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Surface Roughness Evaluation in High-speed Turning of Ti-6Al-4V using Vibration Signals

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ABSTRACT

Ti-6Al-4V is difficult to machine material. It is widely used in a number of applications like aerospace industry, marine application, petroleum refining, surgical implantation, chemical processing, food processing, and electrochemical and its surface roughness is important. In this paper, surface roughness obtained from high-speed turning of Ti-6Al-4V machined using uncoated carbide inserts have been evaluated using vibration signals. Vibration signals have been analyzed using time domain and time-frequency domain. Vibration amplitude measured in the cutting speed direction has been used in developing an artificial neural networks (ANNs) model in time domain. Further, in the time-frequency domain, wavelet packet transform has been used to extract features from the vibration signal in the cutting speed direction and has been used in developing another ANN model to evaluate the surface roughness in terms of R_a, which is a widely used parameter. Multilayer perceptron has been used for model development. Levenberg-Marquardt algorithm has been used for training the model. It has been found that the time-frequency domain features extracted from the vibration signals are effective in surface roughness evaluation, as the ANN model has given a prediction accuracy of 93% on test data.

Key words: *High-speed turning, Surface roughness, Wavelet packet transform, Artificial neural network.*

1. INTRODUCTION

With the wide use of high-performance CNC machines, high-speed machining has demonstrated its superior advantages compared to other manufacturing techniques and widely used in the aerospace industry, automotive industry, and precision engineering industry, etc. It has advantages such as higher material removal rates, high-quality surface finish, lower cost, lower cutting forces ensuing stress-free components, burr-free edges, as well as an increase in productivity [1,2]. The cutting speed employed in high-speed machining is 2-50 times greater when compared to traditional machining. Titanium alloys have been extensively used in the aerospace, biomedical, marine applications, surgical implantation, chemical processing, food processing, electrochemical, automotive, and petroleum industries because of their good strength-to-weight ratio and superior corrosion resistance [3,4]. During machining of titanium alloys with a conventional tool, tool wears progress rapidly because of their low thermal conductivity and high chemical reactivity. Higher temperature is generated in the cutting zone, providing strong adhesion of workpiece material over the tool edge which results in poor machinability. The material in the vicinity of the machined surface undergoes excessive elastic deformation preventing a good surface finish [5]. Hence, to assess the quality of a component, the inspection of surface roughness of the workpiece is very important. Vibration is present between the tool and the workpiece during any machining process. In the case of machining titanium alloys, the vibrations occur mainly due to self-excited vibrations between the workpiece and the cutting tool. There is a need for vibration signal analysis during machining of difficult-to-cut materials, such as titanium and its alloys [6,7]. The wavelet packet transform (WPT) provides for the representation of the original time domain signal in the time-frequency domain. When the WPT is applied to a signal, the output is a "tree" of decomposition packets, where each packet is composed of a series of coefficients [8]. The features, which represent the characteristics of the vibration signals (standard deviation, variance, energy, etc.), were extracted from the wavelet packets which contain more significant information. These features were used for modeling using the artificial neural network (ANN). Xu *et al.* [9] proposed an ANN model for predicting the drill wear with the help of uniquely identified features, which are extracted using the WPT. Pal and Chakraborty [10]

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developed a back propagation neural network model for predicting the surface roughness during turning with a high-speed steel tool, and a comparison had been made between the predicted and measured values.

The main goal of this work is to evaluate the surface roughness of a machined Ti-6Al-4V surface using vibration signals evaluated in time domain and time-frequency domain wavelet transform (WT) techniques. Two neural network models have been developed based on features extracted from both the techniques. A comparison has been made to evaluate which technique is effective in the prediction of surface roughness parameter R_a.

2. EXPERIMENTAL DETAILS

2.1. Work Material and Tool Geometry

Figure 1 shows the experimental setup. The material used for experimentation was Grade 5 titanium alloy (Ti-6Al-4V). Samples are taken in the form of 50 mm diameter and 200 mm length rods. The turning experiments were carried out on a CNC turning center (HMT make Stallion 100SU) with a speed range of 100-3500 rpm. The work material has the following chemical compositions in percentage of weight: Al - 6.02%, Cr - 0.03%, Fe - 0.13%, Mn - 0.04%, V - 3.85%, and Ti - 89.93%. The tool insert used is 883, an uncoated carbide insert (CNMG 12 04 08) with MR4 chip breaker (Seco make). The insert is flat faced and rhomboidal in shape with back and side rake angle of −6°, end cutting edge angle of 5° and tool nose radius of 0.8 mm. The tool holder used is PCLNL 2020 K12 (Seco make). The length of the tool overhang is 60 mm.

