Cutting tool wear progression index via signal element variance

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ABSTRACT

This paper presents a new statistical-based method of cutting tool wear progression in a milling process called Z-rotation method in association with tool wear progression. The method is a kurtosis-based that calculates the signal element variance from its mean as a measurement index. The measurement index can be implicated to determine the severity of wear. The study was conducted to strengthen the shortage in past studies notably considering signal feature extraction for the disintegration of non-deterministic signals. The Cutting force and vibration signals were measured as a tool of sensing element to study wear on the cutting tool edge at the discrete machining conditions. The monitored flank wear progression by the value of the ^{R}Z index, which then outlined in the model data pattern concerning wear and number of samples. Throughout the experimental studies, the index shows a significant degree of nonlinearity that appears in the measured impact. For that reason, the accretion of force components by Z-rotation method has successfully determined the abnormality existed in the signal data for both force and vibration. It corresponds to the number of cutting specifies a strong correlation over wear evolution with the highest correlation coefficient of $R^2 = 0.8702$ and the average value of $R^2 = 0.8147$. The index is more sensitive towards the end of the wear stage compared to the previous methods. Thus, it can be utilised to be the alternative experimental findings for monitoring tool wear progression by using threshold values on certain cutting condition.

Keywords: Statistical analysis; tool condition monitoring; force signal; flank wear; I-kaz^{TM}.

INTRODUCTION

Most signals in nature are exhibit random and non-deterministic characteristics which require challenge techniques for researchers to analysis and processing it. The rth order of moment, M_r is frequently set forth for classification of the random signals. The generated cutting force signal from the metal cutting process consists of several features extracting from time domain and frequency domain [1]. The acceptable elements of any time domain signal, including the

average value, standard deviation, variance, skewness, kurtosis and root mean square (*RMS*) [2,3]. At the same time, a signal can also be from frequency or time-frequency domain such as fast Fourier transform or wavelet transform.

Many contributions regarding the detection of tool wear levels have been proposed, developed, and tested to take a meaningful decision, useful and important features. But most research absence the robustness which is essential for industrial applications primarily because of limited scope regarding machining conditions, and deficient signal processing or poor feature selection [4]. The present study focuses on feature extraction methods based on the time domain, frequency domain, WT, EMD, and multi-domain analysis [5]. This process is the second stage of tool condition monitoring. Available feature analysis such a mathematical model is considered the oldest used technique while methods based on the time domain extract feature information related to the tool state from the time dimension of the signal using time series analyses in conjunction with several statistical parameters. Time series analysis includes methods such as the autoregressive (AR) process, the AR moving average (ARMA) process, and time domain averaging (TDA) [6]. Methods based on the frequency domain extract feature information related to the tool state from the frequency dimension of the signal based on the frequency structure and harmonic components of the signal. These methods first convert sensor signals from the time domain into the frequency domain using the fast Fourier transform (FFT) and then extract feature parameters such as the power spectrum, peak-to-peak amplitude, and tooth frequency [7]. Both methods based on the time and frequency domains can only provide feature information from a single perspective, and both assume that the signal is stationary, which is not suitable for non-stationary signals obtained in milling processes [5]. Multi domain-based methods have received considerable attention in tool condition monitoring (TCM) research for milling processes [5]. Multi-domain-based methods select feature parameters from more than a single domain, including the time domain, frequency domain, and time-frequency domain, to compose candidate feature parameters set, and also apply feature selection or dimensional reduction methods to obtain feature parameters that are strongly related to the tool state. Usually, time-frequency features consist of a high dimensional vector of data that can complicate the computations [8]. Hence dimension reduction seems to be vital for the simplification of the implementation [8]. Sophisticated techniques are slow and require a larger processor and speed [9].

The statistical model is also an often experimented approach in TCM systems. Statistical parameters include the root-mean-square, maximum/minimum, average, standard deviation, and kurtosis of time series data [10,11]. Earlier, statistical analysis in fault detection using skewness and kurtosis was vastly prominent. From systematic experimental data, a relationship functions between the amount of tool wear and signal data is constructed. Previously, researcher applied skewness and kurtosis of force distribution in a fixed frequency band [12]. The frequency distribution pattern of force signals is reporting a significant impact on cutting conditions and tool wear. The distribution parameters like skewness and kurtosis can recognise both stick-slip transitions of chip contact along the tool rake face and flank wear progression [13]. In another study, machining on steel bar's investigation, the skewness and kurtosis have indicated the tool failure catastrophic [14]. The acoustic emission technique was used to monitor the progress of tool wear during turning of silicon carbide up to 0.4 mm, skewness and kurtosis enhanced the monitoring aspect of wear beyond that [15]. Kurtosis and angular power to analyses chatter phenomena were used in

the investigation on the chatter and tool wear monitoring by the stationary and cylostationary tools [16]. They found out that unstable, chaotic motion of the tool and strong anomalous fluctuations of cutting force as early faults diagnosed of tool wear and bearing in high-speed machining.

