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ISO.Wind – A monitoring system for wind parks using passive radar

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Abstract. Intelligent wind park monitoring systems may allow cutting the levelized cost of wind-generated electricity by deploying maintenance personnel more efficiently. The non-contacting passive radar technology and advanced sensing technologies on the plant side offer significant potential for such monitoring systems. The goal of the 3-year-long project ISO.Wind is to identify the most cost-efficient sensing technologies to detect maintenance-relevant damages and to use them for a wind park monitoring system. For this purpose a commercial 3MW wind turbine is instrumented with strain gauges following IEC standard 61400-13 and a network of accelerometers. It is also monitored by passive radar technology. A learning algorithm is developed and fed with available data from the sensor systems and operational data from the instrumented wind turbine. The algorithm is capable of detecting operational patterns and damage cases of the wind turbine. A graphic user interface illustrates these conditions in a comprehensible way. First field measurements show the suitability of the passive radar technology to detect the damage-relevant dynamics of the instrumented wind turbine. Validated simulations of typical damage cases prove that both instrumentation on the plant side and the passive radar sensing technology allow reliable damage detection for the examined wind turbine.

1. Introduction

In 2015 operational expenditures, covering turbine operation and maintenance, made up 24% of the levelized cost of electricity (LCOE) for a 2MW land-based wind turbine and 27% for a bottom-fixed offshore wind turbine [1]. Unscheduled maintenance work causes two thirds of these operational expenditures or more [1,2]. Advanced wind turbine monitoring systems that allow a more targeted and well-anticipated deployment of maintenance personnel may thus help drastically cutting operational expenditures and the LCOE accordingly.

Several recent studies assessed the potential of various sensing technologies for the use in monitoring systems for the purpose of damage detection on wind turbines. Among the proposed sensing technologies for damage detection are the visualization and analysis of surface temperature distributions on rotor blades [3] and the analysis of the signal of an acoustic source installed inside wind turbine blades by a learning algorithm to detect material damages [4]. Other groups employed thin film sensor networks to detect blade damages [5] or used emitted radar-waves to detect damages inside the glass fiber composite structures [6].

For composite materials [7], the wind turbine tower [8] and the rotor [9] several studies show that there is an impact of material damages on the dynamic behavior of those components. Other works

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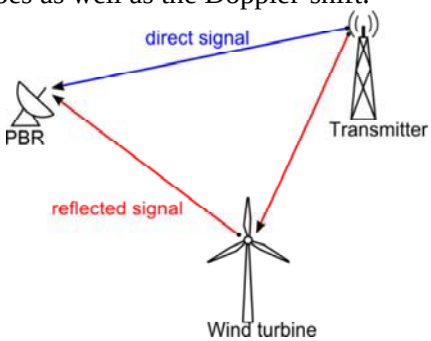
showed the potential of monitoring a turbine's dynamic behavior to detect specific damage events [10] and the potential of radar systems for noncontact structural health monitoring [11].
The overall goal of the 3-year-long research project ISO.Wind (May 2016 – April 2019) is to develop a cost-effective monitoring system for damage detection in wind parks that combines the benefits of the most suitable sensing technologies. A focal point of this project is to assess the suitability of non-invasive passive radar systems [12] for application in wind park monitoring.
The structure of this paper is as follows. Next, the remote passive radar sensing technology and the installed plant-sided instrumentation are described. A proof of correlation demonstrates the consistency between the passive radar sensors and the plant-sided instrumentation. Section 3 illustrates the wind park monitoring system and the operation principle of the damage detection based on the acquired measurement data. In the final section, validated simulations show the impact of defined damage cases on the dynamic behavior of the wind turbine. The simulations demonstrate the detectability of damage cases by the monitoring system on the basis of a varied dynamic wind turbine behavior.

2. Sensing technologies for wind turbine damage detection

A modern 3MW wind turbine is instrumented in Northern Germany to assess the suitability of the remote passive radar sensing technology and the advanced plant-sided instrumentation for their application in a wind park monitoring system for damage detection.

