WIND TURBINE GEARBOXES FAULT DETECTION THROUGH ON-SITE MEASUREMENTS AND VIBRATION SIGNAL PROCESSING

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Abstract

Condition monitoring of gear-based mechanical systems undergoing non-stationary operation conditions is in general very challenging. In particular, this issue is remarkable as regards wind turbine technology because most of the modern wind turbines are geared and gearbox damages account for at least the 20% of unavailability time. For this reason, wind turbines are often equipped with condition monitoring systems (CMS), processing vibration measurements collected at meaningful subcomponents of the gearbox. In this work, a novel approach for the diagnosis of gearbox damages is proposed: the turning point is that vibration measurements are collected at the tower, instead that at the gearbox and can be performed also for machine not provided with specific CMS. This implies that measurement campaigns are quite easily performed and repeatable, also for wind turbine practitioners, and that there is no impact on wind turbine operation and power production. A test case study is discussed: it deals with a wind farm owned by Renvico, featuring 6 wind turbine with 2 MW of rated power each. The vibration measurements at two wind turbines suspected to be damaged and at reference wind turbines 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.

1 Introduction

The diagnosis of gears and bearings faults of gearbox systems [1] is a very important topic, especially if the gear-based mechanical system of interest undergoes non-stationary operation conditions.

The technology of most of the modern wind turbines is based on the transformation of the slow rotor rotational speed (order of 10 revolutions per minute) into the fast generator rotational speed through a gearbox. It is estimated [2] that the unavailability time of a large wind turbine operating in an industrial wind farm is of the order of the 3% and at least the 20% of this quantity is due to gearbox damages. For this reason, therefore, the improvement in gearbox condition monitoring is a crucial step for the target of 100% availability of wind turbines. Therefore, commonly, megawatt-scale wind turbines are equipped with condition monitoring systems, elaborating the vibration measurements collected at meaningful sub-components of the gearbox.

Nevertheless, in the wind energy practitioners community, gearbox vibration data are often under-exploited because of the complexity of the analysis techniques that are required in order to interpret them. Therefore, often it happens that oil particle counting and operation data analysis (especially temperatures, as in [3]) are employed as condition monitoring techniques, despite they provide a late stage fault diagnosis, with respect to vibration analysis.

Therefore, two can be important direction targets as regards wind turbine gearbox condition monitoring through vibration analysis: on one hand, the precision of the diagnosis and on the other hand the simplicity of the methods. As regards the former aspect, there are several recent studies. In [4], data mining algorithms and statistical methods are applied to analyze the jerk data obtained from monitoring the gearbox of a wind turbine: the failed stages of the gearbox are identified in time-domain analysis and frequency-domain analysis. In [5], the proposed techniques are based on three models (signal correlation, extreme vibration, and RMS intensity) and have been validated with a time-domain data-driven approach using condition monitoring data of wind turbines in operation. The results of that study support that monitoring RMS and extreme values serves as a leading indicator for early detection. In [6], the focus is on separating the bearing fault signals from masking signals coming from drivetrain elements like gears or shafts. The separation is based on the assumption that signal components of gears or shafts are deterministic and appear as clear peaks in the frequency spectrum, whereas bearing signals are stochastic due to random jitter on their fundamental period and can be classified as cyclo-stationary [7]. In [8], order analysis is individuated as a useful technique for condition monitoring the planetary stage of wind turbine gearbox. The approach takes advantage of angular resampling to achieve cyclo-stationary vibration signals and lessen the effects due to speed changes. In [9], the objective is condition monitoring of the planetary stage of wind turbine gearboxes: the proposed technique is resampling vibration measurements from time to angular domain, identification of the expected spectral signature for proper residual signal calculation and filtering of any frequency component not related to the planetary stage.

On the grounds of this brief literature survey, it arises that the techniques for the analysis of cyclo-stationary signals are the most employed for an accurate condition monitoring. The type and the quality of data that are requested for this kind of analysis confines the subject mainly to the scientific community and at present discourages the collaboration between industry and academia. Actually, the commercial condition monitoring systems, that are mostly adopted in most operating wind turbines exploited at the industrial level, record vibration measurements only when some trigger events occur and, most of all, don't stock the raw data (commonly, Fourier transforms and-or simple statistical indicators are stocked).

