A model of milling process based on Morlet wavelets decomposition of vibroacoustic signals

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Abstract

The paper considers the problem of online monitoring the condition of cutting tools to avoid its unexpected failure. To approach this problem we proposed a model of milling process based on Morlet decomposition of vibroacoustic signals. In addition, using the wavelets scalogram, we imposed a new condition that helps to improve early wear detection of the cutting tool. The findings of this research reveal the advantages of the proposed model compared to the previously reported models that rely on Haar wavelets and Short-time Fourier transform.

Keywords: milling process; acoustic emission; wear detection; Morlet wavelet decomposition

1. Introduction

The increasing demands for the characteristics of modern gas turbine engines make it necessary to improve the accuracy and reliability of their manufacture. This improvement permits to increase the durability of critically important components such as rotating turbine discs. The processing characteristics sharply deteriorate at high mechanical strength at high temperatures as well as low thermal conductivity of Ti / Ni-based alloys [1-5]. Cutting off parts from nickel-base heat-resistant alloys (for example, Inconel 718, Udimed 720) leads to both a rapid wear of the cutting tool and tool surface [1, 11-16], which can be generally called surface anomalies. These surface anomalies are the result of the bad processing characteristics of nickel-base alloys and the trend of rapid tool wear at cutting regardless of the types of machining operations [11, 12, 14-22]. Aircraft engine manufacturers are developing a monitoring system to detect anomalies in the processing and to react against it [34].

The procedure behind most monitoring systems consists of the following steps. First, it is a need to measure parameters second, these parameters need to be analyzed by means of specific methods such as wavelet decomposition, Shot-time Fourier transform (STFT) and etc. One of the efficient methods of spectral analysis is the wavelet transformation (decomposition), the advantage of which is the possibility to analyze non-stationary signals. The wavelets frequently used in practice are described in [8, 34, 37].

The main purpose of this study is to develop a model of milling process based on Morlet decomposition of vibroacoustic signals and, thus, to propose tool wear condition. This condition is of use in solving the problem of identifying both non-stationary modes and early tool wear.

2. Problem statement

STFT assumes the stationarity of signals during a given time interval [19-22]. It can be expressed by

$$w(\tau,\omega)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty}e^{-jt\omega}f(t)h(t-\tau)dt\,, \tag{1}$$

where $f(t)$ is a given signal, $h(t)$ is a Hanning window [28], τ is a time delay.

The main drawback of STFT is the assumption of stationarity (permanence) of the signal on the time interval of the window. This issue increase errors in the analysis for such dynamic processes as milling process.

Wigner [29, 30] and later Cohen [21] improved the classical Fourier transform (T-F). Results of the Wigner distribution can comprise a cross-interference, because of signal is multicomponent.

Cohen [21] introduced the general class of distribution function in T-F as

$$w(t,\omega)=\frac{1}{2\pi}\iiint e^{-j(\theta t+\tau\omega+\theta\omega)}f(\mu+\tau/2)f^{*}(\mu-\tau/2)\varphi(\theta,\tau)d\mu\,d\tau\,d\theta\,, \tag{2}$$

where $f^{*}(m)$ is the complex conjugate value, $\phi(\theta,\tau)$ is a kernel function, θ is a distribution parameter (in frequency domain).

Choi and Williams [31] made an improvement on Wigner distribution (WD). The Choi-Williams distribution (CWD) is

$$w(t,\omega)=\frac{1}{4\pi^{3/2}}\iint\frac{1}{\sqrt{\tau^{2}/\sigma}}e^{\left[-\left((u-t)^{2}/4r^{2}/\sigma\right)-j\tau\omega\right]}f(\mu+\tau/2)f^{*}(\mu-\tau/2)d\mu\,d\tau\,. \tag{3}$$

If σ is large, CWD approaches to "plan" Wigner distribution. As σ reduces, cross interference decreases [32].

