Response to Reviewers

Manuscript: Impact of inflow conditions and turbine placement on the performance of offshore wind turbines exceeding 7 MW

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The authors thank the editor and the reviewers for their continued evaluation of our manuscript and for the additional constructive feedback provided. We have revised the manuscript accordingly. In what follows, we reproduce each new comment in full and provide a point-by-point response, indicating where the corresponding changes appear in the revised manuscript.

Reviewer 1

Comment 1: Some key technical variables are not clearly defined.

Response: We thank the reviewer for this remark. In the revised manuscript we have clarified the definitions and notation of the main technical variables at their first occurrence and ensured consistent use throughout. Concretely:

- In Sect. 2 we now state explicitly how the wind-speed and turbulence-intensity quantities used in the analysis are derived from SCADA. We define the SCADA “rotor wind speed” as the nacelle (hub-height) wind speed v, define turbulence intensity as $\mathrm{TI} = \sigma_v/\overline{v}$ for each 10 min interval, and specify that “normalized wind speed” in the figures denotes the non-dimensional ratio $\hat{v} = v/v_{\mathrm{rated}}$.
- In Sect. 3.5 we clarify that the linear regression slopes are computed for the normalized power deviation $PD_{\mathrm{norm}} = PD/P_{\mathrm{rated}}$ as a function of TI within each sliding window, i.e. the slope quantifies the change in normalized power deviation per unit change in TI.

We trust that these additions make the definitions of the key technical variables clearer to the reader.

Where: Sect. 2 (SCADA data description) and Sect. 3.5 (Correlation and linear regression slope analysis).

Reviewer 2

> ”Following the comments and recommendation drawn by the three referees, the authors have significantly improved the scientific quality of the manuscript by better detailing the different validation procedures applied to the dataset and strengthening the discussions. Nevertheless, I am still concerned by the validity of the interpretations drawn on the basis of correlations between inflow data that are not free from errors due to wind farm blockage (this issue is admitted by the authors but, because it is not so easy to assess its influence, they decide to ignore it) and wind turbine power signals. The justification provided for the use of a large wind direction sector averaging is not convincing. I fully understand that one needs to have enough samples per sector to ensure converged statistics, but the large sector mixes very different configurations of interactions that smear out the dependence of the power production to the inflow properties. Additionally, the calculation of a high confidence level with which the correlations are obtained proves that the correlation value is well assessed but it does not mean that this value is interpretable. Again, such low levels of correlation are often considered as non-interpretable. The authors referred to an article from Seifert et al (2021) in which some similar levels of Pearson coefficient were obtained, but to circumvent these weak correlations, they used additional statistical tools (as K-means clustering) to try to improve the results and strengthen their conclusions. The accumulation of approximations and potential sources of errors makes it difficult to trust the conclusions on the physical dependence between fine parameters of the inflow (shear, veer and turbulence intensity) and the wind turbines power performance. ”

Comment 1: Nevertheless, I am still concerned by the validity of the interpretations drawn on the basis of correlations between inflow data that are not free from errors due to wind farm blockage (this issue is admitted by the authors but, because it is not so easy to assess its influence, they decide to ignore it) and wind turbine power signals.

Response: We appreciate the reviewer’s comment regarding wind-farm blockage. We agree that blockage is a critical factor in yield assessment (comparing pre-construction resource estimates to realized energy). However, in the present work our objective is to characterize turbine-level performance conditional on the inflow that actually reaches the rotor, rather than to reconstruct a blockage-corrected free-stream or to perform a farm-wide AEP analysis. From this rotor-centric perspective, explicit blockage corrections are outside the scope of the study, for the following reasons:

