Bearing Fault Detection of Electrical Machines Used in Automotive Applications

Loránd Szabó, Daniel Fodorean, Alexandra Vasilache

***Abstract* -- Bearing faults are the most common causes of failure also in the case of electrical machines used in automotive applications. Advanced fault diagnosis methods are required to detect these faults in their incipient phase, even in the harsh, vibration-full environment of vehicles. In the paper the effectiveness of a complex bearing faults detection approach is analyzed. It uses the minimum entropy deconvolution (MED) technique to enhance the ability of an autoregressive (AR) model based filtering technique, designed to detect single point defects in rolling bearings. The detection capabilities of the method were studied by means of processing the measured vibration signals for different bearing conditions of an electrical machine. The study included the analysis of the fault detection effectiveness also in the case when additional random noise was added to the measured signals.**

***Index Terms*--automotive applications, autoregressive filter, ball bearings, electric vehicles, fast Fourier transform, fault detection, induction motors, minimum entropy deconvolution, spectral kurtosis, vibration measurement.**

I. Nomenclature

AI – artificial intelligence
AR – autoregressive
FFT – fast Fourier transform
F_I – inner race fault frequency
F_R – rotor frequency
MED – minimum entropy deconvolution
N_B – number of bearing balls
SK – spectral kurtosis
SNR – signal-to-noise ratio

II. Introduction

THE rolling bearing faults are the most common causes of failure in electrical machines (about 40%) used in any environment: industry, power conversion, automotive, etc. [1]. The incipient bearing faults does not produce important damage, but if the problem is not solved the faults will evolve in time, and finally will produce disastrous failure of the electrical machine. Therefore the as early as possible detection of the bearing faults is very important for all the electrical machines used in any industry. In safety-critical applications (among them also the automotive ones) the reliability of bearings may be even more critical in safeguarding human lives and preventing significant and costly component damages in terms of both time and resources.

The fault detection of all the components of an electrical vehicle is hampered by the existing intensive vibrations having mechanical, aerodynamic and electromagnetic sources. Furthermore the hybrid electrical vehicles are facing also intensive transient powertrain vibrations, due to the starting and stopping of the internal combustion engine in different driving conditions.

The bearing fault detection and condition monitoring requires wide range of multidisciplinary knowledge, therefore it is a challenging topics for specialists working in various fields, as electrical, mechanical and control engineering, signal processing, artificial intelligence (AI), etc.

The bearings faults can be caused by material fatigue, overheating, harsh environments, inadequate storage, contamination, corrosion, wrong handling and installation, etc. The main cause of their failure is due to poor lubrication, which can be easily avoided by adequate maintenance [2].

A great variety of bearing fault detection methods have been developed and used effectively in-field already since the early '80s [3]. Diverse electrical machine quantities, such as current [4], voltage [5], stray flux [6], speed [7], efficiency [8], torque [9], temperature [10] and vibrations [11] were proposed to be monitored to detect the bearing faults.

The main tool for such purposes is the vibration analysis. By means of advanced signal processing techniques it is possible to obtain valuable information on the existence, type and gravity of the bearing faults [12], [13].

Most of the detection techniques are based on analyzes in the frequency domain by means of the Fast and Discrete Fourier Transform (FFT and DFT) [14]. But also other, more efficient methods were proposed in the literature, as envelope [15], [16], kurtograms [17], [18], [19], wavelet, [20] and Hilbert-Huang transform [21] based techniques, Wigner-Ville distribution [22], morphological signal processing [23], and many-many others.

In the last years a lot of promising results were published in the field of automatic condition monitoring and fault prognosis, which can eliminate the human interpretation of the measurement results, and thus increase the effectiveness and diminish the costs of condition monitoring. Such systems are based on advanced AI tools, such as expert system [24], neural network, genetic algorithm [25], fuzzy logic [26], and a lot of others, as statistical [27], [28] and quantitative analysis [29] tools, etc.

The paper is structured as follows: Section III is detailing the applied vibration based bearing fault detection method.