However, the relationship function developed by the statistical way is often a linear model. Therefore, it is unable to explain the non-linearity between dependent and independent variables [17]. These linear statistical models were developed in conjunction with off-process TCM systems. Certain studies used a combination of regression and correlation to arrive at an understanding about the degree of wear [18]. The statistical method has been used in signal analysis quite sometimes where many of them are striving to emerge, unfortunately for tool wear monitoring, no absolute indicator to implicate direct relationship over wear itself. Some researchers have composed a new statistical model to develop perfect features for decomposition of non-deterministic signals [19]. The I-kaz^{TM} method developed by Nuawi [20] provides a coefficient and three dimensional (3D) graphical representation of the measured signal frequency distribution. The I-kaz^{TM} coefficient does not assure consistent positive correlation over tool wear, however 3D graphical show scattered data become expand towards the wear and failure state. In additional the I-kaz^{TM} only applicable for time domain analysis but it's not working for frequency domain analysis. Ismail [21] have developed the I-kaz-3D for signal analysis. It is an extension from the I-kaz^{TM} version, where they integrate a multi-sensor input which has three dimensions of the input vector.

Nevertheless still less effort to develop seamless features analysis for the disintegration of non-deterministic signals [19]. The study was conducted to strengthen the shortage in past studies, namely for I-kaz^{TM} and I-kaz-3D. This paper is dedicated to present a possible technique in signal analysis through a statistical method that has an output index that strongly correlates against tool wear progression. The development of the statistical model on the generated cutting force signal successfully created during the milling process. Nonetheless, the model is expected to be well-working on other types of the input signal and machining processes as well as become the alternative consideration in the tool wear monitoring study. Wear mechanisms may coincide, or one of them may dominate the process. These mechanisms can lead to several types of wear [9,22,23]. However, two types of them which called crater and flank wear are most distinguished. This development is not the intention to study the wear mechanism, but only to track the wear severity index.

EXPERIMENTAL SETUP

An innovative integrated rotating dynamometer was designed and constructed [24] to measure the cutting force in a wireless environment system. This dynamometer utilised strain gauge that is mounted on legged cross beam transducer to measure three components of cutting force based on a rotating cutting force system, namely main cutting force F_c, thrust force F_t and perpendicular cutting force F_{cn}. The system also attached to an accelerometer for additional signal acquisitions as comparison purposes. The tool wear monitoring was prepared during the milling process of P20+Ni tool steel where the end milling type as the cutting tool inserts. The inserts were a batch of tungsten carbide with multi-layer physical vapour deposition (PVD) TiAlN/AlCrN grade ACP200 (Code: AXMT170504PEER-G). Eight sets of milling experiment (see Table. 1) were conducted based on a 2^3 full factorial

design. Various combinations of cutting speed (200 and 373 m/min), feed rate (0.10 and 0.20 mm/tooth), radial depth of cut (0.4 and 0.6 mm) and axial depth of cut is kept constant at 1mm. Details of the experimental arrangement for the recording of sensory signals during tool wear tests were recorded in the earlier paper [24].

Table 1. Experimental set.

Set	Cutting speed v_c (min/min)	Feed rate f (mm/rev)	Depth of cut d_c (mm)
Exp. 1	200	0.1	0.4
Exp. 2	200	0.1	0.6
Exp. 3	200	0.2	0.4
Exp. 4	200	0.2	0.6
Exp. 5	375	0.1	0.4
Exp. 6	375	0.1	0.6
Exp. 7	375	0.2	0.4
Exp. 8	375	0.2	0.6

STATISTICAL MODELLING

The model development is employing both mathematical and statistical features based on a signal element variance scattering around its mean centroid. The method is named *Z-rot* analysis to exhibit data pattern in defining the randomness of data features over the whole lifetime to diagnose inferences.
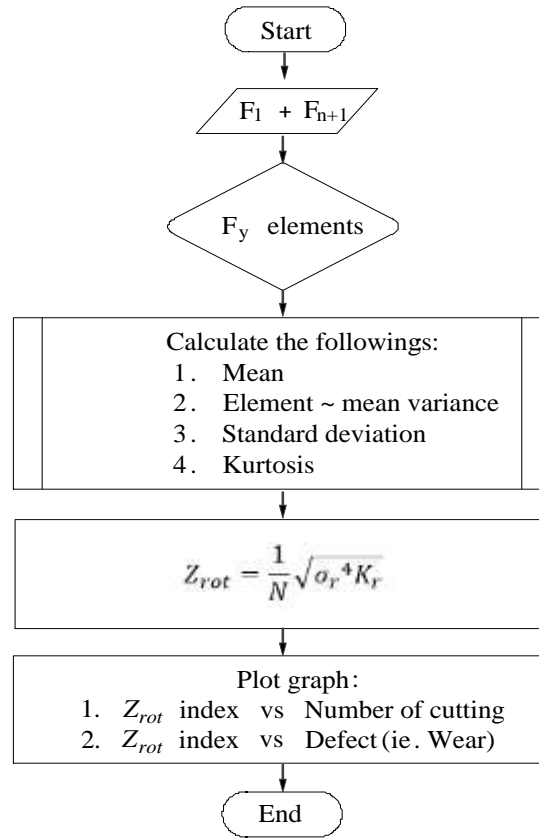
Figure 1. Flowchart of the Z-rotation method.

