

Dear Dr. Dykes,

We are submitting a revised version of our manuscript “Optimal closed-loop wake steering, Part 1: Conventionally neutral atmospheric boundary layer conditions” by M. F. Howland, A. S. Ghate, S. K. Lele, and J. O. Dabiri for consideration for publication in *WES*. We thank the three anonymous referees for their thoughtful comments which have contributed to the development and improvement of the manuscript. Given their comments, we have performed a major revision which has focused on further explanation and statistical quantification of the results of the study and a streamlining of the manuscript’s discussion. We have also provided point-by-point responses to each referee below as well as a version of the manuscript with modification tracking. We hope the revised manuscript is stronger and clearer, and therefore suitable for publication in *WES*.

Best regards,

Michael F. Howland, on behalf of all of the authors of this manuscript  
Stanford University  
Department of Mechanical Engineering

## Response to Referee #1

We thank the referee for their review and their thoughtful comments. Point-to-point responses can be found below, and the relevant changes have been made to the manuscript.

### Comment #1

Wake model. Overall, the inclusion of the wake model seems to be the weak, but predominant, part of the article. That is not a criticism of the wake model itself. The lifting line wake model definitely seems to have merit, and engineering models are important. It is fully understandable that model developers wish to spread their model and test their capabilities. However, the present application should be better addressed and motivated. Does the analysis actually strengthen or weakening the general use of the wake model? Does the inclusion of the wake model improve the potential for closed-loop wind farm control, or are the results so model dependent that one should rather use a more model-free approach?

### Response

Thank you for this comment. We will improve the motivation of the wake model in the manuscript and we will briefly summarize that justification and rationale here. In general, model-free wind farm power maximization has significantly slower rates of convergence than model-based optimization and may therefore be less well suited for closed-loop control in a practical, transient wind farm setting (see recent discussion by [1,2]). Model-free formulations have not been vigorously tested in transient simulation mean conditions aside from the recent paper by Ciri et al (2019) [3].

Given computational cost considerations for real-time control (i.e. computational limitations at an operational wind farm), a focus of the wind farm controls community has been to leverage existing, computationally efficient steady-state wake models for closed-loop control (see, e.g., review by Doekemeijer, Fleming & Willem van Wingerden (2019) [1]).

As the referee has suggested, an overarching objective of the submitted manuscript is to examine the sensitivity of closed-loop wind farm power maximization control to common wake model parameters and assumptions. More specifically, the assumptions invoked in the wake model presented here are functionally similar to assumptions in the popular FLORIS model software. The results in this manuscript suggest that wake models do lead to beneficial power production increases for turbine arrays, provided that the parameters in the wake models can be accurately estimated *a priori* or in a closed-loop fashion.

While model-free wind farm control is an interesting line of research moving forward, generalizations of such approaches to transient atmospheric conditions require further rigorous testing. Future work in this community (as recently discussed at the IEA Topical Expert Meeting on Wind Farm Controls) should establish standard test problems and benchmarks for the comparison of various optimization formulations such as the presently proposed methodology and model-free formulations.

### Comment #2

It seems that the calibration of model parameters frequently ends up compensating for the missing physics, which affects several of my following points. This is also one of the major

self-contradictions within the article. On one hand, the authors repeatedly write that the model is "physics-based", which in isolation is correct. However, the current application of the model also includes several other models/assumptions, which in combination is questionable. It also leads the authors to give statements like:

- "the two parameter lifting line model may be overparameterized, which leads to overfitting."
- "The ability of a one or two parameter analytical wake model ....may enforce unreal-istic model parameters to represent neglected physics."

Clearly, the model does not capture all the physics. Hence, the desirable physics of the original model appears to become a limitation, rather than an benefit, when various additional models and assumptions are combined, see below. The results and the aforementioned quotes indicate these concerns, but it is not reflected in the abstract nor in the conclusion, which hence seems somewhat selective. I will try to elaborate on a number of points, where this seems to have a significant impact.

### **Response**

Thank you for this thorough comment. We will update the abstract and conclusions to further reflect the sensitivity analyses which were a major component of this research.

Due to the underlying assumptions of wake models and yaw misalignment wake deflection models, these methods cannot be expected to capture all relevant physics for full-scale wind farm operation. In fact, the use of state and parameter estimation methodologies to correct unresolved physics or imperfect model assumptions have been commonly used for wind farm controls applications [see e.g. 4, 5].

Within the current closed-loop framework, the goal of the EnKF model parameter estimation is to accurately fit to a current timestep and then to apply those parameters for optimization only for the very next timestep. While it is reasonable to question the generalization of the site-specific fitting, the purpose here is not to create general parameterizations of the model parameters to be used for other conditions or wind farms but to only apply the parameters from one control step to the next. This objective and fitting consequence is thoroughly discussed in the text of this article (and will be detailed in the abstract and conclusion of the updated manuscript as per the referees comments).

More importantly, the predictive ability of this approach was tested here in Figures 21 and 22. As discussed in the manuscript *Section 5.4*, the present wake model approach with EnKF state estimation significantly outperforms the predictive capabilities of the commonly used Gaussian wake model with pre-defined empirical parameters with 5x lower predictive error. Therefore, with the site-specific fitting, the EnKF estimation of the model parameters significantly improves the model predictive ability. The improvement in the predictive ability of wake models with optimized model parameters is also shown in the very recent paper [2] (published online April 29, 2020).

Future work will focus on the constraining of the state estimation methodology to reduce model flexibility to test whether this improves the predictive success.

### **Comment #2(a)(1)**

Model Description and Assumptions:

- The assumption of thrust following  $\cos^2\gamma$  could potentially have a big impact on the results. The article investigates PP, but this seems to be an equally important assumption and the impact should not be neglected.

### **Response**

The authors agree that the wake model assumption of thrust following  $\cos^2(\gamma)$  could also have an influence on the closed-loop control performance. This was not tested in this study since the actuator disk model used directly enforces the thrust to follow  $\cos^2(\gamma)$  and since this assumption is enforced in the lifting line model derivation [6]. In general, the thrust would follow  $\cos^{2p}(\gamma)$ , where  $p$  is likely less than 2 (see e.g. Bastankhah and Porte-Agel (2016) [7]). In this event, the closed-loop model parameter estimation would likely compensate by predicting smaller wake expansion coefficients (which leads to stronger wakes) than the true value given the model expectation of less streamwise thrust than is imposed in reality. We will update the manuscript with further discussion about this wake model assumption.

### **Comment #2(a)(2)**

The article states "Future work should focus on methodologies to robustly estimate PP from SCADA data". That's in principle good, but I question the statement "there is no accepted framework for determining PP" (line 635). It seems that it could be relatively easy to perform simulations using an actuator disc model or an aero-elastic tool, e.g. FAST, to fit both PP and the coefficient for CT as function of yaw for the specific turbine. This would render Section 5.3 obsolete as it stands now. The sensitivity to PP is obviously interesting, but it would seem more appropriate to address it using your reference to Liew et al. as also commented in line 650.

### **Response**

As discussed by Liew *et al.* (2020) [8], both actuator disk theory and blade element momentum theory (e.g. FAST) return  $p=3$ . Wind tunnel experiments [e.g. 9] and large eddy simulations [e.g. 10] have shown that  $p$  is more typically between 1.5-2. Further,  $p$  is likely turbine specific (see e.g. Liew *et al.* (2020) [8]) and has functional dependence on shear, veer, atmospheric stability, wake impingement, and likely other parameters. Field experiments (on-going by the authors) to robustly calculate  $p$  require weeks or months of experimentation due to the functional dependencies mentioned above and are therefore expensive and time consuming. Therefore, the authors believe that the quantification of the influence of  $p$  under model parameter uncertainty are critical to future wake steering deployments.

### **Comment #2(a)(3)**

- Linear superposition: This is a highly questionable assumption, which will also affect the results in terms of the overfitting and parameter compensating for lack of physics. An improved wake superposition has recently been proposed by Zong and Porté-Agel, 2020, which is physically consistent and shows improved results, also for wake steering

### **Response**

While the linear wake superposition method (or sum-of-squares superposition commonly used in FLORIS) are often used, the referee is correct that their physical justification is challenging.

Zong and Porte-Agel (2020) (which was published after this article was submitted for review) have thoroughly addressed this long-standing open-question in the literature. The method of Zong and Porte-Agel (2020) leverages an iterative approach and assumes an empirical, pre-defined prescription of the wake model parameters which differs from the present model approach. Future work will incorporate the new superposition methodology with optimal parameter estimation.

#### **Comment #2(a)(4)**

- Please define the "effective velocity" (line 136). Does that correspond to rotor averaged or based on the power production?

#### **Response**

The effective velocity is the rotor averaged velocity, we will adjust the language in the manuscript to clarify this definition.

#### **Comment #2(b)**

Advection time: This section could be significantly reduced and rephrased. Most of the explanation deals with Taylors hypothesis, but at the end the advection time is adjusted to be twice this "to account for errors associated with the simple advec-tion model". This appears as a somewhat random choice in the current context. The proper explanation could/should involve (conservative) estimates of the wake propagation velocity, i.e. the wake propagates slower than the mean flow. There are numerous references for this.

#### **Response**

Thank you for this comment. We will rephrase this section for brevity and include additional wake propagation references in the manuscript. The invocation of twice the Taylor's hypothesis advection time was to have a strongly conservative estimate. Since the flow is quasi-statistically stationary (i.e. statistically stationary except for inertial oscillations which occur on Coriolis time scales), conservative estimates for the advection time and time-averaging of statistics have been taken. The influence of the advection time scale assumption was tested in the initial manuscript where it was shown that it did not play a significant role in the power production output of the closed-loop control, and the results are given in Table 1. Part 2, which studies the transient diurnal cycle, will investigate these times scales in more detail.

#### **Comment #3**

Introduction. Although a good review is appreciated, it could be shortened and more focused. The section on derating seems too long for an article focusing on wake steering. Wind farm control is a very active field, so new articles are constantly being publish. Hence, I will just recommend the inclusion the recent review by Kheirabadi and Nagamune, 2019, which also quantifies the potentials of wind farm control. As also concluded by Kheirabadi and Nagamune, wake steering has been shown to have the largest potential, but their Figure 4 also reveal that power increase from wake steering is not guaranteed. Hence, some statements could be less assured, e.g. line 116 in the article.

#### **Response**

We will rephrase the introduction and streamline the discussion. We will include the reference to the review paper the referee has noted.

#### **Comment #4**

Steady vs dynamics: Generally, it seems "unfair" to use a steady state model in a dynamic framework, although one can argue if 30min is even dynamic. And by "unfair", I mean on the analytical model. How would the performance be if it was applied on a more realistic control scenario of 5-10min? I suspect this is given in Part 2, but this should be a self-contained article. There are several places, where the wording appears inconsistent. This is particular the case in Section 4, where "the flow is stationary" is used several times and at the same time "the dynamics of the wake" and "counter rotating vortices". Such statements appear contradictory. LES simulations of the flow behind a disc/rotor should not be stationary, even with uniform inflow. The wake will be dynamic (as you mention), e.g. meandering. This is also seen in Figure 5. There it appears as if the two turbines are positioned so close that the first wake doesn't start to meander/breakdown, but the second does. Could the quasi-steady behavior be caused by the coarse resolution of 5-6 cells per disc?

#### **Response**

Thank you for noting this language confusion. The statements should read "statistically stationary" rather than just "stationary" and we will modify the manuscript to improve clarity and we apologize for the confusion this language has caused.

The starting point for closed-loop wake steering control is to leverage existing computationally efficient steady-state wake models and to invoke quasi-stationarity in the flow statistics (see e.g. very recent paper by Doekemeijer et al. (2020), [2]). While the test case in Part 1 explicitly allows for a well-defined assumption of quasi-statistical stationarity, Part 2 will investigate this assumption's utility in a realistic transient ABL state.

Future work should also focus on the synthesis and validation of computationally efficient, transient models for wind farm power prediction.

#### **Comment #5**

Several question arise from Section 4:

- Is uniform inflow a good and representative case? Does it truly provide validation of optimization, because it turns the turbine in the right direction?
- Line 285 states that AD is good for far wake. But is 4D far wake in uniform inflow? A quick back-of-the-envelope assessment for where the far wake start can be done using the engineering expression in Sørensen et al., 2015. For a 0.01% inflow turbulence and propagation velocity of 0.7, I get an estimate of 13-14D downstream, before it is fully transitioned to far wake with a Gaussian velocity deficit, which is another of the model assumptions. What is the implication of this assumption?
- Please rephrase for clarification line 377: "reduced in size and intensity". What is reduced in size and what intensity? The deficit? It would be difficult(=impossible) to see from an instantaneous velocity contour. Similarly, it is not possible to see how the figure "indicating that for larger columns of turbines the potential for power increases due to wake steering are larger" due to the dynamics of the instantaneous flow.

### **Response**

Thank you for this comment. While not physical, uniform inflow (zero freestream turbulence) represents a helpful, well-defined case for algorithmic testing and code validation. As the referee has noted, due to the small turbulence mixing in the wake shear layer, the top-hat profile wake will remain further downstream than in a realistic wind turbine wake. Therefore, this example is not a precise representative case where the assumptions of the wake model are exactly matched.

We will rephrase line 377 for clarity and improve the quality of the figures.

To reduce confusion of this section with physical results (atmospheric boundary layer simulations) we will move this section to the Appendix in the revised manuscript.

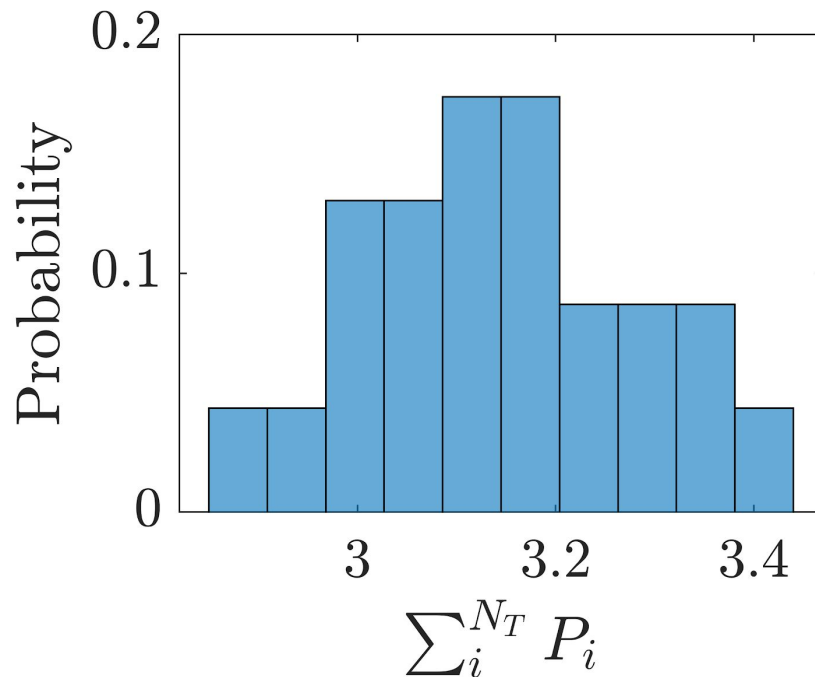
### **Comment #6**

Quantification. Several issues relating to quantification could be improved and clarified.

- Are the power productions in Table 1 normally distribution? Otherwise, the standard deviation could be biased and misleading.
- The inclusion of whether results are significant can only be applauded. Line 434 defines "significant superior...if the mean array power production ....is more than one standard deviation larger than the other". However, the use is biased, because the analysis is essentially only one-sided. The authors only compare controlled mean power - 1 standard deviation to the meanpower of the baseline. The authors should also include the standard deviation of the baseline, because it's two overlapping distributions. That essentially means none of the cases are significantly superior if using the authors definition of statistical significance.

### **Response**

The Figure 1 shows the probability distribution of the six turbine array over the control update steps (from LES case ND2). The sum of the six wind turbine array power production is approximately normal as a function of control update steps. Given the sample data deviation from an exact Gaussian distribution, we will use two statistical tests to check the statistical significance of the LES power production data below.



**Figure 1:** Probability distribution over the control update steps for the sum of the six turbine array power production from LES Case ND2.

While the total turbine array power production is approximately normal as a function of the control update steps, we will demonstrate two statistical tests here to show statistical significance for Cases NA and ND2 by assuming normal distributions or not. The null hypothesis is that the two temporal signals of the sum of the six turbine power production are random samples from the same underlying probability distribution.

**Two-sample T-test (assumes normal distributions):**

P = 6.13E-4, and therefore the null hypothesis is rejected at a 5% significance level.

**Two-sample Kolmogorov-Smirnov test (does not assume normal distributions):**

P = 1.16E-4, and therefore the null hypothesis is rejected at a 5% significance level.

Therefore, the differences between Cases NA and ND2 are statistically significant at a 5% significance level. We will update the manuscript with these further statistical tests for all cases.

**Comment #7(a)**

Zong and Porté-Agel also shows the secondary steering effect, which other recent articles are also investigating, see e.g. King et al., 2020. The secondary steering effect essentially implies that the next wake will also be partly steered for "free"(without power loss). The Liew et al. 2020 reference states that McKay et al. 2013, Bartl et al. 2018, and Hulsman et al.2020, all show that the local inflow direction changes, andthe waked (2nd) turbine should adjust to the inflow. Hence, it would indicate that if the second turbine also yaws 20deg, it actually corresponds to a



larger relative yaw angle. So why would the optimization give the same(or relatively larger) yaw angles for the first 3 turbines?

### **Response**

As demonstrated by the recent studies the referee has discussed, secondary steering is an important aspect of wake steering control. Modeling efforts to capture secondary steering are on-going (King et al. 2020 in review in *WES*) or very recently published (Zong and Porte-Agel (2020), which was published after this manuscript was submitted). The wake model methodology used in this study's simulations did not model secondary steering and therefore this effect will not be directly reflected in the model-optimal yaw angles, although the authors note that the lifting line model with EnKF estimation predicts a generally decreasing trend of yaw misalignment values deeper into the array of turbines (e.g. Figure 8). Future work should examine the efficacy of secondary steering models in closed-loop wake steering control, but is out of the scope of the present study since all LES cases would need to be re-run.

### **Comment #7(b)**

Should the yaw angles not be reduced at least by the secondary effects or is this not capture by the LES?

### **Response**

The yaw angles reported in this manuscript are the local turbine relative yaw misalignment values (i.e. the yaw misalignment of the turbine with respect to its local wind direction measurement), and therefore the secondary steering effect is accounted for in the reporting of the yaw misalignment values from LES but not in the model optimization as discussed in the response to **Comment #7(a)**.

### **Comment #7(c)**

A quick estimate of the power yaw loss with  $PP = 3$ , yields the following table (see table in review). That means the first turbine yawing 15-20deg loses approx. 10-17% of the power compared to its own baseline(also shown in Figure 16). Line 480 states "power production penalty...is significant beyond 40deg". The 40deg seems "random", as one could just as well argue that losses of 10-17% are significant. In order for the entire farm to produce more, this loss should be recovered by the next turbine. However, the next 3 turbines experience similar losses. Therefore, increase in velocity have to compensate for all these turbine losses. If I use estimates from Figure 16, I read an initial power production of approx. 35% and an optimal power production of approx. 50% for the second turbine relative to the first. Hard to see from this rough estimate if the second turbine actually gain more than what the first turbine losses. Archer and Vassel-Be-Hagh also concluded there needs to be at least 2 turbines downstream a yawed turbine to regain the power loss.

### **Response**

Thank you for this comment and for your analysis. We will remove Line 480 for clarity. Figure 16 only plots the power for the first two turbines in the 6 turbine array (to reduce clutter in the Figure). Since it only plots the first two turbines, it should be noted that the gains at turbine 2 do not directly compensate the losses as turbine 1, since the objective is to maximize

the 6 turbine array, not focus on two-turbine sub-optimization problems which reduces global array optimality.

The power production for turbine 2 shown in Figure 16 accounts for the total power, i.e. the power production of turbine 2 accounts for power reduction due to its own yaw misalignment as well as power increases due to turbine 1's yaw misalignment. The largest relative gains in the 6 turbine array will be the turbines further downwind since their relative yaw misalignment is lower (see Figure 14). The total power production for the 6 turbine array is compared to baseline control in Figure 11.

As the referee correctly notes, the conclusion of Archer and Vassel-Be-Hagh (and Howland et al. (2020)) has motivated the use of the 6 turbine array to test closed-loop wake steering in this study rather than a 2 turbine array.

### Comment #7(d)

In order to recover the power loss, the wake velocity have to increase by  $V2/V1 = (0.50/0.35 * CP0/CPyaw)^{(1/3)}$  where  $CP0$  corresponds to my previous table of  $Odegyaw$ , and  $CPyaw$  is the remaining. Hence, the velocity increase ( $V2/V1$ ) on the second turbine needs to be (see table in review). So a 17-20% increase in mean velocity. It would be nice to see some kind of velocity plots, either contour plots before and after control to verify this. Therefore, it would also be nice to see the actual power production of the individual turbines compared to baseline for the various scenarios, because it's difficult to assess which turbines actually make up for the losses and increase the total production in the accumulated plots, e.g. Figure 9. The authors have attempted to do so in Figure 21, but it's very difficult to distinguish. It seems turbines 2, 4 and 5 recover the losses for  $PP = 3$ ? Perhaps use bar plots with clearer standard deviations?

### Response

We will add further plots, tables, and discussion to clarify the quantitative results in these simulations. To address the referee's specific concern, we will articulate some quantitative results here, and include a thorough discussion in the revised manuscript.

Focusing on Case ND2, the power production for each turbine is normalized by the baseline control power production (of the same turbine) and is averaged over the control update steps. The resulting normalized power production values are:

Turbine	Power (normalized by baseline greedy control and averaged over control steps)
1	0.844
2	1.102
3	1.182
4	1.159
5	1.192
6	1.106

As can be seen from the power production values for Case ND2 (normalized by Case NA), turbine 1 loses approximately 15% of its power production but each downwind turbine generates 10-20% higher power production than baseline control. Since turbine 1 generates larger power, its losses influence the array sum more than the gain of the downwind turbines, but collectively, the average array power production increases 4.6% over greedy baseline

control in this case. As can be seen, with more turbines downwind, the potential for wake steering to increase relative power production over greedy control also increases.

### **Minor comments**

#### **Minor comment #1**

The inclusion of FLORIS (Section 5.4) seems superfluous. I suggest to leave it out to keep the analysis more focused, and shorter.

#### **Response**

The authors do not agree that Section 5.4 is superfluous. This section tests the influence of the state estimation methodology and FLORIS is a commonly used wake model whose parameters have been empirically defined such that model-based parameter estimation is not used. This comparison shows that without model parameter estimation the wake model does not fit the baseline power production, and as such, *predicts* power given a yaw misalignment strategy with 5x larger error (Figure 21(b)).

#### **Minor comment #2**

- The definition of 0deg north seems redundant. Where is it used? It seems to be in conflict with Figure 6, as the wind direction with 0deg north would not be 16deg, but a 254deg.

#### **Response**

Thank you for this comment, we will modify the manuscript to clarify the terminology.

#### **Minor comment #3**

Terminology might change over time and for different researchers. Some use kidneyshaped, others curled wake. However, the vortex pair has been observed in the wake behind a yawed turbine prior to 2016 (line 131). The earliest reference I could find was Mikkelsen, 2004, see Section 8.3.

#### **Response**

We will add the reference to Mikkelsen 2004.

#### **Minor comment #4**

- Please introduce/explain Table 1 more when it is first presented.

#### **Response**

We will modify the manuscript accordingly.

#### **Minor comment #4**

Please provide a proper description of the turbine. Line 398: "selections based on NREL 5MW" does not seem reproducible by other scientists.

#### **Response**

The reference to the NREL 5 MW turbine was to clarify the selection of the turbine diameter. All relevant computational parameters of the turbine are detailed in Section 3.

**Minor comment #5**

Details are difficult to see in many of the figures. For instance, reduce the axis limits on Figure 15 and similar. Figure 21 is very hard to distinguish.

**Response**

Thank you for this comment. We will modify the figures accordingly to improve visibility.

## **References**

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## Response to Referee #2

We thank the referee for their review and their thoughtful comments. Point-to-point responses can be found below, and the relevant changes have been made to the manuscript.

### General comments:

#### **Comment #1**

One overall comment I had was I wasn't quite positive of the main, conclusion of the paper. Is that the proposed method is at least successful in the provided tests, or that it is necessary to use a method like this? The paper is a little bit long, I wondered if parts might be condensed also to make more clear what are the bigger, more important, findings? The authors however can freely disregard this suggestion, but I hope this impression is useful.

#### **Response**

Thank you for this helpful comment, we will streamline the discussion in the paper to highlight the main contributions.

