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Interactive comment on

“An analysis of offshore wind farm SCADA measurements to identify key parameters influencing the magnitude of wake effects” by Niko Mittelmeier et al.

Answers to comments of anonymous Referee #1 by

Niko Mittelmeier et al. April 25, 2017

Dear Referee,
Thank you very much for reviewing our paper. Your concern, that our results are only usable for the selected wind speed bin is valid. The proposed signal is dependent on wind speed and therefore a constant threshold is limited useful. We will provide an adjustment to this fact in our answers to your comments. We will also follow your suggestion to develop the arguments in a new way. We focus on the classification of the magnitude of wake effects and show the ability to predict these conditions with the different signals. Your comments helped us to understand where we need to provide more clarity and we hope that our answers to your questions will improve the paper. Our responses to your comments are marked as ***/ Response /***.

The manuscript entitled "An analysis of offshore wind farm SCADA measurements to identify key parameters influencing the magnitude of wake effects" deals with the using of operating information supplied by the wind turbines to assess the atmospheric stability conditions and then to make some conclusions about the wake interaction effects. The objective is fully relevant: wind farms, and particularly offshore ones, are not equipped with meteorological measurements to determine the real-time and reliable meteorological conditions (wind speed, wind direction and particularly atmospheric stability). On the other hand, wind farm models need field data to be validated. The authors attempt to find an indirect way to assess atmospheric stability in order to determine the magnitude of the expected wake effects, according to this parameter.

On the other hand, the methodology used in this manuscript to obtain the presented conclusions does not sound rigorous enough at this stage to be published in a journal. Some hypothesis are too strong and the methodology is not validated.

Please find below the arguments to justify the recommendation:

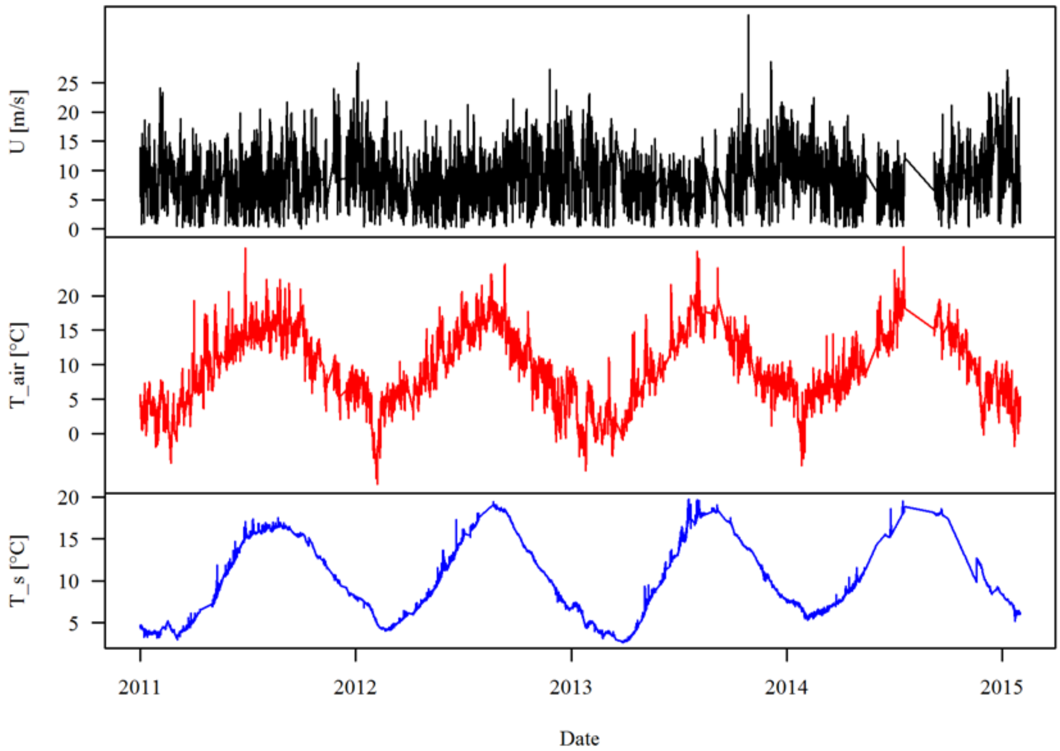
- A direct correlation is expected between the turbulence intensity and the atmospheric stability. Though, for a fixed stability condition, turbulence intensity can have big scatter and particularly at low wind speeds. Reference to the works from Dörenkämper et al. (2012 and 2015) are used to justify this strong simplification but these references are a PhD thesis and a proceeding from a national conference. I would suggest to make references to publications in peer-review journals and to develop the arguments that give the possibility to reduce the stability effect to a turbulence intensity effect, and particularly at low Wind speeds.

