A diagnostic protocol for the monitoring of bearing fault evolution based on blind deconvolution algorithms

M. Buzzoni [1], **E. Soave** [1], **G. D'Elia** [1], **E. Mucchi** [1], **G. Dalpiaz** [1]
[1] University of Ferrara, Department of Mechanical Engineering,
via Saragat 1, 44122 Ferrara, Italy
e-mail: **marco.buzzoni1@unife.it**

Abstract

The detection and identification of bearing faults at their initial stage is pivotal in order to avoid catastrophic failures. However, the vibration contribution related to early stage bearing faults are frequently weak and masked by strong background noise and mechanical interferences. In this scenario, blind deconvolution algorithms can be exploited for extracting impulsive patterns related to incipient bearing faults. Maximum Correlated Kurtosis Deconvolution (MCKD) and Multipoint Optimal Minimum Entropy Deconvolution Adjusted (MOMEDA) proved to be effective for fault diagnosis in rotating machines. However, their effectiveness on monitoring the progressive degradation of rolling element bearings has not yet been exhaustively studied. In this paper, the experimental data from an endurance test are investigated by means of MCKD and MOMEDA. The results in terms of incipient fault detection and fault identification accuracy are discussed from different perspectives, highlighting advantages and limits of such blind deconvolution approaches. In particular, an original diagnostic protocol is proposed, based on a condition indicator computed from the cumulative of the blind deconvolution maximized criterion combined with a non-parametric statistical threshold. The proposed indicator is sensitive to the fault degradation as well as the fault type.

1 Introduction

One of the most frequently failures in rotating machines is represented by bearing faults. The early detection and identification of bearing faults through vibration analysis is a powerful strategy in order to prevent catastrophic failures and to reduce machine downtimes as well. However, the bearing fault identification may be very challenging since the impulsive pattern generated by periodic impacts due to localized faults is often masked by strong background noise, the dynamic response of the structure and other mechanical interferences.

Over the years, several strategies have been proposed for the detection and identification of bearing faults. The most popular signal processing technique for bearing fault identification is the envelope analysis. The envelope analysis is based on extracting the diagnostic information carried by the amplitude modulations caused by the bearing faults after filtering around a resonance frequency band in order to maximize the Signal-to-Noise Ratio (SNR) [1]. Furthermore, many other signal processing techniques have been proposed such as: second-order cyclostationary analysis [2], the (fast) kurtogram [3], Blind Deconvolution methods (BD) [4] and a number of other approaches well summarized in Ref. [5].

The proposed research work is focused on BD algorithms which can be exploited in order to extract a source exhibiting a specific statistical property only from a noisy observation (response), under the hypotheses that the system is unknown and linear time-invariant. The first BD algorithm was introduced by Wiggins [6] in the field of seismic. Its methodology, called Minimum Entropy Deconvolution (MED), blindly estimates an inverse filter which maximizes the kurtosis of the source. It should be noted that even if the name recalls the minimization of the entropy, MED is actually based on the maximization of the kurtosis. In other words, the MED extracts the source having the highest kurtosis. The main limit of this method in rotating machine diagnosis is that it tends to extract the most impulsive source rather than a pattern of periodic impulses, that is how the local faults of rotating machines appear in vibration signals.

McDonald et al. [9] improved the MED proposing a novel BD method, named Maximum Correlated Kurtosis Deconvolution (MCKD), that is rooted on a novel criterion called Correlated Kurtosis (CK). The CK is a criterion sensitive to the impulsiveness related with a certain repetition rate.

Recently, McDonald and Zao [10] proposed another BD method, called Multi-point Optimal Minimum Entropy Deconvolution (MOMEDA) that is an improvement of the BD method proposed in Ref. [11] by Cabrelli. The MOMEDA is based on a criterion called Multipoint Kurtosis (MK) and estimates an inverse filter which minimizes the least square error between the response and the target source that is assumed as a Dirac comb. The MED and the most recent methods, i.e. MCKD and MOMEDA, proved to be effective for the fault identification in rotating machines, with particular reference to gears and bearings.

In particular, the final values of the BD criteria can be exploited for assessing the bearing condition. In this direction, Sawalhi et al. [4] used the kurtosis values after performing MED in order to improve the sensitivity of kurtosis to the bearing faults. Analogously, McDonald et al. [9] exploited the CK after performing MCKD together with a threshold for surveying the condition of a multi-stage gearbox. Despite these promising applications [4, 9], the use of BD methods for monitoring the progressive damage of the system has not yet been exhaustively studied. For instance, the kurtosis is not sensitive to the bearing fault type or the indicator variance can make their interpretation difficult. Thus, these aspects should be investigated in more detail.

This research proposes a diagnostic protocol based on MCKD and MOMEDA exploiting the criteria maximized by the BD algorithms combined with a non-parametric threshold based on the Tukey's test. The core of the proposed methodology is rooted on two novel indicators, called Cumulative Correlated Kurtosis (CCK) and Cumulative Multipoint Kurtosis (CMK) that are derived from CK and MK, respectively.

These indicators overcomes the kurtosis since they allow for identifying the bearing fault being dependent on the fault frequency. Moreover, the CCK and the CMK have two valuable properties for diagnostic purposes: (i) as the sample size increases their variance decreases and (ii) being cumulative quantities, they can keep track of the progressive damage of the bearing. This methodology is then particularly fit for industrial applications which require clear data interpretation and early fault detection capability.

