An analysis of offshore wind farm SCADA measurements to identify key parameters influencing the magnitude of wake effects

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Abstract. Atmospheric conditions have a clear influence on wake effects. Stability classification is usually based on wind speed, turbulence intensity, shear and temperature gradients measured partly at met masts, buoys or LiDARs. The objective of this paper is to find a classification for stability based on wind turbine Supervisory Control and Data Acquisition (SCADA) measurements in order to fit engineering wake models better to the current ambient conditions. Two offshore wind farms with met masts have been used to establish a correlation between met mast stability classification and new aggregated statistical signals based on multiple measurement devices. The significance of these new signals on power production is demonstrated for two wind farms with met masts and validated against data from one further wind farm without a met mast. We found a good correlation between the standard deviation of active power divided by the average power of wind turbines in free flow with the ambient turbulence intensity when the wind turbines were operating in partial load.

1. Introduction

Wake effects are one of the largest sources of losses in offshore energy yield assessment. This makes wake modelling very important and much research is ongoing to improve wake model predictions. In the latest offshore CREYAP [1] benchmark exercise (Comparative Resource and Energy Yield Assessment Procedure) wake modelling was found to be the prediction with the highest variation among the participants.

In order to be able to use a wake model for validating the performance of an operating offshore wind farm [2], prediction uncertainties need to be reduced. Atmospheric stability has been identified as being one main driver for the variation in power production under waked conditions [3] and state of the art engineering wake models for industrial application like Fuga or FarmFlow are able to take stability effects into account [4] [5].

Stability classification is based on measurements from met masts, buoys or is assisted by remote sensing devices such as LiDAR or SoDAR. For offshore use, these devices are very expensive and therefore often not permanently available.

The purpose of this paper is to investigate wind farm operational data and establish methods of identifying correlations between SCADA statistics and wind turbine wake behaviour caused by different atmospheric conditions.

2. Wind farms and measurements

For this investigation, we have selected three offshore wind farms, alpha ventus, Nordsee Ost and Ormonde. The first two wind farms have a well-equipped met mast and provide high quality measurements of hub height wind speed, wind direction, shear and turbulence intensity.

2.1. alpha ventus

The wind farm alpha ventus (AV) is located about 45 km north of the island of Borkum in the North Sea. It consists of twelve turbines of the 5 MW class and has been commissioned in April 2010. The six northern turbines have been manufactured by Senvion. The six turbines in the southern part of the wind farm (produced by Adwen) are not considered in our analysis. The FINO1 research met mast is only 3.2 rotor diameters west of turbine AV4.

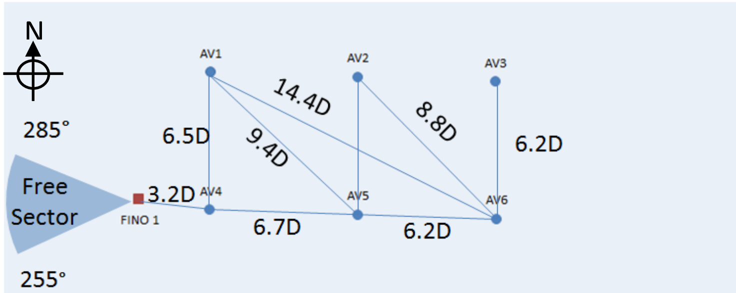

Figure 1: Northern part of alpha ventus and FINO1 met mast layout with free flow sector

The layout of alpha ventus (Figure 1) allows for investigating the wake behaviour in single and double wake conditions for westerly wind directions. No data after the period from 3/2011 to 1/2015 has been used, because the installation of the Trianel wind farm in the west is supposed to have changed the environmental conditions of alpha ventus by adding extra turbulence to the flow.

2.2. Nordsee Ost

The wind farm Nordsee Ost (NO) is located about 35 km north-west of the island of Helgoland in the North Sea and is owned by RWE International (former RWE Innogy). The 48 Senvion turbines have a rated power of 6150 kW each. The met mast is located in the south-western corner of the wind farm (Figure 2). In the south, the neighbouring wind farm Meerwind Ost/Süd reduces the sector of free flow for the met mast as well as the possibilities to study multiple wakes higher than triple wake condition without disturbing effects from Meerwind.

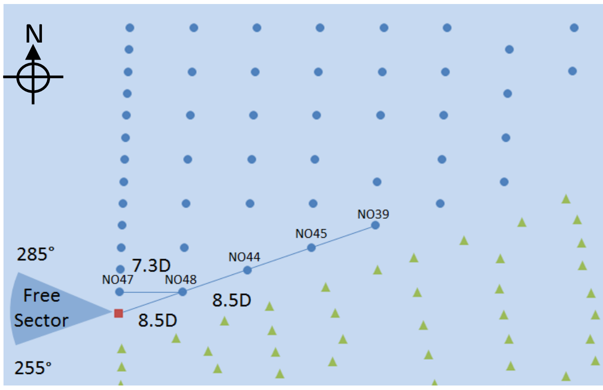

Figure 2: Nordsee Ost (blue cycles) with neighbouring wind farm Meerwind Süd (green triangles) and met mast (red square).

