World Applied Sciences Journal 21 (2): 264-268, 2013
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2013.21.2.2539

Development of Machining Condition Monitoring System Using Piezoelectric Sensor Analyzed by I-Kaz Multilevel Method

[1]*Z. Karim*, [2]*M.Z. Nuawi*, [2]*J.A. Ghani*, [3]*E.A. Azrulhisham and* [2]*S. Abdullah*

[1]Department of Mechanical and Manufacturing Engineering,
Universiti Kuala Lumpur Malaysia France Institute, 43650 Bangi, Selangor, Malaysia
[2]Department of Mechanical and Materials Engineering,
Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, Malaysia
[3]Department of Electrical and Electronic,
Universiti Kuala Lumpur Malaysia France Institute, 43650 Bangi, Selangor, Malaysia

Abstract: Cutting tool wear is found to be the major cause affecting the finished product in term of surface finish quality, dimensional precision and the cost of the defect. This paper proposes the development of a reliable machine condition monitoring system by using a low-cost piezoelectric sensor to monitor the flank wear progression on the cutting tool. The wear of the cutting insert was measured and recorded using Mitutoyo microscope under different operational conditions in turning process. A single channel piezoelectric sensor was mounted at the tool holder to measure the deflection on the cutting tool in the tangential direction during the machining process. The signal was transmitted to the piezoelectric amplifier device, then to data acquisition and finally to the computer system. I-kaz Multilevel method was used to identify and characterize the changes in the signals from the sensor. Under different experimental set up, new tool wear models were successfully formulated. Good agreements between the predicted and measured tool flank wear land width show that the developed machine condition monitoring system can accurately predict tool flank wear. This monitoring system is an efficient and low-cost method for flank wear level prediction which can be used in the real machining industry.

Key words: I-kaz™ · Condition monitoring · I-kaz Multilevel · Flank wear · Signal processing

INTRODUCTION

In recent years, the issue of machine tool downtime continues to plague the machining industries [1]. Tool wear or cutting tool failures typically represent approximately 20% of the downtime of machine tools in industries [2]. It was reported that the cost of cutting tools and their replacement accounts for between 3 to 12% of total production costs [3, 4]. Tool wear is also found to have a direct impact on the work piece in term of surface finish quality, dimensional precision and the cost of the defect finish product [5]. In view of the this matter, there is a real need to devise a tool wear detection system by developing an accurate and a reliable tool condition monitoring system [6]. Several methods have been proposed for tool wear monitoring. Micheletti *et al*. have discussed the direct and indirect methods of tool wear measurement using various tool wear sensors such as radio isotopes as tracers, chemical analysis of tool particles carried by chip and etc. [7]. Direct methods have the advantage of capturing actual geometric changes of the tool wear but are very difficult to obtain due to the continuous contact between the tool and the workpiece and the presence of coolant fluids. Thus, the application of a direct method is limited by these difficulties [8, 9]. Indirect methods have the advantages of being less complicated setup and greater suitability to practical application. These methods correlate the signal features extracted through signal processing steps to tool wear states. Indirect methods include those based on sensing

Corresponding Author: Z. Karim, Department of Mechanical and Manufacturing Engineering,
Universiti Kuala Lumpur Malaysia France Institute, 43650 Bangi, Selangor, Malaysia.

of the acoustic emission [10, 11], cutting forces [12, 13], motor power [14, 15] and other parameter. This study proposes the application of a piezoelectric sensor for monitoring online cutting tool wear by measuring cutting tool deflection and analyzing its signal using a new statistical-based method called Multilevel Integrated Kurtosis based Algorithm for Z-Notch Filter or I-kaz Multilevel [16, 17]. The experiments were carried out using CNC turning machines to collect data which relate the signal features from cutting tool deflection to gradual flank wear or VB. Several equations of flank wear and signal characteristic correlations were derived in order to monitor and predict online flank wear progression.

