wind speed on different sectors of a turbine rotor disk. Each rotating blade is used as a scanning sensor that, travelling across the rotor disk, samples the inflow. From the local speed estimates, the method can reconstruct the vertical wind shear and detect the presence and location on an impinging wake shed by an upstream wind turbine. Shear and wake awareness have multiple uses, from turbine and farm control to monitoring and forecasting.

This validation study is conducted with an experimental data set obtained with two multi-MW wind turbines and a hub-tall met-mast. Practical and simple procedures are presented and demonstrated to correct for the possible miscalibration of sensors.

Results indicate a very good correlation between the estimated vertical shear and the one measured by the met-mast. Additionally, the proposed method exhibits a remarkable ability to locate and track the motion of an impinging wake on an affected rotor.

1 Introduction

Knowledge of the wind turbine inflow can empower several applications. For example, a turbine controller can be improved when scheduled as a function of wind speed (Østergaard et al., 2007). Similarly, a farm controller benefits from knowledge of the atmospheric stability, with its strong effect on wake recovery, and from an improved understanding of wake position (Vollmer et al., 2017), with its crucial implications on power output and loading. Apart from control applications, other usage scenarios include lifetime assessment and fatigue consumption estimation, which are clearly dictated by the inflow conditions experienced by each turbine (Ziegler and Muskulus, 2016). Moreover, wind farm power and wind forecasting, site assessment for wind farm extensions, sector management triggered by wake detection for closely spaced turbines, and estimation of available wind farm power are all additional applications that can profit from knowledge of the inflow affecting each single turbine. Unfortunately, this information is not available on today's wind turbines that, as a consequence, operate "in the dark" based only on a limited awareness of the environment in which they are immersed.

Indeed, turbines are equipped with wind sensors, typically located on the nacelle or the spinner, which are used for aligning the rotor axis into the wind and for identifying whether the cut-in or cut-out wind speeds have been reached. Even though these measurements might be accurate enough for these simple tasks, the actual complexity of the turbine inflow remains completely beyond the reach of such sensors. In addition, wind vanes and anemometers provide pointwise information, while

wind conditions exhibit significant spatial variability not only at the large scale of the farm, as in off-shore plants (Peña et al., 2018) and at complex terrain sites (Lange et al., 2017; Schreiber et al., 2019), but also at the smaller scale of the individual turbine rotor disk (Murphy et al., 2019). More sophisticated measurements can be provided by lidars (Held and Mann, 2019) and other remote sensing technologies, which are however still costly and —being mostly used for assessment, validation and

5 research— are not yet commonly used for production installations.

The concept of using the wind turbine rotor as a wind sensor has been proposed to improve wind condition awareness (Bottasso et al., 2010; Simley and Pao, 2016; Bertelè et al., 2017). In a nutshell, wind sensing uses the response of the rotor —in the form of loads, accelerations and other operational data— to infer the characteristics of the wind blowing on the turbine. Therefore, wind sensing is a sort of model inversion, where the response of the system is used to estimate the disturbance (in

10 this case, the wind). The simplest and probably most widely used wind sensing technique is torque-balance estimation (Ma et al., 1995; Soltani et al., 2013). Thereby, turbine power or torque are used to estimate the rotor-effective wind speed by the power curve or power coefficient. The concept has been more recently extended to estimate other characteristics of the inflow, notably the wind directions and shears, as reviewed in Bertelè et al. (2017).

This paper considers the approach first formulated by Bottasso et al. (2018). Through an aerodynamic "cone" coefficient,

15 this method uses the blade out-of-plane bending moment to estimate the local wind speed at the position occupied by a blade. The method is very similar to the torque-balance estimation of the wind speed, with the important difference that it produces a localized speed estimate instead of a rotor-effective one. The rotating blades therefore operate as scanning sensors that, travelling across the rotor disk, sample the local variability of the inflow. In turn, the local wind speed estimates are used for obtaining two key pieces of information on the inflow: the vertical shear, which is an important load-driver and an indicator of

20 atmospheric stability, and the horizontal shear, which can be used to detect the presence and location of an impinging wake. Today, only a scanning lidar would be able to provide similar information on the inflow, albeit not exactly at the rotor disk —as done here, as the rotor itself is the sensor in this case— and with a very different level of complexity and cost.

The present method has some very interesting features. First, it is model-based, and therefore it does not necessitate of extensive data sets for its training. Second, it is based on an extremely simple model of the rotor (expressed through the

25 cone coefficient), which can be readily computed from a standard aeroelastic model of a wind turbine. Third, the resulting estimator is in the form of a simple look-up-table that is computed off-line, resulting in an on-line on-board implementation of negligible computational cost. Fourth, when load sensors are already installed on the turbine for load-alleviating control or monitoring, this wind sensing technique requires no additional hardware, and therefore its implementation simply amounts to a software upgrade. The wind sensing method considered here has already been tested with Blade Element Momentum (BEM)

30 aeroelastic simulations (Bottasso et al., 2018), large eddy simulations (Schreiber and Wang, 2018), and scaled wind tunnel tests (Campagnolo et al., 2017). Applications related to wake position tracking within a wind farm have been presented in Schreiber et al. (2016) and Bottasso and Schreiber (2018).

Goal of the present paper is to validate the wind sensing approach of Bottasso et al. (2018) in the field. To this end, the method is exercised on a data set obtained with two 3.5 MW turbines, one of which has two blades equipped with load sensors,

and a meteorological mast (met-mast). Since a perfect calibration of the sensors cannot always be guaranteed, another goal of the paper is to present and demonstrate simple and effective methods to correct the measurements and improve accuracy.

The paper is organized as follows. First, the formulation of the wind sensing method is reviewed, including the estimation of rotor-effective and sector-effective wind speeds, as well as of horizontal and vertical shears. Next, the experimental setup

5 is described, including the site layout and the available measurements. The results section represents the core of the paper, and illustrates in detail the performance of the wind sensing technique. A first part of the analysis is concerned with the validation of the vertical shear estimates. Then, the attention is turned to the detection of wake impingement, which is studied by exploiting the waking induced at the site for some wind directions by a neighboring turbine. Finally, the effects of cross-flow are considered, demonstrating that the typical inevitable misalignments between turbine and wind vector do not pollute

10 the estimates. Conclusions and an outlook on future work are given in the last section.

2 Methods

2.1 Rotor and blade-effective wind speed estimation

Considering a steady and uniform wind speed V, the power C_p and cone C_m coefficients are defined as

$$C_\mathrm{p}(\beta,\lambda,q) = \frac{T_\mathrm{aero}\Omega}{0.5\rho A V^3}, \tag{1a}$$

$$C_\mathrm{m}(\beta,\lambda,q,\psi_i) = \frac{m_i}{0.5\rho A R V^2}, \tag{1b}$$

where β is the blade pitch angle, $\lambda = \Omega R/V$ the tip speed ratio, Ω the rotor speed, R is the rotor radius and $A = \pi R^2$ the swept disk area, ρ is the air density and $q = 1/2\rho A V^2$ the dynamic pressure, while T_aero is the aerodynamic torque. The azimuthal position of the ith blade is given by ψ_i, while m_i is its out-of-plane root bending moment. Coefficients C_p and C_m are readily computed using an aeroelastic model of the turbine, today customarily based on a BEM method that, in the present work, is

20 the one implemented in the FAST code (Jonkman and Jonkman, 2018).

Different approaches to estimate wind speed from the power coefficient are reviewed in detail by Soltani et al. (2013). However, following Bottasso et al. (2018), here we use both the power and the cone coefficients: while the former yields a rotor-effective wind speed (i.e., an average quantity over the entire rotor disk), the latter is used to sample the *local* wind speed at the azimuthal position occupied by a blade. Given coefficients C_p and C_m computed for a reference air density ρ_ref, look-

25 up-tables (LUTs) are generated that return wind speeds given measured loads T_aero and m_i, blade pitch β, rotor speed Ω and air density ρ. Noting the rotor-effective wind speed estimated from the torque balance equilibrium as V_TB and the one from blade loads as V_i, the inversion of Eqs. (1) yields

$$V_\mathrm{TB} = \mathrm{LUT}_{C_\mathrm{p}}(\beta,\Omega,T_\mathrm{aero},\frac{\rho}{\rho_\mathrm{ref}}), \tag{2a}$$

$$V_i = \mathrm{LUT}_{C_\mathrm{m}}(\beta,\Omega,\psi,m_i,\frac{\rho}{\rho_\mathrm{ref}}). \tag{2b}$$

Instead of the simple non-linear model inversion adopted here for simplicity, more sophisticated methods can be used, for example based on Kalman filters or input observers (Soltani et al., 2013), which may slightly improve the results at the cost on an increased complexity. A rotor-effective wind speed can also be obtained from the blade-effective ones by simple averaging over all (three) blades:

$$V_{\mathrm{B}} = 1/3 \sum_{i=1}^{3} V_i. \tag{3}$$

Although in a non-uniform inflow the two rotor-effective speeds V_{TB} and V_{B} are not necessarily identical, they are in practice very similar, as shown later on in the results section. The redundancy offered by V_{TB} and V_{B} offers opportunities for sensor calibration, as also described later on.