The wind farm Nordsee Ost has been fully commissioned in 2015. So far not enough data (11/2015 – 4/2016) has been collected to investigate the full wake behaviour. For this reason, only a correlation analysis (described in Section 3.2) was performed.

2.3. Ormonde

The Ormonde wind farm consists of 30 Senvion turbines with a rated power of 5 MW and is owned by Vattenfall. The wind farm is located in the Irish Sea 10 km west of the Isle of Walney.
The farm layout displayed in Figure 3 is structured in a regular array which allows for comparing several single wake, double wake and triple wake situations. The turbine distance for the investigated wake situation is 6.3 D. The neighbouring rows are spaced at 4.3 D. We have selected four turbines in one row. The selected data is from 1/2012 – 1/2014.

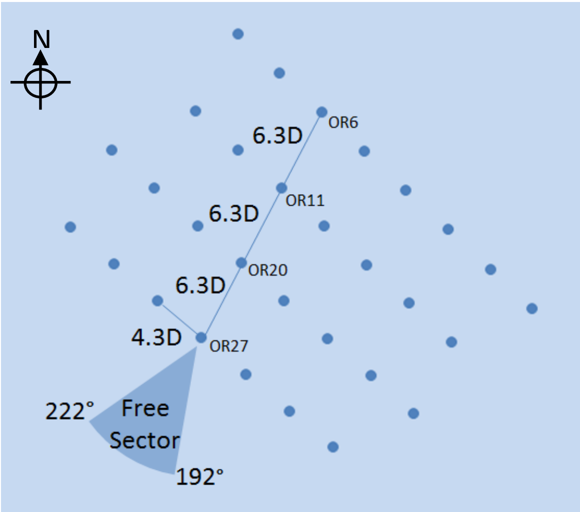

Figure 3: Ormonde wind farm

2.4. SCADA and meteorological data

The SCADA data from all wind farms and the meteorological data consist of 10-minute statistics. Each turbine provides wind speed, wind direction, active power, yaw position, and pitch angle. The operational condition of the wind turbine which is used for the correlation with the met mast turbulence intensity is categorized by the minimum active power > 10kW, the maximum pitch angle < 3° and the standard deviation of the yaw position > 5°. These filter criteria's ensure that no stand stills, curtailments or too large yaw activities are included in the data. Implausible met mast data has been removed and wind directions have been corrected for bias by using the orientation of the maximum wake deficit. For the correlation, only sectors of free flow conditions have been used.

3. Data analysis

3.1. Turbulence, stability and its impact on power production

A stability classification according to the Richardson number expects wind speed and temperature measurements in 10 m and 30 m height. As both met masts fail to fulfil this requirement and as the available temperature measurements have a too large uncertainty to provide reliable stability estimates via the bulk Richardson approach[6], the simplified classification using turbulence intensity at hub height as proposed by Dörenkämper et al. [3], [7] is used for this investigation.

Table 1: Definition of stratification used in present analysis at hub height

Classification	Turbulence Intensity (TI)
Unstable	TI > 6 %
Neutral	6 % ≥ TI ≥ 4 %
Stable	4 % > TI

Based on the turbulence intensity from the met mast SCADA data was divided into three subsets: unstable, neutral and stable (Table 1). The power production for the different subsets, normalised by free flow power production, is compared for single wake and double wake conditions with data from alpha ventus and FINO1.

3.2. Correlation analysis

At wind farms with no met mast we have to rely on other signals to describe the differences in power production under different conditions. To find the best substitute for a met mast measured turbulence intensity several SCADA signals that are affected by turbulence have been chosen and correlated to the met mast turbulence intensity TI_{mast}.

$$TI_{mast} = \frac{\sigma_{u_{mast}}}{\overline{u_{mast}}} \tag{1}$$

$$TI_{WT} = \frac{\sigma_{u_{WT}}}{\overline{u_{WT}}} \tag{2}$$

$$PO_{std} = \sigma_P \tag{3}$$

$$PO_{TI} = \frac{\sigma_P}{\overline{P}} \tag{4}$$

First of all, the turbine turbulence intensity TI_{WT} derived from the nacelle anemometer was compared. Equation (1) for the met mast is analogous to the one for the turbine (Equation (2)), with $\overline{u}$ being the 10 minute averaged horizontal wind speed and its standard deviation σ_u. The next turbine signal of interest is the standard deviation of the turbine power σ_P. A normalisation of this signal by the average power $\overline{P}$, leads to equation (4). All SCADA signals can be obtained under free flow conditions or in waked conditions.

