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Prediction models for on-line cutting tool and machined surface condition monitoring during hard turning considering vibration signal

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Abstract. Turning of hardened steel is an immense issue of interest concerning with machining technology and scientific research. A strategy to analyze vibration signals and its correlation on surface roughness and tool wear has not attracted much breakthrough in research so far in hard machining. Therefore, tool condition monitoring (TCM) study will be definitely worthwhile for the effective application in hard part turning. The current study examines about the online prediction of flank wear and surface roughness monitoring during dry hard turning of AISI 52100 steel (55 ± 1 HRC) utilizing MTCVD multilayer coated carbide insert (TiN/TiCN/Al_2O_3) considering machining parameters and vibration signals through development of prediction model (MLR and MQR) after studying the Pearson correlation coefficient and test for its accuracy. Pearson correlation coefficient for feed on flank wear is utmost pursued by acceleration amplitude of vibration (Vy) in radial direction, depth of cut and cutting speed. Similarly, acceleration amplitude of vibration followed by cutting speed and feed has strong correlation with surface roughness. MQR model predicts well for responses as percentage of error is quite less and cutting speed is obtained to be the most important parameter for vibration signal. Multiple quadratic regression (MQR) models are observed to be noteworthy, effective and adequate to predict response outputs with regards to the combined effect of machining parameters and vibration signals online. A corrective measure can safely be taken with reasonable degree of accuracy during hard turning.

Keywords: Tool condition monitoring / surface roughness / flank wear / hard turning / multiple regression / vibration

1 Introduction

Machining of hardened components are usually done through a traditional abrasive process called grinding using ceramic grinding wheel since the 1970s due to stringent requirement of surface finish and dimensional accuracy [1]. Advancement of super-hard cutting tool materials likely PCBN and ceramic and with the availability of rigid machine tool, machining of hardened components now became possible up to 60–65 HRC through hard turning which replaces slowly the cylindrical grinding for finishing of components. Thus the research is needed to search for economical cutting tool material which may be implemented in an emerging hard machining environment comparable with CBN and ceramic tool. Multilayer-coated carbide cutting tool is the new generation cutting tool material to be explored in machining of hardened steel and its machining performance aspects. This facilitates the machining industries especially in bearing and automotive industries a lot. In hard turning, tool wear is prominent at the edge of cutting insert, which results in poor surface quality. Furthermore, vibrations at the intersection of tool tip-workpiece is prominent which not only affects surface quality, premature failure of cutting tool and tool life but also affects the dimensional accuracy, failure of spindle and life of machine tool.

Hence the correlation of machining parameter (*d, f* and *v*) along with vibration signals like acceleration amplitude in radial force and cutting force direction on tool wear and surface roughness is utmost important in particularly hard machining environment. These are the vital issues that need to be investigated so as to augment the overall industrial productivity and surface finish in hard machining. This section provides the literature review based on tool condition monitoring system followed by the

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literature gap and specific objectives. Further, Section 2 presents in detail experimental procedure. Section 3 discusses the Taguchi L_{18} orthogonal array design and its outcomes. Regression models considering inclusion of machining parameters and vibration signal has been represented in Section 4. Finally, conclusions are summarized in Section 5.

Li [2] reviewed the various work on AE sensing of cutting tool wear during turning process which includes the AE develop in metal cutting practices along with tool wear estimation including neural network, sensor. Since the AE sensitivity to wear out tool and fracture is connected with a large rate of signal response, hence AE-based sensing technical knowledge is the great research exercise to progress intelligent tool condition systems. Bensouilah et al. [3] examined hard machining of cold work tool steel (63 HRC) with CC6050 with TiN coated and uncoated CC650 ceramic tool by verifying with ANOVA. The outcomes disclosed that CC650 is more valuable in minimizing the cutting force elements. The surface roughness induced with the TiN coated ceramic cutting tool is 1.6 times more than the uncoated cutting tool. Paul et al. [4] investigated on hardened AISI 4340 steel by using TiN and TiCN coated tool based on the effect of cutting variables. Influence of cutting fluid application parameters on tool vibration has been analyzed. The conclusion showed better performance behavior like minimization of surface roughness, cutting force, tool flank wear, vibration and cutting temperature. It is revealed that with the proper use of minimal fluid reduces tool vibration in hard turning. Rmili et al. [5] reported a new approach for monitoring and detection of wear on the cutting insert. For measurement of the vibratory signatures, a three-axis piezo-electric accelerometer was used in the turning process. The work piece material used was grey cast iron (FGL 250). At last, an automatic detector was suggested to assess and observe tool wear during the actual experiment. It was revealed that the accelerometer sensors instilation is very simple. In addition, the vibratory signal combination acquisition along with processing methods is found to be economical. Ahmad et al. [6] monitored vibration signals applying low cost piezoelectric ceramic sensor attached on the tool holder during turning. The signal produced from the piezoelectric sensor was analyzed deploying I-kaz™ statistical approach. It was summarized that the measured vibration signal is influenced by the varying tool wear width. The proposed methodology is very necessary to increase the surface quality, reduction of cost and tool failure during machining. Scheffer et al. [7] investigated the force-based monitoring with artificial intelligence (AI) model which is suitable technique to trace tool wear during hard turning. This method facilitated to predict crater and flank wear monitoring during hard turning. Hessainia et al. [8] formulated a model for surface roughness of 42CrMo4 steel using mixed ceramic (Al_2O_3/TiC) through RSM taking considering cutting variables and tool vibrations during hard turning. The research revealed that a well-fitted closeness was noticed among the predicted and the trial results of surface roughness. In addition, it was indicated that the nominal depth of cut has no impact on surface roughness. Dutta et al. [9] reviewed on digital image processing used for easier and fast automatic detection of different tool wears namely crater wear, chipping of tool and tool fracture in tool condition. It was also summarized that quick identification of the influence of vibrations, the condition of insert, machine noise, etc. can be feasible from indirect tool condition monitoring in contrast with direct TCM. Besides, it was revealed that ANFIS is a significant means for close prediction of cutting tool wear during indirect TCM. It was revealed that ANFIS is a significant means for close prediction of cutting tool wear during indirect TCM. Chelladurai et al. [10] experimentally examined the difficulty relating to the flank wear and vibration during the turning process. Applying analysis of variance (ANOVA), empirical models have been developed. Upadhyay et al. [11] analyzed vibration signals to predict surface roughness in hard turning of Ti–6Al–4V alloy using uncoated cemented carbide tools. The amplitude of vibration in axial, tangential and radial directions is measured. Multiple regression models are developed considering pearson correlations between responses with process parameters and vibration amplitudes. ANN model has been developed which can be a part with CIM environment. Both the models are found to be significant and adequate for prediction of better surface quality. Dimla and Dimla [12] focused on monitoring instrument for detecting the wear levels on the cutting insert with the application of on-line condition monitoring systems (TCMS). This suggests that due to incompetent sensor information and process models enhanced TCMSs have not been effectively performed. Therefore, it is required to establish a method that can be engaged for systematic inspection of cutting tool condition during machining i.e. fracture, levels of wear and chipping. Botsaris and Tsanakas [13] suggested that condition monitoring field and fault diagnosis is of interesting topic using signal processing method along with diagnostic tools. In addition to that, acoustic emission signals and vision based direct processes are utilized for identification of tool breakage. Kumar et al. [14] analyzed some machining performance of hardened steel (AISI D2) with coated (multilayer) carbide and uncoated carbide cutting tool during turning. Coted carbide insert performed better during investigation on tool wear, surface roughness, temperature etc. Ozel et al. [15] generated multiple regression along with the neural network model for envisaging flank wear and surface roughness in turning hardened AISI D2 grade (60HRC steel) utilizing ceramic wiper insert. The Neural network model is obtained to be accurate for prediction of output responses such as surface roughness and tool wear. Lalwani et al. [16] examined on surface roughness with cutting force during turning of hardened MDN 250 steel by coated ceramic insert and analyzed the effect of input parameters on responses through response surface methodology. RSM based quadratic model adequately explains the variation of surface roughness. Feed rate is noticed to be the main contributor for surface roughness. A linear model is fitted well for cutting forces with the major significant addition of feed and depth of cut. Afterward, Cutting speed is obtained to be insignificant for both cutting forces and surface roughness respectively. Thrust force component is indicated to be higher compared to cutting force and feed force during hard part turning. Sahin and Motorcu [17] proposed a model of surface roughness by RSM in turning hardened AISI 1015 steel with CBN insert. A good closeness among the predicted and trial data of surface roughness was found. The surface roughness value of 0.823 microns has been achieved during machining hardened steel using CBN tool. More et al. [18] observed that CBN–TiN carbide coated inserts are adequately competent of minimizing cutting costs and will be an alternative to PCBN cutting tools in turning hardened steel. Paiva et al. [19] experimentally investigated machining of AISI 52100 bearing steel by wiper ceramic tool coated with TiN. With the use of wiper inserts and twice feed rate can be used compared to conventional tool geometry to achieve surface roughness nearly half value. Bouacha et al. [20] obtained optimized parameters for the surface finish with cutting force using composite desirability approach and RSM while hard machining of AISI 52100 employing CBN cutting insert. Chinchanikar and Choudhury [21] conducted experimentally on characteristic of coated carbide tool during hard turning considering workpiece hardness and cutting parameters. Optimum machining conditions were found by using response surface methodology and other technique like desirability function approach. Das et al. [22] studied some machinability aspects during turning AISI 4140 grade steel with PVD-TiN coated mixed ceramic ($Al_2O_3 + TiCN$) tool in dry cutting. The experimental values were studied to predict the optimal parameter of supportive surface roughness and flank wear. Applying RSM at 95% confidence level, mathematical models are developed for flank wear and surface roughness. Aouici [23] studied the influence of independent variables and work material hardness on surface quality and cutting force aspects in the turning of hardened AISI H11 steel utilizing CBN cutting tool. Mathematical models were developed through response surface methodology for surface roughness and cutting force components and best cutting conditions are proposed. Kurt and Seker [24] explored turning AISI 52100 hardened steel using PCBN insert and studied the impact of chamfer angle on the cutting forces, principal and von Mises stress and the cutting tool stresses. Critical chamfer angle of 20° is recommended in finishing hard turning. Kumar et al. [25] examined the machinability of multilayer coated carbide insert with respect to tool life, optimization, modeling and economics of machining of AISI D2 steel under dry environment. The reduction of machining cost is noticed during hard turning. Ambhore et al. [26] developed mathematical and ANN model to study vibration acceleration and surface roughness in turning hardened AISI 52100 steel. ANN model proved to be effective in prediction of responses compared to regression. Ukamanal et al. [27] investigated the influence of spray parameters during machining of AISI 316 steel through experimental technique by design of experiment for evaluating cutting temperature, surface roughness and tool wear and optimized the parameters using weighted principal component analysis.

