NRC·CNRC

NRC Publications Archive
Archives des publications du CNRC

In-process self-configuring approach to develop intelligent tool condition monitoring systems

Hassan, Mahmoud; Sadek, Ahmad; Attia, Helmi

This publication could be one of several versions: author's original, accepted manuscript or the publisher's version. / La version de cette publication peut être l'une des suivantes : la version prépublication de l'auteur, la version acceptée du manuscrit ou la version de l'éditeur.
For the publisher's version, please access the DOI link below./ Pour consulter la version de l'éditeur, utilisez le lien DOI ci-dessous.

Publisher's version / Version de l'éditeur:
https://doi.org/10.1016/j.cirp.2024.04.049
CIRP Annals, 2024-05-01

NRC Publications Archive Record / Notice des Archives des publications du CNRC :
https://nrc-publications.canada.ca/eng/view/object/?id=00ca9a6f-070b-4fec-afa4-71698780fdf0
https://publications-cnrc.canada.ca/fra/voir/objet/?id=00ca9a6f-070b-4fec-afa4-71698780fdf0

Access and use of this website and the material on it are subject to the Terms and Conditions set forth at
https://nrc-publications.canada.ca/eng/copyright
READ THESE TERMS AND CONDITIONS CAREFULLY BEFORE USING THIS WEBSITE.

L'accès à ce site Web et l'utilisation de son contenu sont assujettis aux conditions présentées dans le site
https://publications-cnrc.canada.ca/fra/droits
LISEZ CES CONDITIONS ATTENTIVEMENT AVANT D'UTILISER CE SITE WEB.

Questions? Contact the NRC Publications Archive team at PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca. If you wish to email the authors directly, please see the first page of the publication for their contact information.

Vous avez des questions? Nous pouvons vous aider. Pour communiquer directement avec un auteur, consultez la première page de la revue dans laquelle son article a été publié afin de trouver ses coordonnées. Si vous n'arrivez pas à les repérer, communiquez avec nous à PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca.

National Research Council Canada | Conseil national de recherches Canada

Canada

CIRP Annals - Manufacturing Technology 00 (2024) 1–4

Contents lists available at ScienceDirect

CIRP Annals - Manufacturing Technology

journal homepage: https://www.editorialmanager.com/CIRP/default.aspx

In-process self-configuring approach to develop intelligent tool condition monitoring systems

Mahmoud Hassan[a], Ahmad Sadek (2)[a,*], Helmi Attia (1)[a,b]

[a] Aerospace Manufacturing, National Research Council Canada, Montreal, QC, Canada
[b] Department of Mechanical Engineering, McGill University, Montreal, QC, Canada

ARTICLE INFO

Article history:
Available online xxx

Keywords:
Cutting
Machine learning
Condition monitoring

ABSTRACT

A self-configuring real-time tool condition monitoring (TCM) system for milling applications using vibration signals is introduced. A suite of signal processing and machine learning algorithms was developed to define a generalized correlation between distortion-resistant features of usable and worn tools. Using only a few seconds of learning data acquired at the early stage of tool life, the system synthesizes worn tool features in-process to define the decision-making boundaries, independent of the utilized cutting parameters, machines, and sensors. It provides high detection accuracy and reduces the lead time and cost needed for system development and calibration, introducing the plug-and-play concept to TCM.

Crown Copyright © 2024 Published by Elsevier Ltd on behalf of CIRP. All rights reserved.

1. Introduction

Tool condition monitoring (TCM) is crucial for minimizing waste, preventing scraping of expensive parts, maintaining machining quality, and increasing machining efficiency. Available real-time TCM systems utilize indirect measurement of process indicators, such as force, vibration, acoustic emission and power signals, which require extensive scientific expertise and long processing times to define the correlation between the acquired signals and the tool condition [1]. The adoption of artificial intelligence (AI) for TCM has expanded to maximize the system accuracy and reliability while minimizing the system learning effort for effective implementation in an industrial environment featuring a large variability in machining platforms, part material and geometry, tools, and sensor configurations [2].

