Automated Operational Modal Analysis for the Monitoring of a Wind Turbine Blade

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ABSTRACT

Modal analysis has developed into a major technology for the study of structural dynamics in the past several decades. Through it, complex structural dynamics phenomena can be represented in terms of structural invariants, i.e., the modal parameters: natural frequencies, damping ratios and mode shapes. Operational Modal Analysis (OMA) deals with the estimation of modal parameters on vibration data measured for operational conditions, when the excitation on the structure is not measured. In this work, OMA is performed on a wind turbine blade undergoing wind tunnel testing. These tests included different wind speeds, pitch angles and also different health conditions of the blade, where masses of different magnitude were fixed to the blade on different locations to emulate damage conditions. In order to monitor the modal parameters across multiple days of varied tests in the wind tunnel, the Polymax modal parameter estimator was implemented, coupled with an Automated Modal Analysis methodology. This methodology included an automatic modal parameter selection technique, using a Machine Learning (ML) clustering algorithm, coupled with a modal tracking procedure which applied statistical thresholds on the modal parameters' values. The tracking procedure searches for modes similar to the ones calculated for healthy conditions. The results show how the modal parameters of the wind turbine blade vary with the different measured conditions in the wind tunnel. Moreover, a damage detection methodology is implemented to differentiate between the healthy and damaged conditions on the blade, by leveraging an anomaly detection algorithm using the Multivariate Gaussian Distribution (MGD). This algorithm takes as input the modal parameters calculated by the previous Automated Modal Analysis methodology and detects statistical deviations among them which could indicate the presence of damage. All steps of this work contribute to developing an automatic framework able to detect damages on a wind turbine blade, and therefore perform Structural Health Monitoring (SHM) for different operational conditions.

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INTRODUCTION

At present, wind power is an increasingly significant contributor to energy production across many countries and is regarded as one of the most attractive sources of renewable energy. According to recent data, in 2021, the installation of 17.4GW of new wind power capacity in Europe led to wind farms generating 437 TWh of electricity, which met 15% of the electricity demand in the EU-27 and UK [1]. It is expected that by the mid-2020s, wind power will become the top source of electricity in Europe, and by 2030, it is projected to meet 25% of the EU's total electricity requirements [2]. To ensure that wind turbines (WTs) generate optimal energy output, advanced Structural Health Monitoring (SHM) techniques are of paramount importance. Such techniques enable swift detection of damage, enabling timely maintenance and repair operations that prevent expensive damages. Blade malfunction is the fifth most common cause of WT failures, accounting for approximately 6.2% of all WT malfunctions [3].

The term Structural Health Monitoring (SHM) broadly refers to a dependable system that can identify and evaluate any adverse changes in a structure that may occur during regular operation or as a result of damage [4]. Typically, SHM methodologies are developed around the study of the dynamic vibrational behavior of a structure. Modal analysis is an approach that uses a set of modal parameters (such as natural frequencies, damping ratios, and mode shapes) to describe the dynamic behavior of a structure. These parameters are sensitive to damage, making modal analysis a popular technique for the development of SHM methodologies. For instance, deviations in natural frequencies and mode shapes have been used to detect damage in wind turbine blades [5–7]. In order to apply an Automated Modal Analysis methodology, three essential steps are required: modal parameter estimation (MPE), automated modal parameter selection (AMPS), and modal tracking [6, 7].

In addition, Structural Health Monitoring (SHM) techniques have also incorporated Machine Learning (ML) algorithms, taking advantage of their advanced computational capabilities and automatic frameworks. ML algorithms can extract features from data and classify them for defect detection purposes. For instance, Support Vector Machines (SVMs) have been successfully employed to identify structural damage in jacket-type wind turbines in [8]. In [9], SVMs and other algorithms have been used for detecting icing on blades, a common issue arising from operational conditions. These approaches have emerged as promising avenues of research for SHM applications in a variety of fields [10, 11].

