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The Application of I-kaz^{TM}-Based Method for Tool Wear Monitoring using Cutting Force Signal

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Abstract

Tool wear monitoring is important in machining industries for controlling the quality of machined parts that helps to improve the productivity. To date, many monitoring system methods are developed by utilizing various signals, and cutting force is one of the signals in machining process that has been widely used for tool wear monitoring. This paper presents the application of I-kaz based method to analyze the cutting force signal for monitoring the status of tool wear in turning process. Experiments were carried out by turning hardened carbon steel, and cutting force signals were measured by two channels of strain gauges that were mounted on the surface of tool holder. In this study, I-kaz 2D is one of the derivatives of I-kaz^{TM} method that has been utlized to integrate two components of cutting force signals. It differs from the I-kaz method, whereby the signal does not need to be decomposed to three different frequency ranges. The analysis of results using I-kaz 2D and I-kaz^{TM} methods, revealed that both methods can be used to determine tool wear progression during turning process and feed force is very significant due to flank wear.

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Keywords: Tool wear monitoring; I-kaz method; cutting force

Nomenclature

K	kurtosis
N	number of data
s	standard deviation

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x_i	data for *i*-sample
VB	flank wear width (mm)
Z_2^{∞}	I-kaz coefficient in two integrated channels of signal
Z_{Fc}^{∞}	I-kaz coefficient in main cutting force
Z_{Ff}^{∞}	I-kaz coefficient in feed force
σ_L	variance of data of low frequency
σ_H	variance of data of high frequency
σ_V	variance of data of very high frequency

1. Introduction

Tool wear is gradual failure of cutting tools due to regular operation, and it is inevitable. When the machining process continues with a worn tool, the worn tool can deteriorate the quality of machined part, increase the production time and cost, and even cause machine breakdown if the cutting tool suddenly brakes. To avoid catastrophic tool failure, the progression of cutting tool wear from the beginning of the cutting process should be monitored. Progression of tool wear during the cutting process causes the cutting forces to increase. Therefore, cutting force is very suitable to be used as a reference for indirect measurement and monitoring of tool wear. Among the indirect online tool wear monitoring methods, cutting force is one of the most commonly used variable as a tool wear indicator [1].

Previously, numerous methods for the interpretation of cutting force signals have been described by various researchers. Jemielniak et al. [2] used the average and standard deviations values of cutting forces to diagnose the tool wear. They reported that there is a conspicuous relation between tool wear and standard deviation of feed force. Dimla and Lister [1] analyzed static and dynamic cutting force in time and frequency domains. They concluded that the static force was the most sensitive indicator to cutting condition changes such as depth of cut and feed rate. While in the frequency domains, the amplitude of the signal is found to increase monotonically with tool wear and falls sharply prior to the point of entry into the tertiary wear zone. Das et al. [3] used cutting force average and analyzed using force ratio for tool wear estimation. They reported that the increasing of force ratio (F_y/F_x) with the progress of tool wear is evident. Chungchoo and Saini [4] applied skewness and kurtosis of force distribution in fixed frequency band. It is reported that the frequency distribution pattern of force signals is influenced by cutting conditions and tool wear. However, the cutting forces signals have characteristics that can be extracted in both time and frequency domain.

This paper presents the application of the I-kaz™ and I-kaz 2D methods to interpret the cutting force signal for detection the tool wear progression in turning process. The focus is on the assessment of these methods via relationship between coefficient values of I-kaz™ method and tool wear progression then compared the performance results. The I-kaz coefficient including the I-kaz coefficient of main cutting force (Z_{Fc}^{∞}), feed force (Z_{Ff}^{∞}), and I-kaz 2D coefficient (Z_2^{∞}). However, the I-kaz™ method has been used in various study such as to analyze strain signal for fatigue life evaluation [5], to analyze sound signals for sliding wear monitoring of commercial bearing [6], to analyze ultrasound signals for tool life monitoring [7], and also for tool wear monitoring by analyzing the cutting force signals in three channels using I-kaz 3D[8], and two channels using I-kaz 2D [9, 10]. The advantage of I-kaz™ method is the characteristic of signals can be obtained in time and frequency domain and its sensitive to amplitude and frequency changes [11].