1. **Blockage as a resource modification:** Field measurements and modeling show that farm-scale blockage mainly manifests as a quasi-uniform reduction in upstream wind speed extending several rotor diameters, typically of the order of a few percent in both onshore and offshore campaigns (Bleeg et al. (2018); Schneemann et al. (2021)). This primarily shifts the wind-speed distribution and thus the absolute energy yield, but does not by itself prescribe how power responds to variations in local inflow descriptors at the rotor.
2. **Conditioning on local hub-height inflow:** All correlation and variability analyses in this paper are explicitly conditioned on the nacelle-based hub-height wind speed U_{hub} and on inflow descriptors (shear, veer, TI) reconstructed in the selected upwind sector. Data

are binned by U_{hub}, and we examine how power deviations ΔP depend on shear, veer and TI within each wind-speed bin. In this framework we ask: "Does the turbine (or section) produce the expected power given the flow it actually experiences?", not "What would the turbine produce in a hypothetical, undisturbed far-upstream flow?" In other words, we use the term inflow in a rotor-centric sense. This differs from simulation studies, where "inflow" typically denotes an idealized far-upstream boundary condition for the atmospheric boundary layer, and where blockage or cluster effects are treated separately from the inlet profile.

3. **Impact on inflow descriptors and row-to-row contrasts:** Farm-scale blockage may, in principle, slightly modify not only the mean wind speed but also the vertical structure of the inflow. However, over the upwind sector and height range considered here, such effects are expected to act predominantly as a common-mode bias on the inflow profile. Our conclusions rely on relative behaviour—sign patterns and contrasts between front, mid and rear sections, and the evolution with normalized wind speed—rather than on absolute levels of shear, veer or TI. A nearly uniform shift in upstream conditions is therefore unlikely to, by itself, reverse the reported sign changes or section-dependent trends in ΔP. A more problematic configuration for performance assessment would be one in which the inflow is characterized by an instrument located outside the blockage-affected region, representing a systematically different flow regime than that experienced by the turbines under evaluation. In our case, the analysis is conditioned on nacelle-based hub-height wind speed at the turbines, while shear and veer are treated explicitly as upstream proxy descriptors derived from the nacelle lidar installed in a nearby wind farm (with a $\sim 2D$ lidar focus relative to its host turbine and an advection correction applied to the time series).
4. **Action taken in the manuscript:** In response to this concern, we have further clarified this scope in the revised manuscript. The discussion around farm-scale blockage now states explicitly that (i) we do not attempt to reconstruct an undisturbed free-stream wind field, (ii) our findings are interpreted as conditional relationships between turbine-level power deviations and the measured local inflow (U_{hub}, shear, veer, TI), and (iii) a dedicated blockage analysis would be required for refined AEP estimates but lies outside the present performance-characterization study (iv) we now refer consistently to upstream (lidar-derived) shear and veer rather than "free-flow" shear and veer, to avoid implying that these profiles represent an undisturbed far-upstream boundary condition.

Therefore, while we acknowledge that regional blockage alters the upstream wind-speed distribution and hence farm-level yield, our results are not intended as a blockage-corrected resource model. They instead describe robust trends in turbine performance conditioned on the inflow that actually reaches the rotors within the analyzed upwind sector. Applying an external blockage correction to synthesize a hypothetical far-upstream free-stream wind speed would decouple the analysis from the observed operating conditions and introduce additional modeling uncertainty that is not warranted by our objectives.

Where: Sect. 4 (opening paragraphs: blockage and interpretive scope), and Sect. 4.1 (shear/veer results discussion).

Comment 2: The justification provided for the use of a large wind direction sector averaging is not convincing. I fully understand that one needs to have enough samples per sector to ensure converged statistics, but the large sector mixes very different configurations of interactions that smear out the dependence of the power production to the inflow properties.
Response: We appreciate the reviewer's comment regarding the wind-direction sector width. We agree that narrow sectors (e.g. 10°) are essential when the objective is to isolate specific wake configurations, such as a particular full-wake or half-wake alignment. However, the objective of this study is different: we seek to characterize the regime-dependent performance (front vs. mid vs. rear section) under realistic operating conditions, rather than to analyze the impact of the specific flow structure of individual wake interactions.
Our choice of a broad upwind sector (105°) is motivated by the aim to characterize section-wise performance under a representative operating regime for the site, while accounting for directional uncertainty within 10-min SCADA records (wake meandering and direction variability). In this context, the broad sector is used to obtain stable ensemble-average statistics for front/mid/rear comparisons, rather than to isolate a single geometric wake configuration. This approach is consistent with SCADA-based analyses that emphasize the implications of wind-direction variability for wake attribution:

