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A multi-sensor based online tool condition monitoring system for milling process

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Abstract

Tool condition monitoring has been considered as one of the key enabling technologies for manufacturing optimization. Due to the high cost and limited system openness, the relevant developed systems have not been widely adopted by industries, especially Small and Medium-sized Enterprises. In this research, a cost-effective, wireless communication enabled, multi-sensor based tool condition monitoring system has been developed. Various sensor data, such as vibration, cutting force and power data, as well as actual machining parameters, have been collected to support efficient tool condition monitoring and life estimation. The effectiveness of the developed system has been validated via machining cases. The system can be extended to wide manufacturing applications.

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Keywords: Tool condition monitoring, Multipe sensors, Vibration;

1. Introduction

For a machining process, the severe wear of a cutting tool will lead to low machining quality of a workpiece in terms of accuracy and surface roughness. In a worse scenario, it could make a manufactured workpiece disqualified and a machine system deteriorated. According to statistics, more than 75% of the equipment failures in a production process are caused by the severe tool wear or failure [1]. From the economic point of view, Zhang and Zhang [2] presented that about 3% to 12% of production cost is related to the conditions of cutting tools and their replacement. Therefore, it is vital to develop a Tool Condition Monitoring (TCM) system to understand the status of cutting tools efficiently and effectively in order to predict and optimize their lifespans. From [3, 4], it could be summarized that a precise and reliable TCM system could generate 10-50% cutting speed increment, 75% downtime reduction, also about 30% maintenance cost saving [5].

For TCM, the prior research can be divided into two main parts: direct methods and indirect methods. The direct methods require a lot of equipment to measure the conditions of the tools so involve high-cost labors. Due to high costs and inflexibility, the methods are not widely adopted by industries [6]. On the other hand, the indirect methods are to monitor cutting tool conditions by using sensors augmented with effective data analytics. Owing to the flexibility, nowadays, more research and commercial products have used the indirect methods for TCM. For instance, the commercial systems Kistler [7] and Brankamp [8] have been widely used in laboratories to support predicting the lifetime of tools and monitoring the cutting force. However, these commercial systems have not been widely adopted in the industrial sector, especially for Small and Medium-size Enterprises (SMEs), due to the high product cost and incompatible configuration. Huang et al. [9] indicated that a PZT type accelerometer, which measures the vibration signal for TCM, cannot be integrated into the intelligent modules even at a price of $ 500-1000. Hence, it is imperative to develop a low-cost TCM system with high robustness and flexibility, as well as the least human intervention.

Appropriate signals to be used for TCM are essential to ensure the accuracy of the monitoring system. Vibration changes along with the increase of the tool wear, which is

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directly caused by the contact between the tool and the workpiece surface [10]. Siddhpura and Paurobally [11] showed that for TCM the vibration-based study has accounted for more than 20% of the published works. Therefore, the vibration signal should be a reasonable choice to reflect the condition of the cutter. In addition, the process of the tool wear is very complicated due to the fact that abnormal tool conditions could have different forms. A single sensor signal is not able to provide sufficient information to predict tool wear [12]. Recently, a multi-sensor solution, which could effectively eliminate the uncertainty caused by a single sensor monitoring, has drawn more research attention [13]. Different sensor signals can reflect the tool wear from different perspectives. All these data are independent and can be complementary to achieve a more accurate prediction. However, a challenge for utilizing multiple-sensor solution is how to effectively fuse various sensor signals and unearth useful information from the dataset.

This paper is primarily focused on developing a multi-sensor based monitoring system with data fusion capabilities. Real-time TCM is realized to support high accurate predictions on tool wear and product quality. Current, accelerometer and piezoelectric sensors are integrated into the developed TCM system to acquire different signals for decision marking. Furthermore, CNC machining processes have been selected as a case study considering the popularity and complexity of the CNC machining processes. This design of the system provides a low-cost and flexible solution for TCM, suitable for SMEs' applications. It can be also extendable to support wider manufacturing applications.

