Shock and Vibration 9 (2002) 225–234
IOS Press

New technique for evaluation of global vibration levels in rolling bearings

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Abstract. In the last years new technologies and methodologies have been developed for increasing the reliability of fault diagnosis in mechanical equipment, mainly in rotating machinery. Global vibration indexes as RMS, Kurtosis, etc., are widespread known in industry and in addition, are recommended by international norms. Despite that, these parameters do not allow reaching reliable equipment condition diagnosis. They are attractive for their apparent simplicity of interpretation. This work presents a discussion about the diagnosis possibilities based on these traditional parameters. The database used comprises rolling bearings vibration signals taking into account different fault conditions, several shaft speeds and loading. The obtained results show that these global vibration parameters are limited regarding correct fault diagnosis, especially in initial faults condition. As an alternative method a new technique is proposed. This technique seeks to obtain a global parameter that makes better characterization of fault condition. This methodology, named Residual Energy, uses integration of the difference between the power spectrum density of the fault condition and the normal one. The results obtained with this technique are compared with the traditional RMS and Kurtosis.

Keywords: RMS, kurtosis, vibration, rolling bearings, condition monitoring

1. Introduction

In the last few years, predictive maintenance [1,3,9, 12] has been used as an important strategy to improve industrial plant reliability. It minimizes unnecessary expenses and it avoids damaging the components of the machine. The study of new techniques for diagnosis can offers more efficient tools that are more robust and capable of presenting results with high reliability in relation to the state of the equipment. The improved diagnose system can increase the profit of an industry, because in general the effective cost of the maintenance is smaller than the cost of the production loss due to a non programmed stop in a machine.

Among the several techniques used for predictive maintenance, the vibration [4,5,7,10,12] analysis is the most frequently used technique for condition monitoring of a rotating machinery. In this case during machine operation signals of acceleration or velocity are acquired at different positions. Any change in the equipment condition is reflected in the vibration signals. When a good diagnostic system is used, a fault or change in the machinery is easily detected and classified.

This paper compares, some statistical diagnosis techniques applied to rolling bearing's vibration signals. RMS [10,12] is the most commonly used technique for alarm purposes in industrial condition monitoring. Others well know statistical parameters are the Skewness [2] and Kurtosis [6]. In the present work these three parameters are used to analyze different types of defects in rolling bearings, under several shaft speeds and load conditions. The database collected from a test rig has acceleration as well as velocity signals.

To improve the reliability of diagnosis a new technique is proposed, and its performance is compared with the others three. The signals used in this paper do not represent a critical condition but early stages of rolling bearing failure.

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ISSN 1070-9622/02/$8.00

2. Experimental methodology

The experimental test rig is composed by an AC motor that drives a shaft with rolling bearings. A mechanism connected to the system allows a known radial load to be applied on the bearing. A variable speed driver controls the speed of the motor.

Defects can appear on rolling bearing's because of the following problems: incorrect lubrication, contamination through dirt or external particles, use of an inadequate lubricant, incorrect storage of the component, fails in the assembly of the rolling bearing, etc.

A way to classify the defects is by its size in the surface. To simulate different kinds of defects 4 types of defects were used in the outer race of the rolling bearing: a pit (punctual size denominated as p), a located corrosion produced by synthetic sea water for 8 hours (medium size and denominated as C), other corrosion produced by synthetic sea water for 24 hours (medium size and denominated as C1), and a scratched out surface (distributed in all the outer race and denominated as s). A rolling bearing in perfect state was also used to represent the normal pattern (denominated as n). The rolling bearings used were the FAG BO15TVP.

Vibration signals of a rolling bearing were collected using a piezoelectric accelerometer that was mounted in a vertical direction over the top of the bearing. The accelerometer was connected into a load amplifier, with a low-pass analog filter of 2 kHz of cut-off frequency. The filtrated signal was sampled, with a sampling frequency of 5,12 kHz for an A/D converter card mounted in a personal computer. The signal was represented by 2048 points. Both the shaft speed controller and the loading system were calibrated before collecting the data.

For each one of the five defects in a different condition, three signals samples. Six different speeds were used in this experiment ranging from 400 rpm to 1400 rpm and three different conditions of radial loading (200, 400 and 600N, named as load 1,2,3 respectively). The database is composed of 270 acceleration signals and they were numerically integrated composing a new database with velocity signals, having the same size.

3. Traditional methods

The three widespread statistical techniques that are mainly used for alarm purposes in industrial plants are statistical moments of order two, three and four. The mathematical definition of the RMS, Skewness and Kurtosis are presented below.

