

Original Research Article

Use of the Correlation Coefficient for Rotating Machine Monitoring

Abstract - The use of electronics and computer technology in production systems has greatly improved the quality of our industrial products. The productivity of these installations is a function of the maintenance quality applied to the equipment. Several methods are used to monitor the functioning of industrial installations. One of these methods is vibration analysis. The vibration signals from the rotating machines support several types of information related to the working state of the production tool. The processing of this information makes it possible to have decision tools for maintenance. In this work, we propose a method of anticipating the maintenance of rotating machines. The algorithm we propose starts with the removal of 512 point windows during the running time of the ball bearing. Each signal is decomposed by DWT: we obtain the approximation coefficients. These coefficients make it possible to determine the correlation coefficient between the so-called reference window and the other windows following the functioning of the ball bearing. The correlation coefficient is then the fundamental element of the decision. This algorithm has been applied to real vibration data and the results are encouraging.

Keywords: DWT, Correlation coefficient, vibration signals, rotating machines.

1. INTRODUCTION

All productive systems today require more and more an optimization of maintenance. This optimization requires a very rigorous maintenance strategy. The choice of the type of maintenance has an influence on the financial costs associated with the production. Predictive maintenance in general will reduce the probability of surprise failures or limit the degradation of the functioning of a production tool. Corrective maintenance, on the other hand, will allow corrective operations to be carried out after the detection of a failure. This maintenance requires first the investigation of the origin of the malfunction, its nature and then the repairs. This set of activities creates additional costs for the company. Non-invasive control methods, whether by vibration analysis or by acoustic emission, have the same aims: to detect failures by installing different alarm devices. The user defines alarms that correspond to defect detection thresholds. These thresholds, or better, these alarms, are used to identify items that are in the process of being worn and that need to be controlled by maintenance personnel. This makes it possible to plan the maintenance phases [1].

Today, the most widely used and best-known method in the industry is vibration analysis. It developed with the emergence of computer science and with the improvement of signal processing methods. Vibration analysis consists of detecting possible malfunctions and monitoring their evolution in order to plan or defer a mechanical intervention. Indeed, the vibratory signal is the support of several information that inform on the operating status of a rotating machine. This information is often used to monitor installations.

The objective of our work is to propose a new method of monitoring the functioning of a rotating machine. The alert indicator is given by the correlation coefficient in the time-scale domain. In this space the differences in correlation coefficients are clear. This space change aims to significantly reduce false alerts that stress maintenance operators and usefully waste valuable production time.

Preventive maintenance uses several tools, including tribology, thermography, acoustics and vibration analysis. To this end, several works have been proposed. Merzoug M et al., developed a dynamic gearing model including a localized tooth defect. The model consists of a pair of straight wheels. This model incorporates the effects of rigidity and damping [2]. Wang W J and Mc Fadden P D. proposed an algorithm for the early detection of failures by vibratory signature [3]. This algorithm uses image processing techniques to facilitate the automatic interpretation of the vibratory signatures of the gears. The vibration signature of an individual gear in a gearbox is extracted by the synchronous time-domain averaging technique from the total vibration signal measured on the gearbox housing. The time-frequency distribution of the vibratory signature of the gear determined from the spectrogram is treated as an image and early fault detection is performed by interpreting the models in the image by segmentation procedures, connectivity analysis and feature extraction. A. Oulmane et al. proposed a method for detecting wear on a ball bearing. This method consists of transforming the 1D signal of the vibratory signature of a ball bearing into an image. Artificial Neural Networks (ANN) are then used to classify images after normalization. In this way, the diagnosis of bearing defect becomes simply the classification of Fourier descriptors of time-frequency images [4]. Bo Li et al., discussed vibration frequency characteristics of ball bearings for the diagnosis of engine bearing failure. This work then presents another approach for the diagnosis of failures using neural networks and the time/frequency domain for the analysis of bearing vibrations. Vibration simulation is used in the design of various strategies for diagnosing engine rolling defects. The results of simulations and tests carried out in the industrial world indicate that neural networks can be effective tools for the diagnosis of various motor rolling defects [5]. H. Minamihara et al., proposed a simplified method to determine the correlation function through the conditional mean. First, an explicit expression of the probability density function for vibration signals with amplitude limitations is introduced using the well-known Gaussian distribution and Dirac delta functions. The proposed method is has been tested for the detection of malfunctions of a hydroelectric power equipment [6]. J. Rafiee et al. presented a new approach to determining gear malfunctions based on frequency decomposition. For the identification of gear defects, the technique of model recognition by continuous wavelet transformation was applied to the frequency decomposition coefficients [7]. Z.K. Peng et al. proposed a method for detecting ball bearing malfunctions. This method uses the Hilbert-Huang Transform (HHT). This algorithm has good computational efficiency and does not involve the concept of frequency resolution and time resolution. From this point of view, the HHT seems to have the potential to become a perfect tool for detecting ball bearing defects. These authors also improved this algorithm by associating the Wavelet Packet Transform (WPT) [8]. Ma Yuchao et al. proposed a method for identifying structural damage. This method combines the short-term Fourier spectrum and the Wigner-Ville distribution to extract the dominant term [9]. Z.K. Peng F.L. Chu. presented a summary of the work that used wavelets for fault diagnosis of rotating machines, including the following main aspects: time-frequency analysis of signals, fault extraction, detection of signal singularity, signal and weak signal extraction, vibration signal compression, and system