Zhao–Atlas–Marks distribution (ZAMD) [33] reduces the cross interference comprised in multicomponent signals. ZAMD is useful in modeling of small spectral peaks and analyze non-stationary multicomponent signals [32]. ZAMD has a kernel represented by (4), q is permanent.

$$\varphi(\theta,\tau)=g(\tau)|\tau|\frac{\sin(q\theta\tau)}{q\theta\tau}\,. \tag{4}$$

As a result, power spectral density is defined by

$$w(t,\omega)=\frac{1}{4\pi a}\int_{-\infty}^{+\infty} g(\tau)e^{-j\tau\omega}\int_{1-|\tau|a}^{1+|\tau|a} f(\mu+\tau/2)f^*(\mu-\tau/2)d\mu\, d\tau\,. \tag{5}$$

Formant analysis [33] is used to analyze a vibroacoustic signals because these signals have multi-frequency components connected with different anomalies while cutting [35, 6].

The efficiency of time-frequency methods is presented in Fig. 1 [7].

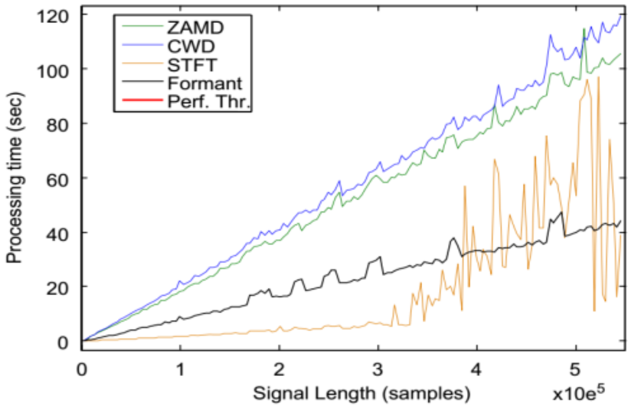

Fig. 1. Comparative efficiency of the STFT, CWD, ZAMD methods and formant-analysis [31].

One of the first and simplest wavelets is the discreet Haar wavelet:

$$\psi(t)=\begin{cases}1,\ 0\le t<1/2,\\ -1,\ 1/2\le t<1,\\ 0,\ t\notin[0,1).\end{cases} \tag{7}$$

The informative parameter characterizing the cutting tool (CT) wear is the dispersion of the detail coefficients of the Haar wavelet decomposition of AE signal. This parameter is insensitive to changes in processing modes [31]. The minimum duration of the analyzed sample is 0.1 s. Wear identification of cutting tool is carried out according to the energy value of the j-th detail factors. For Haar wavelet decomposition, it is advisable to take 3 <j <6. The forecast of CT wear in real time is in correction of the base model estimation from the results of current measurements of the AE signal parameters by an additive component obtained on the basis of extrapolation of the residual function. The study [35] proposes the adaptation of the suggested method for molding conditions by automatic window selection of a fragment of the AE signal which falls on the cutter tooth.

The main drawback of the Haar wavelet is the asymmetric and non-smooth, consequently, an infinite alternation of "petals" arises in the frequency domain due to sharp boundaries in the time domain. The complex Morlet wavelet does not suffer from these drawbacks.

3. A model of milling process based on Morlet wavelets decomposition of vibroacoustic signals

Wavelet transformation coefficients can be defined as [10, 36, 37]:

$$W_\psi(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right)dt\,, \tag{6}$$

where $f(t)$ is a random process, $\psi(t)$ is a chosen wavelet, $a\neq 0$ is a scale parameter, $b\ge 0$ is a shift parameter.

Morlet wavelet is given by

$$\psi(t)=\exp(-jkt)\exp\left(-\frac{t^2}{2}\right), \tag{8}$$

where j is the imaginary unit, parameter $k=2\pi$ [37] controls the time-frequency resolution.

The graphical results of wavelet transformation can be calculated by

$$w_{i,j}=\left|W_\psi(a_i,b_j)\right|^2, \tag{9}$$

where $i = 0,\quad , N_a-1$, $j=0,\quad ,N_b-1$, N_a is a counting scale, N_b is a counting shift.

