Condition monitoring of wind turbine gearboxes through on-site measurement and vibration analysis techniques

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CONDITION MONITORING OF WIND TURBINE GEARBOXES THROUGH ON-SITE MEASUREMENT AND VIBRATION ANALYSIS TECHNIQUES

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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 energy technology because most of the modern wind turbines are geared and gearbox damages account for at least the 20% of their unavailability time. In this work, a new method for the diagnosis of gearbox damages is proposed: the main idea is that vibrations are measured at the tower, instead that at the gearbox. This implies that measurements can be performed without impacting on the wind turbine operation, as desirable by the point of view of wind turbine practitioners. A test case study is discussed: it deals with a wind farm owned by Renvico, featuring 6 wind turbines with 2 MW of rated power each. The vibration measurements at a wind turbine 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 data set via Principal Component Analysis. Finally, a novelty index based on the Mahalanobis distance is used to detect the anomalous conditions at the damaged wind turbine.*

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 target of 100% availability passes through the development of adequate gearbox condition monitoring techniques.

Nevertheless, the elaboration and interpretation of gearbox vibration measurements are complex and this matter of fact produces an under-exploitation of this kind of data in the wind energy practitioners community. Often it happens that oil particle counting and operation data analysis (especially temperatures, as in [3]) are employed for condition monitoring, despite they provide a late stage fault diagnosis, with respect to vibration analysis. On these grounds, it is valuable to develop vibration measurement and analysis techniques that can reliably spread also in the wind energy industry practice and the present study aims at providing a contribution to this objective.

The literature about vibration analysis for wind turbine condition monitoring has been particularly developing in the latest years: for example, 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. In [10], a simplified nonlinear gear model is at first developed, on which a timefrequency analysis method is applied for the easiest understanding; subsequently, the case of varying loads is examined through Empirical Mode Decomposition (EMD), for decomposing the vibration signals into meaningful components associated with specific frequency bands. In [11], a critical analysis of the synchrosqueezing transform for the representation of non-stationary signals is proposed: at this aim, the synchrosqueezing transform is improved using iterative generalized demodulation and the proposed method is validated using both numerically simulated and lab experimental vibration signals of wind turbines planetary gearboxes. For a comprehensive review about wind turbine planetary gearbox condition monitoring techniques on the topics of fundamental analysis, signal processing, feature extraction, and fault detection, refer to [12].

On the grounds of this brief literature survey, it arises that the techniques for the analysis of cyclo-stationary signals are among the most employed and powerful for an accurate gearbox condition monitoring. The downside is that they are particularly demanding as regards the type and the quality of the data. Actually, it should be noticed that operating wind turbines are commonly equipped with commercial condition monitoring systems, recording measurements only when some trigger events occur and, most of all, lacking a raw vibration data stock (commonly, Fourier transforms and-or simple statistical indicators are stocked); cyclo-stationarity analysis techniques instead require the disposal of raw vibration measurements and of precise tachometer data recording the gearbox speed.

As regards the circumvention of the above limitations, one remarkable study is [13], 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 a wind farm sited in Italy, owned by Renvico (a company managing around 340 MW of wind turbines in Italy and France, www.renvicoenergy.com): 6 wind turbines are installed on site and one of them has been diagnosed of a gearbox damage through oil particle counting. Before the gearbox maintenance intervention, a measurement campaign has been contrived and conducted by the University of Perugia. Similarly to the study in [13], vibrations are measured at the towers of the wind turbines of interest. 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, a novelty index based on the Mahalanobis distance is employed for supporting that it is possible to distinguish clearly the measurements of the damaged wind turbines with respect to the references wind turbines.

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 TEST CASE AND THE ON-SITE MEASUREMENTS

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 turbine is indicated in green and the undamaged wind turbines selected as references are indicated in red. The lowest inter-turbine distance on site is of the order of 7 rotor diameters.