3.3. New classification and validation

The new artificial SCADA signal with the highest correlation to the met mast turbulence intensity is used to classify different stratifications. The thresholds are estimated with a two-step approach. First, the power of a turbine in the wake is normalized with the power of a turbine in free flow conditions. This normalized power from a narrow sector of 10° centered at the full wake is divided into three groups. Medium wake effects are ±5% around the median of the normalized power. High wake effects are 5% higher and low wake effects are 5% lower than the median of the normalized power. In the second step the density distribution of the new SCADA signal is plotted for all three groups and the thresholds are selected to achieve best distinction between the three data sets.

The quality of the established relationship in terms of dependency on turbine type, layout and location of the wind farm is tested by applying the same classification on a different wind farm where no met mast is available.

4. Results and discussion

4.1. Turbulence, stability and its impact on power production

Data from almost four years of operation has been used to evaluate the influence of atmospheric stability derived from the turbulence intensity and its impact on the wake development. Figure 4 proves the different wake behaviour under different turbulence conditions. The top row of plots shows the single wake condition of turbine AV5 in the wake of AV4. The second row displays the same evaluation but for the double wake condition of AV6 in the wake of AV4 and AV5. The left side is a normalised power deficit as function of the wind direction for a wind speed range from 7 m/s to 9 m/s. On the right side, there is the normalised power as function of the wind speed for a sector width of 10°. Each graph states the total number N of data points which have been split into stable (blue dots), neutral (green diamonds) and unstable (red triangles) data sets. Each symbol is the average of a 2° bin (1 m/s bin) and the error bars indicate the standard error of the mean.

For the single wake, a clear distinguishable difference between the stable and unstable power deficit is visible. The largest deviation is found in the full wake. The second wake has a less pronounced difference in power which can be explained by the fact, that the first turbine operating in the wake supports the mixing with the ambient wind speed. Another interesting effect is noticeable in the top left plot. The difference in power for the different stabilities is higher at the right side of the deficit. This right drift of the wake in stable conditions has been explained with LES simulations by Vollmer et al. [8].

The turbulence intensity for this classification has been measured at 100 m which is the highest height at the FINO1 met mast. The second height of the FINO1 met mast (90 m) is closer to hub height (92 m), but the strong mast structure and the boom orientation of 135° causes disturbance for wind directions within the selected sector for our investigation. No further correction, e.g. to account for the difference in height was necessary according to the findings of [9].

