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Acoustic emission based drill condition monitoring during drilling of glass/phenolic polymeric composite using wavelet packet transform

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Abstract

Monitoring of tool condition on the basis of sensor signals requires a selection of suitable signal processing technique and monitoring index, to assess the tool condition. In this paper, wavelet packet transform is used as a tool, to characterise the acoustic emission signals released from glass/phenolic polymeric composite during drilling. The results show that the selected monitoring indices from the wavelet packet coefficients are capable of detecting the drill condition effectively.

Keywords: Acoustic emission; Tool condition monitoring; Glass/phenolic; Wavelet packet coefficient; Crest factor

1. Introduction

The use of fibre reinforced composite materials has grown in recent years in every field of engineering due to their inherent advantages over conventional materials. However, due to the presence of two or more dissimilar phases, composite materials pose challenges during machining as well as material characterisation. Drilling is one of the machining processes most widely followed in composite materials, since components made out of composite materials are usually near net shaped which needs mostly mounting holes for assembly integration. Drilling is a complicated process, and many factors determine the wear and life of a drill. Especially with non-homogeneous materials, like composites, the variances in the material randomly affect the life of the tool. Various microscopic damages, such as micro cracking of matrix, debonding at the fibre/matrix interface, fibre breakage, fibre pull-out and localised delaminations are induced by the application of thrust force and impact of the cutting tool with work material during drilling. The level of these damages depends upon the prevailing condition of the cutting tool during machining. In order to avoid damages on the work material due to drill failures, the drills usually get replaced before the end of their useful lives. Even with this expensive precaution, there is no way to predict, avoid, or even detect a sudden drill failure. This calls for a reliable way to monitor the condition of the drill automatically and in-process.

Several studies on in-process monitoring have been focussed on measuring thrust, torque, power and other indicators to detect the tool wear [1]. But among them acoustic emission is considered as one of the accurate monitoring methods in the machining environment. The microscopic damages created by the cutting mechanism and subsequent change in the condition of the tool, release high frequency emission of stored elastic energy which usually travels through the material as transient elastic stress waves. These are known as acoustic emission (AE). They act as in-built tool's state identifying indicator, especially in the case of composite material. The condition of the tool thus could be monitored through the integration of suitable AE sensors on the work piece and studying the corresponding response of the material. The acoustic waves emanated from the work material are usually non-stationary and comprising overlapping transients. Hence, an appropriate method of signal processing technique is essential to characterise the AE signals.

In monitoring tool/processes, sensor signal processing is aimed at extracting features of the sensor signals (called the monitoring indices) that describe the characteristics of the conditions. Depending upon the signals, different processing techniques should be used. When the signals are stationary, either

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time domain statistical analysis or spectral analysis like Fourier transform is used [2]. However, when processing transient components, such as shortly decaying frequency components, like AE, they find difficulty in extracting characteristic features, and many of the useful information gets averaged/lost, while transforming a signal from one domain to another. Thus, attempts have been made to solve this problem by the development of short-time Fourier transform, but only with marginal success. These problems have been successfully eliminated by the introduction of time-frequency distributions. Among the number of time-frequency distributions, wavelet transform is one of the most promising methods followed in engineering.

Wavelet transform has been successfully used in various science and engineering fields, especially in speech recognition and image processing. Currently, the application of wavelet transform has been extended to handle signals that are acquired during machining environment. It has several important properties that make it very attractive for tool condition monitoring. Tansel et al. [3] proposed encoding of thrust force signals of micro drilling operations with wavelet transformations for detection of severe tool damage just before complete tip breakage occurs. Wu et al. [4] have used wavelet packet transform to extract the features from the signals of motor current for real time tool condition monitoring during drilling in transfer machining stations. Suzuki et al. [5] correlated the wavelet transform of the AE signals to the fracture modes of fibre-reinforced composites. Berger et al. [6] have used wavelet transform as a tool to study the dynamic characteristics of cutting processes. Wavelet transform is applied to characterise the transition from high dimensional to low dimensional dynamics in the cutting process at the onset of chatter [7]. In the present study, wavelet packet transform is used to study the condition of the drill during drilling of glass/phenolic composite.

