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Condition monitoring techniques for machine bearings in non-stationary operation

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Abstract

Condition monitoring of machines in non-stationary operations can be considered as one of the major challenges for the research in the field of rotating machinery diagnostics. The applications are ubiquitous: transport systems, energy systems, vehicles, production plants. On these grounds, the present work is devoted to measurement techniques and signal processing methods for the condition monitoring of bearings undergoing non-stationary operation conditions. Several types of experimental set ups are included in the present study and the advantages and drawbacks of each are discussed. For example, on one side an ad-hoc test rig for precision measurements is developed and utilized; on the other side, real scale measurement campaigns at operating non-stationary energy conversion systems (wind turbines) are performed. A special focus on energy systems is important because often in this kind of devices fault detection becomes much more challenging due to the interplay with electromechanical couplings. To face this drawback, the most advanced post-processing techniques need to be used. The application in the real field constitute an important part of this study because the fault diagnosis, and especially its interpretation, are much more challenging with respect to controlled laboratory conditions. The collected measurements are analysed through the most appropriate post-processing techniques employed for non-stationary signals. In the time domain, the statistical features of the signals are addressed through novelty indexes and principal component analysis. The results support that the Mahalanobis distance is an effective index in order to monitor the level of severity of the fault on the actual machine operation condition.

Keywords: Condition monitoring, non-stationary machines

1. Introduction

Condition monitoring of machines in non-stationary operations is one of the major challenges for the research in the field of rotating machinery diagnostics Bartelmus and Zimroz (2009); Lei et al. (2014).

There is a wide literature about the subject and most studies deal with the validation of condition monitoring techniques against test rig measurement campaigns: for example, in Stander and Heyns (2005), the feasibility was

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investigated of monitoring the instantaneous angular speed (IAS) as a means of monitoring the condition of gears that are subjected to fluctuating load conditions. An experimental investigation on a test rig indicated that the IAS of a gear shaft could be monitored with a conventional shaft encoder to indicate a deteriorating gear fault condition. A milestone study about the subject is Stander et al. (2002): test rig experiments have been conducted on a gearbox test rig with different levels of tooth damage severity and the capability of applying fluctuating loads to the gear system. Different levels of fluctuation in constant loads as well as in sinusoidal, step and chirp loads were considered. The test data were order tracked and time synchronously averaged with the rotation of the shaft in order to compensate for the variation in rotational speed induced by the fluctuating loads.

In the latest years, cyclostationarity has emerged as a powerful approach in a wide range of applications, such as in mechanical vibrations and acoustics analysis. The general concept is extending the class of stationary signals to those signals whose statistical properties change periodically with time. In Antoni (2007), similarities, differences and potential pitfalls associated with cyclic spectral analysis as opposed to classical spectral analysis are discussed. In Urbanek et al. (2013), a method is proposed for extracting second-order cyclostationary components from a vibration signal: the preservation of cycle energy variations can help to estimate the influence of varying rotational speed to signal energy. A meaningful validation case is proposed: a wind turbine, which is a classical example of energy conversion device operating under severely non-stationary conditions.

One important critical point as regards condition monitoring of machines operating in non-stationary conditions is that real-world condition monitoring of the devices operating in their working environment is much more challenging with respect to laboratory data analysis. A classical example deals with energy conversion systems, as wind turbines: they are subjected to the turbulence of the wind and therefore to stochastic loads. MW-scale wind turbines typically transform the slow rotor rotation into the fast generator rotation through a gearbox and therefore the monitoring of rolling elements and bearings is particularly complex Salameh et al. (2018); Zhang and Lang (2018); Wang and Garcia-Sanz (2018). Furthermore, it should be noticed that the control system reacts to the wind speed variations by moving a nacelle having a very large inertia and this might affect, for example, the lifetime of yaw Astolfi et al. (2019); Ouanas et al. (2018) and-or pitch Yang et al. (2018); Astolfi (2019) motors. As regards small (kW-scale) horizontal-axis wind turbines (HAWT), the critical point is they are remarkably affected by fatigue, due to the variability of loads that are modulated by very high rotational speeds of the small-sized rotor Castellani et al. (2018c). Furthermore, the mechanical behavior of small HAWTs is strongly affected by the importance of the electromechanical couplings Castellani et al. (2018c), due to fact that the generator constitutes a remarkable fraction of the total mass of the device. To face these drawbacks, the most advanced post-processing techniques of vibration measurements should be used.

