High Resolution Methods for Misalignment Detection in Low Speed Gear Boxes

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Abstract: In low speed gearboxes, shaft rotation and Gear Mesh Frequencies are lower and closer requiring higher spectral resolution in order to identify each one. Normally this problem is avoided increasing the acquisition time. Nevertheless, sometimes load and speed are variables, so the working period on stationary conditions is shorter. In these cases, it is useful to apply other kinds of tools such as the high resolution parametric methods. In this work a parametric method is applied in the misalignment detection of low-speed gears.

Key-Words: Mechanical vibrations, condition monitoring, gears, autoregressive models, low speed, misalignment.

1 Introduction

The main objective of the predictive machinery maintenance is obtaining information about the operative state of the equipment, giving warning information about the development of a breakdown and indicating the position of the element responsible for that effect. The vibratory signal of the system is one of the most important tool for the detection and monitoring of machine failures. There are many different techniques for processing this information, frequency decomposition being the most used. Frequency decomposition permits the analysis of the appearance or modification of specific amplitudes that are related to defect characteristic frequency.

Gearmesh frequency (GMF) and their harmonics characterize the vibration signal in the gearbox. These gearmesh frequencies are modulated by the angular velocity of the shaft, as a consequence of the pitch and profile errors and the variation of the stiffness in the tooth contact. Lateral bands in the frequency spectrum appear as a consequence of the presence of a modulation. This frequency bands are situated around the carrier frequency, and located at a distance equal to the modulating frequency.

The appearance of a fault in a wheel of a gearbox, such as cracks, tooth breakdown, wear, misalignment or bad contact, implies a change in the amplitude and in the number of these lateral bands. Some different phenomena of modulation could be present at the same time, and each one of them produces a different family of lateral bands characterized by the same frequency distance in the spectrum. This is related to the modulating frequency and contains information about the machine diagnostic [1].

When the mechanical system is working at very low angular speed, all these frequencies are very close in the spectrum, and in this case a very high spectral resolution is necessary for the detection and diagnostic. This implies a long acquisition time of vibratory signals in order to achieve the desired resolution. Nevertheless, in some applications, that is not possible because the machinery only works in stationary conditions during a short period of time. Some examples of this kind of situation can be wind power generators, or the firs stages equipment in roller mills. In these cases conventional spectral analysis tools are not more useful because the frequency resolution is not enough to discern the side bands. Therefore it is necessary to apply other kinds of spectral analysis tools which provide a good frequency resolution but using shorter acquisition periods [2].

In this work, parametric methods are applied to detection of gear misalignment. In first place the main features of the periodogram method for spectral estimation that is the most common tool used in the spectral estimation are presented. Following, parametric methods will be introduced paying attention to the two more important aspects characterising their application, that is, the model type and the corresponding order. Finally these methods have been applied to real signals analysing their utility in low-velocity equipment monitoring.

2 Spectral Analyses

The Fast Fourier Transform (FFT) algorithm [3] has been used for the vibratory signal frequency decomposition. As each kind of failure has its own specific spectral signature in the frequency domain, therefore it is possible to identify the failure origin by following the influence of each individual component.

Practical application of the FFT algorithm requires signals of finite length. So, a temporal windowing is carried out before the analysis is done. However, as the window is shorter, the capacity to distinguish close frequencies by the spectrum estimation decreases. A second effect has to be considered, the discrete character of the spectrum. A discrete spectrum implies to do a careful interpretation, in order to avoid some confusion. It is possible that some characteristics will be located in the closest discrete frequencies, or do not appear in the spectrum.

An adequate procedure to carry out the random signal power spectrum estimations is to divide the sequence of the available signal in smaller segments, and to calculate for each segment the square of the modulus of the Discrete Fourier Transform (DFT), called periodogram, and then to average all these periodograms. The main drawbacks of this procedure [4] are:

a) Usually, there is always some residual energy present on the fault frequencies due the manufacturing tolerances and mounting errors. Therefore side bands are difficult to distinguish, because there are many different families of lateral bands and other effects at the same time.
b) The signal of interest could be shaded by the background noise.
c) It is necessary to have a large enough signal register time duration in order to permit averaging of some periodograms.

3 Parametric spectral estimation

The low frequency bandwidth study implies data analysis during some minutes, in order to obtain a good resolution to distinguish the different frequencies involved. In these cases a parametric model permits the reduction of the data acquisition period drastically.

Parametric models are based on modelling vibratory signals as generated from a random process of infinite temporal series x_n [5-7]. Three different types o models can be distinguished: Autoregressive (AR), Moving Average (MA) and combined (ARMA).

