

Response to Reviewer RC1

Dear Bart, thank you so much for the kind words, the thorough review of our manuscript and the numerous suggestions for improvements. Below, we have listed your comments and have provided our response after each one. The changes made to the manuscript are indicated by the boxed texts.

Major comments:

1. The most significant improvement for this manuscript would be an increased clarify and structure, in my eyes. Often, sections are very long and one loses track of the purpose of a section. I would very much like to see the text restructured into more subsections and paragraphs. For example:

- a. Introduction: separate subsections for modern challenges in large-scale implementation.

Response: Thanks for the suggestion. We have added the following headings in the Introduction section: AWC implementation challenges, State of the art, Contribution of this work, Structure of the paper

- b. Introduction: too, much information on the dynamic FarmFlow part. I think you can remove lines 103-110: from "the dynamic simulation..." until "...in real-life measurements." without losing any valuable information in the introduction.

Response: We have removed these lines from the manuscript.

- c. Section 2.3, page 8: why is the derivation of wind direction variability part of the "yaw model"? This, to me, should be part of the inflow/wind field model.

Response: A good point! The organization of Section 2 was not clear enough, and we have now made an attempt to clarify the structure. To this end, Figure 1 has been updated to clearly indicate the four main components of the simulation model: wind field generator, dynamic wake model (dynamic FarmFlow), wind turbines' yaw model, and dynamic robust AWC. The yaw models and the dynamic robust AWC are implemented in a DLL, which is called by the dynamic FarmFlow code at each simulation step. Therefore, the yaw model is not part of the FarmFlow model (as one might probably expect), but is implemented separately in the DLL. Same holds for the added noise to the wind direction signals, coming from FarmFlow, which is included to model the effect of the increased turbulence in the wake on the measured wind direction. To clarify the structure of Section 2, next to the clarifications made in Figure 1, we have modified the name of Section 2 to "Simulation model description" and have updated the text in the beginning of Section 2 as follows:

"The wind farm simulation model consists of a stochastic wind field generator, dynamic wake model (dynamic FarmFlow), wind turbines' yaw model, and dynamic robust AWC. A block scheme of the simulation model is given in Fig. 1, in which the four mentioned main components have been clearly indicated. The yaw models and the dynamic robust AWC are implemented in a dynamic link library (DLL), which is called by the dynamic FarmFlow code at each simulation step...
...The main components are explained separately in more detail in the remainder of this section."

- d. Table 1: this is a table related to validation of the model choices. This seems somewhat out of place to me, since you are still explaining the fundamentals of the model.

Response: The table does seem somewhat misplaced here, indeed, but we could not find any better place for it. It is included to support the idea of adding turbulence-dependent noise term in the wind direction measurements entering the yaw model, resulting in increased yawing of downstream turbines. We could remove the table and the related text, but we do believe it adds value to the discussion. Please, feel free to make a specific advice as to where we could better place the table.

- e. Section 2.4: why is this part of Section 2: "wind farm model"? Typically, the wake/wind farm controller is not considered to be part of the wind farm model, especially in this entire context. Perhaps instead this should become part of Section 3 and Section 3 should become "AWC design"

Response: We believe this comment is much related to comment (c) above, i.e. the lack of clarity of the structure of Section 2. As explained in our response to comment (c) above, the structure has been clarified in the revised manuscript. Section 2 describes the complete simulation model which consists of four main components, as depicted in Fig.1. These are wind field generator, dynamic wake model (dynamic FarmFlow), wind turbines' yaw model, and dynamic robust AWC. Each component of the simulation model is then described in a separate subsection. Section 3 "Robust AWC optimization" is on the optimization of the parameters of the robust AWC (the LuT in Fig. 1), which Section 4 – on the optimization of the dynamic part of the AWC algorithm (LP filter, hysteresis and sampling). To clarify this further in the manuscript, we have included the following text in the beginning of Section 2.4:

"This section describes the structure of the dynamic robust AWC algorithm, represented by the shaded area at the bottom of Fig. 1. The optimization of the parameters of the underlying blocks of this algorithm is topic of Sect. 3 (Robust AWC optimization) and 4 (Dynamic adaptation algorithm optimization)."

- f. Section 3.1: find a way to clearly separate each factor of uncertainty/parameter. Perhaps a bullet point list or subsections/paragraphs.

Response: we have improved the structure to Section 3.1 in the revised manuscript by using a list.

- g. Line 437: can start a new subsection *(see next comment)

Response: see response to next comment.

- h. Latter half of Section 4 vs. Section 5. One shows a basic case study for 3 turbines, and the other shows a more realistic case study with OWEZ. To me, it would make sense to put them both in Section 5 and separate them into two subsections: one for verification/simple study case for understanding, and then one for a more realistic evaluation.

Response: Good idea! We moved the simplified example with 5 turbines from Section 4 to the beginning of Section 5, and making Section 5.1 out of it. The realistic case study with OWEZ became Section 5.2. We added the following text to the beginning of Section 5 to classify this:

“This section presents the results from two case studies. The first one represents a example of robust AWC design performed for a simple farm consisting of a few turbines in a row. The second one represents a realistic case study with dynamic robust AWC applied to an offshore wind farm.”

- i. I read that FarmFlow has been extended to include wake and yaw control dynamics. It also now accepts dynamic wind fields to drive the simulation, including temporal and spatial variations. These are great developments. I would very much appreciate any kind of validation of these new functions. However, with the paper already being as long as it is, perhaps it would be better to present the dynamic FarmFlow plus validation in a separate publication. This would also increase clarity in the current manuscript.

Response: Very valid point. The dynamic part of the FarmFlow model has, unfortunately, not been properly validated yet, and we are currently looking for funding to support this very important work. Some sanity checks have, of course, been done to ensure the output makes sense, but a more rigorous validation is still needed. Once this is done, we will of course consider publication.

2. Please motivate certain statements with the right literature and avoid speculation

- a. In the introduction, I read that the potential AEP gain with AWC is several percents. This seems very high and currently not too realistic based on the recent expert elicitation and field experiments that exist in the literature. Actually, the papers cited with this statement are simulation studies and are better replaced with the Wingerden et al. expert elicitation and field experiments from Howland, Fleming, Simley, Duc and Doekemeijer. This relates to the minor comment on citing literature.

Response: Several percent AEP increase is not stated anywhere in the manuscript. Instead, both in the Abstract and in the Introduction a *possible, or potential, gain of up to a few percent* is mentioned. In my opinion, this is not exaggerating the current knowledge. Indeed, this statement is only backed up by numerical studies, but the field experiments are currently only very limited and provide no basis for estimation of the AEP gains achievable in the future. Furthermore, the paper on expert elicitations does not cover the question of what is the expected AEP increase, but rather the following one: “How much of an increase in energy production is needed to justify implementation?”. In our opinion, due to lack of other evidence, we believe it is better to stick to our initial citations.

- b. Line 33, where the author assumes that the accumulated loads over the whole lifetime of a wind turbine decreases with wake steering, rather than increases, because Siemens-Gamesa is selling a wake steering solution. This reasoning seems flawed to me. We do not fully know under what conditions Siemens-Gamesa is doing wake steering, if they require additional equipment, whether and which loads increase and decrease, when they do, and whether this relates to fatigue or ultimate loads. There is too little information to make any conclusions based on the fact that Siemens-Gamesa is selling wake steering, besides perhaps that it has caught the interest of this OEM.

Response: It is not true that we assume that the lifetime fatigue loads decrease with wake steering because SGRE is selling such a solution. Instead, the manuscript

clearly states: “A more detailed study involving a utility scale wind farm was presented in Kanev et al. (2020), where the impact of wake steering AWC on the structural loads of the turbines during their complete lifetime has been investigated using the so-called loads lookup table (LUT) approach (Reyes et al. 2020). The results demonstrate that, even though by itself yaw misalignment does increase the structural loads of some turbines in specific wind conditions, the wake-induced loading is decreased even more, so that the accumulated loads over the whole lifetime of each wind turbine generally remain lower than without AWC.”.

Nevertheless, we have removed the following sentence in the revised manuscript to avoid any misinterpretations:

“This conclusion is implicitly confirmed by the fact that the industry starts to develop this technology into commercial products (Siemens Gamesa Renewable Energy, 2019).”

- c. Line 134-135, it is stated that wind farm simulations require time scales of tens of seconds. How about wake meandering or finer flow effects? How about large-eddy simulations? Add citations or at least defend this statement. Similarly, motivate choices of spatial resolution and sample time of the inflow.

Response: The wind farm modelling required for this study needs only to include effects necessary for modeling the power production of the wind turbines, the wake meandering, and the yaw dynamics. Higher frequencies ($>1\text{Hz}$) are not correlated across the wind farm and represent local turbulence variations. These are important for the turbine loads, of course, but loads modeling falls outside the scope of the model. Higher frequencies are, however, relevant for the proper modeling of the nacelle yaw dynamics, and are therefore included into the model (but uncorrelated in space). The modelling approach, followed in this work, is actually quite well aligned with earlier work of others: Bossanyi (2018) and Simley (2020). We have now indicated this in the revised manuscript through the following addition at the end of the first paragraph of Section 2.1:

“Notice that this approach is quite similar to those followed by Bossanyi (2018) and Simley et al. (2020), where the authors also split the wind field spectrum into low-frequency (for the wake dynamics) and high-frequency (for the turbine yaw dynamics). In Bossanyi (2018), the same spacial resolution is used for the low-frequency wind field as well.”

Regarding the sampling time, the text states already that it is

“.... roughly equal the time it takes air flow to cover a distance of $2D$.”

Given the fact that $2D$ is the special resolution, we believe this makes sense.

- d. Line 302: motivate natural frequency of meandering

Response: We could not find the text (around line 302) to which this comment relates. However, for the good order, we added a relevant citation in the first paragraph of Section 2.1 in the revised manuscript, regarding the wake meandering modeling on which our choice of $2D$ for the special resolution is based:

“The chosen spacial resolution of the wind fields is around two rotor diameters ($2D$), which is in accordance with the wake meandering modelling in Larsen et al. (2008).”

- e. Would be nice to clearly define the novel contributions in this article vs. what was done in previous work. FarmFlow already existed, but has been made dynamic: that is new, no? Uncertainty quantification is novel, at least for that exhaustive of a parameter set. Robust AWC and hysteresis already existed in literature, right?

Response: Good point. As already mentioned in our response to 1 a), we added a heading “Contribution of this work” in the introduction. We have now also added a summary of the main contributions of the paper for more clarity:

“In summary, the main contributions in this work are as follows:

- Development of dynamic wake model, based on the originally static FarmFlow tool, suitable for design and evaluation of AWC solutions.
- Exhaustive uncertainty quantification analysis, pinpointing the most important uncertainty contributors that need to be considered in a robust AWC design setting.
- Optimization of the parameters of a dynamic AWC algorithm using a wide range of dynamic simulations, with the purpose of maximizing the power gain and minimizing the yaw duty.
- Design and evaluation of a dynamic robust AWC algorithm for a realistic case study with a full scale wind farm.”

Minor comments

1. The abstract contains the general outline of the paper but misses the actual contributions and results. It currently does not suffice as a standalone summary of the paper. Please include the core findings, qualitatively but also quantitatively. For example, depict the parameters that were found to be the most important from the sensitivity analysis, depict the potential AEP gain in percent, and so on.

Response: We have extended the abstract as suggested, by including the following text:

“To this end, an uncertainty quantification analysis has first been performed for a range of variables (wind speed, wind direction, yaw error, turbulence intensity, wind shear, air density, power curve, thrust curve, power loss coefficient due to yawed error), which indicated the wind direction, yaw error, turbulence intensity and the wind velocity as the highest uncertainty contributors. Robust AWC has next been synthesized by including stochastic uncertainties in these parameters. A stationary analysis through stochastic averaging indicated that the robust AWC design only slightly outperforms the nominal one in terms of power gain. For the dynamic design and analysis, the originally stationary FarmFlow wake model has been extended to enable dynamic simulations, including wake dynamics and a dynamic yaw control model. By selecting a certain dynamic adaptation algorithm structure (a low-pass filter, hysteresis, and sample and hold mechanism), a wide range of dynamic simulations has been performed to optimize its parameters for achieving the best balance between power gain and yaw duty. Dynamic simulations for a realistic case study with a full-scale wind farm indicated that the developed dynamic robust AWC results in a large reduction of the yaw duty (30-50% lower) while at the same time improving the overall power gain (2.05% vs. 0.56%), as compared to the conventional nominal AWC.”

2. Generally, and especially when citing literature, you should clarify the test environment used in that publication. The differences between a FLORIS-based simulation study, a SOWFA-based simulation study, a field experiment or a wind tunnel experiment are very significant.

Response: Of course, and we believe we have done that in many places in the original manuscript, such as on Line 55 "...in recent field studies with wake redirection (Fleming et.al., 2020, 2019)", Lines 67-69 "Above-mentioned studies on robust AWC were all performed using a simplified control-oriented wake model, namely the FLOW Redirection and Induction in Steady State (FLORIS) model - an understandable choice given the computational requirements for robust optimization.", Lines 70-71 "...utilizing a different steady-state wake model, called the lifting line model.", Line 83 "In Simley et.al (2020), for instance, dynamic simulations have been performed using the stationary FLORIS wake model", etc. It is unclear to us what the point of this comment is.

3. For literature review: similar work is from M. Sinner et al., 2021, but this only appeared in April 2021. I can understand that the authors had already finished this publication mostly by then. You could consider including it in a revision.

"Power increases using wind direction spatial filtering for wind farm control: Evaluation using FLORIS, modified for dynamic settings", Sinner et al., 2021, JRSE

Response: Thanks for pointing us out to this relevant recent publication, we have of course included a citation in the revised manuscript through the following text in the introduction:

"Combining these techniques with wake steering was considered recently in the work of Sinner et al. (2021) using a modified FLORIS model."

4. Line 96: "This analysis ... the wind velocity." This is a conclusion and should not be part of the introduction. Rather, the introduction should be limited to what topics will be addressed in the article. The same goes for the sentence starting at line 99: "A stationary analysis ... of power gain." Nice, but should go to conclusion.

Response: Agreed. The sentence on Line 96 of the original manuscript has been removed, and the next sentence modified to:

"Based on the results from this analysis, robust yaw misalignment set-points have been optimized with respect to the most significant uncertainty sources, modelled as independent stochastic processes with selected PDFs."

The sentence commencing at Line 99 has been modified to:

"A stationary analysis based on stochastic averaging has been carried out to evaluate the performance of the robust AWC design as compared to the nominal one in terms of power gain."

5. Line 182: "wake generated by a wind turbine is propagated downstream based on the local wind direction variations in its way", I do not understand this.

Response: The sentence has been rephrased as follows:

"To this end, the wake generated by a wind turbine is propagated downstream in such a way that it follows on its way the local wind direction variations in the wind field. This way, both time delay and meandering effects are modelled."

6. Line 183: "because the traveling time ... current time window." I do not understand this.

Response: This sentence has been rephrased as follows:

"Since the travel time of a wake between two turbines takes longer than the simulation sample time, ..."

7. Line 202: "written in an output file", this seems inefficient. Can this not directly be

exchanged through memory or over a network protocol?

Response: This certainly can, and might be implemented in future updates of the software tool.

8. Line 260: On what signal does the LP filter work?

Response: The following clarification was added to the LP filter description:

“As visualized in Fig. 1, the LP filter acts on the wind speed and wind direction signals.”

9. Line 314: You mention that the PDF for turbulence intensity is based on historical data. Does your definition of TI (i.e., being the standard deviation in streamwise direction, match up with the definition in the data? I can imagine that the historical data considers the TI to include both streamwise and cross-stream turbulence.

Response: Our definition of TI in the wake model and in the wind field generator is, in fact, pretty standard, and as such are strictly speaking not exactly matching the definition TI measurements based on 10 minute statistical met mast data (mean value and standard deviation of the measured wind velocity). However, notice that these data is used to construct a rough, though realistic, statistical model of the turbulence intensity *variations*, which serves primarily as an example to based the robust analysis and design on. We do not believe that tinkering around the edges here will improve the value of the paper.

10. Line 349: What optimization algorithm is used? How confident are you that the solution has converged? What are the bounds, e.g., have you limited the minimum and maximum yaw angles?

Response: The following text has been added in Section 3.2 to explain the optimization algorithm used in this study:

“To solve the underlying optimization problems, a tailor made algorithm has been used that requires a minimum number of function evaluations (farm simulations) to converge. The algorithm is similar to the conventional bisection method, but generalized to multivariate objective functions. By confining the optimization variable to lie within an initial n-dimensional box, the gradient of the objective function is evaluated at the centre point at each iteration and the box is reduced in size by keeping only that part that is oriented opposite to the gradient. While this algorithm has no theoretical guarantees to converge to an optimum solution for general nonlinear functions, has been successfully used for many years by the authors and works pretty well for the application at hand, its low calculation effort being its main advantage over alternative algorithms. This allows it to be used in combination with relatively complex wake models such as FarmFlow. To reduce computation time even more, the number of optimization variables is limited to the yaw set-points of the two most upstream turbines in each row of turbines oriented downstream. The yaw set-points for the remaining turbines in the row are linearly decreased between the second turbine and the last one, which has zero yaw misalignment set-point. No limitation has been applied to the yaw set-points in this section.”