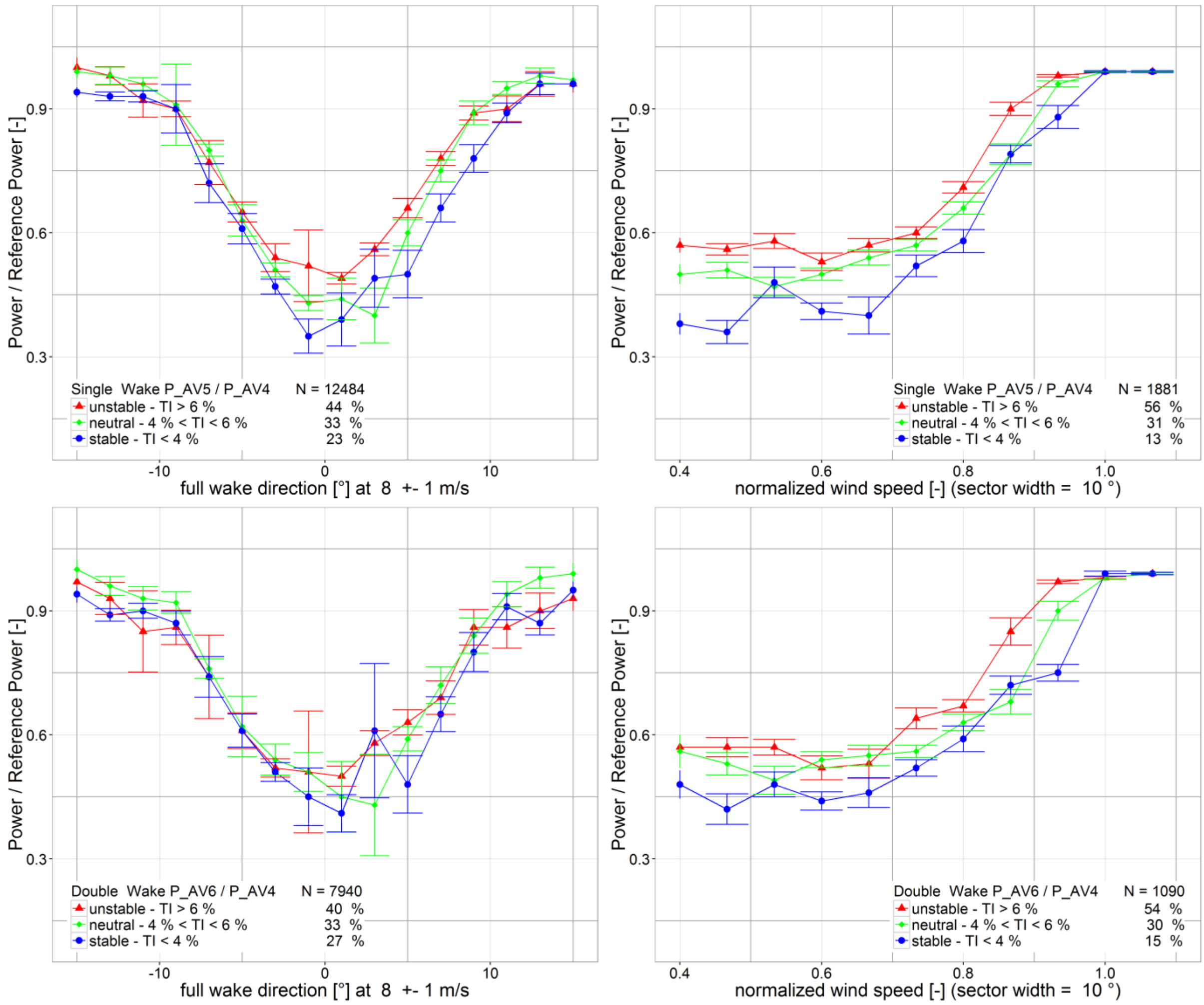

Figure 4: Wake effects in alpha ventus (AV) under different atmospheric conditions. Power of downstream turbine normalised with free flow turbine. Upper row: single wake, lower row: double wake. Left column: Normalised Power as function of wind direction, right column: Normalised power as function of wind speed.

4.2. Correlation analysis

In the next step, we have checked the correlation of the SCADA signals described in Section 3.2 with the turbulence intensity measured at the mast. In Figure 5 a panel plot is displayed. The graphs on the diagonal present the histogram and density distribution for the respective variable. The panels above the diagonal provide the Pearson correlation coefficients. The lower panels are scatter plots for the two variables with a fitted linear regression line for easier identification if linear relations are given or not. The colours of the points indicate the three stability classifications (blue: stable, green: neutral, red: unstable) determined with the met mast turbulence intensity as described in Section 3.1.

The correlation between met mast and turbine TI in subplot (1 , 2) equals to 0.55. This poor result can be explained by the nacelle wind speed measurement position behind the rotor, which induces additional disturbance to the flow.