The proposed procedure is validated by using the run-to-failure test provided by the Center of Intelligent Maintenance System (IMS) of the University of Cincinnati [12]. The results show that the CCK and the CMK overcome the performance of the raw values of CK and MK in terms of early fault detection and identification as well as bearing damage assessment. The results are presented and discussed in order to enlighten the improvements introduced by the proposed method.

Section 2 reviews the application of BD algorithms for bearing fault identification, with a specific focus on MCKD and MOMEDA. Section 3 addresses the new diagnostic method for the detection and identification of rolling elements bearing faults through the definition of a novel condition indicator. Section 4 concerns the experimental validation by using the IMS dataset. Finally Section 5 summarizes the final remarks.

2 Bearing fault identification through Blind Deconvolution algorithms

In general, the response due to a localized bearing fault occurring in a rotating machine can be modeled as a train of impulses convolved with an Impulse Response Function (IRF) that depends on the vibration transfer path between source and excitation. A scheme about how BD works on a simplified signal model is depicted in Figure 1. The term "simplified" refers to the fact that the bearing fault signatures consist of a blend of random (cyclostationary) and periodic contributions [13] but, for the sake of simplicity, we consider only the contribution of the transfer path and the background Gaussian noise. More details about the principle of model bearing fault signatures and how to model them can be found in [14]. Figure 1 is a Single-Input-Single-Output (SISO) model that considers response x as a convolutive mixture of two

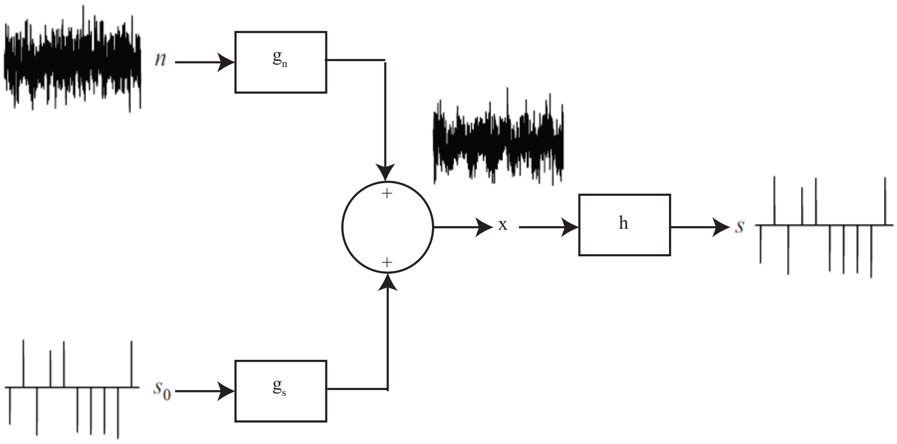

Figure 1: General scheme of blind deconvolution.

contributions: (i) a repetitive train of impulses s_0 which refers to the excitation due to the local fault and (ii) a Gaussian background noise n. Note that all these quantities are a function of time. Both are convolved with their respective impulse response functions depending on the system properties (transmission path, natural frequencies and damping). The schematic in Figure 1 can be then formalized as follows:

$$x = s_0 * g_s + n * g_n \tag{1}$$

where g_s and g_n are the IRFs related to s_0 and n, respectively and $*$ is the convolution operator.

Frequently, g_s and g_n are unknown and the goal of BD methods is to estimate the inverse filter h, assumed to be a FIR filter, that enables the extraction of s_0 just through a noisy observation x. The estimation of the source of interest, s_0, can be achieved considering an arbitrary criterion based on a prior assumption, e.g. assuming that a certain statistical property is strictly related to the target source. Therefore, the BD finds h such that:

$$s = x * h \approx s_0 \tag{2}$$

where s is the estimation of s_0 by means of h. It is important to underline that the approximation symbol refers to the fact that BD methods are not designed for the system identification but for estimating an inverse filter which extracts the source that exhibits the maximum value of a given (statistical) criterion. This research work focuses on two recent BD methods specifically designed for the diagnosis of rotating machines: the MCKD and the MOMEDA. Both criteria have been proposed considering the fact that a criterion which describes the degree of impulsiveness of a vibration signal, e.g. the kurtosis, is often inadequate to deal with mechanical fault signatures. For instance, the vibration signature of a developed bearing fault is typically described by an impulsive contribution which is characterized by a series of impulsive components repeated according to the rotational frequency and the bearing kinematics. Thus, these criteria do not consider only the impulsiveness of the vibration signature but also the repetition rate of the impulses. Thus, they are particularly fit to detect bearing faults.

2.1 Maximum Correlated Kurtosis Deconvolution

The MCKD is an iterative BD algorithm that aims to estimate the source having maximum CK. Unlike the kurtosis which measures the tailedness of a probability distribution and reaches its maximum with signals having a dominant peak, the MCKD is sensitive to signal peakedness according to a given periodicity. The definition of CK is given in the following:

$$CK_M = \frac{\sum_{n=1}^{N} \left(\prod_{m=0}^{M} s_{n-mT} \right)^2}{\left(\sum_{n=1}^{N} s_n^2 \right)^{M+1}} \tag{3}$$

where T is the impulse period and M the number of shifts. The CK combines two features typical of the localized fault signatures, i.e. high kurtosis and repetitive occurrence of the fault. It should be noticed also that the CK is a cyclostationary criterion. Indeed, the numerator of Equation (3) with $M = 1$ is nothing but the autocorrelation function of the instantaneous power of the signal. In this particular case, the CK is a measure of the degree of autocorrelation referenced to a given lag T. Therefore, the CK with $M = 1$ quantifies if the autocorrelation function exhibits periodicities at the fundamental cyclic frequency $1/T$. For this reason, the CK can be considered a cyclostationary criterion since a process which exhibits periodicities in its autocorrelation function is defined as a cyclostationary process.

