Decision support system for tool condition monitoring in milling process using artificial neural network

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T.Mohanraj*, A.Tamilvanan**

*Department of Mechanical Engineering, Amrita School of Engineering, Coimbatore.

Amrita Vishwa Vidyapeetham, India.

**Department of Mechanical Engineering, Kongu Engineering College, Erode

*Email: t_mohanraj@cb.amrita.edu; Corresponding Author.

ABSTRACT

This work discusses the development of tool condition monitoring system (TCMs) during milling of AISI stainless steel 304 using sound pressure and vibration signals. Response Surface Methodology (RSM) was used to design the experiments. The various milling parameters and vegetable-based cutting fluids (VBCFs) were optimized to reduce the surface roughness and flank wear. The experimental results reveal the direct relationship between the flank wear and sound and vibration signals. The various statistical parameters were extracted from the measured signals and given as input data to train the artificial neural network (ANN). From the developed ANN model, the flank wear was predicted with the mean squared error (MSE) of 0.0656 *mm*.

Key words: Stainless steel 304, Milling process, Response Surface Methodology, Surface Roughness, Flank wear, Sound pressure, Vibration signals, Tool Condition Monitoring System.

INTRODUCTION

Tool wear prediction and replacement depends on traditional calculation of wear data from the past years. To fabricate good quality products with minimal cost, a Tool Condition Monitoring system (TCMs) is necessary. The tool condition has been monitored with various sensors called as sensor fusion model (Dimla, 2000). The TCMs was developed with various features taken out from machining force, cutting sound, spindle vibration and current signals. The extracted features were combined to calculate the flank wear (Ghosh et al., 2007). On-line TCMs was designed using Support Vector Machine (SVM) with statistical features of cutting force, torque, AE, and vibration signals. The tool condition was estimated from the SVM results (Kaya et al., 2012). TCMs was designed using SVM with wavelet features of AE and sound signal and attain the better classification accuracy (Zhang et al., 2015).

Different clustering methods were applied for on-line TCM. The wavelet features were extracted from AE, cutting force, vibration signals and found the enhanced performance of fuzzy clustering than other methods (Torabi et al., 2016). Recently, during milling process, tool wear was supervised with cutting force, cutting sound, spindle motor current, and vibration signals. The sensor signals were combined together in FIS, the tool condition was assessed and arrived a conclusion to change the tool / machining conditions (Cuka and Kim, 2017). The various decision making algorithms were used to forecast the surface roughness and wear (Shankar et al., 2019b). A review of TCMs was discussed by (Mohanraj et al., 2020)

Vegetable based cutting fluids (VBCFs) are environment-friendly, inexhaustible, and harmless. The destructive effects of commercial cutting fluids (CFs) can be significantly reduced by employing VBCFs as CFs (Alves and de Oliveira, 2006). Vegetable-oil–based hybrid nano CFs were developed with the nano additives (CNT/MoS_2) with sesame, neem, and mahua oils. In turning process, Sesame-oil based hybrid nano CFs with CNT/MoS_2 enhanced the machining performance in terms of flank wear, surface roughness, cutting force, and temperature compared to dry and commercial CF (Pasam and Gugulothu, 2018).

During machining of TC4 alloy, nano graphene-scattered VBCF (LB 2000) considerably reduce the cutting force, cutting temperature, surface roughness, and surface micro-hardness (Li et al., 2019, Li et al., 2018). Various VBCFs were used for milling the Al 7075-T6 composite and observed that castor oil was performed better than other oils in terms of reduction in flak wear (Mohanraj et al., 2019).

TCMs was designed using various sensors and commercial cutting fluids. The development of TCMs for milling of Stainless Steel (SS) 304 with VBCFs was rarely found in the literature. The VBCFs appreciably decrease the wear and vibration during the milling process. The objective of this work is to develop the TCMs to monitor the tool condition with VBCFs as a CF for milling of SS 304 with cutting sound and vibration signals.

