Response to reviewer's comments - Reviewer 3

Authors: David Onnen, Gunner Chr. Larsen, Wai Hou Lio, Paul Hulsman, Martin Kühn, Vlaho Petrović

Paper Number: WES-2024-188

Title: Field comparison of load-based wind turbine wake tracking with a scanning lidar reference

Color coding: Reviewer comments, authors responses, paper citations

Dear Authors,
I very much enjoyed reading and reviewing your paper. I think it is a very good piece of work, worthy of publication in the *Wind Energy Science* Journal after minor revisions. Especially, I have found the results section very nice. The different events captured by the Lidar and EKF are well explained. In contrast, the Methodology section could deserve more clarifications. I would thus suggest revising mostly the clarity and accuracy in the methodology section, as per the major and minor comments below. If these comments can be addressed, I support a publication in WES.
Best regards,
Reviewer

Dear Reviewer,
First and foremost, thank you for taking the time to read through and review our manuscript. Answering your comments increased the quality of the manuscript. In the following we address each of your comments individually.

With kind regards,
The authors

Major Comments

1) Sect. 1 Introduction: the literature review could deserve to be expanded. I think the list of prior works is good and complete, but some more sentences for each justifying the difference with the present work could be good, to understand better the novelty brought here already from this introduction part.

Thank you for pointing out this aspect. The introduction section was revised. The key novelties to close the research gap are highlighted in bullet points. Furthermore, a reference to the discussion section was added in the introduction, where the outcome of our work is compared and ranged with regard to existing work.

[…] The research gap can be concluded as follows: Existing work for load-based wake tracking lacks either

- a consideration of wake dynamics and time resolution, or
- a field validation, or
- (in case of a field validation) an independent reference to compare with.

The objective of this work is to fill the gap by addressing all three aspects: The works shows direct estimation of the instantaneous wake centre position in a field experiment with two utility-scale wind turbines. The load-based estimate is compared to the wake position probed with a scanning lidar, which serves as an independent reference. To that purpose, the uncertainty of the lidar estimate is quantified using analytic error propagation following the GUM.

[…]

In section 4, the findings are discussed, ranged and compared with literature.

2) Sect. 2.2.1 General EKF setup: you start already defining many abstracts variables and mathematical model, before the main problem has been even clarified, as:
• The physics involved (wake deficit, dynamic wake meandering, wake deflection, etc.)
• The quantities that must be estimated (wake position etc.) and why they are relevant for which applications.
• The main inputs that you use (blade root loads yaw tilt col) and theoretical explanation why they include the relevant information you try to predict.

I think a subsection clarifying these points would be very helpful before the current Sect. 2.2.1.

The general problem statement takes place at the end of the introduction section.

The work shows direct estimation of the instantaneous wake centre position in a field experiment with two utility-scale wind turbines.

In section 2.2, the estimation is initially outlined, before moving to the EKF formulation in 2.2.1. We initially provide the general estimation scheme for overview, thus also the definition of states and measurements. The involved physics are described along with their respective modeling in 2.2.2 and 2.2.3. That way, repetitions can be avoided, even though it requires introducing variables early, without discussing them in detail yet.

We extended in 2.2 for guidance:

Core of the tracking algorithm is an Extended Kalman Filter (EKF), which links the load measurements from a wake-exposed wind turbine with the physical knowledge about the wake dynamics. […]
In section 2.2.1, the EKF formulation and the definition of states and inputs takes place. Section 2.2.2 defines the state transition function f(), including a consideration of the involved wake physics. Section 2.2.3 defines the measurement transition function h(), so the linkage between wake position and rotor loads.

Addressing the 2nd and 3rd point, information was added in the introduction section.

In order to increase the spatial observability of non-uniform turbine inflow, the rotor imbalances - resulting from shear, yaw misalignment or wake impingement - can be encountered (Bertelè et al., 2017). These rotor imbalances, such as yaw- and tilt-moments, are related to the harmonics of the blade root bending moments. The Coleman transform describes the translation from the rotating to the non-rotating coordinate system.
Ultimately relevant for wake-steering control is the wake position within the wind farm, which is the feature that a wind farm controller aims to manipulate. Existing methods for the wake position estimation are […]

The applicability is further discussed in section 4.3.

