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EXPERIMENTAL INVESTIGATION OF TOOL WEAR AND INDUCED VIBRATION IN TURNING HIGH HARDNESS AISI52100 STEEL USING CUTTING PARAMETERS AND TOOL ACCELERATION

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Abstract. *In machining of high hardness steel, vibration of cutting tool increases tool wear which reduces its life. Tool wear is catastrophic in nature and hence investigation of its assessment is important. This study investigates experimentally induced vibration during turning of hardened AISI52100 steel of hardness 54±2 HRC using coated carbide insert. In this context, cutting tool acceleration is measured and used to develop a novel mathematical model based on acquired real time acceleration signals of cutting tool. The obtained model is validated as R^2= 0.93 while its residuals values closely follow the straight line. The predictions are confirmed by conducting conformity test which revealed a close degree of agreement with respect to the experimental values. The Artificial Neural Network (ANN) examination is performed to determine the model regression value. The study shows that the examined reports forecasts of ANN are more exact than regression analysis. The future directon of this investigation is towards developing a low-cost microcontroller-based hardware unit for in-process tool wear monitoring which could be beneficial for small scale industries.*

Key Words: *Tool Wear, Vibration, Regression, Artificial Neural Network*

1. INTRODUCTION

In recent years dry machining for hard materials proved to be one of the promising and eco-friendly alternatives. Turning of high hardness material with hardness range 45-70 HRC is carried out by a single point cutting tool and is referred to as hard turning. It is widely used in aviation, automotive industries for manufacturing components such as

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shafts, bearings, camshaft gears and landing gear, engine attachment fittings and constant velocity joints, and so on [1]. The hardened steels are favored because of their special mechanical properties like high hardness, high wear opposition etc. Among hardened steel, AISI52100 steel is widely used for the production of bearing as it offers the advantages of high wear resistance and rolling fatigue strength [2-3].

Hard turning is made feasible because of cutting edge advancement in tool materials such as Cubic Boron Nitride (CBN), ceramic and coated carbide tools. As of late, carbide tools with different coatings are being utilized as a cheap substitution to expensive PCBN and ceramics tools. Several research studies conducted by Aurich et al. [4], Suresh et al. [5], Chinchanikar and Choudhury [6], Jiang et al. [7] have reported that the low-cost carbide cutting tools with different coatings can achieve the same performance as that of ceramic and CBN/PCBN. But in actual, tool wear is exposed to enormous mechanical burdens and in this way creates vibration all through the process. In hard turning, the cutting tool is subjected to massive mechanical loads and therefore produces vibration throughout the process. Vibration influences the machining performance and specifically tool wear, surface finish and tool life; it also creates unsavory noise in the workplace [8-9]. Therefore, the effect of cutting tool vibrations during the machining process must be studied.

Many researchers have tried to contemplate and investigate the vibrations in metal cutting. Several research studies presented diverse mathematical/statistical predictive models for cutting force, surface roughness, tool vibrations, and tool wear, etc. Models dependent on cutting parameters give a specific estimation of tool wear regardless of tool condition and thus can only help in the selection of the process parameters. To obtain real-time value of tool wear during turning, the model should include a signal that could represent the condition of the tool. Dimla [8] presented tool wear analysis using vibration signals in the machining of EN24 steel. The vibration characteristics showed that the measured wear values correlated well with certain resonant peak frequencies. Salgado et al. [10] reported a significant relationship between surface roughness and tool vibration utilizing soft computing techniques. Abouelatta and Madl [11] reasoned that the thought of hardware vibration alongside cutting parameters expands the precision of a model.

Chen et al. [12] pointed out that the relative vibrations between cutting tool and workpiece cause the poor machined surface quality and unusual tool wear which drops down the profitability. Suresh at al. [5] presented regression model experimental results showed that the cutting speed has higher influence on the tool wear than feed rate depth of cut. Upadhyay et al. [13] developed regression models and reported that feed is the main factor that influences surface roughness followed by acceleration in a radial direction. Hessainia et al. [14] inferred that the feed is the overwhelming component impacting the surface harshness, while vibrations on both radial and tangential have discovered an irrelevant impact on surface unpleasantness. Ghorbani et al. [15] reported tool life predictive models based on fatigue strength of tool material and parameters of tool vibrations for different combination of workpiece and cutting tool.

DMello et al. [16] performed high speed turning experiments on Ti-6Al-4V material using uncoated carbide insert. It is seen that tool vibration in speed direction has a major influence on surface roughness parameter and, feed rate showed a significant effect on surface roughness with more than 70% contribution. Prasad et al. [17] developed multiple linear regression models for the displacement amplitude of the tool. The ANOVA result demonstrates that the displacement of the cutting tool is affected by the workpiece hardness and cutting speed.

Mir and Wani [18] reported regression model for tool wear and surface roughness during hard turning of AISI D2 steel using PCBN, Mixed ceramic and coated carbide tools. The results show that the tool cutting speed has the highest influence on tool wear. Zeqin et al [19] proposed surface roughness model considering the influences of tool-work vibration components in feeding, cutting and in feed cutting directions as inputs. The developed model with three direction vibrations makes a better prediction for the single diamond turned surface.

The majority of the studies focused on predicting surface roughness using vibration signals. Some of the research projects tried to predict tool wear for using vibration signals for workpiece hardness less than 45 HRC. However, less research work has been reported which takes the actual vibration acceleration for monitoring tool wear during hard turning. Thus, the objective of the present work is develop a new mathematical model to predict real-time tool wear based on real-time acceleration of cutting tool in dry turning of hardened AISI52100 steel.