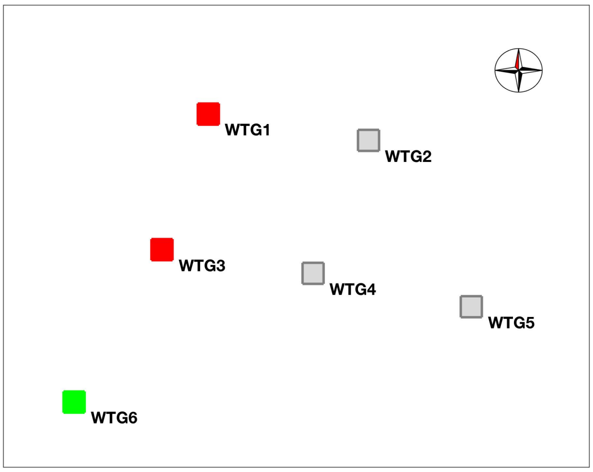

Figure 1: The layout of the wind farm. In green, the damaged wind turbine (WTG06) is indicated and in red the reference wind turbines (WTG01 and WTG03) are indicated.

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.

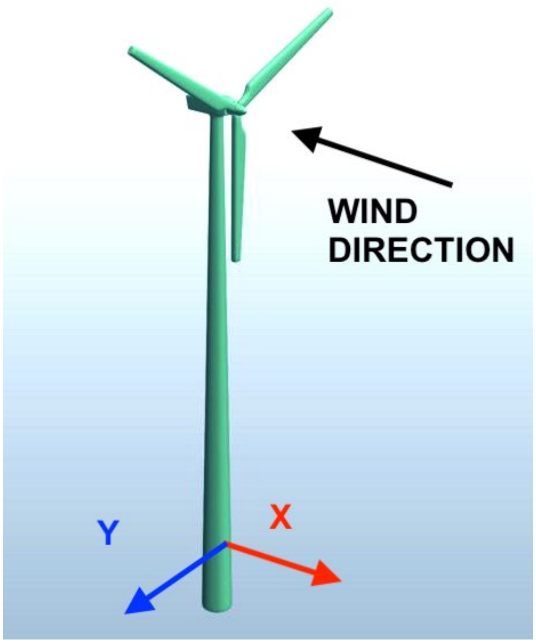

Figure 2: Definition of the reference frame for the longitudinal and the transversal directions.

Operation 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.

TS number	Wind turbine	Wind turbine status	Use
1	WTG01	healthy	reference - calibration
2	WTG03	healthy	reference - calibration
3	WTG03	healthy	validation
4	WTG06	damaged	validation

Table 1: The time series selection.

The information regarding the state of health of the wind turbine must be extracted from these data. In order to disengaging as much as possible from the dependence on the operation conditions at measurement time, the raw data set is processed: the processed data are composed of the difference between vibrations measurements at a given time and at the immediately previous time. The following step is selecting meaningful features for extracting information on the damage. A simple choice is to use common time-domain statistics such as root mean square, peak value, crest factor (peak/RMS) and normalized centered moments (like skewness and kurtosis). These are usually quite sensitive to the operational and environmental conditions and are very fast to compute [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 subparts 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 (4) times the number of computed features (5), while $d = 400$ is the number of samples from the 4 acquisitions of Table 1 placed one after the other.

3 ANALYSIS AND RESULTS

The results about the feature extraction are reported in Figure 3. The samples 0-200 are referred to the training data set for the wind turbine, the samples 201-300 are referred to the validation data set for the wind turbine WTG03 and, finally, the samples 301-400 are referred to the validation data set for the wind turbine WTG06. In the Figure, 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.