Supervised AI learning methods used for TCM possess severe limitations due to their reliance on [1,3]: (i) overwhelmingly large datasets that still do not fully describe the process (i.e., the nonlinear relation between the acquired signals and the tool condition under different cutting conditions), in addition to the sensitivity of acquired signals to surrounding noises, the development and implementation high cost, and the long lead-time, (ii) generation of labelled data for different levels of tool conditions, which is very difficult to attain in an industrial setting, (iii) static datasets which require allocating production resources to perform learning tests to adapt to the changes in process and platform variables, and (iv) TCM devotion to a specific combination of the tool geometry, machine tool and instrumentation utilized for learning. None of such systems utilized the data collected during the production cycle to perform self-configuring of the dynamic system database.

2. In-process self-configuring TCM approach

This research introduces a *self-configuring* TCM approach that overcomes aforementioned TCM limitations. In [4], the authors introduced a wavelet scattering convolution neural network (WSCNN) TCM approach that provides a stable representation of signals in the time-frequency domain. WSCNN extracts key features associated with signal energy, overcoming crucial TCM development challenges in terms of feedback signal sensitivity to cutting conditions and surrounding noise. This minimized the TCM learning effort to one cut per tool condition. In this paper, the authors extend the WSCNN-TCM system by incorporating self-configuring capability to significantly reduce the TCM learning dependency on tool geometry, sensor characteristics, workpiece material, and machining platform.

In the proposed self-configuring approach, shown in Fig. 1, the WSCNN features are extracted from each 1-second segmented triaxial vibration signals in Block (1). The signal distortions due to variation of cutting conditions are linearized by decomposing the signal $x(t)$ into multiscale information across different frequency bandwidths of cascaded wavelet transforms [4]:

$$Wx(s,\tau) = x * \psi_{s,\tau}(t) = \int x(t)\psi_{s,\tau}(t-\tau)\,dt \quad (1)$$

where $\boldsymbol{W}x(s,\tau)$ denotes the wavelet transform of $x(t)$ at scale s and translation τ, and $\psi_{s,\tau}(t)$ represents the scaled and translated wavelet function. The scattering coefficients $\boldsymbol{S}x(\lambda 1,\lambda 2)$ are then calculated through scaling the modulus of the transformed signals:

$$Sx(\lambda 1,\lambda 2) = |Wx * \phi_{\lambda 1}| * \phi_{\lambda 2} \quad (2)$$

where $|\boldsymbol{W}x*\phi_{\lambda 1}|$ signifies the modulus of the convolution of the wavelet transform at the first layer with a low-pass filter $\phi_{\lambda 1}(t)$, and $\phi_{\lambda 2}(t)$ represents a second low-pass filter. The output of the first WSCNN layer is further sifted through more densely spaced sequences of

* Corresponding author.
E-mail address: ahmad.sadek@nrc-cnrc.gc.ca (A. Sadek).

https://doi.org/10.1016/j.cirp.2024.04.049
0007-8506/Crown Copyright © 2024 Published by Elsevier Ltd on behalf of CIRP. All rights reserved.

Please cite this article as: M. Hassan et al., In-process self-configuring approach to develop intelligent tool condition monitoring systems, CIRP Annals - Manufacturing Technology (2024), https://doi.org/10.1016/j.cirp.2024.04.049

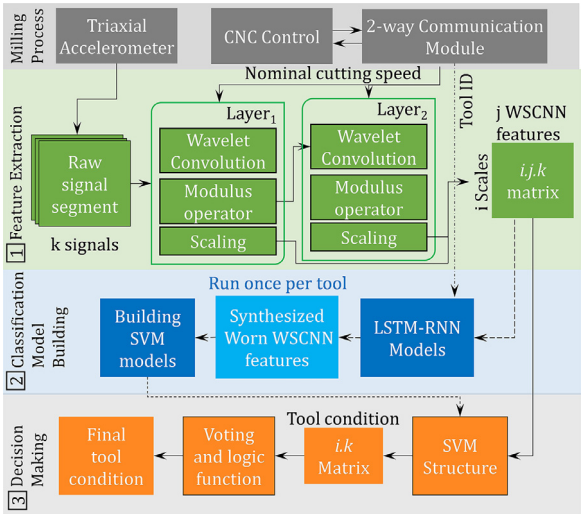


Fig. 1. In-process self-configuring TCM approach.

band filters in the 2nd layer. This ensures that the extracted features represent the signal energy and remain locally invariant to signal distortions, masking the cutting parameters effect. The wavelet band filters of each layer are preselected to extract the WSCNN features at the tool passing frequency and its harmonics, where the effect of tool wear on the processed signals is clearly distinguishable [4]. A 2-way communication module with the machine control was developed for real-time acquisition of speed and tool ID using a PROFIBUS interface module NI cRIO-PB.