The most general model an ARMA(p,q) is defined by,

$$x_n + \hat{a}_1 x_{n-1} + \cdots + \hat{a}_p x_{n-p} = \hat{e}_n + \hat{b}_1 \hat{e}_{n-1} + \cdots + \hat{b}_q \hat{e}_{n-q} \qquad (1)$$

where $\hat{e}_n$ is a noise signal that normally is not pure random. p and q could be arbitrary. If q = 0, the model is AR and if p = 0, the model is MA. The AR models lead to linear equations whereas the other two yield to highly non-linear equations.

The first step, in order to calculate the estimation of the power spectral density, is select the type of parametric model. An adequate model selection has a great importance because the better is the selection the fewer parameters will be necessary to calculate. The model order must be specified once the model type is defined. Maybe this task is the most important on the application of this kind of tools. A too high order can lead to a spectral estimation with no reliable frequency peaks because the signal noise will be also modelled, on the contrary too low order yield to a low frequency resolution that will be not adequate for analysis proposes.

In this work only autoregressive models (AR) have been used. Their application is simpler and the results supplied are satisfactory in the vibratory signal study of interest in this work. In order to complete the field of parametric models, the general procedure is presented when the use of MA or ARMA models could be of interest.

After model selection (in this case the AR), it is necessary to define the order and to calculate the corresponding parameters. In this case, with an AR model, the equations (1), are called the Yule-Walker equations.

There are different AR models, the difference between them is the algorithm implemented for the parameter determination from the linear equation system. The Burg algorithm [8] is based on the arithmetic mean of the direct and regressive prediction error power. The parameters are modelled from the observed data. Other algorithms, such as Yule-Walker method made an intermediate calculation using the correlation matrix. The Levison-Durbin recursive algorithm permits to obtain the Yule-Walker equations power error, been more efficient than the Gaussian elimination.

The model order p selection can be made using different criteria [8-9], as Final Predictor Error (FPE),

$$FPE = \frac{N + (p+1)}{N - (p-1)} s_e^2 \qquad (2)$$

where N is the number of data used and s_e^2 is the noise signal variance. The order p is the value, which minimises this criterion.

Another order selection method is the Akaike Information Criterion,

$$AIC = N \ln s_e^2 + 2p \qquad (3)$$

Both methods for AR models provide a similar order, since they are asymptotically equivalents $AIC = \ln(FPE)$ when N ? 8 .

Finally, according to the equation (4), Power Spectral Density (PSD) is obtained once the model type, model order and parameters are defined.

$$PSD = s^2 \Delta t \left| \frac{B(f)}{A(f)} \right|^2 \qquad (4)$$

where

$$A(f) = Ae^{j2p f \Delta t} = \{a_k\} \rightarrow AR$$
$$B(f) = Be^{j2p f \Delta t} = \{b_k\} \rightarrow MA$$

4 Experimental results

During the study of vibration behaviour of a mill stand power train in order to define condition monitoring strategies arises the interest on the application of parametric methods in the calculation of power spectral density. Specifically, one of the gearboxes driving the first stages of the mill was studied. This kind of machinery supposes a challenge for maintenance team due not only to the low operative speed but also because of the difficulty to achieve a long vibration data record. The machine of interest has suffered several important faults such as bearing races pitting, broken bearing races, cracking and broken teeth. The last one is the most dangerous fault and it is necessary to define a tool in order to detect this situation before it could become a catastrophic failure. It must be emphasized that at this moment maintenance people don't realize about faults until they are in an advanced phase.

The gearbox of interest is driven by an electric motor, it has 5 reduction stages with helical gears. At the end two output shafts turn both milling rolls coupled by universal joints. The milling torque is 304 KNm with an output speed about 10 r.p.m. and an input speed of 825 r.p.m. That makes a global transmission rate of 81. Table 1 contains gear data.

Table 1: Modulus and teeth data for real machine

Stage	**1**	**2**	**3**	**4**	**5**
m (mm)	8	10	14	20	18
z	20/60	20/60	20/60	20/60	31/31

Analysing several of the developed faults the following sequence could be defined. Faults, normally starts in a low speed bearing, nevertheless due to the gearbox configuration it is not easy to detect this one using conventional condition monitoring techniques since the spectra is very rich and it is difficult to identify bearing fault frequencies. Fortunately, due the low speed operation, bearing faults are not as dangerous as in high-speed gearbox so it can still work during a long period of time. The problem is that as the bearing damage progress, shafts suffer a certain misalignment that yields to a gear damage that could finish in a broken tooth. Then, if the misalignment of a shaft is detected the fault could be identified reducing the risk of a catastrophic fault and allowing the planning of the maintenance operations.