MATERIALS AND METHODS

The keyway milling experiment was conducted on LMill-55 CNC vertical machining center (Make: LMW, Coimbatore). The SS 304 (50 *mm* x 50 *mm* x 100 *mm*) was considered as a workpiece, and milling experiments were performed with three-flute TiN coated cemented carbide insert (XDHT-090308 HX-PA 120) of ϕ 25 *mm* cutter. Figure 1 shows the milling setup used for this work.

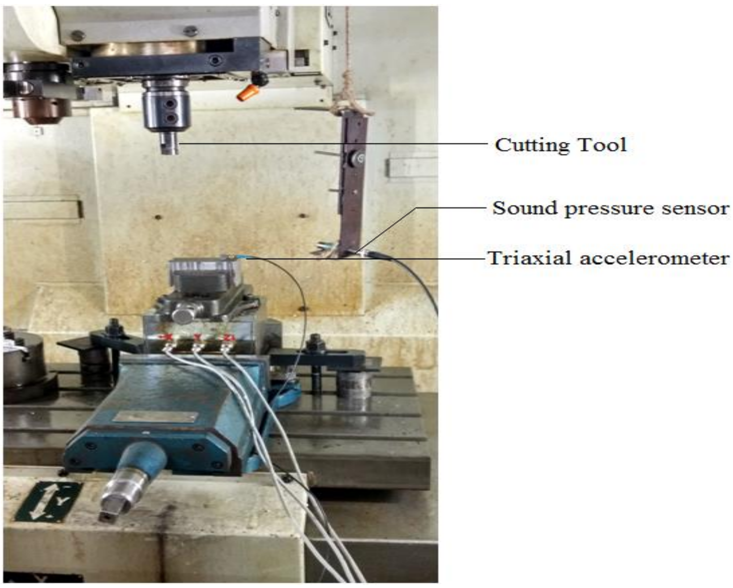

Figure 1Experimental setup

The control parameters namely spindle speed, feedrate and depth of cut with three levels were considered. The experimental design matrix was developed using response surface methodology (RSM)(Gur et al., 2020). The surface roughness and flank wear was assessed with surface roughness tester SJ–410 and Tool Makers' Microscope, respectively. The design matrix along with experimental results was presented in Table 1.

Table 1 Experimental design

Exp. No.	Spindle speed (A) (*rpm*)	Feed (B) (*mm.rev*$^{-1}$)	Depth(C) (*mm*)	Surface roughness(*μm*)	Flank wear (*mm*)
1	750	0.48	1.00	0.88	0.0298
2	1000	0.48	0.75	0.682	0.0332
3	750	1.18	0.75	0.844	0.0331
4	750	0.48	0.75	0.789	0.0325
5	899	0.90	0.90	0.911	0.0322
6	750	0.48	0.75	0.689	0.0321
7	750	0.48	0.75	0.753	0.0322
8	601	0.90	0.90	1.102	0.0328
9	899	0.06	0.60	0.75	0.0352
10	899	0.06	0.90	0.3703	0.0326
11	500	0.48	0.75	0.600	0.0324
12	601	0.90	0.60	0.528	0.0351
13	750	0.23	0.75	0.565	0.0334
14	750	0.48	0.75	0.651	0.0310
15	750	0.48	0.75	0.656	0.0333
16	750	0.48	0.50	0.839	0.0338
17	601	0.06	0.60	0.471	0.0351
18	750	0.48	0.75	0.661	0.0312
19	601	0.06	0.90	0.431	0.0271
20	899	0.90	0.60	0.633	0.0277

The instruments used for measuring the surface roughness and flank wear were given in Figure 2. First stage, the commercial cutting fluid was used, and the milling parameters were adjusted to reduce the surface roughness and flank wear. Later stage, milling process was performed with optimum condition and VBCFs such as neem, cotton seed, castor, palm, groundnut, and rapeseed. For each VBCF, the experiments were replicated for three time and results were obtained. The CF which enhances the surface quality and tool life was selected. Finally, the milling process was performed with selected VBCF and optimum condition to measure the vibration (g) and sound pressure (Pa) signals. The different tool conditions like fresh, working and dull were chosen.

