21st EAWE PhD Seminar on Wind Energy
01-03 October 2025
Athens, Greece

Correlation Analysis between Wind Speed and Structural Strain measurements by FBG sensors in a Wind Turbine

Marie Derison[a,b], **Karima Chah**[a], **Marc Fourmentin**[c], **Patrick Augustin**[c], **Pauline Haezebrouck**[c], **François Vallée**[b], and **Christophe Caucheteur**[a]

[a]APS, University of Mons, Boulevard Dolez 31, 7000 Mons, Belgium
[b]PSMR, University of Mons, Boulevard Dolez 31, 7000 Mons, Belgium
[c]LPCA, Université Littoral Côte d'Opale, Avenue Maurice Schumann 189A, 59140 Dunkerque, France

E-mail: marie.derison@umons.ac.be

Keywords: Fiber Bragg grating sensors, Wind turbine, Dynamic strains, Pearson correlation

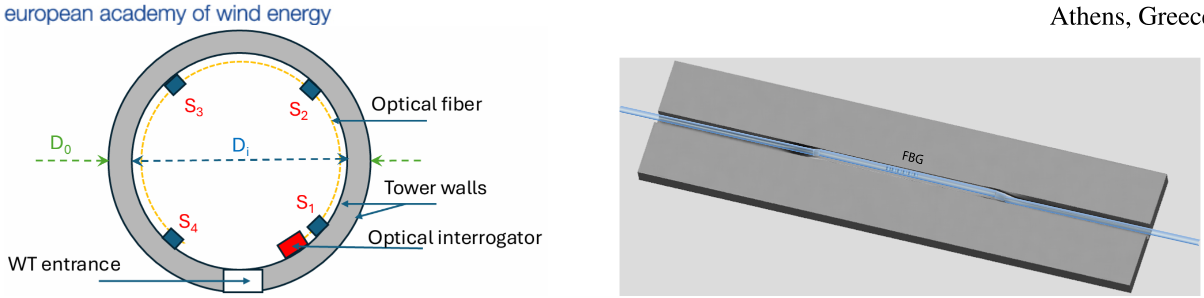
1 Introduction

The structural monitoring of wind turbine is a key aspect of optimising their operation and ensuring their reliability [1]. However, in practice, monitoring structural loads remains a challenge due to the lack of in-situ measurements on operational turbines under real conditions [2]. As a result, load estimation relies on numerical simulations (e.g. OpenFAST) which, although powerful, depend heavily on modelling assumptions and require validation against real-world data. To address these challenges, this paper presents the first results of an experimental campaign involving the deployment of FBG sensors on an onshore wind turbine. The objective is to investigate the correlation between measured strain signals and wind speed measurements. This correlation is motivated by the fact that strain variations observed on the tower are primarily caused by dynamic loads induced by the wind and the rotor operation, as described in [3]. FBG-based sensors are good candidates for real-time measurements of different parameters such as static and dynamic strain as well as temperature. Thanks to their unique advantages (lightness, small size, electromagnetic immunity, quasi-distributed measurements...) [4], they can be integrated into the structure or installed on the surface [5, 6]. This work was carried out as part of the Salomé project, which aims at improving the dynamic monitoring of wind turbines subject to varying atmospheric conditions.

2 Methodology

A measurement campaign was conducted on a 3 MW WinWind D3 onshore wind turbine, owned by the company Innovent and located in Fiefs, France [7]. A total of four packaged fiber Bragg grating (FBG) sensors were glued on the inner walls of the tower at a height of 5 m from the base to capture strain variation under real operating conditions. They were installed at this height for ease of access, as it corresponds to a practical working height inside the tower. The FBGs were fabricated with the NORIA device (Northlab Photonics, Sweden) using a 193 nm excimer laser and the phase mask technique [4]. They are 3 mm long produced into standard single-mode optical fiber from Corning. The FBGs were pre-strained and bonded onto rectangular pads then glued on the tower structure with PLEXSUS MA300 methacrylate adhesive (Figure 1(b)). The pads design allows direct contact of the FBG with the tower surface for better strain transfer. Additional strain-insensitive FBG sensors were used for temperature compensation purposes (ref SEB). A simplified cross-section of the wind turbine tower is shown in Figure 1(a). Data were recorded over a period of approximately 4 hours, with a sampling frequency of 303 Hz, enabling the analysis of high-frequency dynamics. The strain signals consist of wavelength variations measured in nanometers (nm) through BSI-108 optical interrogation unit, manufactured by B-SENS (Mons, Belgium), which provides a spectral resolution of 1 pm. A nearly collocated ultrasonic anemometer operating at 20 Hz (model GILL Instruments, WindMaster) providing 3D wind measurements was deployed on a 7m mast of an Atmospheric Mobile Unit [8], and the wind speeds are expressed in meters per second (m/s).

