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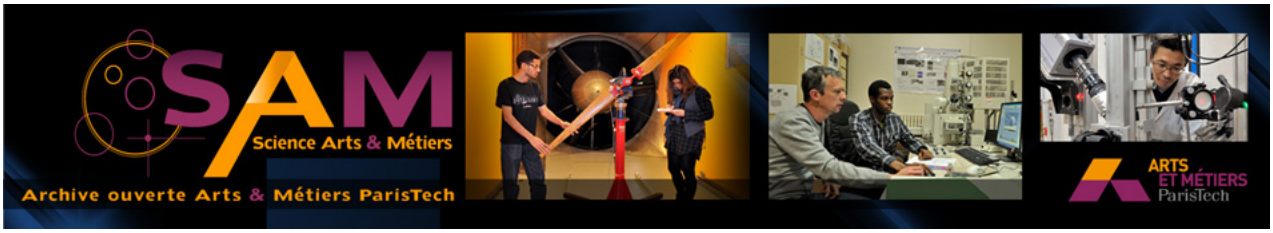

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A Robust Method for Drilling Monitoring using Acoustic Emission

G. Le Moal[1], P. Rabaté[2], G. Moraru[1], P. Véron[1], M. Douilly[2]
[1]Arts et Métiers ParisTech, CNRS, Laboratoire LSIS, 2 cours des Arts et Métiers, Aix-en-Provence, France
[2]EADS Innovation Works, 7 route de Bray, Méaulte, France

Abstract
Acoustic Emission (AE) is considered an efficient tool for monitoring of machining operations, for both tool condition and working piece integrity. However, the use of AE is more challenging in case of drilling, due to heavy dependence of AE signals to process parameters. Monitoring drilling using AE thus requires robust methods to extract useful information in signals. The paper describes such a method that adapts itself to AE signals obtained during drilling, allowing the automatic set-up of an adaptive threshold to perform AE count rate. Experiments have been conducted that show the robustness of the method and its usefulness in drilling monitoring.

Keywords:
Drilling monitoring, Acoustic emission, AE count rate

1 INTRODUCTION

Acoustic emission (AE), which describes the technical discipline and measurement techniques linked to the transient elastic waves resulting from local microdisplacements in a material [1], has been widely used for machining processes monitoring during last years. More specifically, it has been shown to be an effective way to detect cutting tool dysfunctions like tool failure or cutting edge chipping [18,20] because of its ability to detect sudden energy releases in deforming material. Moreover, due to its high frequency working range which is normally not affected by machine vibrations or environmental noises [4], it allows to sense tool wear [10,12,14], and to detect workpiece damages [25], in particular delamination occurring when drilling composite materials [7,8,9].

Concerning drilling, above mentioned applications of AE have been implemented, but the results were not always as good as in some other machining processes. Indeed, it has been observed that using AE in drilling is more complex than in other processes such as turning or milling because the chips trapped between the flute and the cylindrical wall of the hole is a significant additional source of AE. Moreover, when AE sensors are mounted on the workpiece, position of the source of AE in drilling is continuously moving from one hole to another and as the drill goes deeper [2]. Then, isolating the different sources of AE in a drilling operation is considered a formidable task as the mechanism of generation of AE is not completely understood [10,21] and analytical techniques are not completely developed [11]. Thus, some works have been aimed to link identifiable characteristics that distinguishes the different states of drilling mechanism in AE signals [2,3,9]. In particular, advanced statistical pattern recognition methods have been used to classify different cutting tool states from AE signals [27]. However, as AE signals are heavily depending on the machining process parameters [4,6,14], using them for monitoring remains a complicated task, especially in industrial context where operational conditions are often changing. There exists a paradox here, as AE has initially become a monitoring technique in manufacturing due to its sensitivity to process parameters [17]. However, process parameters and/or environmental parameters are often more impacting AE signal than the phenomena that are monitored.

