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Tool condition monitoring in micro-machining of brittle materials using acoustic emission sensor and cutting force dynamometer

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Abstract

Brittle materials, such as ceramics and glass, are challenging to machine due to their tendency to fracture under stress, making tool wear monitoring critical for ensuring machining quality. Consequently, Tool condition monitoring (TCM) is essential in micro-machining brittle materials to enhance precision, tool life, and surface quality. This research aims to investigate the effectiveness of combining an acoustic emission (AE) sensor and cutting force dynamometer for real-time tool wear monitoring in the micro-machining of brittle materials. The experimental setup involved micro-machining operations using a high-precision dynamometer to measure cutting forces, while an acoustic emission sensor was employed to capture high-frequency signals indicative of crack propagation and tool wear. 0.9 mm diameter diamond coated end mills were used to machine single crystal silicon workpiece. The collected data were processed and analysed to correlate the acoustic emission and cutting forces with different stages of tool wear and material removal conditions. Results display a strong correlation between increased cutting forces, amplified acoustic emissions, and the onset of tool wear. The acoustic emission sensor was particularly sensitive in detecting micro-cracks and minor tool degradation that were not immediately apparent from force measurements alone. Additionally, the integration of both sensors provided a comprehensive monitoring system, enabling more accurate predictions of tool life and reducing the risk of catastrophic tool failure.

The study concludes that the combined use of AE sensors and cutting force dynamometers offers a robust, non-intrusive solution for tool condition monitoring in micro-machining brittle materials, enhancing machining performance and reducing downtime due to unexpected tool failures.

Micro-milling, Brittle materials, Tool condition monitoring, Edge chipping, Feature extraction

1. Introduction

Micro-milling is a precision machining process aimed at facilitating an enhanced requirements of high machining efficiency, materials surface characteristics, extremely close tolerances, machine positioning accuracy and dimensions. [1-4]. These processes have gained tremendous grounds due to an increased demand in the miniaturization of manufactured engineering parts and complex features (micro parts) of high integrity, good surface finish, and with accuracy lower than one micron [2-3]. Thereby becoming more fundamental in the automotive, communication, electronics, pharmaceuticals, biomedical, aerospace, and mechanical industries. [2-4].

Brittle materials, such as ceramics, glass, and silicon, play a pivotal role in technological growth due to their unique properties, including high hardness, thermal stability, and electrical insulation. These materials enable miniaturization, durability, and efficiency, driving innovation in high-tech industries. According to the Global Semiconductor Market, silicon was said to be the backbone of the $500+ billion semiconductor industry, powering technologies from microprocessors to memory chips. The advanced ceramics and glass market is projected to reach $143 billion by 2030, driven by growing demand across various industries.

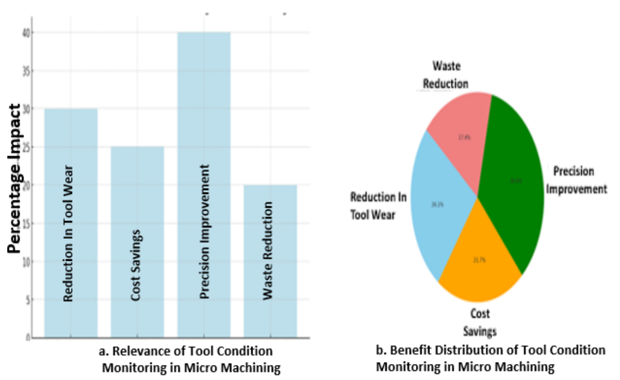

Figure 1. Importance of TCM in Micro Machining

Brittle materials such as silicon and glasses are quite difficult to machine because of their high hardness and low toughness. These materials often deform elastically prior to fracture by the catastrophic propagation of cracks and fracture under impact and cutting. [4]. Despite successfully machining of miniature parts and complex shapes with high accuracy, micro machining encountered problems such as tool wear and tool failure. Tools which are small and long, could not withstand the generation of contact machining forces leading to tool formation, chatter and vibration, and tool stress, thereby causing tool breakage [3]. Machine failure has become more costly and has undesirable effects on the availability and the productivity. Past research shows that tool failure amounts to 20% of total milling machining downtime while cost of tools and tools replacements account for between 3-12% of total processing cost.

Consequently, there is need to develop a robust approach for monitoring tool wear by employing Tool Monitoring Condition (TCM). From the above charts, Figure 1a. highlights the percentage impacts of key benefits, such as reduction in tool wear (30%), cost savings (25%), precision improvement (40%), and waste reduction (20%), while Figure 1b. displays the proportional contribution of each benefit to the overall effectiveness of tool condition monitoring.