On these grounds, there is a growing demand of vibration-based gearbox condition monitoring techniques that could be easily repeatable, without impacting on the wind turbines operation (i.e. without intruding in the gearbox), and whose interpretation could be sufficiently simple and powerful. One remarkable study by this point of view is [10], where sound and vibration measurements collected at the wind turbine towers are employed for condition monitoring of generators. Tower vibration signals are analyzed using Empirical Mode Decomposition (EMD) and the outcomes are correlated with the vibration signals acquired directly from the generator bearings. It is shown that the generator bearing fault signatures are present in the vibrations from the tower.

This study is devoted to the test case of two multi-megawatt wind turbines sited in Italy, owned by Renvico (a company managing around 340 MW of wind turbines in Italy and France, www.renvicoenergy.com). The wind turbines are not equipped with gearbox condition monitoring systems and they have been diagnosed of gearbox damages (of different severity) through the analysis of oil particle counting. Before the gearboxes replacement intervention, a measurement campaign has been conducted by the University of Perugia. The idea is measuring vibrations at the tower: the measurements are collected on the target damaged wind turbines 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. Finally, the novelty indexes based on such time-domain features prove to be suitable to diagnose a damaged condition. It should be noticed that the obtained results allow distinguishing between the two target wind turbines and the corresponding different severity of the gearbox damages.

The manuscript is organized as follows: in Section 2, the test case wind farm, the measurement techniques and equipment and the obtained data sets are described. Section 3 is devoted to the data analysis, feature extraction and results discussion. Finally, in Section 4 some concluding remarks and further directions of this study are indicated.

2 The on-site measurements and the data sets

The wind farm is composed of six multi-megawatt wind turbines and it is sited in southern Italy. The layout of the wind farm is reported in Figure 1, where the damaged wind turbines are indicated in red. The lowest inter-turbine distance on site is of the order of 7 rotor diameters.

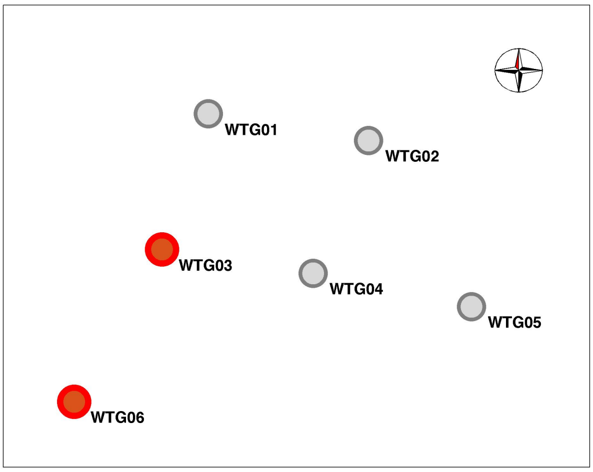

Figure 1: The layout of the wind farm. In red, the damages wind turbines (WTG03 and WTG06) are indicated.

It should be noticed that the damages to WTG03 and WTG06 have different level of severity: actually, the damage at WTG06 was detected through oil particle counting some days before the measurement campaign, while the damage at WTG03 can be considered at incipient stage.

The 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 2. 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. Each acquisition therefore consists of 4 channels sampled at 12.8 kHz for 2 minutes.

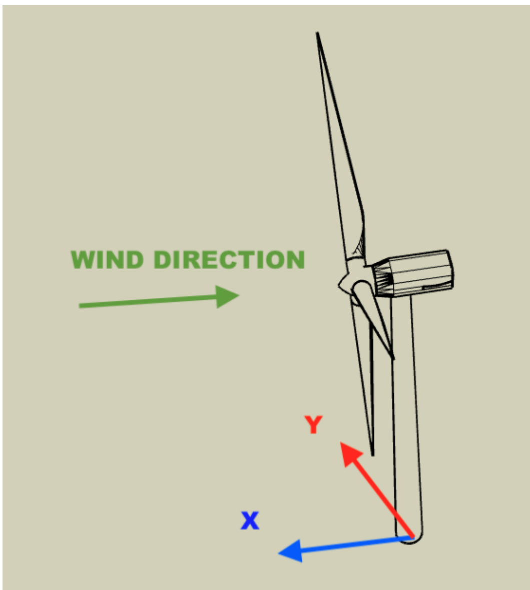

Figure 2: Definition of the reference frame for the longitudinal and the transversal directions.

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 and operation conditions at different wind turbines at the same time.

