



Influence of environmental characteristics on power production in an offshore wind turbine in the Belgian North Sea

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Abstract. Quantifying the influence of inflow atmospheric characteristics on wind turbine's operation is fundamental for performance assessment, operational diagnosis, and the estimation of power production. While it is well-established that wind speed is the primary driver of power output, additional environmental factors such as turbulence intensity, atmospheric stability, shear and veer are also known to influence the rotor captured inflow and the turbine's response. However, isolating and interpreting the contribution of each of these factors remain a continuing effort. This study presents a framework using operational data, as nacelle-mounted lidar, SCADA and environmental data, to analyse the impact of these factors in a single wind turbine in a wind farm on the Belgian offshore zone. A machine-learning model is trained to represent the power production deviation behaviour, and SHapley Additive exPlanations (SHAP) are applied to quantify the contribution of each environmental variable to predicted power output. Results show that, excluding wind speed, turbulence intensity and air density are the biggest predictors in the transition of torque-control to pitch-control of the wind turbine operation, with respective contributions that influence the power deviation prediction of 16.8% and 14.5%. As for higher wind speeds, air density appears as the main influential factors, contributing up to 32.8% for the above-rated wind speed of the power curve.

1 Introduction

Accurate characterisation of atmospheric inflow is essential for both wind turbine design and wind resource assessment. Wind conditions directly influence energy yield estimates, structural loading, and turbine lifetime, thereby affecting the economic viability of wind projects (Wagner et al., 2009; Murphy et al., 2019; Dimitrov et al., 2015). As rotor diameters continue to increase, turbines become increasingly sensitive to vertical and horizontal inflow heterogeneity, amplifying the importance of reliable wind profile characterisation at the rotor scale (Veers et al., 2019). However, standard engineering approaches, such as those embedded in IEC 61400-1 (IEC, 2005), often rely on simplified inflow representations (e.g. power-law shear profiles), which may not capture the variability observed under complex atmospheric conditions. Deviations from such simplified models have been reported during both unusual events and common atmospheric regimes, including low-level jets and stable boundary layers (Firtin et al., 2011; Ryu et al., 2022; Shaler et al., 2023).



Remote sensing technologies have expanded the possibilities for characterising atmospheric inflow by, e.g., complementing the available information from anemometers. In particular, lidar systems provide wind measurements with no flow distortion and have become widely used in offshore environments where conventional meteorological masts are costly or impractical (Hasager et al., 2008; Sharma et al., 2021). While vertically profiling lidars are commonly applied for wind resource assessment (Hasager et al., 2013; Mikkelsen, 2014), nacelle-mounted scanning lidars can measure the rotor-scale inflow during operation and assist in the turbine control, enabling the increase of power production (Simley et al., 2020). Nevertheless, lidar measurements are inherently limited to line-of-sight velocities, requiring wind field reconstruction (WFR) methods and associated flow assumptions to estimate the full wind vector (Wagner et al., 2014). As a result, nacelle lidar data are typically interpreted in conjunction with additional measurements or operational data, such as supervisory control and data acquisition (SCADA) signals and environmental monitoring platforms.

Beyond measurement challenges, a key limitation in current practice is the difficulty to be able to quantify how individual inflow variables such as turbulence, shear, or stability contribute to variations in turbine power output in an interpretable manner. It is known by numerous studies that there is an influence of inflow variables on power production (Wharton and Lundquist, 2012b; Gao et al., 2021). In parallel, data-driven approaches have been increasingly adopted for wind turbine performance modelling and power curve analysis (Wang et al., 2019). However, many machine learning models operate as black boxes (e.g.), providing limited physical insight into how specific inflow features influence turbine behaviour. This lack of interpretability constrains the operational value of data-driven models, particularly for applications requiring physical understanding, such as performance diagnostics, control strategy development, and site-specific design assessment. Simple parametric and regression-based models (e.g. multivariate linear regression (MRL) (Cascianelli et al., 2021)) have been used as interpretable baselines, such as extensions based on air density and turbulence intensity (Pandit et al., 2019), but they often struggle to capture the nonlinear nature of inflow-performance relationships.

The need for interpretability is particularly relevant in operational contexts in which a third party, e.g., transmission system operator, balancing responsible party or manufacturer, is involved. For example, estimating the possible power production, i.e., the power that would have been generated in the absence of an external action caused by the third party, is required to get financial reimbursement for potential losses (Badissy et al., 2021). Current industry practices rely on simplified approaches, such as reference power curves, using wind speed measurements from nacelle or mast anemometers. While these approaches maintain the transparency and ease of interpretation, they might neglect the influence of additional atmospheric factors, known to affect turbine performance. Furthermore, there are measurement technologies that enable the observation of a broader range of environmental features in the same location for a certain period of time, including rotor-scale wind profiles from lidar systems and atmospheric conditions measured by meteorological masts, buoys, and other offshore monitoring platforms.

Recent advances in explainable artificial intelligence provide new opportunities to address this gap. SHapley Additive exPlanations (SHAP), introduced by Lundberg and Lee (2017), offers a theoretically grounded, model-agnostic framework for assessing the contributions of individual input features to model predictions based on cooperative game-theoretic concepts. SHAP has been increasingly applied in renewable energy contexts, including wind power forecasting and performance diagnostics, to identify key drivers of variability and improve model transparency (Machlev et al., 2022). While these studies demonstrate the



potential of explainable machine learning, most applications focus on forecasting tasks or rely on a limited set of input variables. Comprehensive analyses that combine multiple measurement sources and explicitly examine the contribution of atmospheric inflow characteristics to turbine-level power production remain limited.

In this study, this is addressed by combining nacelle-mounted lidar measurements, SCADA data, and environmental observations to investigate the relationship between atmospheric inflow characteristics and turbine power production under real operating conditions. The analysis focuses on a wind turbine in the first row of a wind farm in the Belgian offshore zone. Moreover, due to data confidentiality, the exact location could not be disclosed for the current publication. First, wind profiles are reconstructed from lidar measurements and used to derive key inflow descriptors, including shear and veer. SCADA and atmospheric conditions are used to estimate inflow variables such as turbulence intensity, atmospheric stability and air density. Deviations from standard IEC inflow assumptions are then identified through automated profile classification, enabling the detection of non-power-law wind profiles. A machine learning model is then trained to represent turbine power behaviour, and SHAP analysis is applied to quantify the relative contribution of each environmental factor to the predicted power output deviation across different wind speed regimes. The analysis focuses specifically on freestream turbine-level behaviour, avoiding wake interactions to isolate the relationship between atmospheric inflow and power production. The employed methodology quantifies the impact of each environmental variable has on predicting how much the power output deviates from the expected output, becoming possible the choice of which variable to be included in further prediction methodologies.

The remainder of this paper is structured as follows: Sect. 2 introduces the datasets used; Sect. 3 explains the necessary theoretical background that this work was based on; Sect. 4 details the wind profile estimation, environmental classification and SHAP implementation; Sect. 5 presents the main findings of the influence of local weather in power production.

2 Data collection and filtering

This study uses four in-situ measurement datasets within the Belgian offshore zone: nacelle-mounted LiDAR, single-turbine SCADA data, and environmental measurements from the *Meetnet Vlaamse Banken* (MVB) met-mast and reanalysis data from ERA5 (Hersbach et al., 2023). The nacelle-based lidar measurements are used to reconstruct the upstream wind field and identify wind profiles that deviate from the classical power-law formulation. SCADA data provide turbine operational parameters used to estimate wind direction and turbulence intensity. Environmental features, including air temperature, sea temperature, and wave direction, are obtained from the open-access MVB dataset provided by the Belgian government (en Kust, 2024), and ERA5 dataset is used to extract the needed variables to estimate atmospheric stability and air density.

For the present analysis, three datasets are used:

- **Nacelle-mounted LiDAR:** The deployed lidar system is a continuous-wave ZX lidar (Zephir Ltd.) installed on the nacelle of a first-row wind turbine in an offshore wind farm in the Belgian North Sea. The dataset used in this study spans approximately 10 months, from February 2023 to mid-March 2024. These measurements serve as input to the wind-field reconstruction methodology, which estimates undisturbed inflow profiles upstream of the turbine. The selected turbine



is located in the first row of the wind farm, ensuring that for a subset of wind directions the incoming flow remains unaffected by upstream wake interactions.

– **SCADA data:** Operational data from the SCADA system of the same wind turbine equipped with the lidar are used in this study. Wind speed measurements are obtained from a combination of a cup anemometer and a sonic anemometer installed on the turbine nacelle. These data provide high-frequency (1 s) operational measurements used to derive key flow parameters, including turbulence intensity based on wind speed, and nacelle orientation to complement the lidar-based inflow reconstruction.

