First steps towards the development of structural health monitoring approaches for wind turbines in seismic-prone areas

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ABSTRACT

Regions with high wind resources, which are suitable for the operation of wind turbines, often coincide with earthquake-prone areas. So far, the design of wind turbines in earthquake-risk regions is carried out by simulations only. There is no data from full-scale operating wind turbines for validation purposes available. By conducting a long-term field study in a high-risk seismic area on full-scale running wind turbines, this research project intends to change the current state of the art and provide relevant data, which can be used for the improvement of design guidelines and the setup of structural health monitoring systems contributing to the development of digital twins. To ensure the structural integrity of wind turbines under high loads, modal parameters can be tracked over time. A shift in these parameters can provide insight into potential damages. These parameters can be determined using operational modal analysis, which is applied to an operating wind turbine in an earthquake-prone area. From this preliminary study, the challenge dealing with the harmonic response signal arises. The harmonics, present in the system, are very strong and overlap with the structural properties. Suitable measures have to be taken and appropriate techniques have to be applied to eliminate the harmonic influence in the data for reliable modal identification. Preliminary data from a wind turbine operated in Chile, located in the south-central area, is available for this study, and will be analyzed and discussed in detail. An emphasis is placed on demonstrating the influence and impact of harmonics in the ambient vibration test data. Different time-frequency analysis techniques are applied to the described data set to understand the role of harmonics and their superimposing character on the ambient vibration data. A comparison can be drawn between the results from the data in operation and the ones from standstill measurements. One main parameter of interest is the damping ratio, which is highly dependent on the operating point and loading condition. The insights of this study represent a first step towards the future of structural health monitoring for wind turbines in earthquake-prone areas.

Keywords: Wind energy, earthquake engineering, speed-synchronous vibrations, structural health monitoring

1. INTRODUCTION

Earthquake-induced excitation can lead to often negligible phenomena being amplified that can harm the structural health of wind turbines. These loads can lead to higher modes being excited as well as high displacements and accelerations at the top of the tower, especially harming the rotating components in the nacelle [1]. Higher modes typically describe modes in vertical direction that lead to amplified accelerations at the top [2]. Local damages can appear in critical components. Thus, more experiments have to be performed in order to properly understand the structural behavior of wind turbines under seismically induced loads.

Pitch actuators and bearings have shown the highest probability, which is around 25%, to suffer damage within one year of operation. A fault probability of 20% is attributed to the blades and 18% to the gearbox [3]. This explains, why reliable monitoring approaches for wind turbines are crucial to ensure operation continuity and reduce damages as well as structural failure of certain components. Vibrations represent a core element to assess a machine's structural health. Besides, informative diagrams of the vibration signal in the frequency domain like short-time Fourier transforms or wavelet transforms, modal parameters represent a useful measure to track the machine's condition. Shifts in modal parameters, like the natural frequencies or the mode shapes, over time can be insightful about potential structural changes that can possibly lead to damages.

To obtain these modal parameters under operating conditions, operational modal analysis (OMA) can be applied. This technique relies on the assumption that the ambient excitation of the structure investigated can be described as white Gaussian noise [4]. For rotating machines, this assumption is no longer true because the rotation introduces a harmonic excitation that is superimposing the excitation from other environmental sources. Thus, the measured response will include a harmonic component that can falsify the modal parameter identification. It is, therefore, necessary to either identify or eliminate the influence of these so-called harmonics in the ambient vibration test data from rotating machines. There are numerous approaches that can be applied to these types of data sets. Depending on the boundary conditions some techniques might be more suitable than others. Measures like the kurtosis value or the shape of the probability density function can be helpful to determine the presence of harmonics [5]. More elaborate methods try to find a formulation for the harmonic component that can be subtracted from the original signal in some way [6–8]. Other measures can involve consulting methods that transform the data into a different domain, e.g. frequency domain, which can express the impact of the harmonics in the data. These techniques are especially useful, when long-term measurements are available and the user wants to understand the trends and possibly determine structural changes over time.