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Firstly the measurements are presented, which were used in demonstrating the effectiveness of the proposed fault detection method. Next the theoretical background of the vibration based bearing fault detection is detailed, by defining the fault frequencies specific for each bearing damage type. Also the limitations of the classical FFT based fault detection approach in the case of noisy signals is detailed. Section IV deals with the way as the bearing fault detection method was applied is detailed. The usefulness of the proposed method is analyzed and proved for diverse bearing fault types and loads, including also the cases when significant noise signal is added to the measured data.

III. The Applied Vibration Based Bearing Fault Detection Method

A. Measurement Data

The measurement data used in the paper were taken from the public Condition Based Maintenance Fault Database of the Society for Machinery Failure Prevention Technology [30]. This excellent open access database contains numerous laboratory measurement data sets for healthy and faulty bearings and gears. The defected bearings have outer and inner race faults. The acceleration measurements were performed at various loads.

Digital data was collected at 48,828 and 97,656 samples per seconds, saved and uploaded to the database in MATLAB binary format (*.mat*-files).

B. Theoretical Background

When performing the condition monitoring of bearings the first step taken has to be the inspection of its running conditions. Usually the fault occurrence changes the behavior of the bearings itself. Most common indicators for potential bearing problems are the increased temperature, high vibration or noise level of the machine [31].

If a moving component passes over a defected surface in the bearing, it creates a succession of oscillations which repeat with each pass over the damaged area. The repetition frequency of the impact depends on the position of the fault within the bearing, rotor speed and bearing dimensions [4]. Each bearing component generates specific fault frequencies which can be determined by using specific expressions.

The fundamental cage frequency is given by:

$$F_C = \frac{F_R}{2}\left(1 - \frac{D_b}{D_c}\cos\beta\right) \tag{1}$$

where F_R is the rotor frequency, D_b the diameter of the ball, D_c the pitch diameter of the bearing and β the contact angle (usually 0°), as shown in Fig. 1.

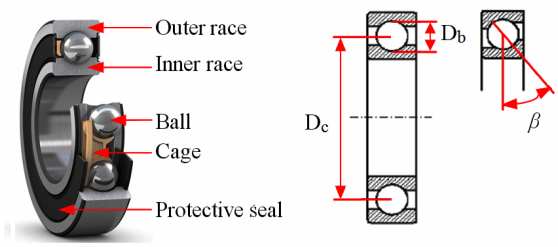

Fig. 1. Basic bearing parameters

The typical frequencies corresponding to the outer and inner race defects can be computed by using the following equations:

$$F_O = \frac{N_B}{2} F_R\left(1 - \frac{D_b}{D_c}\cos\beta\right) \tag{2}$$

$$F_I = \frac{N_B}{2} F_R\left(1 + \frac{D_b}{D_c}\cos\beta\right) \tag{3}$$

where N_B is the number of balls.

The Nice ball bearing used in the tests has the following data: $D_c = 1.245$ in, $N_B = 8$, $D_b = 0.235$ in and $\beta = 0°$ [30]. The fault frequencies for this bearing are given in Table I.

TABLE I
Bearing Fault Frequencies

Speed [r/min]	F_R [Hz]	F_C [Hz]	F_O [Hz]	F_I [Hz]
1500	25	10.14	81.13	118.88

C. FFT Based Fault Detection

Upon the simplest non-invasive vibration based bearing fault detection approach the measured acceleration signal is analyzed in the frequency-domain. If in the frequency spectrum intensive components having the frequency round the integer multiples of the fault frequencies computed by means of equations (1)÷(3) can be detected, it can be concluded that the given bearing is faulty. For this purpose the time domain signal has to be transformed in frequency domain via the FFT algorithm [2], [13].

To exemplify the FFT based vibration fault detection an inner race fault will be considered. The measurements were performed at the maximum load of the machine. First the measured accelerations are given for both the healthy and bearing fault condition of the machine (see Fig. 2 and 3).

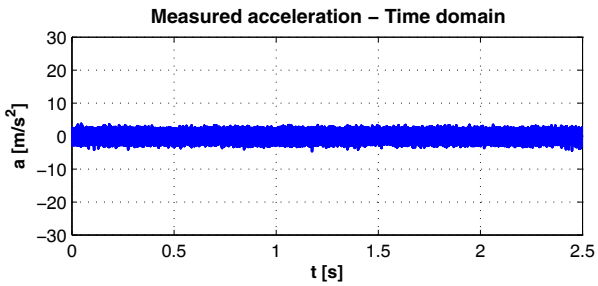

Fig. 2. The acceleration signal measured at full load of the healthy machine. Time domain plot.

