New Regression Model and I-Kaz Method for Online Cutting Tool Wear Monitoring

Jaharah A. Ghani, Muhammad Rizal, Ahmad Sayuti, Mohd Zaki Nuawi, Mohd Nizam Ab. Rahman, and Che Hassan Che Haron

***Abstract*—**This study presents a new method for detecting the cutting tool wear based on the measured cutting force signals using the regression model and I-kaz method. The detection of tool wear was done automatically using the in-house developed regression model and 3D graphic presentation of I-kaz 3D coefficient during machining process. The machining tests were carried out on a CNC turning machine Colchester Master Tornado T4 in dry cutting condition, and Kistler 9255B dynamometer was used to measure the cutting force signals, which then stored and displayed in the DasyLab software. The progression of the cutting tool flank wear land (*VB*) was indicated by the amount of the cutting force generated. Later, the I-kaz was used to analyze all the cutting force signals from beginning of the cut until the rejection stage of the cutting tool. Results of the I-Kaz analysis were represented by various characteristic of I-kaz 3D coefficient and 3D graphic presentation. The I-kaz 3D coefficient number decreases when the tool wear increases. This method can be used for real time tool wear monitoring.

***Keywords*—**mathematical model, I-kaz method, tool wear

I. Introduction

THE wear of a cutting tool is well-known affecting the tool life and the surface quality of the finished product. When wear is beyond a certain threshold, the tool fails catastrophically due to excessive stresses and thermal softening within the tool edge caused by large friction forces.

In general, the tool wears on the two contact zones. Crater wear occurs on the rake face of the tool where the chip moves under friction and normal loads at elevated temperatures, leading to wear. Since all cutting edges have a finite sharpness, the friction between the flank face of the cutting tool and the freshly cut work surface causes flank wear. The crater wear is usually avoided by selecting a cutting speed and tool material that does not have an affinity to diffusion with the work material [1]. The flank wear, on the other hand, leads to loss of cutting edge, and affects the dimension and surface finish quality, therefore, importance to develop tool wear condition monitoring systems. The operator will alert about the tool condition, thus avoiding undesirable condition. Besides, maintaining acceptable flank wear below the rejection criterion is very essential to avoid excessive surface and sub-surface damages on machined components [2].

There are two methods that had been proposed, direct and indirect methods. Direct monitoring methods are such as vision and optical approaches, which measure the geometric parameters of the cutting tool [3], [4]. The direct methods have advantages of capturing actual geometric changes arising from wear of tool. However, direct measurements are very difficult to implement because of the continuous contact between the tool and the workpiece, and almost impossible due to the presence of coolant fluids. The difficulties severely limit the application of direct approach. The indirect methods are achieved by correlating or deducing suitable sensor signals to tool wear states. The advantages are less complicated setup and suitable for practical application. In indirect methods, tool condition is not captured directly, but estimated from the measurable signal feature. This signal feature is extracted through signal processing steps for sensitive and robust representation of its corresponding state. Indirect methods include such as those based on sensing of the cutting forces, vibrations, acoustic emission, and motor current [5].

In most of the studies done, cutting force signals were widely used as a source for detecting the tool wear and tool failure as studied by Lin and Lin (1996), Dimla et al (1999), E. Kuljanic (2005), and Kang-Jae Lee (2007). In practice, the application and interpretation of this parameter has been diverse with more effort concentrated on studying the dynamic characteristic of the cutting force signal and interpreting its relation to tool wear levels. And the other hand, Oraby and Hayhurst (2004) developed models for tool wear and tool life determination using nonlinear regression analysis techniques in terms of the variation of a ratio of force components acting at the tool tip. Srinivas and Kotaiah (2005) developed a neural network model to predict tool wear and cutting force in turning operations for cutting parameters cutting speed, feed and depth of cut.

This paper focuses on indirect methods by online tool wear monitoring using force signals for tool wear detection based on regression model that was built by I-kaz method, which was pioneered by Nuawi (2008). The main objective of this paper is to develop a new mathematical model based on regression for tool wear detection by means measuring cutting force signals.

