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Wind turbine blade damage detection using data-driven techniques

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Abstract. This work presents a simple damage detection strategy for wind turbine blades. In particular, a vibration analysis-based damage detection methodology is proposed that requires only healthy data and detects damage in different locations of the blade. The stated structural health monitoring strategy is based on the extraction of characteristics using statistical metrics as a technique for the recognition and differentiation of healthy test experiments from damaged test experiments with simulated faults created by added mass. In this manner, several metrics are approached to find those that show better classification in processing the data provided by the sensors. Finally, an evaluation process is performed to detect blade damage. The results show that the proposed RMSE metric performs at an ideal level, making it a promising strategy for the detection of blade damage.

Key words

Wind turbine, damage detection, blade, vibration, RMSE.

1. Introduction

In the world, 82% percent of energy consumption comes from fossil fuels [1]. However, according to the BP company, there has been a 1% decrease in the use of fossil fuels in the last year [1]. Renewable primary energy (not including hydro energy) had in 2021 a growth rate of 15% [1]. This rapid growth indicates a trend towards alternative energy sources. One of the most prominent is wind power, which has grown rapidly since 2000 driven by supportive policies and falling costs [2]. Since the wind is free and abundant and will not depreciate over time if used continuously, it is a promising alternative [3]. Wind power works by basically turning the kinetic energy carried out by the wind into electricity by induction in the generator.

As a renewable energy that is emerging as an alternative to fossil fuels, there are some barriers to wind energy [4]. Some of the most optimal places to locate a wind turbine (WT) are extremely remote, making operation and maintenance costs high [3]. In addition, some offshore wind farms are expanding their market share. Due to the challenging environment in the area, the installation, and maintenance of offshore wind farms is difficult.

Rough conditions and prolonged operation of WTs can cause some blade damage that can include cracks and coatings of a foreign material (ice or dirt), delaminating, and damage to the structure [5]. These failures can lead to poor blade performance and, therefore, poor power generation [5]. The possible causes of damage can be classified into the following groups: fatigue, lightning strike, ice, erosion at the leading edge [5]. Typically, each region of the blade is vulnerable to a different failure mechanism. For example, the tip of the blade is constantly affected by raindrops, hail, and other impacts [6]. The most common ways to analyze failure mechanisms are postmortem blade analysis, full-scale testing, incident report analysis, direct monitoring of WTs in operation, and computational modeling of a blade during a stress test [6].

Structural health monitoring (SHM) is non-destructive and is considered highly effective [6]. This process of damage detection implies monitoring a structure over time, extracting features that led to damage, and finally performing statistical analysis to determine the current state and a possible prediction of the state [7]. For example, in 2020 Vidal et al. a methodology for the diagnosis of structural damage in jacket-type foundations is stated based on the criterion

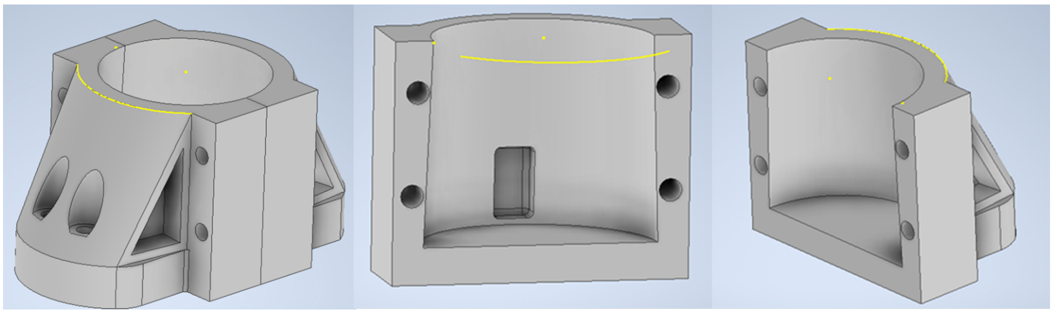

Fig. 1: Design of the blade clamping part in CAD software.

that any damage or structural change produces variations in the vibrational response of the structure [8]. In [9], a 5-MW wind turbine modeled using the NREL FAST code is used to perform a feasibility study to detect structural faults in the blade by analyzing the vibration of the tower. A work that proposes two in-cascade Siamese convolutional neural networks to discern whether the structure is healthy or damaged and, in case damage is detected, to determine the diagnosis of damage (classifies the type of damage) is presented in [10]. Finally, [11] presents an adaptive wavelet packet denoising algorithm applicable to numerous SHM technologies including acoustics, vibrations, and acoustic emission.