2. Wavelet transform

The wavelet transform of an energy limited signal $f(t)$, can be represented by its wavelet transform bases as [8]:

$$f(t) = \frac{1}{c_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} W_s[f(\tau)] \frac{1}{s} \psi\left(\frac{t-\tau}{s}\right) \mathrm{d}s\, \mathrm{d}\tau \qquad (1)$$

where s represents the frequency, t the time shift or 'location', c_ψ a constant depending on the base function and $W_s[f(t)]$ is the wavelet transform defined as

$$W_s[f(\tau)] = \int_{-\infty}^{+\infty} f(t) \frac{1}{s} \psi\left(\frac{t-\tau}{s}\right) \mathrm{d}t. \qquad (2)$$

Eq. (1) implies that the wavelet transform can be considered to be a signal decomposition. It decomposes a signal $f(t)$ into a family of wavelet bases and the weighting coefficients, $W_s[f(\tau)]$, represent the amplitudes at given location τ and frequency s.

Depending on the mother wavelet function, there are various discrete wavelet transform, such as the binary wavelet transform and wavelet packet transform. In this study, the wavelet packet transform is used. The wavelet packet transform decomposes a signal into various components (packets, $P_j^i(t)$, i is packet number and j is the number of levels), based on which the characteristic features of the signal can be captured. In the first resolution, $j=1$, the signal is decomposed into two packets: $P_1^1(t)$ and $P_1^2(t)$. The packet, $P_1^1(t)$, represents the lower frequency component of the signal, while the packet $P_1^2(t)$, represents the higher frequency component of the signal. Then, at the second resolution, $j=2$, each packet is further decomposed into two sub-packets forming $P_2^1(t)$, $P_2^2(t)$, $P_2^3(t)$ and $P_2^4(t)$. This decomposition process continues and at each subsequent resolution, the number of packets doubles while the numbers of data points in the packet are reduced by half.

The wavelet packets contain the information of the signal in different time windows at different resolution. Each packet corresponds to some frequency band. Some packets contain important information while others are relatively unimportant. The packets that contain the characteristic features of the signal are referred to as feature packets. In general, the packets, which have higher energy, are called feature packets. In this paper, energy of the wavelet packet is taken as criteria for the selection of feature packets.

3. Experimental procedure and data acquisition

Drilling experiments were conducted on a universal milling machine. Fig. 1 shows the experimental set up of this study. Experiments were performed on laminated glass/phenolic polymeric composite which are made out of woven glass cloth. HSS

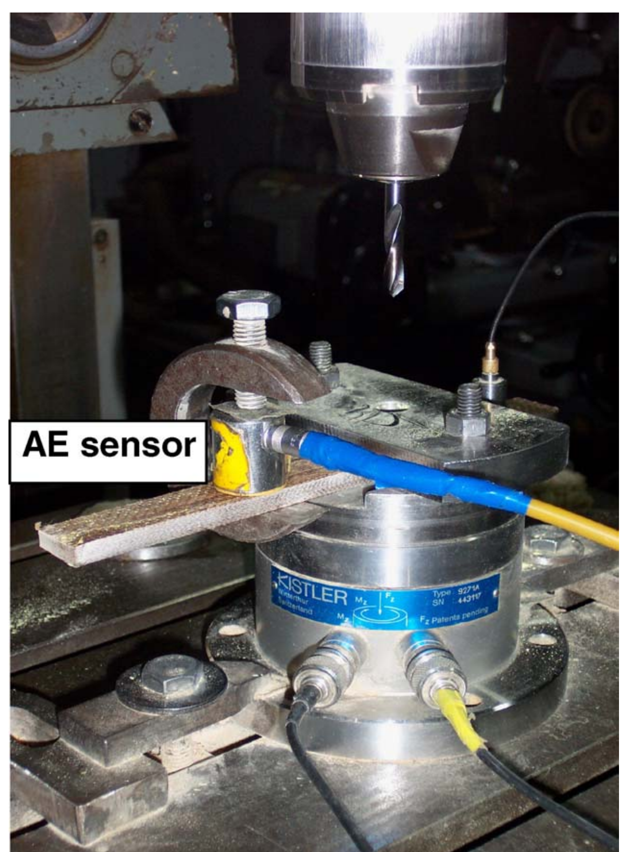

Fig. 1. Experimental set-up.

drill to a diameter 6.5 mm was used during drilling experiments. From the preliminary trials, the cutting parameters were optimised at a cutting speed of 36 m/min and 0.08 mm/rev feed rate for the work and tool material combination. The experiments were carried out without using any coolant. Acoustic emission was measured with a Kistler wide band piezoelectric AE sensor (model 8152A2) by positioning it on the work piece near the tool. At predetermined number of holes, the emanated acoustic waves were acquired using a digital storage oscilloscope and the corresponding flank wear of the drill was evaluated using universal measuring microscope. The acquired AE signals are processed and the characteristic features are extracted using wavelet packet transformation. Fig. 2 shows the schematic of all the components required for tool condition monitoring.

