Impact of local meteorology on wake characteristics at Perdigão

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Abstract. During January – June 2017 a unique data set of Doppler lidar observations of a single wind turbine wake was collected within the Perdigão flow in complex terrain experiment conducted as part of the New European Wind Atlas. Over the six-month period, over 19,000 10-minute scans comprising a combination of; Arc Scans at ten elevation angles, Vertical Azimuth Display and Range Height Indicator scans were conducted. These data were subsequently analysed using a newly-developed automated wake identification and tracking algorithm. In total, over 1,900 ten-minute periods were identified as ‘wake periods’ by the algorithm, over 1000 with coherent wake centres. For these wakes, the detailed 3D volume of the wake characteristics are examined to assess the impact of different meteorological conditions on the magnitude and recovery of the velocity deficit in coherent wakes as they advect downwind.

1. Scanning lidar measurements during the Perdigão experiment

The New European Wind Atlas (NEWA) is a project designed to generate a unified high-resolution and freely available data set of wind resource and wind turbine siting parameters across Europe [1]. The NEWA project also includes a series of measurement field campaigns to improve understanding of flow properties in complex terrain that are of relevance to the wind energy industry and to validate the model downscaling methodology and resulting wind atlas [1]. Under NEWA major field experiments were conducted in Kassel in Germany, offshore in northern Europe, in Alaiz, Spain, in Perdigão, Portugal and Hornamossen in Sweden [1].

The NEWA experiment in Perdigão, Portugal (Figure 1) ran from 25 January 25 to 30 June, 2017 and was a US-European collaboration including scientists from 23 institutions [2]. The site and experimental details of the Perdigão experiment have been described previously [1-4] but in brief the topography is dominated by two parallel ridges that rise to approximately 175 m above the intervening valley and are separated by a horizontal distance of about 1.4 to 1.6 km. Slopes on valley-side of the southwest ridge have an average value of 16%, but exhibit substantial micro-scale variability (Figure 1). The land cover/canopy is also heterogenous with areas of grass/low vegetation in the valley transitioning to coniferous trees on the lower slopes and then mainly eucalyptus trees or bare areas/low shrubs close to and along the ridge. There were two phases of the NEWA - Perdigão experiment; an Extended Monitoring Period (EMP) that ran from January until end of June 2017, and an embedded Intensive Operating Period (IOP) from 1 May to 15 June, 2017. The Perdigão experiment was designed to improve understanding of flow in an environment with topographic and land cover complexity at a range of spatial scales. Here we focus on efforts to improve understanding of the characteristics of WT
wake in complex topography. We thus focus on measurements during the EMP made using Cornell’s Galion Doppler lidar [5] of the wake from 2 MW Enercon E-82 wind turbine (WT, hub-height (HH) ~ 78 m and rotor diameter (D) ~ 82 m) installed on the southwest ridge [3] (Figure 1).

During the NEWA-Perdigão experiment approximately fifty instrumented meteorological towers and numerous remote sensing instruments were operated over a study area of approximately 4 x 4 km (shown in Figure 1) [2,4]. Here we present data from one of the 100 m masts that was located ~ 180 m from the WT on the southwest ridge (Figure 1). This mast was equipped with sonic anemometers at five heights separated by approximately 20 m. The high-frequency data from the sonic anemometer at z ~ 78 m a.g.l. are used here to provide a local estimate of the prevailing atmospheric stability (defined using the Monin-Obukhov length L), wind speed and turbulence intensity in the inflow at WT HH.

Figure 1: Location (inset map of Portugal with Perdigão marked with the purple circle) and topography at Perdigão and location of the scanning Doppler lidar (Dopp. Lidar), the wind turbine and the 100 m meteorological mast (100 m mast) from which data are presented.

