Fault diagnosis of wind turbine gearboxes through on-site measurements and vibrational signal processing

FAULT DIAGNOSIS OF WIND TURBINE GEARBOXES THROUGH ON-SITE MEASUREMENTS AND VIBRATIONAL SIGNAL PROCESSING

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ABSTRACT

Condition monitoring of wind turbine gearboxes has attracted an impressive amount of attention in the wind energy literature. This happens for practical issues, as gearbox damages account for at least the 20% of wind turbines operational unavailability, and for scientific issues as well, because the condition monitoring of gear-based mechanical systems undergoing non-stationary operation is particularly challenging. The present work is devoted to the diagnosis of gearbox damages through a novel approach, designed exclusively for this study, based on on-site measurements and data post-processing. The main point of this method is the relatively easy repeatability, also for wind turbine practitioners, and its low impact on wind turbine operation: actually, the measuring site is not the gearbox itself, but the tower, further from the gearbox but in an easily accessible place. A real test case has been considered: a multi mega-watt wind turbine sited in Italy and owned by the Renvico company. The vibration measurements at the wind turbine suspected to be damaged and at a reference wind turbine are processed through a multivariate Novelty Detection algorithm in the feature space. The application of this algorithm is justified by univariate statistical tests on the time-domain features selected and by a visual inspection of the dataset via Principal Component Analysis. Finally, the novelty indices based on such time-domain features, computed from the accelerometric signals acquired inside the turbine tower, prove to be suitable to highlight a damaged condition in the wind-turbine gearbox, which can be then successfully monitored.

KEYWORDS: wind turbine; gearbox diagnostics; vibration monitoring; time-domain features; ANOVA; PCA; Novelty Detection; Mahalanobis Distance;

1. INTRODUCTION

Gearbox failures account for at least the 20% of total wind turbines downtime [1] and their study has therefore attracted an impressive amount of scientific literature, addressing the criticality of fault diagnosis at the different gearbox sub-components.

The range of wind turbine gearbox fault diagnosis approaches is wide [2] and it diversifies according to this rule of thumb: the more complex the method, the earlier the diagnosis. Wind turbine practitioners often base their evaluation of approaching damages basing on oil particle counting, because of its intuitiveness. Nevertheless, this approach is considered to provide a late fault diagnosis and, for this reason, the use of Supervisory Control And Data Acquisition (SCADA) has been vastly spreading in the wind energy industry in the latest years. The drawback of SCADA-based fault diagnosis is that it is complicated enough that it hasn't reached industrial standards and it is not powerful enough to assure that all the main incoming faults can be detected in time. As a support to this argument, consider that the test case discussed in the present work (a severe gearbox damage on a multi-megawatt wind turbine) has been monitored through the analysis of SCADA wind turbine internal temperature data according to the methods of [3] and it hasn't been diagnosed.

This motivates the growing diffusion of proper condition monitoring techniques for wind turbine gearboxes and bearings. The fact that wind turbine undergo non-stationary operation conditions makes it non-trivial to reliably extract the features of the measured vibration signals and detect incoming faults. In the following, a short review is reported of some meaningful contribution in the recent literature about this subject.

In [4], a Suzlon S88 wind turbine, equipped for measuring vibration signals originating from a damaged bearing inner race, is studied: the proposed diagnosis method is the signal intensity estimator technique and it is argued that this method is capable in detecting and locating crack initiation and propagation in bearings. In [5], a Repower M92 (2.05 MW of rated power) with a Winergy PEAB 4481.0 gearbox is studied. A damage on the bearing outer race, installed on the high-speed shaft, is diagnosed using spectral kurtosis and signal intensity estimator techniques. In [6], a study is conducted on experimental data provided by the National Renewable Energy Laboratory (NREL). Bearing condition monitoring techniques are proposed: in particular, the objective is to separate in the spectrum bearing and gears-shaft contributions. The cepstral editing procedure is employed for this task. In [7], the technique of empirical mode decomposition (EMD) for wind turbine condition monitoring is addressed in its potentiality and criticality: an enhanced EMD is proposed for overcoming the difficulty in segmenting properly the frequency content of the signals. In [8], the health of wind turbine bearings is studied by decomposing the vibration signals in subcomponents and a safety coefficient is formulated basing on the assessment of the Renyi entropy. In [9], a study of fault diagnosis on the drive train of a 1.5 MW is conducted by jointly employing vibration and current signature analysis.