To clarify that this algorithm is used in all optimizations throughout the paper, the following like is added at the end of Section 3.3:

“All optimization problems are solved by using the algorithm, described in Sect. 3.2. The yaw misalignment angles have been limited to ± 30 degrees.”

11. Table 3: the wind speed range seems so high, while in reality you could feed in the wind speed measurements into the LUT, perhaps with an uncertainty bound but definitely smaller than an uncertainty of 8 m/s. How do you defend this decision? Also, how do these findings line up with your earlier work stating that wind speed can be ignored in yaw optimizations?

Response: In fact, the idea is to not use the wind speeds as an argument for the LUT (other than for switching AWC on and off), but rather to have the LUT robust with respect to the whole range of wind speed variations. This is mentioned in the first paragraph of Section 3, as well as in the second bullet point in Section 3.1, where the modeling of the wind speed uncertainty is described. Nevertheless, to better clarify this, the following line is added to the mentioned bullet point:

“Instead, the LUT will be designed to be robust to wind speed variations.”

12. Line 381: I would have expected the yaw-induced power loss coefficient to have a larger effect on the optimal yaw angles, since it directly impacts the energy lost by yawing an upstream wind turbine. Can you reason why this is not the case in this study?

Response: You are absolutely right. Large variations in the yaw-induced power loss coefficient result in significant variations in the optimal yaw set-points. Take, for instance the result for Case 2 in Figure 5, depicted by the middle (green) bar plot. The optimal yaw misalignment of the first turbine is around 22° for yaw-induced power loss coefficient of 2.3, and 35° for a coefficient of 1.3. Computing the corresponding power losses, $\cos(\beta)^\alpha$, one gets 0.84 for $\alpha=2.3$ and $\beta=22^\circ$, and 0.77 for $\alpha=1.3$ and $\beta=35^\circ$. The larger power loss at the first turbine in the later case is then compensated by the corresponding higher yaw misalignment, leading to increased power production downstream. So the results make perfect sense. Including the assumed distribution in Figure 4, however, narrows down the most probable range of variations of the yaw-induced power loss coefficient to below 1.7, leading to a quite small size of the green box in Figure 5. To summarize, the yaw-induced power loss coefficient does affect the optimal yaw set-points, but for the assumed uncertainty model (PDF) this impact remains limited and the parameter does not need to be considered in the robust optimization.

13. Figure 5: yaw angles of -40 deg and + 45 deg seem excessive. Can you explain your choice for allowing yaw angles to go all the way to these values? Since we would never optimize the yaw angles until those limits in practice, this may skew the sensitivity analysis somewhat, no? Perhaps certain parameters are important at high misalignment angles, but really are not that important in the range we expect to yaw the turbines to.

Response: This is, in fact, quite a good point, and not touching upon it is indeed an omission. The optimizations in Section 3.2 have been consciously performed without applying limitations on the yaw misalignment, as the exact limitations that will apply in future applications are not exactly known and the results from the uncertainty quantification analysis should be generic. However, as limitations will apply in practice, we agree it is important to discuss their impact. We have added the following paragraph to Section 3.2 to discuss this important aspect:

“Notice that, due to the fact that no limitations have been imposed, the yaw misalignment set-points are getting quite high in some cases, raising to values of 40 degrees and even higher. Such a high yaw misalignments are currently considered unrealistic in a real-life application. Usually, they are limited to around 30 degrees in many research studies, or to even lower values in the first field tests with wake redirection (Flemming et al., 2017, 2019;

Doekemeijer et al., 2021). It becomes clear from Fig. 5 that by imposing a limitation of ± 30 degrees one would significantly limit the variation in the yaw misalignment set-points. Nevertheless, the main conclusions drawn above in terms of the most significant uncertainty contributors will still hold, with probably only the wind shear disappearing from this list.”

14. Figures 5 & 6: please add legends:

Response: Legends added to Figures 5 and 6!

15. Line 414: should it read 'arg max' instead of 'arg min'?

Response: Of course it should. We have fixed this, as well as 4 other occurrences!

16. Line 434: "...only decent directions...", what are "decent directions"?

Response: This sentence is not present in the revised manuscript. Instead, as explained in the Response to question 10 above, the description of the optimization algorithm has been explained in detail in Section 3.2.

17. Figure 8: neither line is particularly smooth. Does this suggest that the optimization has not converged?

Response: This has to do with the nonlinearity of the objective function, the chosen optimization algorithm, and the termination criterion, indeed. It is, of course, possible to improve the optimizer to get smoother curves, but that would require increasing the calculation time significantly. We believe, however, that this is not really necessary since resulting power gain is not very sensitive on such relatively small variations of the yaw misalignment angles. This fact can be appreciated from Figure 12, noticing that the power gain barely changes between nominal and robust AWC. Smoothing of the yaw set-points can be easily done after the optimization, which does save a lot of calculation effort, especially when designing AWC for the complete spectrum of wind conditions in a full scale wind farm. Robust design does, however, deliver smoother yaw angles in general.

18. Figure 9: "robust AWC" and "nominal AWC (with uncertainty)" are not the same thing, yet it is hard to distinguish them in their definitions. Can you clarify?

Response: We have added the following text at the end of Section 5.1 to clarify the different curves in the figure (now Figure 12 in the revised manuscript due to the change explained in the Response to Major comment 1h):

“For the sake of clarity, the difference between the red curve “nominal AWC (no uncert.)” and the black curve “nominal AWC (with uncert.)” in Fig. 12 is that the former one depicts the power gain evaluated just for the nominal values of the uncertainty parameters (p^{nom}), while the later one represents the gain evaluated by including the whole uncertainty set U through the joint PDF $D_d(p)$. In both cases, the yaw misalignment set-points are the same, namely γ_{nom} , optimized for the nominal values of the parameters p^{nom} , i.e. neglecting the uncertainty, as defined in Eq. (4). The blue curve “robust AWC” corresponds to the case when both the optimization of the yaw set-points and the evaluation of the power gain are performed by accounting for the uncertainty through $D_d(p)$.”

19. Figure 11: 11% Energy gain is very substantial and not particularly realistic for AEP. Maybe repeat that this is for particular 3-turbine case. Also, these figures are hard to see. I would suggest turning them into top-view (2D) contour plots instead. Same goes for Figure 12.

Response: The 11% gain is not for AEP but for the performed simulation conditions only, mean wind velocity of 8 m/s and wind direction varying around 270 degrees. 11% power gain is not at all unusual in such a scenario, as you would agree. We added a clarification about the simulation conditions in Section 4 as follows

"The average wind velocity is 8 ms^{-1} , and the wind direction varies around 270° (see light grey line in Fig. 10)."

20. Line 555: Just to clarify, so dynamic FarmFlow runs 1:1 (6 hours of simulation means 6 hours of computing in real time on a single core)? If so, it may be worth evaluating the potential for a full year of operation (~9,000 CPU hours).

Response: Correct. A full year can easily be calculated on a computer cluster.

21. Line 567: "Notice that the overall gains are lower than one might expect", what would be a reasonable number to expect? 0.5-2% energy gain is still significant if you ask me.

Response: Again, the power gains are not on annual basis (AEP), but for the simulated wind conditions only. You would agree that for the "more beneficial" wind directions the power gain is usually higher than that.

Technical comments

1. Variables should be italic, units should not.

Response: We have carefully gone through the text, including the tables, and changed all noticed occurrences of italic units to regular. The variables were properly typeset in the original manuscript already.

2. Line 4: "by up to a few percentage points." Why percentage points and not percent?

Response: "percentage points" changed to "percent".

3. Line 19: "possible power gains of up to a few percent on annual basis". Can you motivate this further, maybe add citations? To me, it seems that it is more towards a single percent, especially when looking at the most recent field experiments.

Response: This question is quite similar to that posed in Major comment 2a. Please, refer to our response to that comment.

4. Line 20: The second challenge is presented as being mainly due to wake models being of static nature.

Response: As stated in the text: "The second challenge is related to the uncertainty in the predictions for the expected annual energy production (AEP) increase, caused by the simplistic static approach that is currently used to optimize AWC on the one side, and the underlying uncertainties in the modelling used for that purpose on the other side."

5. Figure 1: it says "yaw systems". Should it be "yaw system" since its for a single turbine?

Response: Yes, we changed it to "yaw system".

6. Figure 1: The Robust AWC LUT seems only a function of wind direction and wind speed. Does this mean local WS/WD?

Response: The local wind conditions are used by the AWC algorithm. To clarify this in the text, the following line is added in the first paragraph of Section 2.4:

“In the implementation, used in this work, the AWC algorithm receives the local wind speed and wind direction as measured at turbine level.”

7. Line 149: "frequencies above 10e-3 Hz", should this be "above 10e-3 Hz"?

Response: I don't understand this comment. I believe the sentence is clear: “This Kaimal spectrum is used for frequencies above 10^{-3} Hz, i.e. time scales of 30 minutes and slower.”

8. Line 279: "In this work ... robust design setting." I understand what you mean, but perhaps reformulate it in a clearer way. For example, differentiate between variables included as uncertainties in the optimization process and variables that are used for the real-time interpolation of setpoints.

Response: We have rewritten this text as follows to improve the clarity:

“In this work, the yaw misalignment set-points in the LUT will essentially be a function of the wind direction only. The wind speed signal entering the block “Robust AWC (LUT)” in Fig. 1 is meant to indicate that AWC is only active in a certain range of below rated wind conditions ($4\text{-}12\text{ ms}^{-1}$ used here).”

Response to Reviewer RC2

Dear reviewer, thank you so much for the kind words and the useful comments and suggestions for improvements. Below, we have listed your comments and have provided our response after each one. The changes made to the manuscript are indicated by the boxed texts.

General Comments:

- Section 2.1: Do I understand that wind directions variations occur in the range of 30min - 24hr, and that faster frequencies are uncorrelated spatially? If we expect a wind turbine to yaw something like several times every 10 minutes does this match?

Response: No, in fact both the micro-scale model ($f > 10^{-3}$ Hz) and the meso-scale model ($f < 10^{-3}$ Hz) include spatial correlation, as modelled in equation (1). Kindly note the sentence just before the equation stating "For the complex cross power spectrum between two points in space, r and s , the following expression is used for both the micro and the meso scale spectra ...".

- Could you provide a definition of stochastic programming in general and how it is used in this work?

Response: Definition of the stochastic programming problem, as well as explanation of how it is numerically solved in our work, are explained in detail in Section 3.3. Since the objective function cannot be evaluated in its continuous form, the joint PDF is first discretized and the resulting optimization problem is solved through the algorithm described in Section 3.2. This approach, based on discretization, has already been used by others in this application, and we have included citation to that work in the revised manuscript:

"To solve this problem numerically, the continuous PDFs are discretized as in Rott et al. (2018); Simley et al. (2020)."

Specific comments:

- Page 2: "This conclusion is implicitly confirmed by the fact that the industry starts to develop this technology into commercial products (Siemens Gamesa Renewable Energy, 2019)." Could also be that the loads are higher but not importantly so?

Response: This is certainly true. The point we were trying to make is that the loads don't seem to be an obstacle for the implementation of AWC, but we have removed the following sentence in the revised manuscript to avoid any misinterpretations:

"This conclusion is implicitly confirmed by the fact that the industry starts to develop this technology into commercial products (Siemens Gamesa Renewable Energy, 2019)."

- Page 3: "In a different work, the same author demonstrates that a centralized yaw control strategy, in which information from surrounding wind turbines is used in the yaw control algorithm, can lead to a drastic reduction in the yaw duty and increase the power capture at the same time (Bossanyi, 2019)." This could also be related to the concept of consensus control: Annoni, J., Bay, C., Johnson, K., Dall'Anese, E., Quon, E., Kemper, T., and Fleming, P.: Wind direction estimation using SCADA data with consensus-based optimization, Wind Energ. Sci., 4, 355–368, <https://doi.org/10.5194/wes-4-355-2019>, 2019.

Response: This is definitely a very relevant work, we have included a reference to it in the Introduction through the following text:

"Related to that is the work of Annoni et al. (2019) focused on constructing consensus wind direction estimates."

- This sentence: “This Kaimal spectrum is used for frequencies above 10–3 150 Hz, i.e. time scales of 30 minutes and slower”. If the range is above a frequency, do you mean lower and not slower?

Response: Yes, slower is now changed to lower.

- Page 6: “The parameter $c(\alpha_{rs})$ is the decay factor”. Decay of what?

Response: We have added the following clarification regarding this parameter:

“The parameter $c(\alpha_{rs})$ is the decay factor, a parameter characterizing the decay rate of the coherence function.”

- Page 10: Recommend to explain figure 2 in more detail in the caption

Response: We modified the caption of the figure as follows to make it more explanatory:

“Illustration of the impact of wake on wind measurements and yaw motion of two commercial wind turbines, when the second turbine (T2) is in the wake of the first one (T1). The thin lines represent LP filtered wind direction measurements at the two turbines, while the thick ones -- the nacelle position measurements.”

- Page 13: Don't need to revise the paper, but wanted to note I think some recent papers might point to a distribution for yaw loss exponent centered somewhat higher, or even dependent on wind speed: Simley, E., Fleming, P., Girard, N., Alloin, L., Godefroy, E., and Duc, T.: Results from a Wake Steering Experiment at a Commercial Wind Plant: Investigating the Wind Speed Dependence of Wake Steering Performance, Wind Energ. Sci. Discuss. [preprint], <https://doi.org/10.5194/wes-2021-61>, in review, 2021.

Response: Of course, very relevant work. We have included a reference to it in the text as follows:

“Related to that is the work of Annoni et al. (2019) focused on constructing consensus wind direction estimates.”

- Page 15. “Variations in the thrust curve and the yaw-induced power loss exponent have generally limited impact on the optimal yaw set-points, which suggests that they could be left out from the robust optimization.” This is surprising, at least for the power curve exponent, it would seem that at some loss level it would start to have a strong impact,?

Response: You are absolutely right. Large variations in the yaw-induced power loss coefficient result in significant variations in the optimal yaw set-points. Take, for instance the result for Case 2 in Figure 5, depicted by the middle (green) bar plot. The optimal yaw misalignment of the first turbine is around 22° for yaw-induced power loss coefficient of 2.3, and 35° for a coefficient of 1.3. Computing the corresponding power losses, $\cos(\beta)^\alpha$, one gets 0.84 for $\alpha=2.3$ and $\beta=22^\circ$, and 0.77 for a $\alpha=1.3$ and $\beta=35^\circ$. The larger power loss at the first turbine in the later case is then compensated by the corresponding higher yaw misalignment, leading to increased power production downstream. So the results make perfect sense. Including the assumed distribution in Figure 4, however, narrows down the most probable range of variations of the yaw-induced power loss coefficient to below 1.7, leading to a quite small size of the green box in Figure 5. To summarize, the yaw-induced power loss coefficient does affect the optimal yaw set-points, but for the assumed uncertainty model (PDF) this impact remains limited and the parameter does not need to be considered in the robust optimization.

- Page 19: “The yaw set-points for the remaining turbines in the row are linearly decreased between the second turbine and the last one, which has zero yaw misalignment set-point.” This is a great idea! Is this novel to this paper or has it the concept been used elsewhere?

Response: Well, it’s not really new, this is an approach we use for years to reduce the computational time for the optimization. It is first mentioned in our work:
Kanev, S.; Savenije, F. & Engels, W. Active wake control: an approach to optimize the lifetime operation of wind farms, Wind Energy, 2018, 21, 488-501

- Page 21: Metrics are really useful, the power gain per unit yaw travel increase is very interesting, is this also a novelty of this paper or something used in other papers or other contexts

Response: Well, we haven’t seen these metrics in other publications, but they are probably also not too difficult to invent when one tries to capture the wish to optimize the balance between yaw duty and power gain into a cost function.

- Page 23: Results for hysteresis are very promising. If 4 deg is both the highest value tested and the best overall, does it suggest 5 deg or more should be considered?

Response: Yes, in fact it does. This should be considered in future studies. We have included the following comment in the revised manuscript:

“This result also suggests that even higher values for the hysteresis size be considered in future studies.”

- Page 24: “Having significantly less start/stop events in the reference case than with AWC might first seem counter-intuitive, but does happen”. Did this sentence mean to say the reverse (49% reduction)?

Response: You are completely right, thanks for noticing. We have corrected the sentence as follows:

“Having significantly less start/stop events with AWC than in the reference case might first seem counter-intuitive, but does happen.”

- Page 28: Recommend to cite paper mentioned above on consensus control

Response: Due to a recommendation of the third reviewer to shorten the Conclusions, we have completely removed the topics for future research from the manuscript, including the part related to consensus control.

Response to Reviewer EC1

Dear reviewer, thank you for the useful comments and suggestions for improvements. Below, we have listed your comments and have provided our response after each one. The changes made to the manuscript are indicated by the boxed texts.