1. **Directional uncertainty and wake meandering:** As shown by Gaumond et al. (2014), the instantaneous wind direction within a 10-min SCADA period typically exhibits a standard deviation of 2–3°. As a consequence, wake models and measurements generally agree better when results are averaged over a directional distribution or wider sectors (order 30°) rather than at a single fixed direction. A very narrow sector can give an impression of precision that is not supported by the underlying directional variability and wake meandering.
2. **Ensemble averaging strategy:** By using a broad upwind sector, we effectively perform an ensemble average over a range of transient wake geometries. This reduces the influence of rare, highly specific configurations that may generate high correlations but are not representative of the long-term behavior of the farm. Similar to a recent control-oriented study Simley et al. (2020), we aim for results that reflect the varying and meandering inflow encountered in normal operation, rather than idealized single-direction cases.
3. **Robustness to measurement bias and misalignment:** Wider sectors also make the analysis more robust to small directional misalignments and systematic biases in wind-direction measurement, which Gaumond et al. identify as dominant sources of error when narrow sectors are used.
4. **Generalizability of section-wise contrasts:** A very narrow-sector analysis is inherently site-specific, because it is dominated by the exact geometric layout (row spacing, alignment angles). In contrast, by using a wide sector and ensemble-averaging over multiple wake configurations, we focus on macroscopic behavior of the front, middle and rear sections. The section-dependent contrasts we report (such as the inversion of the shear dependence between front and rear rows) are consistent with wake-recovery and mixing processes and may therefore be qualitatively transferable to other large offshore clusters, although quantitative magnitudes will remain site-specific, rather than being artifacts of

a single layout geometry.

To address the reviewer's concern quantitatively, we have added a sensitivity analysis using a narrower 30° sub-sector, presented in the new Appendix C. In this test, we restrict the analysis to a central 30° window within the original 105° sector and recompute the sliding-window correlations between power deviation and the inflow descriptors. As expected, the reduced number of samples leads to noisier profiles. However, the sign and relative magnitude of the section-to-section differences in inflow–power correlations remain consistent with the wide-sector results. This confirms that our main conclusions reflect robust upwind-sector-mean behavior in the lidar regime and are not artifacts of the chosen sector width.
Where: Sect. 2.2 (Data filtering: Wind-sector selection), Sect. 4 (Results and discussion: shear/veer and TI subsections), and Appendix C.
Comment 3: Additionally, the calculation of a high confidence level with which the correlations are obtained proves that the correlation value is well assessed but it does not mean that this value is interpretable. Again, such low levels of correlation are often considered as non-interpretable. The authors referred to an article from Seifert et al (2021) in which some similar levels of Pearson coefficient were obtained, but to circumvent these weak correlations, they used additional statistical tools (as K-means clustering) to try to improve the results and strengthen their conclusions.
Response: We thank the reviewer for this comment and agree that statistical significance does not automatically ensure physical interpretability. We have further clarified the manuscript to better contextualize the magnitude and role of the reported correlations. Given the large sample size, we emphasize that the reported p-values primarily quantify the precision of the estimated correlations, not the physical importance of the underlying relationship, we therefore interpret correlation magnitudes cautiously and also rely on effect-size diagnostics (slopes and MAD) for quantitative interpretation.

1. **Comparison with field studies:** The reviewer correctly notes that our correlations are modest ($|\rho| \approx 0.15$–0.30). As already discussed in our first-round response and reflected in the revised manuscript, such magnitudes are typical for offshore field measurements of power fluctuations in operating wind farms (e.g. Seifert et al., 2021). In this context, low-to-moderate correlations are expected and are consistent with the modest explanatory power expected from single secondary inflow descriptors in operational SCADA data. Our values lie in the same range and are therefore consistent with what is typically observed in operational SCADA-based field studies. We also agree that, in such field conditions, correlation coefficients alone are not sufficient to interpret the physical impact of the inflow descriptors; this is why the analysis combines these correlation profiles with additional diagnostics (regression slopes of normalized power deviation versus the inflow parameters and MAD-based variability measures) that quantify effect sizes in terms of changes in power deviation, in line with our prior SCADA-based analysis at the same site, where linear models using TI (and related turbulence descriptors) also yielded low correlations with active power Vratsinis et al. (2024).
2. **Interpretation of modest correlations:** We agree that modest $|\rho|$ values can be non-informative if treated as stand-alone indicators. In this study, we therefore do not interpret

