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In-process prediction of surface roughness in turning of Ti–6Al–4V alloy using cutting parameters and vibration signals

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ABSTRACT

In this work, an attempt has been made to use vibration signals for in-process prediction of surface roughness during turning of Ti–6Al–4V alloy. The investigation was carried out in two stages. In the first stage, only acceleration amplitude of tool vibrations in axial, radial and tangential directions were used to develop multiple regression models for prediction of surface roughness. The first and second order regression models thus developed were not found accurate enough (maximum percentage error close to 24%). In the second stage, initially a correlation analysis was performed to determine the degree of association of cutting speed, feed rate, and depth of cut and the acceleration amplitude of vibrations in axial, radial, and tangential directions with surface roughness. Subsequently, based on this analysis, feed rate and depth of cut were included as input parameters aside from the acceleration amplitude of vibrations in radial and tangential directions to develop a refined first order multiple regression model for surface roughness prediction. This model provided good prediction accuracy (maximum percentage error 7.45%) of surface roughness. Finally, an artificial neural network model was developed as it can be readily integrated into a computer integrated manufacturing environment.

1. Introduction

Surface roughness is a vital attribute to achieve the desired product quality. Desired value of surface roughness of a product is generally defined to achieve the required fatigue strength, corrosion resistance, precision fits, tribological and aesthetic requirements. A widely known model to determine the surface roughness is $R_a = s^2/32r$, where s is the feed rate and r is the nose radius. Undoubtedly, feed rate and nose radius affect surface roughness the most, but the surface roughness cannot be predicted with great accuracy with the above relation. The obvious reasons are that the effect of machine tool rigidity, geometry and condition of cutting tool, application of cutting fluid, cutting parameters and vibrations are not considered in the above model [1]. Generally, surface roughness is measured when the process is completed. However, this strategy involves extra cost of rework for parts that fail to measure up to the surface roughness requirement. Therefore, in-process estimation of surface roughness is emerging as a key research area of metal cutting and it is not surprising that a large number of research papers based on regression modeling, artificial neural network, fuzzy, neuro-fuzzy have been published on prediction of surface roughness.

Surface roughness prediction model in terms of cutting speed, feed rate and depth of cut using response surface methodology has been widely reported in literature [2–7]. Lee and Tarng [8] proposed a computer vision technique to inspect the surface roughness. The surface image of the workpiece was captured by digital camera and then with the help of polynomial network a relationship was established between the workpiece image and actual surface roughness. Jiao et al. [9] used neuro-fuzzy approach to model the surface roughness. Abburi and Dixit [10] developed a knowledge-based system using neural networks and fuzzy set theory for the prediction of surface roughness. They reported that IF-THEN set of rules provided as good a

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prediction as the neural networks. Lu [11] developed a prediction model for surface roughness in terms of cutting speed, feed rate and depth of cut using RBF neural network in turning of stainless steel 304L. Basheer et al. [12] used ANN model to predict surface roughness in turning of metal matrix composites using volume of reinforcement, size of reinforcement, tool nose radius, feed rate, and depth of cut. Davim et al. [13] developed ANN based surface roughness prediction models using feed rate, cutting speed and depth of cut as the affecting process parameters in turning of free machining steel. Escamilla et al. [14] developed back propagation and maximum sensibility neural network models to predict surface roughness in machining of Ti–6Al–4V alloy using cutting speed, feed rate and depth of cut as input to neural network. Ramesh et al. [15] used fuzzy technique to predict surface roughness in turning of Ti–6Al–4V alloy using cutting speed, feed rate and depth of cut. Hascahk and Caydas [16] optimized the cutting speed, feed rate and depth of cut for surface roughness using Taguchi technique. Based on ANOVA analysis they concluded that feed rate has the maximum effect on surface roughness followed by depth of cut. Fadare et al. [17] studied the effect of cutting speed, feed rate, and depth of cut in high speed turning of Ti–6Al–4V alloy under conventional cooling environment. They observed that surface roughness was affected the most by feed rate followed by cutting speed and depth of cut. Karayel [18] used ANN for prediction and control of surface roughness using cutting speed, feed rate and depth of cut as input parameters. Asiltürk and Çunkaş [19] developed models for prediction of surface roughness in AISI 1040 steel using ANN and multiple regression technique for various speed, feed rate and depth of cut and reported that ANN provides better prediction of surface roughness than multiple regression technique.

