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On the effects of environmental conditions on wind turbine performance: an offshore case study

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Abstract. Monitoring wind turbine (WT) performance offers a means of identifying abnormal operation, but only if natural disturbances of the operating regime change can be excluded. WT performance monitoring usually relies on the analysis of operational power curves, generally based on data from the supervision control and data acquisition system. However, these curves do not reflect the source of variability, negatively affecting the capabilities for detecting WT abnormal performance. This work aims at understanding and quantifying changes in WT performance variability due to different environmental conditions during normal and wake-free operating conditions, based on an offshore case study. The magnitude of performance fluctuations is highly influenced by environmental conditions, being higher during high turbulence intensity and low wind shear conditions. The Taylor law, with small time windows, is suitable to describe them for low-mid winds in the absence of dedicated wind measurements, often not permanently available offshore, and could potentially result in more effective performance monitoring solutions. Nevertheless, the heteroskedastic nature of the power deviations negatively affects fitting possibilities. The results support the importance of using low data aggregation periods to understand the dynamics of WT performance.

1. Introduction

The wind industry is currently playing a significant role in the transition towards a decarbonised power sector, to such an extent that wind energy is expected to become the largest source of renewable electricity by 2020 [1]. Still, one of the challenges faced by the industry is the high operation and maintenance (O&M) costs, especially in the offshore environment [2].

During the operational phase, monitoring wind turbine's (WT) performance is crucial to ensure a safe, efficient and reliable operation of the asset. Operational power curves, generally based on data from the supervisory control and data acquisition system (SCADA), can provide a clear representation of how well wind energy is being converted into electrical power, but only if natural disturbances of the operating regime change can be excluded. Indeed, it is widely known that power curves vary greatly depending on site conditions [3]. Hence, there is a need to more clearly differentiate between changes in WT performance due to environmental/operational conditions and faulty behaviour to improve WT monitoring strategies.

WT power curve analysis, modelling and monitoring have received considerable research interest over the last decade. Many phases over the lifetime of every wind project rely on accurate



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estimations of wind turbine power curves and their related uncertainty, including annual energy production (AEP) assessments, WT performance monitoring and power forecasting.

The dependency of power curves on environmental parameters such as turbulence intensity (TI), vertical wind shear, or atmospheric stability has been extensively studied for onshore wind farms [3, 4, 5, 6, 7] and to a lesser extent for offshore cases [8, 9]. There is general agreement that, for free-flow conditions, increasing TI and low wind shear lead to lower production at wind speeds near the transition to the rated power, whereas higher production is observed at low wind speeds. The opposite is true for low levels of TI, or high levels of wind shear. However, most of the studies relied on comparisons between power curves obtained through the method of bins, as defined in [10]. As a result, only WT averaged performance has been examined, but not its variability, actually related to power deviations. Understanding WT performance variability is crucial due to its heteroskedastic nature across the different wind speed regimes [11, 12]. The scaling relationship between means and deviations of WT power production has been recently studied through the application of the Taylor Law in [13, 14], highlighting its dependency on local environmental conditions and data time averaging periods. The present work seeks to further explore this relationship and aims at understanding and quantifying changes in WT performance variability due to different environmental conditions during normal and wake-free operation, based on an offshore case study. The usefulness of the Taylor Law for quantifying normal performance variability is assessed here. Having an accurate description and quantification of the natural variability of WT performance for different conditions would enable a conscious definition of thresholds for the detection of abnormal performance, leading therefore to more effective performance monitoring solutions.

This paper is organised as follows. In Section 2, the data from the Anholt offshore wind farm is described in detail, together with the local wind and wave conditions at the featured site. Section 3 details the methodology applied to study WT performance variability. Results are presented and discussed in Section 4, and Section 5 concludes the paper.

2. Data description

2.1. Anholt Wind Farm

For this study, data were made available by Ørsted (formerly DONG energy), as part of their Anholt Data Sharing Initiative [15]. The different data, coming from the WT SCADA system, a ground-based lidar device and a wave buoy, are fully described subsequently.

The Anholt Wind Farm is located on the north-eastern coast of Jutland, Denmark, between Djursland and the island of Anholt (see Fig. 1a). With a total capacity of 400 MW, it is one of the largest operating offshore wind farms, in terms of installed power. The wind farm consists of 111 Siemens 3.6 MW turbines, with a hub height of 81.6 m, covering an area of 88 km². Water depths within the area range between 15 to 19 m, with a distance to the shore of 21 km. The Anholt Wind Farm was connected to the grid in 2013. The layout (see Fig. 1b) was optimised to maximise annual energy production, considering geotechnical conditions as well as the area available and wind turbine interferences. One of the most interesting features of this wind farm is that due to the presence of the Djursland Peninsula, the fetch length for a wind blowing from the west changes abruptly over relatively small changes in wind direction (see Fig. 2). This feature results in important effects on the wind conditions and has prompted its in-depth investigation [16].

Several studies analysing the wind flow and wake effects at this site can be found in the literature [16, 17, 18]. During the Wind Energy Science Conference 2017 [19] held in Lyngby (Denmark), a session was entirely dedicated to the Anholt Wind Farm, covering topics on wake analysis and coastal gradients.