Krishnakumar et al. [28] studied the prediction of tool wear during high speed machining of titanium alloy using vibration signals. Artificial neural network (ANN) model has been found to be effective in prediction of tool condition monitoring compared to decision tree algorithm. Cho et al. [29] studied multiple sensor based tool condition monitoring system in end milling of 4340 steel. Results reveal that tool condition monitoring based on feature level fusion enhances the accuracy of the system using force, vibration and acoustic sensor together. Zhang et al. [30] studied indirect tool condition monitoring approach with wireless triaxial accelerometer to acquire vibrations during milling. Neuro-Fuzzy network outperformed in prediction of tool wear and remaining useful life compared to back propagation neural network (BPNN) and radial basis function network (RBFN). Zhou and Xue [31] proposed multisensory global fusion method for tool condition monitoring in milling operation. Kernel-based extreme learning machine (KELM) and modified Genetic Algorithm (GA) achieved highest prediction precision for optimal parametric combinations. Mali et al. [32] studied sensor based tool wear monitoring system for hard machining of Inconel 718. A good correlation between cutting force and tool wear has been established and can be effectively utilized for online measurement.

It is reported from the literature review that the hard turning now-a-days is an emerging machining process that replaces the traditional grinding operation in many applications due to effectiveness in terms of time, cost, flexibility and environment. First of all, the applicability of the coated carbide (multilayer) tool in hard turning of bearing steel at elevated hardness value of 55 HRC is lacking though it is machined by super-hard tool materials (namely CBN and ceramic). This issue has been addressed in the paper by implementing economical coated carbide cutting tool. Secondly, online simultaneous prediction of flank wear and surface roughness in hard turning considering vibration signals are lacking in the literature. Thus tool condition and machined surface condition monitoring aspects study are essentially required particularly in hard turning which is limited study as per literature. Surface roughness degrades rapidly with the evolution of tool wear. Vibration signals through hard turning also affect the surface finish, dimensional accuracy, and failure of cutting tools. Therefore, vibration signal along with machining parameters should be taken simultaneously as input variables for online prediction and development of surface roughness and flank wear model which is lacking in hard machining and are important issues that need to be explored of overall productivity improvement. A strategy to analyze the vibration signals and its correlation on surface roughness and tool wear has not attracted much breakthroughs in research so far in hard machining. Therefore, tool condition monitoring (TCM) study will be definitely worthwhile and beneficial for the effective application in hard turning. Thus the present research is focused on the following aspects:

- Performing some pilot trial to study the vibration signals in the radial (Vy) and tangential directions (Vz).
- To study the in process accuracy prediction of flank wear and surface roughness considering only vibration signal as input parameter through regression analysis.
- To develop the prediction model (MLR and MQR) using combination of significant machining parameters and

acceleration amplitude of vibration signal as input parameters after studying the Pearson correlation coefficient and test for its accuracy.
– Validation of experimental data and outline possible outcomes.

2 Experimental procedure

The work piece specimen used in the hard part turning experiment was AISI 52100 hardened steel to 55 ± 1 Rockwell of C scale of length and diameter of 120 and 40 mm respectively. The hard turning experiment was performed with the high power rigid precision lathe (Make: HMT, model: NH22) of self-centering chuck revolving center in dry cutting surroundings shown in Figure 1. The MTCVD (TiN/TiCN/Al_2O_3) multilayer coated carbide insert was used in the experiment with ISO designation as CNMG 120408 of K-type HK150 grade which was clamped on the PCLNR2525M12 type tool holder. This gives the geometry of cutting insert as 5° clearance angle, −6° back rake angle, −6° inclination angle, 95° approach angle with nose radius of 0.8 mm. The skin rust layer on the workpiece due to heat treatment was first removed by conducting some preliminary machining operation. The cutting length was fixed as 100 mm at each and every experimental trial. The acceleration amplitude of vibration of cutting tool was assessed with the help of accelerometer (PCB piezotronics of quartz sensing element, 1–4000 Hz frequency range, and ±5% sensitivity) and vibration signal FFT analyzer (Type: OROS-3series/NV, four channel, 1 Hz–20 kHz frequency range and 1 Hz resolution) in both radial cutting force (Vy) and tangential cutting force directions (Vz). In the trial set up as shown in Figure 2, no separate electronics circuit was used. The vibration analyzer OROS-34 (four channels) was used with PCB pizo-electric accelerometer as the probe with BNC connector to measure vibration average amplitude. The commercial software NVGATE (Noise vibration Analysis) by OROS, French make was used to record and study the average vibration amplitude.

Acceleration amplitude of vibration (Vy) in the radial direction is considered in the current study. During machining, the FFT of the vibration signal was performed by fresh cutting tip of the insert and no localized hard surface was encountered during the turning process. The vibration is only because of change in machining parameter like cutting speed, feed and depth of cut not otherwise due to blunt cutting tip or surface rubbing or localized hard surface encountered in the machining process. FFT analyzer was used only to ensure accurate vibration reading without any external factors as cited. However, only average vibration amplitude of time domain signal is used in this paper. Besides, average vibration amplitude was affected by three main significant input parameters such as cutting speed, feed rate, and depth of cut not by cutting speed only; therefore no order tracking was performed.