2. Experimental Procedure and Method

2.1. Materials and machining conditions

Hard turning experiments were performed on SimpleTurn5076 CNC lathe equipped with 7.5 kW spindle power. The workpiece material utilized in this examination was AISI52100 steel. The workpiece rod was heated at 850^0C, then quenched in oil and then being tempered around at 200^0C for two hours, thus producing a tempered martensitic microstructure with a hardness of 54±2 HRC. The workpiece was held in three jaws and supported by a center in the tailstock and all experiments were carried under dry conditions. The hardened steel rods have been trued, centered, and cleaned at a moderate machining speed and feed before conducting experiments. The chemical composition of the workpiece material is 1.03% C, 1.38% Cr, 0.35% Mn, 0.002% P, 0.16% Si, and 0.005% S and remaining Fe. The machining condition, namely, cutting speed, feed and depth of cut are selected on the basis of preliminary experiments, work-piece hardness, literature review and the tool manufacturer’s recommendation. The cutting parameters ranges are cutting speed 60-180 m/min, feed 0.1-0.5 mm/rev, and depth of cut 0.1-0.5 mm.

2.2. Measurement setup

The setup used to measure vibration in feed, radial and, tangential directions, is schematically shown in Fig. 1. A Bruel & Kjaer 4535B001 Type-30859 tri-axial piezoelectric accelerometer with sensitivity 9.8mV/g was placed on tool holder (PCLNR 2525M12) close to the insert. The coated carbide tool insert was selected of ISO designation CNMG120408-MF5 with TH1000 grade. The tool has a rhombic shape with an included angle of 80^0, 4.8mm thickness and nose radius 0.8mm with the following tool geometry: including angles = 80^0, back rake angle = 6^0, clearance angle = 5^0, approach angle = 95^0 and nose radius =0.8 mm. Dino-Lite Digital microscope model: AD4113ZTA with magnification rate 200X was employed to capture images of flank wear after each pass.

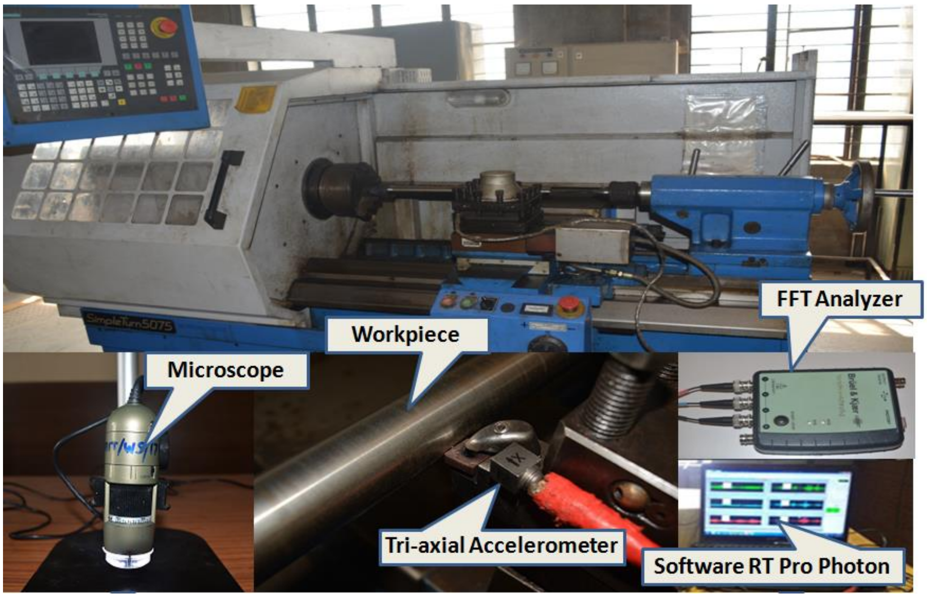

Fig. 1 Experimental setup

2.3. Design of experiments (DOE)

In this work, the Central Composite Rotatable Design (CCRD) technique was implemented for planning trial runs. The design suggested 20 experimental runs which include 8 factorials, 6 axial and 6 replications of center points. In CCRD, a central run was repeated six times to check the repeatability of the output variables. In order to maintain rotatability, the value of α depends upon number of factors in design and it varies in between -1.682 to +1.682 for five levels [20]. The cutting parameters and levels are illustrated in Table 1.

Table 1 Machining parameter levels

Levels	Cutting Speed V (m/min)	Feed f (mm/rev)	Depth of cut d (mm)
-1.682	60	0.1	0.1
-1	90	0.2	0.2
0	120	0.3	0.3
1	150	0.4	0.4
1.682	180	0.5	0.5

3. Results and Discussion

3.1. Vibration analysis

The CCRD recommended 20 experimental runs to be conducted while accelerations in feed V_x, radial V_y and, tangential V_z directions are recorded and tool wear V_B is measured. A new cutting edge is used for each cutting condition. Vibration signals are captured at three locations, at the start, middle, and end of the process. The tool is removed and its wear is measured with the help of a microscope after every pass. This process is repeated until the tool wear reached 0.2 mm. The tools wear images for some cutting parameters are presented in Figs. 2-4.