In this study, a wind tunnel measurement campaign was conducted to analyze the vibration behavior of a composite wind turbine blade subject to wind excitation under both healthy and damaged conditions (damage was simulated by adding masses to the structure). Both accelerometers and strain gauges were installed in the blade to record these measurements. Subsequently, an Automated Modal Analysis methodology was employed to automatically calculate and track the modal parameters for the numerous measurements taken in the wind tunnel. The natural frequencies, one of the modal parameters, were then used as input to an anomaly detection algorithm that leverages the Multivariate Gaussian Distribution.

This paper is structured as follows. The 'Theoretical Background' section introduces the Multivariate Gaussian Distribution (MGD) for anomaly detection. The 'Wind Tunnel Measurements' section describes the experimental setup and the Automated Modal Analysis results. The 'Anomaly Detection' section presents the algorithms used to monitor the health status of the wind turbine blade. Finally, the main conclusions are summarized in the 'Conclusion' section.

THEORETICAL BACKGROUND

Anomaly Detection with the Multivariate Gaussian Distribution

Anomaly detection machine learning algorithms are frequently utilized when datasets contain an unequal distribution of examples among each category. This situation often arises in structural monitoring applications, where the majority of the data is recorded for the structure's healthy state. Attempting to train supervised learning algorithms on such an imbalanced dataset may cause the algorithm to become biased towards the dominant category.

In scenarios where datasets have an imbalanced number of examples between each class, the Multivariate Gaussian Distribution (MGD) can be effectively implemented in an anomaly detection algorithm. This approach involves fitting a MDG to the features of the dataset, denoted as x, using equation 1. By using this method, the algorithm can effectively model the distribution of the data and identify anomalies based on deviations from the expected pattern.

$$p(x, \mu, \Sigma) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} exp(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)) \tag{1}$$

where $\mu = \frac{1}{m}\sum_{i=1}^{m} x(i)$ and represents the vector of the mean values of the features ($\mu \in \mathbb{R}^n$); $\Sigma = \frac{1}{m}\sum_{i=1}^{m}(x(i)-\mu)(x(i)-\mu)^T$, representing the feature's covariance matrix ($\Sigma \in \mathbb{R}^{n\times n}$).

Next, a procedure for automatic threshold selection is applied to learn a threshold value ϵ capable of distinguishing between training examples representing anomalies ($p(x) < \epsilon$) and those representing healthy values of the structure ($p(x) \geq \epsilon$). The performance and working principles of this anomaly detection algorithm on a two-dimensional dataset are shown in Figure 1. The majority of the data is clustered near the center of the distribution, while anomalous data examples lie far from the center and are identified as anomalies (points encircled in red).

WIND TUNNEL MEASUREMENT CAMPAIGN

In this study, a measurement campaign was conducted in a wind tunnel to investigate the behavior of a glass-fiber reinforced polymer (GFRP) blade under wind excitation. Accelerometers and strain gauges were utilized to respectively obtain acceleration and strain measurements during the experimental campaign. Figure 2 depicts the blade mounted in the wind tunnel and the measurement setup.

Figure 3 displays the GFRP blade studied in this work, which was manufactured using uniaxial and biaxial GFRP shells, balsa core, and glue. This blade has a total mass of

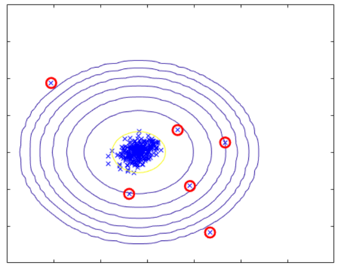


Figure 1. Working principle of anomaly detection using the Multivariate Gaussian Distribution (MGD). Anomalous data will diverge from the bulk of the data fitted by a MGD.