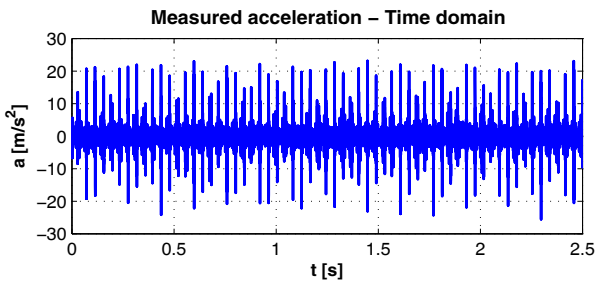

Fig. 3. The acceleration signal measured at full load of the machine having a fault in its inner ring. Time domain plot.

In contrast to the healthy machine, where the measured acceleration is uniform in time, in faulty condition impulse peaks of the acceleration (beats) can be observed due to the passing of the balls front of the defective surface. To emphasize the changes in the frequency content of the acceleration, the signals were processed by means of FFT. The obtained harmonic contents in the 0÷2000 Hz domain for the two machine conditions are shown in Fig. 4 and 5.

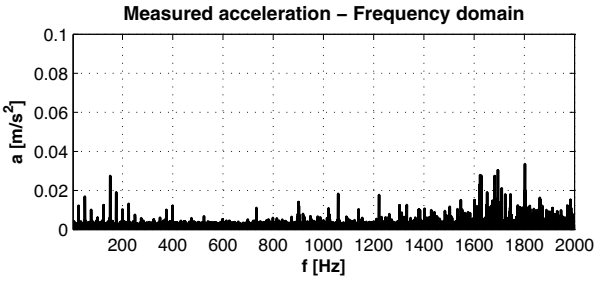

Fig. 4. The acceleration signal measured at full load of the healthy machine. Frequency domain plot.

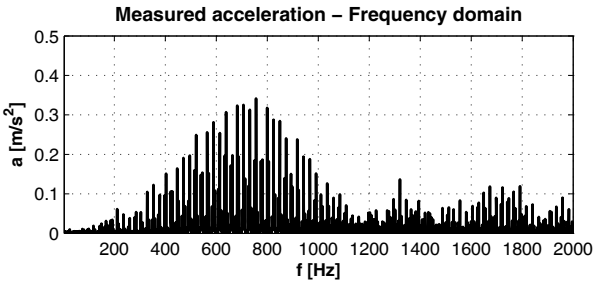

Fig. 5. The acceleration measured at full load of the machine having a fault in its inner ring. Frequency domain plot.

As it can be seen, the harmonic content of the signal measured in the case of the faulted bearing is much stronger than in the case of the healthy machine. Unfortunately, when fault detection of electrical machines used in vehicles has to be performed, the environment is not as clear from vibrations point of view as in a laboratory. Therefore, to analyze the effectiveness of the vibration monitoring based fault detection method in automotive applications a random noise signal was added to the measured acceleration. The frequency spectrum obtained in this case is given in Fig. 6.

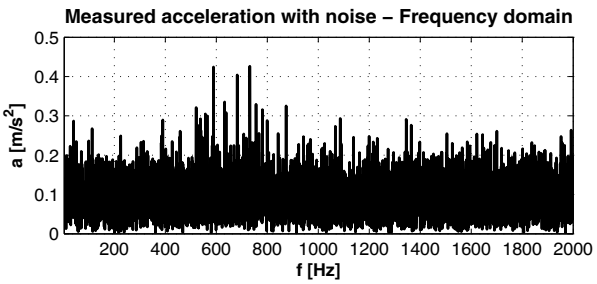

Fig. 6. The acceleration having noise added at full load of the machine having a fault in its inner ring. Frequency domain plot.

