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Fuzzy Subtractive Clustering Based Prediction Approach for Machine Tool Vibration

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***Abstract*--In a machining operation, vibration is frequent problem, which affects the machining performance and in particular, the surface finish and tool life. Mathematical models make it possible to simulate machining vibration quite accurately. Several factors directly or indirectly influence output responses in machining. The objective of this work is to investigate the effects of major input parameters on the output in machining process and to optimize the input parameters. For this Fuzzy Clustering Based artificial Intelligence technique has been used to develop the prediction model using experimental data taken a published work. The predicted values were compared with the collected experimental data and Root Mean Square Error was computed. Less error was found between the experimental and predicted values.**

Key words: machining vibration, Fuzzy Clustering, Root Mean Square Error

1 Introduction

In a machining operation, vibration is frequent problem, which affects the machining performance and in particular, the surface finish and tool life. Severe vibration occurs in the machining environment due to a dynamic motion between the cutting tool and the work piece. Mathematical models make it possible to simulate machining vibration quite accurately, but in practice it is always difficult to avoid vibrations.

Vibration problems generally result in noise, bad surface quality and sometimes tool breakage. The main sources are of two types: forced vibrations and self-generated vibrations.

- Forced vibrations are mainly generated by interrupted cutting (inherent to milling), runout, or vibrations from outside the machine.
- Self generated vibrations are related to the fact that the actual chip thickness depends also on the relative position between tool and work piece during the previous tooth passage. Thus increasing vibrations may appear up to levels which can seriously degrade the machined surface quality.

Several factors directly or indirectly influence output responses in machining. The objective of this research was to investigate the effects of major input parameters on the output in machining process and to optimize the input parameters. Again from the literature review it is evident that though some research wok was under taken into study the influence of machining input parameters on various output responses in machining of mild steel, still there exits some disparities which need to be studied with more detail. In multi-response optimization, it is very difficult to select the optimal setting which can achieve all quality requirements simultaneously. Otherwise optimizing one quality feature may lead severe quality loss to other quality characteristics which may not be accepted by the customers. In order to tackle such a multi-response optimization problem, an attempt will be made in the present work through the analysis of the results obtained from an experimental study.

The rest of the paper is organized as follows: Section II describes the Literature Review. Section III deals with data used, IV the methodology part of work done, followed by results and discussions in section V. In the end , based on the discussion various conclusions are drawn and the future scope for the present work is discussed.

2 Literature Review

Various techniques, such as linear regression, discriminate analysis, decision trees, neural networks etc. have been evolved and applied to predict machine tool vibration. B. P. Kolhe, et. al.,(2015) analysed the CNC lathe cutting tool vibrations supported with and without damping pad. B. P. Kolhe, et. al.,(2015) analysed the CNC lathe cutting tool vibrations supported with and without damping pad. N.Kusuma, Megha Agrawal, P.V.Shashikumar, (2014), worked on the influences of cutting parameters on machine tool vibration & surface finish using MEMS Accelerometer in high precision CNC milling machine. Amit Aherwar, Deepak Unune, BhargavPathri, Jai kishan, (2014), showed from experimental results, the amplitude of vibration of the cutting tool was ascertaining for each machining performance criteria. The significance and percentage contribution of each parameter were determined by Analysis of variance (ANOVA). K. VENKATA RAO, B.S.N. MURTHY, N. MOHAN RAO, (2014), studied the vibration of work piece in boring of AISI 316 steel with cemented carbide tool inserts. A multilayer feed forward artificial neural network (ANN) model was trained with the experimental data using backpropagation algorithm to predict amplitude of work piece vibration. Prof. L. B. Raut1 , Prof. Matin Amin Shaikh2, (2014) developed a model to simulate the vibrational effects of rotating machine parts on the single point cutting tool and cutting force acting on single point cutting tool in turning.

3 Dataset Used

In the present work, the experimental data for predicting the tool vibration using turning process has been taken from the published paper [7]. Here experimental studies were performed on turning process & vibration is measured with the help of accelerometer. This present paper presents an

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experimental study to investigate the effects of cutting parameters like spindle speed, feed and depth of cut on surface finish on EN-8.

4 Fuzzy Subtractive Clustering Based Model Development

4.1 Basic Theory

Fuzzy systems, which is based on fuzzy logic [Zadeh], have attracted the growing attention and interest in different subjects because of the following two useful properties and capabilities: capability of approximating any complex nonlinear system and model determination through the input-output data (learning process). Fuzzy system is adaptive and relies on input-output data rather than on a classical method, so the resulting scheme is valuable, efficient and capable of reflecting changes in the tool vibration behavior in the machining process. Takagi–Sugeno–Kang (TSK) ([2], [3]) fuzzy system is a more general class of fuzzy systems which is used in this work. An automatic data-driven based method for generating the initial fuzzy rules is Chiu's subtractive clustering technique (SCT) [4], which is an extension of the grid-based mountain clustering method [5]. The main idea of the SCT is to obtain useful information by grouping data from a large dataset that represent a system behaviour. Each cluster center obtained by this technique represents a rule. Although the SCT is fast, robust and accurate, the user-specified parameter (the radius of influence of cluster center) in this method, strongly affects the number of rules generated. A large generally results in fewer rules, while a small can produce immoderate number of clusters.