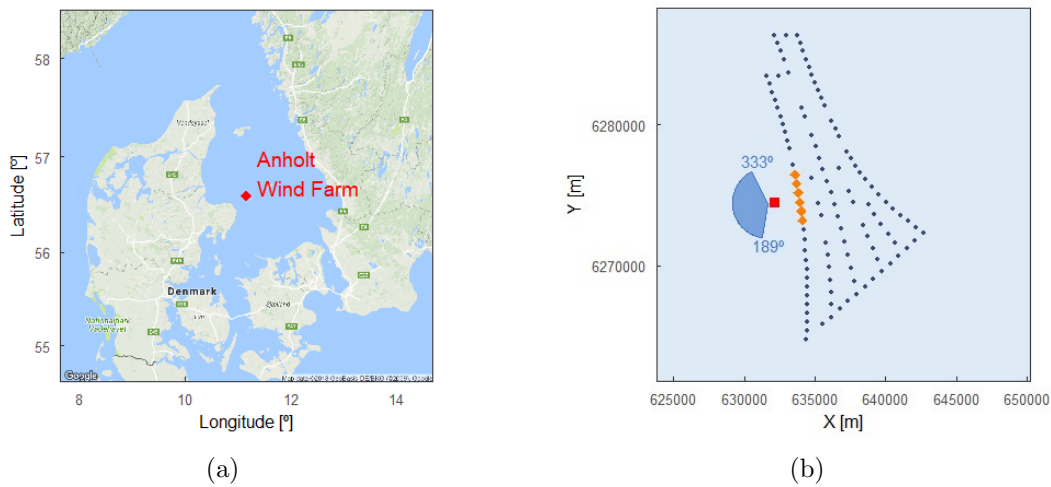


Figure 1: Location of the Anholt wind farm on the north-eastern coast of Jutland, Denmark (a) and layout of the Anholt wind farm showing the wind turbines (orange diamonds), the lidar position (red square) and the wind directions (blue sector) used for this analysis (b).

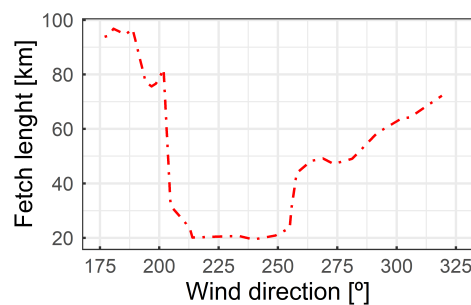


Figure 2: Sea fetch length as a function of wind direction for the Anholt Wind Farm, using the lidar position as a reference.

The operational data consists of 10-minute aggregated SCADA-data recorded over a period of 2.5 years, from January 2013 to June 2015, including the following parameters: power output, pitch angle, rotor speed, yaw position, nacelle wind speed and ambient temperature. For each parameter, the mean, standard deviation, minimum and maximum statistics are reported for the corresponding 10-minute period.

2.2. Lidar data and observed wind conditions

Wind speed and direction data used for this analysis were collected by a Leosphere Windcube v2 lidar. The ground-based vertical profiler lidar was located on the Anholt offshore substation (OSS) at the height of 25 m above the mean sea level (AMSL). The lidar position is illustrated in Figure 1b. Measurements were performed at 10 different ranges, corresponding to the heights of 65, 85, 101, 105, 125, 141, 185, 225, 275 and 315 m AMSL. The lidar device was deployed concurrently to the operation of the Anholt Wind Farm, hence covering 2.5 years of data. To avoid any seasonality effects, only 2 full years of measurements were considered to assess the local wind conditions. During these 2 years, mostly south-westerly winds with a mean wind speed of $9.81 \text{ m}\cdot\text{s}^{-1}$ (see Fig. 3a and 3b) were experienced. Wind measurements recorded at 85 m (the closest to WT hub height) were selected for examining the wind rose and distribution.

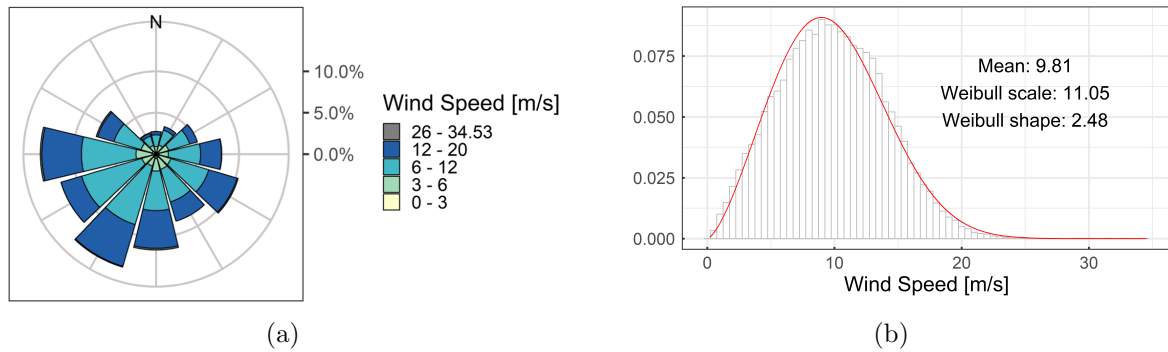


Figure 3: Wind rose of the 85 m wind speed and direction recorded every 10-min by the lidar (a) and Weibull distribution of the 85 m wind speed lidar data (b).

To evaluate the effect of atmospheric conditions on WT performance, lidar data were used to assess the vertical wind shear and TI of the undisturbed inflow into the wind farm. Both environmental parameters were previously studied independently to understand the local wind conditions at the featured site.

The vertical wind shear coefficient α observed during the measurement campaign was estimated based on the lidar wind speed measurements u at different heights z using Equation 1. Lidar observations at heights of $z_1=65$ m and $z_2=105$ m AMSL were selected to estimate the wind shear across the WT rotor.

$$\frac{u(z_2)}{u(z_1)} = \left(\frac{z_2}{z_1}\right)^\alpha \quad (1)$$

The shear across the rotor was estimated using 1-hour moving average wind speeds from the lidar measurements to avoid highly fluctuating wind profiles and to keep the same frequency as the SCADA data. As one can see in Figure 4a, the shear coefficient is strongly affected by the wind direction, due to the variable distance to the coast. The abrupt change in the fetch length observed at wind directions close to 205° (see Fig. 2) results in a substantial variation of the shear.