– **Environmental data:** Environmental measurements is obtained from the Meetnet Vlaamse Banken (MVB) datasets (De Wolf, 1986). The MVB network consists of offshore monitoring stations distributed across the Belgian North Sea, providing long-term meteorological and oceanographic observations. In this study, data from the Westhinder measurement pile are used, located approximately 30 km offshore. The station provides in-situ measurements at approximately 10 m above sea level (a.s.l.), capturing atmospheric and oceanographic variables relevant for inflow characterisation (en Kust, 2024). Finally, although the station is not co-located with the analysed turbine, it provides representative large-scale environmental conditions for the surrounding offshore region. The following instruments are used:

1. A Datawell Directional Waverider buoy for wave parameters;
2. Vaisala WAA151 and WAV151 sensors for wind direction;
3. A Vaisala HMP155 probe for air temperature;
4. An Aanderaa CT4120 sensor for sea temperature.

– **Reanalysis data:** The European Centre for Medium-Range Weather Forecasts (ECMWF) has a long history of reanalyses applications, which use meteorological observations, such as buoys and satellites, for weather forecasting. ERA5 is the fifth generation of atmospheric reanalyses, covering the period from 1940 onward in a 31 km grid resolution and an hourly output Hersbach et al. (2020). The data retrieved is used to estimate air density and atmospheric stability.

2.1 Filtering

Several filtering and preprocessing steps are applied to the combined dataset to ensure data consistency and quality prior to analysis:

1. Lidar

The lidar measures circular scanning patterns upstream of the turbine at a sampling frequency of 50 Hz, scanning one full revolution per second for each scanning plane. The raw line-of-sight (LOS) measurements are processed as follows:

- (i) The raw measurements are averaged spatially and temporally into 10-minute intervals, producing 64 azimuthally averaged positions for each lidar scan.



- (ii) Only measurements located at 2.5 rotor diameters upstream of the turbine are retained in order to minimise rotor induction effects.
- (iii) Quality control is first applied using the manufacturer-provided LOS validity warnings; only data marked as valid are retained, corresponding to approximately 70% of the original dataset.
- (iv) With the exception of the seasonal analysis, an additional directional filter is applied to retain freestream wind directions between south and west, corresponding to the dominant wind sector at the site.
- (v) This directional filtering isolates inflow conditions that are unaffected by wake interactions from neighbouring turbines, ensuring the validity of the wind-field reconstruction methodology (Marini et al., 2024).

After applying these filters, approximately 52% of the initial lidar measurement period is retained.

2. SCADA

The SCADA dataset is processed to keep only normal turbine operating conditions. Within each control region, specific filters are applied to exclude data points of non-representative behaviour:

- (i) The first filter removes all data recordings from below cut-off and above cut-in wind speeds;
- (ii) In the torque control region, it is removed data points with deviations from the expected near-zero pitch angle, as they are indicative of non-nominal turbine operation;
- (iii) At the transition between control regions, data points are filtered based on the combined behaviour of rotor speed and blade pitch angle, to remove observations inconsistent with steady-state operation;
- (iv) In the pitch control region, data points where the turbine output falls below a defined threshold of the rated power are excluded, retaining only observations consistent with normal above-rated operation;
- (v) Finally, it is removed statistical outliers, defined as observations deviating by more than four standard deviations from the mean of the filtered dataset.

After applying these filters, approximately 85% of the original SCADA dataset is retained.

3. MVB and ERA5

The temporal resolution of both datasets is 30 minutes, whereas the reconstructed inflow variables are available at 10-minute intervals. To ensure temporal consistency across datasets the variables are linearly interpolated to a 10-minute temporal resolution.

To ensure consistency across the different data sources, the lidar, SCADA, MVB, and ERA5 are temporally aligned prior to analysis. The final dataset therefore consists of synchronised 10-minute records containing reconstructed inflow properties, turbine operational parameters, and environmental features describing the large-scale atmospheric and oceanographic conditions. Only timestamps for which valid measurements are available across all datasets are retained for the subsequent analysis. Table 1 summarises the main characteristics of the datasets used in this study, including the measurement source, variables used in the analysis, measurement height, temporal resolution, and the available time period.



Table 1. Summary of the datasets used in this study.

Dataset	Variables used	Height	Resolution	Period used
Nacelle lidar	Line-of-sight wind speed and misalignment	[27, 190] m a.s.l.	10 min (processed)	Feb 2023 – Mar 2024
SCADA	Wind speed, yaw angle, turbine status	Nacelle height	1 s (raw), 10 min (aggregated)	Feb 2023 – Mar 2024
MVB station	Wind direction, wave direction, air temperature, sea temperature	10 m a.s.l.	30 min (10 min interpolated)	Feb 2023 – Mar 2024
ERA5	Surface pressure, temperature, dewpoint temperature, eastward and northward turbulence surface stress, surface sensible heat flux, moisture flux	2 m a.s.l.	30 min (10 min interpolated)	Feb 2023 – Mar 2024

3 Environmental factors influencing power production

Observed deviations from the expected turbine power can result from several sources, from changes in the available wind resource to differences between measured and rotor-effective inflow conditions. To interpret these deviations, it is necessary to consider atmospheric and sea-state variables that influence the inflow experienced by the rotor. These variables can be defined from physics and literature.

As air density provides a correction to the available kinetic energy in the flow, the vertical wind shear modulates the effective wind resource experienced across the rotor swept area. Wind veer introduces asymmetric loading across the rotor disc and has been associated with measurable power losses in both observational and modelling studies (Wagner et al., 2009). Turbulence intensity affects the accuracy of wind speed reconstruction from nacelle-mounted cup anemometers through its influence on the nacelle transfer function (Brand et al., 2011).

Atmospheric stability, shapes the vertical profiles of both wind speed and turbulence and has been identified as a significant driver of power curve scatter, particularly at offshore sites where sea surface temperature gradients drive pronounced diurnal stability cycles (St. Martin et al., 2016). The air-sea temperature difference indexes the stability with positive values, with warm air over a cool sea, which promotes a stable stratification, while negative values, with cool air over a warmer sea, drives the convective instability (Wharton and Lundquist, 2012a). Wind-wave misalignment, which arises when remotely generated swell propagates at an angle to the local wind, modifies sea surface roughness and the near-surface turbulence structure, and has been shown to affect offshore power production (Porchetta et al., 2019).



Together, these variables allows to assess how deviations from the expected power response are explained by which
170 atmospheric and sea-state conditions. These variables are defined in this section.

3.1 Shear

Shear is the vertical gradient of wind speed, and is presented as the exponential α in Eq. (1) that defines the wind profile as a power-law gradient. The measurements available for this study allow calculation of the shear exponent between several heights across the rotor area, obtained via least squares optimisation.

$$175 \quad V_z = V_r \left(\frac{z}{z_r} \right)^\alpha \quad (1)$$

where V is the wind speed at a specific height z (see Sect. 4.1), and V_r is the reference speed at height z_r . Although the power-law is often used for wind speed extrapolation, research has demonstrated that it can differ significantly from observed site- and event-specific wind profiles (Cheynet et al., 2024). The IEC 61400-3-1 (IEC, 2019) defines a constant shear exponent of 0.14. However, assuming a constant value introduces uncertainty, as the shear exponent is influenced by diurnal cycles,
180 atmospheric stability, and surface roughness (Yan et al., 2022).

3.2 Veer

Veer is the change in wind direction with height. It occurs due to the balance between the Coriolis force, pressure gradient force, and friction, as well as thermal wind advection and inertial oscillation (Holton and Hakim, 2013). Wind veer affects the wind field impinging on the turbine, influencing wake deflection (Churchfield and Srinivas, 2018; Brugger et al., 2019) and power
185 production (Bardal et al., 2015; Gao et al., 2021). In this paper, veer is calculated according to Eq. (2) (Murphy et al., 2019):

$$\beta_{bulk} = \frac{\theta_{top} - \theta_{bottom}}{z_{top} - z_{bottom}} \quad (2)$$

where θ denotes the wind direction at *top* and *bottom* location in the measurement plan (see Sect. 4.1), measured clockwise from true north. Depending on its sign, the wind flow is considered veering (positive veer) or backing (negative veer). A clockwise rotation with height (veering) is typically associated with power gains, while a counterclockwise rotation (backing) tends to
190 cause power deficits, albeit in a small scale impact (Murphy et al., 2019; Tumenbayar and Ko, 2023).

3.3 Turbulence intensity

Turbulence intensity (TI) is an important inflow parameter that can be used to characterise the wind field variability and its impact on wind turbine performance and structural loading, extensively studied in several studies (St. Martin et al., 2016; Bardal and Sætran, 2017; Anup et al., 2020; Kosović et al., 2026). In atmospheric boundary-layer flows, turbulence arises from a
195 combination of mechanical shear, buoyancy effects, and interactions with surface roughness and obstacles. In practice, TI is usually calculated using wind speed measurements averaged over a fixed time interval, most commonly 10 minutes. A common formulation expresses TI as the ratio of the standard deviation of the longitudinal wind speed component to the mean wind speed



over the same period (IEC, 2005), as seen in Eq. 3. Measurements can be obtained from cup anemometers, sonic anemometers, or lidar systems, depending on the available measurement platform, that are then aggregated to the 10-minute statistics (El-Asha et al., 2017).

$$TI = \frac{\sigma_V}{\bar{V}} \quad (3)$$

where σ_V represents the standard deviation of wind speed and $\bar{V}$ its mean. However, the use of real measurements for inflow parameters statistics, such as turbulence, has its limitations, from instrumentation uncertainty to human errors (Benedict and Gould, 1996). Moreover, to calculate TI with the previously mentioned common formulation, it brings some more specific limitations. First, the assumption of stationary conditions over the averaging interval, which may not hold in certain atmospheric environments or during rapidly evolving meteorological conditions (Chen et al., 2007). Second, TI derived from nacelle-mounted sensors may be biased due to flow distortion caused by the rotor, nacelle structure, and turbine operation (Brand et al., 2011), which can be mitigated by using lidar measurements as input, since there is no flow distortion (Fu et al., 2022b). Additionally, the scalar TI metric provides only a limited representation of atmospheric turbulence, as it does not capture turbulence anisotropy, coherent structures, or spectral characteristics that may influence turbine loading and wake behaviour (Tian et al., 2022).

