AN EMPIRICAL MODE DECOMPOSITION-INDEPENDENT COMPONENT ANALYSIS BASED APPROACH FOR DETECTING LOCALIZED AND DISTRIBUTED FAULTS IN ROLLING BEARING DIAGNOSTICS

Milena Martarelli

Università degli Studi e-Campus, via Isimbardi, Novedrate (CO), Italy
email: milena.martarelli@uniecampus.it

Paolo Chiariotti

Università Politecnica delle Marche, via Brecce Bianche, 60131 Ancona, Italy

Paolo Castellini

Università Politecnica delle Marche, via Brecce Bianche, 60131 Ancona, Italy

Alessandro Sereni

Università Politecnica delle Marche, via Brecce Bianche, 60131 Ancona, Italy

Enrico Primo Tomasini

Università Politecnica delle Marche, via Brecce Bianche, 60131 Ancona, Italy

Rolling bearing diagnostics still represents an open research field, especially when distributed faults are looked for rather than localized faults. In fact, distributed faults are typically due to a progressive growth of surface wear. A low-quality manufacturing, in terms of material or process, can even constitute another cause of distributed fault or representing an accelerating factor for the fault development. Classical strategies adopted for diagnosing localized faults can barely recognize this type of faults. However, certain approaches based on the extraction of the spectral components building the vibrational signature of the bearing can be exploited to diagnose both localized and distributed faults. This paper aims at presenting an approach that can be exploited for this purpose. The algorithm is based on a combined use of Empirical Mode Decomposition (EMD) and Independent Component Analysis (ICA). EMD is exploited as a pre-processing step to decompose the original signal into multiple time-series, the so-called intrinsic mode functions. These time series are then processed by ICA in order to extract those components that can be related to the fault. The non-stationary content of the distributed fault is taken into account by both methods. The effectiveness of the whole procedure in tackling the distributed faults diagnostic issue is presented on simulated data. A sensitivity analysis is presented as well.

Keywords: bearing diagnostics, localized and distributed faults, Empirical Mode Decomposition, Independent Component Analysis

1. Introduction

The identification of distributed faults in rolling bearings still represents an open research field for those working on machine diagnostics. The reason is twofold: it is indeed important to understand if a progressive growth of the bearing surface wear is taking place, e.g. because of a low-quality manufacturing in terms of material or process, in order to schedule maintenance/repair interventions; classical diagnostics strategies developed for localized faults cannot be straightforwardly applied to these defects and, therefore, tailored approaches should be developed. Methods based on the ciclostationary [1] characteristics of the bearing signals have been proposed during the years (see, for instance, [2][3]). Despite powerful, these approaches need the knowledge of a non-damaged status of the bearing, which is, sometimes, a non-trivial information to collect. On the contrary, when dealing with localized faults, a more straightforward identification of the damage is possible, since it can be inferred by the localization of specific deterministic frequencies on the vibration/acoustic signature of the bearing. With these premises, it is quite natural to claim that a signal processing technique which could provide the same easiness of use for distributed faults as for localized faults would represent an interesting alternative to cyclostationarity-based methods.

The approach proposed in this paper aims to answer to this need. Developed by Miao et al. [4], the approach, which utilises Independent Component Analysis (ICA) [5] as processing of signals previously decomposed by the Empirical Mode Decomposition (EMD) method, was already successfully exploited by Martarelli et al. [6] to identify localized faults in rolling bearing in non-destructive vibro-acoustic tests. Since both EMD and ICA can deal with non-stationary phenomena, this approach can represent a good candidate to be tested for the identification of distributed faults. In this sense, the aim of this paper is to check the exploitability and the sensitivity of an EMD-ICA based processing approach for the diagnosis of a distributed fault whose severity is progressively growing. Since the evolution of surface wear, giving rise to the fault, is not easy to reproduce in a controlled way, the technique is tested on a simulated vibration signal taking advantage of a model developed by D'Elia et al. [7]. A comparison of the performance with a standard technique as the Spectral Kurtosis [8] is also presented.