identification. Other applications are also introduced briefly, such as artificial neural networks, wave-based frequency response function, etc. All this shows the importance attached to the maintenance of rotating machines by vibratory analysis by scientists [10]. Eduardo Rubio, Guillermo Ramírez, proposed two methods for detecting gear rattling in mechanical systems. To this end, an experimental rapid return mechanism was built with gears driven by an electric motor. The level of rattling is measured using a performance measurement index. Analysis of the results shows that the application of wavelet transformation significantly improves the indices used for the detection of rattling [11]. Some authors such as Xiao Chaoang et al. or Oyobe et al. have compressed the vibration data for further study [12], [13].

Despite the abundance of work in the field of preventive maintenance through the use of vibration analysis, the monitoring algorithm for ball bearing malfunctions consisting of a discrete wavelet and extraction of the correlation coefficient of vibration data has not yet been tested on vibration signals. The originality of this work lies in the improvement of the detection of bearing defects and in the reduction of the rate of false alarms.

This article consists of three parts: the state of the art, methodology, analysis and interpretation of the results.

2. GENERALITIES ON VIBRATION ANALYSIS

All machines vibrate and the frequency spectrum profile of their vibrations is highly dependent on their operating status. The phenomena of wear, fatigue and aging change the profile of this spectrum. Vibration analysis opens up real diagnostic perspectives and thus becomes an important part of preventive maintenance. An ideal machine would not vibrate, as all the energy would be used to do the work. However, in reality, some of the energy intended to operate the system is dissipated in the structure in the form of vibrations. As the machine ages, the parts deform and slight changes in their dynamic properties appear. Thus, the trees are misaligned, the bearings and ball bearings wear out, the rotors are unbalanced, the play increases. All these factors result in an increase in vibratory energy and therefore a decrease in effective energy. The advantage of vibration signals is that they can be accessed by means of treatments adapted to the characterization of dynamic forces and particularly those resulting from abnormal excitations [14], [15], [16]. The diagram of this treatment is shown in Figure 1

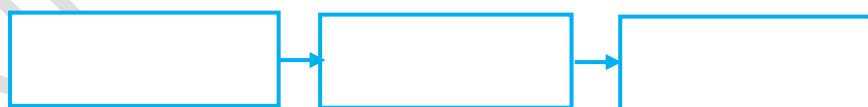


Figure 1. Fault detection chain

Figure 1 shows the general procedure for detecting malfunctions of a rotating machine. The vibratory signal is often complex. It can be a set of amplitude values of the vibration, the acceleration of the rotating element or even the noises born of several causes. Thus, the acquired signal is obtained after pretreatment. The purpose of this pretreatment is to isolate the information we are looking for. It is on this signal that we apply the parameters extraction tools. The analysis of the extracted parameter allows the decision.

3. PROPOSED METHOD

3.1. Parameter Extraction Procedure

The diagram for extracting maintenance decision parameters implemented in our algorithm is given in Figure 2.



Figure 2. Parameters extraction algorithm

Figure 2 represents the decision parameter extraction algorithm. The vibratory signal is decomposed by the DWT. This transformation allows the signal to be decomposed into two components: the approximation signal and the detail signal. The detail signal is made of the edge effects generated by the truncation of each observation window, by vibrations generated by the tolerances of the machining and other noises. All this data is less essential for the maintenance decision. That is why in the remainder of the procedure we retain the approximation signal. Approximation coefficients are used to calculate the correlation coefficient. The correlation coefficient is calculated between the reference window and that of the device's operating suite. The decision is obtained by interpreting the value of the correlation coefficient.

