Statistical analysis of a field database to study stability effects on wind turbine wake properties

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Abstract. Within the frame of the French project ANR SMARTEOLE, a 7-month measurement campaign had been set-up in the north of France to study the wake behaviour of 2 wind turbines, with a set-up using scanning LiDAR scenarii that captured the wakes of 2 wind turbines for different degrees of interactions. An extensive statistical study of the wakes behaviour under neutral atmospheric stability conditions has been already performed. The present study focuses on the effects of other stability conditions on the wake developments and on the meandering process.

1. Introduction and work objectives
In the framework of the French national project SMARTEOLE (2015-2018), control strategies will be tested from the lab to the full scale in order to alleviate load fluctuations that are responsible for the structural fatigue of wind turbines. The load fluctuations are partly due to the turbulent properties of the incoming flow and can be even more severe if a wind turbine is located within the wake of an upstream wind turbine. Within the project, control strategies will be evaluated at the blade, rotor and farm scales, also depending on the time scales, different strategies are considered: shorter time scale load fluctuations can be alleviated by active flow control on blades, whereas moderate time scale load fluctuations can be alleviated by pitch control. A more global strategy considered in wind farm control strategies is to alleviate the wake interactions by operating wind turbine at non-optimum configurations and/or deviating the wind turbine wake by forcing yawed configurations. These strategies require collecting more information about the wake properties when they interact. The first post-processing of the SMARTEOLE field measurement campaign based on the use of a ground-based scanning LiDAR was dedicated to these objectives [1-2]. Thanks to the long duration of the measurement campaign, a statistical approach based on the data classification according to wind direction and magnitude has been performed in order to provide conditional ensemble-averaged velocity fields including the wakes of two wind turbines in interactions (weak to strong interactions). It has been highlighted that the statistical convergence of the ensemble-averaged velocity fields was acceptable from a number of independent scans of 120. The streamwise evolution of the velocity deficits within the wakes was quantified and successfully compared with the empirical model suggested by Aitken et al. [3], when the wakes are out of interactions. The meandering process was also quantified by the standard deviation of the instantaneous wake centerlines and the influence of the interaction level on this process was also studied.
On the other hand, the database processing was restrained to neutral stability conditions, while it is already known that the atmospheric stability can play an important role on the wake recovery and meandering [4-5].

The present paper will therefore illustrate the statistical analysis of the wake properties of 2 wind turbines with different degrees of wake interactions for different stability conditions.

2. Field site and measurement set-up
The scanning LiDAR measurement campaign started in November 2015 and ended up in May 2016. The field site is owned by Engie Green and is located in the Picardie Region, at Ablaincourt-Presoir (Fig. 1). The wind turbines of interest are SMV5 and SMV6. According to the wind rose, the most frequent wind direction comes from the south-west and the SMV5 will experience frequent wind turbine wake interactions from the SMV6 (207°). Wind turbines are Senvion MM82 with a hub height of 80m and a rotor diameter of $D = 82$ m. A pulsed scanning lidar Windcube 200S from Leosphere is located at 1.5km on the east side of the wind turbines of interest in order to capture their both wakes. 3 PPI (Plan Position Indicator) and 1 RHI (Range Height Indicator) have been programmed. Geometrical scanning parameters are in Table 1. PPI azimuth angle range is chosen to capture wind turbine wakes from SMV5 and SMV6 for the most frequent wind directions.

![Figure 1: Field site. Wind turbines of interest are SMV5 and SMV6.](image)

| Elevation angle | Azimuth angle | Accumulation time | Acquisition rate | Acquisition time |
|-----------------|---------------|-------------------|------------------|-----------------|
| PPI #1          | 2.5°          | 248° - 278°       | 0.5s             | 2°.s⁻¹          | 15s             |
| PPI #2          | 3.8°          | 248° - 278°       | 0.5s             | 2°.s⁻¹          | 15s             |
| PPI #3          | 5.2°          | 248° - 278°       | 0.5s             | 2°.s⁻¹          | 15s             |
| RHI #1          | 0° - 10°      | 255°             | 0.5s             | 1°.s⁻¹          | 15s             |

Table1: Description of the Lidar measurement protocols
PPI elevation angles are chosen in order to cross the SMV6 hub height at a downstream distance of $2.5D$, $5D$, and $10D$, respectively, for south-western wind directions. The measurement volume is 25m long (along the line of sight).