The main technical contribution of this paper is the development of a closed-loop wake steering methodology for application in transient ABL flows which does not rely on an open-loop offline yaw misalignment lookup table calculation.

The two main conclusions are: 1) that the wake model, when combined with a state estimation approach, is able to predict the power production for the wind farm in yaw misalignment with significantly less error than the standard approach of an empirically pre-calibrated wake model and 2) model parameter uncertainties, such as the uncertainty in  $P_p$ , can inhibit the success of a wake steering application and these uncertainties must be carefully accounted for.

#### **Comment #2**

What is the model of yaw control within the turbine used? Is the turbine free to yaw at any moment? Most turbines have a built-in yaw control strategy which includes some dead-band about vane angle, and an intentionally delayed response to changes in wind direction. If this was not used, how would it change results if it were?

#### **Response**

The referee is correct that most utility-scale turbines have a native yaw control system which acts outside a deadband of 5-10 degrees based on low-pass filtered wind vane angle measurements. The yaw control strategy used in the present study low-pass filters the wind direction measured at the rotor based on a predefined time constant, leverages the computed turbine-specific wind direction to implement the desired yaw misalignment, and holds the imposed nacelle position for one period of the predefined time constant. This was described on Page 11 Line 315 and will be further expanded on in the revision to improve clarity.

Depending on the dynamics of the ABL, the method we have employed may lead to different results than the method the referee has mentioned. However, in the present conventionally neutral ABL large eddy simulations, the variations in the turbine-specific wind directions as a function of time due to turbulence and inertial oscillations are relatively small (a few degrees)

and therefore the yaw control method we have used and the deadband method will perform very similarly.

For Part 2 of this work, where the closed-loop controller is tested in the transient diurnal cycle, this native yaw control system will likely have a larger impact and we will test various native yaw control strategies.

### **Comment #3**

One general comment I had on the sections related to the  $\cos pP$  parameter, is that the discussions and conclusions are proposed in absolute terms, where relative would be more appropriate. As I understand,  $pP=3$  is "correct" in this LES simulation, and so 2 is  $2/3$  of correct, and 4 is  $4/3$  of correct. Most of the numbers are baselined to a correct value of 3, but should be scaled in other simulations or on physical turbines. My main point is to avoid stating that 2,3 or 4 is better/worse and more under-predicting  $pP$  by  $x\%$  leads to, while over-predicting  $pP$  by  $x\%$  leads to ... In a similar way this would change the statement "a conservative estimate of  $pP=4$ " should be used in cases where it's not yet known could be the more reasonable 125% of the value of the most similar published value (in terms of rated power or rotor size).

### **Response**

Thank you for this comment. The referee is correct that the reference to conservative values of  $P_p$  are relative since they depend on the turbine-specific correct, or maximum likelihood estimate, value of  $P_p$ . The authors suggest that given a confidence interval on  $P_p$  for a given wind turbine, a conservative estimate should be selected for  $P_p$  for the calculation of the yaw misalignment strategy since the underestimate of  $P_p$  leads to power production loss during wake steering. We will modify the manuscript to consider your comment and discuss the  $P_p$  sensitivity in relative terms.

### **Specific comments:**

#### **Comment #1**

The last sentences of the abstract are somewhat confusing before you read the paper

#### **Response**

We will modify the last sentence of the abstract for improved clarity.

#### **Comment #2**

p 13 "likely enhanced in yaw misalignment" see yaw-added recovery in <https://www.wind-energ-sci-discuss.net/wes-2020-3/>

#### **Response**

Thank you for highlighting this paper, we will add the reference to the yaw-added recovery.

**Comment #3**

P23 "wind speed and direction bins of arbitrary size" this seems pretty possible using interpolating functions

**Response**

Thank you for this interesting comment, interpolating functions would be an excellent candidate to use in open-loop lookup table computation.

**Comment #4**

P23: "using a neural network for example" these ideas are theoretically possible but practical observation suggests that any method whose parameters are not human intelligible will have obstacles because it will be difficult to make in-field adjustments

**Response**

The authors agree that methods which are based on first principles or physical phenomena are likely to perform better in a complicated field environment and we leave machine learning questions for future experimentation and improvement.



### **Response to Referee #3**

We thank the referee for their review and their thoughtful comments. Point-to-point responses can be found below, and the relevant changes have been made to the manuscript.

#### **General comments:**

##### **Comment #1(a)**

The introduction could be considerably reduced without harming its quality: the general introduction in wind energy (up until line approx. line 27) can be omitted, the discussion on induction control could be reduced to simply mentioning that dynamic control is much more promising than static (with some key references, i.e. Annoni et al, Campagnolo et al, Munters & Meyers, Frederik et al.)

##### **Response**

We will streamline the introduction review.

##### **Comment #1(b)**

The literature review at the beginning of Section 2.2 can be shortened

##### **Response**

We will shorten the literature review for brevity.

##### **Comment #1(c)**

Section 2.4 basically discusses a straightforward time lag based on Taylor's hypothesis. This could be significantly shortened.

##### **Response**

We will remove this section and state the time lag based on Taylor's hypothesis in a brief fashion.

##### **Comment #1(d)**

Section 2.5 takes up quite a lot of space with again a detailed review, but very little is said related to the current manuscript, other than 'the update frequency is selected according to the dynamics of the problem studied'. Further, 'Comments on the update frequency are made in Section 5.' (l. 270), hinting on a study where the sensitivity to this frequency is analyzed, where is this exactly? Or do the authors refer to the part where a dynamic approach is compared to a lookup table (i.e. Section 5.1)? In the latter case, please rephrase (l. 270) more exactly.

##### **Response**

We will streamline and re-phrase the discussion in Section 2.5 and on Line 270 to improve clarity.

##### **Comment #2(a)**

It would be illustrative if the authors could provide a schematic which shows inputs, outputs, and operations of the algorithm. This could be similar to figure 1 which shows  $\alpha$  and  $\gamma$  as inputs to the state estimation, however their role is not discussed in section 2.2.

**Response**

We will include a schematic to describe the state estimation methodology and clarify the role of  $\alpha$  and  $\gamma$ .

**Comment #2(b)**

Further, the statement 'The EnKF is computationally superior ... but this may lead to spurious correlations in the state representation' is somewhat confusing. Does this affect the results in the current paper?

**Response**

We will remove the statement which does not directly relate to the results of the current paper.

**Comment #2(c)**

The EnKF is particularly well-suited for discretized PDE problems. Why? add a suitable reference perhaps

**Response**

We will remove this statement which is not critical to the current paper.

**Comment #2(d)**

The outcome of the EnKF is a vector with  $k$   $w$  and  $\sigma$  for all turbines except the last one, for which this is not relevant (l 191 p 7). However, in your equations, this last turbine is included in the state estimation, e.g. see Equation (7). Is this correct?

**Response**

Thank you for noting this notation error. The referee is correct that the furthest downwind turbine does not need to be included in the state estimation, and in fact, its parameters are irrelevant for the wake model. We will adjust the state estimation equations accordingly.

**Comment #2(e)**

Equation (18): should all  $\pi$ 's be replace with  $\hat{\pi}$  here? If not, how is  $\pi$  defined?

**Response**

Thank you for noting this typographical error in Equation (18). The  $\pi$ 's should have been  $\psi$ 's and we have fixed the error.

**Comment #3(a)**

The authors use an actuator disk model. Some more details would be welcome. Is it a rotating or non-rotating model (I assume the latter). The ADM is accurate in the far wake, yet at a turbine spacing of  $4D$  it is doubtful whether far wake conditions are met. Somme comments on

this would be welcome. How does the ADM deal with the dependency of thrust forces and power extraction on yaw angle? Is this a standard  $\cos^2(\gamma)$  and  $\cos^3(\gamma)$  respectively? How does this influence conclusions based on the sensitivity of the control framework on  $P_p$  in section 5.3?

G

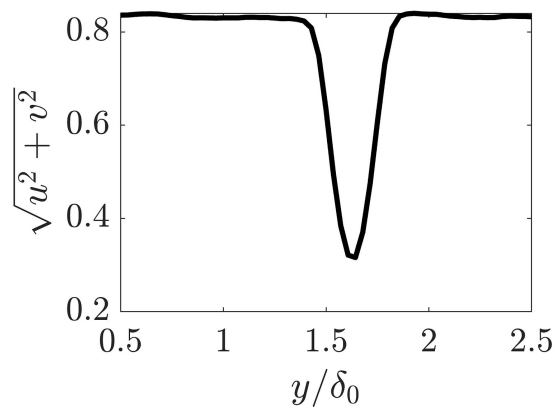
**Response**

The actuator disk model used in the large eddy simulations presented in this study does not include rotation, it is a standard actuator disk model. We will include more details on the ADM in the manuscript and the description is also stated here. The referee is correct to note that the ADM has some discrepancy with the rotating ALM in the near-wake region.

To be clear, the relative turbine spacing in the conventionally neutral ABL simulations is between 4-5D in the mean hub-height wind direction since the spacing is 4D in the x-direction and the turbines are aligned at 18 degrees to the x-axis.

The wind speed profile at the wind turbine hub height approximately 4D downwind of the leading turbine, incident on the second turbine, is shown in Figure 1. The wake profile exhibits a Gaussian shape, rather than a top-hat shape, suggesting that with the turbulence intensity and length scales present in the conventionally neutral ABL LES, 4-5D spacing is sufficient to establish far wake behavior with the actuator disk model used in this study. This is consistent with the expected location of far-wake behavior onset (experimentally found in yawed rotating turbines to be approximately  $x/D=3$  [1]).

The goal of the current study is to test the efficacy of the closed-loop control algorithm, and therefore, the focus was not to precisely match the wakes observed in full-scale wind farms through LES; future work should also incorporate more advanced wind turbine models.



**Figure 1:** Time averaged wind speed profile at  $x/\delta_0=3.5$  at the wind turbine hub height. The flow at this x-location is incident on the second wind turbine in the array. The wind speed exhibits a Gaussian profile, suggesting the onset of far-wake behavior [see e.g. 1].

Within the actuator disk model formulation, the dot product is taken between the incident wind velocity vector and the wind turbine rotor normal vector to calculate the perpendicular velocity vector. The thrust force normal to the rotor area is computed using the perpendicular velocity, the axial induction factor ( $a=0.25$ ), and the coefficient of thrust ( $C_T = 0.75$  in the

current study). The forces are then projected into the computational domain coordinate system. In this fashion, the dependence of the thrust force (with thrust being defined as parallel to the mean velocity at hub height) on the yaw misalignment angle is  $\cos^2(\gamma)$  given uniform inflow conditions. Importantly, with non-uniform flow conditions, the thrust is not guaranteed to follow  $\cos^2(\gamma)$ . The ADM power production is defined as  $P = u_p \cdot F_T$  where  $u_p$  is the velocity perpendicular to the rotor area and  $F_T$  is the thrust force. This results in a power production dependency on the yaw misalignment angle of  $\cos^3(\gamma)$ , again, for uniform inflow conditions only. For heterogeneous flow conditions, the scaling for thrust and power as a function of yaw misalignment is approximately  $\cos^2(\gamma)$  and  $\cos^3(\gamma)$ , respectively, although it may deviate from these approximate scaling expectations. We will include further comments on the ADM in the revised manuscript.

The particular “ground-truth” value of  $P_p$ , as discussed in Section 5.3, is wind turbine model specific. The current LES experiments detail the sensitivity of the wind farm power production, and therefore the efficacy of wake steering, to the estimate of  $P_p$  for a ground-truth  $P_p = 3$ , but the sensitivities noted in the current study are not expected to depend on the particular ground-truth value for  $P_p$ . For example, the current experiments show that an estimate of  $P_p = 2$  when the ground-truth value is 3 leads to power production loss compared to standard operation. For a different wind turbine model with a ground-truth of  $P_p = 2$ , we would then expect an estimate of  $P_p = 1.5$  may lead to undesirable results, for example, while  $P_p = 2$  would be an excellent estimate. The results of the current study are not absolute, in the sense that  $P_p = 4$  is always a good choice, but relative, in the sense that a conservative estimate for  $P_p$  is wise given the  $P_p$  parameter uncertainty which is present in wake steering applications. We have refined the discussion in Section 5.3 to clarify this point.

### **Comment #3(b)**

p.12, l 323 – 325: ‘... without the influence of variable turbine operation, the flow is identical to machine precision between yaw aligned and yaw misaligned cases’. I would suggest rephrasing this. I understand the authors want to convey that both cases are started from identical initial conditions, and any differences can hence be attributed to differences in farm controls. However, stating that these simulations are ‘identical to machine precision’ is somewhat deceptive in the simulation of a chaotic dynamical system. In such systems, differences (even at machine precision levels e.g. by adapting compiler optimization levels), will grow exponentially in time, resulting in a completely different turbulent flow realization. I’m not saying this is the case in the current simulations, but a better phrasing would simply be to remove the ‘to machine precision’ part.

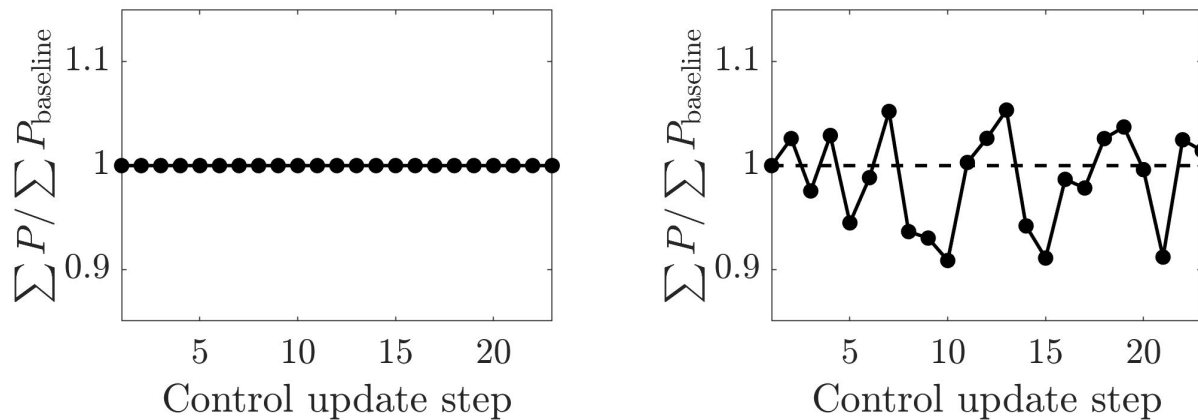
### **Response**

Thank you for this comment. The referee is correct that differences in turbulent systems grow exponentially in time and even modifications in the compiler optimization could cause these differences which grow to  $O(1)$  errors. We have carefully ensured that these floating-point differences are eliminated by fixing the initialization (to machine precision), compiler optimization, and processor topology in the present study to allow for quantitatively rigorous

comparisons between the various control simulations. We have added a footnote to clarify the points the referee has raised.

We can further demonstrate the point the referee has raised here. We perform a numerical experiment with three simulations. In the conventionally neutral LES flow, we fix all parameters and initializations to machine precision and the control architecture is fixed between the three cases. In two cases (#1 and #2), the processor topology is fixed while in the third case (#3), the compiler optimization changes the processor topology. The power production for Cases #2 and #3 normalized by the power from Case #1 are shown below in Figure 2. Cases #1 and #2 remain in quantitative agreement to machine precision while Cases #1 and #3 diverge. The deviation between Cases #1 and #3 are a consequence of round-off differences that occur due to global reduction (sum) operations with modified processor topology.

All comparison cases in this paper were performed with the comparison methodology enforced in Cases #1 and #2.



**Figure 2:** Processor topology experiment. In the left plot, the wind turbine array power production (Case #2) is normalized by a separate LES case (Case #1) with fixed control architecture and initialization as well as a fixed processor topology. In the right plot, the power (Case #3) is normalized by a separate LES case with fixed control architecture and initialization but a modified processor topology (Case #1). The normalized power from Case #3 oscillates around 1 as a function of time.

**Comment #4(a)**

The relatively low grid resolution, combined with the uniform inflow creates a possibly problematic setup where the wake behind the first turbine is artificially stabilized, resulting in very low baseline power in row 2, and hence huge gains to be obtained from any type of control. A remark could be added to the text on this. This is somewhat mentioned in l. 361, but it would be good to mention that this case is highly dependent on things like grid resolution, SGS model, and hence physical results should be interpreted with care.

**Response**

Thank you for this comment. The referee is correct that LES of uniform inflow impinging on wind turbine models at typical LES resolutions leads to an artificial stabilization as mentioned in the discussion in Section 4 (Line 361). This challenge of turbulent transition in wind turbine model wakes for uniform inflow and the influence of the SGS model was discussed in detail in Howland *et al JRSE* (2016) [2]. As a result of this comment, and those of the other referees, we have moved the uniform inflow test case section to the Appendix to reduce confusion between this unphysical algorithmic test case and the physical conventionally neutral LES results.

#### **Comment #4(b)**

Figure 3 and Figure 4: x-axis is labeled time step. Is this simulation time step of control update step? I'm suspecting the latter, but it would be better to be explicit, similar to how axes are labeled in later figures.

#### **Response**

Thank you for noting this typographical error. The x-axes for Figures 3 and 4 should state 'Control update step,' and we have updated the manuscript accordingly.

#### **Comment #4(c)**

p. 14, l. 369: The authors indicate their fear of an overparametrized model which is overfitting by spurious anti-correlation of  $k_w$  and  $\sigma_0$ . Would it make sense / be possible to directly try and obtain these parameters from a time-averaged LES flow field and hence quantify the 'correct' parameter values?

#### **Response**

Thank you for this suggestion. This is an interesting idea and it is possible to quantify an empirical best-fit for the wake spreading rate  $k_w$  in the LES setting. In fact, this has been the previous wake modeling approach to the wind farm controls problem (see e.g. Niayifar & Porte-Agel (2015) [3] and the FLORIS model). However, this methodology is impractical in a field setting for continuous parameter estimation where nacelle-mounted LiDARs are not often available and *a priori* parameterized values for physical constants can lead to inaccurate power predictions (see comparison with empirical Gaussian wake model in Figure 21). The purpose of the present study is to establish a framework which relies only on readily available SCADA data for model parameter estimation, and therefore we have not focused on flow-field empirical parameter fitting in this study. Future work should investigate the efficacy of physics-based constraints during optimization of the wake model parameters, but this is out of the scope of the current study.

#### **Comment #4(d)**

Concluding, the overall added value of this section is quite limited in my opinion. The main contribution would be to have a very basic test case, showing that the EnKF and yaw angles are relatively stable for steady flow conditions. Therefore, I believe it would be better if the section is introduced and discussed with this aim.

#### **Response**

As discussed in the response to **Comment #4(a)**, we have moved this section to the Appendix to focus on the physical results in the conventionally neutral ABL setting.

#### **Comment #5(a)**

Table 1 is introduced early on. However, by itself, the table is insufficiently explained to completely understand which case is which. An example is the NA case, which is not clearly defined in the text until Appendix C. Also, the naming and order in which these cases are presented in the table could be greatly improved. For example, Section 5.1 discusses NL and ND2, whereas ND1 is only introduced in Section 5.2. The naming also gets very confusing later on, e.g. the case with  $P_p = 2$  is called ND4 and  $P_p = 4$  is called ND5. This results in the reader constantly having to go back to Table 1 to recall which case is which. More logical naming would prevent this, e.g. replace ND4 by NDP2, ND5 by NDP4.

#### **Response**

We will describe the cases and Table 1 in more detail and earlier in the manuscript to improve clarity and we have re-named the cases according to the referee's suggestions. Note that we have also switched the names of Case ND1 and ND2 in the revision as per the referee's suggestion.

#### **Comment #5(b)**

The final column in Table 1 is used to determine statistical significance of improvements over the basecase. It would be more illustrative to plot this in a barplot including errorbars, because seeing whether these values overlap for different cases from numerical data is not trivial.

#### **Response**

Thank you for this suggestion, we have incorporated a barplot (Figure 5) with corresponding errorbars to clarify these data and their statistical significance.

#### **Comment #5(c)**

Section 5.1: How is the lookup table in the NL case generated? Is this simply by running 1 control window, and then keeping the yaw angles constant? How robust is this? I.e. how would these steady yaw angles differ if they were generated based upon a state estimation from a different time window / turbulent flow realization? This would have an impact on statistical significance of the results.

#### **Response**

As discussed on Line 416 of the manuscript, the lookup table approach is approximated by: "The lookup table control is approximated by fixing the yaw misalignment angles as a function of time after the initial optimal angles are computed during the first yaw controller update"

Generating the yaw angles in a different time window would lead to small changes in the yaw misalignment values computed by the model-based optimizer as the referee has mentioned. This point was investigated by the authors extensively before submission of the manuscript, although it was not shown for brevity in the already lengthy manuscript. We will articulate the results here and add a brief discussion in the revised manuscript.

While generating yaw misalignment angles in a different time window/turbulent flow realization with slightly different mean wind direction, wind speed, turbulence intensity, etc leads to slightly different values of yaw misalignment, the conclusions of the study are not affected since the changes to the wind farm power production are not statistically significant. This experiment was investigated for Case ND1 and Case ND1R, the robustness version of Case ND1 which is algorithmically identical but initialized at a later LES temporal instance.

The yaw misalignment values implemented in the first control update step of Case ND1 are (from first to last turbine in degrees):

[16.8163, 17.0334, 16.8953, 14.7568, 2.8090, 0.0000]

The increase in power production over baseline control (Case NA) is for Case ND1: 4.59% +/- 2.34%

The yaw misalignment values for Case NL are identical to the first step of Case ND1 by definition.

In a robustness test case, the conventionally neutral ABL LES is run for several more physical hours before the yaw misalignment strategy is switched on the and resulting yaw misalignment values are computed in the separate turbulent time window realization (from first to last turbine in degrees):

[15.5785, 15.8899, 14.4753, 12.1178, 3.7497, 0.0000]

Case ND1 was repeated, starting from the later time, and the increase in power production over baseline control (Case NAR, which was also re-run for the later time window) is for Case ND1R: 5.7% +/- 2.03%

The yaw misalignment values for Case NLR are identical to the first step of Case ND1R by definition. Therefore, changing the time window for the lookup table approximation did not significantly change the yaw misalignment values, as the referee has suggested.

The differences in power production for these two cases are not statistically significant as characterized by a one-sided two-sample Kolmogorov-Smirnov test at a 5% significance level. Further, the yaw misalignment values are qualitatively and quantitatively similar. Therefore, while the specific time wind in which the lookup table (or dynamic yaw) control is implemented has some influence on the quantitative results, we have demonstrated that it does not influence the statistical significance of the results. We have added a discussion in the manuscript to clarify this point.

#### **Comment #5(d)**

Section 5.1: p. 18, l. 438. a lot of explanation is given for a non-significant performance difference. Does this make sense?

#### **Response**

We will modify the discussion to highlight that the result is not statistically significant.

#### **Comment #5(e)**



For figures like 8,9,10,11, it would improve direct interpretability of the figures if the case name was included directly on the plot instead of only in the caption. There is ample whitespace left to do this everywhere.

**Response**

We will add the case numbering to the plots.

**Comment #5(f)**

Section 5.2: p. 22, l. 492 the authors claim ‘The most successful dynamic control framework ... is the static state estimation methodology’. Please add the casename here explicitly (ND3 I presume). Based on what metric is ND3 more successful than ND2? Power extraction differences were mentioned not to be significant.

**Response**

As with **Comment #5(d)**, we will limit the differentiation of cases which are not statistically significant differences.

**Comment #5(g)**

Section 5.2: p. 23, l.496: ‘This potential dependence of  $k_w$  and  $\sigma_0$  on yaw misalignment was not incorporated explicitly ...’ Is this dependence not implicitly accounted for through the EnKF?

**Response**

This is an excellent observation by the referee. The goal of the data-driven EnKF methodology is that the dependence is implicitly accounted for. The authors were suggesting that future work could also incorporate this dependence explicitly in a physics-based modeling strategy. We will clarify this in the manuscript.

**Comment #5(h)**

Section 5.2 last paragraph: This comparison to NL lookup table seems a bit out of place. Could this be moved to Section 5.1? I understand there are chronological dependencies in how you want to write down observations, but the current narrative is somewhat confusing.

**Response**

Thank you for this suggestion, we have reformulated the narrative to improve clarity.

**Comment #5(i)**

Section 5.3 p.25, l.532: ‘Interestingly, ND5 outperforms ND2, but not significantly’ This statement is confusing, if its insignificant, then the outperformance is not to be distinguished from statistical noise, so calling that interesting seems contradictory. Please remove or rephrase

**Response**

As with **Comment #5(d)**, we will remove discussion of statistically insignificant results.

**Comment #5(j)**

Section 5.4: the part on FLORIS can probably be omitted. Further, this section basically also quantifies a dependence on  $P_p$ , which was already the subject of Section 5.3. Consider renaming sections to avoid overlap in their definition.