On these grounds, the present work is devoted to the condition monitoring of wind turbine bearings. Two test cases are considered: the former is the generator bearing of a small HAWT Cai et al. (2016) having 2 meters of rotor diameter with a maximum power of 3 kW Scappatici et al. (2016). As regards the latter case study, there are at disposal cases of damage at the high speed shaft and planetary bearings of the wind turbine gearbox of MW-scale wind turbines. The experimental analysis of the small wind turbine generator bearing has been performed at the R. Balli (www.windtunnel.unipg.it) wind tunnel at the University of Perugia and a generator test rig has been used to analyze the permanent magnet generator driven at different rotational speeds. The application in the wind tunnel constitutes an important part of this study because the fault diagnosis, and especially its interpretation, are much more challenging with respect to controlled test rig conditions. The experimental analysis of the MW-scale generator bearing has been conducted through field tests at the wind farm of interest. A devoted experimental technique has been developed for the scientific objectives of this work: inspired by the study in Mollasalehi et al. (2017), vibration measurements have been collected at the tower of the wind turbine of interest (target) and of reference healthy wind turbines. The challenge is inquiring if it is possible to detect damages inside the wind turbine gearbox through measurements collected at the tower, without interrupting the normal operation of the machine: as shall be discussed in this study, the answers to this question are promising.

As regards the former test case, a preliminary analysis of the small wind turbine generator bearing has been conducted in Castellani et al. (2018b), where cyclostationarity techniques like spectral coherence analysis have been employed. This work is more focused on condition monitoring techniques in the domain of time, as in Daga and Garibaldi (2019). The objective of this kind of approach is a bird's eye view on the device to be monitored: the outcome of the present analysis could reliably be a first step, inspiring further investigations in the frequency domain for precisely locating the damage. The usefulness of this method can be multiple: for example, the analysis in the frequency domain typically requires a precise knowledge of the geometry of the device under monitoring. For devices operating in field (like wind turbines, for example), it is not guaranteed that this kind of information is available to the wind turbine practitioner interested in the condition monitoring task. This limitation can be at least in part circumvented through the type of analysis developed in the present work.

The structure of the manuscript is therefore the following. The experimental facilities and the data at disposal are described in Section 2. The methods are described in Section 3. Results are collected and discussed in Section 4; conclusions are drawn and some further direction of this work is outlined in Section 5.

2. The facilities and the data sets

2.1. Test case 1: small wind turbine generator bearing

Two 1.8 kW PMGs have been tested, collecting mechanical and electric data during wind tunnel ramp and steady test and driving the generators on the test rig at several shaft speeds. The two electric generators are exactly the same model, but one of them was affected by anomalous vibrations and non-optimal performances: this one has been selected as target and the healthy PMG has been selected as reference.

The test rig is displayed in Figure 1: in the figure, the position of the employed accelerometers is indicated. On the generator, uni-axial accelerometers have been fixed in radial positions, in order to be aligned with front and rear bearings. A torque meter was installed on the shaft from the motor to the generator, while rpm were measured thanks to an optical tachometer. Also electrical parameters (voltage and current) were monitored on the brake circuit on the DC resistive load, in order to estimate the power output from the generator. The sampling frequency is 5 kHz.

