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Extracting indicators for cutting tool wearing detection during turning using vibration analysis

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ABSTRACT: The analysis of vibrations generated during conventional turning is one of the reliable means of determining the condition of sensitive components. In this paper, it is clearly presented the necessary steps to extract the indicators in order to be able to detect tool wear during the main three phases of use (running-in, stabilized wear, accelerated wear). It is clearly demonstrated that there is a relationship between the evolution of wear and the measured quantities (vibrations) during machining. To achieve this, we have carried out several measurement campaigns using metal carbide plate tools. Thus, the vibrations generated during the machining operations were recorded along a single axis on the machine tool using a single axial accelerometer positioned on the turret in the vertical direction, perpendicular to the cutting force. The processing of these signals in both the time and frequency domain has proven that vibrations can indeed be used to detect the level of wear.

KEYWORDS: Turning, Cutting tool, Tool wear detection, Vibration analysis, Indicators, Accelerometer.

1 INTRODUCTION

Widely used in a wide range of applications (from aerospace to mechanical industry) [1]. Cost minimization is an essential requirement in all sectors of production because with the globalization of the economy only products made at a reasonable cost can still find their place in the markets. The state of the tool and its life are critical components of the machining cost [2]. It is therefore important to be able to develop wear detection and tool life prediction for rational production time management. The dimensional tolerances and the quality of the machined parts depend on it. There will be no question of preventing wear which is a phenomenon inherent to any cutting process given the stress, friction and temperature levels to which the tool is subjected. But a method for detecting the occurrence of wear and its evolution is a real need in the context of a "just in time" policy of tool change [3,4]. Several works have proposed to use different types of signals resulting from machining such as cutting forces [7], acoustic emission [8], and vibrations [9,10] in order to extract the information needed to perform effective monitoring. Several signal processing techniques have been adopted, including frequency, time, statistical methods and time-frequency joint analysis. Tool monitoring methods are generally classified into two groups whose: 1. the direct methods where wear is directly measured using

optical, radioactive sensors or sensors based on resistance electric; 2. the indirect methods which proceed by an evaluation of the wear on the basis of parameters measured during the cutting process: the cutting force, acoustic emission or vibrations.

2 METHODS OF VIBRATION ANALYSIS

There are various vibration analysis tools to detect and diagnose the early onset of defects. They are generally classified in two large families, temporal and frequency analysis. Time analyzis is based on the statistical analysis of the collected signal; it is applied to simple machines and consist of performing speed measurements in low frequency ranges and acceleration measurements in high- frequency ranges.

2.1 ANALYSIS IN THE TIME DOMAIN

In vibration monitoring, the simplest tools for detection are based on inductors extracted in the time domain. In the time domain, the indicators are generally defined on the basis of static moments [12].

$$f(x) = P(X \prec x) \tag{1}$$

The probability density function is:

$$f(x) = \frac{dF(x)}{dx} \tag{2}$$

The mathematical expectation of a function g (x) is the integral

$$E\{g(x)\} = \int_{-\infty}^{+\infty} g(x) f(x)\, dx \tag{3}$$

The characteristic function of the random variable is defined as the Fourier transform of its probability density function f (x) by means of a sign change. It is given by:

$$E\{g(x)\} = \int_{-\infty}^{+\infty} g(x) f(x)\, dx \tag{4}$$

The transformation will consist in representing the temporal signal in the space of indicators based on the statistical moments whose most used are

influence of vibrations induced by tree rotation. This method uses scalar indicators that make it possible to follow the evolution of a quantity derived from the power or the peak amplitude of the signal. Its value may have no intrinsic meaning, but it is its evolution over time that is significant of the defect. Frequency

content analysis is based on the Fourier transformation. The knowledge of the characteristic frequencies makes it possible to identify and locate the defects resulting from the mechanical components by analysing their spectrum. They are often used for complex machines with many mechanical components.