**Response**

The authors believe that a comparison with an empirical physics-based model without state estimation is warranted to show the benefit of the EnKF on power production predictions. The lifting line model has not received an empirical calibration treatment as the Gaussian wake model has [see ref. 2], and therefore FLORIS was selected as a comparison. It is important to note that this comparison is predominantly a commentary on the success of the EnKF for improving wake model state estimation, rather than a comparison between the lifting line and Gaussian wake models.

## **Minor/technical comments:**

### **Comment #1**

The title of the paper could be improved such that the goal of the research is reflected therein, namely quantifying the sensitivity to design choices in the control framework. Currently, the title 'Optimal closed-loop wake steering' is rather generic, and mentioning that it is 'part 1' of a two-parts paper in my opinion degrades the idea that the current work is self-contained.

### **Response**

Thank you for this comment. This article was titled 'Part 1' since there will be a follow-up 'Part 2' which will focus on wake steering in diurnal cycle simulations. Each article will be self-contained, as the present article is.

### **Comment #2**

p.3, l.79: mentioning that accurately predicting greedy base-line power production is the main challenge in wake steering control, is somewhat exaggerated in my opinion.

### **Response**

We will modify the language in the manuscript to highlight that dynamic wake steering does indeed carry other technical challenges aside from the mentioned baseline power production prediction.

### **Comment #3**

The output of your controller is a time-series of yaw angles  $\gamma(t)$ , do the ADM in the LES directly impose these yaw angles, or is there a limitation on the yaw rates? Figure 3 seems to indicate a very large jump in yaw angle within a single timestep. Is this technically feasible?

### **Response**

Yaw control rates are typically  $\sim 0.5^\circ/\text{s}$ . The largest jump in yaw misalignment in the present study is from greedy control to wake steering control in 'Control update step 1' of the simulations. This jump has a maximum of  $30^\circ$ , which would take approximately 60 seconds to implement. This time is significantly less than the Taylor's hypothesis time lag (Section 2.4) and therefore this yaw rate will not influence the results. For a dynamic wake steering controller with a more rapid yaw update frequency, this effect should be considered.

This was discussed in the original manuscript on Line 480 but we have moved the discussion to the LES formulation Section 3 to improve clarity.

### **Comment #4**

p.7, l. 184: number of turbines  $N_T$ , l. 192: number of turbines  $N_t$  (either use  $N_T$  or  $N_t$ )

### **Response**

We will fix the typographical error.

### **Comment #5**

p.9, l.234: I believe the algorithm should be denoted as Adam, not ADAM

**Response**

We will fix the typographical error.

**Comment #6**

p.10,l.280: add the continuity equation to the momentum equation

**Response**

We will add the continuity equation for completeness.

**Comment #7**

p.10,l.264: psuedo vs. pseudo?

**Response**

Pseudo, we will fix the typographical error.

**Comment #8**

Figure 2 and Figure 6 could be improved by adding a snapshot of a velocity field in addition to the purely schematic domain presentation.

**Response**

We will add a velocity field snapshot.

**Comment #9**

p.13,l.345: in incorporated vs is incorporated

**Response**

We will fix the typographical error.

**Comment #10**

p.20,l.471: proportionality constant  $\sigma$  0

**Response**

Thank you, we will adjust the manuscript accordingly.

**Comment #11**

p.21,l.472: Gaussian wake does NOT have a clear trend

**Response**

We will fix the typographical error.

## **References**

- [1] Bastankhah, M., and F. Porté-Agel. "Wind tunnel study of the wind turbine interaction with a boundary-layer flow: Upwind region, turbine performance, and wake region." *Physics of Fluids* 29.6 (2017): 065105.
- [2] Howland, Michael F., et al. "Wake structure in actuator disk models of wind turbines in yaw under uniform inflow conditions." *Journal of Renewable and Sustainable Energy* 8.4 (2016): 043301.
- [3] Niayifar, Amin, and Fernando Porté-Agel. "A new analytical model for wind farm power prediction." *Journal of physics: conference series*. Vol. 625. No. 1. IOP Publishing, 2015.

# Optimal closed-loop wake steering, Part 1: Conventionally neutral atmospheric boundary layer conditions

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**Abstract.** Strategies for wake loss mitigation through the use of dynamic closed-loop wake steering are investigated using large eddy simulations of conventionally neutral atmospheric boundary layer conditions, where the neutral boundary layer is capped by an inversion and a stable free atmosphere. The closed-loop controller synthesized in this study consists of a physics-based lifting line wake model combined with a data-driven Ensemble Kalman filter (EnKF) state estimation technique to calibrate the wake model as a function of time in a generalized transient atmospheric flow environment. Computationally efficient gradient ascent yaw misalignment selection along with efficient state estimation enables the dynamic yaw calculation for real-time wind farm control. The wake steering controller is tested in a six turbine array embedded in a statistically quasi-stationary conventionally neutral flow with geostrophic forcing and Coriolis effects included. The controller statistically significantly increases power production compared to baseline, greedy, yaw-aligned control ~~although the magnitude of success of the controller depends on the state estimation architecture and the wind farm layout~~ provided that the EnKF estimation is constrained and informed with a physics-based prior belief of the wake model parameters. The influence of the model for the coefficient of power  $C_p$  as a function of the yaw misalignment is characterized. Errors in estimation of the power reduction as a function of yaw misalignment are shown to result in yaw steering configurations that under-perform the baseline yaw aligned configuration. Overestimating the power reduction due to yaw misalignment leads to increased power over greedy operation while underestimating the power reduction leads to decreased power, and therefore, in an application where the influence of yaw misalignment on  $C_p$  is unknown, a conservative estimate should be taken. ~~Sensitivity analyses on the controller architecture, coefficient of power model, wind farm layout, and atmospheric boundary layer state are performed to assess benefits and trade-offs in the design of a wake steering controller for utility-scale application. The physics-based wake model with data assimilation~~ The EnKF-augmented wake model predicts the power production in yaw misalignment with a mean absolute error over the turbines in the farm of  $0.02P_1$ , with  $P_1$  as the power of the leading turbine at the farm, ~~whereas a physics-based~~. A standard wake model with wake spreading based on an empirical turbulence intensity relationship leads to a mean absolute error of  $0.11P_1$ , demonstrating that state estimation improves the predictive capabilities of simplified wake models.

## 25 1 Introduction

Wind and solar energy are likely the only low-carbon energy technologies which are being implemented rapidly enough to mitigate the effects of global warming (IEA, 2017). Since wind energy has a low marginal cost (Bitar et al., 2012), increases in wind farm power production approximately manifest as a reduction in the levelized cost of electricity (LCOE) (Joskow, 2011). While the LCOE of wind energy is already often below those of traditional combined-cycle natural gas and coal (Bilgili et al., 2015; EIA, 2014), continued reductions in wind energy LCOE will likely increase the adoption of this technology (Borenstein, 2012; Ouyang and Lin, 2014) due to improved economics in sub-optimal wind resource areas (Wiser et al., 2015). Modern horizontal axis wind turbines achieve performance approaching the Betz limit (Wiser et al., 2015). However, collections of wind turbines arranged in wind farms suffer from aerodynamic interactions which reduce wind farm power production between 10 and 20% (Barthelmie et al., 2009) due to greedy control schemes which only consider the power maximization of individual wind turbines at the farm. Recent work has focused on the operation of wind turbines in a collective fashion in order to increase the power production of the wind farm through the mitigation of wake interactions (see review by Boersma et al., 2017).

Wind farm power optimization through wake interaction mitigation methods have generally relied on axial induction and yaw misalignment control since these two methodologies do not require significant hardware modifications on traditional horizontal axis wind turbines (Burton et al., 2011). Annoni et al. (2016) utilized a steady-state model to inform the optimal axial induction factors for each wind turbine in an LES of a model wind farm but did not find significant power production improvements over baseline greedy operation. Campagnolo et al. (2016a) found similar results in a wind tunnel experiment of three wind turbines. The full large eddy simulation (LES) adjoint equations were used to optimize the power production by Goit and Meyers (2015). Munters and Meyers (2017) and Munters and Meyers (2018) extended the work of Goit and Meyers (2015) and used dynamic axial induction and yaw misalignment to increase wind farm power production using the full-state adjoint. While these studies achieved successful dynamic power production increases over baseline operation, the computational expense of adjoint LES is similar to standard LES and is currently a challenge to use in real-time wind farm control. Bauweraerts and Meyers (2019) showed that coarse LES can potentially be used for real-time prediction and control but this requires future investigation and is not the focus of the present study. Ciri et al. (2017) used a model-free formulation and dynamic control to increase the power production of a model wind farm and found that downstream wind turbines may also need to change their operational strategy to increase farm performance. Gebraad et al. (2013) also used a model-free gradient-based optimizer to increase the power production of a wind farm by approximately 1%. Park and Law (2016) used data-driven Bayesian ascent to efficiently maximize the power production of a model wind farm using axial induction. As a general conclusion of the present literature, simulations and field experiments of stationary axial induction based on static wake models (models which represent the time averaged behavior of a stationary or quasi-stationary flow) have shown this methodology is unlikely to increase Readers are directed to Knudsen et al. (2015) and Kheirabadi and Nagamune (2019) for recent reviews of wind farm power production in utility-scale wind farms but may improve wind turbine fatigue loading provided that the objective function is carefully proposed

and the fatigue is accurately modeled (see extensive review by Knudsen et al., 2015). Meanwhile, maximization methodologies. Previous simulation studies have shown that wake steering may have more potential than static axial induction control for wind farm power maximization (Annoni et al., 2016; Gebraad et al., 2016a; Campagnolo et al., 2016a), although dynamic axial induction (Park and Law, 2016; Munters and Meyers, 2018; Frederik et al., 2020) or more sophisticated dynamic blade pitch strategies (Frederik et al., 2019) may significantly increase power production (Munters and Meyers, 2018; Frederik et al., 2019, 2020) and require future field experimentation.

Greedy wind turbine operation minimizes the yaw misalignment between the nacelle position and the incoming wind direction. Contemporary wind turbines often operate in small yaw misalignment due to sensor noise and uncertainty (Fleming et al., 2014) leading to sub-optimal power production for the misaligned turbine. However, recent attention has focused on wake steering, the intentional misalignment of certain turbines within a wind farm in order to deflect wakes laterally away from downwind generators (Grant et al., 1997; Jiménez et al., 2010). While the yaw misaligned wind turbine's power production is decreased (Burton et al., 2011; Medici, 2005) (Medici, 2005; Burton et al., 2011), wake steering has been shown to increase the power production of downwind generators in simulations (Fleming et al., 2016; Gebraad et al., 2017; Fleming et al., 2018; Archer and Vassel-Be-Hagh, 2019) and wind tunnel experiments (Adaramola and Krogstad, 2011; Mühle et al., 2018; Bastankhah and Porté-Agel, 2019). Further, the potential for wake steering to increase wind farm power production in wind conditions with wake losses has been observed in full-scale field campaigns with two (Fleming et al., 2017, 2019) and six wind turbines (Howland et al., 2019).

While wake steering has been shown to be a beneficial global wind farm control strategy compared to greedy operation, the selection of the optimal yaw misalignment strategy for each wind turbine at a farm is challenging. The optimal yaw misalignment angles depend on the wake interactions between wind turbines (Gebraad et al., 2017). These wake interactions are dependent on wind speed, wind direction, atmospheric stability, turbulence intensity, local terrain, and other flow features (see e.g. Hansen et al., 2012). Most wake steering control strategies have relied on static engineering wake models such as the FLORIS model (Gebraad et al., 2016a, b; Fleming et al., 2016) or a lifting line model (Shapiro et al., 2018; Howland et al., 2019) to select the optimal yaw misalignment strategy based on a steady, time-averaged assumption of the wind farm flow. Extremum-seeking wake steering control has also been tested by Campagnolo et al. (2016b) using a gradient-based controller. However, these static model approaches may have challenges in establishing the optimal yaw misalignment strategy as a function of time in a transient flow environment such as the stable atmospheric boundary layer (ABL) or the full diurnal cycle (see e.g. Wyngaard, 2010).

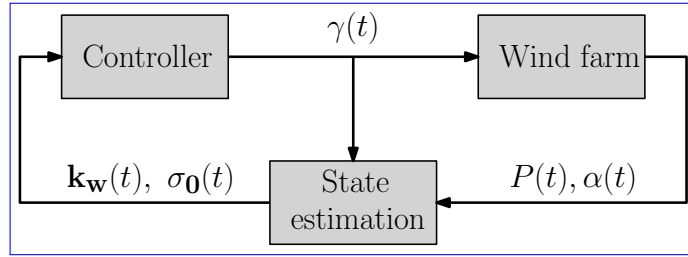
Recent work has focused on the selection of the optimal yaw misalignment angles as a function of time for transient flow applications. The main challenge in this flow environment Ciri et al. (2017) used a model-free formulation and dynamic control to increase the power production of a model wind farm in simulations. While model-free optimization is the subject of promising on-going work, this methodology generally experiences slower rates of convergence and may be less suited to transient flow applications where wind conditions shift rapidly, although future work should compare model-based and model-free formulations in transient flow applications. A significant challenge in transient flow environments is in accurately predicting the power production given greedy baseline control, considering ABL and controller state uncertainty in a utility-scale wind



farm. The ~~combined two-dimensional computational fluid dynamics and adjoint-based optimization model WFSim has been utilized (see e.g. Boersma et al., 2016, 2018; Vali et al., 2019) for control applications. Subsequent studies have used the Ensemble Kalman filter (EnKF) has been leveraged to perform model state estimation as a function of time (Doekemeijer et al., 95 2017) .~~The EnKF filter has been successfully used and~~ for low-order model state estimation for the purpose of receding horizon frequency regulation control (Shapiro et al., 2017) and reference power signal tracking applications (Shapiro et al., 2019). Doekemeijer et al. (2018) found that the EnKF has comparable state estimation performance given either nacelle-mounted LiDAR data or Supervisory Control and Data Acquisition (SCADA) power production data alone. Since very few utility-scale wind turbines have nacelle-mounted LiDAR systems, the successful performance of the EnKF based on SCADA data 100 alone highlights the potential for online model calibration without additional hardware installation. ~~The present computational complexity of the EnKF-WFSim system may limit the applicability to real-time control systems, although recent efforts have focused on the reduction of the simulation time of this method. As such, real-time closed-loop wind farm controllers with online state estimation require reliable analytic wake models such as the FLORIS or lifting line model.~~~~

Static wake model based dynamic control studies have utilized a quasi-static wake steering approach wherein the optimal yaw 105 misalignment angles are computed and stored as a function of wind speed and direction based on static wake models with pre-defined model parameters (Fleming et al., 2019). However, the pre-defined model parameters were calibrated for the ~~FLORIS wake model~~ Gaussian wake model (Bastankhah and Porté-Agel, 2014) based on idealized ~~LES large eddy simulations (LES)~~ and their applicability to a new utility-scale field implementation are unknown *a priori*. Further, there is additional uncertainty associated with the freestream velocity and turbulence intensity measurements in a wind farm environment where the typical 110 sensors are limited to nacelle-mounted anemometers placed directly behind the rotating rotor. The dynamic influence of yaw misalignment on these sensors is unknown (Howland et al., 2019). Recently, Raach et al. (2019) used the FLORIS wake model to design a closed-loop wake steering controller which relies on a downwind facing nacelle-mounted LiDAR system which was able to increase power production in an example nine wind turbine LES case. In order to focus on a low-order methodology which does not require additional hardware installations, we develop closed-loop wake model based wake steering control 115 for the application of data-driven wind farm power maximization based on SCADA power production data. The algorithm was designed for real-time control of utility-scale wind turbines without the requirement of additional hardware or sensor measurement systems and utilizes the gradient-based optimal yaw algorithm developed by Howland et al. (2019). The dynamic wake steering controller implemented in this study does not require historical data to be sorted into pre-selected wind speed and direction bins in order to make optimal yaw misalignment decisions. This is beneficial since the sorting of SCADA data 120 represents a major uncertainty associated with wake steering control (Fleming et al., 2019; Howland et al., 2019).

Analytic wake models require a number of simplifications of the flow physics and wind turbine operation in order to predict wind farm power production in a computationally efficient fashion (see e.g. review by Stevens and Meneveau, 2017). However, compared to model-free control, the wake model encodes a prior belief of the physics of wind farm flows and establishes a base performance given the initial model parameters preceding the perturbations applied by the EnKF (also see discussion by Schreiber et al., 20 125 The selected model-based optimal yaw misalignment angles will depend on the wake deflection model form and parameters, and the model for power production degradation as a function of the yaw misalignment angle. Further, in a low-order, model-



**Figure 1.** Diagram of the dynamic wake steering control system. The wake model parameters as a function of time are  $k_w(t)$  and  $\sigma_0(t)$  and the yaw misalignment angles are given by  $\gamma(t)$ . The power production and wind direction are given by  $P(t)$  and  $\alpha(t)$ , respectively. In open-loop control, the model parameters  $k_w$  and  $\sigma_0$  are fixed as a function of time.

driven power optimization application, the selected yaw misalignment angles will depend on the wind farm layout, wind direction and speed, and stability state of the ABL. The goal of the present study is to analyze the sensitivity of wind farm power production ~~increases through wake steering as a function of~~ to the design of the control system, model for power loss as a function of yaw misalignment, and wind farm layout ~~when leveraging wake steering control.~~

This work represents Part 1 of the results and targets a canonical planetary boundary layer with conventionally neutral stratification. Part 2 will focus on a sensitivity analysis of wake steering control ~~as a function of the~~ with temporally varying stratification and surface heat flux. Section 2 will introduce the dynamic wake steering methodology and EnKF state estimation technique. The LES methodology is introduced in Section 3. The dynamic wake steering ~~will be~~ is validated in a two-turbine uniform inflow LES case in ~~Section Appendix~~ F. In Section 4, the sensitivity to model architecture and parameters ~~as well as wind farm layout~~ is tested in LES of the conventionally neutral ABL with realistic Coriolis forcing. Finally, conclusions are given in Section 5.

## 2 Dynamic wake steering methodology

The present methodology is focused on optimal closed-loop wake steering control as a function of time for transient flow applications. The dynamic wake steering controller is illustrated in Figure 1. The controller entails a forward-pass wake model described in Section 2.1 and a backward pass to compute analytic gradients for gradient-ascent power maximization (Section 2.3). State estimation uses the ensemble Kalman filter described in Section 2.2. The wind farm is simulated using LES (Section 3). The closed-loop control algorithm and implementation is validated in Appendix F for LES of uniform inflow.

### 2.1 Lifting line wake model

Following the observation of counter-rotating vortex pairs shed by wind turbines operating in yaw misalignment in experiments and LES (~~Howland et al., 2016~~) (Mikkelsen et al., 2003; Howland et al., 2016; Bastankhah and Porté-Agel, 2016), Shapiro et al. (2018) developed a wake model for wind turbines in yaw based on Prandtl's lifting line theory. The wake model derived by Shapiro et al. (2018) was reformulated by Howland et al. (2019) to improve computational efficiency and to extract analytic

gradients for the purpose of gradient-based optimization. Readers are directed to Shapiro et al. (2018) for the derivation of the  
 150 initial wake model and to Howland et al. (2019) for the analytic formulation which eliminates the need for domain discretiza-  
 tion. In the two dimensional static wake model, the rotor averaged effective velocity at a downwind wind turbine  $j$  is given as

$$u_{e,j}(x) = u_\infty - \sum_i^{N_f} \frac{\sqrt{2\pi}\delta u_i(x)d_{w,i}(x)D}{16\sigma_{0,i}} \left[ \operatorname{erf} \left( \frac{y_T + D/2 - y_{c,i}(x)}{\sqrt{2}\sigma_{0,i}d_{w,i}(x)} \right) - \operatorname{erf} \left( \frac{y_T - D/2 - y_{c,i}(x)}{\sqrt{2}\sigma_{0,i}d_{w,i}(x)} \right) \right], \quad (1)$$

where  $u_\infty$  is the incoming freestream velocity and  $\delta u_i$  and  $d_{w,i}$  are the velocity deficit and the wake diameter as functions of  
 155  $x$  associated with the upwind turbine  $i$ , respectively. The wind turbine rotor diameter is given by  $D$ . The downwind turbine  
 lateral centroid is  $y_T$  and the lateral wake centroid is  $y_{c,i}$ . The wake model parameters are  $k_w$ , the wake spreading coefficient  
 and  $\sigma_0$ , the proportionality constant for the presumed Gaussian wake. The velocity deficit trailing a single wind turbine is

$$\delta u_i(x) = \frac{\delta u_{0,i}}{d_{w,i}^2(x)} \frac{1}{2} \left[ 1 + \operatorname{erf} \left( \frac{x}{\sqrt{2}D/2} \right) \right], \quad (2)$$

with  $\delta u_{0,i} = 2a_i u_\infty$  and axial induction factor  $a_i = 1/2 \left( 1 - \sqrt{1 - C_{T,i} \cos^2(\gamma_i)} \right)$ . The thrust coefficient is given by  $C_T$  and  
 160 the yaw misalignment angle is given by  $\gamma$ . The wake model assumes the thrust force in the streamwise direction  $T \sim \cos^2(\gamma)$   
 which may not be valid for all wind turbine models (see e.g. Bastankhah and Porté-Agel, 2016). In the present LES cases, the  
 wind turbine model enforces this thrust scaling (see §3) and therefore sensitivity analyses on this assumption are left for future  
 work. Positive and negative yaw misalignment are defined as counter-clockwise and clockwise rotations, respectively, when  
 viewed from above. ~~The inflow wind angle is given by  $\alpha$ , where  $0^\circ$  is north and proceeds clockwise to  $360^\circ$  at north again.~~  
 165 ~~The thrust force in the streamwise direction is assumed to follow actuator disk theory as  $\cos^2(\gamma)$ .~~ The wake diameter as a  
 function of the streamwise location  $x$  is  $d_{w,i}(x) = 1 + k_{w,i} \log(1 + \exp[2(x/D - 1)])$ . Linear superposition of the individual  
 wakes is assumed in Eq. 1 (Lissaman, 1979).

The wake centerline  $y_{c,i}$  is given by

$$y_{c,i} = \int_{x_{0,i}}^x \frac{-\delta v_i(x')}{u_\infty} dx', \quad (3)$$

170 where the spanwise velocity  $\delta v$  is given similar to Eq. 2 with the initial disturbance given analytically as (Shapiro et al., 2018)

$$\delta v_{0,i} = \frac{1}{4} C_{T,i} u_\infty \cos^2(\gamma_i) \sin(\gamma_i). \quad (4)$$

The wind turbine model power is computed as

$$\hat{P}_i = \frac{1}{2} \rho A_i C_p u_{e,i}^3, \quad (5)$$

where  $A$  is the wind turbine rotor area and  $\rho$  is the density of the surrounding air. The model for the coefficient of power  $C_p$  as  
 175 a function of the yaw misalignment remains an open question. Often, the power loss as a function of the yaw misalignment is  
 assumed to follow  $P_{\text{yaw}} \sim P \cos^{P_p}(\gamma)$ , where  $P_p$  is a known parameter. Following actuator disk theory (Burton et al., 2011),

$P_p = 3$ . However, simulations have shown for the NREL 5 MW turbine that  $P_p = 1.88$  (Gebraad et al., 2016a). Recent work has shown that  $P_p$  differs for freestream and waked turbines (Liew et al., 2020). The value of  $P_p$  that results in a satisfactory agreement with experimental data depends on the wind turbine model, ABL shear and veer, and atmospheric stability. In the present study, we will consider  $P_p$  an uncertain parameter and perform sensitivity analysis on it. The uncertainties of the wake model parameters  $k_w$  and  $\sigma_0$  are considered by the state estimation in Section 2.2. The coefficient of power is modeled as

$$C_{P,i} = 4\eta a_{p,i}(1 - a_{p,i})^2 \cos^{P_p}(\gamma_i), \quad (6)$$

with  $a_{p,i} = \frac{1}{2}(1 - \sqrt{1 - C_{T,i}})$ . The parameter  $\eta$  is tuned to match the manufacturer provided yaw-aligned  $C_P$  look-up table (Gebraad et al., 2016a). The applicability of this model is limited to Region II of the wind turbine power curve which is typically between 4 and 15 m/s.

## 2.2 Ensemble Kalman filter state estimation

Engineering wake models rely on parameters which represent physical phenomena, such as the wake spreading rate  $k_w$ . Niayifar and Porté-Agel (2016) proposed the dependence of  $k_w$  on the turbulence intensity which may be measured at a wind farm by nacelle anemometers, and this model has been used in subsequent FLORIS applications (see e.g. Fleming et al., 2018). Shapiro et al. (2019) proposed the use of canonical turbulent wake mixing and a prescribed mixing length model to estimate  $k_w$ . Schreiber et al. (2019) utilized a data-driven approach where error terms are added to the engineering model and SCADA is used for data assimilation to correct the wake model inaccuracies. Gradient optimization-based SCADA data assimilation was used by Howland et al. (2019) to select the model parameters which minimize the model error in producing the site-specific wind farm greedy baseline power production. Howland and Dabiri (2019) subsequently used gradient descent coupled with a genetic algorithm for data assimilation.