In Eq. (2a), T_{aero} is computed from the dynamic torque balance equilibrium $J\dot{\Omega} = T_{\mathrm{aero}} - T_{\mathrm{meas}} - T_{\mathrm{loss}}$, where J is the
10 total rotor, drive-train and generator rotational inertia, while $\dot{\Omega}$ is the rotor acceleration and T_{meas} is the measured torque at the generator. Mechanical losses in the whole drive-train are taken into account by the term T_{loss} (Soltani et al., 2013). Here, for the accuracy of the wind speed estimate, a dynamic model is used to compute the aerodynamic torque. In fact, the energy converted into rotor acceleration or deceleration is typically large, given the large rotational inertia of the system.

A simpler approach is used for Eq. (2b), where the blade dynamic equilibrium is neglected. This way, the out-of-plane
15 bending moment is directly set to the corresponding measured load, i.e. $m_i = m_{i,\mathrm{meas}}$, where $m_{i,\mathrm{meas}}$ is provided by blade-mounted strain gages, optical sensors or similar devices. Although even in this case one could include a flapwise dynamic equilibrium equation, similarly to what done for the torque balance case, the smaller inertia and high damping of this degree of freedom makes this more sophisticated approach superfluous.

The power and cone coefficients of Eqs. (1) are computed when the rotor axis is aligned with the ambient wind direction.
20 Hence, strictly speaking, Eqs. (2) can be used to estimate wind speeds only in the same aligned conditions. However, this is typically not the case in practice, as turbines are often misaligned with respect to the wind by several degrees. It will be shown later on that moderate misalignments do not significantly affect the estimation of wind speeds, and that the effects of larger misalignments can be corrected for.

2.2 Sector-effective wind speed estimation

25 An average wind speed over a rotor sector can be readily computed by averaging the blade-effective estimate V_i between two azimuthal angles ψ_{a} and ψ_{b}:

$$V_{\mathrm{S}} = \int_{A_{\mathrm{S}}} V_i(\psi)\,\mathrm{d}A_{\mathrm{S}}, \tag{4}$$

where $A_{\mathrm{S}} = (\psi_{\mathrm{b}} - \psi_{\mathrm{a}})R^2/2$ is the area of the sector. A new sector-effective speed estimate is generated as soon as a blade leaves the sector.

30 The sector width can be arbitrarily defined. Figure 1 shows the case of the four equally-sized 90-degree-wide sectors used in this work, yielding the four sector-effective wind speed estimates $V_{\mathrm{S,left}}$, $V_{\mathrm{S,right}}$, $V_{\mathrm{S,up}}$, and $V_{\mathrm{S,down}}$. Clearly, a finer sampling

of the inflow over the rotor disk can be achieved by using smaller sectors. With three blades, each of the sectors is updated three times per rotor revolution. With one single instrumented blade, the update frequency reduces to once per revolution.
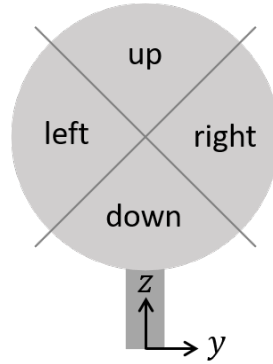
Figure 1. Wind turbine rotor disk with sectors and inflow coordinate system. This naming convention is in the downstream viewing direction.

It was shown in Bottasso et al. (2018) that, for a linear inflow shear and a 90-degree-wide sector, the sector-effective wind speed corresponds to the inflow speed at a distance of approximately $2/3R$ from the hub center.

5 **2.3 Shear estimation**

The vertical wind shear is modeled as a power law profile with exponent α, while the horizontal shear is assumed to be linear with coefficient κ. The inflow wind speed V can therefore be written as

$$V(z,y) = V_{\mathrm{H}} \left(\left(\frac{z}{z_{\mathrm{H}}} \right)^{\alpha} + \kappa \frac{y}{R} \right), \tag{5}$$

where z and y are the vertical and lateral coordinates, respectively, with origin at the turbine foundation, as shown in Fig. 1.
10 Furthermore, V_{H} is the speed at the hub center, which is located at $z = z_{\mathrm{H}}$ and $y = 0$.

Assuming that the sector-effective speed samples the inflow profile at $\pm 2/3R$ along the z and y axes, according to Bottasso et al. (2018), the shear coefficients can be estimated from the sector-effective wind speeds by using Eq. (5), which yields

$$\alpha_{\mathrm{B}} = \ln \left(\frac{V_{\mathrm{S,up}}}{V_{\mathrm{S,down}}} \right) \left(\ln \left(\frac{z_{\mathrm{H}} + 2/3R}{z_{\mathrm{H}} - 2/3R} \right) \right)^{-1}, \tag{6a}$$

$$\kappa_{\mathrm{B}} = \frac{3}{2} \frac{V_{\mathrm{S,right}} - V_{\mathrm{S,left}}}{V_{\mathrm{S,right}} + V_{\mathrm{S,left}}}. \tag{6b}$$

15 This way, the vertical shear is estimated by using the top and bottom sectors, while the horizontal shear by using the two lateral sectors. One could also use all four sectors together, and solve Eq. (5) simultaneously in a least squares sense for both α_{B} and κ_{B}. However, this does not lead to appreciable differences in the results of this paper.

The vertical shear estimate is validated in this work by comparison with an IEC-compliant met-mast, reaching up to hub height. However, shears computed over the whole rotor or over only its lower half can be significantly different; therefore, one
20 should not compare the full-rotor shear obtained by Eq. (6a) with a lower-half-rotor shear provided by a hub-tall met-mast. To

address this issue, a *lower-half-rotor shear estimate* is defined here. This quantity is computed by first averaging the two lateral (left and right) sectors to provide a hub-height speed that, together with the lower sector, is then used to estimate the shear on the sole lower portion of the rotor disk. Using Eq. (5), the lower-half-rotor shear estimate is obtained as

$$\alpha_{\mathrm{lower,B}} = \ln\left(\frac{V_{\mathrm{S,left}} + V_{\mathrm{S,right}}}{2V_{\mathrm{S,down}}}\right)\left(\ln\left(\frac{z_{\mathrm{H}}}{z_{\mathrm{H}} - 2/3R}\right)\right)^{-1}. \tag{7}$$

3   Results

3.1   Experimental setup

This validation study is conducted using an eno114 wind turbine manufactured by eno energy systems GmbH. This turbine, in the following named WT1, has a rated power of 3.5 MW, a rotor diameter $D = 114.9$ m, a hub height $z_{\mathrm{H}} = 92$ m and it is equipped with blade load sensors on two of its three blades. The turbine is installed close to Brusow (Germany), in a flat terrain site approximatively 10 km south of the Western Baltic Sea, characterized by prevailing westerly wind directions. At the site, a second turbine of the same type, named WT2, and a meteorological mast are also installed. Figure 2 shows a satellite image of the site, including the waking directions and distances among the three installations. WT1 is downstream of the met-mast for a wind direction $\Gamma_{\mathrm{MM->WT1}} = 192.5°$, while WT1 is waked by WT2 for $\Gamma_{\mathrm{WT2->WT1}} = 145°$. The met-mast is equipped with anemometers at three different heights, the topmost reaching 91.5 m, which is just half a meter shy of the turbine hub height. The relevant heights of the turbine and met-mast are shown in Fig. 3.

3.2   Measurements

Synchronized measurements of WT1 and the met-mast were made available by the turbine manufacturer and operator for 41 days from October 19 to November 29, 2017. The measurements include main shaft torsion T_{meas}, blade root out-of-plane bending moments for two blades $m_{1,2}$, rotor speed Ω, blade pitch β, and rotor azimuth position ψ. The air density ρ was computed by the ideal gas law using measured air pressure and temperature. Met-mast measurements include wind speed $V_{\mathrm{MM,1-3}}$ at the three heights $z_{\mathrm{MM,1-3}}$, and wind direction Γ_{MM} at the single height $z_{\mathrm{MM,2}}$.

All measurements are sampled at 10 Hz. To eliminate higher frequency turbine dynamics and measurement noise, the rotor speed and torque signals were low pass filtered using a fifth order Butterworth filter with a -3 db cut-off frequency of 6 rpm.