The vibration time series have been organized as indicated in Tables 1 and 2. The WTG01 time series are not labelled with more details (as for example the recording time) because they can be interchanged and the results of the following analysis don't sensibly change.

TS number	Wind turbine	Wind turbine status	Use
1	WTG01	healthy	reference - calibration
2	WTG01	healthy	reference - calibration
3	WTG01	healthy	validation
4	WTG03	damaged	validation

Table 1: The data set for WTG03 damage detection

TS number	Wind turbine	Wind turbine status	Use
1	WTG01	healthy	reference - calibration
2	WTG01	healthy	reference - calibration
3	WTG01	healthy	validation
$\bar{4}$	WTG06	damaged	validation

Table 2: The data set for WTG06 damage detection

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 data set. 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 [11]. 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 considered data sets X results then to be a $n \cdot d$ matrix, where $n = 20$ is the number of channel and feature combinations, while $d = 400$ is the number of samples from the 4 acquisitions of Tables 1 and 2 placed one after the other.

3 Analysis and results

The results about the feature extraction are reported in Figures 3 and 4. The samples 0-200 are referred to the training data set for the wind turbine WTG01, the samples 201-300 are referred to the validation data set for the wind turbine WTG01 and, finally, the samples 301-400 are referred to the validation data set for the wind turbine WTG03 (WTG06, respectively). In the Figures, the training - calibration data set is separated from the validation data set by a black line. The validation data set for the damaged wind turbine is separated from the rest of the data sets through a red line.

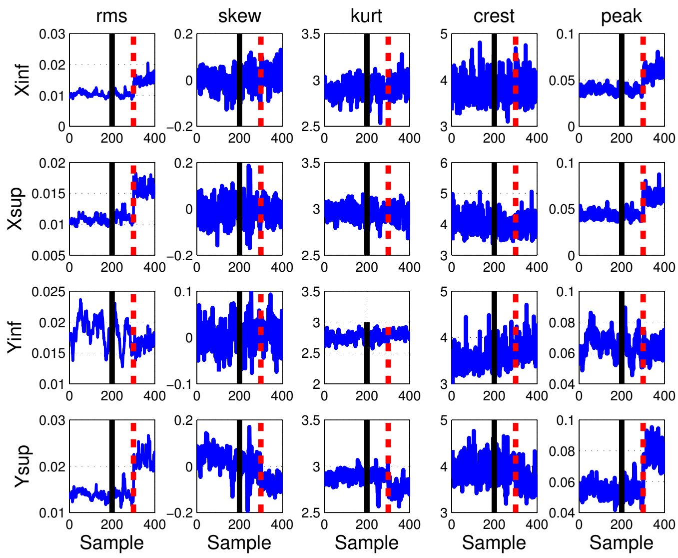

Figure 3: The extracted features for the data sets in Table 1.

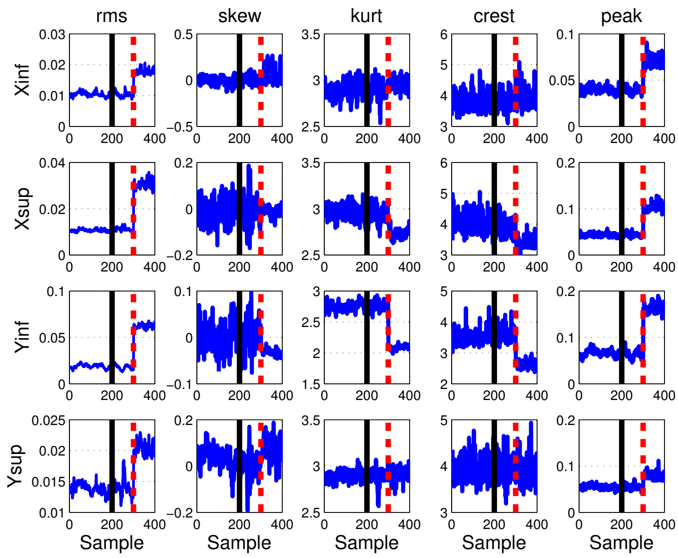

Figure 4: The extracted features for the data sets in Table 2.

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.