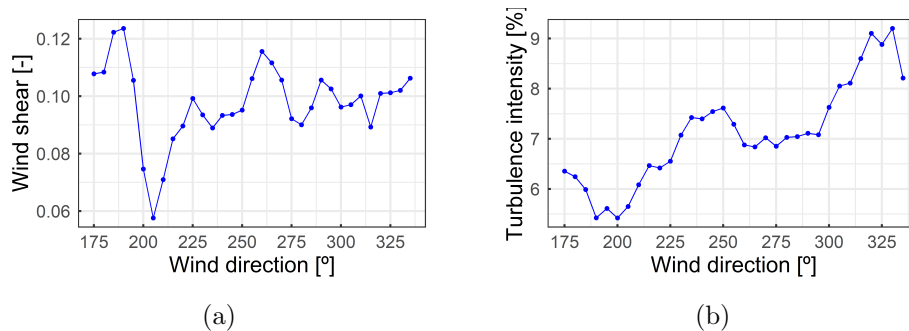


Figure 4: Time-averaged shear coefficient (a) and turbulence intensity (b) as a function of wind direction averaged in 5-degree sectors.

The TI of the wind was estimated based on the ratio of the standard deviation to the mean wind speed measured by the lidar at 85 m. This results in a different estimate of TI than the one that would have been obtained by a sonic or a cup anemometer. Indeed, wind speeds measured by a lidar are averaged across probe volumes that are typically tens of meters in length, so

they act as a low-pass filter for high frequencies. These effects have been widely reported in the literature; the interested reader is referred to [20, 21] for more information. Concerning the directional effects, the TI is also strongly influenced by the fetch length at the Anholt site (see Fig. 4b). As a result, WTs at the Anholt wind farm are exposed to different environmental conditions, in terms of shear and TI of the wind.

2.3. Buoy data and observed wave conditions

Wave data were also available, recorded by a buoy deployed at 25 km to the south of the Anholt OSS, during the same period as the lidar and the wind farm operation. Measurements of mean, maximum and significant wave height, peak and significant wave period, and mean magnetic direction were available among others. The significant wave height (H_s) and the mean wave period (T_s) were selected to characterise the local sea state and to study its potential effect on WT performance. H_s is an important parameter to describe ocean waves distribution and to define the representative wave height of an irregular sea state; it is defined as the mean wave height of the highest third of the waves and is measured in meters. T_s is calculated as the average of the periods of all the wave periods and is measured in seconds. For load estimations on offshore structures and bridges, calculations are based on H_s and the peak wave period (T_p) [22]. Using T_s instead of T_p has the advantage that we can consider the wave periods corresponding to the waves that are also used to calculate H_s . Since the peak period is an extremum of all observations, we do not consider it to be a good representation of the distribution of wave periods.

In earlier investigations of the influence of the wave climate on the wind speed and WT performance [23], the directionality of swell and wind were considered. We are therefore also investigating the alignment of wave direction and wind direction to describe the sea state and its relation with the wind. The angle between wind direction and wave direction can be such that wind and waves are aligned, perpendicular or opposed to each other. The distribution of H_s is illustrated in Figure 5, where the wave rose is shown in Figure 5a and the distribution according to the angle between wind and waves is presented in Figure 5b. In general, very low wave heights are observed at the featured site, what can be explained by the bathymetry of the area, the main wind direction and fetch distributions. A clear dependence of H_s on the alignment between wind and wave direction is observed.

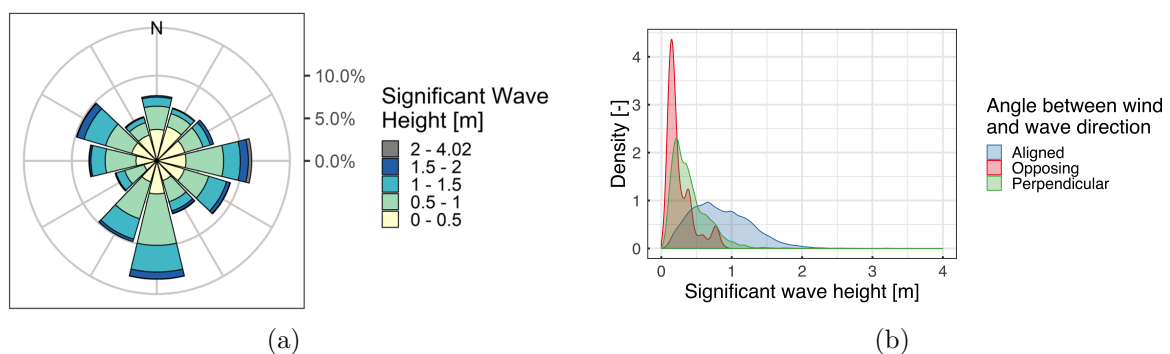


Figure 5: Wave rose (a) and significant wave height distribution according to the angle between wind and wave direction (b).

3. Methodology

As previously mentioned, in this work we examined the influence of different environmental parameters on WT performance. To understand its variability during normal and free-flow

operating conditions, several considerations were applied to the different datasets coming from the SCADA system, the lidar and the buoy. A general framework of the methodology is shown in Figure 6.

