Proceedings of 10th International Conference on Precision, Meso, Micro and Nano Engineering (COPEN 10)
December 07 – 09, 2017, Indian Institute of Technology Madras, Chennai – 600 036 INDIA

Application of EEMD in Determining Tool Chatter Behavior using ANN Approach

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Abstract

Stable cutting zone prediction is the key requirement for retaining high-productivity with enhanced surface quality of work-piece. Tool chatter is one of the factors responsible for abrupt change in surface quality and productivity. In this research work, dependency of cutting parameters on tool chatter has been explore, chatter signals have been recorded by performing experiments at different combinations of cutting parameters on CNC trainer lathe. Further, these recorded signals have been pre-processed by Ensemble empirical mode decomposition technique (EEMD), followed by the selection of dominating intrinsic mode functions (IMFs) using Fourier transform (FT). The preprocessed signals have been used to evaluate a new output parameter i.e. chatter index (CI). Artificial Neural Network (ANN) based on feed forward back propagation network has been proposed for predicting tool chatter in turning process. The input machining parameters considered are depth of cut, feed rate and cutting speed. It has also being deduced that from available different transfer functions, Hyperbolic Tangent transfer function in ANN is best suitable to predict tool chatter severity in turning operation. Moreover, the dependency of cutting parameters on tool chatter has been elaborated.

Keywords: Tool chatter; Signal pre-processing; EEMD; IMF; ANN.

1. INTRODUCTION

Chatter is considered as one of the most important causes of volatility in the cutting process. It not only bounds productivity of machine but also causes poor surface finish and reduces tool life. In the past years, chatter detection has been a topic of immense interest and many chatter detection techniques have been developed by monitoring signals such as; cutting forces [1], tool vibration [2], acoustics [3, 4], etc. The measured signals are processed in different ways. The selection of the suitable method depends on the type of raw signals. Generally, raw signals are of four types viz. stationary and linear, stationary and nonlinear, non-stationary and linear, non-stationary and nonlinear. The most common and effective techniques for processing measured raw signals are; Fast Fourier transform (FFT) analysis, Short time Fourier transform (STFT), Wavelet transform (WT) and Hilbert Huang transform (HHT). The selection of the technique purely depends on the feature we want to extract from the signal. Fast Fourier transform (FFT) transforms the time domain signal into frequency domain. During FFT the time information at corresponding chatter frequency is lost. To eliminate the limitation of FFT, Short time Fourier transform came into existence. This is a windowing technique and has the capability to provide information of both time and frequency. However, STFT has its own limitation because of fixed window size. Thus, some efforts are being made for processing signals with varying window size for chatter detection. Wavelet transforms (WT) is one such technique that has the capability to perform local analysis. It is bit similar to STFT but having additional properties of shifting and scaling the window. Choi and Shin [5] proposed a chatter detection methodology using wavelet-based maximum likelihood parameter estimation algorithm, and this method was validated in both turning and milling process. Aforesaid methods are limited to the analysis of linear and non-stationary raw signals. However, if the signals are non-linear as well as non-stationary, Hilbert Huang Transformation will yield better results. This new approach is developed by the need to analyze the non-linear and non-stationary data. HHT is a powerful time–frequency technique that has been widely used for processing and feature extraction of non-stationary raw signals [6]. Although HHT is a powerful time–frequency analysis method and have several merits, but there are some shortcomings also. It is still not a perfect tool to extract signal features in practical applications, there is a shortcoming of mode mixing in EMD. Mode mixing is a consequence of signal intermittence [7] which frequently happens in chatter signals. The intermittency not only cause serious disturbance in time- frequency distribution, but also scarce the physical meaning of individual IMF. To heal and overcome the effect of intermittency, ensemble empirical mode decomposition (EEMD) [8] has been adopted instead of EMD.