3.4 Atmospheric stability

Atmospheric stability in the lower atmospheric boundary layer governs vertical mixing and strongly influences wind shear, veer, and turbulence characteristics. It reflects the balance between buoyancy and mechanical forcing and is typically characterised using parameters derived from Monin–Obukhov similarity theory, such as the Obukhov length (L) (Holtslag et al., 2014). Stable conditions suppress vertical mixing and are generally associated with increased shear and pronounced directional veer, whereas unstable conditions promote mixing and reduce vertical gradients (Wharton and Lundquist, 2012a). Near-neutral conditions are often associated with wind profiles that follow power-law behaviour, while deviations from standard shear models are more frequently observed under strongly stable or unstable stratification (Sakagami et al., 2015).

The current work, estimates atmospheric stability with the environmental observations from the ERA5 dataset, using Eq. 4 to calculate L (Obukhov, 1971):

$$L = -\frac{u_*^3 \bar{\theta}_v}{k g (\overline{\omega' \theta'})_s} \quad (4)$$

where u_*^3 is the friction velocity, $\bar{\theta}_v$ is the mean virtual potential temperature, k is the dimensionless Von Karman constant, g is the gravitational acceleration and $(\overline{\omega' \theta'})_s$ is the surface virtual potential temperature flux. The Von Karman constant takes the value of 0.4. The other variables are calculated using the corresponding equations with the data retrieved from ERA5 (Service, 2024). Based on the estimated Obukhov length, the atmospheric stability can be classified into different regimes, and the current research follows the classification proposed in Gryning et al. (2007), shown in Table 2. For the SHAP analysis, each atmospheric stability class is given a numerical classification, as the qualitative classification is not interpretable in the SHAP process.



Table 2. Classification of seven categories of atmospheric stability, based on the value of L .

No	Stability Class	Range
7	Very stable	$10 \leq L \leq 50$ m
6	Stable	$50 \leq L \leq 200$ m
5	Neutral-stable	$200 \leq L \leq 500$ m
4	Neutral	$ L \geq 500$ m
3	Neutral-unstable	$-500 \leq L \leq -200$ m
2	Unstable	$-200 \leq L \leq -100$ m
1	Very unstable	$-100 \leq L \leq -50$ m

4 Methodology

4.1 Wind field reconstruction

A lidar measures only the wind speed along its line of sight, so it cannot directly provide all three velocity components. Wind-field-reconstruction (WFR) methods overcome this by combining multiple beam measurements, using analytic formulas or least-squares solutions, to retrieve the full wind vector. These methods typically assume a sufficiently large beam opening angle and are not always limited to retrieving time series of velocity. In some cases the aim is to reconstruct second-order statistics such as the Reynolds stress tensor (Fu et al., 2022a).

The primary goal is to determine the horizontal wind speed and direction at multiple heights across the rotor area using lidar data. This study implements the 2-beam reconstruction method described by Schlipf et al. (2012) and Wagner et al. (2014). As such, two wind field assumptions are made. First, the wind vector is considered two-dimensional, such that the vertical component (in the z -axis direction) is negligible. This assumption allows estimation of the wind components, V_x and V_y , from two LOS measurements (Wagner et al., 2014). Second, horizontal homogeneity is assumed, meaning that wind speed components remain consistent across different measurement locations, with no significant spatial changes in flow characteristics (Borraccino et al., 2016). Finally, an optical head correction is applied to ensure the validity of the governing equations across all heights at which the wind vector is reconstructed.

Based on the computed wind vector components, the wind speed magnitude (V_∞) and wind direction misalignment (Δ) are determined using Eq. (5) and Eq. (6), respectively. The turbine yaw angle, obtained from SCADA (ψ), must also be considered in calculating the wind direction, as Δ represents the misalignment between the wind vector components. To ensure consistency, the lidar is assumed to be aligned with the turbine yaw.

$$V_\infty = \sqrt{V_x^2 + V_y^2} \quad (5)$$

$$\Delta = \arctan2(V_y, V_x) \quad (6)$$

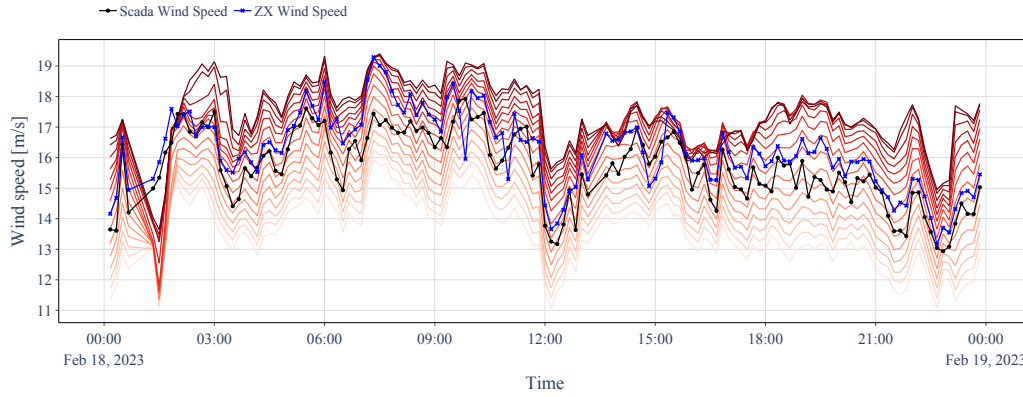


Figure 1. Reconstruction at different heights compared with the ZX “black-box” reconstruction (blue-cross symbol) and the SCADA measurements (black-circle symbol). The red-coloured lines indicate the reconstruction at different heights, with the lightest red indicating the lowest a.s.l. and the darkest red the highest a.s.l. heights.

Figure 1 shows an example of the WFR time series at several heights, ranging from 27 m above sea level (a.s.l.) to 180 m a.s.l. The reconstructed wind speeds are shown in red, with lighter shades corresponding to lower heights and darker shades corresponding to higher heights. The method application within the rotor’s area is further expanded in Appen. A. The reconstructed profiles are compared with the ZX lidar hub-height wind-speed estimate and the SCADA measurements. These multi-height reconstructions allow atmospheric conditions of interest, such as wind shear and veer, to be estimated.

The agreement between the hub-height WFR-reconstructed and SCADA-measured wind speeds is shown in Fig. 2. The comparison gives an R^2 of 0.96 and a bias of 0.13 m s^{-1} , indicating good agreement between the two estimates. This supports the use of the WFR methodology for estimating hub-height wind speed and deriving vertical wind-profile quantities. Further information can be found in Appen. A.

4.2 Atmospheric conditions

Environmental conditions such as air and sea temperatures, wind and wave directions, wind profile, and air density can also influence power production (Saint-Drenan et al., 2020). These are derived from the datasets used in this study, including buoy, measurement pile data near the wind farm and reanalysis data. The wind-wave misalignment (Eq. 7) and air-sea temperature difference (Eq. 8) are given by:

$$\Delta\theta_{WW} = |\theta_{air} - \theta_{sea}| \quad (7)$$

$$\Delta T_{air-sea} = T_{air} - T_{sea} \quad (8)$$

where the subscripts *air* and *sea* denote the horizontal wind and wave directions and temperatures, respectively, expressed using the same directional convention as θ and T . Wind speed profiles are commonly approximated using the power-law relationship, as seen in Eq. 1, but these might not be representative of all wind conditions, such as high wind speeds and rapid directional

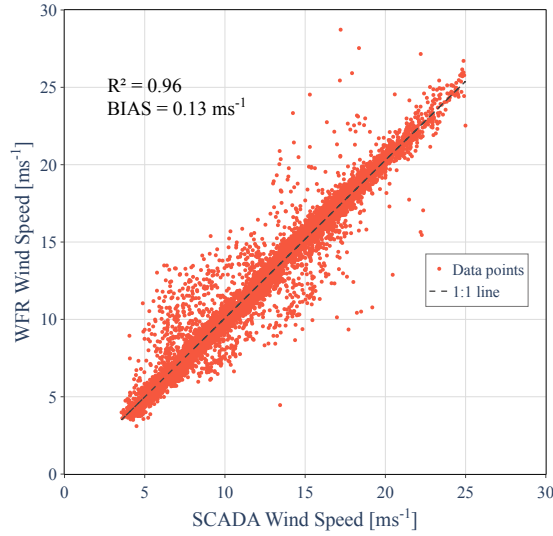


Figure 2. Scatter plot for the duration of the measurement campaign comparing the WFR-reconstructed and SCADA-measured wind speeds.

