Authors' response to Review 1 of "Sensitivity analysis of wake steering optimisation for wind farm power maximisation"

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Main comment

The authors would like to thank the reviewer for the in-depth review of the paper. The authors' responses (in blue) to all major and moderate issues (in black) are included in this document. Minor issues have been addressed with appropriate modifications to the text. All changes are marked in red in the revised manuscript.

Major concerns:

1. I am considerably concerned with the fact that the authors claim [line 135] to be using the exponential loss of power according to the yaw angle as $w = 0.627$ following Fleming et al., (2017), whereas w (pP therein) is therein 1.43 or 1.88 depending on the chosen turbine, and 1.41 when fitted into a cosine function. They need to justify the use of the chosen value ($w = 0.627$) in order to being able to proceed with the paper, otherwise it would be a rejection as this parameter is applied in all the analytical models used (it is embedded in the FLORIS framework). In addition, you are applying the same w value for the different turbines considered, whereas Fleming et al. (2107) evidences a different value when considering different turbines. The validity of this parameter must be checked before proceeding with the rest of the review, because if its invalidity was verified the whole work would be needed to be re-done (thus rejected herein).

   The authors can reassure the reviewer that there is no issue with the w parameter in the manuscript. According to Equation 3, the correction to power due to yaw misalignment is $((\cos\gamma)^w)^3$, with $w = 0.627$, and

   $$((\cos\gamma)^w)^3 = (\cos\gamma)^{w\times 3} = (\cos\gamma)^{pP}.$$

   Hence, the parameter value of $w = 0.627$ used in the manuscript matches the coefficient $pP = 3 \times 0.627 = 1.881$ recommended in Fleming et al. [2017].

   Regarding the reviewer's comment on using the same w value for the NREL 5 MW and the Vestas V-80 2 MW, the authors can confirm that the value of $w = 0.627$ (tuned value for the NREL 5 MW presented in Fleming et al. [2017]) has been also used for the Vestas V-80 2 MW. This decision was made after investigating the influence of w on an SLSQP wake steering optimisation of the Horns Rev wind farm layout (80 Vestas V-80 2 MW) with the GCH wake

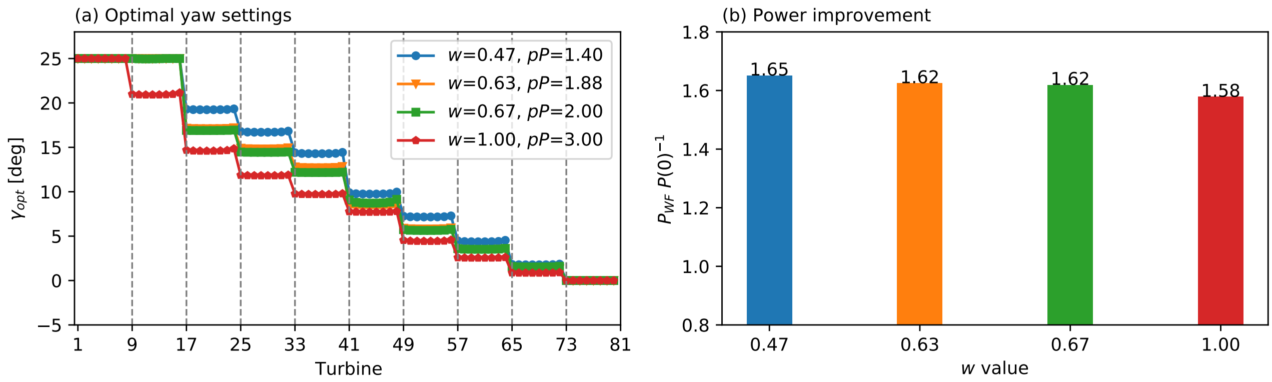

Figure 1: Comparison of optimisation results for different w coefficient values. The farm layout is representative of the Horns Rev wind farm, the optimisation algorithm is SLSQP, and the wake model used is the GCH. (a): optimal set-points per turbine. Dashed lines delimit wind farm rows. (b): resulting objective function (normalised farm power).

model. As it can be seen in Figure 1, the results indicate that the largest variation is 7 % in power improvement and 5 ° in optimal yaw settings for a single turbine. These differences in optimisation results do not fundamentally affect the main trend in the obtained optimal solution (i.e. a monotonic decrease of optimal yaw angles with increasing downstream turbine location) and show that the conclusions of the original manuscript are not affected by the choice of w. It should be noted that there is a lack of power data for the Vestas V-80 2 MW turbine in yawed conditions. As an example, no specific value of w for the Vestas V-80 2 MW is stated in [Dou et al., 2020]. The manuscript has been modified to include the discussion on the validity of w in the presented study.