MATERIALS AND METHODS

Design and Procedure of the Experiment: The material and cutting tool used in this study were S45C steel and CNMG 432-QM respectively. The machining tests were carried out on CNC turning machine Cholchester Ternado 600 Group in dry cutting condition. A single-channel piezoelectric sensor was mounted at the tool holder to measure the deflection on the cutting tool in the tangential direction. The signal was transmitted to the piezoelectric amplifier device, then to data acquisition and finally to the computer system. The machining was done in three different cutting speeds (Vc), 200 m/min, 250 m/min and 300 m/min while the depth of cut and the feed rate were kept constant at 0.8 mm and 0.15 mm/rev respectively. During the experiment, the insert was periodically removed from the tool holder and the flank wear was measured using a graduated scale microscope. The operation was stopped when flank wear value (VB) reached 0.3 mm.

I-Kaz Multilevel Coefficient ($^{L}Z^{8}$): The development of I-kaz Multilevel coefficient ($^{L}Z^{8}$) was inspired by the original I-kaz™ (Z^{8}) which was pioneered by M.Z. Nuawi *et al.* [16]. The new symbol for I-kaz Multilevel coefficient is defined as $^{L}Z^{8}$ in which L is referring to the number of order of signal decomposition. The decomposition of signals in time domain into more frequency bands is to get a better coefficient response especially in the lower part of the frequency spectrum. The new developed coefficient ($^{L}Z^{8}$) is expected to have more sensitivity towards amplitude and frequency change in a signal. In I-kaz Multilevel method, signal decomposition using L^{th} order of Daubechies theorem will result in L number of frequency bands. This algorithm was summarized as presented in Fig. 1.

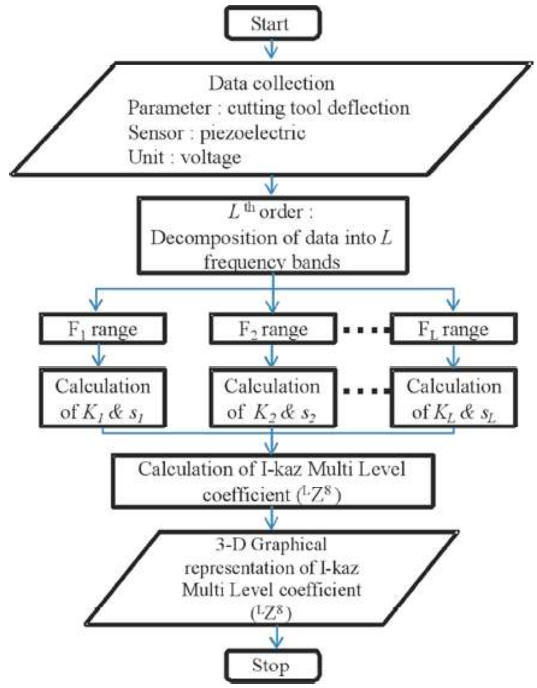

Fig. 1: Flowchart of the I-kaz Multilevel method

The frequency ranges of F_1, F_2, F_3 to F_L in Fig. 1 are depending on the value of L and the maximum frequency of the measured signal, f_{max}. For I-kaz Multilevel with L^{th} order of signal decomposition and for i = 1, 2, 3...L, the frequency ranges are shown below [15]:

$$[F_{i=1\,min} = 0] \quad \le F_{i=1} \le \quad [F_{i=1\,max} = f_{max} / (2^{L-1})] \qquad (1)$$
$$[F_{i=2\,min} = F_{i=1\,max}] \quad \le F_{i=2} \le \quad [F_{i=2\,max} = f_{max} / (2^{L-2})] \qquad (2)$$
$$[F_{i=L\,min} = F_{i=L-1\,max}] \quad \le F_{i=L} \le \quad [F_{i=L\,max} = f_{max} / (2^{L-i})] \qquad (3)$$

The related I-kaz Multilevel coefficient can be calculated as [15]:

$$^{L}Z^{\infty} = \frac{1}{n}\sqrt{K_1 s_1{}^4 + K_2 s_2{}^4 + K_3 s_3{}^4 \ldots + K_L s_L{}^4} \qquad (4)$$

where L indicates the order of signal decomposition. Z. Karim *et al.* in their study used the I-kaz Multilevel coefficient at level 7 of signal decomposition to correlate the wear rate of connecting rod bearing [18].