The experimental setup for measurement of vibration, block image of the measuring system and the flow chart of vibration measuring system was shown in Figures 1, 2 and 3 respectively. Time and frequency domain waveform and the spectrum acquired from single- channel vibration signal analyzer were processed using the software. Flank wear of insert was measured using an optical microscope with image analyzing software (Olympus, STM 6). The life of the cutting insert was over when flank wear at nose radius corner (VBc) exceeds 0.3 mm. The arithmetic surface roughness average (Ra) of the machined component was computed with the help of surface roughness tester (Taylor Hobson, Surtronic 25) with cut-off length of 0.8 mm. The average of three readings at different locations on the circumference of the workpiece was taken.

Fig. 1. Hard machining experimental setup for vibration measurement.

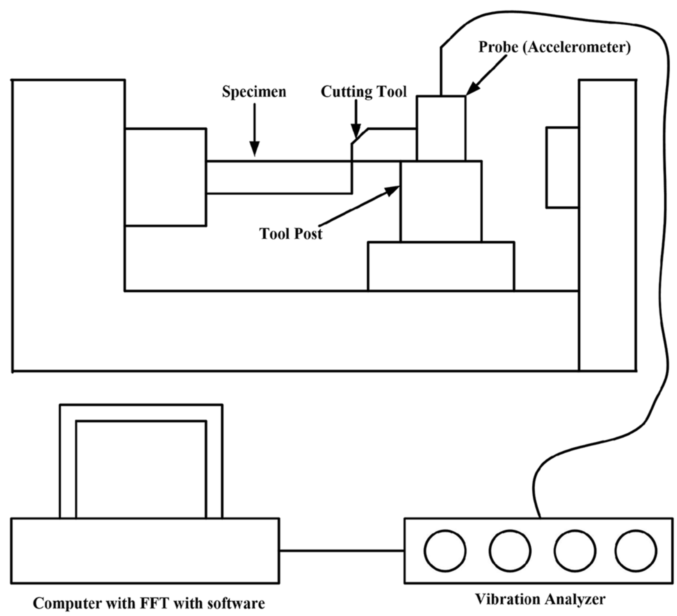


Fig. 2. The block diagram of the measuring system.

3 Preliminary experiment

The preliminary experiment was first conducted to measure the acceleration amplitude of vibration of cutting insert during hard machining in the radial (Vy) i.e. Y-direction and tangential (Vz) i.e. Z-direction respectively. For this, the accelerometer was mounted on the tool holder in both directions separately and vibration signals were captured. The experimental cutting conditions

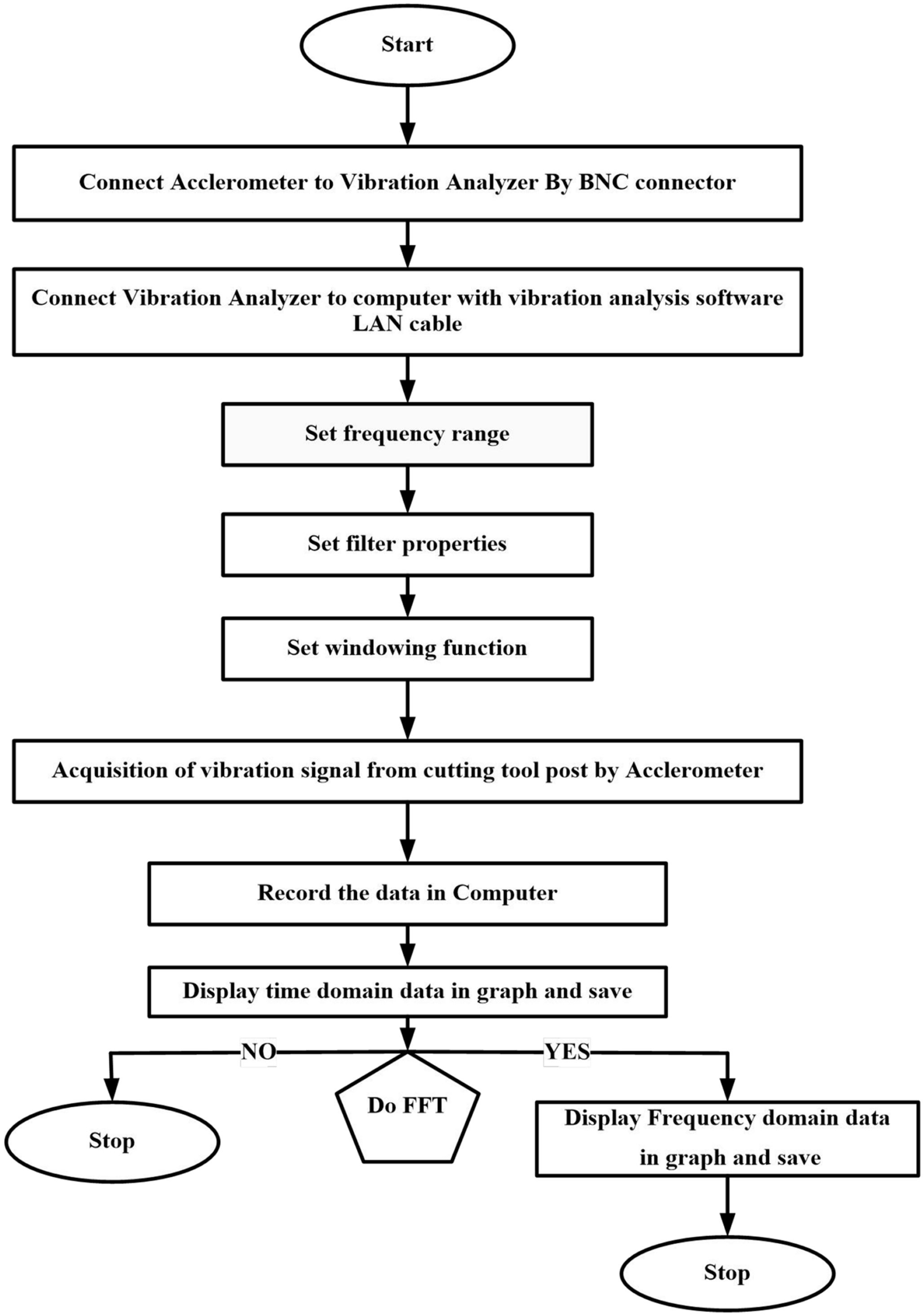


Fig. 3. The flow chart of vibration measuring system.

and test results were shown in Table 1. From the pilot experiment, the acceleration amplitude of vibration of cutting tool in radial direction (Vy) was observed to be more in comparison to tangential direction (Vz) [8,11]. The vibration signal obtained in tangential direction was quite less compared to radial direction. This indicated that the thrust force component in Y-direction (radial) was dominant compared to Z-direction (tangential) during hard turning which is well agreement with many researchers observed during hard turning [14,16,20,25]. This concluded that during hard machining, thrust force component (Fy) is more compared to tangential cutting force (Fz). The acceleration amplitude of tool vibration in radial direction is more detrimental as thrust force

Table 1. Experimental results of acceleration amplitude of vibrations in radial (Vy) and tangential (Vz) directions during preliminary tests.

Run	Depth of cut (d), mm	Feed (f), mm/rev	Cutting speed (v), m/min	Acceleration in radial (Vy), m/s^2	Acceleration in tangential (Vz), m/s^2
1	0.1	0.04	67	0.385	0.133
2	0.1	0.04	113	0.34	0.136
3	0.1	0.04	147	0.61	0.196

Table 2. Experimental conditions.

Machining parameters	Unit	Level		
		1	2	3
Depth of cut (d)	mm	0.1	0.2	0.3
Feed (f)	mm/rev	0.04	0.08	0.12
Cutting speed (v)	m/min	67	113	147

increases which in result affect the surface quality and dimensional closeness of the machined sample. During finish hard turning operation the depth of cut is taken as 0.1 mm that is less than nose radius of insert i.e. 0.8 mm, the cutting was performed at the corner of nose radius and thus vibration and thrust force was observed as increased manner compared to tangential direction. Due to radial component, flank wear occurred in nose corner rather than flank region. Thus in further detailed investigations, only vibration signals in radial direction (Vy) was concentrated which needs to be studied more and monitored subsequently. The online tool wear particularly flank wear and machined surface condition monitoring was studied in detail in next section considering vibration signals in radial direction only.

