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6-Component Operational Modal Analysis of wind turbines for damage detection

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ABSTRACT: The rapid expansion of the wind energy sector has necessitated remote monitoring of wind turbines to ensure safe, reliable, and cost-effective operations. While traditional inspection methods remain in use, there is an increasing shift toward passively monitored, real-time solutions to detect and localize potential damage. The present study makes a novel attempt to explore the potential of 6-component seismic data for use in structural damage detection frameworks for wind turbine monitoring. Measuring both translational and rotational ground motions is a relatively recent advancement in Structural Health Monitoring, offering valuable insights into the dynamic behavior of towers.

In the present study, two 6-component (6-C) seismometers were placed at the foundations of two different wind turbine types in the wind park of Kirchheilingen, Germany. The monitoring campaign lasted 7 weeks and focused on capturing vibrational data during operation. By analyzing these signals, in conjunction with Supervisory Control and Data Acquisition (SCADA) Data from the turbine operator, the research aims to identify patterns indicative of structural damage, such as changes in modal frequencies, damping ratios, or signal coherences. It will contribute to the development of scalable, cost-efficient SHM systems tailored for the wind energy industry. Furthermore, the insights gained could inform future design improvements and predictive maintenance strategies, ultimately supporting the sustainable growth of renewable energy infrastructure.

KEY WORDS: Structural health monitoring; wind turbines; 6C-seismic data; damage detection; renewable energy; operational modal analysis; wind turbine tower

1 INTRODUCTION

Wind energy has become one of the key pillars in the global transition toward sustainable and low-emission power generation. As one of the most environment-friendly alternatives to fossil fuels, wind turbines contribute significantly to meeting international climate targets and reducing carbon footprints. However, as the number and size of installed wind turbines continue to grow, so do the demands on their structural integrity, operational efficiency, and service life. In this context, monitoring the condition and performance of wind turbines has emerged as a critical aspect for both industry and research. Modern sensor technology and data-driven analysis methods allow for the continuous observation of dynamic loads, vibration behavior, and early detection of potential damage. A particular focus lies on the measurement and analysis of vibration signals and the identification of structural eigenfrequencies, as changes in these parameters can indicate material fatigue, loosened connections, or structural weakening. The development of reliable and efficient monitoring techniques is therefore essential — not only for extending the lifetime of wind turbines but also for ensuring economically optimized and safe operation. Previous work on wind turbine monitoring has primarily focused on using SCADA data, strain gauges, accelerometers, and optical fiber sensors [1], [2]. Seismic observations have also been utilized to assess the influence of wind turbines on ground motion and operational states [3]. However, to our knowledge, this study is the first to employ six-component (6C) seismic data — recording translational and rotational ground motion — specifically for the structural health monitoring of a wind turbine.

2 METHODS

2.1 Location and instruments

The experiment was conducted in a wind park near Kirchheilingen, containing multiple wind turbines. Two turbines, differing in tower construction — a steel tower (LDST) and a concrete hybrid tower (CHT) — were selected for detailed analysis. The two turbines, each with a height of 166 meters, were commissioned in September 2022 and are therefore among the latest generation of models.

Their locations, highlighted in blue on the map in Figure 1, are situated only a few hundred meters apart.

Inside each of these turbines at the ground (on the top of foundation), a BlueSeis 3A and a Trillium Compact 120s Seismometer have been placed for a timespan of about seven weeks. The BlueSeis 3A station measures rotations about the three axes and the Trillium compact 120s measures translations providing 6 degree-of-freedom (DOF) data. Figure 2 shows the setup inside of the towers. The rotational seismometer on the

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right as well as the translational seismometer directly next to it forming a 6-component (6C) station.

Additionally, two reference stations - marked in red in figure 1 - were used to characterize the local noise field. Each reference station was equipped with two Trillium Compact 120s seismometers. One station was placed directly next to the foundation of one of the turbines, while the other was located outside the wind park, behind a lake but near a road. During the days of setup of the two 6-component stations inside the tower these reference stations were setup to gain reference data.