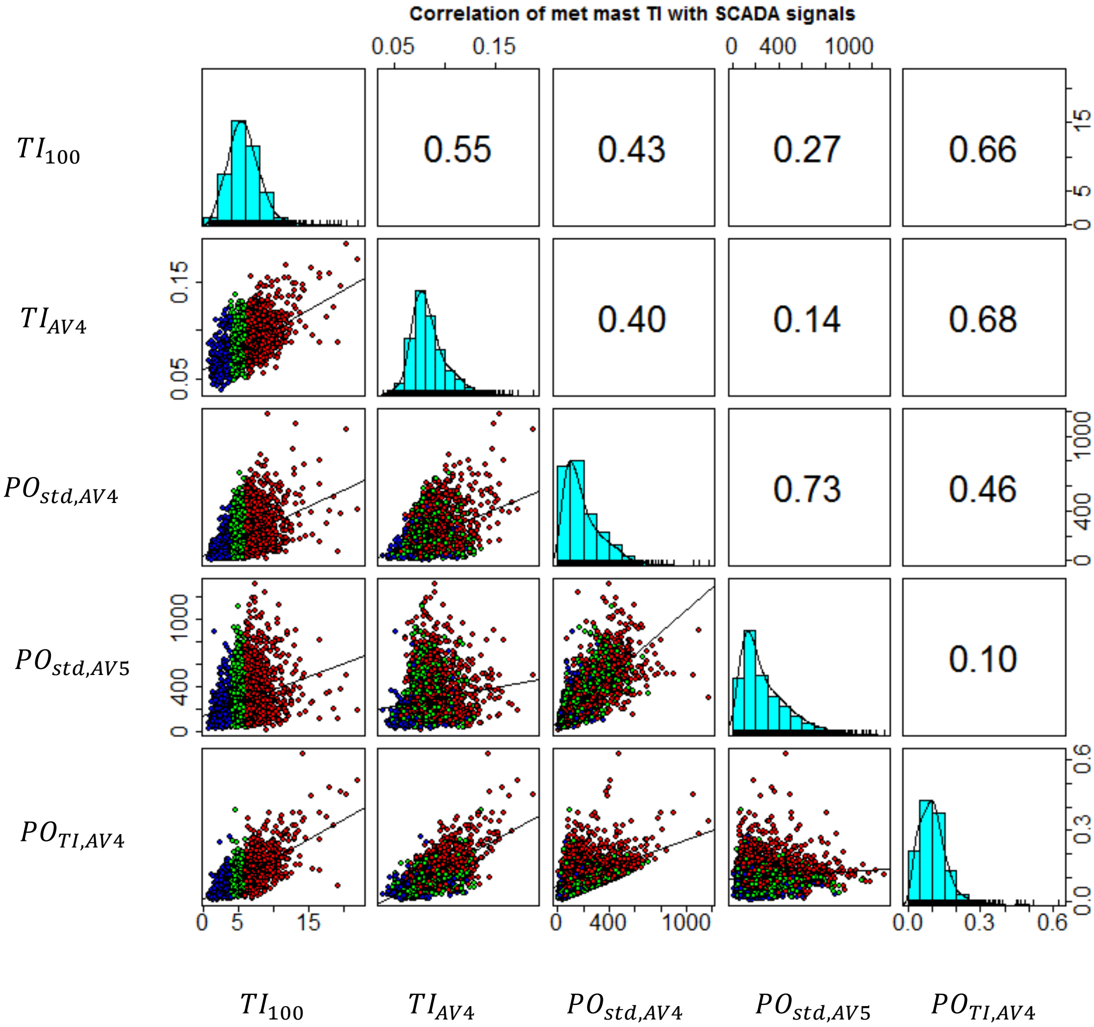

Figure 5: Correlation matrix. Turbulence intensity from met mast (TI_{100}) is correlated with the TI measured with the nacelle anemometer of AV4 (TI_{AV4}), the standard deviation of the 10 min power of AV4 ($PO_{std,AV4}$), the standard deviation of the 10min power of AV5 ($PO_{std,AV5}$) and the standard deviation of the power divided by the average power of AV4 ($PO_{TI,AV4}$)

The highest correlation with the met mast TI is obtained with the standard deviation of the turbine power divided by its average active power ($PO_{TI,AV4}$) in subplot (1 , 5). Although a correlation of 0.66 is not perfect, it is still better than the turbulence measured with the nacelle cup anemometer. Especially in the low turbulence region, the scatter plot proves to be denser. Very similar results were obtained when applying the same analysis to AV1 and AV2.

To check the validity of these results, we used the data from Nordsee Ost. Figure 6 provides the information corresponding to Figure 5 but for a different turbine type and met mast at a different location in the North Sea. With only six months of data recorded, only the correlation analysis has been carried out. For a classification of the wake effects we have to wait for more data to come.