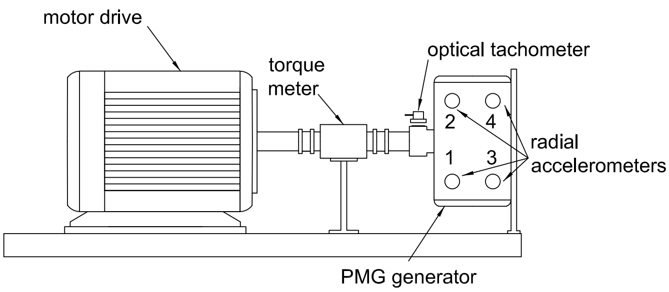

Fig. 1: The test rig for the generators

The test case HAWT is three-bladed, has 2 meters of rotor diameter and the maximum producible power is 3 kW. The overall nacelle mass is 40 kg. The blades are in polymer reinforced with glass fibers and have fixed pitch angle; the minimum chord of the profile is 5 cm and the maximum is 15 cm; the minimum angle of attack for the profile is 1.7° and the maximum is 32°. The hub height is 1.2 meters in the wind tunnel configuration (Figure 3). This prototype has been object of several studies about its design Scappatici et al. (2016) and about its dynamic mechanical behavior Castellani et al. (2017, 2018c,a, 2019).

Fig. 2: The test case HAWT in the wind tunnel.

The R. Balli wind tunnel facility of the University of Perugia (www.windtunnel.unipg.it) has an open test chamber section of 2.2 × 2.2 meters and a recovery section of 2.7 × 2.7 meters. The air can be accelerated up to a maximum speed of 45 m/s using a fan driven by a 375 kW electric motor in a closed loop circuit. The level of turbulence is quite low (< 0.4%). The wind speed is measured by a Pitot tube and a cup anemometer placed at the inlet section. In Figure 3, a scheme of the wind tunnel is reported.

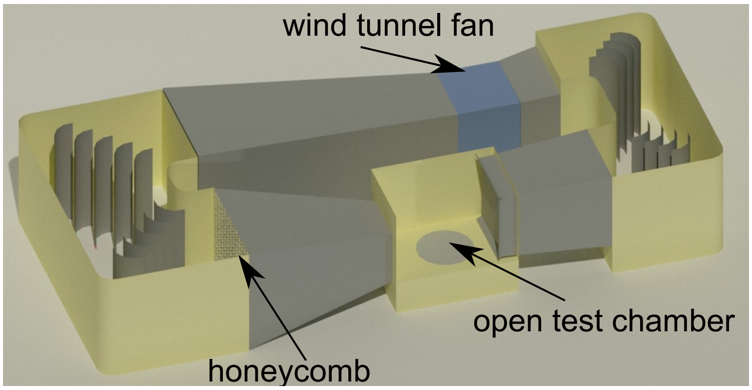

Fig. 3: A scheme of the wind tunnel.

During the wind tunnel tests, vibration measurements are collected through a radial accelerometer near the rear bearing of the shaft. The sampling frequency is 5 kHz. The operational conditions (basically, the rotational speed of the rotor) is contextually measured through a tachometer.

2.2. *Test case 2: MW-scale wind turbine bearings*

The wind farm of interest 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 4. The lowest inter-turbine distance on site is of the order of 7 rotor diameters.

Two field measurement campaigns have been conducted:

1. **Winter 2018** - WTG06 is manifestly damaged (the damage has been detected as well through oil particle counting) at a planetary bearing; WTG03 has an incipient damage at the high speed shaft bearing; WTG01 is taken as reference healthy wind turbine.
2. **Spring 2019** - The damage at WTG06 has been fixed; the damage at WTG03 has worsened; WTG02 is taken as well as healthy reference wind turbine.

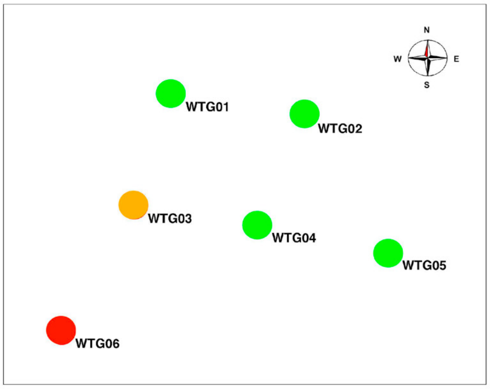

Fig. 4: The layout of the wind farm. The wind turbines of interest are WTG01 and WTG02 (reference healthy wind turbines) and WTG03 and WTG06 (damaged wind turbines, with different levels of severity and recover).