This function is also known as *statistical moments generation function.*

In fact, moments are power coefficients of *jw* in Taylor serie development.

$$E\left\{e^{(jwx)}\right\} = E\left\{1 + (jw)x + \frac{(jw)^2 x^2}{2} + \frac{(jw)^3 x^3}{3} + \ldots\right\} \tag{5}$$

Let's still

$$E\left\{e^{(jwx)}\right\} = 1 + (jw)E\{x\} + \frac{(jw)^2}{2}E\{x^2\} + \frac{(jw)^3}{3}E\{x^3\} \tag{6}$$

The moments of order n are:

$$E\{x^n\} m_n \tag{7}$$

We can easily notice that the moments are derivatives of the characteristic function with respect to jw and computed at the point w = 0

$$m_n = \frac{d^n \Phi(0)}{d(jw)^n} \tag{8}$$

2.1.1 THE EFFECTIVE VALUE (RMS)

Temporary, it measures the energy content in a vibratory signal. For a time series {xi} length n, the RMS value is expressed by:

$$\Phi(w) = \int_{-\infty}^{+\infty} e^{jwx} f(x) dx = E\left\{e^{jwx}\right\} \tag{9}$$

Or x bar is the average value of {xi}. The value of RMS is the square root of the second statistical moment m_2. The calculated RMS value could serve as particularly easy to use inductors [11]: a set of four to ten frequency bands is generally considered for their definition. For a random signal, the amplitude repair function follows a normal distribution of zero mean and sigma standard deviation. The effective RMS value must be 1/3 of the peak value.

2.1.2 COAT OF FLATTENING (KURTOSIS)

It is an indicator of the proportion of samples that deviate slightly from the mean value compared to those that deviate widely. The flattened pace of distribution in relation to the normal distribution is calculated by:

$$Kurt = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{RMS}\right)^4 - 3 \tag{10}$$

The presence of a power term 4 gives considerable weight to the high amplitudes.

The kurtosis makes it possible to detect the appearance of shocks and to follow the evolution of the defects inducing periodic drive forces. The Kurtosis value is 1.5 for a harmonic signal and 3 for a random signal. For a tool in good condition, the value of Kurtosis is of the order of 3 (between 2.75 and 3.25) while it approaches 4 when the tool deteriorates.

2.1.3 CREST FACTOR (CF OR FC)

The crest factor is one of the specific indicators that accentuate the appearance of shocks in the vibrations. The peaks in the time signal will

correspond to an increase in the peak factor. This indicator, like kurtosis, is used for the detection of anomalies that result in shocks linked for example to the contact of degraded surfaces [10]. As soon as the fault appears, the increase in shocks induces the growth of the peak level while the RMS value changes less markedly. This results in a significant increase in the crest factor. The Crest factor is given by:

$$CF = \frac{\max(x_i)}{RMS} \tag{11}$$

If degradation occurs, then the vibration becomes random and the peak ratio becomes greater than 3. The monitoring of the peak report thus makes it possible to detect the appearances of defects, without however making it possible to diagnose the source. In order to better capture the information content of vibration signals, it is always advisable, being in the time domain, to extract the indicators according to carefully chosen frequency ranges. For this purpose, analog and digital filters will provide adequate signal processing. In order for these indicators to be compared, care must be taken that the temporal samples, if they are deduced, are filtered in strictly identical conditions; it has been found that the characteristics of a filter strongly influence the value of the extreme levels. In addition, the peak value comparison could be logically performed only on samples of the same duration, if the signal comprises a random component. A peak factor greater than 6 is characteristic of the occurrence of impulse forces [10].