It should be remarked that the CK [9] has been introduced empirically without explicit mention of its cyclostationary nature. By definition, the parameters of CK (i.e. the FIR filter length L and the number of shifts M) must be properly set in order to achieve satisfying results. In particular M has to be carefully set if MCKD is applied to mechanical vibration signals. In fact, low values of M may not encourage enough the deconvolution of sequential impulses while high values of M, from experience more than 8, could lead to numerical precision issues since the CK can assume very low values.

2.2 Multipoint Optimal Minimum Entropy Deconvolution Adjusted

The MOMEDA is a non-iterative BD method and it is an improvement of the OMEDA. In brief, the MOMEDA estimates a optimal inverse filter (in the Least Square sense) for recovering a source that approximates a target vector t, represented by a Dirac comb. The definition of the MOMEDA criterion is the following:

$$MK = \frac{1}{||t||} \frac{t^T s}{||s||}. \tag{4}$$

Target vector t drives the deconvolution by imposing both spacing and weights of the impulses to be recovered. Since t is defined as a train of equispaced impulses having unit amplitude, this criterion can be considered as a periodic one as opposed to the CK that is a cyclostationary criterion.

Since it is a periodic criterion, it naturally fits with the diagnosis of gears or in any case of periodic fault signature. Indeed, its first application regards the identification of a chipped tooth in a 2-stage gearbox [10]. As said before, bearing fault signatures exhibit second-order cyclostationarity and thus MCKD appears to be more suitable than MOMEDA for the fault detection and identification. However, a recent research [15] proved the effectiveness of MOMEDA for extracting bearing fault signatures taking into account the Case Western database.

3 Proposed diagnostic protocol

3.1 Theoretical formulation

The proposed method is based on condition indicators, namely CK and MK, capable to both detect and identify bearing faults at their early stage. Specifically, this research investigates how the final values of the criteria of MCKD and MOMEDA can be exploited as bearing condition indicators. Particular attention is devoted to verify how these indicators can be used for the real-time monitoring of bearings and for detecting trends related to the progressive degradation of the bearings.

Let $\psi[k]$ be the final value of the BD criterion evaluated from a vibration signal in the time window k. Let us assume that $\psi[k]$ is constituted of three different contributions: a constant (trend) part, a variable part and a Gaussian noise. This model can be formalized as:

$$\psi[k] = \overline{\psi}[k] + \widehat{\psi}[k] + n[k] \tag{5}$$

$\overline{\psi}$ is the constant part of ψ, $\widehat{\psi}$ is the variable part of ψ, n is the additive Gaussian noise.

Hypothesizing that the diagnostic information is retained into $\widehat{\psi}$, $\overline{\psi}$ and n de facto represent masking contributions. Furthermore, variable part $\widehat{\psi}$ is not supposed to be necessarily a monotonically increasing function. This latter property is particularly useful for the design of robust indicators due to the fact that it allows for keeping trace of the "degree of damage" taking into account the whole time history of the component under investigation.

In order to reduce the effects of $\overline{\psi}$ and n, a possible strategy is to consider the cumulative of ψ:

$$c[j] = \frac{1}{j}\sum_{k=1}^{j}\left(\bar{\psi}[k] + \hat{\psi}[k] + n[k]\right). \tag{6}$$

Equation (6) is nothing but the sum of the expected values of all the contributions of ψ. After some simple manipulations, it can be noted that (under the hypothesis of large j) the estimated expected value of n converges to zero while the estimated expected value of $\overline{\psi}$ converges to its true (constant) value. Thus, Equation (6) can be rewritten as follows:

$$c[j] = E\left[\bar{\psi}\right] + \frac{1}{j}\sum_{k=1}^{j}\hat{\psi}[k]. \tag{7}$$

where $E\left[\bullet\right]$ stands for the expected value of $\bullet$. From the physical standpoint, the constant part of ψ, $\overline{\psi}$, describes the healthy condition of the system and the variable one, $\widehat{\psi}$, reflects the occurrence of the bearing fault. At this point, after reducing the Gaussian noise contribution through the cumulative, the constant part $\overline{\psi}$ can be minimized as well by subtracting the expected value of $\overline{\psi}$ which is called $E\left[\bar{\psi}\right]^*$:

$$\beta[j] = c[j] - E\left[\bar{\psi}\right]^* = \frac{1}{j}\sum_{k=1}^{j}\hat{\psi}[k] \tag{8}$$

where $E\left[\bar{\psi}\right]^*$ is the expected value of data referenced to the healthy condition. $E\left[\bar{\psi}\right]^*$ is theoretically unknown but a reasonable estimation can be done by estimating the mean value of $\overline{\psi}$ in the very first part of the acquisition when the component is supposed to be healthy.

