euspen's 21st International Conference & Exhibition, Copenhagen, DK, June 2021
www.euspen.eu

Real-time tool monitoring in a smart machining cell

Guan Leong Tnay[1*]; Binish Mohan[2]; Keng Soon Woon[2]

[1]*Singapore Institute of Manufacturing Technology, Singapore*
[2]*Department of Mechanical Engineering, National University of Singapore*

gltnay@SIMTech.a-star.edu.sg

Abstract
Tool conditions have a direct impact on machining quality. Practical machining applications require reliable tool condition monitoring systems that detect potential tool failures. Two methods are commonly used to monitor tool conditions: direct and indirect sensing. Direct measuring methods involve the use of optical / digital microscopy and automated tool setting system. While indirect measuring methods are usually based on cutting signals like acceleration, force, acoustic emission, etc., and the correlation of these signals with changes in tool conditions. To detect conditions of cutting tools right before failure is necessary to reduce the tooling cost and avoid damage to the workpiece. In this paper, a novel method using non-contact auto tool measurements (ATM) to monitor the tool wear pattern and failure modes such as build-up edge and chipping. Milling experiments are conducted in an automated machining cell which is integrated with the EROWA Job Management System. The result of the wear behavior obtained from ATM and tool wear measured from the digital microscope are calibrated to the signals from spindle load and vibrations with an Artificial Neural Network (ANN) model. This results show that the novel method is capable to detect micro-chipping and predict the tool wear accurately.

Wear; Smart Machining; Tool Condition Monitoring

1. Introduction

To achieve good quality and prevent job failure in machining, it is necessary to have a monitoring system that can real-time monitor the cutting process. Monitoring method has been largely developed [1] in the past. However, all these sensors could be quite costly which most of the workshops are unfordable hence built-in spindle load/ vibration is utilized for monitoring. The signal from the built-in spindle load give the complex relationship to tool wear as compared to other types of sensor, ex. force sensor. In this paper, we presented a novel method using non-contact tool measurement to monitor the cutting behaviour which also explain the chaotic signals of spindle load and vibration signal in Aluminium machining.

2. Methodology

2.1. Smart machining cell architecture

The experimental works are performed with the smart engineering system as shown in Figure 1. The Makino F3 CNC milling machine, Hexagon coordinate measurement machine (CMM) and Fanuc robot arm are integrated by the Erowa Job Management System. Built-in spindle load and vibration sensor is installed in the F3 CNC for monitoring the cutting condition and the Blum Micro Compact NT non-contact auto tool measurement (ATM) for measure the tool length and tool radius. The measuring data are stored in the databased for predict the tool wear.

2.2.Milling experiments

Milling of AL T6061 plate with Daphne Cut HL-25 Synthetic base oil are conducted in F3 3axis CNC machine. The work holding device is using the EROWA chuck ITS diameter 148 with repeatability accuracy of +/-0.001mm as shown in Figure 2. The tool path for the pocket machining is generated from the 3D Experince- Delmia. The cutting parameters for each cycle are depth of cut – Radial= 2.4 mm & Axial= 1 mm, cutting speed= 150 m/min, feedrate= 0.025 f/tooth and diameter 6 mm carbide cutter was used. After each machining cycle, the tool length and radius is measured by ATM. The dimension of the pockets was measured after every 3mm depth.

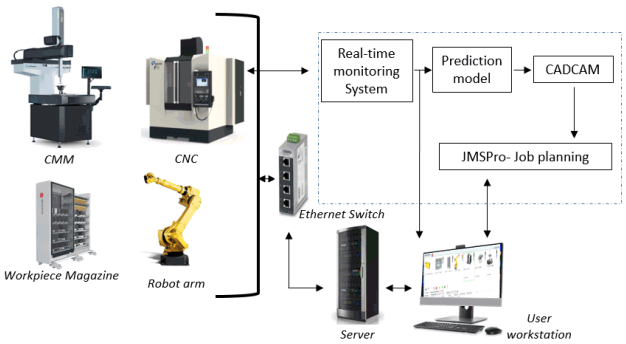

Figure 1. Smart machining cell architecture

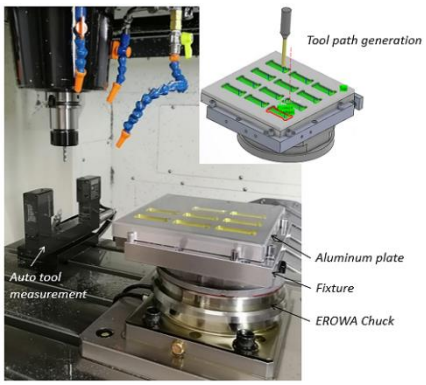

Figure 2. Experimental setup and tool path generation

2.3. Tool wear prediction model

The tool wear prediction model with Artificial Neural Network (ANN) is developed in Matlab [2]. The model was trained under supervised learning using five different sets of data namely, measurement points, spindle load, vibration, tool length, and tool radius. Flank wear was used as the targeted prediction. Training function of TRAINLM is selected to ensure faster convergence and higher accuracy. To further improve the accuracy of the model, 10 neurons in input layer, 7 hidden layer and 30 training times were set. Figure 3 shows predicted flank wear is very close to the experimental outcomes with a R^2 value of 0.9857.