3) Line 212-213: *"Only one stochastic seed per wind field proved sufficient, since the effect of ambient turbulence is low in comparison to the effect of the wake."* I think this is a very dangerous and misleading statement, since ambient turbulence directly affects the effect of the wake when one considers dynamic environment. It is a core element of the DWM model that the ambient turbulence is the main driver of the whole wake propagation and dynamic meandering. Hence, various turbulent seeds can produce very different wake effects based on the DWM. I am quite skeptical that a single seed is enough for convergence. Please justify this statement more in detail, ideally with adding numerical tests and convergence study (possibly as Appendix). Furthermore, when comparing synthetic simulation data with field measurements (as the topic of this paper), extra attention must be given to seed-to-seed variability and binning approaches for measurements data, to obtain statistically converged data. Please elaborate on this.

We see your point and how the highlighted sentence is misleading. In short: we fully agree with your statement regarding the ambient turbulence as the driver of wake meandering and the according implementation in the DWM. We also agree that a different seed will produce a different wake trajectory for a given 10min simulation. For the generation of training data, however, the exact trajectory is not of interest. The meandering helps to populate the spreading of wake positions in the training data in addition to the subsequent lateral shift of the wake-causing turbine WT1 (see Fig. 4). Accordingly, the model fitting at one ambient condition already combines the results of seven simulations with their own wind field (referring to the seven lateral WT1-positions, indicated with different colors in Fig.4).
Our statement regarding the effect of ambient turbulence also addresses the effect of background turbulence.

We have adjusted the section as follows:

Thus, it is decided to only create training data in dependency of the ambient wind speed, resulting in a 1-dimensional lookup-table (LUT) of fitting parameters. This requires 63 simulations (7 WT1 positions and 9 wind speeds, 4-12m/s), each with a duration of 600s, a TI of 10 % and α=0.25. Only one stochastic seed per wind field proved sufficient, since the set for one ambient condition already combines the results of seven simulations with their respective wind field (referring to the seven lateral WT1-positions).

4) In Sect. 2.2.1 you present the state vector as four parameters (yw, zw, vc and wc). Yet, in the whole results part you only show predictions of the lateral wake position (yw). I miss the part where you justify why you only look at yw for the results. Especially because this wind farm has the particularity of having two different hub heights, results on the vertical wake position (zw) could be very interesting to include (and for the application perspective, the vertical position is as important as the lateral one).

In fact, we do consider the vertical position less relevant for the application, because

a) it has lower position variance due to meandering (see e.g. (Braunbehrens & Segalini, 2019)) and is less affected by wind direction changes
b) it cannot be manipulated by wake-steering control

Furthermore, no reference for the vertical wake position is available from the lidar measurements, thus the vertical position could not be compared.

The aspect is justified in section 2.2:

[…] Note, that the estimation task is here formulated for the general, 2-dimensional case, so considering the horizontal and vertical wake position. Due to the measurement setup and the single PPI scans of the lidar, only a comparison of the horizontal component is possible, which is also more relevant. The vertical position is considered less relevant for the application, because *i)* it has lower position variance due to wind direction changes and meandering (Braunbehrens & Segalini, 2019), and *ii)* it cannot be manipulated by wake-steering control.

Minor comments

5) Sect. 2.1 Field experiment: I think there should be proper citations added for each of the measurement devices mentioned (Trimble type 3 Zephyr mode, Thies Clima type 4.3352.00.400, Leosphere WindCube 200S, etc.) in the references.

It was added as you suggest.

Thies-Clima: Data Sheet - Wind Direction Transmitter 4.3151.xx.40x, https://www.thiesclima.com/en/db/dnl/4.3151.xx.40x_wr-geber-firstclass_eng.pdf, 2025a.

Thies-Clima: Data Sheet - Wind Transmitter 4.3352.00.4xx, https://www.thiesclima.com/pdf/en/first-class--ice-classified/wind-transmitter-first-class-advanced-x$\sim$4.3352.00.4xx/, 2025b.

Trimble: Data Sheet - Zephyr 3 GNSS Antenna, https://geonovus.ee/wp-content/uploads/pdf/Datasheet-TrimbleZephyr3.pdf, 2025.

Trujillo, J.-J.: Large scale dynamics of wind turbine wakes, Dissertation, 2017.

Trujillo, J.-J., Bingöl, F., Larsen, G. C., Mann, J., and Kühn, M.: Light detection and ranging measurements of wake dynamics. Part II: two-dimensional scanning, Wind Energy, 14, 61–75, https://doi.org/10.1002/we.402, 2011.

Vaisala: Data Sheet - Windcube 100S/200S/400S, https://www.vaisala.com/sites/default/files/documents/Windcube100_200_400s_3D-Doppler-Lidar-Brochure_WC_BD.pdf, 2025.