The long-term average readings of the two blade load sensors are expected to be equal. However, when comparing the mean sensor values for any of the available days, the relative difference between the two blades was found to be between 4.8 and 5.8%, whereas the absolute differences varied between -100 and -300 kNm. This mismatch between the two blades suggests a consistent miscalibration of the sensors. To correct for this, the first 24 hours of data were used to identify a scaling factor $s = 0.0274$ such that $\overline{m}_1(1+s) = \overline{m}_2(1-s)$, where $\overline{(\cdot)}$ indicates a mean value. This scaling factor was then used to correct the sensor readings for the whole data set. Notice that this scaling simply ensures consistent measurements between the two sensors, but not their absolute accuracy, which is corrected later on by comparison with the rotor-effective wind speed V_{TB}. In
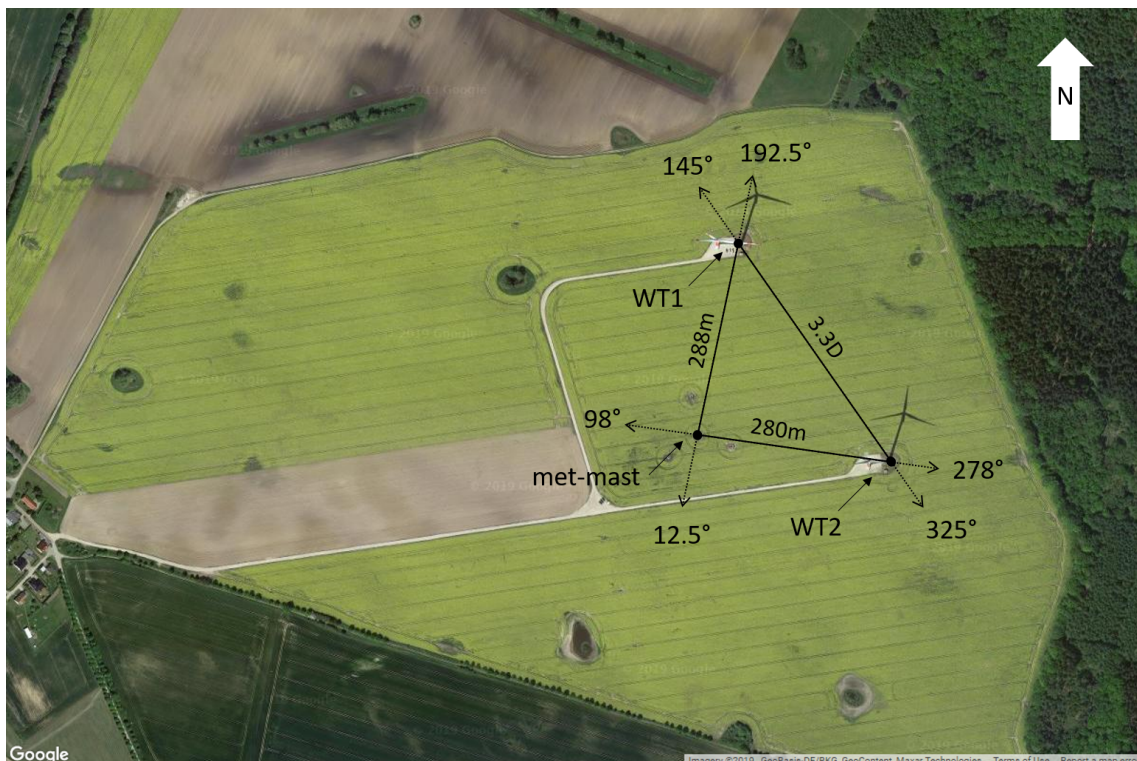
Figure 2. Satellite image with WT1, WT2 and met-mast, including waking directions and distances (© Google Maps).
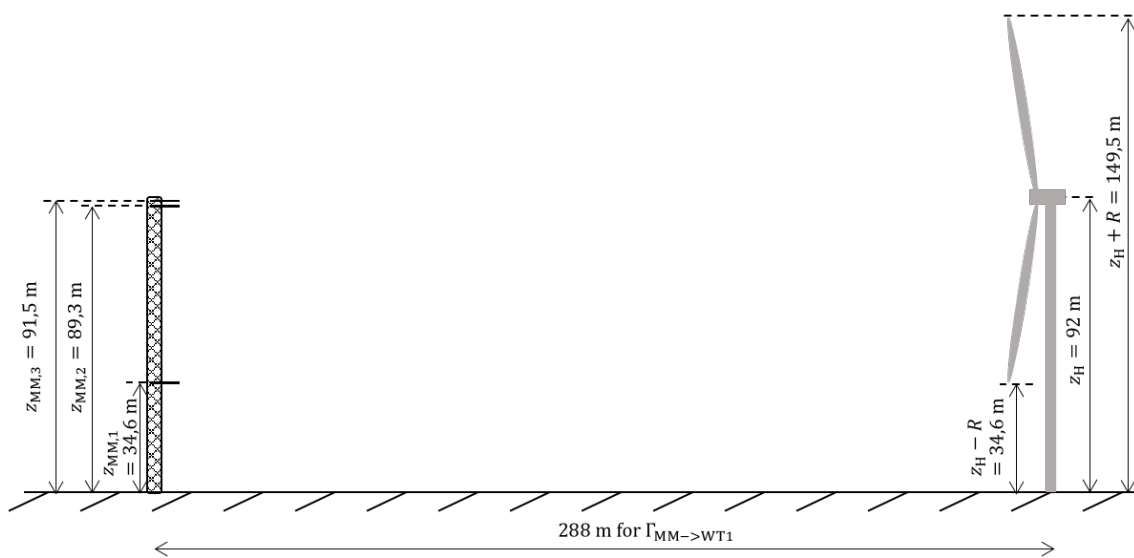
Figure 3. Sketch (to scale) of met-mast and WT1 with relevant dimensions.

fact, as this quantity is based on an independent set of measurements through the torque balance equation, it provides for an opportunity to calibrate the blade load sensors.

The data set was filtered, retaining only measurements corresponding to normal turbine operation with pitch and rotor speed within the LUT limits (see Sect. 3.4). Measurements taken during yawing manoeuvres were also discarded, as additional
5   induced loads can pollute the estimates. After each discarded measurement, an interval of 1 minute for the estimator re-initialization was accounted for. The statistical analysis reported below is conducted with 10-minute averages. Of the initial data set, a total of $4,279$ consecutive 10-minute quantities were obtained, representing approximatively 30 days of operation.

3.3 Reference inflow

The ambient inflow measured by the met-mast is assumed to obey the vertical power law given by Eq. (5). Consequently, the
10   met-mast-measured hub-height reference speed V_{ref} and power exponent α_{MM} were computed as best fits of the mast speed measurements at the three different available heights, i.e.

$$(V_{\mathrm{ref}},\alpha) = \arg\min_{V_{\mathrm{ref}},\alpha} \sum_{i=1}^{3}(V_{\mathrm{PL}}(z_{\mathrm{MM},i},V_{\mathrm{ref}},\alpha) - V_{\mathrm{MM},i})^2. \tag{8}$$

Depending on wind direction, the met-mast is located up to 288 meters upstream of WT1, as shown in Fig. 2 for $\Gamma_{\mathrm{MM->WT1}}$. To synchronize met-mast and turbine measurements, assuming Taylor's frozen turbulence hypothesis, each 10-minute met-mast
15   measurement was time-shifted by $\Delta t = s_{\mathrm{MM->WT1}}/V_{\mathrm{ref}}$, where $s_{\mathrm{MM->WT1}}$ is the downstream distance from met-mast to WT1.

3.4 Look-up-table implementation

An aeroelastic model of the turbine was provided by the turbine manufacturer, implemented in the software FAST (Jonkman and Jonkman, 2018). To compute the power and cone coefficients of Eq. (1), a total of 10,626 dynamic simulations were
20   performed in steady and uniform wind conditions for all combinations of $\beta \in [0:1:20]°$, $\Omega \in [3:0.5:14]$ rpm and $V \in [1:1:22]$ m/s, which took just a few hours on a standard desktop PC. Eliminating the tower and drive-train dynamics, a converged periodic response was achieved in three rotor revolutions.

Considering the last revolution, the power coefficient was computed from the mean torque, while the cone coefficient was obtained from the blade root out-of-plane bending moment of one of the blades as a function of ψ. The look-up-tables were
25   compiled, for each β, Ω and —if applicable— ψ, by computing speed as a function of load, including the cases where the blade is partially or fully stalled.

3.5 Validation of rotor-effective wind speed estimation

First, the rotor-effective speed estimates V_{TB} (computed through the torque balance equilibrium by Eq. (2a)) and V_{B} (computed using blade bending moments by Eq. (3)) are compared to each other and to the reference met-mast speed given by Eq. (8).
30   A direct comparison between V_{TB} and V_{B} revealed that the latter provides systematically slightly higher wind speeds than the

former. This discrepancy may be caused by improper blade load sensor calibration (see Section 3.2) and/or deficiencies of the simulation model used to compute the aerodynamic coefficients. To pragmatically correct these sources of estimation bias, all speed estimates (V_B, $V_\mathrm{S,left}$, $V_\mathrm{S,right}$, $V_\mathrm{S,up}$ and $V_\mathrm{S,down}$) in the remainder of the paper are scaled by a factor $c = 0.928$. This scaling ensures the best correlation between V_B and V_TB, and was identified based on the first 7 days of measured data. Note

5 that a direct scaling of the load measurements is also possible and potentially even more accurate.