A core contribution of this work is the development of long short-term memory recurrent neural network (LSTM) that can predict the values of WSCNN features when the tool gets worn using only the WSCNN features extracted from a usable tool. It maps a generalized correlation between WSCNN features of usable and worn tools, regardless of the tool geometry, sensor type and machining platform. The development of this network, which is described in Section 4, facilitates the utilization of the data collected during the production cycle to perform self-configuration, as shown in Block (2) (Fig. 1). The WSCNN features extracted at the tool early life stage (1 to 3 seconds of stable cutting) are fed to the developed LSTM to predict the values of worn WSCNN features. This process is done once per tool. Features extracted from the new tool using WSCNN and the synthesized worn WSCNN features using LSTM are then utilized to train a structure of binary support vector machine (SVM) models. This structure is then used to define the tool wear state in real-time during the rest of the cutting process, as shown in Block (3). The SVM separates the two tool classes (i.e., usable and worn) using the sequential minimal optimization technique by determining a linear hyperplane function $f(x) = x^*w+b$, where w is minimized to ascertain the widest possible margin between the two classes. The function $f(x)$ defines instances into two categories: $f(x)>0$ for samples belonging to class 1 and $f(x)<0$ for samples belonging to class 2. To cluster nonlinearly separable data, SVM utilizes a slack variable with a penalization parameter, allowing for some samples to fall within the boundary of the separation margin. SVM models were selected due to their versatility in mitigating overfitting and generalization capabilities owing to their inherent design to minimize structural risk [5]. Moreover, they show efficiency in handling limited training data, making them the best candidate for the proposed approach. A voting function is used to render a final decision based on fusing the outputs of the triaxial vibration signals. The approach employs a logic algorithm that discards outlier misclassifications amid the consistently detected tool condition (e.g., a worn class falls between two usable classes).

3. Experimental setup

An extensive experimental investigation was carried out to demonstrate the accuracy of the developed self-configuring TCM system tested with variable machining platforms (machine-tools and sensors) and process parameters (cutting conditions, tool engagement, workpiece material, and tool geometry). Table 1 shows the full factorial test matrix with a total number of 558 milling tests using usable and worn tools, including one repetition. The tests utilized 13 carbide tools with different diameters Φ, number of flutes Z, and corner radii R ranged between 16 mm to 100 mm, 2 to 7, and 0.8 mm to 6.0 mm, respectively. Only Set-1 of tests was used to build and validate the LSTM and to define the usable to worn WSCNN features correlation. Set-2 to Set-7 were carried out to demonstrate the accuracy and generalization of the self-configuring TCM prediction for different combinations of process and platform variables that the system was never trained for. Table 2 shows the combinations of machine tool, sensor, and workpiece material (Al7075T6 and Ti6Al4V) for each test set. The table shows also whether the tests were based on learned tools or learned cutting conditions or both. The tests were carried out on two 5-axis machining centres: DMU 100P duoBlock (vertical, 28 kW spindle power and Siemens 840D control), and Makino A88 (horizontal, 50 kw spindle power and a Fanuc 16iMA control). Straight slot and side milling cuts were performed (with cut lengths of 500 mm and 240 mm for Al7075T6 and Ti6Al4V workpieces, respectively.), except in Set-7, where machining of different features of curved slots, and straight and inclined pockets, shown in Fig. 2 (c), were conducted.

Table 1
Full factorial of nominal cutting conditions.