Vollmer, L., Steinfeld, G., Heinemann, D., and Kühn, M.: Estimating the wake deflection donstream of a wind turbine in different atmospheric stabilities: An LES study, Wind Energy Science, 1, 129–141, https://doi.org/10.5194/wes-1-129-2016, 2016.

6) Sect. 2.1 last paragraph: you mention the active wake steering control applied on WT1 but it would be great to have the yaw schedule added as a plot here for more clarity (scheduled yaw angle of WT1 by wind direction).

Our goal here is not to analyse wake steering, but to detect the wake position. The presence of wake steering controller makes the wake position more dynamic and challenging, but we feel that explaining the wake steering strategy running on WT1 would not benefit the paper.

7) Sect. 2.2 a proper citaton for EKF is missing.

We added this citation for the EKF in section 2.2: (Brown & Hwang, 1992)

8) Line 284: probably a typo (Myaw, Myaw) twice.

Thank you! As you noticed correctly, (Myaw, Mtilt) was meant. It is fixed now.

9) Line 244. Typo reference (?)

Thanks for spotting this. It is fixed in the latest version.

10) Fig. 15: This figure is nice, but it is a bit misleading to represent both metrics as parallel bars, since the RMSE should be as low as possible and the *inRange* should be as high as possible. Please consider possible review of this point (possibly by redefining the metric "*inRange*" into "*NotInRange*" so that it should also be as low as possible). The figure would thus be much easier to interpret in my opinion.

Thanks for the suggestion. However, we prefer keeping the definition as it is. The *inRange* metric allows for a better comparison to the detection ratio used in (Bottasso et al., 2018), as described in section 4.2.

In addition to the mathematical definition in Eq. 22, the figure caption reminds the reader:

[…] the orange bars refer to the right y-axis and represent the *inRange* indicator, so whether the difference between the position estimates is covered by their uncertainty intervals.

References:

Bottasso, C. L., Cacciola, S., & Schreiber, J. (2018). Local wind speed estimation, with application to wake impingement detection. *Renewable Energy*, *116*, 155–168. https://doi.org/10.1016/j.renene.2017.09.044

Braunbehrens, R., & Segalini, A. (2019). A statistical model for wake meandering behind wind turbines. *Journal of Wind Engineering and Industrial Aerodynamics*, *193*(August), 103954. https://doi.org/10.1016/j.jweia.2019.103954

Brown, R. G., & Hwang, P. Y. C. (1992). Introduction to random signals and applied kalman filtering. In *John Wiley* (Vol. 2, Issue 3). https://doi.org/10.1002/rnc.4590020307

Response to reviewer's comments - Reviewer 4

Authors: David Onnen, Gunner Chr. Larsen, Wai Hou Lio, Paul Hulsman, Martin Kühn, Vlaho Petrović

Paper Number: WES-2024-188

Title: Field comparison of load-based wind turbine wake tracking with a scanning lidar reference

Color coding: Reviewer comments, authors responses, paper citations

Dear Reviewer,
First and foremost, thank you for taking the time to read through and review our manuscript. Answering your comments increased the quality of the manuscript. In the following we address each of your comments individually.

With kind regards,
The authors

1) Section 2.2.1 General EKF setup: It is not inherently clear how the Extended Kalman Filter bridges the gap between the measurements and the calculated wake position. Please either provide a reference or explain the Extended Kalman Filter in more detail. In particular, equations (3) – (7) are not explained at all and the variables *f* and *h* are introduced in the text but not explained. How are the gradients for *Fk* and *Hk* computed? Maybe use another variable than *f* here, as this is used for the frequency throughout the rest of the paper.

Thank you for pointing this out. We have done the following in regard to your points:

- We added the reference (Brown & Hwang, 1992) for the EKF in section 2.2.
- The role of each model parameter, used to link wake position and measurements, is described in Table 1.
- The notation f() and h() for the state transfer model and measurement transfer model is standard in literature – thus we would like to keep this. We added this part to introduce the notation:
  Section 2.2.2 defines the state transition function *f*(), and section 2.2.3 defines the measurement transition function *h*().
  Furthermore we ensure a distinction by denoting the cut-off frequency of the meandering f_c and the frequency axis of the spectra in Figure 15 reads "frequency [Hz]" explicitly.
- Eq.3-7 form the standard procedure of the EKF algorithm, following Brown & Hwang. The linearization is explained in more detail:
  The local linearisations of the state transition model and the measurement model around a current state are denoted $\mathbf{F}_k$ and $\mathbf{H}_k$, respectively. They can generally be computed via forward Euler, following Equations 4,5. Note, that the state transition model f(x, n) used in this work can be formulated as a linear operation (see next subsection). Thus, the linearisation in Equation 4 is not necessary and **F** can be directly constructed from Equation 8.