It is worth pointing out that the redundancy of the two estimates V_B and V_TB offers the opportunity to ensure the consistency between different sets of sensors (the ones measuring blade loads and the ones providing rotor torque). For example, here the torque sensors were properly calibrated, as indicated by the independent measurements of the met-mast, while the blade load sensors were not. Therefore, the redundancy was used to calibrate the load sensors against the torque ones. Similar recalibration

10 procedures might be used also in situations were a met-mast is not available, if one can ensure that at least one set of sensors is properly calibrated.
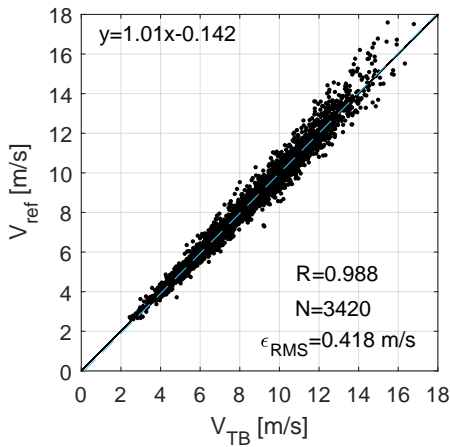
Figure 4. Torque-balance-based rotor-effective wind speed V_TB (Eq. (2a)) vs. met-mast reference wind speed V_ref (Eq. (8)).
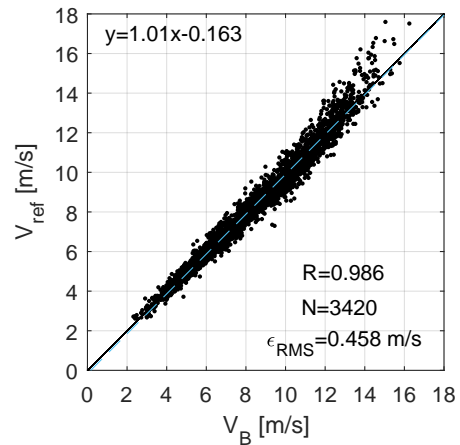
Figure 5. Bending-load-based rotor-effective wind speed V_B (Eq. (3)) vs. met-mast reference wind speed V_ref (Eq. (8)).

After correction, a comparison between met-mast reference speed V_ref and torque balance estimates V_TB and V_B is shown in Figs. 4 and 5, respectively. These results include only $3,420$ data points where the met-mast wind direction lies between $180°$ and $337.5°$, to avoid conditions where the turbine or the met-mast operate in the wake of either WT1 or WT2 (assuming

15 a $\pm35°$ margin). The Pearson correlation coefficient R is approximatively equal to 0.99, while the root mean squared error is $\epsilon_\mathrm{RMS} \approx 0.44$ m/s and the linear best fit ($y = ax + b$) has a slope $a = 1.01$ and an offset $b \approx -0.15$ m/s. These results indicate that, after calibration, the two methods correlate well with the (approximate) ground truth provided by the met-mast, and that both yield very similar estimates.

3.6 Validation of vertical shear estimation

After discarding waked conditions from turbine WT2 (with a $\pm 35°$ margin), an analysis of the long-term mean horizontal shear revealed it to be non-zero. This finding is in contrast with expectations. In fact, while for a narrow wind direction sector some horizontal shear due to local orography or vegetation can be expected, such effects should disappear considering the complete wind rose.

This behavior can be explained by a possible bias in the measurement of the azimuthal position of the rotor, which has the consequence of generating a non-zero horizontal shear and reducing the vertical one. In addition, another effect should be considered: as no blade dynamics were included in the model (see Sect. 2.1), the response of the blade is assumed to instantaneously follow a wind speed change. This is in reality not true, and the actual response will have a phase delay, which appears as yet another source of azimuthal bias.

The expected behavior of the horizontal shear can be used for eliminating these effects. In fact, enforcing a null long-term average horizontal shear corrects both for azimuth sensor bias and for having neglected blade dynamics. To this end, the vertical and horizontal shears were rotated by ψ_{bias}, until a null mean horizontal shear was obtained. Accordingly, the mean vertical shear also reached its maximum. Using again the first 7 days of measurements, the azimuth bias was identified as $\psi_{\text{bias}} = 11.4°$. In the remainder of this work, the sector-effective wind speeds and the two shears are computed using the corrected azimuth signal $\psi_{\text{corr}} = \psi + \psi_{\text{bias}}$.

As previously discussed, the reference inflow profile measured by the met-mast through Eq. (8) only includes measurements up to hub height. Accordingly, the load-based lower-half-rotor vertical shear $\alpha_{\text{lower,B}}$ (computed by Eq.(7) in terms of the two horizontal and the bottom sectors) is the only shear that can be validated with respect to met-mast measurements.

A 12-hour excerpt from the complete set of results is shown in Fig. 6, where 10-minute means of measurements and estimates are provided as functions of time.

The top subplot shows the wind direction Γ_{MM} measured at the met-mast; the direction for which the met-mast is directly upstream of the sensing turbine is $\Gamma_{\text{MM}->\text{WT1}} = 192.5°$, and it is shown by a horizontal solid line.

The second subplot from the top shows the reference wind speed V_{ref} measured at the met-mast, together with the torque-balance V_{TB} and blade-load-based V_{B} rotor-effective speeds. As already noticed, both methods provide very similar results; in addition, especially for wind directions where mast and turbine are nearly aligned, both follow the reference very closely.

25

The third subplot from the top shows again the met-mast reference wind speed at hub height (solid line) and the one at $z_{\text{H}} - 2/3R$ (dashed line). The respective load-based estimates are indicated with a blue solid line and $\bullet$ symbols for the hub height speed, and with a red solid line and $\times$ symbols for the lower height speed. Both estimates correlate well with their respective references, especially when mast and turbine are aligned. The small rotor icon shows, using the color code of the subplot, the two horizontal sectors (used to estimate the hub height wind speed $1/2(V_{\text{S,left}} + V_{\text{S,right}})$) and the lower sector.

30

The last subplot finally shows the mast vertical shear α_{MM} and the load-based estimate $\alpha_{\text{lower,B}}$, computed based on the data shown in the third subplot using Eq. (7). Except for some small underestimation and noise, the load-based shear follows
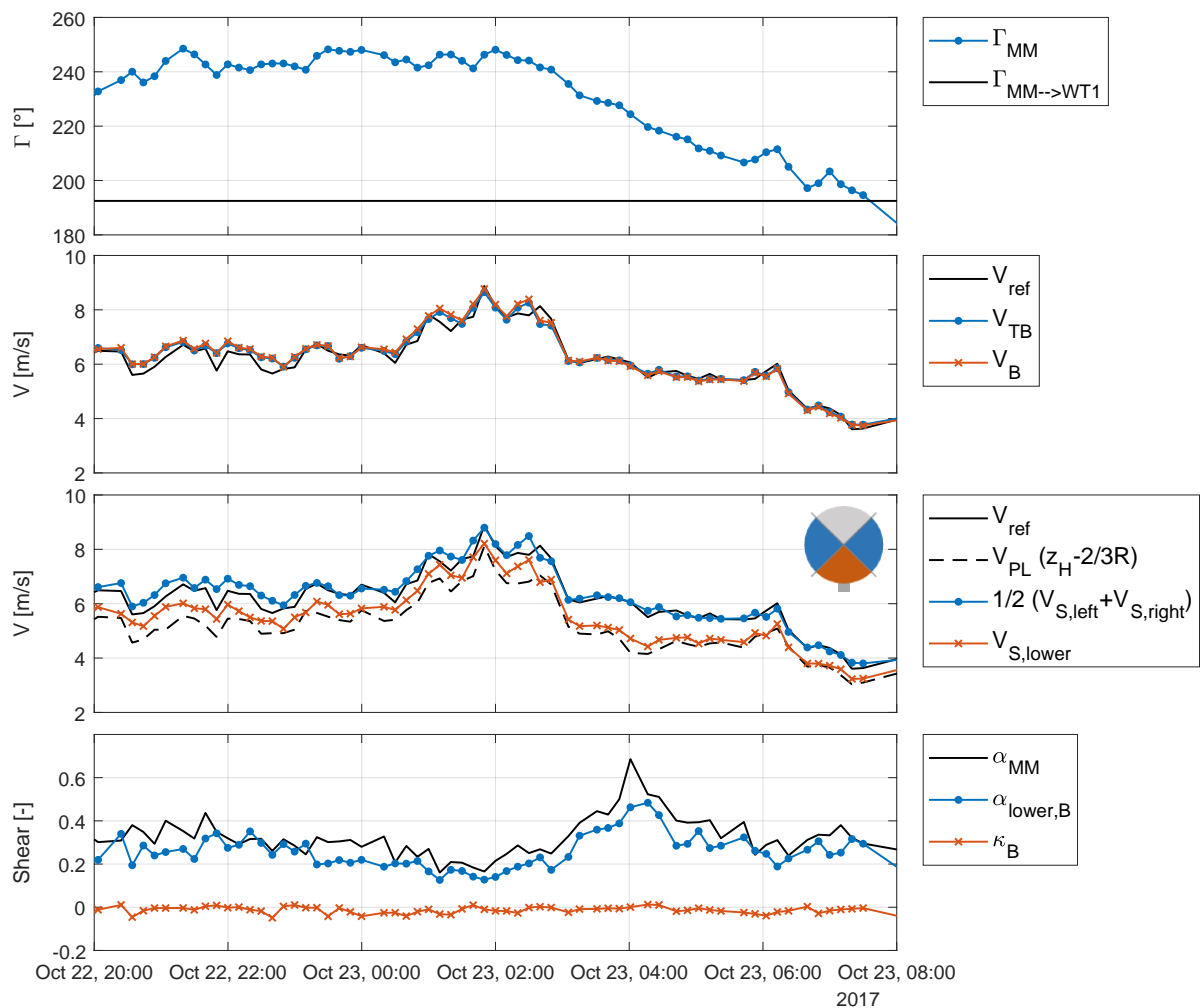
Figure 6. Time series reporting met-mast wind direction (top subplot), met-mast and estimated rotor-effective wind speeds (second subplot), speeds at different heights (third subplot), and met-mast and estimated vertical and horizontal shears (bottom subplot).

the reference quite accurately. The load-based horizontal shear κ_B is also reported in the same figure. Although no met-mast reference is available in this case, as expected the horizontal shear is always essentially null.