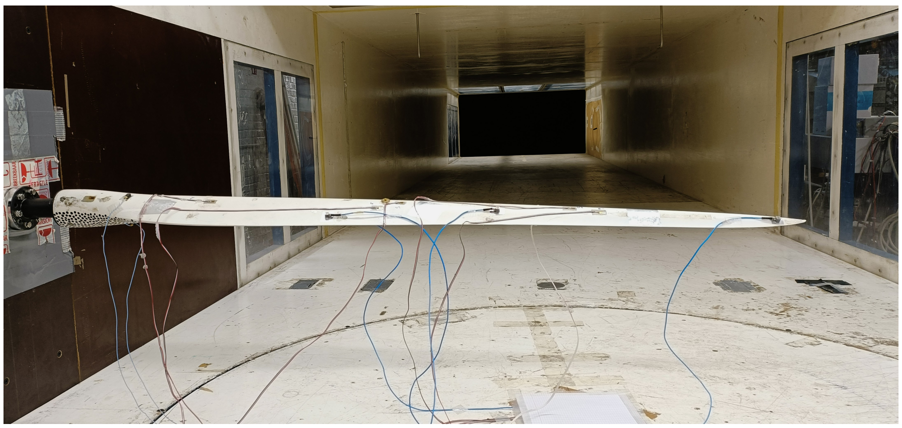


Figure 2. Wind tunnel measurements on the wind turbine blade.

0.720 kg. Additionally, this image also shows the placement of the sensors (accelerometers and strain gauges) on the blade, which were overall distributed on different sections of the blade, going from the root to the tip. The damages were similarly placed in the three depicted locations, close to the root, in the middle, and close to the tip of the blade. These different damage locations were chosen to assess the influence of damage location on the ability of an anomaly detection algorithm to detect structural damage. Figure 4 shows the four different metallic masses which were glued to the blade on the previously mentioned locations, so to simulate damaged states.

Other than the damage location and magnitude, also the wind speed of the tunnel and the pitch angle of the blade were varied. Table I summarizes all the quantities used for each parameter varied in this experimental campaign. The damage location are measured across the length of the blade (root of the blade at 0.000m; tip of the blade at 1.230m). Overall, a total of 307 measurements were collected, 91 for healthy scenarios and 216 for damaged scenarios.

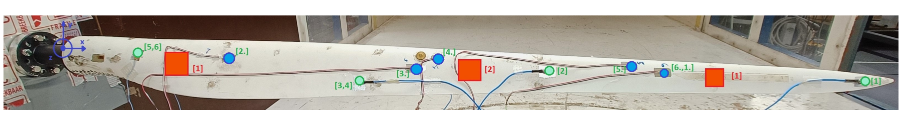


Figure 3. GFRP wind turbine blade with the displayed locations for the: accelerometers (green); strain gauges (blue); damages (red).

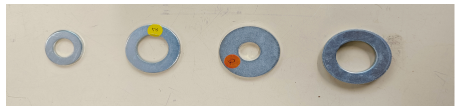


Figure 4. Masses used to simulate damaged states on the wind turbine blade.

TABLE I. VARIED QUANTITIES ON THE MEASUREMENT CAMPAIGN.

Varied quantities on the measurement campaign			
wind speeds (m/s)	**pitch angles (deg)**	**damage locations (m)**	**damage magnitudes (g)**
14.2	15	0.191	7.8
16.2	25	0.655	14.8
18.2	35	1.041	21.8
-	-	-	29.1

AUTOMATED OPERATIONAL MODAL ANALYSIS

The data collected for all the measurements was automatically processed using an Automated Operational Modal Analysis procedure, which comprised three steps: modal parameter estimation; automated modal parameter selection; modal tracking (as shown in figure 5). The former step was performed with the Operational Polymax technique [12], in the Siemens Simcenter Testlab™ software. The step of automatic modal parameter selection was performed with an in-house developed technique, making use of the DBSCAN (density-based spatial clustering of applications with noise) clustering technique. The latter step was performed by applying statistical thresholds to track the modes across multiple measurements, using nine different modesets calculated for healthy conditions of the blade as reference. Considering the statistical thresholds used to correlate a certain mode i with a reference mode ref, 10% was used for the distance of frequency (f), and 40% for the distance of Modal Assurance Criterion (MAC), calculated between two respective mode shapes (ϕ).