The rest of this paper is organized as follows. In section 2, the framework of the system and working principles of sensors will be explained. Section 3 shows the design and procedure of machining experiment to validate the monitoring system, followed by a brief analysis of collected data in Section 4. Section 5 draws conclusions.

2. The multi-sensor monitoring system

In order to be in line with the industrial demand for low-cost, flexible and easily implementable monitoring system, an Arduino developing board has been selected as the hardware platform to equip multiple-sensors for this research. It is an open source micro-control platform costing only US $25. It can be combined with a variety of sensors or devices [14]. To enhance the flexibility and reduce the implementation cost, a wireless communication solution is considered in this work. A Wi-Fi based Arduino Uno board has been selected to form up the sensor nodes. Besides, a local database has been developed to host and manage the multiple sensor data and a big data technology through the Apache Spark has been implemented to organize acquired numerous data and to support further data fusion and analysis. In this study, three types of sensors have been employed to monitor vibration, cutting force and energy consumption profiles of a CNC milling machine. Due to the characteristic of the wireless sensor network, the system can be easily expanded to add more types of sensors into the system. The framework of the monitoring system is depicted in Fig. 1.

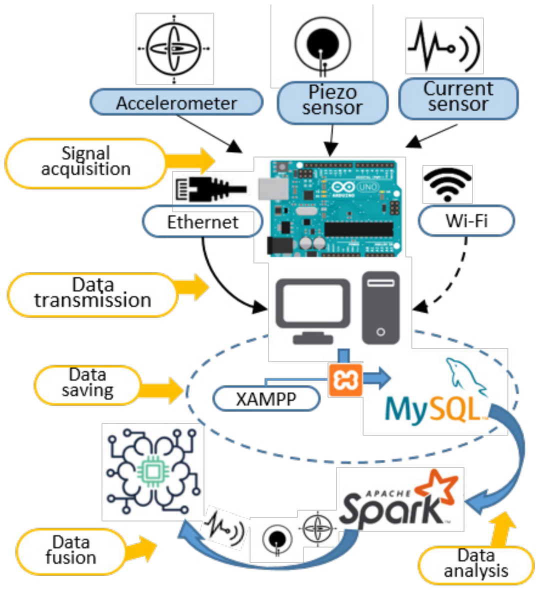

Fig.1. Monitoring system framework

2.1. Accelerometer

For the purpose of measuring the vibration status of the cutting tools, a 3-axis accelerometer (model MMA7361 with datasheet shown in Table 1) has been adopted. In addition, the sensitivity of the MMA7361 is based on the principle of capacitance, making it cheaper and requiring only a single chip to measure the acceleration of triaxle. The measurement of acceleration is based on the displacement change of the chip's central mass between the fixed beams of the capacitance. The conversion formula from the ADC input value to the acceleration is as follows [15]:

$$Acc = \frac{\dfrac{adc\_input \times ref\_v}{1023} - v_0}{sen.} \tag{1}$$

Where,

- Acc = acceleration of each axial,
- adc_input = raw value from accelerometer,
- ref_v = voltage of sensor supply,
- v_o = voltage at 0 acceleration,
- $sen.$ = sensitivity of accelerometer.

Due to gravity, calibration may be done using the acceleration. It follows the principle: the output values of the x and y axial should be 0 because the accelerometer is stationary; the output value of the z axial is 100 that means the acceleration equal to the gravity acceleration (as the unit of the output value is $g \times 10^{-2}$, and g is the acceleration of gravity).