These inference interpretations are beneficial for forthcoming prediction and decision making in machine learning adaptation. The sharpness characteristic of the peak of a frequency-distribution curve in kurtosis has inspired the development of *Z-rot* analysis. Whereas, the '*rot*' acronym is referring to the analysed data that literally 'rotating' about its resultant mean. *Z-rot* is a tracking analysis kurtosis-based use to track the severity of wear. It is expected to show a strong relationship over the wear evolution. The algorithm is in Figure 1 is referring to *Z-rot* analysis that started with a combination of two or more homogenous signal inputs from sensing elements to get a final time domain allocation. Hence, several feature extractions are desirable with the intention to find $^R Z$ index. The analysis starts with the method acquires an accretion of force components, F_y data from two or more channels. The accretion F_y represented as Eqn. (1):

$$F_y = \sum_{i=1}^{n}(F_i) \tag{1}$$

Notation F_i is the sensor signal data, n is the total number of signal data and i^{th} is the number of signal output. Then, determine the average, $\bar{F}_y$ is for the accretion data central tendency represented as Eqn. (2):

$$\bar{F}_y = \frac{1}{n}\sum_{i=1}^{n}(F_y) \tag{2}$$

The n is referring to the total number of data. Variance between each element in F_y from its resultant average will become the input data to determine $^R Z$ index. The variance is established by subtracting each element value with the accretion mean as radius, r in Eqn. (3).

$$r_i = |F_{y,i} - \bar{F}_y|_{i=1} \tag{3}$$

With the purpose of determining how spreading out the elements are, the standard deviation is cast-off as a measure of volatility. When the cutting tool is new, the element data is suspected to bunch around the mean and slowly spread out when the tool is worn out. In general, the more the wear severity, the larger the value of standard deviation and the more spread out the signal elements are in the set. The standard deviation value as in Eqn. (4), is one of a directive factor for signal element instability.

$$\sigma_r = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(r_i - \bar{r})^2} \tag{4}$$

The $\bar{r}$ is the radius average and n is the number of the element. As for fault detection, Kurtosis is used to identify any unusual amplitude existence [25]. For discrete data set the kurtosis, defining K_r *as* in Eqn. (5):

$$K_r = \frac{1}{n\sigma_r^4}\sum_{i=1}^{n}(r_i - \bar{r})^4 \tag{5}$$

Based on the standard deviation and kurtosis value obtained, a sequence of threshold index, $^R Z$ index is established using Eqn. (6), to indicate the current condition and records the wear progression of cutting tool during the machining process. Note that N is the total number of the element.

$$Z_{rot} = \frac{1}{N}\sqrt{\sigma_r{}^4 K_r} \tag{6}$$

The progression of physical defect, i.e., wear is an evolution process happening over a particular time interval in a lifetime. Therefore, the prominent concern of tracking procedure is the consistency of the signal analysis and how effective is the indication [23].

RESULTS AND DISCUSSION

Cutting Force Signal

Figure 2 shows the time domain of cutting force components (F_c, F_t and F_{cn}) during the advancement of tool wear. The cutting forces were measured throughout the entire cutting period. The figure illustrates the tool condition for set Exp.1 began with initial wear (Testing 3, $V_B = 0.012$mm) until tool reached failure state (Testing 43, $V_B = 0.300$mm).
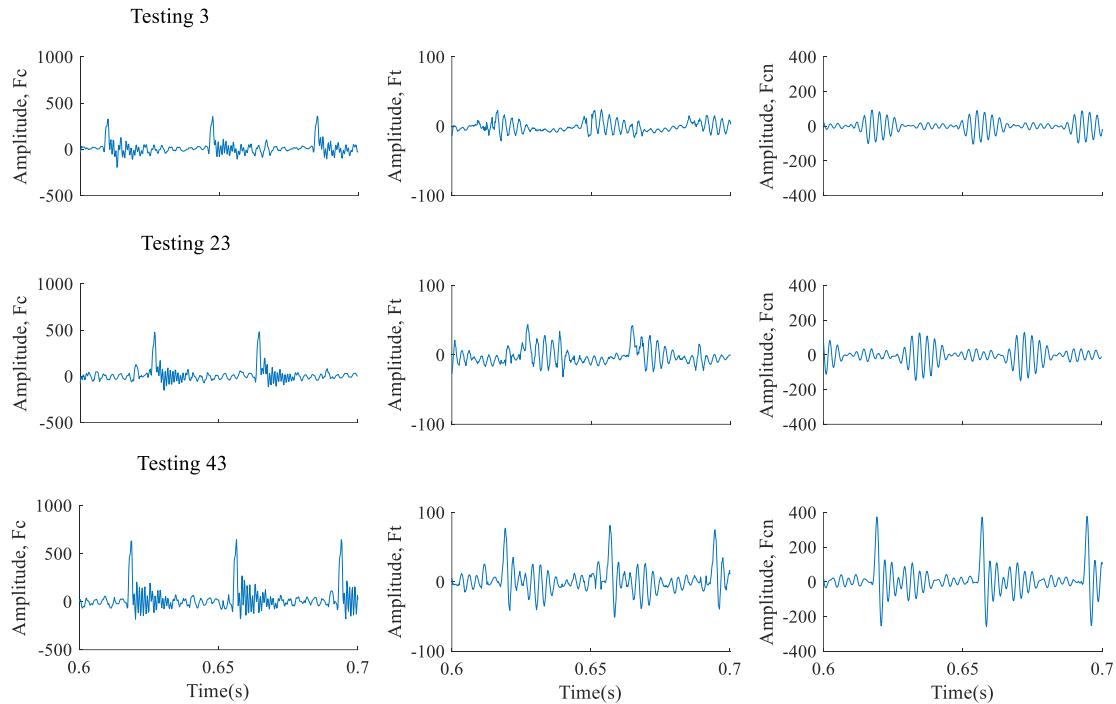

Figure 2. Representative examples of Time domain analysis for the cutting force components for Exp. 1.