The paper is structured as follows: section 2 will give an outline of the method, while section 3 will present the main characteristic of the model utilised to produce the virtual signal; section 4 will present the main analysis aiming at checking the suitability of the approach for the identification of faulted bearings, section 5 will report the main conclusions.

2. EMD-ICA method theoretical description

A detailed discussion on EMD is out the scope of this paper. For that, the interested reader might refer to the work of Rilling et al. [9]. However, for understanding the whole procedure, some key concepts should be provided. EMD is based on the assumption that every signal *x(t)* consists of simpler intrinsic modes of oscillation, the so called Intrinsic Mode Functions (IMFs). Mathematically, this translates in

$$x(t) = \sum_{i=1}^{N} c_i(t) + r_N(t) \quad (1)$$

where $c_i(t)$ represents each IMF and the term $r_N(t)$ is the residual term of the decomposition.
The IMFs should satisfy two conditions:

- the number of extrema and zero crossings may differ by no more than one;
- the local mean is zero.

EMD is also an iterative process that continuously seeks for the best IMFs approximating the original signal. However, this iterative process does not stop until the residual becomes a monotonic function or a constant from which no more IMF can be extracted.

The IMFs found from the sifting steps can be further processed via the Fast Fourier Transform and mapped on the basis of an energetic criterion in frequency domain:

$$I_i = \frac{ESS_i}{\sum_i ESS_i} \tag{2}$$

$$ESS_i = \sum_f (ES_i(f))^2 \tag{3}$$

$$ES_i = \left|\int_{-\infty}^{+\infty} c_i(t) e^{-2\pi i f t} dt\right| \quad . \tag{4}$$

In Equations form (2) to (4) the variable *i* goes from 1 to *N'*, with *N'* being the number of IMFs extracted. Eq. (3) is the representation of the spectrum energy for the i-th component and Eq. (4) is the Fourier Transform magnitude of the signal $c_i(t)$. The IMFs with the *m* largest I_i values are selected for further construction of the ICA model.

As EMD, also ICA is a processing technique that aims to separate a signal (in typical applications a multivariate signal) into subcomponents. The main difference among the two methods is related to the fact that, in ICA, the subcomponents are assumed to be non-Gaussian and statistically independent. This holding, the aim of an ICA algorithm is, starting from the problem

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{5}$$

where:

- **x** is the observation vector,
- **A** is the mixing matrix,
- **s** is the source vector,

to find an unmixing matrix $\mathbf{W} \approx \mathbf{A^{-1}}$ so that $\mathbf{s} \approx \mathbf{y} = \mathbf{Wx}$. Depending on the time dependency nature of the mixing, time invariance or time variance, i.e. including or not time delays/echoes, the problem in Eq. (5) is said to be instantaneous or convolutive. When dealing with bearings, unfortunately, the mixture is to be considered convolutive and techniques which are able to deal also with this kind of problem has to be considered. The FastICA algorithm [5] is one of them. FastICA seeks those independent components maximising the Negentropy function *J*, which can be efficiently described by the proportionality relation:

$$J(y) \propto [E\{G(y)\} - E\{G(v)\}]^2 \tag{6}$$

where *E* is the expectation operator and *v* is a standard gaussian zero-mean unitary-variance variable. Indeed, maximising the non-gaussianity of each independent component implies compliance with the Central Limit theorem, which states that the distribution of the sum of a large number of independent random variables tends to be a Gaussian distribution. The *G* function in Eq. (6) is a non-quadratic non-linear function. Different functions can be exploited as *G* function: the hyperbolic tangent or the skewness one are some, among others.

The IMFs can be processed by FastICA building the **x** vector; however, a centring and whitening operation is performed before applying the FastICA algorithm. If the original signal is carrying the damage information then it should be recognisable among the Independent Components (ICs) obtained from the FastICA processing.