The measurements are conducted as follows: accelerometers are mounted inside the tower of the target and reference wind turbines. They measure the longitudinal (x-axis) and transversal (y-axis) vibrations, as displayed in Figure 5. 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) were used for the acquisition. Each acquisition therefore consists of 4 channels sampled at 12.8 kHz for 2 minutes.

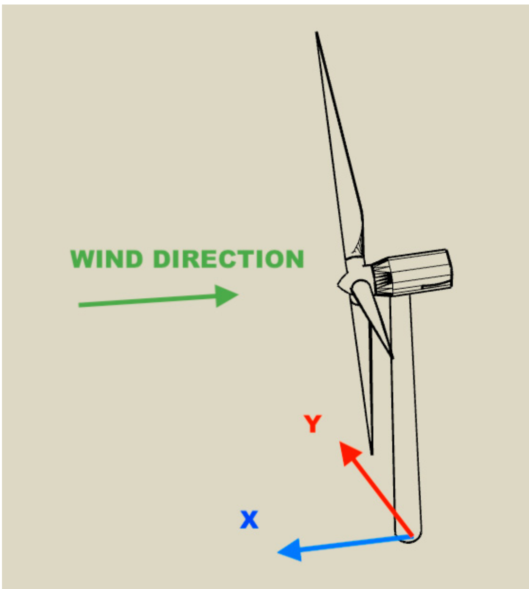

Fig. 5: Definition of the reference frame for the longitudinal and the transverse directions.

3. Methods

The reference and target vibration time series have been organized as indicated in Table 1.

Table 1: The vibration time series arrangement.

TS number	Generator status	Use
1	healthy	reference - calibration
2	healthy	reference - calibration
3	healthy	validation
4	damaged	validation

The information regarding the state of health of the generator bearing must be extracted from these data and in particular the objective is inquiring if the vibration data at the reference and target generators are distinguishable with statistical significance. To ensure the statistical significance of the results, many measurement points are necessary: short, independent (no overlap) chunks of the original signals are obtained by dividing each acquisition in 100 sub-parts. For each sub-part, five time-domain statistical features are computed: root mean square, skewness, kurtosis, peak value and crest factor (peak/RMS). In this way, the processed data set X results being a $n \cdot d$ matrix, where n is the number of channel and feature combinations, while $d = 400$ is the number of samples from the 4 acquisitions of Tables 1 juxtaposed one after the other.

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. For the present study, it has been adopted 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 time series 1 and 2 of Table 1. Subsequently, the validation data sets have been separately projected to the space generated by the first two principal components of the reference data set.

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. 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

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

The reference x distribution is selected as the statistical features matrix extracted from the time series 1 and 2 of Table 1. The target y is selected as the statistical features matrix extracted from respectively time series 3 and 4 of Table 1.

4. Results

4.1. Test case 1: small wind turbine generator bearing

In Figures 6 and 7, the representation of the validation vibration data on the first two principal components of the training data is reported. Figure 6 refers to the test rig data and Figure 7 refers to the wind tunnel data. From these Figures, it clearly arises that the healthy and faulty data sets are distinguishable.

