Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 102 (2021) 276–280

www.elsevier.com/locate/procedia

18th CIRP Conference on Modeling of Machining Operations

Chip segmentation frequency based strategy for tool condition monitoring during turning of Ti-6Al-4V

Germán González[a,*], Daniel Schwär[b], Eric Segebade[a], Michael Heizmann[b], Frederik Zanger[a]

[a]wbk Institute of Production Science, Karlsruhe Institute of Technology (KIT), Kaiserstr. 12, 76131 Karlsruhe, Germany
[b]Institute of Industrial Information Technology (IIIT), Karlsruhe Institute of Technology (KIT), Hertzstr. 16, 76187 Karlsruhe, Germany

* Corresponding author. Tel.: +49-721-608-46316; fax: +49-721-608-45004. *E-mail address:* german.gonzalez@kit.edu

Abstract

Tool condition monitoring in machining reduces downtimes, maximizes productivity rate and improves the quality of the end-product. However, it still poses a challenge due to the complex non-stationary character of the tool wear and the several uncertainties coming from the machining processes. Recent studies provide new strategies for indirect tool monitoring. Unfortunately due to the unbalance between big amounts of data, low accuracy and high complexity they are not feasible in an industrial environment. The present research work proposes a strategy for tool condition monitoring during turning of Ti-6Al-4V using acoustic emission signals and the chip segmentation frequency as measurement variable. Three different approaches for wear estimation using different AE-data processing methods are presented. Through their combination, a strategy for qualitative and quantitative tool wear monitoring is proposed.

Keywords: Condition monitoring; wear; acoustic emission; segmentation frequency.

1. Introduction

Signal processing of acoustic emission (AE) is a well-established technique for process and tool condition monitoring (TCM) due its high sensitivity, the wide information contained in the MHz frequency band and the recent advances in computational technology that allow a real-time processing. AE sensors capture the elastic waves generated by the rapid release of energy from local sources within the workpiece [1]. During the cutting process, these waves propagate through the structural elements of the machine, the tool and the workpiece generating significant information like chip segmentation frequency (f_{cs}), workpiece surface quality and tool health. Kishawy et al. [2] recently published an extensive review of the AE-signal processing techniques most used for monitoring the features mentioned above during conventional cutting processes. The tool wear is usually quantitatively estimated during the process using the AE-signal energy of the full spectrum of frequencies as key indicator. This strategy is time consuming and lacks accuracy when several tool wear mechanisms manifest at the same time. For this reason, this work seeks an alternative to monitoring the full spectrum of frequencies and the process energy. Machining of titanium alloys under conventional cutting conditions produces chips with sawtooth form due to periodic strain localization caused by the prevalence of thermal softening over strain hardening [3]. The chip formation frequency feature was used by Zanger et al. during the broaching process of Ti-6Al-4V to predict tool wear and residual stresses [4].

In this work, tool wear monitoring during longitudinal turning of Ti-6Al-4V is carried out using AE sensors and the chip segmentation frequency is used as indicator variable. First, an experimental set-up is presented based on structure borne sensors and microphones placed next to the cutting edge. Next, several chip formation analysis techniques are introduced to investigate the relation between process parameters and chip segmentation frequency. Finally, different signal processing methods in time and frequency domain are described and their application potential for qualitative and quantitative tool wear prediction is discussed.

10.1016/j.procir.2021.09.047

Nomenclature

AE	Acoustic emission
TCM	Tool condition monitoring
RMS	Root mean square, -
f_{cs}	Chip segmentation frequency, Hz
λ	Chip compression ratio, -
A_0	Ideal chip cross-sections, µm^2
A_1	Real chip cross-sections, µm^2
Δs	Peak-to-peak distance, µm
N	Number of inverse peak to peak distances, -
v_c	Cutting speed, m/min
f	Feed per revolution, mm/rev
r_β	Cutting edge radius, µm
γ	Rake angle, °
K_r	Main cutting angle, °

2. Experimental procedure

Dry longitudinal turning tests were carried out on a vertical turning machine using uncoated carbide inserts type CCMW120404 and Ti-6Al-4V material. As shown in Figure 1, the set up features a static tool while a clamped workpiece rotates and moves downwards. To capture the high frequency vibration of the chip segmentation, three structure borne sensors (Vallen-System type VS45-H) able to measure a frequency range from 10 to 450 kHz were attached to the tool holder. AE-signals were amplified employing a pre-amplifier with a gain of 40 dB. Three ultrasonic microphones were also used to detect airborne sound emissions for filtering purposes. Furthermore, the cutting forces were measured using a force dynamometer. After each cutting pass, tool wear and chips were measured optically using a scanning microscope. A modal analysis was carried out to identify the eigenfrequencies of the system for filtering purposes.