Indicator β describes the evolution of the bearing condition and has two important properties: (i) it is monotonically increasing – so it retains all the variations in its whole time history – and (ii) it is consistent in the sense that the random noise is reduced according to the considered number of samples. This indicator can be therefore exploited for defining a diagnostic protocol in order to monitor bearings. Specifically, when β is close to 0 it means that the variable part of ψ is negligible and thus the system is healthy. When β changes, it means that the bearing condition is changing as well and an incipient bearing fault may be occurring. For this purpose, a non-parametric statistical threshold can be used, such as the thresholds evaluated through the Tukey's method [16]: mild outlier threshold $T_{H,1}$ can be used for establishing when the bearing degradation process starts; outlier threshold $T_{H,2}$ can be used for establishing when the fault is manifest. Such thresholds are called also Tukey's fences and can be calculated by means of the following formula:

$$T_H = Q_3 + k\left(Q_3 - Q_1\right) \tag{9}$$

where Q_3 and Q_1 are the lower and upper quartiles while k is a constant that defines $T_{H,1}$ if $k = 1.5$ and $T_{H,2}$ if $k = 3$. These thresholds are computed taking account the values of β referenced to the first day

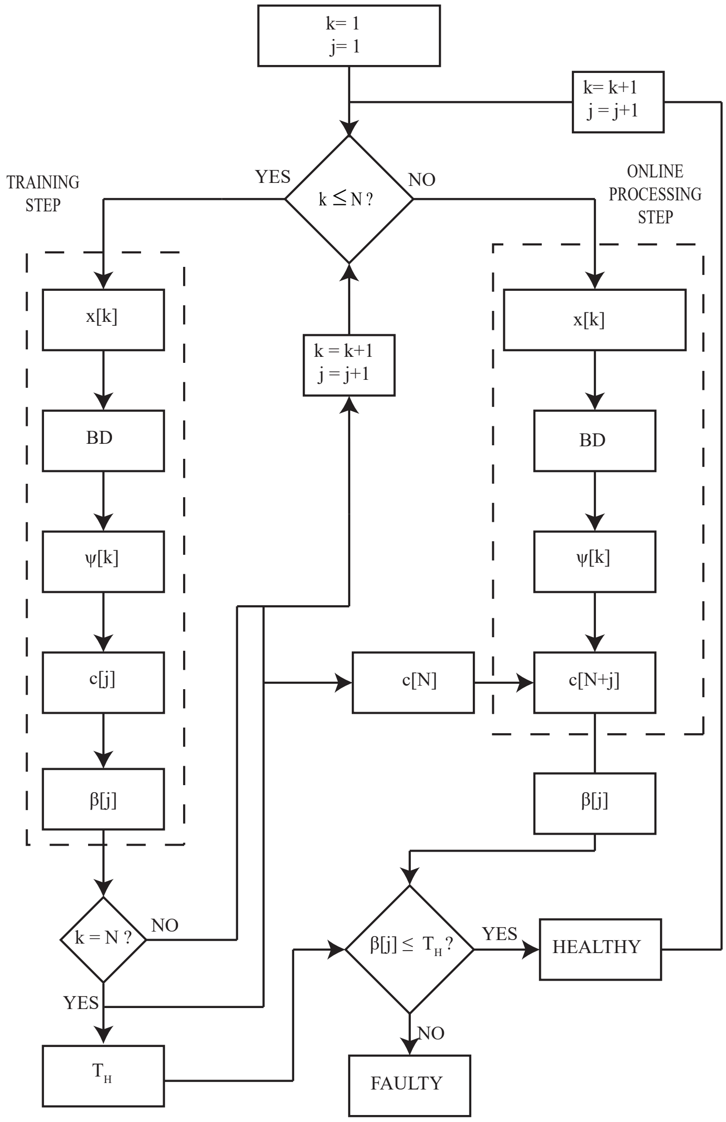

Figure 2: Flow chart of the proposed diagnostic protocol.

of test, under the hypothesis that in this time span the bearings are healthy. Note that the first hours have been discarded since the vibration signature may affected by the contribution of running-in phenomena so the values of β obtained in this time period can be biased and consequently the related thresholds can be overestimated.

The proposed diagnostic protocol is reported schematically in Figure 2 and can be summarized as follows:

1. Training step: perform the BD algorithm on $x[k]$, take the final value of the BD criterion ($\psi[k]$), compute the cumulative function $c[j]$ and then subtract the expected value in order to obtain $\beta[j]$. Repeat this step for the N time spans referenced to the healthy condition in order to compute the thresholds T_H.

2. On-line processing step: perform the BD algorithm on $x[k]$, take the criterion after maximization $\psi[k]$ and compute the cumulative function reduced by the expected value $\beta[j]$.

3. Compare the cumulative function $\beta[j]$ obtained in step 2 and the thresholds T_H calculated in step 1. If $\beta[j] < T_H$, the bearing is healthy and the procedure starts again from step 2. Otherwise, the bearing fault is detected and identified.

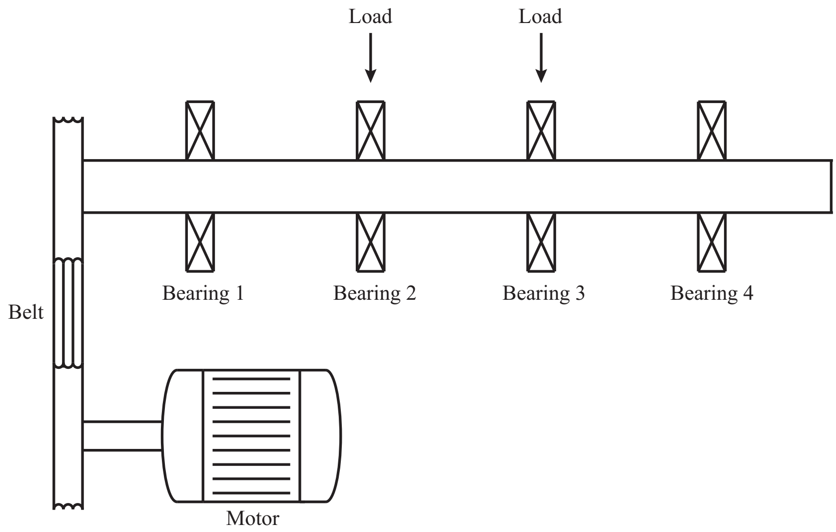

Figure 3: Experimental setup.