The LiDAR can only detect the velocity component along the laser beam. Therefore, to retrieve the wind velocity vector (wind speed and direction), it is necessary to take into account different directions of the laser beam [6]. In the case of a homogeneous wind field, at a certain altitude and in a limited region, the mean value of the LOS velocity has a sine wave dependency on the azimuth angle [6-7]. Then by fitting the LOS velocity at a constant height to a sine wave form, it is possible to determine both the wind direction and the wind speed, assuming that the flow field is stationary within the scanned time. The velocity field is then reconstructed by a correction from the cosine of the difference between the environmental wind direction and the azimuth of the LOS [3, 8].

1-hour averaged meteorological conditions are supplied by local MERRA 2 data, giving access to the hourly 50m-high wind speed $U_{ref}$, wind direction $WD$ and the Monin-Obukhov length $L$. Data are then classified according to these three parameters. A detailed description of the classification process is available in [2].

Considering the data availability for each category, the present study is focused on the wind direction $WD = 233^\circ \pm 6.4^\circ$ (relatively weak interaction between both wind turbine wakes, knowing that the strongest interaction is obtained for $WD = 207^\circ$), the 50m-high MERRA wind speed $U_{ref} = 13m/s \pm 2m/s$ and the following stability conditions:

- **Unstable** ($-1000 < L < 0$)
- **Neutral** ($L < -1000$ or $600 < L$)
- **Stable** ($0 < L < 500$)

### 3. Results and discussion

Table 2 summaries the processed data. The number of PPI scans collected for each category and for each elevation angle is given on the table. The number of scans is sometimes below the limit of 120, for which an acceptable statistical convergence of the meandering magnitude had been proven in a previous study [1]. This illustrates the extreme difficulty to reach statistical convergence on the basis of field measurements, since the boundary conditions of the experiments are out of control.

Through the LiDAR data processing explained earlier, the wind direction can be retrieved for each scan and the ensemble-averaged wind direction can be processed for each category. It is then compared to the one coming from the MERRA2 database for the same periods. The agreement is satisfying since the discrepancy is only 2°. It must be mentioned that the effective velocity at hub height is quite different from the MERRA-2 data (around 11m/s at hub height). This illustrates the lack of accuracy of the MERRA database regarding the velocity assessment very close to the earth surface due to very coarse time and space resolutions, compared to the atmospheric space and time scales in the lower part of the atmosphere. Indeed, previous studies have shown that MERRA-2 reanalysis dataset over - or underestimates the wind speed, depending on the locations and on the absolute wind speeds [9, 10].

| Case      | Wind Direction ($WD$) [$^\circ$] | Power law exp. | No. PPI scans |
|-----------|----------------------------------|----------------|---------------|
|           | LiDAR   | MERRA   | $m$ | $a_j=2.5^\circ$ | $a_j=3.8^\circ$ | $a_j=5.2^\circ$ |
| Unstable  | 233     | 235     | 0.13 | 68        | 83        | 86        |
| Neutral   | 233     | 235     | 0.21 | 306       | 449       | 473       |
| Stable    | 233     | 233     | 0.27 | 71        | 121       | 120       |

**Table2:** Summary of characteristics of the three cases analyzed. The cases were extracted from dates at which the atmosphere was unstable, neutral or stable according to the MERRA-2 dataset.
The power law exponent of the freestream velocity profile is deduced from the ensemble-averaged velocity scan, excluding the wake regions and assuming that the flow is two dimensional (no horizontal dependence) [2]. It is noticeable that the power exponent increases with the atmospheric stability. It is indeed expected that the shear is reduced in an unstable atmospheric boundary layer due to the additional convective mixing, and increased in a stable one.