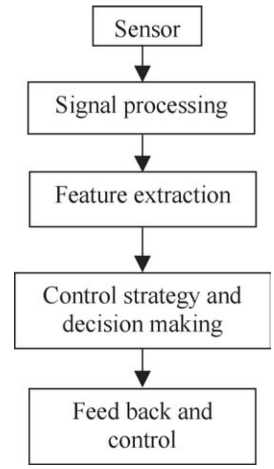

Fig. 2. Components of tool condition monitoring.

4. Results and discussions

Fig. 3(a–c) shows the typical raw waveforms of AE signals in the time domain for different number of holes. It shows that, with the increase in number of holes drilled, the components of the acoustic signals increase due to the development of flank wear. In monitoring of tool condition, the AE signals monitored contain complicated information on the cutting process. To ensure the reliability in tool monitoring system, it is necessary to extract the features that describe the relationship with the tool condition. Thus, the AE signals are decomposed into four levels,

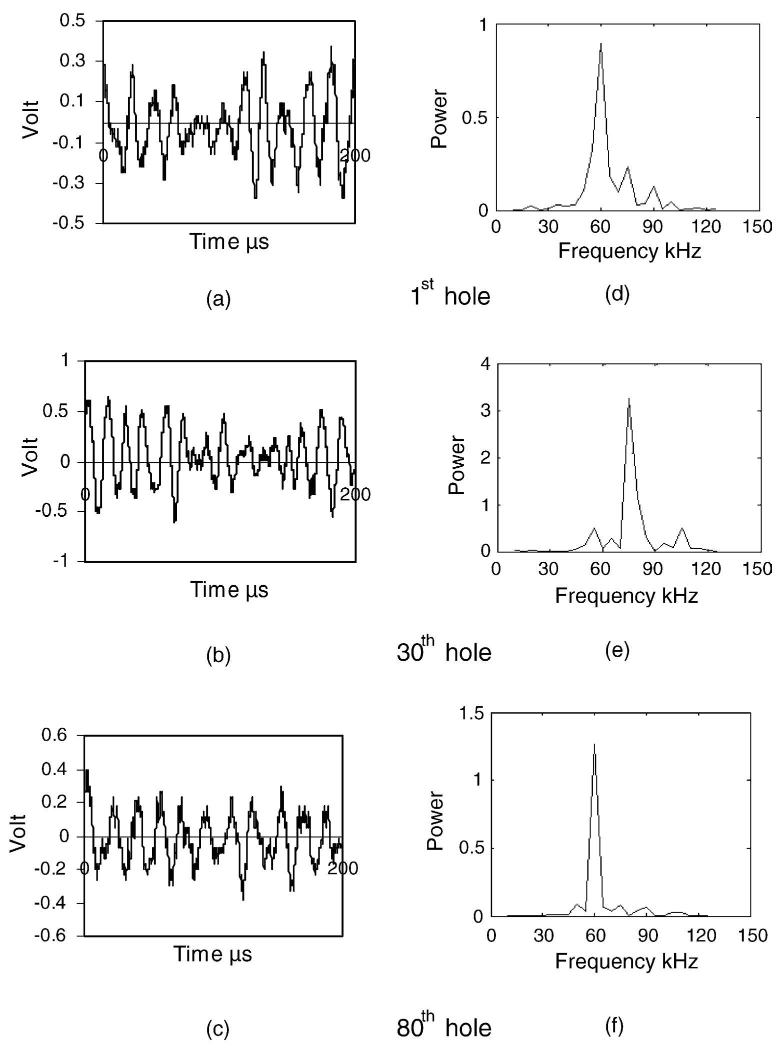

Fig. 3. Raw waveforms and corresponding power spectrum of AE signals for different number of holes.

that is, splitting in to 16 wavelet packets. Each wavelet packet corresponds to each frequency band ranging from 0–156.25 to 2343.75–2500 kHz. Out of 16 packets, it is necessary to select the packets (feature packets) that contain useful information. Based on the energy in each packet, feature packets are selected by calculating the same as per Eq. (3) given below:

$$E_j^i = \sum_{i=1}^{N} [P_j^i(t)]^2 \tag{3}$$

From the decomposition it was observed that for all the holes, the first packet having the highest energy thus was chosen as feature packet.