Wavelet transform

A wavelet Ψ is a square-integrable functions from the space of Hilbert $L^2(\mathbb{R})$, most often oscillating and zero-averaging, chosen as a multi-scale analysis and reconstruction tool. We define a family $\psi_{s,\tau}$ where $(s, \tau) \in \mathbb{R}^+ \times \mathbb{R}$ of wavelets from the mother wavelet Ψ :

$$\forall t \in \mathbb{R}, \psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-\tau}{s}\right) \quad (1)$$

To analyze a square-integrable function in wavelets consists in calculating all its scalar products with the wavelets family. The resulting numbers are called wavelet coefficients, and the operation associating its wavelet coefficients to a function is called wavelet transform. The continuous wavelet transform of a function $f \in L^2(\mathbb{R})$ is defined by:

$$g(s, \tau) = \int_{-\infty}^{+\infty} f(t) \psi_{s,\tau}^*(t) dt \quad (2)$$

For compression applications the Discrete Wavelet Transform (DWT) is used. This transformation is defined by the following equations:

$$a[j-1, k] = \sum_{n=1}^n h[n-2k] a[j, n] \quad (3)$$

$$d[j-1, k] = \sum_{k=1}^n g[n-2k]a[j, n] \quad (4)$$

$$H[\omega] = \sum_{k=1}^n h[k]e^{-jk\omega} \quad (5)$$

$$G[\omega] = \sum_{k=1}^n g[k]e^{-jk\omega} \quad (6)$$

In the equations (3), (4), (5) and (6) $G[\omega]$, $H[\omega]$, $a[j-1, k]$, $d[j-1, k]$ are respectively the low pass filter, the high pass filter, the approximation coefficients and the detail coefficients.

The reconstruction of the signals is done by equation (7).

$$a[j, k] = \sum_n h[n-2k]a[j-1, k] + \sum_n g[n-2k]a[j-1, k] \quad (7)$$

Correlative analysis

Correlative analysis studies the statistical relationships that exist between two sets of data or between two signals. These relationships are due to a dependence of the two signals with an identified or not identified cause. Correlative analysis has many applications. The most common applications include detection of signals embedded in noise, detection of hidden periodicities, recognition and comparison of signals and shapes, location of vibratory sources, etc. The comparison of two samples can be done by using the correlation coefficient. The correlation coefficient is defined by the relation (8).

$$r(X, Y) = \frac{COV(X, Y)}{\sigma_X \sigma_Y} \quad (8)$$

In this relationship, the $COV(X, Y)$ quantity refers to the covariance of variables X and Y and defined by the relationship (9).

$$COV(X, Y) = \frac{1}{N} \sum_{i=1}^N (x - \bar{X})(y_i - \bar{Y}_i) \quad (9)$$

In formulas (8) and (9):

x and Y_i are respectively the sample of the reference window and that of window i ;

\bar{X} and \bar{Y}_i are the means of the reference samples and window i respectively

σ_X and σ_Y are the standard deviations of the reference samples and window i respectively.

The linear correlation coefficient r gives a measure of the intensity and direction of the linear relationship between two variables. The correlation coefficient is between -1 and 1.

3.2. Analysis and interpretation of results

The method presented in this article has been implemented on two real vibratory signals. A first signal is generated by a good bearing and a second signal generated by an used bearing. These two bearings have the same part number SKF7309B. Thus, these signals are recordings of the vibration monitoring of the ball bearing. The acquisition system consists of a portable collector, VIBROTEST 60 and an accelerometer. The signals were acquired with a sampling frequency of 2 kHz. The Acquisition Device model uses a 12-bit CAN. The vibratory parameter chosen for this work is the amplitude variation. The electrical machine used is an asynchronous machine whose parameters are recorded in Figure 1.

Table 1 Parameters of the electric machine used

Nominal phase-phase voltage	400V
Nominal torque	706N.m
nominal current	193A
Current at start-up	1389.6 A
Torque at start-up	1412 N m
nominal frequency	50 Hz
Fréquence nominale	50 Hz
power factor	0.86
Number of pole pairs	2
Nominal power	109.94 kW
Speed of synchronization	1500 tours/min

In this algorithm, the global signal is divided into several observation windows. We used DWT to decompose the truncated signal into low-frequency and high-frequency signals. This transformation allowed us to isolate from the vibratory signal its low frequency part (approximation signal). Also, a signal from the first use of the ball bearing is used as a reference signal. The correlation coefficient between this so-called reference X window and the other Y_i windows that follow are calculated. The results of the malfunction zone are retained and recorded in Table 1

Table 2. Evolution of the correlation coefficient as a function of the observation window