This brief review of the literature concerning the use of AE for machining and drilling monitoring shows that if it is often presented as a promising tool, some theoretical and technical drawbacks are limiting its usage, changing process parameters (including mastered and unmastered changes) in particular. Consequently, in order to exploit AE efficiently for monitoring drilling operations in industrial conditions, robust methodologies aimed at the extraction of useful features in AE signals have to be developed [21]. In this paper, a method is proposed which allows extracting features in AE signals in a robust manner facing process parameters changes. Moreover, it allows taking advantage of the particularities of different states of the drilling operation. It has been developed taking into account both observations coming from the AE literature and statistical characteristics of AE signals, and has been applied on experimental data acquired during two test campaigns of carbon fiber reinforced plastic (CFRP) samples drilling where changing process parameters have been identified.

In a first part, classical usages of AE for drilling monitoring are described, and more especially features of interest that are usually sought in signals. The drawbacks associated with the use of these features for drilling monitoring are also presented and possible solutions are discussed, leading to the proposed approach. In a second part, the guidelines for the construction of the new feature extraction method are given and justified. Then, results provided by the use of this method on experimental data are presented and compared to results obtained with classical approaches.

2 FEATURES OF INTEREST OF AE SIGNALS FOR MACHINING MONITORING

2.1 Energy level

Energy level has usually been considered the best feature of AE signals to indicates the drill condition [5,13]. It has often been used on particular frequency bands of AE signals in order to improve its performance [12,15,16]. However, it has been pointed out that energy, often presented by the RMS value of the AE signals, should be used with precaution and is not always adapted to detect sudden events like catastrophic tool failure [18,19]. Considering a zero mean signal, the RMS is equivalent to the standard deviation which is the square root of the

second order central moment of the signal. Third and fourth normalized central moments, respectively skew and Kurtosis, have been shown to be promising symptoms of catastrophic tool failure [18,21] when applied on the instantaneous RMS value of AE signals. These symptoms are linked with the instability of the cutting process, and are often used for monitoring rotating machinery, especially the Kurtosis which is widely used on acceleration signals to detect shocks as it quantifies their peakedness.

As it is impossible to mount sensors on the rotating drill, the place where most useful information is collected is the workpiece. Unfortunately, it has been shown that the AE signal is influenced by relative positions between the AE source and the sensor, and also by adjacent holes when drilling [26,5]. In order to reduce these harmful influences, solutions have been developed and experienced with sensor mounted on the machine in a way such that the distance from the sensor to the rotating tool remain constant. Positioning sensors on the spindle assembly and on the nose of a robot drilling end-effector did not provide good results because of mechanical spurious noise coming from additional interfaces [5]. More sophisticated systems have been developed showing better results in milling but that are still sensitive to process parameters and should be used in addition with other type of sensors for robust monitoring applications [6].

In absence of an effective system for mounting sensors on rotating tools, better results in term of machining process monitoring have been obtained with AE sensors mounted on the workpiece. It is interesting to note that results of a study concerning the drilling of carbon steel and nodular gray iron shows that distance from the AE sensors to the hole as no significant effect on AE signal [15]. One of the test series performed for this study has been designed to investigate the influence of distance from AE sensor to the drill bit when drilling CFRP. The results presented in Figure 1 clearly show the influence of this distance on the signal energy. Signals acquired during the drilling of holes that are close to the sensor present higher energy levels than ones drilled in the same conditions but further. The drill bit has remain the same to drill the 40 holes and influence of tool wear is also noticeable with the decreasing energy according to hole index. This decrease of the energy level associated with tool wear has already been noticed in [5] and [8]. Energy based features extracted of AE signals are heavily dependent of process parameters like distance from sensor to drill bit, but can also be affected by the presence of elements adding noise to the signals like cutting fluid spray or carbon dust vacuum cleaner for instance. Considering those drawbacks which are difficult to overcome, AE energy based monitoring needs additional efforts to isolate effects of different process parameters.