changes (Debnath et al., 2021). In this study, the power-law wind speed profile is fitted to the measured profile, using 10 different heights along the rotor area. For each sample, the shear coefficient is estimated with Eq. 1, and the agreement between profiles is
 270 quantified using the mean absolute error, as in Eq. 9::

$$\text{MAE} = \frac{1}{N_{\text{heights}}} \sum_{h=1}^{N_{\text{heights}}} |V_h^{\text{est}} - V_h^{\text{fit}}|, \quad (9)$$

where N_{heights} is the number of heights across the rotor area, V_h^{est} is the estimated wind speed at height h , and V_h^{fit} is the corresponding wind speed predicted by the fitted power-law profile. To make this error comparable across different wind speed magnitudes, the MAE was normalized by the median wind speed of the estimated profile, named NMAE, representing the
 275 relative deviation between the observed profile and the power-law representation independently of the wind speed. Finally, air density is also quantified as it has a known influence in energy yields (Jung and Schindler, 2019), and can be defined as in Service (2024) with Eq. 10:

$$\rho = \frac{p}{R_d * T_v} \quad (10)$$

with p the surface pressure taken from ERA5 dataset, R_d the gas constant of dry air (287.06 J/(kgK)), and T_v the virtual
 280 temperature.



4.3 Prediction of power deviation with machine learning modelling

To quantify the influence of reconstructed inflow and environmental features on turbine power production, a two-step methodology was adopted, combining supervised regression with post hoc interpretability analysis. The target variable was defined as the power deviation (PD), computed as

$$PD = P_{SCADA} - P_{curve}, \quad (11)$$

where P_{SCADA} is the measured SCADA power and P_{curve} is the corresponding reference power-curve value. Thus, PD represents the deviation of the observed turbine response from the expected power output based on the power curve.

To serve as baseline, an analysis on the linear contributions of the variables is made with the implementation of a regression model constructed with the chosen environmental predictors: air density, air-sea temperature difference, normalised mean absolute error of the wind speed profile, shear exponent, stability class, turbulence intensity, wind veer, wind direction and speed at hub height, and wind-wave misalignment. This linear baseline provides both interpretable coefficient estimates and a benchmark against non-linear models. The MLR model coefficients are estimated by minimising the residual sum of squares between the observed and predicted PD values (James et al., 2023):

$$\hat{y} = c_0 + c_1 X_1 + c_2 X_2 + \dots + c_n X_n \quad (12)$$

where $\hat{y}$ is the predicted power deviation, $X_1, \dots, X_n$ are the n environmental predictors, $c_1, \dots, c_n$ are the corresponding regression coefficients, and c_0 is the intercept of the linear model. Each coefficient represents the expected change in the predicted PD , in the units of kW , associated with a one-unit increase in the corresponding feature, while all other variables are kept constant. Therefore, the coefficients can be interpreted as empirical sensitivities in the physical units of each variable. However, because the variables have different units and ranges, the absolute magnitudes of the coefficients cannot be directly compared as measures of relative importance.

The next step was to identify the most appropriate machine learning model for predicting PD . Possible models were selected based on approaches commonly used in the literature and were evaluated using predictive performance metrics, namely the coefficient of determination (R^2), Weighted Absolute Percentage Error (WAPE), and Normalized Root Mean Square Error (NRMSE). While WAPE measures the total absolute prediction error as a percentage of the total observed values, NRMSE expresses the root mean squared error relative to the mean of the observed target variable. The focus was placed on ensemble learning methods, such as XGBoost (Chen and Guestrin, 2016), Gradient Boosting (Friedman, 2001), and Random Forest (Amit and Geman, 1997), since these methods have been shown to perform well in wind power forecasting applications (Demolli et al., 2019; Singh and Rizwan, 2022). Their wide use is mainly due to their numerical stability, robustness, and predictive accuracy (Lee et al., 2020; Rajaperumal and Christopher Columbus, 2025).

The selection is made based on the performance metrics obtained from training the models to predict power production. The chosen model was then trained to predict PD using the reconstructed inflow parameters and environmental features as explanatory features. These methods are well suited to wind energy applications because they can capture non-linear relationships and interactions among atmospheric variables while retaining strong predictive skill (Sobolewski et al., 2023). Since the physical

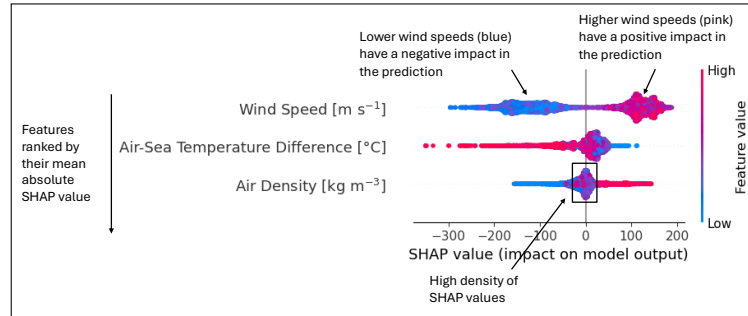


Figure 3. SHAP beeswarm summary plot illustrating the prediction of power deviation using three selected environmental variables. The simplified example is provided to demonstrate how the SHAP results should be interpreted.

drivers of turbine behaviour differ across the power curve, the analysis was performed separately for each operating region,
 315 allowing the influence of the explanatory variables to be examined under distinct aerodynamic regimes.

4.4 SHAP analysis

To interpret the trained model and quantify the contribution of each feature, SHAP introduced by Lundberg and Lee (2017),
 were employed. SHAP is based on cooperative game theory and attributes each prediction to the input features through Shapley
 values. For a given sample, the model output is decomposed into a baseline value and additive feature contributions, such
 320 that each SHAP value represents the contribution of one feature to the prediction while accounting for interactions with the
 remaining inputs. This provides a consistent framework for attributing model predictions to the explanatory variables and has
 been increasingly applied in energy-system modelling and wind-power forecasting studies (Lundberg et al., 2020; Yan and
 Zhang, 2024). The analysis is supported by SHAP summary plots, shown in Fig. 3 as an example, which ranks the environmental
 features according to their importance in the model output. In these plots, each feature's SHAP values are shown across the
 325 dataset, with feature values represented by a colour gradient ranging from low values in blue to high values in pink. The
 horizontal position of each point indicates the direction and magnitude of the feature's impact on the model output, showing
 whether the feature contributes negatively or positively to the prediction.

The SHAP analysis was carried out both on the full dataset and separately for three wind-speed intervals in order to evaluate
 how the relative contribution of each environmental driver varies along the power curve. The intervals were defined with respect
 330 to the turbine rated wind speed, V_{rated} . The first interval, from cut-in wind speed, $V_{\text{cut-in}}$, to 4 m s^{-1} below rated, represents
 the below-rated operating range away from the rated-speed transition. In below-rated operation, turbine control is primarily
 aimed at maximizing energy capture through generator-torque control, whereas above-rated operation relies on blade-pitch
 control to regulate power close to its rated value (Wright and Fingersh, 2008). The second interval, from $V_{\text{rated}} - 4$ to V_{rated} ,
 was defined as a near-rated transition region, coming from the fact that the change between the below-rated and above-rated
 335 control regimes occurs over a finite transition range rather than at a single wind speed. The third interval until cut-off wind
 speed, $V_{\text{cut-off}}$, represents above-rated operation. This binning approach does not simply separate the conventional Region II



and Region III operating regimes, but further isolates the neighbourhood of the rated wind speed, where the control strategy and power-curve sensitivity change rapidly. This allows the SHAP-based feature importance to be examined as a function of the wind-speed regime and helps identify whether the environmental drivers of power deviation differ between below-rated, near-rated, and above-rated operation.

4.4.1 Pearson correlation coefficient

To provide a clear overview of how environmental factors influence turbine performance, it is important to know the dependencies of the drivers of power production. Specifically, it is expected that wind speed might overshadow other influencing factors in terms of predictability of turbine performance. Furthermore, when two features exhibit strong linear dependence, only one is retained for the SHAP analysis to reduce multicollinearity and avoid ambiguity in the attribution of their individual contributions (Lundberg and Lee, 2017). To this end, the Pearson correlation coefficient is used to measure the linear relationship between any two variables, X and Y , as shown in Eq. 13:

$$r_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} \quad (13)$$

where X and Y are the pair of variables from the atmospheric and operational datasets, cov is their covariance and σ_X and σ_Y are their respective standard deviations. The coefficient ranges from -1 to 1 , with its sign indicating the direction of the linear relationship and its absolute magnitude indicating its strength. For the purpose of screening predictors for potential redundancy, pairs of variables with $|r_{X,Y}| > 0.7$ were considered to exhibit strong linear dependence (Dormann et al., 2013). For each pair exceeding this threshold, only one variable was retained for the subsequent SHAP analysis, being chosen the variable with lower measurement error between the pair.