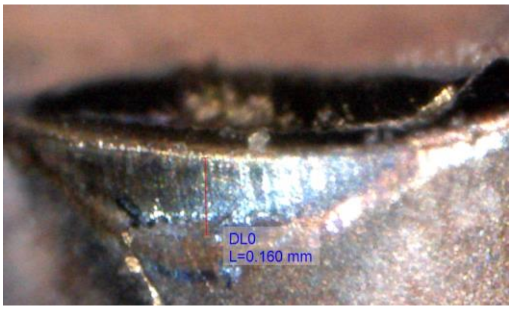

Fig. 2 Tool wear at V= 120 m/min, f = 0.5 mm/rev, d = 0.3 mm

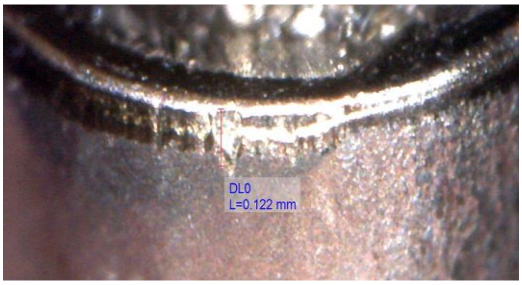

Fig. 3 Tool wear at V=90 m/min, f=0.4 mm/rev, d= 0.4 mm

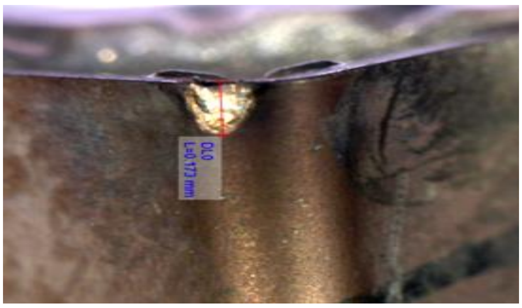

Fig. 4 Tool wear at V=180 m/min, f=0.3 mm/rev, d= 0.3 mm

While conducting experiments, continuous chip formation was observed at cutting condition V = 150 m/min, f = 0.4 mm/ rev and d = 0.2 mm. The continuous types of chips came in contact with the accelerometer mounted near the insert. Therefore, the sudden rise and fall in acceleration values are observed as shown in Fig. 5. Such values are neglected in developing a mathematical model. The frequency response from FFT analyzer revealed fluctuation in vibration frequency in feed, radial, and tangential directions observed from 16 Hz to 15 kHz. The frequency response of cutting tool in tangential direction at cutting condition V = 120 m/min, f = 0.3 mm/ rev, d = 0.3 and V = 120 m/min, f = 0.5 mm/ rev, d = 0.3 mm is shown in Figs. 6 and 7, respectively. It is observed that frequency started increasing onwards 5000Hz. The components of the tool vibration reflect various occurrences during turning in the frequency domain, including the tool holder vibration and machine self-vibration. Fig. 8 represents acceleration signals for a cutting condition at which no chip formations take place and hence the no sudden rise and fall in acceleration values are observed. The tool vibration frequency for different cutting conditions is shown in Table 2. The acceleration amplitude signals without cutting are also captured for a better understanding of the machine vibration level and the response without cutting is illustrated in Fig. 9. It is observed from the acceleration signals that the vibrations of cutting tool during cutting are higher than the vibrations without cutting. Signals acquired do not represent different concurrences of turning. This only shows the vibration of the machine; it is helpful in finding the natural frequency of a tool holder.

Table 2 Tool Frequency at various conditions

Cutting parameter			Frequency range, Hz		
V (m/min)	f (mm/rev)	d (mm)	Vx	Vy	Vz
--	--	--	14-745	19-600	15-1500
150	0.2	0.2	44-9520	26-10695	65-10750
150	0.4	0.2	121-8646	76-11180	96-12810
180	0.3	0.3	16-11160	45-11940	16-10880
90	0.4	0.4	96-9562	35-14130	11-14260
120	0.5	0.3	397-6453	353-6512	107-8342
120	0.3	0.3	59-6550	76-6652	172-8970
60	0.3	0.3	42-8260	23-8760	32-9320
120	0.3	0.3	397-6453	353-6512	107-8342