In the present work, the main aim of this research is to propose a suitable technique for identifying stable cutting zone, specifically in turning operation at given set of parameters. For this, non-linear and non-stationary raw vibration signals have been recorded using microphone by performing experiment. The recorded signals are then decomposed using EEMD. The decomposed signals are termed as intrinsic mode functions (IMFs). These IMFs has been evaluated to obtain a new output parameter called as chatter index (CI). Further, Artificial Neural Network (ANN) based on feed forward back propagation network has been proposed for predicting tool chatter in turning process. Moreover, the dependency of cutting parameters on tool chatter has been elaborated.

2. CHATTER IN MACHINING OPERATION

Machining operation viz. turning, milling, drilling etc. are extremely affected by tool chatter. Self-excited vibrations are mainly responsible for tool chatter. Generally such vibrations are sub divided in two parts primary chatter and secondary chatter [9]. Primary chatter is caused by friction between tool-work-piece, while secondary chatter is caused by the generation of wavy surface on the work piece. This regeneration of wavy surface gives birth to regenerative chatter which is the most destructive among all other vibrations. To identify and evaluate the effect of regenerative chatter various experiments have been performed as elaborated in chapter 3.

3. EXPERIMENTATION

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ISBN: 978-93-80689-28-9

Experiments have been performed on CNC Trainer Lathe Machine: Model – MCL10 for recording the chatter signals, experiments have been conducted at three different sets of input cutting parameters as shown in Table 1. The cutting variables considered are presented in Table 2 and were kept fixed throughout. During experimentation, acoustic vibration signals have been recorded using a microphone, the specifications of the microphone is shown in Table 3. The work piece and cutting tool used are low carbon steel (AISI 1018) and tungsten carbide, respectively. The experimental set up is shown in Fig. 1. One of the recorded signal at given sets of parameters has been shown in Fig. 2.

Table: 1 Combination of cutting parameters

S. No.	Parameter/Level	1	2	3
1	Depth of cut, d (mm)	0.5	1	1.5
2	Feed rate, F (mm/rev.)	0.10	0.15	0.20
3	Cutting speed, S (m/min)	100	150	200

Table: 2 Fixed input parameters

Work-piece material	Low carbon steel (AISI 1018)
Work-piece dimensions	Length: 80 mm, Diameter: 25 mm
Cutting insert	Tungsten carbide
Insert dimensions	3/4'', 3/4'',1/4'' with 1/16'' nose radius
Tool holder	Carboloy MSDNN85-6, neutral shank with 45^0 Side cutting edge angle

Table: 3 Specification of microphone

Model	AHUJA AGN-480
Specialty	Dynamic Unidirectional Microphone
Frequency Response	50-10,000 Hz.
Sensitivity	2.0 mV/Pa
Impedance	600 Ω
Overall Length	470 mm

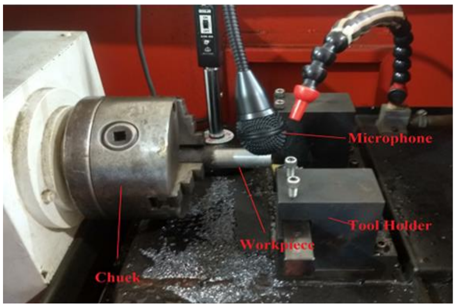

Fig 1. Experimental setup

4. PRINCIPLE OF EMD AND EEMD

4.1 Introduction of EMD

EMD is a process by which data is prepared so that it can be evaluated effectively. It decomposes nearly any signal into finite set of functions and a residue, whose Hilbert transform gives physical instantaneous frequency value. These functions are called intrinsic mode function (IMF). EMD adopts a shifting mechanism and generates more symmetric wave profile of signal by removing the large inequalities in amplitude. It also eliminates the riding waves and thus helps in getting meaningful frequency.