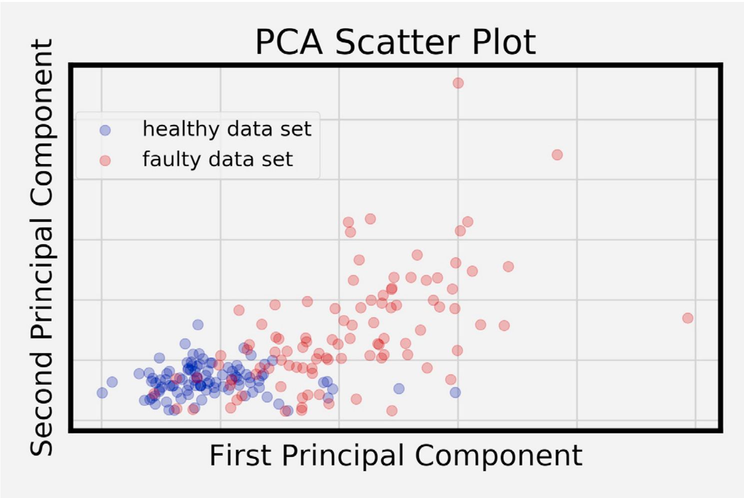

Fig. 6: Vibration data representation on the first two principal components (test-rig).

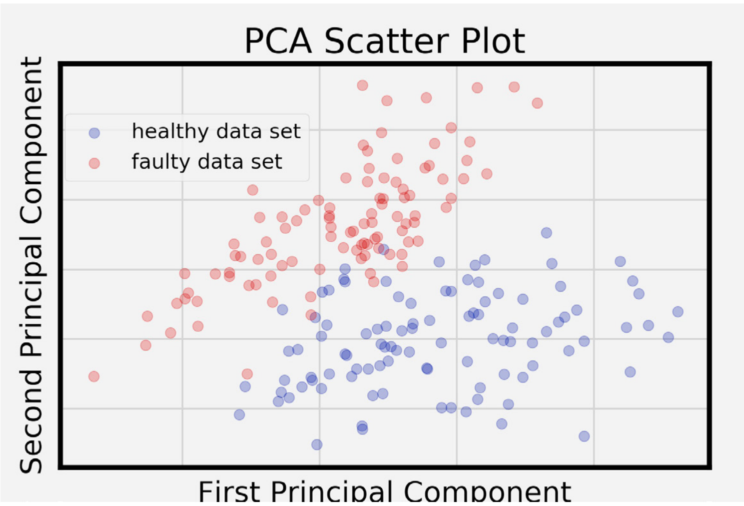

Fig. 7: Vibration data representation on the first two principal components (wind tunnel).

It is further possible to elaborate on the novelty detection (and therefore on the bearing damage diagnosis) by considering the distance between the centers of the Mahalanobis distances distributions for the reference and target bearings. The results are reported for the test rig and wind tunnel data in Figures 8 and 9. It results that the healthy and damaged wind turbines are clearly distinguishable and it is interesting to notice that the wind tunnel data are even more powerful than the test rig data: this is a non-trivial observation because the operation conditions in the wind tunnel, although controlled, involve the whole wind turbine device.

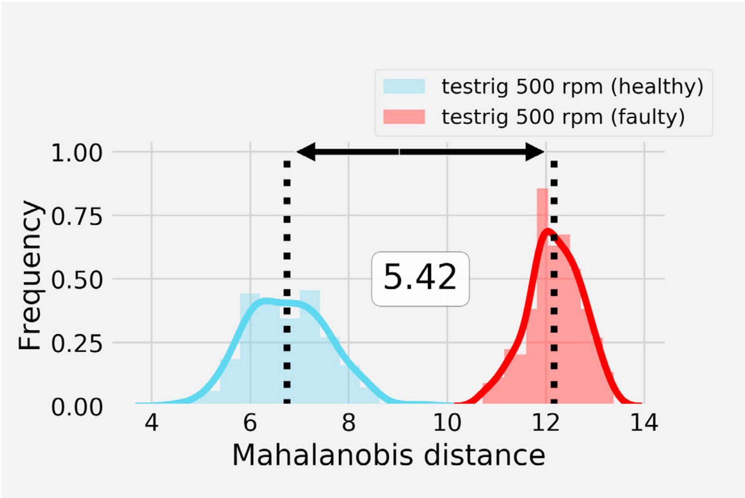

Fig. 8: Mahalanobis distance for the small wind turbine generator at steady rotational regime (test-rig).