2) Section 2.2.2 Dynamic model: The sentence in line 147 'The meandering time scales are thus incorporated with a first-order expression' is confusing. Please explain what exactly you mean by this and show an equation.

The term "first-order expression" refers to a first-order state-space model. The equation of motion for the wake dynamics considers dynamics up to the first derivative of the wake position, thus the crosswise velocity of the wake centre. The according equations are Eq.8a-d. We specified by changing the term to first-order differential equation:

The meandering time scales are thus modelled with first-order differential equations.

3) Section 2.3.1 Coordinate System: The offset in equation (16) corresponds to the 2.7D the turbines are spaced from each other. This is however only mentioned in section 2.1. Please add a sentence here to explain where this offset is coming from.

Thank you, it was added:

The x- and y-offsets in Eq. 16 refer to the 2.7D spacing in ground-based coordinates.

4) Section 2.3.3 Equation (19) is mathematically incorrect, as a vector cannot be squared. Is this meant in a computational sense, i.e. each component of the vector is supposed to be squared? Please specify.

Thank you for pointing this out! We have changed as follows:

Their propagation through the coordinate transform in Equations 14-16) is formulated by Equation 19, following the GUM standard (JCGM, 2020), where the expression $(.)^{\circ 2}$ denotes the element-wise square operation for a vector. Also, the square-root is to be understood element-wise. [...]

$$\begin{bmatrix} \Delta x \\ \Delta y \\ \Delta z \end{bmatrix}_{WT2} = \sqrt{\left(\frac{\partial \boldsymbol{x}_{WT2}}{\partial \gamma_1}\Delta\gamma_1\right)^{\circ 2} + \left(\frac{\partial \boldsymbol{x}_{WT2}}{\partial \gamma_2}\Delta\gamma_2\right)^{\circ 2} + \left(\frac{\partial \boldsymbol{x}_{WT2}}{\partial \delta}\Delta\delta\right)^{\circ 2} + \left(\frac{\partial \boldsymbol{x}_{WT2}}{\partial \chi}\Delta\chi\right)^{\circ 2}}$$

5) Section 3.2 Please explain the variable Ω in Equation (22)

The variable Ω is solely used as a helper variable to ease the readability. It is defined within Equation 22 and matches the description in the paragraph:

[...] The additional metric inRange is introduced in Equation 22, denoting whether the estimates are within each other's 2σ uncertainty range.

6) There are question marks instead of citations in some places (Lines: 30, 64, 244)

This was fixed. We apologise for the inconvenience.

Response to reviewer's comments - Reviewer 5

Authors: David Onnen, Gunner Chr. Larsen, Wai Hou Lio, Paul Hulsman, Martin Kühn, Vlaho Petrovic

Paper Number: WES-2024-188

Title: Field comparison of load-based wind turbine wake tracking with a scanning lidar reference

Color coding: Reviewer comments, authors responses, paper citations

The paper deals with an investigation into the accuracy of a Kalman filter-based wake center tracking strategy using real field data. The topic is already addressed in literature but now the Authors were able to compare the tracking outputs with a reference, which is expected to be more accurate, i.e. a scanning Lidar.
The topic is worth investigating and the work well executed. The manuscript is clear and well organized. I recommend publishing it. At the same time, I suggested some minor corrections and comments. Among all, I consider those listed under the section "Important comments" as something that, if addressed, may significantly improve the manuscript.

Dear Reviewer,
First and foremost, thank you for taking the time to read through and review our manuscript. Answering your comments increased the quality of the manuscript. In the following we address each of your comments individually.

With kind regards,
The authors

Important comments

1) Page 6, equations (8): much is written in relation to the cut-out frequency of the lowpass filter that models the wake meandering, but very little is said about the adequacy of the model. Can Authors enlarge the treatment, possibly including a reference? Moreover, is it possible to detail how the Authors considered the variability of mean wind speed u_∞ and turbulence intensity in such a model?

