International Journal of Engineering and Applied Physics (IJEAP)
Vol. 3, No. 2, May 2023, pp. 743~755
ISSN: 2737-8071

Application of the EEMD Algorithm for the Monitoring of the Cutting Tool wear

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Article Info

Article history:

Received Feb 24, 2023
Revised Mar 20, 2023
Accepted May 02, 2023

Keywords:

Algorithm
EMD
EEMD
Monitoring
Cutting tool
Wear

ABSTRACT

In this work, it is a question of a monitoring of cutting tool wear in mechanical turning. This monitoring is carried out in three phases which correspond to the life of the tool. To achieve this objective of improving the monitoring of the cutting tool, we have proposed the EEMD processing algorithm which decomposes a large signal into small signals (IMFs) by comparing it to the EMD algorithm, which is an algorithm used in the analysis of non-linear and non-stationary signals. The phenomenon of mode mixing is one of the major drawbacks of EMD. The EEMD eliminates the mode mixing effect. The EEMD principle is to add extra white noise to the signal with a certain number of tries.

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1. INTRODUCTION

Despite their common use in the automotive and aeronautical industries, it should be noted that machining with material removal remains the most commonly used manufacturing process in the mechanical industry [1]. However, the influence of cutting tool wear on the quality of the surface condition and the life of the cutting tool remains the main problem that machining professionals are facing. As a rule, it is the high temperature friction generated between the tool and the material that causes the wear of the cutting tool. The tool wear is an evolving phenomenon, which develops around the cutting tool. An excessive wear is detrimental to the quality of the machining [2] and leads to a deterioration of the state of the machined material, for example the quality of the machined surfaces, the imposed geometric tolerances, the holding of the tool on time generates high efforts which effect increases the cutting power and the consumed energy.

Several direct and indirect techniques have been proposed to evaluate the cutting tools wear. The control by direct techniques gives an accurate measurement in the case of spoils wear, but the carrying out of this type of control is difficult in machining [3]. For this reason, several researchers have proposed indirect monitoring techniques where the state of the tool will be estimated by measuring another significant physical quantity, especially the cutting stress which consists of processing the vibration signals generated by the tool during the three phases. The objective of this work is to make a performance comparison between the proposed EEMD algorithm and EMD in order to make a good monitoring of the cutting wear.

2. RESEARCH METHOD

2.1. EMD (Mode empirical decomposition)

Around 1998 and 1999 Huang et al. [4] propose an empirical mode decomposition (EMD) algorithm .This algorithm has been applied in various fields of research such as : an analysis of geophysical and seismic signals (Huang & Wu, 2008) [5], diagnosis of mechanical faults (Moham mad , Siamak , & Mohammad, 2018; Yuan et al., 2018) [6], bioelectrical signal analysis (Hikmat , Maha, & Enas , 2018ÿ; Kumar, Panigrahy , & Sahu , 2018) [7, 13], image processing (Qin, Qiao , Wang, Ren , & Zhu, 2018; Yu , Li, Zhang, Liu, & Max, 2015) [8, 17], and so on.

2.1.1. Principe of EMD

The EMD method is defined by a process qulified sieving (sifting), making the decomposition of a signal possible into basic contributions called empirical modes or IMF (Intrinsic mode functions), which are mono-component AM-FM type signals (in the broad sense), each with zero mean [10,18]. The IMFs extraction is non-linear, but their recombination for the exact reconstruction of the signal is linear. Basing essentially on the natural variations or oscillations of the signal, the EMD allows an interpretation of the present physical phenomena.

The fundamental principle of EMD is to locally describe the oscillations of a signal as a succession of fast oscillations contributions (high frequencies) to slower oscillations (low frequencies). Let us illustrate this in the following examples of a signal s(t) composed of two oscillations (Figure 1): The fast one is the detail function *d(t)* and the slow is the approximation function *a(t)* . [10]

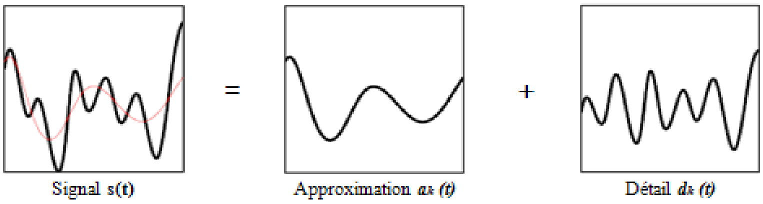


Figure 1.

Figure 1. EMD separates slow oscillations from fast oscillations in a signal. The fast oscillations (high frequencies) are details of the signal and the slow oscillations (low frequencies) are its approximations.

To obtain the following mode, it is sufficient to subtract the fastest oscillation from the original signal and to reiterate the process on the remnant. It is a finite combination of oscillations, which brings us to the following relation [20]:

$$s(t) = d(t) + a(t) \tag{1}$$

After $n$decompositions, the signal can be written:

$$s(t) = \sum_{j=1}^{n} IMF_j(t) + r(t) \tag{2}$$

With:

- $IMF_j(t)$is the $j^{ème}$ oscillation,
- $r(t)$ is the remnant of the decomposition,
- n is the MFIs number.