In this work, non-destructive damage analysis is practiced using vibration analysis and placement of accelerometers specifically for damage detection on WT Enair E30PRO blades. Structural health monitoring on the blade is applied by feature extraction using statistical metrics as a technique for recognition and differentiation of healthy test experiments from damaged test experiments with simulated fault by added mass. In this manner, several metrics are approached to find those that show better classification and noise avoidance in processing the data provided by the sensors. This leads to exploring the root mean squared error more deeply as the strongest proposal to obtain the distance to the threshold, called the baseline. Preprocessing with the median metric is taken into consideration because, when numerical distributions are skewed, the median is typically used to return the center tendency.

The following describes the structure of this work. The experiment configuration on the blade is defined in Section 2. Section 3 contains the proposed methods for detecting blade damage. The results are reported in Section 4. Lastly, the main conclusions are provided in Section 5, as well as future research directions.

2. Experimental setup

The experiment can be conducted using different configurations, such as those described in the works [12] and [13]. To support the blade, one proposed method involves screwing its base horizontally to suspend its weight in the air. However, this type of fixation may result in some mass loss due to the pins, and would require consideration of their impact on the vibrations. Alternatively, a vertical fixation can be used, where the weight of the blade rests on its base, offering different fixation options. Hence, it is decided to position the blade vertically on top of a welded plate on a 850x850x150 mm table. To support the blade, a specially designed support was built using 3D printing as the chosen manufacturing method for the support parts.

Several iterations are made to the design of the support. In particular, in the final improved design, sleeves were included in the support to adjust pressure as a grip, and the presence of a chamfer was defined to reinforce the fastening. Because of the small amount of excitation generated in the experiments, the use of polylactic acid (PLA) as a construction material for the support is sufficient. Figure 1 shows the design of the manufactured support.

Seven triaxial sensors (x, y, and z axes) are placed in a zigzag configuration along the blade, trying to measure accelerations in the most important areas produced by a miniature impact hammer type 8204 with a voltage sensitivity of 2.7. In Figure 2 is possible to see the blade vertically placed with the different sensors located in a zigzag configuration along it.

Finally, this work seeks to detect damage to the WT blade. To simulate it, a bolt with nuts is used to concentrate an added mass in three different places on the blade, as can be seen in Figure 3.

3. Methodology

The stages of the suggested methodology are listed below. First, raw data is collected from the sensors. Second, the reshaping of the data is done to ensure that each new sample contains enough data. Finally, an evaluation of a metric that allows the detection of blade damage is carried out. The following subsections comprehensively describe the different stages mentioned above.

A. *Data acquisition*

The duration of each experiment is 2 minutes, with a sampling frequency of 1651.6 Hz. As a consequence, each of the 21 sensors (seven triaxial sensors) produces 198,194 readings. A medium-force blow from an impact hammer is applied with consistency at 10-second intervals. Six experiments were carried out for each different position of the mass (see Figure 3) that simulate damage, in addition to six