Thanks for this comment - that is an interesting aspect indeed. The topic relates to the split of scales regarding wind speed in the ABL, an aspect well described in (Soltani et al., 2013). In the scope of a rotor-effective wind speed estimator, authors decompose the wind speed into a mean component $\bar{u}$ and a turbulent component u'. The u' is modelled as a Wiener process with coloured noise terms, $\bar{u}$ is considered the following way:

"The average wind speed must be able to vary slowly from zero to at least 30m/s. This is modelled by the simple random walk […], where the incremental covariance […] is set to $2^2/600$, i.e., the standard deviation of the average wind speed variation over 10 min is 2 m/s. " (Soltani et al., 2013)

The split of scales is defined around the scale ratio $\frac{\pi\,\bar{u}}{2L}$, where L is the integral length scale. Considering commonly encountered values of L, the scale ratio has a similar order of magnitude as the cut-off frequency used in our work, which already justifies ignoring the turbulent part of more complex dynamics, since it is below a scale with relevance for wake position shifts. The value of ambient mean wind speed is solely used to schedule the LUT parameter for the load model, described in section 2.2.3. No additional dynamics are considered here. The variability of rotor-effective wind speed of the wake-exposed turbine is probably best correlated with the collective load M_{col}. The measurement covariance entry of M_{col} was fixed in this work. A future consideration, however, could be a self-tuning formulation, following the works of (Ritter, 2020).

Regarding the role of turbulence intensity: Ambient turbulence affects the meandering amplitude, the deficit shape and perturbations (see discussion section 4.2 'Impact of ambient conditions').

The observed increase of RMSE with TI is expected and agrees with simulation studies of load-based estimation (Dong et al., 2021; Onnen et al., 2022) and field results of lidar-based wake estimation (Lio et al., 2021). Higher turbulence intensities affect both the shape of the instantaneous wake deficit and the dynamics of the wake position. The information contained in the blade root loads is typically not sufficient to distinguish between both aspects, especially when their characteristic time scales are overlapping. The definition of the cut-off frequency in the dynamic model of the EKF leads to a rejection of turbulent scales smaller than the rotor scale. Deviations of the wake deficit shape that persist at scales of multiple rotor diameters could be misinterpreted as a change in wake position.

The impact of turbulence intensity on wake mixing can be included when creating higher-dimensional training data, which includes different TIs (see the answer to comment #4 below). Generally, simulations might allow better attempts for a parametric study. Please refer to (Onnen et al., 2022), where the role of turbulence intensity is checked an HAWC2 framework. The HAWC2 implementation of the DWM allows to distinguish ambient turbulence (responsible for wake mixing) and the large scale, meandering-driving turbulence field.

2) Page 9, equation (9): Please, notice that transforming blade loads through the Coleman transformation yields two pieces of information (M_tilt and M_yaw) really close to the nodding and yawing moments that are easier to measure (e.g. strain-gauges on main bearing). Surely, they are not identical (e.g. the nodding moment there will be biased due to rotor weight) but they should carry the very same informative content requested by the detector. Given the fact that "The rotor azimuth angle information of WT2 was not available" (see line 74), this consideration could be practically relevant rather than a pure mathematical comment. Please comment.

This is a very good idea and we have little doubt that such probing would redundantly contain the required information for a similar EKF. If bearing loads were generally available from strain gauges on the bearing or main shaft, or displacement sensors between bedplate and hub, it could be considered an alternative. A concern could be, that manufactures differ strongly regarding the drive train concepts thus different probing specifications needed to be accounted for and a generalizable approach might be difficult to achieve. Meanwhile, blade root bending moment probings leave less room for deviating concepts and are considered rather standard instrumentation on modern wind turbines. For retrofitting purposes on older turbines, however, easier instrumentation would be worth considering. A side note on the rotor azimuth angle: the value was not available in the data recordings, but normally it is available within the control environment of the turbine. When executing the estimator in real-time application on the turbine, it can be expected to be used.

3) Line 170: "The yaw and tilt moment depend on the wake position"; this is true, but they depend on other parameters, such as the shear layer magnitude. Authors cope with this by adding the terms *b* and *c* in eq. (11), to model, among all, also the impact of shear. However, the shear is variable too. Can Authors comment on this fact?

This is a fair point. We fully agree that the shear is variable and we are aware of the present simplification in the given example. The ambient wind shear mainly affects the tilt moment. Due to that, a different shear could be confused for a small shift in vertical wake position, when not fully accounted for by the fitting parameter *c* (also b, considering yaw-tilt-coupling). A solution could be to create training data for multiple shears and create a higher-dimensional LUT that is scheduled with respect to ambient shear (this refers to your comment 4). The shear could be estimated by an upstream (non-waked) turbine. In the example we present, we are limited to assess the lateral wake position, because the single-elevation lidar scans do not grant a reference for the vertical position.