As it can be seen, in a vibration-full environment the fault frequency component cannot be distinguished clearly. The peak to medium ratio of the signal is only 4.58 as compared with 63.74 in the case when the measurements were performed in vibrations free laboratory environment. Therefore, in the case of automotive applications the fault detection based only on the FFT transformation is unsure. The signal has to be filtered and the bearing fault frequency component has to be more clarified for a sure fault detection.

D. *Autoregressive Filtering*

To filter the noisy acceleration signal the Yule-Walker method based AR filter was applied [32]. The optimal order of the filter is computed by means of the maximum kurtosis.

The AR model defines each sample as a linear combination of previous samples. The main challenge is the correct estimation of the coefficients of this combination. For this purpose in the literature several methods are given, as minimizing the mean square error, considering the correlation between the samples, etc. [33], [34].

The advanced AR models used here for the bearing fault detection purpose are based on the so-called Yule–Walker equations, which are connecting the model parameters to the covariance function of the system to be analyzed. In the fault detection algorithm MATLAB *aryule* function is used, which returns the normalized AR parameters corresponding to the input signal vector.

The filter was tuned upon the spectral kurtosis (SK) approach [18]. When a rolling element strikes a single-point defect a mechanical impulse occurs and this excites the resonances of the entire structure. The SK method helps the extraction of these resonance components.

The applied SK optimized for the AR model is effective in extracting and increasing the impulsiveness of fault related frequency components buried in noise [19].

E. *Minimum Entropy Deconvolution*

In order to increase the separation of the typical fault related frequency components from the background noise the measured and AR filtered signal is also passed through Minimum Entropy Deconvolution (MED) data processing, which effectively deconvolves the effect of the transmission paths and clarifies the impulses. The MED name derives from the fact that increasing entropy means increasing disorder, whereas impulsive signals are very structured, requiring all significant frequency components to have zero phase simultaneously at the time of each impulse. Thus, minimizing the entropy maximizes the structure of the measured signal, meanwhile maximizing the kurtosis of the inverse filter output (corresponding to the original input to the system) [13]. Therefore, the MED technique can make use of the phase information of the vibration signal. It is able to search for an optimum set of filter coefficients by means of the higher order statistical characteristics, and can recover the signal with the maximum value of kurtosis [19], [35].

IV. Processing the Measured Vibration Signals

The effectiveness of the applied MED technique to enhance the ability of the AR model based filtering technique was tested first on a set of vibration measurements performed in the case of the electrical machine having an inner race fault in its bearing. To see the effects of each signal processing stage, in all cases the original signal, the output of the AR filtering and the final result obtained via MED processing are given. The results in time and frequency domain are given in Fig. 7 and 8.

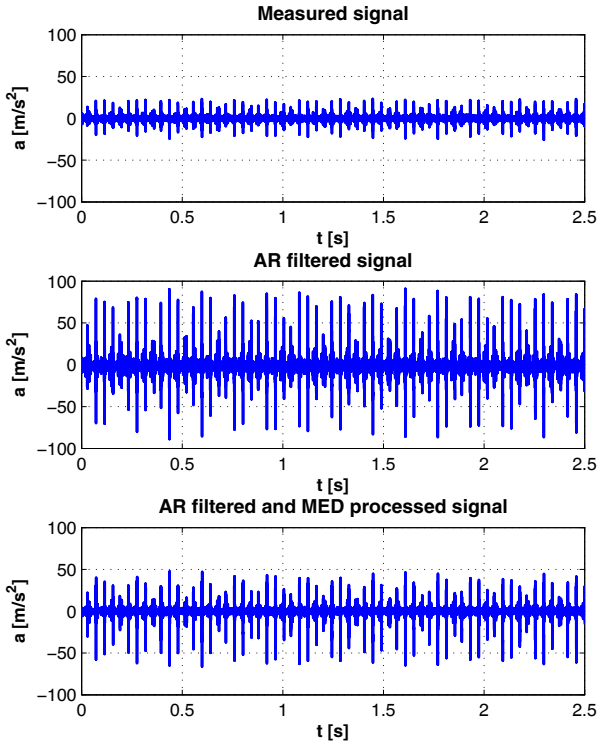

Fig. 7. Results of signal processing performed on the acceleration signal acquired at maximum load of the machine having a fault in its inner ring. Time domain plots