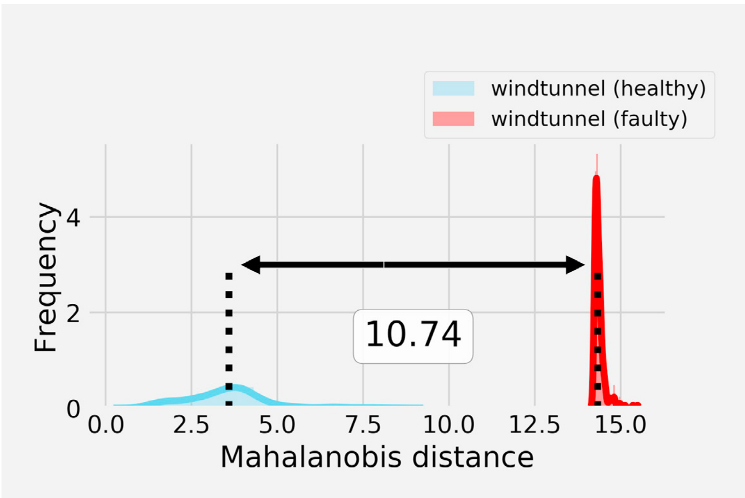

Fig. 9: Mahalanobis distance for the small wind turbine generator at steady rotational regime (windtunnel).

4.2. Test case 2: MW-scale wind turbine generator bearing

In the following Figures, the distance between Mahalanobis distance distributions of the target and reference wind turbines is reported for various selections of measuring campaigns and target wind turbines.
In Figure 10 and 11, results are reported for the Winter 2018 measurement campaign. It arises that the target wind turbines are clearly distinguishable with respect to the reference healthy wind turbine. In the case of the

evident damage (WTG06), the novelty index is of the order of 5 times with respect to the case of incipient damage (WTG03) and this is a good crosscheck of the consistency and responsiveness of the present method.

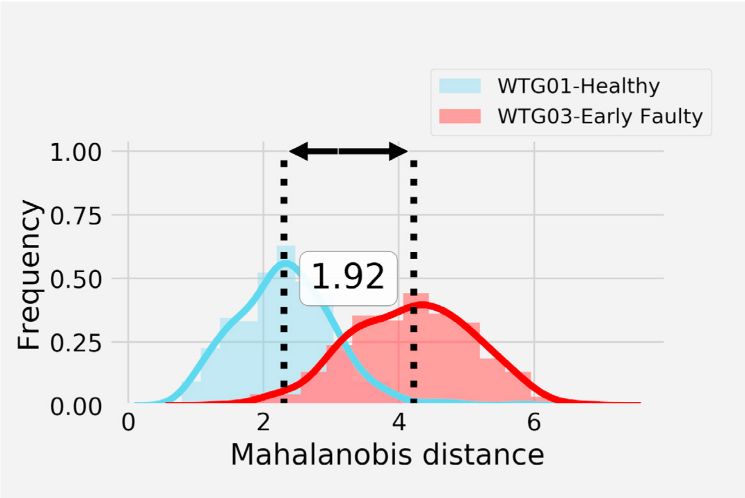

Fig. 10: Mahalanobis distance for healthy (WTG01) and incipiently damaged (WTG03) wind turbines (Winter 2018 campaign).