$$d_{freq} = \frac{|f_{ref} - f_i|}{f_{ref}} \tag{2}$$

$$d_{MAC} = 1 - \frac{|\phi_{ref}\phi_i|^2}{(\phi_{ref}\phi_{ref})(\phi_i\phi_i)} \tag{3}$$

The Operational Modal Analysis (OMA) results for the structure are presented in Table II. While a total of 9 modes were initially identified, a lower number of modes were

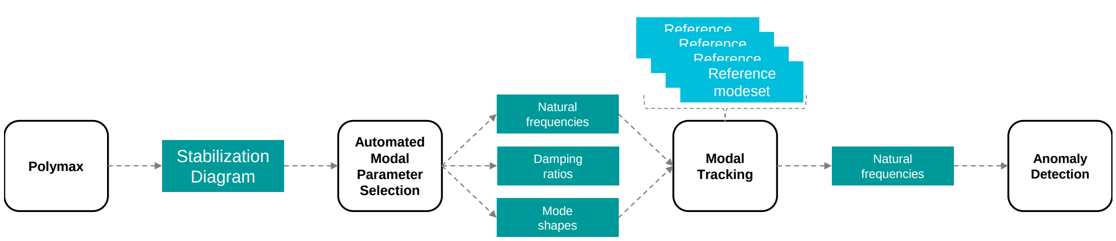
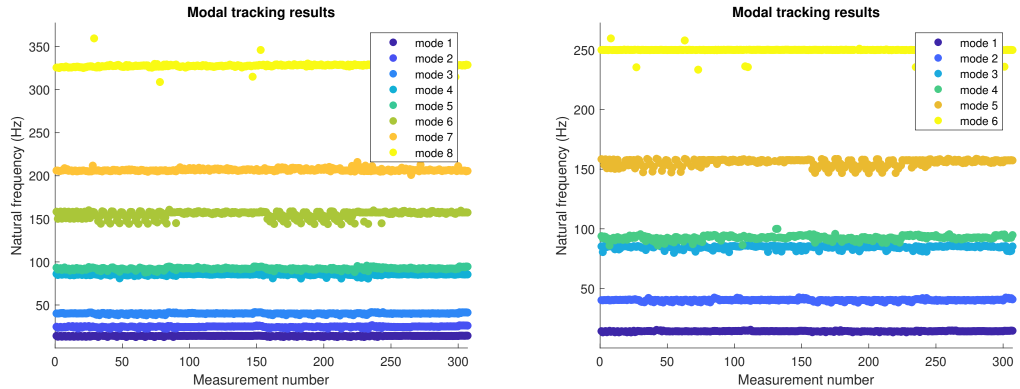


Figure 5. Automated Operational Modal Analysis procedure.



(a) Acceleration modes

(b) Strain modes

Figure 6. Frequencies tracked through the Automated Modal Analysis procedure, for the data of the: a) accelerometers b) strain gauges.

ultimately selected for tracking purposes, as some modes were difficult to identify in the stabilization diagram as they were poorly excited by the wind. For the accelerometers, all but the eight mode (a poorly excited torsional mode) were tracked. For the strain gauges, all but the second, seventh, and ninth modes were tracked. The second and seventh modes were not tracked due to being in-plane bending modes that were difficult to identify on the stabilization diagram, while the signal-to-noise ratio of the strain gauges for the ninth mode was too high.