The EMD is entirely driven by the data of the signal and adapted to it: from where the name intrinsic mode function (IMF) whose idea is to describe a signal s(t) according to its different modes of natural oscillations.

As n is a finite number, if we add all the IMFj as well as the remnant $r(t)$,, we linearly reconstruct the original signal without loss or deformation of the initial information. Although the EMD is a nonlinear approach, the reconstruction of the initial signal, from its modes, is linear.

Even if the concept of MFIs is based more on an intuition than on a very rigorous definition, this function must respect certain criteria as specified below.
An IMF (or empirical mode) is a function such as:

$$IMF:\begin{cases} R \to R \\ t \to IMF_j(t) \end{cases} \tag{3}$$

Which verifies the following conditions:

a) It has zero average.
b) The numbers of extrema and crossings to zero differ at most by 1 (in other words, this means that between a minimum and a successive maximum, an IMF passes through zero).
c) It follows a law of modulation in amplitude and frequency (oscillating behaviour) naturally of mono-component type.

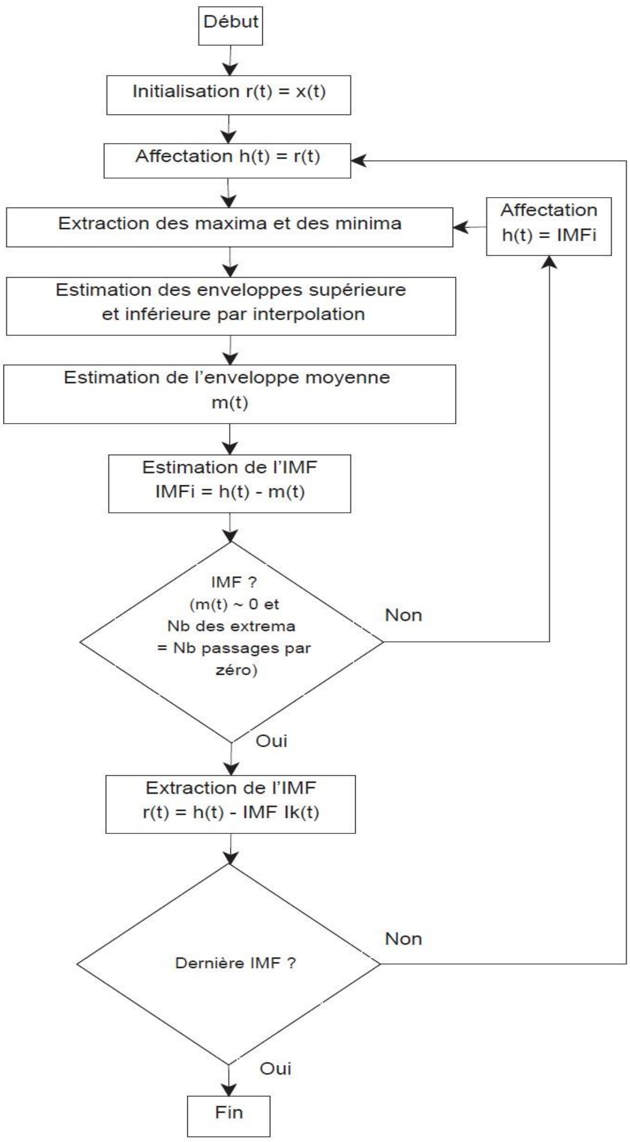


Figure 2. EMD algorithm

2.1.2. Mode mixing problem

The EMD method has been widely applied to the analysis of non-stationary and/or non-linear signals. However, the decomposition results often suffer from mode mixing. The modes mixing consists on the one hand in the appearance of more than one IMF of the same local oscillation, and on the other hand in the dramatic disappearance of the oscillations of low amplitude [9] caused by the non-identification of their extrema and therefore the resulting IMF appears as a mixture of more than one frequency on a period of analysis which makes it lose its physical meaning.

2.2. EEMD

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [2, 5]. The discussion can be made in several sub-chapters.

2.2.1. Principle

The EEMD method was initially introduced [12] to solve the mode mixing problem. Having a signal x(t), its principle is as follows [11]:
We generate N_e realizations, b_i(t), 1 ≤i≤ N_e of equal variance Gaussian white noise
We calculate the noisy signal for each realization σ_i^2

$$S_i(t) = x(t) + b_i(t) \qquad 1 \le i \le N_e \tag{4}$$

And then we extract the N IMFs from this noisy signal using the original EMD method.
TheN_e realizations give access to N_e noisy signals which allow the extraction of $N_e$sets of N IMFs: $IMF_{ki}(t)$,$1 \le k \le N\ et\ 1 \le i \le N_e$. The IMFs of the EEMD method are then the coordinated averages of these N_e sets of NIMFs:

$$IMF_{EEMD_k} = \frac{1}{N}\sum_{i=1}^{N_e} IMF_{ki}\ (t) \qquad 1 \le i \le N \tag{5}$$