The work of [10] is devoted to the use of vibration data for detecting wind turbine gear damage at the planetary stage of the gearbox: the main issue with the study of the planetary stage is that it has low rotational speed (10-20 revolutions per minute if the wind turbine is multi-megawatt), but the wind speed and loads continuously change. Common time-domain statistical indicators (skewness, kurtosis, crest factor and so on) are shown to be not definitely appropriate for this kind of study and it is supported that the time-synchronous averaging technique is effective for the objective. In [11], the order analysis technique is studied for condition monitoring of the planetary stage of wind turbine gearboxes: the main idea is that angular resampling produces ciclostationary signals, diminishing the effects of wind turbine speed changes.

The work of [12] is devoted as well to condition monitoring of planet bearings and planet carrier bearings. A three-level residual analysis technique is employed: it is based on signal angular resampling based on a shaft related to the planetary stage, identification of the expected spectral signature of the gearbox under investigation and, finally, filtering of expected spectral components not related to the planetary stage operation. In [13], the peak and RMS values of vibration signals are employed for wind turbine gearbox fault diagnosis. Three approaches (signal correlation, extreme vibration, RMS intensity models) are presented and their pros and cons for studying different kind of faults are discussed.

From the above review of the literature and to the best of the authors' knowledge, it arises that wind turbine gearbox condition monitoring techniques are based on the analysis (in the time or frequency domain) of vibration signals acquired directly at the sub-components of interest. For this reason, the installation of gearbox condition monitoring systems has been developing in the latest years in the wind energy industry, despite their potentiality often is not exploited in full. However, a considerable amount of wind turbines nowadays is still not equipped with gearbox condition monitoring systems because possibly the cost-benefit balance has not been considered advantageous or simply because they are not recent installations.

It is therefore interesting to study gearbox fault diagnosis techniques impacting as little as possible on the operation of wind turbines and this is precisely one of the motivations of the present work. This study is devoted to the test case of a multi-megawatt wind turbine sited in Italy, owned by Renvico (a company managing around 340 MW of wind turbines in Italy and France [1]). This wind turbine is not equipped with gearbox condition monitoring systems and it has been diagnosed of a severe gearbox damage through the analysis of oil particle counting. Before the gearbox replacement intervention, a measurement campaign has been conducted by the University of Perugia. The idea is measuring vibrations at the tower: on a practical level, this can be relatively easy also for wind turbine practitioners and it doesn't require the shutdown of the wind turbine. The measurements are collected simultaneously on the target damaged wind turbine and on one (or more) reference undamaged wind turbines. Subsequently, the data are processed through a multivariate Novelty Detection algorithm in the feature space. The application of this algorithm is supported by statistical analysis on the time-domain features selected and by a visual inspection of the dataset via Principal Component Analysis. Finally, the novelty indices based on such time-domain features prove to be suitable to diagnose a damaged condition in the wind turbine gearbox.

The innovativeness of the present work therefore is as well in the measurement techniques and in the data-processing methods. The structure of the manuscript is consequently the following: in Section 2, the test case and the on-site measurements are described. In Section 3, the data set is described. Section 4 is devoted to the feature

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extraction from the data. Results are collected and discussed in Section 5. Conclusions and further directions are indicated in Section 6.

2. THE ON-SITE MEASUREMENTS

Six multi-megawatt wind turbines are installed on site. A picture of the wind farm is reported in Figure 1 and a layout is displayed in Figure 2.

Figure 1: A picture of the wind farm.

The point with these wind turbines (and, besides, the motivations of this work) is that one of them is suspected of a gearbox damage detected through oil particle counting, but they are not equipped with gearbox condition monitoring systems measuring vibrations at the gearbox itself.
This has therefore been considered an ideal testing ground for an experimental fault diagnosis method that could be repeatable by wind farm practitioners without stopping the wind turbine, without acting on the gearbox and therefore without losing vast quantities of producible energy.
The on-site measurements are conducted as follows: accelerometers are mounted inside the tower of the wind turbine. They measure the longitudinal (x-axis) and transversal (y-axis) vibrations, as displayed in Figure 3. An overall set of four accelerometers (respectively two on the superior level 7 m above ground and two at the inferior level 2 m above ground) and a microphone (on the inferior level) were used for the acquisition.

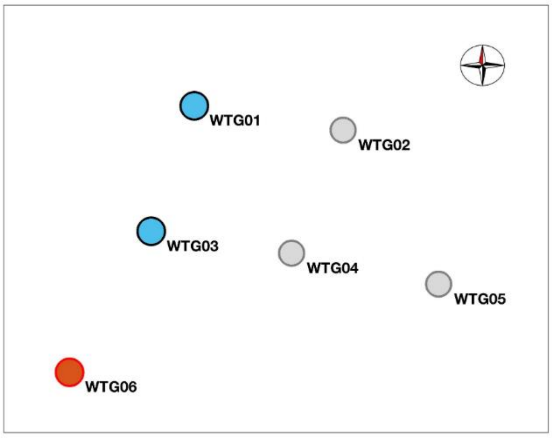

Figure 2: The layout of the wind farm (in red the damaged turbine and in light blue the reference undamaged turbines).