As seen clearly in Figure 2, all the three components of the cutting forces increase as the tool wear develops during cutting. The increase of force amplitude is more visible as the machining approach towards the end [26].

Flank Wear Progression

Figure 3 displays the flank wear relation to the number of cutting. As expected, flank wear progression for all test samples was increasing gradually upon the number of cutting [27]. Flank wear is the factor that controls the tool life for typical PVD [28]. Wear rate increase rapidly at the beginning and then slowly decrease to starts growth linearly. The wear rate increases rapidly again when the tool approaches the end of tool life [29–31] owing to the constant use of the cutting tool will lead to it fractures. Observation proved that the less the linear inclination of the wear is, the longer the tool life becomes. For this reason, as the hardness of the tools increases, the inclination of the wear decreases [28].

Two dominant wear progress regions observed continuously, which are steady-state and instability-failure regions. The steady state region is roughly stable and gradually increase. The flank wear width grew when the contact area between the tooltip and the

workpiece increases, resulting in a friction force to increases as well as the cutting forces [32]. Wear progression vs cutting force is parallel to the previous investigation [26] on the cutting forces, the tool wear and the surface finish obtained in high-speed diamond turning and milling of several materials.
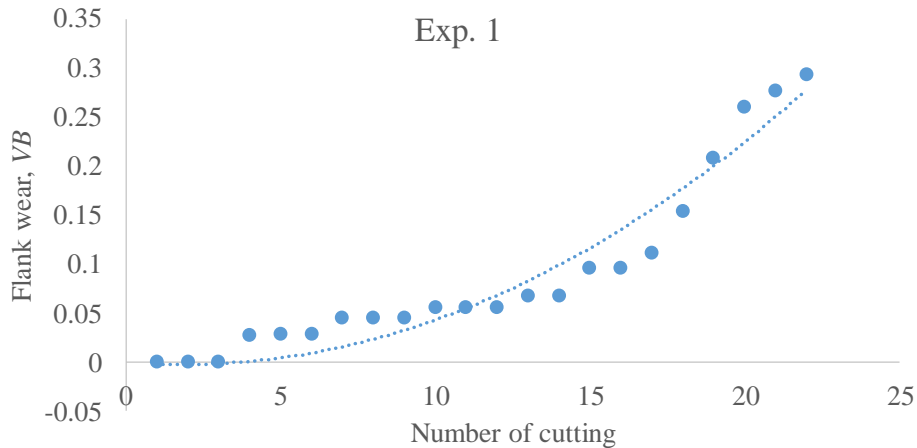

Figure 3. The plot of flank wear, *VB* versus number of cutting.

Z-rotation Method

Z-rotation method is referring to *Z-rot* analysis that started with an accretion of two or more signal inputs from the same type of sensor to get a conclusive time and frequency domain allocation. Figure 4 clarifies the *Z-rot* analysis has successfully manipulated the mounted of signal forces to determine the abnormality existed in the random and non-deterministic signal data.
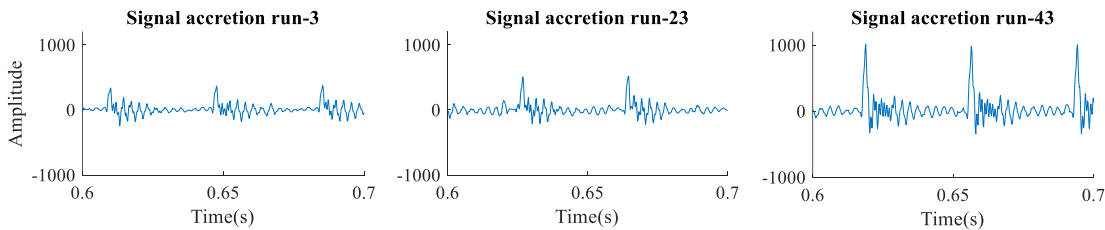

Figure 4. The accretion of cutting force components in the Z-rotation method.

The purpose of the study is to apply new wear tracking analysis of the signal that is generated by the statistical base. As a result, there is a substantial interest throughout the wear evolution progress. The tools are expected to work steadily under normal operation, particularly after the running-in phase.

The *Z-rotation* method is used to characterise the cutting force that absorbed from both dynamometers. The method can correspondingly generate data distribution in the 3D dimension display representing the scatter-degree of data distribution.
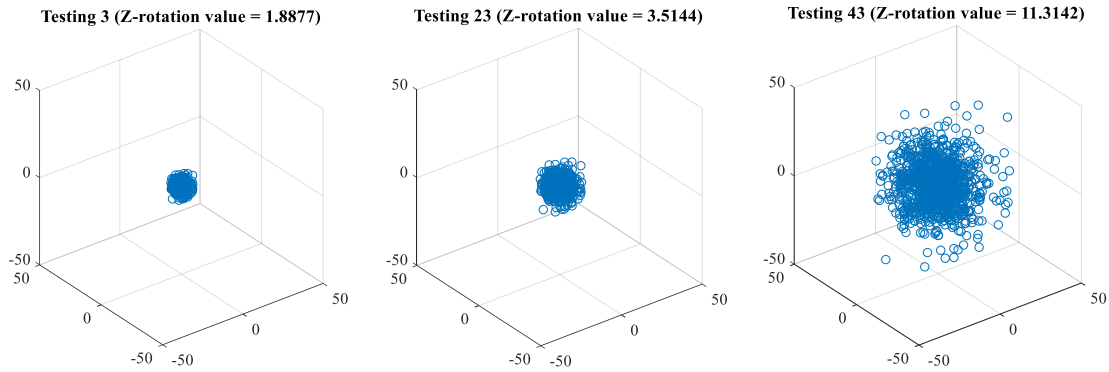
Figure 5. 3D representation for initial, intermediate and last run throughout Exp. 1.