4 Design of experiment and results

The hard turning experiment was devised using Taguchi L_{18} orthogonal array (OA) considering three machining parameters (d, f and v) respectively under dry environment [8,14,22,25,33–35]. The experimental cutting conditions and levels were shown in Table 2 and in total 18 runs were conducted. Cutting parameters are selected based on the recommendations of the tool manufacturer and through previous literatures [8,14,18,33,36]. The experimental outcomes of flank wear (VBc), surface roughness (Ra) and acceleration amplitude of vibration signal (Vy) in radial direction was presented in Table 3. Time and frequency domain waveform and spectrum attained from single channel vibration analyzer in hard part turning at run1 ($d = 0.1$ mm, $f = 0.04$ mm/rev and $v = 67$ m/min) and at run16 ($d = 0.3$ mm, $f = 0.04$ mm/rev and $v = 147$ m/min) were shown in Figure 4. The figure of flank wear of cutting insert at run1 was shown in Figure 5. Table 3 contains discrete levels of input machining parameters and the measured experimental outcomes. The experimental outcomes listed in the table suggest that out of the three machining parameters cutting speed is the most predominant one, whereas depth-of-cut and feed rate have a marginal influence on the experimental results. An increase in acceleration (Vy), flank wears (VBc) and surface roughnesses (Ra) were observed with the increase in cutting speed. The value of acceleration (Vy) always remains greater than 0.5 m/s^2 as there is an increment in cutting speed, which signifies that cutting speed has a significant impact on acceleration.

4.1 Regression models considering inclusion of machining parameters and vibration signal

An attempt has been initiated first to find the correlation of acceleration amplitude of vibration signal (Vy) in radial direction with the output responses such as flank wear and surface roughness. Because of that, linear regression (LR) models and quadratic regression (QR) models have been developed for both responses. From the findings, it is evident that the percentages of error are maximum values and $R2$ values are quite less to predict the responses such as flank wear and surface roughness well and does not fit and adequate enough. Therefore considering vibration signal only to predict responses is insufficient. To improve further, vibration signal along with inclusion of machining parameters have been taken to develop the regression model which has been described below.

The attempt has been made to develop the multiple regression model including the machining parameters (d, f, v) and vibration signal (Vy) in radial direction. Therefore total four input parameters (d, f, v and Vy) are taken together to develop the regression models. However before development of model, it is essential to know about the significant correlation of input parameters on responses. For that, Pearson correlation coefficient [11] of input factors with responses such as flank wear and surface roughness are performed and shown in Table 4. In general, Pearson correlation coefficient lies between −1 and +1. Positive value of correlation coefficient strongly influences the degree of closeness of input factors with the response variables such as VBc and Ra. It is evident from Table 4 that, all the input variables (d, f, v and Vy) have strong correlations with the flank wear as all of them are positive values. Pearson correlation coefficient for feed on flank wear is ultimate pursued by acceleration amplitude

Table 3. Experimental results of Vy, VBc and Ra based on Taguchi L_{18} orthogonal array.

Standard order	Machining parameters			Output quality characteristics		
	Depth of cut (d), mm	Feed (f), mm/rev	Cutting speed (v), m/min	Acceleration (Vy), m/s^2	Flank wear (VBc), mm	Surface roughness (Ra), µm
1	0.1	0.04	67	0.385	0.173	0.91
2	0.1	0.08	113	0.318	0.239	0.80
3	0.1	0.12	147	0.889	0.294	1.18
4	0.2	0.04	67	0.524	0.189	1.02
5	0.2	0.08	113	0.395	0.184	0.72
6	0.2	0.12	147	0.587	0.209	1.42
7	0.3	0.04	113	0.384	0.248	0.72
8	0.3	0.08	147	0.936	0.284	0.85
9	0.3	0.12	67	0.310	0.279	0.71
10	0.1	0.04	147	0.610	0.230	0.91
11	0.1	0.08	67	0.384	0.162	0.69
12	0.1	0.12	113	0.518	0.252	0.87
13	0.2	0.04	113	0.443	0.239	0.71
14	0.2	0.08	147	1.350	0.286	1.07
15	0.2	0.12	67	0.466	0.288	0.81
16	0.3	0.04	147	0.620	0.201	0.83
17	0.3	0.08	67	0.307	0.254	0.66
18	0.3	0.12	113	0.577	0.281	0.87

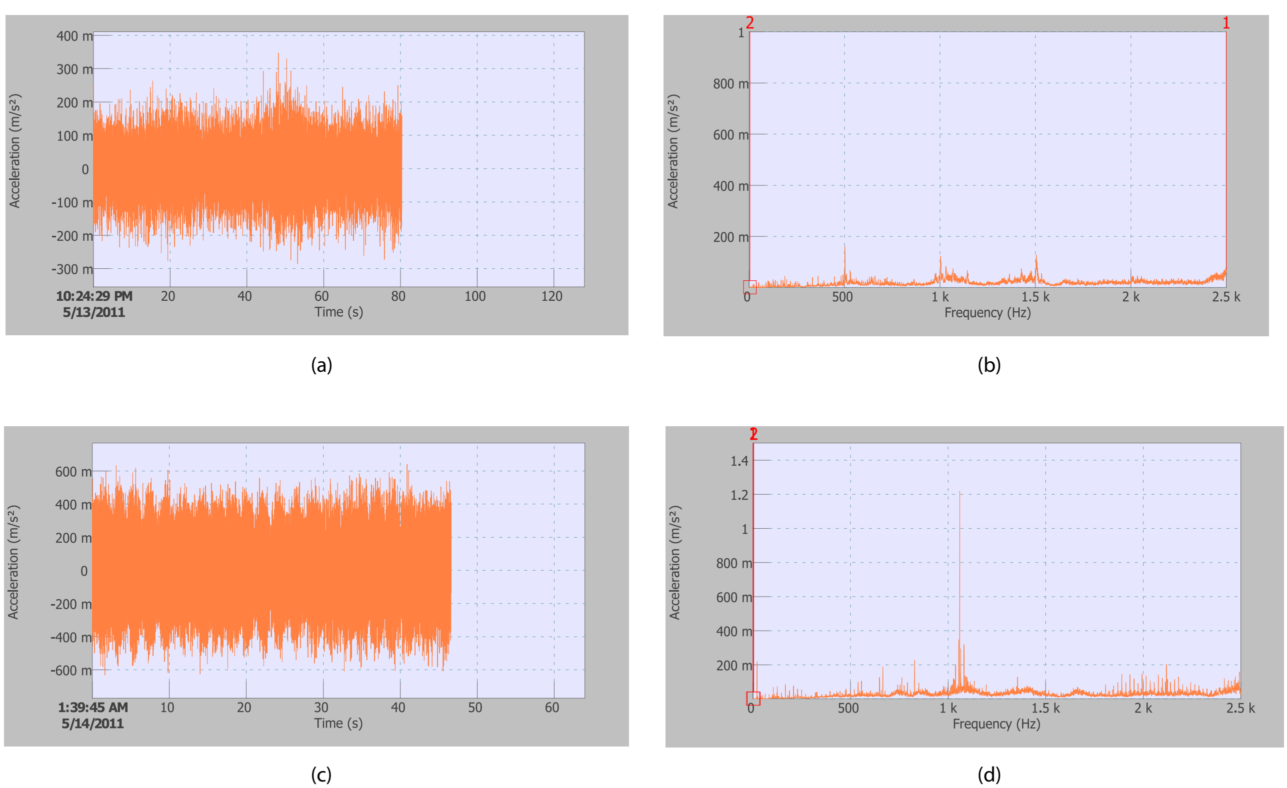


Fig. 4. Time and frequency domain waveform and spectrum obtained from vibration analyzer (a–b) at run 1 and (c–d) at run 16.

