Using Maximum Correlated Kurtosis Deconvolution Method in the Bearing Fault Detection of Wind Turbine Generators

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***Abstract*—Wind turbine generators are safety-critical equipment, which must work without unexpected stops. For this reason, the detection of its faults already in their incipient phase is very important. Most the classical approaches in fault detection cannot be applied in this case due to the high external vibrations of the generators due to the strongly fluctuating input power, special mechanical construction, etc. In the paper a vibration monitoring based bearing fault detection method is analyzed. It applies the maximum correlated kurtosis deconvolution method to extract the fault-typical frequency components from the noisy measured vibration signal. Its usefulness is exemplified with detecting an inner race bearing fault.**

Keywords—ball bearings, fast Fourier transform, fault detection, generators, maximum correlated kurtosis deconvolution, spectral kurtosis, vibration measurement, wind turbines.

I. Introduction

Statistically, rolling bearing faults are one of the most frequent failures of the electrical machines, having a share of round 40% out of the total machine damages [1]. Their early detection is very important, mainly in safety-critical applications, as in automotive, power systems, medical, etc., since the fault of a simple and cheap bearing can cause significant extra costs and losses [2].

The fault detection in the case of the machinery used in wind turbines is hindered due to the existing significant vibrations [3], [4], [5]. Therefore the wide-spread bearing fault detection methods used in industrial environment cannot be used here [6], [7], [8], [9]. More advanced methods are required to extract the bearing fault induced vibration components from the considerable background vibrations, as those based on envelope extraction [10], kurtograms [11], [12], wavelets [13], morphological signal processing [14], etc.

The paper deals with the use of the maximum correlated Kurtosis deconvolution method (MCKD) in bearing fault detection.

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II. Theoretical Background

If a ball is rolling over a damaged surface inside the bearing, it creates a succession of vibrations, which repeat with each pass over the spoiled area. The recurrence frequency of the impact depends on the place of the bearing fault, rotational speed and bearing dimensions [6]. Each bearing fault type is generating specific fault frequencies, which can be determined by using specific expressions, such as written for to the outer and inner race damages:

$$F_o = \frac{N_b}{2} F_r \left(1 - \frac{D_b}{D_c} \cos\beta\right) \tag{1}$$

$$F_i = \frac{N_b}{2} F_r \left(1 + \frac{D_b}{D_c} \cos\beta\right) \tag{2}$$

where F_r is the rotation frequency, N_b and D_b the number of balls and their diameter, D_c the pitch diameter and β the contact angle.

The fault related repeating frequency components in the case of inner race bearing faults are given in Fig. 1. Around each integer multiple of the F_i component two sidebands can be observed at F_r distance before and after each component.

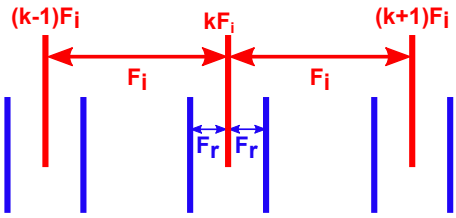


Fig. 1. Repeating frequency components in the case of inner race faults

If in the measured vibration spectra such repeating frequency components can be observed, it is a sure indicator of the existence of an inner race bearing fault.

Hence the fault detection requires the knowledge of the frequencies related to the bearing faults and the spectral analysis of the measured vibration signals.

III. The Maximum Correlated Kurtosis Deconvolution Method

Bearing faults, as also other electrical machines damages, are characterized by series of impulses in their vibrations. These impulses can be highlighted by the frequently used Spectral Kurtosis (SK) method, which extends the classical concept of the kurtosis to that of a frequency function, being able to show how the impulsiveness of a signal is [15].

Earlier, Minimum Entropy Deconvolution (MED) method used for bearing fault detection was reported in several papers [2], [12], [16]. Convergence issues were related in conjunction with this iterative method. Supplementary, the MED method is most fitted for the deconvolution of a single-impulse type input signal, whereas the bearing faults are generating periodic vibration impulses [17]. To solve these problems the Maximum Correlated Kurtosis Deconvolution (MCKD) method was proposed in the literature [18], [19], [20].