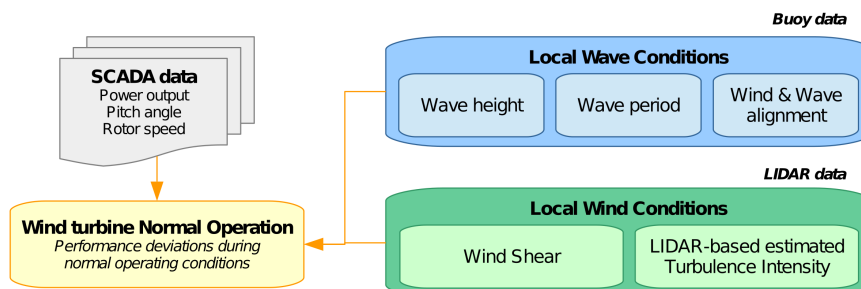


Figure 6: General framework of the applied methodology.

The data from the SCADA system, including WT power output, pitch angle and rotor speed, were combined with the wind measurements from the lidar, and wave measurements from the buoy. Apart from the power production, the pitch angle and rotor speed were also considered, as these also characterise the operation of pitch-regulated WTs. In terms of inflow conditions, to only account for wake-free conditions, six wind turbines from the first array were selected as indicated in Figure 1b. Moreover, only the south-westerly wind sector was considered as based on the lidar wind direction (see Fig. 1b). As a result, 61.0% from the original SCADA data remained available.

Apart from wake-affected operation, WT performance can be affected by the health status of the system, causing downtime and underperformance. For this reason, further filtering was applied to the WT SCADA-data, to only consider WT performance during normal operating conditions. The applied filtering approach was based on a multivariate approach, previously described by two of the authors in [11, 12]. As a result, 55.4% from the original SCADA data were retained for the analysis. The final data coverage was verified throughout the different months of the year to avoid any seasonality effects during the analysis, and was found to be similar.

To account for the effects of the different environmental conditions on WT performance, the considered parameters were categorised into classes. With regards to the wind conditions, three levels of TI were considered, based on the categorisation suggested in [24], to account for WT performance variability during high, medium and low TI conditions. Similarly, four levels were considered for the shear, to account for reverse, low, medium and high shear. The specific categories are presented in Table 1 and Table 2. The categories used to classify TI could correspond to rather unstable, neutral and stable atmospheric conditions respectively. However, due to the lack of necessary data and the complex flow conditions at the Anholt site, the atmospheric stability was not addressed in the present work. As concerns the occurrences in each category, the total number of observations per TI or wind shear category are not presented since the distribution varies with the wind speed. As a result, occurrences in each category are presented by wind speed in Figure 7.

For the sea state characterisation, there is no existing categorisation similar to atmospheric stability. Nevertheless, some categorisations for H_s are available, as the Douglas Sea Scale [25]. Developed in the 1920s, its purpose is to estimate the roughness of the sea. Given the low wave heights observed, a simpler categorisation is proposed in Table 3. The suggested levels for H_s are in line with the approach followed during load conditions. The categories for T_s are

Table 1: Definition of TI levels.

Levels	TI
High	TI >7%
Medium	5% <TI <7%
Low	TI <5%

Table 2: Definition of shear levels.

Levels	Shear
Reverse	$\alpha < 0$
Low	$0 < \alpha < 0.1$
Medium	$0.1 < \alpha < 0.2$
High	$\alpha > 0.2$

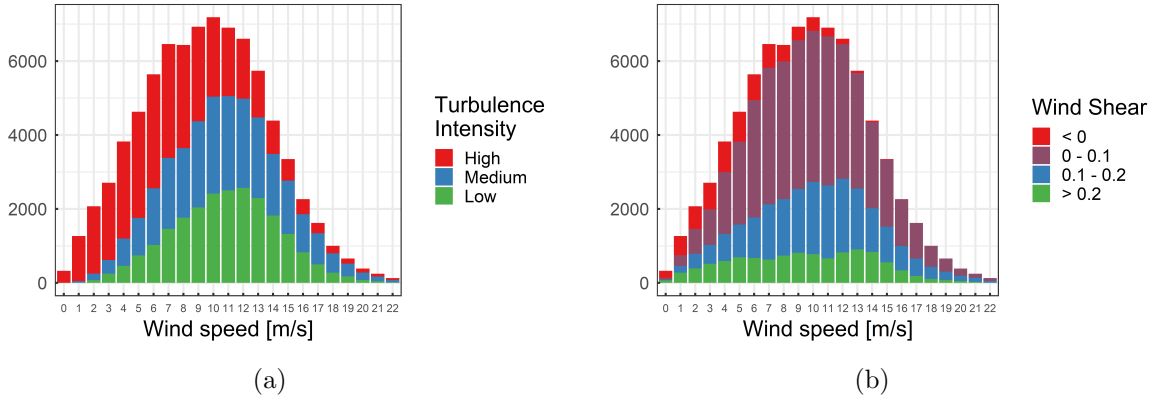


Figure 7: Wind speed distribution according to levels of TI (a) and wind shear (b).

chosen based on the type of wave that is represented by the respective wave period, like surface waves and swell. The alignment between wind and wave direction is also considered. For each direction, the interval spans 45° on both sides to include all directional combinations.

Table 3: Definition of levels for H_s , T_s and the alignment between wind and wave direction.

H_s	T_s	Angle between wind and waves
$0 \text{ m} < H_s < 0.5 \text{ m}$	$T_s < 2 \text{ s}$	Aligned
$0.5 \text{ m} < H_s < 1.0 \text{ m}$	$2 \text{ s} < T_s < 5 \text{ s}$	Perpendicular
$1.0 \text{ m} < H_s < 1.5 \text{ m}$	$T_s > 5 \text{ s}$	Opposed
$H_s > 1.5 \text{ m}$		

Finally, to analyse the WT performance variability the scaling relationship between means and deviations of WT power production, pitch angle and rotor speed was investigated for different environmental conditions, as defined by the levels described herein. Ultimately, the Taylor Law [14] was explored as a measure to quantify the variations in WT performance and also to assess its suitability to describe performance variability.