3. Distributed faulty signal synthesis model

The easiest way to assess the capability of a processing method to deal with certain types of damages is to rely on a mathematical model, since it gives the possibility to create inputs with known characteristics in a fully controlled manner. In this paper, the model developed by D'Elia et al. [7] is exploited for this purpose. The model can reproduce both localized and distributed faults and takes into account non-stationarity as well. Concentrating on the distributed fault model, it should be recalled that this vibration signal model is a mixture of a deterministic term - Eq. (7) and (8) - and a ciclostationary term – Eq. (9). D'Elia et al. describe both term in the angular domain

$$p_{rot}(\theta) = q_{rot} cos\left(\frac{f_c}{f_c}\theta + \frac{f_d}{f_c}\int cos\left(\frac{f_m}{f_c}\theta\right) d\theta\right) \tag{7}$$

$$p_{stiff}(\theta) = q_{stiff} cos\left(\frac{f_c}{f_c}\tau_{stiff}\theta + \frac{f_d}{f_c}\int cos\left(\frac{f_m}{f_c}\theta\right) d\theta\right) \tag{8}$$

$$q(\theta) = 1 + q_{Fault}\, cos\left(\frac{f_c}{f_c}\tau_{fault}\theta + \frac{f_d}{f_c n_r}\tau_{fault}\int cos\left(\frac{f_m}{f_c n_r}\tau_{fault}\theta\right) d\theta\right) \quad (9)$$

thus generating the signal, after moving to the time domain by the use of the rotational velocity information, as:

$$x_d(t) = \mathrm{p_{rot}}(t) + p_{stiff}(t) + q(t)m(t) + n(t) = p(t) + B(t) + n(t) \quad . \quad (10)$$

In Eq. (10), *p(t)* addresses the deterministic component, *B(t)* the ciclostationary component and *n(t)* represents a noise term; the ciclostationary component *B(t)* is a random noise modulated by the fault frequency - time domain interpolation of the term calculated in Eq. (9). In all equations from Eq. (7) to Eq.(9) the following notation is used:

- f_c : carrier component of the shaft speed;
- f_d : frequency deviation of the shaft speed;
- f_m : modulation frequency of the shaft speed;
- q_{rot}, q_{stiff} : amplitude weights of the deterministic components;
- τ_{stiff} : geometrical bearing parameter obtained as $\tau_{stiff} = \frac{n_r}{2}\left(1 - \frac{d}{D}cos(\beta)\right)$;
- τ_{fault} : geometrical parameter that can be expressed, for an inner-race fault, as $\tau_{fault} = \frac{n_r}{2}\left(1 + \frac{d}{D}cos(\beta)\right)$;
- n_r : number of rolling elements;
- d : rolling element diameter in mm;
- D : rolling element pitch circle diameter in mm;
- β: contact angle in deg.

An IC boasting a frequency linked to τ_{fault}, eventually together with some of its harmonics, is a clear symptom of the damage presence, whether or not the damage itself is a distributed or a localized fault.