Here, we will employ the EnKF (Evensen, 2003) state estimate technique along with the wake model described in Section 2.1. The EnKF filter was found to be computationally less expensive than the gradient-based data assimilation used by Howland et al. (2019). The EnKF filter is computationally superior to other Kalman filter methods (extended, unscented, etc.) since there are typically fewer ensemble states than dimensions but this may lead to spurious correlations in the state representation (see e.g. discussion by Doekemeijer et al., 2018; Mandel, 2009). The states and dimensions here represent the wake model instantiations and parameters, respectively. In our state estimation case, the dimension space scales linearly with the number of turbines  $N_T N_t$ , rather than with the  $N_T^2$  or  $N_T^3 N_t^2$  or  $N_t^3$  in a model with a domain discretization (see discussion by Howland et al., 2019). Therefore the number of ensembles, which is a hyperparameter selected by the EnKF user, and dimensions will be of the same order of magnitude. The SCADA power production of each wind turbine is a function of time, denoted  $P_k$ , where  $k$  is the time step index. The goal is to estimate the wake model parameters given SCADA power production data measurements,  $P_k \in \mathbb{R}^{N_t}$ , using the ensemble Kalman filter as a rapid gradient-free optimizer (Cleary et al., 2020). This approach follows previous uses of the EnKF for wake model state estimation (Shapiro et al., 2017; Doekemeijer et al., 2017) but the algorithm is reviewed here. The EnKF is particularly well-suited for discretized partial differential equation systems, often in geophysical applications, and is computationally efficient for the present application as well nonlinear wake model.

210 denoted by  $h$ , also receives the wind speed and direction from the leading turbine, as well as the yaw misalignment of each turbine in the farm. There are two wake model parameters for each upwind turbine and no parameters for the last turbine downwind. The model parameters with  $N_t$  wind turbines at the  $k^{th}$  time step are given by

$$\psi_k = [k_{w,1}, \dots, \underline{k_{w,N_t w, N_t - 1}}, \sigma_{0,1}, \dots, \underline{\sigma_{0,N_t 0, N_t - 1}}]. \quad (7)$$

The modeling and measurement errors are represented by  $\chi = [\chi_{k_w}^T, \chi_{\sigma_0}^T]^T \in \mathbb{R}^{2N_t}$  and  $\varepsilon \in \mathbb{R}^{N_t}$ , respectively. The modeling errors  $\chi_{k_w}$  and  $\chi_{\sigma_0}$  are zero mean and have prescribed variances of  $\sigma_{k_w}^2 = 0.0009$  and  $\sigma_{\sigma_0}^2 = 0.0009$ . The Gaussian random measurement noise  $\varepsilon$  has zero mean and a prescribed standard deviation of  $\sigma_\varepsilon = 0.03 \cdot P_1$ . The hyperparameter variances were selected based on tuning experiments (see Appendix A). In order to estimate the state model parameters, the EnKF ~~filter~~ uses an ensemble of wake model evaluations. The ensemble is given by

$$\Psi = [\psi^{(1)}, \dots, \psi^{(N_e)}] \in \mathbb{R}^{2N_t \times N_e \times 2(N_t - 1) \times N_e}. \quad (8)$$

220 The power predictions are given by the matrix

$$\hat{\Pi} = [\hat{\pi}^{(1)}, \dots, \hat{\pi}^{(N_e)}] \in \mathbb{R}^{N_t \times N_e}, \quad (9)$$

where  $N_e$  is the number of ensembles.

The statistical noise of the power production measurements is given by  $\varepsilon$ . The Gaussian random noise is added to the SCADA measurements for each ensemble

$$225 \quad \xi^{(i)} = P_{\text{data}} + \varepsilon^{(i)}. \quad (10)$$

The perturbed power production ensemble matrix is

$$\Xi = [\xi^{(1)}, \dots, \xi^{(N_e)}] \quad (11)$$

with the perturbation matrix prescribed by

$$\Sigma = [\varepsilon^{(1)}, \dots, \varepsilon^{(N_e)}] \quad (12)$$

230 The mean of the ensemble states and modeled power production is given by

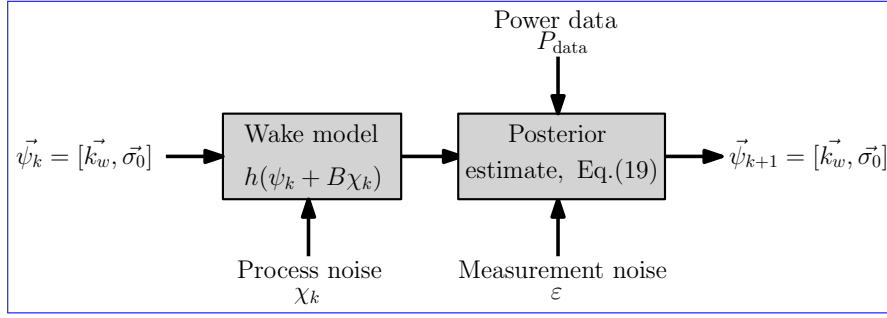
$$\bar{\Psi} = \Psi \mathbf{1}_{N_e} \quad (13)$$

$$\bar{\hat{\Pi}} = \hat{\Pi} \mathbf{1}_{N_e} \quad (14)$$

where  $\mathbf{1}_{N_e} \in \mathbb{R}^{N_e \times N_e}$  is a full matrix where all entries are  $1/N_e$ . The perturbation matrices are

$$\Psi' = \Psi - \bar{\Psi} \quad (15)$$

$$235 \quad \hat{\Pi}' = \hat{\Pi} - \bar{\hat{\Pi}}. \quad (16)$$



**Figure 2.** Schematic of the ensemble Kalman filter parameter estimation methodology. The wake model predicts the power production given wake model parameters  $\psi_k$  from time step  $k$  and the modeled process noise  $\chi$ . The power data from the LES are augmented with modeled measurement noise  $\epsilon$ . The wake model predictions,  $h(\psi_k + B\chi_k)$ , process and measurement noise, and power data are leveraged to compute the parameters in the  $k + 1$  time step  $\psi_{k+1}$  using the measurement analysis step (Eq. 19).

The first step in the EnKF process is an intermediate forecast step

$$\Psi_{k+} = [\psi_k^{(1)} + B\chi_k^{(1)}, \dots, \psi_k^{(N_e)} + B\chi_k^{(N_e)}] \quad (17)$$

$$\hat{\Pi}_{k+} = [h(\pi\psi_k^{(1)} + B\chi_k^{(1)}), \dots, h(\pi\psi_k^{(N_e)} + B\chi_k^{(N_e)})]. \quad (18)$$

where matrix  $B \in \mathbb{R}^{2N_t \times 2N_t}$   $B \in \mathbb{R}^{2(N_t-1) \times 2(N_t-1)}$  is the identity matrix and  $h$  represents the nonlinear wake model described in Section 2.1.

The measurement analysis step is given by

$$\Psi_{k+1} = \Psi_{k+} + \Psi'_{k+} \hat{\Pi}_{k+}^T (\hat{\Pi}_{k+} \hat{\Pi}_{k+}^T + \Sigma_{k+1} \Sigma_{k+1}^T)^{-1} \cdot (\Xi_{k+1} - \hat{\Pi}_{k+}). \quad (19)$$

The final values of  $k_w$  and  $\sigma_0$  for the  $k + 1$  time step are given as the columns of  $\bar{\Psi}_{k+1}$ . The EnKF is repeated for a predefined number of iterations for improved estimation (see Appendix A). The EnKF state estimation then assumes that the parameters  $k_{w,k+1}$  and  $\sigma_{0,k+1}$  will be valid over the succeeding finite time from step  $k + 1$  until step  $k + 2$ . A schematic of the EnKF methodology is shown in Figure 2.

The EnKF is a Kalman filter method which uses the Monte-Carlo sampling of model parameters according to a prescribed Gaussian function to represent the covariance matrix of the probability density function (PDF) of the state vector  $\Psi$ . The likelihood of the data is represented using observations  $\Xi$  and prescribed perturbations  $\Sigma$ . Using the prior PDF of the state ( $k$ ) and data likelihood, the posterior state ( $k + 1$ ) is estimated using Bayes's rule (Eq. 19).

### 2.3 Optimal yaw misalignment optimization

The optimal yaw misalignment angles depend on the wind speed, direction, turbulence intensity, and other key ABL conditions. Within a given condition bin, the number of potential yaw misalignment angle combinations grows exponentially with the number of wind turbines. As such, brute force optimization methods are not sufficient for the selection of the optimal yaw

255 misalignment strategy. Previous studies have considered genetic algorithms (Gebraad et al., 2016a), discrete gradient-based optimization (Gebraad et al., 2017), and analytic gradient-based optimization (Howland et al., 2019). Using gradient-based ~~ADAM~~ Adam optimization (Kingma and Ba, 2014), the gradient update is given by

$$\gamma^{t+1} = \gamma^t - \alpha \frac{m_t}{\sqrt{v_t}}, \quad (20)$$

260 where  $m^t = \beta_1 m^{t-1} + (1 - \beta_1) \frac{\partial \sum \hat{P}}{\partial \gamma}$  and  $v^t = \beta_2 v^{t-1} + (1 - \beta_2) (\frac{\partial \sum \hat{P}}{\partial \gamma})^2$ . The hyperparameters are set to the commonly used values of  $\beta_1 = 0.9$  and  $\beta_2 = 0.999$ , respectively (Kingma and Ba, 2014). The analytic gradients computed by Howland et al. (2019) are used for the gradient-based wind farm power optimization.

## 2.4 Approximate advection timescale

265 Upon the yaw misalignment of an upwind turbine, there is a time lag associated with the advection time scale of the flow for the control decision to influence a downwind turbine. While the advection time depends on the length scale of the turbulent eddy (Del Álamo and Jiménez, 2009; Yang and Howland, 2018; Howland and Yang, 2018), the mean flow advection approximately follows the mean wind speed in wind farms (Taylor, 1938; Lukassen et al., 2018). The number of simulation time steps associated with the approximate advection time between the first and last turbines is computed as

$$T_a = \frac{\Delta s_x}{\bar{u}_{\text{hub}} \Delta t},$$

270 where  $\Delta s_x$  is the distance between the first and last turbine in the streamwise direction and  $\bar{u}_{\text{hub}}$  is the mean streamwise velocity at the wind turbine model hub height at the leading turbine in the farm. The simulation time step is fixed and is  $\Delta t$ , which corresponds to a CFL of less than 1 persistently during runtime. In the computation of wind farm statistics for the utilization of static wake models, the advection time scale is accounted for by initializing the time averaging two advection time scales  $2T_a$  after the yaw misalignments for the wind turbine array have been updated. To account for errors associated with the simple advection model, the time lag is taken as double the advection time scale,  $2T_a$ . The sensitivity of the wind farm 275 power production and model-predicted optimal yaw misalignment angles as a result of the advection time lag are considered in Section 4.

## 2.4 Yaw misalignment temporal update frequency

280 While static wake models are able to capture time averaged wind farm dynamics in stationary flows (see e.g. Stevens and Meneveau, 2017), instantaneous wind speed and direction are constantly changing and challenging to predict. As the stability of the atmosphere transitions during the diurnal cycle, the mean wind conditions as well as turbulence intensity will change with a significant impact on the wake loss magnitude (Hansen et al., 2012). The wake steering strategy must be dynamic to adapt to the instantaneous wind conditions but also requires some time lag according to the advection time scale of the wind farm. The selection of the optimal yaw misalignment angle update frequency will impact the power production of the wind farm. Kanev (2020) found that when utilizing a dynamic wake steering controller in transient flow environments the energy production may decrease as

285 a result of wind direction fluctuations as a function of time. The energy loss was due to the dynamic wake steering controller attempting to follow the wind direction constantly as a function of time, leading to increased yaw duty, and a final yaw update time of 2 minutes was selected.

In a full-scale wake steering field experiment, Fleming et al. (2019) found that wind direction and speed data low-pass filtering resulted in an unintended time lag between the observed conditions and the associated optimal yaw misalignment angles. Finally, Raach et al. (2019) utilized a feedforward-feedback framework to adjust the open-loop predicted optimal yaw misalignment angles continuously based on LiDAR measurements of the wake centroid location, instead of SCADA power measurements, with an update time scale on the order of seconds. In the present study, the yaw misalignment update frequency is selected according to the dynamics of the problem studied. Comments on the update frequency for the conventionally neutral ABL-LES cases are made in Section 4.

### 295 3 Large eddy simulation setup

Large eddy simulations are performed using the open-source ~~pseudo-spectral~~ pseudo-spectral code *PadéOps*<sup>1</sup>. The solver uses 6<sup>th</sup> order compact finite differencing in the vertical direction (Nagarajan et al., 2003) and Fourier collocation in the horizontal directions. Temporal integration uses a fourth order strong stability preserving Runge-Kutta variant (Gottlieb et al., 2011). The LES code has previously been utilized for high Reynolds number ABL flows (Howland et al., 2020a; Ghaisas et al., 2020) and is described in detail by Ghate and Lele (2017). The ABL is modeled as an incompressible, high Reynolds number limit ( $Re \rightarrow \infty$ ) flow with the filtered, nondimensional momentum equations given by

$$\frac{\partial u_i}{\partial t} + u_j \frac{\partial u_i}{\partial x_j} = -\frac{\partial p}{\partial x_i} - \frac{\partial \tau_{ij}}{\partial x_j} + f_i + \frac{\delta_{i3}}{Fr^2}(\theta - \theta_0) - \frac{2}{Ro} \varepsilon_{ijk} \Omega_j u_k - \frac{\partial P^G}{\partial x_i},$$

$$\frac{\partial u_i}{\partial t} + u_j \frac{\partial u_i}{\partial x_j} = -\frac{\partial p}{\partial x_i} - \frac{\partial \tau_{ij}}{\partial x_j} + f_i + \frac{\delta_{i3}}{Fr^2}(\theta - \theta_0) - \frac{2}{Ro} \varepsilon_{ijk} \Omega_j u_k - \frac{\partial P^G}{\partial x_i}, \quad (21)$$

$$305 \quad \frac{\partial u_i}{\partial x_i} = 0 \quad (22)$$

where  $u_i$  is the velocity in the  $x_i$  direction,  $p$  is the nondimensional pressure, and  $P^G$  is the nondimensional geostrophic pressure. The subfilter scale stress tensor is given by  $\tau_{ij}$  and the sigma model is employed (Nicoud et al., 2011). The turbulent Prandtl number used in the subfilter scale model is  $Pr = 0.4$  (Ghate and Lele, 2017). Surface stress and heat flux is computed using a local wall model based on Monin-Obukhov similarity theory with appropriate treatment based on the state of stratification (Basu et al., 2008). The wind turbine forcing is represented by  $f_i$  and ~~an a non-rotating~~ actuator disk model is used (Calaf et al., 2010). The actuator disk thrust force acts parallel to the rotor normal vector. The incident velocity is projected into the rotor disk plane and therefore the dependence of thrust on the yaw misalignment  $\gamma$  in uniform inflow

<sup>1</sup><https://github.com/FPAL-Stanford-University/PadéOps>



conditions would be  $\cos^2(\gamma)$ , although it may deviate from this in sheared and veered inflow conditions. While the actuator disk model is lower fidelity than the actuator line methods, it captures the far wake (far wake is approximately  $x/D > 3$ , see e.g. Bastankhah and Porté-Agel (2017)) accurately for both aligned (Martínez-Tossas et al., 2015) and yaw misalignment wind turbines (Lin and Porté-Agel, 2019). Since the goal of the present study is controller synthesis and sensitivity experiments, more computationally expensive actuator line simulations are left for future work given the large volume of simulations that are run.

Earth's rotational vector is given by  $\Omega = [0, \cos(\phi), \sin(\phi)]$ , where  $\phi$  is the latitude. The traditional approximation, which neglects the horizontal component of Earth's rotation (Leibovich and Lele, 1985)(Leibovich and Lele, 1985; Howland et al., 2018), is not enforced. Therefore, Earth's full rotational vector is included resulting in wind farm dynamics which are sensitive to the direction of the geostrophic wind (Howland et al., 2020b). For simplicity all simulations are performed with west to east geostrophic wind. The Coriolis terms are parameterized by the Rossby number  $Ro = G/\omega L$ , where  $G$  is the geostrophic wind speed magnitude,  $\omega$  is Earth's angular velocity, and  $L$  is the relevant length scale of the problem. All wind speeds used in this study will be normalized by the geostrophic wind speed magnitude. The nondimensional potential temperature is given by  $\theta$ . The buoyancy term is parameterized by the Froude number  $Fr = G/\sqrt{gL}$ , where  $g$  is the gravitational acceleration. The equation for the transport of the filtered nondimensional potential temperature is given by

$$\frac{\partial \theta}{\partial t} + u_j \frac{\partial \theta}{\partial x_j} = -\frac{\partial q_j^{SGS}}{\partial x_j}, \quad (23)$$

where  $q_j^{SGS}$  is the subgrid scale (SGS) heat flux.

The wind is forced by prescribing the geostrophic approximation where the geostrophic pressure gradient drives the mean flow (Hoskins, 1975). The geostrophic pressure balance in the stable free atmosphere is given by

$$\frac{\partial P^G}{\partial x_i} = -\frac{2}{Ro} \varepsilon_{ijk} \Omega_j G_k, \quad (24)$$

with  $G_k$  representing the geostrophic velocity vector.

The simulations utilize a fringe region to force the inflow to a desired profile (Nordström et al., 1999). ~~In the uniform inflow cases, the fringe region forces the flow to a uniform profile. In the~~ In the conventionally neutral ABL cases, the concurrent precursor method is applied wherein a separate LES of the ABL is run without wind turbine models and the fringe region is used to force the primary simulation outflow to match the concurrent precursor simulation outflow (see e.g. Munters et al., 2016; Howland et al., 2020a).

~~For the uniform inflow and conventionally neutral cases, there~~ There is an initial startup transience following the domain initialization. ~~The uniform inflow domain is initialized with  $u = 1$  in the streamwise direction.~~ Detailed comments on the initialization for the conventionally neutral case are given by Howland et al. (2020b). The simulation cases are run until statistical stationarity and quasi-stationarity is reached ~~for the uniform and conventionally neutral cases, respectively.~~ The conventionally neutral case is statistically quasi-stationary due to inertial oscillations (see Allaerts and Meyers, 2015, for a detailed discussion on the conventional case) (see Allaerts and Meyers, 2015, for a detailed discussion on the conventionally neutral ABL statistical quasi-stationarity). Upon convergence, the wake steering control strategy is initiated.

The control is initialized with greedy baseline yaw alignment which is fixed for  $n_T$  time steps. After  $n_T$  simulation steps, with the time averaged power production for each wind turbine measured over the previous  $n_T - 2T_a - n_T - T_a$  time steps, ~~the~~ with the advection time scale given by  $T_a$ , the EnKF state estimation and optimal yaw calculations are performed (Figure 1). The time-lag associated with the advection time scale of the wind farm is estimated by invoking Taylor's hypothesis (see  
350 Appendix C for a brief discussion). The yaw angles are then implemented and held fixed for  $n_T$  time steps and the cycle repeats. The wind speed, wind direction, and power production are averaged in time over the window. The state estimation and yaw misalignment update steps are performed concurrently with a period of  $n_T$  simulation steps. In general, these two processes can be decoupled, although this was not investigated in the present study. Typical utility-scale wind turbines have a yaw rate of approximately  $0.5^\circ/\text{s}$  (Kim and Dalhoff, 2014). For the largest yaw misalignment change in one control update step in this  
355 study of approximately  $30^\circ$ , when the wake steering control is initialized, the yawing action is completed in approximately one minute, which is significantly less than the advection timescale in the flow. Therefore, the yaw rate will not influence the results presented in this study.

In order to compare the power production of the yaw misalignment control strategy with the baseline greedy control, a separate LES case is run for each experiment with yaw aligned control. The two simulations are initialized from identical  
360 domain realizations and the computational timestep  $\Delta t$  is fixed between the two cases. Therefore, without the influence of variable turbine operation, the flow within and around the turbine array is identical to machine precision between the two yaw aligned and yaw misaligned cases<sup>2</sup>. Since this study will consider the conventionally neutral ABL which contains turbulence and inertial oscillations, this separate simulation must be used instead of a comparison with the power production of the first yaw control update step (see Appendix B).

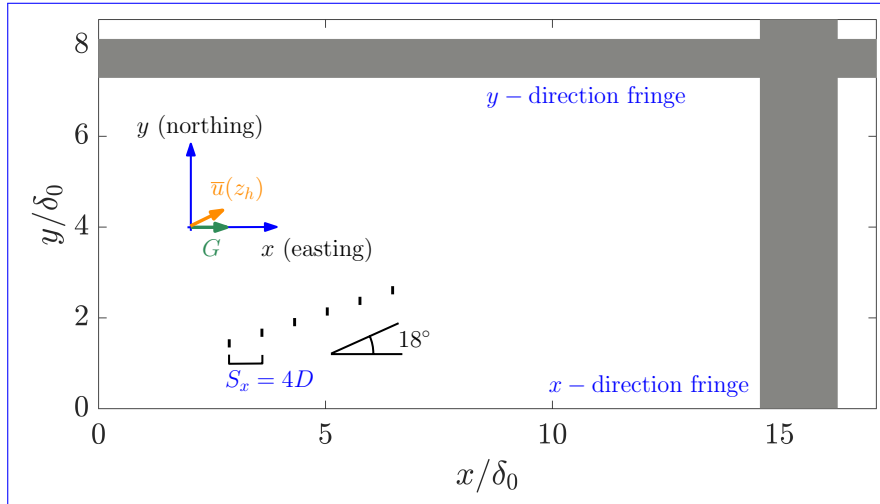
#### 365 4 **Dynamic wake steering uniform inflow LES**

~~In this section, the dynamic closed-loop wake steering controller described by Figure 1 will be used in LES of two turbines operating in uniform inflow. The domain has lengths of  $25D$ ,  $10D$ , and  $10D$  in the  $x$ ,  $y$ , and  $z$  directions, respectively, and the number of grid points are 128, 64, and 64. Two actuator disk model wind turbines are simulated in uniform inflow with slip walls on all sides and a fringe region at the domain exit to force the inflow to a uniform profile. The fringe is used in the~~  
370 ~~last 25% of the computational  $x$  domain. The turbines are located  $4D$  apart in the streamwise direction and are misaligned by  $0.25D$  in the spanwise direction as shown in Figure F1. Due to the spanwise misalignment, the preferential yaw misalignment direction for the upwind turbine is positive (counter-clockwise rotation viewed from above).~~

~~The flow is stationary after the initial startup transient has decayed and therefore the optimal yaw misalignment angles for the two wind turbines are not a function of time. The flow is initialized as described in Section 3. Upon statistical stationarity,~~  
375 ~~the closed-loop wake steering controller is initialized and the flow is run for  $n_T = 10000$  LES time steps to ensure sufficient~~

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<sup>2</sup>In chaotic dynamical systems, differences caused by changes in the compiler optimization will grow exponentially in time (Senoner et al., 2008). We have ensured that these floating-point differences are eliminated by fixing compiler optimization and processor topology to allow for quantitative, temporal comparisons between the LES cases. The results are therefore repeatable to machine precision.