***/ You are right, using only turbulence intensity (TI) is a very strong simplification for stability. To come up to the readers expectations we will add more clarity to the abstract and introduction to make the purpose of the paper more defined.

The idea behind this research is to find a signal that could be used to improve wake model tuning for specific operational conditions. This may help to improve the use of a wake model to detect underperformance as proposed in Mittelmeier et al. (2017). We will show, that the magnitude of wake effect is not only governed by stability but also turbulence intensity and we will show to which extend one can expect an overlapping effect.
For this purpose, we will provide peer reviewed journal publications to base the assumptions on a more solid foundation and evaluate new data to be able to compare a stability description defined by the Monin-Obukhov similarity theory and the SCADA data.

In Hansen et al. (2012), the authors studied wake effects at Horns Rev in different atmospheric conditions. They also compared turbulence intensities for different stability classes as a function of the wind speed. Below 7m/s a clear increase in TI can be noticed. Above 7m/s neutral-unstable conditions are clearly distinguishable from more stable conditions with a constant threshold up to nominal wind speed. Dörenkämper et al. (2014) published their results also at a peer reviewed conference series where they draw the link from stability via shear to turbulence intensity motivated by the studies of (Tambke et al., 2005). In a later study, Sanz Rodrigo et al. (2015) compared different stability classification methodologies with data from FINO 1 and presented the behavior of shear and turbulence intensity for the proposed atmospheric stability classes. The authors concluded, that in this particular cases TI correlates well for stable cases but at near neutral and unstable cases, shear is supposed to enable better distinction between their nine classes.

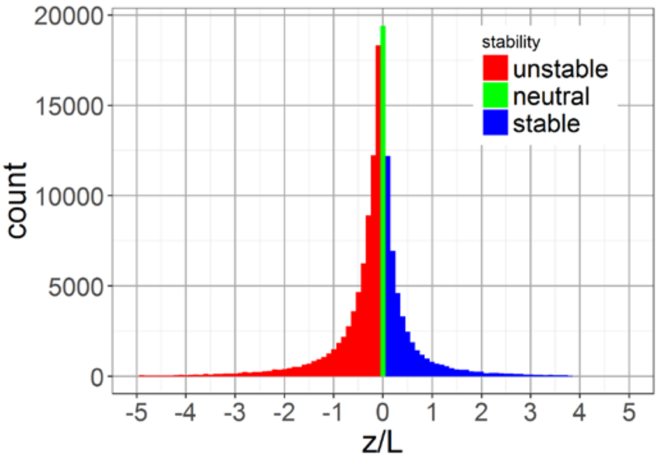
We investigated new data from FINO1 to be able to use a “real” stability classification and not only TI classes.
With latest calibrated temperature data from DEWI (Richard Fruehmann) we were able to follow the approach suggested by Ott and Nielsen (2014) and calculated the dimensionless $\zeta = \frac{z}{L}$ for T_air at 33m. The plot below shows the data availability for the selected period.