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II. METHODOLOGY

A. Experimental Setup and Procedure

The material chosen for machining test was titanium alloy, Ti-6Al-4V. The main characteristics of titanium are high strength, low density and high corrosion resistance to acid, alkali and chlorine. These special characteristics of titanium made it become the first choice in various field such as chemical industry, automotive, biomaterial, shipping and marine applications [2]. Titanium behavior such as chemically reacts with cutting tool at operation temperature, low elasticity modulus and thermal conductivity limits its machinability.

The machining tests were carried out on a CNC lathe machine Colchester Master Tornado T4 in dry cutting condition, and the cutting insert used was Cubic Boron Nitride (CBN). This tool is suitable for turning titanium at high-speed cutting [13]. A Kistler dynamometer type 9255B was mounted on tool post to measure the force signals in the three channels, namely channel I, channel II and channel III. Fig. 2 shows the experimental setup and data acquisition system.

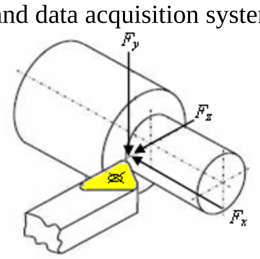


Fig. 1. Force directions on turning process.

Fig. 1 shows cutting force directions in turning process. Three forces direction, namely tangential/cutting force (F_y), axial/feed force (F_x) and radial/thrust force (F_z). Cutting force is represented by channel II, feed force is represented by channel III and radial force is represented by channel I.

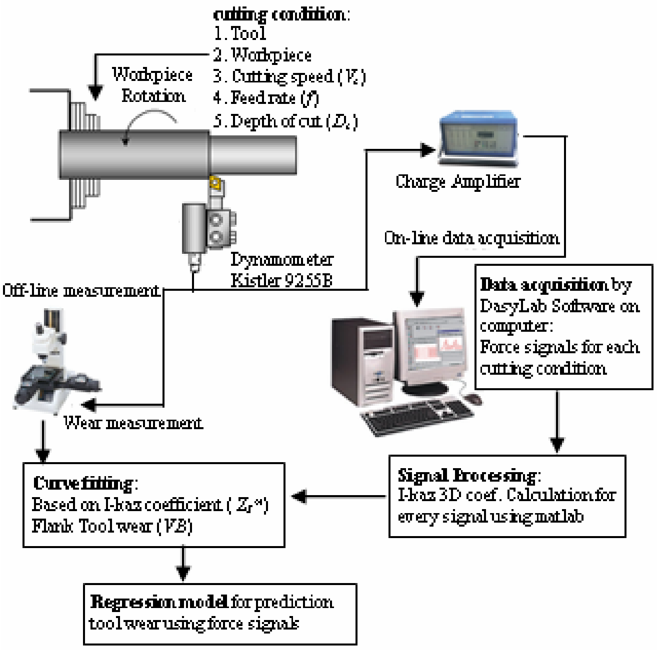


Fig. 2. Experimental setup and system development to prediction tool wear.

Data acquisition process consists of two sets of data collections; i.e. the measurement of the generated dynamic cutting force signals and the flank wear land measurement on the cutting tool edge. Cutting condition were set at cutting speeds of 180 m /min and depth of cut 0.5 mm. Feed rate were set at various feed rates of 0.05 mm/rev and 0.25 mm/rev.

Signals generated by Kistler dynamometer model 9255B are dynamic cutting force signal which are captured and stored by DasyLab software. During the turning operation the insert was periodically removed from the tool holder, and the flank wear on the flank face was measured using a Mitutoyo toolmaker's microscope equipped with graduated scale in mm. The measured parameter to represent the progress of wear was flank tool wear *VB*. The turning operation is stopped and the insert is discarded when *VB* reach 0.3 mm. It is a standard recommended value in defining a tool life end-point criterion based on ISO 3685:1993 [14].