The amplitude of the Gaussian white noise ε is driven by the error rate n ε_n in the end, on the reconstruction of the signal x(t) by summation of the IMFs and by the number N_e of the averages carried out by the relation [28].

$$\varepsilon_n = \frac{\varepsilon}{\sqrt{\mathrm{Ne}}} \tag{6}$$

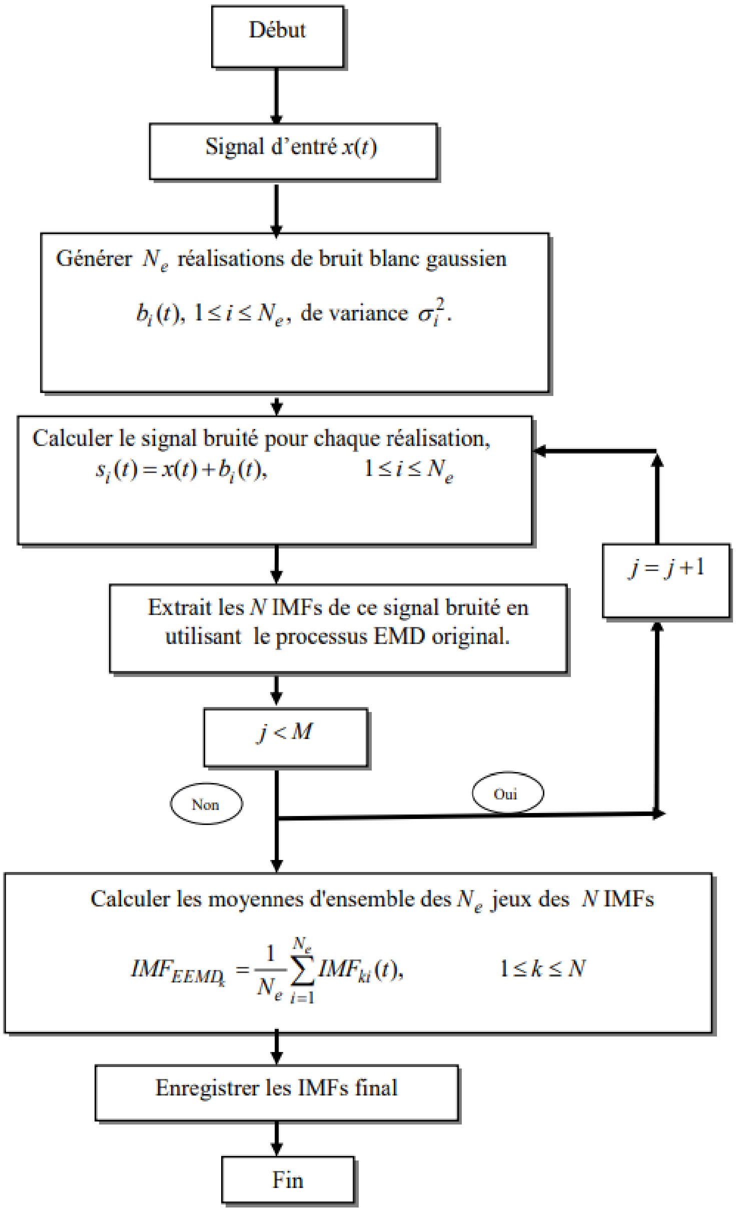


Figure 3. EEMD algorithm

2.2.2. Canceling the mode mixing

The EEMD method solves the mode mixing problem, however the noise amplitude and the number of trials affect the decomposition results. To decompose a signal by the EEMD method, it is first necessary to choose the noise level and the N_e adequate number of trials. The judicious choice of these two parameters will ensure an EEMD decomposition without modes mixing [14].

2.2.3. Signal to noise ratio (SNR)

A systematic approach to noise amplitude selection is achieved by SNR [16, 16]:

$$SNR = 10log_{10}\left(\frac{P_S}{P_b}\right) \tag{7}$$

Where P_S is the signal strength.
And P_b the power of noise.

The values of the ordinates correspond to the different decomposition results [11]:

a) A -1 value represents mode mixing.

b) The value 0 means that there are no redundant IMF components.

c) Positive values represent the number of redundant IMFs. To obtain a good decomposition, the signal must be noisy with a power deduced from the SNR belonging to the range of [37 dB –41dB] which ensures the non-redundancy of the IMFs.

2.2.4. Effect to noise applicatude

If the amplitude of the noise is too small compared to the amplitude of the signal, then the addition of the noise will have no effect on the modes mixing. But, if the amplitude of the noise is too large compared to that of the signal, then the EEMD decomposition will give redundant IMFs components, therefore it is important to find a good number of trials for a good adjustment of the amplitude of noise in order to reduce mode mixing. In this work, the used parameters are listed in the table below [19, 22].

Table 1. Choice of parameter

Algorithm	Number of trials (N_e)	Signal to noise ratio (SNR)
EEMD	1000	37dB

2.2.5. Disadvantage of the EEMD method

Theoretically, the added white noise is completely eliminated by a decomposition using a very high number of trials (infinite) which poses a problem in the EEMD method. So, this method has two drawbacks [20]:

- Difficulty to eliminate noise completely.
- Large calculation time.