The standard deviation in Eq. 4 can be calculated using Eq. 5 [15]:

$$s = \left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{\frac{1}{2}} \qquad (5)$$

The value of Kurtosis K, for descrete data sets in Eq. 4 is defined as in Eq. 6:

$$K = \frac{1}{ns^4}\sum_{i=1}^{n}(x_i - \bar{x})^4 \qquad (6)$$

where x_i is the value of the data point and $\bar{x}$ is the mean of the data and s is the standard deviation value.

RESULTS AND DISCUSSION

Flank Wear Responses: Three experimental machining were performed to collect cutting tool deflection signals. The signals from single channel piezoelectric sensor were used to measure deflection on the cutting tool relating to tangential direction (z) due to cutting force action. The signals and tool wear data were recorded from the first cutting until the cutting tool wear reached 0.3 mm [19]. The overall results of the machining processes were recorded as in Table 1 and the related figures were shown in Fig. 2. From these figures, it can be clearly seen that the flank wear of the cutting tools can be divided into three stages, break-in period, steady state and failure region. As for example, from Fig. 2(a), at the cutting speed of 200 m/min, the VB value between the break-in period and steady state and the VB value between the steady state and failure region were recorded at 0.09 mm and 0.192 mm respectively. The flank wear measurement reaches 0.3 mm faster with the increase of cutting speed.

Table 1: Flank wears measurement for different machining parameter

Tool travel (x 80 mm)	200 m/min (mm)	250 m/min (mm)	300 m/min (mm)
1	0.007	0.015	0.021
2	0.027	0.037	0.041
3	0.046	0.056	0.057
4	0.049	0.079	0.106
5	0.065	0.102	0.133
6	0.071	0.112	0.144
7	0.09	0.114	0.155
8	0.098	0.12	0.157
9	0.118	0.136	0.167
10	0.123	0.157	0.235
11	0.144	0.203	0.274
12	0.155	0.24	0.32
13	0.164	0.269	NA
14	0.165	0.315	NA
15	0.167	NA	NA
16	0.173	NA	NA
17	0.192	NA	NA
18	0.2	NA	NA
19	0.25	NA	NA
20	0.291	NA	NA
21	0.314	NA	NA

Signal Analysis: I-kaz Multi Level coefficient, $^7Z^8$ was utilized in the measurement of the scattered raw data in time domain. This method is very effective in measuring distances of each data point from a centroid signal [14]. The I-kaz™ family of coefficients was found to be very sensitive with the change of amplitude and frequency in measured signals with respect to flank wear. The relationship between $^7Z^8$ coefficient and flank wear was plotted as shown in Fig. 3.