5 Results

In this section, the results obtained in the analysis are shown and discussed. First, the result of the process to select which machine learning method is shown. This is followed by the linear relation analysis, with the results for the Pearson correlation matrix and multivariate linear relation methodology discussed. Finally, the SHAP results for environmental influence in power deviation for different regions within the power curve, are presented and discussed.

5.1 Machine learning model selection based on power-production prediction

Table 3 shows summary of the performance metrics and computational time for each of the tested machine learning model and the multivariate linear regression for the prediction of power production. Moreover, the R^2 is showed for the cross-validation (CV) study. In this study, the training data are divided into five subsets, and the model is trained and validated five times, each time using a different subset for validation.



Table 3. Comparison of model performance using WAPE and NRMSE

Model	CV R^2	Test R^2	WAPE (%)	NRMSE (%)	CV Time (s)
MLR	0.81	0.82	18.2	21.9	0.2
XGBoost	0.98	0.98	3.4	6.2	0.8
Gradient Boosting	0.98	0.98	3.5	6.7	8.8
Random Forest	0.98	0.98	3.1	6.6	16.7

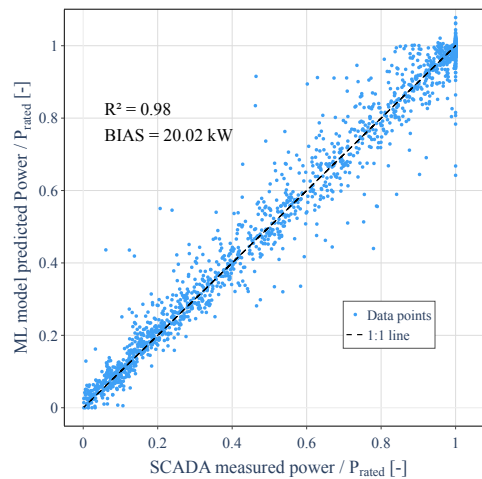


Figure 4. Comparison of GBR-predicted and SCADA-measured of 10-minute averaged power.

365 Among the evaluated models, Random Forest achieved the lowest WAPE, with 3.1%, indicating the lowest overall absolute error relative to the observed values. XGBoost achieved the lowest NRMSE, with 6.2%, suggesting that it produced the lowest squared-error penalty relative to the mean target value. Gradient Boosting remained competitive, with a WAPE of 3.5% and an NRMSE of 6.7%. So, although Random Forest achieved the lowest WAPE and XGBoost achieved the lowest NRMSE, Gradient Boosting produced comparable error values. These results indicate that its predictive performance was close to the

370 best-performing models. Therefore, Gradient Boosting was selected as a suitable compromise between predictive accuracy, methodological simplicity, and robustness. The agreement between the normalised predicted and measured power, presented in Fig. 4, further supports the suitability of the model.

5.2 Linear relation between environmental factors and power deviation

The linear analysis is divided into two parts. First, the Pearson correlation matrix is used to quantify pairwise linear associations

375 between PD and the environmental predictors, as well as among the predictors themselves. This step provides an initial overview

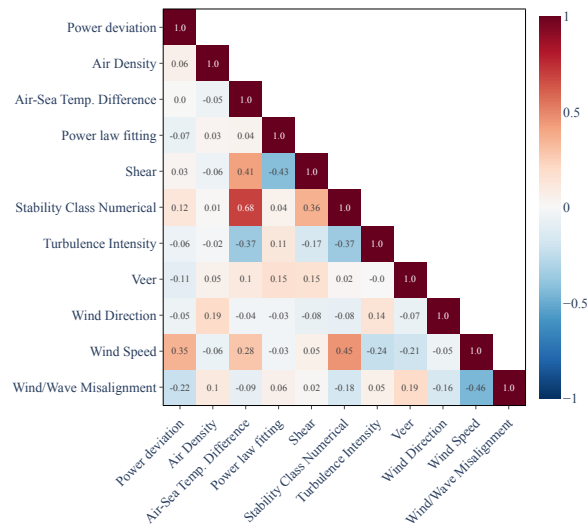


Figure 5. Heatmap of the Pearson correlation coefficients for the analysed features pairs.

of the strength and direction of the linear relationships and helps identify potential collinearity. Second, a MLR model is fitted using the standardized predictors to estimate their combined linear contribution to PD . While the correlation analysis considers each relationship independently, the MLR model evaluates the effect of each variable while controlling for the others.

In Fig. 5, the calculated Pearson correlation coefficients between the possible pairs of the investigated features is shown. This analysis shows that, overall, most correlations are weak to moderate, which is expected since the variables involved are influenced by multiple atmospheric processes and nonlinear effects. Similar behaviour has been reported in offshore studies, where stability, turbulence, and vertical wind structures, such as shear and veer, interact in complex ways not always captured by linear correlations (Albornoz et al., 2022; Kelly and van der Laan, 2023).

Overall, the Pearson correlation coefficients between the environmental features and PD remain modest across all variables, reflecting the nonlinearity nature of offshore atmospheric processes and showing that single-variable linear metrics capture only a fraction of the variability in turbine power response. Among all features, wind speed exhibits the strongest correlation with PD (0.35), so even after normalisation against a reference power curve, wind speed may be still be associated with systematic residuals due to nonlinearities, or simply wind speed inaccuracies, in turbine response, regional inflow effects or by the fact that the warranted power curve not being fully representative. Wind/wave misalignment shows the second strongest absolute correlation with PD (-0.22), rather than being a direct causal effect of wave direction on power, this variable may be acting as a proxy for transitional metocean conditions. The remaining features show weak to negligible correlations with PD . Turbulence intensity (-0.06), wind direction (-0.05), shear (0.03), power law fitting (0.02), air density (0.06), and air-sea temperature



difference (0.0) all fall below any meaningful linear correlation threshold, suggesting that, once wind speed effects are absorbed through the PD formulation, these variables do not exhibit a discernible linear relationship with the residual power response.

395 Beyond the direct correlations with PD , stronger relationships emerge among the inflow and metocean variables themselves, highlighting the coupled nature of offshore operating conditions. Wind speed is moderately correlated with stability class (0.45) and wind/wave misalignment (-0.46), while stability class shows strong internal correlations with air-sea temperature difference (0.68), shear (0.26), and turbulence intensity (-0.37). Stability is linked to temperature and wind conditions through the Obukhov length (Eq. 4), while its inverse association with TI is consistent with enhanced turbulent mixing under unstable conditions
400 (Hansen et al., 2012). Additional correlations between air-sea temperature difference and shear (0.33), and between shear and veer (0.12), are also consistent with stable stratification enhancing vertical wind speed gradients and directional turning (Wharton and Lundquist, 2012a; Kelly and van der Laan, 2023). Finally, to proceed with the SHAP analysis, the stability class numerical feature is chosen to be removed as presents a strong correlation with air-sea temperature difference.

The generally weak correlations observed between PD and most environmental features confirm the limitations of linear
405 metrics in characterising the complex, nonlinear interactions that influence offshore turbine performance. These weak relationships also partly reflect the simplified assumptions inherent in the employed atmospheric stability characterisation. Finally, the SHAP analysis proceeds with all-but-one environmental features, with stability class numerical chosen to be removed due to its strong correlation with air-sea temperature difference and its higher associated error due to the necessary measurements for its estimation.

410 5.2.1 Multivariate linear relation

The derived coefficients from Eq. 12 are summarised in Table 4. The negative coefficients for air-sea temperature difference, NMAE, veer, wind direction, and wind-wave misalignment indicate that, under the linear formulation and conditional on the remaining variables, increases in these quantities are associated with lower predicted values of PD . Conversely, air density, shear, stability classification, turbulence intensity, and wind speed show positive associations with PD .

415 The MLR model results show that a 1 m s^{-1} increase in wind speed is associated with an increase of approximately 19.45 kW in the predicted PD , while all other variables are kept constant. Similarly, an one-unit increase in air-sea temperature difference is associated with a decrease of approximately 17.99 kW in the predicted PD . The coefficient for air density is positive and equal to 1082.04. However, this value corresponds to a full 1 kg m^{-3} increase in air density, which is much larger than the typical variability observed in atmospheric conditions. Therefore, a smaller and more physically realistic change, such as 0.01 kg m^{-3} ,
420 would correspond to an expected increase of approximately 10.82 kW in the predicted PD .

Despite the physical interpretability of the unstandardised coefficients, the coefficient of determination remains low ($R^2 = 0.15$), indicating that the MLR model explains only 15% of the observed variance in PD . This suggests that a linear formulation is not sufficiently flexible to represent the nonlinear and interacting effects that influences power deviations. The MLR model is therefore retained as a baseline method, providing an initial estimate of the direction and magnitude of the linear sensitivities in
425 physical units. More flexible approaches, such as the GBR model and the subsequent SHAP analysis, are expected to provide a more suitable representation of nonlinear effects, variable interactions, and feature importance.



Table 4. Summary of the MLR model for each environmental feature and the corresponding coefficient.

