

Deep-Learning-based damage detection of an experimentally tested full-scale wind turbine blade.

Theodoros VAROUXIS¹, Vasilis DERTIMANIS², Imad ABDALLAH², Eleni CHATZI²,
Vikram PAKRASHI³, Abdollah MALEKJAFARIAN¹

¹ Structural Dynamics and Assessment Laboratory, School of Civil Engineering, University College Dublin, Dublin, Ireland {theodoros.varouxis@ucdconnect.ie}

² Department of Civil, Environmental and Geomatic Engineering, ETH Zurich, Zurich, Switzerland

³ UCD Centre for Mechanics, Dynamical Systems and Risk Laboratory, School of Mechanical and Materials Engineering, University College Dublin, Dublin, Ireland

Abstract. Reducing the operation and maintenance (O&M) costs of wind farms can foster adoption of environmentally sustainable and cost-effective energy sources. O&M costs in Wind Turbines can account up to 35% of the turbine's total levelized cost per KWh, with a large portion attributed to that for wind turbine blades (WTB). In the present study, an experimental campaign for fatigue damage progression monitoring is presented. After subjecting the WTB to cyclic loading, an artificial transverse crack was introduced in the trailing edge (TE). The dynamic response of the blade to three different excitation schemes - white noise, white noise with the inclusion of a fundamental sinusoidal component and a frequency sweep- is obtained via the use of accelerometers, strain gauges and a real-time deflection monitoring system. These tests yielded generated 4 different health states, the initial healthy and 3 damaged states. The progressive damage is presented using frequency response functions (FRFs), while a simple deep-learning damage detection framework is developed. A conventional autoencoder (AE) is trained using the Frequency Response Functions (FRFs) corresponding to the blade's healthy state; then, an unsupervised damage detection algorithm is formulated using the AE.

Keywords: Wind turbine blades, damage detection, fatigue damage, deep auto-encoders

1. Introduction

An estimated 700 000 wind turbine blades are in operation as of 2020 [1], with this figure increasing as politicians and governments are lobbying for further increase in total wind energy capacity. The European Union is pushing for an increase in total wind energy capacity until 2030, with the current capacity of just below 300 GW projected to exceed 500GW [2].



Thus, it is deemed of critical importance to improve the O&M procedures in place, reduce the frequency and severity of incidents necessitating structural intervention - repair or complete overhaul and replacement- and subsequently lower the levelized cost per KWh.

WTB damage mechanisms include, but are not limited to, environmental wear, manufacturing defects, lightning strikes, fatigue accumulation, leading edge (LE) erosion and TE cracks [3,4]. Mitigating this cost will result in lowering the WT levelized cost per KWh. For this, it is imperative to detect and identify damage at the earliest possible stage, leveraging the continuous monitoring of the WTB structure using sensors. The information obtained from these sensors can be used to estimate the structural state of the structure. Vibration-based methods show great potential, mainly due to their versatility and potential to identify damage sensitive features early on [5]. Such methods are based on the fundamental principle that small changes in the structure (i.e. in the form of structural damage) will result in discrepancies in the structure's vibration response. These discrepancies can be then used to detect and identify damage, or even estimate the damage severity [6].

Several studies have been conducted on full-scale testing of wind turbine blades, Farinholt et al. [7] tested two 9-meter CX-100 blades subjected to fatigue loading. One of the blades was manufactured with artificial defects, while both were monitored with accelerometers and strain gauges during the fatigue tests. Fremmelev et al. [8] presented a SHM campaign on a 52-meter WTB where multiple artificial damages were induced and their progression monitored through the application of cyclic loading. The study utilized an accelerometer network, leveraging frequency-domain-based methods and feature extraction for identifying structural damage on its onset. Chen et al. [9] investigated the progression of damage under fatigue loading, in a WTB embedded with artificial defects. Infrared thermography, digital image correlation, and acoustic emission monitoring were employed to monitor the damage progression. Ou et al. [10] provide comprehensive data on how different temperatures affect the blade's dynamics, which is valuable for validating SHM techniques. This benchmark study aims to enhance the reliability of SHM systems by providing a detailed reference for comparing different monitoring methods under realistic operational conditions.