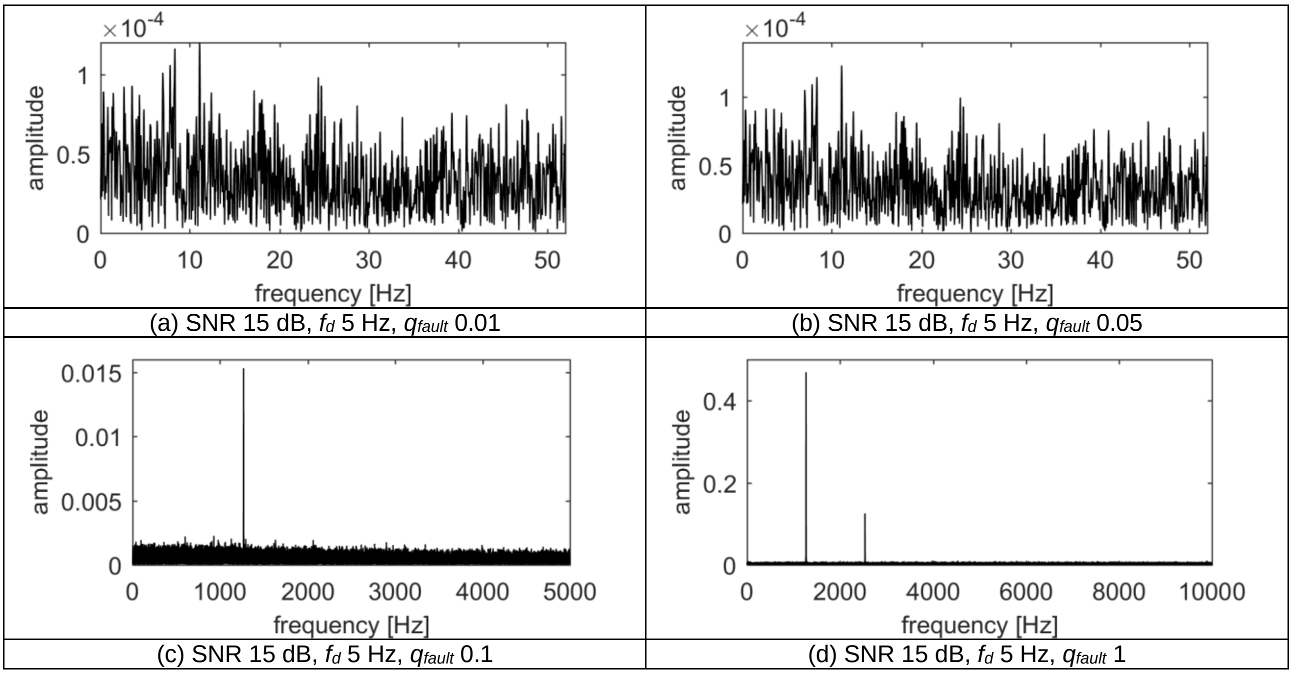
4. Diagnostic method validation

The efficiency of the EMD-ICA method has been tested in relation to the parameters which might influence its performance the most: the SNR, the frequency deviation of the rotation frequency (f_d) and the level of distribution of the defect given by the amplitude (q_{fault}) of the function modulating the ciclostationary component of the signal. It can be expected that, increasing the noise occurring in the signal, the rotation frequency deviation and the extension of the defect, i.e. lowering the SNR, increasing f_d and decreasing q_{fault}, the identification of the frequency linked to the damage would be more difficult. However, the EMD-ICA method will suffer less than a deterministic method as the diagnostic technique based on the conventional Spectral Kurtosis. In order to test this, a set of 128 signals was synthetized. The signals referred to a damaged inner race producing a characteristic frequency of 1270 Hz. The SNR, f_d and q_{fault} were varied as reported in Table **1**. Both the methods were tested on the same set of signals in order to assess their capability in identifying the frequency related to the damage.

Table 1: Value assumed by parameters

Parameter	Value assumed			
SNR [dB]	5	10	15	20
f_d [Hz]	5	10	15	20
q_{fault} [adimensional]	0.01	0.05	0.1	1

As an example, in Figure 1 the envelope spectra obtained by filtering the signal on the basis of the Spectral Kurtosis are reported for an SNR of 15 dB, a frequency deviation of 5 Hz and for the four values of q_{fault}. It is evident that for low q_{fault} (0.01 and 0.05), i.e. for well-developed defect, the Spectral Kurtosis suffers on identifying the optimal filter level. In fact, the calculated filter range does not even include the defect frequency. For q_{fault} equal to 1 the defect is localized and the Spectral Kurtosis works well so that the filter level identified allows to highlight not only the defect characteristic frequency but its first harmonic too.



(a) SNR 15 dB, f_d 5 Hz, q_{fault} 0.01 | (b) SNR 15 dB, f_d 5 Hz, q_{fault} 0.05

(c) SNR 15 dB, f_d 5 Hz, q_{fault} 0.1 | (d) SNR 15 dB, f_d 5 Hz, q_{fault} 1

Figure 1: Envelope spectrum of filtered signals at different defect distribution levels.