In the following sections, these well established techniques like the Hilbert-Huang transform, the short-time Fourier transform, and the wavelet transform will be shortly presented and applied to the preliminary data set available. The results will be discussed to determine the influence of the harmonics and derive subsequent measures to deal with the harmonics allowing for a reliable and successful modal parameter identification in operation. These insights can be counted as a first step towards the development of suitable measures to analyze the data and contribute to the development of structural health monitoring approaches for wind turbines in seismic-prone areas.

2. METHODOLOGY

In the following section, the essential techniques that are applied to the preliminary data set form the operating wind turbine, are described in more detail and their different advantages and disadvantages are pointed out.

2.1. Hilbert-Huang Transform

The Hilbert-Huang transform (HHT) consists of two main steps. First, the empirical mode decomposition (EMD) is applied to the time history data to obtain so-called intrinsic mode functions (IMF), which

can be described as oscillatory signal components. Details on the EMD technique and its underlying assumptions can be found, e.g. in [9]. In the next step, the Hilbert transform is applied to each IMF resulting in the Hilbert spectrum. The frequencies of each IMFs are attributed amplitude values in this last step. The advantage of HHT over other techniques is that it is well suited for data from nonlinear and non-stationary systems, whereas most methods assume an underlying linear system [10]. The Hilbert transform for any function $X(t)$ is given by

$$\mathcal{H} = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{X(\tau)}{t - \tau} d\tau \tag{1}$$

with P being the Cauchy principal value of the singular integral[10]. Its applications reach from oceanography [11], and seismology [12] to gear fault diagnosis [13].

2.2. Short-time Fourier Transform

The short-time Fourier transform (SFT) aims at dividing the time signal $X(t)$ into small time windows and applying the Fourier transform to each time segment. It is suitable to identify harmonic components. It's basic formula is

$$S(f, t) = \sum_{\tau=0}^{K-1} X(\tau) w(\tau - t) e^{-i2\pi f \tau}, \tag{2}$$

where w describes the window function. The root mean square amplitude is illustrated in the time-frequency representation. The method has some limitations related to the window length leading to low resolution. For small windows, the time resolution is precise, but the frequency resolution is deficient, which can make the identification of certain frequencies less accurate, e.g. when frequencies are closely spaced [14].

2.3. Wavelet transform

Wavelet functions are designed to overcome the limitations of Fourier transforms and can specifically analyze non-stationary data [15]. The Fourier transform cannot account for local information of the signal. Wavelet transforms can therefore reveal information that otherwise might be overlooked [16]. Examples for the successful use of wavelet transforms can be found in geophysics, where the technique has been applied to study the terrain of the seafloor [17], the features of atmospheric cold fronts [18] or the effects of atmospheric anomalies on El Niño [19] to name a few.

The most commonly used wavelet is the *Morlet* wavelet, which is mathematically expressed as

$$\Psi = \pi^{-1/4} e^{-i\omega t} e^{-t^2/2} \tag{3}$$

with ω being the frequency and t being the time. The continuous wavelet transform of a discrete signal x_k is defined as the convolution of x_k with the complex conjugate of Ψ^* [15]

$$W_k(s) = \sum_{\tau=0}^{K-1} x_k \Psi^* \left[\frac{\tau - k}{s} \right], \tag{4}$$

where s is the wavelet scale.

3. TEST SETUP

Data is gathered from a wind turbine operated in the south-central area of Chile close to Los Angeles. The hub height is 140 m with a rotor diameter of 150 m, and the nominal power is 4.5 MW. The measurement is taken for around 20 hours with varying rotor and wind speeds. Four sensors are distributed over the

height of the tower, placing them on the individual platforms. The sensor type used for this investigation is a Tromino high-sensitivity seismic sensor that can capture small velocities in three directions. The sampling rate is 128 Hz. The variation of rotor speed over time as well as the locations of the four sensors in the tower are depicted in Fig. 1. The rotor speed is only sampled once every 10 minutes. It is

(a) Scheme of sensor positions.