$|\rho| \approx 0.15$-0.30 as evidence of a strong predictive relationship. Instead, we use the sliding-window correlations primarily as a directional diagnostic to identify (i) the sign of the association within a given wind-speed regime and (ii) consistent front/mid/rear contrasts across regimes. The magnitude of the impact is assessed using effect-size measures (regression slopes of PD_{norm} versus the inflow descriptor and MAD-based variability metrics), reported alongside the observed parameter ranges.

3. **Role of the sliding-window correlation:** We agree that a single global Pearson coefficient can be difficult to interpret when many operating regimes are mixed. For this reason, we do not report only one global value, but use a sliding-window correlation as a function of hub-height wind speed. In practice, the data are ordered by wind speed and the correlation between power deviation and each inflow descriptor is evaluated in overlapping windows along this axis, yielding a correlation profile $\rho(\Delta P, X \mid U)$ rather than a single scalar. This conditional view is more interpretable than a single global coefficient from a physical standpoint, because turbine aerodynamics and control are naturally organized by wind speed (torque versus pitch control, onset of wakes, etc.). It also allows us to resolve changes in the *sign* of the TI contribution across wind-speed regions. In our data, the estimated effect of TI on power deviation (from both the correlation and slope profiles) changes sign with increasing wind speed, which is qualitatively consistent with parametric power-curve models in which TI enters as a correction term that switches from slightly beneficial to detrimental depending on the operating regime Saint-Drenan et al. (2020). The sliding-window correlation thus mitigates the mixing of regimes that would suppress a global coefficient and allows us to focus on the evolution of sign and relative magnitude across wind speed and across rows, which is what is discussed in Sect. 4 (Results and discussion).

4. **Action taken:** In the revised manuscript, we have made the role of these additional diagnostics more explicit. The methodological description in the correlation, slope and variability subsections (Sects. 3.5–3.6) and the corresponding results subsections now state clearly that the sliding-window correlations are used mainly to establish the **sign and pattern** of the dependence (for example, contrasts between front-row and rear-row behavior and changes with wind speed), and that the quantitative assessment of impact relies on the effect-size measures already reported in the original manuscript, namely (i) regression slopes of normalized power deviation versus the inflow parameters, expressed over the observed parameter ranges, and (ii) a median absolute deviation (MAD) metric to characterize the variability of active power. We note that clustering approaches (as in Seifert et al., 2021) can be useful to separate regimes before computing correlations. In our case, the analysis already incorporates an interpretable physics-based regime separation through geometrical grouping (front/mid/rear sections) and wind-sector filtering, which partitions the data according to turbine placement and wake exposure. In the present work, rather than introducing an additional data-driven clustering layer and its associated choices, we strengthened the interpretability by (i) reporting conditional (wind-speed-dependent) correlation profiles and (ii) explicitly pairing these with effect-size diagnostics (slopes and MAD) when drawing conclusions.

Where: Sects. 3.5–3.6 (Correlation and linear regression slope analysis; Power curve variability analysis) and the introductory paragraphs of Sect. 4 (Results and discussion), in particular, the subsection on wind shear and veer correction.

Comment 4: The accumulation of approximations and potential sources of errors makes it difficult to trust the conclusions on the physical dependence between fine parameters of the inflow (shear, veer and turbulence intensity) and the wind turbines power performance.

Response: We thank the reviewer for this important overarching comment. We agree that all the stated limitations of the study must be kept in mind when interpreting any dependence between shear, veer, turbulence intensity and power.