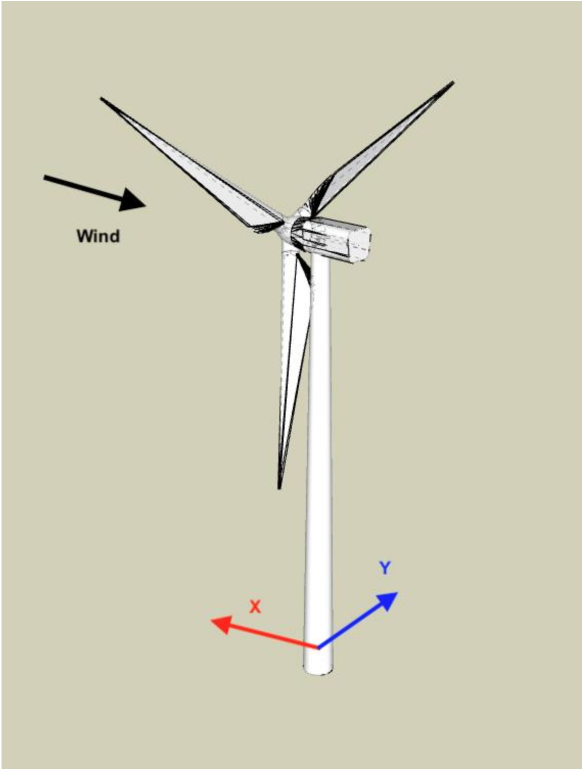

Figure 3: Definition of the reference frame for the longitudinal and the transversal directions.

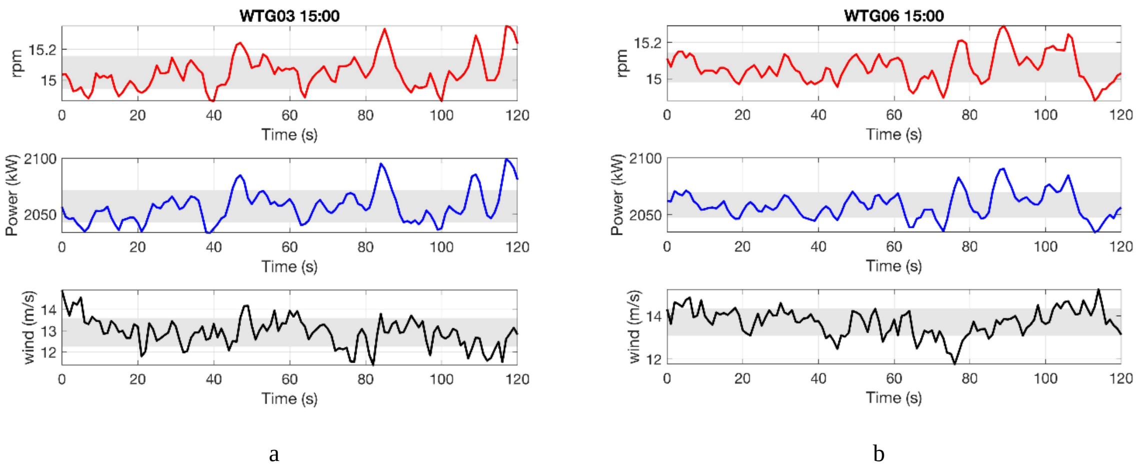

Figure 4: Measurement of the most important parameters during the vibration measurement for WTG03 (a) and WTG06 (b). The grey bar is the average value ± the standard deviation).

Operational data have been provided by the wind turbine manufacturer in real time during the measurement campaign, with a sampling time of the order of the second. These have been used to assess the similarity of the wind conditions at different wind turbines at the same time as displayed in Figure 4.
The philosophy of the method, actually, is the simultaneous measurement of tower accelerations on the wind turbine suspected to be damaged and on one (or more) nearby reference undamaged wind turbine.
Time series have been acquired after having crosschecked, through the time-resolved data, that the target and reference wind turbines were undergoing reasonably similar wind conditions and were working with reasonably similar operating parameters. During the experimental campaign all the turbines were operating at rated power.

