Journal of Machine Engineering, 2018, Vol. 18, No. 1, 5-17
ISSN 1895-7595 (Print) ISSN 2391-8071 (Online)

Received: *06 February 2018* / Accepted: *19 February 2018* / Published online: *12 March 2018*

adaptive control,
tool condition monitoring,
intelligent machining

Mahmoud HASSAN[1]
Ahmad SADEK[2]
M. Helmi ATTIA[1,2*]
Vincent THOMSON[1]

INTELLIGENT MACHINING: REAL-TIME TOOL CONDITION MONITORING AND INTELLIGENT ADAPTIVE CONTROL SYSTEMS

Unmanned manufacturing systems has recently gained great interest due to the ever increasing requirements of optimized machining for the realization of the fourth industrial revolution in manufacturing 'Industry 4.0'. Real-time tool condition monitoring (TCM) and adaptive control (AC) machining system are essential technologies to achieve the required industrial competitive advantage, in terms of reducing cost, increasing productivity, improving quality, and preventing damage to the machined part. New AC systems aim at controlling the process parameters, based on estimating the effects of the sensed real-time machining load on the tool and part integrity. Such an aspect cannot be directly monitored during the machining operation in an industrial environment, which necessitates developing new intelligent model-based process controllers. The new generations of TCM systems target accurate detection of systematic tool wear growth, as well as the prediction of sudden tool failure before damage to the part takes place. This requires applying advanced signal processing techniques to multi-sensor feedback signals, in addition to using ultra-high speed controllers to facilitate robust online decision making within the very short time span (in the order of 10 ms) for high speed machining processes. The development of new generations of Intelligent AC and TCM systems involves developing robust and swift communication of such systems with the CNC machine controller. However, further research is needed to develop the industrial internet of things (IIOT) readiness of such systems, which provides a tremendous potential for increased process reliability, efficiency and sustainability.

1. INTRODUCTION

Smart manufacturing systems provide a dynamic stream of the machine health and performance status data using integrated sensors [1]. This data is integrated with advanced computer modelling and simulation to achieve a robust manufacturing monitoring intelligence [2]. When further combined with real time adaptive control system, the machining process is constantly regulated to the changing tool and component

[1] Department of Mechanical Engineering, McGill University, Montreal, QC, Canada
[2] Aerospace Structures, Materials and Manufacturing, National Research Council Canada, Montreal, QC, Canada
[*] helmi.attia@nrc-cnrc.gc.ca / helmi.attia@mcgill.ca
DOI: 10.5604/01.3001.0010.8811

conditions, within an approved operating process window. This framework will eventually enable manufacturers to achieve optimal production rate, and desired part quality attributes, at lowest cost. To influence this framework, in-depth understanding of TCM and AC fundamentals and their online interactions are essential. Excessive machining forces due to tool wear can cause sudden tool failure and part damage. Machining of critical components, e.g., for aerospace applications, commonly adopt a conservative estimation of the useful tool life to avoid material damage [3]. This impacts the process productivity and cost in applications that involve prolonged machining hours of costly materials. Therefore, online AC systems are deployed to maximize the process productivity and tool life via real-time control of feedrate while maintaining the cutting forces within acceptable limits. Conventional AC systems indirectly monitor the cutting forces via the overall spindle power feedback. However, such feedback cannot indicate the time varying load peaks, which represent the main reason for the tool and part damage. AC systems that depend on empirical models require extensive experimental calibration and cannot estimate the impact of the modified feed on the produced part quality [4]. Applying online AC requires accurate estimation of the impact of the controlled machining conditions, at the estimated level of tool wear, on the produced part quality, to avoid unnecessary process interventions [5].

Tool failure is a complex phenomenon that manifests itself in different and diverse ways:

1. *Wear*: Change in the cutting edge shape, resulting from progressive loss of tool material [6].
2. *Brittle fracture (chipping)*: Crack occurrence in the cutting part of a tool followed by the loss of small fragments of tool material [6].
3. *Breakage*: Loss of a major portion of the tool, which terminates the tool cutting ability [7].

Empirical models such as Taylor tool life equation is not accurate enough to predict tool life due to the complexity of the machining process [8]. Hence, an effective TCM system keeps the cutting tool under surveillance to safeguard the workpiece from damage. It deals with the uncertainty of tool life prediction by estimating the tool condition, based on direct or indirect methods. Direct methods, which rely on direct measurements such as vision methods, can capture actual geometric changes of tool wear but very difficult to implement online [9]. Conversely, indirect methods can be implemented online as they use the existing relationships between process parameters and the process-born features to monitor the tool condition. However, they are very much dependent on the type of machining process and its process parameters [2]. Indirect TCM systems can be categorized based on the failure detection time to three classes; namely, pre-failure, failure and post-failure detection systems. For lengthy tool defect processes such as wear, post failure detection can be tolerated. While for sudden tool failure such as tool chipping and/or breakage, it is crucial to sense the pre-failure phase to provide a time window for corrective actions to safeguard the machined part. Tool edge chipping due to mechanical and thermal loadings in intermittent cutting processes is detrimental but does not prevent cutting totally. However, if it remains undetected, it leads to total tool breakage [7] and adversely affects the surface integrity of the machined part. Studies have demonstrated that this is the dominant failure mode of carbide end mills in high speed roughing operations [10].