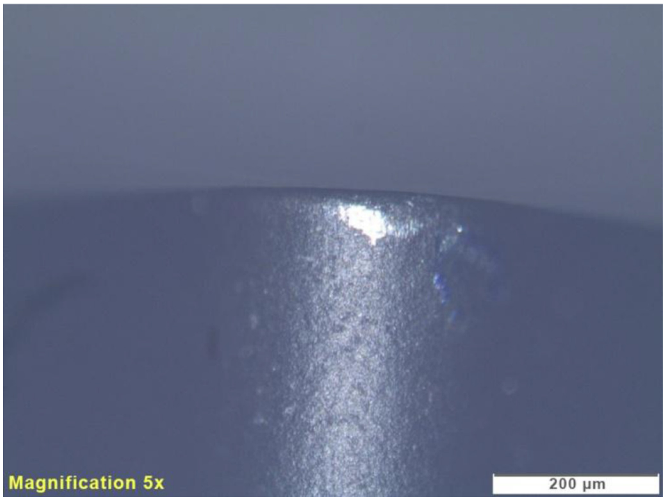


Fig. 5. Flank wear of insert at run1 ($d = 0.1$ mm, $f = 0.04$ mm/rev and $v = 67$ m/min).

Table 4. Pearson correlation coefficient of parameters with *VBc* and *Ra*.

Parameter	Pearson correlation coefficient for *VBc*	Pearson correlation coefficient for *Ra*
Depth of cut (d)	0.319	−0.258
Feed (f)	0.523	0.273
Cutting speed (v)	0.26	0.492
Acceleration in radial direction (Vy)	0.432	0.533

of vibration in radial direction (Vy), depth of cut and cutting speed. Similarly, acceleration amplitude, cutting speed and feed have strong correlation with supportive surface roughness [11].

Depth of cut shows the weak correlation with the surface roughness as the value becomes negative i.e. −0.258 and thus not considered during the development of model. Therefore regression models have been upgraded in view of strong correlation of input cutting parameters with the response outputs only. Two models have been established i.e. first multiple linear regression model (MLR) and secondly multiple quadratic regression model (MQR).

4.2 Multiple linear regression model (MLR) for *VBc* and *Ra* including machining parameters and vibration signal

As d, f, v and Vy have strong correlations with *VBc*, multiple linear regression model (MLR) has been formulated and shown in equation (1).

$$\begin{aligned}\text{Flank wear}\,(VBc) = {} & 0.1202 + 0.1626\,d + 0.6253\,f \\ & +0.0000\,v + 0.0598\,Vy, R^2 \\ & = 52\%, R^2(\text{pred}) = 15.2\%, R^2(\text{adj}) \\ & = 37.23\% \end{aligned} \tag{1}$$

Similarly, f, v and Vy have the strong correlation with surface roughness ignoring weak correlation of depth of cut, the multiple linear regression models for surface roughness is shown in equation (2).

$$\begin{aligned}\text{Surface roughness}\,(Ra) = {} & 0.4558 + 1.3932\,f \\ & +0.0016\,v + 0.2395\,Vy, R^2 \\ & = 37.65\%, R^2(\text{pred}) \\ & = 0\%, R^2(\text{adj}) = 24.29\% \end{aligned} \tag{2}$$

The coefficient of determination (R^2) value for flank wear is observed to be 52% and for surface roughness, it is obtained to be 37.65%. However, the R^2 value considering both machining parameters and vibration signal equations (1) and (2) has been increased considerably compared to LR and QR model considering vibration signal only. So, the prediction accuracy has been improved significantly. The ANOVA has been executed to find the significance of model at 95% confidence level depending on its P-value (probability of significance). The model is significant only when its P-value is lower than 0.05. ANOVA for both flank wear and surface roughness are presented in Table 5 [37,38]. Flank wear MLR model is found to be significant whereas surface roughness MLR model is insignificant as their P-value exceeds 0.05. The average percentage of error for flank wear and surface roughness for MLR models are found to be 11.34% and 11.9% respectively (Tab. 6). The maximum percentage of error for flank wear is 27.27% and for surface roughness, it is found to be 30.28%. The confirmation test has been performed and results of validation test of MLR model and their percentage of error has been shown in Table 7. The average percentage of error in validation test has been found to be 13.8% and 16.07% respectively whereas highest percentage of error for flank wear is 17.27% and for surface roughness, it is 28%.

4.3 Multiple quadratic regression model (MQR) for *VBc* and *Ra* including machining parameters and vibration signal

To improve further the accuracy of model, multiple quadratic regression model (MQR) have been developed for flank wear and surface roughness considering significant correlation of input parameters with the responses which has been obtained earlier from Pearson correlation analysis. The MQR model for *VBc* is shown in equation (3) with R^2 value. The R^2 value of *VBc* is observed to be higher (0.99) and approaches to 1 compared to MLR model and explains 99.96% of variability of response. Table 8

Table 5. Results of ANOVA for (a) flank wear and (b) surface roughness MLR model.

Source	*df*	Seq SS	Adj SS	Adj MS	*F*	*P*	Remarks
(a) Regression	4	0.0164	0.0164	0.0041	3.52	0.037	Significant
Linear	4	0.0164	0.0164	0.0041	3.52	0.037	Significant
d	1	0.0032	0.0031	0.0031	2.71	0.124	Insignificant
f	1	0.0086	0.0073	0.0073	6.3	0.026	Significant
v	1	0.0021	0.0000	0.0000	0.00	0.948	Insignificant
Vy	3	0.0024	0.0024	0.0024	2.07	0.173	Insignificant
Residual error	13	0.0152	0.0152	0.0011			
Total	17	0.0317					
(b) Regression	3	0.2436	0.2436	0.0812	2.82	0.077	Insignificant
Linear	3	0.2436	0.2436	0.0812	2.82	0.077	Insignificant
f	1	0.0481	0.0366	0.0366	1.27	0.279	Insignificant
v	1	0.1566	0.028	0.028	0.97	0.341	Insignificant
Vy	1	0.0388	0.0388	0.0388	1.35	0.265	Insignificant
Residual error	14	0.4034	0.4034	0.0288			
Total	17	0.647					

Table 6. Values predicted by MLR models and their percentage of error for flank wear and surface roughness considering both machining parameter and vibration signal.

Standard order	Experimental VBc (mm)	Experimental Ra (μm)	Predicted VBc (mm)	Predicted Ra (μm)	% of error (VBc)	% of error (Ra)
1	0.173	0.91	0.186	0.71	−7.51	21.97
2	0.239	0.80	0.208	0.82	12.97	−2.5
3	0.294	1.18	0.268	1.07	8.84	9.32
4	0.189	1.02	0.211	0.74	−11.64	27.45
5	0.184	0.72	0.229	0.84	−24.45	−16.66
6	0.209	1.42	0.266	0.99	−27.27	30.28
7	0.248	0.72	0.219	0.78	11.69	−8.33
8	0.284	0.85	0.278	1.02	2.11	−20
9	0.279	0.71	0.264	0.8	5.37	−12.67
10	0.230	0.91	0.201	0.89	12.6	2.19
11	0.162	0.69	0.211	0.76	−30.24	−10.14
12	0.252	0.87	0.245	0.92	2.77	−5.74
13	0.239	0.71	0.207	0.79	13.38	−11.26
14	0.286	1.07	0.287	1.12	−0.34	−4.67
15	0.288	0.81	0.257	0.84	10.76	−3.7
16	0.201	0.83	0.234	0.89	−16.41	−7.22
17	0.254	0.66	0.239	0.74	5.9	−12.12
18	0.281	0.87	0.281	0.94	0	−8.04
Average percentage error (%)					11.34	11.9

represents ANOVA table for flank wear and model is said to be mathematically noteworthy as its P-value is below 0.05 at a level of confidence i.e. 95%.

The accuracy of model can be further enhanced by backward elimination method [11]. The coefficients with the greater P-value i.e. more than 0.05 is eliminated first and subsequently refined model is developed by considering only important terms. Table 8a indicates the coefficients such as v^2 and $v \times Vy$ are insignificant as its P-value is above 0.05 (0.068 and 0.059). Therefore, deleting the insignificant coefficients from equation (3), the refined MQR model for flank wear is shown in equation (4).

Table 7. Results of validation test of MLR model and their percentage of error.

Depth of cut (mm)	Feed (mm/rev)	Cutting speed (m/min)	Acceleration in Y-direction (m/s^2)	Experimental *VBc*	Experimental *Ra*	Predicted (*VBc*)	Predicted (*Ra*)	% of error (*VBc*)	% of error (*Ra*)
0.1	0.08	147	0.664	0.195	0.75	0.22	0.96	−12.82	−28
0.2	0.08	67	0.362	0.191	0.68	0.224	0.76	−17.27	−11.76
0.3	0.12	147	1.435	0.297	1.35	0.33	1.2	−11.11	11.11
0.2	0.12	113	0.502	0.228	0.82	0.26	0.93	−14.03	−13.41
Average percentage of error (%)								13.8	16.07

Table 8. Results of ANOVA for (a) flank wear and (b) surface roughness MQR model.