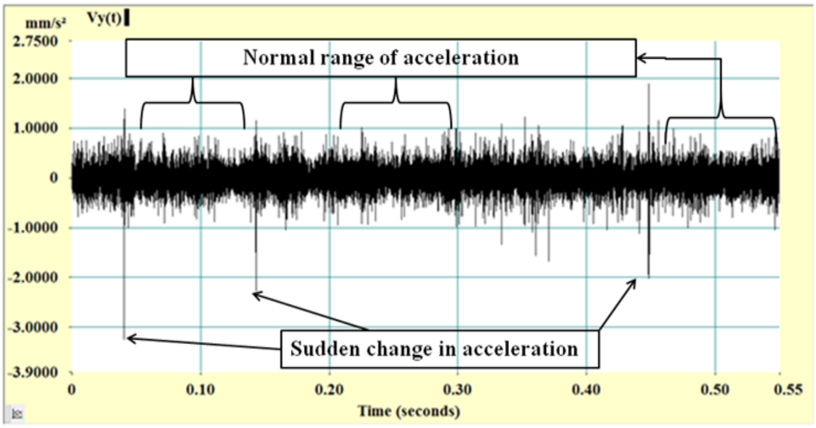

Fig. 5 Acceleration response for V = 150 m/min, f = 0.4 mm/ rev and d = 0.2 mm

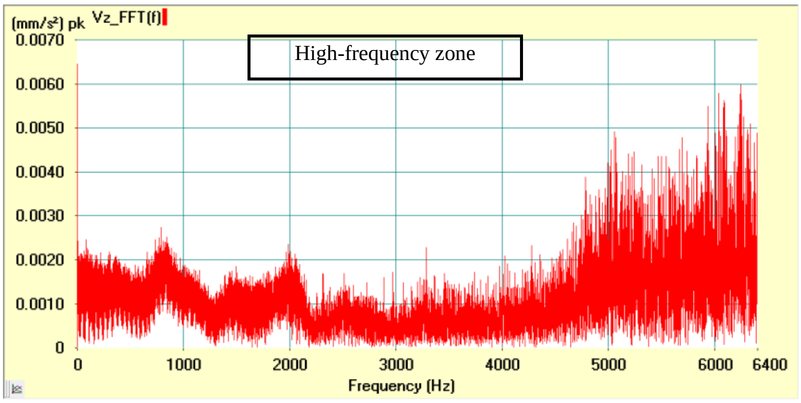

Fig. 6 Acceleration response for V = 120 m/min, f = 0.3 mm/ rev and d = 0.3 mm

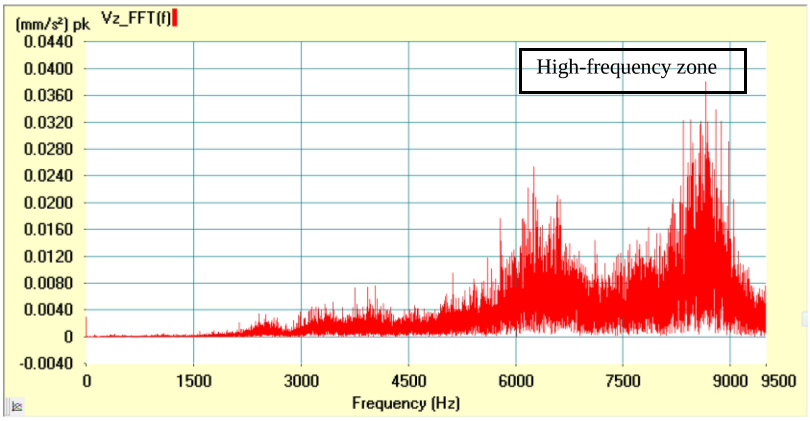

Fig. 7 Acceleration response for V = 120 m/min, f = 0.5 mm/ rev and d = 0.3 mm

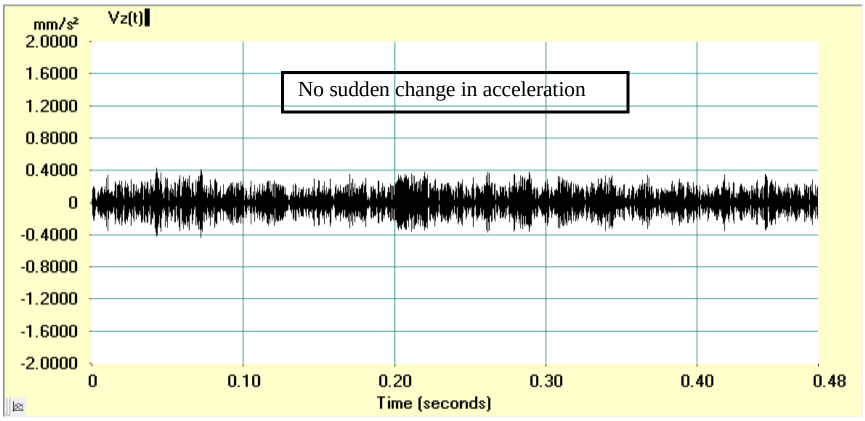

Fig. 8 Acceleration response for V = 120 m/min, f = 0.3 mm/ rev and d = 0.1 mm

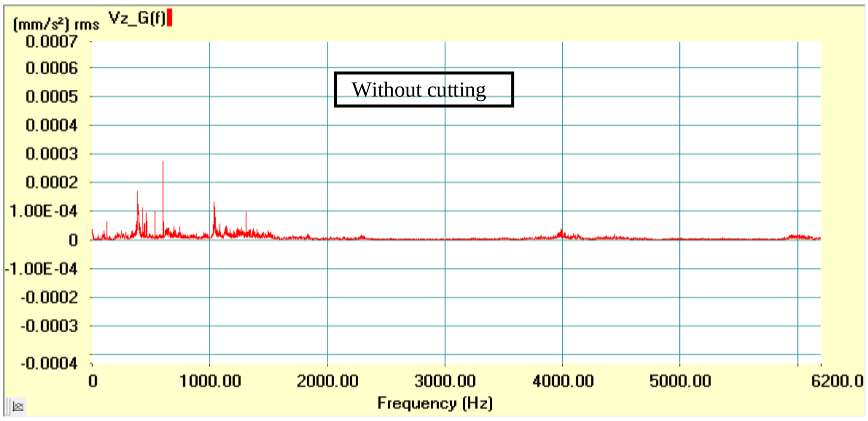

Fig. 9 Acceleration Vs Frequency graph for without cutting

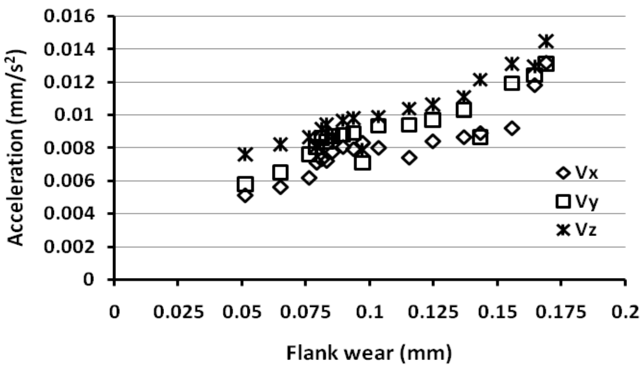

Fig. 10 Acceleration vs. Flank wear at V=60m/min, f=0.3mm/rev, d=0.3mm

The variation of tool acceleration for different values of tool wear at cutting speed 60 m/min, feed f=0.3 mm/rev and depth of cut d=0.3 mm is shown in Fig. 10. The acceleration of the cutting tool in the tangential direction is observed as higher than that in the feed and radial directions. A similar trend is also observed for other cutting conditions. At the start of the cutting process, the acceleration signals increase for tool wear 0.05-0.08 mm. This is because of the sharp edge of the flank rapidly wears out due to a high initial pressure; it is accurately detected by an increase in acceleration amplitude in the feed, radial and, tangential directions. For tool wear 0.085-1.35 mm, the acceleration signals increases with the uniform rate. It is additionally observed that when the device wear is more than 1.35 mm, the tool wear rate increases because of the increase in the interface temperature and the normal pressure on the flank. This ultimately results