Gear misalignments could be detected analysing the gearmesh frequencies (GMF) and their harmonics as well as their side bands. In this case the gearbox configuration has the same partial transmission rate for several stages (20/60) doing more difficult to discern between GMF harmonics, then it was considered to analyse only the GMF side bands in order to detect misalignment.

There is another problem that is related to the period of time that the gearbox is working in stationary conditions. Each rolling mill stage works on two wires that go into the stage at different times. So there are three operating modes defined by the number of wires that are on the stage at time. These are: No wires, 1 wire and 2 wires. These modes are changing and is not possible a long data acquisition in stationary conditions. The preferred operating mode and also the longer is that corresponding to 2 wires since it is the highest load to the system. This mode has a maximum duration about 45 to 50 seconds in the best case. Nevertheless this situation could require some minutes to appear, doing the acquisition time very tedious.

As there are not vibration data registers about normal and fault condition, a laboratory gear set with the same features as the real machine was built in order to allow fault simulation. The most important faults were developed on the two last reduction stages that is the reason because only these two were considered on the design of the laboratory set. The gear test set developed (see figure 1) has a 1.1 Kw electric drive, two reduction stages, two output shafts, and two pneumatic brakes located in the output shafts, which act as loads, simulating the lamination rollers.

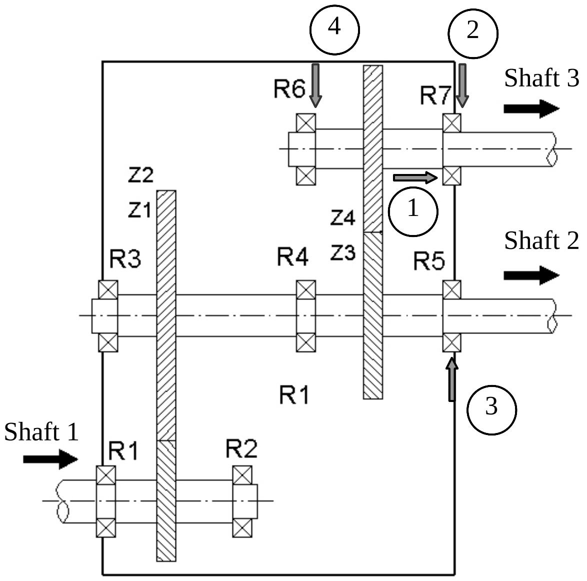

Fig. 1.- Gear test set up

Data acquisition has been carried out using four piezoelectric accelerometers B&K model 4398 located in points called 1 to 4 as appears in figure 3. Position 1 register axial vibrations as long as positions 2, 3 and 4 done the same in radial direction. The electric drive provides an input velocity of 32 rpm, which yield the nominal gearmesh frequencies indicated in Table 2.

Table 2. Gearmesh frequencies.

Pair	Teeth	Rotation frequency (Hz)	GMF
Z1-Z2	20/60	0.533/0.177	10.666
Z3-Z4	31/31	0.177/0.177	5.5111

In order to study the misalignment, shaft 3 was moved in radial direction on support called R7. Displacements that move shafts away are considered as positives as long as these that bring shafts nearer are considered as negatives. Five misalignment cases were considered: -0.5 mm, No Fault , 0.5 mm, 1.3 mm and 2.4 mm. For each one, four tests were developed for different loads at 100%, 75%, 50% and 25% of the maximum load. That means a total of 20 vibration data registers with four channels each one.

Base spectra is modified by misalignment, changing the amplitude of GMF harmonics, and providing a higher number of side bands located around the GMF with frequency increments equal to the defect frequency. In this case the defect frequency is that of the shaft, which means that side bands will be spaced a frequency of 0.177 Hz around the GMF of 5.5111 Hz. So a high resolution spectrum is required for seeing the side bands. In order to achieve a good resolution at least four spectra lines must be defined between each side band, that means a resolution about 0.04425 Hz which supposes an acquisition time about 22.5 seconds.

On the laboratory set it is possible to acquire data without time limit allowing long registers and as a consequence good frequency resolution. Five minutes of vibration were taken at a sampling frequency of 10 kHz as the interest is on the low frequency original were resampled to a frequency of 40 Hz.