Remarks:

- Pg 1. “considered as the most potential technology” please add a citation
Response: We don’t quite understand this comment, as there were already three citations in the original manuscript: “More specifically, the wake redirection approach to AWC, employing intentional yaw misalignment to steer wakes away from downstream turbines, is currently considered as the most potential technology with respect to power production increase, with possible power gains of up to a few percent on annual basis (Kanev et al., 2018; Gebraad et al., 2017; Fleming et al., 2016).”
Please, let us know if there is any specific publication that is more suitable to cite here, and we will be happy to include it.
- Pg 3. “is quite unrealistic” also a rather bold statement
Response: We rephrased the sentence “As such, this model is quite unrealistic as it completely neglects spacial inflow variations” as follows

“However, it completely neglects spatial inflow variations.”
- It is “spatial” instead of “special”?
Response: We used the word “spacial”, but agree that “spatial” is more commonly used. We have now replaced all occurrences of “spacial” with “spatial”.
- Section 2, at the beginning they talk about different sample rates (yaw vs flow) and there they question arises if you can do that. Later in the article they explain that the flow has two time scales (fast and slow).
Response: We have added the following sentence at the beginning of Section 2 in the revised manuscript to clarify this point:

“This is achieved by superimposing higher frequency noise to the wind directions coming from the wake model.”
- Fig. 1. is really nice
Response: Thank you
- Pg. 7. “because” ...”because” (two sentences in a row)
Response: The repetition has been removed by rephrasing the first sentence as follows:

“Since the travel time of a wake between two turbines takes longer than the simulation sample time, the arriving wakes from upstream turbines need to be time synchronized with the departure of wakes in the current time window.”
- Pg. 7. How the steps are explained it is just not clear. It is also not relevant that you are working with DLL’s
Response: The text explaining the different steps in the simulation of the wake model has been revised as follows:

“1. For a given time instant, the simulation starts with the most upstream turbine with respect to the farm-average wind direction, and ends with the most downstream turbine.
 2. For a given turbine, all arriving wakes (if any), are determined using wake information calculated at previous time instances and stored in memory in Step 5
 3. From the undisturbed wind field and arriving wakes, a rotor averaged wind speed and wind direction is calculated.
 4. Given the determined rotor averaged wind conditions, and the yaw position (coming from the yaw system model in Step 8, see also Fig. 1), the yaw misalignment angle is computed. Subsequently, the power production and rotor thrust force are determined, and a wake calculation is started using the (stationary) wake model in FarmFlow for the given turbine.
 5. The wake is calculated until reaches a downstream turbine (if any). The path of the calculated wake is determined using the time varying wind direction in the undisturbed wind field, resulting in wake meandering. The wake information is then stored in memory, including the time of arrival at the downstream turbine for use in the wake simulation of that turbine at a later time instant in Step 2.
 6. The simulation continues with the following most upstream turbine until all turbines have been simulated for the current time instant.
 7. The input and output data for all turbines are written in an output file, which forms the interface to a dynamic link library (DLL) that implements the yaw system dynamics and the dynamic robust AWC algorithm.
 8. The DLL is called, which updates the yaw positions of all turbines, and communicates this information back to FarmFlow. The simulation of the next time instant is initiated in Step 1.”

- Section 3, this should really be connected to ongoing efforts/frameworks

Response: We have revised the second paragraph in Section 3 as follows to reflect the contribution of the present work to existing one:

“This section considers the synthesis of robust AWC in which a number of parameters is treated as uncertain, continuing along the lines of previous work by Quick et al. (2020). Here, a more extensive list of uncertain parameters is treated, consisting of quantities related to model parameter uncertainty, measurement uncertainty and input variability, all treated in a unified stochastic framework using PDFs (Sect. 3.1). The impact of these uncertainties on the optimal yaw set-points is quantified through forward uncertainty propagation (Sect. 3.2). To this end, the PDFs are sampled and the underlying simulations are performed using the conventional (static) FarmFlow wake model. This allows to evaluate how much the optimal yaw set-points change as result of variations in the different uncertain parameters within their assumed uncertainty sets, so that it can be decided which uncertain parameters should be included into the robust optimization. In Quick et al. (2020) a similar analysis is performed by focusing on the impact of variations in the sizes of the uncertainty sets instead. Finally, the robust AWC design is performed by solving a stochastic programming problem through discretization of the probability distributions to arrive at a finite number of scenarios (Sect. 3.3), similar to Rott et al. (2018); Simley et al. (2020).”

In addition, regarding the wind direction variability having the largest impact, the following line is added to the list of observations, made in Section 3.2:

“This conclusion confirms earlier observations by \citet{Quick:WES20}.”

- Pg 22. Figure 11 is not clear, Figure 12 is better (color) but still hard to read

Response: We have updated Figure 11 by plotting the surfaces in color. Notice that it has become Figure 9 in the revised manuscript, as result of part of Section 4 having been moved to Section 5 in response to a suggestion of the first reviewer.

- Conclusion: is a conclusion of a research report and should be shortened. It should answer the research question (is there a research question?).

Response: We have significantly shortened the length of the Conclusions by removing the whole last paragraph related to possible topics of future research. In addition, we have stated the research question more clearly in the beginning of the Conclusions as follows:

“The aim of this paper is to develop a framework for the design of dynamic robust AWC for optimizing the balance between the yaw duty and the power gain under realistic conditions, accounting for wind resource variability and model and measurement uncertainty, as well as to assess its benefits with respect to the conventional nominal AWC design.”

We believe the remainder of the section is clearly focused on this research question, briefly explaining the methodology and focusing on the conclusions drawn from the obtained results.

Dynamic robust active wake control

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Abstract. Active Wake Control (AWC) is a strategy for operating wind farms in a way to maximize the overall power production and/or reduce structural loading on the wind turbines. Many recent studies indicate that this technology, and more specifically the so-called wake redirection approach to AWC, have a significant potential for increasing the annual energy production (AEP) by up to a few ~~percentage points~~percent. The current state-of-the-art approach is to optimize AWC for a range of static wind conditions, which is expected to perform sub-optimally in real-life due to the continuous variations of the wind resource and the very slow yaw dynamics of the turbines. Recent work has addressed this variability in a robust design setting with the focus on maximizing the energy capture (robust AWC). This paper continues on this line of research, and develops a *dynamic* robust AWC strategy that aims to optimize the balance between maximum power production (requiring increased level of yawing) and minimum loads on the yaw drive (requiring limited yaw motion). ~~It is shown with a~~

To this end, an uncertainty quantification analysis has first been performed for a range of variables (wind speed, wind direction, yaw error, turbulence intensity, wind shear, air density, power curve, thrust curve, power loss coefficient due to yawed error), which indicated the wind direction, yaw error, turbulence intensity and the wind velocity as the highest uncertainty contributors. Robust AWC has next been synthesized by including stochastic uncertainties in these parameters. A stationary analysis through stochastic averaging indicated that the robust AWC design only slightly outperforms the nominal one in terms of power gain. For the dynamic design and analysis, the originally stationary FarmFlow wake model has been extended to enable dynamic simulations, including wake dynamics and a dynamic yaw control model. By selecting a certain dynamic adaptation algorithm structure (a low-pass filter, hysteresis, and sample and hold mechanism), a wide range of dynamic simulations has been performed to optimize its parameters for achieving the best balance between power gain and yaw duty. Dynamic simulations for a realistic case study with a full-scale wind farm indicated that the developed dynamic robust AWC can result in a large reduction of the loading on the yaw drive yaw duty (30-50% lower) while at the same time improving the overall power gain (2.05% vs. 0.56%), as compared to the conventional nominal AWC.

1 Introduction

During the last decade, the field of active wake control (AWC) has been widely studied by many researchers worldwide. AWC is an approach to operate the wind turbines in a wind farm in a collaborative manner with the aim of reducing the negative effects of the wakes behind wind turbines on the overall power production and the individual wind turbines' structural loading (Andersson et al., 2021; Kheirabadi and Nagamune, 2019; Boersma et al., 2017). More specifically, the wake redirection

approach to AWC, employing intentional yaw misalignment to steer wakes away from downstream turbines, is currently considered as the most potential technology with respect to power production increase, with possible power gains of up to a few percent on annual basis (Kanev et al., 2018; Gebraad et al., 2017; Fleming et al., 2016).

30 AWC implementation challenges

At present, large scale implementation of wake redirection AWC is hampered by two main challenges. The first one concerns the increased risk perception due to the required operation under significant yaw misalignment, driven by the lack of comprehensive understanding of the impact on the structural loading on the turbines, often in combination with restrictive obligations in service contracts. The second challenge is related to the uncertainty in the predictions for the expected annual
35 energy production (AEP) increase, caused by the simplistic static approach that is currently used to optimize AWC on the one side, and the underlying uncertainties in the modelling used for that purpose on the other side. Within the past few years, some initial results addressing these challenges have started to appear in the literature. With respect to the first one, for instance, most existing studies are limited to just one or two turbines (Fleming et al., 2013, 2015; Croce et al., 2020; Zalkind and Pao, 2016). A more detailed study involving a utility scale wind farm was presented in Kanev et al. (2020), where the impact of wake
40 steering AWC on the structural loads of the turbines during their complete lifetime has been investigated using the so-called loads lookup table (LUT) approach (Reyes et al., 2020). The results demonstrate that, even though by itself yaw misalignment does increase the structural loads of some turbines in specific wind conditions, the wake-induced loading is decreased even more, so that the accumulated loads over the whole lifetime of each wind turbine generally remain lower than without AWC. ~~This conclusion is implicitly confirmed by the fact that the industry starts to develop this technology into commercial products (Siemens Gamesa Renewable Energy, 2019).~~

To sort out the second challenge, however, further research is required. The uncertainty in the AEP predictions is driven by a wide range of factors: the variability in the wind resource, wake meandering, uncertainties in the environmental conditions (atmospheric stability, turbulence, shear, veer, etc.), the slow dynamics of the yaw system, wake model uncertainties, measurement uncertainties, etc. Disregarding these, as done in the current state-of-the-art approach to AWC design that relies on
50 optimization under stationary conditions, gives rise to suboptimal performance in real-life, i.e. lower power gain or, possibly even loss of power. To ensure maximum power gain in the field, it is essential to move from the current static approach to dynamic robust AWC design that properly accounts for the mentioned variabilities and uncertainties. One way to achieve that is by means of a two-stage approach, where the term “robust” relates to the selection of static yaw misalignment set-points that maximize power production in the presence of uncertainties (either deterministic, or stochastic), while the “dynamic” part
55 deals with the adaptation of the set-points based on the highly varying wind resource measurements aiming to optimize the balance between maximal power gain and minimal loading on the yaw drive. The importance of achieving both robustness and optimized yaw dynamics has become apparent in recent field studies with wake redirection (Fleming et al., 2020, 2019).

State of the art

The topic of robust AWC design has already attracted the attention of some researchers. Quick et al. (2017) considered
60 yaw angle uncertainty into the optimization for the yaw misalignment set-points. The uncertainty was modelled in a stochastic setting assuming Gaussian probability density function (PDF). This work was followed by Rott et al. (2018), where robustness

with respect to wind direction variability and wind direction measurement uncertainty was considered, both modelled through a single PDF. Later on, in 2020, two relevant publications appeared. In the first one, Simley et al. (2020) presented results on robust AWC optimization including uncertainty in both the wind direction and the yaw position. They evaluated the performance of the robust AWC in case studies with different wind turbine spacings and turbulence intensities. The second work was published by Quick et al. (2020), and considers robustness with respect to a range of uncertain parameters, namely wind speed, wind directions, turbulence intensity, wind shear and yaw angle. The authors used a polynomial chaos expansion approach to deal with the underlying high computational complexity of the resulting optimization, and demonstrated that the wind direction is the most significant contributor to uncertainty in the power predictions. Above-mentioned studies on robust AWC were all performed using a simplified control-oriented wake model, namely the FLOW Redirection and Induction in Steady State (FLORIS) model – an understandable choice given the computational requirements for robust optimization. Finally, Howland (2021) studied AWC robustness with respect to model parameter uncertainty and wind direction uncertainty, utilizing a different steady-state wake model, called the lifting line model. The author uses an Ensemble Kalman filter to estimate the relevant wake model parameters and the corresponding probability distributions. In the simulation setup considered there it appeared that including model uncertainty gives rise to a more significant improvement than wind direction uncertainty. It should also be pointed out that, as an alternative to the robust design of yaw offset set-points that are valid for a range of conditions, one could consider adaptive solutions in which the yaw set-points are updated in real-life based on (estimates of) the actual operating conditions. Such an approach is pursued in Howland et al. (2020), where a gradient ascent algorithm updates the yaw offsets at each iteration based on analytically derived gradients for the lifting line wake model, the parameters of which are estimated online.

With respect to dynamic AWC, there is only very limited research published so far. There are, however, numerous publications in which dynamic (or quasi-static) simulations are performed with AWC, that include the yaw system dynamics and variations in the wind conditions. However, the parameters of the AWC adaptation algorithm in these studies, typically a low pass filter acting on the wind direction and wind speed, are not optimized with respect to the power gain and/or the yaw duty. In Simley et al. (2020), for instance, dynamic simulations have been performed using the stationary FLORIS wake model by propagating the low-frequency components of the wind through the model (neglecting spatiotemporal inflow variations), and adding high-frequency components on top of those at turbine level to feed the yaw system model. In terms of dynamics, a more realistic wake model is used by Bossanyi (2018) that includes turbine and wake dynamic effects and utilizes a stochastic wind field correlated across the wind farm. The dynamic model has been used to simulate AWC and evaluate the impact on farm power and turbine loads. However, even though the authors state to have done a few iterations in choosing parameters of the dynamic AWC algorithm that appear to work reasonably, the presented study does not extend to the point of optimizing the AWC parameters with respect to energy production and yaw duty. In a different work, the same author demonstrates that a centralized yaw control strategy, in which information from surrounding wind turbines is used in the yaw control algorithm, can lead to a drastic reduction in the yaw duty and increase the power capture at the same time (Bossanyi, 2019). ~~Even though AWC is not considered in that study, it is mentioned by the author that the proposed yaw control strategy would be beneficial in AWC as well~~ Related to that is the work of Annoni et al. (2019) focused on constructing consensus wind direction estimates.

Combining these techniques with wake steering was considered recently in the work of Sinner et al. (2021) using a modified FLORIS model. Finally, in Kanev (2020) some initial results with optimizing the parameters of a dynamic AWC have been presented. Although the findings there clearly support the necessity of properly optimizing the dynamics of the AWC algorithm, the conclusions there remain of limited value due to the simplified modelling approach employed. More specifically, the stationary FLORIS model was used there, extended with a simple time delay model representing wake dynamics. ~~As such, this model is quite unrealistic as~~ However, it completely neglects ~~spacial~~-spatial inflow variations. Also missing in the modelling approach there is the impact of the increased turbulence in front of waked turbines on their wind measurements, and the resulting increased turbine yawing at downstream turbines.

Contribution of this work

The present work extends on above mentioned research in focusing on dynamic robust AWC. The first part of the study concerns *robust* design and analysis using stationary simulations with FarmFlow, a 3D parabolized Reynolds-averaged Navier Stokes code with prescribed pressure gradients and $k - \epsilon$ turbulence model (Bot and Kanev, 2020). The starting point is the selection of varying or uncertain quantities that can affect the performance of the AWC. To this end, an uncertainty quantification analysis has been performed for a range of variables (wind speed, wind direction, yaw error, turbulence intensity, wind shear, air density, power curve, thrust curve, power loss coefficient due to yawed error). ~~This analysis indicated that the highest uncertainty contributors are the wind direction, yaw error, turbulence intensity and the wind velocity.~~ Subsequently, Based on the results from this analysis, robust yaw misalignment set-points have been optimized with respect to ~~uncertainties in these parameters~~the most significant uncertainty sources, modelled as independent stochastic processes with selected PDFs. A stationary analysis based on stochastic averaging ~~indicated that the~~has been carried out to evaluate the performance of the robust AWC design ~~slightly outperforms as compared to~~ the nominal one in terms of power gain.

With the robust AWC in place, the second part of this study continues with the *dynamic* design and analysis. To this end, the originally stationary FarmFlow wake model has been extended to enable dynamic simulations, including wake dynamics and a dynamic yaw control model. ~~The dynamic simulation model is fed by a realistic wind field including temporal and spacial inflow variations, that include both micro-scale (fast turbulence variations ranging up to several hundreds of meters) and meso-scale (slow variations extending to ten kilometres and more), with corresponding coherence functions and cross power spectra that relate the stochastic properties between different points in space, and including terms to model the flow advection. The yaw dynamics are modelled at a faster sample rate than the wake model, and an additional higher frequency stochastic signal is added to the yaw error to model the increased noise in the yaw error measurements that enter into the yaw position controller. The size of this added noise is made dependent on the turbulence intensity in the flow in front of the turbine. This gives rise to an increased yaw activity of downstream wind turbines, as seen in real-life measurements.~~ Next, an AWC dynamic adaptation algorithm is considered, consisting of a low-pass (LP) filter, a hysteresis, and sample and hold mechanism, similar to (Kanev, 2020). Numerous dynamic simulations have been performed with different dynamic adaptation parameters, both with nominal and robust AWC yaw set-points. Based on the results from these simulations, the optimal parametrization of the dynamic AWC are determined. The resulting dynamic robust AWC is shown to deliver a large reduction in the yaw duty in combination with increase in the power gain as compared to the nominal AWC solution.