2.2. Cutting Conditions

Experiments have been carried out at different cutting speeds of 150, 175, 200 m/min, the feed rate of 0.15, 0.2, 0.25 mm/rev and depth of cut of 0.8, 1, and 1.2 mm. The length of each cut was 48 mm (for one machining pass).

2.3. Measurement of Tool Wear

Measurement of flank wear, nose wear, and crater wear has been done after each machining pass using a Mitutoyo tool maker’s microscope (TM 505/510) which has a magnification of ×15, with provision for measurement using 2 µm in horizontal and vertical directions with the least count of 0.005 mm. Experiments were carried out till the nose and flank wear reached 0.4 mm.

2.4. Measurement of Vibration Signals

The cutting tool vibrations during the cutting process have been measured online using a Model 65-10 Isotron tri-axial accelerometer. The accelerometer senses the vibration signals in three different directions, i.e., depth of cut, speed, and feed directions (V_x, V_y and V_z respectively). The vibration signals were sent to a DNA-PPCx, power DNA cube (UEI make) at a sampling frequency of 10 kHz. From power DNA, the signals were finally sent to a laptop through ethernet cable and stored for further analysis using Labview software.

2.5. Measurement of Surface Roughness Parameter

The measurement of surface roughness was done after each machining pass using Taylor Hobson Taly Surf 50, a stylus type instrument. Surface roughness parameters R_a (arithmetic average surface roughness) has been measured considering 2.5 mm as the sampling length. The measurement was done at three different locations 120° apart on the surface of the workpiece and average values have been considered.

3. WT FOR VIBRATION SIGNAL ANALYSIS

Wavelet analysis is a new method for solving difficult problems in mathematics, physics, engineering, etc. The applications of WT include wave propagation, data compression, signal processing, image processing, pattern recognition, etc. [11]. The WT analyses the low-frequency content of a signal with a wide duration function and conversely analyses high-frequency content with a short-duration function. WT is a tool that decomposes a signal into different frequency (scale) components, and then considering each component by translating (positioning) it along the length of the signal and simultaneously matching it with the original signal. It gives the information about the signal both in frequency and time domains as it can be used to analyze non-stationary signals like those from machining. Traditionally, the WT is characterized as continuous, discrete, and WPT.

3.1. WPT

The WPT is a general form of wavelet decomposition that offers a wide range of possibilities for signal analysis. During wavelet decomposition, the original signal S is split into shifted and scaled versions of mother wavelet. In this work, the vibration signals are sampled at a sampling frequency of 10 kHz and for 10 s, it contains 100,000 data point. In WPT, both detail and approximation components are decomposed. The signal S is split into two frequency bands: An approximation A and a detail D. The first approximation A is then split into second approximation and detail as AA and AD respectively and the first detail D is split into second level approximation and detail as DA and DD, respectively. Figure 2 shows the third level decomposition of the signal S. This process can be repeated up to required n levels. The wavelet packet decomposition can be represented as a “tree” of packets in which each packet contains a different number of coefficients. A wavelet packet function is a function with three indices (j, n, k) satisfying:

$$W_{j,k}(t) = 2^{-j/2} W_n(2^{-j} t - k) \quad (1)$$

Where, k and j are the translation and index of scale operations, respectively. Wavelet packet functions are defined as:

$$W_{2n}\left(x\right)=\sqrt{2}\sum_{k}h(k)W_{n}\left(2x-k\right) \tag{2}$$

$$W_{2n+1}\left(x\right)=\sqrt{2}\sum_{k}g(k)W_{n}\left(2x-k\right) \tag{3}$$

Where g(k) and h(k) are the high- and low-pass filters, $W_n(x) = \phi(x)$ is the scaling function and $W_1(x) = \psi(x)$ is the wavelet function.

3.2. Selection of Best Mother Wavelet Function

Mother wavelet is a base for the analysis of a given signal in WT. The selection of the mother wavelet is a crucial factor as it affects the result obtained by applying WT. Hence, one has to find out the degree of correlation between the given signal and the mother wavelet.

Rafiee and Tse [12] proposed an algorithm for selection of mother wavelet for faulty gearbox signal based on the variance values of the wavelet packets. In this paper, the same criteria have been used. 20 mother wavelets have been taken randomly from the three families of wavelets namely Coiflets, Daubechies and Symlet and the sample result for six mother wavelets are shown in Table 1.