B. Signal Analysis

The signal analysis methods used is a statistical signal processing based on Kurtosis, I-Kaz method. The I-kaz method was pioneered by Nuawi (2007). He studied random or nondeterministic signal characteristics. In order to classify the random signals, the r-th order of moment M_r is frequently used. The r-th order of moment, M_r for the discrete signal in the frequency band can be written as:

$$M_r = \frac{1}{N}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^r \quad (1)$$

Where N is the number of data, x_i is data value at the instantaneous point and $\bar{x}$ is the mean. The (1) has brought to the derivation of kurtosis. Kurtosis, which is the signal 4th statistical moment, is a global signal statistic which is highly sensitive to the spikiness of the data. For discrete data sets the kurtosis, K is defined as:

$$K = \frac{1}{N\sigma^4}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^4 \quad (2)$$

Where N is the number of data, σ is the variance; x_i is the data value at the instantaneous point and $\bar{x}$ is the mean of the data. The kurtosis value is approximately 3.0 for a Gaussian distribution. Higher kurtosis values indicate the presence of more extreme values than should be found in a Gaussian distribution. Kurtosis is used in engineering for detection of fault symptoms because of its sensitivity to high amplitude events.

Based on kurtosis, the method provides a three dimensional graphical representation of the measured signal frequency distribution. Specifically, the time domain signal was decomposed into three frequency channels. In order to measure the degree of scattering of the data distribution, the I-kaz coefficient calculates the distance of each data point from the signal's centroid [12]. I-kaz coefficient was defined as:

$$I-kaz\ \ 3\mathrm{D}\, coef = \sqrt{\frac{1}{N}\left(M_4^{I}\right) + \frac{1}{N}\left(M_4^{II}\right) + \frac{1}{N}\left(M_4^{III}\right)} \quad (3)$$

Where N is the number of data and M_4^I, M_4^{II}, M_4^{III} are the 4-th order of moment in channel-I, channel-II and channel-III respectively. The I-kaz coefficient as indirect copyright as (4) and the symbol of Z_3^∞ was used to represents the I-kaz coefficient.

$$Z_3^\infty = \frac{1}{N}\sqrt{K_I s_I^4 + K_{II} s_{II}^4 + K_{III} s_{III}^4} \tag{4}$$

Where N is the number of data, K_I, K_{II} and K_{II} are the kurtosis of signal in ch-I, ch-II and ch-III and s_I, s_{II} and s_{III} are the standard deviation of signal in ch-I, ch-II and ch-III respectively.

III. Result and Discussion

Experimental results of cutting force measurement during turning process were divided by two cutting set parameter. First, at cutting speed of 180 m/min, depth of cut of 0.5 mm and feed rate of 0.05 mm/rev. Secondly, at cutting speed of 180 m/min, depth of cut of 0.5 mm and feed rate of 0.25 mm/rev.

At feed rate of 0.05 mm/rev, the total time taken to reach flank wear equal to 0.3 mm was 1200 second. The I-kaz 3D coefficients (Z_3^∞) were calculated based from the wear measurement results using (4) was given in Table I. Table II shows the result obtained at feed rate of 0.25 mm/rev.

TABLE I
EXPERIMENTAL RESULT OF FLANK WEAR AND I-KAZ 3D AT CUTTING SPEED, V_C = 180 M/MIN, FEED RATE, F = 0.05 MM/REV AND DEPTH OF CUT, DC = 0.50 MM RESPECTIVELY.

Time (s)	Flank wear, *VB* (mm)	I-kaz 3D coef. Z_3^∞	Axial Force Fx (N)	Tangential Force Fy (N)	Radial Force Fz (N)
10	0.02	0.0139	54.5	60.3	60.5
450	0.12	0.0064	86.4	91.3	91.7
840	0.18	0.0053	93.4	93.7	93.6
1110	0.25	0.0046	70.4	78.1	72.6
1200	0.29	0.0021	82.1	94.4	85.9

TABLE II
EXPERIMENTAL RESULT OF FLANK WEAR AND I-KAZ 3D AT CUTTING SPEED, V_C = 180 M/MIN, FEED RATE, F = 0.25 MM/REV AND DEPTH OF CUT, DC = 0.50 MM RESPECTIVELY.