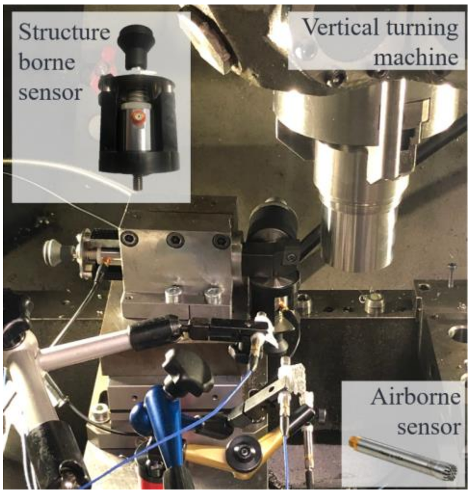

Figure 1: Experimental Setup.

The effect of the process parameters and the tool wear on the chip segmentation frequency was analyzed. The process parameters and tool geometries are listed in Table 1.

Table 1. Process parameters and tool geometries.

v_c m/min	f mm/rev	a_p mm	r_β µm	γ °	K_r °
120, 200, 300	0.1, 0.2, 0.3	0.30	50	0, 4, -7	95, 75, 50

3. Optical analysis of the chip segmentation

The optical measurement of the chips produced during the turning process is challenging, since the process kinematic generates an uneven chip with regard to its thickness and geometry. In order to obtain the segmentation frequency of the sawtooth chips, a section of approximately 5 mm length was measured using a confocal laser scanning microscope as shown in Figure 2. To consider the chip compression in the analysis, as presented in our previous publication [5], a compression factor λ was introduced as the ratio of the chip cross-sections before (A_0) and after (A_1) machining. A_0 is calculated analytically by integrating the distance between two tool tips taking into account the tool orientation, the cutting depth and the feed rate. Almost identical results can be achieved purely analytically or with the help of a CAD program. A_1 is calculated using the weight per length of the chip fragments and the density according to $A_1 = m_{chip} / (l_{chip} \cdot \rho_{Ti\text{-}6Al\text{-}4V})$.

Since the curling of the chip affects the results with respect to the segment peaks, the peak-to-peak distances Δs were measured. The chip segmentation frequency f_{cs} was then calculated as $f_{cs} = (v_c / \Delta s_{mean}) \cdot \lambda$. The chip's morphology presents primary and secondary segmentation zones. When evaluating the secondary segments, a high standard deviation is observed, which represents the variability along a chip. This is due to the increasing uncertainty in the subjective evaluation of these small peak-to-peak distances. For this reason, the segmentation frequency of the primary segments will be investigated and used as indicator variable when recording and processing AE-signals.

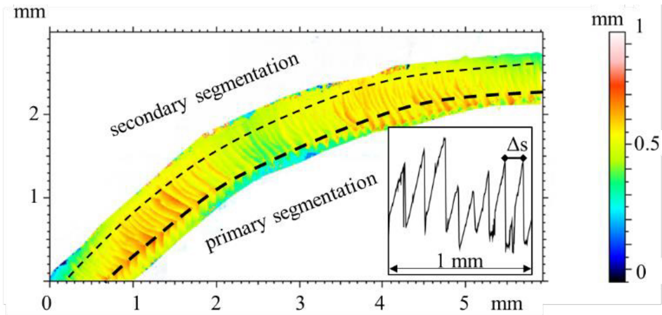

Figure 2: Chip segmentation analysis using confocal scanning microscopy.

4. Segmentation frequency monitoring using AE

The AE-signals from both structure and airborne sensors were recorded with a sampling frequency of 1 MHz and a resolution of 16 bit. First the measured signals are assigned to a current state over time and the tool state is classified as in cut or out of cut. These states can be distinguished from one another by considering the energy of the signal. The structure borne signals are used to detect whether the tool is in contact with the workpiece, since a significant increase of the energy can be seen as soon as the cutting process starts. In many cases when the tool is very close to the workpiece but not in cut, an increase of energy is measured by the structure borne sensors leading to inaccuracies in the signal post-processing. For this reason, the airborne signals of the microphones are used in combination with the structure borne signals to measure the process energy and to detect accurately the moments when the cutting processes starts and ends. For this purpose, a method based on principal component analysis (PCA) [6] is used to combine the energies of the signals. Therefore, the absolute value of the normed first vector of the PCA is used to combine the energy of all signals. With a subsequent k-means classification [7], a threshold value is automatically found with which the time location of the cutting process can be identified.