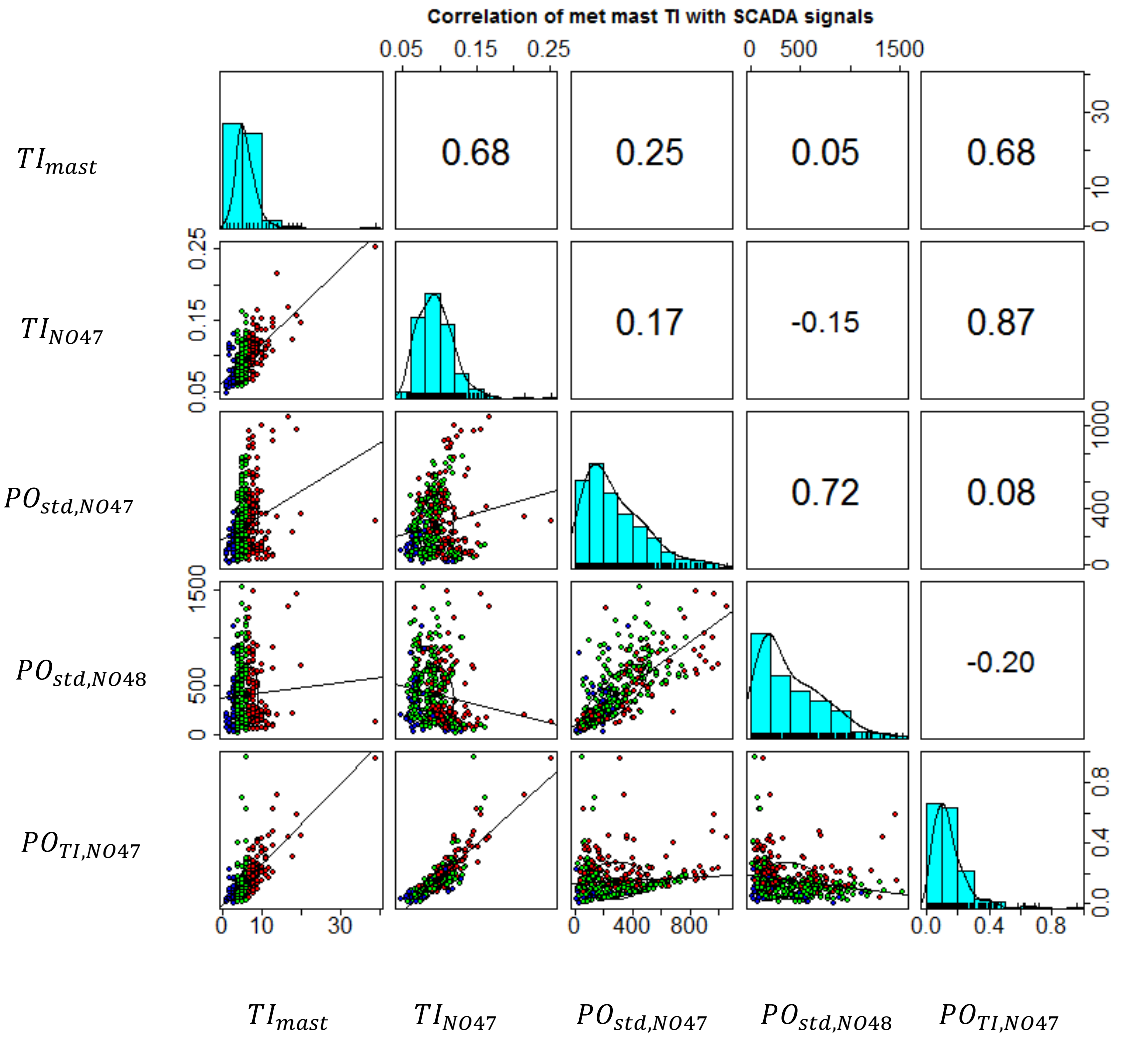

Figure 6: Correlation analysis. Turbulence intensity (TI_{mast}) measured at hub height is correlated with the TI measured with the nacelle anemometer of NO47 (TI_{NO47}), the standard deviation of the 10 min power of NO47 ($PO_{std,NO47}$), the standard deviation of the 10 min power of NO48 ($PO_{std,NO48}$), the standard deviation of the power divided by the average power of NO47 ($PO_{TI,NO47}$)

The correlation analysis for the Nordsee Ost data provides equally good results (0.68) for the TI_{NO47} derived from the nacelle cup anemometer and the $PO_{TI,NO47}$ signal. A different blade design and the distinct turbine nacelle met mast layout might be the reason for these results.

Both correlation analyses have proved that the new artificial SCADA signal, derived from the standard deviation of the power divided by its average active power are suitable to substitute a met mast TI_{mast} for our purpose. In the next Section, we check the impact of this new signal on the estimated power production in the wake.

4.3. New classification and validation

In Section 4.2 we demonstrated the correlation of the SCADA signal (PO_{TI}) derived by the standard deviation of the power divided by its average power with the turbulence intensity measured at a met mast in free flow conditions. In the next step, the ability of this signal to distinguish between different environmental stratification has been analysed. Table 2shows the proposed thresholds for the different classifications.

Table 2: Definition of stratification used in present analysis

Classification	Power Intensity (PO_{TI})
Unstable	$PO_{TI} > 13\ \%$
Neutral	$13\ \% \geq PO_{TI} \geq 7\ \%$
Stable	$7\ \% > PO_{TI}$

Figure 7 is the same illustration as Figure 4 but the new SCADA signal PO_{TI} provided the new classification. A clear difference in power production between stable and unstable cases can be identified in the single wake. The differences in double wake are again less pronounced. Compared to the TI classification, the curves for the neutral case are not as clear as in-between the stable and unstable curves and in the normalized power curve plots (right column) the stable conditions can only be highlighted up to the wind speed of rated power for the free flow turbine. This can be explained with the fact, that at rated power the pitch controller is governing the turbine reaction on turbulence intensity. This leads in equation (4) to a significant decrease of the numerator and keeps the denominator constant.