The scalogramms are obtained from (9) as

$$y_i=\frac{1}{N_b}\sum_{j=0}^{N_b-1} w_{i,j}\,, \tag{10}$$

We propose to use the equation (11) to calculate area under curve of scalogramms:

$$s = \Delta\omega\left(\frac{y_0 + y_{N-1}}{2} + \sum_{i=1}^{N-2} y_i\right), \tag{11}$$

where $\Delta\omega$ is a frequency of quantization interval, y is a scalogramm, N is a counting rate of scalogramms.

We use a new identification criterion (12) to analyze processing parameters. This criterion is a cross-factor $CF_{\Delta\omega}$ of the spectral energy density in the frequency bands $\Delta\omega_{\max} \subset \Delta\omega_{\Sigma}$ of every local maximum of scalogramms. We built the scalogramms in the frequency intervals $\Delta\omega_{\Sigma}$.

$$CF_{\Delta\omega_{\max}} = \frac{\Delta\omega_{\Sigma}}{\Delta\omega_{\max}} \frac{\int\limits_{\Delta\omega_{\max}} w_{i,j} d\omega}{\int\limits_{\Delta\omega_{\Sigma}} w_{i,j} d\omega}. \tag{12}$$

To identify wear the following equations were considered:

$$k_{\Delta\omega_{\max}} = \frac{CF_{\Delta\omega_{\max}}(t_0)}{CF_{\Delta\omega_{\max}}(t_d)}, \tag{13}$$

where t_0 is the time of tool work without wear out, t_d is the time of tool work with wear out.

In accordance with equations (11-13), the calculation of the wear identification coefficient can be made by:

$$k_{\Delta\omega_{\max}} = \frac{s_{\Sigma}(t_d) \cdot s_{\Delta\omega_{\max}}(t_0)}{s_{\Sigma}(t_0) \cdot s_{\Delta\omega_{\max}}(t_d)}. \tag{14}$$

4. Results

4.1. Experiments design

The phenomena explained by the dislocation theory, of deformation distortions of the crystal lattice, friction, the formation and extension of cracks, phase transformations leads to AE. In metal cutting, the processes arised at an interaction between the part and tool are the most important sources of AE [23].

We register acoustic emission and power cutting of milling by the lateral and end surfaces of the milling tool. The main system element for measuring power cutting is the piezo-multicomponent dynamometer Kistler – Type 9257B (Switzerland) This dynamometer was installed at the base of the machining center Micron UCP 800. We use the LTR22 analog to frequency converter to record vibroacoustic signals with the microphone sensor (OCTAFON-110).

The connection scheme of the experimental setup for data collection is shown in Fig. 3.

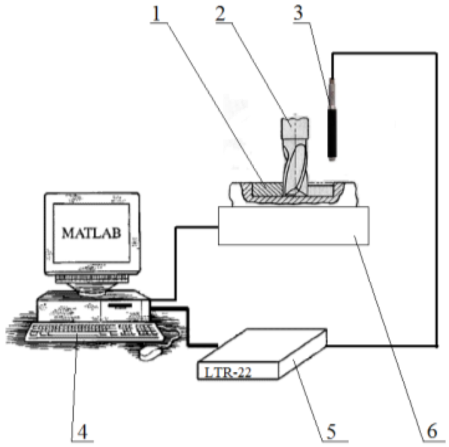

Fig. 2. Scheme of AE parameter measurement: 1 - sample, 2 – milling cutter, 3 – microphone- vibration meter, 4 – PC with software ПК, 5 – crane system LTR22, 6 – dynamometric table built up on the machine platen.

We used the four-tooth carbide monolithic milling tool by Seco JHP 780120E2R15Q0Z4-M64 with a diameter of 12 mm. In the experiments, we used new milling tools and tools with worn teeth, Fig. 4.