Source	*df*	Seq SS	Adj SS	Adj MS	*F*	*P*	Remarks
(a) Regression	14	0.0317	0.0317	0.0022	491.2	0.000	Significant
Linear	4	0.0164	0.007	0.0017	383.9	0.000	Significant
d	1	0.0032	0.0003	0.0003	85.7	0.003	Significant
f	1	0.0086	0.0019	0.0019	430.54	0.000	Significant
v	1	0.0021	0.0032	0.0032	702.38	0.000	Significant
Vy	1	0.0024	0.0035	0.0035	761.15	0.000	Significant
Square	4	0.0039	0.0028	0.0007	154.8	0.001	Significant
d^2	1	0.001	0.0001	0.0001	24.01	0.016	Significant
f^2	1	0.0005	0.0023	0.0023	504.06	0.000	Significant
v^2	1	0.0016	0.0000	0.0000	7.81	0.068	Insignificant
V^2y	1	0.0007	0.0001	0.0001	25.66	0.015	Significant
Interaction	6	0.0112	0.0112	0.0018	406.92	0.000	Significant
$d \times f$	1	0.0000	0.0006	0.0006	149.89	0.001	Significant
$d \times v$	1	0.0039	0.0073	0.0073	1588.61	0.000	Significant
$d \times Vy$	1	0.002	0.0047	0.0047	1039.51	0.000	Significant
$f \times v$	1	0.0005	0.0039	0.0039	856.34	0.000	Significant
$f \times Vy$	1	0.0046	0.0036	0.0036	791.19	0.000	Significant
$v \times Vy$	1	0.0000	0.0000	0.0000	8.8	0.059	Insignificant
Residual error	3	0.0000	0.0000	0.0000			
Total	17	0.0317					
(b) Regression	9	0.6427	0.6427	0.0714	133.79	0.000	Significant
Linear	3	0.2436	0.3261	0.1087	203.66	0.000	Significant
f	1	0.0481	0.0811	0.0811	151.99	0.000	Significant
v	1	0.1566	0.1592	0.1592	298.29	0.000	Significant
Vy	1	0.0388	0.0193	0.0193	36.32	0.000	Significant
Square	3	0.1246	0.1922	0.064	120.07	0.000	Significant
f^2	1	0.0779	0.0307	0.0307	57.6	0.000	Significant
v^2	1	0.0466	0.1096	0.1096	205.46	0.000	Significant
V^2y	1	0.0000	0.0591	0.0591	110.75	0.000	Significant
Interaction	3	0.2745	0.2745	0.0915	171.45	0.000	Significant
$f \times v$	1	0.2038	0.0914	0.0914	171.4	0.000	Significant
$f \times Vy$	1	0.0192	0.0003	0.0003	0.68	0.434	Insignificant
$v \times Vy$	1	0.0513	0.0513	0.0513	96.25	0.000	Significant
Residual error	8	0.0042	0.0042	0.0005			
Total	17	0.647					

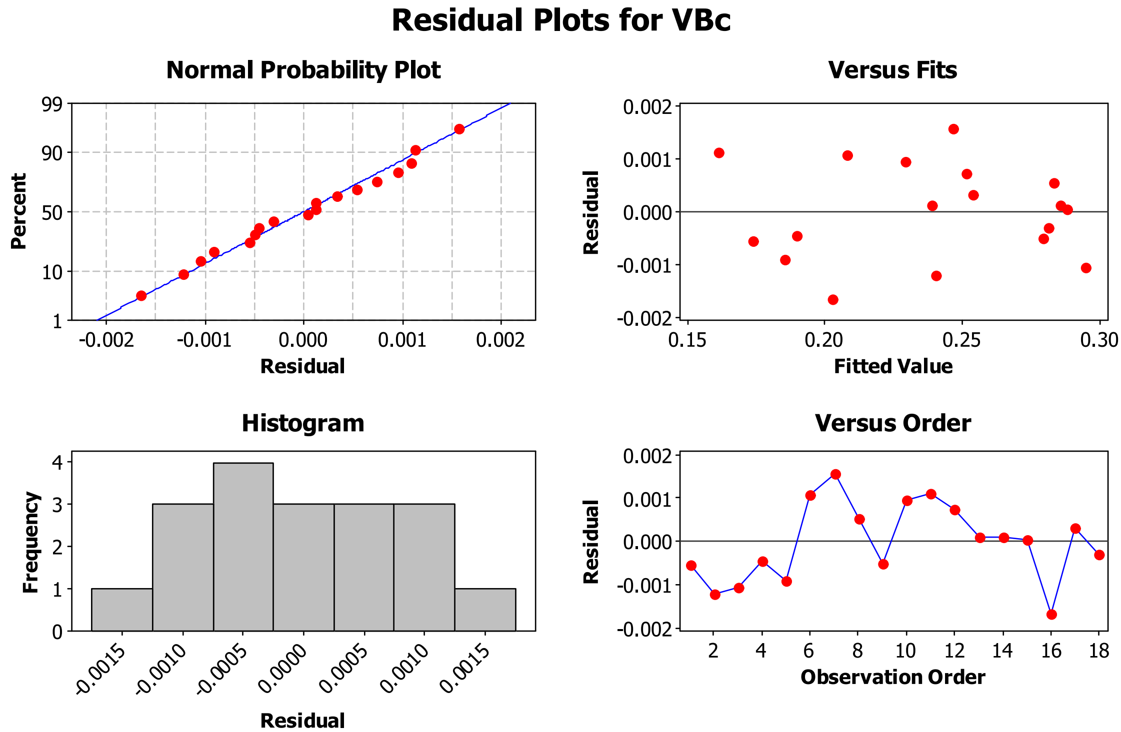


Fig. 6. Residual plot of flank wear during MQR modelling.

$$\text{Flank wear}\,(VBc) = 0.3421 + 0.6257\,d - 4.3466\,f + 0.0055\,v - 1.3468\,Vy + 0.7611\,d^2 + 26.5502\,f^2 - 0.0000\,v^2 + 0.0919\,V^2y - 3.1548\,df - 0.0183\,dv + 2.8725\,dVy - 0.0241\,fv + 7.1851\,fVy + 0.0012\,vVy,\ R^2 = 99.96\%,\ R^2(\text{pred}) = 97.46\%,\ R^2(\text{adj}) = 99.75\% \quad (3)$$

Refined MQR model for VBc

$$\text{Flank wear}\,(VBc) = 0.3421 + 0.6257\,d - 4.3466\,f + 0.0055\,v - 1.3468\,Vy + 0.7611\,d^2 + 26.5502\,f^2 + 0.0919\,V^2y - 3.1548\,df - 0.0183\,dv + 2.8725\,dVy - 0.0241\,fv + 7.1851\,fVy \quad (4)$$

Similarly, MQR model for surface roughness is shown in equation (5) and indicates higher R^2 value close to one (99.34%). After deleting the insignificant coefficient derived from Table 8b such as $f\times Vy$ (P-value is 0.434) from equation (5), the refined MQR model for surface roughness is shown in equation (6).

$$\text{Surface roughness}\,(Ra) = 2.6588 - 20.1182\,f - 0.0353\,v + 1.575\,Vy + 72.216\,f^2 + 0.0002\,v^2 + 1.5502\,V^2y + 0.1082\,fv - 1.7057\,fVy - 0.03\,vVy,\ R^2 = 99.34\%,\ R^2(\text{pred}) = 94.18\%,\ R^2(\text{adj}) = 98.6\% \quad (5)$$

Refined MQR model for Ra

$$\text{Surface roughness}\,(Ra) = 2.6588 - 20.1182\,f - 0.0353\,v + 1.575\,Vy + 72.216\,f^2 + 0.0002\,v^2 + 1.5502\,V^2y + 0.1082\,fv - 0.03\,vVy, \quad (6)$$

The residuals plot for flank wear and surface roughness are presented in Figures 6 and 7 respectively. From the normal probability plot, residuals lie near to straight line indicating significance of both MQR models. The mean percentage of error for flank wear is only 0.34% whereas for surface roughness, it is only 1.22% which has been revealed in Table 9. The maximum percentage of error for flank wear is obtained to be 0.99% only whereas for surface roughness, it is found to be only 4.81%.