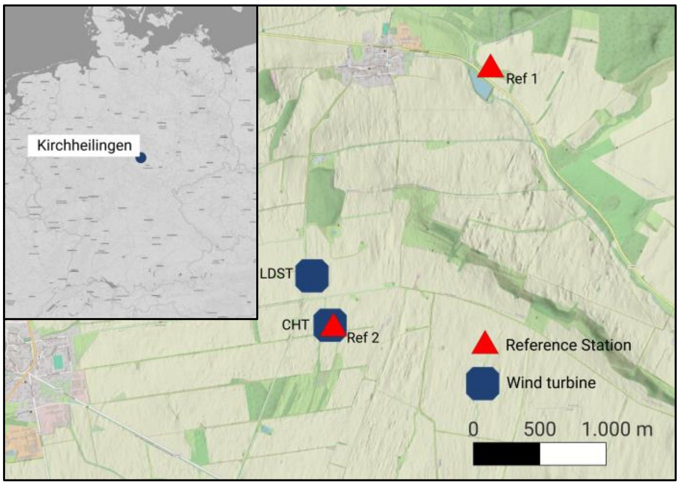

Figure 1. Location of the two wind-turbines in Kirchheilingen monitored using BlueSeis3A and Trillium Compact for 7 weeks.

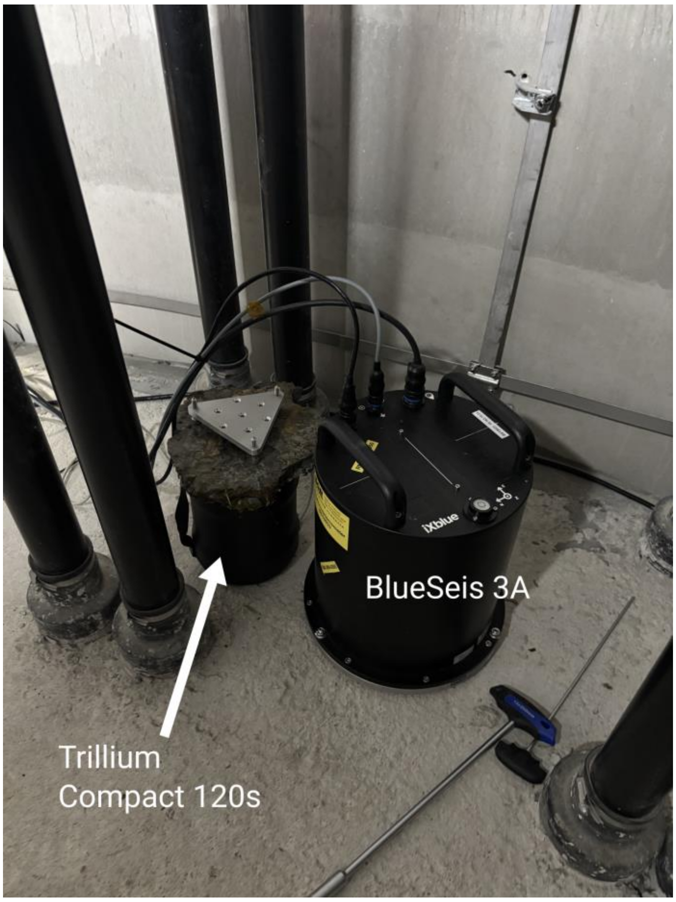

Figure 2. Example setup of instruments

2.2 *Data acquisition*

The experiment was carried out over a period of seven weeks, beginning on November 18, 2024, and concluding on January 9, 2025. This specific timeframe was chosen to coincide with a period of typically high wind activity, increasing the likelihood of capturing a wide range of operational states of the turbine. Additionally, we aimed to collect data during non-operational hours, hoping to observe the tower's behavior under different load conditions. The data of the 6-C stations was saved to local disks which were carried after the experiment. SCADA data (Supervisory Control and Data Acquisition) is collected by sensors at the turbine to provide engineers with valuable data for monitoring and maintaining the turbine. The data is collected in databases to which we have access. Data such as the rotor speed, windspeed and temperature are just a few of the environmental data. Combining these datasets, seismic and SCADA data might be good to get clearer insights into the dynamics of the tower and therefore for a setup on the structural health monitoring of the tower.