Time (s)	Flank wear, *VB* (mm)	I-kaz 3D coef. Z_3^∞	Axial Force Fx (N)	Tangential Force Fy (N)	Radial Force Fz (N)
6	0.03	0.0207	3.4	29.3	15.0
16	0.07	0.0101	70.2	114.3	85.9
20	0.16	0.0099	89.5	134.5	105.5
36	0.31	0.0043	115.4	159.3	108.4

Force signals were measured by mean on-line data acquisition from turning process, captured and stored in Dasylab software. Whereas flank wear (*VB*) data was measured using off-line microscope.

It can be seen in fig. 3 and 4 that the cutting force (F_y) is showed by red polynomial line, axial force (F_x) is showed by green line and radial force (F_z) is showed by black line. A curve fit method was used with cubic polynomial regression and coefficient of multiple determination R-squared (R^2) at feed rate 0.05 mm/rev is 0.91 and feed rate 0.25 mm/rev is 1.0.

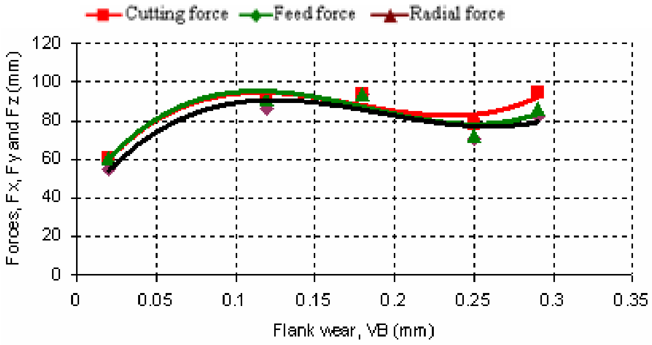


Fig. 3. The forces versus flank wear plot at feed rate 0.05 mm/rev

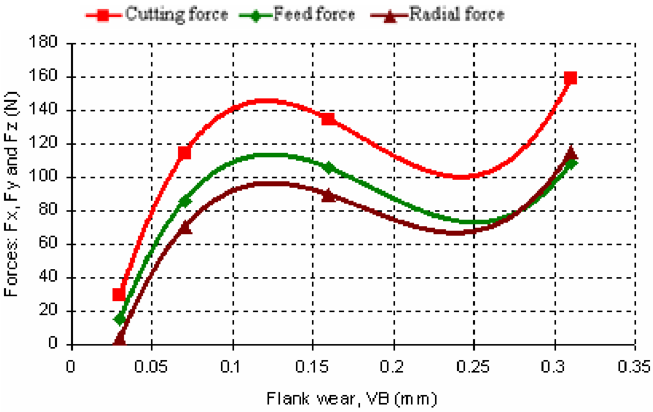


Fig. 4. The forces versus flank wear plot at feed rate 0.25 mm/rev

A. *Mathematical Model for Prediction Flank Wear*

Graphical detection tool wear will be developed based on previous section, i.e. using I-kaz 3D coefficient for every cutting force signal, and then plotted against flank wear land as shown at fig. 5 below.