Several signals such as forces, acoustic emissions, vibrations, spindle motor power and feed motor current have been reported as good indicators of tool failure detection [2]. Among these methods, the driving motor current has high potential for industrial applications, for being non-intrusive and due to its low cost and high flexibility. Additionally, the conventional TCM signal processing techniques can be classified into: (a) *trend analysis*, which aims at detecting abnormal events in the signal trend compared to the signal history; e.g., changes in time or frequency domain, and (b) *pattern recognition*, which distinguishes between signal segment patterns for different tool conditions. Although combining these two types helps to gather an adequate amount of signal information, it has never been reported in the literature.

Tool pre-failure is defined as the phase of the onset of damage to failure occurrence [11]. In literature, detection of this phase was discussed from the tool wear perspective only [12,13], as it is a lengthy and gradual mechanism. In contrast, pre-failure due to abrupt causes; namely, chipping and breakage, has never been addressed in intermittent cutting. In addition, the bulk of the research work focused on detecting the changes in acquired signals after tool breakage. A significant drawback with TCM systems is that they detect tool breakage within one second [14], by which time, in high speed cutting processes, the workpiece surface integrity may be impaired.

To detect tool condition, the extracted features from the sensor feedback must fulfill the following requirements [15]: (a) identify tool condition under variable cutting conditions and different workpiece and tool materials, and (b) be uniquely distinguishable, to avoid interference with other process irregularities; e.g., material inclusions. Many TCM systems suffer from the lack of key features extraction and generalization, which reduce the systems accuracy and increase their learning efforts. This is mainly due to the absence of a standalone-sensor and a highly informative signal processing technique capable of indicating the tool condition under the high dynamics of complex machining processes. Recent laboratory attempts improved their performance by using multi-sensors and/or multi-signal processing techniques to enrich the system certainty [16]. However, for online applications, this may increase the system response time and lead to unnecessary alarms if the signals are not fused. Numerous multi-sensor systems have been developed based on artificial intelligence techniques, such as linear discriminant analysis, fuzzy logic and support vector machine to fuse acquired signals. These techniques provide high accuracy and prompt response, compared to conventional neural networks [17]. Multi-sensor fusion guarantees a high level of decision certainty, whereas using two signal-processing types for each signal helps gather an adequate amount of signal information. None of the available TCM systems combines both components to achieve such a desirable performance. Additionally, they did not consider working in an AC environment.

2. AC-TCM GENERAL APPROACH

A TCM system should be flexible enough to deal with the high dynamics of an adaptive controlled process. Hence, it is crucial to characterize and select the appropriate means for sensing, monitoring and defining tool pre-failure, failure and post-failure detection due to catastrophic wear, brittle fracture and/or breakage. This process will be a building block in developing a robust and real-time signal processing and decision-making algorithms that can process the feedback signals of multiple sensors, and communicate a decision to the machine controller in the existence of AC environment to safeguard the workpiece. The outcome of these algorithms should be *unaffected* by the different ranges of cutting parameters; namely, the cutting speed, feed and depth of cut, as well as the tool and workpiece materials and cutting tool diameter and number of flutes. The system should also include a self-learning algorithm that can enhance the previous algorithms' performance under process variations. The system learning processes should also be minimized as possible. The AC-TCM system should be applicable to different ranges of cutting applications of different part sizes and materials. To fulfill the abovementioned requirements and constraints, a generalized approach is proposed and shown in Fig. 1.