4.2 Parameter Selection

In the present work ANFIS Network Structure model consisting of one input layer with eight input variables and an output layer consisting of effort as the output variable. This is shown in Fig.1 below.

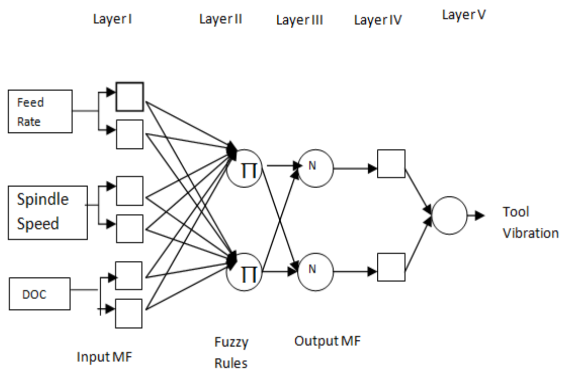

Fig. 1: Architecture for Fuzzy Subtractive Based Clustering Based model

ANFIS [11],[14] is a judicious integration of FIS and ANN, capable of learning, high-level thinking and reasoning and it combines the benefits of these two techniques into a single capsule. Identification of the rule base is the key of a FIS. The problems are (1) there are no standard methods for transforming human knowledge or experience into rule base; and (2) it is required to further tune the MFs to minimise the output error and to maximise the performance. Now to generate a FIS using ANFIS, it is significant to choose proper parameter, inclusive of the number of membership functions (MFs) for each individual antecedent variables. It is also important to select proper parameters for learning and refining process, including the initial step size (ss). In the present work the commonly used rule extraction method applied for FIS identification and refinement is subtractive clustering. MATLAB Fuzzy Logic Toolbox [4] has been used to simulate the ANFIS.

Here the initial parameters of the ANFIS are identified using the subtractive clustering method [8]. However, the parameters of the subtractive clustering algorithm still need to be specified. The clustering radius is very important parameter in the subtractive clustering algorithm and is optimally determined through a trial and error procedure. By varying the clustering radius r_a between 1 to 0.1 with 0.01 step size, the most appropriate parameters are got by reducing the root mean squared error obtained on a representative validation set. Clustering radius r_b is selected as 1.5 r_a. For other parameters default values are used in the subtractive clustering algorithm.

Gaussian membership functions are used for each fuzzy set in the fuzzy system. The number of membership functions and fuzzy rules required for a particular ANFIS is determined through the subtractive clustering algorithm. Gaussian membership function parameters are optimally determined using the hybrid learning algorithm. ANFIS training is done for 500 epochs.

Gaussian membership function has been used as the input membership function and linear membership function for the output function. Here separate set of input and output data has been used as input arguments. In MATLAB *genfis2* generates a Sugeno-type FIS structure using subtractive clustering. Since there is only one output, *genfis2* has been used to generate an initial FIS for ANFIS training. *genfis2* achieves this by extract a set of rules that models the data performance. The rule extraction method initially uses the *subclust* function to determine the number of rules and antecedent membership functions and then uses linear least squares estimation to determine each rule's consequent equations. This function generates a FIS system that contains a set of fuzzy rules to cover the feature space.

The parameters used in the model for training ANFIS are given in Table 1 and the rule extraction method used are given in Table 2. Table 3 summerizes the results of types and values of model parameters used for training ANFIS.

Table 1. Parameters used in all the models for training ANFIS

Rule extraction method used	Subtractive clustering
Input MF type	Gaussian membership ('gaussmf')
Input partitioning	variable
Output MF Type	Linear
Number of output MFs	one
Training algorithm	Hybrid learning
Training epoch number	500
Initial step size	0.01

Table 2. Rule extraction method used for training ANFIS

Rule Extraction Method	Type
And method	'prod'
Or method	'probor'
Defuzzy method	'wtever'
Implication method	'prod'
Aggregation method	'max'

Table 3. Values of parameters used for training ANFIS

No. of nodes	22
No. of linear parameters	8
No. of non-linear parameters	12
Total no. of parameters	20
No. of training data pairs	20
No. of testing data pairs	11
No. of fuzzy rules	2

5 Results and Discussions

ANFIS model having five input variables are trained and tested by ANFIS method and their performances compared and evaluated based on training and testing data. The best fit model structure is determined according to criteria of performance evaluation. The performances of the ANFIS model are shown in Fig. 2 & 3 and their RMSE values both for training and testing data are 90.60 and 92.08 respectively (Table 4 below).