In recent years, the application of deep learning techniques in the field of structural health monitoring of WTBs has increasingly gained prominence. Preciado-Grijalva et al. [11] presented a method to detect anomalies in WTB due to ice formation using variational recurrent autoencoders (VRAEs). Avendaño-Valencia and Chatzi [12] proposed use of a Gaussian Process Regression Vector AR (GPR-VAR) model, which forms a hierarchical Bayesian representation, for damage detection in WTBs. The proposed methodology's accuracy was 96%, showing the potential of VRAE in enhancing predictive maintenance of WTBs. Guo et al. [13] showcases the effectiveness and efficiency in damage identification of a deep convolutional neural network (CNN) compared to mature machine learning framework, like the support vector machine and VGG16. Tavares et al. [14] combines vibration-based SHM with an Anomaly Detection AE (ADAE). The ADAE is developed alongside a multivariate gaussian anomaly detection (MGAD), the first is applied on Frequency Response Functions (FRFs) and the latter on modal parameters. The ADAE was able to detect damage more accurately compared to the MGAD based method.

The novel contributions of this study can be summarized as follows:

1. Deployment of an array of accelerometers, strain gauges and a real-time deflection monitoring system allowing capturing the dynamic behaviour of a wind turbine blade during the progression of fatigue damage. This establishes the possibility of looking into fatigue from different kinematic outputs, as well as creating the possibility of sensor fusion in future.

2. Three different excitation schemes - white noise, white noise with the inclusion of a fundamental sinusoidal component and a frequency sweep - were employed during the WTB's condition monitoring.
3. The experiments provide precise control over the loading conditions enabling the simulation of damage scenarios to the blade's operational lifecycle.

Such experiments can become useful benchmarks for comparing different techniques of damage detection in the future. This includes fatigue of the inner structural part and TE crack damage- can be explored using the synergy of different excitation schemes and sensor technologies. The potential of this experimental setup is evident from the damage detection results obtained from a deep-learning based framework.

3. Experimental Setup

3.1 The Aventa AV-7 wind turbine

The physical blade is part of a full-scale WT (the Aventa AV-7 "Light Wind Turbine", sold under the Leichtwindanlagen© name – details can be found in Table 1). The blade is clamped on a sturdy wall (Figure 1). The blade is subjected to the input of an electromechanical shaker using a purpose build structure, attached to an aluminium plate. This structure consists of two aluminium parts bolted together with one of them later bolted to the shaker. The latter is bolted to an aluminium plate that's glued to the blade's surface using an industrial-grade adhesive.

Table 1. Energy generation properties and dimensions of the Aventa AV-7 wind turbine. Details and further comments can be found on [15]

Rated power	6.4 kW	Rotor diameter	12.8 m
Cut-in wind speed	1.5 m/s	Number of blades	3
Cut-out wind speed	14 m/s	Hub height	18 m



Figure 1. The blade from the Aventa AV-7 "Light Wind Turbine", that was sold and copyrighted under the Leichtwindanlagen© name, mounted on a sturdy wall in Bauhalle, ETH Zurich. Low pressure (LP) side.

The blade consists of a three-part stainless-steel geometry, a fiberglass composite outer shell and a styrofoam core between the two. The three-part steel geometry is the structural part of the blade that is comprised by two hollow cylindrical tubes followed by an elongated ellipsoid of decreasing area. The decreasing area aided by the decrease in steel thickness when transitioning from the first to the second aims at lowering the blade's mass distribution towards the tip. The fiberglass outer shell follows the design pattern of the era this blade was being developed (from the late 1990s to the early 2000s), with a small twist angle. Finally, the Styrofoam core acts as the connection between the inner structural and outer aerodynamical parts. While it prevents buckling effects to take place on the latter, that would otherwise be a frequent occurrence due to the small thickness of the fiberglass shell.