The lidar from which data are reported was placed approximately 1 km northeast of the WT in the central valley at an elevation approximately 244 m below the WT HH. This lidar system is a Galion G4000 pulsed scanning Doppler lidar. It has the following characteristics; Wavelength 1.56 μm, pulse duration 200 ns, range upto 4 km, range gate size 30 m, aperture diameter 75 mm, pulse repetition frequency 20 kHz, sampling frequency 100 MHz, dwell time 1 s [5]. All data presented herein derive from lidar returns that exhibit signal to noise ratios above 1.015. The scan pattern used incorporated vertical azimuth display (VAD), range height indicator (RHI) and arc scan (plan position indication, PPI) scans. The arc scans were conducted over a 60° arc towards the WT and employed a scan pattern with telescoping arc span close to the direct azimuth angle to the WT (227°, Figure 2, and [3]). The scan configuration protocol is based on the following considerations: (a) That the arc span (i.e. range of azimuth angles) is sufficient to capture WT wakes over a wide range of wind directions focused around southwesterly. (b) That the arc span is discretized with sufficient resolution to accurately identify wake location. (c) That the arc scans cover a sufficient range of elevation angles that the wakes can be tracked and characterized irrespective of whether the wakes are terrain following or lofted as they propagate downstream from the WT [6]. (d) That the scan pattern also include RHI directly towards the turbine and 3-4 VAD scans to characterize other aspects of the flow regime (including a first estimate of the wind speed and direction at the elevation of the WT hub-height (WT HH)). (e) That the scan pattern be completed within 10 minutes to allow for sufficient temporal resolution of the wake characteristics (i.e. that the temporal disjunct nature of the data be limited to ≤ 10-minutes).
Figure 2: Overview of the scan pattern used in the scanning Doppler lidar to capture wakes advected from the wind turbine out over the central valley (example wakes are indicated from the WT as either lofted or terrain following). The measurement at each range gate of 30 m is shown by a dot.

Data availability from the Doppler lidar during the EMP is generally high, and data from over 19,000 10 minute scans are available for analysis. However, very high temperatures occurred during May and June that resulted in thermal shutdowns and caused loss of 7 and 16% of 10-minute periods, respectively.

2. Wake detection algorithm

A goal of the workflow developed for the wake detection algorithm is that it should operate autonomously (i.e. without the need of data from other instruments). Thus, a first step in the automated wake detection processing is that data from the VAD scans at a height equivalent to WT HH are evaluated to determine if the wind direction is southwesterly (indicating a high likelihood that the WT wake would be advected into the lidar scanned volume). Then the inflow wind speed and direction at the WT HH from the arc scans is used to confirm that the wind direction was southwesterly and that the wind speed was above WT cut-in. The meteorology during the experiment was broadly as expected with predominant wind directions from northeast to southwest (i.e. cross valley), but with a high frequency of northeasterly flow [4]. Thus, from six months of measurements 1972 10-minute periods are identified as potential wake cases (see details in [3]).

The background flow at Perdigão exhibits a high degree of complexity and spatiotemporal variability [2-4,6], and represents a key challenge to determining inflow and freestream conditions in WT wake analyses [7]. This flow complexity renders it difficult to both identify the location of a WT wake and quantify the magnitude of the wake deficit. Given the complexity of the background wind field as flow (and embedded WT wake) moves downstream (downslope) in the lee of the southwest ridge, the wake detection algorithm works by, for each 10-minute period, first extracting line of sight velocities on a number of vertical slices (i.e. planes of wind speeds) at 2, 2.5, 3, 3.5, 4 and 4.5 rotor diameters (D) downstream from the WT, then for each 20-m increment in the vertical determining a mean line of sight (LoS, radial) wind speed and computing line-of-sight (LoS) wind speed anomaly at each lidar scan point relative to that mean background wind speed derived from all measurements at that distance from the WTHH in 20 m horizontal slices. These anomaly fields are then subject to cubic spline interpolation to generate a mesh with a resolution in the vertical and horizontal of 10 m. As shown by the example in Figure 3, the wake is evident in the raw radial velocity fields, but is clearer in the anomaly fields.
Figure 3: Observations from 5 May 2017 at 23:58 UTC. Left: Raw radial velocity fields on planes located 2, 3 and 4 rotor diameters (D) downstream of the WT. Centre: Mean profiles of the line of sight (LoS) wind speeds (i.e. background(z)) at those distances. Right: LoS velocity anomalies from the lidar and as an interpolated field. The vertical axis shows height normalized to the WT HH.

The location of the wake centre at each downstream distance is identified by the automated detection algorithm starting in the geometrically-identified location based on the inflow wind direction and then incrementally searching for a larger local maximum in the velocity deficit field (i.e. the maximum difference between the background LoS profile windspeed at the specific height, \( U_0 \), and the line-of-sight (LoS) wind speed, \( U \)). Once this has been identified on each vertical plane at 2, 2.5, 3, 3.5, 4 and 4.5 rotor diameters (D) downstream, wake characteristics (e.g. wake location and velocity deficit) are computed and used to quantify vertical and horizontal meander and the magnitude and recovery of the velocity deficit with downstream distance (the focus here).