Figure 5 exhibits the 3D representation of the ^RZ index for the sharp cutting tool ($V_B = 0$ mm) with an index value of 1.8877. The width of flank wear is expanding throughout machining as the index value increased to 4.7968. The machining process under given parameters proceed until the tool failure ($V_B > 0.3$ mm) that recorded the last index value of 11.3142 for experimental set 1. The 3D graphics display a spread transformation from small (initial run) to bigger (last run) sphere distribution. The spherical like distribution indicates the revolution of the ^RZ index and regress the progression of wear. All experimental sets demonstrated the same occurrence pattern distribution during the machining process under different settings of machining condition. The displays verify the helpfulness of Z-rotation method as wear progression tracking procedure.

Statistical tools on force signals generate parameters with different information content. The new developed statistical method is deployed to interpret the cutting force signal (F_c, F_t and F_{cn}) for tool wear progression detection. Cutting tool condition analysis is permissible using *Z-rot* analysis by calculating the Z_{rot} index for every signal measured during the cutting process. The plot of ^RZ index versus flank wear value in Figure 6 obtains a nonlinear propagation curve of wear evolution. Throughout the experimental studies, the ^RZ index appeared to an extensive degree of nonlinearity of measured impact.
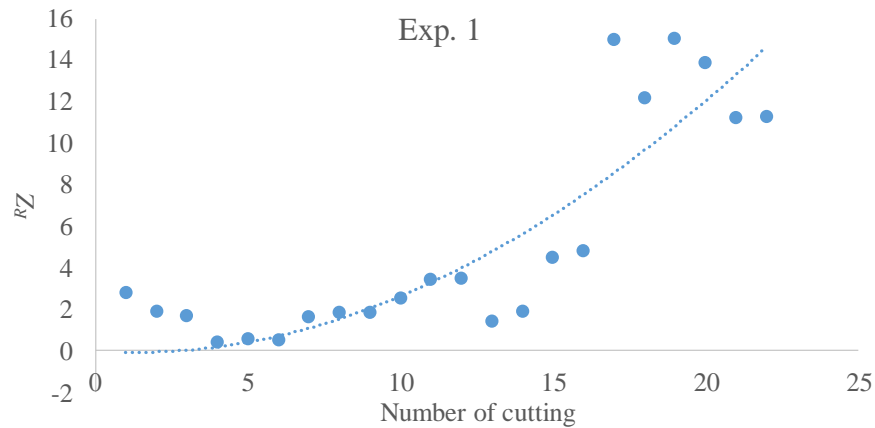

Figure 6. The plot of *Z-rot* index versus number of cutting.

Figure 6 shows the ^RZ index corresponds with the number of cutting. An explicit offset between ^RZ index at specific values is believed to be in instability state phase where failure lean towards to occur. The increasing index value happened before the final failure, machining length and wear volumes increase at the beginning, and then take a stable increment state before it rises sharply towards the end. The plot indicates a good correlation between the cutting forces and flank wear in milling operations.

To validate a correlation between ^RZ index with wear progression, a line of the best curve fit in Figure 7 shows, a positive slope which means it is moving higher as it moves from left to right where there is a positive correlation between the wear and ^RZ index. The data points are very close to the line of best fit showing that there is a strong correlation between the variables. According to the study conducted by [33], the effective process of selecting a signal is through a relationship between the change of signal amplitude and flank wear of the cutting tool. Points should be near to the curve line in the scatter plot where the correlation coefficient can range in value from -1 to +1. Correlation coefficients having $R^2 > 0.6$ values is selected as an effective signal feature for the monitoring process. The average correlation coefficient between flank wear (*VB*) and ^RZ index is $R^2 = 0.8147$, with the highest correlation coefficient of $R^2 = 0.8702$ obtained from the Exp. 3.
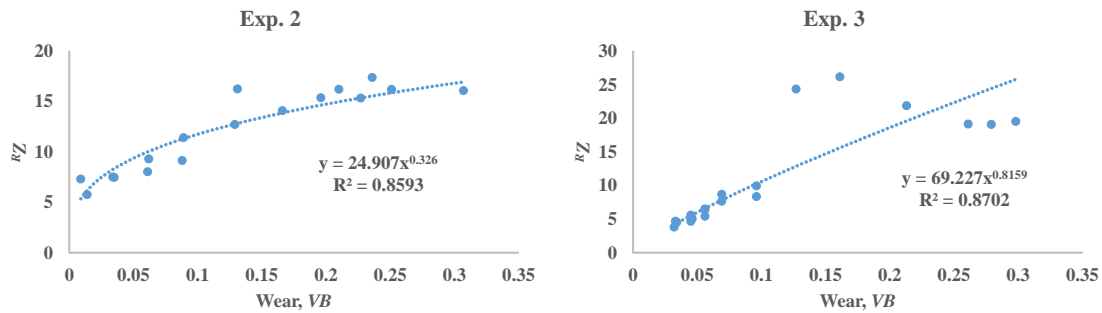

Figure 7. Wear versus ^RZ index.