4.1 Time domain characteristics of AE signals

Once the start and end of the cutting process have been identified along the measurement time, features have to be extracted to obtain a time variant characterization of the signals. A well-known feature to indirect measurement and tracking of tool wear is the root mean square RMS value, that can be obtained from the structure borne signals by:

$$RMS(t) = \sqrt{|s(t)|^2 * \gamma(t)} \tag{1}$$

where $s(t)$ is the signal which is convolved with a window function $\gamma(t)$, in this case a Hanning function of length T. Figure 3a shows the raw signal with sawtooth waveform obtained from a structure borne sensor. Figure 3b shows the RMS value calculated from that raw signal using Equation 1.

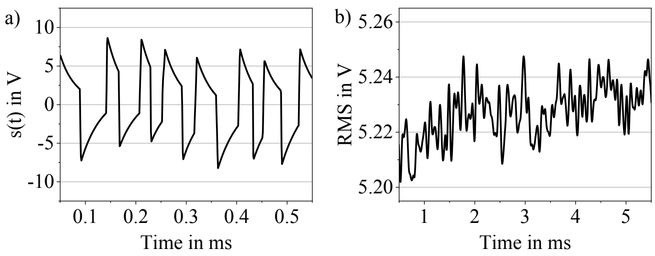

Figure 3: a) Raw signal of one structure borne sensor; b) RMS values.

4.2 Frequency domain characteristics of AE signals

Another feature of the signals is the frequency. Since the structure borne sensors measure the acceleration of vibrations, the sawtooth waveforms present very large step discontinuities when the direction of force changes. The distance between these steps correlates with the consecutively segmented chip formation caused by the ductile material failure along the adiabatic shear band in the primary shear zone.

For each cutting test, the periodogram of the structure-borne signals is obtained. However, later investigations have shown that classic frequency analyses, such as the periodogram, which are based on a Short-Time-Fourier-Transform, are no longer optimal for evaluating the structure-borne sound signals, since they work with harmonic functions. Using harmonic functions in combination with long filter lengths required for the necessary frequency resolution are not ideal for the analysis of signals with large jump discontinuities. Therefore, a method was developed to evaluate the structure-borne sound signals in the time domain, which uses the zero crossing points, as shown in Figure 4a to estimate the chip segmentation frequency. The distance between the positive/negative zero crossings are interpolated and then converted by inverting into a frequency. As can be seen in Figure 4a the periodicity of the structure borne signal just as the segmentation frequency have a high variance over time. Hence the statistics of these frequencies can be shown in a histogram as in Figure 4b of the estimated frequencies and using the number of inverse peak to peak distances N, from a signal chunk of length T = 10 ms. To approximate the maximum of the histogram, the median of the frequencies can be used to get a clearer feature for chip segmentation frequency estimation than the analysis of the periodogram. To get a more robust feature the median is calculated from the frequencies below 70 kHz. Since higher frequencies of the chip segmentation frequencies are implausible they are considered as disturbance and are excluded in order to achieve the best possible approximation of the maxima of the histogram.

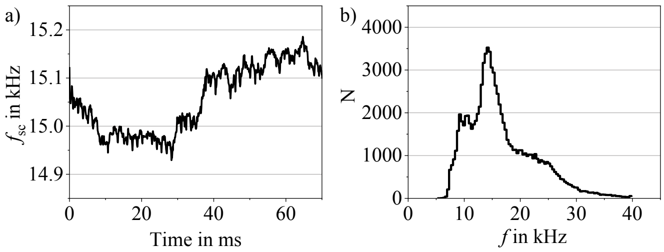

Figure 4: a) Trend of the median estimated from the zero crossing distances below 70 kHz; b) Histogram of the frequencies calculated from the distances between the zero crossings.