2. In sections 4.2.1 and 4.2.2 the authors show several times that, the used optimization algorithm (SLSQP) has serious problems to find global maxima for each turbine individually and therefore for the overall wind farm. Then in Section 4.2.3 they show the results statistics or TuRBO and SLSQP, showing a clear outperforming by TuRBO, a stochastic optimization approach. Indeed, the fact that stochastic algorithms present higher skill than gradient-based algorithms is shown in contributions such as e.g, see Kuo et al., 2020: "Wind Farm Yaw Optimization via Random Search Algorithm". For both reasons, it is worrying surprising that they do not apply TuRBO for the analysis of the long sections 4.2.1 and 4.2.2. Please re-do 4.2.1 and 4.2.2 sections (at least also) for the TuRBO algorithm, or consider dismissing such sections.

   The purpose of Sections 4.2.1 and 4.2.2 is to highlight not only that unconstrained gradient-based optimisation can perform poorly, but also to explain why this happens. The observations made in this section (i.e., initial condition sensitivity and cost function bimodality) then motivate the proposed solutions to this problem via global optimisation (TuRBO) or constrained gradient-based optimisation in Section 4.3. For this reason, the authors believe that the insights gained in Sections 4.2.1 and 4.2.2 are necessary to motivate the paper.

   To address the reviewer's comment, the authors have:

   1. Re-run the optimisation presented in Figure 5 to include the output of the TuRBO algorithm. These new results are discussed at the end of section 4.2.1 and now provide further motivation for the statistical comparison of TuRBO and SLSQP in Section 4.3.

2. Replaced the ten indicative SLSQP optimization runs from Figure 4 with an analogous sample of ten optimisation runs selected from the 50 cases studied in Section 4.3. Consequently, both TuRBO and SLSQP have been applied to every initialisation case considered in Figures 4,5 and 8. For legibility, TuRBO's output for the ten cases of Figure 4 is not shown, but note that the improved performance of TuRBO can now be inferred from the statistical results presented in Figure 8.
3. Added more discussion to Sections 4.2 and 4.3 comparing the pros and cons of stochastic algorithms versus constrained/unconstrained gradient-based algorithms.

Finally, the purpose of Section 4.2.2 is only to discuss the geometry of the underlying objective functions for each wake model and use any observations to understand the poor performance of gradient-based wake steering optimisation. No optimisation is performed in this section, meaning that it is not possible to generate extra results here using TuRBO.

3. With their statement at Line 370: "To the best of the authors' knowledge, the work by Dou et al. (2020) is the only published study in which wake steering optimisation is performed on the Horns Rev farm layout" the authors seem not to handle the literature in depth, as they fail to raise other contributions such as the one by Zong and Porté-Agel (2021): 'Experimental investigation and analytical modelling of active yaw control for wind farm power optimization' (Section 6). This will entail (at least) serious implications in their discussion on their obtained results.

   The authors thank the reviewer for raising this additional work, which is valuable to include. Nevertheless, it is clear that only a few studies on wake steering optimisation for the Horns Rev farm layout have been published to date, meaning that it does not have serious implications for the manuscript discussion. This study by Zong and Porté-Agel [2021], which uses gradient-based optimisation, requires explicit knowledge of the optimal solution to define appropriate initial yaw angles which guarantee optimiser convergence. This is a strong limitation to which our work offers a simpler alternative based on constrained gradient-based optimisation (Section 4.3). The revised manuscript has been modified accordingly to reflect this comment from the reviewer.

4. As a follow-up from point 3, a flagrant lack of state of the art on wake steering optimization contributions (at least those on open-loop) is noted in the introduction.

   The authors' intention in the original submission was to present a concise overview of the literature on wake steering optimisation, as they wanted the focus of the paper to be on the results and new optimisation approaches proposed. To address the reviewer's comment, the introduction in the revised manuscript has been expanded to include a wider discussion of the literature on wake steering optimisation.

5. Numerous descriptive elements of the introduction and methodology are misplaced (those at the introduction should be at the methodology and vice-versa), and the paper shows in general serious lack of appropriate writing style. All my comments regarding these two aspects are indicated in the attached PDF.

   The authors appreciate the reviewer's comment even if they disagree with the use of the word "serious" to describe their writing style. Numerous appropriate modifications have been made in the revised manuscript following this comment in an attempt to improve the quality of the study.

6. Finally, due to the fact that the analytical models used were not validated against ground truth (field campaigns) or more robust representations (e.g., wind tunnel experiments, high resolution numerical simulations as LES), it is very difficult to detect which analytical model is actually performing better. Therefore I would at least recommend to apply the optimized yaw angles obtained with a given model into the rest of models (inter-model cross-validation), and check how solutions perform.

   As stated in Section 2, lines 106–107 of the original manuscript, the study does not seek to identify which wake model is best for wake steering optimisation in terms of modelling accuracy. Much past literature, such as [Göçmen et al., 2022, King et al., 2022], addresses this research question. The purpose of this submission study is instead to identify and analyse situations in which wake steering optimisation is highly sensitive to either wake model choice or the optimisation strategy used.