3. THE DATASET

Finally, the analysed dataset is composed of a total of 4 acquisitions on three different turbines, at two different time instants. This dataset is anyway divided in 2 subsets, as dictated by pattern recognition problems practice, to produce a training set and a second independent set, essential to validate the procedure. In this case the acquisitions on the healthy turbines WTG01 and WTG03 at 17.20 were used as a reference to calibrate the algorithm on a healthy condition, while the acquisitions on the turbine WTG03 (the same, healthy one) and on the possibly damaged turbine WTG06 at 15.00 were kept for validation, as summarized in Table 1.

Table 1: The dataset

1	`WTG01 @ 17.20`	HEALTHY	Reference → Calibration: Training
2	`WTG03 @ 17.20`		
3	`WTG03 @ 15.00`		Validation
4	`WTG06 @ 15.00`	DAMAGED	

Each acquisition consists of 5 channels sampled at 12.8 kHz for 2 minutes:

- 4 are meant to record accelerations at 2 levels (*inferior* and *superior*) in 2 directions (*X* almost parallel to the wind direction and *Y* orthogonal to *X*)
- 1 recording from a microphone (at *inferior* level).

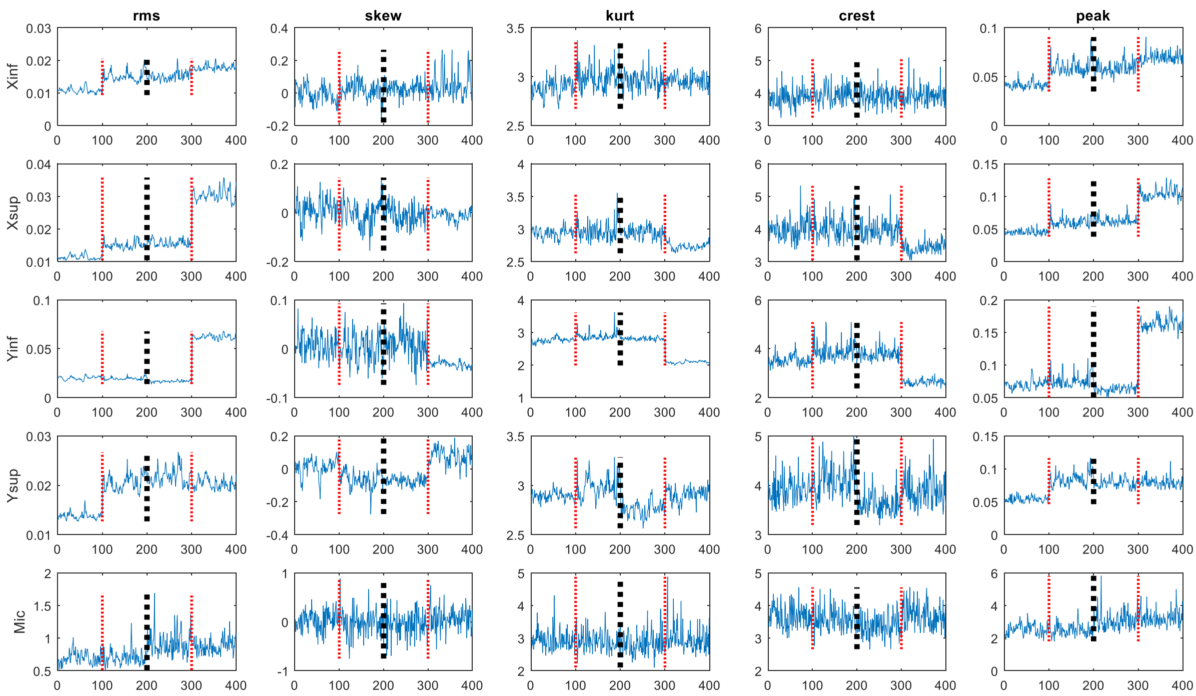

Figure 5: The extracted features
The samples 0-100 are referred to the machine WTG01 at time 17.20, 101-200 to WTG03 at 17.20, 201-300 to WTG03 at 15.00 and samples 301-400 are from WTG06 (the damaged wind turbine) at 15.00. The first 2 sets are used for calibration and are separated from the last 2, left for validation, by the black dotted line.

4. FEATURES EXTRACTION FROM THE ORIGINAL DATASET

As introduced in the previous section, the original dataset is composed by 4 acquisitions of 5 channels each. The information regarding the state of health of the wind turbine must be extracted from these data. In order to highlight it, some features can be extracted from the raw dataset. Obviously, the choice of these characteristic parameters is strongly affecting the ability to perform a damage detection, so that they should be selected wisely. A simple choice is to use common time-domain statistics such as *root mean square*, *skewness*, *kurtosis*, *peak value* and *crest factor* (peak/RMS). These are usually quite sensitive to the operational and environmental conditions and are very fast to compute, so that they are suitable for a preliminary analysis [14].