The complexity of the background flow not only leads to ambiguity in defining the ‘freestream’ wind profile, but also generates very complex wakes that are frequently not axi-symmetric and exhibit incoherent shapes and even multiple lobes. Coherent wakes are defined as wakes that exhibit a clear (single) centre with a location that is consistent between the algorithm and subjective inspection of the anomaly fields and raw line-of-sight velocity planes [3]. These coherent wakes tend to occur in conditions that are characterized by; (a) slightly lower turbulence intensity than the average, (b) more stable than the average, and (c) wind directions that are close to the wake centreline (of 227° from the lidar to the WT, Figure 1) than the average. Conversely, multiple lobe wakes tend to occur under; (a) high turbulence intensity, (b) unstable stratification and with (c) larger offset wind directions from 227°. Here we focus on the coherent wake cases where a single, well-defined, wake centre is identified by the wake processing algorithm and confirmed by subjective examination of the downstream anomaly fields. The requirement that meteorological data from the sonic anemometer deployed on the 100-m meteorological mast are also available to allow conditional sampling of wake velocity deficits by
stability conditions, inflow wind speed and turbulence intensity reduces the number of coherent wake cases 1010 to a sample size of 519 10-minute periods. These data are analysed to generate the velocity deficit statistics presented in the following section.

3. Wake metrics: velocity deficit

3.1 Observed velocity deficit relationship to wind speed

As described above, the velocity deficit \( v_d \) at each downstream distance in the centre of the wake is derived from the observed LoS wind speed anomalies. Thus, \( v_d \) is calculated from the background flow at that location as described using the background LoS velocity \( U_0 \) computed as the mean radial velocity on 20 m horizontal slices at that distance from the WT and minus observed LoS velocity in the centre of the wake \( U \) at that height and downstream distance:

\[
v_d = U_0 - U
\]

This method for deriving velocity deficits from the background flow at multiple downwind distances downstream of the WT means the values of \( v_d \) are relatively insensitive to evolution of the flow in which the wake is embedded. However, it further means that the ratio of \( v_d \) to the inflow wind speed at the WTHH as derived from the sonic anemometer data can appear to exceed the Betz limit since \( v_d \) is determined locally and not from a single inflow wind speed.

The mean \( v_d \) at the wake centre for the coherent wakes shows a gradual recovery with downstream distance (Figure 4). Despite the scatter in the data, after 3 D, \( v_d \) shows an almost linear recovery with distance and extrapolates to 0 ms\(^{-1}\) at \( \sim 14 \) D (linear equation \( v_d = 0.27 \times D - 3.84 \)). There is little difference between the results using all the observations and those where the data from the meteorological mast are available indicating the results are not strongly biased by the missing observations from the sonic anemometer during February and March.

![Figure 4: Mean velocity deficit \( v_d \) (±0.5 std. dev.) at the wake centre determined for different distances downstream (expressed in rotor diameters \( D \) from 2 to 4.5 \( D \)). Results from all coherent wake cases \( (n = 1010) \) are shown in black and for those that occurred when sonic anemometer data are available from the meteorological mast \( (z = 78 \) m) are shown in blue \( (n = 519) \). Results by stability class are shown in cyan (stable; \( z/L > 0.08 \)), grey (neutral; \( z/L < 0.08 \)), red (unstable; \( z/L < -0.08 \)). The numbers in parentheses indicate the number \( (n) \) of ten-minute periods in each sample.](image)

Previous research has indicated recovery of the wake velocity deficit \( (v_d) \) depends on the wind speed, turbulence intensity, atmospheric stability and boundary-layer height [8]. Figure 4 shows the mean \( v_d \) from all coherent wake cases as a function of downstream distance and conditionally sampled in three
stability classes \((z/L)\) where \(z\) is height and \(L\) is the Monin-Obukhov length); stable: \(z/L>0.08\), neutral: \(z/L<0.08\), unstable: \(z/L<-0.08\) \[8\]. There are relatively few near-neutral conditions \((z/L<0.08)\), Figure 4) in part due to selection of times when coherent wake centre cases are identified but also because data are only reported for periods when sonic anemometer data are available to characterize the inflow conditions (April-June 2017). The slope of a fit to the mean \(vd\) conditionally sampled by stability class and presented as a function of downstream distance implies the rate of recovery of the wake velocity deficit is slightly higher in unstable conditions.