Table 1. Datasheet of the 3-axis accelerometer MMA7361

Characteristic	Value
Supply Voltage (V)	3.3 or 5
Sensitivity (mv/g)	800 (1.5g), 206 (6g)
Bandwidth Response (HZ)	400 (X, Y), 300 (Z)

2.2. Current sensor

For monitoring energy consumption, the YHDC current sensor (Datasheet in Table 2) has been employed in this design. This sensor is a widely used transformer for the measurement of Alternating Current (AC). The output value of the sensor does not consider any instantaneous current, as the current direction and size are continuously changing in a circuit. Instead, the output value is I_{RMS}, which is called the root mean square current. It is used to describe the average strength of the current, and its direction can be ignored [16]. The voltage is relatively stable and around 230 volts in the UK, so the measured power is calculated as:

$$P = 230 \times I_{RMS} \tag{2}$$

Table 2. Datasheet of the YHDC clamp current sensor

Input current	Output voltage	Turn ratio	Work temperature
0-100A	0-50mV	100A:0.05A	-25℃～+70℃

2.3. Piezoelectric sensor

With the purpose of the cutting force measurement, two piezoelectric disk sensors (Datasheet in Table 3) have been integrated into the design. The piezoelectric effect reflects the change in force or acceleration through the change of the output charge. The relationship between the cutting force in the milling process and the signals of these two piezo sensors can be established using experiments.

Table 3. Datasheet of Piezoelectric disk sensor

Resonant frequency	Insulation resistance	Maximum input voltage	Operating temperature range
6.5±0.7KHz	100MΩ Min	30Vp-p	-20℃ to +70℃

3. Design of experiment

To assess the capability of the developed system, an experiment has been designed to use the accelerometer, piezoelectric sensor and current sensor to monitor the milling process for tool life prediction. The acquired data are evaluated according to the Taylor's equation [17], which is a common empirical formula for tool life prediction. The general form of the Taylor's equation is expressed as:

$$V_c T^n \times a_p V_f = C \tag{3}$$

Where V_c is the cutting speed, T is the tool life in Minutes, n is an exponent that depends on the specific tool level and used materials, determines the slope of the tool life curve. a_p is the depth of cut, V_f is the feed rate, and C is a constant that depends on the machine and workpiece material.

To generate a more accurate prediction on tool life, some expanded formulas for the Taylor tool life model has been proposed [18]. In the formulas more machining variables need to be obtained. This leads to the prediction model to become far more complex. Eslamian [19] pointed out that expanding the model may produce inconsistent results when multiple parameters are changed at the same time. To this end, Equation 3 is used in this study.

According to the Taylor's equation, the cutting speed (V_c), feed rate (V_f) and depth of cutting (a_p), which are highly related to the tool life, have been considered in this experiment. Based on the recommend values of milling spindle speed and feed indicated in [20], the experimental parameters used in this work are listed in Table 4.

Table 4. Cutting parameter

No.	Spindle speed N (RPM)	Feed f_z (mm/tooth)
1	2000	0.0127
2	2500	0.0203
3	3500	0.0254
4	4500	0.0508

For the milling process, the cutting speed V_c in m/min can be expressed as equation 4, and the feed rate V_f in mm/min can be indicated as equation 5.

$$V_c = \frac{\pi D N}{1000} \tag{4}$$

$$V_f = N Z f_z \tag{5}$$

Where,

- D= tool diameter (mm, the value is 12 in this experiment),
- N = spindle speed (RPM),
- Z = number of cutter flute (Z=4 in this experiment),
- f_z = feed (mm/tooth).

With 4 different parameters of spindle speed and feed, 16 parameter combinations have been designed by Taguchi method, shown in Table 5. In order to achieve a good surface quality, the depth of cut has been carefully designed based on the classical method provided in [21].

Table 5. Experiment parameters

No.	Spindle speed N (RPM)	Cutting speed V_c (m/min)	Feed rate V_f (mm/min)	Depth of cut a_p (mm)	Width of cut (mm)
1	2000	75	102	1.5	12
2	2000	75	203	2	12
3	2000	75	356	2.5	12
4	2000	75	914	3	12
5	2500	94	102	2	12
6	2500	94	203	1.5	12
7	2500	94	356	3	12
8	2500	94	914	2.5	12
9	3500	132	102	2.5	12
10	3500	132	203	3	12
11	3500	132	356	1.5	12
12	3500	132	914	2	12
13	4500	170	102	3	12
14	4500	170	203	2.5	12
15	4500	170	356	2	12
16	4500	170	914	1.5	12

The system is shown in Fig. 2. All the experiments have been carried out on an SYIL X4 CNC machine by using 4 flutes 12mm HSS milling cutter to machine aluminum blocks.