To judge the effectiveness of prediction ability of MQR model, validation experiments are performed within the selected ranges of parametric condition and shown in Table 10. Time and frequency domain waveform and spectrum in hard turning at validation test ($d = 0.3$ mm, $f = 0.12$ mm/rev and $v = 147$ m/min) is shown in Figure 8. The average percentage of error for validation experiment of MQR model has been found to be 4.17% for flank wear and 4.37% for surface roughness respectively which is quite less than the validation experiment for MLR model i.e. 13.8% for VBc and 16.07% for Ra (Tab. 9). Furthermore, cutting speed is obtained to be the most significant machining factor for inducing the acceleration amplitude of vibration in hard machining study (Tab. 11) and needs to be controlled as it not only affects the cutting tool wear but also on the surface roughness. Feed and depth of cut do not

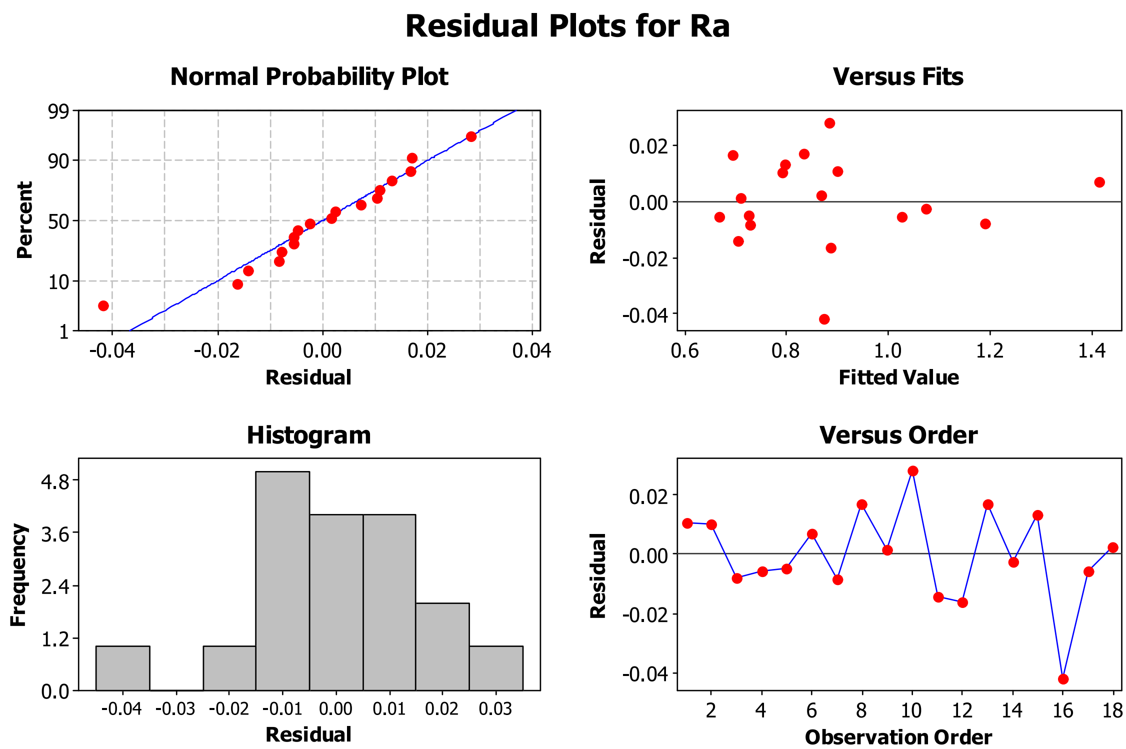


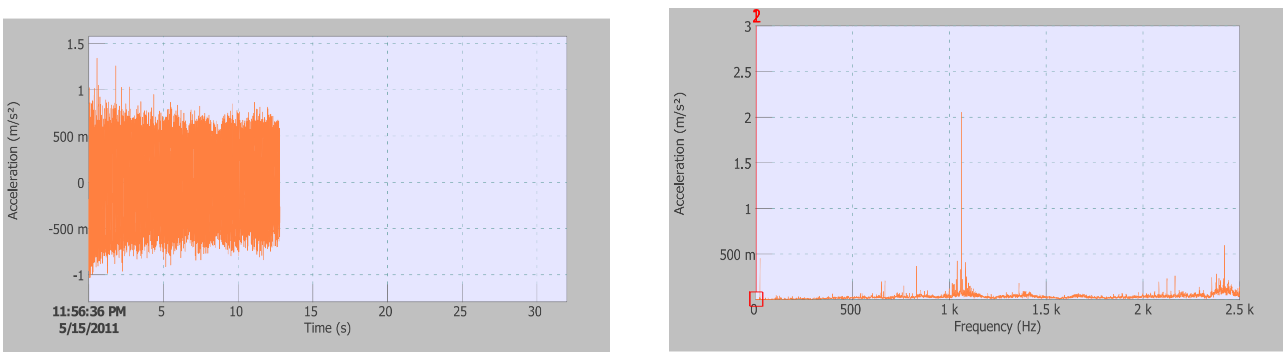
Fig. 7. Residual plot of surface roughness during MQR modelling.

Table 9. Values predicted by refined MQR model and their percentage of error for flank wear and surface roughness.

Standard order	Experimental *VBc* (mm)	Experimental *Ra* (μm)	Predicted *VBc* (mm)	Predicted *Ra* (μm)	% of error (*VBc*)	% of error (*Ra*)
1	0.173	0.91	0.174	0.89	−0.57	2.19
2	0.239	0.80	0.24	0.79	−0.41	1.25
3	0.294	1.18	0.295	1.18	−0.34	0
4	0.189	1.02	0.189	1.02	0	0
5	0.184	0.72	0.185	0.72	−0.54	0
6	0.209	1.42	0.208	1.41	0.47	0.7
7	0.248	0.72	0.246	0.72	0.8	0
8	0.284	0.85	0.283	0.83	0.35	2.35
9	0.279	0.71	0.28	0.7	−0.35	1.4
10	0.230	0.91	0.229	0.88	0.43	3.29
11	0.162	0.69	0.161	0.7	0.61	−1.44
12	0.252	0.87	0.251	0.88	0.39	−1.14
13	0.239	0.71	0.239	0.69	0	2.81
14	0.286	1.07	0.286	1.07	0	0
15	0.288	0.81	0.288	0.79	0	2.46
16	0.201	0.83	0.203	0.87	−0.99	−4.81
17	0.254	0.66	0.254	0.66	0	0
18	0.281	0.87	0.281	0.86	0	1.14
Average percentage error (%)					0.34	1.22

Table 10. Results of validation test of refined MQR models and their percentage of error.

Depth of cut (mm)	Feed (mm/rev)	Cutting speed (m/min)	Acceleration in Y-direction (m/s^2)	Experimental *VBc*	Experimental *Ra*	Predicted (*VBc*)	Predicted (*Ra*)	% of error (*VBc*)	% of error (*Ra*)
0.1	0.08	147	0.664	0.195	0.75	0.183	0.72	6.15	4
0.2	0.08	67	0.362	0.191	0.68	0.202	0.65	−5.75	4.41
0.3	0.12	147	1.435	0.297	1.35	0.306	1.44	−3.03	−6.66
0.2	0.12	113	0.502	0.228	0.82	0.232	0.8	−1.75	2.43
Average percentage of error (%)								4.17	4.37



(a) (b)

Fig. 8. (a–b) Time and frequency domain waveform and spectrum in hard turning at validation test ($d = 0.3$ mm, $f = 0.12$ mm/rev and $v = 147$ m/min).

Table 11. Analysis of variance for acceleration amplitude of vibration (*Vy*).

