Authors reply to comments from referee #2

Dear Referee # 2
thank you very much for the review and the comments, which I will discuss in detail below.

RC1. *I am missing a discussion of the relation between the readings from a wind vane and the wind direction as a model input. For RANS types of models like FLORIS, the wind direction input is the ensemble mean value. This is NOT a stochastic variable, just a number with a sharp value - no matter how 'dynamic' the wind vane output looks. The Reynolds' decomposition takes care of fluctuations around the mean, so why is it relevant to use a distribution of inputs? You don't offer an explanation. I happen to agree with you that a single five (ten) minute average is insufficient, although not for reasons you give me. At the same time I don't understand what you are trying to achieve by passing raw wind vane readings as model input*

AC. The wake model FLORIS, which was used for this investigation, is a combination of the Jensen model (Jensen, 1983; Katic et al., 1986) with the wake deflection model presented by Jiménez (Jiménez et al., 2009) and further adjustments, detailed in (Gebraad et al., 2016). The model is parameterized to match power measurements obtained from 10-min LES simulations. The input of the model is the main wind direction, which, I agree, also represents the empirical mean wind direction. However, as already mentioned in the manuscript, conventional LES simulations do not reproduce dynamic changes of the wind direction, but rather consider a constant main wind direction. Only comparably small fluctuations of the wind direction are generated by the simulated turbulence. While this is useful for the qualitative analysis of specific situations, it does not represent the measurements we have made in the field. Gaumond et al. (Gaumond et al., 2014) proposed to use a wide span of wind directions as model input and to calculate the (normally distributed) weighted average to successfully account for the measured distribution of wind directions within 10 minutes. Among others he also used the Jensen model. We have extended this approach to also account for other uncertainties, as explained in the manuscript, and applied it to 5 minute periods of time within an optimization. The results of Gaumond are also the motivation to use the empirical 5-min dstribution of wind vane measurements as input for the model in the evaluation of control algorithms in Section 3.3. in the manuscript.
For a better explanation of the method in the manuscript Section 3 was revised and the following paragraph is added:

> p.9 ll. 8: This is in accordance with (Gaumond et al., 2014), who used a range of wind directions together with weightings corresponding to normal distributions as model input for similar wake models to take into account the variability of 10 min wind direction time series, and thus could improve the agreement of model results with measurements.

> p.14. ll. 18: Also, according to (Gaumond et al., 2014) the wind direction distribution as model input gives a better agreement with measured data. Therefore we use the empiric distribution for every time series, respectively.

RC2. *There IS a statistical uncertainty on five minutes averages (used as estimates of abstract ensemble mean values). However, you study 5 minutes standard deviation (std) estimates of the wind vane data, which is not the same. What is the relevance in terms of model input uncertainty? The std is an upper bound on std of the average, but is it a good one?. You seem to assume that the std is an adequate measure of the robustness. Do you?, and if so why is the std an adequate measure? How should the robustness parameter be quantified?*

AC. In the manuscript the hypothesis was tested whether the 5 minutes wind direction time series can be approximated by a normal distribution. Since this hypothesis was confirmed for the majority of the data, the standard deviations of the time series were calculated because the statistics of normally distributed random variables can be fully described by the mean and the standard deviation. The standard deviation therefore serves only to describe the respective time series and should not be used to estimate the uncertainty of the mean. In order to consider the wind direction changes within the 5 minutes in the optimization, a normally distributed weighting was used in the optimization according to Gaumond (Gaumond et al., 2014). In the evaluation, it was examined whether this method can also be used to compensate for further uncertainties, such as measurement inaccuracies and the deviation due to the time offset when the yaw angle follows the wind direction measurement. Increasing the robustness parameter and thus the standard deviation in the optimization implies that all errors are assumed to be normally distributed, since only in this case can the variances of the various uncertainties be summed up. We have not tested this hypothesis for the other uncertainties, but nevertheless the results show that the normal distribution is sufficient to improve the robustness of the control. To clarify this issue in the manuscript a paragraph will be added, which simultaneously addresses the next comment (see below) As already mentioned in the discussion of the manuscript, the results should only be understood as an indication and further investigations with simulations of higher fidelity and measurements in the free field should be carried out.

RC3. *The control algorithm in sec. 3.3 uses a prediction of the mean wind direction 5 minutes ahead. My guess is that the five minutes separation is a major source of uncertainty. The rms change between consequetive ten minutes averages of the wind direction is typically 5 degrees, a little less for 5 minutes. This could be used as a lower bound on the uncertainty. This can easily be derived from the met data (the pdf is double sided exponential).*

AC. The prediction of the mean wind direction of the 5 minutes ahead is based on the persistence method, which means that the control algorithm assumes that the best guess for the mean of the next 5 minutes wind direction time series is the mean of the current time series. The deviation of the mean is treated as uncertainty and I agree that this causes a large part of the overall uncertainty. As mentioned above, we assume in the manuscript that the robustness parameter and thus the normally distributed wind direction input of the optimization compensates this uncertainty accordingly. However, it was not tested whether this error is normally distributed. Therefore, we analysed the deviations of the successive mean values and created the histogram see Figure 1. As you mentioned the double sided exponential (Laplace) distribution can be fitted reasonably well to the empirical probability density distribution, although in this case a location scaled t-distribution results in a better fit (see Figure 1 (right)).