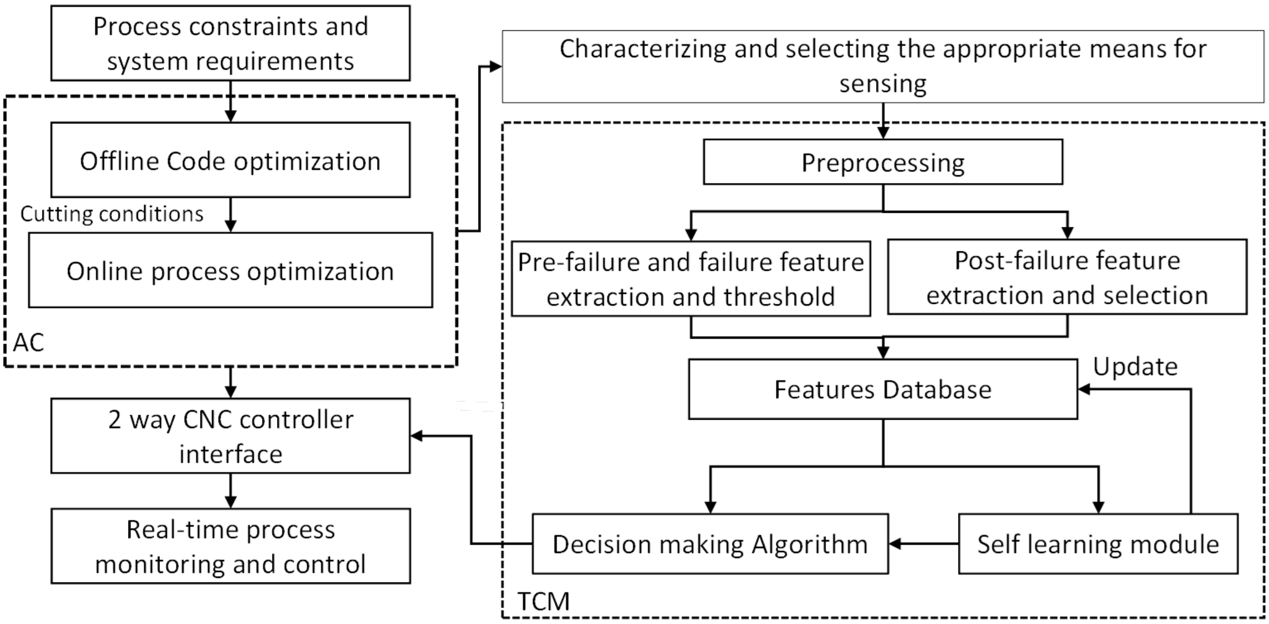

Fig. 1. AC-TCM general approach

A near-optimum NC code should be generated to optimize the cutting conditions with respect to the cutting forces, tool path and tool deterioration phenomena. To deal with the process high dynamics, the NC code should be controlled and optimized online during the cutting process to maintain almost constant cutting forces. Process feedback signals should be characterized for different levels of individual and combined cutting tool defects; to investigate different types of tool failure under different types of cutting conditions and paths with and without the presence of an AC environment. Signals should be characterized for tool pre-failure, failure and post-failure detection, and correlated to the cutting conditions, tool geometry, tool path and condition. To develop a generalized TCM model, acquired signals must be preprocessed to mask the effect of the cutting conditions, tool geometry and the AC system. Subsequently, they should be processed using pattern recognition and trend analysis techniques to extract generalized descriptive features and to define appropriate threshold functions. A database library should be built to link each signal-extracted feature vector to the tool condition, path and family they represent. A decision-making algorithm should be created as well based on fusing the extracted features to increase the system certainty. In addition, a self-learning module is proposed due to the signal and process variations. Based on the available features database, this module should increase the TCM system accuracy by analyzing the biased/unidentified signal feedback, classifying the tool condition and updating the database. In real-time applications, the developed algorithms outcome commands should be fed to the CNC controller using a specified communication algorithm. This algorithm provides real-time control of the cutting process to safeguard the produced part.

3. MODEL-BASED ADAPTIVE CONTROL OF MACHINING PROCESSES

The new generation of online model-based AC systems for drilling of fiber reinforced polymers (FRPs) was presented in [18]. The system generates the online corrective actions based on accurate model predictions of the time-varying cutting forces and temperature, and the associated entry/exit delamination and thermal damage at different cutting conditions and wear levels during drilling of multi-layered FRPs. The offline model predictions are used to identify correlations between the online measured average power and the tool wear level and the critical limits of physical and thermal damage occurrence. The developed correlations are incorporated into the online AC system and are used to generate the appropriate corrective action. Figure 2 shows the adopted approach to develop a model-based AC system for drilling. The offline phase of the AC system receives the model inputs (block 1), which include the material cutting pressures, tool geometry, material configuration and cutting conditions. The generalized predictive model (block 2) is used to achieve the following:

- Offline optimization of the drilling conditions in the NC program (block 5) for maximum productivity and damage-free part machined by a sharp tool, using the limits of the predicted damage (block 3).
- Building the database of correlations (block 4) that relate the drilling forces and tool wear levels, at different cutting conditions.

In the online phase, the first hole is drilled (block 6) using a fresh tool at the optimized drilling conditions. The motor power feedback is fed to the online AC interface (block 8), which uses the model-based force-wear correlations (block 4) to estimate the tool wear level and the subsequent occurrence of delamination and/or thermal damage (block 9). The decision making algorithm (block 10) uses such assessment to recommend one of the following corrective actions, before drilling the next hole: (a) Maintain the same feed of current hole, (b) Maximize the drilling feed for the evaluated wear level, within the constraint of damage-free holes, or (c) Recommend tool change, if the maximum allowable tool wear level is reached.