In summary, the main contributions in this work are as follows:

- Development of dynamic wake model, based on the originally static FarmFlow tool, suitable for design and evaluation of AWC solutions.
- Exhaustive uncertainty quantification analysis, pinpointing the most important uncertainty contributors that need to be considered in a robust AWC design setting.
- Optimization of the parameters of a dynamic AWC algorithm using a wide range of dynamic simulations, with the purpose of maximizing the power gain and minimizing the yaw duty.
- Design and evaluation of a dynamic robust AWC algorithm for a realistic case study with a full scale wind farm.

Structure of the paper

The remaining part of the manuscript is organized as follows. The next section summarizes the modelling used in the study. Sect. 3 outlines the the uncertainty quantification analysis, the selection of the dominant uncertainties, the design of robust AWC with respect to these and, finally, gives the results from a stationary robust analysis. Next, the optimization of the AWC dynamic adaptation algorithm is discussed in Sect. 4. Sect. 5 goes on with demonstrating the benefits from the developed dynamic robust AWC methodology on a case study with a model of an existing offshore wind farm. The manuscript is concluded with some final remarks in Sect. 6.

2 Wind farm Simulation model description

The wind farm simulation model consists of a stochastic wind field generator, dynamic wake model (dynamic FarmFlow), ~~model of the~~ wind turbines' yaw systemsmodel, and dynamic robust AWC. A block scheme of the simulation model is given in Fig. 1. ~~The~~, in which the four mentioned main components have been clearly indicated. The yaw models and the dynamic robust AWC are implemented in a dynamic link library (DLL), which is called by the dynamic FarmFlow code at each simulation step. The different line colors are meant to indicate different sample times. The base sampling rate (black lines) is set by the wind field time series (typically ~~0.1 Hz~~ 0.1 Hz or slower). The yaw model operates at faster sampling rates (green lines) to enable realistic modelling of the yaw motion (e.g. ~~1 Hz~~ 1 Hz), which is important to assess the impact of AWC on the yaw duty. This is achieved by superimposing higher frequency noise to the wind directions coming from the wake model. The actual simulation model has a much more extensive interface between the wake model and the AWC algorithm enabling a wide range of possible future applications, but is visualized here in a simplified way, sufficient for the present discussion. Finally, part of the AWC algorithm may operate at slower sampling rates (red lines). The main components are explained separately in more detail in the remainder of this section.

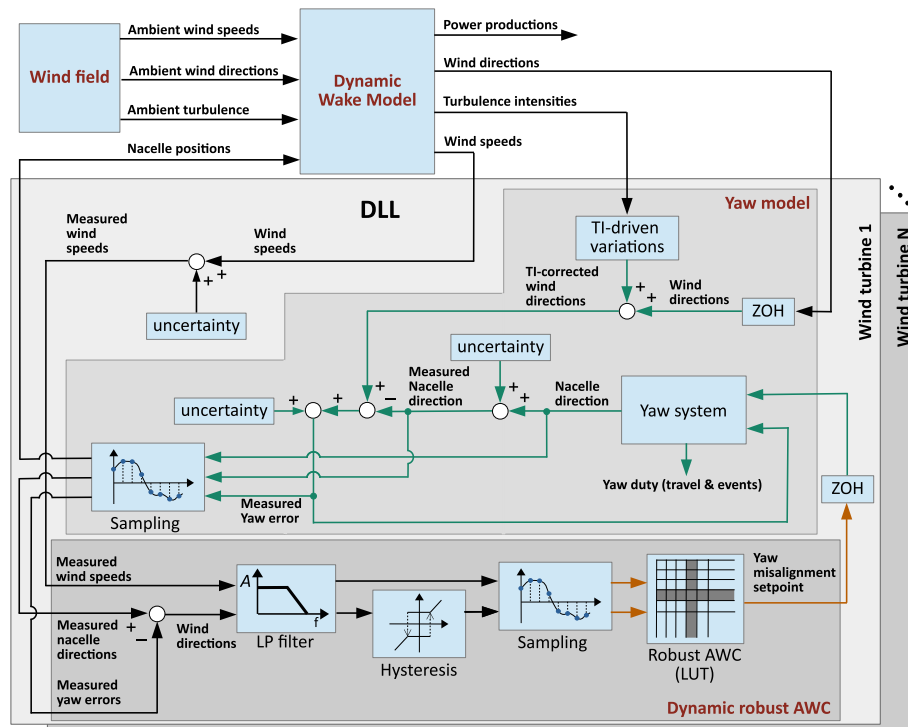


Figure 1. Block scheme of the simulation model

160 **2.1 Wind field**

A stochastic wind field generator is created that produces two-dimensional wind fields with spatiotemporal variations, enabling dynamic wind farm simulations for analysis and design of wind farm control strategies. Control-oriented wind farm simulations require much slower time scales (tens of seconds) than the aerodynamic simulations needed for evaluating wind turbine controls (which are typically in the tens to hundreds of milliseconds range). Moreover, wind farm simulations require wind fields that extend beyond the traditional duration in wind turbine simulations, usually limited to ten minutes wind fields with a ~~spacial~~ spatial range of up to several hundred meters (micro scale). The size of some current wind farms extend to ten kilometres or even more (meso scale). The approach to wind field generation followed in this work is based on modelling of both micro and meso scale effects. The chosen ~~spacial~~ spatial resolution of the wind fields is around two rotor diameters (2D), ~~while the~~ which is in accordance with the wake meandering modelling in Larsen et al. (2008). The sample time is in the order of 10-30 s (roughly equal the time it takes air flow to cover a distance of 2D). Notice that this approach is quite similar to those followed by Bossanyi (2018) and Simley et al. (2020), where the authors also split the wind field spectrum into low-frequency (for the wake dynamics) and high-frequency (for the turbine yaw dynamics). In Bossanyi (2018), the same spatial resolution is used for the low-frequency wind field as well.

Micro scale (fast) wind variations are modelled using the Kaimal spectrum, rewritten as function of the wave number
 175 $\nu = f/U_m$, as suggested in Bossanyi (2018)

$$\frac{U_m S_{micro}(\nu)}{\sigma_m^2} = \frac{4L}{(1 + 6L\nu)^{\frac{5}{3}}},$$

with f being the frequency, L – the integral scale parameter ($L = 340.2$ m for the longitudinal wind component, and $L = 113.4$ m for the lateral wind component in accordance with IEC 61400-1-3:2005 (2005)), and U_m and σ_m being the wind velocity and its standard deviation. Writing the spectrum in this form allows the generation of long time series independent on U_m or
 180 σ_m , which need not to be constant. Generated time-series are then scaled to obtain the wind realization based on the actual (slow) variation of U_m and σ_m coming from the generated meso-scale winds. This Kaimal spectrum is used for frequencies above 10^{-3} Hz, i.e. time scales of 30 minutes and ~~slower~~lower. The upper limit of the frequency range is $U_m/(2D)$, based on an assumed grid size of $2D$. This implies $10^{-3}/U_m \leq \nu \leq 1/(2D)$, where finally the lower is substituted by $4 \cdot 10^{-5}$ ~~m~~⁻¹m⁻¹ (corresponding to the maximal expected wind speed of 25 ~~ms~~⁻¹ms⁻¹) to remove the dependency on U_m completely.

185 The meso-scale (slow) wind variations, in the order to 10 minutes or longer, are modelled by the auto power spectrum

$$S_{meso}(f) = a_1 f^{-5/3} + a_2 f^{-3}$$

with $a_1 = 3 \cdot 10^{-4}$ and $a_2 = 3 \cdot 10^{-11}$ fitted to measurement data (Larsén et al., 2013). This spectrum is representative in the frequency interval $10^{-5} \leq f \leq 10^{-3}$, i.e. approximately between 30 minutes and one day, and valid for both the longitudinal and lateral wind component.

190 For the complex cross power spectrum between two points in space, r and s , the following expression is used for both the micro and the meso scale spectra (denoted below shortly as S) and is adopted from Sørensen et al. (2002)

$$S_{rs}(f) = \gamma(f, d_{rs}, U_0) S(f) e^{-j2\pi f \tau_{rs}(U_0)}, \quad (1)$$

where d_{rs} is the distance between the two points, U_0 is the average wind velocity, $\tau_{rs}(U_0) = (\cos(\alpha_{rs})d_{rs})/U_0$ is the time delay, i.e. the time it takes to move downstream from point r to point s at the average wind velocity U_0 ,

195 $\gamma(f, d_{rs}, U_0) = \exp^{-c(\alpha_{rs})d_{rs}f/U_0}$

is the coherence function between the points r and s , and α_{rs} denotes the angle between the line through the points and r and s and the wind velocity vector. The advection of the airflow downstream is modelled by the exponent term in Eq. (1).

The parameter $c(\alpha_{rs})$ is the decay factor, a parameter characterizing the decay rate of the coherence function. There is no uniformity in the literature with respect to the decay factor. In this work, the decay parameter $c(\alpha_{rs}) = 5.9 - 1.8 \cos(2\alpha_{rc})$, as
 200 suggested by Larsén et al. (2013), has been used.

The generation of time series from auto and cross power spectra follows the standard approach of generating frequency domain signals with amplitudes complying with the specified spectra and random phases, and applying inverse fast Fourier transform to construct the time series (Veers, 1988).

2.2 Dynamic wake model

205 In this work a dynamic wake model is developed based on TNO's wake model FarmFlow (Bot and Kanev, 2020), a Parabolized Reynolds-averaged Navier-Stokes code with prescribed pressure gradients to calculate the flow in wind farms. Based on the rotor averaged wind speeds, the power and induced velocities are determined from measured power and thrust curves. The pressure gradients in the near wake region are prescribed as a function of the thrust force coefficient. To this end, a database is used containing precomputed pressure gradients obtained from a panel method with an actuator disk model in which the wake
210 is represented by discrete constant strength vortex rings. The basic background flow is modelled by an atmospheric wind shear model based on Monin-Obukhov similarity theory. The original FarmFlow model solves stationary flow throughout the wind farm.

For the development and analysis of dynamic AWC algorithms, FarmFlow has been extended to model a quasi-dynamic flow in two-dimensional wind fields at hub height (see Sect. 2.1) with spatiotemporal variations. To this end, the wake generated by
215 a wind turbine is propagated downstream ~~based on~~ in such a way that it follows on its way the local wind direction variations ~~on its way, thereby modelling in the wind field. This way,~~ both time delay and meandering effects are modelled. The simulation time is equal to the time step in the wind field time series. ~~Because the traveling time of the wakes~~ Since the travel time of a wake between two turbines takes ~~much~~ longer than the ~~time window of a simulation period~~ simulation sample time, the arriving wakes from upstream turbines need to be time synchronized with the departure of wakes in the current time window. Because
220 the streamlines of the two-dimensional wind fields are curved and are varying in time, the trajectory of each wake needs to be corrected at the location of arrival, based on the trajectory of the undisturbed flow. After the correction, the wakes are stored in memory including the time and location of arrival. In summary, the quasi-dynamic wind farm simulation is realized as follows:

1. ~~A simulation for the current time window of the wind field~~ For a given time instant, the simulation starts with the most upstream turbine with respect to the farm-average wind direction, and ends with the most downstream turbine, ~~as seen from the average wind direction.~~
225
2. ~~Before the wake simulation for a turbine starts, arriving upstream wakes at the current time instant are first determined, if any~~ For a given turbine, using the wake information stored all arriving wakes (if any), are determined using wake information calculated at previous time instances (and stored in memory in Step 5).
3. From the undisturbed wind field and arriving wakes, ~~the a~~ rotor averaged wind speed and wind direction is calculated.
- 230 4. Given the determined rotor averaged wind ~~speed and the nacelle direction conditions, and the yaw position~~ (coming from the yaw system model ~~, see in Step 8, see also~~ Fig. 1), the yaw misalignment angle is computed. Subsequently, the power ~~and thrust values of the turbine are determined and a static wake calculation~~ production and rotor thrust force are determined, and a wake calculation is started using the (stationary) wake model in FarmFlow ~~is started~~ for the given turbine ~~only~~.
- 235 5. The wake is calculated until ~~it hits reaches~~ a downstream turbine ~~, if any, in which process the precise location of the wake is corrected for~~ (if any). The path of the calculated wake is determined using the time varying wind direction ~~from~~

in the undisturbed wind field, resulting in wake meandering. The wake information is then stored in memory, including the time of arrival at the downstream turbine for use in the wake simulation of that turbine ~~later on (performed in step 2).~~ at a later time instant in Step 2.

- 240 6. The simulation continues with the ~~next~~ following most upstream turbine until all turbines ~~are finished within~~ have been simulated for the current time instant.
7. The input and output data for all turbines are written in an output file, which forms the interface to a dynamic link library (DLL) that implements the yaw system dynamics and the dynamic robust AWC algorithm.
8. The DLL is called, which updates the yaw ~~position for each turbine~~ positions of all turbines, and communicates this
245 information back to FarmFlow, ~~and the next simulation step is started (step 1).~~ The simulation of the next time instant is initiated in Step 1.

This process is repeated until the simulations for all time periods are finished.

2.3 Yaw model

Similarly to Bossanyi (2018), the yaw system model is simplified to a constant rate motion at ~~0.35° s⁻¹~~ 0.35° s⁻¹ and a simple
250 yaw controller activating the yawing motion when the LP filtered difference between the yaw misalignment and its set-point exceeds 8°. A second order Butterworth LP filter with cut-off frequency of ~~1/60 Hz~~ 1/60 Hz has been used. As depicted in Fig. 1, the outputs of the yaw model are the nacelle position and the yaw duty (yaw travel and number of yaw on-off events). The inputs are the yaw misalignment set-point and the measured yaw misalignment. The later is constructed as the difference between the measured local wind direction (coming from the wake model) and the measured nacelle direction. The measured
255 values are formed by perturbing the actual quantities with uncertainties, i.e. terms representing variability of the measurand, measurement noise and uncertainty. These uncertain terms can be either stochastic or deterministic (e.g. measurement bias).

As pointed out already, the yaw system model operates at faster sampling rates than the wake model. This allows to model the yaw dynamics properly to enable realistic assessment of the impact of AWC on the yaw duty. To account for the higher variability of wind direction measurements that are taken at higher sampling frequencies, additional noise is superimposed on
260 the wind directions coming from the wake model. Besides the higher sampling frequency, there is another source of increased noise on the wind directions, namely the turbulence intensity of the air flow impinging the turbine. Operating in the wake of other turbines, a wind turbine will measure an increased level of wind direction variations. These, together with the additional noise due to higher sampling frequency, are represented by the block named “TI-driven variations” in Fig. 1. The additional noise signal, added by this block, is generated based on the standard deviation of the wind velocity in front of the wind turbine.
265 More specifically, denoting $\tilde{\phi}(t) = \tan \frac{v(t)}{u(t)}$ as the angle between the longitudinal ($u(t)$) and lateral ($v(t)$) components of the wind vector, representing variations of the wind direction around its average value ϕ_0 , it can be shown using the Taylor series approximation of degree one around the point ($u = u_0, v = 0$) that

$$\tilde{\phi}(t) \approx \frac{v(t)}{u_0}.$$

This implies that the standard deviation of the wind direction $\phi(t)$ can be expressed as $\sigma_{WD} = \sigma_v/u_0$, where σ_v is the standard deviation of the lateral wind component. In free stream, IEC 61400-1-3:2005 (2005) recommends for σ_v the expression $\sigma_v = 0.8\sigma_u$, which allows one to approximate the standard deviation of the wind direction to the turbulence intensity, namely

$$\sigma_{WD} \approx \frac{0.8\sigma_u}{u_0} = 0.8TI(u).$$

Assuming that this expression is representative for both the ambient flow as well as the wake, one can write $\sigma_{WD,amb} = 0.8TI_{amb}$ for the ambient wind direction, and $\sigma_{WD,wake} = 0.8TI_{wake}$ for that in the wake. In the simulation model, the ambient turbulence intensity, TI_{amb} , comes from the wind field generator, while the turbulence intensity of the wake in front of a wind turbine, TI_{wake} , is calculated by the wake model FarmFlow. The purpose of the block “TI-driven variations” in Fig. 1 is to add additional noise to the higher frequency wind directions used in the yaw system model to obtain $\sigma_{WD,wake} = 0.8TI_{wake}$. This additional noise is generated using the Kaimal spectrum with standard deviation $\sigma_{WD,add}$ according to the following expression, which is a direct consequence of the derivation outlined above

$$\sigma_{WD,add} = 0.8\sqrt{\max\{0, TI_{wake}^2 - TI_{amb}^2\}}.$$

This results in increased variations of the measured wind direction at turbines operating in wake condition, which in turn gives rise to increased yaw motion. This fact is observed in real-life as well, as supported by the data presented in Table 1. These data are obtained using high frequency measurements of wind speed, wind direction and nacelle position on two commercial wind turbines in the 2.5MW range, located on flat terrain at a distance of around four rotor diameters. The turbines operate both in free stream for Southern winds, while the second turbine (T2) operates in the wake of the first one (T1) for Western winds. The last row in the table shows that, in wake, T2 experiences lower wind velocity and higher turbulence intensity than the free stream turbine T1, as expected. It also shows that T2 measures increased variation in the measured wind direction and, unsurprisingly, higher yaw duty. This can be observed in the time series of LP filtered wind direction and raw nacelle position measurements for the two turbines in Fig. 2, which is for the Western wind situation. For Southern winds the responses are comparable (not shown in the Figure). These results support the concept of modelling increased wind direction variability and yaw activity for waked turbines. Notice that the developed model cannot be easily validated by only using such SCADA data, since the reported turbulence intensities in the table are computed from measurements disturbed by the rotor. Nevertheless, the model produces comparable results in terms of yaw motion and is considered sufficient for the purpose of this work.