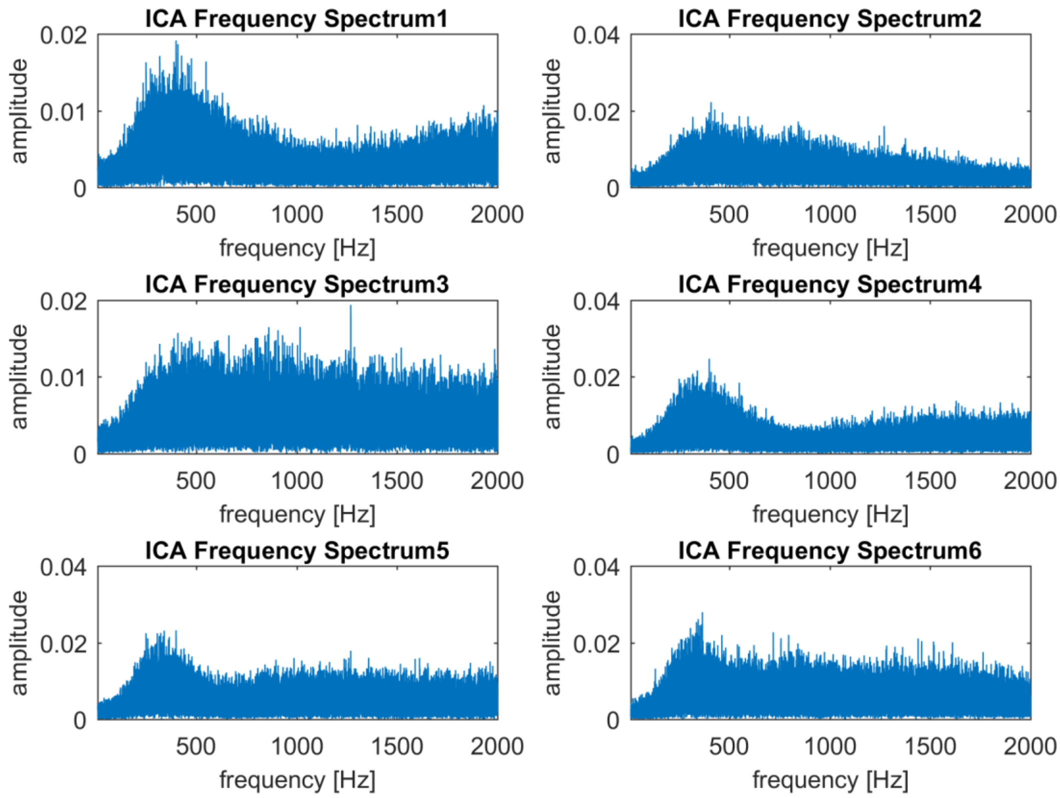


Figure 2: First six ICAs spectra for q_{fault} 0.01.