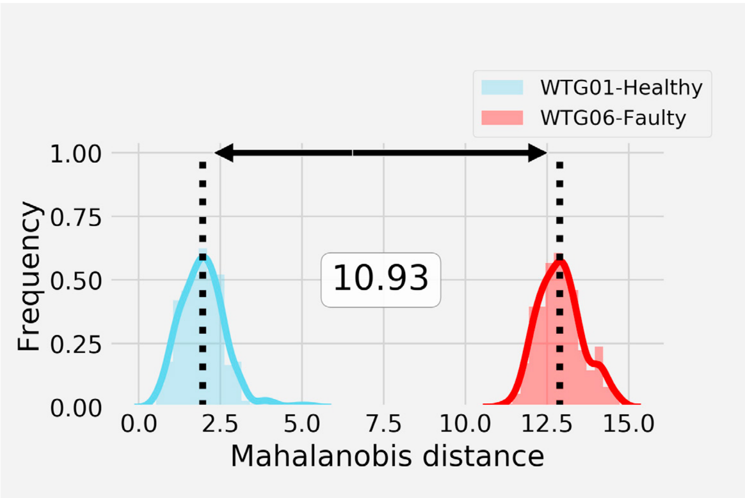

Fig. 11: Mahalanobis distance for healthy (WTG01) and evidently damaged (WTG06) wind turbines (Winter 2018 campaign).

Figures 12 and 13 refer to the Spring 2019 measurement campaign. WTG06 (the damaged wind turbine for Winter 2018 measurement campaign) can be taken as reference because the wind turbine manufacturer in the meantime had intervened and fixed the damage. The Mahalanobis distance distribution for WTG06 is compared against WTG03 (the damaged wind turbine, because the incipient damage has evolved from Winter 2018 to Spring 2019) and against another reference healthy wind turbine (WTG02). It clearly arises that WTG03 can be distinguished with respect to WTG06 and it further arises that WTG06 is barely distinguishable with respect to WTG02. These results are consistent and shed a favorable light on the idea that the proposed methods are useful for gearbox damage detection.

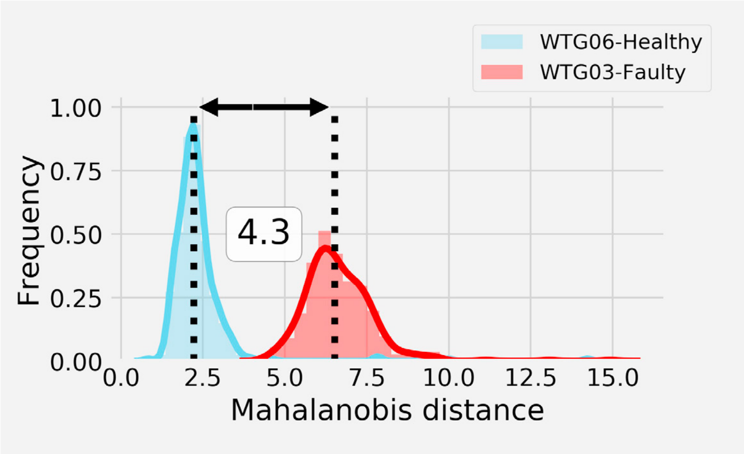

Fig. 12: Mahalanobis distance for healthy (WTG06) and damaged (WTG03) wind turbines (Spring 2019 campaign).

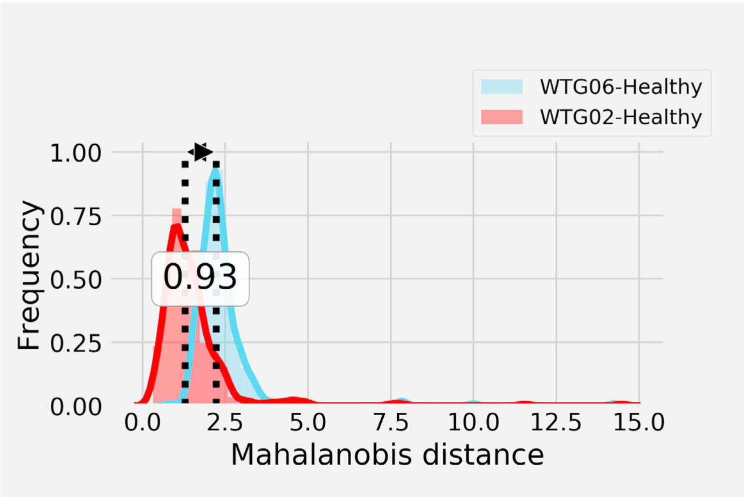

Fig. 13: Mahalanobis distance for two healthy (WTG02 and WTG06) wind turbines (Spring 2019 measuring campaign).