2. I-kaz™ Method

The main idea of the I-kaz™ method is to decompose a dynamic signal into three frequency ranges including a low-frequency (LF) range of 0 – $0.25f_{max}$, a high-frequency (HF) range of $0.25f_{max}$ – $0.5f_{max}$ and a very high-frequency (VF) range of $0.5f_{max}$. In order to measure the scattering of the data distribution, the variance σ^2 for each frequency band is calculated, as shown in Eq. (1). The variance determines the average magnitude deviation of instantaneous points with respect to the mean value.

$$\sigma_L^2 = \frac{\sum_{i=1}^{N}\left(x_i^L - \mu_L\right)^2}{N};\ \sigma_H^2 = \frac{\sum_{i=1}^{N}\left(x_i^H - \mu_H\right)^2}{N};\ \sigma_V^2 = \frac{\sum_{i=1}^{N}\left(x_i^V - \mu_V\right)^2}{N}; \tag{1}$$

where σ_L^2, σ_H^2, σ_V^2 and x_i^L, x_i^H, x_i^V are the variances and data for the *i*-sample of time in the *LF*, *HF* and *VF* range, respectively. Whereas μ_L, μ_H and μ_V are the means of each frequency bands, and *N* is the number of data points. Since the I-kaz™ method was developed based on the concept of data scattering about the data centroid and classified the display according to inferential statistics, the I-kaz coefficient can be symbolized by Z^∞ and written in terms of the variance, σ^2, as shown in Eq. (2) and Eq. (3).

$$Z^\infty = \sqrt{\left(\sigma_L^2\right)^2 + \left(\sigma_H^2\right)^2 + \left(\sigma_V^2\right)^2} \tag{2}$$

$$Z^\infty = \sqrt{\frac{\sum_{i=1}^{N}\left(x_i^L - \mu_L\right)^2}{N^2} + \frac{\sum_{i=1}^{N}\left(x_i^H - \mu_H\right)^2}{N^2} + \frac{\sum_{i=1}^{N}\left(x_i^V - \mu_V\right)^2}{N^2}} \tag{3}$$

Eq. (3) can be simplified in terms of the kurtosis and standard deviation. The kurtosis, *K*, is the signal's 4th statistical moment, which is the global signal statistic and is highly sensitive to the spikiness of the data. The Gaussian distribution of the kurtosis value is approximately 3.0. A higher kurtosis value indicates the presence of more extreme values than should be normally found in a Gaussian distribution. The kurtosis can be defined as:

$$K = \frac{1}{Ns^4}\sum_{i=1}^{N}\left(x_i - \mu\right)^4 \tag{4}$$

where *N* is the number of data, *s* is the standard deviation. Therefore, Eq. (2) can be written in terms of the kurtosis, *K,* and the standard deviation, *s*, as:

$$Z^\infty = \frac{1}{N}\sqrt{K_L s_L^4 + K_H s_H^4 + K_V s_V^4} \tag{5}$$

where K_L, K_H, and K_V are the kurtosis of the signal in the LF, HF and VF ranges, and s_L, s_H, s_V are the standard deviations of signal in the LF, HF and VF ranges, respectively.

I-kaz 2D emerged from I-kaz™ method, which analyzed signals from two channels or two sensors. It differs from the I-kaz™ method, whereby the signal does not need to be decomposed to three different frequency ranges. But, each signal is computed directly by using kurtosis and standard deviation. Therefore, the I-kaz 2D coefficient can be symbolized by Z_2^∞ and written as following:

$$Z_2^\infty = \frac{1}{N}\sqrt{K_I s_I^4 + K_{II} s_{II}^4} \tag{6}$$

where *N* is the number of data points, K_I and K_{II} are the kurtosis of signal in channel I and channel II, and s_I and s_{II} are the standard deviation of signal in channel I and channel II respectively.

3. Experimental Procedures

The machining tests were performed on a CNC Colchester Master Tornado T4 lathe machine under dry cutting conditions. An orthogonal insert was used in the experiments for machining of a hardened JIS S45C carbon steel bar. The dimensions of the material were 200 mm in length and 85 mm in diameter. The tool insert used was a coated carbide insert (Toolmex CNMG120404-MB) with NC30P grade 5. The tool had a rhombic 80º shape, 4.76 mm thickness and a 0.4 mm nose radius. The complete illustration of experimental set up is shown in Fig. 1.

