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TOOL WEAR MONITORING USING MACRO FIBRE COMPOSITE AS A VIBRATION SENSOR VIA I-KAZ™ STATISTICAL SIGNAL ANALYSIS

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ABSTRACT

Tool failure is a major and undesirable occurrence affecting the overall operating cost and time as the machining needs to be done once again to fix the mistake. Therefore, this paper introduced an efficient and inexpensive way to overcome the problem by developing tool wear monitoring system using Macro-Fibre Composite (MFC) sensor via alternative statistical signal analysis method, namely Integrated Kurtosis-based Algorithm for Z-notch filter (I-kaz™). A piece of MFC sensor amplified by a power module was mounted on a tool holder in the turning machine to capture vibration signal data using data-logger while cutting the workpiece. The operation ran continuously until criteria of 0.3 mm tool wear achieved with the help of a microscope for wear measurement. The machining was set at 250 and 300 m/min of cutting speeds, while the feed and depth of cut were kept constant at 0.25 mm/rev and 0.12 mm respectively. The raw data were then extracted and observed in time and frequency domain before statistically analysed as soon as the experiment finished. The reliability of I-kaz™ method was made to the test by performing correlation with the wear progression data using regression analysis to derive the best equation model and comparing it with one of the global statistical features, namely root means square (rms). The final result indicated that the measured tool wear directly proportional to I-kaz coefficient, where the increment of wear progression increasing the I-kaz coefficient value. It came with the best fit of quadratic polynomial regression models, producing acceptable correlation of determination, R^2 of 0.83 and 0.93 while rms having lower values of 0.65 and 0.83. The outcome of the result also showed that the proposed study of using I-kaz™ to analyse the vibration signal from MFC sensor was much more reliable than the rms feature. It can be used to monitor tool wear efficiently with 1.8 to 15.9 % of error using I-kaz™ while the latter showed a higher percentage of error from 3.4 to 30.1 which nearly as twice as higher.

Keywords: tool wear monitoring, piezoelectric, macro fibre composite, MFC, vibration, statistical signal analysis, I-kaz.

INTRODUCTION

Industrial technology have grown rapidly over the century, thus, machine monitoring system must undergo a tremendous change to suit the needs. Machine monitoring system is a process of monitoring the condition of machine when operate. The system is essential especially for unmanned machining, as it capable of identifying machining system defects or failures and their location. That way, maintenance works can be done according to plan, making sure the machine instrument and system are in good condition and can be used regularly. This indirectly prevent any further loss and shorten the time and cost needed to accomplish certain operation. A good machining monitoring can be developed by a better understanding on the basic operation of machine being handled, identified parameter, workpiece and cutting tool's type of material, wear of tool or insert, and method for monitoring (Byrne et al., 1995; Sick, 2002).

Tool wear is the most undesirable and crucial part to be monitored as it impacted the overall process of machining operations and affecting them economically (Waydande et al., 2016). As the machine tool failure and downtime issue continues to plague the machining industries, it becoming one of the major problem in producing good products. Wear of the tool is majorly affecting the surface quality and dimension accuracy of finished workpiece, undesirably consuming a lot of machining operation cost and time to redo and correct the mistake and the defected product being made. Cutting tools need to be replaced periodically with a new one as soon as they wear out before they fail catastrophically, in order to improve the overall performance of the operation output. Among all of the wear, flank wear is the one having a major occurrence in tool failure, and becoming the critical criteria in determining the overall tool life. The growth of flank wear progression degrades surface quality, widen the contact area, and increases heat generation (Snr, 2000). Based on that matter, there is a real need to devise a reliable and accurate tool wear detection system to monitor the flank wear progression automatically.

This study mainly developed to investigate the capability and effectiveness of MFC sensor in tool wear monitoring by using I-kaz™ statistical signal analysis for a high level of data interpretation. The MFC was used to detect the vibration signature coming from the interaction between workpiece and cutting tool during the turning process. Vibration data from MFC and wear progression data were recorded, observed and then analysed with statistical features. The results from the study including observation of signal data in time and frequency domain, correlation, relationship and also the reliability of I-kaz™ toward wear progression were discussed and concluded.

Tool condition monitoring

Tool condition monitoring (TCM) can be described as a process of observing the damages happened to the cutting tool during machining operation by certain accountable process mechanics. Real-time and online tool

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monitoring systems have been heavily studied, developed and reviewed by several researchers (Bhuiyan & Choudhury, 2014; Sick, 2002; Snr, 2000). The condition of the cutting tool especially the wear progression can be predicted relatively well without pausing the operation and observing optically. Two monitoring methods introduced in tool wear detection system, which were direct and indirect monitoring. Direct monitoring closely related to the optical and visual approach, in which the cutting tool geometry parameter was measured. Indirect monitoring involved the use of suitable signal sensors to acquire the signal data caused by the wear progression. Tool wear could be determined numerically by analyse the machining signals, such as cutting force, sound, vibration, acoustic emission, torque and power, and temperature (Ambhore et al., 2015; Bhuiyan & Choudhury, 2014; Sick, 2002; Snr, 2000; Waydande et al., 2016). Hence, it could predict the actual wear by empirically determined correlations without inspecting them optical or visually. Indirect monitoring was suitable and meant to be used for online tool condition monitoring as it did not interrupt the cutting operation. However, considering there are a lot of sensors available nowadays, choosing a suitable sensor for a suitable application is still a matter of discretion and therefore needs to be fully cautious and judicious.