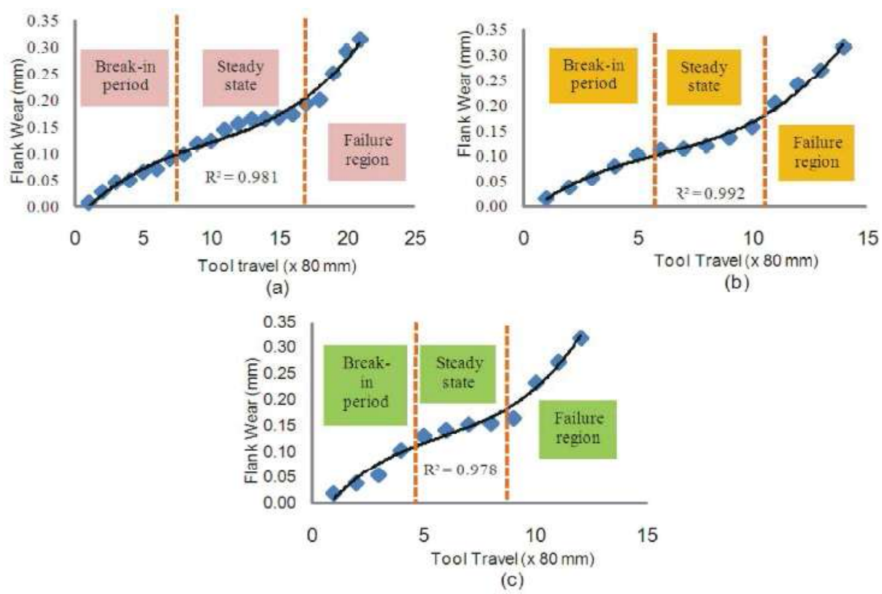

Fig. 2: The plot of VB Vs tool travel (a) Vc=200 m/min, (b) Vc=250 m/min, (c) Vc=300 m/min

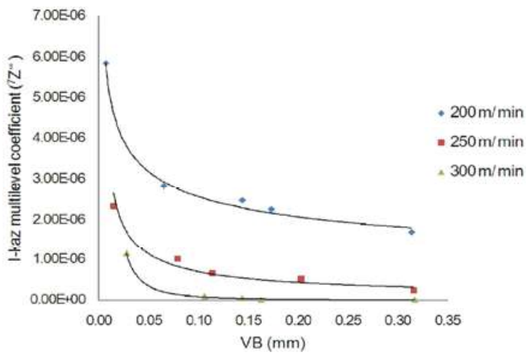

Fig. 3: Correlation between the I-kaz Multilevel coefficient and flank wear at various cutting parameter.

Fig. 3 shows that the experimental data based on cutting tool deflection signals can be used as an input parameter for flank wear prediction. The R-square value of the regression coefficients at Vc = 200 m/min is 0.985; when Vc = 250 m/min 0.939 and when Vc = 300 m/min is 0.932. Comparing these R-square values, the best regression is indicated at Vc = 200 m/min. Based on the results of curve fitting a new equation is derived, which can be used to detect the flank wear. The equation based on power-law curve fitting is shown as Eq. (7) below,

$$y = ax^{-n} \tag{7}$$

where y is the value of I-kaz Multilevel coefficient, $^{7}Z^{8}$. x represents the value of flank wear (VB), a is the coefficient of x and n is a constants. The values of a and n are depending on the shape of the power curve of I-kaz Multilevel versus flank wear. Therefore, Eq. (7) can be written as:

$$^{7}Z^{8} = a(\mathrm{VB})^{-n} \tag{8}$$

Similarly, the value of a and n are depending on the shape of the power curve and in this experiment the power curve shape is related to the value of cutting speed, Vc. In this case, when cutting at Vc = 200 m/min and f = 0.15 mm/rev, the values of a and n were $1{\times}10^{-6}$ and -0.31 respectively. A similar finding was reported in the study of online monitoring of cutting tool wear using low-cost technique and user friendly graphical user interface (GUI) [20].

CONCLUSION

This study aimed to apply a new technique to monitor and predict flank wear in CNC turning processes, using a low-cost piezoelectric sensor. A new correlation has been developed between the I-kaz Multilevel coefficient of the raw signal and flank wear data. The regression trend of its correlation shows a power-law curve with the R-square values of the regression coefficient between 0.932 and 0.985. This regression was the main formula for flank wear prediction. This prediction system is able to give an early indication of flank wear status in the cutting tool without disassembling it to measure the actual flank wear. This will promotes the uninterrupted machining operation in producing a part within the acceptance quality level.

ACKNOWLEDGEMENT

The authors wish to express their gratitute to Universiti Kebangsaan Malaysia and Ministry of Higher Education, through the fund of UKM-KK-02-FRGS0131-2011, for supporting this research.