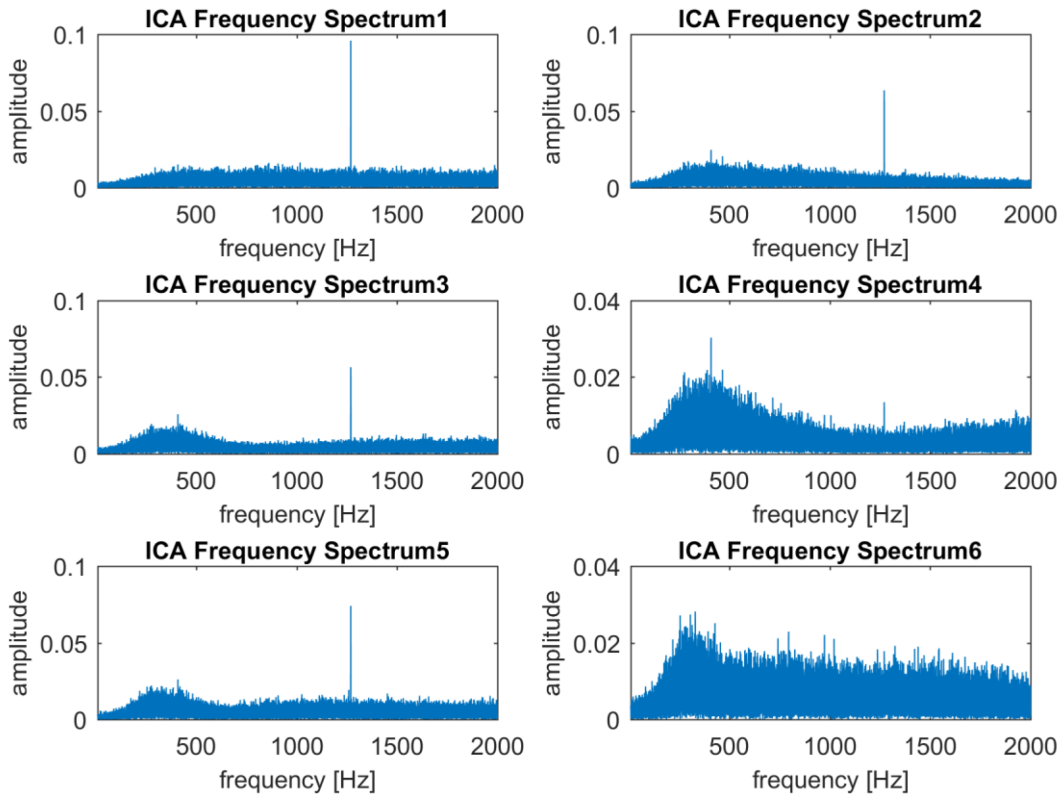


Figure 3: First six ICAs spectra for q_{fault} 0.05.