a b

Figure 2 a) Measurement of surface roughness b) Flank wear

Sound pressure (Pa) and workpiece vibration (g) signals were measured using a Microphone (Make: GRAS) and a Tri-axial accelerometer (Make: Dytran) in that order. The microphone was mounted at a distance of 30 *cm* from cutting zone to measure the sound pressure signal and safeguard the sensor from coolant. The signals were acquired using NI 9274 data acquisition card and the obtained signals were processed using LabVIEW software.

RESULTS AND DISCUSSION

Analysis for surface roughness

Analysis of variance (ANOVA) is used to identify the most significant process parameters (Gür, 2013). ANOVA for surface roughness was shown in Table 2. The main effect of feed (B) (Shankar et al., 2016, Subramaniam and Thangamuthu, 2017), two-level interaction of feed and depth (BC) were most considerable terms for surface roughness. Additionally, two-level interaction of spindle speed and depth (AC), second order term of feed (B^2) and depth (C^2) were found as substantial. Feedrate had the maximum percentage contribution of 38.2 % and it had physical significance. Previous work (Sahin and Motorcu, 2005, Vikrama et al., 2015, Khorasani and Yazdi, 2015, Zhang et al., 2016) reported that feed was deciding factor for surface quality. The spindle speed and depth had very less impact on surface roughness. The same effect of depth of cut was found in milling of AA7039/Al_2O_3 composites (Karabulut, 2015).

Table 2 Analysis for surface roughness

Source	Sum of squares	df	Mean Square	F Value	p-Value Prob>F	% Contribution
Model	0.5623	9	0.0624	21.06	< 0.0001	--
A	0.0053	1	0.0053	1.801	0.2092	0.90
B	0.2261	1	0.2261	76.232	< 0.0001	38.21
C	0.0183	1	0.0183	6.200	0.0320	3.11
AB	0.0115	1	0.0115	3.90	0.0765	1.96
AC	0.0505	1	0.0505	17.02	0.0021	8.53
BC	0.2021	1	0.2021	68.128	< 0.0001	34.15
A^2	0.0109	1	0.0109	3.706	0.0831	1.86
B^2	0.0264	1	0.0264	8.913	0.0137	4.47
C^2	0.0356	1	0.0356	12.002	0.0061	6.02
Residual	0.0296	10	0.0029			
Lack of Fit	0.0129	5	0.0025	0.776	0.6063	
Pure Error	0.0167	5	0.0033			
Cor. Total	0.5920	19				
R^2= 0.9499; Adjusted R^2 =0.9048; predicted R^2 = 0.7554: Adequate Precision=19.38						

Analysis for wear

ANOVA result for wear (Vb) is presented in Table 3. Depth (C), effect of speed and feed (AB) and effect of feed and depth (BC) and effect of speed and depth (AC) were found as considerable cutting parameter for Vb. Flank wear dependent on interaction effect of spindle speed and feed (AB). Here the combined effect of spindle speed and feed had the highest percentage of 25.20 complied by the combined effect of BC had 22.69 %. The influence of spindle speed and depth (AC) had 20.53 % contribution. The depth (C) had significant contribution of 21.44 %. The result of spindle speed and feed alone does not have any statistical significance on flank wear (Kaya et al., 2012). From the literature, most significant parameters for flank wear was A, B, A^2 and B^2 (Arokiadass et al., 2012).