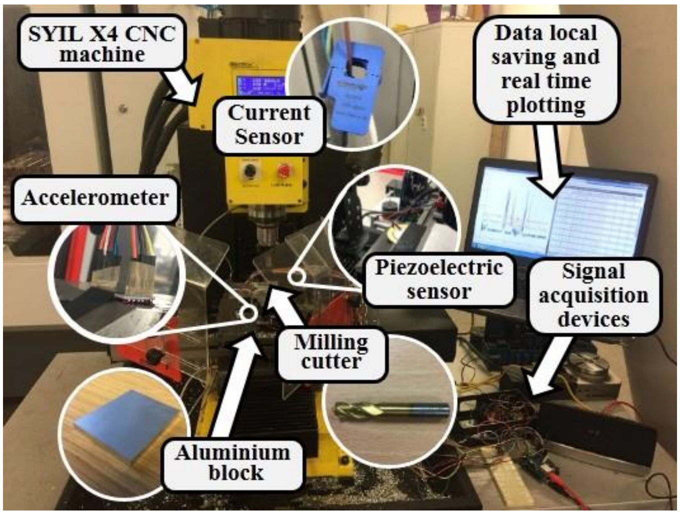

Fig. 2. System setup of machining process monitoring

4. Result analysis

As shown in Fig. 3, 16 slots have been machined with different parameter combinations on 3 aluminum blocks, respectively. 62023 samples of sensor data during the entire experiment process, each sample containing 8 different signals, acquired from 2 piezoelectric sensors, a 3 Axes acceleration sensor, and 3 phases power sensors, have been collected by the monitoring system steadily and stored in a Big Data database.

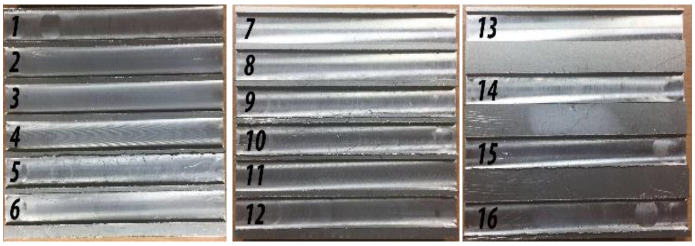

Fig. 3. Workpiece after machining

4.1 Signal analysis based on process monitoring

The total power and 3-axis acceleration captured during the experiment process are plotted in Fig. 4(a) and Fig. 5(a) respectively. From the power graph, it is noted that the highest value of power occurs at the initial stage (highlighted in red box) of the experiment which is close to 3500W. This anomaly is explained later on. The lowest power appears at the standby stage that is about 230W. From Time 21:03:36 onwards, a stable and continuous processing phase starts, and the average power is 690W. For acceleration in Fig. 5(a), the x- and y- axial acceleration values in the initial stage reach 0.1g and the z axial peaks reach nearly 6g. The values at the standby stage are 0g for x- and y-axis and 1g for z-axis, respectively. Based on the calibration principle of the accelerometer described in Section 2, the accelerometer is stationary at this time, the acceleration values in x- and y-axial in the continuous processing stage is about 0.05g, and 0.4g in the z-axis. The signs of acceleration represent the two opposite directions of acceleration. It can be observed that the trends of the power and acceleration graphs show substantial similarity, thus, the system can be confirmed able to collect signals to reflect the processing status.