3 DATA ANALYSIS & RESULTS

The reference stations marked in Figure 1 already show expected results. The noise level at the outer station is significantly lower than at the directly next to the turbine. This meets the expectation. However, stable frequency bands are still observed between 1-10 Hertz and amplitudes are quite high for frequencies below 1 Hertz for the station which is far away. Figure 3 shows a spectrogram for the reference station which is near one turbine. The black line indicates the speed of the Rotor which lines up with the frequencies above 10 Hertz. There can be seen other frequencies such as this steady one between 25 to 30 Hertz which is likely to be caused by turbine operation. The short peaks over a wide frequency band between 22:30 and 23.00 local time could be related to the nacelle turning into the wind.

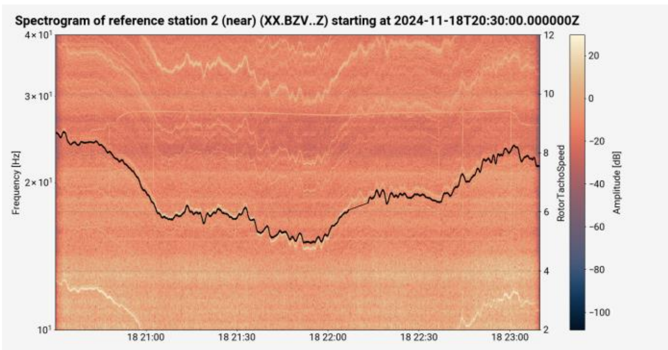

Figure 3. Frequencies rotor speed

To gain better insights into the frequencies recorded at the tower, Power Spectral Densities (PSDs) were calculated. The seismic signal from the Trillium Compact sensor was divided into two-minute time sections to ensure relatively constant conditions. For each of these sections, the corresponding rotor

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speed was averaged and assigned to specific rotor speed ranges. The PSD for each time section was then calculated and colored according to its assigned rotor speed range. This approach allows differentiation of the PSDs based on the rotor speeds that drive turbine motion and induce seismic signals. Figure 4 shows the PSD peaks for all time sections. Differences in both amplitudes and frequencies can be observed. For instance, the frequency peak above 10 Hz appears to increase in amplitude with higher rotor speeds. Higher amplitudes, particularly at low frequencies, seem to be associated with elevated rotor speeds. The dominant peak at 1 Hz is clearly visible. Furthermore, a shift from lower to higher frequencies around 14 Hz with increasing rotor speed can be clearly identified and connected to the generator speed. Spectrograms also revealed sudden changes in frequency over time, likely related to variations in generator behavior.

Following the methodology of Neuffer et al. [1], we calculated hodograms for the translational seismic data at the bottom of the foundation. Hodograms provide a graphical representation of seismic motion in two dimensions over time. These hodograms illustrate the seismic movement of the turbine at the foundation, with time represented by color. By filtering for specific frequency bands, in this case between 0.9 and 1.1 Hz, which covers the dominant frequency, we observe smooth movement in particular directions.

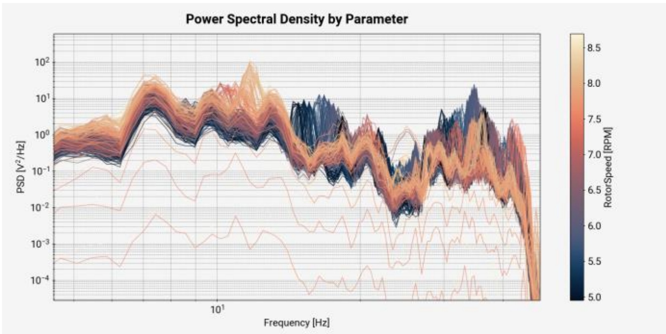

Figure 4. Power Spectral Density with respect to Frequency plot

The calculation was performed for all three planes: East-North, East-Vertical (Z), and North-Vertical (Z) directions. Figure 5 illustrates the corresponding hodogram. Focusing on the East-North (E-N) plane, which represents the bending of the tower, it becomes evident that the bending is predominantly polarized in one direction, but changes over time, in this case, within approximately 6 seconds. There is a main direction of bending, which raises the question of whether the tower predominantly bends in alignment with the wind direction. To further explore this, we calculate the covariance matrices along with their eigenvectors and eigenvalues, which allows us to determine a linearity factor with a directional component. The linearity index L is defined as 1 minus the ratio of these eigenvalues. A value close to 1 indicates high linearity, while a value close to 0 suggests circular motion for the respective time sections.