2. Experimental Set Up

An attempt was made to monitor the tool condition (in-process) using Acoustic Emission (AE) and cutting force dynamometer sensors in micro milling of brittle materials. The machining task was performed using a CNC Mini-Mill/GX with an NSK NR-3060S ceramic bearing spindle powered by a NSK EM-3060 350W brushless motor. The allowable motor speed of the spindle is between 5,000-60,000 rpm. milling machine has an XYZ table resolution of 0.0001 mm.

Cutting force and acoustic wave signals were taken during the milling operation with the aid of a dynamometer and acoustic emission sensors respectively. These sensors are to be mounted closely to the cutter-workpiece interface on the milling machine as shown in the Figure 2. Tool wear and tool failure are evaluated against some machining parameters to ascertain the relationship between flank wear, cutting edge, AE signals and cutting force dynamometer signals in micro milling of silicon and glass.

Glass and silicon workpiece samples were both cut to sizes of 40 mm by 20 mm and were waxed on an aluminium plate of 65mm X 40mm X 15mm using a VWR-355 Hotplate. The specification of these materials is shown in Table 1. The plate is then clamped on the three-axis Kistler 9256C mini dynamometer, and Kistler Piezotron 8152C AE sensor screwed with an M6 to the plate.

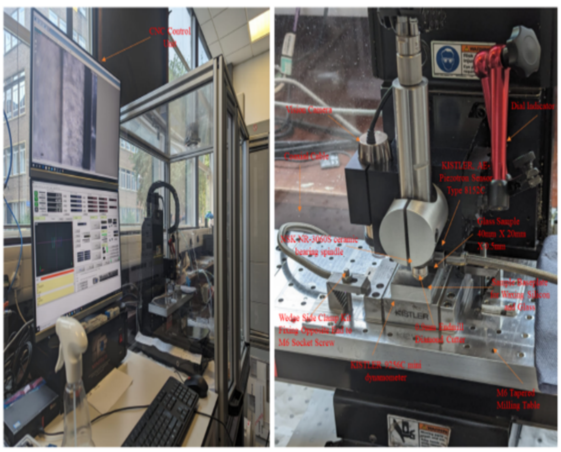

Figure 2. Experimental Setup for Micro Milling

The AE and cutting force signals are acquired at a sampling frequency of 100 kHz and 40 kHz respectively. Micro-Precision short carbide + Graphix 888507G0090 cutting tool of 0.9 mm diameter end mill (2 flute) with a 30° Helix angle was used for the slot milling operation throughout the experiment.

Table 1. Material Specification

Material Specification	Silicon	Glass
Density (Kg/m3)	2329	2465
Young's Modulus (Pa)	1.63E+11	6.99E+10
Poisson Ratio	0.27	0.215
Coeff. of Thermal Expan. (K^{-1})	2.58E-06	9.34E-06

Six sets of experiments (3 each for silicon and glass) were performed to machine 12 slots size each on the workpiece using new tool, slightly worn-out tool, and severely worn-out tool. A total of twelve (12) diamond cutting tools were used, with each of the experiment performed six (6) times. The tool in each experiment is used to perform the continuous milling process until it reaches a bad stage (completely worn-out). A spindle speed of 25,000 rpm, a 30 µm depth of cut, and a feed rate of 1 µm/rev were used as the machining parameters for glass. The same parameters were applied for machining silicon, except for the depth of cut, which was set to 15 µm.

3. Tool Wear Monitoring

The direct and indirect methods of TCM were adopted and compared in this research work. In the direct TCM method, after each of the experimental tasks, the cutting edge (or flank face) and workpiece machining surface were examined and analysed first with a DinoCapture 2.0 camera and later checked for proper viewing and analysis under Scanning Electron Microscopy (SEM). These images were properly monitored under the same vision systems and compared with that of the new tool.