Piezoelectric-based sensor

Piezoelectricity is the generation of electrical charge that accumulates in response to the applied mechanical stress or force exerted on specific solid materials (Vives, 2008). The piezoelectric elements have been used extensively in sensing and actuation applications and showed a promising result. For example, Ramli *et al.* (2017) underwent modal analysis experiment using piezoelectric polymer film sensor and showed good agreement with accelerometer sensor in finding modal parameter.

Up until now, there are three types of piezoelectric based materials, commonly named as piezoceramic, piezo-polymer, and piezoceramic fibre or composite (Henry Angelo Sodano, 2003). The most notable commercialise example of the one described above is lead zerconate titanate (PZT), polyvinyldene fluoride film (PVDF), and micro-fibre composite (MFC) respectively. Among them, PZT materials was well known for structural actuation and sensing application. For example, Li et al. (2013) developed a mechanism of acoustic energy harvesting at low frequency by using PZT cantilever plates inside a quarter-wavelength straight tube resonator. Also, M. A. F. Ahmad et al. (2015) utilised the piezoceramic (PZT material) sensor in tool wear monitoring by correlating the wear progression with the statistical coefficient derived from sensor signal output. PZT materials showed a promising result, but practically impose particular limitation in a real application. For instance, extra attention needed during the bonding and handling procedure as they are extremely brittle, and therefore making their flexibility to curve along the contact surface somewhat poor. Hence, MFC was brought out by NASA Langley Center to tackle the described problems. The main benefits of using MFC actuators are their high performance, durability and flexibility, which were better than PZT (Henry A Sodano et al., 2004). It has been produced by sticking the interdigitated electrode polyamide films on the top and bottom of piezoceramic fibres and glued them together with structural epoxies between them, as shown in Figure-1 below:

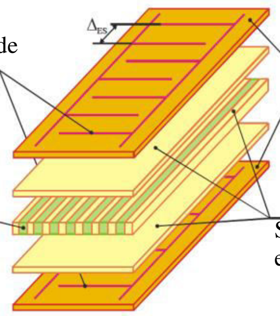

Figure-1. Schematic structure of the MFC.

Past studies had proved that MFC could be used as a sensor and also actuator for individual application. It worked exceptionally well as a part of modal-testing and control system, as previously done by Gao et al. (2013). Besides, it was reliable and worked wonder in energy harvesting applications where it showed high efficiency and reliability towards the energy conversion and accumulation (Ju et al., 2015).

Statistical signal analysis method

Statistical methods are essential as interpretive aids to present and reveal data at several levels of detail (Chatfied & Collins, 2013). Random signals are frequently analysed, classified and quantified by descriptive statistical features of global signal statistics, where the most commonly used are mean, root mean square (rms), standard deviation, variance, kurtosis and skewness (Arslan et al., 2016; Bhuiyan & Choudhury, 2014). For a signal with n-number of data points, the mean value is given by equation (1) below:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$

Where x_i is the value of the data point. The standard deviation is defined as in equation (2):

$$s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2} \quad (2)$$

Meanwhile, the variance is just the square of standard deviation as described below:

$$\sigma = s^2 \quad (3)$$

The 4th signal statistical moment of kurtosis, K, is highly sensitive to spikiness of the data. Kurtosis, K is defined as in equation (4):

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$$K = \frac{1}{n\sigma^4}\sum_{i=1}^{n}(x_i - \mu)^4 \quad (4)$$

Skewness, S is determined based on the equation (5):

$$S = \frac{1}{ns^3}\sum_{i=1}^{n}(x_i - \mu)^3 \quad (5)$$

Among the global signal statistics, rms feature was frequently used in indirect tool condition monitoring as it was quite sensitive to the signal signature, showing a good correlation towards tool wear (Bhuiyan & Choudhury, 2014). For a signal with discrete data sets, rms is calculated as in equation (6) below:

$$rms = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \quad (6)$$

Integrated Kurtosis-based Algorithm for Z-notch filter (I-kaz^{TM}) statistical signal analysis was pioneered by Nuawi et al. (2008) and have been applied and tested in a wide variety of fields, including whole-body vibration exposure prediction, musical instrument sound clusterisation, mechanical properties characterisation, sliding (Gao *et al.*, 2013)wear evaluation and tool condition monitoring prediction system (Ab Aziz et al., 2016; M. A. F. Ahmad et al., 2017; M. S. Ahmad et al., 2016; Karim et al., 2015; Rizal *et al.*, 2013). I-kaz^{TM} was developed based on the degree of scattering of data concerning its centroid. The signal data were decomposing into three frequency range by considering the 2nd order of the Daubechies concept and the coefficient of I-kaz was derived to represent the signal feature numerically. I-kaz coefficient, Z^{∞} can be defined as in equation (7):

$$Z^{\infty} = \frac{1}{n}\sqrt{K_L s_L^4 + K_H s_H^4 + K_V s_V^4} \quad (7)$$

Symbol of n represents the number of data, K_L, K_H, K_V and s_L, s_H, s_V are kurtosis and standard deviation for low, high, and very high-frequency range respectively. This alternative statistical method is mainly developed as a supplement to the existing ones to provide more accurate and reliable signal feature towards the measured parameter.