A first synchronization step was carried out to align the datasets temporally. Since both signals were sampled at different rates, a resampling operation was necessary to enable linear correlation analysis. Rather than interpolating

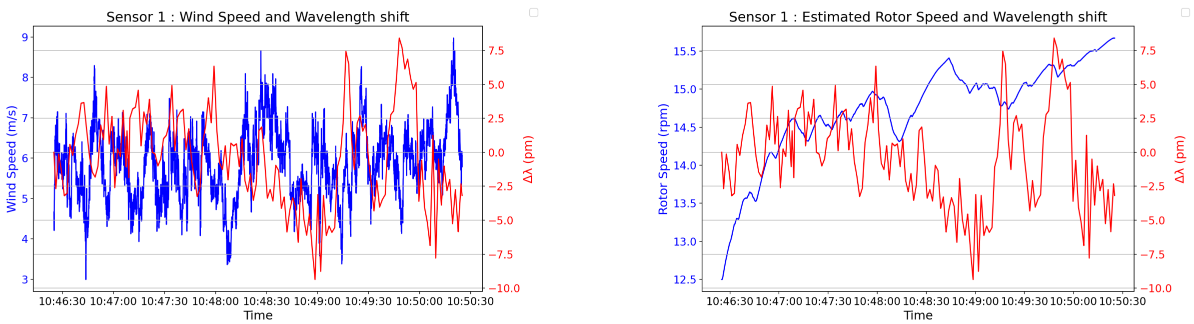


(a) Simplified scheme of the cross-section of the WT tower. D_o and D_i refer to outer and inner diameter of the WT respectively and S_1 to S_4 are the FBG strain sensors.

(b) FBG sensor bonded onto a pad

Figure 1: Setup of the measurement campaign

the wind signal, which would have introduced unrealistic assumptions on high-frequency wind behaviour, the FBG signals were downsampled to 20 Hz to match the wind data. An illustration of the preprocessed data is shown in Figure 2(a), where both the wind speed and one of the resampled FBG signals are displayed over a 4-minute time window. In addition to the linear correlation between these two signals, a more indirect linear correlation was also analysed between the strain variations and the rotor speed estimation. Indeed, this variable could not be directly measured during this campaign, it was then estimated using wind speed measurements, theoretical principles of maximum power point tracking (MPPT) and including the rotor inertia [9, 10]. Figure 2(b) shows a time window of the strain variations synchronized with the estimated blade rotational speed.



(a) 4-min Sub-window of the evolution of the wind speed (blue) and the resampled FBG sensor data (red)

(b) 4-min Sub-window of the evolution of the estimated rotor speed (blue) and the resampled FBG sensor data (red)

Figure 2: Data acquisition during the measurement campaign

A potential linear relationship between two time series can be determined by calculating the Pearson correlation factor. It is a statistical tool often used to indicate if two signals are linearly correlated [11]. It can be calculated as shown in Equation 1 where X = (x1,x2,. . . ,xn) and Y = (y1,y2,. . . ,yn) represent both signals [12].

$$r_{XY} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{1}$$

The Pearson coefficient r_{XY} varies between -1 and 1. Values close to -1 or 1 indicate a strong linear relationship, while values near 0 indicate weak or no linear correlation. In this study, only the intensity of the correlation is of interest. Therefore, the correlation factor is considered in absolute value. However, the use of the Pearson coefficient assumes that the signals are both normalized and stationary. In practice, the strain and wind signals collected during the measurement campaign are non-stationary, meaning their statistical properties evolve over time. To address this, a segmentation approach was adopted: both signals were divided into shorter time windows, within which the stationarity assumption is considered reasonable. It appeared that the most suitable setup for calculating the correlation between our two signals is a 1-second sliding window applied over a total duration of 15 to 30 seconds, providing a good balance between local stationarity and sufficient data points. For each of these sliding windows, the Pearson correlation coefficient was therefore computed while allowing for time shifts between the signals.