Window Number ^o	(X,Y1)	(X,Y2)	(X,Y3)	(X,Y4)	(X,Y5)	(X,Y6)	(X,Y7)	(X,Y8)	(X,Y9)	(X,Y10)
r(X,Yi)	0.89	0.8	0.7	0.5	0.3	0.1	0.1	0.1	0.04	0.03

The results in Table 1 show the different values of the correlation coefficients obtained during the observation. These correlation coefficients are in absolute values because the sign of the coefficient does not provide any additional information for this work. It is in this work to follow the vibratory behaviour of a ball bearing. To do this we compare a window of 512 points taken at the beginning of use of the ball bearing. This reference window is named X and will be compared to a series of successive windows of the same signal and size. Thus, we were able to observe the evolution of the difference between the reference window and the other windows that follow. The indicator of this development is the correlation coefficient. In this algorithm, the use of DWT makes it possible to separate low-frequency and high-frequency signals. High-frequency signals are often derived from mechanical manufacturing

tolerances. These manufacturing defects are the source of early alarms. This is how the approximation signal was chosen for this work. Moreover, the decimation made during the wavelet decomposition reduced the data of the sampled window by half. The data to be manipulated later is reduced; this results in a significant decrease in the computational load of the algorithm. The observation of the ten successive windows presented in this work shows that the coefficients of correlation evolve in a decreasing manner with the duration of functioning of the device. The comparison of the reference window X with the other ten successive windows, shows first a strong correlation for the windows Y1, Y2 and Y3 with the reference window. This strong correlation indicates that the ball bearing is still functioning properly. From window Y4 the correlation coefficient decreases until almost cancels itself. The low correlation coefficients indicate the change in ball bearing functioning. Therefore, a maintenance decision is required. This development is shown in Figure 3.

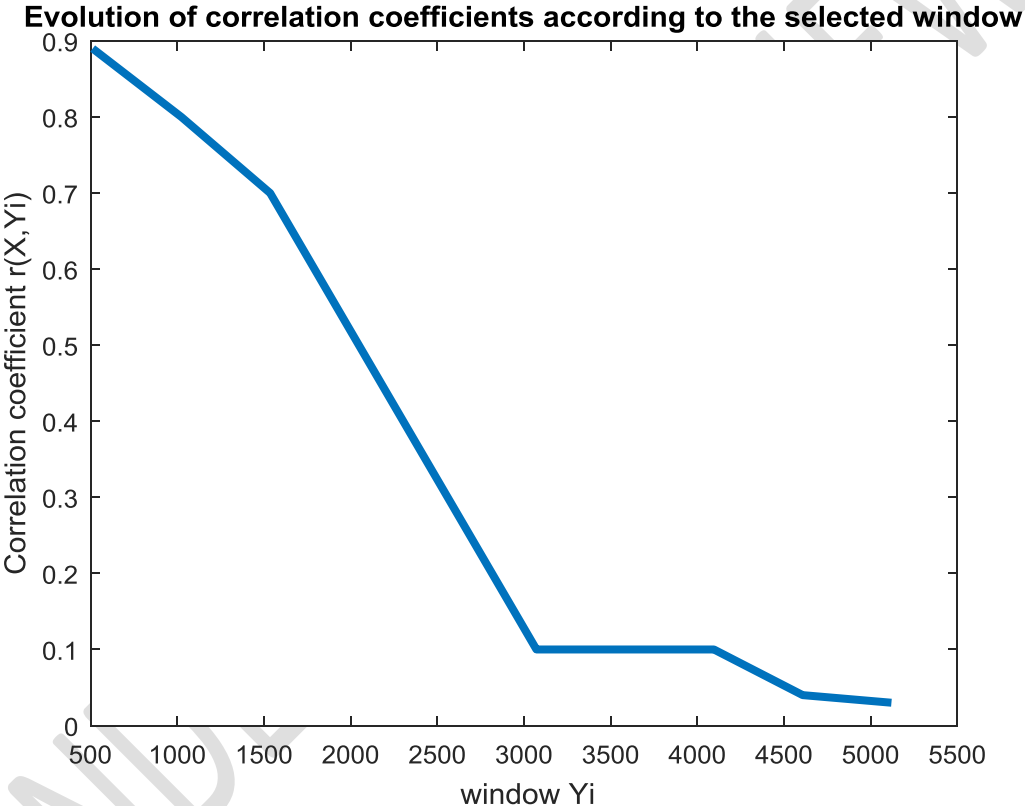


Figure 3. Evolution of the correlation coefficient in the ball bearing malfunction zone