Set #	Tool*	v_c (m/min)	f_z (mm/tooth)	a_p (mm)	a_e (Φ%)	No. of cuts
	Φ16Z2R04	700		3.0, 5.0		
	Φ16Z2R33					
	Φ20Z2R04	880				
	Φ20Z2R33					
	Φ25Z2R04	1,100	0.1, 0.14		100	160
1	Φ25Z2R33					
	Φ25Z3R04					
	Φ25Z3R33					
	Φ50Z4R04	2,200				
	Φ50Z4R33					
2	Φ20Z2R33	880	0.1	5.0	20, 40, . . .,100	20
	Φ50Z4R04	2,200	0.1, 0.125	3.0, 5.0	10, 20, . . . 90	144
3	Φ50Z4R33	2,200	0.1, 0.125	5.0	20, 40, . . .,100	94
4	Φ100Z7R08	188	0.2, 0.4	0.7, 1.5	30	16
5	Φ32Z3R33	50	0.08, 0.12	5.0	25, 50, 75	22
	Φ50Z4R60	50	0.08, 0.1	4.0, 7.0	25, 50, 75	48
6	Φ50Z4R60	50	0.08, 0.12	4.0, 7.0	25, 50, 100	48
7	Φ25Z2R33	1,100	Variable	Variable	Variable	6

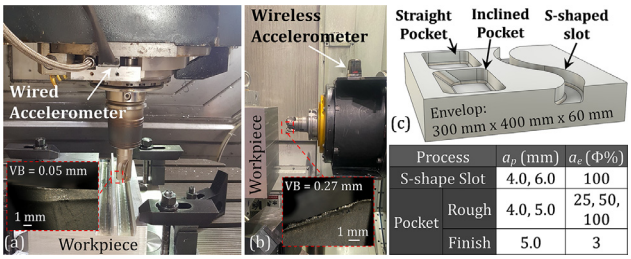
* *Φxx*, *Zx* and *Rxx* stands for the tool diameter in mm, number of flutes and corner radius in tenths of mm, respectively. Runout error ≤ 13 μm.

Table. 2
Testing platforms and parameters.

Set #	Machine	Accelerometer	*Material*	Learned tool?	Learned cutting conditions?
1	DMU 100	PCB 356A01	Al7075T6	Yes	Yes
2	DMU 100	PCB 356A01	Al7075T6	Yes	No
3	DMU 100	WITNESS	Al7075T6	Yes	No
4	DMU 100	WITNESS	Al7075T6	No	No
5	DMU 100	PCB 356*A71*	Ti6Al4V	No	No
6	Makino 88	G-Link-200	Ti6Al4V	No	No
7	DMU100	PCB 356A01	Al7075T6	Yes	No

Fig. 2 shows the experimental setup and instrumented machines. Four triaxial accelerometers were employed independently: (1) a lightweight voltage-output accelerometer (PCB 356A01), (2) a miniature charge-output (PCB 356A71), (3) a battery-powered wireless micro-electromechanical system (MEMS) MicroStrain G-LINK-200 accelerometer, and (4) a developed self-powered, miniature wireless MEMS accelerometer WITNESS [6]. These accelerometers have different characteristics in terms of sensitivity and measuring range. The self-configuring TCM performance was tested using signals from each of the accelerometers individually, sampled between 1.5 kHz

Please cite this article as: M. Hassan et al., In-process self-configuring approach to develop intelligent tool condition monitoring systems, CIRP Annals - Manufacturing Technology (2024), https://doi.org/10.1016/j.cirp.2024.04.049



Process		a_p (mm)	a_e (Φ%)
S-shape Slot		4.0, 6.0	100
Pocket	Rough	4.0, 5.0	25, 50, 100
	Finish	5.0	3

Fig.. 2. Experimental setups on (a) DMU 100 and (b) Makino A88 machining centres, and (c) Set-7 Part geometry.

and 10 kHz based on the tool rotational speed to maintain high resolution of the acquired signals. All accelerometers were mounted on the spindle head. Tool wear was measured using a ZEISS Smartzoom5 digital microscope. A flank wear (VB) value of 0.25 mm was used as a tool-life ending criterion. Tools with VB below this threshold are considered usable. Accelerated tool flank wear and chipping were generated on the cutting edges through controlled milling processes prior to performing the cutting tests, excluding crater and build-up-edge wear. To validate the system accuracy through different stages of tool life, tests were conducted using a randomly selected tool (Φ32Z3R33, Set-5) to capture the evolution of VB up to 0.65 mm using different cutting condition combinations.