To assess the significance of the correlation values obtained, a preliminary step was carried out by computing the Pearson coefficient between the FBG strain signals and a randomly generated white noise signal. This allowed the definition of a realistic threshold below which linear correlation values are likely to be attributed to randomness. Therefore, only correlation values exceeding this threshold were considered potentially meaningful.

3 Results

This section presents and discusses the results obtained from computing the linear correlation coefficients between the different signals. As a first step, Figure 3 shows the distribution of the Pearson correlation coefficient obtained when correlating a white noise signal with the FBG strain signals. As expected, the distribution exhibits a high density near zero, reflecting an almost null linear correlation in most cases. The 95th percentile of the resulting distribution was approximately 0.08, meaning that 95% of the correlations between strain and random noise remained below this value. The highest observed value was around 0.15. To account for a safety margin and ensure that only robust correlations are considered, a conservative threshold of 0.2 was therefore selected.

Following this preliminary analysis, the linear correlation was computed between the FBG strain signals and the measured wind speed. As shown in Figure 4(a), a notable share of values exceed the 0.2 threshold, indicating some degree of linear correlation. However, the distribution remains dense near lower values, suggesting that the correlation is moderate and not consistently strong across all time windows and sensors. However, when examining the results shown in Figure 4(b), which displays the linear correlation between the estimated rotor speed and the strain signals, a stronger and more consistent relationship can be observed. The distribution of Pearson factor shows a noticeable concentration of values closer to 1, indicating a higher level of linear correlation across a larger number of time windows. This suggests that the strain variations captured by the FBG sensors are more directly influenced by the rotational dynamics of the rotor than by local wind speed measurements alone. It should be noted that the rotor speed remains an estimation and not a direct measurement. Therefore, residual low correlation values observed in some windows may be due to discrepancies between the estimated and actual rotor behaviour during the measurement period.

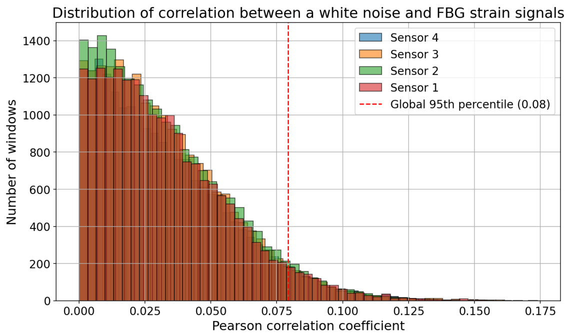
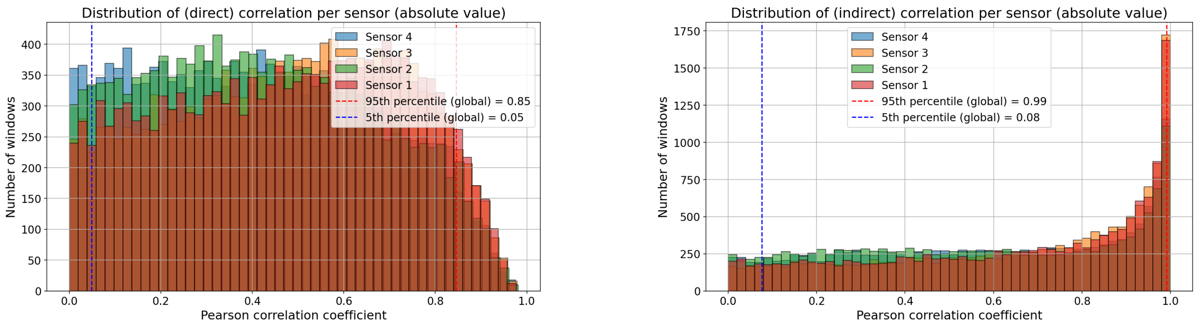