METHODOLOGY

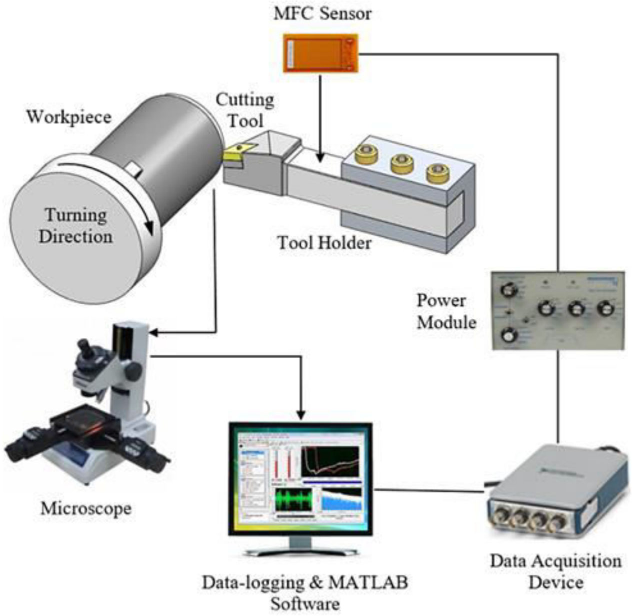


Figure-2. Schematic illustration of the research.

The schematic illustration and the flowchart of the research were depicted in Figures 2 and 3. The experiment was carried out by using Cholchester Tornado T8 CNC turning the machine to cut 40 HRC of hardened AISI 4340 round bar workpiece. The process started by cutting the workpiece with 100 mm of the length of tool travel per run in a dry condition. The cutting tool used was Sumitomo AC2000 with 0.4 mm nose radius. While machining, the work was divided into two sections, consisting of MFC sensor signal acquisition from vibration signature and flank wear measurement of the cutting tool.

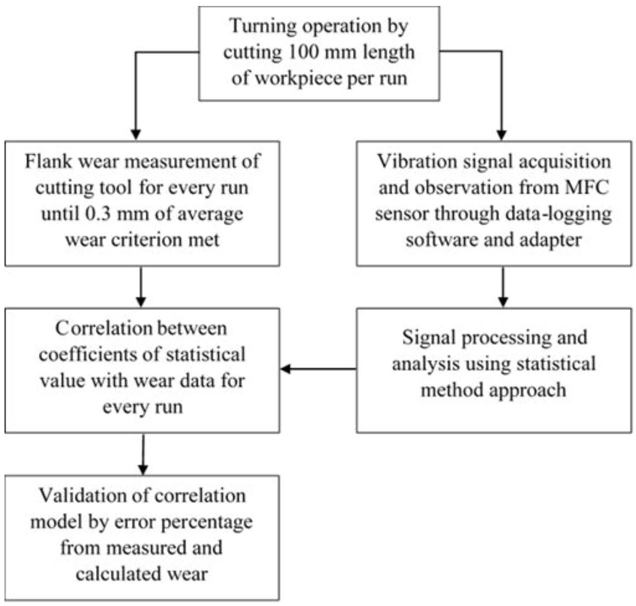


Figure-3. Flowchart of the research.

The MFC sensor was mounted on DCLNR2020K12 tool holder perpendicular with cutting force direction and placed 47 mm from the edge of the cutting tool to MFC's centre, as asserted by Ghani et al. (2012). They found out that the described value was the optimum distance for a sensor mounted on a tool holder to acquire accurate signals resulted from deflection or vibration. Table-1 below shows the detail specification of MFC used in this experiment.

Table-1. Specification and properties of MFC.

Type	P2 M2814
Overall dimensions	0.036 m x 0.016 m
Active area dimensions (*lc, bc*)	0.028 m x 0.014 m
Capacitance (*Cp*)	~ 26 nF
PZT material type	Navy Type II
Max voltage	-50 to +360 V
Max tensile strain	4500 ppm
Thickness (*tc*)	0.0003 m
Piezoelectric coefficient (*d31*)	-3.7E-10 C/N
Young's Modulus (*Yc*)	30.336 GPa

The raw vibration signals captured by MFC while cutting were amplified using Piezo Lab Amplifier power module and obtained using NI 9234 data acquisition module before being observed in the computer via data-logging software.