Feature	Coefficient (c_n)
Air density	1082.04
Air-sea temperature difference	-17.99
NMAE	-302.83
Shear	167.49
Stability classification numerical	2.24
Turbulence intensity	1.49
Veer	-73.28
Wind direction	-0.91
Wind speed	19.45
Wind-wave misalignment	-0.79

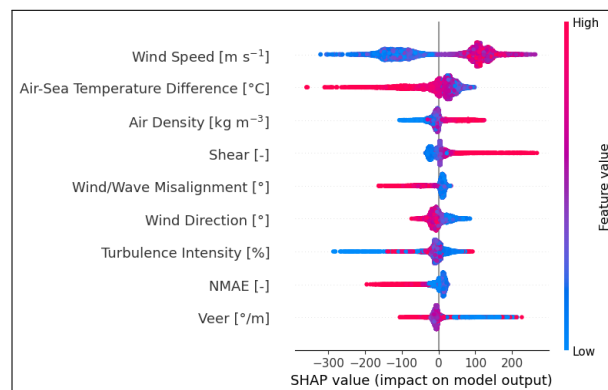


Figure 6. SHAP summary plot of the environmental features impact in *PD* prediction for all wind speeds combined.

5.3 Impact assessment of environmental factors on power production

The machine learning model selection process and the corresponding performance metrics are presented in Appendix 5.1. From this comparison, the Gradient Boosting Regressor was selected as the final predictive model and used as the basis for the SHAP interpretability analysis.

Figure 6 shows the SHAP summary plot computed over the full wind speed range. In a SHAP beeswarm plot, each point represents one observation, as the horizontal position gives the SHAP value, i.e., the contribution of that feature to the model prediction relative to the model baseline, the colour indicates the feature value from low to high. Features are ordered by their contribution to the model output, using mean absolute SHAP values.

The observed SHAP summary plot indicates that wind speed is the dominant predictor, followed by air–sea temperature difference, stability class, air density, wind direction, wind/wave misalignment, shear, turbulence intensity, veer, and NMAE.



Table 5. Physical range (minimum, maximum and mid-point values) for each of the features for the $V_{\text{cut-in}}$ to $V_{\text{rated}} - 4$ interval.

Feature	Minimum	Maximum	Mid-point
Air–Sea temperature difference [$^{\circ}\text{C}$]	-7.4	6.9	-0.25
Wind Speed [m s^{-1}]	$V_{\text{cut-in}}$	$V_{\text{rated}} - 4$	-
Turbulence Intensity [%]	3.4	35.6	19.5
Shear [-]	-1.4	1.5	0.05
Air density [kg m^{-3}]	1.2	1.3	1.25
NMAE [-]	0.0	0.9	0.45
Veer [$^{\circ}/\text{m}$]	-0.6	0.8	0.1
Wind direction [$^{\circ}$]	180.0	270.0	225.0
Wind/Wave Misalignment [$^{\circ}$]	0.0	180.0	90.0

Low wind-speed values are primarily associated with negative SHAP contributions, whereas high wind-speed values produce positive contributions, showing that the model predicts lower than the baseline responses under low wind-speed conditions and higher than the baseline responses under high wind-speed conditions.

440 The clustered observations, e.g. wind speed for +200 and -300 SHAP contribution, suggests that the model has learned distinct operating regimes rather than a simple linear relationship. These clusters represent then groups of observations for which the feature contributes similarly to the prediction across the model-attribution regimes. Similar clustered patterns may arise from nonlinear model behaviour, tree-based decision paths, interactions with other atmospheric variables, or uneven data density across operating conditions. Accordingly, the SHAP results are interpreted as model-specific evidence of predictor influence
 445 rather than causal effects.

In the following sections, the wind speed binned SHAP analysis is discussed to examine whether the drivers of PD change across the different turbine operating regimes. Since PD is defined relative to the reference power curve, the SHAP contribution of wind speed should not be interpreted as the direct cubic dependence of power on wind speed. Instead, it represents the residual wind speed dependent structure in the model, i.e., deviations from the reference power curve behaviour that remains after the
 450 normalisation. The comparison between bins therefore indicates how the relevance and sign of environmental predictors change with operating regime.

5.3.1 Below rated wind speed regime

Figure 7 shows the SHAP distribution for the below-rated regime, with the corresponding physical ranges reported in Table 5. In this interval, the largest SHAP spread is associated with the air-sea temperature difference, followed by turbulence intensity and
 455 wind speed.

The air-sea temperature difference emerges as the most influential predictor, and it has a strong negative SHAP contribution for higher values and moderate positive impact once inverts the sign. Despite the normalisation done using the power curve,

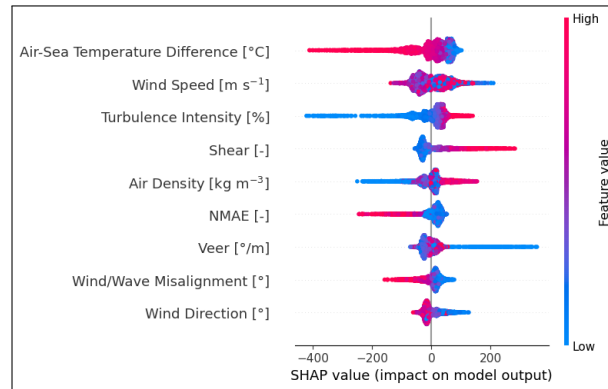


Figure 7. SHAP summary plot of the environmental features impact in PD prediction for $V_{\text{cut-in}}$ to $V_{\text{rated}} - 4$ interval.

wind speed remains influential, but its mixed SHAP pattern and higher wind speeds with a negative impact suggests that, within Region II, there is a non linear relation between the contribution of wind speed in the prediction of the power deviation. TI is the third most influential predictor, and its positive SHAP contribution at high values indicates that elevated turbulence tends to increase PD , whereas low-turbulence conditions are associated with negative deviations. This is consistent with earlier work showing that turbulence modifies turbine power curves and can enhance power production at lower wind speeds relative to a reference curve (St. Martin et al., 2016; Hansen et al., 2012).

Wind shear exhibits a strong and predominantly positive contribution, indicating that stronger shear tends to produce positive power deviations in Region II when power is referenced to a standard curve based on hub-height wind speed. This interpretation agrees with studies showing that rotor-disk shear changes the effective inflow seen by the turbine and can shift power production away from the hub-height-based expectation (Murphy et al., 2019). Variations in air density show to influence the difference between measured power and the reference power curve. The SHAP results are consistent with the expectation for lower air-density observations, generally shows negative contributions to PD . Although there is a non monotonic effect clustered near zero, higher air density observations are mostly associated with a positive contribution. This effect may reflect the limited observed density variability and interactions with wind speed, stability, or controller behaviour, rather than a stand-alone density effect. This is followed by the NMAE influence, which its negative contribution associated with large suggests that cases in which the rotor-layer profile departs strongly from a simple power-law description tend to produce underperformance relative to the reference curve, which is physically consistent with stratified offshore profiles and shear-enhanced events that are poorly captured by simplified profile assumptions (Debnath et al., 2021).

Directional veer is in the bottom three most influential features and it presents a less monotonic effect than shear, which is in line with evidence that veer affects power production but generally exerts a smaller influence than shear (Murphy et al., 2019; Kim et al., 2021). Since the analysis focus in a free-stream sector of the wind farm, the directional dependence most likely reflects changes in free-stream marine-boundary-layer conditions across sectors rather than a wake contamination (Shaw et al., 2022). Likewise, for a bottom-fixed turbine the contribution of wind/wave misalignment should not be interpreted as a



Table 6. Physical range (minimum, maximum and mid-point values) for each of the features for the $V_{\text{rated}} - 4$ to V_{rated} interval.

Feature	Minimum	Maximum	Mid-point
Wind Speed [ms^{-1}]	$V_{\text{rated}} - 4$	V_{rated}	-
Turbulence Intensity [%]	3.4	28.6	16.0
Air density [kg m^{-3}]	1.2	1.3	1.25
Air–Sea temperature difference [$^{\circ}\text{C}$]	-7.8	6.4	-0.7
Wind direction [$^{\circ}$]	180.0	270.0	225.0
NMAE [-]	0.0	2.4	1.2
Shear [-]	-2.8	1.1	-0.85
Veer [$^{\circ}/\text{m}$]	-0.6	0.8	0.1
Wind/Wave Misalignment [$^{\circ}$]	0.0	177.0	88.5

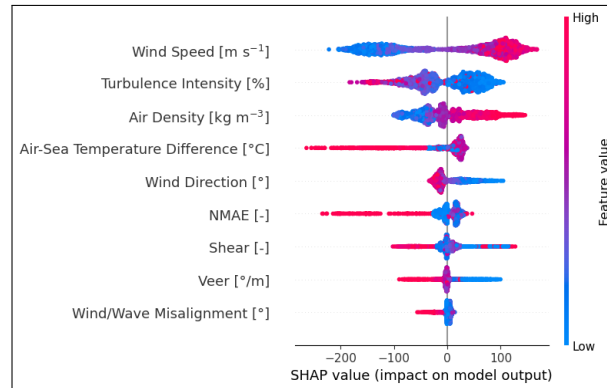


Figure 8. SHAP summary plot of the environmental features impact in PD prediction for $V_{\text{rated}} - 4$ to V_{rated} interval.

platform-motion effect. Instead, it is more plausibly acting as a sea-state descriptor that modifies air-sea momentum transfer, aerodynamic roughness, and hence the rotor-layer wind profile and turbulence level (Porchetta et al., 2019; Ferčák et al., 2022). These studies showed that wind-wave alignment can alter offshore roughness length, that wave effects can extend to hub height, and that swell can modify hub-height wind speed, turbulence, and turbine operation. Finally,

5.3.2 Transition between below rated and rated wind speeds

As wind speed increases towards the rated set point, shown in Fig. 8 together with the corresponding physical ranges in Table 6, the SHAP contributions changes. This shift might indicate that, in the transition between below-rated to rated wind speeds, PD is governed less by turbulence alone and more by the combined effect of stability, rotor-layer shear and proximity to the rated operating point.