3.2 Instrumentation

The experimental setup is shown in Figure 2. A total of 7 accelerometers are mounted on the blade in a semi-dense sensor array (each sensor highlighted with a green circle) with an electromechanical shaker (TIRA© Vibration Test System TV 5220/LS-120) used to artificially excite the blade (highlighted with a red circle). A total of 10 strain gauges are mounted on the blade in a straight-line (each sensor highlighted with a yellow circle), on top of the projection of the middle-point of the internal structural part. An additional 4 strain gauges are employed in a 0^0 - 90^0 rosette close to the location of the TE crack. 10 real-time deflection monitoring points were also installed (each sensor highlighted with a purple circle). The aluminium plate that's glued to the blade's surface using an industrial-grade adhesive is also visible. Mounted on that plate is an additional accelerometer that is considered to be measuring the excitation inputted into the system. In the present work only the output of the accelerometers were considered.

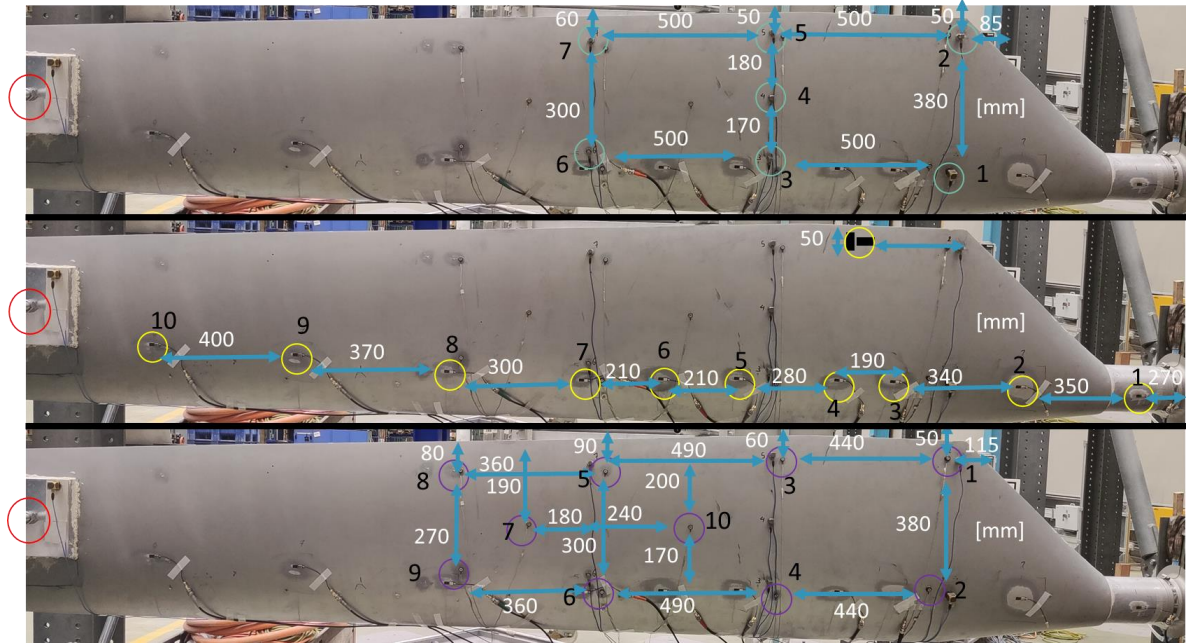


Figure 2. Location of the accelerometers on the blade (green circles) located at the Bauhalle, ETH Zurich (upper). Location of the strain gauges on the blade (yellow circles) located at the Bauhalle, ETH Zurich (middle). Location of the NDI system on the blade (purple circles) located at the Bauhalle, ETH Zurich (lower). On the left an electromechanical shaker (red circle) is mounted on the blade using a glued aluminium plate to adapt the shaker's stinger to the blade's curvature. High pressure (HP) side.