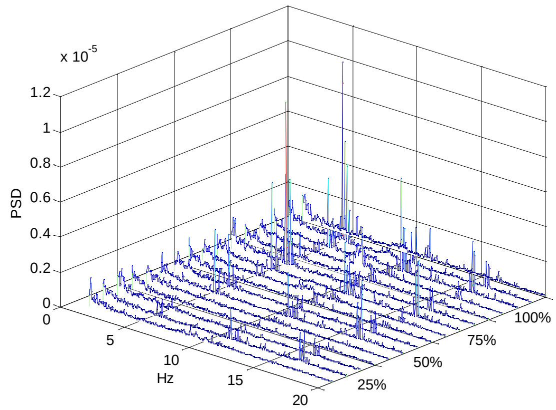

Fig. 2.- NO FAULT condition PSD Spectra, for each channel and load.

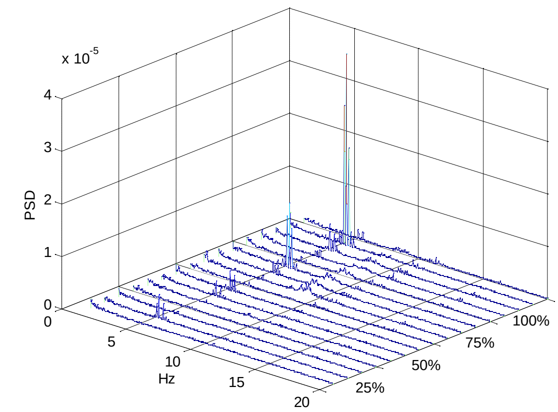

Fig. 3.- 0.5 mm misaligment PSD Spectra for each channel and load.

Figure 2 shows the resulting spectra for normal condition and figure 3 corresponds to the 0.5 mm misalignment case. These spectra have been obtained using a length of 1024 data averaging for the whole register that has a total of 12032 data points.

It can be appreciated that misalignment increases the 1XGMF and their lateral bands. The effects on the amplitude of the GMF harmonics are not very significant and similar results are obtained for the other misalignment cases. Therefore, for misalignment detection, attention must be focus on the GMF side bands.

For applying parametric methods, sensor position 3 and load case of 100% was selected. Figure 4 shows the resulting spectra for each misalignment filtered around the GMF. It can be appreciated the increment on the side bands amplitude.

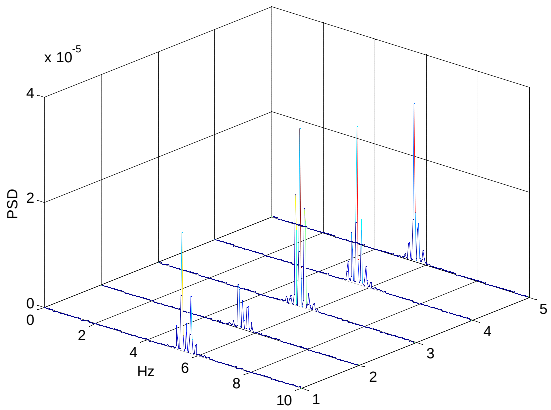

Fig. 4.- Spectra for chanel 3, load 100% (1024 lines, 1024 data points), (1) –0.5 mm; (2) No Fault; (3) 0.5 mm; (4) 1.3 mm (5) 2.3 mm.

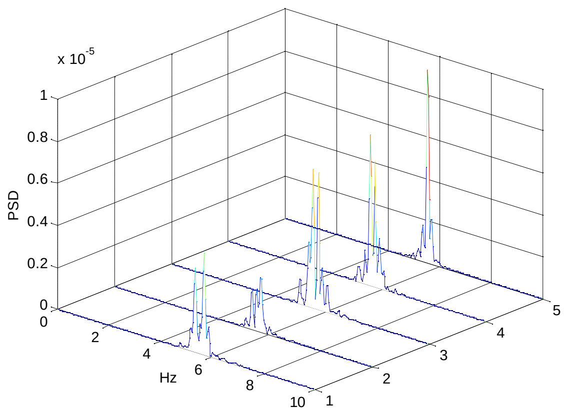

Fig. 5.- Spectra for chanel 3, load 100% (1024 lines, 512 data points), (1) –0.5 mm; (2) No Fault; (3) 0.5 mm; (4) 1.3 mm (5) 2.3 mm.

A reduction in the number of data points used for periodogram calculation degrades the resulting spectra. In this case zero padding was used in order to achieve the same frequency resolution. Figure 5 and 6 show the results for data length of 512 and 256 points. So, it is no possible to identify easily the fault condition as the side bands are masked.