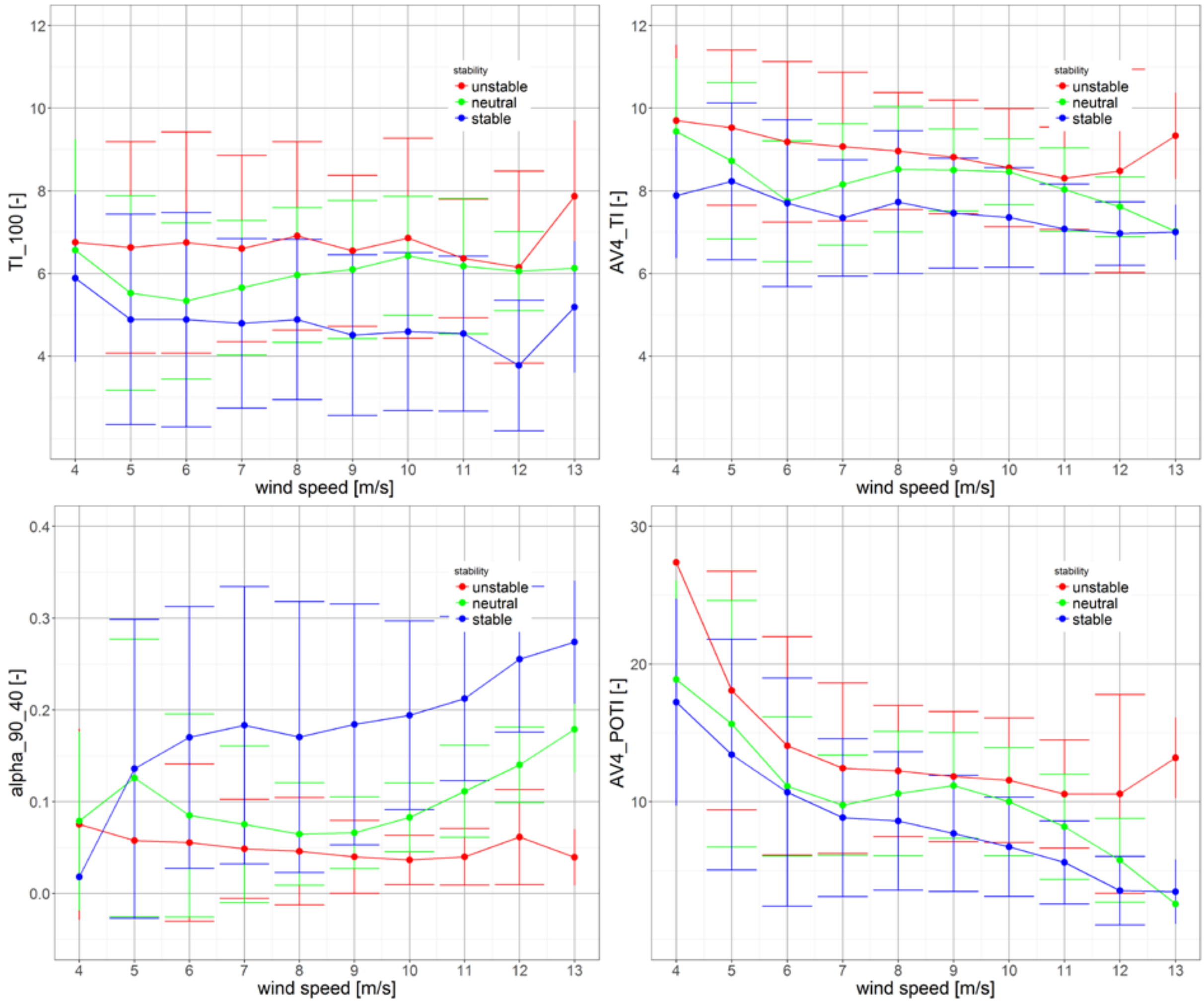
We decided to keep the number of classes at three ("unstable", "neutral" and "stable") based on the following table:

Category	Range
Unstable	$\zeta < -0.05$
Neutral	$-0.05 \leq \zeta \leq 0.05$
Stable	$\zeta > 0.05$

(We will add more description of the methodology for the estimation of thresholds in Section 3.3) The estimated thresholds have also been proposed by Rajewski et al. (2013).
This leads to the following histogram for the three classes.



In the plot below, we have used the new stability classification based on $\zeta = z/L$. Bin averaged turbulence intensity (TI_100) measured at the met mast and at the nacelle (AV4_TI) as well as met mast shear (alpha_90_40) and AV4_POTI are plotted for each class as function of the wind speed. The selected wind speed bin of 8 ± 1m/s is quite well distinguishable with constant thresholds for all the provided variables. But whereas turbulence intensity from the met mast is fairly constant for the whole presented range, shear and POTI are showing a much stronger dependency on wind speed.



The plots above confirm the statement made by Tambke et al. (2005) and Sanz Rodrigo et al. (2015), that shear enables a more clear distinction between the atmospheric stability classes. The error bars, indicating one standard deviation are not overlapping anymore for stable and unstable class above 8 m/s.

As you have suggested, we will develop the arguments in a new way. We describe how to classify low and high wake effects and use this characteristic to evaluate the predictability based on stability, turbulence intensity and turbine SCADA data classes. Then we provide an overview on the different occurrences of the described environmental conditions.

Determination of thresholds:
At first we select the normalized power (waked turbine, normalized by the power of a free flow turbine) for a small sector (10°) in the full wake for the relevant wind speed range (8 ± 1 m/s) (Fig 1a). Secondly we eliminate the dependency on wind direction by normalizing the normalized power for each wind direction bin (binwidth = 2°) with its mean value (Fig. 1b).