2.2 Acoustic emission count rate

AE count rate, which is defined as the number of times the amplitude has exceeded a threshold in a specified unit of time [1], has also been investigated and linked to drill flank wear [22,23] and cutting tool crater wear in turning [14]. Although AE count rate and tool wear seemed well correlated, the data presented significant scatter and many problems inhibits the usage of this relationship in process monitoring. Indeed, it has been pointed out that such a system would have to be calibrated for each specific machining condition and the selection of a threshold level for the AE count rate would be somewhat arbitrary [14,24].

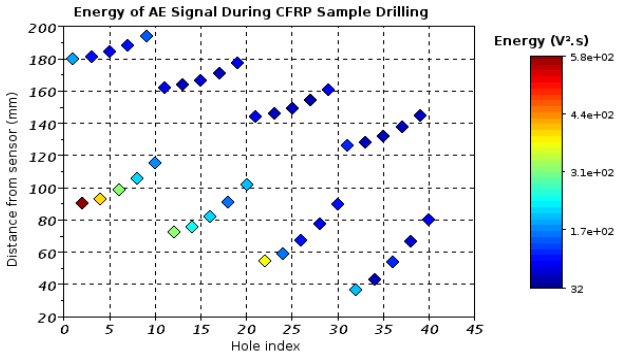


Figure 1: Influence of distance from sensor to hole and of number of holes drilled on AE signal energy

Those drawbacks do not allow drilling monitoring in industrial conditions. However, a simple statistical comparison of AE signals obtained during drilling and noise (AE signal obtained when the drilling system is operating outside of the CFRP sample) can make one think that AE count rate is a relevant feature for drilling monitoring. Indeed, the distributions of measured points composing the drilling phase signal and the noise phase signal present differences showing that high amplitude pikes are more numerous in the signal during the drilling phase, and so may be linked to some phenomena occurring during material cutting. Then, counting those pikes during the drilling phase can be interesting to observe changes linked with the drill or workpiece condition.

In order to quantify the difference between the number of high amplitude pikes occurring during the noise and drilling phases, the size of the C_{95} 95% coverage interval of the normalized signal distribution is used. A larger C_{95} coverage interval means that the distribution presents a bigger tail, and so contains more high amplitude pikes. It also allows avoiding influence of extreme points that appears in the noise and are not visible during the drilling operation. Table 1 contains the means of the C_{95} of each hole for the two different test campaigns and shows that for both, the drilling phase presents more high amplitude pikes than the noise phase.

In order to implement an AE count rate algorithm, a threshold needs to be set. Issues concerning process parameters changes compromise the relevance of a fixed threshold. For instance, if the distance between the AE sensor and the drilled hole in CFRP vary during a test campaign, and so energy levels of acquired signals present variations like illustrated in Figure 1, using the same threshold to perform count rate on each hole will lead to unusable results. Moreover, even in absence of energy variation from one hole to another, fixing a threshold would remain a problem considering the case of industrial monitoring because it would have to be calibrated for each specific machining condition, causing a lack of flexibility, and the selection of a threshold level for the AE count rate would also be arbitrary.

Test campaign	Number of drilled holes	Noise phase normalized $\overline{C_{95}}$	Drilling phase normalized $\overline{C_{95}}$
1	103	3.33	3.98
2	40	3.31	3.99

Table 1: Means of the noise and drill phases normalized EA signals C_{95} for the two test campaigns

In order to overcome the difficulties involved by setting up a threshold, it is interesting to have an adaptive threshold which allows attenuating effects of changing process parameters. However, a simple threshold presents another drawback: it does not allow performing count rate on transient phases of AE signals. Drilling operations can be divided in four different stages [3]: contact friction when the chisel edge is extruding the top of the workpiece, drilling when the cutting edges are cutting the workpiece material, piercing action when the material resisting stiffness is lower than the compressive thrust force exerted by the drill bit, and finally, at the end of the drilling operation, peripheral friction is induced by the rotation of the drill bit within the hole's cylindrical wall. Peripheral friction starts since the tool margins enters the material and is added to the cut linked phenomena in the AE signals. In order to facilitate the extraction of features of interest, it is useful to isolate the different phenomena occurring during these stages.