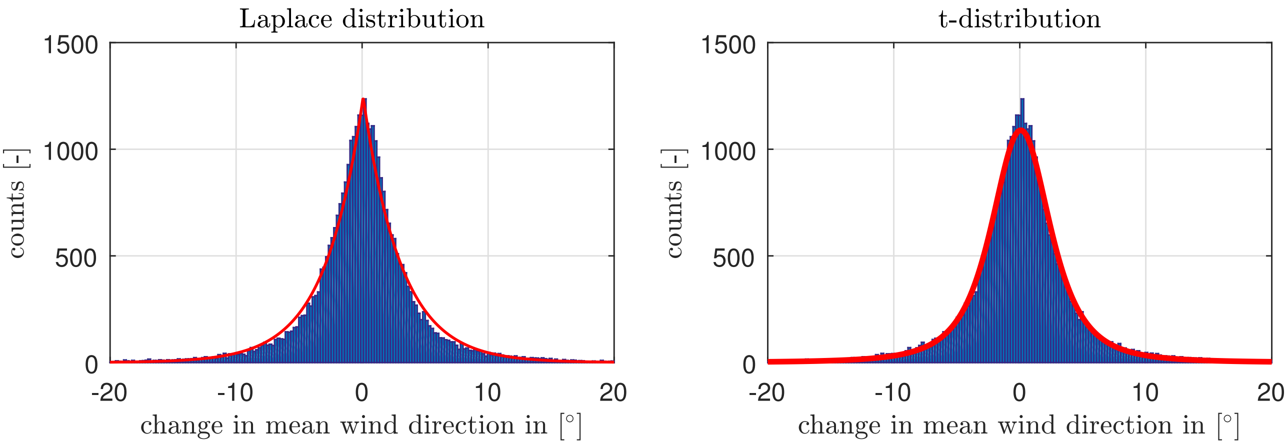

Figure 1: (Left) Histogram of the changes of the mean values of successive wind direction time series with a fitted Laplace distribution. (Right) Histogram of the changes of the mean values of successive wind direction time series with a fitted t-distribution.

The optimization is designed to be able to incorporate any kind of distribution as a component and therefore it is possible to integrate a t-distribution (or other distribution) in combination with a normal distribution by the convolution of both, however we do not change the presented method in the manuscript for two reasons. First, we want to demonstrate a rather simple method for the robust control algorithm and the single robustness parameter makes it easy and intuitive to adjust the robustness. Second, the results in the evaluation of the robust control algorithm show promising results with the current method.

To improve the manuscript in terms of clarity the right part of Figure 1 and the following paragraph will be added to the discussion part:

> p.18 ll.13f: In addition, we have assumed that all uncertainties that occur can be estimated by a normal distribution. This assumption proved to be sufficient in the evaluation, but individual sources of uncertainty can still be further investigated. The deviations of the mean values from successive wind direction time series, for example, seem to be well described by a t-distribution (see Figure 1). This finding could be used for the selection of the weightings in the optimization to improve the optimization. We have decided against this at this point, since an important aspect of this yaw control is its relative simplicity. By integrating a further distribution (by convolution with the normal distribution) the robustness could no longer be described by the robustness parameter alone.

RC4. *'Without loss of generality'. This phrase is used in several places without justification. Please drop it and admit the loss.*

AC. Thank you for this remark. The places where this was used were revised and adjusted as follows:

> p.5 ll.15f: We assume that the turbines run at a constant axial induction factor of $a_j = \frac{1}{3}$ for all j and the power output P_j of each turbine is normalized with respect to the power output of a turbine in undisturbed inflow conditions, since we are focussing on the influence of the yaw angle on the relative change of turbine power.

> p.9 ll.15: For the analysis we assume that a wind direction bias is negligible.

RC5. *figs 11 and 12. Popt/Pgreedy = 0.6between 11 and 12. The points melt together so that the density of points is lost. Perhaps smaller point size works better or maybe something different, like error bars?*

AC. For better understandability the variable $P_{\text{gain}} := \overline{\frac{P_{\text{opt}}}{P_{\text{greedy}}}} - 1$ is introduced in Section 3.3. and for better visibility of the scatter density in the Figures 11 and 12 the upper and lower quartiles as well as the median are added to the plots.

References

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