Fig. 3. Milling cutters for carrying out the research.

The machining process with variable allowance was simulated to analyze the influence of the cutting depth on the acoustic emission parameters and the stability of the wear identification technique. The processed sample of steel 45 was a blank part with a stepwise increase in allowance during milling (Fig. 4). A special groove on the surface of the blank part is designed to simulate intermittent cutting.

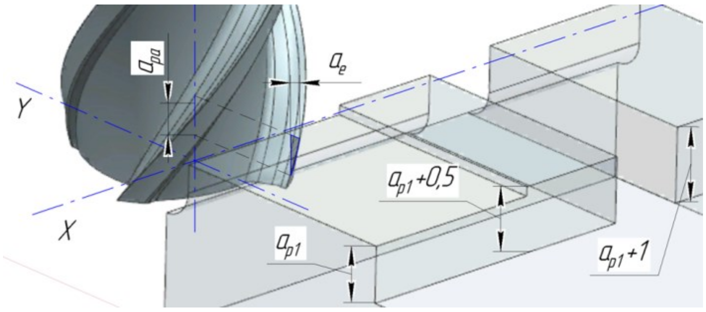

Fig. 4. Experimental sample.

The cutting conditions for the experiments are given in Table 1.

Table 1. Technological cutting parameters for material Steel 45.

Cutting speed 50 m/min			
№ exp.	F, mm/tooth	Ap, mm	Ae, mm
1			0,2
2	0,05	2	0,3
3			0,4