The drill bit entry into the material is a phase when only contact friction and cutting occur, therefore it is of particular interest for monitoring cutting edges wear, chipping or other degradation mechanism. However, AE signal acquired during the drill entry into the material is transient because of the increasing quantity of cut material (Figure 2), and cannot be efficiently treated with a simple threshold. The idea developed in this work is to build an adaptive and scalable threshold which follows the signal shape and allows counting the events that are remarkable considering both the AE signal characteristics and the goals of the monitoring operation.

Building an adaptive and scalable threshold

The goal of a scalable threshold is to determine what is considered as a remarkable event at each moment of the signal. AE signals acquired during drilling present Gaussian like distributions, and the most extreme points seems to be linked with material cutting phenomena. Thus, the threshold level can be set considering the occurrence probability P_{event} of the events that are wanted to be taken into account. Then, using a Gaussian law table, P_{event} is used to determine the number n_σ with which to multiply the standard deviation σ_p of the signal portion that is considered in order to set up the threshold. Using this scheme for each signal portion gives a set of P points, each one giving a threshold level for a given signal portion. To be done, this requires to divide the signal in P different time portions. The choice of such a portion duration is governed by two parameters: the number P of points that will be used to build the threshold, which is also the number of portions, and the total duration of the signal extract of interest T_{signal}.

They are linked together by the following relationship:

$$T_p \times P \leq T_{signal} \quad (1)$$

where T_p stands for the portions duration. Both parameters present constraints to deal with: the more number of portions P, the better the threshold will adapt itself to the signal shape, but the portions duration T_p must be long enough for their statistical distributions to be representative of the signal and give a coherent σ_p to determine the threshold level given by $n_\sigma \times \sigma$. Depending on the complexity of the shape that is wanted for the scalable threshold, a minimal number P of points can be required, then T_p can be chosen with respect to (1).

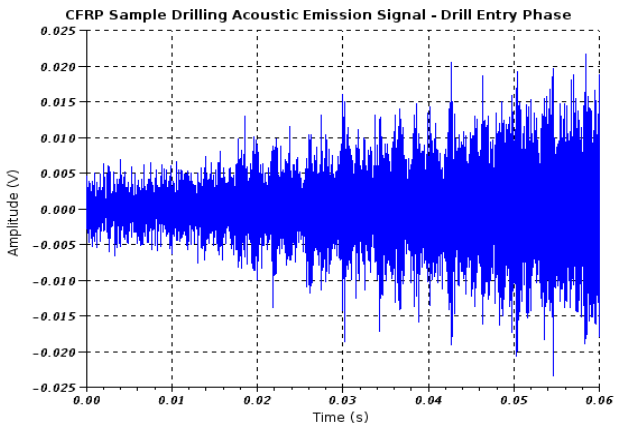


Figure 2: Transient AE signal acquired during the entry of the drill bit in the material

Considering our case study, the scalable threshold needs to adapt itself to different kinds of shapes. The potential of the drill entry phase, during which the signal energy is increasing, has been emphasized in a previous section, but the drilling phase during which the energy level remains quite stable also contains useful information on the drilling operation. Moreover, in case of blind holes, a decrease of the AE signal energy is visible as the feed decreases because of the spindle translation movement deceleration, so the threshold has to adapt too because the cutting speed reduction has significant influence on AE signals [21]. As the threshold needs to be defined for every moment of the signal, we propose to build a parametric function that fits on the P previously determined points. A simple function which adapts itself to all the above mentioned kind of shapes is the sigmoid function defined by:

$$s(t) = d + \frac{a}{1 + e^{q(t-p)}} \quad (2)$$

The little number of parameters allows using a reduced set of points P which is an advantage for short duration signals like the drill bit entry or spindle translation movement decelerating phases. As the problem is simple, fitting the function with the previously determined points can be done using any non-linear optimization algorithm. For instance, the Levenberg-Marquardt algorithm has been used in this work. Once the threshold is set in function of the wanted remarkableness of pikes driven by the user defined parameter P_{event}, an events count algorithm can be applied to perform AE rate count.