Fig. 1a

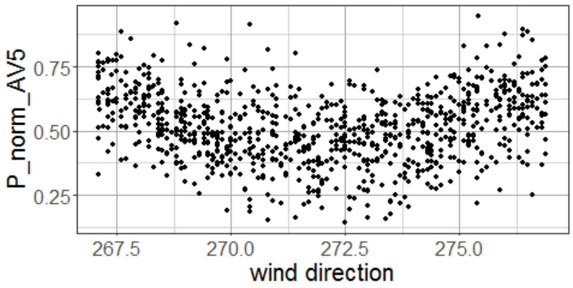
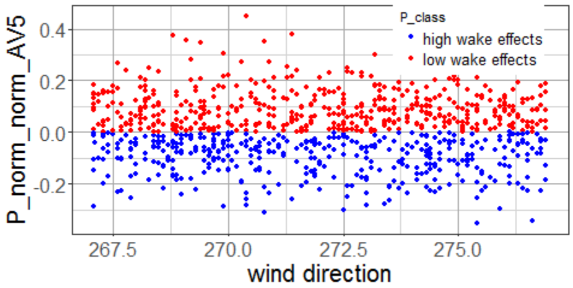


Fig. 1b



The third step divides the data set into high wake effects (values < 0) and low wake effects (values >= 0) and the density distribution of the variable of interest is plotted for these two data sets (Fig 2). We use the median for each density distribution to allocate thresholds.

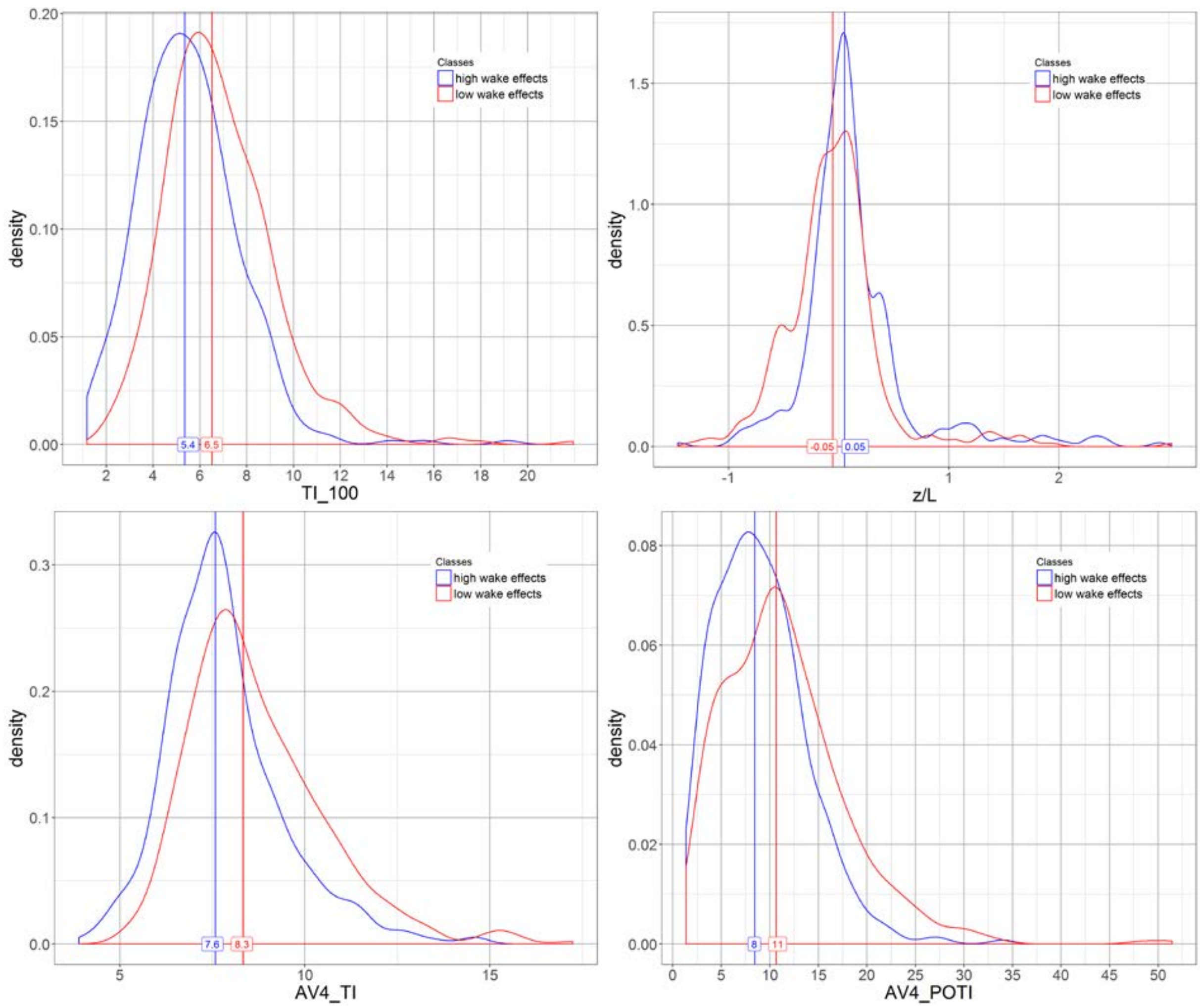
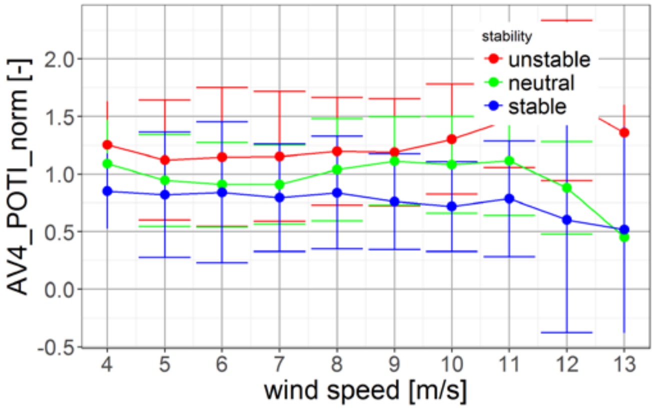