3. RESULTS AND DISCUSSION

3.1. Chain acquisition

The vibration signals generated during machining were measured using an acquisition and analysis system, consisting of software and a piezoelectric accelerometer (X, Y, Z) compressed by a moving mass solicited by the vibrations to which the sensor is subjected. For good acquisition, the **PCB type sensor 080A27** was placed as close as possible to the machining area and on a fixed location in accordance with **figure 4**
In the case of our work, we chose the perpendicular axis to the part (the axis: X) the one that corresponds to the performed operation, turning to record more information.
This chain is composed of:

- The laptop, to visualize the signals.
- NI 9171 cDAQ+Module acquisition system.

Piezoelectric sensor.

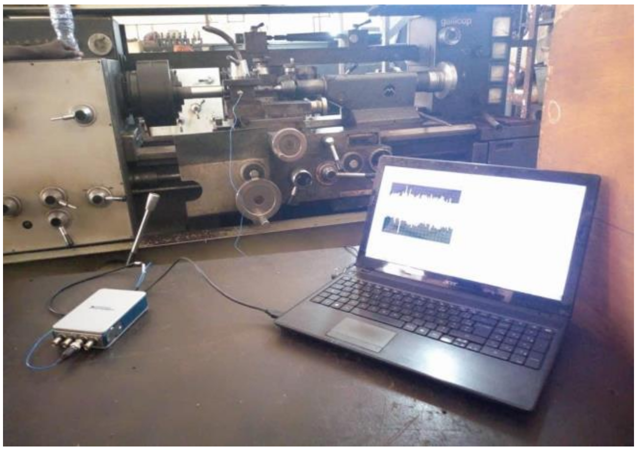


Figure 4. Chain acquisition.

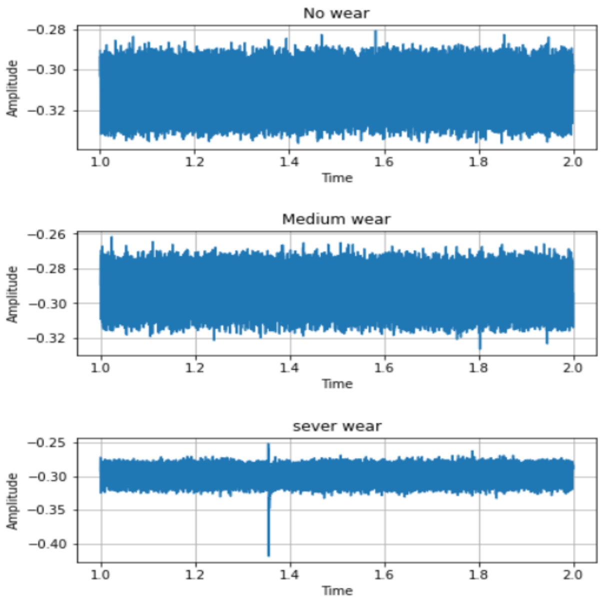
The vibration measurements are made by using the cDAQ+Module NI 9171 acquisition system from National Instrument on which the NI9215 module is mounted with the BNC connector (figure 4).

Figure 5. cDAQ Acquisition System with 9215 Module

A piezoelectric accelerometer (X, Y, Z) is attached to the upper carriage of the trainard using a magnetic base compressed by a mobile mass stressed by the vibrations to which the **PCB 080A27** type sensor is submitted with the sensitivity of 100 mV/g.