3 EXPERIMENTAL RESULTS

3.1 Experimental set up

Test campaigns have been conducted using a 3-axis CNC machine. Two 6.35mm carbide drill bits designed for CFRP and titanium stacks drilling have been used, the first one to drill 103 holes, and the second to drill 40 holes. The stacks were 18mm thick, 7mm of CFRP and 11mm of TA6V titanium. The drill operation was divided in two parts: 6.5mm were drilled in the CFRP, then the cutting parameters were changed to drill the titanium sample. External micro-lubrication was used. An Euro Physical Acoustics 9220 AE sensor has been used with 40dB amplification and 40-1100KHz bandwidth in-line pre-amplifier. It was sealed to the CFRP samples with silicone gel. A picture of the drill has been taken automatically after every drilled hole in order to visualize the drill bit state.

3.2 *Adaptive and scalable threshold set up*

The threshold parameters have been set up with respect to (1) considering the worst application case: the drill bit entry phase which presents a 0.05s duration. In order to perform a good curve fit with a sigmoid function, a minimal number P of portions has been set to 10. A minimum portion duration T_p has also been fixed to 0.002s in order to obtain a distribution of the points which is representative of the AE drilling signal. Then, considering those constraints and a 0.01s margin on the drill bit entry phase duration, 3 possible (P, T_p) parameters sets have been chosen in the space of possible parameters values to be evaluated. The space of possible parameters and the chosen parameters sets are presented in Figure 3 and the parameters sets are detailed in Table 2.

The same parameters have been used to perform feature extraction on the signals issued from the drill entry and the drilling phase in order to evaluate the method flexibility facing different signal shapes and characteristics. To evaluate the parameters influence, the 3 parameters sets have been used to perform AE count rate for each test campaign, both for the drill entry phase and the drilling phase. Differences between the AE count rate results obtained using each parameters set have then been computed, and the maximum difference and the standard deviation have been calculated for each couple of parameters sets. The results are reported in Table 3 and show that the parameters sets PS_2 and PS_3 give much closer results than when PS_1 is involved. In particular, the maximum difference can achieve very high level when using PS_1, which is due to the bad behavior of the optimization operation aiming to fit the sigmoid function on the P calculated points with a reduced number of data points. This phenomenon is visible for holes 50, 72, 78 and 98 on Figure 4 obtained after performing AE count rate with the three parameters sets on the drill entry phase of the 103 holes realized during the first test campaign. The similarity between the results obtained using PS_2 and PS_3 shows that a 0.002s portion duration is sufficient to give a representative statistical description of the signal. In order to avoid instabilities of the method due to optimization problems, PS_3 is chosen as the parameter set to perform feature extraction on the test campaigns data in the following.

Parameters Set	P	$T_p(s)$
PS_1	10	0.0030
PS_2	12	0.0025
PS_3	15	0.0020

Table 2: Evaluated parameters sets

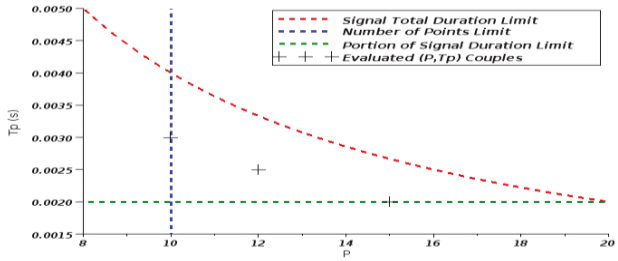


Figure 3: Space of possible parameters values and evaluated parameters sets (P, T_p)