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:

$$\hat{F} = \frac{\frac{\sigma_{bg}^2}{G-1}}{\frac{\sigma_{wg}^2}{N-G}} \simeq F(G-1, N-G), \tag{1}$$

where

$$\sigma_{bg}^2 = \sum_{j=1}^{G} \frac{n_j}{N} (\bar{y} - \mu_j)^2, \tag{2}$$

$$\sigma_{wg}^2 = \frac{1}{N}\sum_{j=1}^{G}\sum_{i=1}^{n_j}(\bar{y}_{ij}-\mu_j)^2\,, \tag{3}$$

with G being the number of groups of size n_j, N being the global number of samples with overall average $\bar{y}$, σ_{bg}^2 being the variance between the groups, σ_{wg}^2 being the variance within the groups (basically the average of the variance computed in each group) [12, 13]. The null hypothesis H_0 will be accepted with a confidence level $1-\alpha$ if the summary $\hat{F}$ is less extreme than a critical value $F^{\alpha}(G-1,N-G)$. 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 less than α (typically, 5%), H_0 is rejected. The concepts of critical value and p-value are summarized in Figure 5.

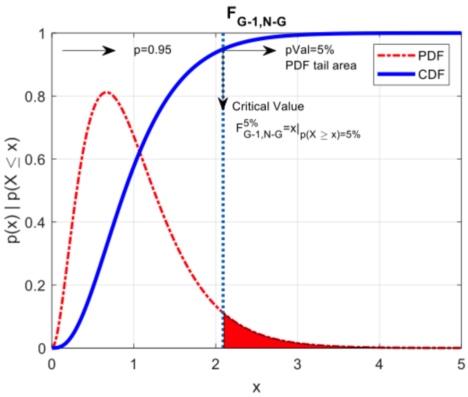

Figure 5: $F(G-1,N-G)$ distribution, with highlighted the 5% critical value and the concept of p-value.

In this analysis, the data sets are divided in 2 groups: the healthy one contains the first 300 samples (time series 1 to 3), while the last 100 samples, coming from the damaged and turbines WTG03 and WTG06 (time series 4 and $\bar{4}$), 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 Studentâs t-test. Furthermore, the ANOVA is a univariate technique, so it will be repeated per each channel and feature combination (20 times). The results are reported in Tables 3 and 4.

Feature / Channel	Xinf	Xsup	Yinf	Ysup
RMS	$< 10^{-32}$	$< 10^{-32}$	$9 \cdot 10^{-13}$	$< 10^{-32}$
Skewness	$< 10^{-8}$	0.4	0.4	$< 10^{-32}$
Kurtosis	$< 10^{-12}$	0.6	$< 10^{-12}$	$< 10^{-32}$
Crest	0.005	0.8	$< 10^{-19}$	$< 10^{-22}$
Peak	$< 10^{-32}$	$< 10^{-32}$	0.01	$< 10^{-32}$

Table 3: ANOVA p-values for the data sets in Table 1. The red cells are used to highlight the acceptance of H_0 (p-value$>$ 5%), which implies a more difficult damage detection.

Feature / Channel	Xinf	Xsup	Yinf	Ysup
RMS	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$
Skewness	$< 10^{-13}$	0.2	$< 10^{-32}$	$< 10^{-32}$
Kurtosis	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$	0.01
Crest	0.001	$< 10^{-32}$	$< 10^{-32}$	0.6
Peak	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$

Table 4: ANOVA p-values for the data sets in Table 2. The red cells are used to highlight the acceptance of H_0 (p-value$>$ 5%), which implies a more difficult damage detection.

The Principal Component Analysis (PCA) is a technique widely used in multivariate statistics, in particular for the purpose of allowing the visualization of multi-dimensional data sets using projections on the first 2 or 3 principal components. This dimension reduction is not really advisable for diagnostic purposes, as the condition-information may, in principle, be hidden in the neglected principal components, making the detection more challenging. In any case, it is used in this analysis as a qualitative visualization of the data set under a different point of view, resulting from the transform produced by the technique. The PCA uses 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.

The PCA transform has been applied to the reference data set: the statistical features matrix extracted from the WTG01 time series 1 and 2 of Tables 1 and 2. Subsequently, the validation data sets have been separately projected to the space generated by the first two principal components of the reference data set. The results are reported in Figures 6 and 7, from which it arises that the data set of WTG06 is more easily distinguishable with respect to the calibration data set than the data set of WTG03. As regards Figure 7, the indication is that the visual inspection based on the first two principal components can be sufficient for detecting an anomaly.