3.1. RMS

The RMS value is related to the energy of the signal. In many cases the appearances of the defect are directly detected by the increase of the vibration level of the machine. This means that RMS calculated in a certain frequency band can be used for fault detection. The results of RMS can be compared with normalized values or even with values previously collected. The RMS value is calculated in the following way:

$$\text{RMS} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i)^2} \tag{1}$$

3.2. Skewness

Skewness is the statistical moment of the third order, normalized by the standard deviation to the third power.

$$s = \frac{1}{N\sigma^3}\sum_{i=1}^{N}[x_i - m]^3 \tag{2}$$

Where σ is the standard deviation, m is the average of the signal and x_i are the amplitudes of the signal. This moment indicates the asymmetry of the probability density function (pdf), meaning the deviation degree from the symmetry of a distribution. If the calculated value of Skewness is negative the curve (pdf) is shifted to the left and if that value is positive the curve is shifted for the right. If it is null, the curve is perfectly symmetric.

3.3. Kurtosis

Kurtosis is defined as the fourth statistical moment, normalized by the standard deviation to the fourth power, which is shown below.

$$K = \frac{1}{N\sigma^4}\sum_{i=1}^{N}(x_i - m)^4 \tag{3}$$

Kurtosis represents a measure of the flattening of the density probability function near the average value. A well-known value of the Kurtosis is for the normal distribution, that is 3.

As a parameter for diagnosing faults in the rolling bearing, the values of Kurtosis increase with the growth of the defect. That happens because the pulses generated increase by the passage of the rolling elements over the defect [10].

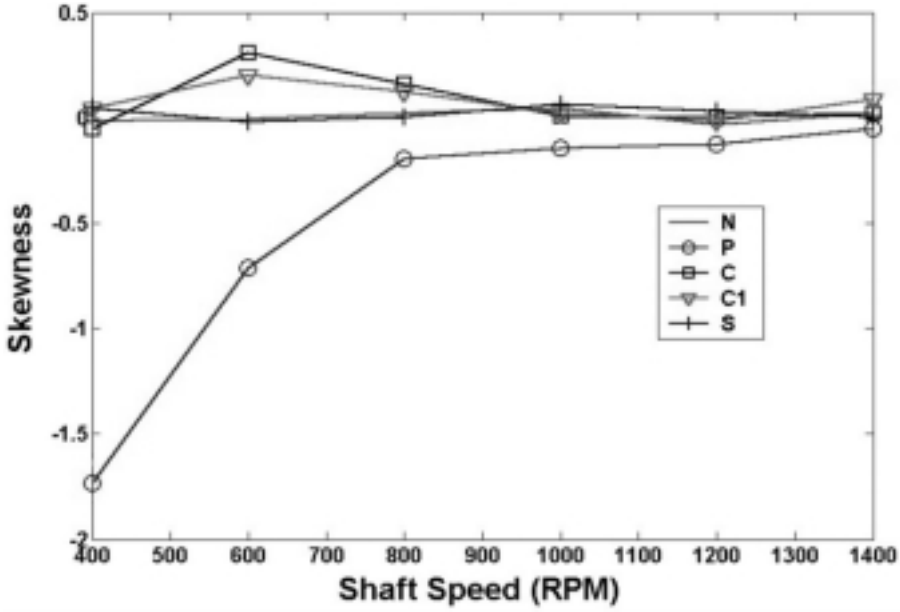

Fig. 1. Skewness of the acceleration signal as a function of the rotating shaft speed, load 3.

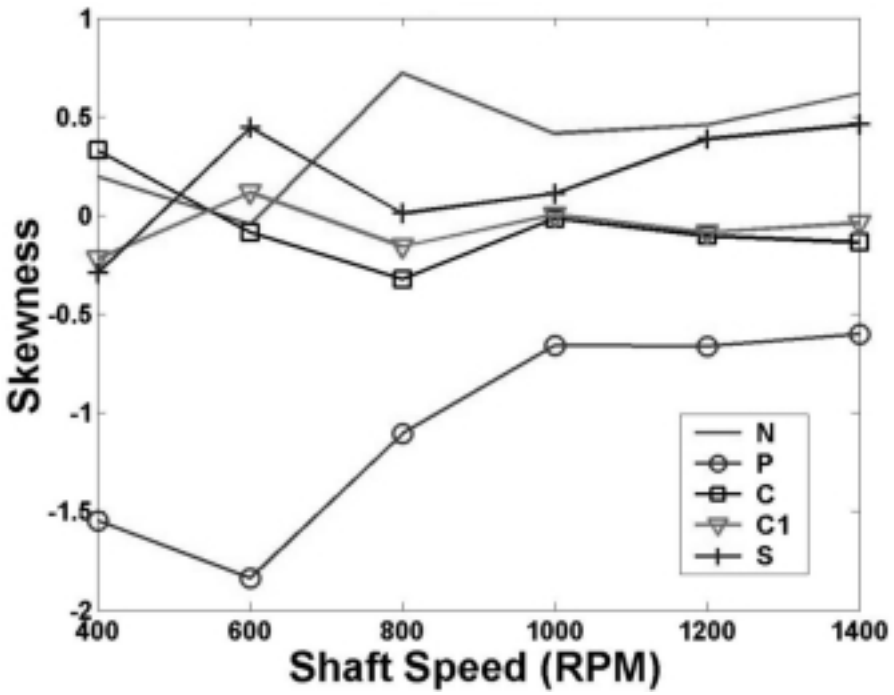

Fig. 2. Skewness of the velocity signal as a function of the rotating shaft speed, load 3.