2.1. Remote passive radar sensing technology

The so-called passive radar technology developed by the Fraunhofer-Institute FHR does not require any kind of installations on the monitored wind turbine itself. Instead, only several receiving radar units are distributed within the wind farm for this technology (Figure 1b), since the technology relies on the European DVB-T radio standard as a radar wave source. If such radar technology should prove suitable, it could provide a very cost-effective way of monitoring the operation of wind turbines in wind farms.
Passive bistatic radars (PBR) represent a class of bistatic radar systems that operates without dedicated emissions of an electromagnetic signal. Instead, they exploit radio transmissions emitted by other sources and other purposes to perform the task of target detection and localization.
Such signals of opportunity include FM radio broadcast, Digital Audio Broadcast (DAB), Digital Video Broadcast (DVB-T), satellites and Global System for Mobile communications (GSM) base stations [13], [14], [15], [16], [17].
The principle of operation of a PBR is based on cross-correlating a reference channel containing the transmitted direct signal with a surveillance channel containing the reflections from the environment. A generic bistatic radar geometry is sketched in Figure 1a. In a typical operational scenario a PBR receiver measures the time difference of arrival (TDOA) between the direct signal and the reflected echoes as well as the Doppler-shift.



(a)


(b)

Figure 1. Bistatic radar geometry with wind turbine as target (a). PBR sensor PARASOL mounted to the side of a wind turbine tower (b).

Wind turbines represent physically large structures with sizable rotating blades that reflect a substantial portion of the transmitted signal to the receiver. The received signal echoes vary with the rotation of the blades caused by the Doppler effect. The influence on the operation of radars have been reported and investigated in a variety of studies [18],[19],[20]. Signal processing techniques such as short time Fourier transformations (STFT) proved to be well suited to analyze these kinds of transient signals, while the signal periodicity could be extracted through cepstral analyses [21].
In order to resolve the much more subtle signal components modulated by the vibrations of a wind turbine's stationary components, signal-processing schemes were employed that permitted the coherent integration of the received signals over much higher integration times. This allowed improving the frequency resolution in the base band region from 1Hz down to 0.0648Hz in order to resolve the structure's natural frequencies.
While signal processing allows for high resolution in the frequency domain, echoes separation in the range domain is dependent on the bandwidth of the signal of opportunity. Even relatively high bandwidth transmission standards such as DVB-T offer only a radial range resolution in the order of 10^{1}m. Resolving point-scattering from different structural components of a wind turbine is therefore limited to the separation of signals originating from the tower (including the nacelle) and from the turbine blades.
The results presented in this paper were obtained with data provided by a PBR, which is currently being developed at Fraunhofer-Institute FHR. The so called PARASOL sensor is a two channel passive radar system that operates in the ultra-high frequency (UHF) region ranging from 450 MHz to 850 MHz in order to exploit the transmissions of the German DVB-T broadcasting network.
At this frequency range, Rayleigh scattering applies (particle size of precipitation is small compared to the wavelength). Attenuation effects are therefore expected to be below 10^{-2}dB/km and meteorological conditions can be considered negligible [22].
Figure 1b shows the antenna system of a PARASOL sensor covered with a transparent radome mounted to the side of a wind turbine tower at a height of 8m and a distance of 4,9km from the instrumented wind turbine. . A raid storage cluster allows the recording of the wind turbine echo returns for multiple months.
A DVB-T transmitter near the town of Bredstedt was used as illuminator of opportunity, which is located at a distance of 3.8km from the PARASOL sensor. The horizontally polarized signal is transmitted at a center frequency of 514MHz and the effective radiate power directed at sensor is listed as 50kW.