The healthy positive correlations among the two variables indicate the ^RZ index is a variable feature that has a strong relationship and effects the monitored flank wear progression. As a comparison of statistical analysis used in the different process like turning to project good correlation between cutting force and wear agreed in the previous studies [12]. They used the method of skewness and kurtosis of the distribution of force within a fixed frequency band.

Cutting Force Descriptions

Z-rot analysis has successfully manipulated the force signals resultant to determine the abnormality that existed in the random signal data. The relative sharp tools at the initial stage of machining under dry cutting conditions produce low cutting forces [34] that lead to the more moderate ^RZ index. With the increasing number of cutting process, the rounded tool edge generated higher friction coefficient and widen the contact area among the tool/chip and tool/workpiece interface [29,35,36]. Since the friction force increased drastically, will yield a significant increment in the cutting force components. As a result, the tool has a greater tendency to fracture as it pushed away from the machined surface by a majority of the resultant force [3].

Consequently, the aforementioned in Figure 2, high cutting force components have been captured throughout the machining process. The ^RZ index becomes higher towards the end in all datasets during the study due to the changes in signals amplitude and frequency of the cutting forces. After some time, noticeable wear progression, for instance, BUE, flank wear, crater wear, flaking, chipping, and notching would appear [16,23,37]. Under the circumstances, Figure 8 shows some of the datasets reveal a curious pattern that seems to have sudden and progressively increase and decrease of the ^RZ index in all datasets testing.
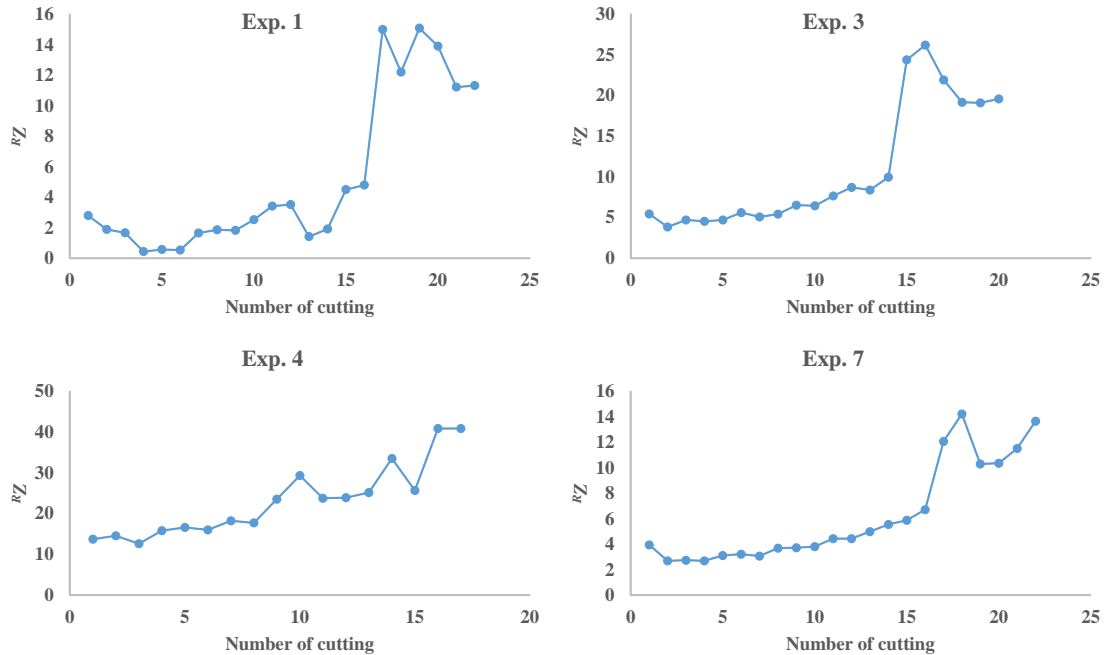

Figure 8. Unexpected amplitude changes in ^RZ plots.

The distinctiveness presence in the ^RZ plots expresses an unexpected amplitude change phenomena originated in the force signals. The sudden index escalation caused by high cutting force came to pass on the tool edge during the machining of the test sample. It is an indication of tool damage as it statistically changes in the shape of the signal [38]. The example in Figure 8, point 17 in Exp. 1 has suddenly increased with the ^RZ index of 14.9946. Whereas, in the rest of testings, the acceleration existed at a specific point are illustrated in the figure respectively.

The sudden increase of ^RZ index does not guarantee to produce a higher increment of wear land width. As in Figure 8, it is widely observed that the tendency for wear area to become worn is increasing over time. However, a small increment of flank wear width occurred at the mid-stage of the steady stage of gradual wear as compared to at the beginning of continuous wear. The phenomenon [39] is called wear competition based on the interaction of abrasive wear and sliding action with surface severities that leads to surface smoothing. Meanwhile, a sharp decline tends to produce broader wear width [3] happens in all experiment sets.