4. Results obtained using the traditional methods

The results obtained using the skewness to diagnose and to classify the faults of the database were very poor.

Figures 1 and 2 represent some calculated values of the skewness for acceleration and velocity signals. It can be observed that for the acceleration signals the negative values of the skewness are low enough to char-

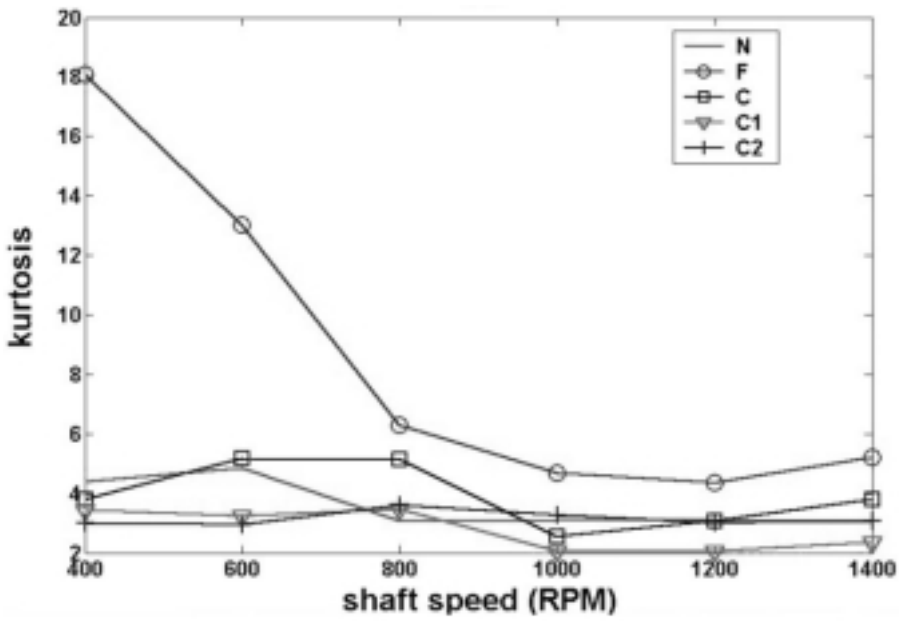

Fig. 3. Kurtosis of the acceleration signal as a function of the rotating shaft speed, load 3.

acterize the pit fault in low shaft speeds. That indicates a deviation for the left in the pdf of the signal. In the velocity signal, there is a better characterization of the other defects. Although that is not enough for a reliable diagnosis it accentuates the difference between the pit fault and the others for all shaft speeds.

It is not possible to see any difference between the normal signal and the scratched one at any shaft speed. From the analyses of all skewness graphics (not all of them are presented is this paper), he it can be seen that the effect of the loading does not appear to be important in the behavior of the Skewness.

Figures 3 and 4 show results using Kurtosis, for acceleration and velocity signals. It can be seen that Kurtosis of the acceleration signals as well as the Skewness has the same performance in low shaft speeds. In both cases, it is possible to identify the pit fault type. The same behavior was observed for the Kurtosis of the velocity signals.

From these results, it can be verified that this method is not good enough for diagnosis. For both the Kurtosis and Skewness there are no significant variations of this behavior considering different loadings.

Figures 5 and 6 show the RMS as a function of the shaft speed for all the fault types.

The results obtained for RMS show that the values tend to increase as the rotation speed increases for the acceleration signals and velocity signals. This differentiates this method of the previous ones, because, the classification and diagnosis get better with the increase of the rotation.

The increase of the value for RMS with the shaft speed was expected, because in many cases the increase of the power of the machine generates an increase of energy dissipated by vibration and RMS can be related with the energy of the vibration signal.

The results obtained by applying RMS for velocity and acceleration signals are similar. Although this method is widely used in industrial environment, in this case, it does not seem to be the best practice. The Figs 5 and 6 show that using this parameter and considering low shaft speed, it is only possible to identify the rolling bearing with a pit fault.