4.2. Experiment results

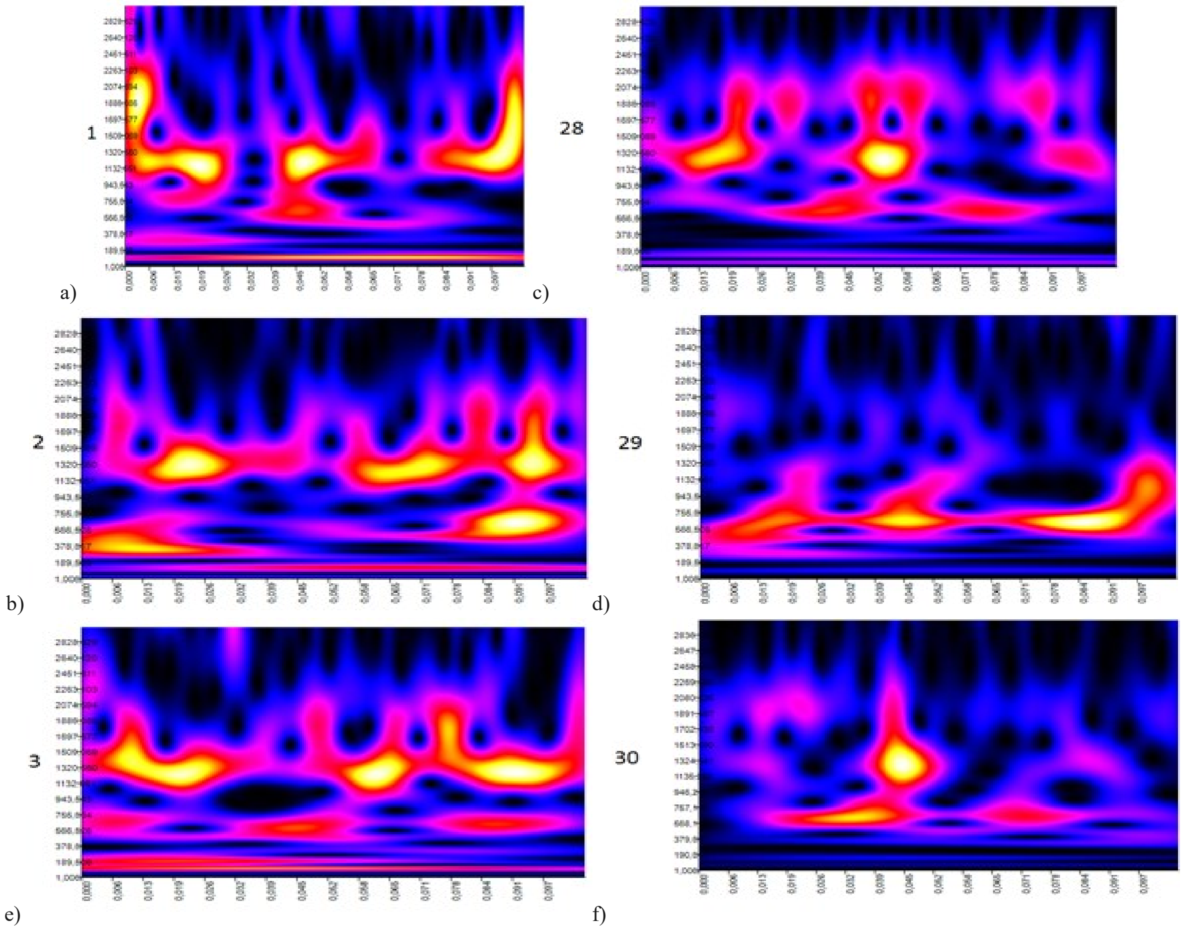

Fig.5. Wavelet spectrum of analyzed signals.

We use six different AE signals to analyze the cutting process with a multi-tooth tool. The signals denoted by the numbers 1, 2, 3 and 28, 29, 30 correspond to the regimes of Table 1 and are obtained by examining the new tool (a, b, c) and the worn tool (r, d, e). Fig. 5 shows the wavelet spectrum calculated by (9), where the X-axis of the wavelet spectrum graph represents the time in seconds, and the Y-axis represents the frequency in rad/s. The larger the value of the spectrum is, the lighter the pattern is.

Fig. 6 shows the scalogramms of the analyzed signals, which were obtained on the basis of the wavelet spectrum by (10).

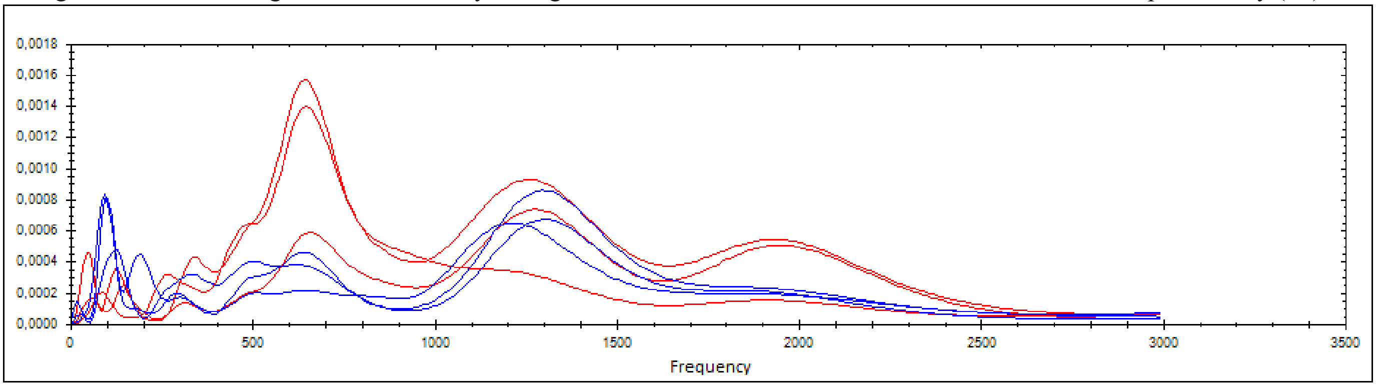

Fig.6. Scalogramms of analyzed signals.

The blue color shows the scalogramms of the signals corresponding to the state of the new tool, and the red one shows the worn tool.