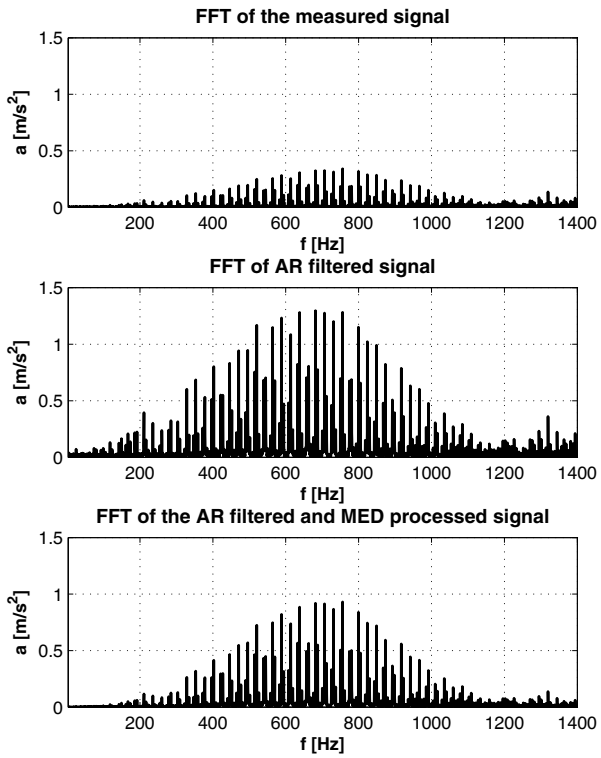

Fig. 8. Results of signal processing performed on the acceleration signal acquired at maximum load of the machine having a fault in its inner ring. Frequency domain plots.

Already in the time domain plot it can be clearly observed that the peak values of acceleration were strongly increased by means of the applied signal processing techniques. This effect is clearer observable in the frequency domain plots. The representative bearing faults frequency components in the acceleration signal spectrum are more and more sharpened after each data processing stage. Finally they are amplified to be over a relatively high value of 0.6 m/s^2.

It should be of interest also to see how the applied signal processing methods acts upon the kurtosis level of the signal. For this purpose the fast kurtograms of the signals via a fast decimated filterbank tree were computed [36]. For the 131,072 samples acquired in this case 10 decomposition levels were taken into account.

In Fig. 9 and 10 the obtained kurtograms are given for the original signal and for the output of the data processing.

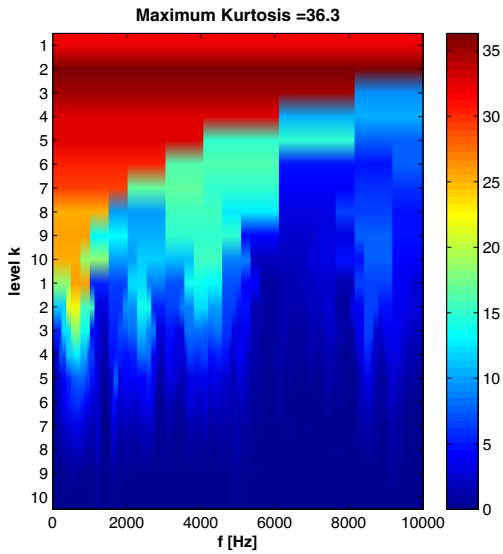

Fig. 9. The kurtogram obtained for the acquired acceleration signal

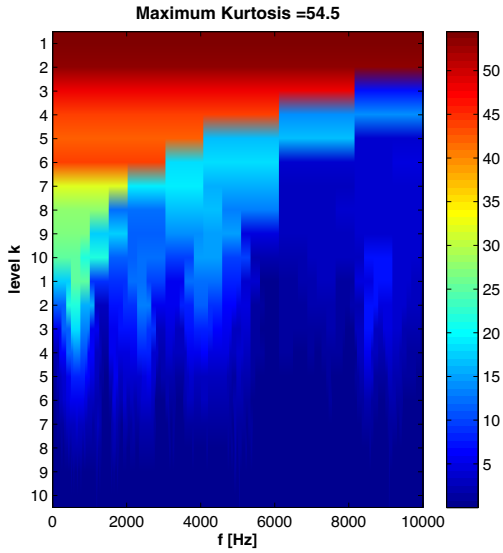

Fig. 10. The kurtogram of the acceleration signal after processing it by means of the MED method

The data from these figures emphasize the ability of the signal processing method to increase the "peakedness" of the signal to make easier the detection of fault related components in the acceleration spectrum. The maximum kurtosis level was raised from 36.3 to 54.5. But more important is that after the two stages of signal processing the maximum kurtosis level is obtained on the entire frequency spectrum considered, thus improving the efficiency of the bearing fault detection.

