Prediction of tool wear in milling of Inconel 625 using and integrated kurtosis-based algorithm with vibration signals

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Abstract. Tool wear may depreciate the quality of the machined product owing to its poor surface roughness and dimensional inaccuracy. Tool condition monitoring system (TCMs) is necessary for the manufacturing industry to obtain better quality products with minimal time and improve productivity. Currently, TCMs uses different sensor signals and features to examine the tool wear. In this work, an Integrated kurtosis-based algorithm for Z-filter (I-Kaz) 2D and 3D analysis is employed to examine the vibration signals in milling of Inconel 625 for monitoring the tool condition during the milling process. The results from vibration signals revealed that the I-Kaz coefficient correlates with flank wear. I-Kaz coefficient was increased for raise in flank wear. When the I-Kaz 2D coefficient value increased above 0.5, it indicates that the tool was worn out and has to be replaced.

Keywords: Milling, Inconel 625, tool wear, vibration, kurtosis, standard deviation, skewness, I-Kaz, Tool condition monitoring.

1. Introduction
Cutting tool wear is to be an anticipated process in the metal cutting process which is owing to the contact between the workpiece and tool. The progress of wear has to be examined, and if the machining operation continued with the dull tool, it can degrade the surface quality, raise the machining cost, and also leads to the breakage of machine tools. Tool life prediction based on Taylor’s equation does not render adequate details about the cutting tool life [1]. Sometimes it may lead to underutilization or overutilization of the cutting tool which leads to loss of money. Tool condition monitoring (TCMs) system is required to decrease the downtime of the machine and replaces the cutting tool at right time. In TCMs signals, like cutting force, sound, vibration [2], spindle current, surface roughness, temperature, tool images, AE [3] were employed to examine the tool wear [4]. From the sensor signals, the most significant features were extracted. The extracted features were utilized to design the TCMs with machine learning algorithms [5, 6].

The vibration signals were collected during turning of EN24 with grooved inserts. It was found that
an extracted vibration feature was linked with tool wear. The raise in tool wear leads to increase tool-workpiece contact area which raises the friction and augment the vibration value [7]. Yesilyurt and Ozturk found that when tool wear augmented gradually, vibration features were raised considerably [8]. During end-milling operation, vibration signals were captured and frequency domain features were obtained. The authors found a large variation in frequency levels for different tools [9]. The various feature reduction and machine learning algorithms for TCM were discussed [10].

Tool wear was monitored by analyzing surface roughness and workpiece vibration during the boring process. It was proved that the magnitude of workpiece vibration increased along with the progress of the tool wear [11]. Vibration signals during the machining process was acquired and condition monitoring approach was employed to classify the tool condition. They found that the proposed method was successfully utilized for monitoring the chatter and tool wear [12]. The strain gauge-based tool dynamometer was developed and tested [13] and the control parameter for minimum cutting force, tool wear rate, and surface roughness were identified [14, 15]. During machining, various methods for monitoring the tool wear was reviewed [16, 17].

The effect of vegetable-based cutting fluids (VBCFs) on cutting force and vibration signal during machining of the 7075-T6 hybrid aluminum composite was examined and found the enhanced performance of palm oil than other oils [18]. The VBCFs were considered as sustainable cutting fluid to enhance the green manufacturing process [19, 20]. The vibration signals collected from the wireless vibration sensor with a continuous hidden Markov model was successfully utilized to analyze the tool condition [21]. The vibration signals had a significant variation with the tool condition. A better correlation was obtained with tool wear and the power spectrum of vibration signals. Tool condition was predicted from the hidden features of vibration signals through proper feature extraction. I-Kaz method was widely used to extract the features [22-24]. Recently, tool condition was monitored using vibration signatures using vegetable-based cutting oil and found that vibration features enhanced with an increase in flank wear [16, 25].

Up to the knowledge of the author’s, no work is presented to monitor the tool condition using an integrated kurtosis-based algorithm for Z-filter (I-Kaz) 2D & 3D coefficients of vibration signals in the machining of Inconel 625 with VBCF as a coolant. The present work discusses the use of the I-Kaz 2D & 3D technique to understand the progress of tool wear in milling operation. I-Kaz including 2D coefficient of vibration in Y & Z directions and 3D coefficients of vibration in X, Y & Z directions. The focus is on the assessment of tool wear using I-Kaz 2D and 3D coefficients.