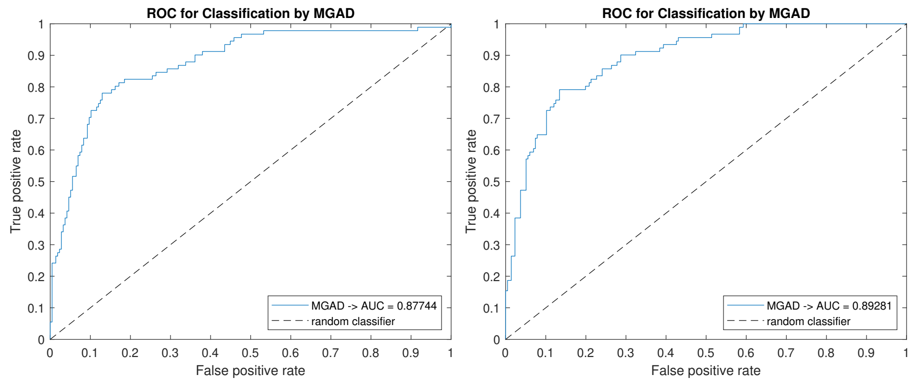
TABLE II. NATURAL FREQUENCIES AND DAMPING RATIOS IDENTIFIED FOR THE WIND TURBINE BLADE

mode number	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
natural frequency (Hz)	14.1	25.0	40.2	85.7	98.5	158.1	206.1	247.9	328.5
damping ratio (%)	4.7	1.8	3.2	1.7	2.1	1.8	1.2	2.0	0.9

The results of modal tracking are shown in the figures 6 respectively for the acceleration and strain data. For acceleration data, the eight modes mentioned in the previous paragraph can be distinguished with the different colors, as for the six modes tracked with strain data. As expected, there is some variance across the natural frequencies due to the inclusion of measurements with damaged scenarios of the blade. This can be seen as section of divergent natural frequencies amongst the tracking results shown in the figures 6.

ANOMALY DETECTION

To develop a Structural Health Monitoring (SHM) methodology for detecting damage states on wind turbine blades subject to wind excitation, the Multivariate Gaussian Distribution was applied in an anomaly detection algorithm, as explained in the theoretical section. The input of this algorithm were the natural frequencies tracked with the automated modal analysis methodology, shown in figures 6a and 6a. The healthy dataset was divided into a training set containing 70% of the data, a validation set containing



(a) Acceleration data (b) Strain data

Figure 7. Receiver Operating Characteristic (ROC) curve obtained with the Anomaly Detection algorithm for the data of the: a) accelerometers b) strain gauges

15% of the remaining healthy data along with an equal number of damaged samples, and a test set containing the remaining data. The Multivariate Gaussian Distribution was fitted to the healthy training data, and the validation dataset was used to automatically determine the threshold for separating anomalies. Alternatively, this step could be performed by applying a threshold calculated based on a certain number of standard deviations from the healthy data, without a validation dataset.

Figures 7a and 7b show the Receiver Operating Characteristic (ROC) curves obtained with the anomaly detection algorithm applied both to the acceleration and strain data. Additionally, the Area Under Curve (AUC) obtained for both classifications is shown in these figures. The AUC represents a collective measure of the performance obtained with this technique across all possible thresholds used for classification. The overall results are presented in table III, indicating that although fewer strain modes were tracked compared to acceleration modes, the use of strain data led to higher accuracy in anomaly detection.

TABLE III. RESULTS OF THE ANOMALY DETECTION ALGORITHM

	Accelerometers	**Strain gauges**
Area Under Curve (%)	86.11	87.75
Validation Accuracy (%)	76.9	87.5
Test Accuracy (%)	75.5	84.7

CONCLUDING REMARKS

In summary, a robust Structural Health Monitoring (SHM) methodology was successfully developed for detecting damages on a wind turbine blade using operational data obtained from its vibration under wind excitation. This methodology involved an Automated Operational Modal Analysis step, followed by an anomaly detection algorithm utilizing the Multivariate Gaussian Distribution (MGD). Both acceleration and strain data were processed, resulting in high detection accuracy, with slightly better performance achieved by using strain data. Future work will focus on examining the impact of using a reduced number of sensors on the detection accuracy of blade anomalies.

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