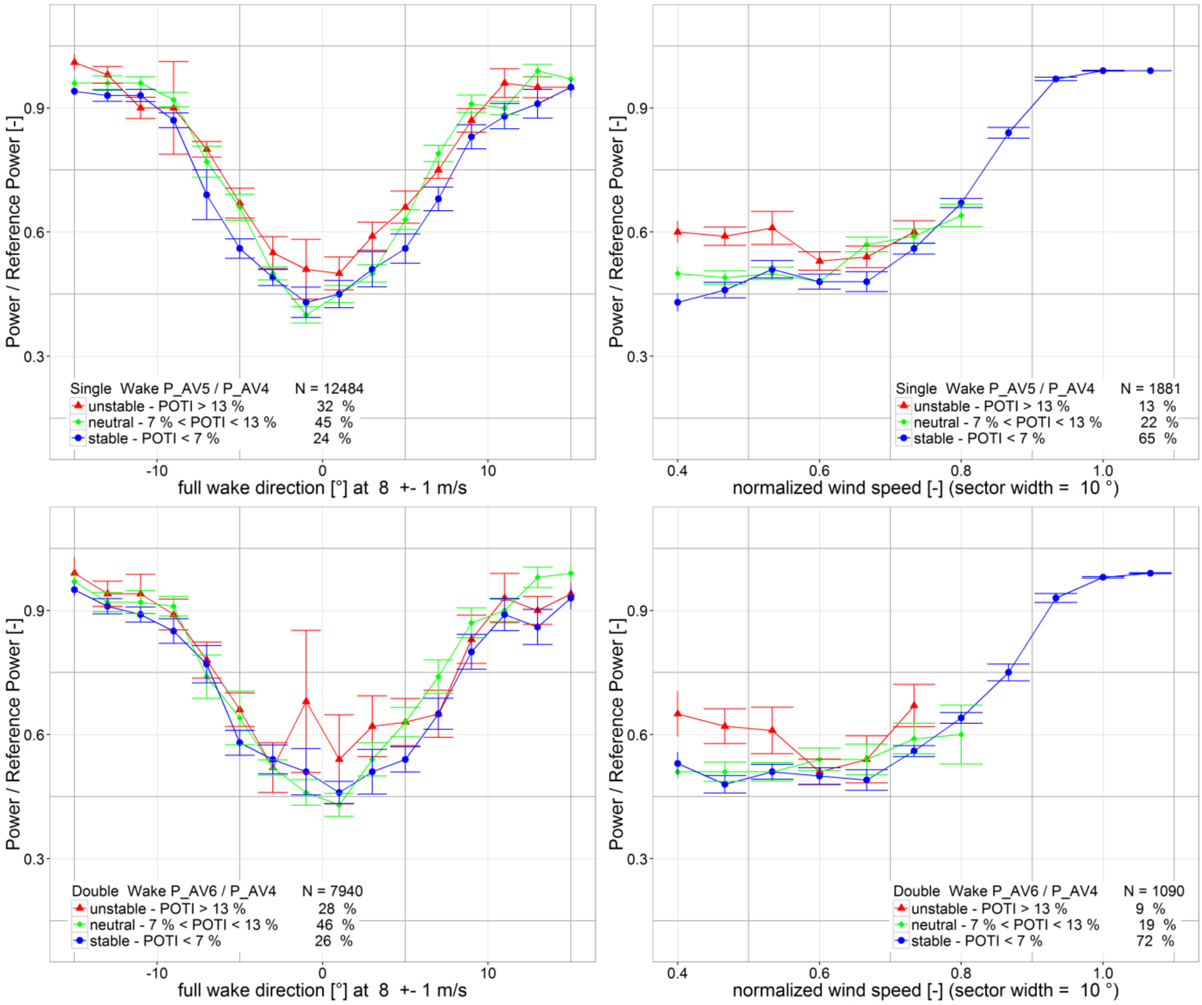

Figure 7: Stability classification with the PO_{TI} value. Power of waked turbine normalised with free flow turbine. Upper row: single wake, lower row: double wake. Left column: Normalised Power as function of wind direction, right column: Normalised power as function of wind speed.