5. The proposed method

5.1. The residual energy method

The results presented above show the limitations of these statistical values, mainly as alarm parameters in a diagnosis system. These parameters can give a correct diagnosis only for some conditions and fault types. Methods based in the spectral behavior of the signals, as those based in the Fourier Transform, and in the envelope analysis can give a better diagnostic and even be used to classify the fault types. On the other hand, scalars parameters are practical for alarm purposes,

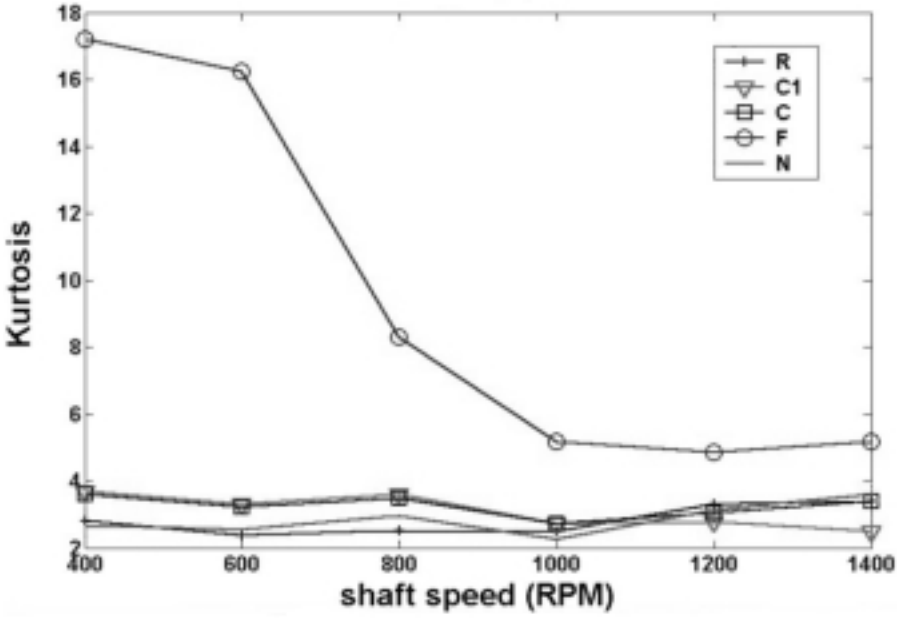

Fig. 4. Kurtosis of the velocity signal as a function of the rotating shaft speed, load 3.

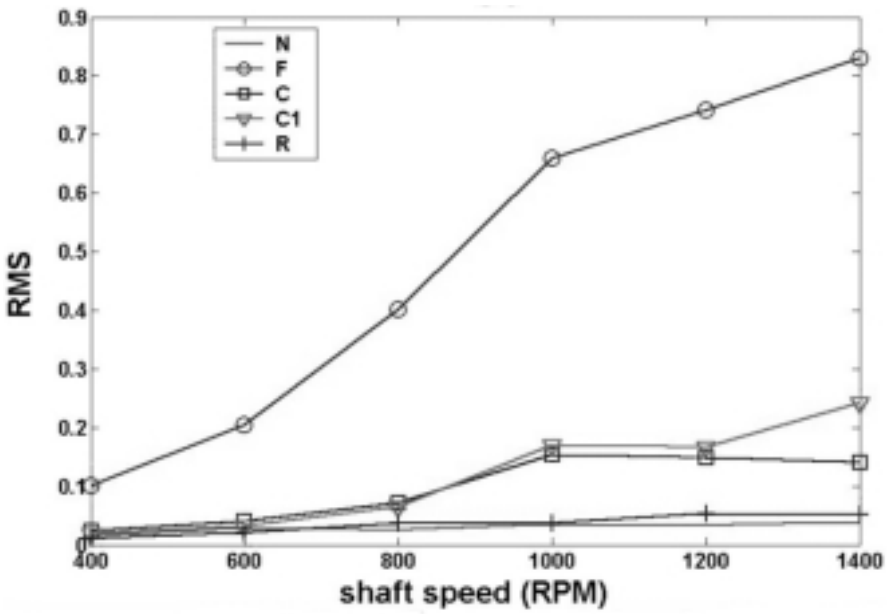

Fig. 5. RMS of the acceleration signal as a function of the rotating shaft speed, load 3.

they are easy to interpret and do not need a specific qualification of the technical analyst.

Taking into account this two ideas, a new technique is proposed with the objective of improving the diagnosis possibility of scalars parameters. The idea is to use the spectral information of the signals, which has better information of the fault signature, comparing this information with a normal condition signal, and in a some way, to convert this new information to a scalar parameter.