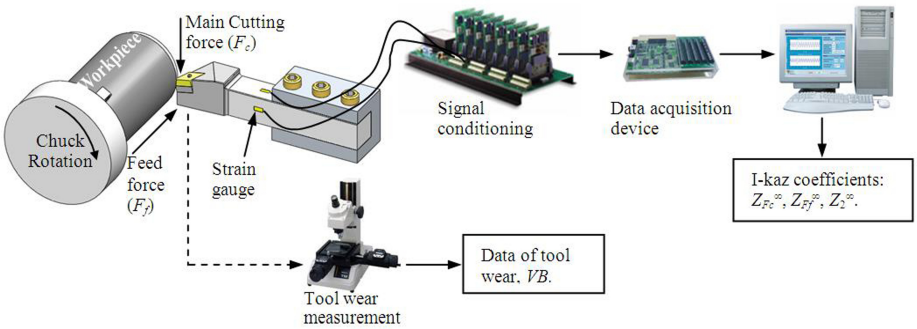

Fig. 1. Illustration of experimental setup

The experiment conducted in this study was deployed by using low cost sensors which consist of two strain gauges as shown in Fig. 1. The data acquisition system consists of a signal conditioner (OM2-163 and OM2-8608-230AC), a data acquisition device (DT9836) and MATLAB software. A simple tool holder (PDJNR2020-43) that has a sectional shape of 20 x 20 mm was used for mounting the strain gauges on the top and the left side of the tool holder to measure the cutting forces due to the deflection in both the tangential direction, F_c (main cutting force) and feed direction, F_f (feed force). The distance of strain gauge to the tip of tool insert was fixed at 45 mm. The sensor configuration used a quarter-bridge strain gauge set in the signal conditioning device. The cutting force signals were collected at sampling rate of 1 kHz, and then analyzed by the computer using signal analysis based on the I-kaz™ and I-kaz 2D methods.

The experiment test in this study was conducted cutting speed equal to 200 m/min, feed rate equal to 0.20 mm/rev, and depth of cut equal to 1.2 mm. This cutting condition was selected based on the real turning operation of hardened carbon steel carried out in one of the local automotive industries. 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. The measured parameter to represent the progress of wear was the average flank wear land, *VB*. The flank wear data were recorded since the first cutting pass until the flank wear reached 0.3 mm. It is a standard recommended value in defining a tool life end-point criterion based on ISO 3685-1993.

4. Results and Discussion

The measured force signals from initial first cutting until end of cutting are recorded. In Fig. 2 shows the three steps of cutting force generated during turning using two channels of strain gauge. It was observed that the changes of tool wear followed by changes of the cutting force signal. From the signals display, the main cutting force (F_c) is greater than the feed force (F_f) during the turning process. But, the feed force rapidly increases than cutting force as flank wear increases. This is possibly due to the rubbing friction on the flank surface that contributes to more feed force. The present findings are similar with previous researcher's findings [3].

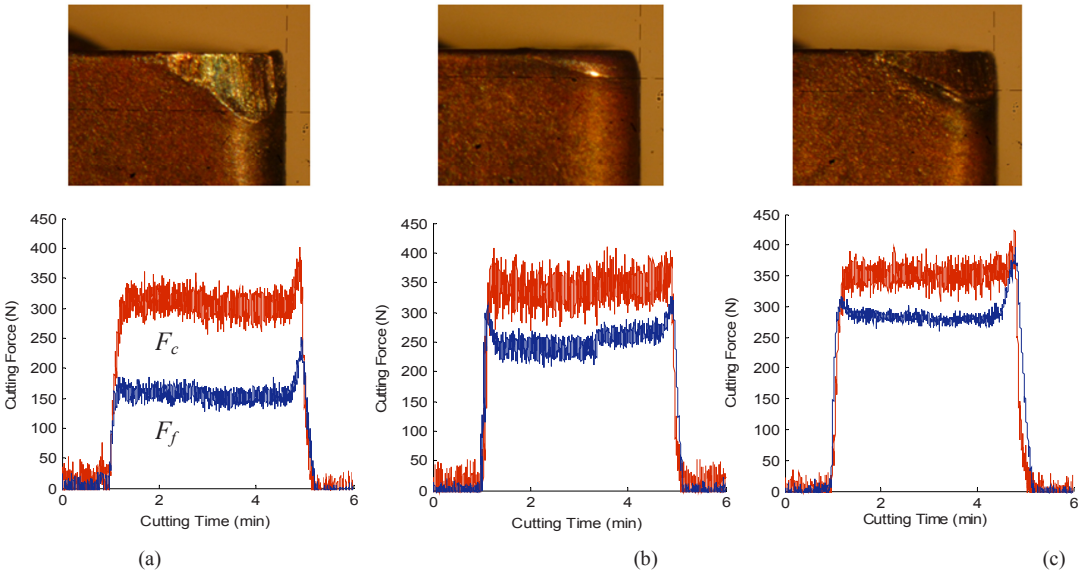

Fig. 2. The cutting forces during turning process:
(a) at flank wear = 0.102 mm, (b) at flank wear = 0.185 mm, and (c) at end of cutting, flank wear = 0.306 mm.