To ensure the statistical significance of the results, many measurement points are necessary. These features will be then extracted on short, independent (no overlap) chunks of the original signals. In particular, each acquisition is divided in 100 sub-parts on which the five features are computed.

The result of this operation is graphically summarized in Figure 5.

Finally, the considered dataset X_r is a $n \cdot d$ matrix, where $d = 25$ is the number of channel and feature combinations, while $n = 400$ is the number of samples from the 4 acquisitions of Table 1 placed one after the other.

5. ANALYSIS AND RESULTS

A statistical approach is used in this paper to test if some diagnostic information can be obtained from the data, basically assessing the goodness of the selected features. The study starts with a univariate Analysis Of Variance (ANOVA), able to infer from the data the hypothesis that no statistical difference is detected among the groups, meaning that all the groups come from the same distribution. Then, a Principal Component Analysis (PCA) is proposed with the aim of visualizing the multidimensional dataset. Finally, a novelty detection through the Mahalanobis distance is performed to find the acquisitions that, deviating from the reference (healthy) condition, are “novel” and may then disclose the presence of a fault.

5.1. The analysis of variance (ANOVA)

The ANOVA is a statistical tool to test the omnibus (*variance based*) null hypothesis:

H_0: *all the considered groups populations come from the same distribution, meaning that no significant difference is detectable.*

This hypothesis will be accepted or rejected according to a statistical summary $\hat{F}$, which, under the assumptions of independence, normality and homoscedasticity of the original data, follows a Fisher distribution. Namely:

$$\sigma_{bg}^2 = \sum_{j=1}^{G} \frac{n_j}{N} \left(\bar{y} - \mu_j\right)^2 \qquad \sigma_{wg}^2 = \frac{1}{N} \sum_{j=1}^{G} \sum_{i=1}^{n_j} \left(y_{ij} - \mu_j\right)^2 \qquad \hat{F} = \frac{\sigma_{bg}^2 / G-1}{\sigma_{wg}^2 / N-G} \sim F_{(G-1,N-G)}$$

where G is the number of groups of size n_j and mean μ_j, N is the global number of samples with overall average $\bar{y}$, σ_{bg}^2 is the variance between the groups and σ_{wg}^2 is the variance within the groups, basically the average of the variance computed in each group [15,16].

The H_0 will be finally accepted at a confidence $1 - \alpha$ if the summary $\hat{F}$ is less extreme than a critical value $\boldsymbol{F}^{\boldsymbol{\alpha}}_{(\boldsymbol{G-1},\boldsymbol{N-G})}$. A corresponding p-value can also be computed. It coincides with the probability of the summary to be more extreme than the observed $\hat{F}$, assuming H_0 to be true. If this value is lower than 5%, H_0 is commonly rejected. The concepts of critical value and p-value are summarized in Figure 6.

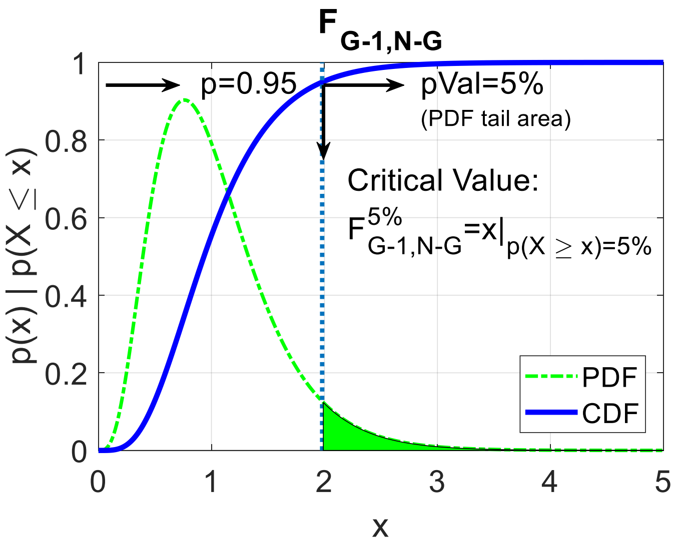

Figure 6: $F_{(G-1,N-G)}$ distribution. The 5% critical value and the corresponding p-value are reported.