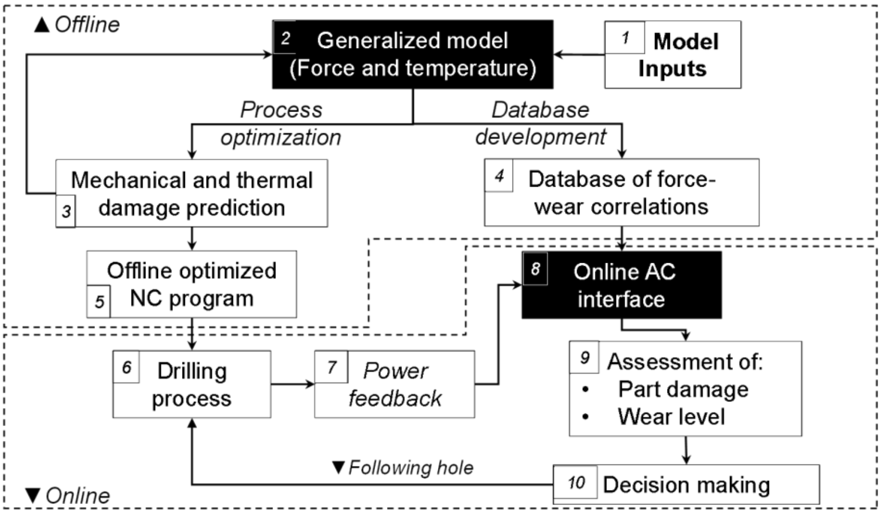

Fig. 2. Layout of the model-based adaptive control system for drilling of FRPs

The details of the predictive model used have been presented in [19]. The experimental validation of the model predictions showed an error of 15% and 5% for the axial force and delamination defect predictions, respectively. The thermal damage predictions were in full agreement with the experimental validation. The performance of the AC system was tested for preventing the occurrence of delamination or thermal damage associated with excessive cutting energy due to tool wear. The initial drilling conditions were selected to achieve maximum productivity and damage-free hole quality. Such requirements were fulfilled by drilling an 8.6 mm thick CFRP laminate using a point drill at n=12,000 rpm and f=0.1 mm/rev.

Figure 3 shows the process performance with and without activating the online AC system, for drilling the 146 holes. For the case of applying the AC system (Fig. 3.a), holes were drilled using the initial feed (f= 0.1 mm/rev) until the maximum force limit for delamination was reached after 69 holes. However, at that point the end of tool life was not reached yet. Therefore, the decision making algorithm decided to continue drilling with a reduced feed of (f= 0.09 mm/rev) for step 2 where the same tool was used to drill 24 more holes until the maximum force limit for delamination was reached again due to further tool wear.

The AC system assessment of tool life showed that the tool was still useful for drilling at step 3 by further reducing the feed automatically to f=0.08 mm/rev, which allowed drilling 53 more holes. This corresponds to a total number of drilled holes of 146 using the same tool. At this point, it was predicted that after 146, thermal damage was approached, and the cycle time will be too large due to low feeds, so the decision of changing the tool was made. Figure 3.b shows the case of drilling the 146 holes at a constant feed f=0.1 mm/rev without applying the online AC system. In this case, the tool would have needed to be changed 2 times in order to avoid the anticipated material damage. The constant drilling feed without AC resulted in a shorter total drilling time (62.78 s) compared to that of the variable feed (69.62 s) in the case of online AC. However, in addition to the tool cost reduction, applying the AC reduced the total cycle time by 45%

compared to that of the constant feed, which accounts for the time needed to perform two tool changes (40 seconds per tool change).

The online AC system also standardizes the corrective actions to eliminate the human decision for either premature tool changes or overuse of tool, which increases the risk of damage. It should be noted that the type of wear considered in this system, is the progressive flank wear in solid carbide tools, which is one of the most common types that occur in drilling of CFRPs [20]. Predicting and preventing sudden tool breakage requires advanced TCM systems that can detect signs of tool prefailure in the feedback signal, as will be discussed in section 5.

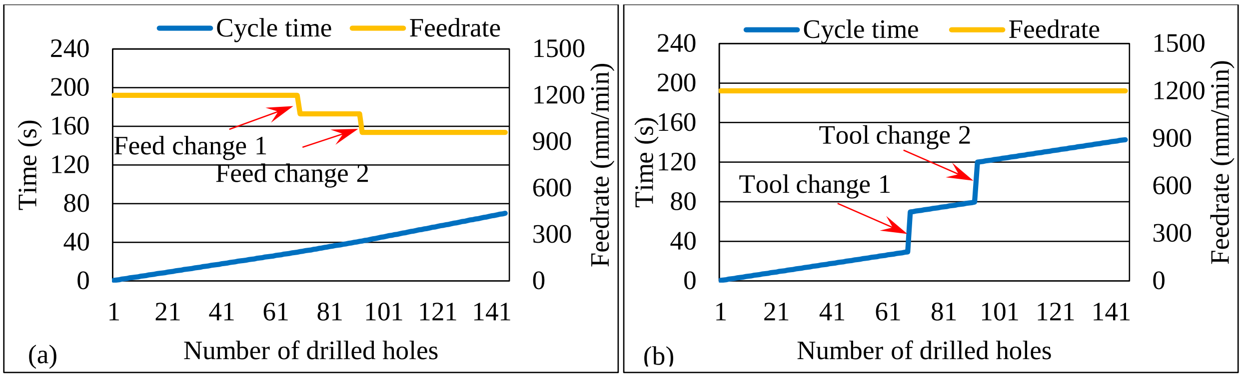

Fig. 3. Process performance (a) with and (b) without the online model-based AC system