Figure 5 shows \(vd\) conditionally sampled by inflow wind speed and downstream distance. Perhaps surprisingly given the terrain complexity, \(vd\) shows the expected near-linear decreases with distance except for the highest wind speed bin considered (10 ms\(^{-1}\)). Although the absolute magnitude of \(vd\) is larger for higher wind speeds, relative \(vd\) is larger for lower wind speeds. For example, \(vd\) normalized to the inflow wind speed at 2 D is 0.70 at 3 ms\(^{-1}\) and 0.45 at 10 ms\(^{-1}\). Consistent with previous research, on average the recovery of the normalized wake velocity deficit \((vd / \text{inflow wind speed})\) is faster under lower inflow wind speeds (Figure 5).

**Figure 5:** \(vd\) conditionally sampled by inflow wind speed from the sonic anemometer on the 100-m meteorological mast (discretized in 1 ms\(^{-1}\) bins) and downstream distance (in rotor diameters, \(D\)). Top: Mean \(vd\) at each downstream distance normalized by inflow wind speed. Middle: Mean \(vd\) (± 1 std. dev.) for each downstream distance. Bottom: Mean \(vd\) from observations (solid circles) as a function of downstream distance along with results from eqn. 4 with \(k=0.075\) (dashed lines and open triangles).
3.2 Estimating $v_d$ from the Jensen wake model

The Jensen wake model [9] was developed for use in flat homogeneous terrain, and describes the wake expansion as follows:

$$D_X = D_0 + 2kX$$

(2)

where $D_X$ is the wake width in rotor diameters

$D_0$ is the original rotor diameter

$k$ is the expansion coefficient (0.075 is typically used for land [7])

$X$ is the distance downstream of the WT in rotor diameters

Accordingly, $v_d$ (defined as $U_0 - U$, where $U_0$ is the freestream inflow) can be calculated from [9]:

$$1 - \frac{U}{U_0} = \left(1 - \sqrt{1 - c_t}\right)\left(1 + \frac{2kX}{D}\right)^2$$

(3)

$$v_d = U_0 - \left(1 - \left(1 - \sqrt{1 - c_t}\right)\left(1 + \frac{2kX}{D}\right)^2\right)U_0$$

(4)

As illustrated by eqn 4 a main driver of the initial $v_d$ magnitude immediately downstream of a WT is the thrust coefficient $c_t$ which is a function of wind speed [8]. For the Enercon E-82 WT the thrust coefficient is 0.78±0.011 for the range of inflow wind speeds (3-10 ms$^{-1}$) for which > 26 observations are available in each 1 ms$^{-1}$ bin. Thus, $c_t=0.78$ is used to derive values of $v_d$ from eqn. 4. The $v_d$ estimated from the Jensen model (eqn 4) are closest to the observations for inflow wind speeds of 6-7 ms$^{-1}$, but are broadly consistent with the observational estimates across the entire range of inflow wind speeds with smallest $v_d$ at low inflow wind speeds and a near-linear recovery of $v_d$ with distance. At lower wind speeds $v_d$ from the observations is always larger than predicted by eqn. 4 while at higher wind speeds $v_d$ from the observations is of larger magnitude for smaller distances but does not recover as quickly as predicted (Figure 5). Nonetheless, this analysis provides partial validation of the automated wake detection methodology. Further, the degree of agreement between the Jensen model and the mean wake recovery (and dependence on inflow wind speed) indicates some degree of fidelity of the Jensen model for a single wind turbine wake even in complex terrain, particularly given:

- The high uncertainty in determining the true inflow velocity at WTHH given the complexity of flow along the ridge line.
- The location of the wake centre is subject to some sampling uncertainty.
- The location of the wake centre exhibits high variability and at lower inflow wind speeds in frequently lofted at short distances downstream of the WT [3].

3.3 Observed velocity deficit relationship to turbulence intensity

One of the major challenges in this type of analysis is to deconvolve the impact of wind speed, turbulence intensity ($TI$) and atmospheric stability ($z/L$) on the magnitude of $v_d$ given the inter-dependence of these meteorological properties. Further complicating this research is that, as described above, the inflow characteristics used to conditionally sample the wake data (e.g. $z/L$ and $TI$) are subject to some uncertainty due to the very high spatiotemporal variability resulting from complexity of the site, and the limitations of using a surface-layer parameterization to describe stability. Nevertheless, decomposing the sources of $v_d$ variability is essential to advancing physical understanding of wake dynamics. Thus, analyses were undertaken in which $v_d$ is conditionally sampled by the joint probability of these properties (see surfaces of $v_d$ is conditionally sampled by both wind speed and inflow $TI$ in Figure 6). The climatology of wake deficits, inflow wind speed and $TI$ as a function of different stability classes shown in Figure 7 and the analysis presented herein Figure 6 indicates that:

- While the magnitude of $v_d$ exhibits consistent behaviour with wind speed the co-dependence on inflow $TI$ is less clear possibly partly due to the low number of cases with near-neutral stability (Figure 4).
- At this site, WT HH mean inflow wind speeds in stable conditions do not appear to exceed those observed in unstable conditions, but wind speeds in near-neutral $z/L$ classes are somewhat higher (mean value of ~ 8 ms$^{-1}$, versus 5-6 ms$^{-1}$ in unstable and stable classes).
- Mean $TI$ is lower in stable conditions.
There is a high frequency of stable situations. There is a functional dependence of mean $vd$ on $z/L$, with smaller mean $vd$ in stable conditions than in unstable conditions, but both are smaller than the mean $vd$ than in neutral conditions at all distances from the WT with near-linear decreases in $vd$ as distance increases (Figure 4 and Figure 7). The observation that highest $vd$ are found in near-neutral conditions may be related to the bias in the inflow wind speeds mentioned above. As shown in Figure 7, mean $vd$ at each downwind distance (2-4.5 D) is largest in near-neutral (higher mean wind speed) conditions. The lower $vd$ shown in Figure 7 for stable conditions may arise from the slightly lower wind speeds and $TI$ but may also be related to other conditions that are not considered here (such as spatial gradients in vertical wind shear and thermal stratification from the ridge into the valley).

**Figure 6:** $vd$ as a joint function of the inflow wind speed and turbulence intensity ($TI$) as derived from measurements by the sonic anemometer at 78 m on the meteorological mast, for 2D, 3D and 4D downstream from the WT.
Figure 7: Climatology of the inflow wind speed \( (U) \), turbulence intensity \( (TI) \) and frequency of occurrence of stability classes \( (z/L) \) for the 519 wake cases reported herein. Also shown is mean \( \text{vd} \) by stability classes and distance downstream from the WT in rotor diameters \( (D) \).

4. Conclusions
The relationship between wind farm efficiency and meteorological variables offshore has previously indicated that wind speed is the main driver of wake magnitude and thus power losses, with \( TI \) and stability also playing important roles [8,10]. It has also been shown that wind turbine wakes behave more similarly in unstable and near-neutral conditions to stable conditions, indicating that the magnitude and behaviour of wakes in stable conditions is linked to an additional variable such as the rate of transport of turbulent kinetic downwards or the boundary-layer height. Deconvolving the drivers of wind turbine wake behaviour and recovery has proved difficult in homogeneous environments and is even more challenging in complex terrain.

A dataset of wind retrievals comprising 19,384 10-minute periods was collected using a scanning Doppler lidar during a six-month field campaign at the Perdigão site in Portugal. These data were collected to examine the downstream behaviour of wakes generated by a single WT deployed in extremely complex terrain. An automated wake detection algorithm has been developed for use in complex terrain and is applied to this data set firstly to identify 1,900 potential wake cases and then to develop quantitative wake characteristics for each case. The potential wake cases are identified as all 10-minute periods with wind speeds and direction that indicate the WT wake was advected into the scanned area and that have sufficient observations to generate a freestream wind field from which velocity deficits can be computed for distances downwind of 2-4.5 rotor diameters \( (D) \).

Cases with a clearly defined wake centre are analysed here to explore the dependence of the wake velocity deficit on downstream distance, wind speed, turbulence intensity and stability. It is shown that
the velocity deficit is largest in high wind speed conditions and decreases almost linearly with downstream distance. The observed mean wake deficits thus behave in a manner that is consistent with the Jensen linear wake expansion model. Consistent with previous results, the relative velocity deficit is higher at lower wind speeds. The mean velocity deficit does not show a strong relationship with inflow turbulence intensity but is clearly of smaller magnitude when the inflow conditions are stably stratified.

The observational data set that is presented herein illustrates the high variability in wake behaviour (and velocity deficits) in complex terrain, but the mean tendencies exhibit broad consistency with a priori physical expectations and linear expansion models. Further research is required to identify causes of the large variability of velocity deficits for small variation of inflow wind speeds. Future work will employ machine learning approaches to determine the degree to which that variability can be explained by near-surface local atmospheric properties and will integrate output from Large Eddy Simulations (LES) to better characterize the background flow field.

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