Figure 6. IMI635A01 Accelerometer

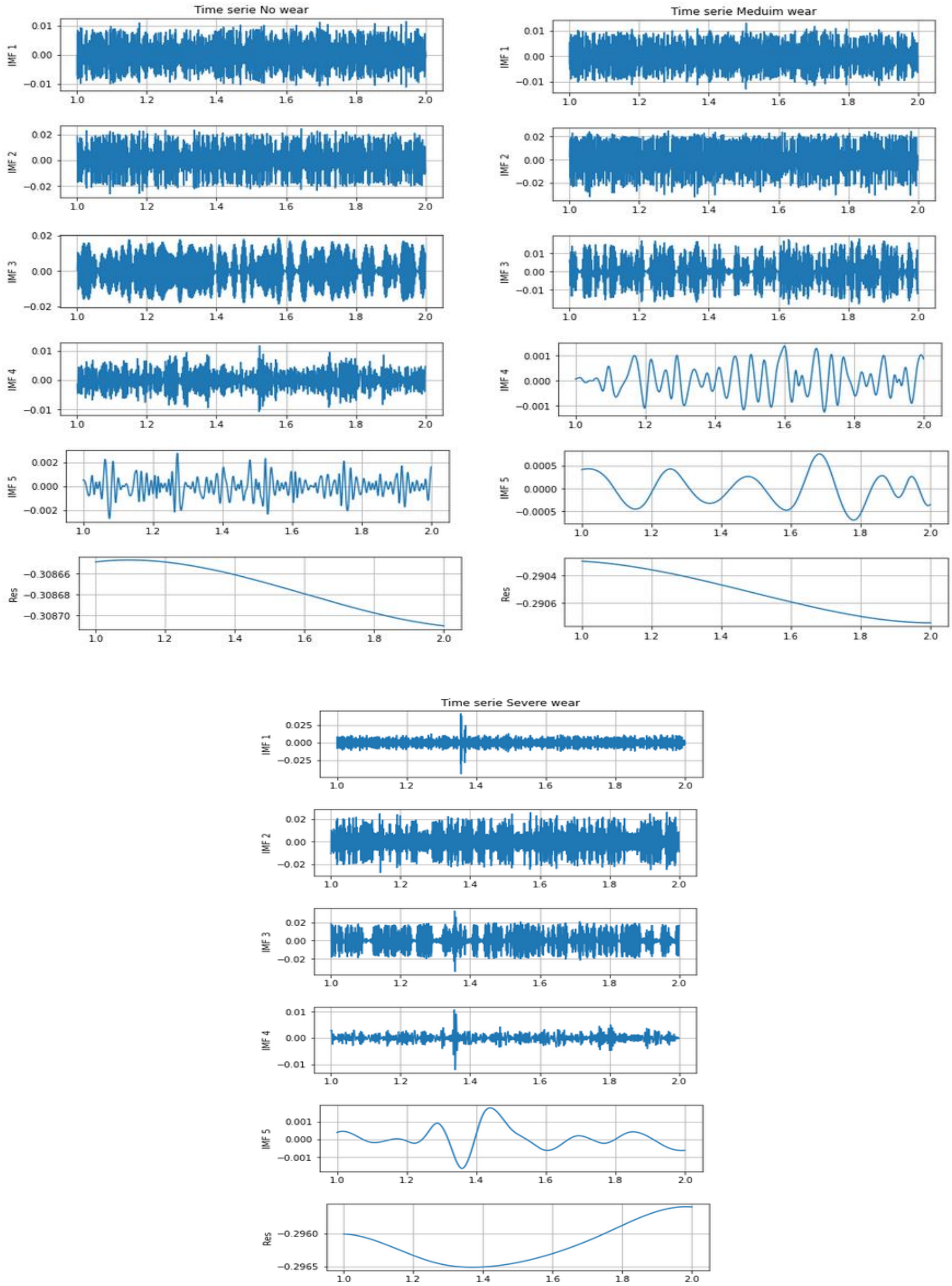
The vibrations are sampled at 10,000 Hz. Signals are recorded after a few seconds to be able to detect any change in the vibration signal due to the evolution of the tool wear.



Fugure 7. The 3 phases of cutting tool wear

3.2. Resultes

- **EMD**



Fugure 7. The decomposition of the signal into IMFs with the EMD algorithm on the left, the IMFs of the No wear on the right, the IMFs of the Meduim wear state and at the bottom in the middle the IMFs of the Severe wear state.