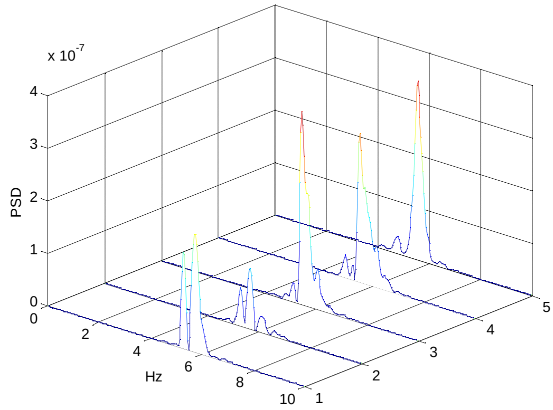

Fig. 6.- Spectra for chanel 3, load 100% (1024 lines, 256 data points), (1) –0.5 mm; (2) No Fault; (3) 0.5 mm; (4) 1.3 mm (5) 2.3 mm.

The parametric spectra was obtained using only 256 data points. The model order was selected using the No Fault condition carrying out the parameter estimation by the Burg algorithm. Table 3 contains the order obtained using the Akaike (AIC) and Final Prediction Error (FPE) criteria.

Table 3.- Estimated orders for the No Fault condition using, Akaike (AIC) and Final Prediction Error (FPE) for 256 data points.

Sensor	**Load**			
	25% AIC/FPE	**50% AIC/FPE**	**75% AIC/FPE**	**100% AIC/FPE**
1	117/117	119/105	120/120	103/103
2	116/109	103/103	120/120	120/111
3	103/103	119/110	112/112	105/105
4	112/111	119/112	115/103	74/74

Figure 7 contains the spectra obtained by the parametric method using only 256 data points. So it is possible to identify the fault condition with an acquisition of 6.4 seconds. In real machinery this fact increases the acquisition possibilities, allowing to improve the diagnostics capability of a maintenance team.

As the interest is focused on the detection of a rise in the side bands magnitude and in order to do easier the fault identification by the maintenance people it is not necessary to use a parametric model of high order. Figure 8 shows as is possible to have a good indicator using a model order of 8. In this case is not possible to identify lateral bands but is clear the increase on the energy content of the frequency band of interest and appear enough for detection and diagnostic of this kind of fault.

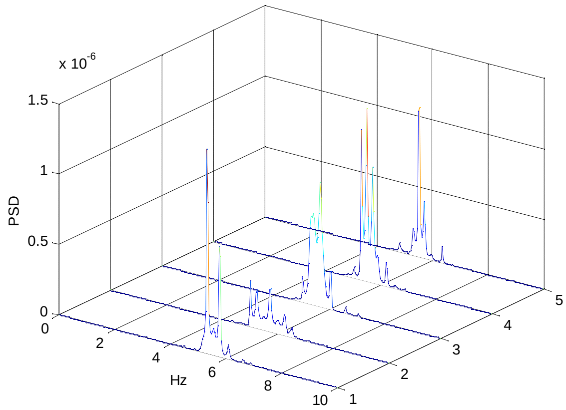

Fig. 7.- Parametric Spectra for chanel 3, load 100% (1024 lines, 256 data points, Order 105), (1) –0.5 mm; (2) No Fault; (3) 0.5 mm; (4) 1.3 mm (5) 2.3 mm.

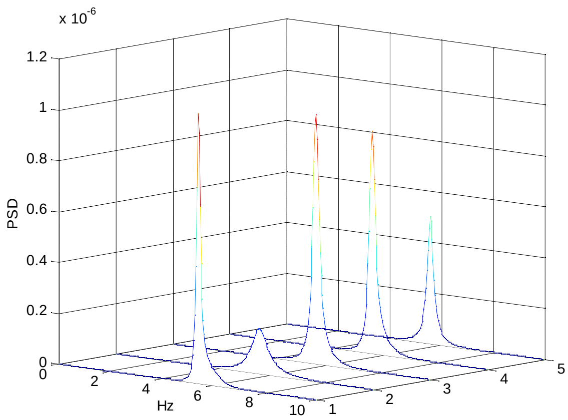

Fig. 8.- Parametric Spectra for chanel 3, load 100% (1024 lines, 256 data points, Order 8), (1) –0.5 mm; (2) No Fault; (3) 0.5 mm; (4) 1.3 mm (5) 2.3 mm.

5 Conclusions

Unconventional spectral estimation tools are useful when high resolution frequency is desired but there are limitations on the acquisition period. In this work parametric methods are used on detection of gear misalignment in machinery working at low speed. Parametric methods provide the possibility to reduce the time period in order to achieve enough information to do a good diagnostic. The main difficulty to apply this kind of tools is the selection of the autoregressive model order. In this task several criteria can be used. Nevertheless, it has been showed the possibility of using a reduced order that could be good enough for misalignment detection.

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