Identification of tool wear status and correlation of chip morphology in micro-end milling of mild steel (SAE 1017) using acoustic emission signal

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Abstract. This study describes the identification of micro-end mill wear by means of acoustic emission (AE) signals received from an AE sensor during the micro-end milling (slot milling) of mild steel. The obtained AE signals were processed in the time-domain to compute root mean square (RMS) and dominant frequency and amplitude are obtained from frequency-domain. The RMS value shows the linear trend with the tool wear, and helps to classify the tool wear regions, such as initial, progressive and accelerated wear regions. The Welch power spectral density and spectrogram (short term Fourier transform) analysis help to identify the tool rotational, tool passing and machining frequencies. The discrete wavelet transformation (DWT) technique is used to discretize the AE signal in to five frequency ranges. AE specific energy was obtained from the discretized AE signals. The AE specific energy indicated that a combined type of material removal mechanism occurred in micro-end milling, similar to the macro-end milling. However, ploughing is also observed from the surface topography. Chip structures are also studied and correlated with the micro-end mill wear for tool wear identification.

1. Introduction
The requirement of micro-components is rapidly increasing in many fields, such as medicinal, electronics, biotechnology, automotive, etc. To meet these demands, various micro-manufacturing techniques have been used. Tool oriented micromachining is a micro-manufacturing method used for making 3D micro-components, with instigated structures in varieties of materials [1]. It uses the scale down version of the conventional tools, to produce component with less than 500µm [2]. Micro-endmilling is one type of the tool oriented micro-machining processes for fabricating micro-components, like micro size dies, impellers, nozzles, etc. [3].

For productive industrial applications of the micro-endmilling process, there is a need to increase the reliability during machining. The major factors affect the reliability of the process is the condition or status of the tool. If the worn-out tool is used beyond its limits, it will affect the quality in terms of dimension, form and accuracy of the finished components. Due to the size of the micro-tool, it is very difficult to predict the tool life, tool failure, etc. Therefore, the tool monitoring in micro-endmilling is
essential in order to improve its reliability [4]. Only limited studies are attempted to monitor the tool condition, especially in tool oriented micro-machining environments, using different sensors such as cutting force dynamometer, accelerometer, AE sensor, etc. [5]. Among these, the AE sensor is seems to be more reliable for TCM in the micro-manufacturing environment, because of its high frequency content, and also because it is not affected by the external noise [6].

AE signal is the stress waves produced by the energy release by the materials while it undergoes deformation, which has been successfully used to monitor the tool wear, tool failure, etc [7]. The occurrence of AE signal during metal cutting are may be due to deformation of the workpiece, chip formation, friction between the tool and the workpiece, friction between the tool and the chip, impact of chip on the tool, chip fracture, tool failure, etc. [8]. AE signals during micro-endmilling consist of continuous and transient elastic waves [9].

The literature review related to the analysis of the AE signal is briefly presented here. Dolinsek et al. [10] compared the tool wear with the AE signal. They found that the AE energy increases with tool wear status and the dominated frequency range is lies between from 100 kHz to 610 kHz. Chung and Geddam [11] observed that the AE sensor changes with respect to the tool wear than the torque and force sensors signals. Haber et al. [12] monitored the tool wear in endmilling. They noted that the mean and peak values of the AE signal are able to clearly distinguish between good and worn-out tools. They also monitored the condition of tool by the spectrum analysis and found that the AE signal is very sensitive to tool conditions and the dominant frequency lies between 100 kHz-160 kHz. Jemielniak et al. [13] found a strong relationship between tool wear and the AE signals. They have also observed the tooth passing frequency at 1207 Hz during every single pass of the micro-endmill.

The literature review also indicates that the signals acquired from the AE sensor are processed using different methods, such as Fast Fourier transformations (FFT), short term Fourier transformations (STFT) and discrete wavelet transformation (DWT),etc. apart from the time domain and frequency domain (FFT). These methods were mainly employed in monitoring the tool condition in macro-regime machining [14]. However, these techniques are not mainly used in micron level machining. The AE signals are stochastic in nature, current researchers applied the standard method like the Fourier transform (FT) to correlate the signals with the tool condition [15]. However, this method does not give appropriate frequency resolution, and no information of time components for the particular event during machining. Therefore, STFT is used to process the signals. The various frequency regions are shown in different dimensions in time window. The short duration time (window) shows signal ranges of high frequency components, whereas the long duration windows indicates the small variations in the signal of the lower frequency bands. However, the resolution of STFT varies with respect to the length of the signal. To overcome these issues, researchers used the Wavelet Transformation (WT) technique [16]. The main feature of WT is that, it can extract data from the raw AE signal by discretizing the signal into a group of different frequencies (lower and higher levels) bandwidth. Further details about WT can be obtained from Li [17].