- **EEMD**

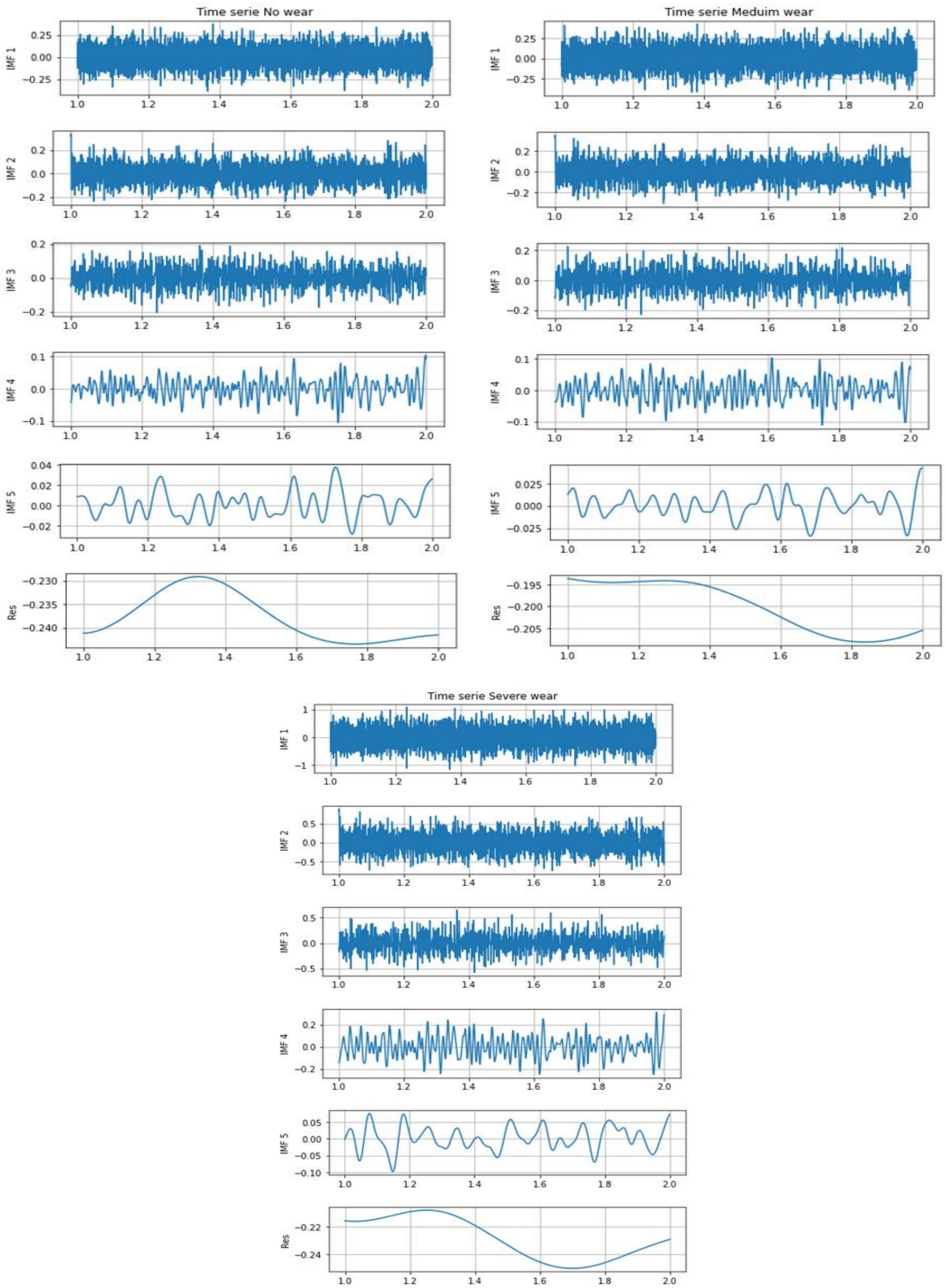


Figure 9. The decomposition of the signal into IMFs with the EEMD algorithm on the left, the IMFs of the No wear on the right, the IMFs of the Medium wear state and at the bottom in the middle the IMFs of the Severe wear state.

3.3. Interpretation of results

After the signal decomposition of our 3 phases of the cutting tool wear with the EMD algorithm, we notice that in almost all the IMFs of our 3 phases of wear, there is a problem of mode mixing. The IMF1, 2, 3 and 4 of all the 3 phases have a mode mixing problem, (Figure 10) illustrates these IMFs ; this leads us to say that the EMD algorithm has therefore difficulties in separating the two mode.

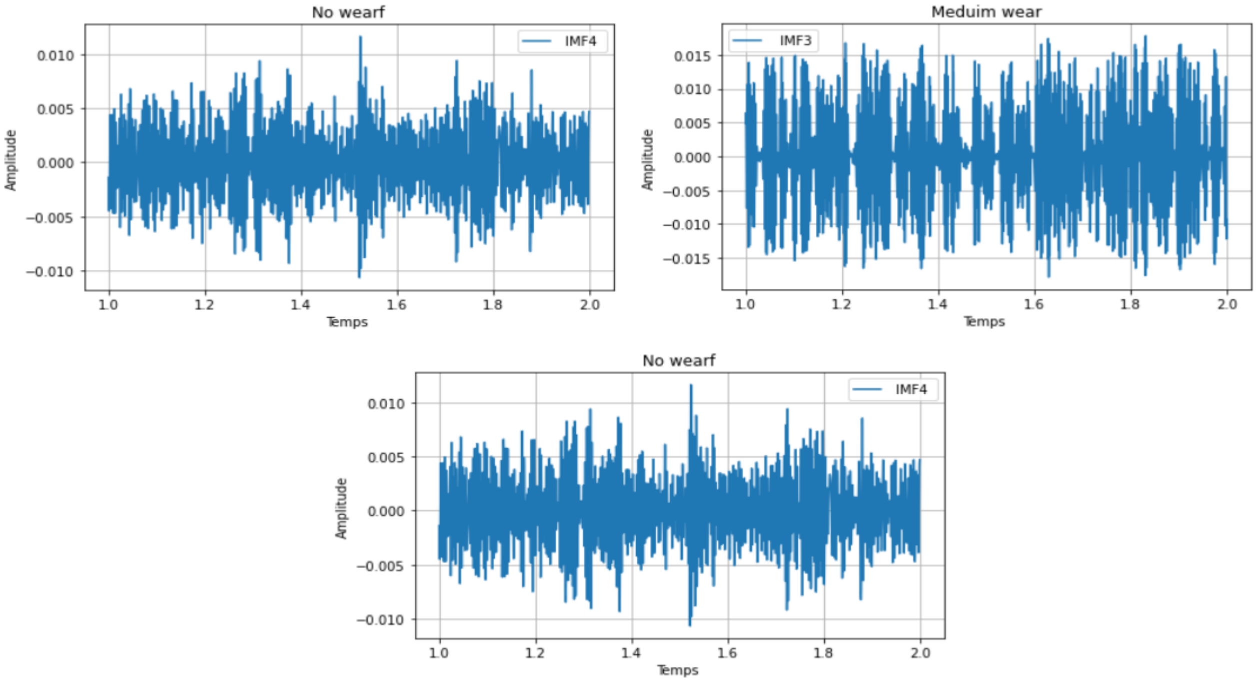


Figure 10. EMD mode mix issue

To solve the problem of mode mixing, EEMD has been proposed, where white Gaussian noises of finite amplitude are added to the original signal during the decomposition process. However, to overcome that problem of mode mixing, the noise amplitude must be controlled. Notice that with the EEMD algorithm the IMF1, 2 and 3 represent the high frequency and IMF4 the low frequency, (Figure 11) illustrates. In this article we will use the EEMD algorithm to monitor cutting wear.