2.4 Dynamic robust AWC

~~The~~ This section describes the structure of the dynamic robust AWC ~~consists of the following blocks (see algorithm, represented by the shaded area at the bottom of Fig. 1): LUT containing the yaw misalignment set-points for all wind turbines in the wind farm as function of the~~. The optimization of the parameters of the underlying blocks of this algorithm is topic of Sect. 3 (Robust AWC optimization) and 4 (Dynamic adaptation algorithm optimization). In the implementation, used in this work, the AWC algorithm receives the local wind speed and wind direction, ~~obtained through stochastic program that accounts for uncertainty in a number of parameters (see Sect. 3 for more details). The optimization is performed using the conventional (stationary) FarmFlow model for a range of wind conditions to populate the LUT as measured at turbine level.~~

Table 1. Impact of wake on wind measurements and yaw motion of two commercial wind turbines

Turbine	Inflow	wind speed			wind direction		Yaw duty	
		STD [ms ⁻¹ ms ⁻¹]	mean [ms ⁻¹ ms ⁻¹]	TI [-]	STD [°]	mean [°]	travel [°]	nr. events [-]
T1	free stream	2.41	10.00	0.24	15.66	179.56	39.32	6
T2	free stream	2.43	10.63	0.23	15.69	182.84	43.85	8
T1	free stream	1.37	7.12	0.19	11.91	271.28	23.09	4
T2	in wake	1.66	4.50	0.37	17.43	278.86	81.50	9

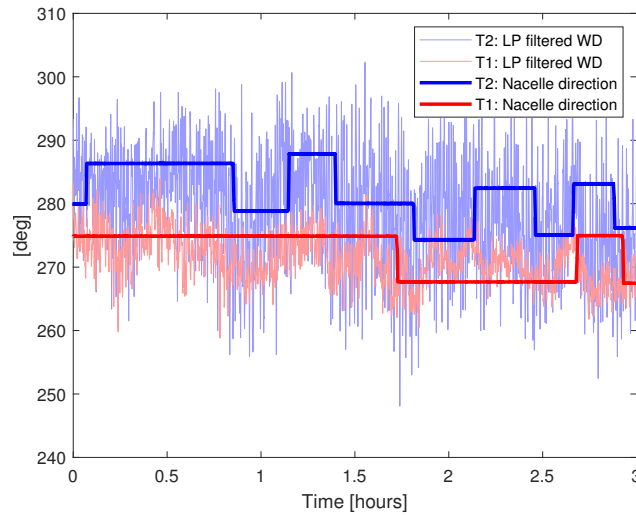


Figure 2. ~~Impact-Illustration~~ of the impact of wake on wind measurements and yaw motion of two commercial wind turbines, when the second turbine (T2) is in the wake of the first one (T1). The thin lines represent LP filtered wind direction measurements at the two turbines, while the think ones – the nacelle position measurements.

The dynamic robust AWC consists of the following blocks (see Fig. 1):

- LP filter: a second order Butterworth lowpass filter, the cutoff frequency of which will be varied to study its impact on the power gain and yaw duty. As visualized in Fig. 1, the LP filter acts on the wind speed and wind direction signals.
- Hysteresis: adding hysteresis on the (filtered) wind direction signal, centred at wind directions where the yaw misalignment set-points change sign, can reduce the yaw duty as demonstrated in earlier by Kanev (2020). The hysteresis logic for a given turbine is defined as

$$\mathcal{H}(b) : \phi_{hyst}(k) = \begin{cases} \phi_{hyst}(k-1) & |\phi_{LP}(k) - \phi_c| \leq b \\ \phi_{LP}(k) & \text{otherwise} \end{cases}$$

wherein ϕ_c is any wind direction for which the yaw misalignment set-point for that turbine changes sign, $\phi_{LP}(k)$ is the LP filtered wind direction (input to the hysteresis), and b defines the hysteresis size. Based on the findings in Kanev (2020), a wider range of hysteresis sizes are considered in the present work (b up to 4°).

- Sampling: limits the update rate of the yaw misalignment set-points, i.e. the frequency at which they are communicated to the yaw controller implemented in the yaw system model.
- LUT containing the yaw misalignment set-points for all wind turbines in the wind farm as function of the wind speed and wind direction, obtained through stochastic program that accounts for uncertainty in a number of parameters (see Sect. 3 for more details). The optimization is performed using the conventional (stationary) FarmFlow model for a range of wind conditions to populate the LUT.

The robustness of the AWC is realized through the robust design of the LUT, while the last three components of the AWC controller in the list above represent the dynamic adaptation algorithm. The robust design through stochastic programming will be discussed in Sect. 3. The quantities to which robustness is to be achieved are selected through uncertainty quantification in Sect. 3.2. The selection of dynamic adaptation algorithm parameters (LP filter cut-off frequency, hysteresis size and sample time) to optimize the balance between power gain and yaw duty is topic of Sect. 4.

3 Robust AWC optimization

The conventional approach to (nominal) AWC design involves the synthesis of LUT containing yaw misalignment set-points for the wind turbines in the farm, optimized for a range of input conditions. These include at least the wind direction (Kanev et al., 2018), but sometimes also the wind speed or other atmospheric conditions such as the turbulence intensity (Bossanyi, 2018; Doekemeijer et al., 2021). In this work, the yaw misalignment set-points ~~will depend only on~~ in the LUT will essentially be a function of the wind direction ~~while the influence of other parameters on their optimal choice will be considered through stochastic uncertainties in a robust design setting. Nevertheless, some dependency on the wind speeds is inevitable as AWC should not be active above the rated power production of the farm. In other words, above a certain wind velocity (12 ms^{-1} only. The wind speed signal entering the block “Robust AWC (LUT)” in Fig. 1 is meant to indicate that AWC is only active in a certain range of below rated wind conditions ($4\text{--}12\text{ ms}^{-1}$ used here)~~ the yaw set-points should be phased out. Same holds for too low wind velocities (here 4 ms^{-1}), where large misalignment may interfere with the start-up process.

This section considers the synthesis of robust AWC in which a number of parameters is treated as uncertain. ~~These consist of,~~ continuing along the lines of previous work by Quick et al. (2020). Here, a more extensive list of uncertain parameters is treated, consisting of quantities related to model parameter uncertainty, measurement uncertainty and input variability, all treated in a unified stochastic framework using PDFs (Sect. 3.1). The impact of these uncertainties on the optimal yaw set-points is quantified through forward uncertainty propagation (Sect. 3.2). To this end, the PDFs are sampled and the underlying simulations are performed using the conventional (static) FarmFlow wake model. ~~The robust~~ This allows to evaluate how much the optimal yaw set-points change as result of variations in the different uncertain parameters within their assumed uncertainty sets,

Table 2. Uncertain parameters considered in the uncertainty quantification framework, their assumed ranges and stochastic modelling

Parameter	Uncertainty type	Range	PDF
Wind direction	Variability and measurement uncertainty	$[-10, 10]^\circ$	Normal ($\mu = \phi_{LUT}, \sigma = 4.25^\circ$)
Wind speed	Variability	$[4, 12] \text{ ms}^{-1} \text{ms}^{-1}$	Weibull ($k = 2.24, A = 9.3$)
Turbulence intensity	Variability	$[4, 20] \%$	Weibull ($k = 3, A = 0.073$)
Yaw error	Variability and measurement uncertainty	$[-10, 10]^\circ$	Laplace ($\mu = 0, \nu = 5^\circ$)
Wind shear exponent	Variability and model uncertainty	$[0.04, 0.20]$	Normal ($\mu = 0.12, \sigma = 0.05$)
Air density	Variability	$[1.18, 1.38] \text{ kgm}^{-3} \text{kgm}^{-3}$	Normal ($\sigma = 0.015$)
Yawed power loss exp.	Model uncertainty	$[1.3, 2.3]$	biased inverse Gaussian ($\mu = 0.52, \lambda = 8$)
Thrust curve variation	Model uncertainty	$[-10, 10] \%$	Normal ($\mu = C_{t,nom}, \sigma = 10/3 \%$)
Power curve variation	Model uncertainty	$[-5, 5] \%$	Normal ($\mu = C_{p,nom}, \sigma = 5/3 \%$)

so that it can be decided which uncertain parameters should be included into the robust optimization. In Quick et al. (2020) a similar analysis is performed by focusing on the impact of variations in the sizes of the uncertainty sets instead. Finally, the robust AWC design is performed by solving a stochastic programming problem through discretization of the probability distributions to arrive at a finite number of scenarios (Sect. 3.3), similar to Rott et al. (2018); Simley et al. (2020).

3.1 Uncertainty modelling

The uncertainties considered in this work are listed in Table 2, together with their type, assumed range and the PDFs used for their modelling. For instance, the The latter are described in the list below:

- the wind direction is required in the AWC algorithm as input, and since it is derived from the measured nacelle direction and yaw error, it will be subjected to measurement uncertainty. Next to that, the actual wind direction will vary with respect to the one entering the LUT, denoted in the table as ϕ_{LUT} , due to the applied signal processing in the AWC algorithm (see Fig. 1). The table indicates that the measurement uncertainty and variability are modelled together with a normal distribution with PDF

$$p_{\text{normal}}(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

with standard deviation $\sigma = 4.25$ and mean value equal to the wind direction entering the LUT, $\mu = \phi_{LUT}$. Notice that the value for the standard deviation is difficult to compute accurately because it needs to reflect the difference between the wind direction variations responsible for the wake meandering, say ϕ_{meand} , and ϕ_{LUT} , and the former cannot be exactly specified. The value of 4.25, used here, is determined by using the high frequency measurement data, discussed in Sect. 2.3. To this end, 5s LP filtering is applied to the high-frequency wind direction measurements to represent ϕ_{meand} , and 20s LP filtering to model ϕ_{LUT} , and a normal distribution has been fitted to the difference between the two signals, wherein the standard deviation has slightly been increased to account for the impact of measurement uncertainty on the

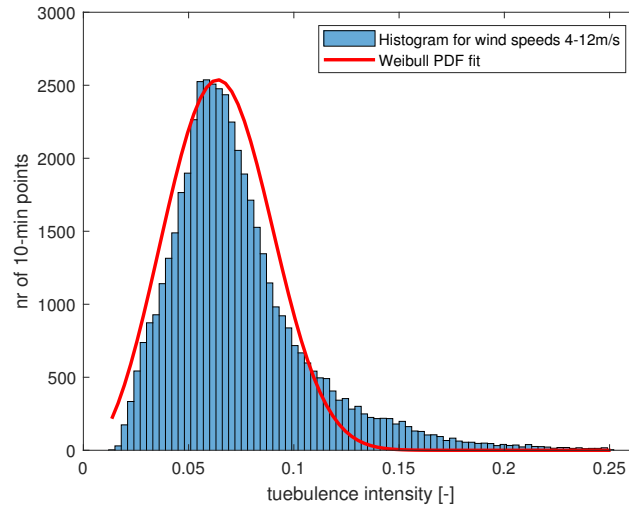


Figure 3. Histogram of turbulence intensity computed using 20 months of wind measurements on an offshore met mast, and a Weibull PDF fit. Only data corresponding to wind speeds in the interval $[4,12] \text{ m s}^{-1}$ have been used in constructing the histogram

lower frequency signal ϕ_{LUT} . Notice that the so determined value does NOT differ much from that used in earlier research (Simley et al., 2020; Rott et al., 2018; Quick et al., 2020).

- The wind speed, as already mentioned, will not be used as input to the LUT (other than for defining the wind speed region in which intentional yaw misalignment will be applied). Instead, the LUT will be designed to be robust to wind speed variations. Therefore, only variability of the wind speed signal is considered, hence neglecting the effect of measurement uncertainty which is much smaller in our setting. For its variability, a standard Weibull distribution of the form

$$p_{\text{Weibull}}(x, k, A) = \frac{k}{A} \left(\frac{x}{A} \right)^{k-1} e^{-(x/A)^k}$$

is used, and the values for its parameters k and A , reported in Table 2, representative for a commercial offshore wind farm in the North sea.

- To determine a suitable PDF for the turbulence intensity, twenty months of 10 min statistical data has been used from a met mast located offshore in free stream. From these data, a histogram has been constructed for the turbulence intensity for wind velocities in the range of $4\text{--}12 \text{ m s}^{-1}$ since, as mentioned already, in this study AWC is not active outside this interval. The histogram is depicted in Fig. 3, and shows similarity with the Weibull distribution. A fit delivered parameters $k = 3$, and $A = 0.073$, for which the fitted PDF looks quite reasonable, even though the probability of values above 0.15 is underestimated.

- The PDF parametrizations for yaw error and wind shear exponent have been adopted from Quick et al. (2020). The Laplace distribution, assumed for the yaw error uncertainty is defined as

$$p_{\text{Laplace}}(x, \mu, \nu) = \frac{1}{2\nu} e^{-|x-\mu|/\nu}.$$

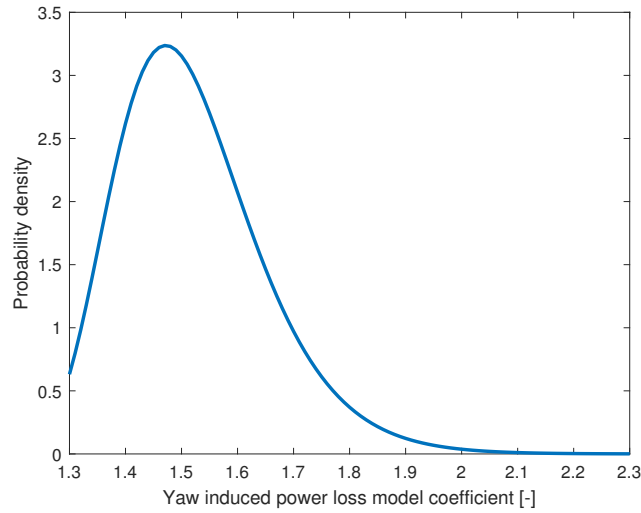


Figure 4. PDF used for representing model uncertainty in the yaw-induced power loss coefficient

- The uncertainty on the air density has been based on the results in Ulazia et al. (2019), where a study is carried out on the variability of the air density offshore. The statistical indicators, reported there, are a first quartile value of 1.21 and third quartile value of 1.25. The resulting interquartile range of $IQR = 0.02$ is then used here to determine the standard deviation for which the normal distribution exhibits the same IQR , i.e. $\sigma = IQR/1.35 \approx 0.015$.
- The parameter denoted as “yawed power loss exp.” in Table 2 refers to the exponent a in the power reduction factor $\cos(\beta)^a$ by which the power production of a non-yawed turbine is scaled to model the production of a turbine operating at yaw misalignment angle of β . There is a large variety of values for a in the literature, ranging between 1.3 and 2.3. In Fleming et al. (2017) a value of 1.44 has been fitted to field measurements. Similar value has been derived for another commercial wind turbine, used in the study Doekemeijer et al. (2021). For this reason, a skewed PDF is selected here, defined as

$$p_{\text{biG}}(x, \mu, \lambda) = \sqrt{\frac{\lambda}{2\pi(x-1)^3}} e^{-\lambda(x-1-\mu)^2/(2\mu^2(x-1))}$$

with highest probabilities clustered at the lower side of the range, see Fig. 4. The selected PDF is such that for $p_{\text{biG}}(x+1, \mu, \lambda)$ it becomes equivalent to the inverse Gaussian distribution, and is therefore referred to as “biased inverse Gaussian” in Table 2. The mode of the PDF, at 1.47, aligns quite well with mentioned field results.

- Finally, the uncertainties on the thrust and power curves are modelled relative changes (percentages) of their nominal curves, i.e. $\pm 5\%$ uncertainty range on the power curve, and $\pm 10\%$ on the thrust curve. The modification of the power curve is realized through scaling of the wind speed to ensure that rated power remains unchanged. Normal distributions are then assumed, centred at nominal values, and with standard deviations such that $\pm 3\sigma$ coincide the selected uncertainty ranges.