3.3 External excitation

The blade was excited using a TIRA electromechanical shaker, with two excitation scenarios in place; one for inducing fatigue damage and one for condition monitoring purposes. The former was a sinusoidal load of constant amplitude and frequency. The applied input amplitude was 36.5mm and the frequency was experimentally tested to match the 1st flapwise frequency with the addition of the electromechanical shaker and mounting geometry to the system. The mounting produced a small increase in the 1st flapwise frequency from 3.6Hz to 3.7Hz, which was the constant loading frequency. Three different excitation schemes were implemented, to select the best one to perform damage detection with. The excitations include i) Gaussian white noise (0-2KHz spectrum), ii) Gaussian white noise with the inclusion of three sinusoidal components simulating the excitation due to the rotor hub rotation, and iii) a frequency sweep from 20Hz to 2KHz. In the present work, only the white noise excitation scheme is considered. The white noise was created with MATLAB's *wgn*

command and low-pass filtered to 2KHz to comply with the electromechanical shaker's limitations.

The motivation behind the 0-2KHz spectrum lies the operational limits of the electromechanical shaker used in this study as well as the current literature on WTB damage detection. The benefit of using medium-to-high frequency ranges has shown potential in the literature [16], [17], including situations where damage was a combination of accumulated fatigue damage and artificial cracks. The sampling frequency for the accelerometers was set at 4800Hz.

3.4 The different damage scenarios

Fatigue damage was induced via a sinusoidal load of constant amplitude and frequency of 3.7Hz, matched to the 1st flapwise frequency of the wind turbine blade with the addition of the mounting geometry and as tested after mounting on the electromechanical shaker. This led to a displacement response amplitude of 26.5mm and the frequency was experimentally tested to match the 1st flapwise frequency with the addition of the electromechanical shaker and mounting geometry to the system (3.7 Hz). Before initiating the experiments, a finite element (FE) model of the internal structural part of the WTB was used to assess the stress distribution along its length. The complex internal geometry prohibits an intuitional approach to estimates of stress. The cross-sectional areas decrease in a step-wise manner in the form of discrete geometries with different thickness while in the elongated ellipsoid segment there was decreasing in an almost linear manner in the form of decreasing the dimensions of the elongated ellipsoid under the same thickness. The TE crack was placed in a critical position according to existing literature [18]. The crack length was 40mm, as shown in Figure 3. The size of the TE crack was determined by the size of the rotating tool that was available to perform the cut.

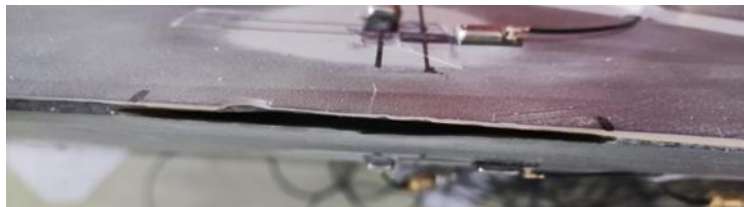


Figure 3. The 4cm TE crack, the employed strain gauges in a 0°-90° rosette are also visible.

The location of interest for both incipient damage mechanisms led to employing the sensors in the grid array (Figure 2). This also allowed to a certain extent, for the potential of investigating global and local effects caused by fatigue and TE crack damage in the extended frequency bandwidth of excitation [16]. Several damage states are considered in this regard as indicated in Table 2. Damages 1 & 2 correspond to the state after 2h and 4h of fatigue loading, respectively. This corresponds to 26,000 and 52,000 loading cycles of high amplitude at the 1st flapwise frequency (3.7 Hz), as estimated after mounting. Damage 3 corresponds to the state after 52,000 loading cycles and the TE crack.

Table 2. The acquired states with the corresponding damage.