REFERENCES

1. Rehorn, A.G., J. Jiang and E. Orban, 2005. State-of-the-art methods and results in tool condition monitoring: a review, Int. J. Adv. Manuf. Tech., 26: 693-710.
2. Bhattacharyyaa, P., D. Senguptaa and S. Mukhopadhyay, 2007. Cutting force-based real-time estimation of tool wear in face milling using a combination of signal processing techniques, Mechanical Systems and Signal Processing, 21: 2665-2683.
3. Kurada, S. and C. Bradley, 1997. A review of machine vision sensors for tool condition monitoring, Comput. Ind. 34: 55-72.
4. Castejon, M., E. Alegre, J. Barreiro and L.K. Hernandez, 2007. On-line tool wear monitoring using geometric descriptors from digital images, Int. J. Mach. Tools Manuf., 47: 1847-1853.
5. Sick, B., 2002. On-line and indirect tool wear monitoring in turning with artificial neural networks: a review of more than a decade of research, Mech. Syst. Signal Process. 16(4): 487-546.
6. Kilundu, B., *et al*., 2010. Tool wear monitoring by machine learning techniques and singular spectrum analysis, Mechanical Systems and Signal Processing (2010), doi:10.1016/j. ymssp. 2010.07.014.
7. Micheletti, G.F., *et al*., 1976. In process tool wear sensors for cutting operations, Ann. CIRP, 25: 483-495.

8. Shahabi, H.H. and M.M. Ratnam, 2009. In-cycle monitoring of tool nose wear and surface roughness of turned parts using machine vision, Int. J. Adv. Manuf. Tech., 40: 1148-1157.
9. Ghani, J.A., M. Rizal, M.Z. Nuawi, C.H.C. Haron and R. Ramli, 2010. Statistical analysis for detection of cutting tool wear based on regression model, in: Proceedings of the International Multi-Conference of Engineers and Computer Scientists, III: 1784-1788.
10. Teti, R. and A. Manzoni, 1998. Tool Wear State Identification by Fuzzy Logic Processing of Fused Sensor Data. 1st CIRP Int. Sem. on ICME, Capri, 1-3: 687-691.
11. Kamarthi, S.V., G.S. Sankar, P.H. Cohen and S.R.T. Kumara, 1991. On-line Tool Wear Monitoring Using a Kohonen's Feature Map. Int. Conf. on ANNIE'91, St. Louis, MO, 10-13(1): 639-644.
12. Rawat, S. and H. Attia, 2009. Characterization of the Dry High Speed Drilling Process of Woven Composites Using Machinability Maps Approach. CIRP Annals, 58(1): 105-108.
13. Axinte, D., 2007. An Experimental Analysis of Damped Coupled Vibrations in Broaching. International Journal of Machine Tools and Manufacture, 47(14): 2182-2188.
14. Brophy, B., K. Kelly and G. Byrne, 2002. AI-based Condition Monitoring of the Drilling Process. Journal of Materials Processing Technology, 124: 305-310.
15. Shi, D., D. Axinte and N. Gindy, 2007. Development of an Online Machining Process Monitoring System: A Case Study of the Broaching Process. International Journal of Advanced Manufacturing Technology 34(1-2): 34-46.
16. Nuawi, M.Z., M.J.M. Nor, N. Jamaludin, S. Abdullah, F. Lamin and C.K.E. Nizwan, 2008. Development of Integrated Kurtosis-Based Algorithm for Z-Filter Technique. Journal of Applied Sciences, 8: 1541-1547.
17. Karim, Z., M.Z. Nuawi, J.A. Ghani, S. Abdullah and M.J. Ghazali, 2011. Optimization of Integrated Kurtosis-Based Algorithm for Z-Filter (I-kaz™) Coefficient Using Multi Level Signal Decomposition Technique. World Applied Sciences Journal, 14(10): 1541-1548.
18. Karim, Z., M.Z. Nuawi, J.A. Ghani, S. Abdullah and M.J. Ghazali, 2012. Wear Monitoring of Connecting Rod Bearing Via Air-Borne Method Analyzed by Using I-kaz Multilevel Value, 2012. Advanced Materials Research, 445: 941-946.
19. ISO (International Organization for Standardization) (Ed.), 1993. Tool-life Testing with Single-Point Turning Tools (ISO 3685), 2nd edition, Reference Number ISO, pp: 3685.
20. Ghani, J.A., M. Rizal, M.Z. Nuawi, M.J. Ghazali and C.H.C. Haron, 2011. Monitoring online cutting tool wear using low-cost technique and user friendly GUI, Wear, 271: 2619-2624.