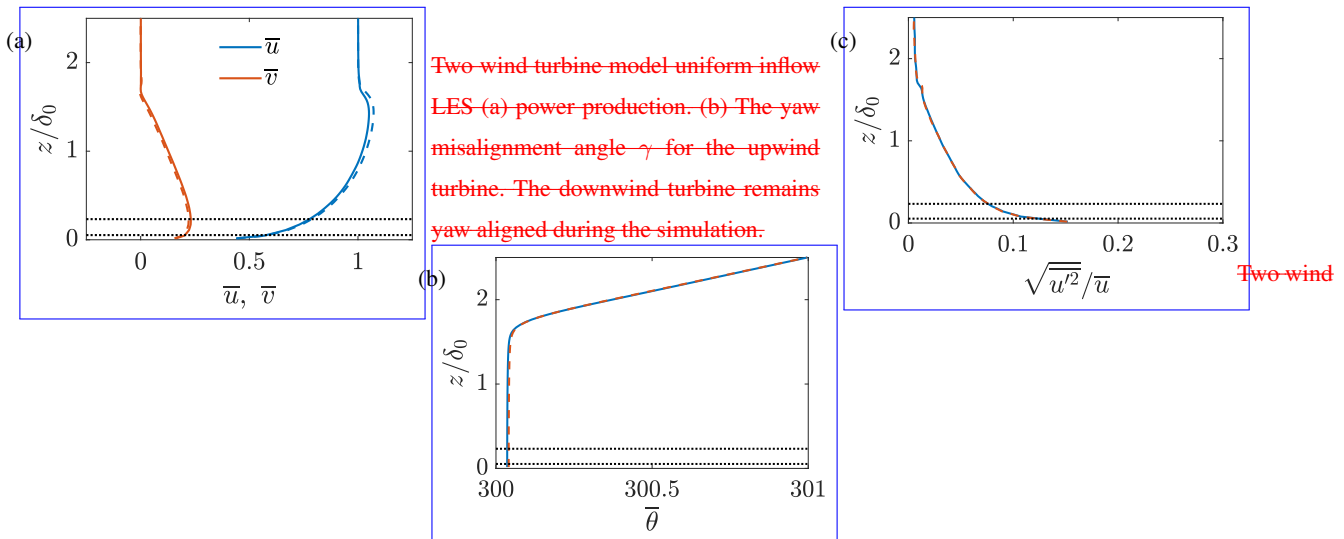
**Figure 3.** Uniform inflow LES Conventionally neutral six wind turbine finite wind farm simulation actuator-disk model layout setup. The fringe region geostrophic wind direction is represented by the dashed black line west to east and the  $x$ -axis is aligned with the geostrophic wind turbines are shown direction. The mean wind direction at hub height,  $\tan^{-1}(\bar{v}/\bar{u}) \approx 16^\circ$  but is not known *a priori* in the simulation and varies as solid black lines a function of time. The wind turbine array is offset from alignment in the  $x$ -direction by  $18^\circ$ . The initial boundary layer height  $\delta_0$  is 700 meters and does not change significantly during runtime (see Figure 4). Fringe functions are applied in the  $x$  and  $y$  directions to establish a finite wind farm simulation.

380 averaging. The time averaging is initialized following the advection time of the wind farm (see Section C) and therefore there are  $n_T - 2T_a$  timesteps within each time averaging window. wind turbines have a rotor diameter of 126 meters and a hub height of 100 meters. The thrust coefficient is  $C_T = 0.75$ . The initial boundary layer height is 700 meters. The domain size is  $12 \times 6 \times 2.4$  kilometers in the  $x$ ,  $y$ , and  $z$  directions, respectively, with  $z$  representing the wall-normal coordinate.

385 The number of grid points is  $480 \times 240 \times 192$  with a grid spacing of  $25\text{m} \times 25\text{m} \times 12.5\text{m}$ . The grid spacing is uniform and the mesh size is similar to previous studies (Allaerts and Meyers, 2015) and a grid convergence study was performed by (Howland et al., 2020b) for the conventionally neutral ABL. Six model wind turbines are incorporated in the domain and the layout within the computational domain is shown in Figure 3. The Rossby number based on the wind turbine diameter is 544 and the Froude number is 0.14. The vertical profiles of velocity, potential temperature, and streamwise turbulence intensity for the precursor simulation for two domain snapshots are shown in Figure 4.

#### 4 Dynamic wake steering conventionally neutral atmospheric boundary layer LES

In this section, we will utilize the closed-loop wake steering controller that was validated in Section F for uniform inflow in in the conventionally neutral ABL. While the conventionally neutral ABL is statistically quasi-stationary, the optimal yaw misalignment angles will vary as a function of time due to turbulence, large-scale streamwise structures (Önder and Meyers, 2018),



turbine model uniform inflow LES (a)  $k_w$  and  $\sigma_0$  for the upwind turbine and (b)  $\hat{P}$  and  $P$  for the downwind turbine.

The sum of power production for the two turbine pair as a function of the control update steps is shown in Figure F2(a). The power production is normalized by the greedy control simulation. The power production for the first yaw controller update time step is equal to 1 since yaw misalignment has not been implemented and the model is gathering power production data to be used for the first EnKF data assimilation pass. The power production increases in the second time step when yaw misalignment is incorporated for the upwind turbine (Figure F2(b)). The controller correctly commands the upwind turbine to positive yaw misalignment. While the flow is stationary, the upwind turbine yaw misalignment angle changes marginally after the second time step. These changes can be attributed to modifications to the wake model parameters as a function of time as estimated by the EnKF (Figure F3(a)). The estimated model parameters vary in time in this stationary flow due to standard error of the mean with limited samples within a given time window of length  $T$ , due to the influence of the yaw misalignment of the dynamics on the wake, and due to the limited number of ensembles  $N_e$  in the EnKF.

The wake model parameters have a functional dependence on the yaw misalignment of the turbines within the wind farm. The wake of a yaw misaligned turbine is narrower than the same turbine when yaw aligned (Archer and Vasel-Be-Hagh, 2019). The wake spreading rate  $k_w$  dictates the wake recovery rate. Yaw misalignment also reduces the axial induction factor of the wind turbine and therefore affects the wake recovery. Further, since wind turbines in yaw misalignment generate large-scale counter-rotating vortices (Howland et al., 2016), the wake recovery rate will likely be enhanced in yaw misalignment (Fleming et al., 2018). As a result of these vortices, the wake will have top-down asymmetry and this will influence  $\sigma_0$ . While the present model neglects the vertical dimension, the development of a controls-oriented model which incorporates the curled wake asymmetry is ongoing (Martínez-Tossas et al., 2019). Future work should characterize the influence of yaw misalignment on the wake spreading rate.

The state-estimated power production for the downwind turbine is compared to the LES power production in Figure F3(b). The downwind turbine's power production in the greedy control strategy is low (approximately  $0.2P_T$ ) due to the freestream inflow condition and close streamwise direction spacing. The EnKF results in an accurate power production estimation using the lifting-line model. While the wake model parameters are changing as a function of time (Figure F3(a)), the power production estimate for the downwind turbine is not significantly affected. The wake model parameters  $k_w$  and  $\sigma_0$  are anti-correlated as a function of time. Within the two-parameter lifting-line model, increasing  $k_w$  or  $\sigma_0$  reduces the wake effect for the downwind turbine. With the LES power production of the downwind turbine and the yaw misalignment of the upwind turbine approximately fixed, the state estimation increases one parameter and reduces the other parameter to remain consistent in the estimation of the downwind power. This indicates, similarly to the results in Appendix A, that the two parameter lifting-line model may be overparameterized which may lead to overfitting. The accuracy of the EnKF state estimation and lifting line model in the prediction of the power production in yaw misalignment will be tested in Section 4. This accuracy will implicitly measure the impact of overfitting in the model. Since there is no wake impinging on the upwind turbine, the state estimation has no impact on the

390 and inertial oscillations. A suite of LES cases is run to test the influence of the controller architecture design, state estimation design,  $P_p$  estimate (Eq. 6), and the wind farm layout on the power production increases over greedy baseline operation as a result of wake steering control. Each sensitivity study represents a new LES case which is run using the concurrent precursor methodology described in Section 3.

All quasi-steady conventionally neutral ABL simulations have a yaw controller update of  $n_T = 1000$  time steps which approximately equal to  $\tau = 3000$  seconds or 50 minutes. The advection time scale from the first to the last wind turbine in the array is approximately 9 minutes and the time lag is taken as two times the approximate advection time scale based on Taylor's Hypothesis. Therefore, each update contains approximately 30 minutes of statistical averaging, or about 600 time steps. The long time averaging window was selected since the flow is statistically quasi-stationary and to ensure temporal averages with reduced noise. In transitioning ABL environments, the time averaging window should likely be reduced (Kanev, 2020). The greedy baseline controller yaw alignment is updated according to the same timescales based on the mean wind direction measured locally by each wind turbine. The nacelle position for the yaw misaligned turbines is based on the wind direction measurement at each local turbine as well as the controller estimated optimal yaw misalignment angles, i.e.  $n_\alpha = \alpha + \gamma$  where  $n_\alpha$  is the nacelle position and  $\alpha$  is the wind direction incident to the wind turbine.

~~The wind turbines have a rotor diameter of 126 meters and a hub height of 100 meters (selections based on NREL 5 MW turbine, Jonkman). The thrust coefficient is  $C_T = 0.75$ . The initial boundary layer height is 700 meters. The domain size is  $12 \times 6 \times 2.4$  kilometers in the  $x$ ,  $y$ , and  $z$  directions, respectively, with  $z$  representing the wall-normal coordinate. The number of grid points is  $480 \times 240 \times 192$  with a grid spacing of  $25\text{m} \times 25\text{m} \times 12.5\text{m}$ . The grid spacing is uniform and the mesh size is similar to previous studies (Allaerts and Meyers, 2015) and a grid convergence study was performed by (Howland et al., 2020b) for the conventionally neutral ABL. Six model wind turbines are incorporated in the domain and the layout within the computational domain is shown in Figure 3. The Rossby number based on the wind turbine diameter is 544 and the Froude number is 0.14. The vertical profiles of velocity, potential temperature, and streamwise turbulence intensity for the precursor simulation for two domain snapshots are shown in Figure 4.~~

~~Conventionally neutral six wind turbine finite wind farm simulation setup. The geostrophic wind direction is west to east and the  $x$ -axis is aligned with the geostrophic wind direction. The mean wind direction at hub height,  $\tan^{-1}(\bar{v}/\bar{u}) \approx 16^\circ$  but is not known a priori in the simulation and varies as a function of time. The wind turbine array is offset from alignment in the  $x$ -direction by  $18^\circ$ . The initial boundary layer height  $\delta_0$  is 700 meters and does not change significantly during runtime (see Figure 4). Fringe functions are applied in the  $x$  and  $y$  directions to establish a finite wind farm simulation.~~

~~Horizontally averaged concurrent precursor conventionally neutral ABL LES (a) velocity, (b) potential temperature, and (c) turbulence intensity. Two different instantaneous domain snapshots are shown in solid (early) and dashed (late) lines. Dashed-dotted lines show the extents of the turbine rotor area.~~

This section is organized as follows: Section 4.1 examines the sensitivity of the wind turbine array power production to the wake steering controller design. Section 4.2 tests the sensitivity to the state estimation methodology. The sensitivity of the wake steering control to the estimate of  $P_p$  is discussed in Section 4.3. The accuracy of the wake model power predictions

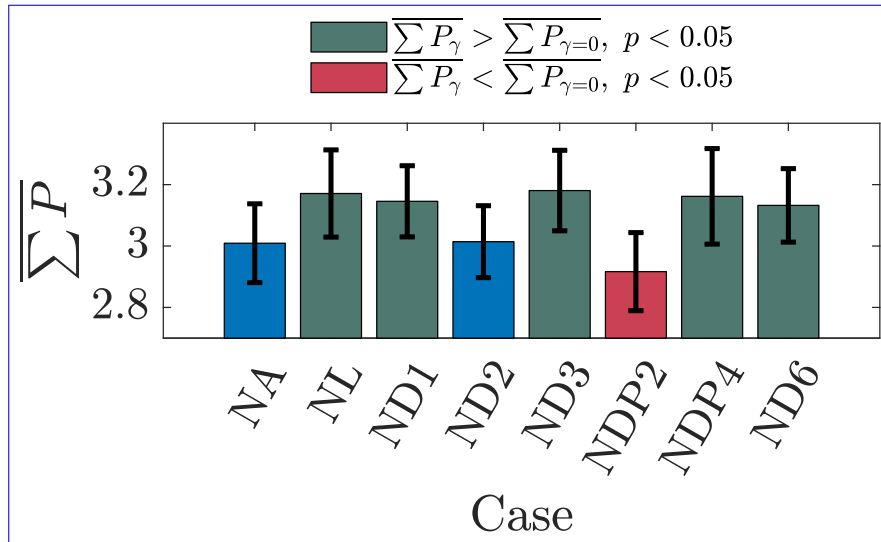
Case	Steering	Static yaw	Static $k_w, \sigma_0$	Advection	Feedforward $k_w, \sigma_0$	$P_p \hat{P}_R$	$\frac{\sum P - \sum P_{\text{aligned}}}{\sum P_{\text{aligned}}} (\%)$	$\sum \bar{P} \pm \text{STD}(\sum P)$
Wind turbine column alignment 18°								
NA	-	-	-	✓	-	3	-	3.01 ± 0.13
NL	✓	✓	✓	✓	-	3	5.4	3.17 ± 0.14
ND1	✓	-	-	✓	-✓	3	0.2-4.6	3.01 ± 0.12 3.15 ± 0.1
ND2	✓	-	-	✓	-	3	4.6-0.2	3.15 ± 0.14 3.01 ± 0.1
ND3	✓	-	✓	✓	-	3	5.7	3.18 ± 0.13
<del>ND4</del> -NDP2	✓	-	-	✓	✓	2	-3.0	2.92 ± 0.13
<del>ND5</del> -NDP4	✓	-	-	✓	✓	4	5.1	3.16 ± 0.16
ND6	✓	-	-	-	✓	3	4.2	3.13 ± 0.12
Wind turbine column alignment 14°								
NA14	-	-	-	✓	-	3	-	2.96 ± 0.09
ND141	✓	-	-	✓	✓	3	1.1	2.99 ± 0.10
ND142	✓	-	✓	✓	-	3	1.0	2.99 ± 0.11

**Table 1.** The conventionally neutral finite wind farm wake steering cases. The mean power production increase with respect to yaw aligned operation is calculated over approximately 24 hours of physical wind farm operation. Case NA is yaw aligned wind farm operation. Case NL approximates open-loop lookup table based control. Cases beginning with ND are dynamic, closed-loop control cases with various control architectures as denoted in the table. The wake model estimate for  $P_p$  is  $\hat{P}_R$ .

is discussed in Section 4.4. ~~Finally, Section Appendix E characterizes the influence of the wind farm alignment on the wake steering power production increase. The conventionally neutral ABL wake steering results are summarized in Table 1.~~

The conventionally neutral ABL wake steering LES cases and results are summarized in Table 1. Baseline yaw aligned wind turbine operation is given by Case NA, where the yaw alignment is updated at the same temporal frequency as the dynamic yaw control is updated to ensure quantitative comparisons as a function of time. Case NL approximates open-loop lookup table operation, where the yaw misalignment is prescribed as a function of the incident wind speed and direction rather than dynamically adapting to the local inflow conditions. Cases ND1, ND2, and ND3 use dynamic wake steering control with varying parameter estimation techniques. In Case ND1 the wake model parameters are optimized continuously based on a fixed parameter initialization. Cases ND1 and NL are discussed in detail in §4.1. In Case ND2, the model parameters are optimized continuously in time based on an initialization using the previous time step optimal parameters, and finally Case ND3 fixes the wake model parameters after the estimation in the first control update step. The influence of the state estimation techniques are discussed in detail in §4.2. Cases NDP2 and NDP4 modify the wake model estimate for  $P_p$  and are described in more detail in §4.3. Finally, Case ND6 is the same as Case ND1 except it sets the advection time  $T_a = 0$ . Cases NA14, ND141, and ND142 modify the wind farm alignment to 14° with respect to the horizontal axis and are described in more detail in Appendix E.

The statistical significance of the array power productions for the various wake steering cases with respect to baseline control Case NA are shown in Figure 5. The statistical significance is characterized with one-sided two-sample Kolmogorov-Smirnov

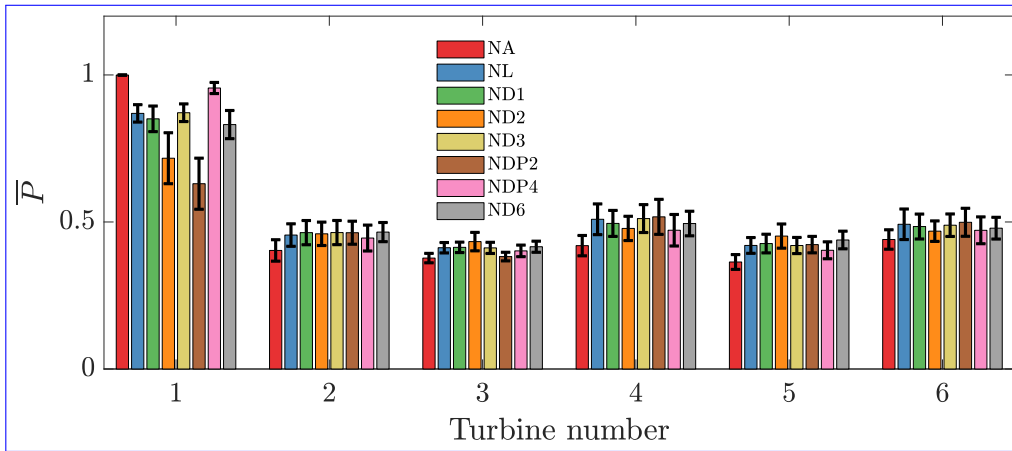


**Figure 5.** Time averaged sum of the six turbine array power production for the conventionally neutral ABL LES cases described in Table 1. The errorbars denote one standard deviation in the power production. The power production is normalized by the leading turbine  $P_1$  in baseline control conditions. The statistical significance of the wake steering power production difference with respect to baseline control Case NA are indicated by the colors. The statistical significance is characterized by a one-sided two-sample Kolmogorov-Smirnov test at a 5% significance level. Case NA is blue and Case ND2 does not have statistically significantly greater power production than Case NA. Green cases have statistically significantly ( $p < 0.05$ ) more power than Case NA. Red cases have statistically significantly ( $p < 0.05$ ) less power than Case NA.

440 tests for the given case with respect to baseline control Case NA at a 5% significance level. The Kolmogorov-Smirnov test  
 was selected since it does not enforce a normal distribution assumption on the data. Cases NL, ND1, ND3, NDP4, and ND6  
 produce significantly more power than baseline control Case NA. Case NDP2 produces significantly less power than baseline  
 control and Case ND2 is not significantly different than Case NA. None of the Cases NL, ND1, ND3, NDP4, and ND6 are  
 significantly different from each other. The power production for each turbine for each wake steering case is shown in Figure  
 445 6.

#### 4.1 Comparison between dynamic and quasi-static wake steering approaches

The dynamic wake steering controller described in Figure 1 is compared to lookup table static control in this section. Since the  
 flow is statistically quasi-stationary, the mean wind speed and direction at hub height do not change significantly as a function  
 of time. Therefore, during simulation, the flow remains at wind conditions which would be associated with one wind speed  
 450 and direction bin in tabulated lookup table wake steering control. The lookup table control is approximated by fixing the yaw  
 misalignment angles as a function of time after the initial optimal angles are computed during the first yaw controller update  
 (Case NL). Numerical experiments (not shown for brevity) demonstrated that modifying the control update step from which



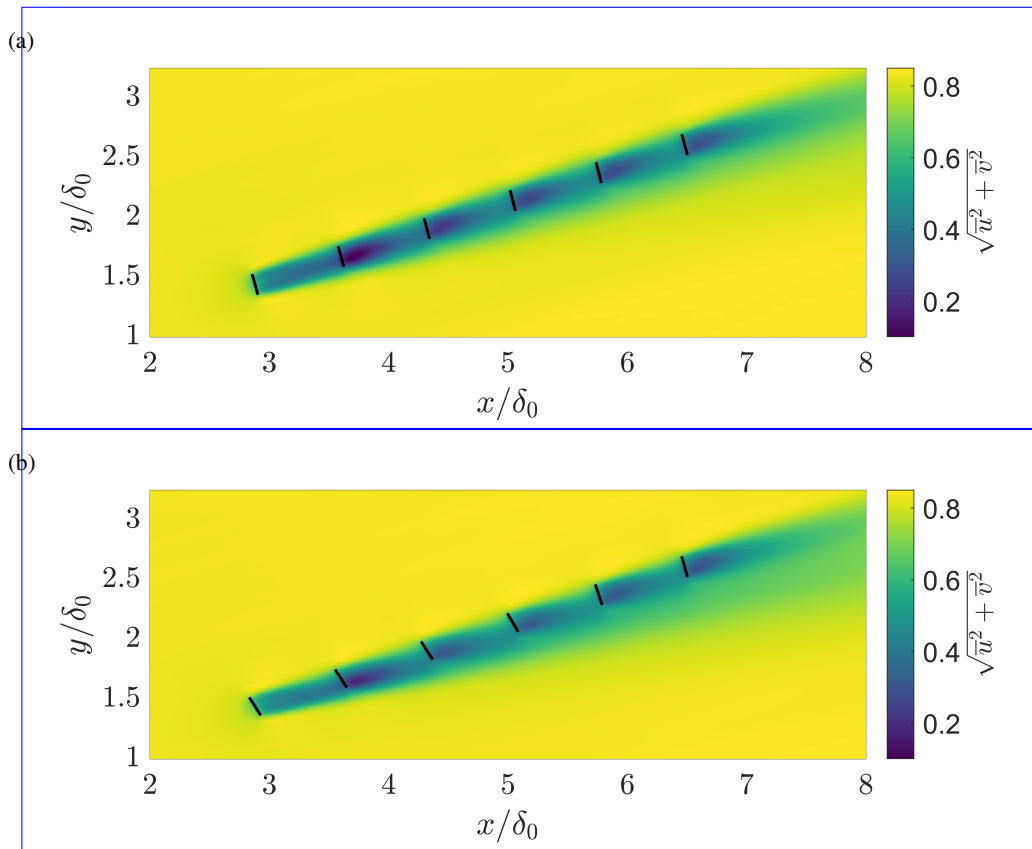
**Figure 6.** Time averaged power production for each turbine in each wake steering case. The errorbars denote one standard deviation in the power production. The power production is normalized by the leading turbine  $P_1$  in baseline control conditions.

the lookup yaw misalignment values were computed did not have a statistically significant influence on the results for Case NL. The dynamic yaw controller is represented by Case ~~ND2~~-ND1. The time averaged wind speed at the wind turbine hub height for Cases NA and NL are shown in Figure 7. As a result of the positive yaw misalignment strategy in Case NL (Figure 7(b)), the individual and collective array wakes are deflected in the clockwise direction compared to the aligned configuration of Case NA (Figure 7(a)).

The yaw misalignment angles as a function of the yaw controller updates for Cases NL and ~~ND2~~-ND1 are shown in Figure 8. The yaw angles in this study are defined as the misalignment with respect to the local inflow direction incident on the particular turbine in the array. While the lifting line model does not explicitly incorporate the effects of secondary steering for which model development is on-going (see e.g. King et al., 2020), the model selects yaw misalignment angles which are large for the first turbine and generally decrease further into the wind farm, which is consistent with the optimal values found by recent wind tunnel experiments (Bastankhah and Porté-Agel, 2019). Since the flow is statistically quasi-stationary, the dynamic algorithm yaw misalignment angles do not change significantly as a function of time. There are a few yaw misalignment changes on the order of  $10^\circ$  during one yaw update. ~~The change in yaw misalignment in a single control update is not limited explicitly in this study. The~~ The time averaged power productions as a function of the yaw controller updates for the two cases are shown in Figure 9. The qualitative trends in power production are similar between the two cases. Quantitatively, the lookup table static yaw misalignment Case NL increased the power production 5.4% with respect to the baseline greedy control while the dynamic yaw Case ~~ND2~~-ND1 increased the power by 4.6%.

The quantitative influence of wake steering is a function of the layout and ABL conditions. As the focus of the present study is assessing the sensitivity of wake steering to controller architecture, model parameters, and wind farm layout, measures of the statistical significance of the results are useful. However, the statistical significance of the results (e.g. whether Case NL significantly outperformed Case ~~ND2~~-ND1) does not indicate, necessarily, that lookup table control is better than the dynamic

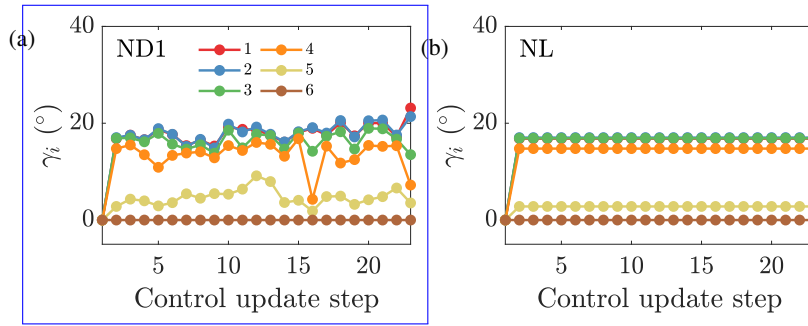




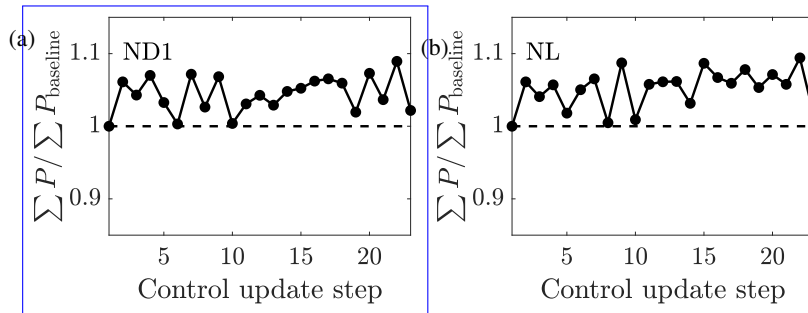
**Figure 7.** Time averaged wind speed  $\sqrt{\bar{u}^2 + \bar{v}^2}$  at the wind turbine hub height of  $z \approx 100$  meters for (a) baseline yaw aligned control Case NA and (b) wake steering control Case NL. The wind turbines are shown with black lines. The yaw misalignment values for Case NL are shown in Figure 8.

controller used in Case ND2-ND1 for all wake steering applications but rather, that it was better for the specific ABL setup  
 475 and computational time window of the experiment. ~~In this study, we will consider a control case to be significantly superior to another if the mean array power production averaged over the control update steps is more than one standard deviation larger than the other case. The mean and standard deviations of the array power productions over the control update steps.~~ The statistical significance of the power production increase with respect to baseline control Case NA are shown in Table 1, Figure 5. Cases NL and ND2-ND1 have significantly higher power than Case NA but the power in Case NL is not significantly higher  
 480 than in Case ND2-ND1.