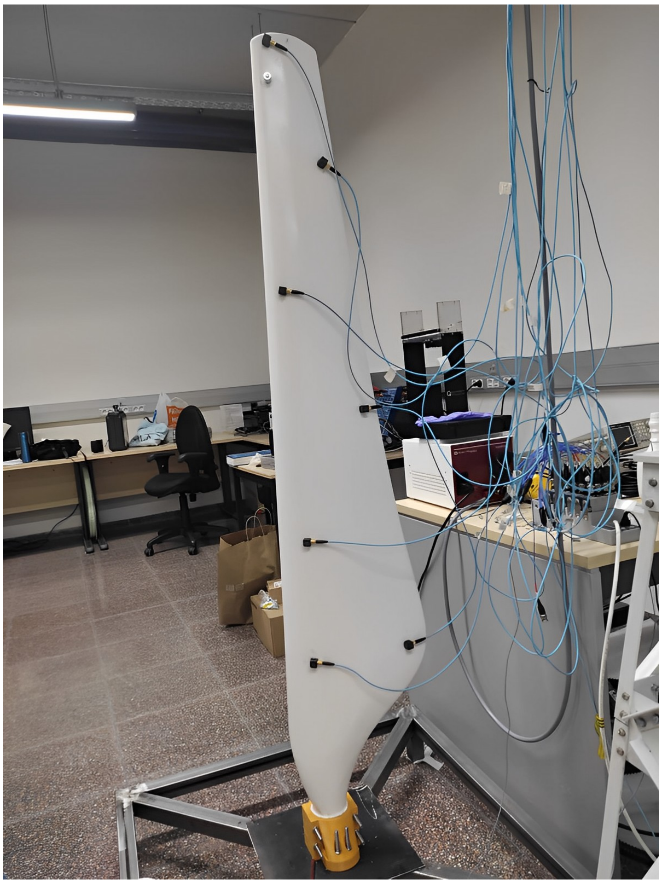

Fig. 2: Experiment configuration with sensors located in a zigzag configuration along the blade.

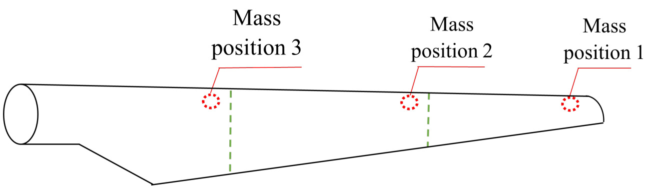

Fig. 3: Mass positions in the WT blade.

experiments without mass accumulation that simulate a blade in a healthy state.

The different experiments carried out are classified into two categories, depending on their use throughout the damage detection methodology. The first category is the baseline-type experiments, which is made up only of healthy experiments that will serve as a reference. The second category is the test experiments that are compared with respect to the baseline experiments, and thus test if the methodology works and is capable of helping us to classify properly when the data come from a healthy or damaged blade. Table I presents the number of experiments for each category.

Table II shows the data obtained from each experiment. The number of timestamps (198,194) determines the number of rows, and the number of columns reflects the number of sensors.

Table I. Classification of experiments.

	State	Quantity
Baseline	Healthy	4
Test	Healthy	2
	Damage 1	6
	Damage 2	6
	Damage 3	6

B. *Data Reshape*

To ensure that each sample that is processed has enough information from each sensor for posterior metrics evaluation, in this section, a feature engineering approach (data reshaping) is used. In this study, new samples are created that contain information from 8 seconds of data from the moment the hammer blow is generated. Since hammer blows are applied every ten seconds (as noted above), the remaining two seconds are removed. This is done to analyze the information from the impact to the subsequent vibration behavior that exists in the blade, without capturing information from the samples generated by the next blow of the hammer (since this process was carried out manually). Recall that the sampling rate is 1651.6 Hz. Therefore, the first 13,214 values in each column (approximately eight seconds of data) are modified by relocating them to columns in the same row. Then, the next 3,303 values (representing two seconds of information) are removed. Finally, the same process is repeated every 10 seconds after each hammer stroke, as can be seen in Figure 4. Table III shows the matrix scheme after the reshape process.

Fig. 4: Relocation of eight seconds of sample.