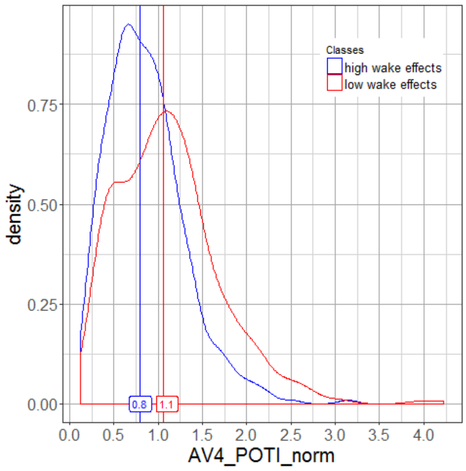
Fig 2. Data density for different variables based on low and high wake effects. The median for each distribution is highlighted with a vertical line. The data corresponds to a wind speed bin of 8 ± 1 m/s and a sector width of 10° around the full wake.

Note:
The TI and POTI thresholds have slightly changed compared to our first version of the paper. The difference in TI thresholds is due to the fact, that we have used the values from Dörenkämper (2015) and now we are suggesting this new methodology.
POTI thresholds have also slightly changed from the old version of our paper because the criteria was visual inspected and now we propose to use the median. In this way, the results should be reproducible now.

To overcome the shortfall of AV4_POTI signal having a strong dependency on wind speed, we propose a normalization of this signal with a third order polynomial.



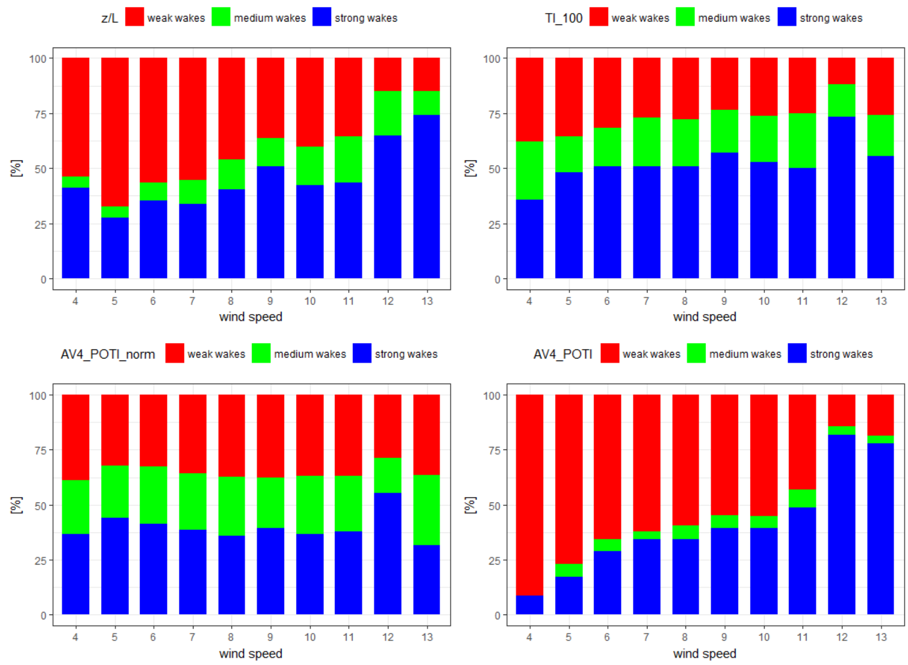
When applying the same methodology to AV4_POTI_norm as described above, we obtain density distributions as below:



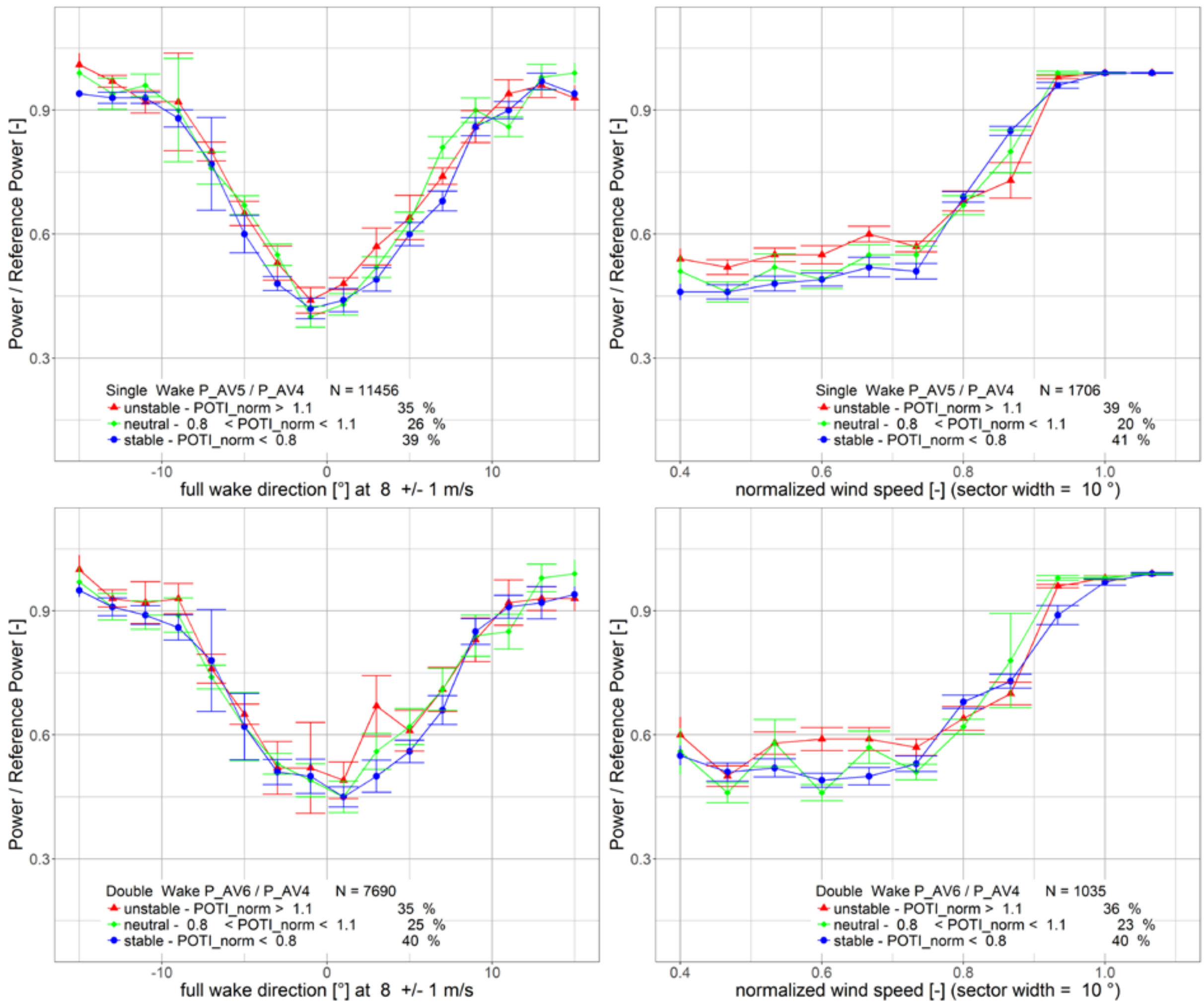
The table below summarizes the different classes:

Category	$\zeta = z/L$ **[-]**	**TI_100 [%]**	**AV4_POTI_norm [-]**
Weak wakes	$\zeta < -0.05$	TI_100 $< 5.4\%$	$POTI_{norm} < 0.8$
Medium wakes	$-0.05 \leq \zeta \leq 0.05$	$5.4 \leq T_{100} \leq 6.5$	$0.8 \leq POTI_{norm} \leq 1.1$
Strong wakes	$\zeta > 0.05$	$T_{100} > 6.5$	$POTI_{norm} > 1.1$

Looking at the distributions for each class, one can see an improvement from POTI to POTI_norm. Latter is much more comparable to the turbulence intensity measured at the met mast.