The abnormal peak values of the power and acceleration captured during the initial stage are caused by a failure cutting, shown in Fig. 6. The graphs in the processing phase are shown in Fig. 4 (b) and Fig. 5 (b), which are corresponding to the red boxes in Fig. 4 (a) and Fig. 5 (a). Compared with normal cutting, the failure cutting shows large fluctuations in power level, and the average power of the failure cutting is about 1288W, and the energy consumption is 0.42kwh, which is 3.5 times bigger than the normal machining with the same parameter. Moreover, the similar results can be seen from Fig. 5 (b), the acceleration values in the three-axes change rapidly with larger amplitudes than the normal cutting, especially in z - axis, which shows good correlation with the power plotting. This indicates that the vibration level of the cutter during abnormal condition was far stronger than that of the normal cutting, which is in line with Mukhopadhyay et al. [22~~1~~] statement that vibration sensor signal amplitude increases, corresponds to the energy increment that generated by the tool flank wear. This proves the potential of the system for the monitoring of tool wear.

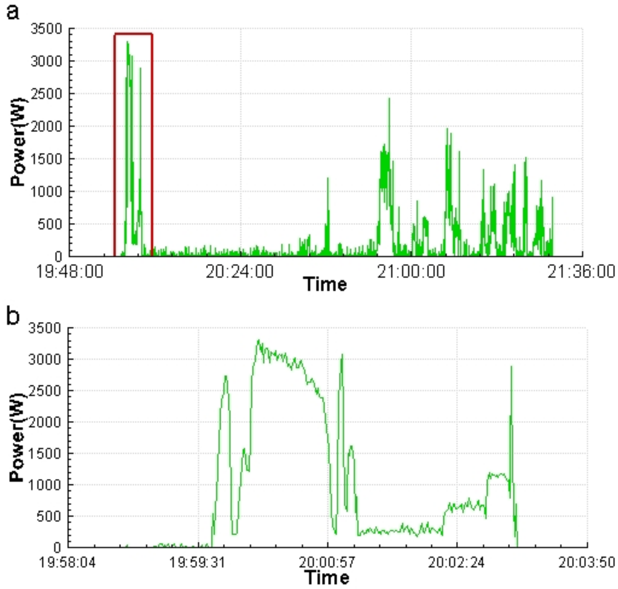

Fig. 4. (a) Power against time; (b) The enlarged failure zone (red box in (a))

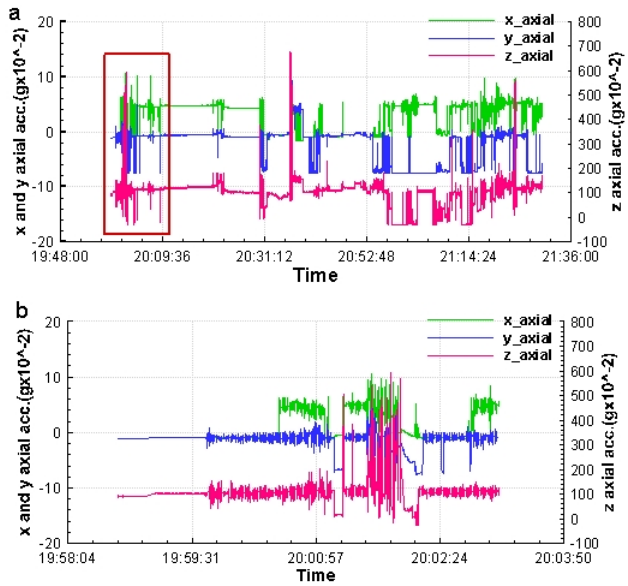

Fig. 5. (a) Acceleration against time; (b) The enlarged failure zone (red in (a))

Fig. 6. Machining with an opposite spindle rotation direction

In the experiment, two piezoelectric sensors are mounted on both sides of the longitudinal workpiece holder, to collect the relevant signals reflecting the cutting force. The results are depicted in Fig. 7. By comparing to the power and acceleration signals, the pattern of the cutting force signal is under a low degree of correspondence with the actual machining situation. This is probably because the principle of the sensor is more suitable for the sudden increase force, not sensitive to small changes, and the mounting location seems not efficient. Therefore, a further data amplify method and the investigation of a proper mounting position will be considered in the future work, to make the piezoelectric achieve the desired function.