	0	1	2	…	…	20
13214 RELOCATED	A1	B1	C1	D1	E1	U1
	A2	B2	C2	D2	E2	U2
	…	…	…	…	…	…
	…	…	…	…	…	…
	…	…	…	…	…	…
	A13214	B13214	C13214	…	…	U13214
3303 ELIMINATED	A13215	B13215	C13215	…	…	U13215
	A13216	B13216	C13216	…	…	U13216
	…	…	…	…	…	…
	…	…	…	…	…	…
	A16517	B16517	C16517	…	…	U16517
13214 RELOCATED	A16518	B16518	C16518	…	…	U16518
	A16519	B16519	C16519	…	…	U16519
	…	…	…	…	…	…
	…	…	…	…	…	…
	…	…	…	…	…	…
	A29731	B29731	C29731	…	…	U29731
3303 ELIMINATED	A29732	B29732	C29732	…	…	U29732
	A29733	B29733	C29733	…	…	U29733
	…	…	…	…	…	…
	…	…	…	…	…	…
	…	…	…	…	…	…
	A33034	B33034	C33034	…	…	U33034
	A33035	B33035	C33035	…	…	U33035
	A33036	B33036	C33036	…	…	U33036
	…	…	…	…	…	…
	…	…	…	…	…	…
	…	…	…	…	…	…
	A198194	B198194	C198194	D198194	E198194	U198194

Table II. Data matrix scheme.

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**…**	**20**
A1	B1	C1	D1	E1	F1	G1	H1	…	U1
A2	B2	C2	D2	E2	F2	G2	H2	…	U2
…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…
A198193	B198193	C198193	D198193	E198193	F198193	G198193	H198193	…	U198193
A198194	B198194	C198194	D198194	E198194	F198194	G198194	H198194	…	U198194

Table III. Reshaped data matrix scheme.

0				**1**				**…**	**20**			
A1	A2	…	A13214	B1	B2	…	B13214	…	U1	U2	…	U13214
A16518	A16519	…	A29731	B16518	B16519	…	B29731	…	U16518	U16519	…	U29731
…	…	…	…	…	…	…	…	…	…	…	…	…
A165161	A165162	…	A178374	B165161	B165162	…	B178374	…	U165161	U165162	…	U178374
A181678	A181679	…	A194891	B181678	B181679	…	B194891	…	U181678	U181679	…	U194891

C. Metrics evaluation

Finally, a metric evaluation process is carried out to detect damage to the blade studied. This process has two stages, as indicated below.

1) Baseline metric evaluation: First, the four baseline experiments are concatenated. Then, the median of each eight-second sample is calculated for each sensor. That is, a median will be obtained for sensor 0, another for sensor 1, and so on up to sensor 20, as can be seen in the Table IV. Then, a reference healthy median is defined by averaging of the medians for each sensor, obtaining a single vector of 21 values (one for each sensor). This vector is called healthy reference vector.

Table IV. Median calculation baseline.

0	**1**	**…**	**20**
$\bar{A}_1$	$\bar{B}_1$	…	$\bar{U}_1$
$\bar{A}_2$	$\bar{B}_2$	…	$\bar{U}_2$
…	…	…	…
$\bar{A}_{11}$	$\bar{B}_{11}$	…	$\bar{U}_{11}$
$\bar{A}_{12}$	$\bar{B}_{12}$	…	$\bar{U}_{12}$

2) Test experiments: In this stage, the test experiments are not concatenated, as it is desired to evaluate each experiment separately to detect whether each of its 8-second samples belongs to a damage-causing experiment or is in a healthy state. For this reason, for each sensor in each experiment, the medians of their samples are calculated (as was done in the baseline experiments), obtaining 21 values for each sample. This vector is called the test vector. Then, the root mean squared error (RMSE) between each test vector sample and the healthy reference vector is measured. The RMSE Equation is the following.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{\gamma}_i - \gamma_i\right)^2}, \qquad (1)$$

where, $\hat{\gamma}$ is the test vector sample values, γ is the healthy reference vector values, i is the sensor number ($0 \leq i \leq 20$), and the parameter N is equal to the total number of sensors.

If the RMSE is small, it means that the sample of the test experiments has information that is quite similar to that of the baseline experiments, so the sample is classified as healthy. Otherwise, if the RMSE has a high value, it means that the sample is from a case of blade damage.

4. Results

This section presents a discussion of the results obtained by the proposed methodology.