Table 3 Analysis for flank wear

Source	Sum of squares	df	Mean Square	F Value	p-Value Prob>F	% Contribution
Model	$8.26x10^{-5}$	6	$1.38x10^{-5}$	21.234	< 0.0001	--
A	$6.10x10^{-7}$	1	$6.1x10^{-7}$	0.9404	0.3499	0.67
B	$1.87x10^{-7}$	1	$1.87x10^{-7}$	0.2889	0.6000	0.21
C	$1.95x10^{-5}$	1	$1.95x10^{-5}$	30.1077	0.0001	21.44
AB	$2.29x10^{-5}$	1	$2.29x10^{-5}$	35.3905	< 0.0001	25.20

AC	1.87×10^{-5}	1	1.87×10^{-5}	28.8203	0.0001	20.53
BC	2.07×10^{-5}	1	2.06×10^{-5}	31.8573	< 0.0001	22.69
Residual	8.43×10^{-6}	13	6.48×10^{-7}			
Lack of Fit	4.84×10^{-6}	8	6.05×10^{-7}	0.8425	0.6060	
Pure Error	3.59×10^{-6}	5	7.18×10^{-7}			
Cor. Total	9.10×10^{-5}	19				
R^2= 0.9015; Adjusted R^2 =0.8560; predicted R^2 = 0.7877; Adequate precision=17.89						

Optimization of milling parameters

The optimal milling parameters for machining AISI SS 304 within the chosen range of milling parameters was found which minimizes the surface roughness (Ra), and flank wear (Vb) during milling process. The RSM desirability function was utilized to optimize the process parameters. The numerical optimization was utilized to find the points which maximize the desirability function. From RSM optimization, speed of 601 *rpm*, feedrate of 0.06 $mm.\ rev^{-1}$ and depth of 0.88 *mm* were identified as optimal process parameter for machining of AISI stainless steel 304. The verification trial was performed with obtained optimum condition and experimental values were compared with predicted values. The result was given in Table 4.

Table 4 Confirmation test results

Surface roughness (μm)			Flank wear (*mm*)		
Experiment	Prediction	% Error	Experiment	Prediction	% Error
0.4325	0.4206	2.75	0.0281	0.0271	3.55

After finding the optimum condition, the VBCFs were used a CF and milling process was conducted thrice. The flank wear was recorded, and average value was used to select the CF. Table 5 presents the flank wear details for different VBCFs. High viscosity of VBCFs ensured more stable lubrication across the process temperature range and reduce the cutting zone temperature and form a thin layer. This behaviour of VBCFs reduces friction between workpiece and tool which leads to possible reduction of heat produced at tool – workpiece interface. The strong intermolecular interactions providing a more stable viscosity and also flexible to changes in temperature (Gerpen et al., 2004). Moreover, the viscosity of castor oil is more than other VBCFs. This reduced the friction among tool & work piece, and easily removed the heat generated at tool – workpiece interface. During machining process, castor oil exhibits least wear and roughness compared to other VBCFs. So, castor oil exhibits better performance than other VBCFs and selected as a CF for design of TCMs.

DESIGN OF TCMS FOR AISI STAINLESS STEEL 304

Effect of flank wear on sound signal

The acquired sound pressure signal during machining with different cutting tool is shown in Figure 3. The maximum value of sound produced for worn tool was 6 *Pa*. The stainless steel 304 was one of the difficult to cut material and presence of harder particles may be the reason for the higher amplitude of sound pressure. Figure 3 shows that raise in flank wear leads to rise in sound pressure. Once the tool lost its effective cutting edge, tool – work part contact area was increased and not capable to manufacture the superiority products. The similar tendency was noticed in literatures (Kopač and Šali, 2001, Ghosh et al., 2007, Raja et al., 2013).