State	# of experiments ¹	Fatigue damage (cycles)	TE crack (cm)
Healthy	68	-	-
Damage_1	68	26 000	-
Damage_2	68	52 000	-
Damage_3	68	52 000	4

¹Each experiment has a duration of 15s, resulting in a time series of 72 000 points across 7 sensors

3. The proposed damage detection framework

In this section, the details of the AE model used in this paper are explained. An AE Neural Network architecture consists of two parts, an encoder and a decoder. The encoder part aims to map the input $x \in R^d$ to a compressed latent representation $z \in R^r$, with typically $r \ll d$. The decoder part is then trained to map the latent representation back to the high dimensional space $\tilde{x} \in R^d$. The AE is then optimized to map the output back to itself, i.e. $\|\tilde{x} - x\| \cong 0$ [19]. Generally, AE architectures are used to create a parsimonious representation of a physical process. Another interesting application of AE is damage detection. By training the AE to map a high-dimensional input $x_o \in R^d$ from the initial state of the structure, denoted “healthy” you can use the network to check whether an input from an unknown state $x_u \in R^d$ pertains to the presence of damage or not.

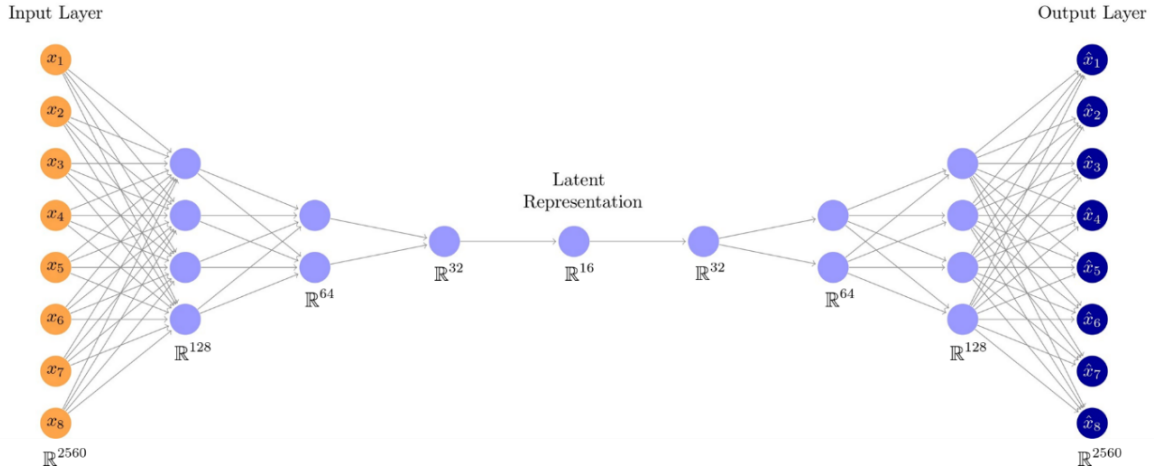


Figure 4. Schematic representation of the proposed undercomplete AE. The encoder and decoder parts both consist of 3 hidden layers of decreasing width 128-64-32. The Latent Representation (bottleneck layer) layer consists of 16 units.

The damage detection framework is formulated via use of the RMSE between an input y and the reconstructed from the AE output is calculated for the validation set using:

$$RMSE(y, \tilde{y}) = \sqrt{\frac{\sum_{i=0}^{N-1} (y_i - \tilde{y}_i)^2}{N}} \quad (\text{Eq. 1})$$

Given the maximum RMSE for the validation set, denoted as T and the calculated RMSE for an input corresponding to an unknown state x_u and the corresponding reconstructed output $\tilde{x}_u$ the two following possibilities are considered:

$$\begin{aligned} RMSE(x_u, \tilde{x}_u) \leq T &\rightarrow x_u \text{ corresponds to the healthy state} \\ RMSE(x_u, \tilde{x}_u) > T &\rightarrow x_u \text{ corresponds to the damaged state} \end{aligned}$$

A deep AE network is trained to map an FRF to a low-dimensional space and then back to itself. The capacity of the AE was chosen focusing on reducing the likelihood of overfitting.

A schematic representation of the AE can be found in Figure 4, while a detailed explanation of the layers and architecture parameters in Table 3. Finally, to enhance the performance of the autoencoder (AE), two intermediate batch-normalization layers were added.