490 Wind speed shows the largest SHAP spread in this interval, with lower wind speeds mostly associated with negative SHAP contributions, and higher wind speeds associated with positive contributions. It might indicate that the model still identifies systematic under- or over-performance relative to the reference curve depending on the turbine position within the transition interval. TI shows a clear change in sign compared with the below-rated regime, the strongest negative SHAP contributions are associated with high turbulence conditions, whereas lower TI values tend to contribute positively to PD . Increased turbulence
 495 can enhance power production below rated by increasing the probability of higher instantaneous inflow speeds, but near rated it can also contribute to negative deviations through unsteady loading, control activity, and departures from the reference power-curve assumptions (St. Martin et al., 2016; Hansen et al., 2012). Air density shows a more ordered pattern than in the below-rated interval, with lower-density observations generally contributing negatively and higher-density observations contributing weakly positively.

500 With a moderate continued relevance of NMAE, shear, and veer indicates that the rotor-layer inflow profile remains important as the turbine approaches rated wind speed. Larger NMAE values suggest that cases departing from a simple power-law profile are associated with underperformance relative to the reference curve. The negative contribution of larger veer is consistent with studies showing that vertical changes in wind direction can reduce the alignment between the rotor plane and the inflow across the swept area, thereby affecting power generation (Gao et al., 2021; Tumenbayar and Ko, 2023). The inversion of the shear
 505 contribution relative to the below-rated regime suggests that the benefit or penalty of rotor-layer shear is not fixed, but depends on the operating region and on how the rotor-equivalent inflow differs from the hub-height reference (Murphy et al., 2019).

As for the marine boundary-layer and directional descriptors, wind direction is again interpreted as a free-stream sector descriptor, while wind/wave misalignment is retained as a proxy for sea-state-dependent roughness and offshore boundary-layer structure. For air-sea temperatures, larger positive differences show a negative impact in power deviations which might indicate
 510 that more stable marine conditions continue to be impactful in this regime. This is again consistent with previous studies showing that atmospheric stability modifies turbine power characteristics through changes in vertical mixing, turbulence intensity and rotor-layer inflow structure. Overall, the transition regime is characterised by a redistribution of importance and shows a combined influence of wind speed with inflow characteristic and marine conditions.

5.3.3 Rated wind speed regime

515 In the fully rated regime, shown in Fig. 9 together with the corresponding physical ranges in Table 7, the overall SHAP spread is reduced for most predictors compared with the lower wind-speed intervals. This compression is consistent with the fact that, once rated operation is reached, the turbine response becomes increasingly constrained by the control system rather than by the direct conversion of additional available wind power.

Air density has the largest mean SHAP contribution in this interval, followed by the air-sea temperature difference and
 520 wind speed. Larger density values are generally associated with negative SHAP contributions in this regime, unlike in the transition interval. However, it is relevant to highlight once again the limited range of values for this feature. The air-sea temperature difference remains important, but its SHAP spread is smaller than in the below-rated regime, indicating that thermal stratification-related information is still present but less dominant. Wind speed ranks below air density and air-sea temperature



Table 7. Physical range (minimum, maximum and mid-point values) for each of the features for the V_{rated} to $V_{\text{cut-off}}$ interval.

Feature	Minimum	Maximum	Mid-point
Air density [kg m^{-3}]	1.2	1.3	1.25
Air–Sea temperature difference [$^{\circ}\text{C}$]	-9.0	6.4	-1.3
Wind Speed [m s^{-1}]	V_{rated}	$V_{\text{cut-off}}$	-
Wind direction [$^{\circ}$]	180.0	270.0	225.0
Veer [$^{\circ}/\text{m}$]	-0.8	0.6	-0.1
Turbulence Intensity [%]	3.1	28.6	15.85
Shear [-]	-0.4	0.7	0.15
Wind/Wave Misalignment [$^{\circ}$]	0.0	177.7	88.85
NMAE [-]	0.1	8.6	4.35

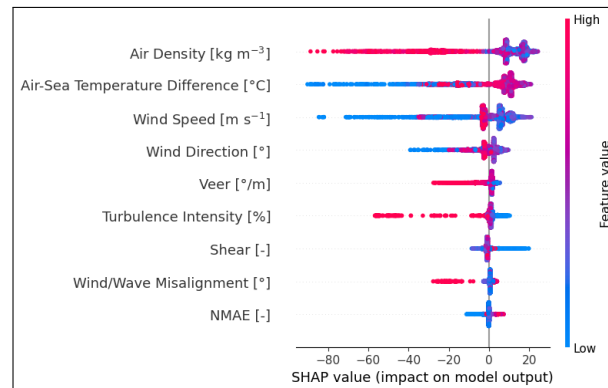


Figure 9. SHAP summary plot of the environmental features impact in PD prediction for V_{rated} to $V_{\text{cut-off}}$ interval.

525 difference in this interval. The highest wind speeds are mostly clustered near zero SHAP contribution, while the wider positive and negative SHAP values occur closer to the lower end of the rated interval. Shear, veer, turbulence intensity, wind/wave misalignment, and NMAE show smaller contributions than in the lower wind-speed intervals. Low shear values are associated with more positive SHAP contributions, while stronger shear tends to be closer to neutral or negative. High turbulence conditions produce a negative SHAP tail, whereas low turbulence values are associated with weakly positive or near-zero contributions.

530 The rated-regime pattern is consistent with the behaviour of a pitch-regulated turbine. Once the rated set point is reached, additional available kinetic energy cannot be converted into a proportional increase in electrical power. Instead, the controller acts to limit power and loads, so environmental variables affect PD mainly by perturbing aerodynamic loading, pitch activity, and the ability of the turbine to maintain the reference power output. Furthermore, when looking into particular features, earlier studies show that turbulence effects on power production depend on wind-speed region (St. Martin et al., 2016; Hansen et al., 2012). Under rated operation, high turbulence is more likely to be associated with unsteady loading, pitch-control activity, and



Table 8. Normalised mean absolute SHAP contribution of each environmental predictor for the three analysed wind-speed bins. Values are expressed as percentages of the total mean absolute SHAP contribution within each bin

Feature	$[V_{\text{cut-in}}, V_{\text{rated}} - 4[$	$[V_{\text{rated}} - 4, V_{\text{rated}}[$	$[V_{\text{rated}}, V_{\text{cut-off}}]$
Air density	10.5	14.5	32.8
Air–Sea temperature difference	17.4	10.4	24.8
NMAE	9.4	5.9	1.9
Shear	13.1	5.5	3.3
Turbulence Intensity	13.4	16.8	4.7
Veer	7.9	2.7	5.0
Wind direction	7.2	7.1	7.5
Wind speed	13.5	35.4	17.3
Wind/Wave Misalignment	7.6	1.7	2.7

deviations from ideal power regulation, rather than with enhanced below-rated power capture. Similarly, shear and veer remain physically relevant because they modify the inflow across the rotor disk, but their influence is no longer expressed primarily through increased rotor-equivalent wind speed. Instead, strong rotor-layer non-uniformity can contribute to uneven loading and control-induced deviations from the reference curve (Murphy et al., 2019; Gao et al., 2021; Tumenbayar and Ko, 2023).

5.3.4 Summary of all wind speed regimes

Table 8 summarises the normalised mean absolute SHAP contribution of each feature within each wind-speed bin. Since the values are normalised by the total mean absolute SHAP contribution in each bin, they indicate the relative contribution of each predictor to the model output within that operating interval.

The binned analysis shows that the relative contribution of the predictors changes with wind-speed regime. In the below-rated interval, air-sea temperature difference has the largest contribution (17.4%), followed by wind speed (13.5%), turbulence intensity (13.4%), and shear (13.1%). The relatively close values of these features suggest that below-rated *PD* is not attributed to a single dominant predictor, but rather to a combination of stability-related conditions, turbulence, residual wind-speed dependence, and rotor-layer inflow structure.

In the transition interval, the ranking changes substantially, with wind speed becoming the dominant contributor (35.4%), followed by turbulence intensity (16.8%) and air density (14.5%). Because *PD* is defined relative to the reference power curve, the high contribution of wind speed should be interpreted as residual wind-speed-dependent structures within the transition region. This might suggest that, as the turbine approaches rated operation, deviations from the reference curve remain strongly dependent on the position within the transition interval, together with turbulence and density-related variations in the inflow.