Surface roughness during the process changes as the tool wears out. So, the surface roughness prediction model using cutting parameters as input were good enough only for selection of cutting parameters to achieve a desired surface finish. Therefore, a signal that could represent the interaction between the tool and workpiece should be used as input in in-process prediction model of surface roughness. Vibrations/cutting forces during the process were used as inputs in the surface roughness prediction model to serve this purpose. Risbood et al. [20] developed ANN models for the prediction of surface roughness using cutting speed, feed rate, depth of cut and acceleration of radial vibration of tool holder as input to the model. Kirby et al. [21] developed in-process multiple regression surface roughness prediction system using feed rate and vibration along *x*, *y* and *z*-axis. Ozel and Karpat [22] developed prediction models for surface roughness and tool wear using regression and ANN technique in hard turning operations. They used two different neural network groups for prediction of surface roughness and tool wear. In one group, they used tool edge geometry, hardness, cutting speed, feed rate and length of cut as input parameters whereas in the other group they used cutting force signals alongwith hardness, cutting speed, feed rate and length of cut as input parameter. Neural network models using cutting force inputs with a single output provided better results than neural networks with two outputs. Kirby and Chen [23] developed a fuzzy-nets-based surface roughness prediction system for turning operation using feed rate, spindle speed and tangential vibration data.

Purpose of this study is to determine whether only vibration signals can be used in in-process prediction of surface roughness during turning of Ti–6Al–4V alloy. If only vibration signals are not able to provide good prediction then to select a set of significant cutting parameters and vibration signals to predict surface roughness with sufficient accuracy using multiple regression and artificial neural network technique.

2. Experimental details

Ti–6Al–4V alloy was used as work material in the experimental study. The chemical composition of the used Ti–6Al–4V is shown in Table 1. Workpiece was held between three jaw chuck and revolving centre of a rigid, high power precision lathe (model: NH22; Make: HMT, India) to increase the rigidity of machining system. A schematic diagram of the experimental set-up is shown in Fig. 1. Experiments were carried out with uncoated cemented carbide inserts of ISO S grade (CNMG120408) held in PCBNR 2525 M12 (Mitsubishi Material Co.) tool holder. Tool geometry is as follows:

back rake angle $= -6^\circ$,
side rake angle $= -6^\circ$,
principal cutting edge angle $= 75^\circ$,
end cutting edge angle $= 5^\circ$,
nose radius $= 0.8$ mm

Experiments were conducted under flood cooling using 5% water emulsion of Vasco 1000, a commercially available, water miscible, vegetable oil based cutting fluid. The cutting parameters used in the experimental study and their levels are given in Table 2.

The acceleration amplitude of tool vibration was measured with a tri-axial accelerometer (Make: Kistler, Type: 8766A50) which was connected to NI 9233 data acquisition module and NI c-DAQ for digitization of the vibration signals. These digitized signals were then processed using the NI LabView SignalExpress Software. Average surface roughness (R_a) was measured using Veeco WYKO NT1100 surface profilometer with WYKO Vision32 V2.303 software using vertical scanning interferometry (VSI) mode at 1× scan speed, 10× magnification and full resolution. Four measurements of surface roughness were taken at different locations and the average value was used in the analysis.

3. Experimental design and results

In this work, experiments were conducted according to the Box Behnken Design (BBD) of Response Surface Methodology. Experimental design involves variation of three factors (cutting speed, feed rate and depth of cut) at three

Table 1
Chemical composition of Ti–6Al–4V alloy.