Fig. 3(d–f) show the corresponding power spectra of the AE signals analysed from the waveforms given in Fig. 3(a–c). From the figures, it can be seen that with an increase in number of holes, a visible change both in the frequency and amplitude results, indicating the deterioration in tool status. The change in the energy during drilling of 30th hole represents the energy emitted from fibre-matrix debonding and related defects with frequency centred at about 80 kHz. There exist other sources in the signal with both low frequency and low energy representing failures, such as micro cracking. A shift in the frequency from 80 to 60 kHz is seen, while drilling at 80th hole (Fig. 3(c)) indicating the rubbing mode of the drill flank with the surface of drilled hole and thereby reduction in the energy.

Fig. 4 shows the wavelet packet coefficients of the feature packets of the corresponding signals represented in Fig. 3. From the figure, it can be seen that the magnitude of the wavelet packet coefficients are sensitive to change of tool states. During drilling of the first hole, the tool is fresh, cutting is smoother thus producing uniform wavelet coefficients demonstrating cutting of the fibres. As the number of holes drilled increases, the magnitude of wavelet coefficients increases, indicating deterioration in tool condition. At 30th hole, an increase in the amplitude of wavelet coefficients at all data points can be seen, showing the long duration of the high frequency components. This long duration of the frequency components indicates that the damages, like matrix cracking and delamination continues for a while even after the fibre breakage. This coincides the analysis of AE signals in failure modes, reported by Qing-Qing and Iwamoto [9].

The variation in the rms of the wavelet coefficients of the feature packet with respect to number of holes is illustrated in Fig. 5. From the figure, a distinct change in the wavelet coefficients can be seen as the number of holes drilled increases, due to change in the condition of drill. However, the information from the feature packets needs to be processed further, to assess the condition of the tool effectively. Thus, the following methodology is adopted for further processing.

It should be noted that each feature packet contains a set of data that uniquely describe the original signal. Then it is often useful to use certain indices to describe the characteristic of the data in the feature packets. Several types of indices like mean, variance, rms, peak-to-valley, etc. are used. In this study, a crest factor (C) calculated as per Eq. (4) (different from normally used in statistics) is used as a monitoring index to study the condition

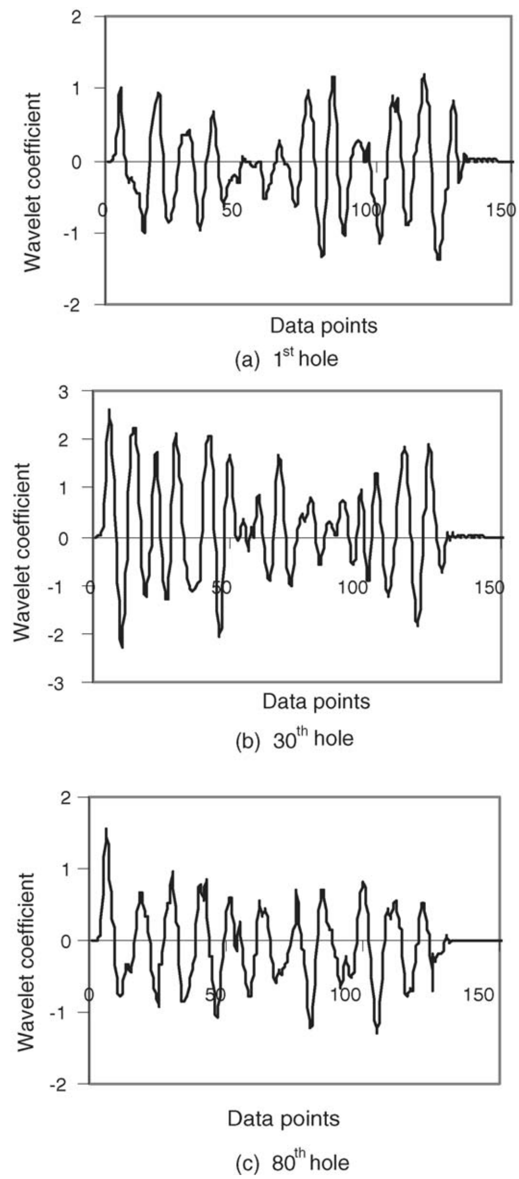

Fig. 4. Wavelet packet coefficients of AE for different number of holes.