4. LSTM development and validation

The synthesis of WSCNN features for worn tools necessitates defining a correlation between usable and worn features across diverse tool geometries. This entails an examination of the effect of cutting tool geometry parameters (tool diameter, number of flutes, and corner radius) on the WSCNN features' values. Features extracted from the tests conducted using usable tools in Set-1 were utilized for this study. Results showed a linear correlation between WSCNN features and the tool geometry parameters: direct proportionality to corner radius and inverse proportionality to tool diameter and the number of flutes. Similar linear correlations were found for features extracted from worn tools. These correlations allowed projecting the correlation generated between usable and worn WSCNN features for one tool geometry to other tool geometries. However, it is unfeasible to analytically describe this projection function at different scales of WSCNN features for different tool geometries, machining platforms and sensor types. Therefore, to automatically define the usable to worn WSCNN features correlation, a sequence-to-sequence long short-term memory recurrent neural network (LSTM) model was developed [7] to model the progressive dependencies between the two tool conditions in the WSCNN coefficients over wavelet filter bands.

The developed LSTM model consisted of four types of layers, namely, sequence input, LSTM, fully connected, and regression output layers. The sequence layer standardizes WSCNN features length for the LSTM layer via padding, splitting, and truncating. Subsequently, the LSTM layer learns long-term dependencies between WSCNN features over different frequency bands, by utilizing the evolution of the WSCNN features values over LSTM learning iterations to update the network predictions [7]. Three LSTM models were developed for the radial, tangential and axial vibrations respectively. Due to the WSCNN features generalization capability, these models were trained offline using only 40 cuts of Set-1 (tests conducted at one feedrate and depth of cut combination for 10 tools and 4 cutting speeds). The network input was the features extracted from usable tools and the output is the predictions of the WSCNN values at worn tool state. The rest of Set-1 tests (120 cuts) were utilized for LSTM validation. The fusion of the discriminative capability of WSCNN features to linearize the effect of cutting and setup parameters, the capacity of LSTM to learn and model complicated sequential patterns, and the ability to utilize information from previous frequency bands allowed capturing both local and global WSCNN feature patterns. This enabled the interpolation of the usable-to-worn correlation for different tool parameters and eliminated the need for network relearning for different tools, materials, machine setups and sensors with different frequency response functions.

Hyperbolic tangent function was employed as activation function for updating LSTM layer states due to its non-linearity mapping, and gradient-friendly properties. The key parameters influencing the regression process, namely, the number of LSTM layers, the number of hidden units per layer, and the dropout percentage, were optimized for network accuracy and generalization capability. The network optimization step led to utilizing two unidirectional LSTM layers, 200 hidden units per layer and 15 % dropout to achieve a root mean square error, R-squared, and mean absolute error of 0.05, 0.98 and 0.02, respectively. Fig. 3 (a) shows the high correlation between the synthesized WSCNN features (i.e., LSTM predictions) and the WSCNN features of worn tools of Set-1. Such accuracy is maintained along different tools and setups due to the proportional correlation between the WSCNN features and tool geometry parameters. This is evident in Fig. 3 (b) that shows the WSCNN features at usable and worn state and the synthesized worn features for an unlearned tool, sensor and cutting condition. Although the combination of WSCNN and LSTM models should mask the effect of other tool geometric features, e.g., rake angle, on the TCM performance, this factor has not been tested yet.

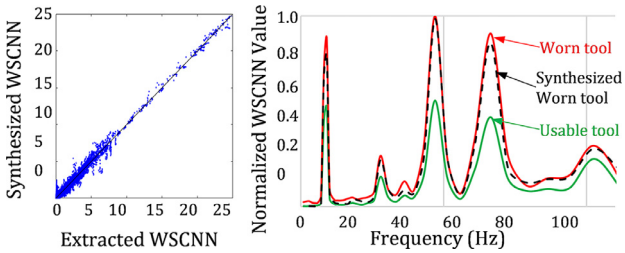


Fig.. 3. Actual and synthesized WSCNN features of LSTM using (a) training data and (b) an unlearned data sequence of tool Φ32Z3R33.