2. Experimental Procedure

To develop TCMs, machining was performed on a CNC L-Mill 55 (manufactured by Lakshmi Machine Works, Coimbatore, Tamilnadu) under wet cutting conditions. Experimental setup used for this work is illustrated in Figure 1. A cutter of 25 mm diameter with cemented carbide (XDHT-090308 HX-PA 120) inserts was used for machining of Inconel 625. This PA120 grade tool is mostly used for cutting harder materials. The Inconel 625 is widely used for various aerospace applications. The workpiece dimension was 125 mm x 125 mm x 100 mm. The experiments were conducted using optimal process parameters (speed - 221 rpm, feed - 0.02 mm/rev & depth - 0.17 mm) [26]. During the keyway milling process, good, normal (0.2 mm wear), and worn out (>0.3 mm wear) tools were used to experiment. The castor oil was employed as a cutting fluid to reduce the tool wear.
Figure 1. Experimental setup

The vibration signals were acquired from the Tri-axial accelerometer using NI 9234 vibration measurement data acquisition card during the machining process. The data acquisition system includes the Tri-axial accelerometer sensor, signal conditioning unit, and LabVIEW application software. The tri-axial accelerometer sensor was positioned on the corner of the workpiece with the aid of glue.

2.1 Feature Extraction

The intension of feature extraction is considerably decreasing the dimensions of raw signals acquired during the machining process. It is also used to select the significant information of tool wear from the measured signals. The researchers used various methods to relate the extracted features from the signals to tool wear. In this paper, I-Kaz was employed for analyzing the signals. In the I-Kaz, both constructive and expressive statistics were used. This approach was based on the conception of data dispersion about the centroid and classification according to the statistical data [22]. I-Kaz coefficient is estimated from the values of kurtosis (K) and standard deviation (SD). The equation for the calculation of I-Kaz was given below.

\[
Z = \frac{1}{N} \sqrt{K_L S_L^4 + K_H S_H^4 + K_V S_V^4}
\]  

Where N - number of data, K_L, K_H, and K_V – Values of in Low frequency (LF) (range of 0–0.25 f_max), High frequency (HF) (range of 0.25 f_max– 0.5 f_max), and Very high frequency (VF) ranges (< 0.5 f_max), and S_L, S_H, S_V – Values of SD in LF, HF and VF ranges, correspondingly. I-Kaz 2D and I-Kaz 3D were materialized from the I-Kaz, which investigates the signals from two (V_y & V_z) and three (V_x, V_y & V_z) channels respectively. It is a variant of the I-Kaz method, in this method the signals need not be split into three different frequency ranges (LF, HF, VF). The coefficient is directly calculated from K and the SD of the respective channel signals. Therefore, the I-Kaz 2D and I-Kaz 3D coefficient is represented as \( Z_L \) and \( Z_V \) given below.
\[ Z_2^\infty = \frac{1}{N} \sqrt{K_I S_I^4 + K_{II} S_{II}^4} \]  

(2)

\[ Z_3^\infty = \frac{1}{N} \sqrt{K_I S_I^4 + K_{II} S_{II}^4 + K_{III} S_{III}^4} \]  

(3)

\( N \) - number of data points, \( K_I, K_{II}, \) and \( K_{III} \) - K value in channel I, channel II, and channel III and \( S_I, S_{II}, \) and \( S_{III} \) - SD value in the channel I, channel II and channel III correspondingly.

This method was employed to extract the features of the vibration signal which was measured from the accelerometer during the milling process. The LabVIEW software was employed to monitor the vibration signal and to extract the K and SD to compute I-Kaz coefficients. The I-Kaz coefficients were utilized to estimate the tool condition.

3. Results and Discussion

Vibration signals for different tools were shown in Figure 2. For a good tool, the vibration level was very low compared to other tools. Initially, the vibration amplitude was slightly high at the starting of the machining process, owing to immediate contact established within the tool edge and workpiece. The vibration signals during the metal cutting process are sensitive to variation in tool wear [27, 28] and it can be efficiently used to examine the tool wear. Figure 2 illustrates the average vibration signals in the Y direction for good, working, and worn-out tools. The good tool exhibited the least vibration and in the range of 0.0245 g – 0.328 g. The worn-out tool exhibited maximum amplitude of vibration varies from 0.120 g – 5 g. The amplitude of vibration for the working tool was varied from 0.0780 g – 1.320 g. The vibration amplitude for the worn-out tool was significantly higher compared to good and working tools.

![Mean Vy](image)

Figure 2. Average vibration signals in the Y direction

From Figure 2, it was evident that vibration amplitude for the worn-out tool was significantly
increased from low to high level. The same results were noticed in the earlier literature [29, 30] Figures 3-5 show the RMS, skewness, and kurtosis of vibration signals along Y direction for three different tools. The good tool had the least RMS vibration value of 0.5 g (Figure 3). Conversely, the working tool exhibited a slightly higher vibration (0.097 g to 1.521 g) than a good tool. During the primary stage of the material removal process, the tool has a sharp cutting edge and established a contact within the tool nose and work part only. As a result, the vibration was very small compared to working and worn-out tools. The worn-out tool exhibited the highest vibration RMS amplitude (5.7 g).