2.2. Plant-sided sensing technology

The sensing technologies that are installed on the mechanical structure of the wind turbine (at several tower sections, the nacelle and all 3 blades) by the Fraunhofer-Institutes LBF and IWES cover comprehensive strain gauge installations following IEC standard 61400-13, the application of sensor networks of accelerometers and the use of sensors to detect additional operational parameters of the wind turbine.
Aside from covering IEC standard 61400-13, modal parameters of the wind turbines structure are identified automatically and continuously for the purpose of this project. To accomplish this a monitoring system based on distributed vibration measurements has been installed. The data acquisition unit consists of a smart sensor network with five sensor nodes and 20 measurement channels. Such systems can use sensitive IEPE-sensors in a laboratory-grade or MEMS-sensors as low-cost alternative for long term installations. Minimum cabling esnures the monitoring system is simple to install on large structures and acquires data during the wind turbine's operation. Using the Random Decrement Method, the vibrations signals sampled at 100 Hz at the sensor nodes are transformed into signatures packages with a data compression of factor 50 or more [23]. Each of these packages contains information about the structural behavior of the wind turbine during one hour and the packages are transferred from the wind turbine to the research institutes using mobile remote access to the smart sensor network. Details about the smart sensor network, the Random Decrement

Method for data acquisition and Operational Modal Analysis for the extraction of modal parameters can be found in [24]. Using a batch processing, several features are extracted from the signatures packages. Those incorporate e.g. different mode shapes of the wind turbine's tower, corresponding modal frequencies, spectra of singular values and counts of trigger events. Those features are the information that is uploaded to the database for the wind park monitoring system as described below.
The Fraunhofer-Institute IWES's system is designed to measure loads, accelerations, operational and meteorological parameters. Tower bending moments are measured using full-bridge strain gauges at the bottom, the middle and the top of the tower in two perpendicular directions. All three rotor blades are instrumented with two full-bridges to measure the bending moments at the blade root in edge- and flapwise direction.
The yaw position of the nacelle is monitored with a rotary encoder. The blade pitch is measured using a laser distance sensor at the pitch hydraulic cylinder of one rotor blade. The rotor azimuth is measured with a MEMS-inclinometer. All signals are measured at a sampling rate 50 Hz and stored locally.. The data is downloaded frequently using a modem.
To measure wind speed and direction, air temperature, air pressure and humidity a Gallion-LiDAR was used for a measurement period of several months. Thereafter a nacelle mounted cup anemometer was used to measure wind speed. During a parallel measurement phase of the cup anemometer and the LiDAR a database to create a nacelle transfer function (NTF) was generated. After completion of the NTF the LiDAR was uninstalled. The yaw position of the nacelle was used as wind direction, air pressure and temperature were retrieved from a nearby public weather station.
The overall uncertainty including all parts of the measurement chain added up to an overall uncertainty below 5% according to an uncertainty analysis following the GUM guideline.

2.3. Proof of correlation between passive radar and plant-sided instrumentation

Both the passive radar system and the plant-sided instrumentation permanently monitored the dynamic behavior of the instrumented wind turbine during the period from 21st to 28th of November 2017. The measurement data acquired during this time period allows assessing the correlation between both sensing technologies. To demonstrate the capability of a sensing technology to capture both the plant's mode of operation and its dynamic behavior, it needs to be able to capture the rotor rotational frequency P and the first eigen frequency of the wind turbine with sufficient precision.
Figure 2 shows a time series of the detected rotor rotational frequencies. As can be seen in Figure 2, both the passive radar sensing technology (by use of turbine's radar reflection signal) and the plant-sided instrumentation (via an inclinometer installed close to the rotor's rotational axis) reliably capture the rotor rotational frequency P and thus the turbine's mode of operation.