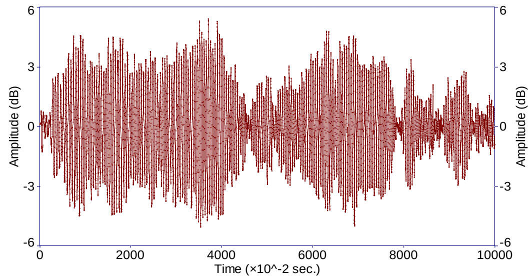

Fig 2. Recorded signal at Depth of cut (d) 0.5 mm, Feed rate (F) 0.10 mm/rev. and cutting speed (S) 100 m/min.

The principle of EMD and EEMD is almost similar, in the present study the methodology adopted is as follows;
Chatter signal x(t), is processed by EMD method [10], finally a decomposition of the signal into 'N' number of IMFs and a residue R_N has been accomplished as presented by;

$$x(t) = \sum_{n=1}^{N} H_n + R_N \qquad (1)$$

The IMFs, H_1, H_2, H_3……H_N, are nearly mono component signals and include different frequency bands ranging from high to low. The frequency components contained in each frequency band are different and they change with the variation of signal x(t), while R_N represents the central tendency of signal x(t).
Further H_1 to H_N IMFs are evaluated to identify the chatter dominating mode.

4.2 EEMD and mode mixing problem of EMD

Empirical Mode Decomposition [7] is an adaptive method very effective to analyze non-linear and non-stationary signals. However, EMD experiences some problems too; one of the very significant problem is "mode mixing". It resembles the presence of very distinct amplitude in a mode, or the presence of very similar amplitudes in different modes. To overcome this problem, a new method was proposed which was named as "Ensemble Empirical Mode Decomposition" (EEMD) [8]. This method performs the EMD over an ensemble of the signal and Gaussian white noise. The addition of white Gaussian noise solves the mode mixing problem by filling the whole time-frequency space [11]. The decomposed IMFs have been shown in Fig. 3.
Fig. 3 also consist of the Fourier transforms of the IMFs, it has been noticed that the amplitude of Fourier transform of IMF 6 is maximum i.e. around 30 db. This higher amplitude resembles chatter as chatter is a nonlinear phenomenon with higher amplitude. The remaining frequency transform viz. from IMF 7 to 14 are not taking part in chatter detection due to lower amplitude. Hence for this particular set of signal IMF 6 is dominantly responsible for chatter. Similarly 26 other sets have been examined to identify the respective dominating IMF for chatter.
After identifying the dominating IMFs, a new output parameter chatter index (CI) have been calculated using the formula as shown in equation 2. The calculated chatter index for different IMFs have been shown in Table 4. Moreover, for analyzing the data by Artificial neural network (ANN) the input parameters have been converted into normalized form as the range of cutting speed (100 to 200) is numerically too large as compared to depth of cut (0.5 to 1.5) and feed rate (0.1 to 0.2).