The sampling frequency rate was set to be 25600 kHz. Flank wear (Vb) was measured in the end of every run until 0.3 mm of average flank wear according to ISO 3685 (1993) standard criteria achieved. The experimental set was established with cutting speed (V_C) of 250 m/min and 300 m/min, while feed rate (F_R) and depth of cut (D_{OC}) were kept constant at 0.25 mm/rev and 0.12mm respectively, as shown in Table-2. By doing this, the primary contributing factor of tool wear progression will be the manipulated cutting speed.

Table-2. Experimental set.

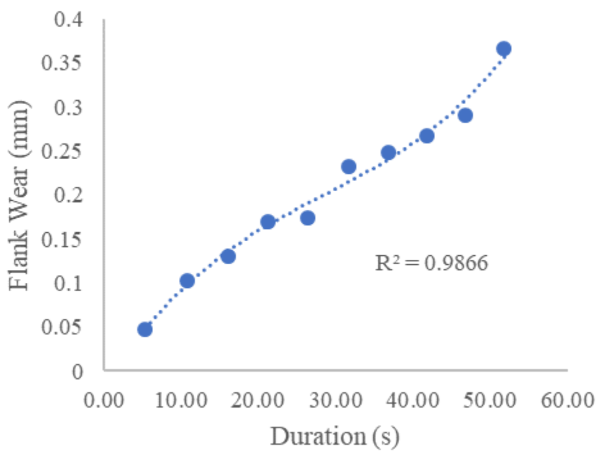
Set	**V_C** (m/min)	**D_{OC}** (mm)	**F_R** (mm/rev)
1	250	0.12	0.25
2	300	0.12	0.25

After all the signal data extracted and observed, they were analysed using two signal features, which were I-kaz™ and rms statistical method. Correlation between these two signal features with the obtained flank wear data were then conducted and observed to investigate the effectiveness of MFC sensor towards wear progression. It was done to find the most sensitive and reliable feature between those two with the least error derived from correlation model in validation stage.

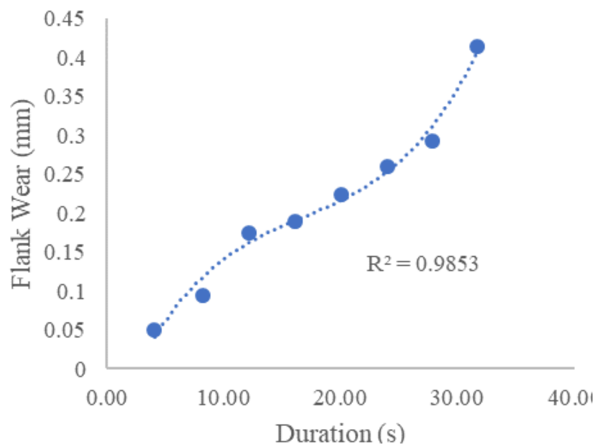
RESULT AND DISCUSSIONS

Flank wear response against time

Figure-3 shows the relationship that form curved lines between flank wear (Vb) data and the time made until 0.3 mm of wear achieved. The curve illustrations represented by three regions or state, which are the break-in period, steady-state and lastly the failure region, as defined in the theory of tool life curve (Groover, 2007). It took around 51.8 seconds to entirely wear at 250 m/min of cutting speed while only 31.7 seconds for 300 m/min. Here can be concluded that the increase of cutting speed will shorten the lifespan of the cutting tool. Meanwhile, the correlation of determination, R^2 for both of the sets is around 0.98 as denoted from the figure. Henceforth, it can be summarised that flank wear measurement and time captured were done exceptionally well and met the criteria of tool life curve. The signal acquired were then observed and analysed as the flank wear data were taken in good measure.



(a)



(b)

Figure-4. Flank wears progression against time for (a) 250 m/min and (b) 300 m/min of cutting speed.

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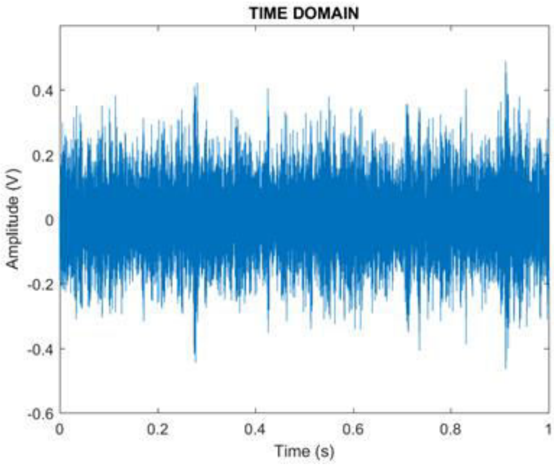
Signal observation towards wear progression in time-frequency domain

The signal amplitudes in time domain at initial until the end of wear criteria are displayed in Figure 5 and 6. For each set, (a) is the signal amplitude at initial wear formation, and (b) is the amplitude generated at the end of wear, achieving 0.3 mm of average flank wear As shown, the amplitudes produced were varied as the wear progressing. Roughly, vibration signal amplitudes increased and much spikier when tool wear expanded. They even showed the same rising pattern from both of the experimental set with different cutting speed. But still, the differences could not be seen clearly with our naked eye. Therefore, there was a need to quantify the signal numerically into meaningful and several levels of detail, and this was where the statistical signal analysis played its role.