Figure 3: Distribution of Pearson factor for correlation with a white noise



(a) Distribution of Pearson factor for correlation with wind speed

(b) Distribution of Pearson factor for correlation with estimated rotor speed

Figure 4: Correlation results

4 Conclusion and Future Work

This study presents the first results of an experimental campaign carried out on an onshore wind turbine equipped with FBG sensors. The analysis focused on investigating the linear correlation between the measured strain signals and two influencing variables: wind speed and derived rotor speed. While a small linear correlation was observed with wind speed, a more consistent linear relationship was found between strain and rotor speed. This illustrates the dominant influence of rotor dynamics on the tower structural behaviour and confirms the relevance of FBG sensors for wind turbine applications.

Future works will include a frequency-domain analysis to complement the current time-domain approach, aiming to improve the understanding of dynamics effects and to identify frequencies associated with rotor operation or structural responses.

Acknowledgements

The authors gratefully acknowledge the financial support received from Walloon Region of Belgium through the Interreg VI France-Wallonie-Vlaanderen program co-funded by the European Union, under SALOME project (No. 0100240). They also would like to thank InnoVent for providing access to their wind turbine.

References

[1] Yihui Tong et al. "Materials Design and Structural Health Monitoring of Horizontal Axis Offshore Wind Turbines: A State-of-the-Art Review". In: *Materials* 18.2 (2025), p. 329. ISSN: 1996-1944.

[2] Soichiro Kiyoki, Shigeo Yoshida, and Mostafa A. Rushdi. "Machine Learning-Based Prediction of 2 MW Wind Turbine Tower Loads During Power Production Based on Nacelle Behavior". In: *Energies* 18.1 (2025), p. 216. ISSN: 1996-1073.

[3] Minjuan He et al. "Structural monitoring of an onshore wind turbine foundation using strain sensors". In: *Structure and Infrastructure Engineering* 15.3 (2019), pp. 314–333. ISSN: 1573-2479, 1744-8980.

[4] Andreas Othonos and Kyriacos Kalli. *Fiber Bragg Gratings: Fundamentals and Applications in Telecommunications and Sensing*. Artech House Publishers, 1999. ISBN: 978-0-89006-344-6.

[5] Kerstin Schroeder et al. "A fibre Bragg grating sensor system monitors operational load in a wind turbine rotor blade". In: *Measurement Science and Technology* 17 (2006), pp. 1167–1172. ISSN: 1361-6501.

[6] Bastien Van Esbeen et al. "Vertical axis wind turbine monitoring using FBG sensors". In: *European Workshop on Optical Fibre Sensors (EWOFS 2023)*. Vol. 12643. Backup Publisher: International Society for Optics and Photonics. SPIE, 2023, 126430O.

[7] WinWinD Ltd. *WWD-3 Owner's manual*. Datasheet transmitted by InnoVent, owner of the WT. 2012.

[8] Patrick Augustin et al. "Impact of Sea Breeze Dynamics on Atmospheric Pollutants and Their Toxicity in Industrial and Urban Coastal Environments". In: *Remote Sensing* 12.4 (2020), p. 648. ISSN: 2072-4292.

[9] Jayshree Pande et al. "A Review of Maximum Power Point Tracking Algorithms for Wind Energy Conversion Systems". In: *Journal of Marine Science and Engineering* 9.11 (2021), p. 1187.

[10] Chun Tang et al. "Effects of inertia on dynamic performance of wind turbines". In: *2008 Australasian Universities Power Engineering Conference (AUPEC)*. 2009, pp. 1–6.

[11] Manfred Mudelsee. "Estimating Pearson's Correlation Coefficient with Bootstrap Confidence Interval from Serially Dependent Time Series". In: *Mathematical Geology* 35.6 (2003), pp. 651–665. ISSN: 1573-8868.

[12] Maria Bermudez-Edo, Payam Barnaghi, and Klaus Moessner. "Analysing real world data streams with spatio-temporal correlations: Entropy vs. Pearson correlation". en. In: *Automation in Construction* 88 (2018), pp. 87–100. ISSN: 09265805.