The Correlated Kurtosis (CK), the key factor of the method, is a deconvolution norm, which depends on the periodic character of the fault induced vibration impulses. Its use has the advantage of not requiring an autoregressive filtering of the input signal before the deconvolution. During the application of this method a Finite Impulse Response (FIR) filter is defined, which enables the maximization of the CK, resulting in a high kurtosis level, and more emphasizing the periodicity of the vibration pulses [18].

The required deconvolution norm can be defined as [18]:

$$CK_1(T) = \frac{\sum_{n=1}^{N} \left(y_n \cdot y_{n-T}\right)^2}{\left(\sum_{n=1}^{N} y_n^2\right)^2} \tag{3}$$

where N is the number of samples in the measured signal, T and L are the periodicity and length of the FIR filter, and y_n is the filtered signal:

$$y_n = \sum_{k=1}^{L} f_k \cdot x_{n-k+1}\,,\ x_0 = 0\,,\ y_n = 0 \ \text{ for } n \neq 1, 2, \cdots, N \tag{4}$$

f_n being the FIR filter coefficients, and x_n the values of the measured signal.

The MCKD method lays on the maximization of the deconvolution norm [18]:

$$MCKD_1(T) = \max_f \frac{\sum_{n=1}^{N} \left(y_n \cdot y_{n-T}\right)^2}{\left(\sum_{n=1}^{N} y_n^2\right)^2} \tag{5}$$

This procedure is iterative due to the non-linearity of the equations. The steps to follow are described in length in [18].

IV. The Measured Data

All the measured data used for testing the MCKD based fault detection method were taken from the public database of the *Society for Machinery Failure Prevention Technology* (MFPT) [21]. The bearing fault dataset on their website was provided to support researchers working in the field of bearing fault detection. The dataset contains results of several laboratory tests performed with an electrical machine without any damage and having inner and outer race bearing faults. The laboratory experiments were performed at different loads of the tested induction machine [22].

The bearings of the tested induction machine were of Nice-type, having the following parameters: $D_c = 1.245''$, $N_b = 8$, $D_b = 0.235''$ and $\beta = 0°$.

All the vibration data were acquired at 48,828 samples per seconds and saved in MATLAB binary format (.mat-files).

V. Testing the MCKD Method

The main goal of the study performed for testing the MCKD method was to prove its usefulness also for vibration signals having significant noise level, as they can be collected from an in-field working electrical generator of a wind turbine. For this purpose, a random noise signal of maximum 15 m/s^2 was added to the measured accelerations. The effect of noise on the measured signal can be very clearly seen in Fig. 2, where the time domain plots for the healthy machine are given.

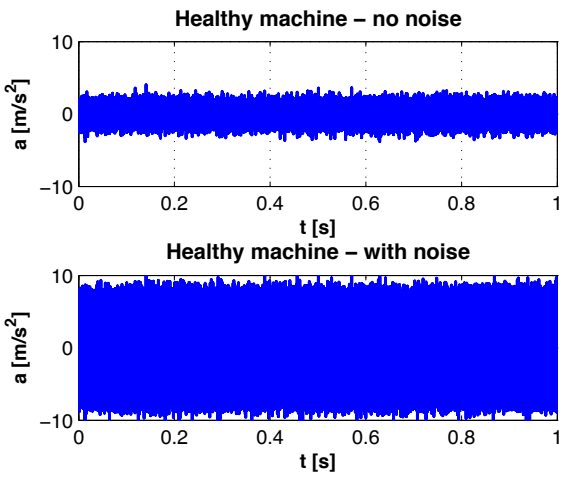


Fig. 2. Time domain plots of the acceleration signal acquired from the induction machine not having any faults. The measured signal and that with random noise added

As it can be seen in Fig. 2, the added intensive random noise is completely covering the measured signal.

Upon the classical approach of the vibration monitoring based bearing fault detection the fault-related frequency components, as those given by (1) and (2), are searched in the frequency spectrum of the measured signal.