4. Results and discussion

4.1. Relation between wind and wave conditions

It is widely known that wind and waves are closely related. For this reason, the relation between the wind and the selected parameters to describe the sea state was analysed prior to study the potential effect of the local sea state on WT performance. Results are illustrated in Figure 8. As can be seen, almost all the wind observations occurred during calm sea conditions ($H_s < 1.5$), small surface waves ($2 \text{ s} < T_s < 5 \text{ s}$) and when the wind and wave direction were aligned. For this reason, the wave conditions were not considered further to analyse their effect on WT

performance variability. The lack of observations within some levels would lead to no statistical significance.

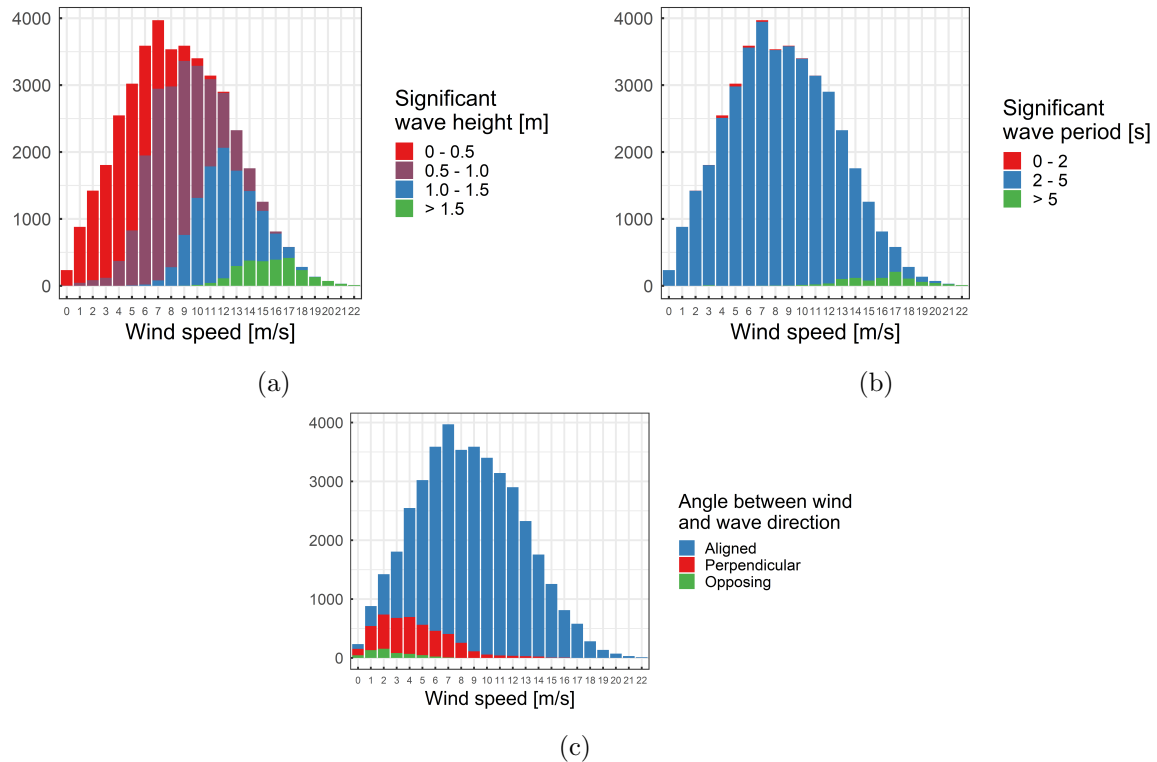


Figure 8: Wind speed distribution according to levels of H_s (a), T_s (b) and the angle between wind and wave direction (c).

4.2. WT performance variability under different wind conditions

The relation between means and deviations of WT power production, pitch angle and rotor speed for the different levels of TI and one of the selected WTs is illustrated in Figure 9. Results according to the defined levels of shear are shown in Figure 10. All the curves were produced using bins of power, pitch angle and rotor speed respectively. For simplification purposes, only results for one selected WT among the six highlighted in Figure 1b are presented in this section. Nevertheless, all the studied WTs show similar results and would therefore lead to the same interpretation and conclusions.

As can be seen in both Figure 9 and Figure 10, the three operational parameters exhibit a higher degree of variability during lower shear and higher TI conditions, although the smallest differences between levels are observed for the rotor speed. The heteroskedastic nature of the WT performance across the different wind speed regimes is therefore dependent on the environmental conditions. This nature is mainly due to the interaction between the control strategy of pitch-regulated WTs and the inflow conditions.

While some effects of the wind conditions can be seen on averaged values and power curves, the effects are more evident in the presented results. Furthermore, they confirm the difficulty of assessing the uncertainty related to WT power curve models and to detect the source of variability during the monitoring phase of WT performance.