Based in the hypothesis (that can be verified a posteriori) that a vibrational signal from a fault rolling bear-

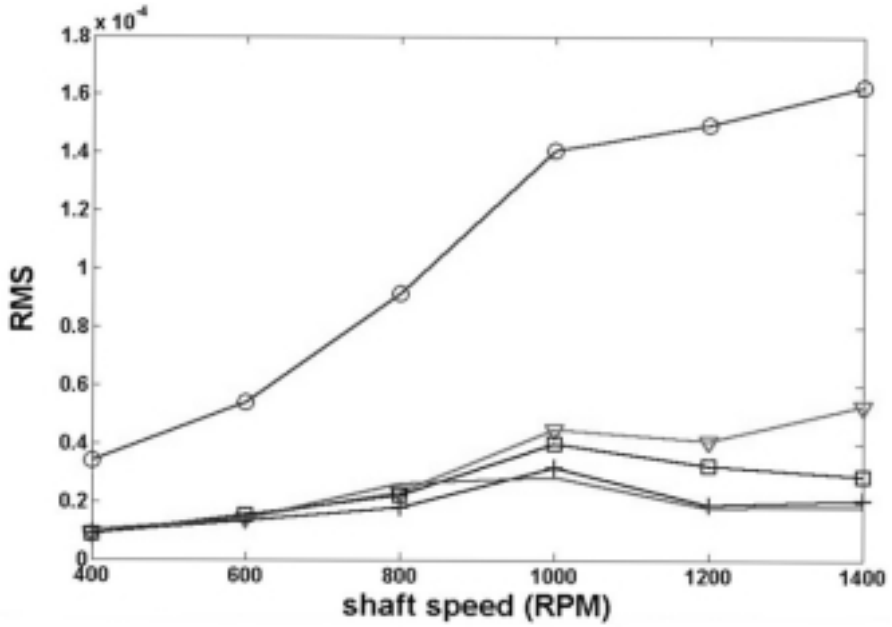

Fig. 6. RMS of the velocity signal as a function of the rotating shaft speed, load 3.

ing can be obtained by the superposition of the normal and a fault condition behavior, it is possible to write:

$$s_d(t) = n(t) + d(t) \tag{4}$$

where: $s_d(t)$ is the signal of a fault rolling bearing; $n(t)$ is the normal condition signal; $d(t)$ is the fault characteristic signal.

The main interest is to extract the defect characteristic of $s_d(t)$, by isolating the signal $d(t)$ from $s_d(t)$. However it is not possible to isolate this characteristic signal in the time domain. At least there is a phase problem to take care among the spectral components of the signals $s_d(t)$ and $n(t)$ (in this database a trigger was not used during the acquisition process). If Eq. (4) is translated to the frequency domain:

$$s_d(t) = n(t) + d(t) \;\Leftrightarrow\; S_d(f) = N(f) + D(f)$$
$$\Leftrightarrow\; D(f) = S_d(f) - N(f) \tag{5}$$

where $S_d(f)$, $N(f)$ and $D(f)$ are the spectral estimation of the signals $s_d(t)$, $n(t)$ and $d(t)$, respectively. The determination of $D(f)$ has a major problem related with the negatives amplitudes that can appear. Two solutions can be proposed: to set such values to zero or to take the absolute value of $D(f)$. The second solution will be taken and the spectral representation of the fault characteristic signals will be the modulus of the difference between the spectral representation of $s_d(f)$ and $n(f)$:

$$D(f) = |S_d(f) - N(f)| \tag{6}$$

Figure 7 shows an example of the Power Spectrum Density estimation (PSD) of a normal signal compared to the spectrum of a signal with defect (c1), where it is possible to observe the difference between the two spectra. They were obtained by the Welch Method [8]. In Fig. 8 the spectral representation of the fault characteristic signal $D(f)$ is shown. In order to traduce this spectral information in a scalar parameter which can be used for diagnose purpose, the area under the Fig. 8 is calculated resulting a number, named Residual Energy (ER).

$$\text{ER}(S_d) = \int_0^f D(f)df \tag{7}$$

As the area under PSD estimation is the signal energy (for a given time duration) in its frequency band, the ER parameter represents the energy of the signal that is obtained by the spectral difference between the baseline and the analyzed signal, and is correlated with the fault characteristic of the rolling bearing. This method supposes a good statistical estimation of the PSD of the signals $s_d(t)$ and $n(t)$, to avoid noise interference in the ER parameter.

Figure 9 shows the procedure to obtain the ER value.

It is worth to point out that this parameter depends on the existence of a baseline, which can be considered as a good representation of the normal condition of