in a sub-surface plastic flow and sometimes leads to catastrophic tool failure. The tool vibration shows quick response with a higher rate of tool wear. Vibrations in the radial directions are observed as high when contrasted with those in the feed and radial directions. Fig. 11 shows the acceleration of the cutting tool at different stages of tool wear.

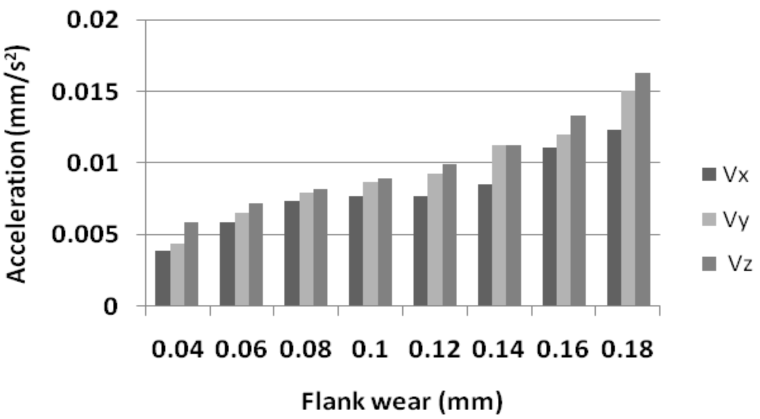

Fig. 11 Acceleration Vs tool wear at V=120 m/min, f=0.3 mm/rev, d=0.3 mm

Fig. 12 (a-c) shows the trend of acceleration amplitude with varying cutting speed, feed and, depth of cut. The vibration signals have an increasing pattern with an increase in cutting speed increase as appeared in Fig. 12(a). The cutting speed has a noteworthy effect on vibration in each of the three directions because frequency depends upon the rotational speed of the workpiece. Vibration amplitude in the tangential direction is found higher than in the feed and radial directions. Fig. 12(b) enlisted the feed rate effect at 100 mm/min cutting speed and at 0.5 mm depth of cut. From the figure it is seen that the vibration signals are observed as high for low values of feed and decrease further with an increase in feed rate. Fig. 13(c) reports variation in acceleration with the varying depth of cut and for constant feed 0.3 mm/rev and cutting speed 100 mm/min. The tool acceleration observes an increase in the tangential direction with the increase of depth of cut followed by the radial and feed directions. This is in good agreement with Suresh et al [5].

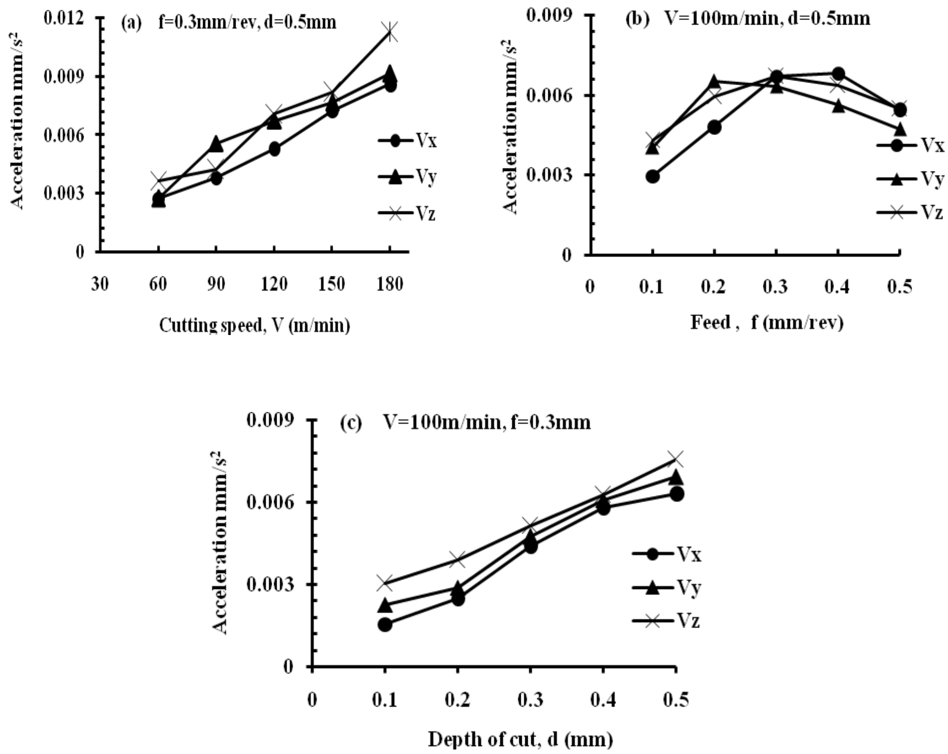

Fig. 12 Variation in acceleration for varying (a) cutting speed (b) feed (c) depth of cut