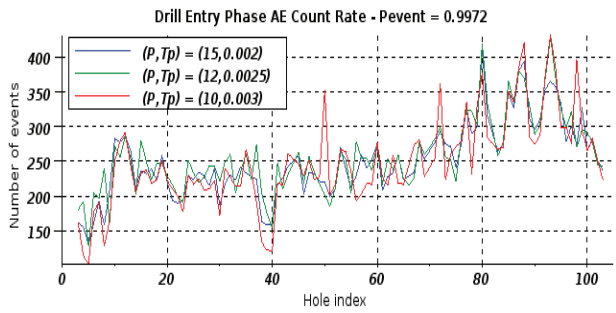


Figure 4: Results of AE count rate performed on the first test campaign drill bit entry phase data with the 3 parameters sets

3.3 Results and discussion

Influence of P_{event}

In order to emphasize the influence of the P_{event} parameter, AE count rate has been performed with 2 different values of the parameter. Results obtained for the first test campaign are depicted in Figure 5 and show an interesting behavior. When using a 0.9972 probability to set the threshold, a trend is visible as the number of drilled holes increases, whereas for P_{event}=0.9999 only high amplitude points (holes number 56, 85 and 99) are remarkable. Using the pictures of the drill bit taken after each hole, those high amplitude points reveal drill bit cutting edges alterations visible in Figure 6. No picture has been taken after the 99th hole because of a camera problem.

The same operation has been performed on the second test campaign data and results shows that even if no trend is visible when P_{event}=0.9972 because of the reduced number of drilled holes, variations of AE count rate between holes are much more important when P_{event} =0.9999 is used (ratio of 29 between the extreme values against a ratio of 2.5 when P_{event}=0.9972) showing the ability of this setting to isolate some drillings. P_{event} is a parameter driving the type of events that are wanted to be seen: at low levels it allows to follow trends that we suppose to be linked with tool wear, and high levels make possible to isolate sudden events like tool cutting edges sudden alterations.

		$P_{event} = 0.9972, \quad n_\sigma = 3$						$P_{event} = 0.9999, \quad n_\sigma = 5$					
		PS_1 & PS_2		PS_1 & PS_3		PS_2 & PS_3		PS_1 & PS_2		PS_1 & PS_3		PS_2 & PS_3	
		std	**max**	**std**	**max**	**std**	**max**	**std**	**max**	**std**	**max**	**std**	**max**
TC_1	**Drill entry phase**	*28.61*	*78*	*31.01*	*156*	*24.54*	*81*	*16.08*	*79*	*19.1*	*115*	*9.01*	*36*
	Drilling phase	*190.53*	*431*	*274.09*	*851*	*210.58*	*480*	*8.11*	*20*	*9.39*	*26*	*8.04*	*23*
TC_2	**Drill entry phase**	*31.56*	*114*	*29.23*	*96*	*29.55*	*93*	*11.99*	*61*	*5.34*	*20*	*9.57*	*57*
	Drilling phase	*206.59*	*573*	*222.03*	*840*	*157.28*	*375*	*9.06*	*30*	*11.9*	*53*	*8.48*	*25*
$\sum$		***457.29***	***1196***	***556.36***	***1943***	***421.95***	***1029***	***45.24***	***190***	***45.8***	***214***	***35.1***	***141***

Table 3: Analysis of the differences between results obtained performing AE count rate with each parameters set