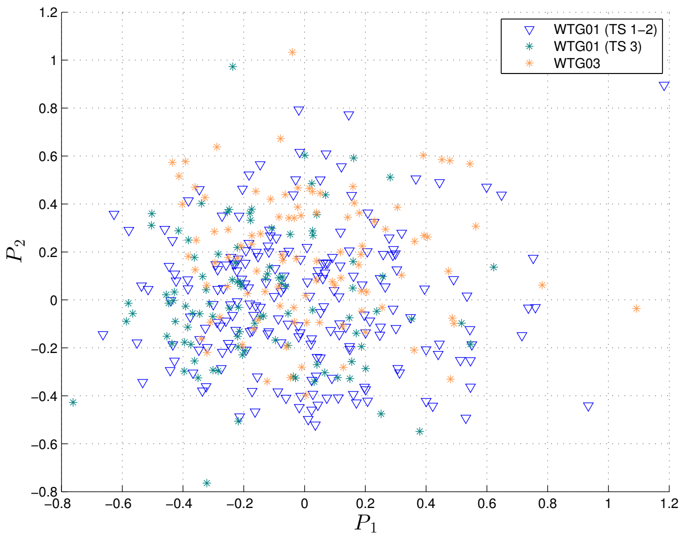

Figure 6: Projection of the data from Figure 3 to the space generated by the two principal components of the calibration data set (first 200 samples in Figure 3)

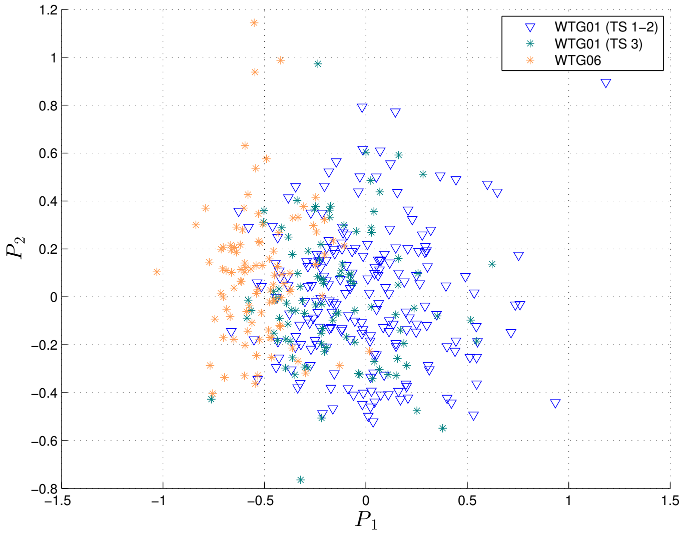

Figure 7: Projection of the data from Figure 4 to the space generated by the two principal components of the calibration data set (first 200 samples in Figure 4)

In statistics, the detection of anomalies can be performed pointwise, looking for the degree of discordance of each sample in a data set. 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 discordance will depend on a measure of distance from the reference distribution, usually called Novelty Index (NI) on which a threshold can be defined [14]. The Mahalanobis distance is the optimal candidate for evaluating discordance in a multi-dimensional space, because it is non-dimensional and scale-invariant, and takes into account the correlations of the data set. The Mahalanobis distance between one measurement y (possibly multi-dimensional) and the x distribution, whose covariance matrix is S, is given by

$$d_M(y) = \sqrt{(y-\bar{x})\, S^{-1}\, (y-\bar{x})}. \tag{4}$$

In the following, the reference x distribution is selected as the statistical features matrix extracted from the WTG01 time series 1 and 2 of Tables 1 and 2. The target y is selected as the statistical features matrix extracted from respectively time series 3 (WTG01), 4 (WTG03), $\bar{4}$ (WTG06).

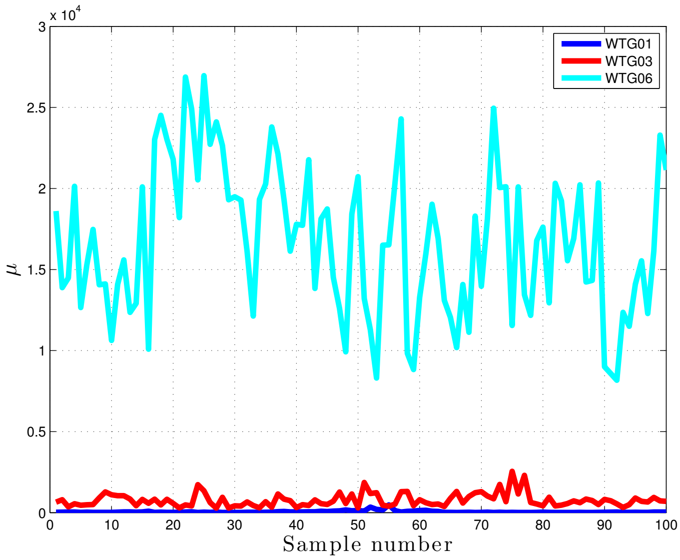

Figure 8: The Mahalanobis distance μ with respect to the calibration WTG01 data set: WTG01, WTG03, WTG06.