Note that in this paper, the novel indicator β will be called in two different ways: Cumulative Correlated Kurtosis (CCK) and Cumulative Multipoint Kurtosis (CMK). The former refers to the diagnostic procedure that exploits the MCKD while the latter refers to the diagnostic procedure that exploits the MOMEDA.

4 Experimental verification

4.1 Setup

The data used in this experimental verification have been provided by the Center of Intelligent Maintenance System (IMS) of the University of Cincinnati [12]. The test rig is composed of four bearings type Rexnord ZA-115 tied on the same shaft, as shown in Figure 3.

This test has been performed at constant speed of 2000 rpm with a load of 27.7 kN applied on bearings 2 and 3. The vibration signals have been collected by four accelerometers type $PCB\ 253B33$ mounted in radial direction. The vibration signals have been recorded with a sampling frequency of 20.48 kHz with a rate of 1 s of acquisition each 10 minutes. After 7 days, corresponding to 16.4 minutes of actual acquisition, the test has been stopped and an outer race fault, occurred in Bearing 1, has been detected.

4.2 Results and discussion

The experimental data have been investigated by means of the BD algorithms described in Section 2, specifically MCKD and MOMEDA. The final values of the BD criteria, respectively CK and MK, have been computed for signal segments of duration 1 s in order to monitor the progressive damage of the bearings during the endurance test. According to the technical report provided by the experimenters, an outer race fault has been occurred in Bearing 1. Hence, only the accelerometer placed on bearing 1 have been considered.

Figure 4 and Figure 5 depict the application of the proposed diagnostic protocol on the IMS dataset, respectively starting from MCKD and MOMEDA analysis: (a) represents the CK and MK values estimated for each signal segments of the endurance test, (b) shows the smoothed values of the previous CK and MK values, called for simplicity Smoothed Correlated Kurtosis (SMK) and Smoothed Multipoint Kurtosis (SMK) while (c) reports the values of the proposed indicator, namely CCK and CMK. All these figures include the non-parametric statistical thresholds, calculated as described in Section 3, in order to compare the time

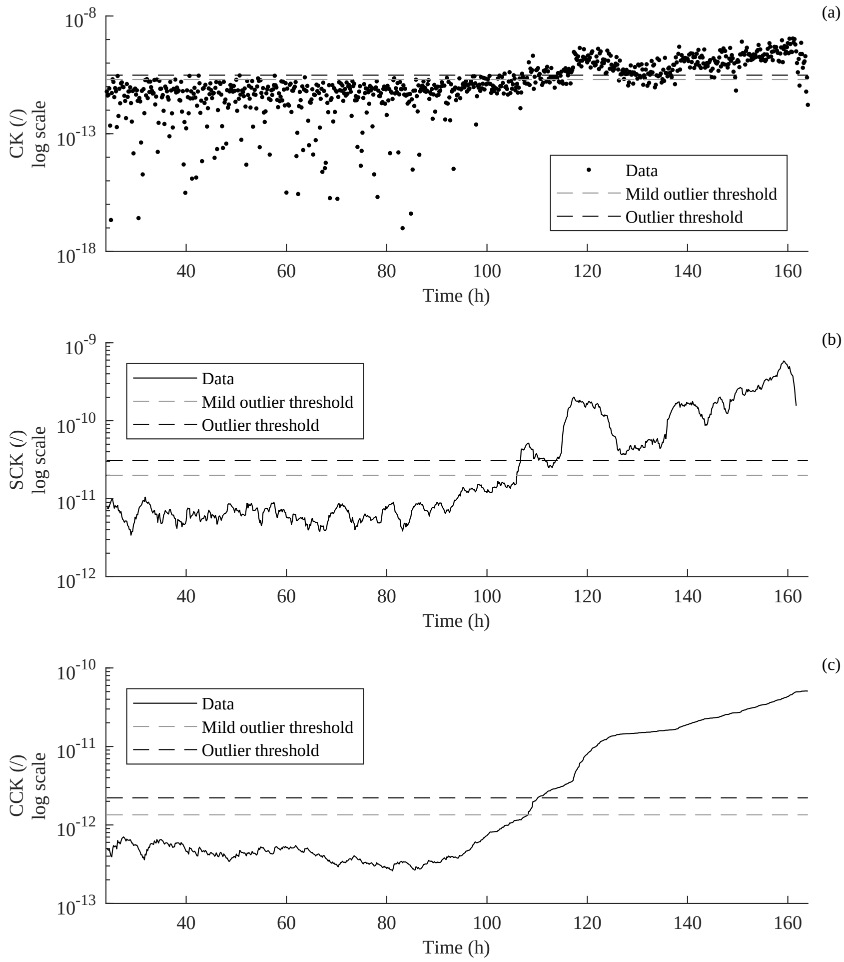

Figure 4: Application of proposed method with MCKD: (a) CK values, (b) smoothed CK values (moving average), (c) cumulative CK values. The considered prior period is referenced to the outer race bearing fault.

instant of appearance of the bearing fault. Note that the SCK and the SMK have been computed by means of moving average and that these results are referenced to the prior period related to the outer race bearing fault.