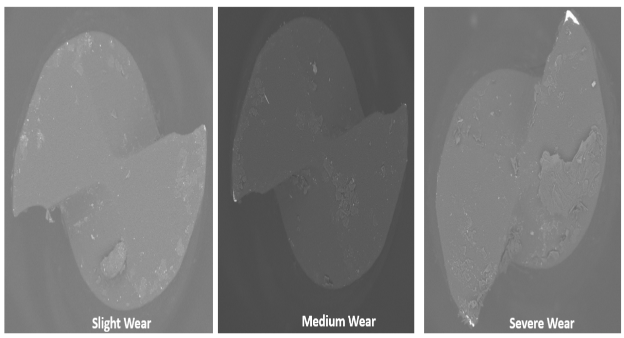

Figure 3. Tool Wear Stages

Variations in cutting edge radius was used as a criterion for tool wear measurement. The ratio of the used cutting tool edge radius, after each experiment, to the new cutting tool edge diameter was used to compare and determine the various tool wear values, VB. Plotting the tool wear value, VB with the cutting length (or machining time) defines the tool wear stages. These stages are identified as the slight wear, steady wear, and severe wear (Figure 4). This analysis is then compared to the features extracted from the signal processing using time domain, frequency domain (Figure5.) and wavelet decompositions (Figure 6). A TCM model is trained and predicted.

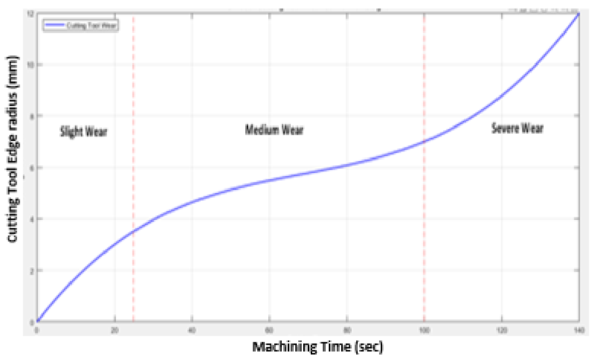

Figure 4. Change in tool wear VB value with the number of cutting times.

The indirect TCM method entails four basic processes such as data acquisition, data processing, features extraction and training a prediction model. Data acquisition (DAQ) system collects measurement data of physical conditions and send same to the computer for storage, monitoring, and/or processing, for future analysis. It is basically made of an analogue-to-digital (ADC) converter and output/display unit. The acquired signals were processed for amplification, filtering, denoising and feature extractions. These signals were represented in time domain, frequency domain and time-frequency domain. The processing of cutting force and AE signals for all the experiments are carried out using 7-Level 1-D Continuous Wavelet Decomposition method with Db-4 5]. The spectral densities of the respective signals are shown in Figure 5 and 6.

The feature selection process employed a multi-stage approach to identify the most relevant predictors for tool wear in micro milling. Initially, we extracted an extensive set of features across time domain (statistical moments, peak-to-valley ratios), frequency domain (power spectral density, dominant frequencies), and wavelet domain (energy distribution across decomposition levels).

The selection criteria are primarily based on two quantitative methods:

i. Principal Component Analysis: We identified features contributing significantly to the first three principal components, which accounted for 87% of data variance.
ii. Information gain ranking: Features were ranked by their information gain with respect to tool wear classes, with a threshold of 0.5 used for feature inclusion.

The selection methodology prioritized features demonstrating both statistical significance ($p < 0.01$) and physical relevance to the micro milling process mechanics. This balanced approach ensured the model captured meaningful signal patterns while maintaining computational efficiency.