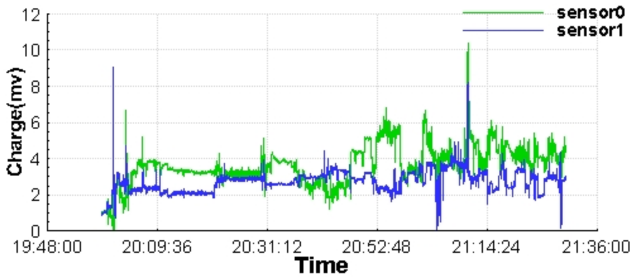

Fig. 7. Charge against time for the piezoelectric sensor

4.2 Signal analysis based on tool life

Based on the obtained data, the total acceleration and power values for every slot under normal condition have been averaged. The graph is shown in Fig. 8. It can be seen that, among the machining processes of the 16 slots, the maximum power appears at the machining of the 6th slot, which is about 1100W. The minimum value is close to 300W, which is for the machining of the 3rd and 8th slot. For acceleration, the highest value is about 1.3g at the 4th machining and the minimum is 0.3g at the 8th machining. In addition, the polyline can confirm again that the signals of the power and acceleration obtained by the system fit to a certain degree. In simple terms, the values of power and acceleration are in the similar trends. This result shows the data fusion in the future is promising.

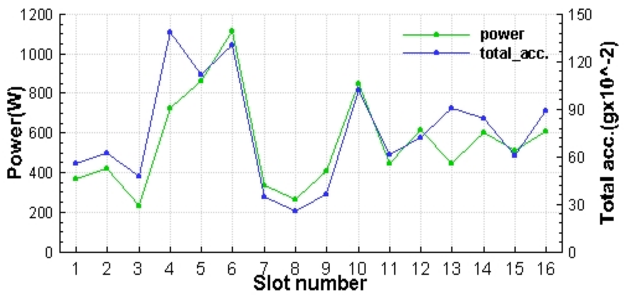

Fig. 8. Power and total acceleration for 16 slots

In this experiment, the Taguchi orthogonal method has been employed to design the parameter combination within cutting speed, feed rate and depth of cutting. After averaging the total acceleration and power values for every slot, the average values and parameter factors are inputted into the Taguchi analysis. The main effects plot for means is obtained as is shown in Fig. 9. It can be found out that the result is consistent with the finding of Taylor and other studies [23]. The cutting speed performs a significant effect both on the acceleration and power, followed by the feed rate and the depth of cutting. Thus, it shows that the data collected by this system has the feasibility to establish the relationship between parameters and tool life, which will be carried out in future studies.