Figure 5 shows the calculated RMSE between the healthy reference vector and each of the eight-second samples from the test experiments (for each type of damage). As can be seen, healthy samples have a much smaller error than samples with different damage, reaching a maximum value approximately equal to 0.5. However, the errors for the samples of the different damage reach values greater than 3. This means that this methodology, in a simple way, allows the detection of incipient damage in some part of the blade. This gives wind farm operators time to go check the blade to plan any maintenance.

5. Conclusions and future works

In this work, a simple damage detection strategy is proposed and tested, without much computational cost, at different locations of a WT blade. In particular, a damage detection methodology is deployed that requires only healthy data. The conceived damage detection methodology performed at an ideal level, achieving 100% accuracy. The results show that the proposed RMSE metric is promising as a simple SHM strategy to detect early blade damage at different locations.

In summary, the advantages of the proposed damage detection methodology that should be highlighted are the following.

- There is no need for historical faulty data.

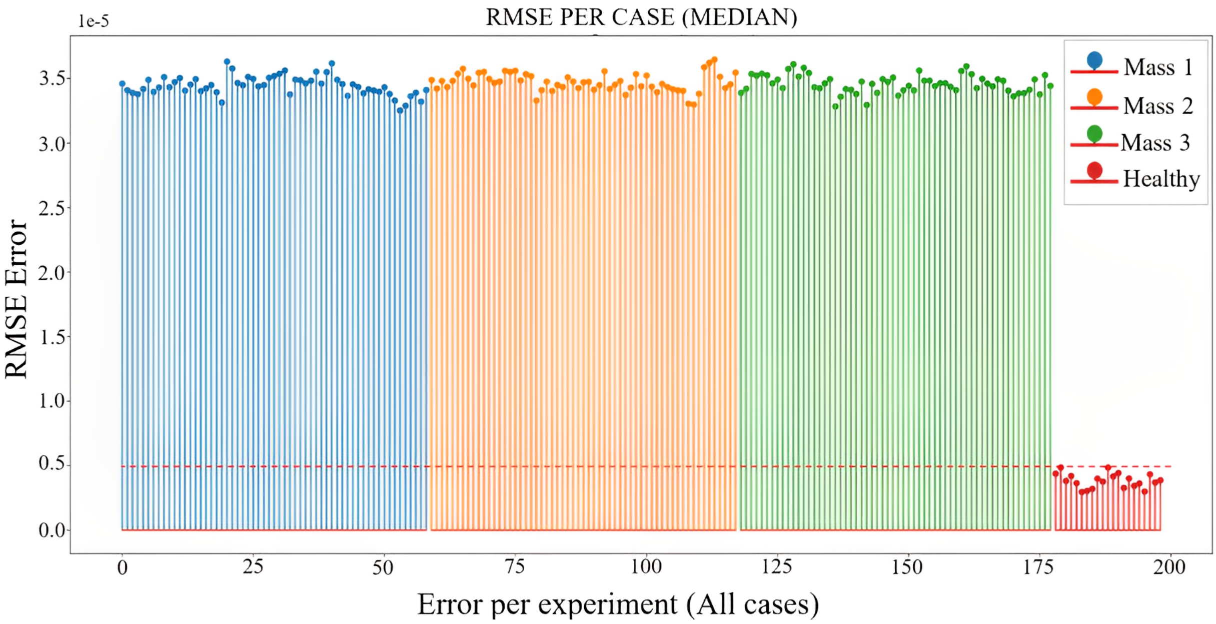

Fig. 5: Graph of RMSE metric applied per case.

- It is based only on the output vibration data gathered by the accelerometer sensors (the excitation given by the wind is assumed to be unknown). Thus, it is a vibration-response-only methodology.
- The performance indicators show a result of 100%.

However, the main disadvantage, which will be faced as an immediate future work, is that it is necessary to validate the proposed strategy in a more realistic environment that takes into account various environmental and operational conditions.

Finally, other techniques related to data analysis such as neural networks should be studied, as they have interesting properties that initially make them appropriate for the problem under consideration.

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