Figure 3 represents a set of ten (10) windows taken from the malfunction area. We note that up to the fifth observation window, the slope of the curve is large and beyond the fifth window the slope of this curve weakens. The shape of the slope is given by the index coefficient of the line here, it is represented by the correlation coefficient. The values of the correlation coefficient included in the range $] 0.5; 1]$, indicates a strong correlation. This means that windows with such values have a strong resemblance to the reference window. The ball bearing can be said to be functioning normally. The values of the correlation coefficient in the range $[0; 0.5]$ indicate a low correlation; this low correlation implies a low resemblance between the sampled windows and the reference window. The functioning of the bearing in this part is not good. Thus, an alarm level can be proposed for preventive

maintenance. The display of the reference signals and the Y7 window, for example, is shown in Figure 4.

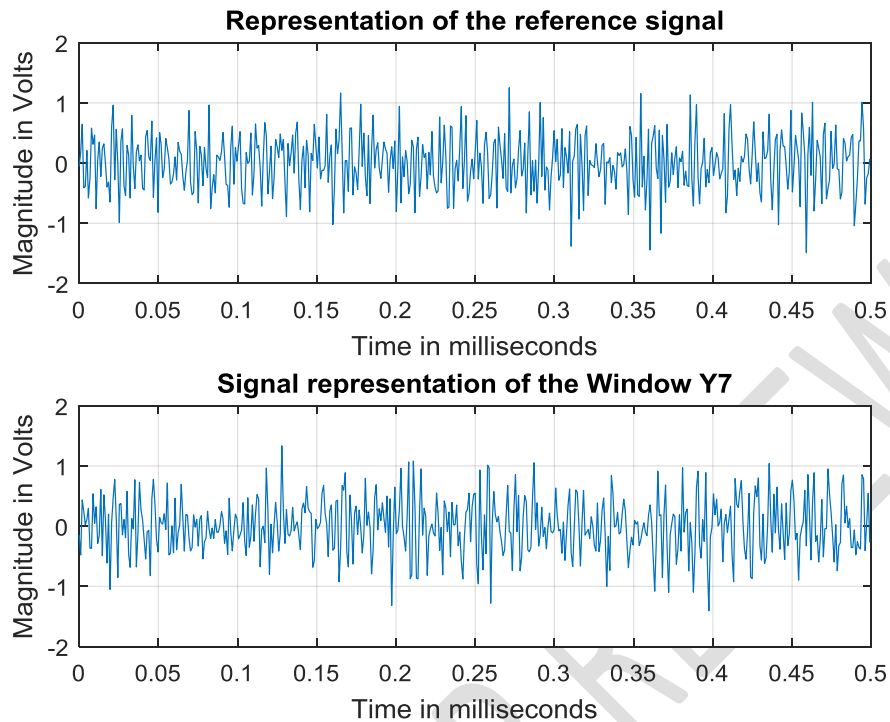


Figure 4 Comparison of the reference signal with that of the Y7 window

Figure 4 shows the comparison between the reference signal and the signal taken at window Y7 of the ball bearing malfunction zone. This comparison is carried out by our algorithm. The morphological difference between the two signals is clearly evident. This difference confirms the theoretical conclusions proposed by the interpretation of the value of the correlation coefficient $r(X, Y7)=0.1$. These results show that the functioning of the ball bearing at this time represented by the Y7 window is abnormal. Going back in time, we can find the date of the beginning of the malfunction and therefore we can set the alarm threshold for the need of preventive maintenance by vibration analysis.

4. CONCLUSION

In this article we have presented a method of preventive maintenance by vibration analysis. Table 1, Figure 3 and Figure 4 show that the qualitative results of the proposed method are very good. The correct interpretation of these results lies in the division of the positive interval of the domain of existence of the correlation coefficients into two equal parts. Thus, we can use the value of the correlation coefficient equal to 0.5 as the threshold value to give warnings of the need for preventive maintenance of the device. The particularity of this algorithm which uses DWT and the extraction of the correlation coefficient lies in the reduction of the number of early alarms and the determination of a threshold indicator of the good functioning of the device. Also, the decimation of the data during the application of the DWT significantly reduces the computational load of the algorithm. Thus, we can say that our algorithm is accurate and of low computational complexity (for a sample of 512 points). However, reference should also be made to the opinion of the mechanical engineer who

specializes in rotating machinery maintenance. However, reference should also be made to the opinion of the mechanical engineer who specializes in rotating machinery maintenance. In the further of this work, we think of its experimental validation in a factory in Franceville, Gabon

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