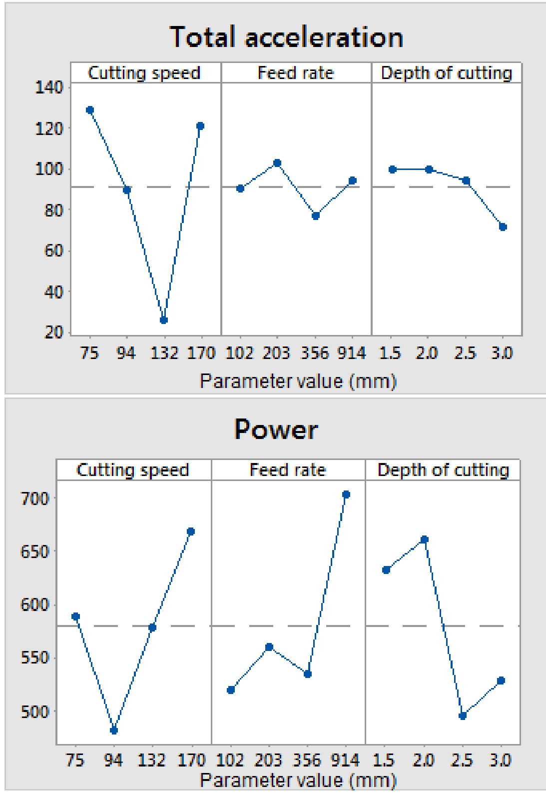

Fig. 9. Main Effects Plot for Means of the acceleration and power

The processing time of 16 slots with the same parameters is about 39 mins and the power increment is shown in Fig. 10. It can be inferred that power increment graph is consistent with the curve of the Taylor tool wear shown in Fig. 11. The rapidly increasing stage of power is within 5 mins of machining start, which in the interval *a* (shown in Fig. 10). It corresponds to the initial rapid stage of the tool wear. Then the increment gets slower, which is in the interval *b* (shown in Fig. 10), corresponding to the stable stage of tool wear. Due to the insufficient processing time of experiments, the accelerated stage of tool wear, however, has not been reflected in the graph. Despite this, the graph of the power increment power is aligned with the Taylor curve. It confirms the system provides feasible tool wear monitoring.

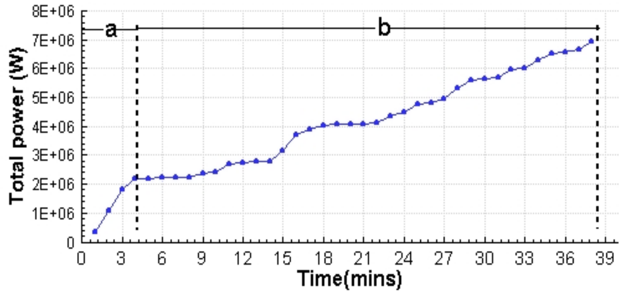

Fig. 10. Power superposition

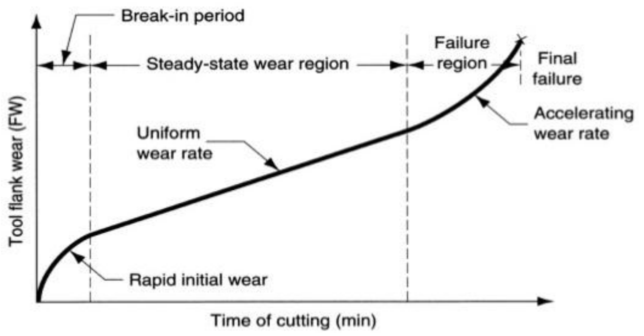

Fig. 11. Taylor tool wear curve [17]

5. Conclusions

A low-cost and flexible multi-sensor TCM system has been developed. The monitoring system has been set up with a 4-axis CNC milling machine in the laboratory to collect experimental data. Signals of power, vibration and cutting force have been collected from the machine for predicting tool wear. A Taguchi method has been employed to design the experiments. The data obtained by the system shows that the selected sensors demonstrate a good ability to capture the status of the cutting tools. Further data analysis shows that the relationship between the machining parameters and tool life can be established using the monitoring system. Moreover, analysis is given to prove that this low-cost and flexible monitoring system is feasible and effective for tool wear monitoring It is suitable to support SMEs' applications.

Future research includes: comparing and calibrating the proposed monitoring system with existing commercial cutting force and vibration systems provided from Kistler, appending more appropriate data analysis algorithms into the system to enhance its intelligence and data fusion; extending the current monitoring system from milling machining to other application areas. In particular, this system will be used to support a PU process to provide real-time monitoring of the status of the resin chemistry used for tooling board manufacturing. More types of sensors such as flowmeter, pressure and temperature sensors will be integrated into the system for this application.

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Reference

[1] García Plaza, E. and Núñez López, P. Surface roughness monitoring by singular spectrum analysis of vibration signals. Journal Mechanical Systems and Signal Processing, 2017, 84, 516-530.

[2] Zhang, C. and Zhang, J. On-line tool wear measurement for ball-end milling cutter based on machine vision. Computers In Industry, 2013, 64 (6), 708-719.

[3] Barreiro, J., Fernández-Abia, A., González-Laguna, A. and Pereira, O. TCM system in contour milling of very thick-very large steel plates based on vibration and AE signals. Journal of Materials Processing Technology, 2017, 246, 144-157.