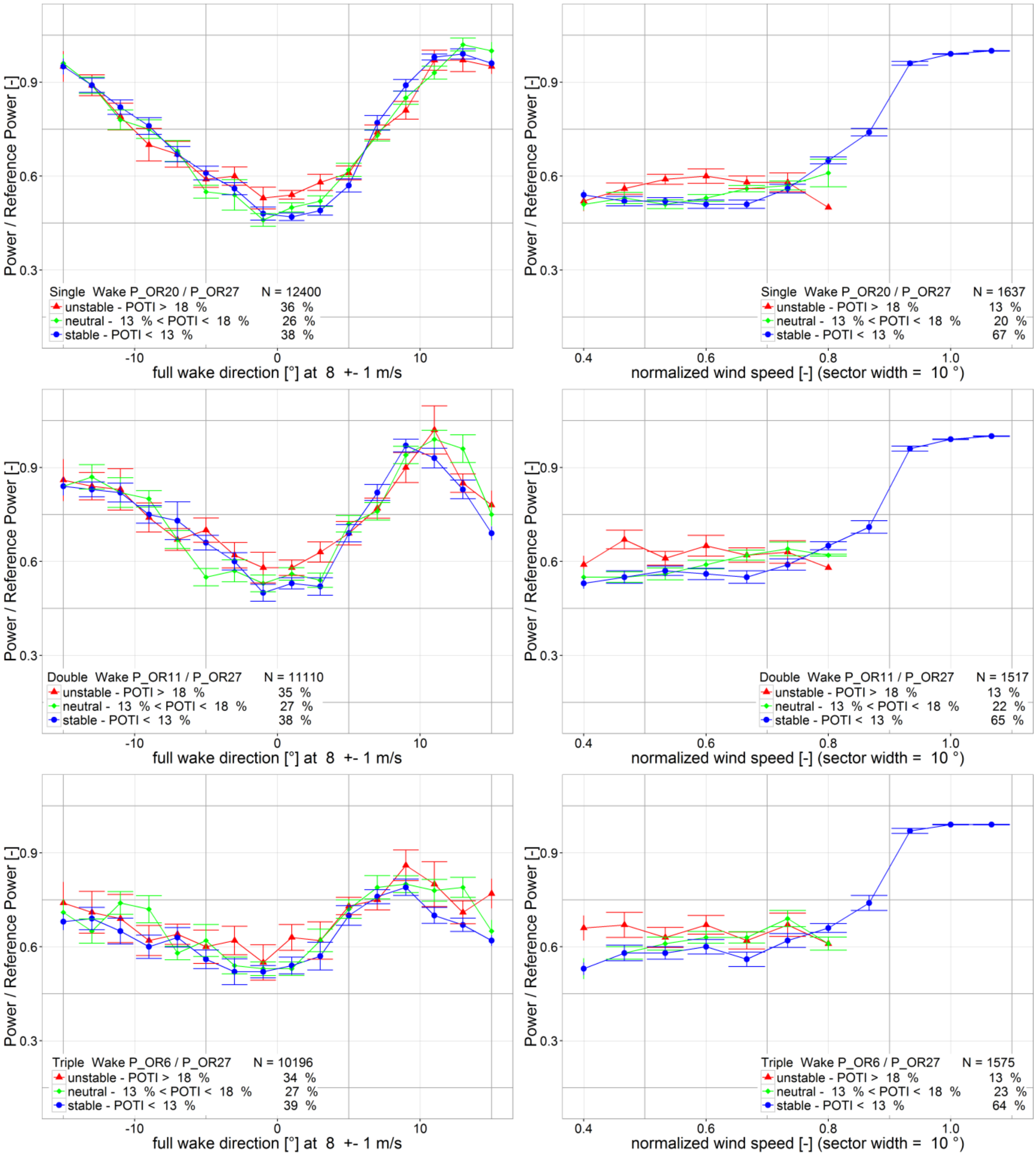

Figure 8: Wake effects in Ormonde (OR) under different atmospheric conditions. Power of downstream turbine normalised with free flow turbine. First row: single wake, second row: double wake and third row: triple wake. Left column: Normalised Power as function of wind direction, right column: Normalised power as function of wind speed.

Finally the transferability of this knowledge to other wind farms where no met mast is available is of interest. Figure 8 is a similar illustration as Figure 4 and Figure 7. With south westerly wind direction, we focused in Ormonde on single wake, double wake and triple wake conditions behind turbine number 27 for a sector of 10° around the full wake situation.

It was not possible to use exactly the same thresholds for the classification which is a result of the usage of different controller versions in alpha ventus and Ormonde. Table 3 provides the new thresholds for the different classifications in Ormonde, estimated as described in Section 3.3

Table 3: Definition of stratification used in present analysis

Classification	Power Intensity (PO_{TI})
Unstable	PO_{TI} > 18 %
Neutral	18 % > PO_{TI} > 13 %
Stable	13 % > PO_{TI}

In general the PO_{TI} signal in Ormonde is on a higher level. The Ormonde controller conceals the effect of different stratification more than the alpha ventus controller. Further investigations are necessary to account for the controller properties and to fill the wind speed range [0.75 – 1], beyond the rated wind speed of the turbine in free flow conditions. It is still possible to identify different wake behaviour for the different classes but the effect is less clear than in alpha ventus.

In performance monitoring of offshore wind farms the newly aggregated SCADA signals can be used as an auxiliary quantity to classify different atmospheric stability conditions. Advanced engineering wake models which are able to take turbulence intensity or stability parameters into account, can be parameterized by these artificial turbine signals in order to improve their prediction of wind turbine power production under waked conditions.

5. Conclusions

Measured data from three different offshore wind farms and two met masts has been analysed to identify different impact on power production at turbines operating in the wake. We have validated the described method in [7], which proposes to use the turbulence intensity, to describe the power production in the wake. A correlation analysis was performed and for wind speeds in partial load operation, the standard deviation of the power divided by its average power (PO_{TI}) was identified having similar behaviour than the turbulence intensity. A classification of different turbine behaviour based on PO_{TI} was analysed and compared to the classification with turbulence intensity TI.

Both signals can distinguish between stronger and weaker wake effects. A transferability of the findings from one turbine to the next is only possible under the prerequisite of having the same turbine type and controller version.

Using PO_{TI} to predict wakes more accurate is a promising approach, but further investigations are necessary to take controller properties into account and to fill the wind speed range beyond the rated wind speed.

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