Now that the possible sources of uncertainty are described and modelled, the next section continues with analysing the impact of these on the performance of the AWC algorithm.

3.2 Uncertainty quantification

The uncertainty quantification analysis has been carried out with the purpose to identify the uncertainties with the most significant impact on the performance of the AWC algorithm, measured in terms of optimal yaw misalignment set-points and power gain. The most dominant uncertainties are then to be considered in the robust AWC design framework, discussed in the next section. The reason to look for reduction in the number of uncertainties in the robust optimization is to lower the computational complexity to a manageable level.

The analysis in this section is performed as follows. First, a number of equally distant samples is selected for each uncertain quantity within its assumed range (see Table 2). Next, for each uncertainty sample, the yaw misalignment set-points were optimized for a row of five 3 MW wind turbines with 90 m rotor diameter for the following three cases

Case 1 inter-turbine spacing of five rotor diameters (5D) and wind direction aligned with the row

Case 2 inter-turbine spacing of 7D and wind direction aligned with the row

Case 3 inter-turbine spacing of 7D and wind direction an angle of 4° with respect to the row

To solve the underlying optimization problems, a tailor made algorithm has been used that requires a minimum number of function evaluations (farm simulations) to converge. The algorithm is similar to the conventional bisection method, but generalized to multivariate objective functions. By confining the optimization variable to lie within an initial n-dimensional box, the gradient of the objective function is evaluated at the centre point at each iteration and the box is reduced in size by keeping only that part that is oriented opposite to the gradient. While this algorithm has no theoretical guarantees to converge to an optimum solution for general nonlinear functions, has been successfully used for many years by the authors and works pretty well for the application at hand, its low calculation effort being its main advantage over alternative algorithms. This allows it to be used in combination with relatively complex wake models such as FarmFlow. To reduce computation time even more, the number of optimization variables is limited to the yaw set-points of the two most upstream turbines in each row of turbines oriented downstream. The yaw set-points for the remaining turbines in the row are linearly decreased between the second turbine and the last one, which has zero yaw misalignment set-point. No limitation has been applied to the yaw set-points in this section.

The yaw misalignment angles are optimized for one uncertainty parameter at a time, keeping all other parameters at their nominal values. More precisely, let p_i be a given parameter from the list in Table 2, \mathcal{U}_i be the corresponding uncertainty range, and $\mathcal{D}_i(p_i)$ – its PDF. For a given sample $p_i^{(r)} \in \mathcal{U}_i$ of the parameter p_i , and keeping the remaining parameters at their nominal values (i.e. $p_j = p_j^{(nom)} \in \mathcal{U}_j$, $j \neq i$), conventional (non-robust) AWC design solves the optimization problem of finding the vector of best yaw misalignment set-points $\gamma = [\gamma_1, \dots, \gamma_N]$, N being the number of turbines, with respect to the total power

production of the wind farm, i.e.

$$430 \quad \gamma_{det}(p_i^{(r)}) = \arg \min_{\gamma} \max_{\gamma} \sum_{t=1}^N P_t \left(\gamma | p_i = p_i^{(r)}, p_j = p_j^{(nom)}, j \neq i \right).$$

Notice that each individual turbine's power production, P_t , may depend on the yaw misalignments of other turbines through the wake effects. The optimal power gain for sample $p_i^{(r)}$ is then defined as

$$\delta P_{opt}(p_i^{(r)}) = \left(\sum_{t=1}^N P_t \left(\gamma_{det}(p_r) | p_i = p_i^{(r)}, p_j = p_j^{(nom)}, j \neq i \right) \right) / \left(\sum_{t=1}^N P_t \left(\gamma = 0 | p_i = p_i^{(r)}, p_j = p_j^{(nom)}, j \neq i \right) \right).$$

Table 3 gives for each parameter p_i its uncertainty set \mathcal{U}_i , the selected step size in the uncertainty sampling (resulting in
 435 samples $p_i^{(r)}$, $r = 1, 2, \dots$ for which the yaw misalignments are optimized), as well as the nominal values of the parameters ($p_j^{(nom)}$). The resulting optimal yaw misalignment angles $\gamma_{det}(p_i^{(r)})$ are statistically summarized with the box plots in Fig. 5. In the figure, three box plots per parameter are depicted, corresponding to the considered three cases. Each box plot gives the minimum and the maximum value (upper and lower line segment), the first and third quartile (lower and upper sides of the boxes), and the median (line segment inside the box).

440 The following observations can be made from the figure

- Variations in the power coefficient and the air density have no impact on the optimal yaw misalignment set-points, which is expected as these parameters have little to no influence on the wake deficits behind the turbines
- Wind direction variability has by far the largest impact on the optimal yaw misalignment set-points which, of course, is due to their very pronounced influence on the wake locations with respect to downstream turbines. Clearly, this
 445 parameter is the most important one to consider in a robust AWC setting. This conclusion confirms earlier observations by Quick et al. (2020).
- Other quantities, variations of which lead to significant changes in the optimal yaw set-points, are the wind speed, yaw error, turbulence intensity, and wind shear. Notice that for some turbulence intensity and wind speed cases the minimum yaw misalignment values are equal to zero, which occur for uncertainty samples around the edges of their
 450 ranges of variation. For measurable quantities (such as the wind speed), such values can better be excluded from the robust optimization when possible and be used instead to deactivate AWC.
- Variations in the thrust curve and the yaw-induced power loss exponent have generally limited impact on the optimal yaw set-points, which suggests that they could be left out from the robust optimization.

Notice that, due to the fact that no limitations have been imposed, the yaw misalignment set-points are getting quite high in
 455 some cases, raising up to values of 40° and even higher. Such a high yaw misalignments are currently considered unrealistic in a real-life application. Usually, they are limited to around 30° in many research studies, or to even lower values in the first field tests with wake redirection (Fleming et al., 2017, 2019; Doekemeijer et al., 2021). It becomes clear from Fig. 5 that by imposing a limitation of ±30° one would significantly limit the variation in the yaw misalignment set-points. Nevertheless, the

Table 3. Sampling of the uncertainties for the purpose of uncertainty quantification

Parameter	Range	Step size	Nominal value
Wind direction	$[-10, 10]^\circ$	1°	0° (Cases 1,2), 4° (Case3)
Wind speed	$[4, 12] \text{ } \cancel{ms^{-1}} \text{ } \underline{ms^{-1}}$	$1 \text{ } \cancel{ms^{-1}} \text{ } \underline{ms^{-1}}$	$8 \text{ } \cancel{ms^{-1}} \text{ } \underline{ms^{-1}}$
Turbulence intensity	$[4, 20] \%$	1%	7%
Yaw error	$[-10, 10]^\circ$	1°	0°
Wind shear exponent	$[0.04, 0.20]$	0.02	0.09
Air density	$[1.18, 1.38] \text{ } \cancel{kgm^{-3}} \text{ } \underline{kgm^{-3}}$	$0.02 \text{ } \cancel{kgm^{-3}} \text{ } \underline{kgm^{-3}}$	$1.225 \text{ } \cancel{kgm^{-3}} \text{ } \underline{kgm^{-3}}$
Yawed power loss exp.	$[1.3, 2.3]$	0.1	1.43
Thrust curve variation	$[-10, 10] \%$	2%	0
Power curve variation	$[-5, 5] \%$	1%	0

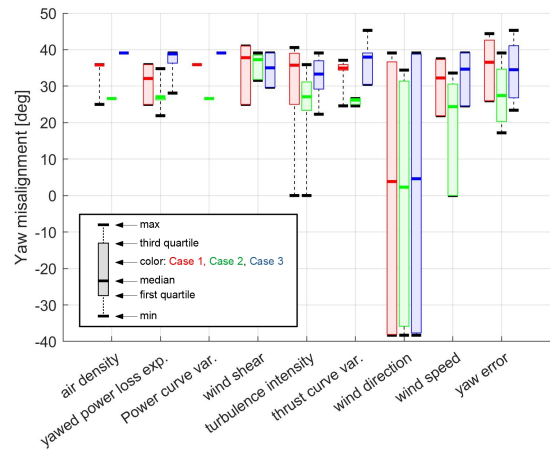


Figure 5. Box plots for the optimal yaw misalignment angles of the most upstream turbine, evaluated for the considered parameters and setup cases

main conclusions drawn above in terms of the most significant uncertainty contributors will still hold, with probably only the
460 wind shear disappearing from this list.

Next, the sensitivity of the power gain by AWC to variations in the uncertain parameters is considered. The reason for doing that is that it might happen that the variations in a given parameter lead to large changes in the corresponding optimal yaw set-points, but limited variation in the power gains, in which case inclusion of the parameter in question into the robust AWC design will also be unnecessary. Therefore, simulations have performed for the selected uncertainty samples, as described above, $p_i^{(r)}$,
465 $r = 1, 2, \dots$, but with the turbines' yaw misalignment set-points fixed over the whole uncertainty interval for a given parameter. The power gain sensitivity analysis is carried out as follows. For each parameter, its most probable sample (modal value),

$p_i^{(mod)}$, is selected and the yaw misalignment angles are optimized for that value, while keeping all other parameters at their nominal value ($p_j = p_j^{(nom)}$, $j \neq i$), i.e.

$$\gamma_{fix}(p_i^{(mod)}) = \arg \min_{\gamma} \max_{\gamma} \sum_{t=1}^N P_t \left(\gamma | p_i = p_i^{(mod)}, p_j = p_j^{(nom)}, j \neq i \right).$$

470 For each parameter sample (p_i^r , $r = 1, 2, \dots$), the power ratio is then computed as

$$\delta P_{fix}(p_i^r) = \left(\sum_{t=1}^N P_t \left(\gamma_{fix}(p_i^{(mod)}) | p_i = p_i^r, p_j = p_j^{(nom)}, j \neq i \right) \right) / \left(\sum_{t=1}^N P_t \left(\gamma = 0 | p_i = p_i^r, p_j = p_j^{(nom)}, j \neq i \right) \right).$$

By optimizing for one single uncertainty value ($p_i^{(mod)}$), evaluating the power gain with the resulting (fixed) yaw set-points ($\gamma_{fix}(p_i^{(mod)})$) for the whole uncertainty range ($\delta P_{fix}(p_i^r)$), and comparing these to the optimized power gains for each single uncertainty sample separately ($\delta P_{opt}(p_i^r)$), one gets insight into the maximum amount of power gain improvement achievable
 475 by means of robust AWC. If there is little to no difference between δP_{fix} and δP_{opt} for a given parameter, then it can be left out from the robust design even if it has significant impact on the optimal yaw set-points. The difference ($\delta P_{opt} - \delta P_{fix}$) is depicted statistically with the box plots in Fig. 6. A value of 0.05 in the figure, indicates that for some uncertainty realization $p_i^{(r)}$ the optimal power gain δP_{opt} is 5% higher the power ratio δP_{fix} for fixed yaw set-points. Therefore, values close to zero in the figure indicate that the uncertainty on the corresponding parameter is not important to include in the robust AWC
 480 design because that will not lead to a significant improvement in the power gain compared to the case when the AWC design is performed with the parameter kept at its modal value. This is the case for the first four parameters depicted in Fig. 6 (air density, yaw-induced power loss exponent, power curve, and wind shear), and to a lesser extend for the sixth one (thrust curve). It is interesting to observe that wind shear can now be excluded from the robust optimization, while it passed the first relevance test based on the optimal yaw misalignment set-points.

485 In summary, the conclusion is that the uncertainty on the following parameters is to be considered in the robust AWC design framework: wind direction, wind speed, yaw error and turbulence intensity.

3.3 Robust design and stationary analysis

As discussed in the previous section, the robust AWC optimization will account for uncertainties in the wind direction, wind speed, yaw error and turbulence intensity, with the uncertainty modelled stochastically by means of PDFs (see Sect. 3.1). Then,
 490 for a given stationary wind direction ϕ_{LUT} , the robust AWC design problem, will ideally require the solution to the following stochastic programming problem

$$\gamma_{rob}(\phi_{LUT}) = \arg \min_{\gamma} \max_{\gamma} \int \sum_{t=1}^N P_t(\gamma | p, \phi_{LUT}) \mathcal{D}(p) dp, \quad (2)$$

wherein the four element vector p represents the considered uncertain parameters, the set \mathcal{U} defines their range of variation (in accordance with Table 2), and \mathcal{D} – their joint PDF which, due to assumed dependency between the parameters, equals here the

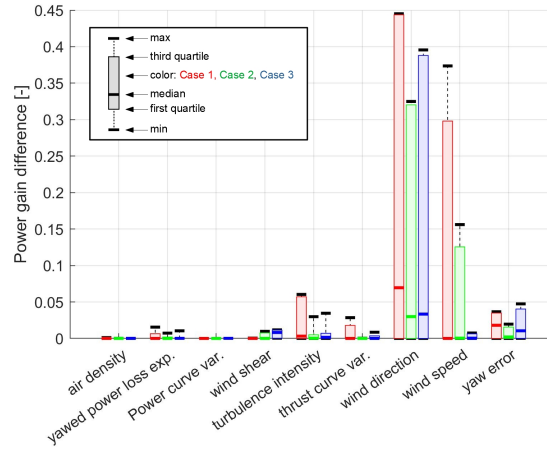


Figure 6. Box plots for the difference between the power gains obtained for the considered uncertainty samples with fixed (optimized for the model value of the uncertain parameter) and varying (optimized for each uncertainty sample individually) yaw misalignment set-points

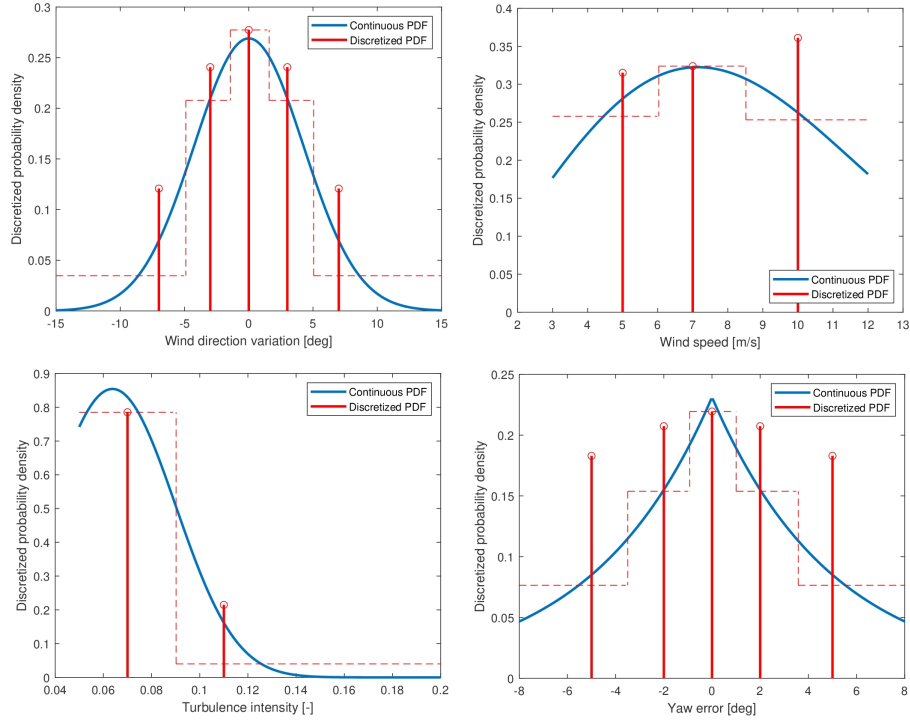


Figure 7. PDFs for the uncertain parameters considered for robust optimization

495 product of the four individual PDFs. This optimization problem needs to be solved separately for all relevant wind directions to populate the whole LUT with the optimized yaw set-points, which represents the robust AWC.