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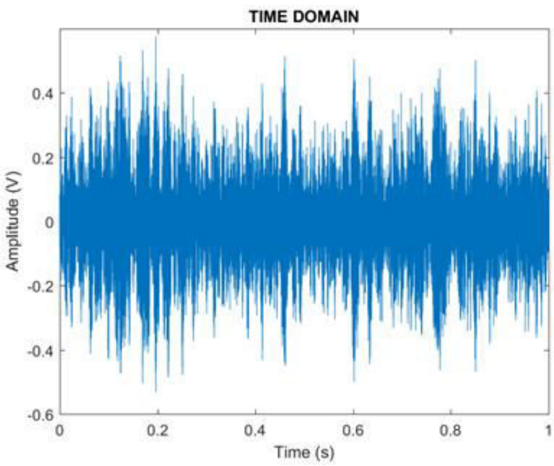
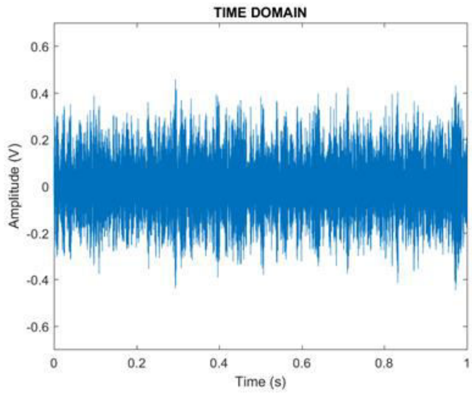
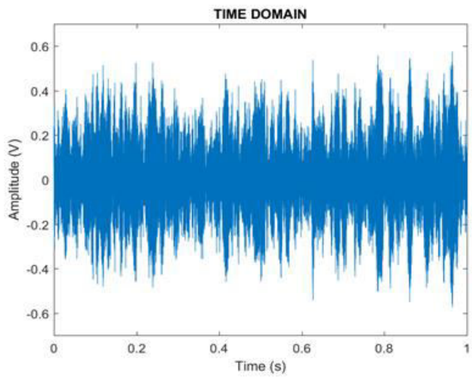


(b)

Figure-5. Time domain for 250 m/min of cutting speed at (a) Vb= 0.047 mm and (b) Vb=0.366 mm.



(a)



(b)

Figure-6. Time domain for 300 m/min of cutting speed at (a) Vb= 0.050 mm and (b) Vb=0.414 mm.

The time domains for all of the data including the one shown in Figures 5 and 6 were then converted into frequency domain using Fast Fourier Transform by utilising MATLAB software. Figure 6 and 7 show spectra graph charts that cover all the frequency domain response from initial time until final indicated the end of wear. As a result, there were 5 peaks of frequency components of vibration signature. The frequency components were found around 800 Hz, 1900 Hz, 5900 Hz, 7500 Hz and 10000 Hz. Among all of the peaks, the range of approximately 5900 to 10000 Hz of frequencies showed a complete opposite pattern between the experimental sets. For 250 m/min, the magnitude on 5900-7500 Hz components were high while at 10000 Hz, they were low. Somehow, it was differed for 300 m/min as they showed small at first and high magnitude at latter. On the other hand, the same pattern between experiment sets on 800 Hz and 1900 Hz of frequency components was identified. 800 Hz of magnitude frequency was constant throughout the wear duration, whereas it was varied for the latter one.

The dominant frequency happened to be around 1900 Hz where it showed the highest magnitude. It showed an increment of magnitude when wear increased for every duration until 0.3 mm of wear criteria met. Both of the sets showed the same increasing pattern of magnitude. Tables 3 and 4 presented the recorded magnitudes of every vibration response at a peak of 1900 Hz frequency for both sets.

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Table-3. Magnitudes change with wear progression for 250 m/min in certain durations.

Set 1 (250 m/min)		
Magnitude	**Duration** (s)	**Wear** (mm)
279.8	5.36	0.047
319.8	10.72	0.103
271.2	16.08	0.131
284.1	21.27	0.169
329.7	26.45	0.174
318.4	31.63	0.232
323.5	36.81	0.249
392.8	41.81	0.268
523.2	46.81	0.291
836.9	51.81	0.366

Table-4. Magnitudes change with wear progression for 300 m/min in certain durations.