[4] Rehorn, A., Jiang, J., Orban, P. and Bordatchev, E. State-of-the-art methods and results in tool condition monitoring: A review. The International Journal of Advanced Manufacturing Technology, 2004, 26 (7-8), 942-942.

[5] Dimla, D. Sensor signals for tool-wear monitoring in metal cutting operations—a review of methods. International Journal of Machine Tools and Manufacture, 2000, 40 (8), 1073-1098.

[6] Kim, J., Moon, D., Lee, D., Kim, J., Kang, M. and Kim, K. Tool wear measuring technique on the machine using CCD and exclusive jig. Journal of Materials Processing Technology, 2002, 130-131, 668-674.

[7] Auchet, S., Chevrier, P., Lacour, M. and Lipinski, P. A new method of cutting force measurement based on command voltages of active electro-magnetic bearings". International Journal of Machine Tools and Manufacture, 2004, 44 (14), 1441-1449.

[8] Mandal, S. Applicability of tool condition monitoring methods used for conventional milling in micromilling: A comparative review. Journal of Industrial Engineering, 2014, 1-8.

[9] Huang, C., Lee, R. and Yang, S. Implement of low cost MEMS accelerometers for vibration monitoring of milling process. in applied system innovation (ICASI), 2016 International Conference. IEEE.

[10] Zhang, C., Yao, X., Zhang, J. and Jin, H. Tool condition monitoring and remaining useful life prognostic based on a wireless sensor in dry milling operations. Sensors, 2016, 16 (6), 795.

[11] Siddhpura, A. and Paurobally, R. A review of flank wear prediction methods for tool condition monitoring in a turning process. The International Journal of Advanced Manufacturing Technology, 2012, 65 (1-4), 371-393.

[12] Xie, N., Zheng, B., Xie, X. and Liu. X. Research on the multi-sensor fusion-based tool condition recognition system. World Congress on Intelligent Control and Automation (WCICA), 2014 11th World Congress.

[13] Fu, P. and Hope. A. fuzzy neural hybrid system for cutting tool condition monitoring. 2006 International Conference in Machine Learning and Cybernetics. Dalian, China: IEEE. 2006.

[14] Lockridge, G., Dzwonkowski, B., Nelson, R. and Powers, S. Development of a low-cost arduino-based sonde for coastal applications. Sensors, 2016, 16 (4), 528.

[15] Learn.openenergymonitor.org. Learn | OpenEnergyMonitor. [online] Available at: https://learn.openenergymonitor.org/ [Accessed 24 Dec. 2017].

[16] NXP Semiconductors [online] Available at: https://www.nxp.com/ [Accessed 28 December 2017]

[17] Karandikar, J., Abbas, A. and Schmitz, T. Tool life prediction using Bayesian updating. Part 2: Turning tool life using a Markov chain Monte Carlo approach. Precision Engineering, 2014, 38 (1), 18-27.

[18] Grzesik, W. Advanced machining processes of metallic materials theory, modelling and applications. San Diego: Elsevier, 2008, pp.427-428.

[19] Eslamian, S. Handbook of engineering hydrology. CRC Press, 2014, pp.23-25.

[20] Sandvik. End milling of slots. [online] Available at: https://www.sandvik.coromant.com/en-us/knowledge/milling/application_overview/slot_milling/end_milling_of_slots [Accessed 30 Nov. 2017].

[21] Uddeholm Corrax. CUTTING DATA RECOMMENDATIONS. [online] Available at: https://www.uddeholm.com/files/Cutting_Data_Corrax_eng.pdf [04 Dec. 2007]

[22] Ibrahim, M., Sreedharan, T., Fadhlul Hadi, N., Mustapa, M., Ismail, A., Hassan, M. and Tajul Arifin, A. The effect of cutting speed and feed rate on surface roughness and tool wear when machining D2 steel. Materials Science Forum, 2017, 909, 80-85.

[23] Mukhopadhyay, C., Jayakumar, T., Raj, B. and Venugopal, S. Statistical analysis of acoustic emission signals generated during turning of a metal matrix composite. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 2012, 34 (2), 145-154.