The analysis of scalogramm of acoustic signal shows that it is possible to distinguish 3 characteristic maxima localized in the following frequency bands (in rad/s): $\Delta\omega_{low} = 550 - 750$, $\Delta\omega_{mid} = 1200 - 1500$, $\Delta\omega_{hi} = 1950 - 2100$.

The values of local maximum were calculated by (11). Results are shown in Table 2.

Table 2. The area of local maximum of scalogramms.

Frequency bands of local maximum $\Delta\omega_{\max}$, rad/s	$S_{\Delta\omega_{\max}}(t_0)$ - new tool			$S_{\Delta\omega_{\max}}(t_d)$ - worn tool		
	Mode 1	Mode 2	Mode 3	Mode 1	Mode 2	Mode 3
550-750	0,06213	0,0823	0,13359	0,17766	0,62313	0,44226
1200-1500	0,44037	0,31129	0,54264	0,32205	0,09416	0,44105
1950-2100	0,10634	0,09448	0,12908	0,31057	0,09919	0,351
Total area of scalogramms S_Σ	0,62765	0,65945	0,77467	0,88101	0,80046	1,32121

The wear coefficient $k_{\Delta\omega_{\max}}$ for 3 modes are given in table 3.

Table 3. Wear coefficient values.

Frequency bands of local maximum, rad/s		Mode 1	Mode 2	Mode 3
$\Delta\omega_{low}$	550-750	0,491	0,160	0,515
$\Delta\omega_{mid}$	1200-1500	1,919	4,013	1,626
$\Delta\omega_{hi}$	1950-2100	0,481	1,156	0,486

The results of analysis are presented in Table 3. These results make it possible to see the characteristic feature: in the low-frequency region (550-750 rad/s), as the tool wear, $k_{\Delta\omega_{\max}}$ decreases, and in the area of conditionally medium frequencies region (1200-1500 rad/s) – increases.

The revealed regularity helps to formulate the condition for the appearance of a critical wear value when machining with a multi-tooth tool:

$$\begin{cases} k_{\Delta\omega_{\max}}(t) \le k_{low}, & \Delta v_{\max} = \Delta v_{low}, \\ k_{\Delta\omega_{\max}}(t) \ge k_{mid}, & \Delta v_{\max} = \Delta v_{mid}, \end{cases} \quad t < t_d, \tag{15}$$

where k_{low}, k_{mid} are the limit values of the wear identification coefficient for the low and medium frequency range, respectively.

In other words, as the cutting tool wear, the spectral density of the energy of the Morlet wavelet image in the low-frequency region $\Delta\omega_{low}$ increases ($k_{\Delta\omega_{\max}}$ decreases), and in the medium frequencies region $\Delta\omega_{mid}$ decreases ($k_{\Delta\omega_{\max}}$ increases).

5. Conclusion

A model of milling process based on Morlet decomposition of vibroacoustic signals were proposed. Analyzing of the wavelet scalogramms of the signal at various processing modes, we received stable frequency bands of local maxima: 550-750 rad/s, 1200-1500 rad/s and 1950-2100 rad/s. Authors obtained trends to change the spectral energy density at the tool wear for the first and second frequency bands. The cross-factor $CF_{\Delta\omega_{\max}}$ can serve a numerical characteristic of change of this trend. The cross-factor determined by the dependence (10) and equal to the ratio of the average spectral density of the signal energy in the frequency bands of the local maximum of the scalogramm to the average spectral energy density throughout the frequency region of the scalogramm resolution. To identify the wear we proposed a new coefficient $k_{\Delta\omega_{\max}}$ that equal to the ratio of the cross-factors of acoustic emission signals for a new and wear tool, respectively. The coefficient of the wear identification increases where the dimensional wear increases in low-frequency region. These coefficient decreases in medium frequencies region. The experimentally determined regularity of the change a new condition that helps to improve early wear detection of the cutting tool made it possible to formalize the tool wear model with criterial constraints on the dependence.

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