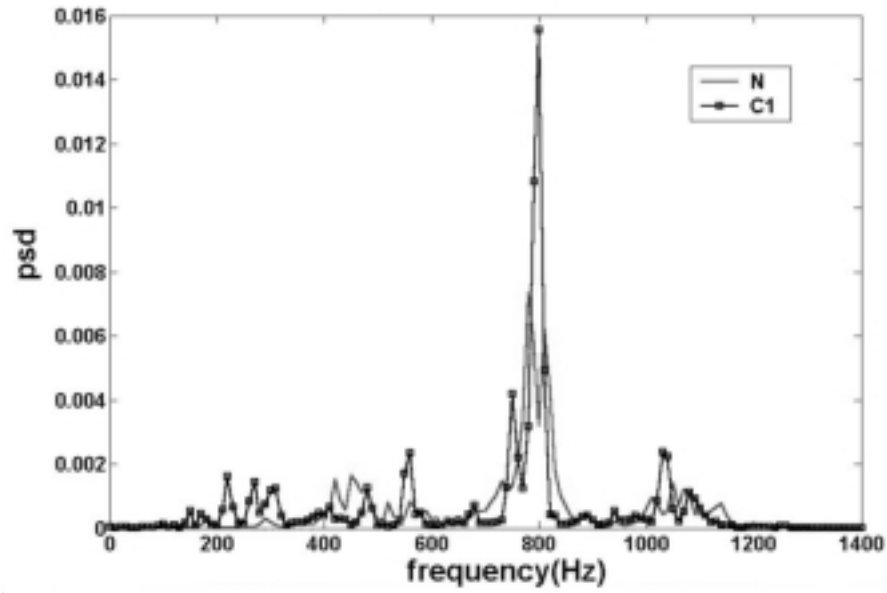

Fig. 7. Power Spectral Density of the normal bearing signal and of c1 signal.

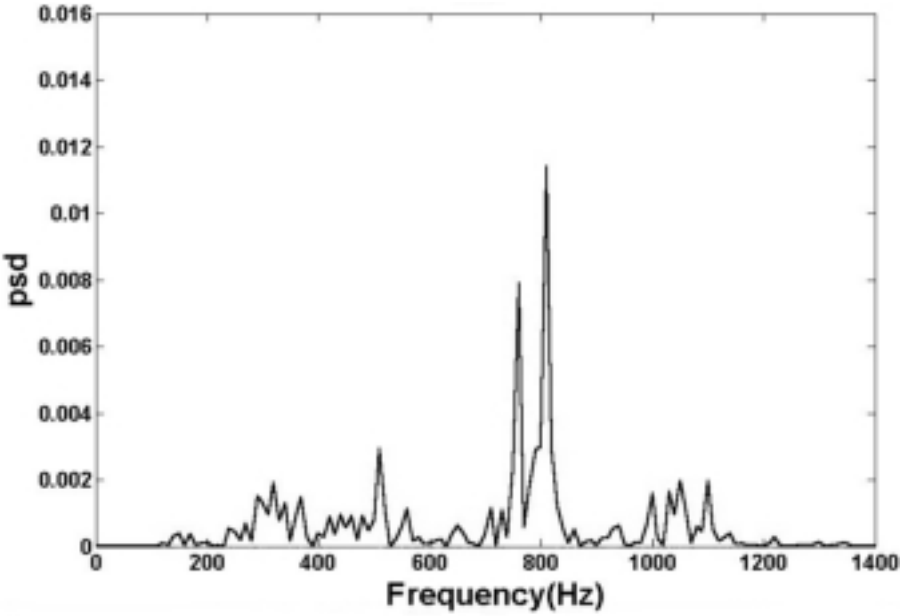

Fig. 8. Spectral representation of the fault characteristic signal $D(f)$.

the rolling bearing. In the industrial environment the existence of a baseline is a common procedure.

5.2. Diagnostic results obtained with the ER method

The ER parameter was calculated for each signal of the database, for each load and shaft speed condition.

In order to analyze the influence of the variations of the normal condition signal (the baseline) in the ER value, three different normal signals, measured at different time were used. For each one of the three pairs of possible combination (named N1, N2, N3) , it was calculated the ER value (for each shaft speed and radial load condition). These values are shown in Figs 10, 11

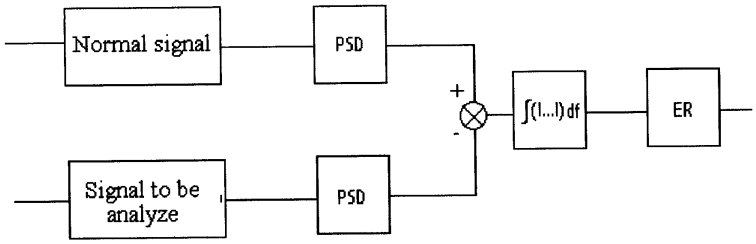

Fig. 9. Scheme of the ER parameter determination.