In this analysis, the dataset is divided in 2 groups: the healthy one contains the first 300 samples, while the last 100 samples, coming from the damaged WTG06, are labelled as damaged. The assumption of normality can be considered verified with enough confidence. The same does not hold for the homoscedasticity (equal variance in the different groups), but the ANOVA is commonly considered robust to such violations, so that the trustworthiness of the results will not be affected. It is relevant to point out that in this case, which uses 2 groups only, the ANOVA reduces to a Student's t-test. Furthermore, the ANOVA is a univariate technique, so it will be repeated per each channel and feature combination (25 times). This will enable to make some considerations about the more relevant channels and features for diagnosing a damage. The results are reported in Table 2.

Table 2: ANOVA p-values – the red is used to highlight the acceptance of H_0 ($p - value > 5\%$), which implies a more difficult damage detection.

Feature \ Channel	Xinf	Xsup	Yinf	Ysup	Mic
RMS	2.33 e-48	5.24 e-220	0	2.71 e-05	1.15 e-08
Skewness	2.74 e-06	0.033	1.51 e-34	1.42 e-54	6.14 e-03
Kurtosis	0.330	4.02 e-62	2.66 e-222	0.019	0.023
Crest	0.661	8.26 e-50	1.81 e-117	0.646	1.53 e-4
Peak	1.81 e-40	3.54 e-160	9.22 e-260	2.06 e-05	2.92 e-18

Focusing on Table 2, it is easy to notice that the p-values are in general very small, implying the rejection of H_0. The damage is then proved to be detectable also using such simple time-domain features. This is true in particular for channel *Yinf*, which shows the smallest p-values. On the contrary, channel *Mic*, channel *Ysup* and channel *Xinf* are less performing in detecting the damage using Skewness, Kurtosis and Crest. Because of this, considering also the different nature of the *Mic* acquisition, the fifth channel will not be considered in the following analysis, which will try to aggregate the diagnostic information of all the 5 features from the 4 accelerometers, using a multivariate approach.

Finally, the considered dataset X will be a $n \cdot d$ matrix, where $n = 400$ will be the number of samples, while $d = 20$ will be the number of the considered channel and feature combinations.

5.2. The Principal Component Analysis (PCA)

The PCA is a technique widely used in multivariate statistics, in particular for the purpose of allowing the visualization of multi-dimensional datasets using projections on the first 2 or 3 principal components.
This dimensionality reduction is not really advisable for diagnostic purposes, as the condition-information may, in principle, be hidden in the following, neglected, principal components, making the detection more challenging. In any case, it is used in this analysis as an intermediate step to visualize the dataset under a different point of view, resulting from the transform produced by the technique.
The PCA uses indeed an orthogonal space transform to convert a set of correlated quantities into the uncorrelated variables called principal components. This transform is basically a rotation of the space in such a way that the first principal component will explain the largest possible variance, while each succeeding component will show the highest possible variance under the constraint of orthogonality with the preceding ones. This is usually accomplished by eigenvalue decomposition of the data covariance matrix, often after mean centering [17].
The result of the PCA applied to the centered, healthy reference set (WTG01 and 03 at 17.20) in the 20-dimensional space (4 channels, 5 features) are reported in Figure 7 and Figure 8, where the validation set is also projected according to the same mapping.
In Figure 8 one can easily notice that 2 clusters arise. The damaged acquisitions (in red) can be clearly separated by all the other healthy points (both from the calibration and the validation sets). The first component is then enough to perform the damage detection. In order to compare the weights of the features involved in the linear combination producing the first principal component, a PCA is repeated on the standardized features (centered and normalized on the standard deviation). The absolute value of the weights for the first principal component are reported in Table 3. As it is easy to notice, the features kurtosis and crest shows the highest absolute weights, proving to be the most influent in the computation. Furthermore, the higher weights are used with Yinf, which confirms to be the most informative channel (N.B. note from Figure 5 that the selected features do not vary in the same range of values, so that the PCA on the standardized features is needed to meaningfully compare the weights involved in PC1).
In any case, as it is not advisable to neglect the information from the less informative channel-feature combinations, another transform is finally proposed, based on the Mahalanobis distance novelty detection. Aggregating all the channels and features, this method tries to enhance the damage related information hidden in the dataset.