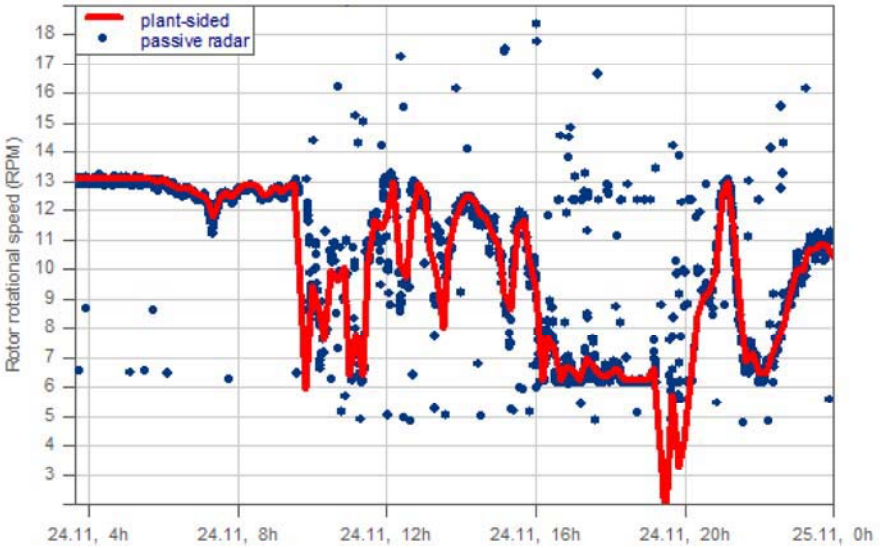


Figure 2. Time series of measured rotor rotational speed for plant-sided instrumentation (red) and passive radar system (blue)

The time series in Figure 3 over several days shows that the passive radar sensing technology (by use of turbine's radar reflection signal) and the plant-sided instrumentation (via strain-gauges installed at various tower sections) consistently detect the dominant plant's eigen frequency at approximately 0.24 Hz. The error in the detected frequency between both sensing technologies is 0.8%.
Above findings show that the passive radar sensing technology reliably detects a wind turbine's mode of operation and its dynamic behavior. The accuracy with respect to the detected frequency is sufficient for the detection of relevant damage cases, as will be shown in section 4 of this work.

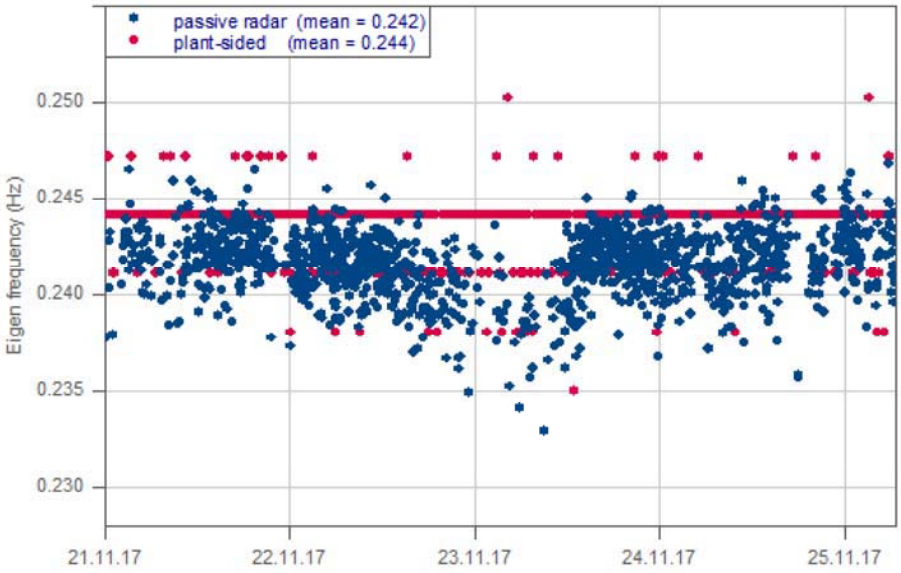


Figure 3. Time series of acquired plant's eigen frequency measured with passive radar (blue) and plant-sided instrumentation (red)

3. Wind park monitoring system for damage detection

For the supervision of the wind turbines, a data-driven condition-monitoring system is proposed. The basic idea is to use historic process data (e.g. passive radar, strain gauges, acceleration sensors or

SCADA data) representing the normal state of the turbine, train a mathematical model and in a subsequent step compare the model with real-time data. If there is a relevant deviation between model and measurement data, this indicates a possible damage. The proposed algorithm covers several steps, which are sketched in Figure 5 and described in the following section.