5. Results and discussion

5.1 Monitoring of the chip segmentation frequency

Using the parameters listed in Table 1 a full factorial study was carried out to investigate the behaviour of the chip segmentation during the turning process. Cutting tools were changed after each cutting test and the machining time was set to ensure reaching steady state. The chip segmentation frequencies were extracted from the AE-signals measured with the structure borne sensor located in cutting direction using the medians of the zero-crossing method. The primary segmentation path was also directly measured in five different sections of each chip using a confocal laser scanning microscope in order to validate the AE-measurements. Figure 5 shows the estimated segmentation frequencies as a) cutting speed, b) feed per revolution, c) rake angle and d) main cutting angle vary.

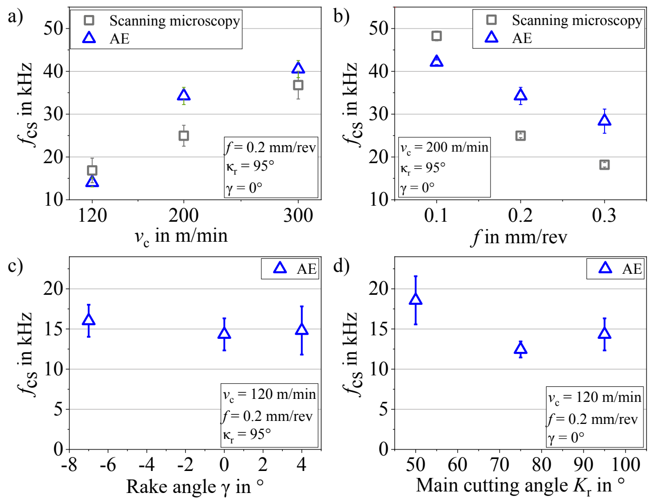

Figure 5: Segmentation frequency obtained by structure-borne signals post-processing and direct analysis by scanning microscopy from turning process with variable a) cutting speed, b) feed, c) rake angle and d) main cutting angle.

Chip segmentation frequencies obtained from the AE-signals do not accurately correlate with the scanning microscopy measurements; however, they present the same tendency. This deviation can presumably be traced back to measurement errors in the calculations of the chip compression ratio, due to the very low weight of the chip segments.

5.2 *AE for monitoring tool wear*

As well as the process parameters, the tool wear also influences the chip segmentation frequency. At low cutting speeds and feeds, stable and almost linear abrasive wear appears at the tool flank face. When using more severe cutting parameters, the abrasive wear is combined with crater and adhesive wear at the rake face, which produces an irregular chip formation and in most of the cases leads to tool breakage. In this chapter three approaches for tool monitoring under different cutting conditions are presented.

The first method for tool wear monitoring is the analysis of the cutting process energy using the RMS value. This technique allows a quantitative prediction of the tool wear and tool breakage based on a strong empirical characterization. Typically, for the calculation of the RMS value and its correlation with the tool wear the entire frequency spectrum is used [8], however the energy of the cutting process and the chip formation phenomena resides only in a specific frequency interval. Therefore, a signal bandwidth of 30 kHz with midpoint in the chip segmentation frequency was analyzed by applying a Gaussian window and used to calculate the RMS values. This reduces the calculation times significantly and provides more reliable information. Figure 6 shows the RMS values obtained from cutting processes with stable abrasive wear on the flank face and with dominant adhesive wear on the rake face respectively. On the one hand Figure 6a shows the RMS values correspond to the structure borne sensors placed on the tool in cutting (in blue color) and feed direction (in red color) respectively. The first observation is that the process energy is higher in cutting direction, which correlates with the measured forces in which the cutting force is also higher. For this reason, the sensor in cutting position was selected to measure the segmentation frequencies and to monitor the tool wear. The RMS values show almost linear tendencies, as well as the trend of the measured abrasive flank wear. On the other hand, Figure 6b shows an almost linear tendency at the beginning of the signal, as in the previous figure. However the higher cutting speed used in this tests quickly produces the appearing of adhesive wear on the rake face leading to unstable chip formation and tool breakage (t = 8.5 s).

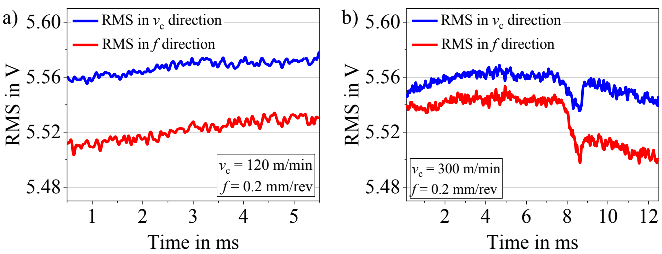

Figure 6: RMS values corresponding a) to a stable process with linear flank face abrasive wear evolution and b) to an unstable process with dominant nonlinear adhesive wear on the tool rake face and tool breakage.