Table 3. Proposed AE network architecture breakdown and parameters

Module	Layer Name	Width	Activation
Encoder	Input Layer	2560	-
	Encoder Hidden Layer #1	128	ReLU ¹
	Encoder Hidden Layer #2	64	ReLU ¹
	Encoder Hidden Layer #3	32	ReLU ¹
	Bottleneck Layer	16	ReLU ¹
Decoder	Decoder Hidden Layer #1	32	ReLU ¹
	Decoder Hidden Layer #2	64	ReLU ¹
	Decoder Hidden Layer #3	128	ReLU ¹
	Output Layer	2560	-

¹ReLU refers to the rectified linear unit function.

4. Results and Discussion

The mean values were subtracted from each of the corresponding 68 individual time series for each health states of the structure along with responses from each accelerometer. Subsequently, FRF estimates were calculated using MATLAB's *modalfreq* function for each of the individual time series (Figure 5, Welch's method, segment length 8192 and 90% overlap [20]). The segment that appears to be most sensitive to fatigue damage is the medium-to-high frequencies [250-1250]Hz (Figure 5).

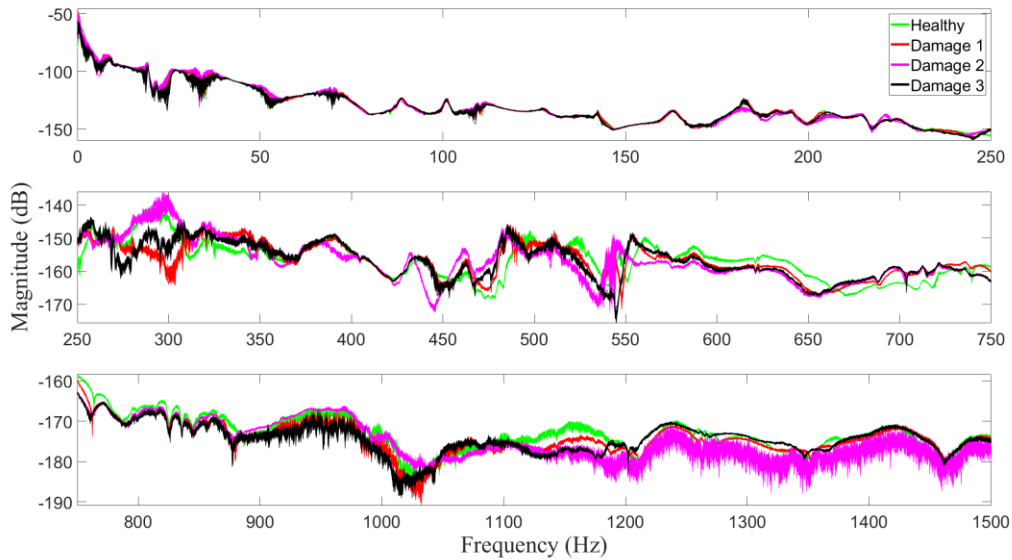


Figure 5. FRF estimates for the healthy and damage 1-3 states based on Welch's method. The frequency ranges 0Hz – 250Hz (upper), 250Hz-750Hz Frequency range (middle) and 750Hz-1500 Hz Frequency range (lower) are considered in this figure.

Two further steps were made for the AE training:

1. The average of the FRFs across all accelerometers was used to train, validate and use the AE in a damage detection framework. This allowed for lower-dimensional input to the AE with 2560 points compared to 17920 points, thereby greatly reducing the size of the AE and improving overfitting issues.

2. To improve training accuracy and speed, the input was scaled from 0 to 1 with the corresponding minimum and maximum values. The FRFs used to train the AE included the points corresponding to the 0Hz to 1500Hz spectrum.

This second step greatly improved training accuracy issues with the AE, and allowed for a simpler network along with a low-dimensional latent representation. The Adam optimizer [21] was used, with the learning rate reduced from 0.01 by 10% every 50 epochs for a total of 400 epochs. For the training of the AE, 50 of the 68 available Healthy FRFs were used, reserving the rest for a validation set [22].