~~Although it is not significant, there are several possible reasons for the static yaw misalignment's slightly superior performance compared to the dynamic yaw controller. The yaw selection may overfit to the previous time window and select angles which are suboptimal for the next time window (tested further in Section 4.2). The~~ The relationship between the wake model power prediction and the measured LES power production is shown for the two cases in Figure 10. The wake model overpredicts the



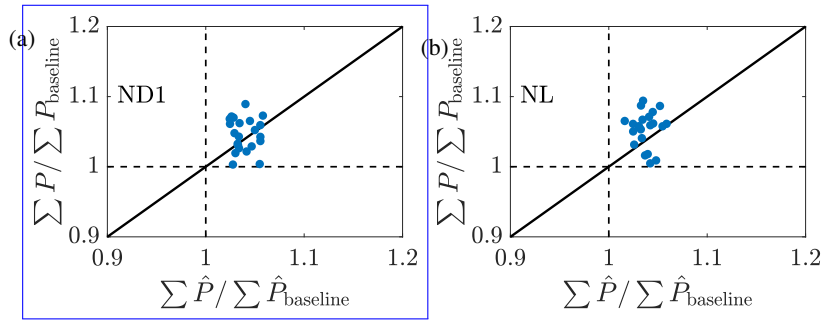
**Figure 8.** Wind farm yaw misalignment angles  $\gamma_i$  for each turbine for (a) online control using the initial parameters to initialize the next state (ND1) and (b) and the lookup table control (NL).



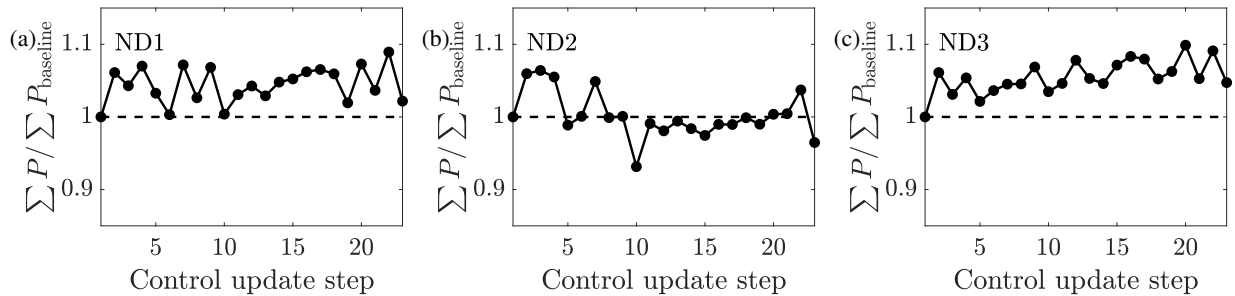
**Figure 9.** Time averaged wind farm power production as a function of the control update steps for (a) online control using the initial parameters to initialize the next state (ND1) and (b) and the lookup table control (NL). The wind farm power is normalized by the power production of the aligned wind farm case.

485 power production in yaw misalignment more for the dynamic yaw control than the lookup table control. After the first time  
 step, the wake model no longer has any state information for the LES power production with greedy baseline control since the  
 previous state had yaw misalignment. When the wake model overpredicts the expected LES power, the wake model parameters  
 are updated to a state which expects larger wake loss effects in baseline control; therefore, the yaw misalignment angles are  
 increased at the next time step. The yaw misalignment angles for the leading turbine oscillate around the lookup table optimal  
 490 forecast which was based on calibration with power data from greedy baseline control alone (Figure 8). The dynamic yaw  
 increased power slightly less than the static yaw misalignment case, but not significantly less. However, eliminating the need  
 to tabulate historical data and the complexity of implementing a lookup table-based controller could be beneficial in a practical  
 controller setting. Further, the conventionally neutral boundary layer does not occur often in practice (Hess, 2004). Therefore,  
 in a practical setting, the wind direction and speed at hub height will not be fixed for multiple hours as in this test problem.

495 In Case ND6, the power productions are time averaged over the full  $n_T$  window without considering the advection time scale  
 in the controller design. The power production increase over greedy control is 4.2% in this case which is less than the 4.6%



**Figure 10.** Relationship between the LES wind farm power production compared to the wake model wind farm power production prediction for (a) online control using the initial parameters to initialize the next state (ND1) and (b) and the lookup table control (NL). The wind farm power is normalized by the power production of the aligned wind farm case. The LES power production is given by  $P$  and the wake model prediction is given by  $\hat{P}$ .



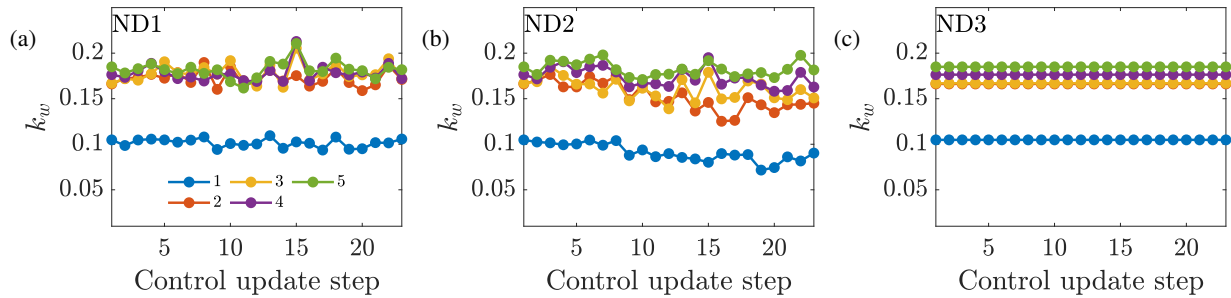
**Figure 11.** Time averaged wind farm power production as a function of the control update steps for (a) online control using the **previous optimal-initial** parameters to initialize the next state (ND1), (b) online control using the **initial-previous optimal** parameters to initialize the next state (ND2), and (c) and the static state estimation control (ND3). The wind farm power is normalized by the power production of the aligned wind farm case.

increase when considering the advection time lag (Case **ND2**ND1), although this difference is not significant. The dynamics of the closed-loop controller over long experimental horizons are tested in a 50 control update simulation in Appendix D.

## 4.2 Influence of the state estimation

500 The influence of the state estimation methodology is tested in this section. Within the conventionally neutral ABL, three experiments are run, focused on the state estimation initialization. In The initial model parameters in the EnKF state estimation are held fixed at  $k_w = 0.1$  and  $\sigma_0 = 0.25$  in Case ND1. In Case ND2, the optimal EnKF estimated parameters from the previous time step are used to initialize the state estimation of the current time step. ~~The initial model parameters are held fixed at  $k_w = 0.1$  and  $\sigma_0 = 0.25$  in Case ND2.~~ Finally, Case ND3 fixes the model parameters after the first time step. Case ND3 differs

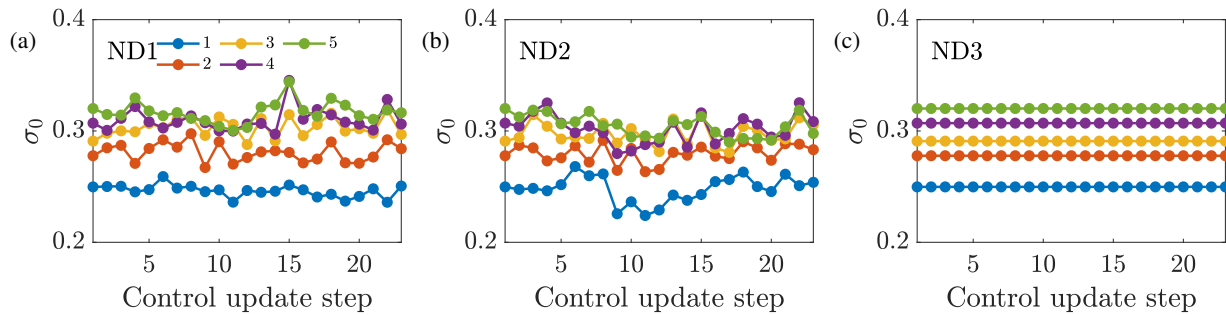
505 from Case NL from Section 4.1 since the optimal yaw misalignment angles may vary as a function of time while the model parameters do not.



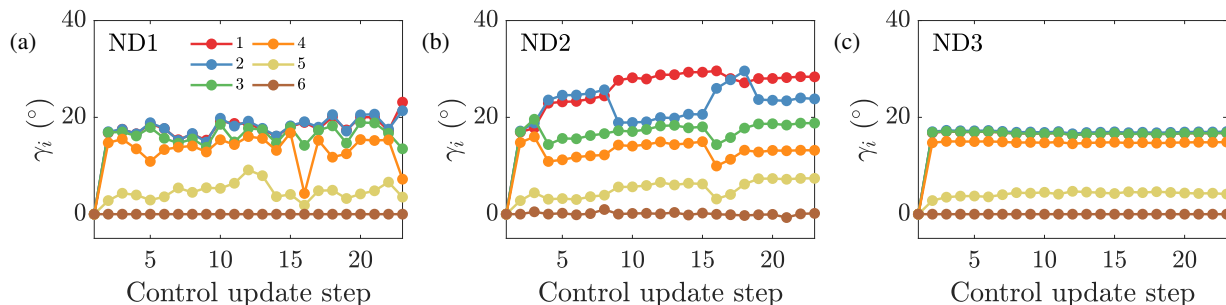
**Figure 12.** Wake spreading coefficient for each turbine in the wind farm for (a) online control using the previous-optimal-initial parameters to initialize the next state (ND1), (b) online control using the initial-previous optimal parameters to initialize the next state (ND2), and (c) and the static state estimation control (ND3).

The power productions as a function of the yaw controller update for the three cases are shown in Figure 11. Case ND1-ND2 has significantly less power production than Cases ND2-ND1 and ND3. The time averaged power production increases with respect to the baseline, greedy control is 0.2%, 4.6%, 0.2%, and 5.7% for cases ND1, ND2, and ND3, respectively. The power production in Cases ND2-ND1 and ND3 are significantly higher than Case NA while Case ND1-ND2 is not. Further, Cases ND2-ND1 and ND3 are significantly better than ND1-ND2 but Case ND3 is not significantly better than ND2-ND1. In the EnKF methodology described in Section 2.2, the update step to the wake parameters is limited by the imposed parameter variance ( $\sigma_{k_w}$  and  $\sigma_{\sigma_0}$ ). Therefore, the initialization of the EnKF with fixed parameters limits the perturbation of the estimated parameters as a function of time whereas the initialization with the previous optimal parameters allows  $k_w$  and  $\sigma_0$  to vary more significantly over time. The EnKF estimated  $k_w$  and  $\sigma_0$  for the three cases are shown in Figures 12 and 13, respectively. While the proportionality constant  $\sigma_0$  of the presumed Gaussian wake does not have a clear trend for Case ND1-ND2, the estimated wake spreading rate  $k_w$  is clearly decreasing for all wind turbines as a function of time. For Case ND2-ND1, the estimated model parameters do not have a clear trend and remain approximately constant as a function of time. As the estimated wake spreading rate is decreased, the wake model predicts worsening wake interactions and lower array power production given greedy baseline control. As a result, the model predicted optimal yaw misalignment angles increase as a function of time for Case ND1-ND2 as shown in Figure 14(a). While Cases ND2-ND1 and ND3 predict the optimal yaw misalignment for the most upwind turbine to be approximately  $20^\circ$ , and decreasing  $\gamma$  moving downwind, Case ND1-ND2 increases the yaw misalignment for the upwind turbine to as high as  $30^\circ$ . ~~While this case was not run further, it is not expected that this trend would continue unboundedly with controller instability since the power production penalty as a function of increased yaw misalignment is significant beyond  $40^\circ$ . The typical yaw rate for utility-scale horizontal axis wind turbines is around 0.5 degrees per second. For the largest discrete yaw misalignment change in the present study of  $\approx 30^\circ$  (Figure 14(a)), the yaw misalignment change would take  $\approx 75$  seconds. This time is significantly less than the advection time  $T_a$ , and is therefore does not impact the control system and power production results here.~~

The relationship between the model predicted and LES measured power production for the three cases is shown in Figure 15. Case ND1-ND2 has an increased occurrence of wake model over-prediction of the power production while Case ND3 has



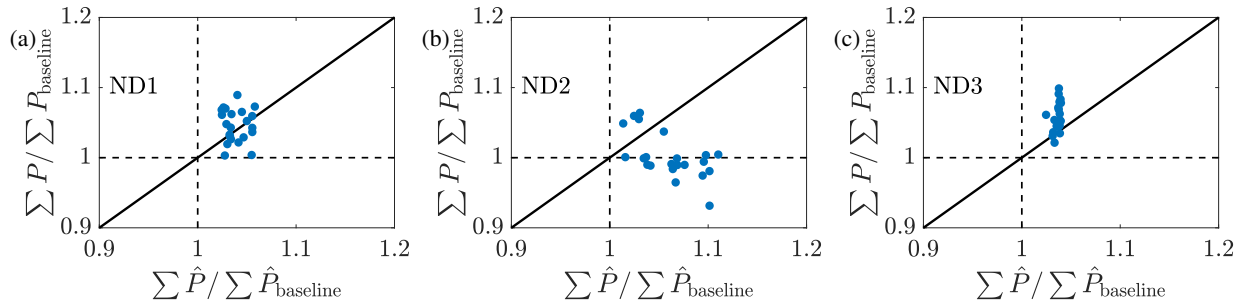
**Figure 13.** Proportionality constant for the presumed Gaussian wake for each turbine in the wind farm for (a) online control using the previous optimal-initial parameters to initialize the next state (ND1), (b) online control using the initial-previous optimal parameters to initialize the next state (ND2), and (c) and the static state estimation control (ND3).



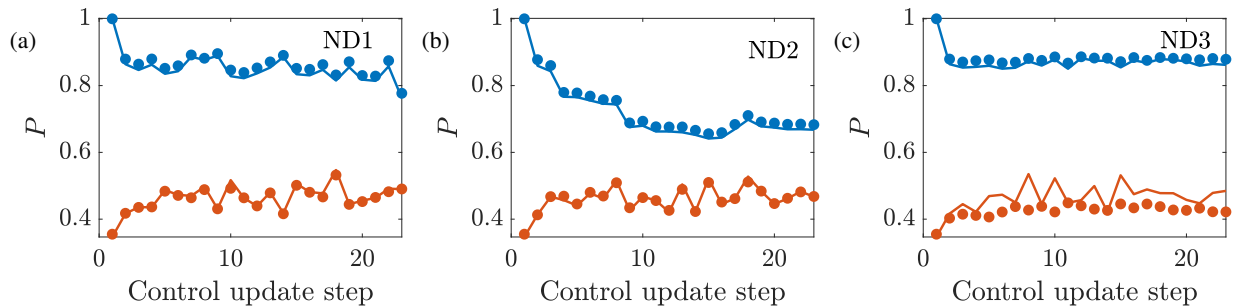
**Figure 14.** Yaw misalignment angles for each turbine in the wind farm for (a) online control using the previous optimal-initial parameters to initialize the next state (ND1), (b) online control using the initial-previous optimal parameters to initialize the next state (ND2), and (c) and the static state estimation control (ND3).

an increased occurrence of wake model under-prediction. Case ND2-ND1 has approximately equal occurrence of under- and over- prediction. The efficacy of the state estimation is shown in Figure 16. Both Cases ND1 and ND2 are able to estimate the power production for the downwind turbine in the baseline, greedy operation (the first time step) and with yaw misalignment. Since Case ND3 uses static state estimation, there are some discrepancies between the LES power production and the lifting  
535 line model (Figure 16(c)). The power production for the most upwind turbine is modeled accurately using  $P_p = 3$ , although the LES power production is generally slightly lower, indicating  $P_p > 3$  for this ADM and ABL state.

The most successful dynamic control framework utilized in the conventionally neutral ABL is the static state estimation methodology (Case ND3, although the differences between Cases ND1 (parameter estimation from standard initialization), ND3 (static parameters after first control step), and NL (static yaw angles after first control step) are not significant. While  
540 the optimal yaw misalignment angles change slightly as a function of time (Figure 14), the wake model parameters are fixed. Since the flow is statistically quasi-stationary, the wake model parameters should not change significantly as a function of time. However, the wake model parameters may have a function-functional dependence on  $\gamma$ , the yaw misalignment for the upwind



**Figure 15.** Relationship between the LES wind farm power production compared to the wake model wind farm power production prediction for (a) online control using the [previous-optimal-initial](#) parameters to initialize the next state (ND1), (b) online control using the [initial-previous-optimal](#) parameters to initialize the next state (ND2), and (c) and the static state estimation control (ND3). The LES power production is given by  $P$  and the wake model prediction is given by  $\hat{P}$ .

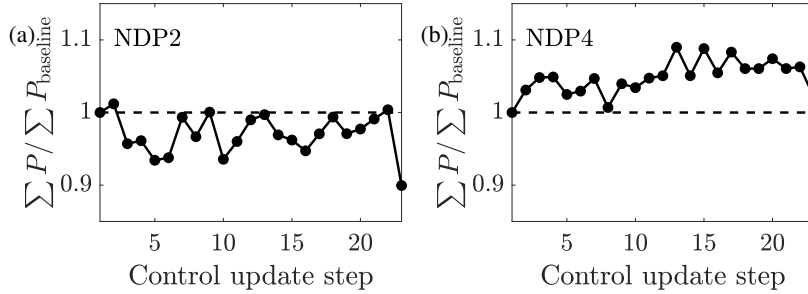


**Figure 16.** Time averaged power production for the first and second wind turbines in the wind farm as a function of the control update steps for (a) online control using the [previous-optimal-initial](#) parameters to initialize the next state (ND1), (b) online control using the [initial-previous-optimal](#) parameters to initialize the next state (ND2), and (c) and the static state estimation control (ND3). The LES power production is given by  $P$  and the wake model state estimation is given by  $\hat{P}$ .

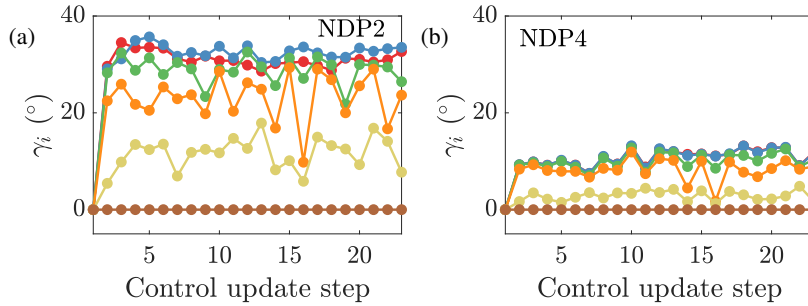
turbines. This potential dependence of  $k_w$  and  $\sigma_0$  on yaw misalignment was not incorporated explicitly in the present modeling framework, [although it is incorporated implicitly through the state estimation](#), and is recommended for future work.

545 The static state estimation with dynamic yaw controller is able to outperform the lookup table control (Table 1). This indicates that while the wake model parameters are fixed, the optimal yaw misalignment angles differ even with changes to the mean wind direction less than  $1^\circ$ . As such, the lookup table based yaw misalignment strategy is unlikely to be optimal in a general setting since it relies on wind speed and direction bins of arbitrary size. Instead, in a lookup table approach, the wake model parameters could be tabulated instead of the optimal yaw misalignment angles. Optimal yaw misalignments can be

550 calculated dynamically, on-the-fly using the computationally efficient model described in Section 2.1 or a mid-fidelity model (e.g. WFSim, Boersma et al., 2018) could be used to compute discrete yaw angles in wind condition bins and the continuous optimal yaw function could be approximated using [interpolating functions or](#) a neural network, for example.



**Figure 17.** Time averaged wind farm power production as a function of the control update step for online control using the initial parameters to initialize the next state and (a)  $P_p = 2$ ,  $\hat{P}_p = 2$  (ND4NDP2) and (b)  $P_p = 4$ ,  $\hat{P}_p = 4$  (ND5NDP4). The wind farm power is normalized by the power production of the aligned wind farm case.

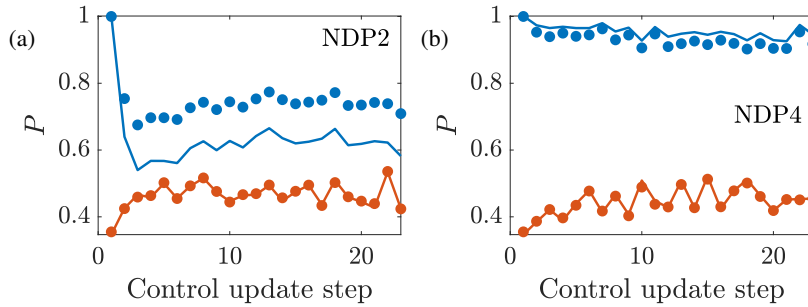


**Figure 18.** Yaw misalignment angles for each turbine in the wind farm for online control using the initial parameters to initialize the next state and (a)  $P_p = 2$ ,  $\hat{P}_p = 2$  (ND4NDP2) and (b)  $P_p = 4$ ,  $\hat{P}_p = 4$  (ND5NDP4).

### 4.3 Influence of the estimate of $P_p$ in the wake model

The wind turbine power production as a function of the yaw misalignment in the wake model is given by Eq. 6. The parameter  $P_p$  is uncertain. Following actuator disk theory,  $P_p = 3$ ,  $\hat{P}_p \approx 3$ , although experiments typically show  $P_p \leq 2$  for wind turbines and wind turbine models with rotation (e.g. Medici, 2005). With the ADM used presently,  $P_p = 3$  should be an accurate approximation but will be imperfect since actuator disk theory applies only to one-dimensional spatially uniform, steady flow. Since  $P_p$  is wind turbine and likely site-specific, it is likely in a wake steering application that, the precise value of  $P_p$  is generally unknown *a priori*. In this section, we will model  $P_p$  as 2 (ND4) and 4 (ND5),  $\hat{P}_p = 2$  (NDP2) and  $\hat{P}_p = 4$  (NDP4) using the same control architecture as Case ND2.  $P_p = 2$  ND1, where  $\hat{P}_p$  denotes the wake model estimate for  $P_p$ .  $\hat{P}_p = 2$  will lead to an underestimate of the power production loss due to yaw misalignment and  $P_p = 4$ ,  $\hat{P}_p = 4$  will lead to an overestimate. Given that the value of  $P_p$  is turbine-specific, the influence of the  $P_p$  uncertainty described in this section should be considered relative to the true value of  $P_p = 3$ , and the conclusions apply with respect to the scaled values of  $\hat{P}_p/P_p$ . For a different turbine model with  $P_p = 2$ , for example, similar values of  $\hat{P}_p/P_p$  would yield qualitatively similar results.