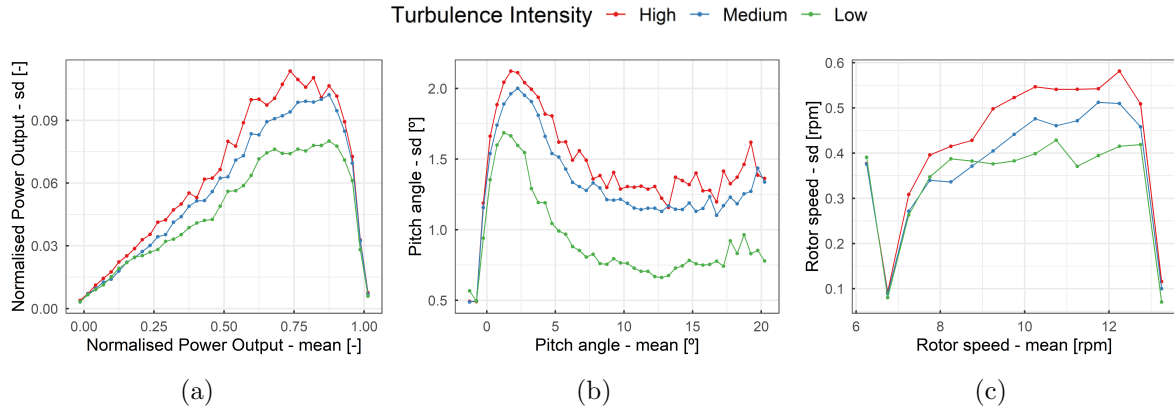


Figure 9: Standard deviation versus the mean power (a), pitch angle (b) and rotor speed (c) for different levels of TI.

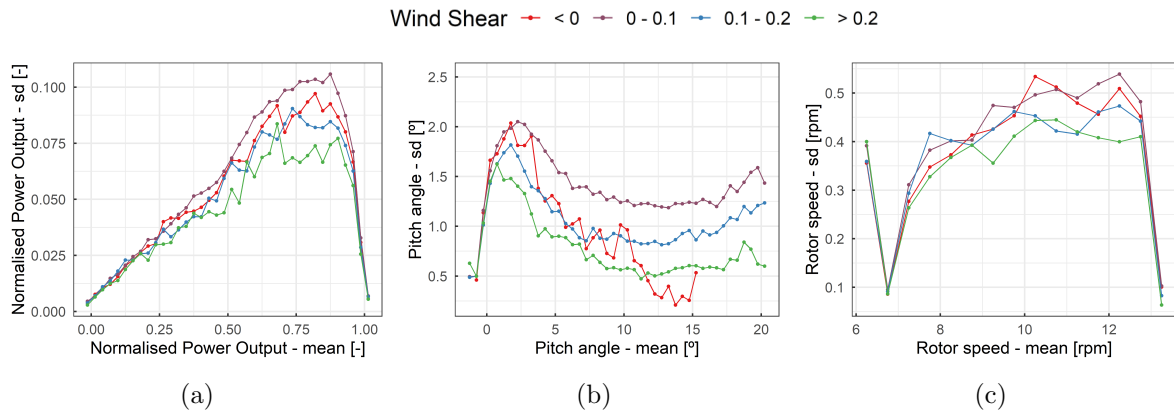


Figure 10: Standard deviation versus the mean power (a), pitch angle (b) and rotor speed (c) for different levels of shear.

4.3. Taylor Law for WT power data

The Taylor law, or temporal fluctuation scaling, is a scaling relationship between the standard deviation α_τ and the mean $\langle x \rangle$ of a signal $x(t)$ defined in Equation 2, where τ is the time window corresponding to the time scales explored, λ_τ is the Taylor exponent and C_0 is a constant.

$$\alpha_\tau = C_0 \langle x \rangle^{\lambda_\tau} \quad (2)$$

This law, established in 1961 in the field of ecology [26], characterise λ_τ as a scaling factor between 0 and 1; values close to 0.5 correspond to systems where the internal factors drive dynamics whereas values close to 1 reveal that external factors drive the dynamics of the system. In the case of WT power production during normal conditions, λ values closer to 0.5 would reveal that the performance variability is due to natural variability of the system's operation together with the uncertainty related to sensor measurements. On the contrary, higher values of λ , closer to 1, would point to external or environmental factors as the cause for the performance variability. As suggested in [13, 14], the Taylor Law can be a way to quantify the variability of WT performance. Its application was studied in the present work for different time windows as well as for different wind conditions.

First, different time windows were studied independently from the environmental conditions. Results for one selected WT are illustrated in Figure 11, although all the studied WTs led to similar results. Data aggregating periods of 10-minute, 30-minute, 1-hour, 2-hour, 3-hour, 4-hour, 5-hour, 6-hour, 12-hour, and 1-day were considered. As one can see, from data aggregating periods higher than 30-minute, λ_τ shows values close to 0.5 while short aggregation periods produce values closer to 1 (see Fig. 11a). Consequently, low data aggregation periods are desired to account for the WT dynamic behaviour due to turbulent wind conditions, as expected. Only 10-minute SCADA data were considered in this study, but higher values of λ_τ could be expected when using raw SCADA-data of high resolution, more suitable to describe WT dynamics [12].