Element	Ti	Al	V	Others
Weight Percentage	89.61	6.1	3.87	Balance

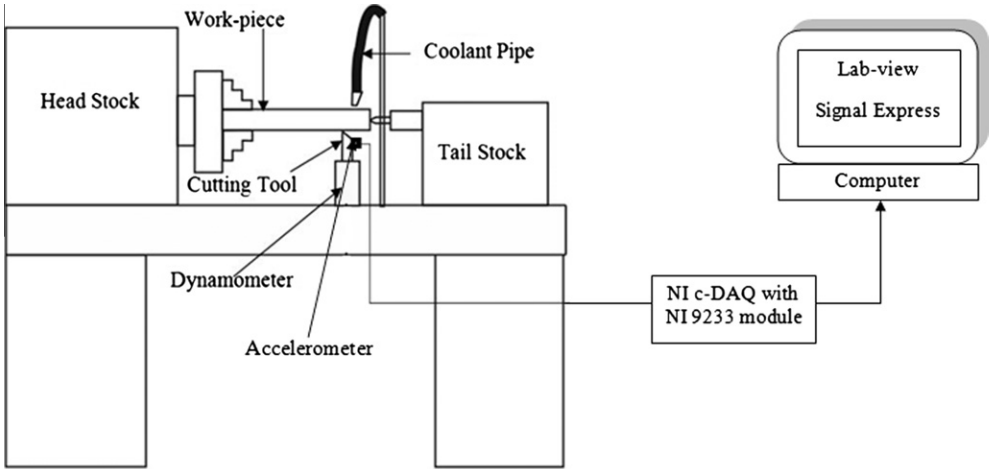

Fig. 1. Schematic of experimental setup.

Table 2
Levels of independent variables for turning.

Variable	Unit	Level		
		1	2	3
Cutting Speed (v)	m/min	50	70	90
Feed rate (s)	mm/rev	0.16	0.20	0.24
Depth of cut (t)	mm	1	1.5	2

levels as mentioned in Table 2. This requires 15 experimental runs including three replications of centre point. Table 3 shows the parametric combinations for the experiments and the experimental values of acceleration amplitude of vibration (RMS value) in axial (V_X), radial (V_Y) and tangential (V_Z) directions and surface roughness (R_a).

4. Development of prediction models and analysis

4.1. Multiple regression model using only vibration signals

An effort has been made in this work to determine whether the cutting parameters can be completely replaced by vibration signals to predict the surface roughness i.e., can the vibration signal responses obtained from the experiments be used as input parameters for prediction of surface roughness? From the fundamental concepts of design of experiment, it follows that in Box Behnken Design of Response Surface Methodology, use of vibration signals to predict the surface roughness is not possible as the vibrations cannot be directly controlled to serve as independent variables. Therefore, multiple regression method was used to obtain first order and second order models from the analysis of the data of unplanned experiments [24]. These first order (Eq. (1)) and second order (Eq. (2)) models were used for prediction of surface roughness as a function of acceleration amplitudes of vibration in radial, axial and tangential directions.

First order model (FOM)

$$\text{Surface roughness } (R_a) = 1.84 - 2.05\,V_X + 0.124\,V_Y + 0.084\,V_Z$$
$$R^2 = 52.8\% \tag{1}$$

Second order model (SOM)

$$\begin{aligned}\text{Surface roughness } (R_a) = {} & -27.6 + 171\,V_X + 0.43\,V_Y \\ & - 1.1\,V_Z - 247\,V_X^2 - 0.0167\,V_Y^2 \\ & + 0.47\,V_Z^2 + 0.24\,V_X * V_Y - 0.126\,V_Y \\ & * V_Z - 0.7\,V_X * V_Z\end{aligned} \tag{2}$$
$$R^2 = 70.5\%$$

Table 3
Parametric combinations for the experiments and the experimental values.

Standard order	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	V_X (g)	V_Y (g)	V_Z (g)	R_a (μm)
1	50	0.16	1.5	0.35	2.49	1.64	1.58
2	90	0.16	1.5	0.32	4.56	1.75	1.54
3	50	0.24	1.5	0.33	4.83	1.79	2.34
4	90	0.24	1.5	0.33	6.33	3.05	2.31
5	50	0.20	1.0	0.33	2.56	1.19	1.73
6	90	0.20	1.0	0.32	2.81	2.08	1.61
7	50	0.20	2.0	0.35	3.01	1.75	1.83
8	90	0.20	2.0	0.33	3.83	2.27	1.77
9	70	0.16	1.0	0.37	3.92	1.63	1.51
10	70	0.24	1.0	0.35	6.05	1.61	2.24
11	70	0.16	2.0	0.39	4.84	1.65	1.73
12	70	0.24	2.0	0.36	7.87	1.61	2.39
13	70	0.20	1.5	0.38	6.54	1.79	1.92
14	70	0.20	1.5	0.37	6.94	1.74	1.94
15	70	0.20	1.5	0.31	6.20	1.62	1.89