After an event like tool breakage, the RMS value changes its trend, which can be ascending or, as in Figure 6b, descending.

To build an empirical model for tool wear monitoring, the tool wear evolution has to be compared with the RMS values. Figure 7 shows this comparison, and additionally the comparison with the cutting force. The incremental ΔRMS values show, as well as the cutting force values, an ascending tendency when the tool wear increases.

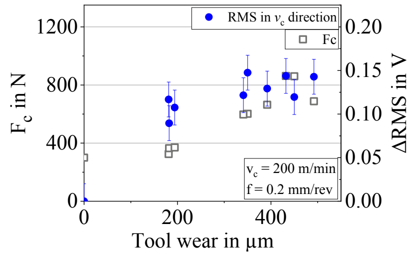

Figure 7: RMS value obtained from the AE-signals and cutting force at different stages of abrasive tool wear on the flank face.

The second strategy for tool wear monitoring focuses on the measurement and tracking of the chip segmentation frequency f_{cs} and its dependency on the process parameters.

Figure 8a shows the chip segmentation frequency obtained using the zero crossing median of the signals from Figure 7. The segmentation frequency initially increases up to a stable level where it remains constant until the tool is completely worn.

Figure 8b shows the chip's primary segmentation frequency measured by scanning microscopy and obtained from the AE-signals using the zero crossing medians as in Figure 8a.

Since the results do not show continuous values but steps, slopes and peaks, these values represent a mean over the whole cut. The chip segmentation frequency does not change significantly even though the wear increases. The tool wear presented on the tools was abrasive on the flank face during the entire process. It is to be noted that the wear-affected zone was exhausted here beyond a usual level.

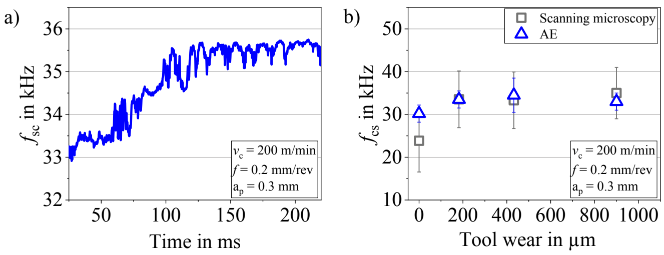

Figure 8: a) AE measured chip segmentation frequency, b) its evolution at different stages of flank wear and AE validation using scanning microscopy.

The chip segmentation frequency is however affected by the changes in the cutting edge geometry. The identification of these changes in the chip segmentation frequency leads to the estimation of the tool wear type and the tool breakage.

Figure 9 shows the chip segmentation frequency obtained using zero crossing medians of a process with severe cutting parameters. The signal presents at the beginning a stable zone followed by an increment, an abrupt decrease in frequency and a damping period to a stable position. This behaviour corresponds to the adhesion of workpiece material on the rake face and its release.

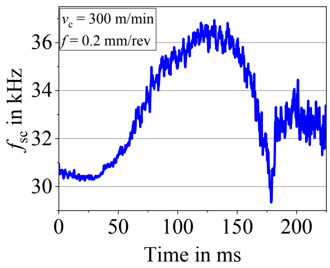

Figure 9: AE measured chip segmentation frequency under severe cutting conditions.

The third presented method combines the previous two methods and uses the histograms of the signals to give not only qualitative but also quantitative information of the tool wear. Figure 10 shows three histograms of the signal shown in Figure 9 corresponding to three signal intervals and three discrete tool wear states.

The first histogram corresponds to the beginning of the cutting process, the interval 10 - 30 ms, where the insert has no significant wear. The histogram shows a main f_{cs} of 31 kHz.

The second histogram corresponds to the interval 150 - 180 ms. After this time the tool presented flank wear of 100 µm and significant adhesive wear on the rake face. The histogram signal is much wider as the previous one due to the loss of periodicity in the chip formation. Also a change in f_{cs} can be seen, which splits in two due to the change in the geometry of the cutting edge leading to a second segmentation frequency at 24 kHz.