   Regarding cross-validation, Table 1 shows, for the Horns Rev example of Section 4.3, the farm power increase for the Jensen, Multizone and Gaussian models when (i) using optimal decision variables computed using the GCH model and (ii) using the optimal decision variables from the original submission. For all three models, lower farm power increases are achieved using the optimal CGH yaw angles. This implies that optimising using the Jensen, Multizone, and Gaussian models will not give the characteristic row-monotonic behaviour of the optimal GCH yaw angles.

   As noted in [Zong and Porté-Agel, 2021], this row-by-row decrease in optimal yaw angles arises due to secondary-steering effects, which are captured in the GCH model but are not in the Gaussian model. It is therefore arguable that optimisation using the GCH model exhibits the best performance out of all models considered.

   Some text has been added in the revised manuscript to discuss inter-model cross-validation and which wake model is potentially performing better.

Case	Jensen $P_{wf}P(0)^{-1}$	Multizone $P_{wf}P(0)^{-1}$	Gaussian $P_{wf}P(0)^{-1}$
Original model γ_{opt}	1.04	1.83	1.12
GCH γ_{opt}	1.03	1.39	1.07

Table 1: Inter-model cross-validation for C1+C2 optimisation results of the Horns Rev case.

Moderate concerns (orange comments extracted from the reviewer's PDF file):

1. L146: *"80 Vestas V-80 2 MW turbines"*.

   Reviewer's comment: You apply the same w value to different turbines, even though in Fleming et al., (2017) a considerable w (pP therein) difference is found among different turbines. Please justify.

   Please refer to authors' reply for major concern 1.

2. L173-L174: *"Moreover, a single trust region is used in all cases to enable a fair comparison with the SLSQP algorithm"*

   Reviewer's comment: Could you please explain why a fair comparison is attained by only considering ONE of the trust regions at TuRBO?

If multiple trust regions are used, then TuRBO uses a multiple starting point search and fits a different Gaussian process model in each trust region. Hence, a single run of TuRBO would be comparable, in complexity, to multiple runs of SLSQP. Therefore, the simplest fair comparison between the two methods is to use a single trust region for TuRBO, initialised with the same conditions as those used for each SLSQP optimisation. To address this comment, a clarification has been added to Section 3.1 of the revised manuscript.

3. L335-L336: *"Higher mean values are obtained for all models by the global TuRBO algorithm."*

   Reviewer's comment: If you want to keep sections 4.2.1 and 4.2.2 you must re-do them in terms of (at least also) TuRBO. It does not make any sense to show them in terms of just SLSQP when they are performing that poorly, especially when you are showing now these comparisons with an outperforming aproach such as TuRBO.

   Please refer to authors' reply for major concern 2.

4. L348-L352: *"It is interesting that the best-performing SLSQP run (blue markers) converges after fewer iterations, and to a higher farm power, than the indicative TuRBO case presented and, in fact, outperforms all TuRBO runs (see Figure 8). This suggests that, if initialised in the region of attraction of a global (or near-global) maxima, a gradient-based optimiser may exhibit faster convergence than a generic global strategy."*

   L356-L361: *"Finally, it is interesting to note that while the optimal wake velocity fields in Figures 9-b and 9-c are visually similar, they are not identical: the TuRBO solution has 1.5 % lower farm power, and requires 55 % more evaluations to find it. This confirms a possible, albeit counter-intuitive, advantage of the rapid local convergence enjoyed by gradient-based optimisers. Indeed, the quasi-Newton algorithm employed in SLSQP is well-known (Deuflhard, 2011) to possess rapid locally-quadratic convergence rates, which may partially explain this observation."*

   Reviewer's comment: However, due to the high variability of runs in results not validated against ground truth (field data) or at least more robust reproductions (wind tunnel, high resol. simulations such as LES), it is very hard to justify an option with such big dispersion as with SLSQP. In absence of such validation, it would be preferable to trust the optimizer providing more reliability in terms of least dispersed results and higher average performance (i.e., TuRBO). Please justify more robustly or remove.

   A clarification has been added to Section 4.2.3 to emphasise that unconstrained optimisation using SLSQP gives more variable results than TuRBO and, consequently, that TuRBO should be viewed as a more robust optimiser than unconstrained SLSQP.

   Text has also been added to emphasise that: (i) SLSQP's variability is precisely the motivation for considering constrained optimisation in Section 4.3; and (ii) that, as shown in Figure 11, extra constraints can significantly reduce the variability of SLSQP. Consequently, the authors argue that appropriately constrained gradient-based optimisation is also a viable solution to robust wake steering optimisation.

5. L369-L370: *"To the best of the authors' knowledge, the work by Dou et al. (2020) is the only published study in which wake steering optimisation is performed on the Horns Rev farm layout."*

   Reviewer's comment: The authors knowledge is incomplete. Please check Zong and Porté-Agel (2021): 'Experimental investigation and analytical modelling of active yaw control for wind farm power optimization' (Section 6).

Please refer to authors' reply for major concern 3.

Minor concerns (yellow comments in the reviewer's PDF file):

These comments are addressed directly in the revised manuscript (red colour in the text). The authors have also dealt with the recommendations from the referee to remove small pieces of text when they felt that it was appropriate to do so.

References

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