3.2 Regression analysis (RA)

A new multiple regression model is proposed as a function of cutting parameters and tool acceleration in three directions; it is described below,

$$V_B = aX_1 + bX_2 + cX_3 + dX_4 + eX_5 + g \tag{1}$$

where X_1 is the cutting speed, X_2 the feed, X_3 the depth of cut, X_4 the acceleration in feed direction(V_x), X_5 the acceleration in radial direction (V_y), X_6 the acceleration in tangential direction (V_z) and *a*, *b*, *c*, *d*, *e*, *f*, and *g* are constants. The statistical analysis treatment is performed on the obtained results using the Datafit Statistical customize tool. In the analysis, a confidence level of 95% is chosen. The analysis of variance (ANOVA) results shows that the statistical significance of the fitted model is evaluated by p-value (Prob>F) and F-value. All p-values less than 0.5 indicate the corresponding term is highly significant. Terms with a p-value higher than 0.05, are considered as insignificant for the model. The regression equation is obtained:

$$V_B = 1.4055X_1 + 0.1015X_2 + 0.1348X_3 + 0.3341X_4 + 0.4192X_5 - 0.1958X_6 - 0.1277 \tag{2}$$

The goodness of the model is checked by regression coefficient (R^2) value. R^2 value close to 1 is desirable. R^2 value for the tool wear model is found as 0.93 which is fairly enough and which concludes that the factor cutting speed, feed and depth of cut, accelerations V_x, V_y and V_z have a significant effect on tool wear and can provide reliable estimates. The diagnostics checking of the model has been carried by examining the residuals. From the normal probability plot, it is observed that the residuals lie close to a straight line with maximum error 11% which illustrates that the error is normally distributed; the model does not indicate any inadequacy and it provides reliable prediction. Some experiments have been conducted for different cutting parameters which are not the part of a designed experimental set. The machining parameter used for the selected test and the corresponding output is presented in Table 3. Tool wear comparison between experimental and RA model is presented in Table 4.

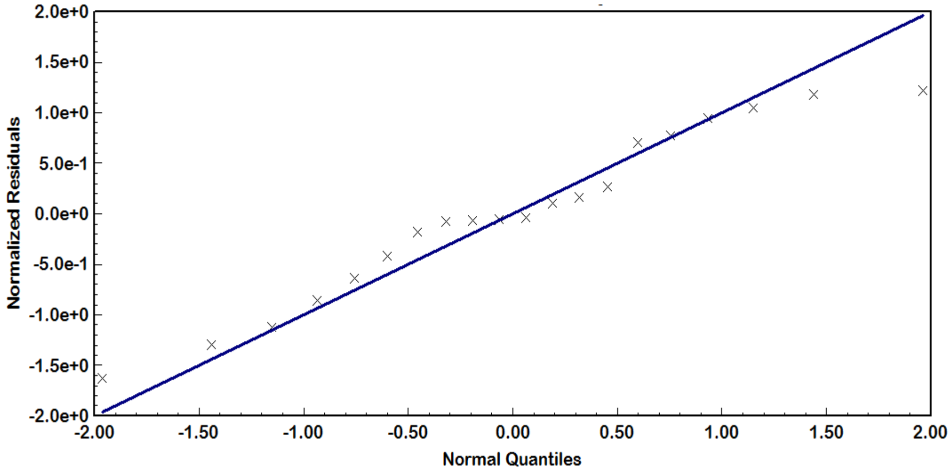

Fig. 13 Residual plot for tool wear

Table 3 Confirmation test-cutting condition and acceleration values

Run	Conditions	V_x mm/sec^2	V_y mm/sec^2	V_z mm/sec^2
1	V=75m/min, f=0.15mm/rev, d=0.25mm	0.0214	0.0325	0.0412
2	V=135m/min, f=0.45mm/rev, d=0.35mm	0.01862	0.0235	0.0256
3	V=165m/min, f=0.15mm/rev, d=0.45mm	0.0835	0.0723	0.07345

Table 4 Tool wear comparison between experimental and RA model

Run	Conditions	V_B-Experiment (mm)	V_B-Model (mm)	Error %
1	V=75m/min, f=0.15mm/rev, d=0.25mm	0.186	0.177	4.83
2	V=135m/min, f=0.45mm/rev, d=0.35mm	0.195	0.199	-2.05
3	V=165m/min, f=0.15mm/rev, d=0.45mm	0.201	0.194	3.48

3.3. Artificial neural network

Artificial neural networks (ANNs) are computation models intended to reproduce the way in which the human mind forms data. Artificial neural network modeling is found very useful in solving nonlinear and complex problems in the field of engineering. Typically an ANN network is comprised of three layers, namely, input layer, hidden layer, and output layer. ANN requires sufficient input and output data instead of a mathematical equation [20]. ANNs can combine and incorporate both literature-based and experimental data to solve problems. The conduct of a neural system is controlled by the exchange elements of its neurons, by the learning rule, and by the structure itself. In the ANN model, many input and target sets are utilized to set up a network. The network is re-adjusted on the basis of a comparison between output and target until the network output yields the target [21-22]. The neural network is created in MATLAB software of version R2012. The training data used during training of the neural network is collected from 20 experiments and back-propagation algorithm based on Levenberg- Marquardt back is used. To train the ANN model, V, f, d, Vx, Vy and Vz are considered as input data whereas tool wear V_B is taken as an output parameter. The basic layout of the ANN model is as shown in Fig. 14.