From Figure 8, it is possible to clearly distinguish between wind turbine WTG01 and wind turbines WTG03 and especially WTG06. The Mahalanobis distance therefore qualifies to be particularly responsive for novelty detection issues.

4 Conclusions

A novel approach for damage detection of a wind turbine gearbox was proposed in this study. One main novelty is that the accelerometric acquisitions were performed inside the tower of the wind turbines of interest because, despite the distance with respect to the gearbox, it is 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. One reference healthy wind turbine and two wind turbinse affected by different damage severity have been selected as test cases for the measurement campaigns proposed in the present study.

Subsequently, a Novelty detection procedure was set up, based on the calculation and the elaboration of 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 techniques proved that the damages can be detected. Finally, the Mahalanobis Novelty detection showed optimal results in detecting the possible damage, given the large margin which separates the supposedly damaged wind turbines from the healthy wind turbine. 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 makes 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: this is supported by the responsiveness of the proposed methods (especially the Mahalanobis distance analysis) with respect to the severity of the damages (Figure 8). The straightforward further direction of the present work is therefore the analysis of the evolution in time of the same test case.

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References

[1] J. Rafiee, F. Arvani, A. Harifi, & M.H. Sadeghi, *Intelligent condition monitoring of a gearbox using artificial neural network*, Mechanical systems and signal processing, 21(4), 1746-1754.

[2] P. Tchakoua, R. Wamkeue, M. Ouhrouche, F. Slaoui-Hasnaoui, T. Tameghe, & G. Ekemb, *Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges*, Energies, 7(4), 2595-2630.

[3] D. Astolfi, F. Castellani, & L. Terzi, *Fault prevention and diagnosis through SCADA temperature data analysis of an onshore wind farm*, Diagnostyka, 15.

[4] Z. Zhang, A. Verma, & A. Kusiak, *Fault analysis and condition monitoring of the wind turbine gearbox*, IEEE transactions on energy conversion, 27(2), 526-535.

[5] J. Igba, K. Alemzadeh, C. Durugbo, & E.T. Eiriksson, *Analysing RMS and peak values of vibration signals for condition monitoring of wind turbine gearboxes*, Renewable Energy, 91, 90-106.

[6] C. Peeters, P. Guillaume, & J. Helsen, *Vibration-based bearing fault detection for operations and maintenance cost reduction in wind energy*, Renewable Energy, 116, 74-87.

[7] J. Antoni, *Cyclic spectral analysis in practice*, Mechanical Systems and Signal Processing, 21(2), 597-630.

[8] F. Yanhui, L. Jiawei, Q. Yingning, Y. Wenxian, & D. Infield, *Study on order analysis for condition monitoring wind turbine gearbox*, 3rd Renewable Power Generation Conference (RPG 2014).

[9] G.A. Skrimpas, T. Ursin, C. Sweeney, K. Marhadi, N. Mijatovic, & J. Holboell, *Residual signal feature extraction for gearbox planetary stage fault detection*, Wind Energy, 20(8), 1389-1404.

[10] E. Mollasalehi, D. Wood., & Q. Sun, *Indicative fault diagnosis of wind turbine generator bearings using tower sound and vibration*, Energies, 10(11), 1853.

[11] A. P. Daga, L. Garibaldi, A. Fasana, & S. Marchesiello, *ANOVA and other statistical tools for bearing damage detection*, International Conference Surveillance 9, Fez (Morocco), 22-24 May 2017.

[12] H. Scheffe, *The analysis of variance*, John Wiley Sons, 1959.

[13] H. Sahai, & M.I. Ageel, *The analysis of variance: fixed, random and mixed models*, Springer Science Business Media, 2012

[14] K. Worden, G. Manson, & N.R. Fieller, *Damage detection using outlier analysis*, Journal of Sound and Vibration, 229(3), 647-667.