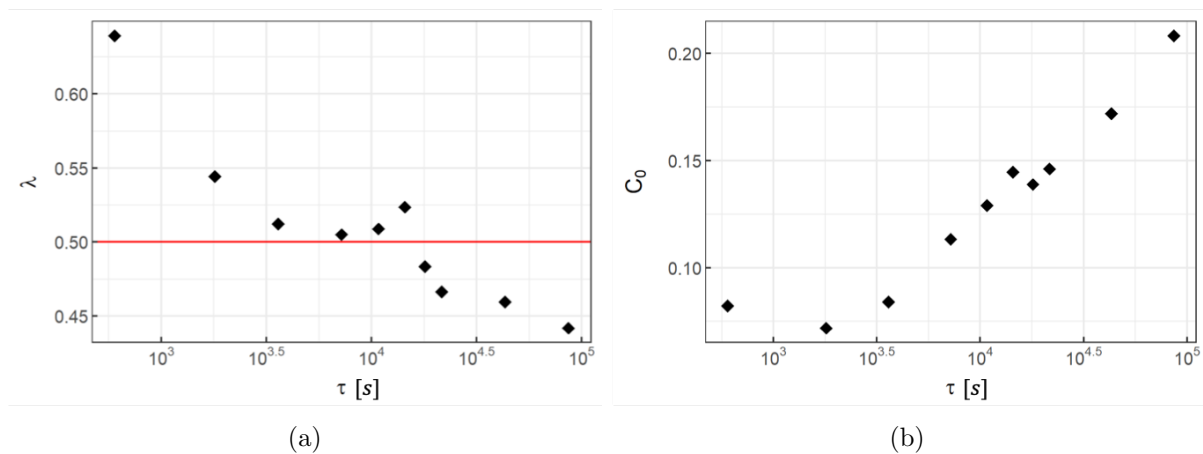


Figure 11: Evolution of the Taylor exponent λ_τ (a) and the constant C_0 (b) versus different time windows.

SCADA-data of 10-minute resolution was then used to analyse the variations of λ_τ and C_0 according to the different levels of TI and shear, as illustrated in Figure 12. In this case, only power values below 90% of the rated power were considered to avoid the strong drop of the standard deviation as seen in both Figure 9 and Figure 10.

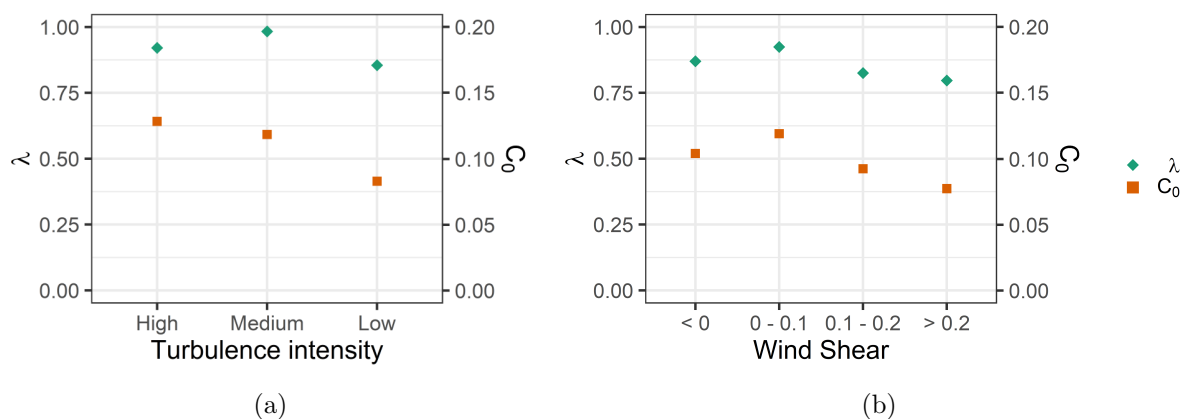


Figure 12: λ_τ and C_0 for different levels of TI (a) and shear (b) for 10-minute SCADA WT power data.

Concerning the levels of TI, slight variations of λ_τ are observed in Figure 12a (always close to 0.8) while C_0 decreases significantly with the level of TI, varying from 0.13 for high turbulent conditions to 0.8 for low turbulent conditions. More significant changes can be seen for both parameters for the different levels of shear (see Fig. 12b), although the same pattern is observed. This confirms again the dependency of WT performance variability on the environmental conditions.

Finally, the parameters obtained were tested according to their fitting possibilities, to describe the relationship between the standard deviation and the mean power output as recorded in 10-minute SCADA data. Both the empirical and theoretical (based on the Taylor Law) relationships are illustrated in Figure 13 for one selected WT.

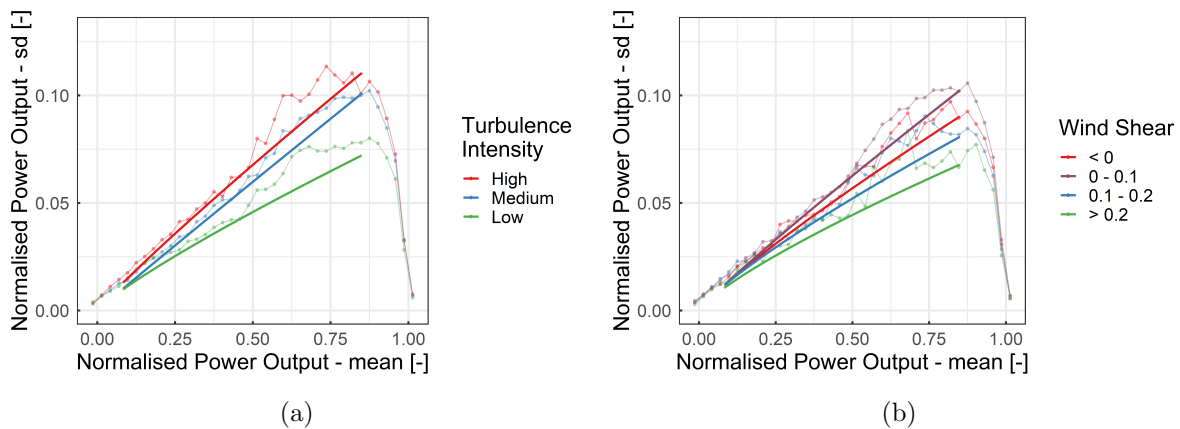


Figure 13: Empirical and theoretical scaling relationship between standard deviation and mean power for different levels of TI (a) and shear (b).