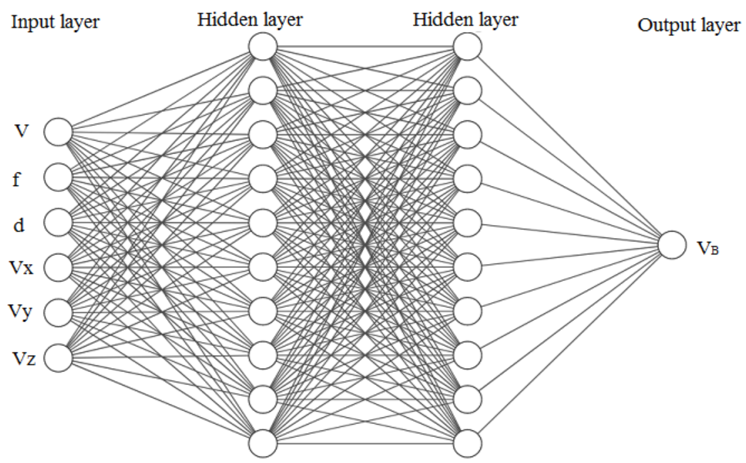

Fig. 14 ANN Network

Table 5 Tool wear comparison

Run no.	V_B-Experiment (mm)	V_B-ANN (mm)	Error %
3	0.184	0.168	8.69
7	0.193	0.189	2.07
10	0.199	0.194	2.51
18	0.186	0.179	3.76

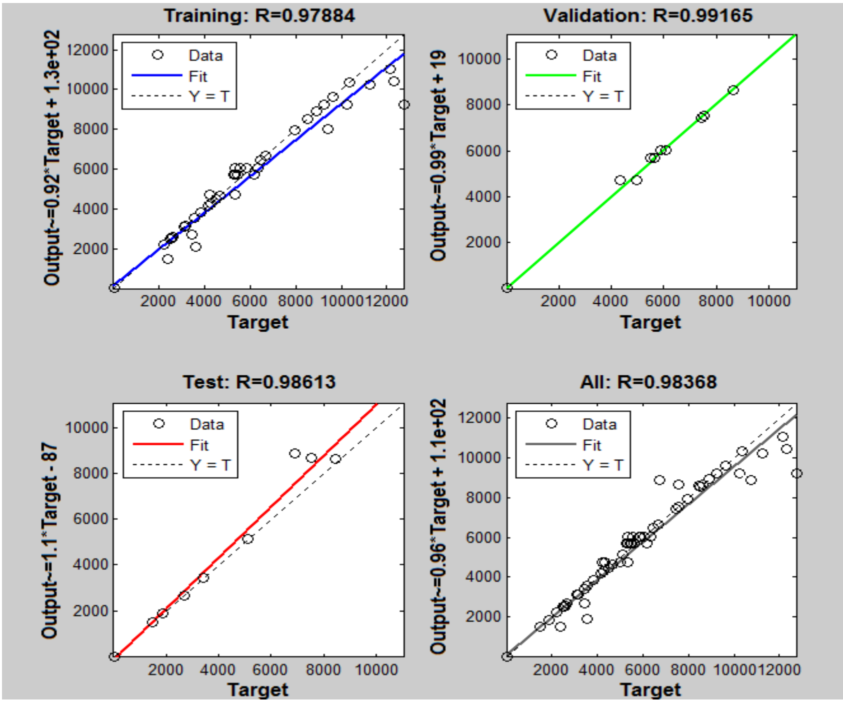

Fig. 15 Regression plot for tool wear

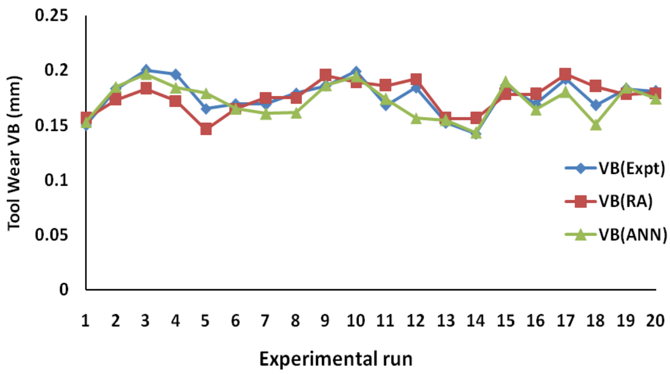

Fig. 16 Tool wear comparison between experimental, RA and ANN approach

The optimal performance of the network is evaluated based on performance parameter correlation coefficient value (R) for both training and testing data for tool wear prediction in an ANN model. The correlation coefficient for the tool wear model is observed as 0.98. The closeness of the ANN model predictions to the experimental results is high; the correlation coefficient between the ANN model predictions and the experimental results are close to 1. Fig. 15 shows regression curves ANN training, testing, validation, and the overall data set for V_B. From Tables 4 and 5, it can be seen that the predicted values by RA and ANN approach, for tool wear (V_B) are closer to each other with an acceptable margin of error. The maximum error found between ANN model predictions and experimental results are found 9.74%, and between ANN model predictions and experimental results is observed as 8.69% and comparison is shown in Fig. 16. Therefore, the proposed tool wear model can be effectively used for predicting tool wear.

4. CONCLUSION

In this paper, the attempt has been made to utilize vibration signals in order to evaluate tool wear in dry turning of hardened AISI52100 steel using PVD coated carbide insert CNMG120480 of coating layers TiSiN-TiAlN. This investigation proposes a new tool wear prediction model based on real-time acceleration signals which will provide real time tool wear. The advantage of the proposed model is examined by R^2 value and is found as 0.89 which is close to one. Also, the diagnostics checking of the model has been carried by examining the residuals. It is observed that the residuals lie close to a straight line which illustrates that the error is normally distributed; the model does not indicate any inadequacy and it provides reliable prediction. Further, the ANN model is developed and the regression value for the model is found as 0.98. Both models anticipated the tool wear within reasonable accuracy making them suitable for real-time prediction. The vibration frequency is observed in the range 16-15kHz. The vibration in the tangential direction is found higher for the variable cutting conditions. The future work of this investigation is to develop a hardware unit for in-process tool wear monitoring suited for small scale factories.