In the rated interval, the largest contributions are associated with air density (32.8%) and air-sea temperature difference (24.8%), while wind speed contributes 17.3% and the remaining variables have smaller relative contributions. This redistribution



555 is consistent with a regime in which the turbine response is increasingly constrained by power regulation. In this region region,
 higher wind speeds are not expected increase power production, and the remaining variability in PD is more likely associated
 with changes in aerodynamic loading, thermodynamic conditions, and control response.

6 Conclusions

This study investigated how reconstructed inflow and environmental features influence wind turbine power deviation relative to a
 560 reference power curve, focused on how these effects vary across different operating regions. The motivation for this work arises
 from operational contexts in which possible power production must be estimated transparently, for example when assessing
 losses associated with external actions by third parties. In such cases, current industry practice often relies on simplified reference
 power-curve approaches based primarily on wind speed, which are straightforward to interpret but may neglect additional
 atmospheric factors known to affect turbine performance.

565 To address this limitation, a Gradient Boosting regression model combined with SHAP-based interpretability analysis was
 applied to quantify the influence of rotor-area inflow and environmental conditions based on power deviation. The results show
 that the dominant drivers are regime dependent, with the constant of wind speed being always in the top three most influential
 drivers. In Region II, power deviation is governed primarily by inflow quality, with turbulence intensity and shear as the leading
 predictors. In the transition between Regions II and III, the importance shifts towards air-sea temperature difference and shear,
 570 indicating that atmospheric stability and rotor-area wind distribution become increasingly important as the turbine approaches
 rated operation. In Region III, the influence of most variables is attenuated, consistent with the growing dominance of active
 pitch control, while turbulence intensity and wind speed remain the main sources of variability.

The current study provides an overview and quantification of how impactful each environmental variable is in a machine
 learning model to predict power deviation. This allows to focus in the most relevant variables independently of the modelling
 575 methodology to be applied, from black-box machine learning models to standardized approaches. Furthermore, these findings
 further confirms that deviations from reference power curves cannot be explained by wind speed alone and that the relevant
 atmospheric drivers depend on the turbine operating regime. IEC 61400-12-1 accounts for four atmospheric and inflow-related
 effects in power performance assessment: turbulence intensity, wind shear, wind veer, and air density (IEC, 2017). The present
 findings indicate, however, that air-sea temperature difference is an additional influential variable not explicitly captured by these
 580 corrections. As this variable can be interpreted as a proxy for atmospheric stability, its relevance suggests that stability-related
 effects remain unrepresented in conventional power correction frameworks. More broadly, the results have shown that an
 interpretable machine-learning framework can retain the transparency needed for operational applications while extending
 conventional power-curve analysis to account for additional environmental effects. This is particularly relevant for possible
 power production estimation, where a physically grounded and explainable quantification of atmospheric influence may support
 585 more robust assessment of turbine underperformance and associated financial claims.

Finally, SHAP explanations have known limitations. The resulting feature attributions depend on the fitted model, the selected
 predictors, the representation of those predictors, and the background data used to estimate expected model outputs. Empirical



evidence indicates that SHAP values and variable rankings can fluctuate across different background samples, particularly with smaller samples, while recent work also shows that common feature-engineering choices can affect SHAP-based explanations (Yuan et al., 2022). This analysis also focused on freestream turbine-level conditions, which does not explicitly account for wake interactions that may influence turbine performance in wind farm environments. Moreover, the machine is still incorporated into a wind farm which has inherently blockage effect due to the cluster of wind turbines in its vicinity.

At the same time, the proposed methodology should be viewed as a complement to, rather than a replacement for, existing reference-based approaches. Its applicability depends on the availability of higher-quality inflow and environmental measurements, such as lidar-derived wind profiles and concurrent offshore meteorological observations, which are not always available in standard operational settings. Further work should therefore examine the transferability of the approach across different turbines, sites and atmospheric conditions, and evaluate how such models may be simplified for practical deployment without losing the interpretability required in industrial and contractual contexts.

Appendix A: Wind field reconstruction and non confirming power law wind profiles

This appendix provides additional information on the wind field reconstruction (WFR) used in the analysis and on the identification of wind profiles that do not conform to the standard power-law formulation.

As the chosen lidar instrument measures along a circle in the rotor area, the presented equations are applied at different heights. In Fig. A1, the selected volumes (N) along the height are illustrated. For each of these volumes (i), both assumptions described above are applied, and a set of LOS measurements is related to the wind vector through a matrix dependent on the lidar's cone angle. The wind vector is then obtained by solving a least-squares optimisation formulation that minimises the difference between the observed LOS and the reconstructed wind field.

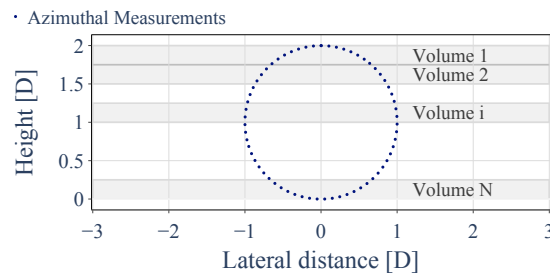


Figure A1. Schematic of the circle created with 64-averaged azimuthal positions projected in two dimensions, normalised with the wind turbine's rotor. Light grey illustrates how the circle is separated into volumes (i) used for the reconstruction at that respective height.

Non-conforming power-law profiles were identified by comparing the WFR-estimated vertical wind-speed profiles with the profiles predicted by the standard power-law formulation. The discrepancy was quantified using the normalised mean absolute error between the reconstructed profile and the corresponding power-law fit. An example of a non-conforming profile is shown

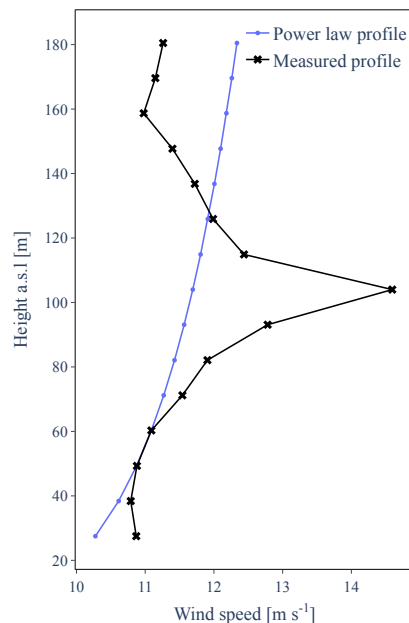


Figure A2. Example of a reconstructed wind-speed profile that does not conform to the standard power-law profile.

610 in Fig. A2. Moreover, the use of root-mean squared error was also used to detect these profiles, but produced no difference in the ML choice process and subsequent SHAP analysis.

The mean wind-shear coefficient over the measurement campaign, calculated using Eq. 1, was 0.062. Although offshore conditions often support the use of a standard power-law profile (Wharton and Lundquist, 2012a), deviations from this assumption were observed in the present dataset. Approximately 87% of the estimated shear coefficients were between 0 and 0.14, while
 615 around 8% were negative, indicating wind-speed profiles that decrease with height and therefore do not follow the conventional positive-shear power-law profile (Yan et al., 2022). The distribution of all valid estimated shear coefficients is shown in Fig. A3.

Following IEC 61400-1 (IEC, 2005), the extreme wind-shear exponent is taken as 0.2. In this study, shear coefficients above this threshold are therefore classified as high-shear events. These events accounted for less than 5% of the valid estimated shear values.

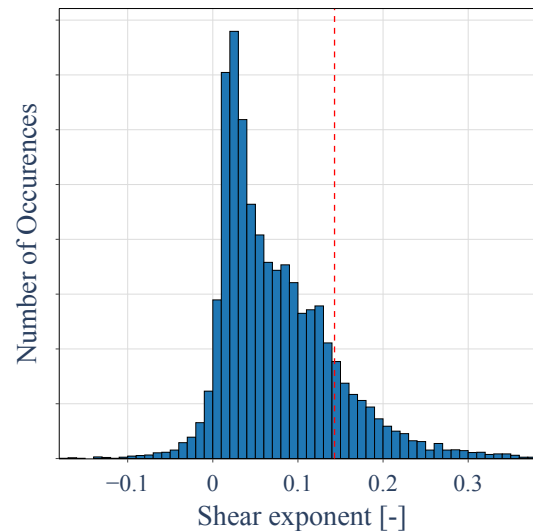


Figure A3. Distribution of the estimated power-law wind-shear exponent, α . The red dashed line denotes $\alpha = 0.14$.

620 *Code and data availability.* The data supporting the findings of this study are not publicly available due to confidentiality restrictions under non-disclosure agreements with the data provider.

Author contributions. R.M. has made the data curation and formal analysis, as well as the writing, revision and editing of the original draft and the final manuscript. K.V. conceptualised and conducted the experimental work to generate part of the data used in this study and the manuscript revision. P.J.D. and T.V., have validated results and contributed during the revision and editing of the manuscript. E.C and J.H., have
 625 provided supervision, along contributing for the manuscript conceptualization and execution. Finally, J.H. has secured the funding necessary for this work.

Competing interests. At least one of the (co-)authors is a member of the editorial board of Wind Energy Science.

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