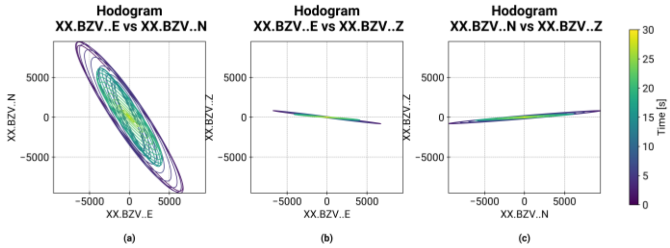

Figure 5. Hodograms for frequencies between 0.9-1 Hertz in the (a) East-North direction (b) Vertical-East direction and (c) Vertical-North direction.

We calculated linearity indices and vectors over short time windows during which translational motion was dominant. By filtering for high linearity values, we minimize the effects of whirling motions and identify the principal direction angles for each time section. Figure 6 displays the principal direction angles for the wind turbine tower alongside the measured wind direction. The wind direction is taken from the SCADA data, with the angle of the wind being subtracted by 180 degrees. This means that if the tower were to bend in the direction of the wind, we would observe that in the data. However, we instead see an offset of about 30–50 degrees for both towers. Furthermore, we notice that the principal direction angles align with the wind direction, but the tower seems to exhibit some inertia when the wind direction changes, as the principal direction angles do not increase as much as the wind itself. We also observe different principal direction angles across various frequency bands, though the reason for this remains unclear.

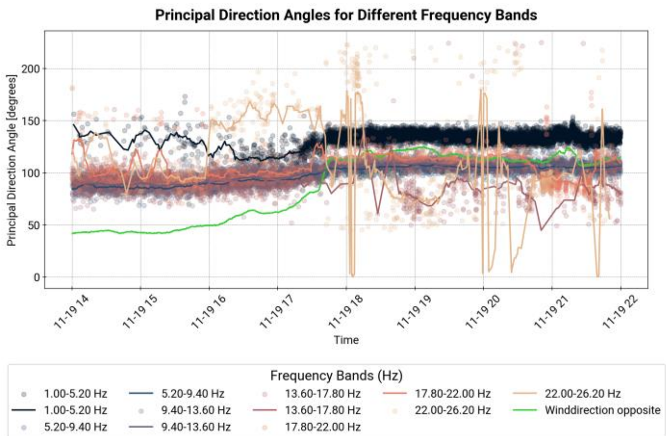

Figure 6. Principal direction angles for different frequency bands.

4 FURTHER INVESTIGATION

As the present study is one of the first to leverage the three-component rotational ground-motions combined with translations for structural health monitoring of wind-turbines, we aim to determine how the 6-component measurements can be used to reliably replicate some of the SCADA data. One of the most important parameter measured as a part of SCADA data is the acceleration at the top of the tower. We aim to use this acceleration data from the top of the tower, located inside the nacelle, and compare it with the acceleration data at the bottom. By doing so, we may be able to predict the movement of the tower at the top. Additionally, we hope to extrapolate the

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displacement at the bottom, assuming the stiff end is located inside or at the bottom of the foundation. This would allow us to measure the tower's eigenmodes. Given the extended time span of the data, we aim to detect any differences in the eigenfrequencies and modes over time. If successful, this approach could help identify structural damage using directional information. Previous studies [4], [5] have demonstrated such damage identification based on translational acceleration data through operational modal analysis.

To further investigate the dynamics of the wind turbine tower, we plan to use Campbell diagrams, wavelet transformations, and stabilization diagrams. We want to investigate more signal coherences, damping ratios and the advantage of rotation motion measurements for the structural health monitoring.

5 CONCLUSION

In this study, we identified significant eigenfrequencies in the seismic data and successfully correlated them with environmental changes. The Power Spectral Densities (PSDs) revealed distinct peaks corresponding to these eigenfrequencies. Hodograms further demonstrated the linear movement of the tower, with a slight offset relative to the wind speed and noticeable differences across various frequency bands. These observations suggest that the tower's behavior is influenced by both the wind and its structural dynamics. Ongoing investigations include the use of Campbell diagrams, wavelet transformations, and additional analyses to gain deeper insights into the tower's dynamic response.

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