The signal has been decomposed to the third level using WPT technique. All the signals corresponding to each machining pass have been decomposed. There are eight packets in the third level for each signal, and each packet contains different number of coefficients. The variance values of the individual packet have been calculated. A similar procedure has been followed to calculate the variance for remaining machining passes. The average value of the variance has been calculated for an individual packet for an experiment. Hence, finally, there will be 8 average variance values for one condition. Of 8 values, the sum of 4 highest values has been calculated for each mother wavelet, which has been summed up and this value is called as "SUMVAR" [12]. It has been found that there is no change in the results obtained by changing the level of decomposition. Out of 20 wavelet functions, the one which has the maximum "SUMVAR" value is "db-44." Hence, "db-44" is considered as the suitable mother wavelet. The variance value is calculated using:

$$\sigma^2_{(3,p)}=\frac{\sum_{k=1}^{m}\left(W_{(3,p)}\left(k\right)-\overline{W_{(3,p)}\left(k\right)}\right)^2}{m} \tag{4}$$

Where, p is the number of wavelet packets, m is the number of coefficients in each wavelet packet, $W_{(3,p)}(k)$ is the values of the individual wavelet packet coefficients and $\overline{W_{(3,p)}(k)}$ is the mean value of the wavelet packet coefficient.

3.3. Selection of Dominant Wavelet Packet

The need for dominant wavelet packets is significant since not all the packets contain desired information. Hence, the dominant wavelet packet has been selected from the packet which contains the maximum amount of energy. The dominant wavelet packet is then used for feature extraction. The packets in the third level can be denoted as $W_{(3p)}$ (p=0, 1...., 7). Of 8 packets in the third level, $W_{(30)}$ and $W_{(36)}$ have the maximum amount of energy and can be considered as the dominant wavelet packets. It depended on the cutting conditions used, for some $W_{(3,0)}$ and some $W_{(3,6)}$, have been found to be dominant. The energy in each wavelet packet can be calculated as:

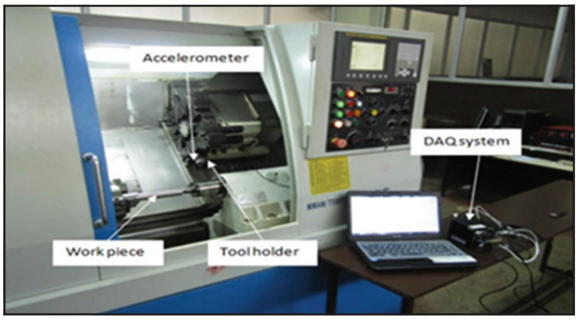

Figure 1: Experimental setup for measurement of cutting vibrations.

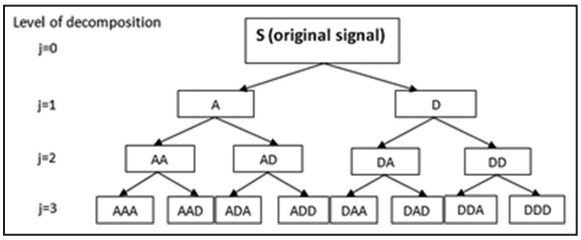

Figure 2: Third level of wavelet packet decomposition tree for the measured vibration signals.

Table 1: "SUMVAR" values for different mother wavelets.

Mother wavelet	SUMVAR
Db2	36,980.5
Db3	37,586.9
Db10	38,511.2
Db44	38,556.8
Sym2	36,980.1
Coif2	37,915.0

Cutting conditions considered: v=200 m/min, f=0.15 mm/rev and d=1.2 mm

$$E_{(3,p)} = \frac{1}{n_p}\int_{k=1}^{n_p} W_{3,p}^2(k) \quad (5)$$

Where, $E_{(3,p)}$ is the energy of the wavelet coefficients for packet p in the third level, n_p is the number of wavelet coefficients in packet p, and $W_{(3,p)}(k)$ is the k^{th} coefficient (k=1 to n_p).

3.4. Feature Extraction

Feature extraction is an important requirement in any modeling effort. Accordingly, four statistical features have been extracted from the dominant wavelet packets, and these features contain information of the original signal. These are mean, variance, standard deviation, and kurtosis [4].