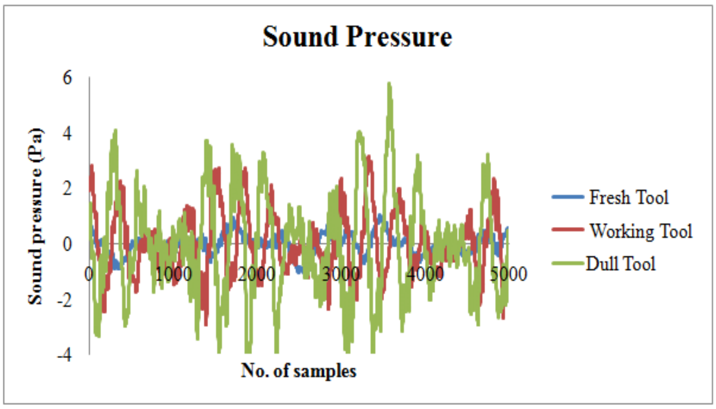

Figure 3 Sound pressure values for different tools

The sound value for various tool condition clearly illustrated that sound for dull tool was higher than other two tools. While the cutting tool turns faulty, it augments the contact region and nose radius. At that moment, extra area was in contact with milling surface. That leads to elevate the sound level. The variation in milling parameter and incidence of any fault (breakage, built up edge) should alter the level of sound pressure (Tekıner and Yeşılyurt, 2004). Initial cutting sound was little high owing to initial interaction of cutting tool & workpiece. In dull tool, contact area was increased due to increase in flank wear and it produced the maximum sound pressure (Shankar et al., 2019a).

Effect of flank wear on vibration signals

The resultant vibration for different tools was presented in Figure 4. To analyse the consequence of all three-axis vibration, resultant vibration was considered. The vibration in Y axis had a significant effect since it was the feed direction of the machine. The new tool had a least resultant vibration in the range of 0 – 3 *g*. During early phase of machining, tool is sharp and there is only interaction between the nose radius and work part. So, vibration was very lesser than other tools (Mohanraj and Shanmugam, 2021).

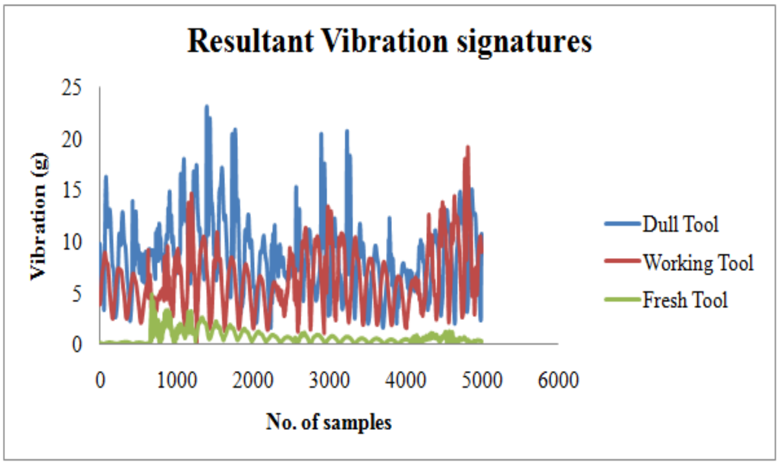

Figure 4 Resultant vibration signatures for different tools

When tool crosses the primary wear stage, tool wear land increased very minimally and maintains uniform contact between tool & work part. So, the identical vibration was continued. The dull tool lost its effective cutting edge, and which enlarged the tool – workpiece contact area, and friction, results in elevation of vibration. During machining of Inconel 625 (Shankar et al., 2019a, Krishnakumar et al., 2015), the similar trend was noticed. From the above Figures, it was evident that raise in flank wear leads to rise in vibration. The same trend was found in literatures (Chelladurai et al., 2008, Orhan et al., 2007, Dimla and Lister, 2000, Pai and D'Mello, 2015, Mohanraj et al., 2021a). The optical image for the fresh and dull tool was shown in Figure 5.