According to Fig. 2, when flank wear about 0.102 mm, the average cutting force is 310 N. After cutting about 17 minutes or flank wear = 0.306 mm, the average cutting force increases to 357 N or 13.16%. Meanwhile, the average feed force at the initial first cutting is only 158 N, and at the end of cutting it increases to about 285 N or 44.56%.

The results of the I-kaz based analysis of the force signals along the cutting process, i.e. sharp tool or flank wear is 0.102 mm, intermediate sharp (flank wear = 0.185 mm), and worn tool or the end cutting (flank wear = 0.306 mm) in turning process are shown in Fig. 3. The raw signals from machining are directly calculated using the Eq. (5) and Eq. (6). Fig. 3(a), 3(b), 3(c) show the plots of I-kaz 2D in two dimensional graphical representations of amplitude scattering for main cutting force and feed force signals. It can be observed that the changes of data scattering are very significant due to progression of flank wear. Fig. 3(d), 3(e), 3(f), and 3(g), 3(h), 3(i) show the results of the I-kaz analysis plots for each channel i.e. main cutting force and feed force signals. Prior to plotting in three axis representations, the signals are decomposed into three frequency ranges. The results visually show that the space of scattering in both main cutting force and feed force are increased due to progression of flank wear. But, the feed force increases prominently and more apparent than the main cutting force. The effect of progression of flank wear can also seen by changes of I-kaz coefficient as shown in Fig. 4.