Source	*df*	SS	MS	*F*	*P*	Remarks
d	2	0.0464	0.0232	0.6	0.568	Insignificant
f	2	0.0437	0.0218	0.56	0.586	Insignificant
v	2	0.6925	0.3462	8.89	0.005	Significant
Error	11	0.4282	0.0389			
Total	17	1.2109				

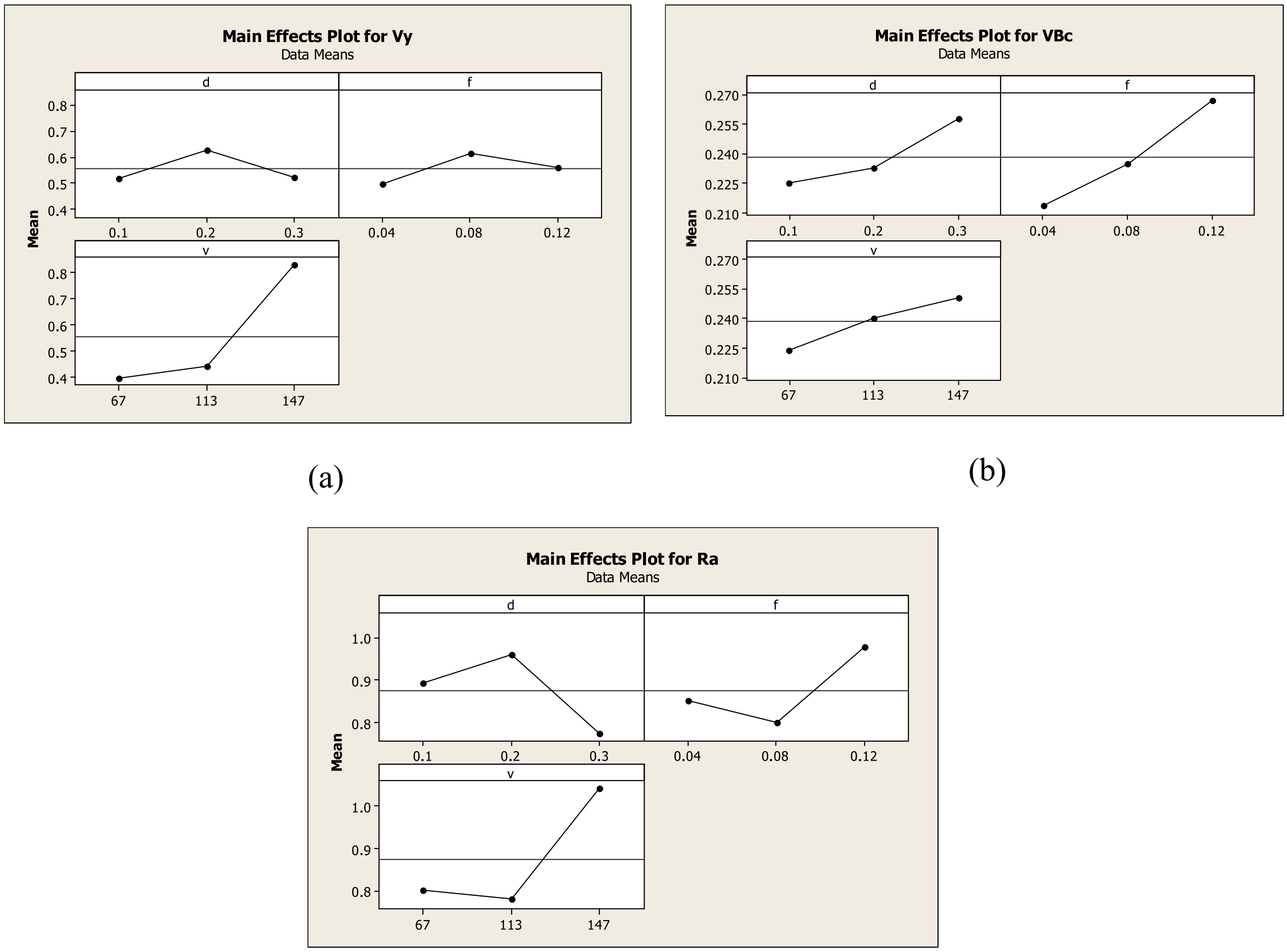
exhibit any statistical significance on vibration signals from ANOVA study. Similarly from the main effect plot (Fig. 9), Vibration amplitude indicates the sharp rise with the cutting speed compared to feed and depth of cut. Flank wear of cutting insert increases with the increase of all cutting parameters i.e. cutting speed, feed and depth of cut whereas feed rate influences more on the surface roughness as evident from main effect plot.

Thus, MQR model predicts well for responses compared to MLR model as percentage of error is quite less and model is said to be significant, adequate and effective to predict flank wear and surface roughness considering combined effect of machining factors and vibration signals online in hard turning of bearing steel implementing coated carbide (multilayer) cutting tool in dry condition. Tool condition monitoring extensively contributes to the automation process which in turn increases the productivity and machining efficiency. With the help of tool condition monitoring system, the hard machining process can be on line monitored for both flank wear and surface finish with the decision can be taken for tool changing based on criteria of pre-set flank wear limit.

5 Conclusions

The significance of research findings are summarized below:

– The present investigation focuses on online prediction of flank wear and surface roughness while turning of AISI 52100 hardened bearing steel under dry environment considering only vibration signals. The correlation of



(a) (b) (c)

Fig. 9. Main effect plot of (a) Vy, (b) VBc and (c) Ra.

machining parameters and acceleration amplitude of vibration in radial direction on responses is also presented.

- The prediction model using vibration signals only does not provide accurate results because of low R^2 value and the maximum percentage of error. Secondly, prediction models such as MLR and MQR are developed considering both machining parameters and vibration signal in radial direction after considering significant effect of all parameters on responses through Pearson correlation analysis.
- Pearson correlation coefficient for feed on flank wear is utmost pursued by acceleration amplitude of vibration (Vy) in radial direction, depth of cut and cutting speed. Similarly, acceleration amplitude of vibration followed by cutting speed and feed has strong correlation with surface roughness. The nominal depth of cut shows the weak correlation with the surface roughness as the value becomes negative i.e. −0.258.
- Therefore two models have been developed i.e. first multiple linear regression model (MLR) and secondly multiple quadratic regression model (MQR) considering strong correlation of process variables with the response outputs only. MQR model predicts well for responses compared to MLR model as percentage of error is quite less (0.34% for flank wear and 1.22% for surface roughness) and model is said to be noteworthy, effective, and adequate to predict flank wear and surface roughness considering combined effect of machining parameters and vibration signals.
- The average percentage of error for validation experiment of MQR model has been found to be 4.17% for flank wear and 4.37% for surface roughness respectively which is quite less than the validation experiment for MLR model i.e. 13.8% for VBc and 16.07% for Ra. Thus, MQR model predicts well for responses compared to the MLR model and is said to be adequate, significant, and efficient considering the combined sway of machining variables and vibration signals online in hard turning.
- Further, cutting speed is obtained to be the most important parameter for vibration signal in hard turning analysis. Consequently, a corrective measure can safely be taken in proper time through online prediction and control on flank wear and surface roughness with reasonable degree of accuracy during hard turning.

Nomenclature

d	depth of cut (mm)
f	feed (mm/rev)
v	cutting speed (m/min)
VBc	flank wear at nose corner (mm)
Ra	arithmetic surface roughness average (µm)
DF	degrees of freedom
MS	mean square
P	probability of significance
LR	Linear regression
OA	Orthogonal array
QR	quadratic regression
Vy	vibration signal in Y-direction (m/s^2)
Vz	vibration signal in Z-direction (m/s^2)
PCBN	Polycrystalline Cubic Boron Nitride
AISI	American Iron and Steel Institute
HRC	Rockwell hardness
MLR	Multiple linear regression
CVD	chemical vapour deposition
r	nose radius (mm)
SS	sum of squares
F	variance ratio
ANOVA	analysis of variance
MQR	Multiple quadratic regression
CBN	cubic boron nitride
R^2(adj)	Adjusted R^2
R^2	coefficient of determination
R^2(pred)	Predicted R^2
TCM	Tool condition monitoring

Conflict of interest

Authors declare no conflict of interest.

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