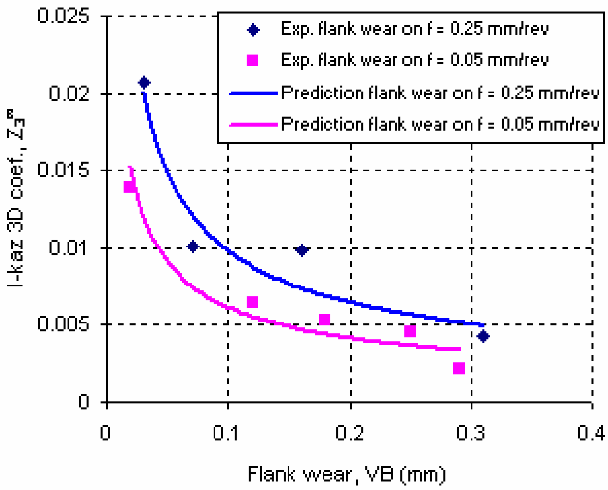


Fig. 5. Curve fitting of flank wear prediction

The coefficient of multiple determination R-squared (R^2) for the developed regression based model on power-law curve fit are 0.82 and 0.89.

Form of fitting equation in fig. 5 is power-law equation that according to the following equation:

$$y = ax^{-n} \tag{5}$$

Where y is the value of I-kaz 3D coefficient, Z_3^∞. a and n are constant coefficient which depend on cutting condition, and x is the value of flank wear, VB. Therefore, Eq. (3.1) can be written as:

$$Z_3^\infty = a(VB)^{-n} \tag{6}$$

The developed equation for tool wear prediction is as below:

$$VB = \left(\frac{a}{Z_3^\infty}\right)^{1/n} \tag{7}$$

By using curve fitting, at cutting speed 180 m/min, depth of cut 0.5 mm and feed rate 0.05 mm/rev, the result of coefficient obtained:

a = 0.0017

n = 0.57

Therefore,

$$VB = \left(\frac{0.0017}{Z_3^\infty}\right)^{1/0.57} \tag{8}$$

At cutting speed 180 m/min, depth of cut 0.5 mm and feed rate 0.25 mm/rev, the result of coefficient obtained:

a = 0.0025

n = 0.60

Therefore:

$$VB = \left(\frac{0.0025}{Z_3^\infty}\right)^{1/0.60} \tag{9}$$

As observed, the equation from curve on fig 5. and (8) that flank wear prediction before cutting is not zero ($VB \neq 0$). So, it is assumed that the cutting tool at the first cutting has flank wear land about 0.01 mm and Z_3^∞ about 0.02347 as shown in Fig. 6. When flank wear land equal to 0.3 mm, I-kaz 3D coefficient is about 0.003377. This means, the cutting process should be stopped at Z_3^∞ closed on 0.003377. Because after flank wear 0.3 mm, cutting tool was worn out and this will consequently risen the risk of cutting tool failure and affect the quality of machined surfaced.

Same as fig. 6 based on the curve in fig 5. and (9) assumed the first cutting flank wear also about 0.01 mm, but Z_3^∞ about 0.03963 and the last cutting at VB = 0.3 mm, Z_3^∞ = 0.005148 as such as Fig. 7.

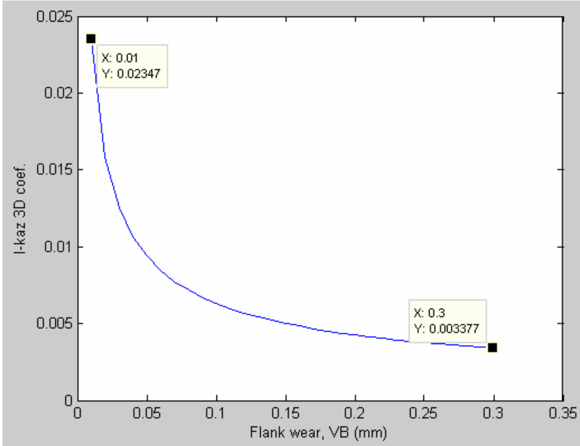


Fig. 6. The value flank wear assumption before cutting at feed rate 0.05 mm/rev.