The third histogram corresponds to the interval 200 - 230 ms, where the AE-signal is stable again and the tools are worn presenting a bigger cutting edge radius. Here a change in f_{cs} compared with the first histogram is clearly appreciated.

With the aid of the histograms and increasing the number of processed signal intervals the type of the tool wear can be estimated.

This method can be combined with the RMS method to carry out qualitative and quantitative estimations. The values obtained with the presented methods are potential candidates to be investigated with e.g. advanced pattern classification techniques [9] in order to automatically identify the tool wear stage and type.

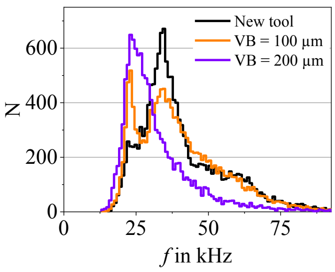

Figure 10: Histograms obtained from the zero crossing median diagram of Figure 9 at different signal intervals and tool wear states.

6. Conclusions

This paper presents a chip-segmentation-frequency-based strategy for tool wear monitoring using AE-signals from structure borne and airborne sensors during the turning process of Ti-6Al-4V. The key findings of this work are:

- The variation of the chip segmentation frequency with the process parameters and tool wear is presented.
- Abrasive wear does not affect the segmentation frequency significantly, but causes an increase in the amplitude of the signals, which can be identified calculating the RMS value.
- When using severe cutting parameters, crater and adhesive wear appears, which significantly changes the chip segmentation frequency as well as the process energy generated.
- Three AE-signal processing techniques: RMS, cross-zero medians and histograms and their application to TCM are introduced and experimentally validated.

Consequently, the acoustically measured chip segmentation frequency f_{cs} can be considered a process characteristic variable with high potential for TCM for machining of Ti-6Al-4V alloy.

7. Outlook: frequency range selection

To predict the interval where the segmentation frequencies appear and thus configure the AE-signal acquisition a Finite Element Method (FEM) based strategy was developed. To determine the mean value of the segmentation frequency range the chip formation process was simulated in a 3D-FEM model. The material behavior was modeled using modified Johnson–Cook flow stress and failure models. Calibration and results of the model are subject of future publications.

Acknowledgements

The scientific work has been supported by the DFG within the research priority program SPP 2086 (ZA 785/3-1). The authors thank the DFG for this funding and intensive technical support.

References

[1] Roth J.T, Djurdjanovic D, Yang X, Mears L, Kufgess T. Quality and Inspection of Machining Operations: Tool Condition Monitoring. Journal of Manufacturing Science and Engineering 132 (2010) 041015:1-16.
[2] Kishawy H.A, Hegab H, Umer U, Mohany A. Application of acoustic emissions in machining processes: analysis and critical review. International Journal of Advanced Manufacturing Technology 98 (2018) 1391–1407.
[3] Barry J, Byrne G, Lennon D. Observations on chip formation and acoustic emission in machining Ti–6Al–4V alloy. International Journal of Machine Tools and Manufacture 45 (2001) 1055-1070.
[4] Zanger F, Kacaras A, Bächle M, Schwabe M, Puente León F, Schulze V. FEM simulation and acoustic emission based characterization of chip segmentation frequency in machining of Ti-6Al-4V. Procedia CIRP 72 (2018) 1421–1426.
[5] Schwär D, González G, Segebade E, Zanger F, Heizmann M. Evaluation of the acoustic emission caused by the chip segmentation frequency during machining of titanium alloy. Technisches Messen, 87 (2020) 11:714–720.
[6] Beyerer J, Richter M, Nagel M. Pattern recognition. Introduction, features, classifiers and principles. Walter de Gruyter GmbH, Berlin, Boston. (2018) ISBN: 311053794X.
[7] Arthur D, Vassilvitskii S. k-means++: The Advantages of Careful Seeding. Technical Report, Stanford. (2006).
[8] Farrelly F. A., Petri A, Pitolli L, Pontuate G, Tagliani A, Novi Inverardi, P. L. Statistical Properties of Acoustic Emission Signals From Metal Cutting Processes. J. Acoust. Soc. Am. 116 (2004) 2:981–986.
[9] Sun J, Hong G.S, Wong Y.S, Rahman M, Wang Z.G. Effective Training Data Selection In Tool Condition Monitoring System. Int. J. Mach. Tools Manuf., 46 (2006) 2:218–224.