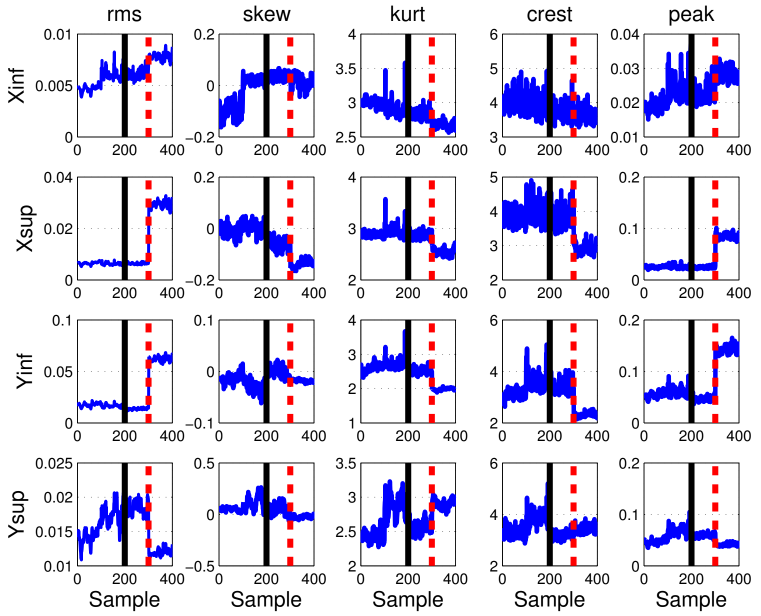

Figure 3: The extracted features for the data sets in Table 1.

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:

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

where

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

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

with G being the number of groups of size n_j, N being the global number of samples with overall average $\bar{y}$, σ^2_{bg} being the variance between the groups, σ^2_{wg} being the variance within the groups (basically the average of the variance computed in each group) [15, 16]. 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 4.

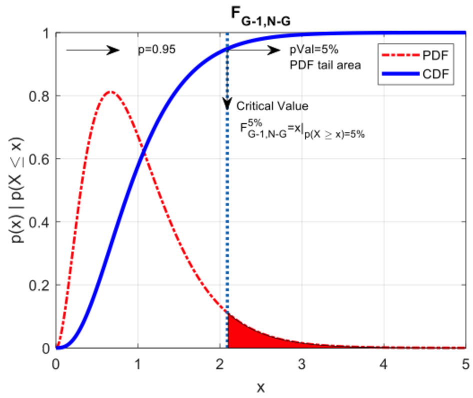

Figure 4: $F(G-1, N-G)$ distribution, with highlighted the 5% critical value and the concept of p-value.

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 wind turbine WTG06 (time series 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 Students 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 Table 2.

Feature / Channel	Xinf	Xsup	Yinf	Ysup
RMS	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$
Skewness	$8 \cdot 10^{-4}$	$< 10^{-32}$	0.03	$< 10^{-32}$
Kurtosis	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$
Crest	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$	0.9
Peak	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$	$< 10^{-32}$

Table 2: 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. The yellow cells highlight the p-value$< 5\%$, but with values comparable to the threshold.

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 decomposition of the calibration data set is visually reported in Figure 5, up to the first 4 principal components.

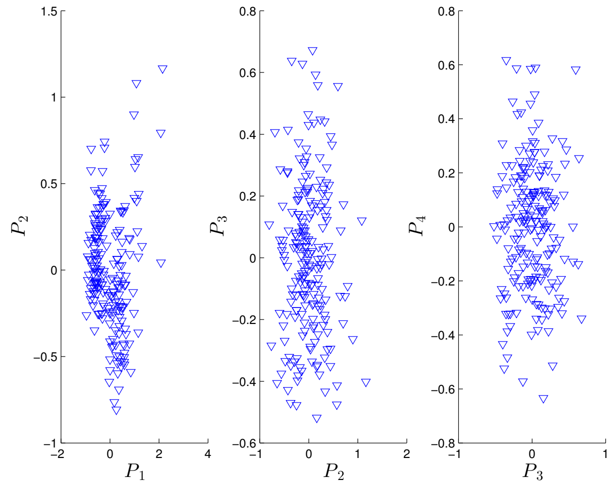

Figure 5: PCA of the calibration set.