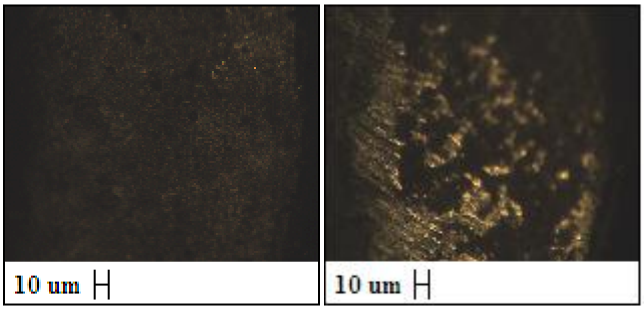

Figure 5 Optical image of the cutting tool (a) New tool (b) Dull tool

Design and Development of TCMs using ANN

The widely used Backpropagation Neural Network (BPNN) was employed for estimating the tool condition in milling process. The advantages of using BPNN algorithm is the ability to model, estimate mathematically and match the non-linear model (Taskin et al., 2008). The statistical parameters like RMS, kurtosis, skewness, and mean of sound pressure, and resultant vibration were used as inputs for NN predictor. The flank wear was considered as the output data and it was given as target. The TRAINLM (Levenberg-Marquardt backpropagation) function was selected as NN training function. Learning and performance functions of LEARNGDM (Gradient descent momentum weight / bias learning function) and Mean Squared Error (MSE) was considered respectively. TANSIG (Hyperbolic tangent sigmoid) transfer function was employed to estimate the output from its network input.

The number of hidden nodes was started with 10 and gradually increased up to 30 to obtain the optimal performance. The number of iterations was set as 1000. The training process started with the above said initial conditions. The best performance was obtained at 5th iteration with the best validation performance of 0.0656 *mm* MSE. Figure 6 shows performance graph of the developed NN estimator. The 75 % of data (1050 samples) were utilized for training purpose and 25 % (450 samples) were used for testing and validation purpose (Mohanraj et al., 2021b). The lower value of MSE provides the better performance.