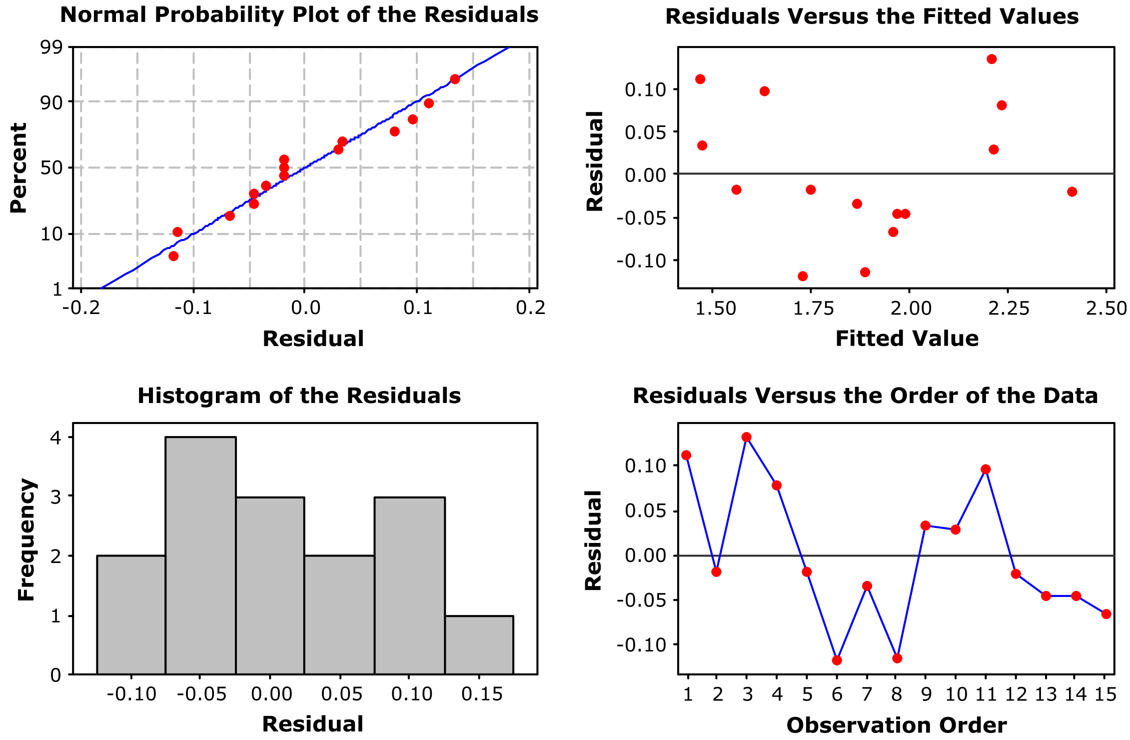

Fig. 2. Plot of residuals for refined model.

Table 4
Values predicted by FOM and SOM and their percentage error.

Standard order	Experimental R_a (μm)	FOM predicted R_a (μm)	SOM predicted R_a (μm)	% Error in values predicted by FOM	% Error in values predicted by SOM
1	1.58	1.57	1.71	0.63	−8.23
2	1.54	1.9	1.91	−23.38	−24.03
3	2.34	1.91	2.04	18.38	12.82
4	2.31	2.2	2.37	4.76	−2.60
5	1.73	1.58	1.82	8.67	−5.20
6	1.61	1.71	1.66	−6.21	−3.11
7	1.83	1.64	1.81	10.38	1.09
8	1.77	1.83	1.94	−3.39	−9.60
9	1.51	1.7	1.86	−12.58	−23.18
10	2.24	2.01	2.32	10.27	−3.57
11	1.73	1.78	1.67	−2.89	3.47
12	2.39	2.21	2.42	7.53	−1.26
13	1.92	2.02	1.99	−5.21	−3.65
14	1.94	2.09	2.19	−7.73	−12.89
15	1.89	2.11	1.99	−11.64	−5.29
Average percentage error				8.91	8.00

R^2 value of FOM was 52.8% whereas that of SOM was 70.5%. This implies that even SOM can only explain 70.5% variation in surface roughness. Average percentage error for FOM and SOM are 8.91% and 8% respectively whereas the maximum percentage error was close to 24% for both the models (Table 4). Percentage error for each experimental run was calculated by the following relation.

$$\%\,\text{error} = \frac{\text{experimental value} - \text{predicted value}}{\text{experimental value}} \times 100 \qquad (3)$$

In order to validate the developed FOM and SOM, additional experiments were performed with the same range of parameters used in the main experimental work. The input parameters and the corresponding acceleration amplitudes and surface roughness values are shown in Table 5.