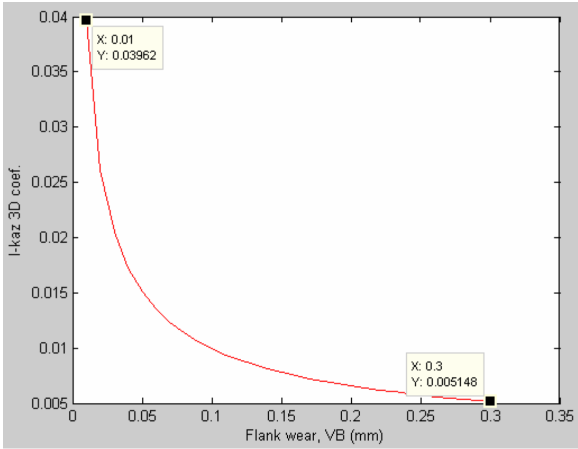
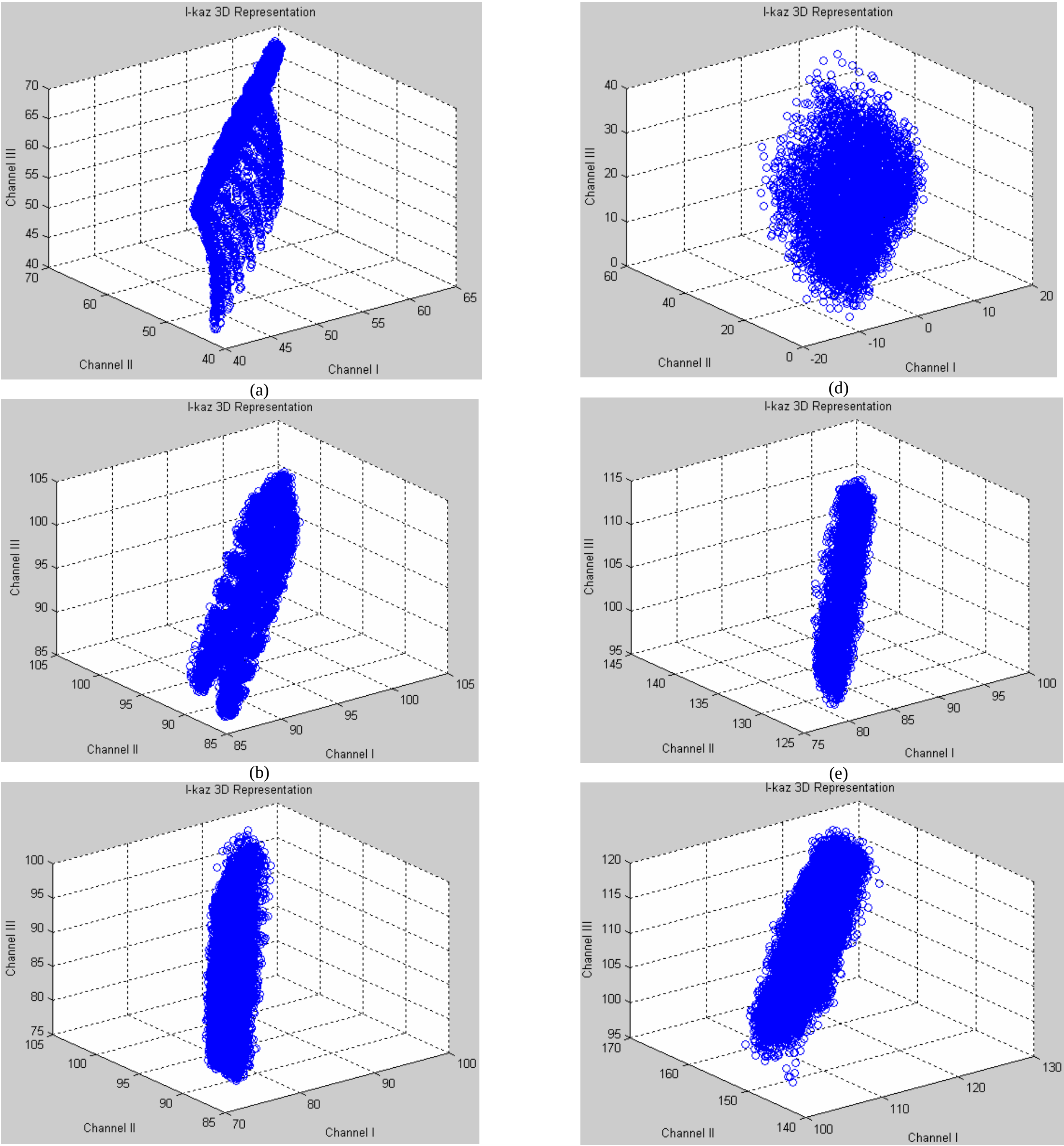