As one can see in Figure 13, the Taylor Law can describe the scaling relationship for a limited region. For values approaching the transition to the rated power operational regime, the standard deviation of the WT power output is higher than described by the Taylor Law. This is due to high heteroskedasticity of WT performance. As a consequence, the Taylor law, with small time windows, is suitable, only for low to mid wind speeds, to describe WT power output fluctuations. Better results could be expected from the use of raw SCADA-data recorded at higher resolutions.

Both parameters C_0 and λ from fitting the Taylor Law to the 10-minute SCADA power data, together with the goodness of the fit as described by the R^2 parameter (square of the Pearson correlation coefficient) are presented for the six analysed WTs for the different levels of TI (see Fig. 14) and for the different levels of shear (see Fig. 15).

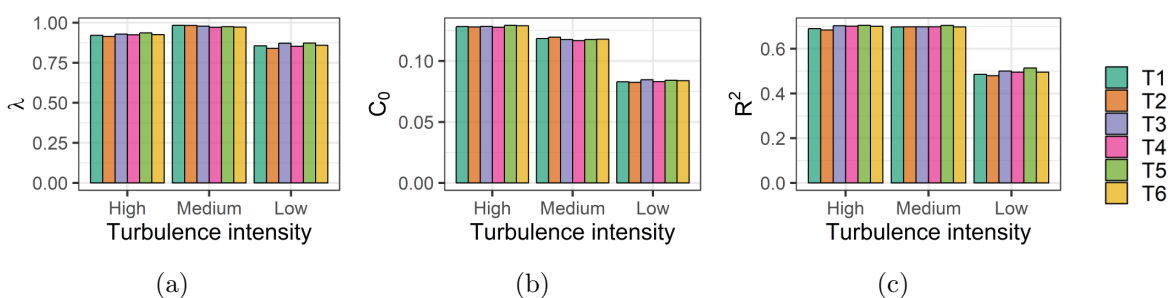


Figure 14: λ_τ (a), C_0 (b) and R^2 (c) for different levels of TI for 10-minute WT power data.

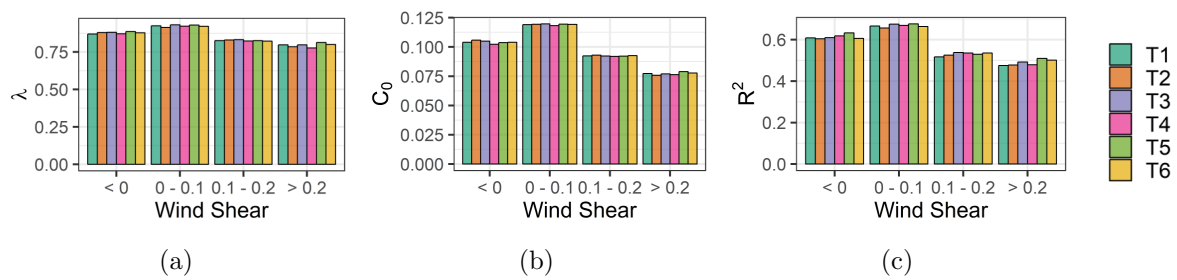


Figure 15: λ_τ (a), C_0 (b) and R^2 (c) for different levels of shear for 10-minute WT power data.

As already discussed, very similar values of the Taylor Law's parameters are observed across the different turbines, supporting that the suggested approach could be applied generically to quantify the natural variability of WT performance at different conditions, given the power production. However, as can be seen in Figure 14c and Figure 15c the values of R^2 are repeatedly lower than 0.7, especially for low wind turbulent or high wind shear conditions. As a result, the suitability of the Taylor Law for quantifying the normal variability of WT performance is limited.

5. Conclusions

This paper examines the variability of WT performance for different environmental conditions under wake and fault-free operating conditions for an offshore case study. To this end, the scaling relationship between the standard deviation and the mean of the main operational parameters recorded by the WT SCADA system, is analysed for different levels of turbulence intensity and wind shear, derived from a lidar concurrently deployed at the featured site.

Although different environmental conditions can affect the typical WT power curves, the differences in WT performance become more evident when analysing its variability. WT performance exhibit a higher degree of variability during lower wind shear and higher turbulence intensity conditions. This confirms the difficulty in assessing the uncertainty related to WT power prediction, either for the estimation of the annual energy production (AEP), the detection of deviations due to an abnormal operation or for forecasting purposes.

WT performance is highly variable due to both different environmental conditions or malfunction of the system. Having a better understanding of the natural variability could lead to an effective detection of any variation due to an abnormal condition of the WT and therefore to improve monitoring solutions. The Taylor law applied to WT power data can contribute to the description and quantification of WT performance variability under normal operating conditions for low to mid wind speeds. Nevertheless, its fitting possibilities are negatively affected by the high heteroskedasticity of WT performance and therefore its usefulness is limited, especially for high wind speeds. Further research should explore the use of SCADA data of higher resolutions.

Finally, SCADA data used to characterise WT performance do not reflect the source of variability, either natural (due to environmental conditions) or artificial (plant induced) fluctuations. The assessment of environmental conditions is usually based on measurements from meteorological masts or lidar, that are expensive and scarce, especially offshore. As a result, there is a need to improve this assessment based on the solely use of SCADA data, as done in [27, 24], to comprehend the different environmental conditions for improved WT power prediction and monitoring.

Author contributions

Elena Gonzalez conducted the research work and wrote the paper. Laura Valdecabres contributed to the assessment of wind conditions. Helene Seyr aided in using buoy data for the sea state characterisation. Julio J Melero supervised the research work.

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