Table 3: PC1 absolute weights for the standardized features (centered and normalized on their standard deviation)

	Xinf	***Xsup***	***Yinf***	***Ysup***
rms	0,0008	0,0006	0,0001	0,0011
skew	0,0035	0,0009	0,0014	0,0115
kurt	0,0237	0,0153	0,0338	0,0240
crest	0,0295	0,0212	0,0963	0,0516
peak	0,0035	0,0028	0,0022	0,0055

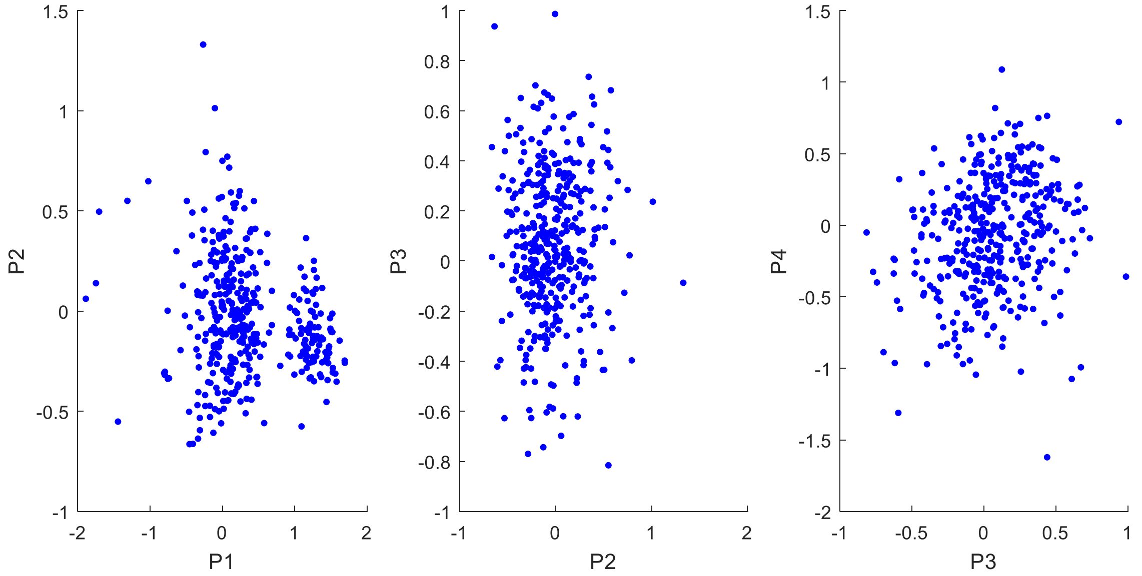

Figure 7: The first four principal components (P1 to P4) coming from PCA of the centered referenced set are reported in scatterplots – the validation set is added, projected on the same principal space.

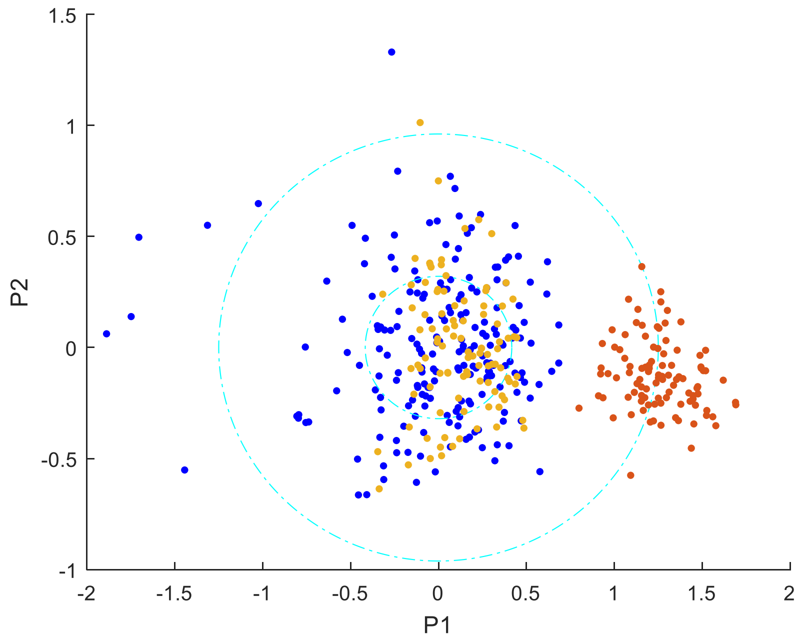

Figure 8: Zoom of the space generated by the first 2 principal components (Figure 7) highlighting the healthy reference set (BLUE), the healthy validation set (yellow) and the damaged set (red).

5.3. Novelty detection

In statistics, the detection of anomalies can be performed pointwise, looking for the degree of discordancy of each sample in a dataset. A discordant measure is commonly defined "outlier", when, being inconsistent with the others, is believed to be generated by an alternate mechanism. The judgment on discordancy will depend on a measure of distance from the reference distribution, usually called Novelty Index (NI), on which a threshold can be defined [18, 19].