2.2 FREQUENCY DOMAIN ANALYSIS

The interest of this analysis is thus to eliminate the noises that disturb the reading of the signal (climatic, for example) of which a curve testifies, and to distinguish the different elements which interfere in the composition

$$x(f)=\int_{-\infty}^{+\infty}x(t)e^{-j2\pi ft}dt \tag{12}$$

where x (f) is the Fourier transform, *t* is the time variable, *f* is the frequency variable allows the transition from the time domain to the frequency domain. This representation makes it possible to know the spectral content of energy or power, present in the signal at the frequency *f,* and thus to detect the presence of a defect generating a periodic shock at a fault frequency. In practice, the Fast-Discrete Fourier Transform (FFT) is used on digitized signals:

$$\sum_{-\infty}^{+\infty}\left|x(n)^2\right|=\int_{-1/2}^{1/2}\left|x(f)^2\right|df \tag{13}$$

Allowing to realize that, since the first member is by definition the temporal energy of the signal, *| X (f) 2 |* is interpreted as the distribution of energy along the frequency axis. The square of the Fourier transform module, referred to as the observation time, is called the power spectral density (PSD) or power spectrum. It has the advantage of being correlated with the severity of a defect. It is the frequency representation (power spectrum) most used in the vibratory diagnosis of the elements of rotating machines, bearings, cutting tools, etc...

$$PSD(f)=\frac{\left|x(f)^2\right|}{d} \tag{14}$$

Where is the weighted power spectral density, x (k) represents the discrete signal to be analysed, f (k) the weighting window, N the number of samples taken from the time signal.

3 EXPERIMENTAL STUDY

3.1 FRAMEWORK OF THE STUDY

The machining tests were carried out at the mechanical compound ISTA university on a classic HYDROGALLIC brand lathe, it carries a two-speed Siemens motor with 10 HP power supplied with three-phase 3 × 220, a mandrel 250 mm, 45 mm spindle bore, the corresponding spindle speeds are: 40 to 2000 rpm with a working feed rate of 0.005 to 4.5 mm with an approximate net weight of 2200 kg. The material chosen is a hard steel, and the dimensions of the machined cylinder are 300 mm in length and 50 in diameter we have used the tools in plate and the monoblock in metal carbide.

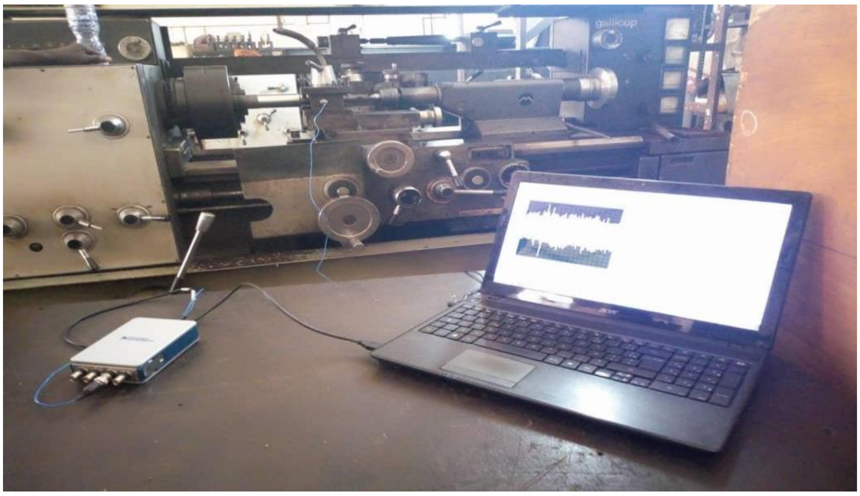

Fig. 1. Acquisition device

3.1.1 SENSORS AND ACQUISITION OF VIBRATORY SIGNALS

In the experimental steps, the first problem needed to be solved on site was the positioning of the sensor regardless of the tool change and on a fixed part of the machine. There are several places in the machine that are inaccessible, which limits the number of sensors and their positioning. In this spirit, the accelerometer used is fixed on the turret to measure the vibratory responses in the cutting tool along the machine axis:

The measurement of the accelerometric signals during machining was performed using an acquisition chain composed of a mono-axial type piezoelectric accelerometer and a National Instrument (NI) acquisition system including the Compact DAQ on which we mounted the module 9233 for the conditioning of these signals is controlled by the software LabVIEW which allowed us to program the acquisition interface, the sampling frequency is 25000 Hz, and the number of samples of 250000 so we recorded responses generated during machining in its entirety. In order to better follow the evolution of wear, in-situ expertise has been systematically performed. This expertise consisted of an optical microscope observation at magnification up to 4 times the actual size with a measurement uncertainty of 2 percent. This is to measure the flank wear of our cutting tools (plate).