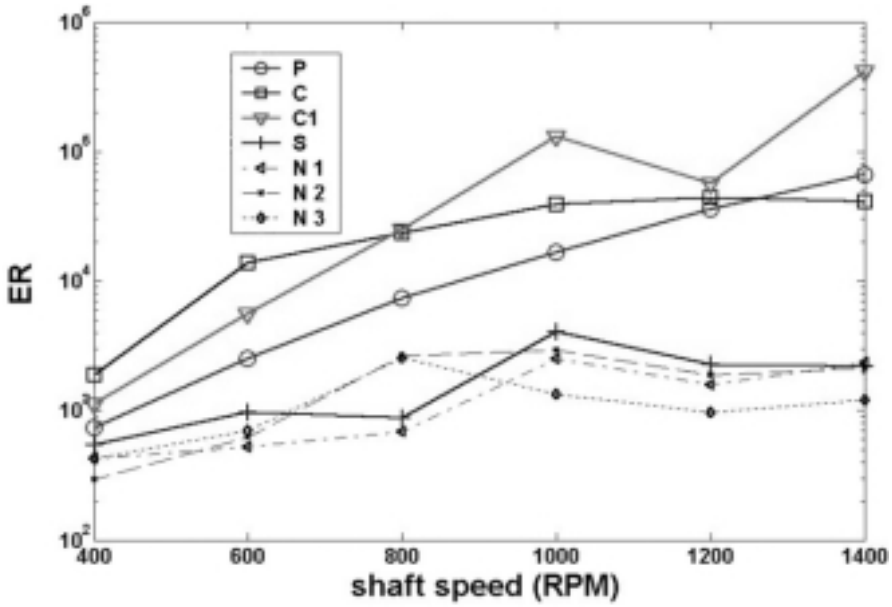

Fig. 10. ER of the acceleration signal as a function of the rotating shaft speed, load 1.

and 12, represented by lines with different marks. It is possible to notice that the variation of normal signal is very small, meaning that one sample of the signal, for the normal condition, can be used to represent the baseline of the rolling bearing. In all of these three figures it were used a logarithmic scale to represent the ER values.

In Figs 10, 11 and 12 the ER values of the four fault types are also shown. These Figures show that this method can separate all defects except the scratched one, considering all the test condition. In many cases it can differentiate even the scratched one.

Comparing with the results obtained with the three statistical methods, presented in Section 4, the ER method gives better diagnosis possibilities than the traditional ones.

With the ER method it is possible to distinguish between the normal and fault condition (with exception of the scratched type) in all the shaft speed and radial load condition. However the classification of each type of fault depends on the radial load condition. For higher values of this load, it is possible to separate the pit type from the others, and the corrosion condition from the others.

All the faults are incipient defects, but the scratched seems to be the critical for diagnosis purposes. It was not possible to diagnoses this defect in any condition, with any traditional method.

Regarding the ER values for velocity signals the results were goods but not as good as the results for the acceleration signals.

5.3. Discussion

An usual alarm fault procedure in industry uses the RMS parameter of an analyzing signal, and compares this value with a RMS obtained from a baseline for

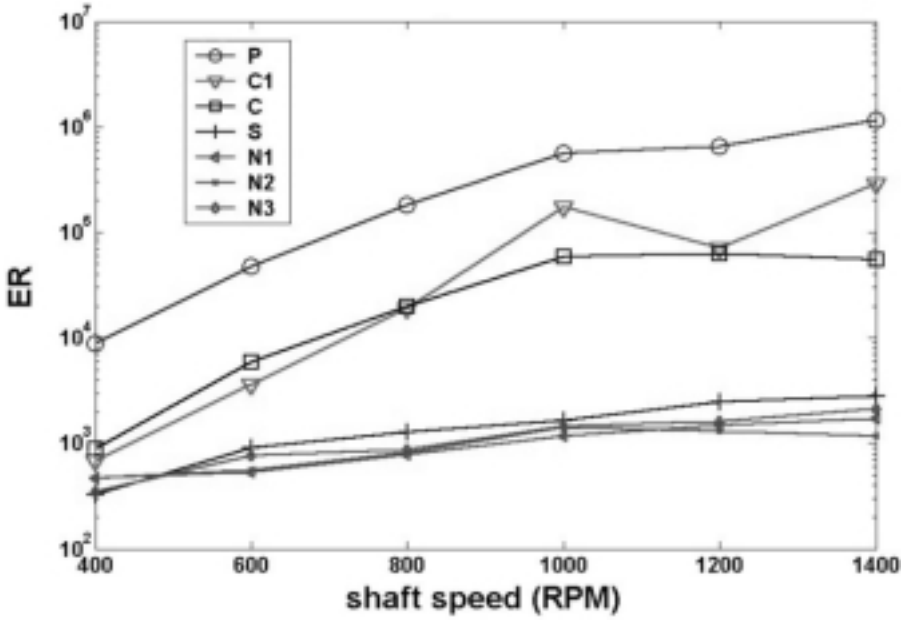

Fig. 11. ER of the acceleration signal as a function of the rotating shaft speed, load 2.