The Mahalanobis distance (MD) is the optimal candidate for evaluating discordancy in a multi-dimensional space, because it is unitless and scale-invariant, and takes into account the correlations of the data set. MD can be formulated as

$$MD(X) = \sqrt{(X-\mu)^T S^{-1} (X-\mu)} \equiv NI$$

where S is the estimated covariance matrix of the reference distribution, X is the $n \cdot d$ dataset matrix and μ is the mean vector of the reference distribution.
The judgement of novelty, which in this context is considered related to the presence of a possible damage and will be used to trigger an alarm, is performed comparing the NIs to a properly selected threshold. In this paper, such a threshold is generated through several repeated Monte Carlo (MC) simulations of a p-dimensional Gaussian distribution. Drawing n observations in p variables and computing the NIs, the maximum operator could be used to generate a robust threshold, for example taking the 99th percentile of the maxima distribution [18].
The Mahalanobis distance of each point from the reference distribution (the calibration set), used as Novelty index, is reported in Figure 9.

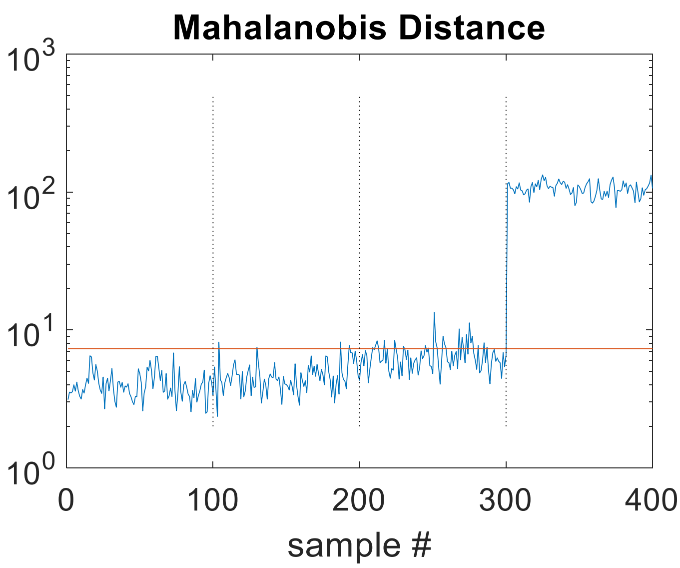

Figure 9: Mahalanobis Distance from the Calibration set (samples 1-200) – samples 201-300 are the healthy set used for validation, while samples 301-400 correspond to the damaged condition

In Figure 9 one can notice that the NIs of the damaged set are all very large and can be easily distinguished from the healthy NIs, allowing a perfect damage detection with no missed alarms.
Unfortunately, the calibration set is not very big and is then non-representative of the entire variability in the different operational and environmental conditions. This explains why the proposed MC threshold is crossed many times in the healthy validation set, implying a way too high false alarm rate. The considerable distance of the damaged NIs anyway, provides a wide margin to improve the threshold without increasing the missed alarms, demonstrating the goodness of the detection.

6. CONCLUSIONS

A novel approach for damage detection of a wind turbine gearbox is proposed in this paper. One main novelty, with respect to the state of the art in the literature, is that the accelerometric acquisitions were performed inside the tower, in a place farther from the gearbox but easily accessible by the turbine practitioners without shutting down the wind turbine. This measurement technique is a distinctive part of the outcome of the present work. Subsequently, a Novelty detection algorithm was set up, based on common time domain features like RMS, Skewness, Kurtosis, Crest factor and Peak value.

The analysis started with an ANOVA and a PCA, two fundamental tools in univariate and multivariate statistics. Both the techniques proved the detectability of the damage using the selected features. In particular, the features *kurtosis* and *crest* demonstrated to be the most influent, while *Yinf* resulted the most informative channel for damage detection. The *Mic* channel was on the contrary neglected for the multivariate analysis, because of the different nature of the sensor and due to the poorer detectability.
Finally, the Mahalanobis Novelty detection showed optimal results in detecting the possible damage, given the large margin which separates the supposedly damaged NIs from the healthy NIs computed both in the calibration and in the validation phase. This algorithm also proved to be a good unsupervised damage detection technique considering the quickness, the simplicity and the full independence from human interaction, which make it suitable for real time implementation.
Overall, the whole gearbox vibration monitoring methodology can be considered validated by the test. The simple, non-invasive measurement system composed of just 2 biaxial accelerometers placed in accessible locations at 2 levels inside the tower of the wind turbine, together with the Novelty detection algorithm applied on the common time-domain features extracted, demonstrated indeed to provide a robust monitoring system, which can be easily integrated in existing installations. This system can, in principle, enable to monitor also the damage evolution in time, establishing the foundations for further works on prognostics, which could optimize the wind turbines maintenance regimes, ensuring higher reliability and minimal down times.

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