4 TEST PROCEDURE

The measurement campaigns cover the three steps of the use of the tool corresponding to the following states:

- New tool (N)
- Low wear (FU)
- Advanced (High) wear (UA)

The purpose of this operation was to reproduce a realistic wear of the cutting inserts in turning, particularly the turning. For this, the cutting conditions are:

- Speed of advance Vf = 0.2 mm / rev,
- The depth of pass ap = 2mm,
- Constant cutting speed Vc = 100 mm / min without lubrication (dry machining)

5 CRITERIA FOR EVALUATING THE LIFE OF A CUTTING TOOL

The definition of tool life according to ISO 8688: "This is the time to total cut of the tool to reach a specified value of life criterion ". Under normal machining conditions, flank wear is considered to be the predominant wear. The development of this type of wear on the cutting tool is not a random phenomenon, but we can observe three phases during the life of the tool (new tool, low wear and advanced wear). If the fringe of this wear is uniform, it is advisable to accept a wear width, denoted *Vb,* equal to 0.3 mm. If no, the allowable limit is 0.6 mm. In our case, the limit evaluation of the life of the cutting tool has been fixed at 0.3 mm.

6 RESULTS AND DISCUSSION

6.1 DIRECT CONTROL OF THE CUTTING TOOL

The experimental companion described previously allowed us to note several observations of the flank surface with the help of the optical microscope since its new state until the end of its lifetime or its collapse La (Vb = 1mm).

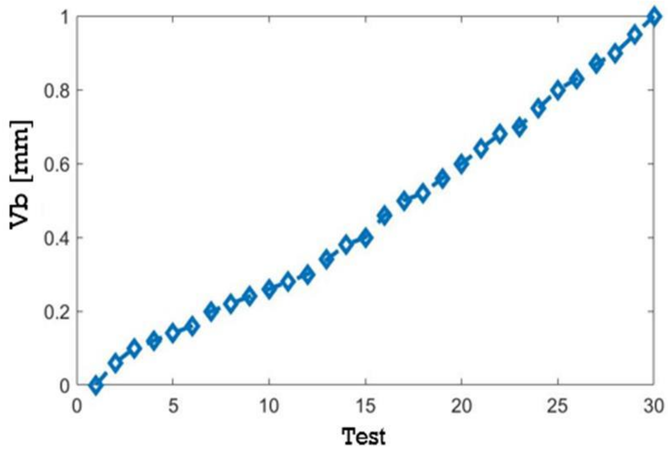

Fig. 2. Evolution of draft wear values according to the tests

6.2 EXTRACTION OF INDICATORS

Figure 3 shows three typical signals of the three wear phases of the tool. These signals are measured in the direction of the cutting force. We notice a decrease in the amplitude of the vibration signals with wear. This is mainly due to the contribution of certain high frequencies, which are less excited in the case of used tools. The physical explanation of this phenomenon is not yet clear to us. The analysis of the spectra of the signals (fig. 4) reveals nothing particular at first glance. The high frequencies are differently excited by each level of wear. However, if we look at what happens in the low frequency, particularly at the spindle rotation frequency (fig. 5), we can clearly see that in the case of wear we have more energy at this frequency. This can of course also be due to other phenomena such as unbalance. But since among these different tests no change has been made to justify the introduction of the unbalance, the wear remains the only cause explaining the effect on the frequency of 25Hz. Indeed, in case of wear the friction process at the tool-work piece interface may be variable and contain this component at the rotation frequency.