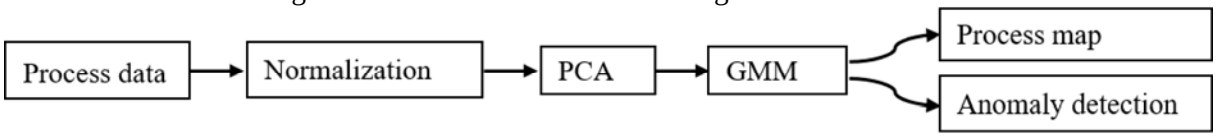


Figure 4. Workflow of the data-driven condition-monitoring system

3.1. Algorithm for the wind park monitoring system

It is assumed that $x[k] \in \mathbb{R}$ with $k = 1 \dots K$ is the time series of a process variable with the mean value μ and standard deviation σ. Hence, the set of all process variables is described as $X = \left[x_1[k], x_2[k], \dots, x_p[k]\right]$ with P the set of process variables resulting in the matrix $\boldsymbol{X} \epsilon \mathbb{R}^{(K \times P)}$. The normalization of each variable is then carried out as $\boldsymbol{Z} = \frac{x_j - \mu_j}{\sigma_j}$.

Principal Component analysis (PCA): The PCA (Figure 5) is used for dimensionality reduction of the initial data set. Calculating the principal components is carried out by computing the eigenvectors of the covariance matrix $\boldsymbol{\Sigma} \epsilon \mathbb{R}^{P \times P}$. Next, the eigenvalues $\boldsymbol{\lambda}$ of the covariance matrix are determined and sorted in descending order, resulting in the diagonal matrix $\boldsymbol{\Lambda} \epsilon \mathbb{R}^{P \times P}$. Finally, the corresponding eigenvectors $\boldsymbol{\Lambda}$ are calculated and summarized in columns, giving the matrix $\boldsymbol{\Gamma} \epsilon \mathbb{R}^{P \times \mathrm{P}}$. $\boldsymbol{\Gamma}$ is subsequently used to perform the linear transformation $\boldsymbol{Z} \rightarrow \boldsymbol{Y} = \boldsymbol{\Gamma}^{\boldsymbol{T}} \boldsymbol{Z}$, while $\boldsymbol{Y}$ contains the PCs.

Gaussian Mixture Models (GMM): A GMM (Figure 5) is a parametric statistical model, which assumes that the data originates from several Gaussian sources. In detail, a GMM is defined as

$$p(x|\Theta) = \sum_{i=1}^{K} \omega_i p_i(x|\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i) \tag{1}$$

with K being the number of density components, ω_i, with $\omega_i \geq 0$ and $\sum_{i=1}^{K} \omega_i = 1$, the mixture weightings and $p_i(x|\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$ the individual Gaussian distributions with $\boldsymbol{\mu}_i$ being the mean vector and $\boldsymbol{\Sigma}_i$ the covariance matrix. The log-probability, which is used as index for the anomaly detection for one sample $\boldsymbol{x} \epsilon \mathbb{R}^{1 \times P}$ is then determined as

$$\hat{a} = \sum_{p=1}^{P} \log \sum_{i=1}^{K} \omega_i \, p(\boldsymbol{x}|\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i) \tag{2}$$

with $\hat{a} \in \mathbb{R}$.. Training the GMM with measurement data means estimating the weightings ω_i, the mean value $\boldsymbol{\mu}_i$ and the covariance , $\boldsymbol{\Sigma}_i$ which is done following an Expectation Maximization (EM) algorithm (Figure 5).

3.2. Operation principle of damage detection

The operating principle is exemplary shown on the structural health monitoring of a rotor blade. As input data, the FFTs of the edgewise blade bending moment, shown in Figure 5 upper left plot, are used for anomaly detection. Following the algorithmic work flow, the first two principal components are determined from the FFTs and used as training data for the GMMs. This results in the process map and trajectory shown in Figure 5 upper right. The trained GMM is visualized in terms of isobars, while the trajectory close to a dark blue area, indicates a normal state and a drift into the direction of yellow isobars means that the trained GMM differs from the measurements and hence indicates a possible damage. Finally, this result can be quantified by the calculation of the logarithmic probability $\hat{a}$, which is shown in the lower subplot in Figure 5 on the right. A value close to zero means that the system is running in normal state, while large negative values indicate an anomaly. During the investigated time period the wind turbine ran normal, meaning that no anomaly was detected by the system.