4. TOOL POST-FAILURE DETECTION

One of the main drawback of the available TCM systems is the extensive experimental work needed for system learning in order to build a reliable database of features corresponding to different cutting conditions, tool geometries and tool paths. This effort has been minimized by the pre-processing approach introduced in [21]. This approach significantly reduces the required experimental system learning in intermittent cutting operations by masking the effect of the cutting conditions and magnifying the effect of the tool condition. This approach is applicable for the spindle motor current and cutting forces as well. It first filters the acquired signals using the second passing frequency, as a low pass filter, to reduce the signal noises without affecting its fundamental features. Filtered signals are then segmented per tool rotation in the time domain and each segment is normalized with respect to its maxima. The segmentation process provides comparable patterns owing to the repetitive nature of the milling process. An overlapping moving frame is used for the segmentation in order to remove any constraints on the segmented pattern boundaries to match the starting and ending points of the tool/workpiece engagement. Such an action removes the constraints on the segmentation timing and hence provided more ‘generalized features’. Additionally, the normalization process minimizes the effect of the cutting forces represented in the depth of cut and feed as they mainly control the segment peak value during the cutting process. This pre-processing approach has provided unified patterns, independent of the cutting speed, feed and depth of cut. Such patterns are crucial for pattern recognition based TCM systems to minimize the processing time and improves the system reliability. Figure 4 shows the normalized resultant force segments for a fresh and worn tool at the same cutting conditions. The change in the cutting edge geometry, due to tool wear, increased the contact time between the tool and the workpiece, and provided wider peaks in the normalized domain. Such result alters the values of the extracted features in the time and frequency domains, which can be used to detect the level of tool wear.

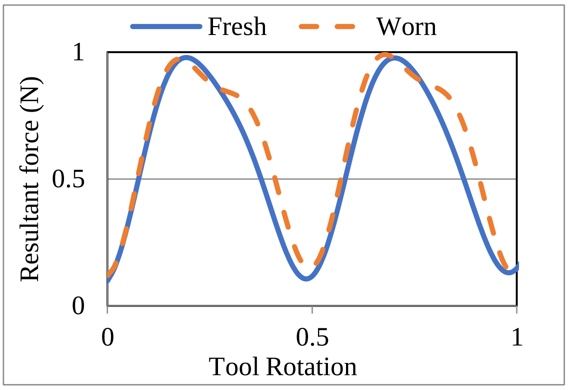

Fig. 4. Shows the normalized segments for a fresh and worn tool

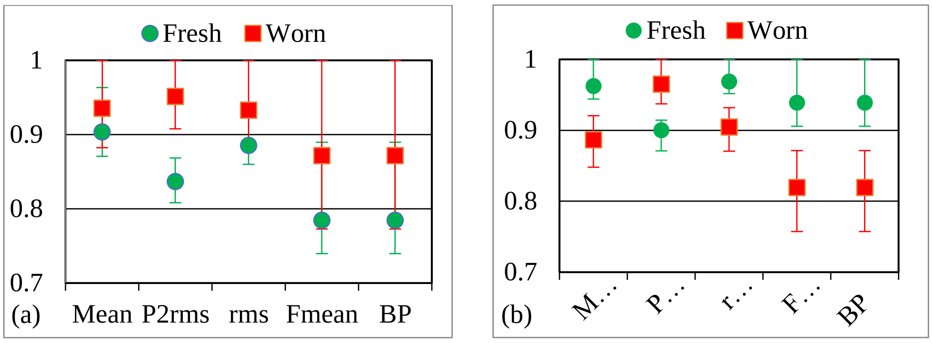

Fig. 5. Features extracted from the resultant current signals (a) before pre-processing and (b) after pre-processing

These extracted features can be used in a pattern recognition technique to classify the tool condition. In [21], more than 40 extracted features have been ranked according to their sensitivity to the tool condition using the results of an N-way ANOVA test. The highest ranked features of the spindle motor current signal in a milling process were the signal mean (*M*), maximum peak of periodogram (P_p), root mean square (*rms*), peak to root mean square ratio (*P2*rms), mean frequency (F_{mean}), band power (*BP*), median frequency (F_{med}), maximum peak of welch power spectral energy (P_w), kurtosis (*K*), minimum (*min*) and variance (*Var*). Figure 5 demonstrates the deviation in the normalized mean values of top ranked features before and after pre-processing for different cutting feed and depth of cut using fresh and worn tools. As seen in this figure, the approach was able to separate the features extracted from the spindle motor current signals into two mutually exclusive clusters according to their tool condition. The pre-processing approach and the ranking analysis results were employed to optimize a Linear Discriminant Analysis LDA model to detect the tool condition in a milling operation. This model was trained using the features extracted from only one cutting condition while tested using new dataset generated from three different cutting conditions. The results have shown that the approach has effectively masked the cutting conditions and signal noises effect on the extracted features and accentuate the tool condition effect. It also provided a robust classification with an accuracy of 93.5% and minimized the learning effort by 75%.

The same pre-processing approach have been applied in [22] to detect tool breakage in milling operations. In this work, the most indicative statistical features that extracted from a power simulated parameter feedback signal have been identified. Based on these features, a K-Nearest Neighbour technique have been applied to capture the tool fracture regardless of the cutting parameters. Using only 3 features, namely the segment minimum value, variance and median frequency, the results have shown a minimum accuracy of 97.5%. The computing time for the pre-processing approach, feature extraction and classification was 1.5 ms, which is equivalent to 0.25 tool rotation at rotational speed of 10,000 rpm. The robustness of the approach allows initiating a corrective action before the broken tool causes irreversible damage to the part.