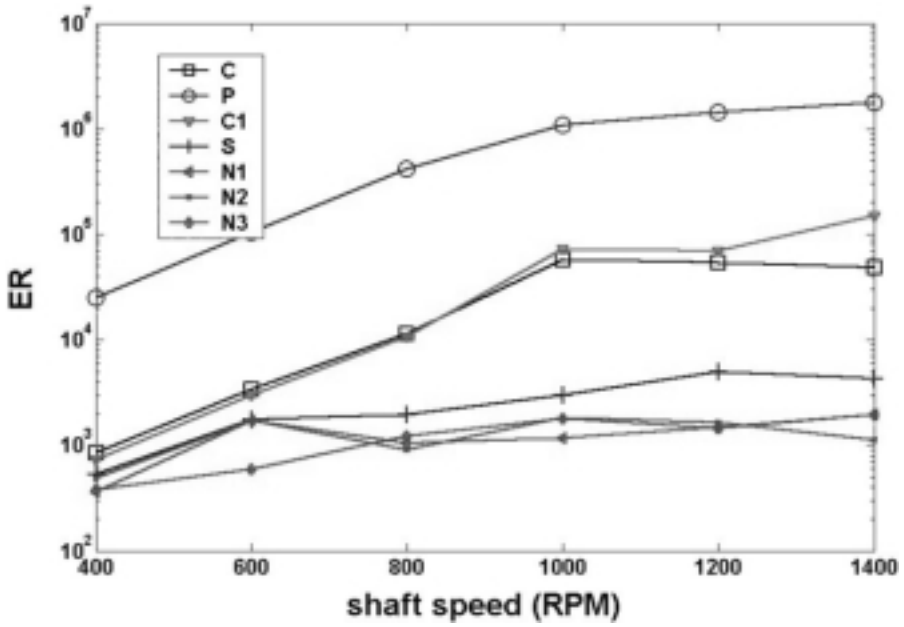

Fig. 12. ER of the acceleration signal as a function of the rotating shaft speed, load 3.

diagnosis purpose. It means that the difference between the RMS of the analyzed signal and the baseline is used.

The ER method was more sensitive than the RMS normally applied in industrial plants, especially considering incipient defects and low rotations. It also gave better results at low shaft speed, which is exactly where traditional RMS presented the worst results.

It worth to point out that the method is sensitive to changes in the machinery speed. This occurs because two classes of frequencies compose the spectrum of the signal of rotating machinery: the ones that do not variety with the shaft speed (natural frequencies) and

the ones that are dependent of the shaft speed.

If the baseline is established in a certain shaft speed and the signal to be analyzed is acquired in a lightly different speed, a false difference can appear in $D(f)$. For instance, if the normal baseline signal was obtained with the machine at 1400 RPM and the signal to be analyzed is obtained with the machine at 1500 RPM (difference of 1.7 Hz), it is expected that some frequency peaks will appear in different places of the spectrum. This will be responsible for high values in the residual spectrum and the ER parameter can indicate a wrong diagnose. This problem can be overcome by degrading the spectral resolution using frequency windows: the spectral representation can be divided in windows with width corresponding to frequencies speed variations and a new spectral representation is obtained by calculating for each window the integral before starting the ER procedure.

As it can be done for traditional RMS, the ER parameter can be used in several ways. It can be calculated only for specific frequencies bands (at natural frequencies, or at rolling bearing fault frequencies [1]); or else, it can be calculated using the PSD of the envelope [11] of the signal.

6. Conclusions

A data base of defected rolling bearing vibrations signals was used to analyze the diagnosis possibilities of three statistical parameters commonly employed in predictive maintenance: RMS, Skewness and Kurtosis. This database is composed by four fault types in the outer race: a pit, two different levels of corrosion and a scratched race. The vibration signals were measured in six different shaft speed and three radial loads conditions. A second database composed by velocity vibration signals was obtained by numerical integration of the original database.

The results show that, in general, the use of acceleration signals gives better possibilities of detection than the velocity signals, for all the parameters analyzed in this work.

For diagnostic purpose, the Skewness is the worst among the three parameters. With Kurtosis it was possible to detect only the pit fault, in low rotation. The RMS value for acceleration signals gave better results than for velocity signals. In both cases, the detection performance of the RMS increases with the shaft speed allowing detecting the pit and the two corrosion conditions.

It was not possible to detect the scratched fault type with any of these three parameters.

To improve the diagnosis possibilities of scalar parameters, it was proposed in this work a new parameter named Residual Energy (ER). It is a scalar value obtained from the integration of the difference between the Power Spectral Density of a fault signal and a normal one.

With the ER method, it was clearly possible to distinguish a normal rolling bearing from the ones with defect, considering all the loadings and shaft speeds, except, in some cases, the scratched one.

Comparing the detection performance among the three classical parameters and the ER parameter, this last one has the best results.

Future studies are needed to analyze the reliability of the ER parameter in other cases of fault condition, and extending its application mainly in an industrial plant context.

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