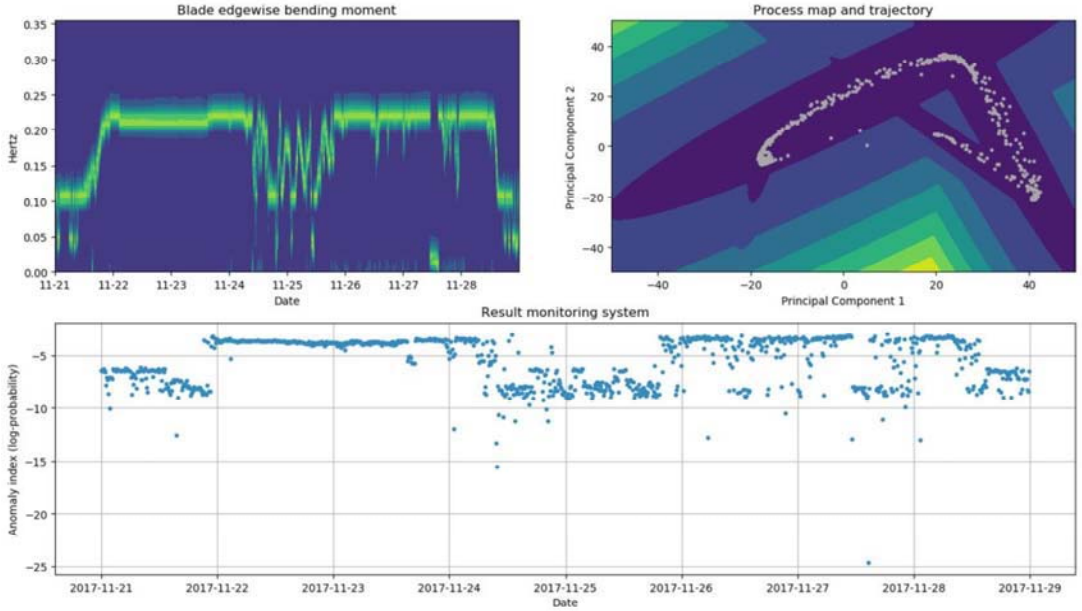


Figure 5. Results of the monitoring system. Left upper plot: FFTs of the blade bending moment edgewise. Right upper subplot: First two principal components with GMM. Bottom: Resulting anomaly index of the proposed monitoring system.

4. Predicted detectability of damage cases

4.1. Damage of tower segments

The steel tower of the reference turbine has a total height of 90m and consists of five segments, joined via flange connections. Due to alternating stresses, certain screws of the flange connection might fracture or become loose, resulting in reduced stiffness of the flange connection. This will have an influence on the natural frequencies of the tower. The change could be measured by the passive radar and detected by the data-driven wind park monitoring system. To quantify the influence of failed screws onto the natural frequency, a detailed FE-model of the tower was set up. The stiffening effect of the flange connections was considered as well as the thickness variation along the tower height. The first flange connections were modelled with 100 preloaded flexible screws and contact interactions at the surfaces. The tower head mass was represented as a point mass and the soil stiffness was reduced by a rotational spring. Gradually adjacent screws were removed from the flange and the natural frequency was determined. Figure 6 displays the reduction of the first natural tower frequency in relation to the amount of failed screws.

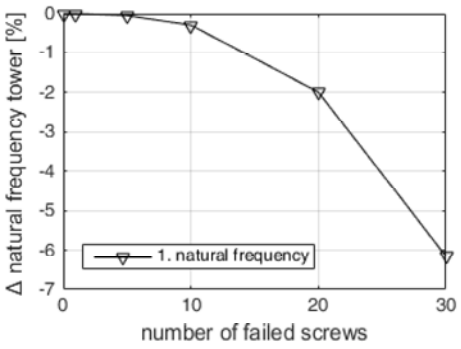


Figure 6. Simulated change of the natural frequency depending on the amount of failed screws

4.2. Damage of tower foundation

Depending on the soil condition, a different foundation is used. The reference turbine is mounted on a piled foundation. Softening of the soil or damages of the foundation can lead to a reduction of the foundation stiffness and therefore to a decrease in the natural frequency of the tower. In case the natural frequency matches the rotation frequency of the rotor, resonance will occur, which can damage the whole turbine. To analyse the effect of failed piles the rotational stiffness of the foundation and soil is distributed along 22 translational springs, representing the piles. Figure 7 shows the reduction of the first natural frequency of the tower depending on the number of damaged piles.