Figure 7 shows the correlation between the lower-half-rotor shears $\alpha_{\mathrm{lower,B}}$ and α_{MM}. Only wind directions from $190°$ up to $200°$ are included in the figure, resulting in $N = 155$ 10-minute data points. These conditions contain the direction where
5   the met-mast is directly upstream of WT1. The Pearson correlation coefficient is $R = 0.92$. The shear is underestimated with respect to the met-mast reference by a factor $1/a = 0.88$, obtained by the linear best fit ($y = ax + b$) shown in the figure with a blue dashed line. By looking at the third plot from the top in Fig. 6, a comparison of the wind speed at hub height and at $z_H - 2/3R$ with their respective met-mast references indicates that the former is quite accurate, while the latter has a small positive bias. This difference could possibly be caused by a non-ideal power law inflow profile, leading to a biased
10 met-mast reference shear, although a definitive explanation of this mismatch could not be reached with the present data set. Figure 8 shows the correlation between the full-rotor shear $\alpha_{\mathrm{lower,B}}$ and the lower-half-rotor shear α_{MM}. As the two shears are computed over two different vertical distances, their correlation is lower than in the case of Fig. 7, as expected.
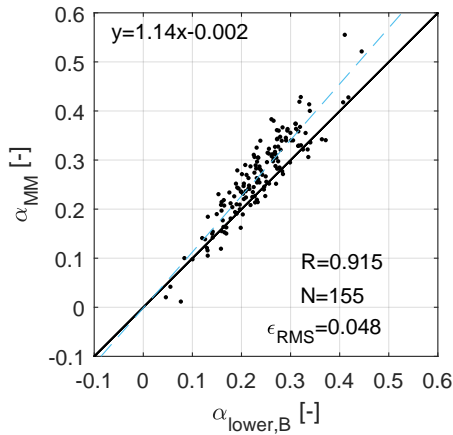
Figure 7. Correlation between the lower-half-rotor vertical shear $\alpha_{\mathrm{lower,B}}$ and the met-mast shear (up to hub height) α_{MM}, for wind directions from $190°$ to $200°$.
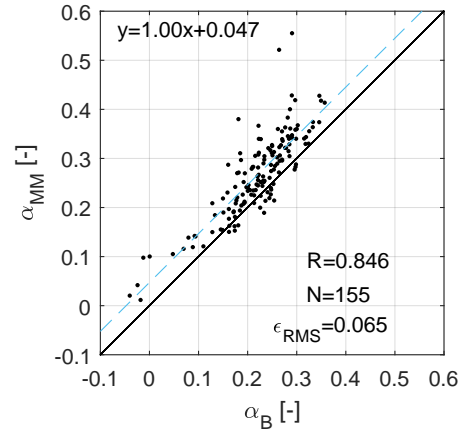
Figure 8. Correlation between the rotor-equivalent (full rotor) vertical shear α_B and the met-mast shear (up to hub height) α_{MM}, for wind directions from $190°$ to $200°$

A more complete overview of the results, including a broader range of wind directions, is shown in Fig. 9. The x-axis reports wind directions from $180°$ to $340°$, in $10°$-wide bins. All results of Fig. 7 fall in the second bin from the left. The
15 number of available measurements N within each bin is shown in the first subplot from the top. The second subplot shows the Pearson correlation coefficient R, between the met-mast reference α_{MM} and the load-based shear estimate $\alpha_{\mathrm{lower,B}}$. Here and in the other plots, a blue solid line indicates results for the lower-half-rotor shear, while a red dashed line is used for the full-rotor shear. The best correlation is achieved for the wind direction where the met-mast is directly upstream of the turbine ($\Gamma_{\mathrm{MM->WT1}} = 192.5°$). For the same wind direction bin, also the minimum root mean squared error is achieved, as shown in
20 the third subplot from the top. Considering that all wind directions are for unwaked met-mast and turbine, these results suggest

the presence of a spatial shear variation, probably caused by the local vegetation. This interpretation is also confirmed by the last two subplots, which show the linear best fit coefficients a and b. For wind directions up to $235°$, the slope coefficient a achieves values between 1.01 and 1.16, increasing up to 1.64 in the remaining wind directions. The constant b is nearly zero for all wind direction values.
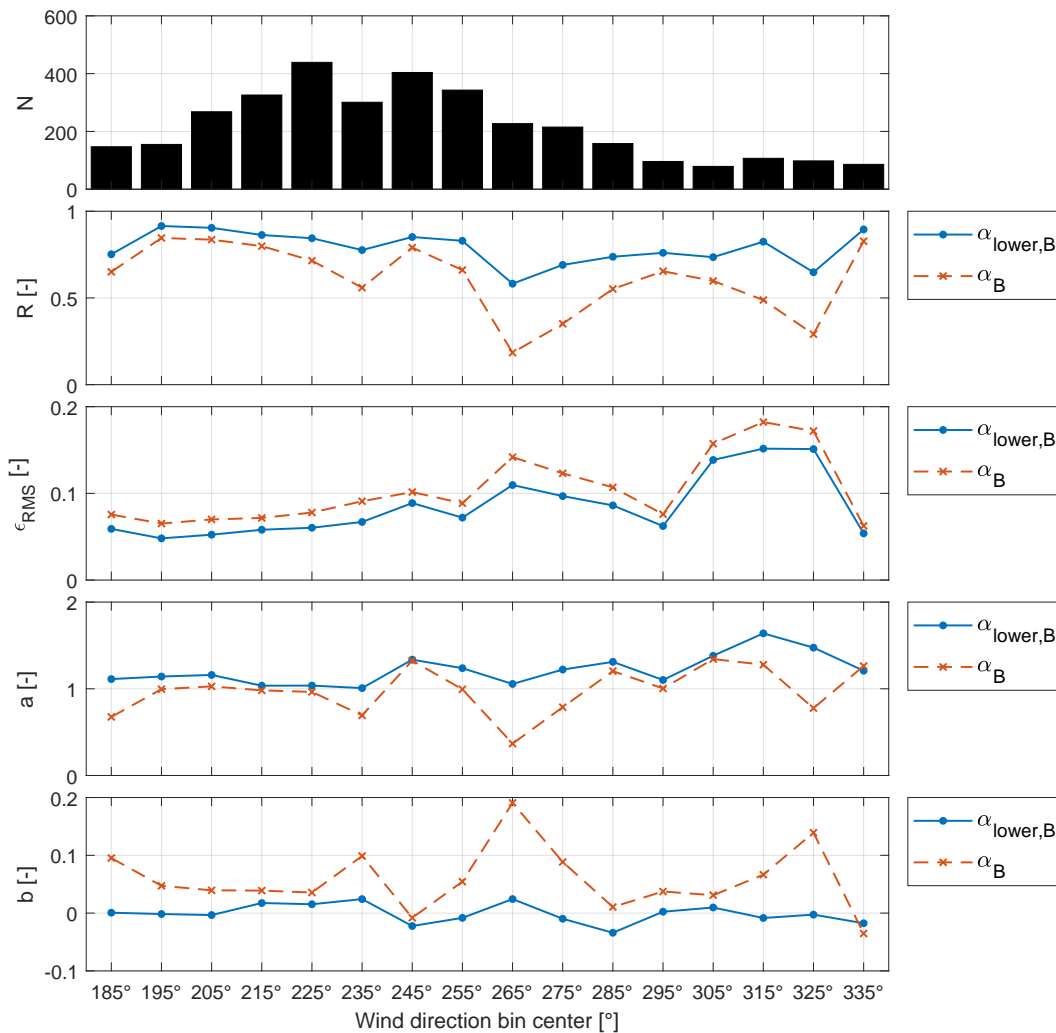
Figure 9. Statistics of the shear estimates as functions of wind direction. Blue solid line: lower-half-rotor shear; red dashed line: full-rotor shear. Top subplot: number of 10-minute data points; second subplot: Pearson correlation coefficient; third subplot: root mean squared errors; fourth and fifth subplots: linear best fit coefficients ($y = ax + b$).