REFERENCES

1. Shihab, S.K., Khan, Z.A., Mohammad, A. Siddiquee, A.R., 2014, *A review of turning of hard steels used in bearing and automotive applications*, Production & Manufacturing Research: An Open Access Journal, 2(1), pp. 24-49.
2. Chinchanikar, S., Choudhury, S.K., 2015, *Machining of hardened steel – experimental investigations, performance modeling and cooling techniques: A review*, International Journal of Machine Tools & Manufacture, 89, pp. 95-109.
3. Aouici, H., Bouchelaghem, H., Yallese, M. Elbah, M.A., Fnides, B., 2014, *Machinability investigation in hard turning of AISI D3 cold work steel with ceramic tool using response surface methodology*, International Journal for Advance Manufacturing Technology, 73, pp. 1775–1788.
4. Aurich, J.C., Eyrisch, T., Zimmermann, M., 2012, *Effect of the coating system on the tool performance when turning heat treated AISI 4140*, Procedia CIRP, 1, pp. 214 – 219.
5. Suresh, R., Basavarajappa, S., Samuel, G.L., 2012, *Some studies on hard turning of AISI 4340 steel using multilayer coated carbide tool*, Measurement, 45(7), pp. 1872–1884.
6. Chinchanikar, S., Choudhury, S.K., 2016, *Cutting force modeling considering tool wear effect during turning of hardened AISI 4340 alloy steel using multi-layer TiCN/Al2O3/TiN-coated carbide tools*, International Journal of Advanced Manufacturing Technology, 83, pp.1749–1762.

7. Jiang, W., More, A.S., Brown, W.D., Malshe, A.P., 2006, *A cBN-TiN composite coating for carbide inserts: coating characterization and its applications for finish hard turning*, Surface & Coatings Technology, 201, pp. 2443–2449.
8. Dimla, D.E. Snr., 2002, *The correlation of vibration signal features to cutting tool wear in a metal turning operation*, International Journal of Advanced Manufacturing Technology, 19, pp. 705–713.
9. Teti, R., Jemielniak, K., O'Donnell, G., Dornfeld, D., 2010, *Advanced monitoring of machining operations*, CIRP Annals-Manufacturing Technology, 79(2), pp.717-739.
10. Salgado, D.R., Cambero, I., Olivenza, J.M.H., Sanz-Calcedo, J.G., Nunez Lopez, P.J., Plaza, E.G., 2013, *Tool wear estimation for different workpiece materials using the same monitoring system*, Procedia Engineering, 63, pp. 608 – 615.
11. Abouelatta, O.B., Madl, J., 2001, *Surface roughness prediction based on cutting parameters and tool vibrations in turning operations*, Journal of Materials Processing Technology, 118(1), pp. 269–277.
12. Chen, B., Chen, X., Li, B., He, Z., Cao, H., Cai, G., 2011, *Reliability estimation for cutting tools based on logistic regression model using vibration signals*, Mechanical Systems and Signal Processing, 25(7), pp. 2526–2537.
13. Upadhyay, V., Jain, P.K., Mehta, N.K., 2013, *In-process prediction of surface roughness in turning of Ti–6Al–4V alloy using cutting parameters and vibration signals*, Measurement, 46, pp.154–160.
14. Hessainia, Z., Belbah, A., Yallese, M.A., Mabrouki, T., Rigal, J.F., 2013, *On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations*, Measurement, 46(5), pp. 1671–1681.
15. Ghorbani, S., Kopilov, V.V., Polushin, N.I., Rogov, V.A., 2018, *Experimental and analytical research on relationship between tool life and vibration in cutting process*, Archives of Civil and Mechanical Engineering, 18, pp. 844-862.
16. D'Mello, G., Srinivasa, P.P., Puneet, N.P., Ning, F., 2016, *Surface roughness evaluation using cutting vibrations in high speed turning of Ti-6Al-4V- an experimental approach*, International Journal of Machining and Machinability of Materials, 18(3), pp. 288-312.
17. Prasad, B.S., Babu, M.P., 2017, *Correlation between vibration amplitude and tool wear in turning: Numerical and experimental analysis,* Engineering Science and Technology an International Journal, 20, pp.197–211.
18. Mir, M.J., Wani, M.F., 2018, *Modelling and analysis of tool wear and surface roughness in hard turning of AISI D2 steel using response surface methodology*, International Journal of Industrial Engineering Computations, 9, pp. 63–74.
19. Zeqin, L., Sujuan, W., Xindu, C., 2018, *Modeling and prediction of surface topography with three tool-work vibration components in single-point diamond turning*, International Journal of Advanced Manufacturing Technology, 98, pp. 1627–1639.
20. Montgomery, D.C., 2014, *Design and analysis of experiments,* 8th edition. Wiley, pp. 288-292.
21. Albu, A., Precup, R., Teban, T., 2019, *Results and challenges of artificial neural networks used for decision-making and control in medical applications*, Facta Universitatis-Series Mechanical Engineering, 17(3), pp. 285 – 308.
22. Yilmaz, M., Kayabasi, E., Akbaba, M., 2019, *Determination of the effects of operating conditions on the output power of the inverter and the power quality using an artificial neural network*, Engineering Science and Technology, an International Journal, 22, pp. 1068–1076.