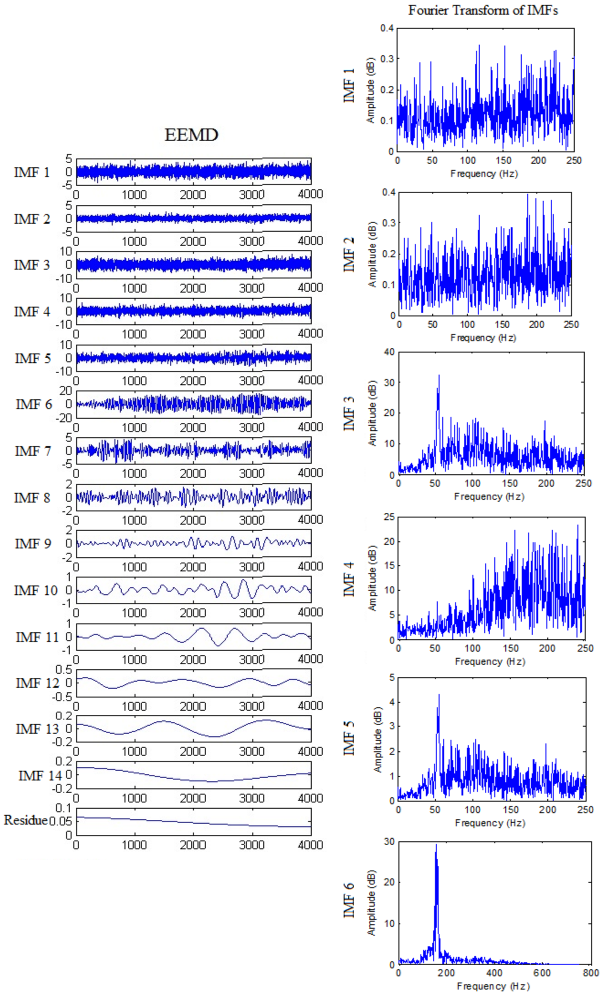

Fig 3. Intrinsic mode function and respective Fourier transform

Hence, for smooth training and testing purpose, the input and output parameters have been converted into normalized form, which have been shown in Table 4. Here, the normalized values are in the range of -1 to +1. The transformation of actual variables into normalized form has been done by using the relations as shown in equation 3.

$$CI = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2} \tag{2}$$

$$D_N = D/1.5;\ S_N = S/200;\ F_N = F/0.2;\ CI_N = CI/6 \tag{3}$$

5. ANN TRAINING AND TESTING

ANN training has been done for 27 experimental values. The ANN architecture consists of 3-neurons in input layer (D, S and F), 10-neurons in first hidden layer, 5-neuron in second hidden layer and 1 neuron in output layer (CI). The selection of number of hidden layers have been done on the basis of established theory given by Heaton [12]. The transfer function used in the presented work is hyperbolic tangent. The selection of transfer function depends on the R- values. For which all the suitable transfer functions viz. hyperbolic tangent, Gaussian and Sigmoid have been used one after the other for modelling. The obtained R-value have been shown in Table 5. Moreover, the percentage error in predicting the output by these three aforesaid models have been compared to identify the most suitable one.

Table: 4 Combination of cutting parameters and calculated chatter index

Exp. no.	D	D_N	S	S_N	F	F_N	CI	CI_N
1	0.5	0.33	100	0.5	0.1	0.5	1.23	0.205
2	0.5	0.33	100	0.5	0.15	0.75	1.42	0.236
3	0.5	0.33	100	0.5	0.2	1	1.03	0.171
4	0.5	0.33	150	0.75	0.1	0.5	1.23	0.205
5	0.5	0.33	150	0.75	0.15	0.75	1.52	0.253
6	0.5	0.33	150	0.75	0.2	1	1.41	0.235
7	0.5	0.33	200	1	0.1	0.5	3.52	0.586
8	0.5	0.33	200	1	0.15	0.75	3.23	0.538
9	0.5	0.33	200	1	0.2	1	3.51	0.585
10	1	0.66	100	0.5	0.1	0.5	2.99	0.498
11	1	0.66	100	0.5	0.15	0.75	3.41	0.568
12	1	0.66	100	0.5	0.2	1	2.92	0.486
13	1	0.66	150	0.75	0.1	0.5	2.42	0.403
14	1	0.66	150	0.75	0.15	0.75	2.31	0.385
15	1	0.66	150	0.75	0.2	1	1.32	0.220
16	1	0.66	200	1	0.1	0.5	4.23	0.705
17	1	0.66	200	1	0.15	0.75	4.44	0.740
18	1	0.66	200	1	0.2	1	3.32	0.553
19	1.5	1	100	0.5	0.1	0.5	5.32	0.886
20	1.5	1	100	0.5	0.15	0.75	5.22	0.870
21	1.5	1	100	0.5	0.2	1	4.42	0.736
22	1.5	1	150	0.75	0.1	0.5	4.14	0.690
23	1.5	1	150	0.75	0.15	0.75	4.42	0.736
24	1.5	1	150	0.75	0.2	1	2.42	0.403
25	1.5	1	200	1	0.1	0.5	5.55	0.925
26	1.5	1	200	1	0.15	0.75	5.63	0.938
27	1.5	1	200	1	0.2	1	4.32	0.720