^RZ index is more sensitive in capturing signal changes towards the end of the wear progression. The comparison made in line with the previous analysis done by Ismail et. Al

(2016). Figure 9 illustrates the sensitive segment of the ^RZ index compared with I-kaz-3D in tracking wear progression. The pattern was similar, over some time, ^RZ index continues to distinctly rise higher than I-kaz-3D towards the end of the cutting. Since Z-rotation is analysed the signal components using accretion technique at the beginning and then determine each of the elements variance from the signal average. Whereas I-kaz-3D is simply piling up the signal together as an input, and afterwards processing the signal in the same way as the I-kaz^{TM} do which decomposing the summed-signal into three frequency levels.
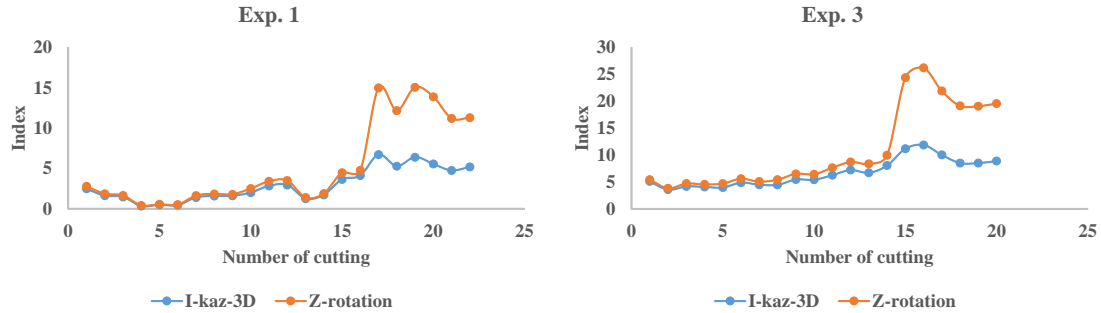

Figure 9. Comparison analysis between Z-rotation and I-kaz-3D method.

Consequently, high cutting force components captured throughout the machining process. The increasing value of the ^RZ index in all dataset of this study is due to the changes in signal amplitude and frequency of the cutting forces. The index becomes higher towards the end because of the element variance within the accretion signal upon its means. Therefore it is suitable to determine tool wear progression during the milling process. The analysis can be utilised to gather alternative parameter for tool wear monitoring observation by using threshold values on satisfied cutting condition.

Comparison of Cutting Force and Vibration Signal
The fluctuations of the cutting force components in machining are reflecting the vibration spectra of the cutting tools. The sensitive accelerometer can directly sense the cutting vibration signals, which are to offer excellent possibilities for in-process diagnosis of many important machining phenomena including tool wear [40]. Figure 10 shows a dynamic process of tool edge wear causes the cutting forces to increase as to vibration increasing as well with the ^RZ index.
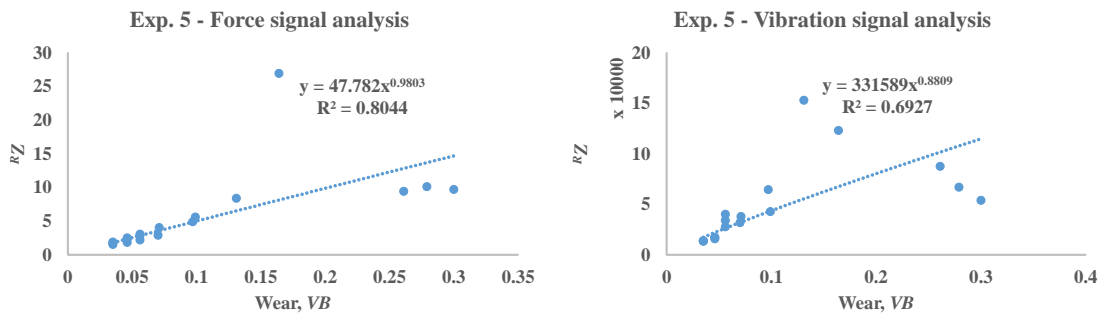

Figure 10. Comparison analysis between force and vibration analysis

From the example observations and analyses made above, it is clear that the cutting vibrations do not necessarily have the same fluctuating pattern as cutting forces in machining with either a sharp tool or a worn tool. In machining with a sharp tool and with a worn tool, the cutting forces configuration can be similar to each of experimental sets, but the vibration magnitude can be very different. Also, larger cutting forces do not necessarily lead to larger vibration amplitudes. Since pure vibration signal carries spare environmental noise than the force signal does [8] thus reducing the vibration amplitude. According to [41], as flank wear-land progresses with machining time, the larger contact area increases the amount of workpiece material being deformed elastically. Thus increases the frictional damping and reduces vibrations. During the time, if flank wear exceeds a certain threshold, the stronger excitation caused by more massive cutting force becomes dominant, with a consequent increase in vibration. The increment in both force and vibration signals is reflected through ^{R}Z index imply the robustness of the analysis method across different type of sensor input.