5. Experimental results and discussion

The developed LSTMs were integrated in the self-configuring TCM system, as shown in Fig. 1, to synthesize worn WSCNN features out of the features extracted from usable tools. At this stage, no offline learning is needed. For each tool in Table 1, the WSCNN features extracted from the vibration signals generated during the first 1 to 3 seconds of stable cutting at the early stage of tool life were utilized to synthesize the worn features values using the developed LSTM models. The cutting conditions for this training were arbitrarily selected. Usable and synthesized worn features were then employed to develop the SVM models' structure for decision making to define the tool wear state in real-time. The developed self-configuring system has achieved 100 % detection accuracy for all 160 full immersion tests of Set-1 (for Al7075T6 workpiece material). As described in Section 4, this set was partially utilized to develop the LSTM model for worn WSCNN features synthesizing. Therefore, it is essential to benchmark the proposed self-configuring approach using unlearned cutting conditions, tool paths, and platforms. In Set-2, where a subset of the tests conducted in Set-1 was conducted for unlearned partial emersion conditions and cutting conditions, the self-configuring approach has achieved a detection accuracy of 96 % over the 164 tests. In Set-3, the proposed approach achieved 94 % accuracy over 94 full and partial immersion cutting tests for unlearned cutting conditions, using a different accelerometer type. A 100 % accuracy was achieved in Set-4, when an unlearned tool was utilized with the same sensor used in Set-3, extrapolating of the learned tool diameter and number of flutes in the LSTM models.

For Set-5, milling tests of a different workpiece material (Ti6Al4V) were conducted using a combination of two unlearned tools and different cutting conditions and sensor type. Fig. 4 shows the performance of the self-configuring TCM system throughout the evolution of the tool life span. The high level of agreement between the measured VB and the system output is evident. This system was able to

Please cite this article as: M. Hassan et al., In-process self-configuring approach to develop intelligent tool condition monitoring systems, CIRP Annals - Manufacturing Technology (2024), https://doi.org/10.1016/j.cirp.2024.04.049

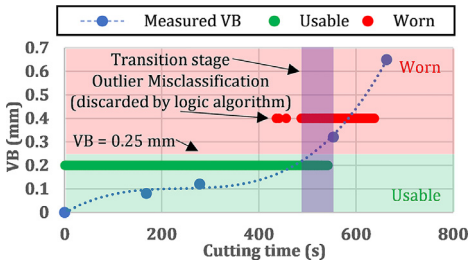


Fig.. 4. Tool wear evolution detection, Tool Φ32Z3R33 (Set-5 Table 1).

accurately detect the tool condition as usable until it reached a VB of 0.21 mm after 485 seconds of cutting. This was followed by a 60 second transition period, where the system output alters between "usable" and "worn" condition near the VB learning boundary (0.21 mm < VB < 0.32 mm). As cutting proceeded beyond such limit, a worn tool condition was detected in agreement with the measured VB. The system showed an accuracy of 97 % in detecting the tool wear state for this set of tests. It should be noted that any outlier misclassifications (shown in Fig. 4 for demonstration) is discarded by the logic algorithm, described in Section 2.

To test the self-configuring TCM system capability with new platforms, Set-6 tests included conventional milling of Ti6Al4V on an unlearned machining centre (MAKINO 88) using unlearned tool geometries, cutting conditions and a commercial battery-powered wireless accelerometer. The system showed 94 % accuracy in detecting the tool wear state at these conditions. This is attributed to: (i) the WSCNN features capability to steadily preserve the energy induced in the vibration signals by tool wear regardless of the cutting conditions, (ii) the WSCNN features' linear correlation with tool geometry parameters, and (iii) the generalization of the developed LSTM in modelling the sequence-to-sequence correlation between usable and worn WSCNN features.

To demonstrate the performance of the developed self-configuring TCM system in real industrial applications, Set-7 tests were conducted to machine curved slots, and straight and inclined pockets (Fig. 2(c)). Fig. 5 shows the system output during rough milling and finishing of an inclined pocket using worn and usable tools, respectively. Despite the variations in tool path and cutting conditions, the system has demonstrated 100 % accuracy in defining the tool wear state. An "air cut" status is presented by the system logic function when > 50 % of the processed signal segment does not include tool-workpiece interaction. The generalization and high reliability of the system can be assessed by the fact that it has an average accuracy of 97 % throughout the 558 cutting tests, shown in Table 1, even when unlearned workpiece materials, tools cutting conditions, platforms and instrumentation were used.