The damage detection was carried out by setting a user defined threshold T to be equal to the maximum RMSE of the validation set (Figure 6 the user define threshold is visualized with a red line). Then the RMSE between the reconstructed and original FRFs were calculated for the 3 damage states. Fatigue damage detection is effective, as the Damage Indicator (DI) for all damage states are greater than the threshold T . The DI for the damaged states is four times higher than the corresponding for the healthy states.

The RMSE between FRFs corresponding to the same state follows a similar trend and increases between states of increasing damage severity for the two states corresponding to fatigue damage. Consequently, this approach allows for damage identification between the two states. On the other hand, for the state with the inclusion of the TE crack, the DI decreases and this can be attributed to the proposed AE being a “black-box model” [23]. The FRF corresponding to the Damage_2 state (Figure 5) has increased magnitude variation, when compared to the other states. Having trained the AE to map a “smoother” FRF, this can result in the DI being greater than the one corresponding to Damage 3.

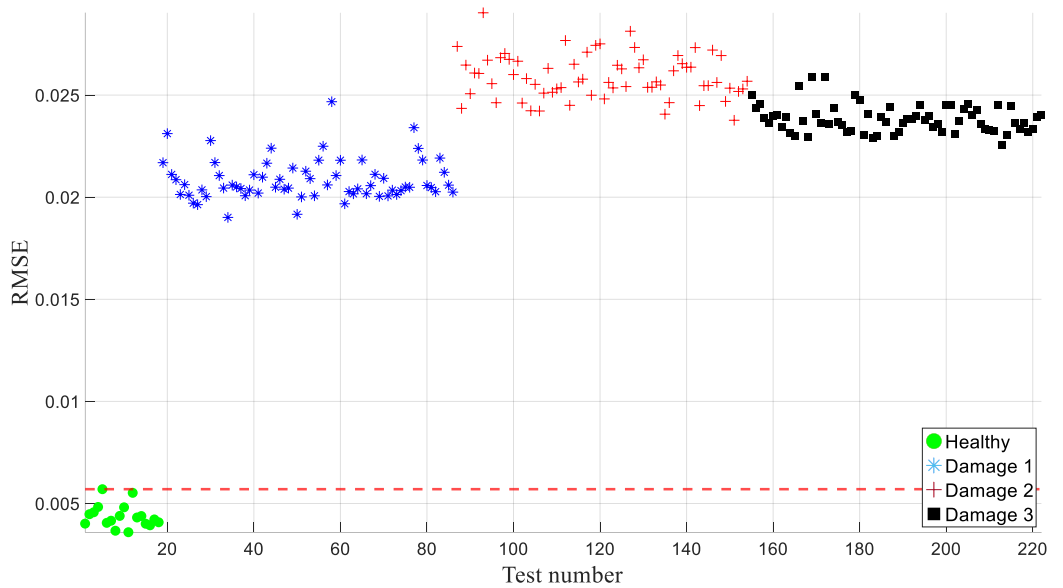


Figure 6. RMSE between original and reconstructed FRFs. The RMSE acts as a DI for performing damage detection. The red line is indicative of the user defined threshold.

5. Concluding remarks

This work presents an experimental campaign focusing the fatigue damage progression on a full-scale wind turbine blade. A detailed instrumentation is followed with white noise excitation of the structure. Subsequently, responses to different damage scenarios are explored by considering the responses obtained in the range of sensors deployed in this structure. The experimental campaign is expected to be and serve as a test benchmark in

future. An autoencoder (AE) based damage detection approach is proposed in this paper. The tests indicate that the damage indicator (DI) in this AE based damage detection approach is about four times greater in the damaged states as compared to the healthy state. A shortcoming of the AE model is also highlighted, where mixed damage scenarios do not necessarily lead to a monotonically increasing DI, which can be due to inadequate training of AE. Future investigations will expand this AE based approach for more complex scenarios.

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