(b) Rotor speed during the measurement.
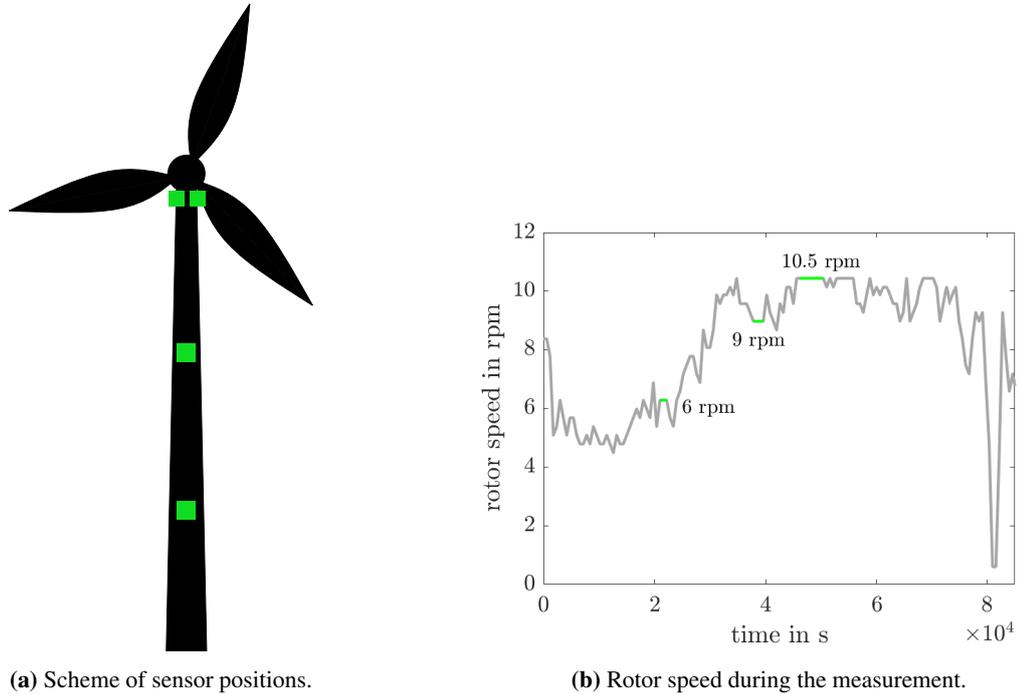
Figure 1: Sensor locations and rotor speed variation.

therefore not captured synchronously to the measured vibration data.

3.1. Reference results in standstill condition

From previous work [20], the modal parameters (natural frequencies and damping ratios) have been determined in standstill condition of the turbine. These results, which serve as a reference for the operating condition, are depicted in Tab. 1.

Table 1: Modal parameters from reference measurement in standstill conditions [20].

| Mode	Frequency [Hz]	Damping [%]
1	0.14	1.25
2	0.14	1.38
3	0.56	1.84
4	0.67	0.68
5	1.08	0.94
6	1.16	0.18

4. RESULTS

The influence of the harmonics and first results from the operational modal analysis are presented and discussed in the following section.

4.1. Impact of the harmonics

In [8], an approach has been introduced to depict the energy spectrum of an acquired signal, which is useful to distinguish harmonics from structural modes as their signal energy exceeds the energy level