Researchers also made attempts to compare the AE signal with chip structure and chip formation. Barry et al. (2001) identified the important source of the AE signal in metal cutting is during the formation of the buildup edges (BUE) between the chip and the tool. Simoneau et al. [18] observed the uncut-chip thickness \( t_{um} \) reaches its threshold limit, the chip formation process changes from an unbroken to a quasi-shear extrusion in micro-endmilling. It is also observed that shearing and ploughing are the predominant material removal mechanism. Jackson [19] found that the cutting tool bending contributes significantly to primary chip curl. Mian et al. [19] positively correlate the specific AE energy of the decomposed frequency bands using discrete wavelet transformation technique with the chip morphology. Wang et al. [20] studied the chip formation mechanism using a hybrid FEM–analytical in micro-milling operation.

From the earlier research study, it is identified that the uses of the AE sensor has not been properly utilized in micro-endmilling. Hence, this work is an attempt to classify the tool wear regions in the micro-endmilling of mild steel with respect to AE signal. The AE signals are analyzed in the time
domain, FFT, STFT and WT. The chip formation mechanism is studied based on the AE specific energy. The chip structure is studied by correlate the tool wear region.

2. Experimental Procedure

Figure 1 shows the MIKROTOOLS made micromachining machine tool (Model: DT110) in which this study is carried out. The workpiece material is Steel alloy–SAE 1017 and its composition found by optical emission spectrometry are Carbon 0.25%, Manganese 0.51%, Phosphorus 0.06%, Sulphur 0.028% and Silicon 0.167%. The uncoated SPEED tungsten carbide tool is used in this work (Model: UMIE 3052) of 400 mm diameter, 35° helix angle and flute length of 0.8 mm. The experiments were carried out with the spindle speed of 2800 rpm, axial depth of cut of 50 μm and feed rate of 2 μm/flute. These ranges are fixed based on the initial experimental studies made, using the design of experiments (DoE) approach. The flank wear is only taken in this research, since the depth of cut is low of 50 μm. The experiments were done in dry nature till the tool was broken.

![Figure 1. Photograph of the experimental setup.](image)

The Kistler make AE sensor (Model: 8152) is used to acquire the signal during micro-endmilling, which is attached to the workpiece with help of a clamping screw (Fig. 1). The range of AE signal frequency is from 50-900 kHz. A piezotron coupler is employed to analyses the observed AE signals. Thereafter, the AE signals are changed in to digital signals, by the multichannel analog to digital converter. The processing of AE signal are carried out as per the earlier procedure for frequency domain (FFT), STFT and WT analyses [16]. The received AE signals are discretized into 5 various frequencies with 3db bandwidth, using the algorithm of DWT in MATLAB® (R 2016).

The tool wear (flank wear) and chip width is calculated using a noncontact video measuring system (Model: 2010F). The resolution of the system is 0.001 mm with the magnification range of 34–220 X. The tool wear is noted for every 120 s of machining. The mean of the two flank wear (VB1max and VB2max) data measured in the micro-endmill is assumed as tool wear (VB). The surface roughness (Ra) is tested on the surface of the workpiece at various points, along the feed direction, using non-contact surface roughness measurement equipment with cut of length of 0.8 mm and 5.6 mm of traverse length. The mean value is observed is shown in Table 1.