To solve this problem numerically, the continuous PDFs are discretized [as in Rott et al. \(2018\); Simley et al. \(2020\)](#). This is done by selecting a number of discrete samples for each uncertain parameter and calculating the probability for a given sample through integration of the continuous PDF over the interval that corresponds to this sample (see Fig. 7). In this discretization process, an attempt has been made to limit the total number of samples as much as possible while still trying to reasonably approximate the PDFs. Since uncertainty on the wind direction was shown to have the largest impact on AWC, it was discretized using more points (five) than for the wind speed and turbulence intensity PDFs (for which, respectively, three and two points have been used). Due to the symmetry in the PDF for the yaw error, the number of points used there is also five, giving a total number of 150 ($= 5 \times 5 \times 3 \times 2$) joint uncertainty samples. Due to the computational complexity of the FarmFlow wake model, with the simulations run on 100 cores in this study, it was beneficial to reduce the number of cases even further. This was done by removing all parameter combinations for which the joint cumulative probability distribution function is lower than 0.05, resulting in a final number of 121 samples. Denoting \mathcal{U}_d as the set containing these 121 uncertainty samples for the vector parameter p , and $\mathcal{D}_d(p)$ as the discretized joint PDF, the initial robust AWC optimization problem in Eq. (2) is approximated as follows

$$\gamma_{rob}(\phi_{LUT}) = \arg \min_{\gamma} \max_{p \in \mathcal{U}_d} \sum_{t=1}^N P_t(\gamma|p, \phi_{LUT}) \mathcal{D}_d(p), \quad (3)$$

which constitutes the optimization problem considered in this work for synthesizing robust AWC. ~~For solving the problem numerically, a modified pattern search optimization algorithm is used in which only decent directions are evaluated in order to save computational effort. For the same purpose, the number of optimization variables is limited to the yaw set-points of the two most upstream turbines in each downstream-oriented row of turbines. The yaw set-points for the remaining turbines in the row are linearly decreased between the second turbine and the last one, which has zero yaw misalignment set-point.~~

~~To exemplify the robust AWC design, consider the single-row layout consisting of five 3-MW wind turbines, with 90-m rotor diameter, separated at a distance of 7D (equivalent to the setup in Cases 2 and 3 in [All optimization problems are solved by using the algorithm, described in Sect. 3.2](#)). The robust optimization problem in Eq. is solved for wind directions ranging from 248° to 292° at a step of 1°, an interval centred around the row orientation of 270°. In addition to that, a nominal AWC optimization is performed for the nominal values of the uncertainties $p^{(nom)} \in \mathcal{U}$.~~

$$\gamma_{nom}(\phi_{LUT}) = \arg \min_{\gamma} \sum_{t=1}^N P_t(\gamma|p^{(nom)}, \phi_{LUT}),$$

~~while evaluating the robust power gain, $\delta P(\gamma_{nom}, \phi_{LUT})$, including the uncertainties. The robust power gain for given yaw misalignment set-points γ and wind direction ϕ_{LUT} is computed using the discretized joint PDF~~

$$\delta P_{rob}(\gamma, \phi_{LUT}) = \frac{\left(\sum_{p \in \mathcal{U}_d} \sum_{t=1}^N P_t(\gamma|p, \phi_{LUT}) \mathcal{D}_d(p) \right)}{\left(\sum_{p \in \mathcal{U}_d} \sum_{t=1}^N P_t(0|p, \phi_{LUT}) \mathcal{D}_d(p) \right)}.$$

~~The results are summarized in Fig. 11 and 12, depicting the first turbine's optimized yaw misalignment set-point and power gain for the complete turbine array, respectively, for the considered range of wind directions. The results show that the robust~~

yaw misalignments exhibit lower maximum values, extend over a larger interval of wind directions and are smoother. This is expected to have a positive effect on the yaw duty, which will be evaluated with dynamic simulations in Sect. 4. In terms of robust power gain under robust AWC, $\delta P_{rob}(\gamma_{rob}, \phi_{LUT})$ (blue curve in Fig. 12), as compared to a nominal AWC, $\delta P_{rob}(\gamma_{nom}, \phi_{LUT})$ (black curve in 12); however, the improvement by robust AWC is quite limited. The red curve in Fig. 12 gives the nominal power gain (excluding uncertainties) under nominal AWC. Yaw misalignment angles for the first turbine in the row The yaw misalignment angles have been limited to $\pm 30^\circ$.

Power gain by nominal and robust AWC for a row of five turbines

4 Dynamic adaptation algorithm optimization

Now that the robust AWC optimization has been discussed in the previous section, the focus here is on the optimal selection of the parameters of the dynamics adaptation algorithm, described in Sect. 2.4. The single-row layout considered in Sect. 3.2 and 3.3 is considered sufficient for this purpose, while a more realistic assessment will be performed using a full-scale wind farm model in Sect. 5. For the simulations here, wind field time series have been generated using the approach in Sect. 2.1. The wind field has a duration of 6 h and sample time of 10 s, and average turbulence intensity of 7%. The simulations have been carried out with different combinations of dynamic adaptation parameters (see Sect. 2.4) from the sets:

- LP filter time constant: 20, 30, 45, 60, 120, 300, 600 s. Notice that, since the sample time is 10 s, time constant of 20 s implies no filtering at all as the filter cut-off frequency then coincides with the Nyquist frequency.
- hysteresis size: 0, 1, 2, 3, 4°
- sample time: 10, 20, 30, 40, 50, 60, 120, 300, 600 s

Each combination of parameters is simulated twice, namely in with LUTs containing yaw misalignment set-points from nominal and robust AWC optimizations, as discussed in Sect. 3.3. Adding a reference simulation scenario without AWC results in a total of 631 simulations ($= 7 \times 5 \times 9 \times 2 + 1$). In the sequel, the notation $DynPars(a, b, c)$ will be used to indicate a given combination of these parameters, with a being the LP filter cut-off frequency, b – the size parameter for the hysteresis, and c – the AWC output sample time.

To exemplify the yaw motion for a few dynamic adaptation parameter scenarios, Fig. 8 is provided. Both in the left and right-hand plots, the light grey lines represent the wind direction variations at the first wind turbine in the row, while the solid black lines give the nacelle direction (abbreviated as NacDir in the plots) in the situation with AWC inactive. The remaining lines depict the nacelle direction with dynamic robust AWC for selected dynamic adaptation parameters. More specifically, on the left-hand side plot, the blue line represents the yaw position with instant adaptation of the yaw set-points, and the dashed black line – with the optimized adaptation parameters ($DynPars(60, 4, 10)$), the choice of which is explained below. The red line in the plot on the left corresponds to the situation with maximum hysteresis size ($DynPars(20, 4, 10)$). In the right hand side figure, the blue and red plots give the results with maximum AWC sampling time ($DynPars(20, 0, 600)$) and maximum LP filter time constant ($DynPars(600, 0, 10)$). It can be concluded from the plots that the hysteresis size has the most pronounced

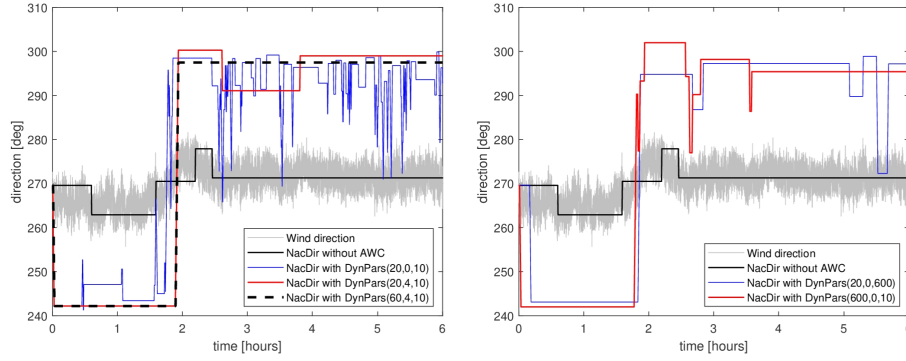


Figure 8. Yaw motion with AWC under different dynamic adaptation parameters

impact on the yaw duty (red and dashed black lines to the left). Long AWC sampling time (blue line in the right plot) does
 560 reduce the yaw excursions, but also results in the yaw misalignment angles being held constant at possibly suboptimal values
 for long periods of time, which may detrimental for the power gain. Long LP filter time constant appears to result in some
 seemingly unnecessary yaw excursions during changes in the set-points.

The following key performance indicators (KIPs) have been evaluated for each simulation:

- energy gain: the relative increase of the wind farm energy production achieved by AWC
- 565 – average yaw travel: the amount of angular displacement travelled by all wind turbines' nacelles on the average
- worst-case yaw travel: the highest amount of angular displacement travelled by any nacelle
- average number of yaw events: the amount of start/stop yaw actions performed by all nacelles on the average
- worst-case number of yaw events: the highest amount of start/stop yaw actions performed by any nacelle
- power gain per unit yaw travel increase: relative wind farm power production gain by AWC divided by the relative
 570 increase of average yaw travel due to AWC
- power gain per unit yaw events increase: relative wind farm power production gain by AWC divided by the relative
 increase of average yaw number of yaw events due to AWC

The KPIs are depicted in the surface plots in Fig. 9 (energy gain) and Fig. 10 (remaining KPIs).

Figure 9 provides comparison between the energy gains achieved by robust and nominal AWC for different adaptation
 575 parameters. The left-hand side plot corresponds to the situation with no hysteresis ($DynPars(a,0,c)$), while the right-hand
 side one is for the maximal considered hysteresis size ($DynPars(a,4,c)$). It can be observed that, without hysteresis (left
 plot), the energy gain by robust AWC is higher than that with nominal AWC, and the improvement remains consistent over
 the whole range of adaptation parameters considered. Interestingly, the energy gain slightly increases for higher LP filter time
 constants, which is probably due to the stochasticity in the simulated wind field: too fast an adaptation results in the yaw

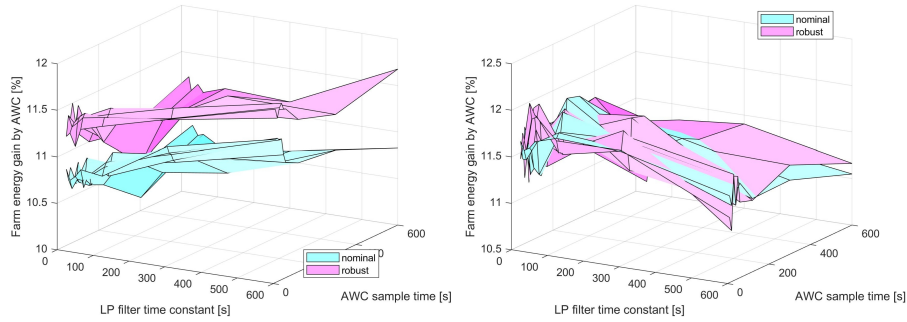


Figure 9. Energy gain by dynamic robust AWC and dynamic nominal AWC without hysteresis (left) and with 4° hysteresis (right)

misalignments trying to follow local variations of the wind direction, giving suboptimal AWC performance in terms of energy gain. This effect is strongly reduced when the largest hysteresis is in place, as seen in the right-hand side plot in Fig. 9. The local wind direction variations falling within the $\pm 4^\circ$ hysteresis zone will not appear in the yaw set-points any more, so any further LP filtering does not improve the energy gain. In fact, in that case a slight decrease in the energy gain is observed with increasing the LP filter time constant, which is attributed to the increased delay and decreased alertness of the yaw set-points to global wind direction changes.

Another interesting observation from Fig. 9 is that the case with large hysteresis gives rise to higher overall energy gain, while at the same time difference between nominal and robust AWC gets smaller.

Next, the KPIs related to yaw duty are discussed using the plots in Fig. 10, where they are expressed relatively with respect to the reference case without AWC. With respect to the four considered measures for yaw duty (yaw travel and number of start/stop events, each expressed either as an average or as a worst-case over the different turbines), the general conclusion can be drawn that increasing the hysteresis size significantly reduces the yaw duty, where huge reductions are observed for the cases with lower LP filter time constants and AWC sample times (i.e. for faster adaptation strategies). With the largest hysteresis sizes considered, the yaw duty is lowest and practically independent on the remaining adaptation parameters. This is a welcome result since, as explained above, these hysteresis sizes also turned out to improve the energy gain. Because of that, the power gain per unit yaw travel (or yaw event), depicted in the two plots on the bottom of Fig. 10, is highest for the largest considered hysteresis sizes.

In summary, it can be concluded that the following adaptation parameter choices deliver best results in terms of balancing the power gain and the yaw duty, which is probably best captured by the KPIs power gain per unit yaw travel increase and power gain per unit yaw events increase:

- hysteresis size: 4° . This popped up as the most effective parameter to reduce yaw duty and increase power gain. With the highest considered hysteresis in place, the remaining two parameters have only limited impact on the AWC performance. [This result also suggests that even higher values for the hysteresis size be considered in future studies.](#)
- LP filter time constant: 60 s.

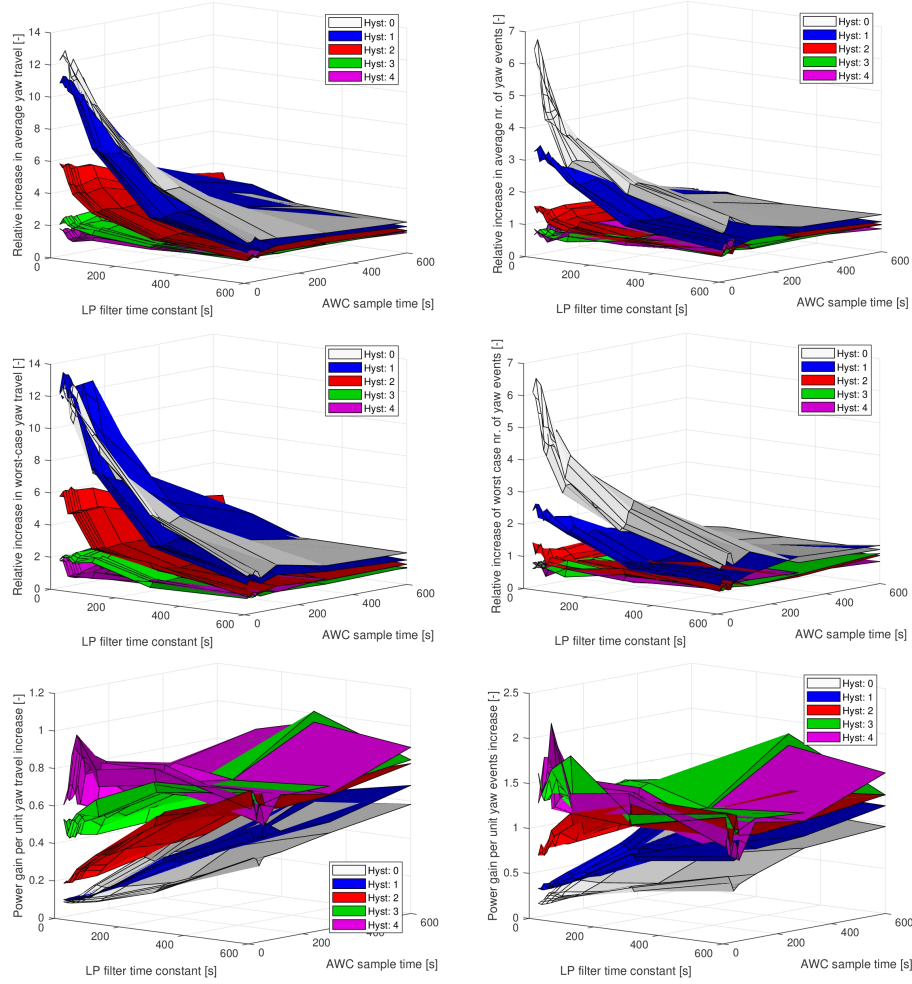


Figure 10. KPIs for the simulations with dynamic robust AWC: average and worst-case yaw travel, average and worst-case number of yaw start/stop events, and power gain per unity yaw travel and per unity yaw start/stop events

- sample time: 10 s.

605 With these adaptation parameters, the following results are achieved by the optimized dynamic robust AWC algorithm in terms of energy gain and yaw duty for the considered case study, all expressed relatively with respect to reference case (AWC-free):

- energy gain: relative increase of 12% in the wind farm energy production
 - average yaw travel: relative increase of just 1.13 (i.e. 13% increase), which is seems quite acceptable given the fact the
- 610 AWC requires the nacelle to travel substantially between positive and negative offsets as the wind direction changes.

- worst-case yaw travel: relative change of 0.95 (i.e. 5% reduction) in worst-case yaw travel. Since in the reference case it is the last turbine in the row that gets worst-case yaw travel in the simulation, this result shows that it remains higher than the yaw travel of the first four turbines even under dynamic robust AWC.
- average number of yaw events: relative change of 0.51 (i.e. 49% reduction) in average number of start/stop yaw actions. Having significantly less start/stop events with AWC than in the reference case ~~than with AWC~~ might first seem ~~counter-intuitive~~counter-intuitive, but does happen. The reason for this is the negative slope in the yaw misalignment set-points to the right of their maximum value (and to the left of their minimum value), see Fig. 11, which has a damping effect on the yaw motion. It can be observed, for instance, in the left-hand side plot Fig. 8 for the first turbine in the row (compare the solid black line with the dashed black line). For the remaining turbines (not plotted here) this effect is even more pronounced as they are yawed more often in the reference case.
- worst-case number of yaw events: relative change of 0.67 (i.e. 33% reduction) in worst-case number of yaw events.

Altogether, it can be concluded that the results are rather positive with dynamic robust AWC achieving high energy gain and overall reduction in the number of yaw events, at quite limited negative impact on the average yaw travel.

5 Case ~~study~~studies

This section presents the results from two case studies. The first one represents a example of robust AWC design performed for a simple farm consisting of a few turbines in a row. The second one represents a realistic case study with dynamic robust AWC applied to an offshore wind farm.