Next the effectiveness of the applied signal processing method will be analyzed for the case when to the measured acceleration a significant, maximum 12.5 m/s^2 amplitude random noise was added, meaning SNR=-5.3). Also for this case the plots after each signal processing step in time and frequency domains are given (see Fig. 11 and 12).

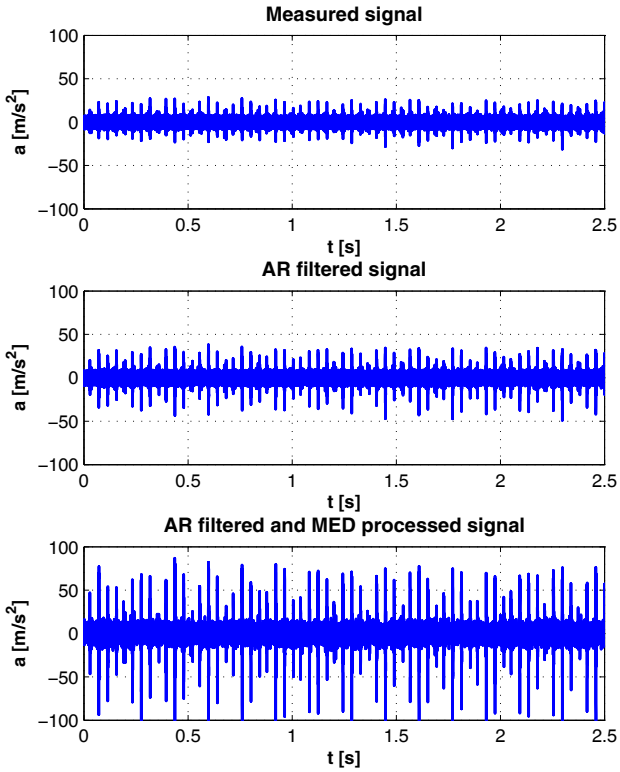

Fig. 11. Results in time domain for noisy input signal. Inner race fault.

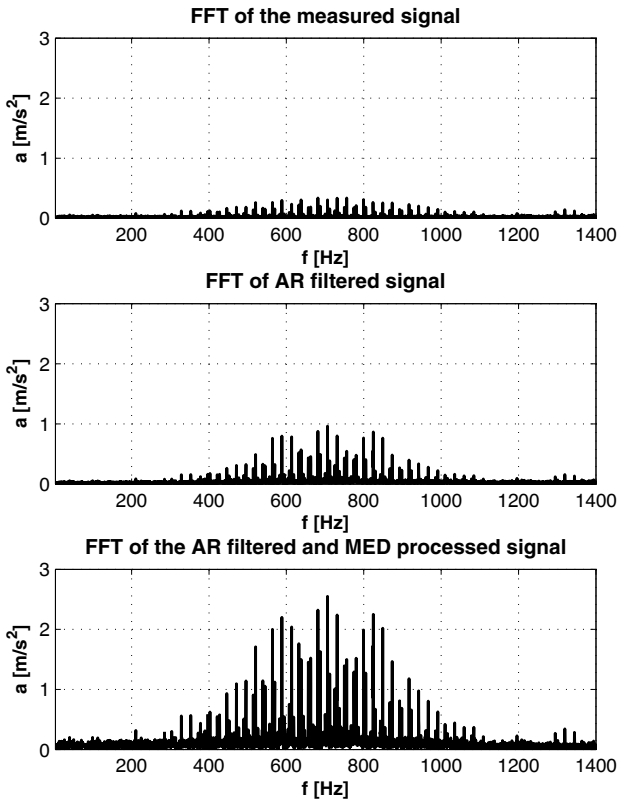

Fig. 12. Results in frequency domain for noisy acceleration signal. Inner race fault.