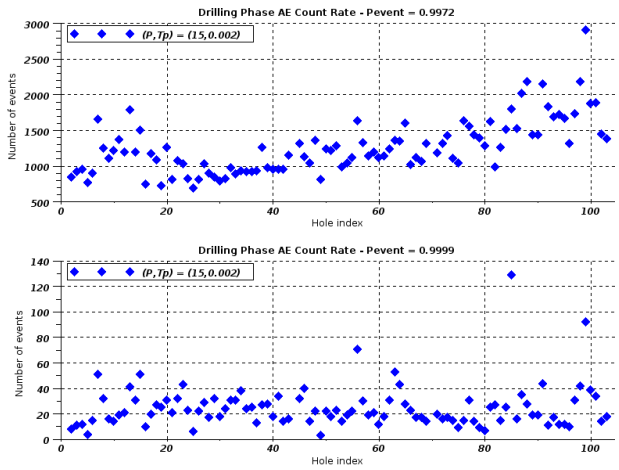
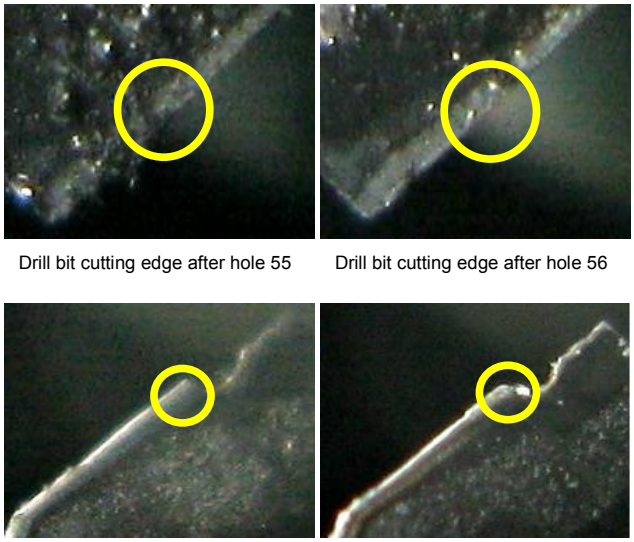


Figure 5: Results of AE count rate performed on the first test campaign with P_{event}=0.9972 and P_{event}=0.9999



Drill bit cutting edge after hole 55 Drill bit cutting edge after hole 56

Drill bit cutting edge after hole 84 Drill bit cutting edge after hole 85

Figure 6: Pictures of the drill bit taken after 55, 56, 84 and 85 holes. AE signals that are remarkable after performing AE count rate (holes 56 & 85) correspond to drill bit cutting edges chipping

Differences between energy and AE count rate

Results obtained using energy level and AE count rate have been compared. For the first test campaign, Figure 7 shows that AE count rate performed on the drill bit entry phase allows obtaining a trend in function of the number of holes drilled with the cutting tool, probably linked with tool wear. Using AE signal energy, a trend may also be observed, but numerous 'outside of the trend' points make difficult its exploitation for monitoring. Those energy variations are not due to mastered process parameters changes, and no explanation about their causes is available for the moment. In the same manner, for the second test campaign where only 40 holes have been drilled but the distance from AE sensor to drill bit vary significantly between consecutive holes, the energy in AE signal during drilling phase presents high differences from one hole to another that make the exploitation of the data impossible. The AE count rate provides better results: when energy levels present a ratio of 6 between two consecutive points, AE count rate maximum ratio is 2.5. The drill entry phase results lead to the same conclusions concerning both the two test campaigns: AE count rate attenuates variations due to distance from sensor to drill and maybe of other influence factors.

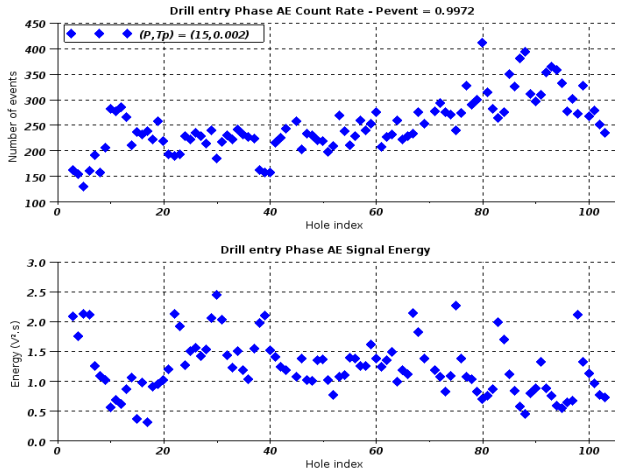


Figure 7: AE count rate and energy levels of drill bit entry phase AE signals for the 1st test campaign