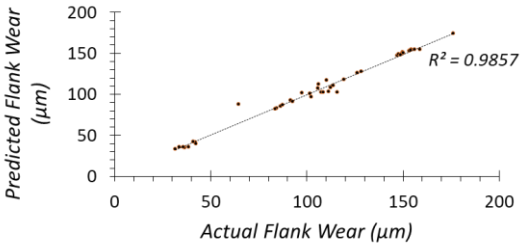

Figure 3. Tool wear prediction with ANN model

3. Results & Discussion

The ATM is able to accurately measure in the micron-scale, which allows us to understand the signals behaviour and diameter tool wear (Figure 4). Due to the tool worn out the workpiece pocket size also reducing gradually (Figure 5). Spindle load and vibration with RMS value are compared to the tool length measurement as shown in Figure 6. An interesting finding was observed in which the tool length data followed the inverse moving average trend line (red doted line) of the spindle load and same trend line to the vibration. And it was also observed that the tool length further increased up to certain cutting length then reduced again. This phenomenon is due to built-up edge (BUE). When the BUEs are detached from the cutting edge, the tool length is seemingly reduced. In addition, BUEs also lead to overcut on the surface, where the subsequent cut will become shallower. Therefore, the spindle load is lesser than the previous cut, once the BUE is removed. Then the cutter will resume to the actual cut, and resulted in increasing load again as shown in Figure 7. The cyclical BUE formation and collapse will weaken the cutting edge progressively and finally leading to edge chipping.

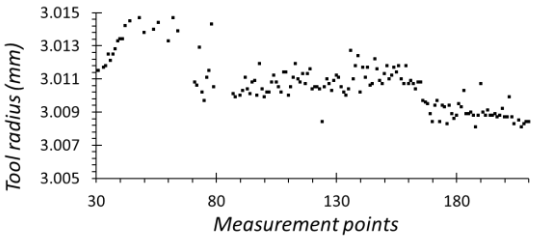

Figure 4. Cutting tool dimeter worn out which measured by ATM

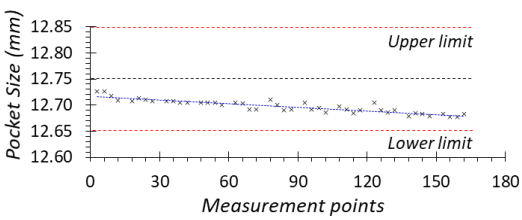

Figure 5. The dimension of the pockets measured by CMM

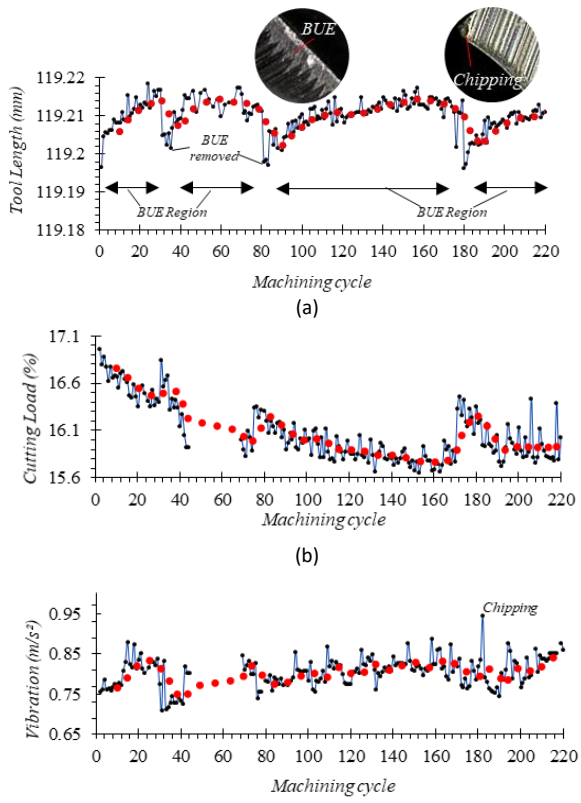

Figure 6. Comparison between build-up edge generation on the cutting edge using (a) ATM, (b) spindle load and (c) spindle vibration

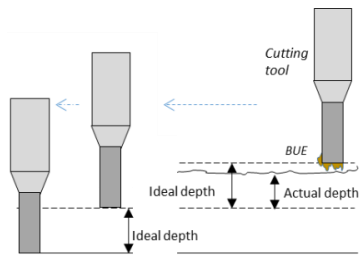

Figure 7. The effect of build-up edge causing the material over cut

4. Conclusion

In this paper, an interesting finding was discovered from the ATM. Result shows the ATM could accurately detect the BUE and tool diameter worn out, which allow us to understand the unusual cutting load and vibration signal behaviour. With that, the tool wear prediction ANN model was successfully developed. Extensive experimental study with different parameters will be carry out in the future works.

Acknowledgement

The authors gratefully acknowledge the generous support of SIMTech, Model Factory partners; Makino, Erowa, Hexagon & Dassult System for providing the equipment & software to carry out this research work. This work is supported by A*STAR IAF-PP Cyber-Physical Production System - Towards Contextual and Intelligent Response (A19C1a0018).

References

[1] Chandra Nath 2020, Integrated tool condition monitoring systems and their applications: A comprehensive review, *Procedia Manufacturing 48*, 852-863

[2] T. Mikolajczyk et al. 2018, Predicting tool life in turning operations using neural networks and image processing, Mech. Syst. Signal Process., **104**, 503-513