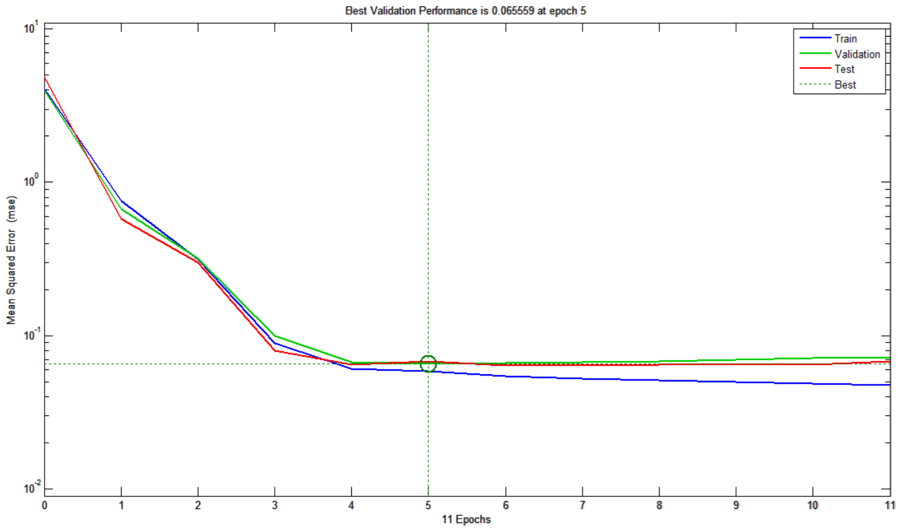

Figure 6 ANN Performance graph

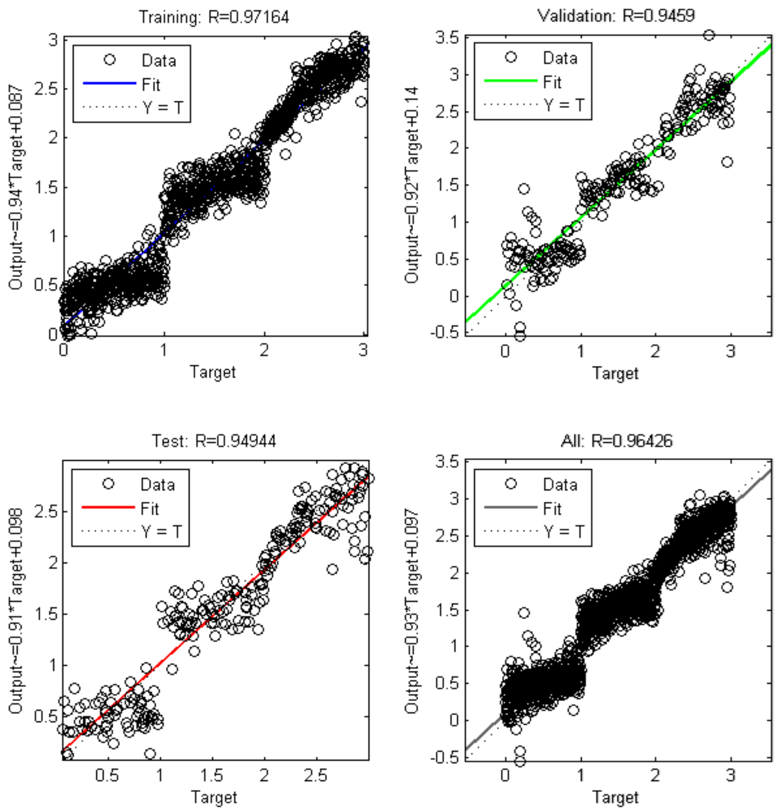

Figure 7 Regression plot

When MSE closer to zero, indicates the designed estimator has no errors. Here the designed NN estimator had MSE of 0.0585 *mm* during training phase. During testing phase, the NN had MSE of 0.06788 *mm*. This performance level is satisfied for TCMs application. Further, the prediction accuracy can be enhanced by applying machine learning algorithms (Krishnakumar et al., 2018a, Krishnakumar et al., 2018c, Krishnakumar et al., 2018b).

The regression coefficient for the designed NN estimator was presented in Figure 7. For training phase, testing phase, and validation the regression coefficient was 0.9716, 0.9494, and 0.9459 respectively. The overall regression coefficient was 0.9642. The VBCFs have good friction reduction abilities and the friction was reduced during tool-workpiece contact which produced better surface finish. The VBCFs have a capability of creating thin layer which enhances the boundary lubrication, as a result reduce the friction at tool - workpiece contact zone which decreases the flank wear. Surface roughness was enhanced slightly, due to the temperature reduction in machining zone (Mohanraj et al., 2019).

The enhancement of friction owing to rise in contact zone generates elevated vibration signals, results in raise in amplitude of vibration signals. Beyond the certain level of flank wear, considerable increase in contact area was observed, for the reason of plastic deformation and speeding up of tool wear. The amplitude change of dull tool may be due to the deformation behavior of material in shear zone. When the flank wear increased, it increases the contact area between tool & work material. Also, it increases tool nose radius and the tool becomes dull to remove the material from the workpiece.

CONCLUSION

The keyway milling experiments were carry out on AISI SS 304, using cemented carbide insert (WIDIA XDHT-090308HX-PA120) for tool wear estimation and the process were monitored using sound pressure, and vibration signals. An effort was geared up to design a simple low cost TCMs, using sensor fusion technique. The results arrived from the experiment was presented below.

- Feed was the most significant factor for surface quality.
- Surface roughness augmented with raise in feed. Larger feed values augment the temperature and reduce the bonding strength in the work material which affects the surface quality

- The temperature at tool - workpiece contact was increased, while speed and depth were increased which decreases the tool life
- The speed of 601 *rpm*, feed of 0.06 $mm.rev^{-1}$ and depth of 0.88 *mm* was obtained as optimal process parameter
- Castor oil exhibits the minimum flank wear. Due to high viscosity, cutting fluid greatly reduces the cutting zone temperature and hence reduced the flank wear
- The output of NN was accessed to monitor the tool wear. When NN result reaches the value of 3, cutting tool has to be substituted for further operations

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