For z/L, weak wakes cases seem to become less frequent with increasing wind speed. POTI seams to overestimate this trend. TI_100 and AV4_POTI_norm provide similar results. Using AV_POTI_norm as a classifier, we obtain the following wake plot:



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- LiDAR measurements at Nord See wind farm NO : PPI planes are described as horizontal. LiDAR is located on the helicopter platform from the wind turbine NO48. One therefore guess that is corresponds to an altitude close to the hub height. Consequently, the laser beam should meet the wind turbine rotors NO44 and NO45, leading to unusable data in the vicinity of both rotors. On the other hand, on Figure 4, the visualizations of the velocity field, as well as the normalized velocity evolution versus the downwind distance do not present any unresolved areas close to the rotors. The velocity induction through the rotor is presented and discussed. Please explain how these data were reconstructed close to the rotors.

***/ Yes, you are right. Hard targets like blades and nacelle prevent a reasonable wind speed measurement. Due to the fact, that we are using multiple PPI-scans to obtain a 10-min average value, there are wind speed measurements available in the rotor plane.
To derive the wind speeds for Fig. 4 (top), a raster layer was generated. While raster cells with multiple measurements are averaged, values with empty cells are linearly interpolated. In this way, the blind region at each nacelle and areas between the beam directions show interpolated wind speeds.

We will add the following text:
“Hard targets like blades and nacelle prevent reasonable wind speed measurement. Wind speeds at these blind regions and between the beam directions are linearly interpolated. “
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- §3.3 New classification and validation. This part is confusing. The authors determine a classification of the wake effect on the basis of the median of the normalized power of a wind turbine in wake interaction. It means that the intensity of the wake effect is determined by its statistical occurrence and not by its strength. Please elaborate an argumentation to justify this strategy of classification

***/ You are right, this part has been not sufficiently described. In our data example we obtained a mean = 0.516 and a median = 0.5108 which is very close together (0.0052). We decided to use the median because the mean was effected by some outliers. A deeper analysis of these outliers revealed that an additional filter criteria for the data is needed. The new filter removes 10-min intervals when one of the turbines has had a downtime in the interval before. In this way the flow throw the wind farm gets another 10-min time to develop. Additionally data with a power ratio > 1 meaning that the turbine in the wake produces more than a free flow turbine has been deleted (only two values). After removing these outliers, mean and median have now a difference of 0.0015. We agree that it is more appropriate to use the mean when enough care for outliers has been taken.

We will describe the new filtering in 2.4 and change 3.3 to “mean” instead of median.
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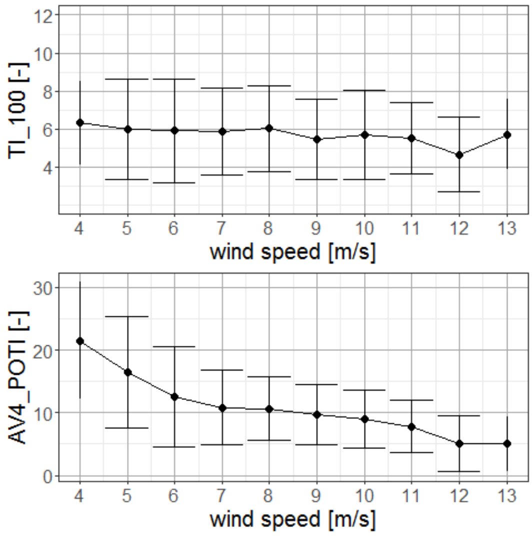
- §4.2 Correlation analysis. It is not clear whether the data are sorted only according to the turbulence intensity or also to the wind speed (as performed in Fig. 5). If the data are not sorted according to the wind speed, it means that different operating conditions are plotted without distinction in this correlation matrix. How can one expect to get strong correlations between data coming from the incoming flow conditions (fully independent of the operation parameters) and operation-driven data coming from the wind turbines without any additional filters ? Could you please show the evolution of the relative power fluctuation PO_TI with the WT power or with the wind speed? Regardless of this crucial point, one cannot state that the level of correlation is acceptable in order to use this information as a representation of the turbulence intensity, and even less of the atmospheric stability.

***/ You are right. Please find below the requested plots. Within the wind speed range of interest, the turbine signal is much more dependent on wind speed than the measured turbulence intensity at the met mast. All our wake plots are based on the wind speed bin 8 ± 1 m/s. In this range the correlation is higher, than for the other wind speeds.