5. TOOL PRE-FAILURE AND FAILURE DETECTION

In abrupt failure modes, the failure evolution is usually represented by unstable propagation of an existing crack followed by a chipping and/or a breakage event. Therefore, it is vital to study the effectiveness of the indirect process signals to reliably detect, in real-time applications, the tool pre-failure, as well as the failure occurrence due to chipping/breakage. In [23], an experimental setup was devised to induce cyclic impact load on the cutting tool tip in an intermittent turning operation. This type of test allows characterizing the features of the signals collected by various sensors (forces, vibrations, AE and driving motor power) due to unstable crack propagation and tool edge chipping, while ensuring minimal tool wear. Figure 6 shows the normalized feedback signals of the (a) resultant force, (b) vibrations in the feed direction and (c) acoustic emission root mean square (AE_{rms}) for the pre-failure, failure and post-failure stages of a chipping of 0.1 mm on the cutting edge. In coincidence with the tool chipping event, a peak in the resultant force and vibration signals were observed, as shown in Figure 6 (a) and (b). the sensitivity of the cutting forces to the breakage event is due to their sensitivity to tool geometry changes [24]. While the high vibrations generated due to the tool chipping caused an instant high burst in the acquired vibration signals, regardless of the vibrations coming from the tool/workpiece engagements. This shows the cutting forces and vibration signals capabilities to capture tool chipping as small as 0.1mm. However, these raw signals did not show any changes during the pre-failure phase (i.e. unstable crack propagation).

For the AE_{rms} signal, a low peak value followed by a high energy peak were observed at the onset of fracture. In addition, a high peak in the AE_{rms} was captured earlier by three sequential engagements between tool and workpiece (Figure 6.c). This event can be related to the tool pre-failure stage, which is characterized by unstable crack propagation. This peak was not observed in the other measured signals. This is attributed to the AE signal sensitivity to elastic stress waves produced by the release of strain energy during the course of crack evolution [23]. This response recommends using the AE_{rms} signal for real-time tool pre-failure detection as it will allow a sufficient time window of three tool/workpiece engagements in intermittent cutting operations to take the appropriate corrective action. For aerospace applications of high speed milling, typically the cutting speed varies between 6,000-20,000 rpm, which provides a window of 9-30 ms to predict tool chipping/fracture, before a complete tool failure.

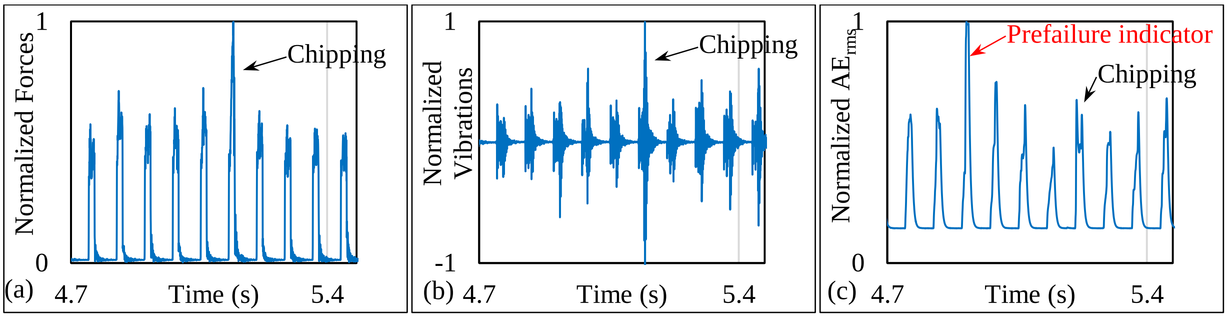

Fig. 6. Normalized signals of (a) resultant force (b) vibrations in feed direction and (c) acoustic emission rms AE_{rms}

A statistical study of the AE_{rms} and vibration signals was carried on at the tool pre-failure, failure and post-failure stages to select the most indicative features to be correlated to the tool condition. The signals were pre-processed using the approach provided in [21] before feature extraction. Figure 7 shows the indicative extracted features for (a) the AE_{rms} and (b) the vibration in the feed direction signals.

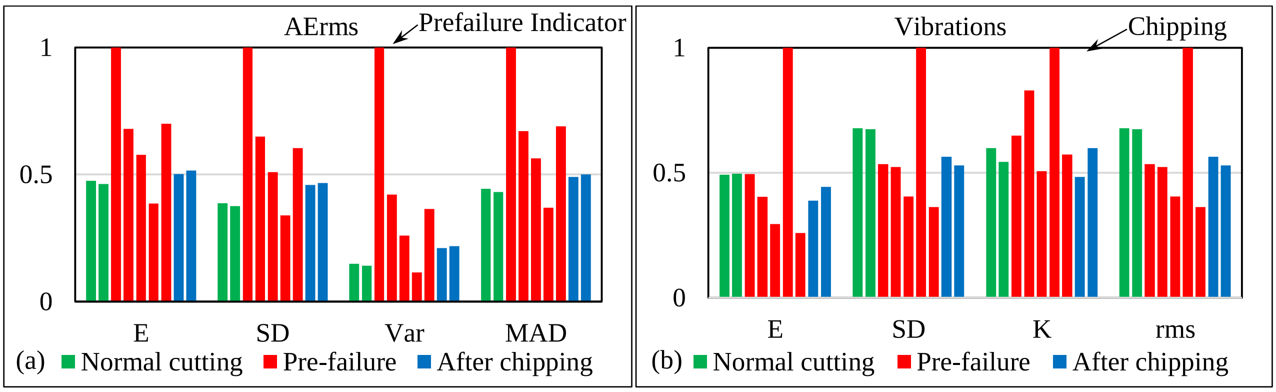

Fig. 7. Normalized feature values of the (a) AE_{rms} and (b) Vibrations in the feed direction signals extracted for pre-failure and failure onset compared to normal cutting and post-failure stages