Figure 4(a) and Figure 5(a) clearly show that the trend of CK and MK is substantially constant taking into account the first hundred hours of test. Reasonably, this behavior means that the bearings can be considered healthy in this time span. Then, the values change, according to the model given in Equation (5): the variable part $\widehat{\psi}$ is no longer negligible with respect to the other contributions. Therefore, it can be noticed a time-dependent deviation with respect to the constant trend exhibited in the first part of test. From the physical point of view, it can be deduced that this variation is directly related to the appearance of a bearing fault. Moreover, the time-dependent variation of the indicators are not monotonically increasing but oscillatory. This fluctuating trend reflects the different stages of the bearing fault development and propagation which can be briefly summarized as consecutive phases of damaging and healing until the complete breakdown, as explained in Ref. [17],

In order to estimate the time instants associated to the fault appearance, the indicators must be compared with the thresholds calculated through the Tukey's method. Considering Figure 4(a) and Figure 5(a), one

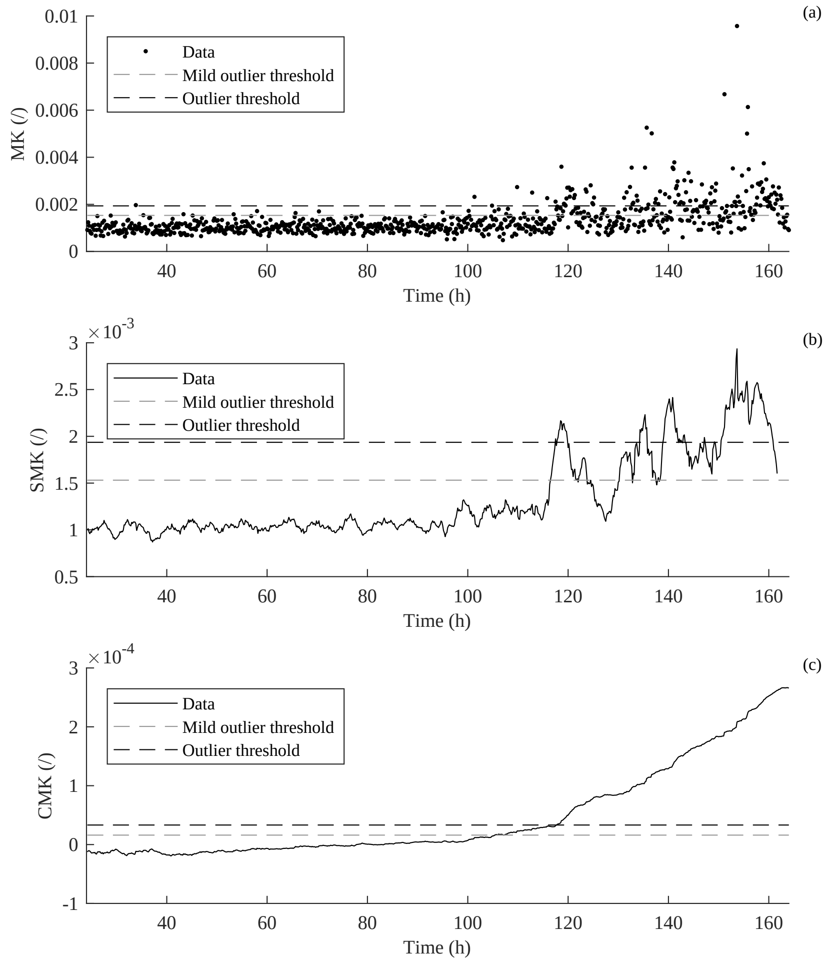

Figure 5: Application of proposed method with MOMEDA: (a) MK values, (b) smoothed MK values (moving average), (c) cumulative MK values. The considered prior period is referenced to the outer race bearing fault.

can immediately find two drawbacks on the use of the raw BD criteria, hereafter called ψ in general terms but referenced to CK and MK. The first one is related to the dispersion of the values of ψ: although the major part of the values remains below the thresholds during the early stage of the test, some values cross the threshold although no fault has occurred. The second one regards the behavior of the variable part, $\widehat{\psi}$, during the last stage of test: this variable contribution does not appear as a monotonically increasing function and thus the raw indicator ψ is not a good candidate for describing the bearing damage level since the bearing damage is irreversible.

The first issue, i.e. the variance of ψ, can be mitigated by using a smoothing technique, such as the moving average. This approach improves the results by reducing the dispersion of the indicators, as reported in Figure 4(b) and Figure 5(b). Indeed, the indicators (SCK and SMK) lie below the thresholds in the healthy stage but, during the faulty stage, is not able to represent the evolution of the fault with a strictly growing trend.