Set 2 (300 m/min)		
Magnitude	**Duration** (s)	**Wear** (mm)
394.9	4.11	0.050
388.5	8.22	0.095
525.7	12.18	0.175
584.1	16.14	0.189
546.0	20.10	0.224
681.0	24.06	0.259
697.4	27.86	0.292
1126.0	31.67	0.414

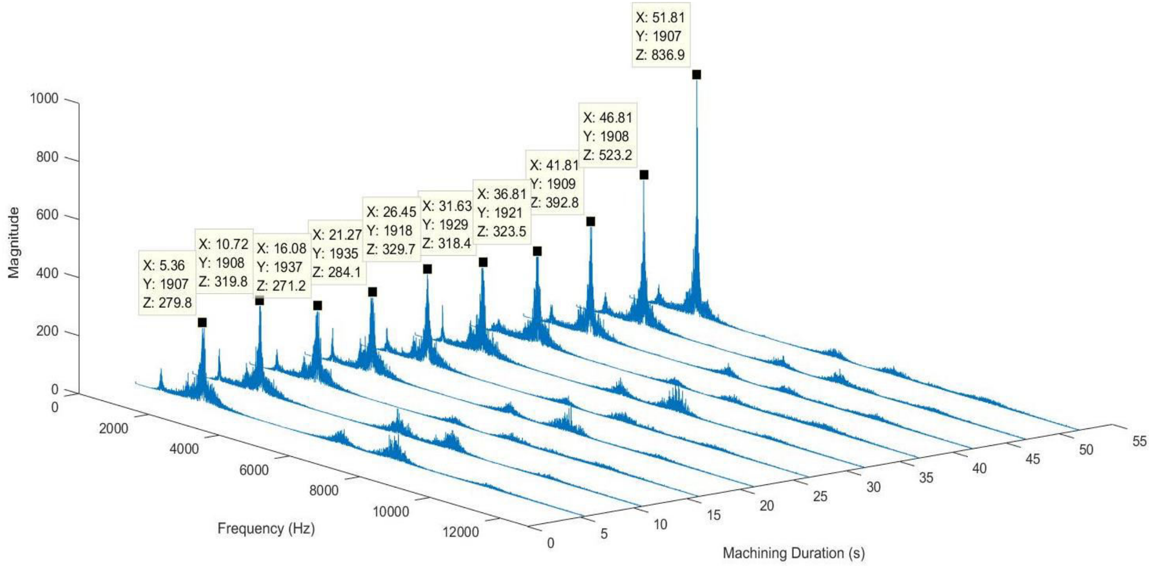

Figure-7. Spectra analysis graph for 250 m/min of cutting speed from start until fully wear.

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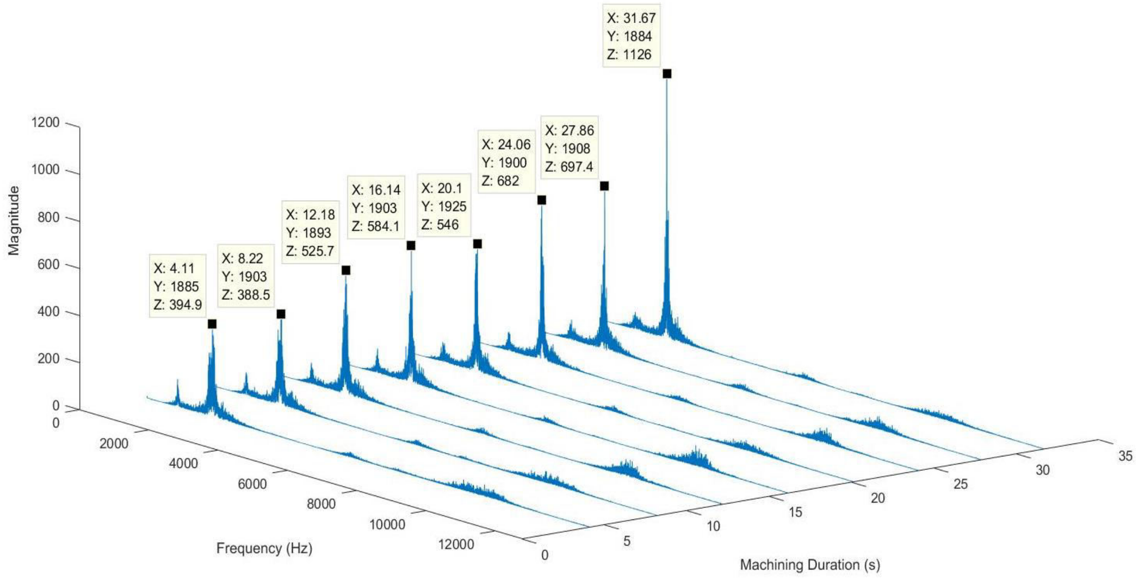

Figure-8. Spectra analysis graph for 300 m/min of cutting speed from start until fully wear.

Despite that, the magnitudes at 300 m/min were higher than those at 250 m/min. But surprisingly, the vibration response still happened in the same place, which was at 1900 Hz. Hence, the frequency components around 1900 Hz were the vibration signature and response due to the wear progression. For that reason, the other peaks were assumed to be the white noises that consist of a background, environmental and also machine noise coming from the manipulated machining parameter. However, by ignoring the noises, it might comprised useful information that we could not see optically with naked eyes. Thus, the signal data need to be analysed statistically using selected statistical features and correlated with the wear data to provide us with quantitative of relevant information.