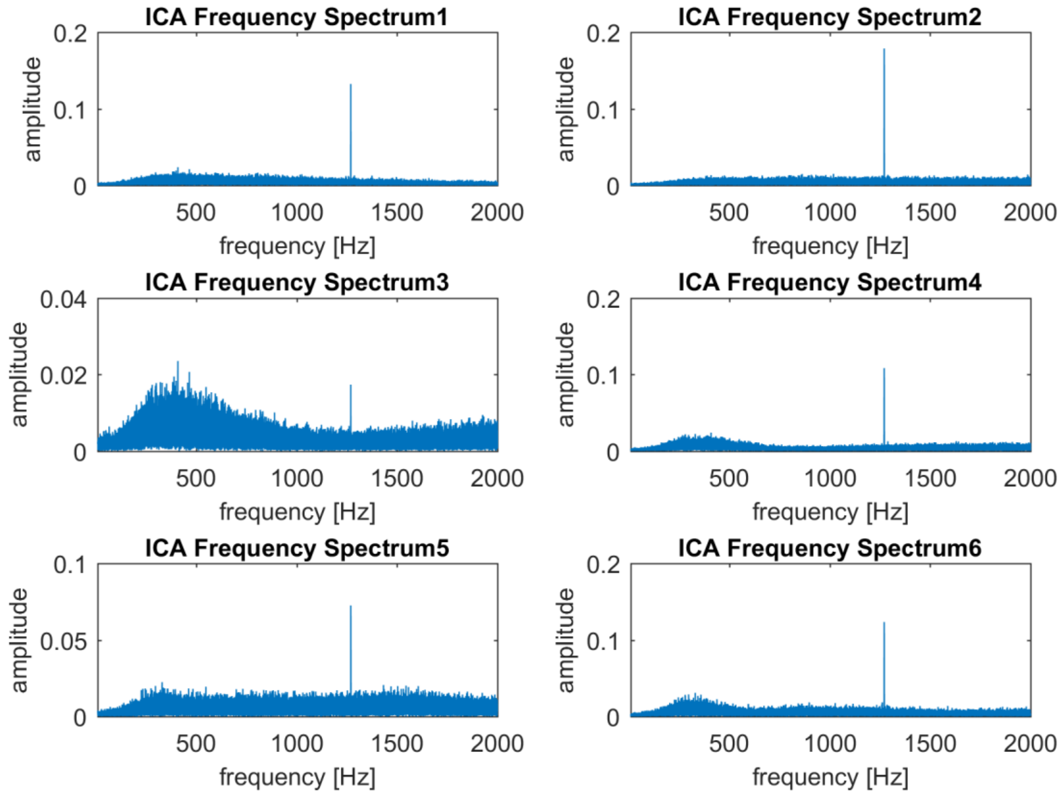


Figure 4: First six ICAs spectra for q_{fault} 0.1.

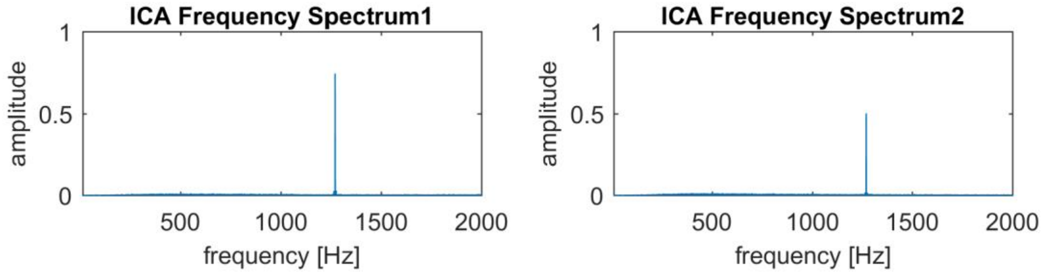


Figure 5: First six ICAs spectra for q_{fault} 1.

The same signals analysed with the Spectral Kurtosis method have been analysed with the EMD-ICA one and the ICA spectra are given from Figure 2 to Figure 5. Even though the ICA spectra obtained for the well-developed defect (q_{fault} 0.01, Figure 2) present a high noise level the characteristic frequency is evident in the third IC. By increasing q_{fault}, the characteristic frequency becomes more and more evident in all ICs.

A summary of the cases when Spectral Kurtosis (SK) and EMD-ICA methods are working properly is reported in Table 2, where only f_d and q_{fault} are considered because the SNR does not influence both the methods.

Table 2: Working condition of EMD-ICA method in comparison with the Spectral Kurtosis one

q_{fault} \ f_d [Hz]	5	10	15	20
0.01	SK x EMD-ICA ✓	SK x EMD-ICA ✓	SK x EMD-ICA ✓	SK x EMD-ICA ✓
0.05	SK x EMD-ICA ✓	SK x EMD-ICA ✓	SK x EMD-ICA ✓	SK x EMD-ICA ✓
0.1	SK ✓ EMD-ICA ✓	SK ✓ EMD-ICA ✓	SK ✓ EMD-ICA ✓	SK ✓ EMD-ICA ✓
1	SK ✓ EMD-ICA ✓	SK ✓ EMD-ICA ✓	SK ✓ EMD-ICA ✓	SK ✓ EMD-ICA ✓

5. Conclusions

The paper was intended to show a diagnostic procedure targeted to the identification of distributed faults in rolling bearing. The method proposed is based on a hierarchical use of EMD and ICA, in which ICA is applied on IMFs obtained by the siftening process produced by EMD. A sensitivity analysis to noise contamination, shaft speed variation and fault extension was performed in order to identify the parameter mostly affecting the performance of the approach. In order to perform this analysis, a model derived to synthetize distributed faults in rolling bearings running in non-stationary conditions was exploited. The method resulted to be robust to noise pollution, as well as to shaft speed variation. The fault extension was found to be the parameter affecting the most the performance of the method, even though the spectral characteristics linked to the fault in the inner race of the bearing was identified in all conditions tested. The EMD-ICA method proposed thus represents a valuable tool to assess the health status of rolling bearings.

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