As it can be seen, the fault characteristic frequency components are deeply buried in the high noise of the acceleration signal. Therefore, without any additional signal processing method these components cannot serve for fault detection. But due to the ability of the applied two-steps signal processing the peak to medium ratio of the signal was increased from 17.78 to 154.70, namely near by 9 times.

Analyzing the frequency spectrum of the acceleration in the case of an inner race fault it can be observed that the signals have the greatest amplitude in the 500÷900 Hz domain (see Fig. 13). Several series of impulses are present at periodic frequency rate.

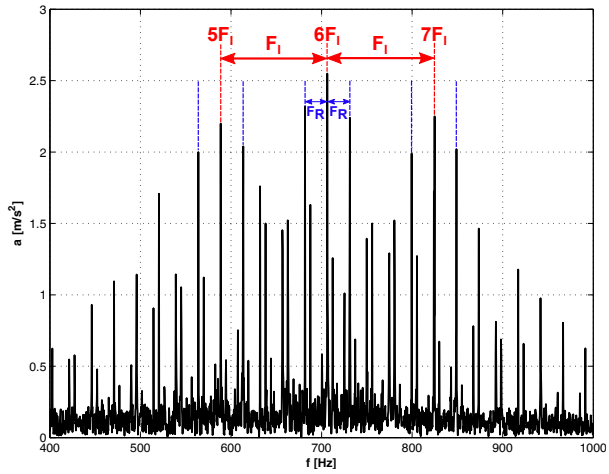

Fig. 13. The inner bearing fault related frequency components in the spectrum of the acceleration signal.

In the above mentioned domain three integer multiples of F_I can be identified: $5 \cdot F_I = 594.4$ Hz, $6 \cdot F_I = 713.28$ Hz and $7 \cdot F_I = 832.16$ Hz. Supplementary, also their speed related sideband components are detectable in Fig. 13. These are shifted by $F_R = 50$ Hz before and after the fault frequency components. For example, round the $6 \cdot F_I$ frequency two sideband components can be identified at $6 \cdot F_I - F_R = 663.28$ Hz and $6 \cdot F_I + F_R = 763.28$ Hz. By distinguishing all these frequency components the inner race fault of the bearing can be certainly identified [19].

Next the effectiveness of the detection method at lower motor loads will be studied. In these cases the amplitude of the vibrations are smaller and the distinguishing of the fault related frequency components is more complicated. At low loads the sharpening of the vibration impulses is more critical than at higher loads.

The machine having a bearing with inner race fault was tested at lower loads. The results of the above detailed signal processing at 100, 83, 33 and 17% of the maximum load are given in Fig. 14. Also in this case a maximum 12.5 m/s^2 random noise was added to the measured signal. As it can be seen, the integer multiples of the inner race fault frequency can be clearly identified also at the lowest load level considered. Of course, as the load is lower the identification is less easy to perform due to the reduced peak to medium ratio of the signal. This ratio computed for the 0÷1400 Hz domain at 17% percent of the maximum load is only 7.39, while at full load is three times more, equal to 21.64.