It was decided to not add further degrees of freedom to the training data in this paper, in order to not introduce further unknowns that might complicate the interpretation of the results. We suspect that the influence of shear on the wake deficit (e.g. wake asymmetry) is not fully represented in the DWM-implementation.

The respective paragraph in section 2.2.3 was extended.

The impact of shear on the wake deficit is not fully accounted for in the simulation environment, especially in relation to wake-asymmetry (as discussed later in section 4.1). Thus, it is decided to only create training data in dependency of the ambient wind speed, resulting in a 1-dimensional lookup-table (LUT) of fitting parameters. This requires 63 simulations (7 WT1 positions and 9 wind speeds, 4-12m/s), each with a duration of 600s, a TI of 10 % and α=0.25. Only one stochastic seed per wind field proved sufficient, since the set for one ambient condition already combines the results of seven simulations with their respective wind field (referring to the seven lateral WT1-positions). Depending on the scenario, a higher-dimensional LUT can be required. A consideration of ambient TI is required in case of larger streamwise spacing, to adequately resolve the impact of turbulent mixing in the far-wake region. Also, including ambient shear could be a further step, preferably with a refined modeling of its impact on the wake deficit.

4) Line 210 and subsequent: important considerations. Good to see them here. Can the Authors provide insight into the possible application of the methodology using field data where one cannot control and decide a priori the inflow conditions to use to train the model?

Thanks for the comment. In principle, the spread of inflow conditions that cannot be known a priori can be covered by adding dimensions to the LUT. Thus, training data for a broader set of ambient conditions would be created and the model parameter scheduled with respect to these conditions (see previous comment), as it is already done with respect to ambient wind speed in the presented example. For an online-implementation, the ambient conditions then need to be estimated by another turbine, as shown e.g. in (Bertelè et al., 2021; Soltani et al., 2013). We suspect that one turbine alone struggles to simultaneously estimate both wakes and 'undisturbed' ambient conditions, due to limited observability. Coupling estimations from several turbines might be the best solution here, as discussed in section 4.3 'Applicability', referring e.g. to the works of (Becker et al., 2022).

Minor comments

1) Line 30 and 64: missing references.

Thanks for noticing and sorry for the error. It was fixed. The missing reference is: (Kidambi Sekar et al., 2024)

2) Figure 9: consider increasing plot dimensions.

Thanks for pointing this out. We will consider the dimensions and ensure readability when preparing for the double-column format used for final publication.

3) Figure 9b: consider the possibility to add a new figure, representing the error between "Geometry" and "Geometry + Jimenez" versus the lidar estimate. This could improve the interpretation of the results.

We see your point here. Yet, we deliberately decided to focus on the lidar reference in this paper. The take-away of Figure 9b is mainly: 'the lidar catches more wake position spread than suggested by the *steady* approaches "Geometry" and "Jimenez" '. The field assessment of the Jiminez model or wake trajectory with and without yaw misalignment is a topic in itself and considered beyond the scope of this paper (see e.g. (Bromm et al., 2018)).

4) Section 3.1.2: at what downstream distance is the speed deficit measured by the Lidar?

The approximate downstream distance is 2.7D – 100m ≈ 240 m. Note, however, that this value can slightly change based on the instantaneous constellation in the farm, i.e. a yaw angle difference of WT1 and WT2. This is why the consistent probing sector is defined w.r.t. the WT2-based coordinate system – always probing at the fixed distance of [-90m, -110m] upstream of WT2. This is described in the following section 2.3.2.

5) Comments on Fig.12: it is important to notice that the estimator is able to detect wake impingement on both sides of the rotor (left/right). I totally understand that maybe Authors considered it self-evident or trivial, but this is the very first capability that a wake detector must have.

Thank you for highlighting this aspect! You are right that this not a default capability. We mention this aspect in the introduction:

[…] Yet, the observability is limited, as shown e.g. by (Doekemeijer et al., 2020), where the estimator can hardly distinguish which half of the rotor is exposed to a partial wake, especially under uncertain wind direction information. In order to increase the spatial observability of non-uniform turbine inflow, the rotor imbalances - resulting from shear, yaw misalignment or wake impingement - can be encountered […]

References

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