of the structural responses. An example for the energy spectrum calculated at 10.5 rpm of the wind turbine is displayed in Fig. 2. Compared to other applications, like a vessel with a rotating propeller or
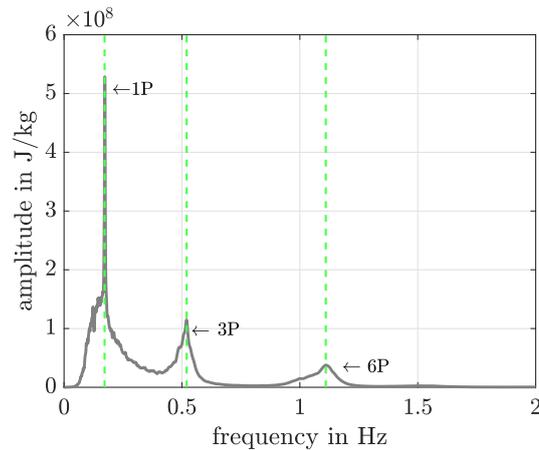

Figure 2: Energyspectrum calculated for data at around 10.5 rpm rotor speed

an axial compressor test rig in operation, the signal energy of the harmonics present in the wind turbine data exceed the amplitude level by an order of magnitude 10^4. This explains their strong impact on the ambient vibration data and the challenge associated with a reliable modal identification in operation.

The fact that the harmonics are not depicted as clear, sharp peaks in the energy spectrum but are expanded towards low amplitude values, shows that there are rotor speed variations, which are not captured by the sparse rotor speed measurement of the internal SCADA (Supervisory Control and Data Acquisition). The rotor speed variations lead to a higher frequency content of the harmonics resulting in the observable broader peaks.

4.2. Time-frequency analysis

The three techniques explained in Sec. 2. are applied to the available data set. In Fig. 3 the data from the complete 20 hour measurement is used to assess the influence of the rotor-induced vibrations. Both,

(a) HHT

(b) CWT

(c) SFT
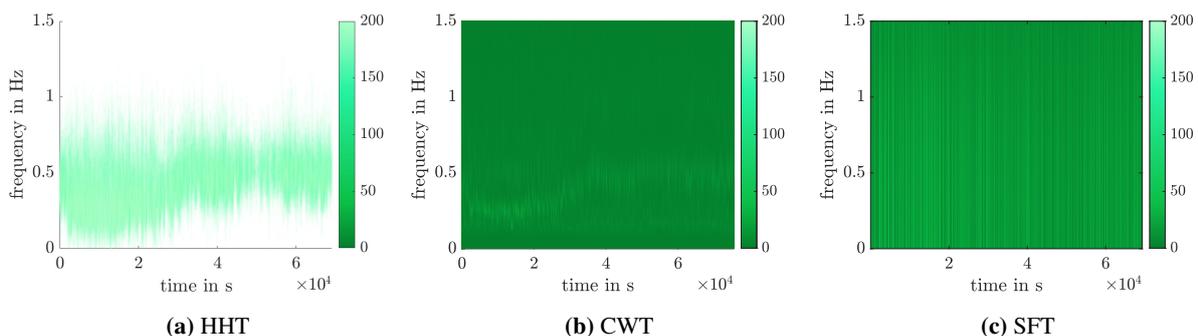
Figure 3: Comparison of different time-frequency analysis techniques applied to the data set of the operating wind turbine.

HHT and CWT show the changing rotor speed behavior over time. The weakest tool among the three techniques compared, is the SFT. Basically, no useful information about the behavior of the harmonics can be extracted. The advantages of CWT and HHT come into play as they are well suited to resolve instantaneous and local effects, in contrast to the Fourier transform. Nonlinear effects are expected to be insignificant, therefore, the HHT does not offer any benefit over the CWT. As a consequence, the CWT is depicted in more detail in Fig. 4a, with a smaller amplitude scale that makes the impact of the rotor speed even more visible. The CWT shows both the first and third harmonic, the second one with