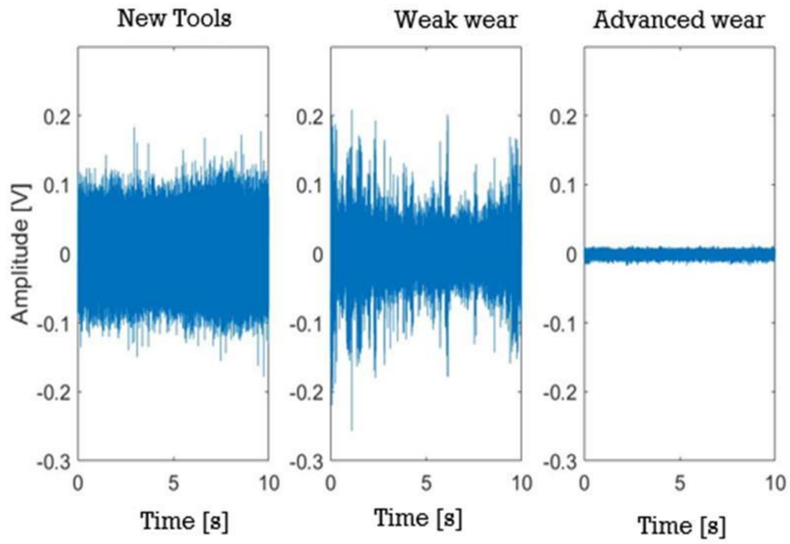

Fig. 3. Typical time signals

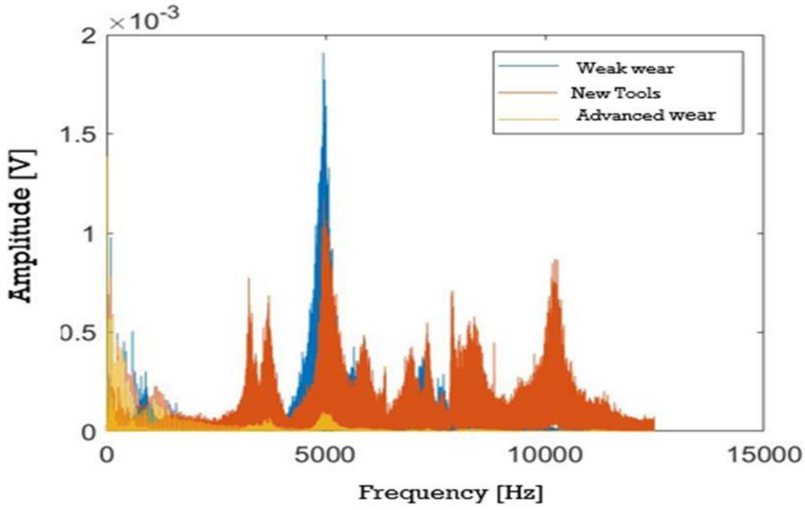

Fig. 4. Spectra of vibratory signals

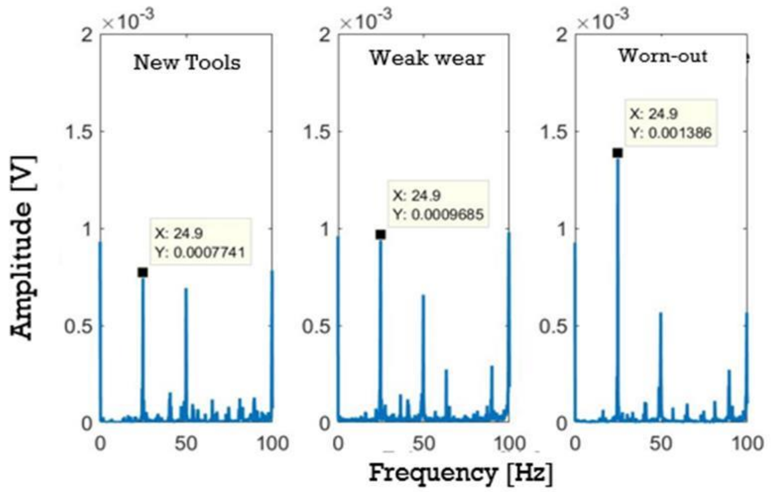

Fig. 5. Low Frequency Components

6.2.1 EXTRACTION OF TIME INDICATORS

Monitoring the temporal or statistical indicators are used as fault detection tools. Several researches have used these indicators successfully, the RMS is a time indicator that measures the energy content in a vibratory signal.