The figure demonstrates the variation in features at pre-failure phase and failure onset compared to normal cutting and post-failure stages. The features have shown unique trends/values during the pre-failure stage and the failure onset compared to the normal cutting and post-failure stages. The features extracted from the vibration signals during the pre-failure phase have slightly changed in values. However, the variation in these features is insignificant to be used as a pre-failure indicator. On the other hand the AE_{rms} extracted features have shown significant difference during both the pre-failure phase and failure onset. These features variation can be combined with the raw signal peak values to increase the certainty of tool pre-failure detection. Moreover, the AE sensor can fulfill the requirements of real industrial environment applications as it can be implemented without major modification of the machining setups and the machine tool.

It should be noted that the spindle motor power signal did not show a significant increase at the chipping event compared to the normal cutting peak value, which disagree with reported findings in literature [25-27]. This can be linked to the small chipping size (0.1 mm) and the limited sensing bandwidth due to the inertia of the driving motor rotor, which act as a low pass filter at the same motor frequency [28], whereas abrupt failure is a high frequency event.

6. CONCLUSIONS AND FUTURE PERSPECTIVE OF INTELLIGENT MACHINING

This paper presented a generalizing tool condition monitoring approaches for developing intelligent TCM systems that are (a) sensitive to the changes in tool conditions, (b) insensitive to the cutting conditions and AC environments, (c) possessing high level of decision certainty using minimum learning efforts, and (d) performing signal processing and decision making in an appropriate time span. For applying these systems to complex machining processes, further efforts are needed to build a self-learning module that can deal with the high dynamics and variations of these processes. This module should have access to read and edit the TCM system features database as well as the CNC machine controller. The module is anticipated to maintain the logic of the monitoring process to increase the system accuracy. It is expected to mainly depend on artificial intelligence classifiers that analyze the cutting process feedback data from the CNC controller as well as the process-born signals. In case of illogic classification, e.g., classifying two sequential segments as a new and a totally worn tool, the module will diagnose this output depending on the system database, cutting parameters and tool condition history. This output will be used to update the system baseline via a self-learning algorithm.

For tool pre-failure detection, the presented work has demonstrated the potential of the AE signals to detect the unstable crack propagation preceding tool chipping/breakage in a time span of order of 10 ms. Further work is needed to provide a more general system that can detect the pre-failure evolution phase and quantitatively relate the AE signal to the amount of crack propagation for complex machining processes. It should also ensure a reliable and robust tool pre-failure and failure indicator in a timely manner. Detecting the AE waves associated with the generation of new surfaces during unstable crack propagation in intermittent cutting is challenging due: (a) the nonlinearity of the generated AE signal, (b) the non-stationary nature of the stochastic unstable crack propagation process, (c) the contamination of the crack propagation bursts in the AE_{rms} signal by the bursts coming from the force variation, chip formations, rubbing between the tool and workpiece, and the plastic deformation [29], and (d) the infinitesimal time spans of the high frequency bursts inherent in unstable crack propagation. This leaves a relatively short time (on millisecond-scale) for taking corrective actions after detection. In addition, this requires using ultra-high-speed controllers to facilitate robust online decision making within the very short time span for high speed machining processes and a quick stopping mechanism to overcome the inertia of stopping the cutting machine. Such topics would provide a tremendous potential for increased process reliability, efficiency and sustainability.

ACKNOWLEDGEMENT

The authors acknowledge the financial support of the Natural Sciences and Engineering Research Council of Canada (NSERC), and the support of the Advanced Manufacturing Program, and the Aerospace Advanced Material Removal Laboratory of the National Research Council of Canada (NRC-CNRC), where all the tests were conducted.