It is interesting to notice that the novelty index is considerably higher for WTG06 (Winter 2018 campaign) with respect to WTG03 (Spring 2019 campaign). This can be reasonably interpreted on the grounds of some evidences: the damage at WTG06 was more severe and actually it was detected also through oil particle counting, which is considered a late stage technique with respect to vibration analysis. Furthermore, the damages at WTG03 and WTG06 were located at bearings of different subcomponents: for WTG06, the damage was at a planetary gearbox bearing, while for WTG03 the damage was at the high speed shaft bearing. A further development of the present work is inquiring the relation between the novelty index and the damage location, basing on statistics and on considerations about the vibration transmission to the tower.

5. Conclusions

This study has been devoted to condition monitoring of bearings of rotating machinery operating under non-stationary conditions. The focus of the study has been devoted to the processing of vibration signals acquired at the test cases of interest through ad-hoc measurement campaigns.

Two test cases have been selected: a small wind turbine PMG and MW-scale wind turbine bearings. For both test cases, data have been acquired at the devices suspected to be damaged (target) and at reference identical devices, assumed to be healthy (reference).

As regards the small wind turbine generator, vibration measurements have been acquired at a test rig, driving the generator at different rotational speed, and in the R. Balli wind tunnel of the University of Perugia. In both cases, the operation conditions are controlled but in the wind tunnel the generators are mounted on the whole wind turbine device. It is therefore interesting to inquire what kind of data are more powerful for generator bearing condition monitoring.

As regards the MW-scale wind turbine bearings, inspired by Mollasalehi et al. (2017), vibration measurements have been collected at the tower of the wind turbines of interest. This procedure has a clear pro in the fact that the wind turbine operation must not be stopped or externally controlled: therefore, the procedure is easily repeatable and has no impact on the wind turbines. On the other way round, the operation conditions are evidently not controlled and non-predictable. Furthermore, another non-trivial aspect is given by the fact that measurements are collected slightly above the wind turbine tower base and the bearings of interest are in the gearbox, placed in the nacelle several meters above. This procedure treats the gearbox like a black box and it is not obvious that the novelty detection between a damaged and a healthy wind turbine is responsive. The results, collected in Section 4.2, provide promising answers to the above issues.

The vibration data have been processed in the time-domain, through the analysis of the most common statistical features (peak/rms, skewness, kurtosis, and so on) on independent chunks extracted from the vibration acquisitions. The data have been divided in training set (from the reference wind turbines) and validation sets (from the reference and target wind turbines). The results in this work indicate that it has been possible to distinguish between the validation data set of the target and reference devices through the use of Principal Component Analysis and Mahalanobis distance.

It is interesting to notice that, for the small wind turbine PMG test case, the novelty detection through the wind tunnel data analysis has been at least as powerful as through the test rig data analysis. This can probably be interpreted as due to the fact that the electromechanical coupling remarkably characterizes the global vibration behavior of a small-sized wind turbine, because the generator constitutes a relevant fraction of the total mass of the device. Therefore, it can be argued that the wind tunnel data can be more useful for an analysis in the time-domain, aimed at a bird's eye view condition monitoring. The results collected in Castellani et al. (2018b) indicate that the data analysis in the frequency domain is necessary for a precise location of the damage: at this aim, the test rig data result being more adequate because they involve only the subcomponent of interest and therefore are less noisy.

Several are the further direction of the present study. An important development is the analysis of the MW-scale wind turbine vibration data in the frequency domain. Actually, it would be particularly valuable to understand if vibrations collected at the tower base can successfully be analyzed in the frequency domain for condition monitoring of gearbox subcomponents. This kind of study is ongoing and the first obtained developments are promising: this would have relevant technical implications for condition monitoring of MW-scale wind turbines. Another important development regards thresholds identification for the novelty index: this can be achieved on one hand by collecting more test case studies and on the other hand by relating other techniques (like the ones in the frequency domain) to those proposed in the present work.

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