The power productions as a function of the yaw update steps for Cases ND4 and ND5-NDP2 and NDP4 are shown in Figure 17. Case ND4 with  $P_p = 2$  NDP2 with  $\hat{P}_p = 2$  has 3.0% less power production than baseline greedy operation while Case ND5



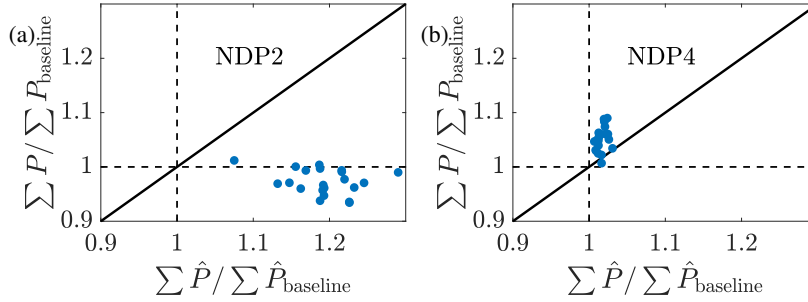
**Figure 19.** Time averaged power production for the first and second wind turbines in the wind farm as a function of the control update steps for online control using the initial parameters to initialize the next state and (a)  $P_p=2$ ,  $\hat{P}_p=2$  (ND4NDP2) and (b)  $P_p=4$ ,  $\hat{P}_p=4$  (ND5NDP4). The LES power production is given by  $P$  and the wake model state estimation is given by  $\hat{P}$ .

with  $P_p=4$  NDP4 with  $\hat{P}_p=4$  has 5.1% more power than baseline control. Case ND2 and ND5 are significantly better than ND4. With  $P_p=2$  ND1 and NDP4 have significantly higher power production than NDP2. With  $\hat{P}_p=2$ , the model prediction for the optimal yaw misalignment angles are high, with the first three upwind turbines misaligning by almost  $\gamma = 40^\circ$  (Figure 18(a)). With  $P_p=4$ ,  $\hat{P}_p=4$ , the penalty for yaw misalignment is significant and no turbine misaligns more than  $\gamma = 20^\circ$  (Figure 18(b)). For the present conventionally neutral ABL and ADM implemented,  $3 < P_p < 4$  for the leading upwind turbine. The success of Case ND5 with  $P_p=4$  NDP4 with  $\hat{P}_p=4$  suggests that small yaw misalignments can still increase the wind farm power production significantly with respect to the baseline greedy control.

The LES power productions and EnKF state estimated powers as a function of the yaw control updates are shown for the two  $P_p$ ,  $\hat{P}_p$  cases in Figure 19. For Case ND4, the upwind turbine power production is significantly over-predicted. The EnKF does not estimate the state for the most upwind turbine since there are no wake model parameters which influence its production. The power production for the second wind turbine is accurately estimated even with  $P_p=2$ ,  $\hat{P}_p=2$ . This again shows that the state estimation with a two-parameter model is likely overparameterized where the EnKF is making up compensating for the incorrect  $P_p$  model by altering  $k_w$  and  $\sigma_0$  unphysically, although the consequence of this effect in the accuracy of the power predictions will be discussed in §4.4. The power productions and EnKF estimations for the first two wind turbines for Case ND5 show that  $P_p=4$ ,  $\hat{P}_p=4$  is a more accurate estimate than  $P_p=2$ ,  $\hat{P}_p=2$ . Again, the downwind turbine power is estimated accurately with the incorrect value of  $P_p$ ,  $\hat{P}_p$ .

The comparison between the wake model power predictions against the LES power production are shown in Figure 20. With  $P_p=2$ ,  $\hat{P}_p=2$  (Figure 20(a)), the wake model significantly overpredicts the power production of the wind turbine array with expected power increases over the baseline of 25% but a power decrease with respect to the baseline realized. On the other hand, with  $P_p=4$ ,  $\hat{P}_p=4$  (Figure 20(b)), the wake model underpredicts the power production of the wind turbine array for nearly all control update steps. Interestingly, Case ND5 outperforms Case ND2 ( $P_p=3$ ), but not significantly. Comparing Figures 15(b) and 20(b), it is clear that, in this simulation, the lifting line model prediction of downwind turbine power is less conservative as a function of increasing  $\gamma$ . Therefore, the model is likely slightly over-estimating the true optimal yaw misalignment angle magnitudes when  $P_p=3$ .





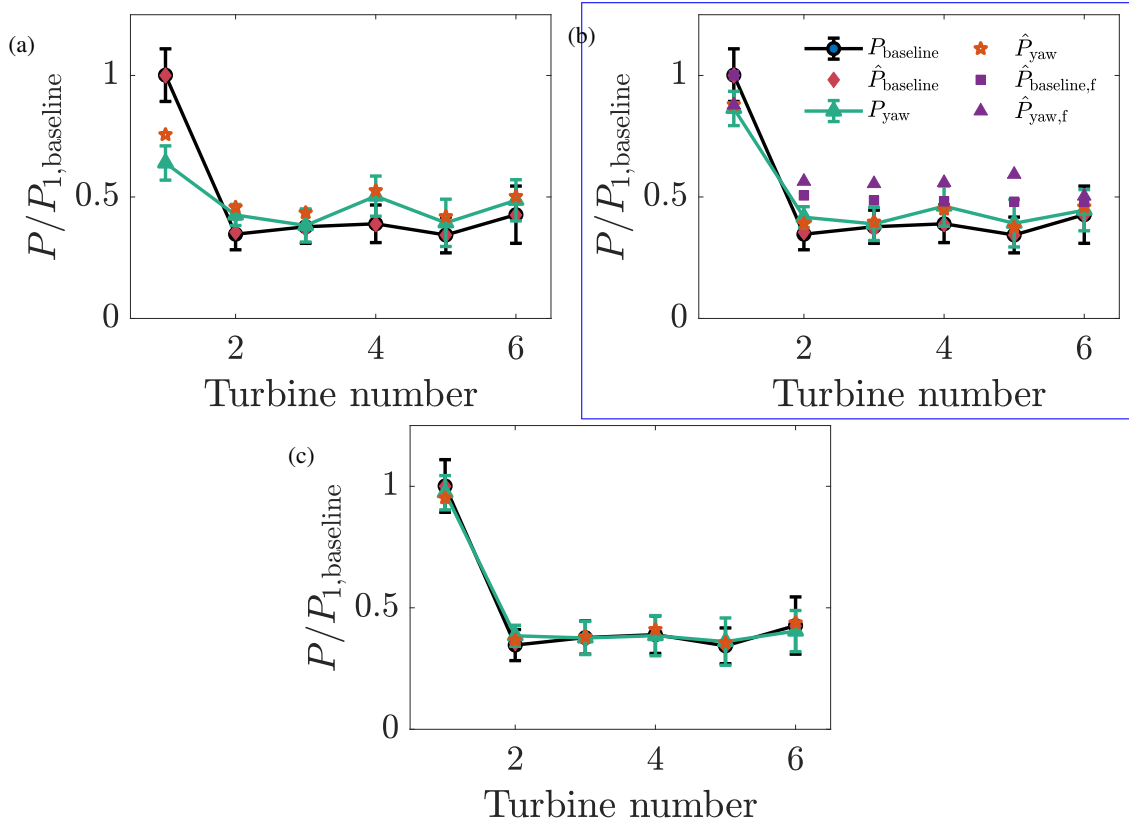
**Figure 20.** Relationship between the LES wind farm power production compared to the wake model wind farm power production prediction for online control using the initial parameters to initialize the next state and (a)  $P_p = 2 \hat{P}_p = 2$  (NDP2) and (b)  $P_p = 4 \hat{P}_p = 4$  (NDP4). The LES power production is given by  $P$  and the wake model prediction is given by  $\hat{P}$ .

Overall, the sensitivity analysis on  $P_p$  suggests that given a model application where  $P_p$  is unknown, a conservative estimation should be taken (e. g.  $P_p = 4$ ). With the present data-driven dynamic controller, underestimating  $P_p$  leads to the wake model estimating a state which would lead to high wake losses with baseline greedy control. There is no pathway for the state estimation to discern the discrepancy between an incorrect  $P_p$  model or, for example, changing atmospheric conditions which are giving rise to worsening wake losses given baseline control. Future work should focus on methodologies to robustly estimate  $P_p$  from SCADA data. [Further, the potential deviation of the wind turbine thrust from  \$\cos^2\(\gamma\)\$  \(Bastankhah and Porté-Agel, 2016\) should be investigated in a similar manner as  \$P\_p\$  in future work.](#)

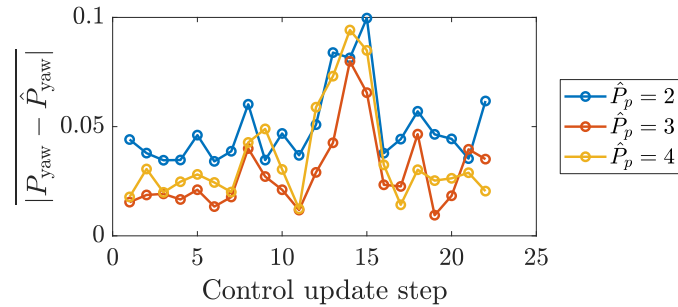
#### 4.4 Accuracy of wake model predictions

The accuracy of the wake model power predictions are assessed in this section by comparing the LES power measurements to the wake model power predictions from the previous time step. As detailed in Section 3, the simulation is initialized with greedy yaw alignment which is held fixed for  $n_T$  time steps (control update 1), after which yaw misalignment angles are implemented for  $n_T$  steps (control update 2). The yaw angles are subsequently updated dynamically every  $n_T$  simulation steps. At control update 1, the previous  $n_T$  steps of yaw aligned operation are used to compute  $P_{\text{baseline}}$ , the time averaged power production for each wind turbine.  $P_{\text{baseline}}$  is used to estimate  $k_w$  and  $\sigma_0$  using the EnKF such that  $|P_{\text{baseline}} - \hat{P}_{\text{baseline}}|$  is minimized. With the estimated model parameters, the optimal yaw misalignment angles are computed for each wind turbine. Using  $k_w$  and  $\sigma_0$  estimated and the optimal yaw angles computed at control update 1,  $\hat{P}_{\text{yaw}}$  is predicted which is attempting to represent  $P_{\text{yaw}}$ , the average power production over the  $n_T$  steps following control update 1. The computation of  $P_{\text{yaw}}$  is completed at control update 2 and can be compared directly to  $\hat{P}_{\text{yaw}}$  to validate the predictive capabilities of the lifting line model and the estimated model parameters. In short,  $\hat{P}_{\text{baseline}}$  represented  $P_{\text{baseline}}$  and it is an estimation or fit because the model had knowledge of  $P_{\text{baseline}}$ .  $\hat{P}_{\text{yaw}}$  is a prediction since the model had no knowledge of  $P_{\text{yaw}}$ . The LES measured and wake model estimated and predicted power productions are shown in Figure 21 for  $P_p = 2 \hat{P}_p = 2, 3, \text{ and } 4$ .

The mean absolute error for the lifting line model power estimation was 0.0037 for all three cases since  $P_p$  does not affect the fitting with yaw aligned control enforced. The mean absolute errors for the lifting line model power predictions were 0.044,



**Figure 21.** Wind turbine power production from LES  $P$  and wake model  $\hat{P}$ .  $P_{1,\text{baseline}}$  is the LES power production for the leading upwind turbine from control update step 1 where the wind farm is operated with greedy baseline control.  $\hat{P}_{\text{baseline}}$  is the wake model fit to  $P_{\text{baseline}}$  using EnKF estimation.  $P_{\text{yaw}}$  is the LES power production for control update step 2 with yaw misalignment incorporated.  $\hat{P}_{\text{yaw}}$  is the wake model prediction of  $P_{\text{yaw}}$  using  $k_w$  and  $\sigma_0$  fit based on control update step 1 and with the optimal yaw misalignment angles which were implemented by control update step 1. The wake model estimate for  $P_{\text{yaw}}$  given by  $\hat{P}_{\text{yaw}}$  is (a)  $P_p=2, \hat{P}_p=2$ , (b)  $P_p=3, \hat{P}_p=3$ , and (c)  $P_p=4, \hat{P}_p=4$ . The error bars represent one standard deviation in the power data as a function of time. The subscript ‘f’ denotes power predictions from the FLORIS wake model (Annoni et al., 2018) with the Gaussian wake model (Bastankhah and Porté-Agel, 2014) and model parameters prescribed by Niayifar and Porté-Agel (2016).



**Figure 22.** The mean absolute errors for the lifting line model predictions as a function of the control update step for the conventionally neutral ABL with  $P_p = 2$ ,  $\hat{P}_p = 2$ , 3, and 4.

0.015, and 0.018, given as a fraction of  $P_{1,\text{baseline}}$ , for  $P_p = 2$ ,  $\hat{P}_p = 2$ , 3, and 4, respectively. The mean absolute errors as a  
 615 function of the control update steps for the three simulations are shown in Figure 22. The average over the control update steps  
 of the mean absolute errors for the three cases are 0.05, 0.029, and 0.036 for  $P_p = 2$ ,  $\hat{P}_p = 2$ , 3, and 4, respectively. Qualitatively,  
 $P_p = 3$ ,  $\hat{P}_p = 3$  and 4 results in predictions which are accurate and within one standard deviation of the mean.  $P_p = 2$ ,  $\hat{P}_p = 2$   
 results in more inaccurate predictions, with elevated inaccuracy for the leading upwind turbine. Overall, these results, in tandem  
 with the field experiment results of Howland et al. (2019), suggest that the lifting line model (Shapiro et al., 2018) provides  
 620 accurate predictions of the power production of wind farms within yaw misalignment given data-driven calibration to yaw  
 aligned operational data.

The baseline and yaw misaligned power predictions using the FLORIS wake model package (Annoni et al., 2018) is also  
 shown in Figure 21. The FLORIS model implementation uses the Gaussian wake model (Bastankhah and Porté-Agel, 2014)  
 with the wake spreading rate  $k^*$  approximated using the empirical LES fit between  $k^*$  and the turbulence intensity given by  
 625 Niayifar and Porté-Agel (2016). Since the Gaussian wake model parameters are not calibrated to the site-specific LES of this  
 wind farm, the inaccuracy in representing  $P_{\text{baseline}}$  is expected according to the typical fidelity of engineering wake models  
 (Stevens and Meneveau, 2017). The mean absolute error for the power production prediction in yaw misalignment averaged  
 over the six wind turbines in the array is  $0.02P_{1,\text{baseline}}$  and  $0.11P_{1,\text{baseline}}$  for the lifting line model with data assimilation  
 and the Gaussian model with an empirical wake spreading rate as a function of turbulence intensity, respectively.  $P_{1,\text{baseline}}$  is  
 630 the power production of the leading upwind turbine in greedy control. The EnKF data assimilation has reduced the error in the  
 prediction of the power production in yaw misalignment by an order of magnitude compared to *a priori* prescribed empirical  
 model parameters. Since the greedy wake losses in FLORIS differ from the LES power production, FLORIS will also predict  
 different yaw misalignment angles in its model-based optimization. For greenfield applications before wind farm construction,  
 SCADA data is not available and data assimilation methods cannot be used, necessitating empirical methods such as those  
 635 suggested by Niayifar and Porté-Agel (2016). For operational wind farm control optimization, site-specific data assimilation  
 increases the accuracy of the model predictions (Figure 21(b)).

## 4.5 Influence of the wind farm alignment

The wake losses and potential for wake steering to increase wind turbine array power production depends on the wind turbine layout (see e.g. experiments by Bossuyt et al., 2017). In the previous section, the six wind turbines were aligned at an angle of 18° from the horizontal (Figure 3). The mean wind direction at hub height is approximately 15°-16° in this conventionally neutral ABL. In this section, the wind turbine column alignment is changed to 14° from the horizontal and the array is embedded within the same conventionally neutral ABL. As a result of this array alignment, the optimal yaw misalignment angles will change from positive (counter-clockwise rotation viewed from above) to negative (clockwise). It should be noted that this sensitivity analysis is not a controlled experiment to test the benefit of yawing in opposite directions since asymmetries exist in the conventionally neutral ABL as a result of the veer angle and the magnitude of partial waking is not held fixed between the two layouts.

Yaw misalignment angles for each turbine in the wind farm for online control using (a) the initial parameters to initialize the next state (ND141) and (b) static state estimation parameters (ND142) for wind farm alignment at 14°.

Time averaged wind farm power production as a function of the control update step for online control using (a) the initial parameters to initialize the next state (ND141) and (b) static state estimation parameters for wind farm alignment at 14° (ND142). The wind farm power is normalized by the power production of the aligned wind farm case.

For the wind turbine array aligned at 14°, the dynamic wake steering controller is tested with dynamic (ND141) and static state estimation (ND142). With a wind farm alignment along 14° and the mean wind direction at hub height of approximately 15°-16°, the optimal yaw misalignment angles are negative (clockwise viewed from above). The yaw misalignment angles implemented as a function of the control update steps are shown in Figure E1 for dynamic and static state estimation architectures. The qualitative magnitude of the yaw misalignment angles are similar to the angles selected for the 18° alignment case (Section 4.1).

The power productions for the two wake steering controllers are shown in Figure E2. The temporally averaged power production increase over baseline, greedy operation is 1.1% and 1.0% for the dynamic and static state estimation cases, respectively. There is no significant difference in the mean power production between these two state estimation methodologies for this wind farm alignment (see Table 1). Further, neither wake steering control case increases power significantly over greedy control. While the power production increase over the greedy control is less for the 14° case with negative yaw misalignment than for the 18° case with positive yaw misalignment this is not a controlled experiment since the degree of partial waking is different between the two cases. The wind farm has more direct wake interactions, with less partial waking, for the 14° alignment as evidenced by the lower power production in greedy control (Table 1). Previous simulations have shown that for a controlled experiment of direct wind farm alignment, positive yaw misalignment (counter-clockwise) is superior to negative yaw misalignment (clockwise) (see e.g. Fleming et al., 2015; Miao et al., 2016), although this will depend on the specific ABL and wind farm layout simulated. Archer and Vasel-Be-Hagh (2019) proposed that this difference is a function of Coriolis forces in the ABL, although future work should quantify the effect of latitude and hemisphere locations as well as the influence of non-traditional effects (Howland et al., 2020b). The degree of power production increase as a result of wake steering is a strong

function of the wind farm alignment with respect to the wind direction at hub height, the turbine spacing, the shear, and veer. The present simulations reveal that it is reasonable to capture increases in power production with negative (clockwise) wake steering even with a wind turbine model with  $P_p \approx 3$ .

## 5 Conclusions

675 A suite of large eddy simulations has been performed to characterize the performance of a dynamic, closed-loop wake steering wind farm control strategy. The controller was designed for the application of real-time utility-scale wind farm control based on only SCADA data without requiring a LiDAR on site. ~~The physics- and data-driven ensemble Kalman filter and wake model based controller was validated in uniform inflow LES before being tested in conventionally neutral ABL conditions with Coriolis, shear, and veer.~~ The analytic gradient ascent optimal yaw selection allows for real-time dynamic wind farm  
680 control. ~~The sensitivity of the power production increase via wake steering over greedy, yaw aligned control was characterized as a function of the controller architecture,  $P_p$ , state estimation architecture, wind farm layout, and ABL conditions.~~ main technical contribution of this paper is the development of a closed-loop wake steering methodology for application in transient ABL flows which does not rely on an open-loop offline yaw misalignment lookup table calculation.

Within the statistically quasi-stationary conventionally neutral ABL, the optimal yaw misalignment angles do not change  
685 significantly with time. Within this simplified ABL environment, ~~a static wake steering strategy, where the yaw misalignments do not change, increased power production by 5.4% with respect to baseline greedy control. Dynamic wake steering with dynamic state estimation increased power production by 4.6%, slightly less than the static yaw misalignment strategy but not significantly.~~ wake steering control with fixed, lookup table yaw misalignment values, dynamic yaw values with continuous state estimation, and dynamic yaw values with fixed state estimation all yielded significantly more power than baseline control,  
690 although the differences between the three control architectures were not significant. The highest power production occurred with a wake steering strategy where the model parameters were fixed and the state estimation was not performed every control update step but the yaw misalignment angles were updated according to the local wind conditions. This result ~~indicates~~ suggests that in a lookup table wake steering approach, the wake model parameters should be tabulated and the yaw angles should be calculated on-the-fly given exact local wind conditions, rather than direct optimal yaw misalignment angle tabulation. ~~All three of these wake steering cases increased power significantly over greedy, aligned control although the differences between the three control architectures were not significant.~~

The importance of the model for individual wind turbine power production degradation as a function of the yaw misalignment angle, and in particular  $P_p$ , was demonstrated where  ~~$P_p = 3$   $\hat{P}_p = 3$  or 4 lead to an increase in power production with respect to greedy operation while  $P_p = 2$   $\hat{P}_p = 2$  lead to a loss in power.~~ Wake steering cases with, with the true  $P_p = 3$  and 4 led to a significant increase in power production compared to greedy control while  $P_p = 2$  did not. Since  $P_p$  depends on the  
700 wind turbine model and ABL characteristics ~~and there is no accepted general framework for determining  $P_p$ ,~~ this should be investigated in future work. ~~With  $P_p = 3$ , the~~

705 The wake model does not capture all relevant physical phenomena present in this flow (see specific assumptions in wake model derivation in §2.1), but the power production is fit accurately as a function of time with the two parameter model. While this success may suggest that the site- and time-specific state estimation may correct for physics which are unresolved in the model, with  $\hat{P}_p = P_p = 3$ , the wake model makes accurate forecasts of the power production over a future time horizon given the yaw misalignment strategy that is implemented, provided that the wake model parameter modifications are constrained by the state estimation algorithm initialization as in Case ND1, rather than unconstrained as a function of time as in Case ND2. This accuracy gives confidence to the data-driven EnKF state estimation and lifting line wake model for the application of wake steering control. The combined lifting line model and EnKF state estimation has an order of magnitude reduced predictive error than the Gaussian wake model with an empirical wake spreading rate in this conventionally neutral ABL simulation.

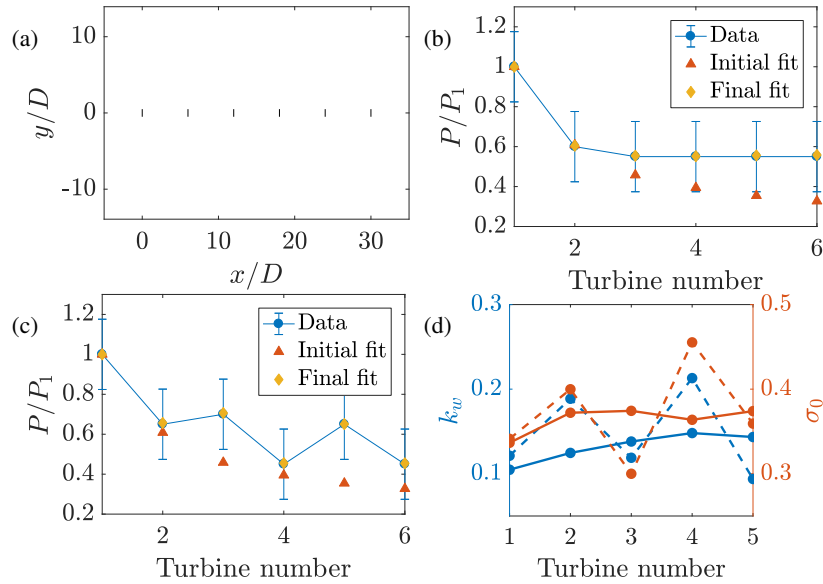
~~The results are qualitatively similar when a wind farm of different alignment is embedded within the conventionally neutral ABL. The power production is decreased with a wind farm alignment of  $14^\circ$  compared to  $18^\circ$  and with a clockwise yaw misalignment compared to a counter-clockwise, although this was not a controlled experiment of the influence of the direction of yaw misalignment.~~ The magnitude of model parameter modifications as a function of time are implicitly constrained in this study by the hyperparameters of the EnKF estimation algorithm. Future work should investigate the predictive capabilities for combined data-driven and wake model approaches with explicit constraints on the model parameters.

720 While the conventionally neutral ABL cases were not designed to model a specific wind farm and to compare to field data, this LES testbed paradigm is useful for the rapid prototyping of optimal wind farm control architectures. The main purpose of this study was predominantly to establish the dynamic wake steering framework and perform sensitivity analysis on the controller architecture rather than the ABL or LES setup. The uncertainties and sensitivities in this study associated with the wall model, subfilter scale model, wind turbine model, and ABL characteristics such as boundary layer inversion height were not investigated in detail and are left for future work. More reliable and generalizable estimates for  $P_p$  (?)(Liew et al., 2020), or generally  $C_p$  as a function of  $\gamma$ , should be investigated. Future work should also investigate the influence of latitude and geostrophic wind direction on wake steering control performance (Howland et al., 2020b). Finally, the controller should be tested using other LES codes and in field experiments to assess the generalization of the results. Part 2 of this study will implement the dynamic optimal controller in transient ABL conditions such as the stable ABL and the diurnal cycle.

730 *Code and data availability.* The code is open-source and available at <https://github.com/FPAL-Stanford-University/PadeOps>. The GitHub repository branch for incompressible wind farm simulations is ‘igridSGS.’ The data will be open-access and published on the Stanford Digital Repository (<https://sdr.stanford.edu/>) upon publication.