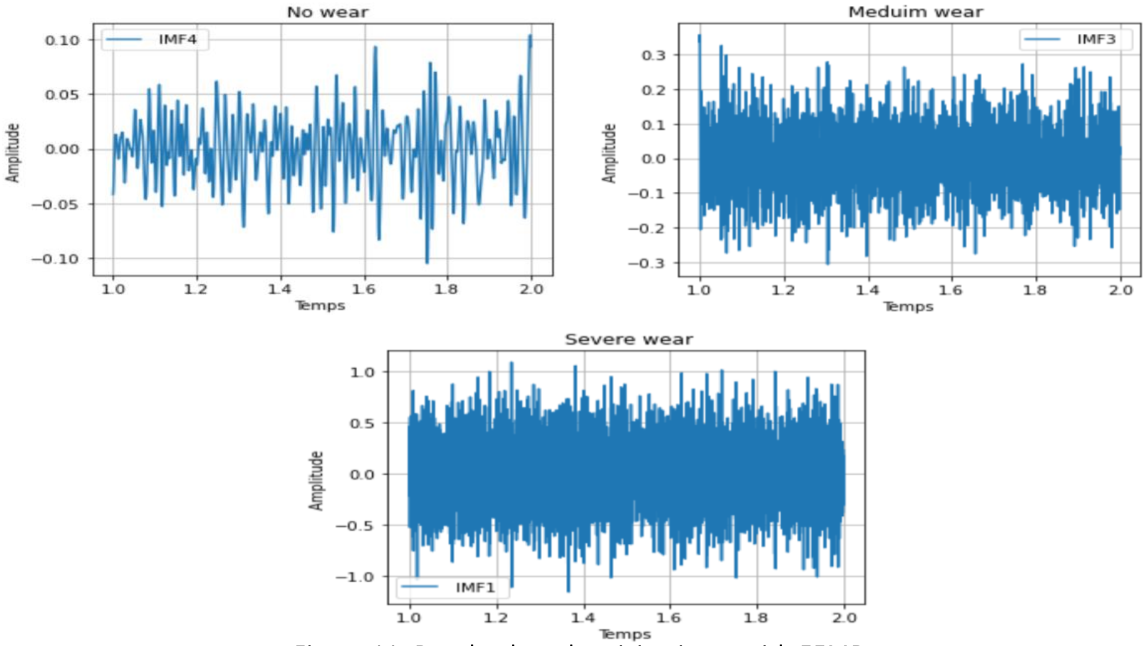


Figure 11. Resolved mode mixing issue with EEMD

3.4. Application of statiscal inducators in IMF4

Statistical monitoring indicators are reckoned to know the influence of noise in the signal and finally to detect faults. According to the results of (table 2) of the IMF1 of the EMD and the IMF4 of the EEMD the mask effect generated by the introduced noise decreases the sensitivity of the indicator, as shown by the kurtosis and the skewness, on one hand.

On the other hand, the energy represented by the effective value (RMS) increases with the noise. By applying the EMD and EEMD to the three indicators RMS, Kurtosis and Skewness of each mode, we have found that the kurtosis and skewness are very influenced by the noise and for this we observe this disturbance of values in the representation. They are unable to follow the tool evolution normally. Then, the effective value (RMS) is the only indicator that gives us more information.

Table 2. Applications of indicators in IMF 1 for e EMD and IMF4 for EEMD in the 3 phases

Method	Indicators	No wear	Medium wear	Severe wear
EMD	RMS	0.0037	0.00406	0.00432
	KURTOSIS	2.74494	2.62288	9.7995
	SKEWNESS	0.05090	0.03769	-0.0477
EEMD	RMS	0.0303	0.03522	0.096117
	KURTOSIS	3.4146	2.9873	2.90499
	SKEWNESS	-0.0459	-0.03686	0.09523

3.5. Application of the FFT in the IMF1 and IMF4

To each IMF extracted in the original signal, we have chosen the IMF1 and IMF4 which are information carriers; we have applied the Fourier transform to obtain its spectrum. The reason for applying the Fourier transform allows us to locate and define the magnitude of the defect.
The figures below show the IMFs signals and their spectra:

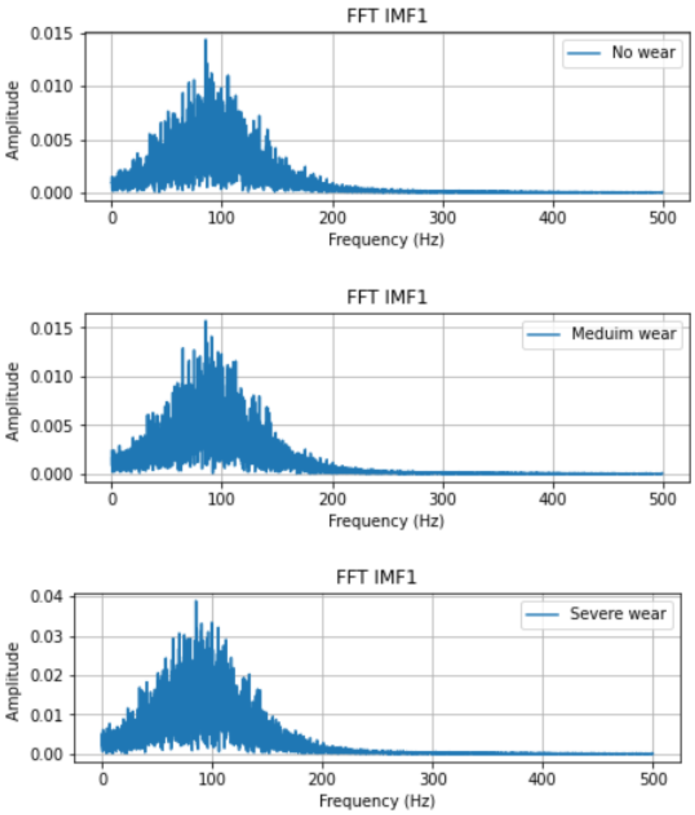


Figure 12. The Spectra of IMF1 of there phases.

We have found that the evolution of wear in the three phases is increasingly in relation to frequency and amplitude. This explain the degradation of the tool in the last stage (severe wear) with 90 Hz of the frequency and an amplitude of 0.040.

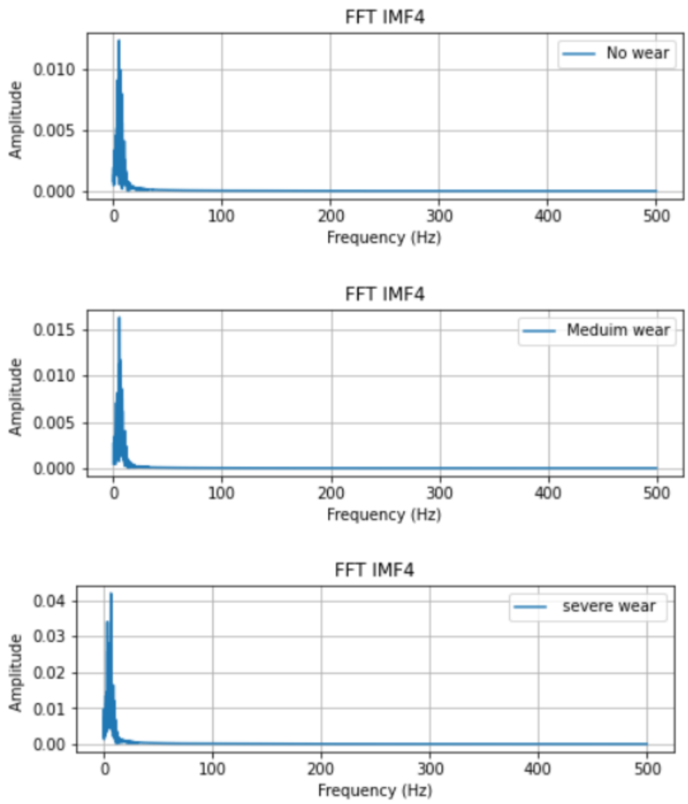


Figure 13. The Spectra of IMF4 of there phases.

We note that the three IMFs start with a high frequency after a degradation in the low frequency; this leads us to say that the EMD is a decomposition from high frequency to low frequency with the presence of supporting values.

4. CONCLUSION

Vibrations are a major issue in machining and one of the most limiting factors for reproductivity. In order to carry out an effective follow-up, we were interested in the monitoring the cutting tool wear in turning with the appropriate methods. In this work, we have used **temporal methods which** are more based on the statistical analysis of the collected signal, which make possible the follow-up of a quantity evolution deriving from the power or from the peak amplitude of the signal. The three indicators used are: RMS, KURTOSIS and SKEWNESS. We have also used the frequency method based on the Fourier transform, which allowed us to identify and locate defects from mechanical components by analyzing their spectrum. On one hand on the other hand, in this case, it is necessary to look for techniques that allow approaching even more optimally. That is why we proposed to use the EEMD method; the objective was to make a performance comparison between the EMD method which poses the problem of mode mixing and the EEMD method which was created to effectively solve the problem of mode mixing. Moreover, it is important to underline that for eliminating the problem of mixing in the decomposition, it is necessary to make a good choice of the signal-to-noise ratio and a very high number of tests. We conclude that it is the EEMD algorithm that gives the best results. The results obtained can serve as good indicators for operators and production engineers to detect and predict the life of cutting tools.

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