On each selected scan, a wake tracking procedure is applied in order to identify the instantaneous wake centerline location \( y_w(x_{WD}/D) \) and the associated minimum of velocity within the wake \( V_{minw}(x_{WD}/D) \) (see [2] and [11] for wake tracking procedure). The standard deviation of this collection of wake centerlines \( \sigma_{y_w}(x_{WD}/D) \) gives an indication on the meandering magnitude. The ensemble-average of the minimum velocity within the wake, non-dimensionalised by the external velocity at hub height, gives access to the dimensionless velocity deficit \( VD(x_{WD}/D) \).

Figure 2 (left) shows the streamwise evolution of the velocity deficits \( VD \) within the wakes of SMV5 and SMV6 wind turbines for the three different stability conditions. They are compared with the empirical law suggested by Aitken et al. [3]: \( VD(x) = 0.56(x/D)^{-0.57} \).

![Figure 2](image-url)

**Figure 2.** Velocity deficits (left) and standard deviation from wake centerlines (right) versus the distance downstream of the WT SMV6 for the elevation angle \( \alpha_2 = 3.8^\circ \) and for different stability conditions: unstable (top), neutral (middle) and stable (bottom). In red the SMV6 curve and in black the SMV5 curve. Blue lines represent the empirical law suggested by Aitken et al. [3]. Gray rectangles mark the area of influence of the WTs where measurements were contaminated by reflection on the rotor.
First, it can be noticed that the induction zones, where the velocity deficits increase, are clearly identifiable on all plots, up to a distance of 1.5D downstream of wind turbines. Further downstream, the velocity deficits decrease, following roughly the decay predicted by the empirical law. On the other hand, the unstable case provides larger velocity deficits than other configurations for both wind turbines. These larger deficits disappear from a distance of 4-5 diameters and their evolution collapses again to the empirical law.

Figure 2 (right) shows the streamwise evolution of the standard deviation of the wake centerline positions, which is an indicator of wake meandering, for both wind turbines and for the three different stability conditions. The shape of each single curve is roughly similar: First, a decrease of the standard deviation in the induction zone. This is difficult to justify with physical reasons, but these measurement areas might be excluded from our investigation since local LiDAR measurements can be spoiled by the wind turbine presence and some data interpolation had been performed. Farther downstream, an increase of standard deviation is visible up to 3-4D and then a decrease again, due to the wake recovery, leading to weaker velocity deficits and making the wake tracking method more uncertain.

Regarding the stability effects, the slope of the streamwise evolution of the standard deviation of the wake centerlines is higher for unstable conditions and lower for stable conditions. This result was expected considering the additional convective motion encountered in unstable flows. It is also noticeable that both wind turbine wakes present the same meandering magnitude and the same slopes in the intermediate zones, giving confidence to the present analysis.

The substantial higher values of standard deviation of the near wake of SMV5 are ascribed to its interaction with SMV6 wake (even if the normal distance between both mean wake centerlines is around 2D). Indeed, the parametrical study on wind direction effect performed in [2] has shown that the standard deviation of the near-wake centerlines of SMV5 was directly linked to the degree of wake interactions.

4. Conclusions
A 7-month measurement campaign had been set-up in the north of France to study the wake behavior of 2 wind turbines. This duration ensures an acceptable statistical convergence of the ensemble-averaged flow fields obtained after a classification according to the wind speed, the wind direction and the atmospheric stability. The present paper has focused on the influence of the stability on the wake recovery and meandering. It has been shown that the velocity deficit evolution downstream of the wind turbine was not very sensitive to this parameter and was collapsing after 4D, at the farthest, with the empirical law proposed by Aitken et al. The influence of the stability on the meandering process was identified through the streamwise evolution of the standard deviation of the wake centerlines. This value increases faster for unstable conditions, and slower for stable conditions, indicating that the meandering process is emphasized by the thermal instability of the atmospheric flow.

The present results illustrate therefore expected trends from stability effects but provide a statistical analysis of field measurements that can be used for wake model validation.

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