Table 5
Predicted value of surface roughness and percentage error of FOM and SOM during validation.

Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	V_X (g)	V_Y (g)	V_Z (g)	Experimental surface roughness (μm)	Surface roughness predicted by FOM (μm)	Percentage error (FOM)	Surface roughness Predicted by SOM (μm)	Percentage error (SOM)
50	0.2	1.5	0.36	3.96	1.58	1.87	1.73	7.71	1.98	−5.92
90	0.2	1.5	0.33	4.55	2.41	1.76	1.93	−9.67	2.04	−16.10
50	0.24	1	0.36	3.84	1.63	2.24	1.72	23.43	1.94	13.31
90	0.24	1	0.34	4.31	2.31	2.18	1.87	14.15	2.04	6.23
70	0.2	1	0.37	5.01	1.89	1.73	1.86	−7.60	1.95	−12.89
Average percentage error								12.50		10.89

Table 6
Pearson correlation coefficient of parameters with surface roughness.

Parameter	Pearson correlation coefficient
Cutting speed	−0.079
Feed rate	0.918
Depth of cut	0.198
Acceleration in *x*-direction (V_X)	−0.001
Acceleration in *y*-direction (V_Y)	0.692
Acceleration in *z*-direction (V_Z)	0.273

Table 7
Values predicted by refined model (Eq. (4)) and their percentage error.

Standard order	Experimental R_a (μm)	Predicted R_a (μm)	% Error
1	1.58	1.47	6.96
2	1.54	1.56	−1.3
3	2.34	2.21	5.56
4	2.31	2.23	3.46
5	1.73	1.75	−1.16
6	1.61	1.73	−7.45
7	1.83	1.86	−1.64
8	1.77	1.88	−6.21
9	1.51	1.48	1.99
10	2.24	2.21	1.34
11	1.73	1.63	5.78
12	2.39	2.41	−0.84
13	1.92	1.97	−2.6
14	1.94	1.99	−2.58
15	1.89	1.96	−3.7
Average Percentage error			3.50

Table 8
Analysis of variance.

Source	Degree of freedom	Sum of squares	Mean sum of squares	F ratio	P value Prob > F
Regression	4	1.17964	0.29491	34.40	<0.0001
Residual error	10	0.08574	0.00857		
Total	14	1.26537			

It is evident from Table 5 that average percentage error for FOM and SOM is 12.50% and 10.89% respectively whereas the maximum percentage error for FOM is 23.43% and for SOM it is 16.10%.

4.2. Multiple regression model using cutting parameters and vibration signals

Based on the work of Kirby et al. [21], it seems that inclusion of cutting parameters alongwith vibration signal can further improve the prediction of regression model. So for development of regression model there are total six input parameters (three acceleration amplitude and three cutting parameters) to consider. However, it is important to know which among the six input parameters have a significant role in prediction of surface roughness. Therefore, correlation analysis was performed to determine the degree of association of input parameters with surface roughness. Correlation coefficient lies between −1 and +1. A negative correlation coefficient represents inverse proportional relationship and positive correlation coefficient represents direct proportional relationship between the variables. A zero value of correlation coefficient represents no association between the variables. Pearson correlation coefficient for input parameters is shown in Table 6. It is evident from Table 6 that cutting speed and acceleration amplitude of vibration in axial direction are weakly related with surface roughness as the correlation coefficient is close to zero. Pearson correlation coefficient for feed rate was maximum followed by acceleration amplitude of vibration in radial direction, depth of cut and acceleration amplitude of vibration in tangential direction. Therefore, the regression model was refined by including, feed rate, depth of cut, V_Y and V_Z as shown below:

$$\text{Surface roughness} = -0.035 + 7.96 * s + 0.116 * t + 0.0455 * V_Y - 0.0351 * V_Z \quad (4)$$

$$R^2 = 93.2\%$$

R^2 value of the model is 93.2%, which shows that the model can explain 93.2% of total variations in surface roughness. Percentage error of prediction with this model is shown in Table 7. The maximum percentage error was 7.45% whereas average percentage error was 3.5%. So, the prediction accuracy was improved as compared to previous models. Analysis of variance was performed to determine the significance of regression model and the results are shown in Table 8. The p value '*Prob > F*' of the model signifies that the model is highly significant. Residuals plot for surface roughness is shown in Fig. 2. From the normal probability plot of the residuals, it is evident that the residuals lie close to a straight line. With validation data, the average

Table 9
Predicted value of surface roughness and percentage error during validation.

Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	V_X (g)	V_Y (g)	V_Z (g)	Experimental Surface roughness (μm)	Surface roughness Predicted by MRM[a] (μm)	Percentage error (MRM)	Surface roughness predicted by ANN (μm)	Percentage error (ANN)
50	0.2	1.5	0.36	3.96	1.58	1.87	1.86	0.76	1.77	5.35
90	0.2	1.5	0.33	4.55	2.41	1.76	1.85	−5.31	1.75	0.57
50	0.24	1	0.36	3.84	1.63	2.24	2.11	5.85	2.32	−3.57
90	0.24	1	0.34	4.31	2.31	2.18	2.11	3.38	2.32	−6.42
70	0.2	1	0.37	5.01	1.89	1.73	1.83	−6.05	1.81	−4.62
Average percentage error								4.27		4.11

[a] Calculated from Eq. (4).

percentage error in prediction was 4.27% whereas maximum percentage error was 6.05% (Table 9).

4.3. Neural network model

Artificial Neural Network (ANN) is a mathematical or computational model inspired by biological neurons. ANN models are widely used due to their capability to capture the complex and nonlinear interrelationship between input and output dataset. Neural network creates its implicit knowledge during training phase. Back Propagation (BP) is one of the most frequently used training algorithms in neural networks. However, standard BP algorithm suffers from serious problem of slow convergence and inability to avoid local minima. Levenberg–Marquardt algorithm is relatively faster but consumes more memory [25]. Therefore back propagation with Levenberg–Marquardt (LM) is used for training the network.

To develop a neural network model, feed rate, depth of cut, acceleration amplitude of vibration in radial and tangential direction were taken as input parameters. A neural network with four neurons in input layer and one neuron in the output layer corresponding to four inputs and one output respectively with single hidden layer was designed and trained with Levenberg–Marquardt (LM) learning rule. Single hidden layer was selected as it is adequate for large number of applications [26]. The number of neurons in hidden layers is selected on trial and error basis. The tangent of sigmoid function is used in the hidden layer whereas the output layer has pure linear neuron. Neural network architecture that provides the best prediction accuracy is shown in Fig. 3. It comprises four input neurons corresponding to feed rate, depth of cut, acceleration amplitude of vibration in radial and tangential direction, five neurons in the hidden layer and one output neuron for surface roughness. The training parameters are as follows:

Frequency of progress displays (in epochs) = 10.
Max. number of epochs to train = 1000.
Sum squared error goal = 1×10^{-6}.

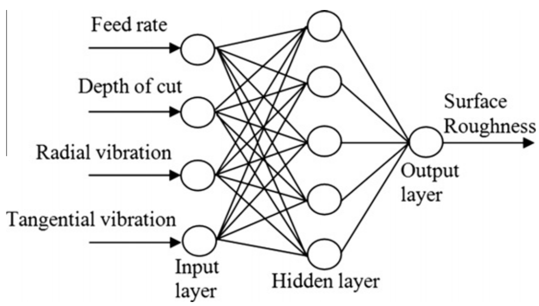

Fig. 3. Neural network architecture.

To test the prediction ability of developed neural network model, the model was tested with the validation data given in Table 9. Average percentage error for ANN model was 4.11% and maximum percentage error was 6.42%. Therefore, the developed models can be effectively used for inprocess prediction of surface roughness.

5. Conclusions

In this work an attempt has been made to initially predict surface roughness by using acceleration amplitude of vibration in axial, radial and tangential direction. First order and second order multiple regression models using only vibration signals were developed and based on R^2 value and maximum percentage error neither of the two was found to have satisfactory prediction ability. Consequently, Pearson correlation coefficient was used to determine the correlation between surface roughness and cutting parameters and acceleration amplitude of vibrations. Pearson correlation coefficient for feed rate was maximum followed by acceleration amplitude of vibration in radial direction, depth of cut and acceleration amplitude of vibration in tangential direction. Based on Pearson correlation coefficient multiple regression model was developed using above mentioned input parameters. As this model was found accurate enough, neural network model was developed using the same combination of input parameters. To check the adequacy of developed models, the models were validated with the data not used in development of models. Both the models predicted the surface roughness within reasonable accuracy making them suitable for inprocess prediction. Thus the use of in-process surface roughness prediction can provide a opportunity to take intime corrective action to control the surface finish within required limits.

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