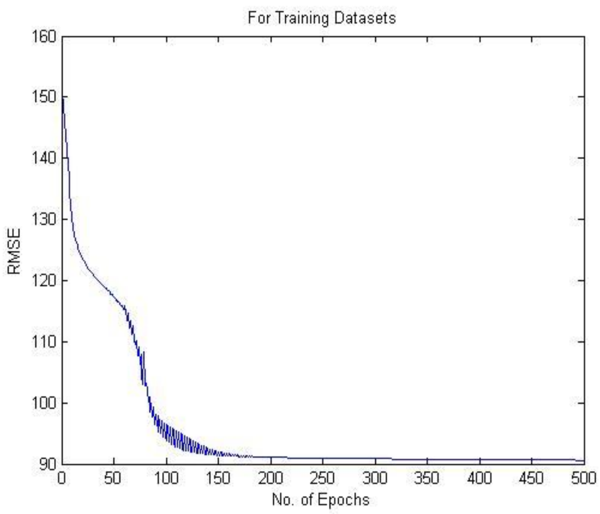

Fig. 2: Graphical representation of the model error for Training datasets

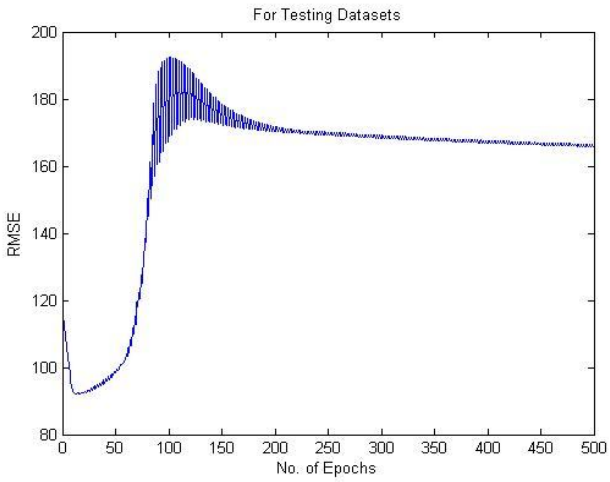

Fig. 3: Graphical representation of the modelerror for Testing datasets

Table 4. RMSE Values for Datasets

	Training Datasets	Testing Datasets	Total Datasets
RMSE	90.60	92.08	91.34

A comparative plot of both observed and predicted (ANFIS_Output) tool vibration values for training (Obs_Trg_Data) and testing (Obs_Tst_Data) data are summerised in Fig. 4 and Fig. 5 below.

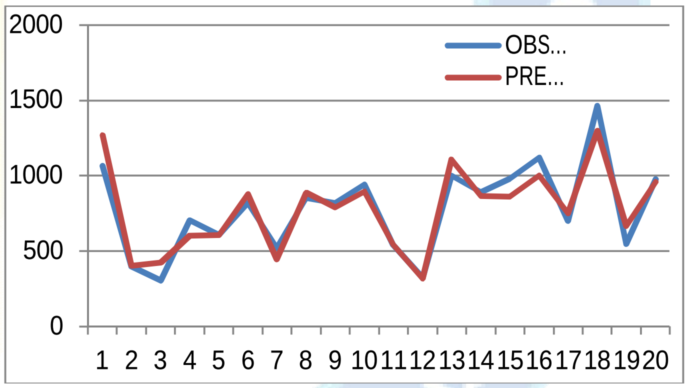

Fig. 4: Comparative plot of Predicted vs. Observed Tool Vibration values for training data

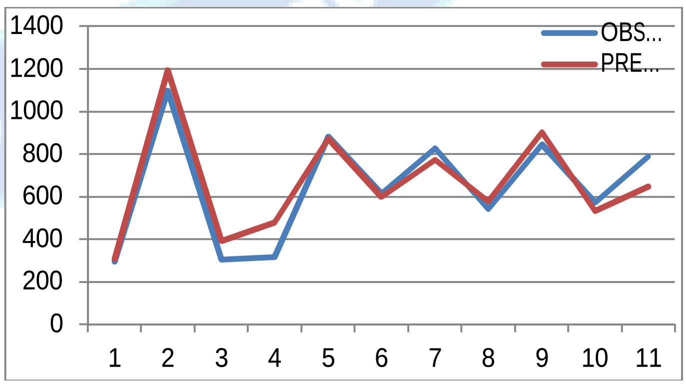

Fig. 5: Comparative Plot of Predicted vs. Observed Tool Vibration values for testing data

6 Conclusion

In the present chapter, applicability and capability of Fuzzy Subtractive Clustering based approach to develop a prediction model prior to the implementation of the actual machining has been investigated. Fuzzy models have been shown to be very effective techniques for the modelling of nonlinear, uncertain and complex systems. Subtractive Clustering is a fast one-pass algorithm for estimating the number of clusters and determining the cluster centres in a set of data . The studies has been carried out using MATLAB simulation environment. In all three input variable were used, consisting of Spindle Speed *S*, Feed rate *F*, and Depth of Cut *DOC*.and one output variable as tool vibration. From the analysis of the above results, given under heading Results and Discussions, it is seen that the tool vibration prediction model developed using Fuzzy Subtractive Clustering based approachin ANFIS technique has been able to perform well. This can be concluded from the analysis of the results given in Figures 3 and 4. The performances of the ANFIS model in terms of RMSE values both for training and testing data are 90.60, corresponding to epoch no. 500 and 92.08, corresponding to epoch no. 6 respectively.

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