Correlation of statistical signal coefficient with wear progression

At this stage, the raw signal data were analysed using statistical signal analysis method to convert them to meaningful and descriptive numerical values. Two signal features have been selected for correlation process, which were I-kaz^{TM} and rms. I-kaz^{TM} is an alternative signal analysis method while rms was widely used as a statistical feature in tool wear monitoring. The coefficient of I-kaz, Z^{∞} is calculated based on Equation (7) while rms value is derived from Equation (6) above. The values of both I-kaz coefficient and rms with wear progression were tabulated in Table-5.

Table-5. I-kaz coefficients and rms values for certain wear progression until 0.3 mm of wear achieved.

Set 1 (250 m/min)			**Set 2** (300 m/min)		
Measured wear (mm)	**I-kaz coefficient, Z^{∞}**	**rms**	**Measured wear** (mm)	**I-kaz coefficient, Z^{∞}**	**rms**
0.047	7.08E-07	0.110796	0.050	9.68E-07	0.127124
0.103	6.94E-07	0.111438	0.095	1.05E-06	0.132041
0.131	7.84E-07	0.116696	0.175	1.37E-06	0.151583
0.169	8.3E-07	0.118762	0.189	1.35E-06	0.148517
0.174	7.22E-07	0.108819	0.224	1.52E-06	0.157582
0.232	8.51E-07	0.113338	0.259	1.73E-06	0.16769
0.249	9.67E-07	0.122111	0.292	1.49E-06	0.149528
0.268	8.45E-07	0.117834	0.414	2.37E-06	0.219600
0.291	9.62E-07	0.125372	-	-	-
0.366	1.34E-06	0.143915	-	-	-

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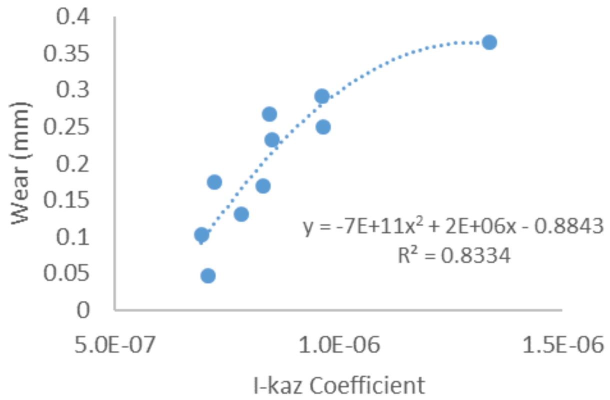
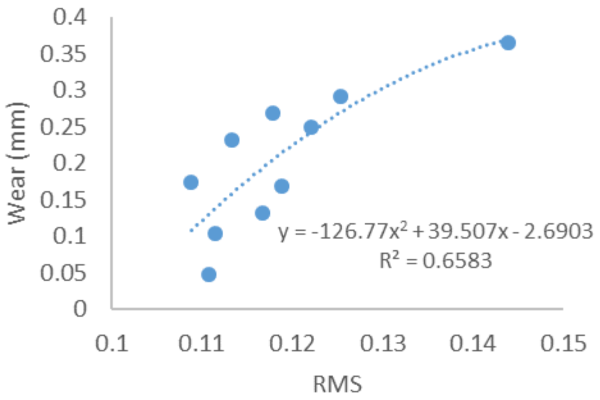
Both of these signal features were then correlated with the wear progression data to obtain the relationship and extract the relevant information numerically. The correlation was done using regression analysis where the polynomial of quadratic function was chosen as the best fit for the output variables for both of the sets. The regression models for both features are illustrated as in Figures 9 and 10.



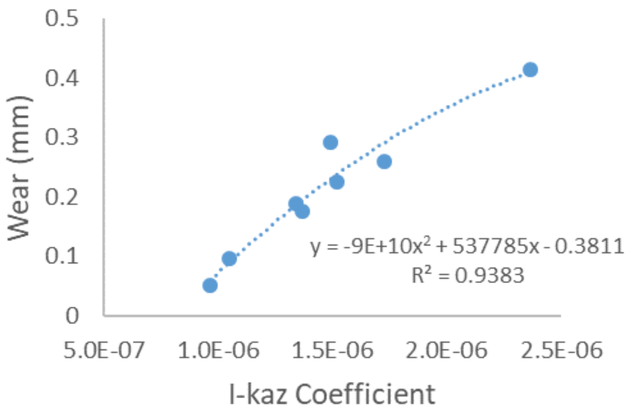
(a)



(b)

Figure-9. Correlation between flank wear with (a) I-kaz coefficients and (b) rms values for 250 m/min of cutting speed.

As shown, a quadratic polynomial was implemented on all the regression lines because it indicated the highest R^2 compared with other models. For a set of 250 m/min, it showed R^2 with a value of 0.8334 from I-kaz^{TM}, while it was only 0.6583 for rms. Meanwhile, it was higher at 300 m/min with 0.9383 and 0.8799 of R^2 for I-kaz^{TM} and rms respectively. However and still, R^2 from I-kaz^{TM} were much higher than the rms. The R^2 needs to be 0.8 and above in order to get an acceptable result in predicting the wear progression later on. Therefore, the regression models from I-kaz^{TM} were much more relevant as it approximated the real data points and showed a strong statistical relationship and dependency towards wear progression data.