REFERENCES

[1] UHLMANN E., HOHWIELER E., GEISERt C., 2017, *Intelligent production systems in the era of industrie 4.0-changing mindsets and business models*, Journal of Machine Engineering, 17/2, 5-24.
[2] TETI R., JEMIELNIAK K., O'DONNELL G., DORNFELD D., 2010, *Advanced monitoring of machining operations*, CIRP Annals-Manufacturing Technology, 59/2, 717-739.
[3] ZUPERL U., KIKER E., JEZERNIK K., 2006, *Adaptive force control in high-speed machining by using a system of neural networks*, 2006 IEEE International Symposium on Industrial Electronics, IEEE.
[4] ZUPERL U., CUS F., REIBENSCHUH M., 2010, *Modeling and adaptive force control of milling by using artificial techniques*, Journal of Intelligent Manufacturing, 23/5, 1805-1815.
[5] ALTINTAS Y., 2014, *Adaptive control*, CIRP Encyclopedia of Production Engineering, Springer Berlin Heidelberg, 17-19.
[6] ISO8688-2, 1989, *Tool life testing in milling – part 2: End milling*, International Organization for Standardization, Geneva, Switzerland, International Standard, first edition.
[7] ALTINTAS Y., 2012, *Manufacturing automation: Metal cutting mechanics, machine tool vibrations, and cnc design*, University of Cambridge press.
[8] GRZESIK W., 2008, *Advanced machining processes of metallic materials: Theory, modelling and applications*, Elsevier.
[9] ZHANG D., 2011, *An adaptive procedure for tool life prediction in face milling*, Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology, p. 1350650111414332.
[10] LIU Z Q., AI X., ZHANG H., WANG Z.T., WAN Y., 2002, *Wear patterns and mechanisms of cutting tools in high-speed face milling*, Journal of Materials Processing Technology, 129/1-3, 222-226.
[11] LEI X., 2006, *Typical phases of pre-failure damage in granitic rocks under differential compression*, Geological Society, London, Special Publications, 261/1, 11-29.
[12] KONDO E., SHIMANA K., 2012, *Monitoring of prefailure phase and detection of tool breakage in micro-drilling operations*, Procedia CIRP, 1/0, 581-586.
[13] HSUEH Y-W., YANG C-Y., 2008, *Prediction of tool breakage in face milling using support vector machine*, Int J Adv Manuf Technol, 37/9-10, 872-880.
[14] WANG S-M., HO C-D., TSAI P-C., YEN C., 2014, *Study of an efficient real-time monitoring and control system for bue and cutter breakage for cnc machine tools*, Int J Precis Eng Manuf, 15/6, 1109-1115.
[15] WANG L., GAO R.X., 2006, *Condition monitoring and control for intelligent manufacturing*, Springer.
[16] BHUIYAN M., CHOUDHURY I., 2014, *13.22-review of sensor applications in tool condition monitoring in machining*, Comprehensive Materials Processing, 13, 539-569.
[17] ENTEZARI-MALEKI R., REZAEI A., MINAEI-BIDGOLI B., 2009, *Comparison of classification methods based on the type of attributes and sample size*, Journal of Convergence Information Technology, 4/3, 94-102.

[18] SADEK A., MESHREKI M., ATTIA M. H., 2016, *Adaptive and smart machining: Intelligent model-based online adaptive control system for drilling of frps*, Proc. Wiener Produktionstechnik Kongress, Adaptive & Smart Manufacturing.

[19] SADEK A., SHI B., MESHREKI M., DUQUESNE J., ATTIA M.H., 2015, *Prediction and control of drilling-induced damage in fibre-reinforced polymers using a new hybrid force and temperature modelling approach*, CIRP Annals, 64/1, 89-92.

[20] RAWAT S., AND ATTIA H., 2009, *Characterization of the dry high speed drilling process of woven composites using machinability maps approach*, CIRP Annals, 58/1, 105-108.

[21] HASSAN M., SADEK A., ATTIA M.H., THOMSON V., 2017, *A novel generalized approach for real-time tool condition monitoring*, Journal of Manufacturing Science and Engineering, 140/2, 021010-021010-021018.

[22] HASSAN M., SADEK A., DAMIR A., ATTIA H., THOMSON V., 2017, *Real-time tool breakage detection using k-nearest neighbor method in milling operations*, Canadian Aeronautics and Space Institute – CASI 63rd Aeronautics conference AERO17.

[23] HASSAN M., SADEK A., DAMIR A., ATTIA M., THOMSON V., 2016, *Tool pre-failure monitoring in intermittent cutting operations*, Proc. ASME 2016 International Mechanical Engineering Congress and Exposition, American Society of Mechanical Engineers, V002T002A049-V002T002A049.

[24] LIU C., WU J-Q., LIU H-L., LI G-H., TAN G-Y., 2015, *Geometry features of breakage section and variation of cutting force for end mills after brittle breakage*, Int J Adv Manuf Technol, 1-14.

[25] AMER W., GROSVENOR R.I., PRICKETT P.W., 2006, *Sweeping filters and tooth rotation energy estimation (tree) techniques for machine tool condition monitoring*, International Journal of Machine Tools and Manufacture, 46/9, 1045-1052.

[26] PRICKETT P.W., GROSVENOR R.I., 2007, *A microcontroller-based milling process monitoring and management system*, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 221/2, 357-362.

[27] SIDDIQUI R.A., AMER W., AHSAN Q., GROSVENOR R.I., PRICKETT P. W., 2007, *Multi-band infinite impulse response filtering using microcontrollers for e-monitoring applications*, Microprocessors and Microsystems, 31/6, 370-380.

[28] ABELLAN-NEBOT J., ROMERO SUBIRÓN F., 2010, *A review of machining monitoring systems based on artificial intelligence process models*, Int J Adv Manuf Technol, 47/1-4, 237-257.

[29] HASE A., WADA M., KOGA T., MISHINA H., 2014, *The relationship between acoustic emission signals and cutting phenomena in turning process.* The International Journal of Advanced Manufacturing Technology, 70/5-8, 947–955.