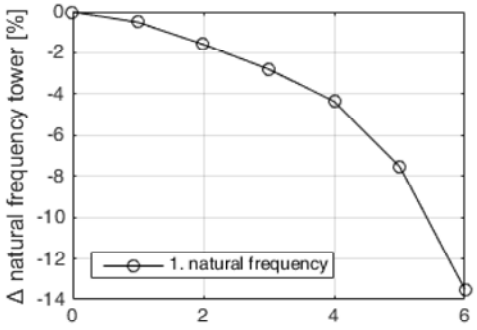


Figure 7. Simulated change of the natural frequency depending on the amount of failed piles

4.3. Contamination and icing of blades

Under certain conditions ice can attach to the blades. Falling ice is a high security risk. Therefore, a reliable detection of attached ice is required to reliably shutdown the turbine in case of icing. Additionally, an unequal ice distribution will create a dynamic unbalance, leading to higher loads on the turbine and its components. Attached ice changes the mass distribution of the blade and therefore the natural frequency of the blade. To quantify the influence, a detailed FE-Model of the NREL 61.5 meter reference blade was generated. The ice is modelled as an additional layer located irregularly on the leading edge. Figure 8 shows the reduction of the edge- and flapwise first natural frequency of the blade depending on the mass of the ice. Both bending modes are affected equally.

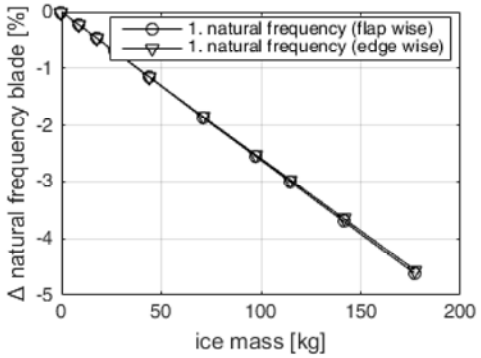


Figure 8. Simulated change of the natural frequency of the blade depending on the ice mass

4.4. Damage of individual rotor blades

Due to fatigue, wear or lightning strikes, cracks can occur on the surface of the blade or its inner supporting structure. These cracks grow and can lead to fatal failures. Therefore, damaged blades must be detected and repaired or replaced. Cracks reduce the local stiffness of the blade and subsequently have an influence on certain natural frequencies of the blade. A crack in the spar caps, perpendicular to the fiber direction, was introduced into FE-model of section 4.3. Figure 9 shows the reduction of the first edge- and flapwise natural frequency with respect to the relative crack length (crack length/ belt wide). It can be observed that the influence on the flapwise mode is higher due to the fact that the stiffness of the spar caps is higher in flap-wise direction.

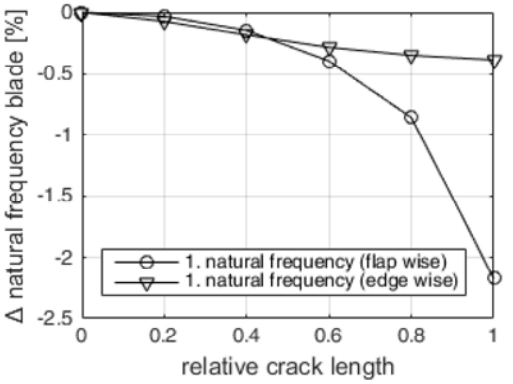


Figure 9. Simulated change of the natural frequency of the blade depending on the relative crack length

5. Conclusions

A novel monitoring system for wind farms that relies on passive radar technology is developed. This passive radar technology does not require any instrumentation on the monitored wind turbine. It was found that the dynamic behavior and operational patterns of the wind turbine can be captured with the used passive radar sensing technology. Furthermore, the captured dynamics of the wind turbine can be used in a monitoring system to detect several types of damage events.

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