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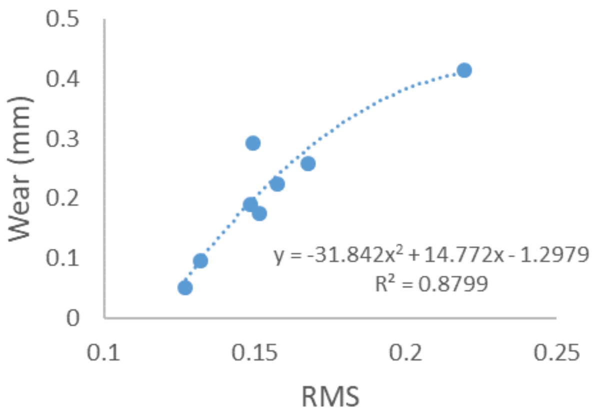

(b)

Figure-10. Correlation between flank wear with (a) I-kaz coefficients and (b) rms values for 300 m/min of cutting speed.

Validation for tool wear prediction

Through the construction of the regression models as in Figure 8 and 9, the derived polynomial equations are presented as in equation (8) - (11) below. $V_{B250}^{Z\infty}$ and $V_{B300}^{Z\infty}$ are defined as calculated wear from I-kaz coefficients while V_{B250}^{rms} and V_{B300}^{rms} are from rms values at 250 m/min and 300 m/min of cutting speed respectively.

$$V_{B250}^{Z\infty} = -7E + 11x^2 + 2E + 06x - 0.8843 \quad (8)$$

$$V_{B250}^{rms} = -126.77x^2 + 39.507x - 2.6903 \quad (9)$$

$$V_{B300}^{Z\infty} = -9E + 10x^2 + 537785x - 0.3811 \quad (10)$$

$$V_{B300}^{rms} = -31.842x^2 + 14.772x - 1.2979 \quad (11)$$

The experiment was redone once again with the same parameter as in Table 2 to verify and test the model equations described above for repeatability Wear measurement and signal data were recorded and extracted at 3 different points until end of wear. Then, the signal

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data were analysed with statistical signal features by using the same equation as in Equation (6) and (7). All the statistical features were entered into the model in Equations (8) until (11) to acquire the calculated wear values. The percentages of error were then calculated by comparing the measured wear with the calculated wear as in Equation 12 below. All the results were tabulated in Table 6 for set 1 (250 m/min) and Table 7 for set 2 (300 m/min).

$$Error = \frac{|Measured\ Wear - Calculated\ Wear|}{Measured\ Wear} \times 100\% \qquad (12)$$

Table-6. Comparison between calculated wear of I-kaz^{TM} and rms with measured wear values for 250 m/min cutting speed.

I-kaz coefficient	RMS	Measured wear (mm)	Calculated wear (mm)		Error (%)	
			I-kaz^{TM}	rms	I-kaz^{TM}	rms
6.97E-07	0.110041	0.152	0.170	0.122	11.6	19.7
8.12E-07	0.114176	0.24	0.278	0.168	15.9	30.1
9.50E-07	0.124757	0.337	0.384	0.265	13.9	21.3

Table-7. Comparison between calculated wear of I-kaz^{TM} and rms with measured wear values for 300 m/min cutting speed.

I-kaz coefficient	RMS	Measured wear (mm)	Calculated wear (mm)		Error (%)	
			I-kaz^{TM}	rms	I-kaz^{TM}	rms
1.00E-06	0.130022	0.074	0.068	0.084	8.0	14.2
1.44E-06	0.152493	0.198	0.207	0.214	4.4	8.2
1.81E-06	0.175335	0.303	0.297	0.313	1.8	3.4

To summarise the outcome above, the error for I-kaz^{TM} was from 1.8 to 15.9 % while the rms was nearly twice higher, up to a range of 3.4 to 30.1 % for both of the experimental sets. Therefore henceforth, I-kaz^{TM} statistical feature was much more efficient in predicting the wear progression using MFC sensor than the rms value.

CONCLUSIONS

Through the study, tool wear monitoring system using a low cost, lightweight MFC sensor has been successfully developed by utilising the I-kaz^{TM} statistical signal analysis method. Flank wear measurement and time captured have been done exceptionally well and met the criteria of tool life curve theory. For the signal in time-frequency domain has indicated an increase of amplitude and spikiness as the flank wear becoming larger and the vibration responses triggered from wear progression have been identified at a peak around 1900 Hz of frequency. Throughout the correlation and validation stage, the I-kaz^{TM} has been recognised to be more efficient and reliable than rms statistical feature in monitoring tool wear progression using MFC sensor.

In the future work, further study needs to be done where the researchers should compare the MFC which is a piezoceramic composite with the other variation of piezoelectric materials, such as piezoceramic (PZT) and piezo-polymer (PVDF) on tool wear monitoring system with the same machining parameter and condition. The comparison should be made to investigate the performance including reliability; flexibility and durability among them and also to reveal which one are more prominent in tool condition monitoring.

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