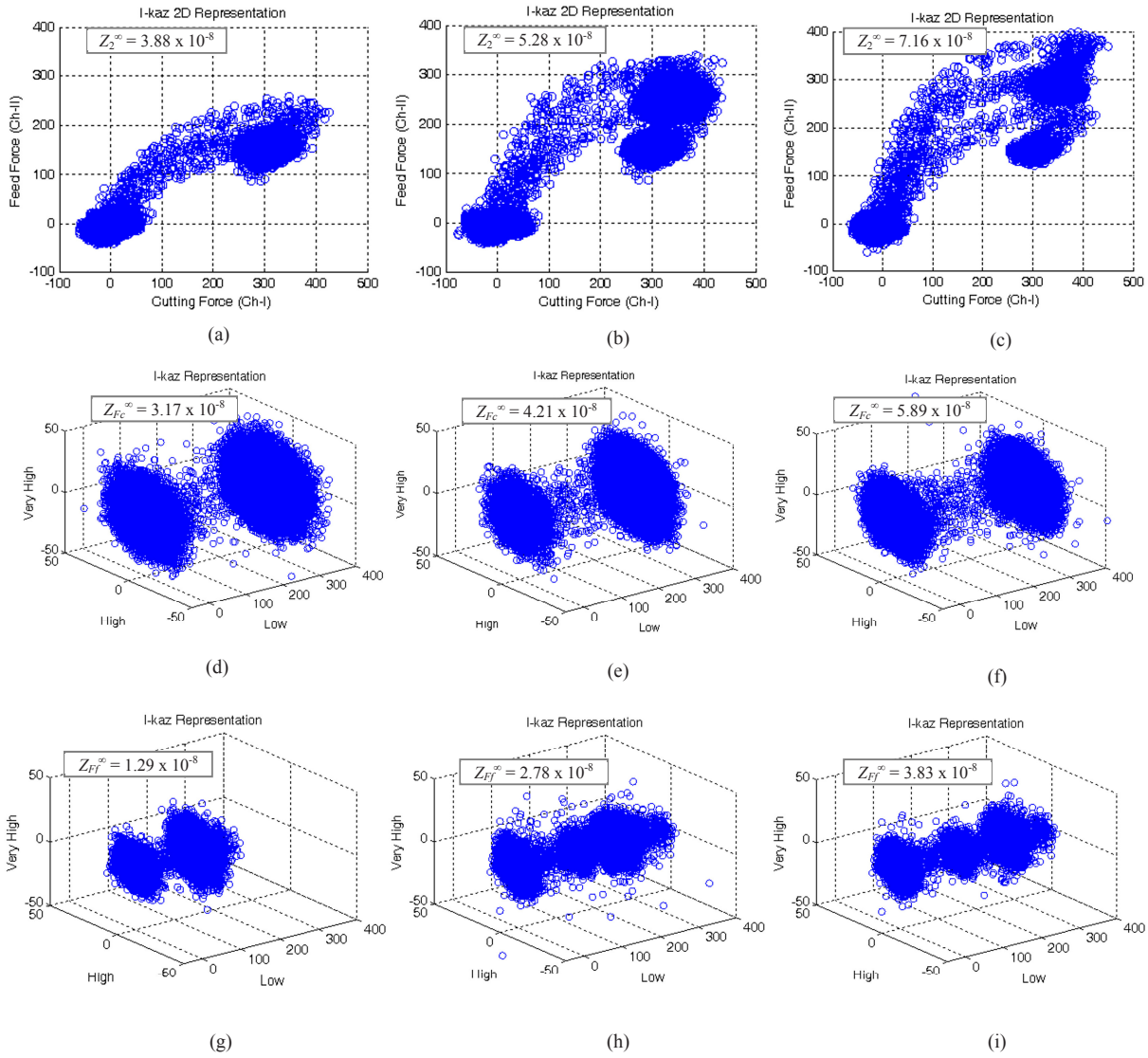

Fig. 3. I-kaz display of graphical representations for cutting force during turning process from the sharp tool (VB = 0.102 mm), middle cutting or still sharp tool (VB = 0.185 mm), and worn tool or the end cutting (VB = 0.306); (a), (b), (c) I-kaz 2D display; (d), (e), (f) I-kaz three dimensional of main cutting force; and (g), (h), (i) I-kaz three dimensional of feed force.

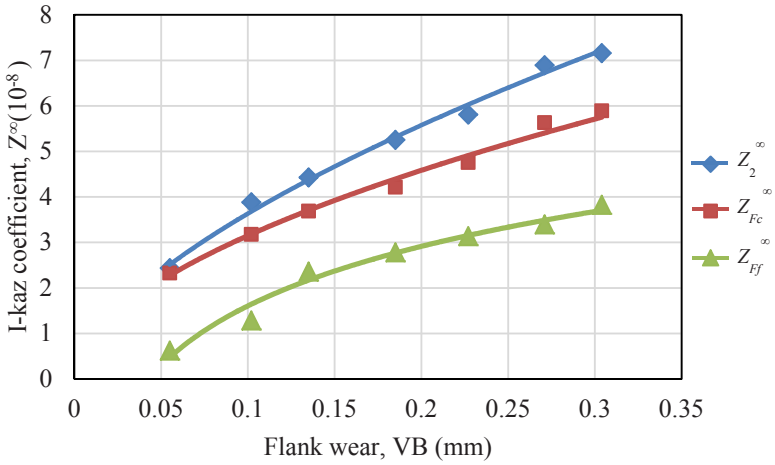

Fig. 4. Correlation of tool wear and I-kaz coefficient.

An interesting correlation between I-kaz coefficient and tool wear progression is shown in Fig. 4. It can be seen that the increasing in flank wear value causes the I-kaz coefficient values to increase. The increase coefficients of I-kaz in feed force has the biggest percentage of about 69.58%, followed by I-kaz 2D coefficient of about 37.52%, and the lowest is I-kaz coefficient in cutting force of about 28.64%. Increasing of I-kaz coefficients in all cases from this study is similar with earlier findings that I-kaz coefficient increases due to changes in signals amplitude and frequency of the cutting forces [10-12]. By comparing these two methods approach, the highest increasing is I-kaz coefficient in feed force. But, the flank wear can also be determined by visualization, and the I-kaz 2D display of graphical representations is more significant than other displays. Therefore, both I-kaz 2D and I-kaz™ method can applied to determine tool wear progression during turning process. They can be utilized to be the parameters for monitoring of tool wear by using threshold values on certain cutting condition.

5. Conclusion

I-kaz™ method and its derivation like I-kaz 2D are suitable to analyze force signals in turning process for tool wear monitoring. It provides a multi-resolution analysis which can be used in both coefficient values and graphical display representations. These results reveal that feed force is very significant due to flank wear, and I-kaz 2D is suitable to visualize any changes in the signals.

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