4. ANN

4.1. Introduction to ANN

Neural networks are widely used artificial intelligence tools which are suitable for modeling in various applications due to their ability to learn complex nonlinear and multivariable relationships between process parameters [13]. In this study, a feed forward multi-layered neural network has been used to predict the surface roughness.

4.2. Multilayer Perceptron (MLP)

It consists of three layers: An input layer, hidden layers, and an output layer. The neurons present in the hidden and the output layer perform non-linear transformations of the signal. Finally, the overall output is obtained from the output layer by summing up the resulting vectors obtained from the hidden layers.

Each input is given to the network, and the neurons will generate the output. During training, the output is compared with the desired value using known input data which are fed to the network and by varying the weights between the neurons. The mean squared error (MSE) will be calculated between the predicted output and the desired output. The error is then minimized by varying the number of hidden neurons, and the network is trained again. The MSE can be calculated as:

$$\text{MSE} = \frac{(\text{Predicted value} - \text{Experimental value})^2}{2} \quad (6)$$

4.3. Model Development

In this study, the MLP model is developed using neural network toolbox in MATLAB R2014b, and the hidden neurons have been varied from 5 to 30 with an interval of 5 hidden neurons to find out the best prediction accuracy. The desired goal of 0.001 has been taken and the network training is carried out until the target is reached. The learning rate of 0.01 and maximum number of epochs of 1000 has been taken. Altogether 289 sets of data have been collected. Of these, 246 data have been used for training the network and remaining 43 data have been used as test data and the prediction accuracy of the network has been calculated. A comparison has been made between the two to select which model is better in predicting the output (R_a). Levenberg-Marquardt (trainlm) has been used as a training algorithm which is available in the MATLAB toolbox for training the neural network model. Tansigmoid function has been used as a transfer function in the hidden and output layer neurons.

Two MLP models have been developed: One considering wavelet packet features (time-frequency domain) and other considering time domain vibration signals (V_y). The other parameters considered commonly for both the models are machining conditions (speed, feed, and depth of cut) and tool wear. The output of the model is the surface roughness parameter (R_a). Table 2 gives the MLP modeling results for both model types.

5. RESULTS AND DISCUSSION

The study evaluates the performance of MLP for predicting surface roughness parameter R_a. From

Table 2: MLP model performance for prediction of R_a.

Number of hidden neurons	With time-frequency domain features (Model 1)				With time domain features (Model 2)			
	MSE	Epochs reached	Prediction accuracy (%)		MSE	Epochs reached	Prediction accuracy (%)	
			Training data	Testing data			Training data	Testing data
5	0.0133	279	97.96	69.76	0.0167	799	97.96	83.72
10	0.00404	1000	100	72.09	0.00554	1000	99.59	88.37
15	0.00107	1000	100	88.37	0.00294	1000	100	88.37
20	0.000998	40	100	90.69	0.001	882	100	76.74
25	0.000976	24	100	88.37	0.000997	32	100	88.37
30	0.000954	19	100	93.02	0.000988	26	100	86.04

MSE=Mean squared error, MLP=Multilayer perceptron

Table 2, it is seen that model one based on WP features, gives the best result for 30 neurons in 19 epochs taking the least processing time with a prediction accuracy of 100% for training data and 93.02% for test data achieving a mean square error of 0.000954. Furthermore, it is seen that as the number of hidden neurons increases the performance on the test data improved, resulting in a larger network. For model 2 based on the time domain vibration signals, for 15 hidden neurons, the best prediction accuracy of 100% for training data and 88.37% for test data with a mean square error of 0.00294, is achieved, but it required 1000 epochs for training.

Thus, use of WP based features resulted in higher prediction accuracies with smaller training error, but the network is large, whereas, with time domain signals, the network generated is compact, but resulted in lower prediction accuracies and higher training error.

6. CONCLUSION

This work is concerned with surface roughness evaluation in high-speed turning of Ti-6Al-4V using uncoated carbide inserts. WPT has been used to analyze the vibration signals. A suitable mother wavelet has been selected for the analysis. Four features have been extracted from the dominant wavelet packets. Two ANN models based on MLP have been developed using WPT based features extracted from vibration signals and using time domain vibration signals. It has been found that use of WPT for analyzing the vibration signals can be used in surface roughness evaluation with a prediction accuracy of 93% on test data. Thus, use of WT can be effectively carried out in analyzing vibration signals for surface roughness evaluation in high-speed turning of Ti-6Al 4V alloy.

7. ACKNOWLEDGMENTS

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***Bibliographical Sketch**

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