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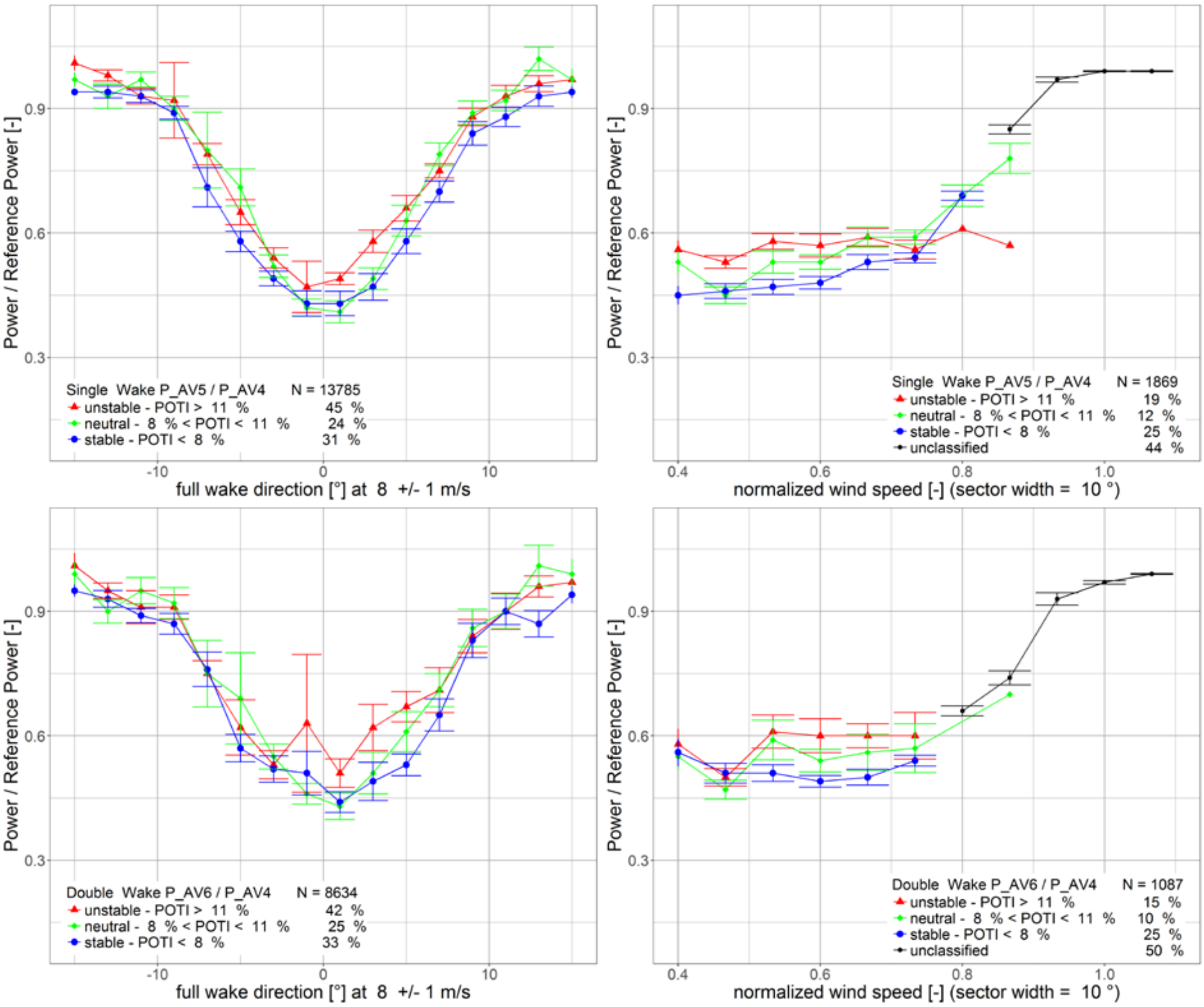
- §4.3.1 New classification and validation on Alpha Ventus. By applying the new classification; discrepancies in the power production due to the assessed stability is rather small and difficult to interpret. By comparing Fig 5 and Fig 9, one notice that the frequency of occurrence of each stability class is also totally dependent of the classification method. For instance, on the top-right plot, the unstable case occurrence is 13% of samples for the new classification, instead of 56% with the classification based on turbulence intensity. It show again the poor correlation between both information.

***/ In Fig. 9 the % values are biased because the “stable” class also contains all data where the turbine controller has already started with the main pitch activity which leads to a lower standard deviation of the power. We have to filter this part of the operation before displaying the proportions of the classes. We will call this part of the data “unclassified”. The corrected plot is provided below:



We think this plot is not relevant anymore. We would like to show the new classification based on the normalized AV4_POTI_norm. (As provided for the answer of your first comment)
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- The thresholds used in the new classification are different for each tested wind farms. It is justified by the fact that the wind turbines are different. But how can one explain that thresholds are different on the same wind farm (Ormonde) but for different wind directions?

/We assume that this has been an error due to the fact that POTI was very much dependent on wind speed. With the new proposed method to use a normalized values we can stick to the same classification even for different turbines, cause the turbine behavior is canceled out. /