5   Looking at the plots, it appears that the full-rotor shear differs from the lower-half-rotor shear, as already reported by Murphy et al. (2019) and as also observed earlier here in Fig. 7. The validation of the full-rotor shear estimated by the proposed method

would necessitate a met-mast reaching the rotor top height or a velocity-azimuth display (VAD) lidar, which however were not available in the present research. Nonetheless, the results obtained for the lower-half-rotor shear appear to be very encouraging, and there is no technical reason why similar results should not be achievable for shear estimates over the entire rotor disk.

3.7 Validation of wake detection

5   As no measured reference for the horizontal shear was available for this study, the wake of the second turbine was used for a qualitative validation. This wake interference study nicely illustrates the very interesting wake detection capabilities of the proposed method.

Figure 10 reports a time series corresponding to 12 hours of operation, which experienced wind direction changes from approximatively $100°$ to $180°$. This data subset includes a significant duration where WT1 is waked by WT2. The first subplot 10   from the top shows the met-mast wind direction Γ_{MM}, where the waking direction $\Gamma_{WT2->WT1}$ is reported as an horizontal solid line (cf. also Fig. 2). The second subplot shows the reference met-mast wind speed V_{ref}, as well as the load-based rotor-equivalent estimates V_{TB} and V_B. The third subplot shows the sector-effective wind speeds $V_{S,right}/V_{ref}$ and $V_{S,left}/V_{ref}$ for the two horizontal sectors , non-dimensionalized by the met-mast reference wind speed. The small rotor icon shows, using the color code of the subplot, the left (red) and right (blue) sectors. The last subplot reports the horizontal shear estimate κ_B 15   computed according to Eq. (6b).

Vertical dashed lines are used to highlight four time instants, labelled with the letters from A to D. For each of these time instants, the position of the wakes of the two turbines is visualized in the lower part of Fig. 10 using the FLORIS wake model (Doekemeijer and Storm, 2019). The yellow color indicates the ambient wind speed, while the blue color is used for the lower speed in the wakes. The rotor disk of WT2 is shown with a solid black line, while a red line is used for the left sector of WT1 20   and a blue line for the right one. Finally, the small cross symbol indicates the met-mast (MM) position.

At instant A (time equal to 02:05), Fig. 10 shows that the wind direction reaches $130°$ and the left sector of WT1 gets waked by WT2, as clearly illustrated by a reduced speed in the left sector and a positive horizontal shear. At time instant B (02:35), the wind direction has turned back to $122°$: as the turbine is not waked anymore, the estimated shear is null and an equal wind speed is estimated on both the left and right sectors. The rotor-effective wind speed is slightly smaller than the met-mast 25   reference value; however, for this wind direction, the met-mast is not aligned with the turbine, which might explain this small discrepancy. At time instant C (03:45), the wind direction has increased and WT1 is waked again ($\Gamma_{WT2->WT1} = 145°$): after an initial reduction in the left sector speed, also the right sector is affected (dropping below 0.7), indicating a full waked condition. This is further confirmed by the reduction in the rotor-effective wind speeds with respect to the one measured by the met-mast. Later, a wake impingement on the right sector is observed at time 05:00, followed by a second full waking at 30   time 05:30. At instant D (06:20), the wind direction has increases to $159°$ and both sectors operate again in nearly free stream. Accordingly, the rotor-effective wind speeds increase to reach the met-mast reference. Later again, the wind direction varies slightly, leading to partial wake impingements on the right side until, finally (at ≈ 12.00), the wind direction increases further and the horizontal shear becomes almost zero.
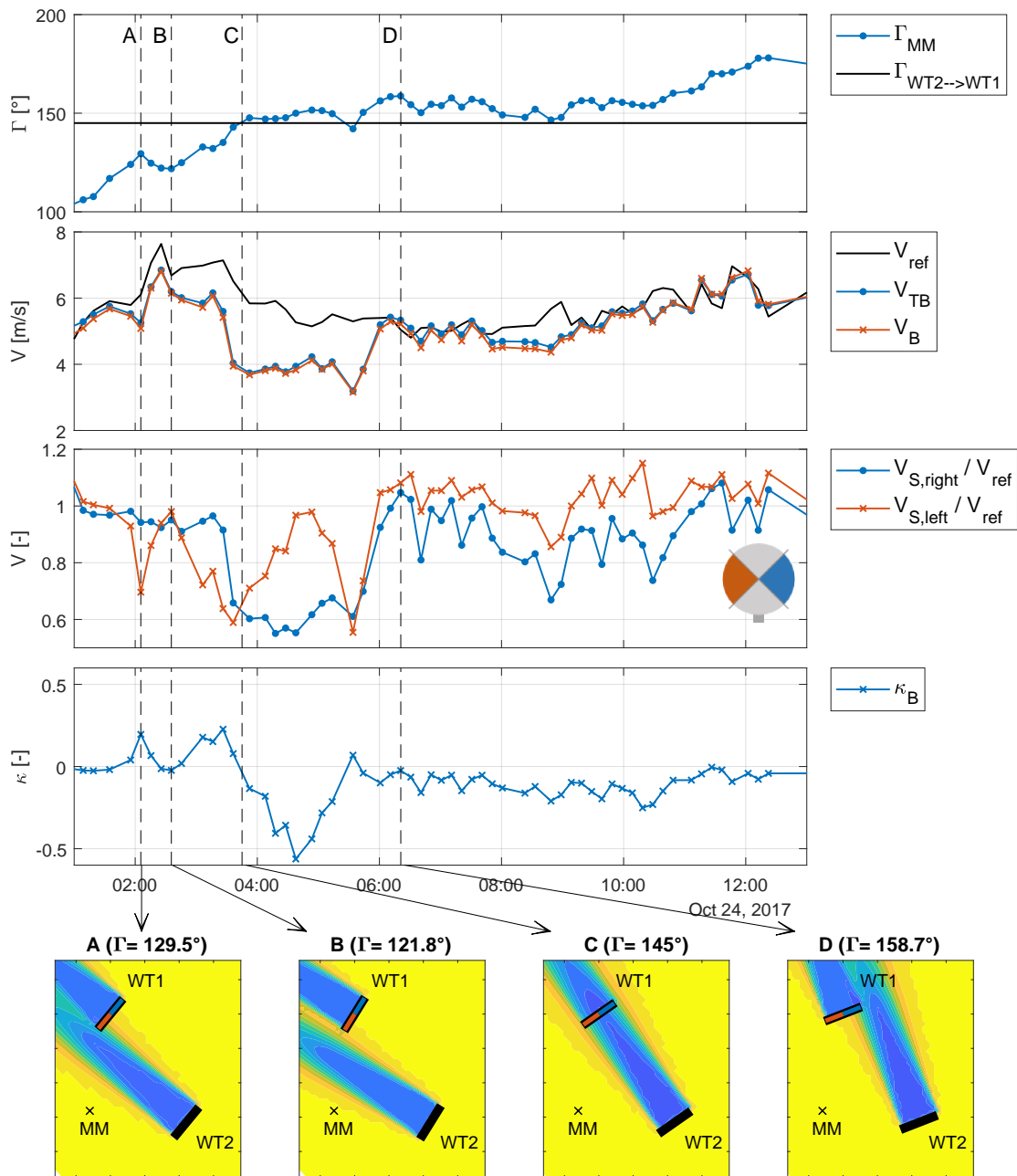
Figure 10. Time series characterized by varying wake interference conditions, with met-mast wind direction (first subplot from the top), reference met-mast wind speed and rotor-effective wind speed estimates (second subplot), left and right sector-effective speed estimates (third subplot), and horizontal shear estimate (fourth subplot). Lower part of the figure: wake visualizations based on the FLORIS model for different wind directions at time instants A through D.

This time series very nicely illustrates how the horizontal sector-effective wind speeds and the horizontal shear can be used to understand the instantaneous position of a wake with respect to an affected turbine rotor disk.