At this point, let us consider β defined in Equation (8) as the absolute error between the expected value $E[\bar{\psi}]^*$ and the actual cumulative indicator c. By definition, β has two important properties: (i) its variance

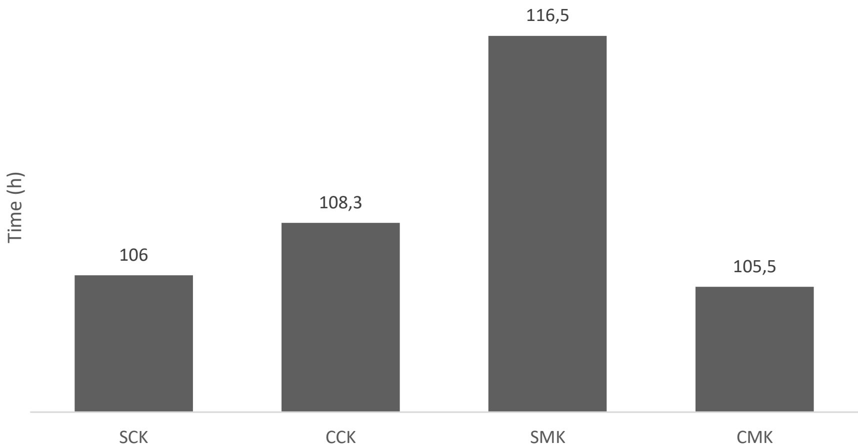

Figure 6: Time associated to the appearance of the outer race bearing fault.

decreases when the number of observation increases and (ii) it is a strictly growing function in presence of non-nil values of $\widehat{\psi}$. Figure 4(c) and Figure 5(c) show the values of CCK and CMK estimated through the procedure depicted in Figure 2. As expected, CCK and CMK return a smoother trend with respect to the raw values of CK and MK (see Figure 4(a) and Figure 5(a)). At the same time, the dispersion is reduced as well with respect to the smoothed values of CK and MK (see Figure 4(b) and Figure 5(b)). CCK and SMK show a strictly growing trend that makes the monitoring of the bearing conditions and the fault detection easier and returns also a consistent information about the overall damage level of the bearing. Therefore, this experimental verification demonstrates that β has a lower dispersion with respect to the raw indicator and that β is actually a monotonically growing function. These properties open to different scenarios concerning the industrial applications, in particular on the use of β as an indicator for the overall damage level of the bearing. Furthermore, the use of thresholds for the bearing fault detection is strongly improved thanks to the reduction of the data dispersion.

Figure 6 reports the time instants when the indicators cross threshold $T_{H,1}$ with reference to the results reported in Figure 4 and Figure 5. Considering the results related to the MCKD (first and second column of Figure 6), both SMK and CMK provide approximatively the same time, specifically 108 and 106 hours, respectively. This slight difference can be explained since MCKD is based on a cyclostationary criterion and thus is particularly fit for the early fault detection of bearings. Considering the results related to the MOMEDA (third and fourth column of Figure 6), SMK and CMK provide values that are significantly different, i.e. 116 and 105 hours, respectively. Comparing the times related to the CK and the MK (first and third column of Figure 6), it can be noticed a significant difference in favor of the CK, due to the fact that the CK is a cyclostationary indicator – thus sensitive to cyclostationary signals as the bearing fault signatures – while MK is a periodic indicator. This difference is reduced if we consider the times referenced to the CCK and the CMK (second and fourth column of Figure 6). This demonstrates that the proposed method is able to improve the effectiveness of the MK for the bearing fault detection in addition to its desired properties for the definition of a robust bearing damage indicator.

Until now, the analyses have been performed by using as a prior period the one referenced to the outer race fault. A further and necessary investigation is how the method behaves taking into account also the other possible prior fault periods, i.e. the one related to the inner race fault and the one related to the ball bearing. The results of this other analysis, in terms of CMK and CCK trend, is summarized and shown in Figure 7. According to the previous considerations, the expectation is that the estimated trends should remain below the thresholds throughout the test. It is possible to note that all the trends, after a first stage, are decreasing so we can deduce that the only fault occurred on bearing is the one on the outer race, according to what has been detected experimentally on the physical system. It is worth noting also that the CCK estimated by using

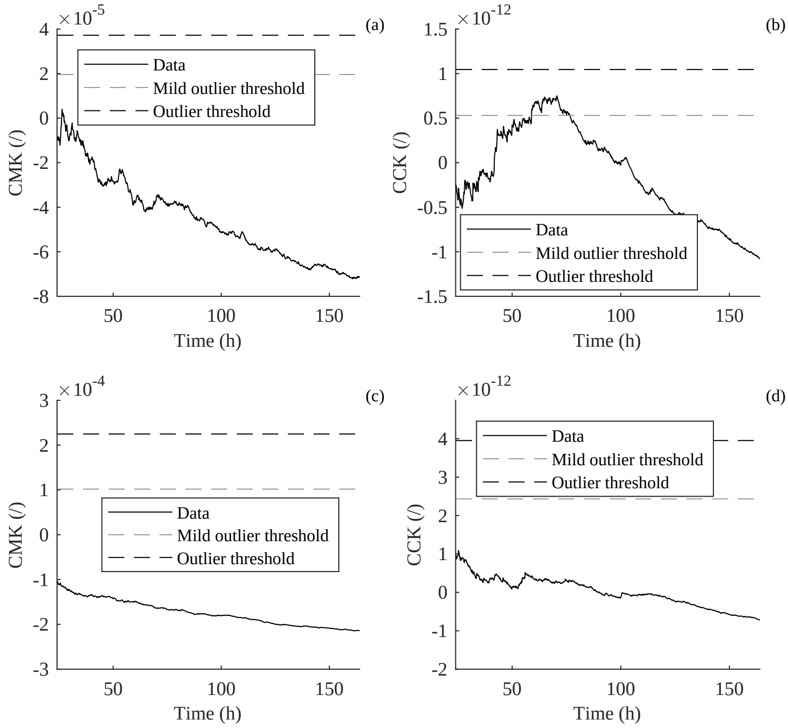

Figure 7: Application of the proposed method considering (a-b) the inner race fault frequency and (c-d) rolling element fault frequency.

the inner race fault frequency as a reference prior period (see Figure 7(b)) actually crosses the mild-outlier threshold but just for a short time span and, above all, never crosses the outlier threshold.