In our studies the measured vibrations collected from the induction machine having a bearing with an inner race fault and loaded at its rated load were used. The speed of the machine at this load was 1485 r/min, meaning a rotation frequency of $F_r = 24.75$ Hz.

In these conditions, the basic inner race fault frequency given by (2) is $F_i = 117.7$ Hz. The integer multiples of this

frequency component and the values of its sidebands (upon those shown in Fig. 1) are given in Table I.

TABLE I. MULTIPLES OF THE FREQUENCY INDICATING AN INNER RACE FAULT AND ITS SIDEBANDS AT F_R=24.75 Hz

k	$k \cdot F_i - F_r$ (Hz)	$k \cdot F_i$ (Hz)	$k \cdot F_i + F_r$ (Hz)
2	210.6	235.4	260.1
3	328.3	353.1	377.8
4	446	470.7	495.5
5	563.7	588.4	613.2
6	681.4	706.1	730.9
7	799.1	823.8	848.6
8	916.7	941.5	966.2
9	1034.4	1059.2	1083.9
10	1152.1	1176.9	1201.6

Performing the Fast Fourier Transform (FFT) based spectral analysis of the acquired acceleration signals the plots given in Fig. 3 are obtained.

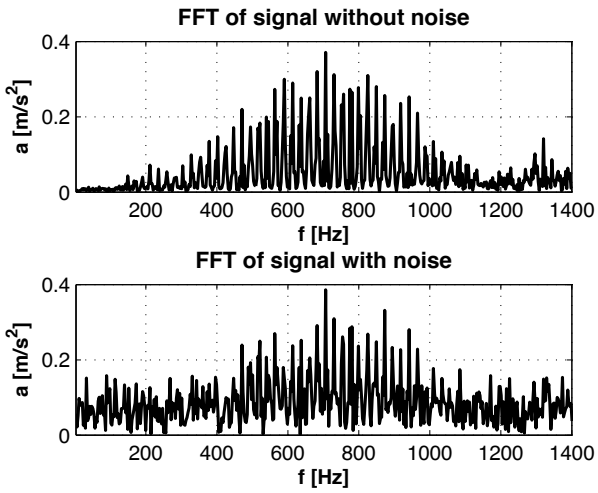


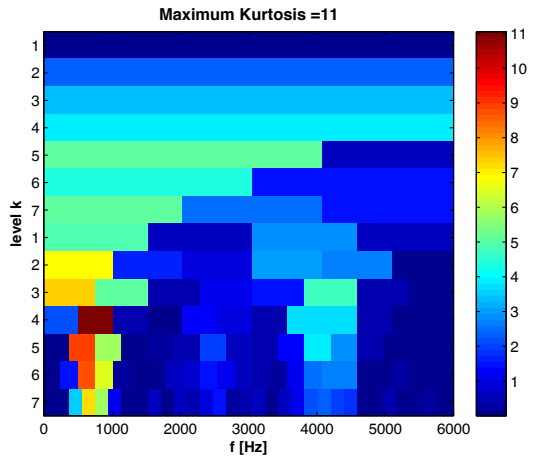
Fig. 3. Frequency domain plots of the acceleration signal acquired from the induction machine not having any faults. The measured signal without and with random noise added

As it can be seen, the added random noise has a significant influence on the spectral content of the vibration signal. Therefore, when applying vibration based fault detection methods in the case of electrical machines working in harsh, vibration full environment, the extraction of the fault characterizing frequency components can be done very hardly, or even it can be impossible.

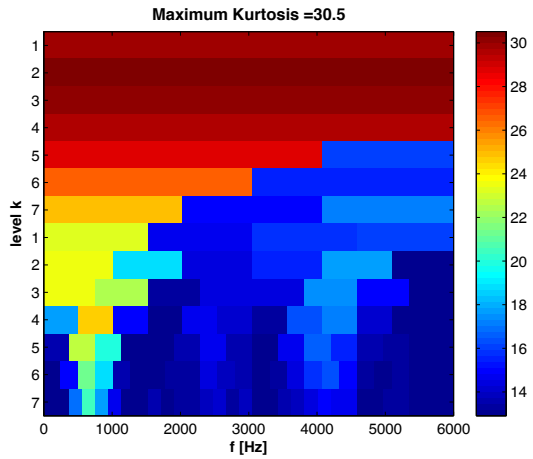
For such cases, among them also that of electrical generators used in wind energy conversion systems, the MCKD method (presented in details in Section III) can be a viable solution. The MCKD method can filter the periodic bearing faults induced typical vibration impulses also from a very noisy signal.