Figure 11 reports extended results, showing all available 10-minute values as functions of met-mast wind direction within the range from $\Gamma_{\mathrm{WT2->WT1}} - 45° = 100°$ to $\Gamma_{\mathrm{WT2->WT1}} + 45° = 190°$. The waking wind direction from WT2 onto WT1

5 ($\Gamma_{\mathrm{WT2->WT1}}$) is indicated by a vertical dashed line.
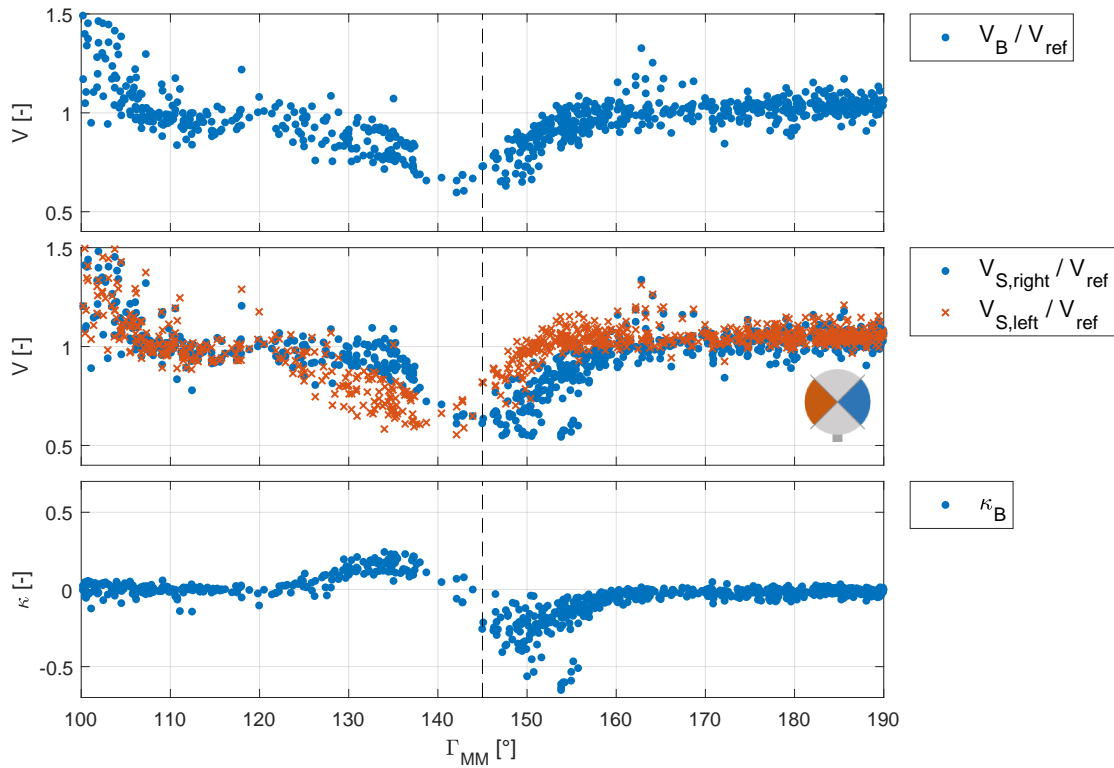
Figure 11. Wind speeds and shear at the WT1 rotor disk as functions of wind direction. Top subplot: non-dimensional load-based rotor-effective wind speed. Central subplot: left and right sector-effective wind speeds. Bottom subplot: horizontal shear.

The first subplot from the top shows the rotor-effective wind speed $V_{\mathrm{B}}/V_{\mathrm{ref}}$, non-dimensionalized by the reference speed of the met-mast. Values larger than one can be observed for wind directions close to $100°$, as the wake of WT2 is affecting the met-mast (see Fig. 2). For wind directions close to $145°$, lower speeds are observed, caused by the wake of WT2 impinging on WT1. For other wind directions, the speed stays close to one, even though some scatter can be observed.

10 The central subplot shows the non-dimensional sector-effective wind speeds $V_{\mathrm{S,right}}/V_{\mathrm{ref}}$ and $V_{\mathrm{S,left}}/V_{\mathrm{ref}}$. The small rotor icon shows, using the color code of the subplot, the left (red) and right (blue) sectors. For wind directions between $\approx 125°$ and $140°$, the local wind speed is smaller in the left sector, indicating that the wake of WT2 is affecting mainly that portion of the rotor disk. Similarly, for wind directions between $145°$ and $\approx 160°$, the right sector is affected by the presence of the wake.

The bottom subplot shows the horizontal shear estimate. This quantity is close to zero for all wind conditions, except around the waking direction. Positive values indicate a left-sided wake impingement, while negative values a right-sided one. Note that the scatter observed in the first two subplots, e.g. for wind directions between $160°$ and $170°$, seems not to be caused by wake interaction but rather by variations in the reference wind speed, as the horizontal shear is not affected.

5 For wind directions close to $140°$, only very few measurement points are available. This suggests that the lower-than-ambient wind speed within the wake of WT2 triggers frequent shutdowns of WT1. Figure 12 shows in $2°$-wide bins the probability of the WT1 status indicating "no operation". Wind directions were based on the met-mast, using all available days without discarding any data point. Indeed, mean direction bins close to $\Gamma_{\mathrm{WT2->WT1}} = 145°$ support the hypothesis of frequent wake-induced turbine shutdowns. Additionally, Fig. 12 reports a maximum for the bin centered at $141°$. This, together with the shear

10 shown in Fig. 11, suggests a small bias in the met-mast wind direction measurement and/or that the wake is not developing exactly along the downstream direction. Indeed, the latter is a well known phenomenon observed in vertically sheared flows (Vollmer et al., 2016).
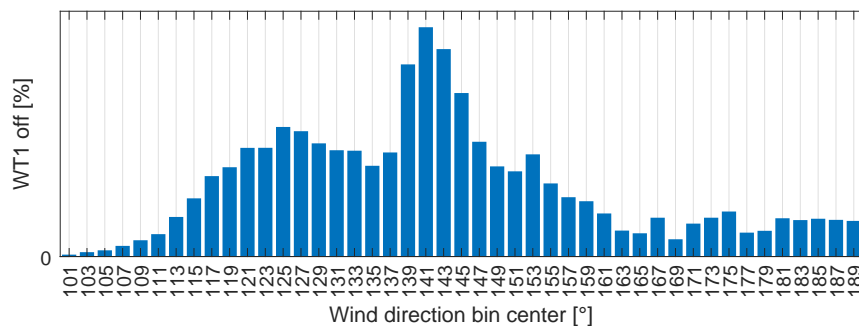
Figure 12. Probability of WT2 being in "no operation" state as a function of met-mast wind direction (using 10 Hz measurements of all available days).

These results demonstrate a remarkable ability of the proposed local speed and shear estimates to identify whether and to which extend a downstream turbine operates in the wake of an upstream machine. Note also that the met-mast reference wind

15 direction is just a point measurement at one single height above the ground. In addition, other unknown inflow parameters, such as for example veer, may affect wake development. Therefore, the scatter of some of the data points in Fig. 11 is not necessarily due to inaccuracies of the wind estimator, but rather due to the indirect, incomplete and pointwise measurement of the reference wake position.

3.8 Effect of turbine misalignment on estimates

20 As previously mentioned in Sect. 2.1, in theory the present method is formulated for turbines aligned with the ambient wind direction. However, in practice this happens only quite rarely, as every turbine in general operates with some degree of mis-alignment with respect to the incoming wind vector. This is mainly due to two reasons. First, the on-board wind vane(s) may

not always provide an exact measurement of the local wind direction. Second, yaw control strategies generally avoid an excessively aggressive tracking of changes in wind direction. In fact, a turbine will typically yaw only when its misalignment with the wind has been above a certain threshold for a long-enough duration of time. This is done to limit duty cycle and yaw expenditure, given the very considerable mass of the rotor-nacelle system and the rather modest power capture loss caused by

5   a misalignment of a few degrees.

Since the hypothesis on which the theory is based differs from the situation encountered in practice, it is necessary to show that the typical misalignments of normal turbine operation do not pollute the speed and shear estimates provided by the proposed method. This is done here by showing that shears and misalignment are indeed uncorrelated.

To this end, Fig. 13 shows the rotor-effective wind speed as well as the horizontal and vertical shear estimates as functions of

10   the turbine-wind misalignment angle $\Gamma_{\mathrm{rel,WT1}}$. The misalignment is measured using the on-board wind vane. As this instrument may be not always very precise on some turbines, the misalignment angle was also computed by using the met-mast wind direction together with the turbine absolute orientation; however, in the present case no significant difference was observed between these two methods of computing the misalignment angle. The results of the figure only include data points for wind directions between $180°$ and $337.5°$, to avoid waked conditions.

15   The first subplot reports the non-dimensional rotor-effective wind speed V_{B}. This quantity decreases for increasing misalignment angle, as shown by the second order polynomial fit reported with a dashed line. Such behaviour is completely expected and can be corrected for, if the misalignment is known, by using the cosine law (Gebraad et al., 2015; Fleming et al., 2017; Schreiber et al., 2017).

As shown, the rotor-equivalent wind speed is clearly correlated with misalignment, because the effective speed orthogonal to

20   the rotor plane varies as a function of this angle. However, there is no reason why the vertical and horizontal shears —which are physical characteristics of the inflow— should also exhibit a similar dependency. To verify this fact, the central subplot shows the horizontal shear estimate κ_{B}, which is almost constant with respect to misalignment angle (and also very close to zero). Finally, the bottom subplot shows the vertical shear α_{B}. It appears that both shears have only a very marginal dependency on wind misalignment, as shown by the parabolic best fits reported with dashed lines in the plots. The larger fluctuations of the

25   vertical shear compared to the horizontal one are probably caused by varying ambient inflow conditions.

The data shows that the shears are essentially uncorrelated with misalignment. These results demonstrate that the proposed method works without significant errors for turbine-wind misalignment angles up to $\approx \pm 10°$.