(a) Morlet

(b) Bump
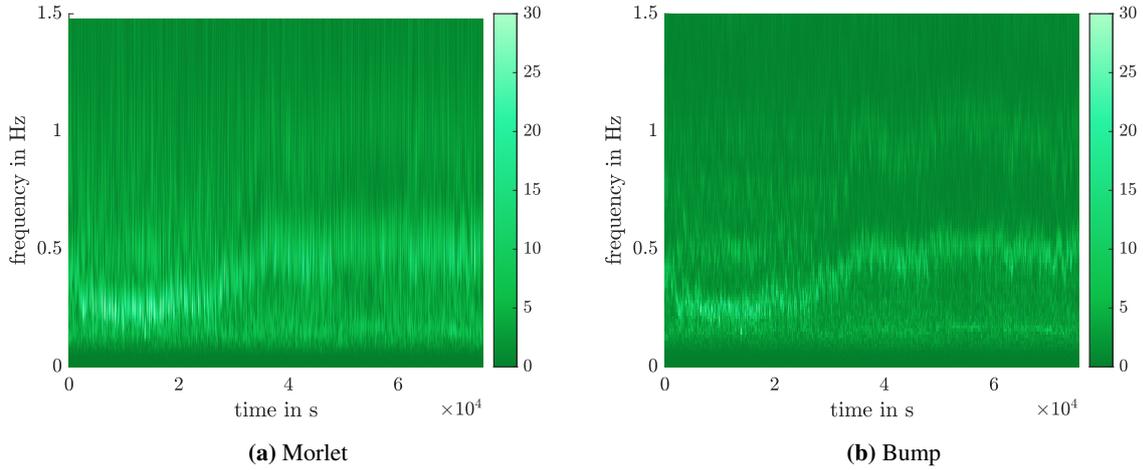
Figure 4: CWT of entire data set at higher amplitude resolution.

a smaller amplitude level, which are expected to be the main harmonic frequencies to be present in the acquired data. For the analysis in Fig. 4a, the default Morlet wavelet has been applied. As a comparison, the bump wavelet [21] has been applied in Fig. 4b. It shows a more condensed frequency impact of the harmonics compared to the default CWT. The bump wavelet is characterized by a narrower variance in frequency, and wider variance in time. On the one hand, this results in a distinguished frequency localization and on the other hand it leads to deficient time localization [22]. As the frequency content is of higher interest, the bump wavelet is applied in the following investigations.

Figure 5 shows the CWT for all three constant rotor speeds, see Fig. 1, analyzed with OMA techniques. Especially the first (1p), third (3p), and sixth (6p) harmonic are very clear in Fig. 5b and 5c, whereas the

(a) 6 rpm

(b) 9 rpm

(c) 10.5 rpm
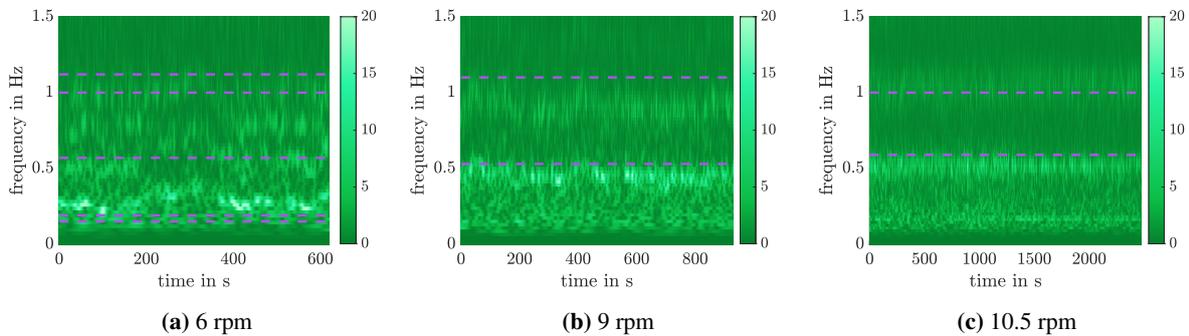
Figure 5: Comparison of different time-frequency analysis techniques applied to the data set of the operating wind turbine. The purple dotted line shows the identified natural frequencies.

impact of the harmonics in Fig. 5a is more fluctuant. With this in mind, the next step contains the actual modal parameter identification for those three time segments with a constant rotor speed taken out of the whole hour-long measurement.