Z-rotation method has remarkably provides a pronounced connection between force signal wear in the time domain. Nonetheless, some vibration signal shows the amazing result when display in the frequency domain rather than in time domain. Figure 11 shows the time domain and frequency domain of vibration accelerations of the cutting process detected during the advancement of tool wear.
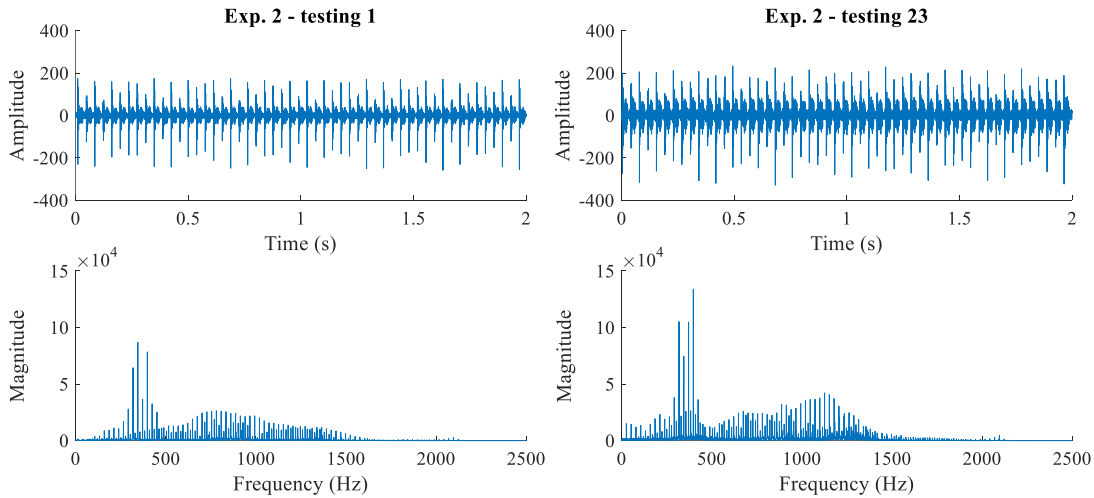

Figure 11. Time domain and FFT analysis for vibrations signal set Exp. 2.

In the time domain, vibration signal does not show much difference in term of its amplitude. On the other hand, it can be seen in the frequency domain the high-frequency activities occur at low-frequency regions covering up to 500Hz and contain the most condition indicating information about the cutting process. The dominant frequency activities occur at relatively low and middle-frequency regions. The other frequency activities take place around after 500Hz up to 1500Hz which is the reflection of the damped natural frequency of the tool-workpiece system [42]. It can be comprehended in all experimental sets that characteristics of the frequency components located at the high-frequency region change with the advancement of wear. They occupy a larger frequency span around range between 500Hz and 1500Hz, and their amplitudes rise when the severity of wear is increased.

Figure 12 explains the statistics of the perceived vibration signals at the mentioned cutting condition in time and frequency domain. During the very early phase of wear development, the amplitude of the vibration acceleration is slightly increased which is correspondingly reflected by the ^RZ index in the time domain. However, at sometimes when the wear starts developing on the tool's cutting edges, the ^RZ index is reduced in the time domain but not in the frequency domain. The index in the frequency domain keeps gradually increased with the advancement of wear until it reaches to the point of tool failure.
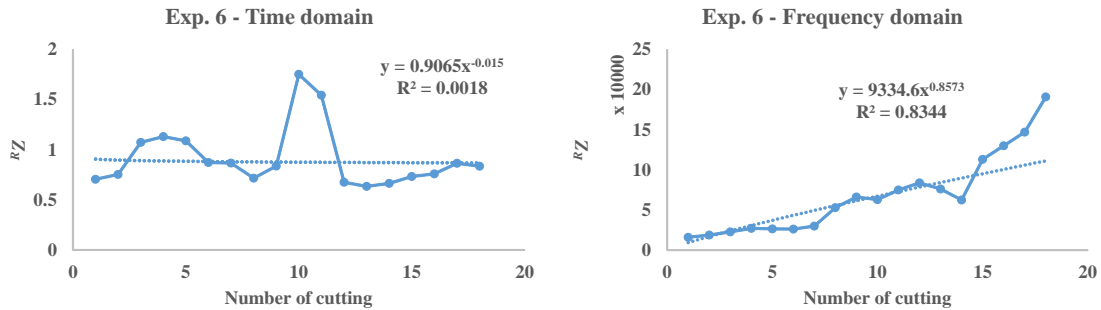

Figure 12. Vibration analysis using Z-rotation method

In leverage of Z-rotation analysis, vibration signal shows the amazing result when display in the frequency domain rather than in time domain. When the wear width is fully developed over the flank surfaces at the end of wear test, the amplitude of the vibration signal magnitude represented by ^RZ index is notably increased. The symptoms of tool wear are favourably revealed in the vibration signal. In brief, cutting forces are determined by material property, tool geometry, cutting conditions, and so on. The cutting forces not only determine the cutting vibration but also by the structural rigidity (such as damping and stiffness) of the tool–work–machine system [43]. Henceforward, acceptable measurement index based on the frequency domain of fast Fourier transform is possible as another alternate parameter in future decision making.

CONCLUSION

The new statistical method was developed in favour to deliver a simple and time-saving and yet sensitive with a gradual change in the wear process state. It's a homogenous multi-sensor signal analyser for both in time and frequency domain. The analysis was done on the cutting force (F_c,F_t and F_{cn}) and vibration signal for tool wear progression detection. Throughout the experimental studies, the ^RZ index shows some significant degree of nonlinearity that appears in the measured impact. For that reason, the accretion of force components by Z-rotation method has successfully determined the abnormality existed in the signal data for both force components and vibration. It corresponds to the number of cutting specifies a strong correlation over wear evolution with the highest correlation coefficient of $R^2 = 0.8702$ and the average value of $R^2 = 0.8147$. The index is more sensitive towards the end of wear stage compared to the previous method to visualise slight changes in the signals. Thus, it can be utilised to be the alternative experimental findings for monitoring tool wear progression by using threshold values on certain cutting condition. Finally, the new developed statistical

modelling of random signals proved to be universal and tolerant to noise and well-extrapolated for the forthcoming purposes of decision making.

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