Larger turbine misalignment angles would be necessary for wake steering control (Fleming et al., 2017), where the rotor is intentionally pointed away from the wind to deflect the wake laterally. The performance of the proposed method could not be

30   tested in such conditions within the present research, as no large misalignment angles were present in the available data set. However, even in that case, the procedure illustrated here could be used for pragmatically correcting possible errors caused by misalignment. In fact, by plotting shears as functions of misalignment angle, a best-fit correction function could be readily derived and used for correcting the estimates, if necessary.
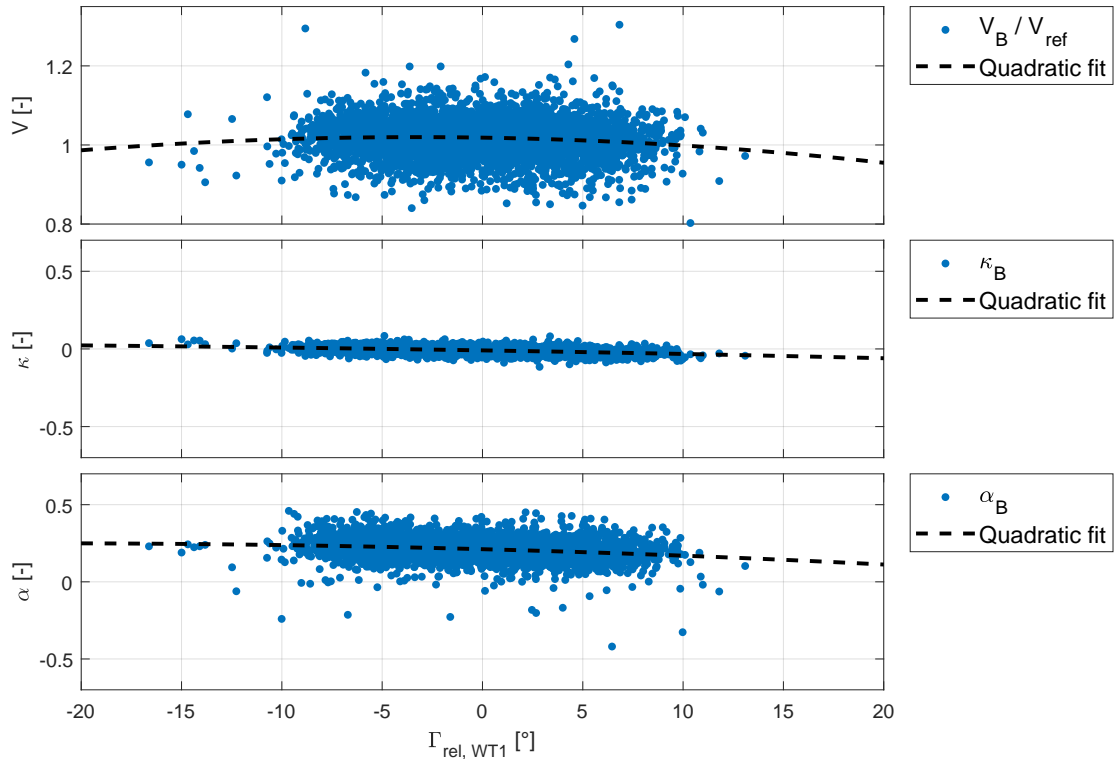
Figure 13. From top to bottom: rotor-effective wind speed V_B, horizontal shear κ_B and vertical shear α_B, all plotted as functions of wind turbine misalignment angle $\Gamma_{\mathrm{rel,WT1}}$.

4   Conclusions

A method to estimate the local wind speeds over sectors of the rotor disk has been tested on a 3.5 MW wind turbine. Results have been compared to reference values obtained with a nearby met-mast. For some wind directions, the sensing turbine is waked by a second machine. This feature of the test site has been exploited for demonstrating the ability of the proposed local

5   wind sensing technique to detect wake impingement.

Based on the field test results showed herein, the following conclusions can be drawn:

– A rotor-effective wind speed can be estimated from blade out-of-plane bending moments, with a quality that is nearly indistinguishable from the well known torque-balance method.

– The vertical wind shear estimated from out-of-plane bending moments correlates very well with the met-mast reference.

10   The best results were obtained when the mast is directly upstream of the turbine. This indicates that some of the scatter

in the results is simply due to a lack of knowledge of the exact ground truth, rather than to a lack of accuracy of the proposed method.

- The vertical shear measured by the met-mast up to hub height differs from the shear measured over the whole rotor disk. Clearly, this is simply a feature of the flow, and not of the method tested here.

- The local wind speeds estimated on two lateral sectors of the rotor disk show the clear fingerprint of an impinging wake shed by a neighbouring turbine. By looking at the two sectors, one can distinguish left, right or full wake overlaps.

- Simple and very practical techniques can be used to correct for various sources of error, including not perfectly calibrated load or azimuth sensors, as well as model approximations.

The present load-based wind estimation method provides for a remarkably simple and effective opportunity to estimate

10 atmospheric inflow conditions on operating turbines. The method is based on readily-available quantities that can be easily computed from a standard model of a wind turbine, and does not need to be trained from extensive data sets. The on-board implementation uses pre-computed look-up-tables. and hence has a negligible computational cost. When load sensors are already installed on a turbine, for example for load-reducing control, this novel wind sensing capability is simply obtained as a software upgrade. Wind sensing opens up a number of opportunities that can profit from a better knowledge of the inflow,

15 including turbine and wind farm control, lifetime consumption estimation, predictive maintenance and forecasting, among others.

Code and data availability. The operational data and turbine model used in this research are the property of eno energy systems GmbH. An implementation of the estimator can be obtained by contacting the authors.

Nomenclature

20 BEM     Blade Element Momentum

LUT     Look-up-table

MM     Met-mast or meteorological mast

WT1     Wind turbine 1 (sensing turbine)

WT2     Wind turbine 2

25

a     Linear best fit constant ($y = ax + b$)

A     Rotor disk area

A_S     Sector area

b     Linear best fit constant ($y = ax + b$)

30 C_m     Cone coefficient

	C_p	Power coefficient
	c	Speed estimate scaling factor
	D	Rotor diameter
	J	Total rotational inertia
5	m_i	Blade root out-of-plane bending moment of blade i
	$m_{i,\mathrm{meas}}$	Measured blade root out-of-plane bending moment of blade i
	N	Number of measurements
	q	Dynamic pressure
	R	Rotor radius or Pearson correlation coefficient
10	s	Load scaling factor
	$s_{\mathrm{MM->WT1}}$	Downstream distance between met-mast and wind turbine WT1
	T_aero	Aerodynamic torque
	T_meas	Measured torque
	V	Wind speed
15	V_B	Blade-load estimated rotor-effective wind speed
	V_H	Wind speed at hub height
	V_i	Blade-effective wind speed estimate of blade i
	$V_{\mathrm{MM},i}$	Met-mast measured wind speed at height i
	V_PL	Power law inflow profile
20	V_ref	Met-mast measured reference wind speed of inflow profile
	V_S	Sector-effective wind speed
	$V_{\mathrm{S,left/right/up/down}}$	Load-based estimation of left/right/up/down sector
	V_TB	Torque-balance estimated rotor-effective wind speed
	y	Lateral position
25	z	Height above ground
	z_H	Hub height
	$z_{\mathrm{MM},i}$	Installation height of sensor i on met-mast
	α	Vertical shear exponent
30	α_B	Load-based estimated vertical shear exponent
	$\alpha_{\mathrm{lower,B}}$	Load-based estimated vertical shear exponent on lower half of rotor disk
	α_MM	Met-mast-measured vertical shear exponent
	β	Blade pitch angle
	Γ	Wind direction (clockwise from due North)
35	$\Gamma_{\mathrm{A->B}}$	Direction of wind blowing from point A to B (clockwise from due North)

Γ_{MM}	Wind direction at met-mast
$\Gamma_{\mathrm{rel,WT1}}$	Relative wind direction at nacelle of WT1
Δt	Time delay between measurement at met-mast and turbine
ϵ_{RMS}	Root mean squared error
κ	Horizontal shear coefficient
κ_{B}	Load-based estimated horizontal shear coefficient
λ	Tip speed ratio
ρ	Air density
ρ_{ref}	Reference air density
ψ	Blade azimuth position
ψ_{a}	Blade azimuth position, beginning of sector
ψ_{b}	Blade azimuth position, end of sector
ψ_{bias}	Blade azimuth measurement offset
ψ_{corr}	Corrected azimuth measurement
Ω	Rotor speed
$\dot{\Omega}$	Rotor acceleration

5 (at κ)
10 (at ψ)
15 (at Ω)

Author contributions. JS conducted the main research work and prepared a first draft of the manuscript. CLB developed the core idea of load-based wind sensing, supervised the research and contributed to the writing of the paper. MB assisted in the measurement post-processing
20 and analysis. All authors provided important input to this research work through discussions, feedback and by improving the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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