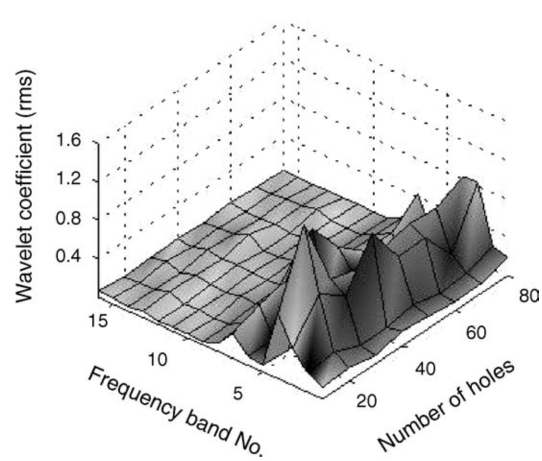

Fig. 5. Variation of wavelet feature packets at different number of holes.

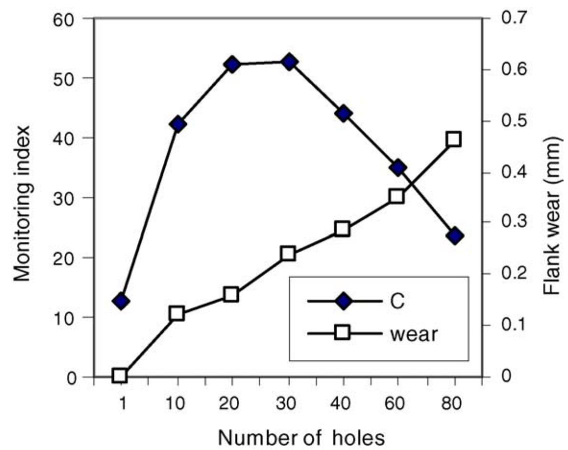

Fig. 6. Variation in monitoring index under different number of holes.

of the drill.

$$C_j^i = \frac{T_j^i}{\bar{E}_j^i} \tag{4}$$

where,

$T_j^i = \max\{P_j^i(t)\}^2 - \min\{P_j^i(t)\}^2$, $\quad N_j =$ no. of data points in feature packets

$\bar{E}_j^i = \frac{1}{N_j}\sum_{i=1}^{N_j} P_j^i(t)$, $\quad P_j^i =$ wavelet coefficients in feature packets

Typical variation in monitoring index and tool wear with number of holes is illustrated in Fig. 6. From the illustration, it can be seen that the value of the monitoring index increases rapidly up to 10 holes, showing the running-in wear of the drill. Between 10 and 30 holes it raises progressively indicating the normal wear of the drill. Beyond 30 holes, it starts decreasing, possibly due to rubbing of worn drill flank with work material, thus leading to low energy release. Also, the decrease in monitoring index beyond wear of 0.2 mm could be due to dampening of the AE signals by the thermal influence associated with worn cutting edges in rubbing mode at higher tool wear condition. Corresponding to change in trend of the monitoring index at 52, a sudden increase in flank wear is seen (about 30 holes), which clearly indicates a threshold for limiting the usable drill condition for drilling of glass/phenolic polymeric composite. Thus, from the Fig. 6, a control/monitoring strategy can be found out as, *if* $C_{i+1} \geq C_i$, *then* tool is in useful condition *else* worn tool. However, this monitoring strategy can be supplemented by conducting several experimental samples and studying the pattern if any, which results among the wavelet coefficients at different tool conditions to establish alarm thresholds that can facilitate real time tool condition monitoring.

5. Conclusions

From the above study, the following conclusions can be drawn:

- The AE energy is found to decrease with tool wear. Hence, AE monitoring can facilitate in-process monitoring and control of drilling process.
- The wavelet coefficients are capable of representing changes in the response of the material due to change in the condition of the tool.
- Using wavelet packet transform, the key features of sensor signals (AE) can be extracted.
- The monitoring index extracted from wavelet coefficients of feature packets can reliably detect the condition of the tool.

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