3. Result and Discussion

The classification of the tool wear regions with the results obtained from Ra, chip width and the AE_RMS signals processed in the time domain, FFT, STFT and WT is discussed in session.
Table 1. Experimental result in time and frequency domain.

| Ex. No | Machining time (s) | Tool wear (µm) | Rₐ (µm) | Chip width (µm) | AE_RMS (µV) | Tool rotational Dominant frequency (kHz) | Amplitude (µV) | Tool passing Dominant frequency (kHz) | Amplitude (µV) | Machining Dominant frequency (kHz) | Amplitude (µV) |
|--------|--------------------|----------------|---------|-----------------|-------------|------------------------------------------|----------------|--------------------------------------|----------------|-----------------------------------|----------------|
| 1      | 120                | 9              | 0.234   | 89.5            | 0.043       | 65                                       | 0.177         | 128                                  | 0.245          | 234                               | 0.304          |
| 2      | 240                | 19             | 0.175   | 99.5            | 0.054       | 65                                       | 0.173         | 128                                  | 0.216          | 270                               | 0.231          |
| 3      | 360                | 23             | 0.196   | 63.0            | 0.055       | 65                                       | 0.164         | 128                                  | 0.236          | 258                               | 0.136          |
| 4      | 480                | 24             | 0.175   | 73.5            | 0.055       | 65                                       | 0.175         | 128                                  | 0.180          | 221                               | 0.105          |
| 5      | 600                | 25             | 0.165   | 76.5            | 0.055       | 65                                       | 0.237         | 128                                  | 0.331          | 234                               | 0.096          |
| 6      | 720                | 26             | 0.142   | 59.5            | 0.055       | 65                                       | 0.279         | 128                                  | 0.159          | 221                               | 0.099          |
| 7      | 840                | 32             | 0.202   | 73.5            | 0.064       | 65                                       | 0.222         | 128                                  | 0.183          | 234                               | 0.055          |
| 8      | 960                | 35             | 0.142   | 72.0            | 0.064       | 65                                       | 0.253         | 128                                  | 0.154          | 220                               | 0.097          |
| 9      | 1050               | 37             | 0.184   | 89.5            | 0.064       | 65                                       | 0.272         | 128                                  | 0.172          | 221                               | 0.090          |

Figure 2. AE signal Vs machining time (speed of 2800 rpm, axial DOC of 50 µm and feed rate of 2 µm/flute).

Table 1 exhibits the experimental values of the tool wear, Rₐ, chip thickness and the AE_RMS signal processed in time as well as in the frequency domain. Figure 2 shows the typical AE signal obtained in the time domain. Figure 3 shows the response graph of the AE_RMS with the machining time. The AE_RMS values have shown good association with respect to the tool wear. From figure 3 based on the AE_RMS values and tool wear, the tool wear regions in micro-endmilling may be identified as initial, progressive and accelerated wear regions. From Table 1 and figure 3, it is noted that the tool wear linearly increases with the machining time up to 19 µm may be due to run-in wear. In the middle region there shows the progressive wear up to 32 µm as the machining time increases and at the end it again increases from 32 µm to 37 µm, which indicates the accelerated wear. It is noted that the minimum tool wear is found in progressive wear region. This result shows the tool wear behavior of micro-endmilling is similar to that of macro-endmilling.
From Table 1, it is observed that the $R_a$ and chip width are in non-linear trend with respect to the wear rate. This is because of the non-continuous cutting, and also the influence of the size effect (ratio of micro-endmill nose radius to the uncut chip thickness). The literature also indicates that the formation of the buildup edges and re-disposition of buildup edges on the chips influence the non-linear trend of $R_a$ and chip width, with the response of the tool wear (Sooraj and Jose., 2011).

Figure 4 shows the spectra (power spectral density (PSD)) of the AE signal with the wear rate. From Table 1 and figure 4 it is found that most of the dominant frequencies occur at three different regions around 65 kHz, 128 kHz and 220 kHz-270 kHz. The high frequency region around 220 kHz-270 kHz indicates the machining frequency (micro-endmilling). The other frequency activities occur at low frequency regions such as 65 kHz and 128 kHz, indicating the tool rotational frequency and tool passing frequency. From figure 4 it is also noted that, the peak value of the dominant frequency for tool rotation (65 kHz) is found to increase with time, while the amplitude of the tool passing and machining frequencies are found to decrease.
Figure 5. Welch power spectra of the AE signal.

Figure 6. Typical spectrogram and AE signal in time domain (tool wear 9 μm).

Figure 5 shows the Welch power spectral density of AE signals with wear rate. From figure 5 the tool rotational frequency (65 kHz), tool passing frequency (128 kHz) and machining frequency (220-270 kHz) are observed. From figure 5 it is also recorded that the AE signal above 300 kHz of frequency are not significant.