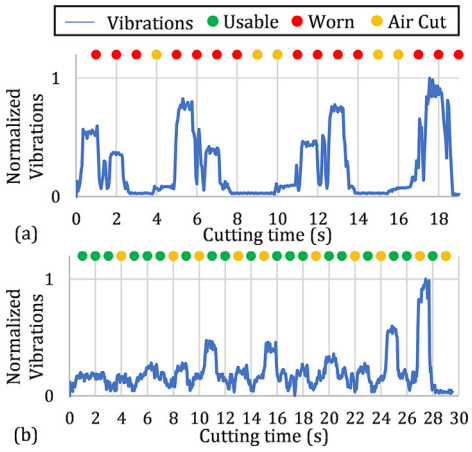


Fig.. 5. (a) Roughing using worn tool, and (b) finishing using unworn (usable) tool to machine an inclined pocket in Set-7I.

A cost comparison was conducted between the self-configuring TCM system and the generalized TCM system in [4]. The latter reduced lead time and learning effort by up to 97 % compared to typical learning approaches in literature, using only one cut per tool condition for training. However, its learning was confined to specific machine, sensor, tool geometry, workpiece material, and cutting speed combinations. Both systems require the same non-recurring cost for initial learning tests (e.g., 40 short cuts from Set-1). However, the self-configuring TCM system utilizes these tests to develop LSTM models to avoid recurring costs needed to expand the learning range to cover the abovementioned confining aspects. For instance, expanding the [4] system to cover Sets 2 to 7 would double the cost due to the additional learning tests needed.

6. Conclusions

A generalized in-process self-configuring approach was developed for real-time detection of tool wear state of milling tools, which is an enabling technology for a new generation of TCM intelligence. The presented development overcomes the limitations of available TCM systems in literature and provides high detection accuracy using only one to three seconds of signals acquired in-process. This was achieved by developing a generalized correlation between features extracted from usable and worn tools. A suite of machine learning algorithms for multi-signal processing and fusion was developed to extract a stream of representative features and build decision-making boundaries in real-time. This system is insensitive to the surrounding noise and significantly reduces the time and cost associated with a TCM system's deployment and expansion, which make it a unique candidate for implementation in industrial facilities. Such TCM framework isolates the variability of the machining process (tool geometry, workpiece material, cutting conditions, tool engagement) and platform (machine tool and sensor type). To the authors' best knowledge, this capability has never been attained by AI-based TCM systems reported in the open literature, thus responding to the industrial need for unsupervised TCM for multi-axis milling.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Mahmoud Hassan: Conceptualization, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. **Ahmad Sadek:** Conceptualization, Funding acquisition, Project administration, Resources, Validation, Visualization, Writing – review & editing. **Helmi Attia:** Investigation, Supervision, Validation, Visualization, Writing – review & editing.

References

[1] Teti R, Mourtzis D, D'Addona DM, Caggiano A (2022) Process Monitoring of Machining. *CIRP Annals* 71:529–552.
[2] Mohamed A, Hassan M, M'Saoubi R, Attia H (2022) Tool Condition Monitoring for High-Performance Machining Systems - A Review. *Sensors* 22:2206.
[3] Denkena B, Wichmann M, Noske H, Stoppel D (2023) Boundary Conditions for the Application of Machine Learning Based Monitoring Systems for Supervised Anomaly Detection in Machining. *Procedia CIRP* 118:519–524.
[4] Hassan M, Sadek A, Attia M (2021) Novel Sensor-Based Tool Wear Monitoring Approach for Seamless Implementation in High Speed Milling Applications. *CIRP Annals* .
[5] Liu C, Li Y, Zhou G, Shen W (2018) A Sensor Fusion and Support Vector Machine Based Approach for Recognition of Complex Machining Conditions. *Journal of Intelligent Manufacturing* 29:1739–1752.
[6] Hassan M, Sadek A, Attia MH (2022) Intelligent Cyber-Physical Monitoring and Control of I4.0 Machining Systems - An Overview and Future Perspectives. *Journal of Machine Engineering* .
[7] Hochreiter S, Schmidhuber J (1997) Long Short-Term Memory. *Neural Computation* 9:1735–1780.

Please cite this article as: M. Hassan et al., In-process self-configuring approach to develop intelligent tool condition monitoring systems, CIRP Annals - Manufacturing Technology (2024), https://doi.org/10.1016/j.cirp.2024.04.049