Fig. 7. The value flank wear assumption before cutting at feed rate 0.25 mm/rev.

Comparing the predicted curve model at feed rate 0.05 mm/rev and curve model at feed rate 0.25, apparently there is differences in value of Z_3^∞ for predicted flank wear land. The range for Z_3^∞ at feed rate 0.05 mm/rev (0.02347 – 0.003377) is lower than the range of Z_3^∞ at feed rate 0.25 mm/rev (0.03962 – 0.005148). Therefore, the value of Z_3^∞ very much depends on the cutting condition parameter, and in this study is the feed rate.

The force signals have various characteristic at certain condition of flank wear. By using I-kaz method, beside the I-kaz 3D coefficient value, the signals could generate 3D graphical presentation that show the value of Z_3^∞. According to Fig. 8 shows that channel I is distribution of feed force data, channel II is distribution of cutting force data and channel III is distribution of radial force data. This figure shows alteration of range of cutting force signal distribution. When increasing flank wear, the range will shrink. These result same with trend of Z_3^∞ value.



(a) (b) (c) (d) (e) (f)

Fig. 8. 3D graphical representation that show the value of Z_3^{∞} at feed rate 0.05 mm/rev (a) Good condition, Z_3^{∞}= 0.0139 VB = 0.02, (b) Transition condition, Z_3^{∞}= 0.0053 VB = 0.18, (c) Wear condition, Z_3^{∞}= 0.0021 VB = 0.29 ; and feed rate 0.25 mm/rev (d) Good condition, Z_3^{∞}= 0.0207 VB = 0.03, (e) Transition condition, Z_3^{∞}= 0.0121 VB = 0.17 and (f) Wear condition, Z_3^{∞}= 0.0043 VB = 0.31.

For example, at feed rate of 0.25 mm/rev, the value of I-kaz 3D coefficient for the first cutting (0.0207) is bigger than cutting at flank wear equal to 0.17 mm (0.0121). Because at flank wear equal to 0.03 mm, the force generated only about 3 – 30 Newton with bigger scattering data than at flank wear equal to 0.17 mm. That means, the I-kaz 3D value will be decreasing while forces or flank wear value increasing. As shown at fig. 6 and 7, the Z_3^{∞} will keep on reducing until flank wear equal to 0.3 mm.

IV. Conclusion

This paper discussed on cutting tool wear detection and prediction using regression model based on I-kaz method. Tool wear is a time dependent process in which tool wear increases gradually with the cutting time. From the analysis and calculation of I-kaz 3D coefficient (Z_3^∞), the relationship is obtained between the I-kaz 3D coefficient and the flank wear value, and is given by: $Z_3^\infty = a(VB)^{-n}$. Where a and n are coefficient that the value depend on cutting condition that are cutting speed, feed rate and depth of cut. From this equation, at the same cutting condition, a new model for prediction flank wear land is obtained as:

$$VB = \left(\frac{a}{Z_3^\infty}\right)^{1/n}$$

The value of Z_3^∞ was obtained from signal acquisition during turning process. In order to use the developed equation for prediction flank wear land, assumption is made at the first cutting the flank wear is equal to 0.01 mm, although before the cutting process take place.

Acknowledgement

The authors would like to thank the Government of Malaysia and Universiti Kebangsaan Malaysia for their financial support under UKM-GUP-BTT-07-25-025 Grant.

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