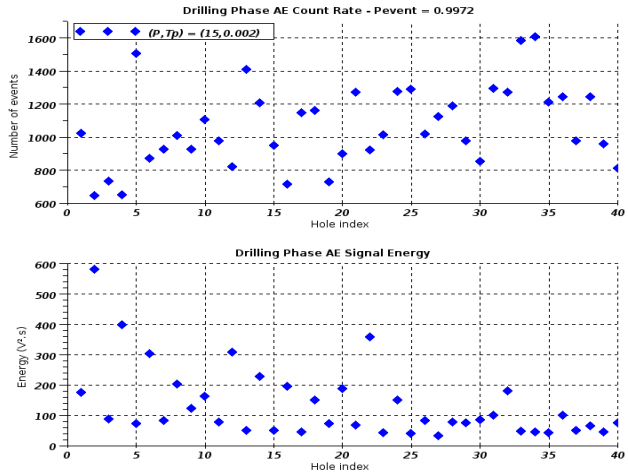


Figure 8: AE count rate and energy levels of drilling phase AE signals for the 2nd test campaign

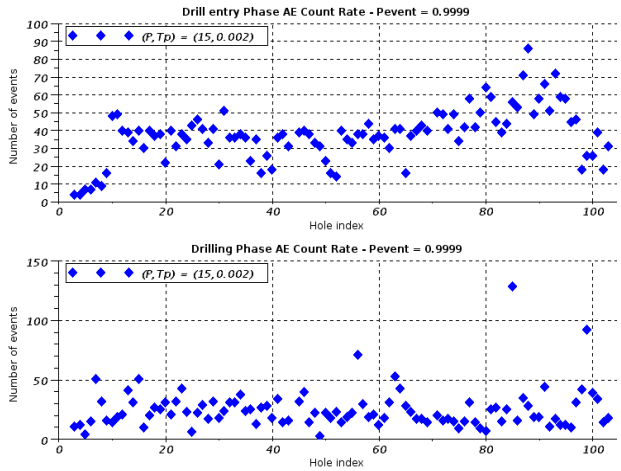


Figure 9: Comparison between AE count rate performed for the drill entry and drilling phases of the first test campaign using P_{event}=0.9999

Interest of the drilling phases separation

Figure 9 allows comparing results of AE count rate using 0.9999 for P_{event} and shows the interest of the separation of the different phases of the drilling operation. It shows very different results between the drill entry phase and the drilling phase. As explained at the beginning of this section, performing AE count rate with P_{event} set to 0.9999 allows one to see sudden events linked with tool cutting edges condition. Performing the same operation on the

drill entry phase gives a trend. The high amplitude pikes hiding the trend for the drilling phase are probably not visible during the drill bit entry phase because the cutting edges alteration occurred during the drilling phase which takes place just after.

4 CONCLUSION

A brief review on the use of acoustic emission in machining, and drilling in particular, has been done and showed a lack of robust methods for monitoring applications. This is essentially due to the classical approaches inability to handle perturbations induced by changing process parameters. We propose an auto-adaptive method which allows to overcome this issue, and also to take advantage of the different phases of the drilling operation specificities. Experimental results show the robustness of the method facing controlled process parameters changes, and also its good detection ability both for sudden events like cutting edge chipping and progressive phenomena like tool wear. In a future work, a better statistical description of AE signals and a bigger database of signals acquired during test campaigns may lead to better results in terms of detection ability and allow the implementation of classifiers able to monitor the cutting tool condition in a robust manner.

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