Subsequently, also the two 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, from which it arises that the data set of WTG06 is clearly distinguishable with respect to the calibration data set and to the validation data set of WTG03. As regards Figure 6, the indication is that the visual inspection based on the first two principal components can be sufficient for detecting an anomaly.

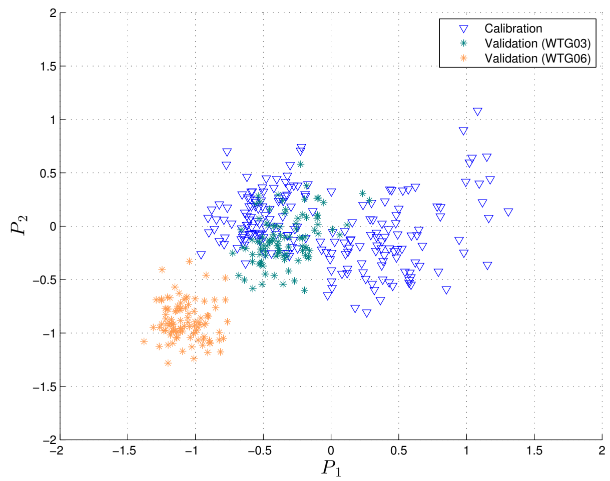

Figure 6: Projection of the data from Figure 3 to the space generated by the two principal components of the calibration data set (first 200 samples in Figure 3)

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 [17]. 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 calibration data set of Table 1. The target y is selected as the statistical features matrix extracted from the validation data set in Table 1.

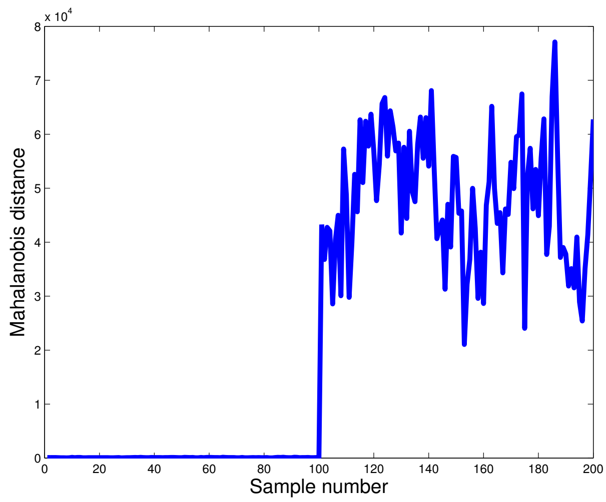

Figure 7: The Mahalanobis distance μ of the validation data set with respect to the calibration data set.

From Figure 7, it is possible to clearly distinguish between the samples of wind turbine WTG03 (1-100) and those of wind turbines WTG06 (101-200). The Mahalanobis distance therefore qualifies to be particularly responsive for novelty detection issues.

4 CONCLUSIONS

A new approach for condition monitoring of wind turbine gearboxes has been proposed in this study. The main novelty is that the vibration measurements are collected 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. Two reference healthy wind turbines and a damaged one from a wind farm featuring in total 6 multi-megawatt wind turbines have been selected as test cases for the measurement campaigns proposed in the present study.

A Novelty detection procedure has been set up for processing the collected measurements: it is based on the calculation and the elaboration of common time domain features like RMS, Skewness, Kurtosis, Crest factor and Peak value. Two fundamental techniques adopted in this work for novelty detection are ANOVA and Principal Component Analysis: using both methods, the damage has been successfully detected. Finally, the Mahalanobis Novelty detection showed optimal results in identifying 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 can supported by the responsiveness of the proposed methods (especially the Mahalanobis distance analysis) with respect to the severity of the damages (Figure 7). 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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