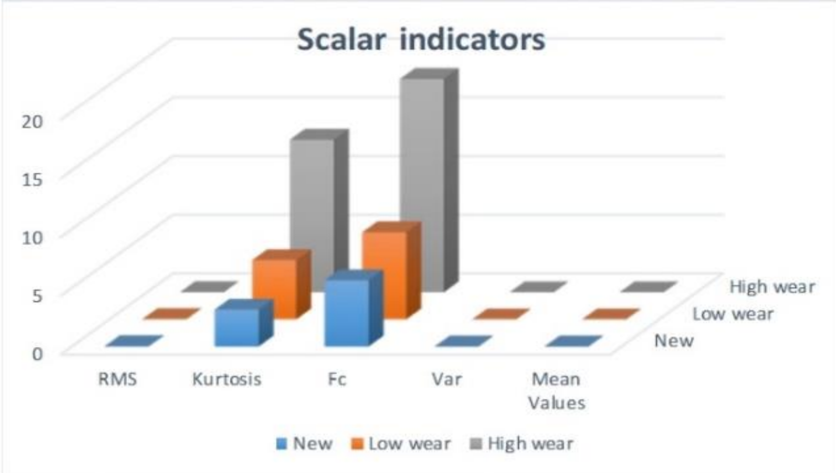

Fig. 6. Evolution of some statistical indicators

We observed a decrease in the vibratory level of the tool with wear. For Kurtosis (Figure 6) and Crest Factor (Figure 6), which are indicators of the impulsive nature of the signal, we observe a difference between the new state and the worn states. For a vibratory signal of a system in good working order, the distribution follows the normal law and the Kurtosis value is 1; 5. This value goes to 3 for a random signal. In our study, we noted a Kurtosis of the order of 3 (between 2.75 and 3; 25) for a tool in good condition as it approaches 5 when the tool deteriorates. In the last deterioration phase of the tool, values greater than 10 were observed. The average of the signals (Figure 6) increases with wear.

7 Conclusion And Outlook

Vibrations are the root of many problems during machining operations. They can have several causes, in particular, the inadequacy between the cutting.

Parameters and the tool-material torque and tool wear. Vibrations can, therefore, be used to detect the level of wear. This is of undeniable importance if we want to be able to implement a "just-in-time" tool change policy in order to minimize the quality losses of machined parts and the negative influence on the means of production.

In this work, we were interested in monitoring the wear of the cutting tool during turning. In order to ensure effective monitoring, we recorded the vibration responses recorded during machining during machining and used direct control of the cutting tool under the microscope to estimate the value of wear and tear on the draft. In the time domain, the RMS value, kurtosis and peak factor were found to be potential indicators of wear. In the frequency domain, rich information about wear was detected at the spindle rotation frequency. The results obtained can be used as good indicators for operators to detect and predict the life of tools. This will contribute to rational management of production time and guarantee dimensional tolerances and the quality of machined parts. Currently, with the drop in the price of measuring and signal processing equipment, it is easy to imagine permanently equipping machines with tools with vibration sensors and processors for data processing.

In perspective, a track is to exploit the results obtained for the implementation for automatic monitoring of cutting tool wear based on artificial intelligence (neural networks, KNN, Bayesian networks, etc.) and also the extension of this work to the case of high-speed machining where it is envisaged to merge data from the vibratory analysis with those of the cutting and acoustic emission forces.

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