5.1 Simplified example of robust AWC design

To exemplify the robust AWC design, consider the single-row layout consisting of five 3 MW wind turbines, with 90 m rotor diameter, separated at a distance of 7D (equivalent to the setup in Cases 2 and 3 in Sect. 3.2). The robust optimization problem in Eq. (3) is solved for wind directions ranging from 248° to 292° at a step of 1°, an interval centred around the row orientation of 270°. In addition to that, a nominal AWC optimization is performed for the nominal values of the uncertainties $p^{(nom)} \in \mathcal{U}$,

$$\gamma_{nom}(\phi_{LUT}) = \arg \max_{\gamma} \sum_{t=1}^N P_t \left(\gamma | p^{(nom)}, \phi_{LUT} \right), \quad (4)$$

while evaluating the robust power gain, $\delta P(\gamma_{rob}, \phi_{LUT})$, including the uncertainties. The robust power gain for given yaw misalignment set-points γ and wind direction ϕ_{LUT} is computed using the discretized joint PDF

$$\delta P_{rob}(\gamma, \phi_{LUT}) = \left(\sum_{p \in \mathcal{U}_d} \sum_{t=1}^N P_t(\gamma | p, \phi_{LUT}) \mathcal{D}_d(p) \right) / \left(\sum_{p \in \mathcal{U}_d} \sum_{t=1}^N P_t(0 | p, \phi_{LUT}) \mathcal{D}_d(p) \right).$$

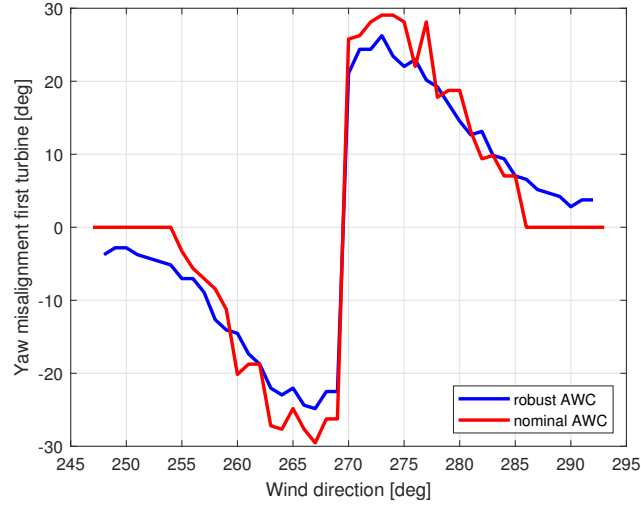


Figure 11. Yaw misalignment angles for the first turbine in the row

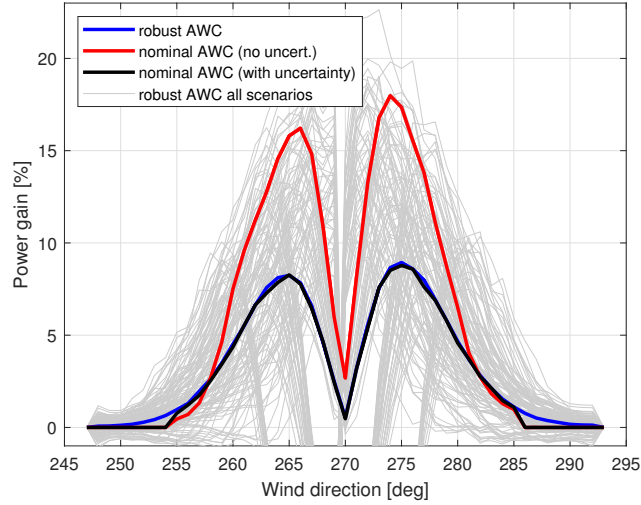


Figure 12. Power gain by nominal and robust AWC for a row of five turbines

The results are summarized in Fig. 11 and 12, depicting the first turbine's optimized yaw misalignment set-point and power gain for the complete turbine array, respectively, for the considered range of wind directions. The results show that the robust yaw misalignments exhibit lower maximum values, extend over a larger interval of wind directions and are smoother. This is expected to have a positive effect on the yaw duty, which will be evaluated with dynamic simulations in Sect. 4. In terms of robust power gain under robust AWC, $\delta P_{rob}(\gamma_{rob}, \phi_{LUT})$ (blue curve in Fig. 12), as compared to a nominal AWC, $\delta P_{rob}(\gamma_{nom}, \phi_{LUT})$ (black curve in 12), however, the improvement by robust AWC is quite limited. The red curve in Fig. 12 gives the nominal power gain (excluding uncertainties) under nominal AWC. For the sake of clarity, the difference between

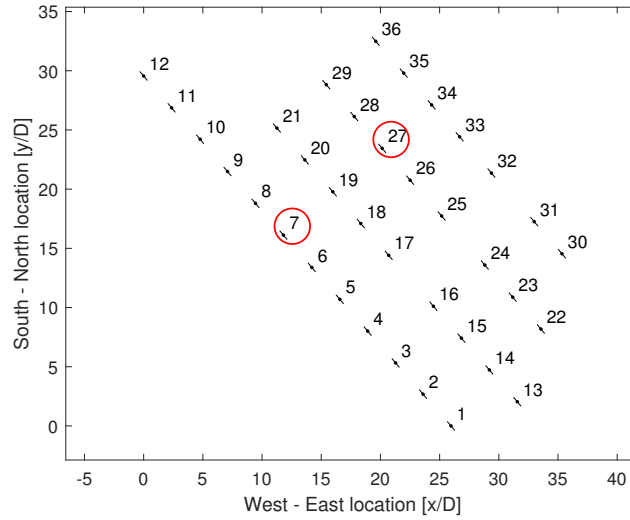


Figure 13. Layout of the OWEZ wind farm with the rotors oriented towards the average wind direction in the simulation, and with two selected for scoping wind turbines encircled.

the red curve “nominal AWC (no uncert.)” and the black curve “nominal AWC (with uncert.)” in Fig. 12 is that the former one depicts the power gain evaluated just for the nominal values of the uncertainty parameters ($p^{(nom)}$), while the later one represents the gain evaluated by including the whole uncertainty set \mathcal{U} through the joint PDF $\mathcal{D}_d(p)$. In both cases, the yaw misalignment set-points are the same, namely γ_{nom} , optimized for the nominal values of the parameters $p^{(nom)}$, i.e. neglecting the uncertainty, as defined in Eq. (4). The blue curve “robust AWC” corresponds to the case when both the optimization of the yaw set-points and the evaluation of the power gain are performed by accounting for the uncertainty through $\mathcal{D}_d(p)$.

5.2 Full-scale case study with dynamic robust AWC

In this section, the dynamic robust AWC approach is evaluated on a model of an existing full-scale offshore wind farm, namely the Offshore Windpark Egmond aan Zee (OWEZ). The layout of the wind farm OWEZ is given in Fig. 13 with the rotor diameter ($D = 90m$) as unit, and where the rotor diameters (the line segments) have been drawn 50% larger for more clarity. The wind farm is located at a distance of around 14 km off the Dutch coast, and consists of 36 Vestas wind turbines of 3 MW each. The turbines are modelled in FarmFlow through their power and thrust curves (CERC, 2016).

For the OWEZ wind farm, nominal and robust AWC controllers have been designed. The robust design is performed by taking into account the same uncertain quantities as in Sect. 3.2 and 3.3, i.e. wind direction, wind speed, yaw error and turbulence intensity. For this wind farm, wind field time series of duration 6 h, sampled at 10 s, have been generated using the approach in Sect. 2.1. The ~~spacial~~-spatial resolution of the wind field is 200 m. On the average, the wind direction is 230°(South-West), the wind velocity is 8 ms^{-1} , and turbulence intensity is 7%. The average wind velocity is 8 ms^{-1} , and the wind direction varies around 270°(see light grey line in Fig.14). For the AWC’s dynamic adaptation algorithm, the

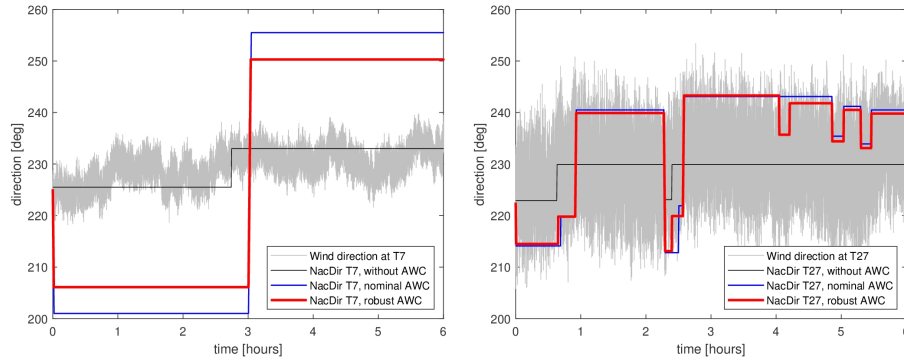


Figure 14. Wind direction and nacelle orientation for two selected wind turbines, $T7$ and $T27$, and three cases: without AWC, with dynamic nominal AWC and dynamic robust AWC. The sizes of the rotors are exaggerated by 50% for better readability of the figure.

optimized parameters from Sect. 4 have been used. The same adaptation parameters have been used with both nominal and robust AWC to enable evaluation of the added value of performing robust AWC optimization over the conventional nominal design.

Three dynamic simulations have been carried out, one without AWC (serving as reference case), one with nominal AWC and one with robust AWC. Each of these simulations took around 6 hours to complete on a single core. As an illustration, the local wind direction and the nacelle orientation for two selected wind turbines, those encircled in the layout plot in Fig. 13, are given in Fig. 14 for the three mentioned cases. Turbine $T7$ (left-hand side plot) is operating in free stream conditions for the simulated wind direction, while turbine $T27$ is in double wake situation and, hence, experiencing larger variations in the wind direction in accordance with the modelling described in Sect. 2.3. Because of that, the nacelle of $T27$ makes more often excursions than that of $T7$ in the reference case without AWC (black lines in the figure), resulting in higher yaw duty. This becomes even more pronounced when looking at the yaw motion under nominal (blue curves) and robust AWC (red curves).

Finally, the results from the simulations have been evaluated in terms of the KPIs, defined in Sect. 4. The results are summarized in Table 4 for the three simulated cases. Besides the absolute values of the KPIs for the three scenarios, the table provides between brackets the relative increases with respect to the reference case without AWC. The following observations can be made from the table:

- In terms of energy production, dynamic robust AWC improves significantly over the nominal AWC (2.05% vs 0.56% energy gain). Notice that the overall gains are lower than one might expect, which is to a large extent due to the somewhat irregular layout, especially in the lower right and upper left parts of the farm.
- The yaw travel, both average and worst-case, is significantly lower under robust AWC, which is partially due to the lower yaw misalignment set-points under this strategy as compared to nominal AWC. Compared to the reference case without AWC, the yaw travel under dynamic robust AWC is higher (factor 2.5-2.7), which is primarily due to the transitions between positive and negative misalignment. Notice that the reported values are only representative for the simulated

Table 4. Summary of results from OWEZ simulations

KPI	No AWC	dynamic nominal AWC (increase)	dynamic robust AWC (increase)
Energy production [MWh]	166.19	167.13 (0.56%)	169.59 (2.05%)
Average yaw travel [°]	23.8	96.8 ($\times 4.1$)	63.5 ($\times 2.7$)
Worst-case yaw travel [°]	87.3	399.5 ($\times 4.6$)	217.3 ($\times 2.5$)
Average nr. yaw events [-]	3.5	7.7 ($\times 2.2$)	5.3 ($\times 1.5$)
Worst-case nr. yaw events [-]	13	30 ($\times 2.3$)	14 ($\times 1.1$)

wind conditions (with, on the average, wind direction aligned with turbine rows), and will be significantly lower on annual basis.

- The number of start/stop yaw events with the robust controller are also lower than with the nominal one. The increase with respect to the reference case is relatively low in this case (1.1-1.5), which on annual basis is expected to be even lower.

6 Conclusions

~~This paper considers~~ The aim of this paper is to develop a framework for the design of dynamic robust AWC ~~that aims at~~ for optimizing the balance between the yaw duty and the power gain ~~in under~~ in under realistic conditions, ~~i.e. in the presence of~~ accounting for wind resource variability and ~~measurement and model uncertainty~~ model and measurement uncertainty, as well as to assess its benefits with respect to the conventional nominal AWC design. The starting ~~point was~~ point was an uncertainty quantification analysis performed for the following variables: wind speed, wind direction, yaw error, turbulence intensity, wind shear, air density, power curve, thrust curve, power loss coefficient due to yawed error. This analysis indicated that the wind direction, yaw error, turbulence intensity and the wind velocity are the most important quantities to include in a robust AWC optimization. To this end, the variabilities and uncertainties are modelled as stochastic processes with corresponding PDFs, and the yaw misalignment set-point optimization is addressed as a stochastic programming problem through discretization of the probability distributions to arrive at a finite number of scenarios. A stationary analysis based on stochastic averaging using the PDFs of the uncertain parameters indicated that the robust AWC design slightly outperforms the nominal one in terms of power gain.

Subsequently, the design of the dynamic adaptation algorithm is considered, for the purpose of which the originally stationary FarmFlow wake model has been extended to enable dynamic simulations, including wake meandering and dynamic yaw control. The dynamic simulation model is fed by a realistic wind field including temporal and ~~spacial~~ spatial inflow variations, with variations ranging from the micro-scale to meso-scale. Additional wind measurement noise is added for turbines operating in wake conditions, dependent on the local turbulence intensity, to model the increased yaw activity of downstream turbines, as observed in real-life measurements. Next, an AWC dynamic adaptation algorithm is considered, consisting of a low-pass filter,

a hysteresis, and sample and hold mechanism. The parameters of these three building blocks have been optimized through a range of dynamic simulations with a five turbine array. It is shown that large-size hysteresis ($\pm 4^\circ$) in combination with a low-pass filter with 60 s time constant and 10 s AWC sample time achieve the best trade-off between power and yaw duty. With these parameters, a reduction in the average number of yaw start/stop events of almost 50% and a power gain of 12% with respect to the reference scenario without AWC was achieved for the considered simulation. The yaw travel increased on the average by 13%, but its worst-case value over the turbines decreased by 5%.

Finally, the dynamic robust AWC approach is evaluated on a full-scale offshore wind farm model, for which both nominal and robust AWC controllers have been designed. The same (optimized) adaptation parameters have been used with both nominal and robust AWC to enable evaluation of the added value of performing robust AWC optimization. In the dynamic simulations performed, the robust AWC solution significantly improved over the nominal AWC one in terms of both power gain (2.05% vs 0.56% increase) and yaw duty (around 30-50% lower). Compared to the case without AWC, dynamic robust AWC increases the yaw duty somewhat, especially in terms of yaw travel (factor 2.5-2.7 higher). However, in terms of number of start/stop events, which is probably a more relevant indicator for the yaw loading, the increase is less significant (10-50%). It is important to note that the reported values are only representative for the simulated wind conditions (with, on the average, wind direction aligned with turbine rows), and is expected to be lower on annual basis.

~~The initial results in this paper underline the importance of optimizing AWC with respect to the real-life operating conditions, including wind resource variations and uncertainty in the measurements and modelling. Some topics that require further investigation in the future are:-~~

- ~~– performance analysis on annual basis: simulations need to be performed for the whole range of possible wind conditions are required to assess the annual impact of dynamic robust AWC on the power production and yaw duty.-~~
- ~~– deterministic (measurement) uncertainties: the current study is based on a stochastic representation of variabilities and uncertainties. For some quantities, e.g. measurement bias or wake model parameter uncertainties, a deterministic setting might be more suitable, in which the optimization ensures best performance in the worst case uncertainty scenario. As wind resource variability will remain of stochastic nature, the robust design methodology should account for both stochastic and deterministic uncertainties.-~~
- ~~– joint PDF: in the present work, all considered stochastic quantities were assumed independent. In reality, there is dependency between some variables, e.g. turbulence intensity depends on the wind velocity. To capture such dependencies properly, joint PDFs need to be used.-~~
- ~~– yaw set-points driven by consensus wind direction: to further reduce uncertainty in the wind direction measurements and, ultimately, the yaw duty, it might be beneficial to feed the AWC algorithm with a “consensus” wind direction signal constructed using measurements from several nearby turbines. An example for such an approach is the centralized yaw control method, originally developed in Bossanyi (2019) to reduce yaw duty on wind turbine level, which might be beneficial when used in AWC as well.-~~

- include global blockage effects in wake modelling: these effect, currently under investigation, are expected to play an important role in improving the modelling accuracy for large wind farms.
 - LiDAR-based feedforward AWC: using forward-looking LiDARs at upstream wind turbines, in combination with feedforward AWC control, is expected to be quite beneficial due to the very slow dynamics of the yaw system.
- 745 – wind direction dependent measurement offset: recent research (Raach et al., 2019, Sect. 8) indicates that when a turbine stands in a partial wake situation, its wind direction measurement is biased by up to a few degrees. Future research is required to properly model this phenomenon, analyse its impact on the performance of AWC and develop a compensating scheme.

Code availability. The simulations have been performed with FarmFlow, a proprietary tool developed by TNO.

750 *Author contributions.* EB developed the dynamic FarmFlow model, wrote Sect. 2.2, and reviewed the manuscript. The rest of the work was carried out by SK.

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