5 Final remarks

BD methods proved to be effective for the diagnosis of bearings. In particular, the final values of the BD criterion can represent a convenient strategy for the assessment of the bearing condition. Despite some promising applications [4, 9], the use of BD methods for monitoring the progressive damage of the system has not yet been exhaustively studied.

In order to partially fill this gap, this research focuses on the development of a diagnostic protocol based on a novel condition indicator derived from the cumulative of the criterion maximized by the BD algorithm. The fault detection is assessed by using Tukey's statistic thresholds. Specifically, the proposed indicators, i.e. CCK and CMK that are derived form the CK and MK, are sensitive to the fault frequency and keeps track of the progressive damage of the bearing. Moreover, by definition, as the sample size increases their variance decreases. This aspect represents an improvement with respect to the other similar applications reported in [4, 9].

The proposed methodology has been verified on the IMS run-to-failure test by comparing the diagnostics performance of the proposed indicator with respect to the raw values of the BD criteria. The results show that the proposed methodology improve the effectiveness of the criteria of MCKD and MOMEDA for the bearing fault detection in terms of early fault diagnosis and clarity of data interpretation.

Acknowledgements

This research work has made use of data provided by the Center for Intelligent Maintenance Systems (IMS), University of Cincinnati. The analyses have been performed through the Matlab code within the Minimum Entropy Deconvolution Multipack kindly coded and provided by Geoff McDonald.

References

[1] P. Borghesani, P. Pennacchi, S. Chatterton *The relationship between kurtosis- and envelope-based indexes for the diagnostic of rolling element bearings* Mechanical Systems and Signal Processing. Vol. 43, No. 1-2, (2014), pp. 25-43.

[2] G. D'Elia, M. Cocconcelli, E. Mucchi, and G. Dalpiaz *Combining blind separation and cyclostationary techniques for monitoring distributed wear in gearbox rolling bearings*, Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, Vol. 231, No. 6, (2001), pp. 1113-1128. doi:10.1006/mssp.2001.1418.

[3] J. Antoni *Fast computation of the kurtogram for the detection of transient faults* Mechanical Systems and Signal Processing. Vol. 21, No. 1, (2007), pp. 108-124.

[4] N. Sawalhi, R.B. Randall, H. Endo *The enhancement of fault detection and diagnosis in rolling element bearings using minimum entropy deconvolution combined with spectral kurtosis* Mechanical Systems and Signal Processing. Vol. 21, No. 6, (2007), pp. 26162633.

[5] R.B. Randall, J. Antoni *Rolling element bearing diagnostics-A tutorial* Mechanical Systems and Signal Processing. Vol. 25, No. 2, (2011), pp. 485520.

[6] R. A. Wiggins, *Minimum entropy deconvolution*, Geoexploration. Vol. 16, No. 1-2, (1978), pp. 2135.

[7] J Antoni and R. B. Randall, *A Stochastic Model for Simulation and Diagnostics of Rolling Element Bearings With Localized Faults*, Journal of Vibration and Acoustics. Vol. 125, No. 3, (2003), p. 282.

[8] J. Antoni, F. Bonnardot, A. Raad, and M. El Badaoui, *Cyclostationary modelling of rotating machine vibration signals*, Mechanical Systems and Signal Processing. Vol. 18, No. 6, (2004), pp. 12851314.

[9] G. L. McDonald, Q. Zhao, and M. J. Zuo, *Maximum correlated Kurtosis deconvolution and application on gear tooth chip fault detection*, Mechanical Systems and Signal Processing. Vol. 33, (Nov. 2012), pp. 237255.

[10] G. L. McDonald and Q. Zhao, *Multipoint Optimal Minimum Entropy Deconvolution and Convolution Fix: Application to vibration fault detection*, Mechanical Systems and Signal Processing. Vol. 82, (2017), pp. 461477.

[11] Carlos A. Cabrelli, *Minimum entropy deconvolution and simplicity: A noniterative algorithm*, GEOPHYSICS. Vol. 50, No. 3, (1985), pp. 393-413.

[12] J. Lee, H. Qiu, G. Yu, J.Lin, *Rexnord Technical Services, Bearing Data Set, IMS, University of Cincinnati, NASA Ames Prognostics Data Repository.*, 2007. url: http://ti.arc.nasa.gov/project/prognostic-data-repository.

[13] J. Antoni., *Cyclic spectral analysis of rolling-element bearing signals: Facts and fictions* Journal of Sound and Vibration, Vol. 304, No. 3-5, (2017), pp. 497-529.

[14] G. DElia, M. Cocconcelli, E. Mucchi *An algorithm for the simulation of faulted bearings in non-stationary conditions* Meccanica. Vol. 53, No. 4, (2017), pp. 1-20.

[15] Y. Wang, N. Hu, L. Hu, Z. Cheng, *Rolling bearing fault diagnosis based on multipoint optimal minimum entropy deconvolution adjusted technique and direct spectral analysis*, *Proceedings of The 2017 Prognostics and System Health Management Conference, Harbin, China, 2017 9-12 July*, Harbin (2017).

[16] J. W. Tukey, *Exploratory data analysis* Addison-Wesley Publishing Company, (1977).

[17] T. Williams, X. Ribandeira, S. Billington, T. Kurfess, *Rolling element bearing diagnostics in run-to-failure lifetime testing*, Mechanical Systems and Signal Processing. Vol. 15, No. 5, (2016), pp. 979-993.