In the revised manuscript, we address this in two ways:

1. **Clarified scope and approximations in the main text:** Sect. 2 now explicitly documents the lidar–farm separation, the advection procedure and the NORA3-based consistency checks for shear and veer, and explains how extreme inflow conditions are filtered. In the introduction to Sect. 4 (Results and discussion), we then summarize how these choices affect the interpretation of the inflow–power relationships. In particular, we emphasize that (i) modest pairwise correlations are expected for secondary inflow descriptors in operational data, (ii) the analysis is conditioned on the measured nacelle wind speed and locally derived inflow descriptors (TI, shear, veer) within the selected upwind sector, and (iii) we do not attempt to reconstruct an undisturbed free stream or to correct farm-scale blockage explicitly. The trends reported in Sect. 4 are therefore framed as conditional dependencies under the observed operating conditions at this site, rather than as blockage-corrected resource estimates or generic AEP laws.
2. **Robustness checks and combined diagnostics:** Beyond the significance of the Pearson coefficients, we rely on a small set of simple, complementary diagnostics. As detailed in Sects. 3.5–3.6 and recalled at the start of Sect. 4, the sliding-window correlations are used primarily to establish the sign and pattern of the dependence across wind speed and across sections, while effect sizes are quantified via regression slopes (normalized power deviation versus each inflow descriptor) and MAD-based variability metrics. In addition, a new sensitivity analysis using a narrower 30° directional sub-sector (Appendix C) shows that the qualitative front/mid/rear contrasts and sign changes in the inflow–power relationships remain consistent despite reduced sample sizes. These checks are designed to demonstrate that the conclusions do not rely on a single metric or a single sector choice, but emerge consistently across several complementary diagnostics and sector definitions.

These clarifications and additions acknowledge the main approximations, set limits on the scope of our claims, and support that the reported associations between shear, veer, turbulence intensity and power deviations are modest but consistently observed in the operational data within the analysed inflow regime.

Where: Sect. 2 (Data collection and filtering), the introductory paragraphs of Sect. 4 (Results and discussion), Sects. 3.5–3.6 (Correlation and linear regression slope analysis; Power curve variability analysis), and the new directional-sensitivity analysis in Appendix C.

References

James Bleeg, Mark Purcell, Renzo Ruisi, and Elizabeth Traiger. Wind farm blockage and the consequences of neglecting its impact on energy production. *Energies*, 11(6):1609, 2018.

M. Gaumond, P.-E. Réthoré, S. Ott, A. Peña, A. Bechmann, and K. S. Hansen. Evaluation of the wind direction uncertainty and its impact on wake modeling at the horns rev offshore wind farm. *Wind Energy*, 17(8):1169–1178, 2014. doi: https://doi.org/10.1002/we.1625. URL `https://onlinelibrary.wiley.com/doi/abs/10.1002/we.1625`.

Yves-Marie Saint-Drenan, Romain Besseau, Malte Jansen, Iain Staffell, Alberto Troccoli, Laurent Dubus, Johannes Schmidt, Katharina Gruber, Sofia G. Simões, and Siegfried Heier. A parametric model for wind turbine power curves incorporating environmental conditions. *Renewable Energy*, 157:754–768, 2020. ISSN 0960-1481. doi: 10.1016/j.renene.2020.04.123. URL `www.sciencedirect.com/science/article/pii/S0960148120306613`.

J. Schneemann, F. Theuer, A. Rott, M. Dörenkämper, and M. Kühn. Offshore wind farm global blockage measured with scanning lidar. *Wind Energy Science*, 6(2):521–538, 2021. doi: 10.5194/wes-6-521-2021. URL `https://wes.copernicus.org/articles/6/521/2021/`.

E. Simley, P. Fleming, and J. King. Design and analysis of a wake steering controller with wind direction variability. *Wind Energy Science*, 5(2):451–468, 2020. doi: 10.5194/wes-5-451-2020. URL `https://wes.copernicus.org/articles/5/451/2020/`.

Konstantinos Vratsinis, Lukas Pauscher, Pieter-Jan Daems, Jeroen Van Beeck, and Jan Helsen. Impact of inflow characteristics on the instantaneous power production using detrended fluctuation analysis. *Journal of Physics: Conference Series*, 2767(9):092071, jun 2024. doi: 10.1088/1742-6596/2767/9/092071.