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Analysis of Vibration And Surface Finish in Turning of En8

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ABSTRACT

In this paper, an attempt has been made to use vibration signals for inprocess prediction of surface roughness during turning of EN8 alloy. The investigation was carried out to determine the relationship between cutting speed , feed rate ,depth of cut and the amplitude of vibrations with the surface roughness .In this analysis cutting speed ,feed rate ,depth of cut were included as input parameters asides to get the amplitude of vibration in surface roughness prediction .

Experimental and theoretical analyses were done and a variation of 8 % is determined**.**

Keywords: Vibration, Surface Roughness, EN8 alloy.

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I. INTRODUCTION

Vibration plays a major role in the machine while its functioning .In turning and other machining operation surface roughness is the desired product quality. Surface roughness can be generally obtained by the mathematical relation ,$Ra=S^2/32r$, where S is the feed rate and r is the tool nose radius .From the above relation we can determine the surface roughness easily .It states that surface roughness mainly depends on the feed rate and the tool nose radius but we can't get the accuracy in the surface roughness while using this relation .Many reasons affect the surface roughness of the work piece some of them are tool geometry , tool rigidity ,cutting tool condition ,cutting fluid , cutting parameter and vibrations Generally after completion of the process we will measure the surface roughness . It involves extra cost of rework for parts that fail to measure the surface roughness requirement. In metal cutting operations, the estimation of surface roughness is the research area and a large number of research papers based on artificial neural network, regression model, fuzzy have been published. Surface roughness prediction in terms of cutting speed, feed rate, and depth of cut using methodology has been widely studied in literature [1, 6].Lee and Tarng [7] proposed a computer vision technique to inspect the surface roughness .The surface image was captured by the digital camera and then a relationship was established between the work piece image and actual surface roughness .Jiao et al [8] used neuro-fuzzy approach to model the surface roughness. Lu [9] developed a model for prediction of surface roughness in terms of cutting speed, feed rate, and depth of cut using RBF neural network in turning of stainless steel 304L.Ramesh et al [10] used fuzzy technique to predict surface roughness in turning of Ti-6Al-4V alloy using cutting speed, feed rate, and depth of cut .Fadare et al [11] 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 the surface roughness was mostly affected by the feed rate followed by cutting speed and depth of cut .Asilturk and Cunkas [12] developed a model 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. Due to the wear in the tool the surface roughness may vary during the process. So the prediction of surface roughness using cutting parameters as inputs were good enough for the selection of cutting parameter to achieve the required surface roughness. Kirby et al [13] developed in-process multiple regression surface roughness prediction system using feed rate and vibration along x, y and z – axis. Kirby and Chen [14] developed a fuzzy-nets-based surface roughness prediction system for turning operation using feed rate, spindle speed and tangential vibration data.

II. EXPERIMENTAL DETAILS.

EN8 was used as work material in the experimental study .The chemical composition of the EN8 is shown in Table 1 .Work piece was held between the tree jaw chuck and revolving centre of a rigid , high power precision lathe . Experiments were carried out with coated carbide inserts of ISO S grade held in the tool holder . DNMG (DNMG150608) tool were used in the experiment . The tool geometry is as follows Nose radius=0.8 mm

The cutting parameters used in the experimental study and their levels are given in Table 2.

Table 1 Chemical composition of EN8.

Element Composition	(%)
Carbon	0.35-0.45
Manganese	0.6-1.0
Silicon	0.05-0.35
Phosphorous	0.06 max
Sulphur	0.06 max

Table 2 Levels of variables for turning

Variable	**Unit**	**Level**		
		1	**2**	**3**
Cutting Speed	m/min	60	80	100
Feed Rate	Mm/rev	0.16	0.18	0.20
Depth of Cut	Mm	1	1.5	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 Signal Express Software. Average surface roughness (Ra) 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.

III. EXPERIMENTAL DESIGN

In this work, experiments were conducted according to the Response Surface Methodology. Experimental design involves variation of three factors (cutting speed, feed rate and depth of cut) at three 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 (VX), radial (VY) and tangential (VZ) directions and surface roughness (Ra).

IV. 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. These first order (Eq. (1)) models were used for prediction of surface roughness as a function of acceleration amplitudes of vibration in radial, axial and tangential directions.

Table 3 Experimental values.

Cutting Speed	**Feed**	**Depth of Cut**	**Vx**	**Vy**	**Vz**	**Ra**
60	0.16	1.5	0.36	2.51	1.59	1.54
80	0.16	1.5	0.38	3.96	1.76	1.59
100	0.2	2.0	0.33	2.89	1.53	2.13
60	0.2	2.0	0.36	5.32	2.89	2.43
80	0.18	1.5	0.34	3.83	1.62	1.89
60	0.18	1.0	0.36	4.02	1.86	1.78
60	0.16	1.0	0.35	3.94	1.53	1.63

First order model (FOM)
Surface roughness (Ra)= 1.89 – 2.15 Vx+ 0.124 Vy+ 0.084 Vz
Percentage error for each experimental run was calculated by the following relation.
Percentage error = [(experimental value - predicted value)/ experimental value]*100

Table 4 Values predicted by FOM and their percentage error.

Experimental (Ra) (µm)	**FOM predicted Ra(µm)**	**% Error in valuespredicted byFOM**
1.54	1.56	-1.29
1.59	1.71	-7.5
2.13	1.96	7.9
2.43	2.01	8.2
1.89	1.77	6.3
1.78	1.77	0.56
1.63	1.75	-7.3

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.

4.2. Multiple regression model using cutting parameters and vibration signals

Based on the work of Kirby et al. [14], it seems that inclusion of cutting parameters along with 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. It is evident from Table 3 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, VY and VZ as shown below:

Surface roughness =-0.135 + 7.84 *s +0.213 *t+ 0.046 * Vy - 0.035 *Vz

IV. 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 multiple regression models using only vibration signals were developed and based on Ra 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 analysis prediction.

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