**Figure 3.** RMS vibration signal in the Y direction

**Figure 4.** Skewness of vibration signal in the Y direction
Figure 4 presented the skewness value of different tools. The skewness value of vibration for good tool varied from -0.53 g to 2.47 g. The worn-out tool exhibited the maximum skewness level of 3.6 g. Figure 5 shows the Kurtosis (K) values of different tools. K value for the good tool was scattered between 1.6 g to 14.7 g. The maximum K value of 27 g was exhibited by the worn-out tool. While the tool reaches the secondary phase of tool wear establish, and maintain the identical contact within the tool and workpiece. Hence the vibration was sustained at the same level. Owing to that, the vibration amplitude of the working tool was apparent in comparison with the worn-out tool. From Figures 2-5, it was evident that the worn-out tool exhibited a higher amplitude of vibration than other tools. This trend was in line with the turning of steel [31]. An upsurge in wear starts to augment in vibration amplitude was found in Figure 3. The same fashion was observed in earlier literature [26, 29, 32-34].

The values of average, K, RMS [35], and skewness were augmented with raise in flank wear. Owing to worsen cutting edges, augmented wear leads to enlarging the contact area within the workpiece and tool. Thus, the vibration level is also augmented. Normally, the magnitude of vibration augmented with raise in flank wear [29, 32, 33]. Based on K and SD for vibration in X, Y, and Z direction, I-Kaz coefficients were calculated. This I-Kaz coefficient was accessed to predict the tool wear. This analysis exposed that the I-Kaz method was employed for monitoring the tool condition during the milling process. The coefficient of I-Kaz is employed to estimate the variation in statistical parameters of vibration signals, mathematically. The larger value of I-Kaz was identified corresponding to the rise in flank wear as illustrated in Figures 6 & 7.
Figure 6. I-Kaz 3D coefficients for different tools

Figure 7. I-Kaz 2D coefficients for different tools
The I-Kaz 3D coefficients were computed using vibration signals in the X, Y, and Z directions. The vibration along X direction was very minimal compared to the Y and Z-axis. The I-Kaz 3D coefficients from the good tool varied from 0.00069648 to 0.01337379 and for the working tool varied from 0.0006532 to 0.0076956. The worn-out tool had the maximum coefficient value up to 0.01707. When the I-Kaz 3D coefficient value increased beyond 0.014, it designates the worn-out condition of the tool.

The I-Kaz 2D coefficient was computed using vibration in Y & Z direction. SD & K values for Y and Z direction vibration signals were used to arrive at the coefficients. The I-Kaz coefficient for good tool varied from 0.000109 to 0.23895731. The worn-out tool had a maximum value of 1.389373. The high value was obtained due to the high amplitude of vibration in the Y & Z-axis for the worn-out tool. During the machining process, when the wear increases, the vibration signal also increased. Due to this I-Kaz coefficients also increased. This similar trend was found during the machining of AISI P20 steel and milling of Inconel [24, 36]. The cutting parameters were maintained as constant to reduce the variation in vibration due to the effect of change process parameters. When the I-Kaz 2D coefficient value increased above 0.5, it indicates the tool becomes worn out and has to be replaced for further operation. From Figures 6 and 7, it was evident that I-Kaz coefficients had a considerable relationship with the development of flank wear. When the flank wear increases, I-Kaz coefficients also increased. In earlier literature also a similar trend was noticed[23] that uses I-Kaz 2D coefficients to investigate the machining force in the turning process and found that I-Kaz 2D coefficients were increased due to an increase in flank wear.

4. Conclusions

The statistical approach based on I-Kaz was employed to examine the vibration signals. This method was identified as a significant technique to analyze the vibration signal and consistent for monitoring the tool condition during milling of Inconel 625. I-Kaz 2D & 3D coefficients were estimated from vibration in Y, X-axis, and X, Y, Z-axes respectively. The variation in vibration signals owing to flank wear was observed by a considerable increase in I-Kaz coefficients. I-Kaz 2D was more significant than I-Kaz 3D. The vibration in the Y & Z direction had a significant effect on the progress of flank wear. When the I-Kaz 2D coefficient exceeds 0.5, it indicates the tool becomes worn out and has to be replaced. This method is assessed to identify the flank wear in an earlier stage and can be practiced in manufacturing industries.

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