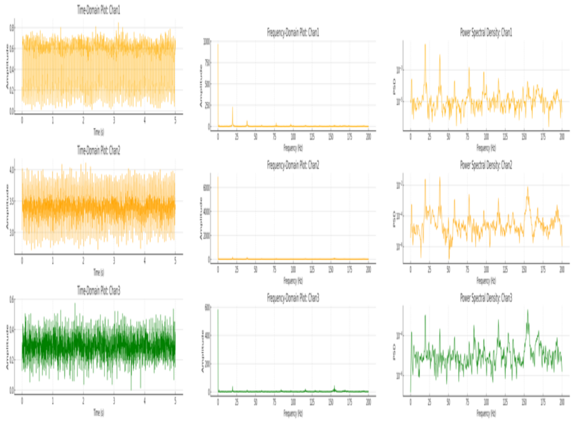

Figure 5a. Power Spectrum Density from the AE Signals

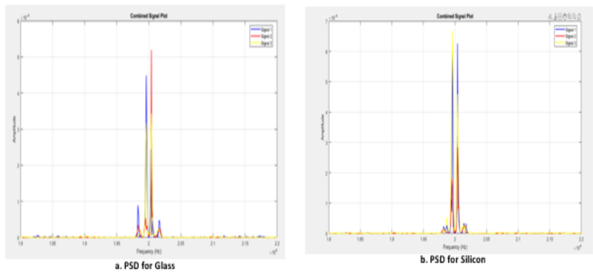

Figure 5b. Power Spectrum Density from the AE Signals

Just like other common features, the Power Spectrum Density (PSD) possess same trend (with the AE signals) and reflects how the power of each signal is distributed across the frequency range, particularly focusing on a region centred around 2×10^4 Hz. For all three wear conditions (for both glass and silicon), most of the energy is concentrated near 2×10^4 Hz, suggesting that this frequency band is critical for diagnosing wear. The progression from slight wear (S1) → medium wear (S2) → severe wear (S3) shows an increase in both the number and magnitude of peaks. The Power Spectrum Density plot reveals a clear progression of energy across the three wear conditions: S1 - Low vibration energy (stable tool condition), S2 - Increased energy and new peaks (medium wear) and S3 - Highest energy and sharp peaks (severe wear). This trend indicates that wear severity introduces more excitation into the system, resulting in higher energy across the spectrum. The emergence of new frequency peaks in S2 and S3, which are absent or minimal in S1, may be attributed to specific fault mechanisms or vibration modes induced by wear. Hence, there is a clear relationship between PSD amplitude and wear severity, as higher PSD values in S2 and S3 reflect the growing impact of wear on the system. The PSD analysis confirms that the frequency band near 2×10^4 Hz is a critical diagnostic region for identifying and monitoring wear in the tool.

Figure 6. Power Spectrum Density from the Force Signals

Similarly, the overall trend of increasing PSD values with wear level progression (Slight to Medium to Severe) is still evident. This suggests that higher wear levels generally lead to increased vibration energy across the frequency spectrum. A summary of the overall comparison for PSD for the cutting force signals is shown below.

Table 2: Overall Comparison Between the Force Signals

Aspect	Slight Wear	Medium Wear	Severe Wear
Low Frequency Power (0 – 50Hz)	Concentrated with sharp peaks	Increased and broader peaks	Distributed and irregular
High Frequency Power (>100Hz)	Minimal	Noticeable	Significant
Peak Sharpness	Sharp and direct	Broader and less distinct	Highly irregular
Channel Behaviour	Consistent across channels	Increasing variability	High variability

4. Prediction Model

Most extracted features from AE signals in time domain, frequency domain and wavelet decompositions have a trend, and unlike the force signals. These features were selected and trained to predict a monitoring model first with Random Forest classification and then using Neural Network (Figure 7).

The Principal Component Analysis (PCA) plot, (Fig 7a), illustrates the distribution of data points after reducing dimensionality to two principal components. The data points are well spread across different regions of the plot.

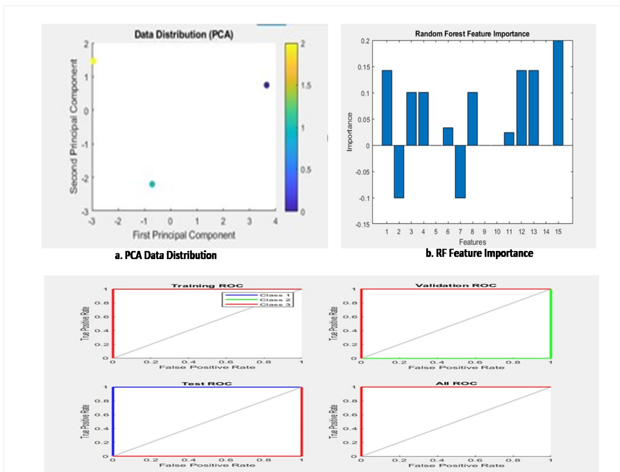

Figure 7. Predictive Trained Model

The scattered point in different colours shows different wear conditions. The clear separation proves that the PCA effectively distinguish between wear states. The extracted time domain, frequency domain and wavelet decomposition features were tested for their level of importance using Random Forest model. Figure 7b shows the extracted feature importance for a RF model with spectral energy (feature 15) having the highest importance in contributing positively to the model's predictions. The Receiver Operating Characteristic (ROC) curve (Figure 7c) shows the relationship between True Positive Rate (TPR) and the False Positive Rate (FPR) for each class during training, validation, and testing phases. The classifier achieves 100% sensitivity and specificity with none of the ROC line lie along the grey line. This consistency across the Training, Validation, Test, and All ROC plots confirms that the model generalizes well without overfitting to the training data.

5. Conclusion

Performance of tool condition monitoring was analysed with micro machining of brittle materials using AE sensor and dynamometer. Signals were collected, processed and analysed for the two materials using same machining parameters. The extracted features from the AE signals (for silicon and glass) correlates with the direct TCM method as the extracted features possess significant trends, thereby indicating tool wear stages. The extracted force signals show no significant trend. A predictive TCM model was then developed with Neural Network algorithm for tool condition monitoring.

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