4.3. Modal identification

To assess the modal parameters of the wind turbine in operation, the stochastic subspace identification (SSI) [4] has been used. The results are depicted in Tab. 2. Next to the depicted modal parameters for 6 rpm, natural frequencies at 0.25 Hz, 0.32 Hz, 0.36 Hz, and 0.49 Hz have been identified with 2.0%, 1.1%, 1.1%, and 0.9% damping. Modes 3* and 4* are asterisked as they do not match values from the standstill observations, but were characterized by distinct peaks in the singular value representation and a chain of stable poles in the analysis. The impact of the rotor speed at 6 rpm was less significant than

Table 2: Modal parameters from measurement in operation at rpm.

	6 rpm		9 rpm		10.5 rpm	
Mode	Frequency [Hz]	Damping [%]	Frequency [Hz]	Damping [%]	Frequency [Hz]	Damping [%]
1	0.15	3.3				
2	0.19	8.5				
3*	0.46	1.1			0.45	1.7
3	0.57	0.5	0.53	0.3	0.59	0.9
4*	0.78	0.7				
5	1.00	0.9			1.00	0.3
6	1.12	1.4	1.1	0.6		
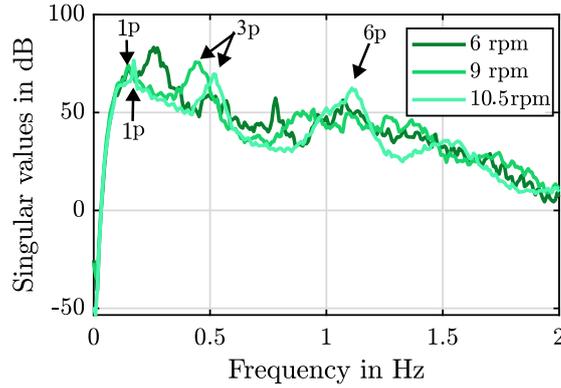
Figure 6: First singular values of the three rotor speeds' power spectral density

for the other two rotor speeds. This becomes evident when looking at the first singular values of the power spectral density depicted for all three rotor speeds in Fig. 6. Distinct peaks for the first and third harmonic can be observed at 9 rpm and 10.5 rpm. For 10.5 rpm, the influence of the sixth harmonic is also visible. This explains the fact that less modal parameters have been identified for these two data sets compared to the one at 6 rpm.

To validate that the identified natural frequencies in operation fit the results from the standstill measurements, the modes shapes have to be compared in future analyses. Confirming expectations, the damping for the first two modes is at least three times higher than in standstill condition, which could be related to the impact of additional aerodynamic damping in operating conditions. To fill out the other fields in Tab. 2, further investigations have to be carried out taking into account techniques to minimize the harmonics' influence.

5. CONCLUSIONS

In this current study, the strong impact of the rotor speed harmonics in operating wind turbines became evident and the challenge associated with identifying the modal parameters correctly. Applying different methods of time-frequency analyses, the Continuous Wavelet Transform has proven to be effective in revealing the influence of the harmonics and pointing them out to the user.

In future investigations, it is crucial to capture the rotor speed information synchronously to the vibration data to enable an improved handling of the harmonics. For the reliable identification of the modal parameters in operation, different techniques can be applied that try to find a formulation for the harmonic response part to eliminate it from the acquired ambient vibration data.

It is currently planned to instrument a wind turbine tower on Northern Vancouver Island operated in the Cape Scott wind farm with four acceleration sensors, one on each platform, while capturing the phase information of the shaft simultaneously. The area is located in a seismic-prone zone. The collection of

data over a long period of time will enable the researchers to investigate different loading scenarios as well as seismic conditions and their impact on the dynamic and structural behavior on the wind turbine to provide validation data for future simulation and design processes.

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