In ANN testing these 27 predicted values corresponding to each transfer function have been compared with the experimental output values and then percentage error is evaluated using the relation;

$$e_{ai} = \left(\frac{V_E - V_P}{V_E}\right) \times 100\% \tag{5}$$

where, e_{ai} represents average individual error, V_E and V_P are the experimental and predicted values, respectively. Fig. 4 represents the comparison between different transfer functions. It has been found that hyperbolic tangent transfer function is best suitable. Likewise, Fig. 5 shows the comparison between the predicted values of CI obtained from ANN using hyperbolic tangent function and experimentally acquired values of CI.

Table: 5 R-Values of different transfer functions

R- Value	Hyperbolic Tangent	Gaussian	Sigmoid
Training	0.989	0.949	0.638
Testing	0.978	0.902	0.299

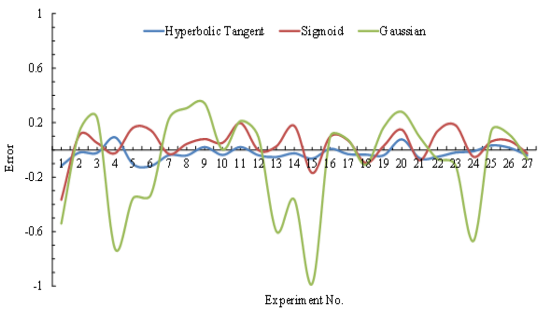

Fig 4. Comparison between different transfer functions

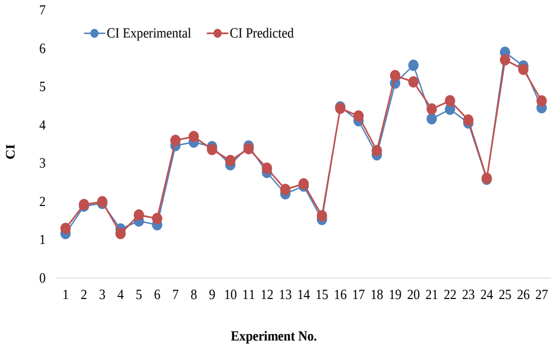

Fig 5. Experimental and predicted values of CI

6. STABLE CUTTING ZONE PREDICTION

The results obtained using hyperbolic tangent transfer function have been assessed to obtain stable cutting zone. Thereby, a contour plot has been drawn as shown in Fig. 6, which represents the dependency of different input parameters with respect to output i.e. CI.

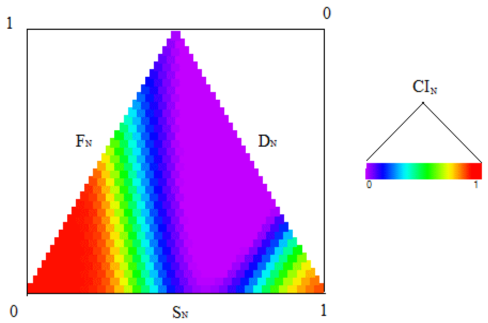

Fig 6. Contour plot for D_N, S_N, F_N and CI_N

The region with red color in the plot resembles higher value of CI. Similarly, the region with green color represents moderate CI, while the region with violet color represents minimum chatter index. The value of CI resembles the surface quality of the work-piece, higher the value of CI more surface irregularities and vice versa. Therefore, the best cutting zone can be selected from the contour plot with minimum value of CI.

7. CONCLUSIONS

This study focuses on the assessment of stable cutting zone for sophisticated CNC turning process using Ensemble Empirical Mode Decomposition and ANN techniques. In the present work, contaminations associated with the recorded signals have been considered and sieved out of the acquired raw signals. Moreover, ANN has been used to figure out the dependency of chatter index on cutting parameters. This technique can serve as a guideline to the engineers for the processing of expensive work materials at preferable cutting zone with lower chatter.

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