Simply said, the MCKD method is improving the kurtosis of the input signal over the entire frequency domain of interest. Practically, it makes "fat the tails" of signal, and thinner and higher its peaks. By means of the kurtosis, the peakedness of the signal can be measured. Therefore, it is a good indicator of signal impulsiveness in the context of fault detection of rotating components, as the bearings of the electrical machines.

The kurtosis of the vibration signal before and after the MCKD based filtering is given in Fig. 4.



a) before filtering



b) after applying the MCKD filtering

Fig. 4. The color plots of the signal kurtosis

As it can be seen, the MCKD filtering had a very good effect on the signal in discussion, at least what its kurtosis is concerned. The maximum kurtosis nearly was tripled (from 11 to 30.5). What is more important, the kurtosis improvement was performed on the entire frequency domain (0÷6 kHz). As it can be seen in Fig. 4a, the highest kurtosis values are obtained only near 750 Hz, and the kurtosis is low outside this frequency domain. But after applying the MCKD filtering, the highest kurtosis values covering the entire frequency range (see Fig. 4b).

After processing the acquired vibration signals by the means of the MCKD method, FFT can be applied and the fault-related specific frequency components can be clearly evidenced in the acceleration spectrum. For illustrating this, the frequency spectrum of the vibration signal measured and MCKD filtered in the case of the induction machine having an inner race bearing fault is given in Fig. 5.

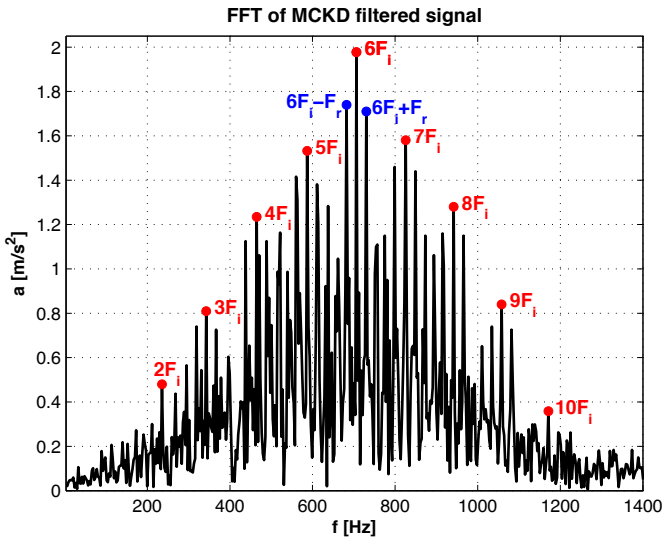


Fig. 5. Frequency domain plot of the acceleration signal acquired from the induction machine having one of its bearings an inner race fault, and filtered by means of MCKD

The repeating impulses are in perfect accordance with the theoretical expectations illustrated in Fig. 1. Also around these main impulses the right and left sideband components can be easily observed. As concerning the frequencies of these impulses, it can be affirmed that the identifiable values are exactly those included in Table I. All these together means that the applied MCKD filtering is an excellent method for evidencing the vibration impulses due to bearing faults also when the electrical machine in discussion is working in a hard, significant vibrations full environment.

VI. Conclusions

The applied data processing method enables the considerable deconvolving of the periodic series of vibration impulses due to bearing faults. By the proper design of a FIR-type filter a specific norm criterion, called the CK has to be maximized.

It was proved, that the MCKD method can be useful in bearing fault detections also in those cases when the machinery is exploited in vibration full environment (as usually the electrical generators of wind turbines), where other vibration based fault detection techniques are not assuring the expected results. The method can be applied also for the fault detection of all the bearings and gears of the entire wind turbine system.

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