Figure 5 shows the typical spectrogram (time-frequency domains) generated, using the STFT method considering one tooth and two teeth cutting. From figure 6, it is observed that the narrow band width of the frequency spectrum appears at 65 kHz and 128 kHz, during tool rotation and tool passing respectively, while the wide bandwidth of the frequency spectrum appears at the machining frequency from 220 kHz-270 kHz. However, the spectrogram does not provide any significant information on the tool wear status. Therefore, the WT technique is performed to correlate with the tool wear status, which is detailed below. In the WT, the AE signal is discretized into Five different frequency ranges, named as, D1,D2,D3,D4 and D5 respectively with the frequency ranges (500-1000 kHz), (250-500 kHz), (125-250 kHz), (62.5-125 kHz) and (32.25-62.5 kHz).
Figure 7. Specific energy distributions of the discretized AE signal.

Figure 8. Surface topography of the machined surface.

Figure 9. Tool images at the various stages of the machining.
Figure 10. Chip structure at different tool wear rate.

The AE energy is directly proportional to the area under the AE waveform. It is calculated using the following Eq. 1.

\[ E_{AE} = \int_{t_0}^{t_1} (V_{AE}(t))^2 \text{dt} \]  

where \( V_{AE}(t) \) - recorded voltage for each decomposed AE signals (i=1 to 5), \( t_0 \) to \( t_1 \) is the starting and ending time of the acquired AE signals.

The AE specific energies are calculated to analyse the discretized AE signal, and are presented in figure 7. Figure 7 shows the discretized signals D1, D2 and D5 are not sensitive whereas the D3 and D4 are sensitive with the wear rate. The D3 and D4 values have shown increasing and decreasing trends. The higher AE specific energy distribution at the D3 and D4 shows that shearing dominates during material removal (Lee at al., 2006). Figure 7 indicates that during the initial wear region, the AE specific energy is high. However, lower values are observed at the progressive wear region. This indicates that a lower order of generation of AE occurs during the effective tool/workpiece interface. In the accelerated wear region, it is noted an increasing AE specific energy value. This may be due to the rubbing/ploughing action because of the increased tool edge radius. These phenomena can also be
observed from the surface topography of the machined surface in figure 7. Figure 8 also indicates the ploughing effects as the tool wear progresses from the lower to the higher levels.

Figure 9 shows the SEM photography of the tool wear at different time intervals. During the initial stages, the tool is found to be fresh (new), and generates chips with large and continuously curved shapes (figure 10a to figure 10c). During the progressive wear region the chips are found to be mostly flat and without any curling (figure 10d to figure 10f). During the accelerated wear region the chips were found to be short coma and without curling (figure 10g to figure 10i). The formation of short coma chips without curling indicates that the tool has reached the end of its life. Hence, the chip formation process during micro-endmilling also helps to classify the tool wear regions.

4. Conclusions
In this study, AE based tool wear identification was carried out during the micro-endmilling of mild steel. The collected AE signals were processed in the time domain, FFT, STFT, and WT analyses. The Welch power spectral density and spectrogram analysis were used to identify the dominant frequencies. The DWT technique was also used to decompose the AE signals. The higher AE specific energy of the decomposed AE signal is correlated with the chip formation mechanism. The chip structure are also used to identify the different tool wear regions.

1. Wear rate in micro-end mill shows the linear trend with the machining time and AE_{RMS}, where as a non-linear trend is observed with R_a and chip width.
2. Three different tool wear regions like macro-regime machining are identified, such as initial wear (up to 19 µm), progressive wear (up to 32µm) and accelerated wear (up to 37 µm).
3. From the spectrum analysis, it is observed that the micro-endmilling exhibits three dominant frequency activities at three different regions, such as the tool rotational frequency (65 kHz), tool passing frequency (128 kHz) and machining frequency (220 kHz to 270 kHz) in the micro-end mill.
4. Among the discretized AE signals, it is found that the D3 and D4 of (125-250 kHz) and (62.5-125 kHz) levels are dominant during machining due to shearing. The specific energies of the discretized AE signals help to indicate the chip formation mechanism.
5. The levels of AE specific energy are high when the ploughing is more dominant than the shearing.
6. From the chip morphology studies, it has been found that the formation of short coma chips without curling indicates that the tool has reached the end of its life.

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