## Appendix A: EnKF test model problem

The state estimation EnKF algorithm and implementation is tested using a six wind turbine model wind farm with artificial data. Six 1.8 MW Vestas V80 wind turbines are modeled with incoming wind speed of  $u_\infty = 7.5$  m/s. The turbines are



**Figure A1.** (a) Model problem setup. (b,c) The EnKF model fits for the model problem with two prescribed, artificial mean power profiles and Gaussian random noise. (d) Model parameters shown with solid (b) and dashed (c) lines. The wake model parameters for the last turbine downwind are not shown since they do not impact the state estimation accuracy.

spaced  $6D$  apart in the streamwise direction and are directly aligned in the spanwise direction as shown in Figure A1(a).  
 735 The [test problem was used for hyperparameter selection to achieve estimations of the artificial power production with low mean absolute error.](#) The parameters selected for the EnKF algorithm are  $\sigma_{k_w} = 0.001$ ,  $\sigma_{\sigma_0} = 0.001$ , and  $\sigma_P = 0.1$ . The initial wake model parameters were selected as  $k_w = 0.1$  and  $\sigma_0 = 0.35$  for each wind turbine in the array. The model is run with a specified, artificial mean power production profile with Gaussian random noise superposed. The model is run over 1000 model time step iterations with  $N_e = 100$ . The initial and final model calibrations are shown in Figure A1(b,c). The EnKF combined  
 740 with the lifting line model is able to fit the artificial wind farm data with sufficient accuracy for two different power production profiles.

As shown in Figure A1(b,c), the EnKF state estimation combined with the lifting line model are able to reproduce the power production for the artificial data to high accuracy. ~~The~~ [While the](#) ability for a ~~one or~~ two parameter analytic wake model to capture arbitrarily generated power production profiles should be investigated in future studies ~~as the model may~~  
 745 ~~enforce unrealistic model parameters to represent neglected physics (Schreiber et al., 2019).~~ [The validity of](#) this data-driven framework is validated in the LES test cases in a comparison between model power predictions and LES power measurements (Section ~~4~~ [4.4](#)) [where the state estimation significantly reduces the power predictions compared to standard empirical wake model approaches.](#)

## Appendix B: ~~Extended conventionally neutral simulation~~

750 ~~The conventionally neutral ABL Case ND2 is run for 50 control update steps and the results are shown in Figure D1. The controller does not become unstable as a function of time and the magnitude of yaw misalignment angles are approximately constant.~~

~~Wind farm (a) yaw misalignment angles, (b)  $k_w$ , and (c)  $\sigma_0$  as a function of the control update steps for the extended ND2 case.~~

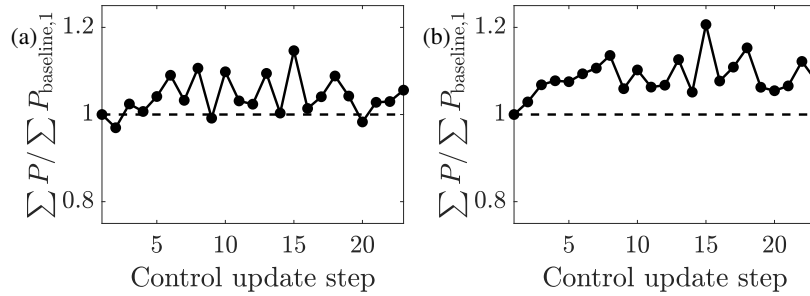
## 755 **Appendix B: Influence of local atmospheric conditions on wind turbine array power production**

The quantification of the influence of new control methods on the wind farm power production is challenging in an experimental setting. In a computational environment, simulations with identical initial conditions and fixed time stepping schemes can be used to quantify the influence of the operational modifications in a controlled experiment. In a field experiment environment, since wind conditions are constantly changing and are not repeatable due to the nature of atmospheric flows, this quantification  
760 is more challenging. Complex terrain and differences in the manufacturing and operation of turbines in standard control leads to substantial discrepancies in the instantaneous power production of freestream turbines at wind farms. Therefore, comparing yaw misaligned columns of turbines to yaw aligned leads to uncertainty in analysis. Further, conditional averages based on wind speed, direction, turbulence intensity, and atmospheric conditions may not sufficiently capture the potential physical mechanisms which influence power production. To quantify this impact in the present simulations, the power productions  
765 as a function of the control update steps can be compared to the first control update step in the statistically quasi-stationary conventionally neutral ABL flow. Inertial oscillations, turbulence, and sampling error will cause discrepancies between the first and subsequent control update steps even with the yaw aligned control strategy held fixed in the statistically quasi-stationary flow. The average power production compared to the first yaw control update step is 4.3% and 9.0% higher for the yaw aligned (Case NA) and dynamic closed-loop control (Case ~~ND2~~ND1), respectively. The increase observed in Case NA indicates that  
770 the simulation had not completely converged to the statistically quasi-stationary state upon control initialization although this does not affect the qualitative conclusions of Section 4. The true increase in power production due to wake steering in Case ~~ND2~~ND1 compared to Case NA is 4.6% over the same simulation temporal window. These results highlight the need to develop robust statistical methods to analyze the impact of changing wind farm control strategies compared to the baseline.

## **Appendix C: Approximate advection timescale**

775 Upon the yaw misalignment of an upwind turbine, there is a time lag associated with the advection time scale of the flow for the control decision to influence a downwind turbine. While the advection time depends on the length scale of the turbulent eddy (DeI Álamo and Jiménez, 2009; Yang and Howland, 2018; Howland and Yang, 2018), the mean flow advection approximately follows the mean wind speed in wind farms (Taylor, 1938; Lukassen et al., 2018). The number of simulation





**Figure B1.** Time averaged power production as a function of time normalized by the time averaged power production of the first control update step for yaw aligned greedy control. (a) Yaw aligned greedy control (Case NA) and (b) closed-loop dynamic control (Case ~~ND2~~ND1).

time steps associated with the approximate advection time between the first and last turbines is computed as

$$780 \quad T = \frac{\Delta s_x}{\bar{u}_{\text{hub}} \Delta t}, \quad (\text{C1})$$

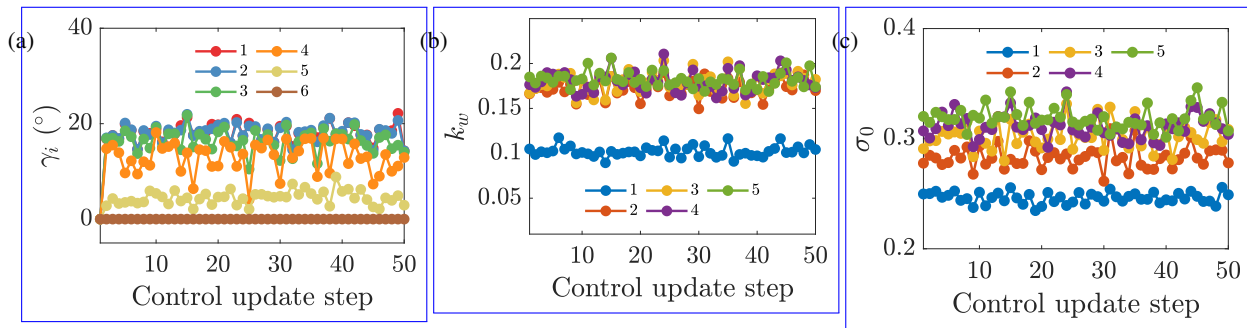
where  $\Delta s_x$  is the distance between the first and last turbine in the streamwise direction and  $\bar{u}_{\text{hub}}$  is the mean streamwise velocity at the wind turbine model hub height at the leading turbine in the farm. The simulation time step is fixed and is  $\Delta t$ , which corresponds to a CFL of less than 1 persistently during runtime. In the computation of wind farm statistics for the utilization of static wake models, the advection time scale is accounted for by initializing the time averaging two advection time scales  $T_a = 2T$  after the yaw misalignments for the wind turbine array have been updated. To account for errors associated with the simple advection model, the time lag is taken as double the advection time scale,  $T_a = 2T$ , although this advection time scale did not have a statistically significant influence on the results as shown in Table 1 and Figure 5.

#### Appendix D: Extended conventionally neutral simulation

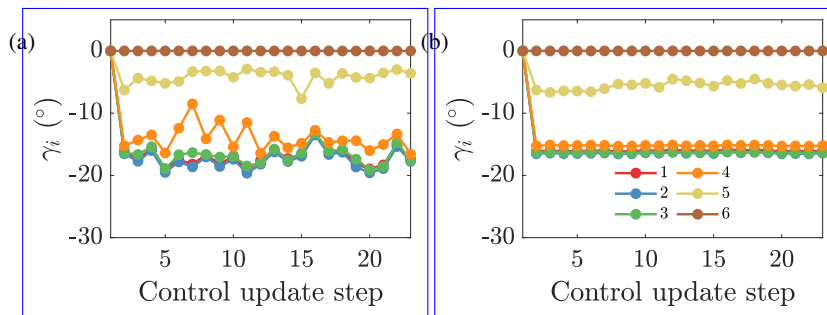
790 The conventionally neutral ABL Case ND1 is run for 50 control update steps and the results are shown in Figure D1. The controller does not become unstable as a function of time and the magnitude of yaw misalignment angles are approximately constant.

#### Appendix E: Influence of the wind farm alignment in the conventionally neutral ABL

795 The wake losses and potential for wake steering to increase wind turbine array power production depends on the wind turbine layout (see e.g. experiments by Bossuyt et al., 2017). In the previous section, the six wind turbines were aligned at an angle of  $18^\circ$  from the horizontal (Figure 3). The mean wind direction at hub height is approximately  $15^\circ$ - $16^\circ$  in this conventionally neutral ABL. In this section, the wind turbine column alignment is changed to  $14^\circ$  from the horizontal and the array is embedded within the same conventionally neutral ABL. As a result of this array alignment, the optimal yaw misalignment angles will change from positive (counter-clockwise rotation viewed from above) to negative (clockwise). It should be noted



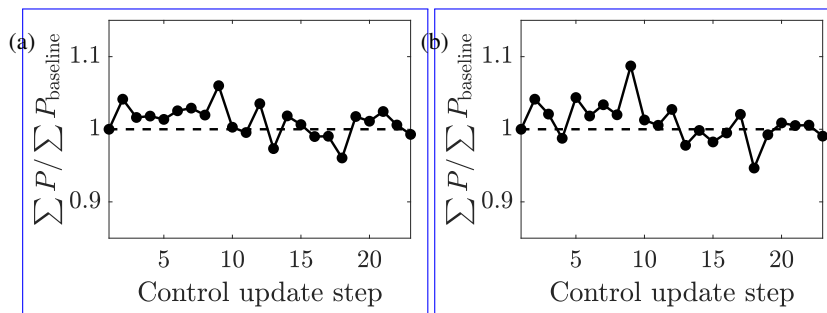
**Figure D1.** Wind farm (a) yaw misalignment angles, (b)  $k_w$ , and (c)  $\sigma_0$  as a function of the control update steps for the extended ND1 case.



**Figure E1.** Yaw misalignment angles for each turbine in the wind farm for online control using (a) the initial parameters to initialize the next state (ND141) and (b) static state estimation parameters (ND142) for wind farm alignment at  $14^\circ$ .

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that this sensitivity analysis is not a controlled experiment to test the benefit of yawing in opposite directions since asymmetries exist in the conventionally neutral ABL as a result of the veer angle and the magnitude of partial waking is not held fixed between the two layouts.



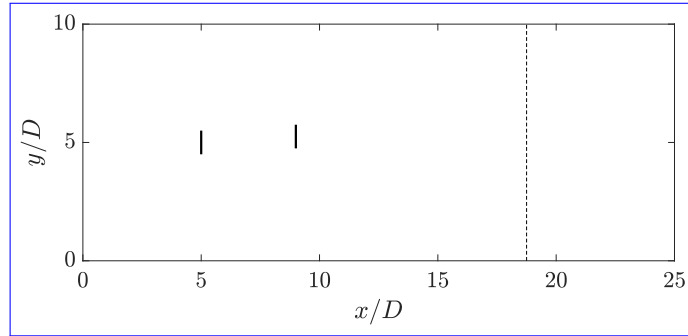
**Figure E2.** Time averaged wind farm power production as a function of the control update step for online control using (a) the initial parameters to initialize the next state (ND141) and (b) static state estimation parameters for wind farm alignment at  $14^\circ$  (ND142). The wind farm power is normalized by the power production of the aligned wind farm case.

For the wind turbine array aligned at  $14^\circ$ , the dynamic wake steering controller is tested with dynamic (ND141) and static state estimation (ND142). With a wind farm alignment along  $14^\circ$  and the mean wind direction at hub height of approximately  $15^\circ$ - $16^\circ$ , the optimal yaw misalignment angles are negative (clockwise viewed from above). The yaw misalignment angles implemented as a function of the control update steps are shown in Figure E1 for dynamic and static state estimation architectures. The qualitative magnitude of the yaw misalignment angles are similar to the angles selected for the  $18^\circ$  alignment case (Section 4.1).

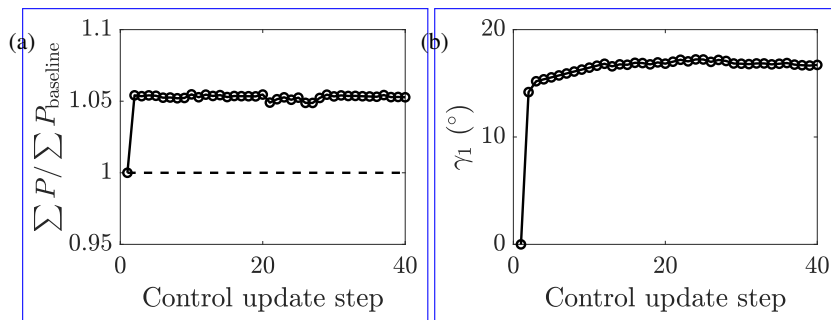
The power productions for the two wake steering controllers are shown in Figure E2. The temporally averaged power production increase over baseline, greedy operation is 1.1% and 1.0% for the dynamic and static state estimation cases, respectively. There is no significant difference in the mean power production between these two state estimation methodologies for this wind farm alignment (see Table 1). Further, neither wake steering control case increases power significantly over greedy control. While the power production increase over the greedy control is less for the  $14^\circ$  case with negative yaw misalignment than for the  $18^\circ$  case with positive yaw misalignment this is not a controlled experiment since the degree of partial waking is different between the two cases. The wind farm has more direct wake interactions, with less partial waking, for the  $14^\circ$  alignment as evidenced by the lower power production in greedy control (Table 1). Previous simulations have shown that for a controlled experiment of direct wind farm alignment, positive yaw misalignment (counter-clockwise) is superior to negative yaw misalignment (clockwise) (see e.g. Fleming et al., 2015; Miao et al., 2016), although this will depend on the specific ABL and wind farm layout simulated. Archer and Vassel-Be-Hagh (2019) proposed that this difference is a function of Coriolis forces in the ABL, although future work should quantify the effect of latitude and hemisphere locations as well as the influence of non-traditional effects (Howland et al., 2020b). The degree of power production increase as a result of wake steering is a strong function of the wind farm alignment with respect to the wind direction at hub height, the turbine spacing, the shear, and veer. The present simulations reveal that it is reasonable to capture increases in power production with negative (clockwise) wake steering even with a wind turbine model with  $P_p \approx 3$ .

## Appendix F: Dynamic wake steering uniform inflow LES

In this section, the dynamic closed-loop wake steering controller described by Figure 1 will be used in LES of two turbines operating in uniform inflow. Uniform inflow is not physical, and depending on the LES resolution, the results will be dependent on the sub-grid scale model due to the sharp shear layer and reduced mixing of the test case (see detailed discussion by Howland et al., 2016). However, uniform inflow provides a useful statistically stationary test case for the validation of the closed-loop wake steering methodology. The domain has lengths of  $25D$ ,  $10D$ , and  $10D$  in the  $x$ ,  $y$ , and  $z$  directions, respectively, and the number of grid points are 128, 64, and 64. Two actuator disk model wind turbines are simulated in uniform inflow with slip walls on all sides and a fringe region at the domain exit to force the inflow to a uniform profile. The fringe is used in the last 25% of the computational  $x$  domain. The turbines are located  $4D$  apart in the streamwise direction and are misaligned by  $0.25D$  in the spanwise direction as shown in Figure F1. Due to the spanwise misalignment, the preferential yaw misalignment direction for the upwind turbine is positive (counter-clockwise rotation viewed from above).



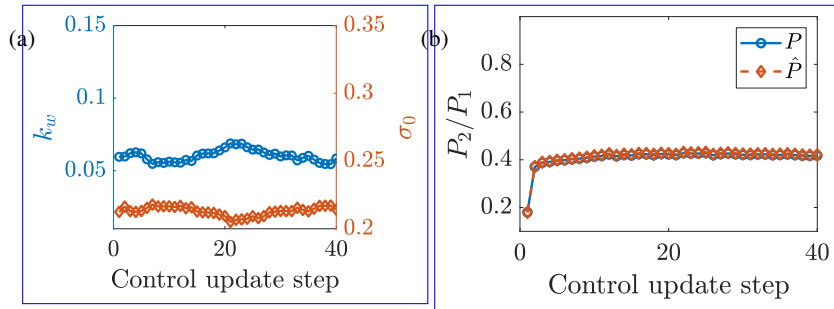
**Figure F1.** Uniform inflow LES simulation actuator disk model layout. The fringe region is represented by the dashed black line and the wind turbines are shown as solid black lines.



**Figure F2.** Two wind turbine model uniform inflow LES (a) power production. (b) The yaw misalignment angle  $\gamma$  for the upwind turbine. The downwind turbine remains yaw aligned during the simulation.

835 The flow is statistically stationary after the initial startup transient has decayed and therefore the optimal yaw misalignment  
 angles for the two wind turbines are not a function of time. The flow is initialized with  $u = 1$ . Upon statistical stationarity,  
 the closed-loop wake steering controller is initialized and the flow is run for  $n_T = 10000$  LES time steps to ensure sufficient  
 averaging. The time averaging is initialized following the advection time of the wind farm (see Section C) and therefore there  
 are  $n_T - T_a$  timesteps within each time averaging window.

840 The sum of power production for the two turbine pair as a function of the control update steps is shown in Figure F2(a). The  
 power production is normalized by the greedy control simulation. The power production for the first yaw controller update time  
 step is equal to 1 since yaw misalignment has not been implemented and the model is gathering power production data to be  
 used for the first EnKF data assimilation pass. The power production increases in the second time step when yaw misalignment  
 is incorporated for the upwind turbine (Figure F2(b)). The controller correctly commands the upwind turbine to positive yaw  
 845 misalignment. While the flow is statistically stationary, the upwind turbine yaw misalignment angle changes marginally after  
 the second time step. These changes can be attributed to modifications to the wake model parameters as a function of time as  
 estimated by the EnKF (Figure F3(a)). The estimated model parameters vary in time in this statistically stationary flow due



**Figure F3.** Two wind turbine model uniform inflow LES (a)  $k_w$  and  $\sigma_0$  for the upwind turbine and (b)  $\hat{P}$  and  $P$  for the downwind turbine.

to standard error of the mean with limited samples within a given time window of length  $T$ , due to the influence of the yaw misalignment of the dynamics on the wake, and due to the limited number of ensembles  $N_e$  in the EnKF.

850 The wake model parameters have a functional dependence on the yaw misalignment of the turbines within the wind farm. The wake of a yaw misaligned turbine is narrower than the same turbine when yaw aligned (Archer and Vassel-Be-Hagh, 2019). The wake spreading rate  $k_w$  dictates the wake recovery rate. Yaw misalignment also reduces the axial induction factor of the wind turbine and therefore affects the wake recovery. Further, since wind turbines in yaw misalignment generate large-scale counter rotating vortices (Howland et al., 2016), the wake recovery rate will likely be enhanced in yaw misalignment (Fleming et al., 2018)

855 due to a reduction in the axial induction and yaw added recovery (King et al., 2020). As a result of these vortices, the wake will have top-down asymmetry and this will influence  $\sigma_0$ . While the present model neglects the vertical dimension, the development of a controls-oriented model which incorporates the curled wake asymmetry is ongoing (Martínez-Tossas et al., 2019). Future work should characterize the influence of yaw misalignment on the wake spreading rate.

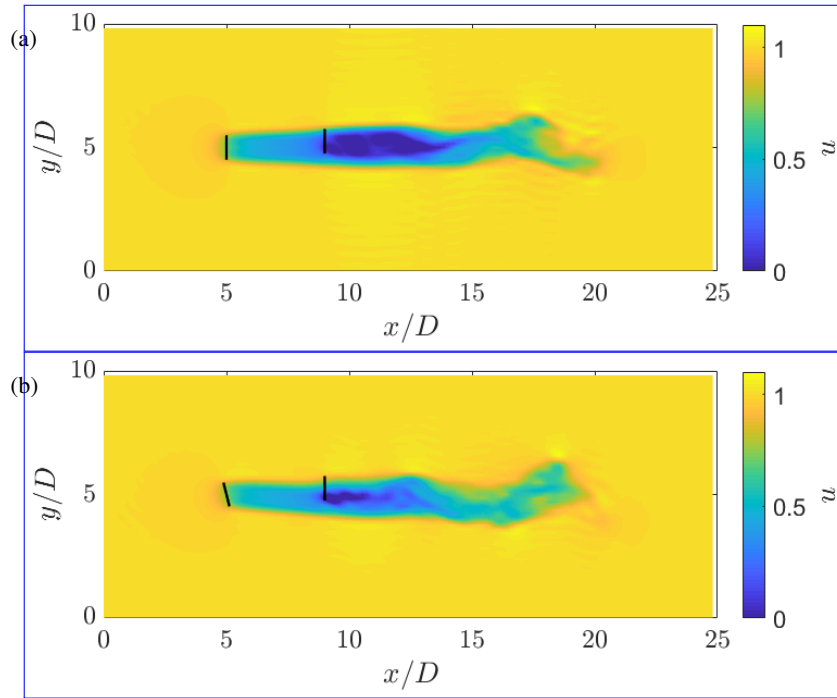
The state-estimated power production for the downwind turbine is compared to the LES power production in Figure F3(b).

860 The downwind turbine's power production in the greedy control strategy is low (approximately  $0.2P_1$ ) due to the freestream inflow condition and close streamwise direction spacing. The EnKF results in an accurate power production estimation using the lifting line model. While the wake model parameters are changing as a function of time (Figure F3(a)), the power production estimate for the downwind turbine is not significantly affected. The wake model parameters  $k_w$  and  $\sigma_0$  are anti-correlated as a function of time. Within the two-parameter lifting line model, increasing  $k_w$  or  $\sigma_0$  reduces the wake effect for the

865 downwind turbine. With the LES power production of the downwind turbine and the yaw misalignment of the upwind turbine approximately fixed, the state estimation increases one parameter and reduces the other parameter to remain consistent in the estimation of the downwind power. This indicates, similarly to the results in Appendix A, that the two parameter lifting line model may be overparameterized, and a single parameter model, with fixed  $\sigma_0$  for example, may suffice (Shapiro et al., 2019). The accuracy of the EnKF state estimation and lifting line model in the prediction of the power production in yaw misalignment

870 is tested in Section 4.4. This accuracy will implicitly measure the impact of the site-specific fitting in the model.

The control architecture used in the uniform inflow case is the same as Case ND2, where the estimated model parameters from the previous time step are used to initialize the parameters for the estimation at the next time step. As discussed in



**Figure F4.** Two wind turbine model uniform inflow LES instantaneous streamwise velocity  $u$  snapshot with (a) no yaw misalignment (b) after the last time step of dynamic wake steering.

§4.2, this allows the parameters to change significantly over time compared to their initialization state. By fixing the EnKF initialization (as done in Case ND1), the modifications to the wake model parameters are limited by the hyperparameters  $\sigma_{b_{\text{yaw}}}$  and  $\sigma_{\sigma_0}$ . Since there is no wake impinging on the upwind turbine, the state estimation has no impact on the power prediction of the upwind turbine since there are no wake model parameters to estimate. The accuracy of the upwind turbine model prediction will be governed by the fidelity of the cosine model and  $P_p$ , given by Eq. 6.

875

The instantaneous streamwise velocity is visualized in Figures F4(a) and (b) for the baseline greedy yaw control and the optimal yaw misalignment angle, respectively. As a result of the yaw misalignment, the wake is partially laterally deflected away from the downwind turbine. The yaw misalignment increases the magnitude of the streamwise velocity in the wake region.

880

*Author contributions.* M.F.H., S.K.L., and J.O.D. conceived the work. A.S.G. and M.F.H. developed the LES code. M.F.H. conducted analysis. M.F.H. wrote the manuscript. All authors contributed to edits.

*Competing interests.* The authors declare no conflicts of interest.

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