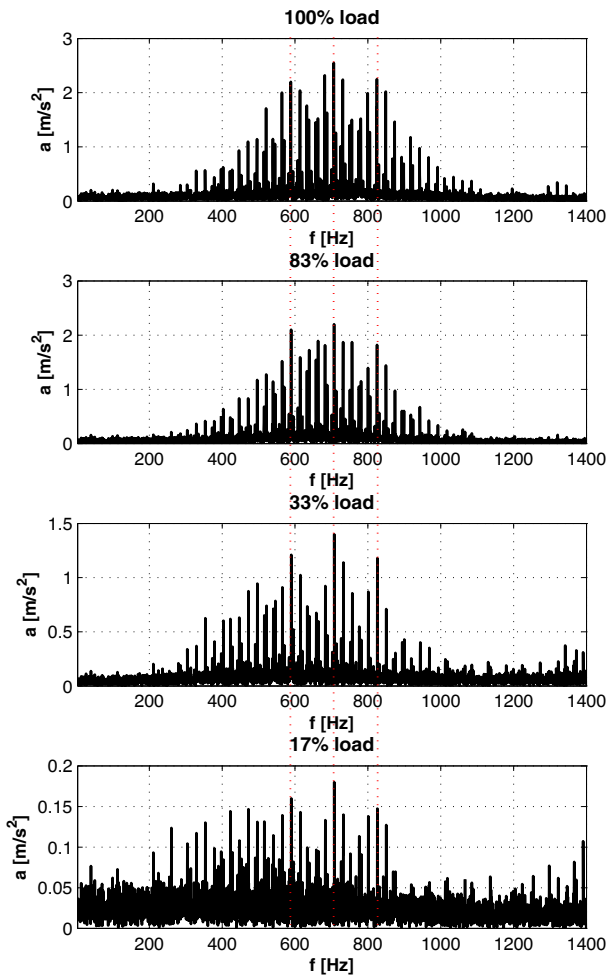

Fig. 14. Results in frequency domain for noisy acceleration signal acquired at different loads of the electrical machine having inner race bearing fault.

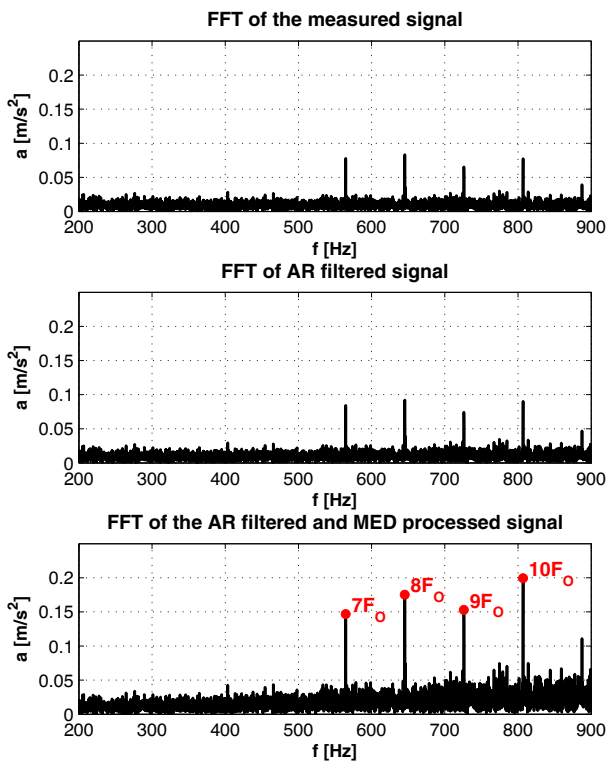

Fig. 15. Results in frequency domain for noisy acceleration signal. Outer race fault.

Finally, the applicability of the signal processing method in detection of other bearing faults was also investigated. In Fig. 15 the results of the data processing performed on a noisy acceleration signal acquired from an electrical machine having outer race bearing fault is given. As it can be seen, some integer multiples of the outer race fault related frequency are strongly amplified in the spectrum.

V. Conclusions

In automotive applications the vibration monitoring based fault detection is difficult due to the superposing of strong vibrations on the measured signals. To successfully extract the fault related frequency components from very noisy acceleration signal a combined complex signal processing method was applied. As it could be observed, the fault related information is contained in the spacing of the impulses rather than in their frequency content itself, which are bearing type and rotor speed related.

The effectiveness of this method was proved both for inner and outer race bearing faults. The effect of processing the raw acquired acceleration signal is clearly observable in all the studied cases. The integer multiples of the ball-pass frequencies of the inner and outer race were made clearly visible despite of strong vibration noises.

The proposed combined signal processing method can be extended to all the vibration based fault detection methods.

A main advantage of this approach is the lack of case-related tuning necessity.

Future work in the field include the integration of the bearing fault detection algorithm in the modular Hardware-in-the-Loop (HiL) platform for testing competitive and highly efficient hybrid electric vehicles under development at CAREESD, Technical University of Cluj-Napoca [37].

Also the possibility to add the developed fault detection method to the standardized On-Board Diagnostics (OBD) computer-based system will be taken into study to increase the safety, functionality, reliability, and maintainability of electrical vehicles.

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