Cutting Velocity and Chip Load Dependent Force Prediction in High Speed Micromilling of Ti6Al4V Using Deep Learning Method

WCMNM 2021

S. Gururaja[1], Kundan K. Singh[2]

[1, 2] *Birla Institute of Technology & Science Pilani, Hyderabad Campus, Hyderabad-500078, India*

Abstract

Micromilling process uses the micro cutting tool whose diameter can be as low as 20 µm. The low diameter of the cutting tool makes it highly susceptible to chatter during machining attributed to low flexural rigidity of cutting tool. High speed strategy has been adopted to reduce the chip load which reduces the cutting force and hence chatter occurrence is reduced. High speed micromilling process has to be carried out with stable process parameters to produce the surface with desired quality. The stable process parameters are generated using machining process modeling. However, the accuracy of generated stable process parameters depends on the accuracy of predicted force. High speed machining changes the cutting forces when machining is carried out at different cutting velocities especially for the machining of low thermal diffusivity based material like Ti-alloy. Consequently, a velocity and chip load dependent cutting coefficients has been found to be a most accurate way of predicting the cutting forces during high speed micromilling process. The determination of velocity and chip load dependent cutting force requires the nonlinear fitment between cutting velocity, chip load and cutting coefficients. The accuracy of fitment for nonlinear regression depends on the velocity and chip load selected for the cutting coefficients fitment. The difficulty in carrying out the machining at all the cutting velocities further complicates the prediction of cutting forces. Alternatively, deep leaning method proposed in the present work based on the back propagation neural network uses weight update technique to arrive at most accurate nonlinear relationship of cutting coefficients with the cutting velocity and chip load. The three hidden layers has been found to be giving least error between the predicted and observed value of the cutting coefficients. The number of iteration has also been optimized in the present work. A comparison has also been carried between the force predicted with cutting coefficients obtained using nonlinear regression method and deep learning method. The predicted cutting force using deep learning method in X-direction and Y-direction gives an error of 13% and 4% at 100000 rpm with respect to experimental cutting forces. The predicted waveform has also been found to closer to the nature of cutting force obtained experimentally.

Keywords: Micromilling, high speed machining, cutting coefficient, cutting force, machine learning, Titanium

1. Introduction

The demand for micromilling process is increasing day by day to produce the products with high aspect ratio features. Different industries which use the products manufactured by micromilling process are biomedical, aerospace, avionics, automobile, microelectronics and energy-producing industries. The selection of stable process parameters is of utmost importance to eliminate the chatter during micromilling process. The selection of stable process is obtained through generated stability lobe diagram which gives the combination of stable spindle speed and depth of cut. However, the accuracy of stability lobe diagram depends on the accuracy of cutting coefficients used for the cutting force modelling. The use of feed comparable to edge radius of cutting tool induces the size effect in micromilling process [1]. The high speed machining excites the high frequency modes of micro cutting tool and also changes the cutting forces especially for machining of low thermal diffusivity material like Ti and Ni-alloy. Consequently, the cutting coefficients of mechanistic cutting force modelling approach for force prediction in high speed machining cannot be assumed independent of process parameters like cutting velocity and chip load. Jin and Altintas et al. [1] has obtained the cutting coefficient as a nonlinear function of chip load by fitting the curve using least square error minimization approach. Afazov et al. [2] estimated the cutting force as nonlinear function of cutting velocity and chip load.

The use of high speed more than 100000 rpm requires the defining of the cutting velocity zone in very precise way to achieve the goodness of fitness more than 85% to predict the cutting coefficients as a nonlinear function of cutting velocity and chip load. The fitment of cutting coefficient as a function of cutting velocity and chip load for all cutting velocity without defining the cutting velocity range reduced the goodness of fitment [3]. Liu and Guo [4] proposed a hybrid approach by integrating the data driven machine learning approach and process mechanics to predict the specific cutting energy in milling. They used the tree-based gradient boosting method and concluded that the machine learning approach improved the accuracy of predicted specific cutting energy. Artificial neural network can predict the cutting forces during helical end-milling of carbon fibre reinforces polymers as proposed by Kalla et al. [5]. Specific cutting energies were taken as continuous function of fiber orientation and chip thickness by Kalla et al. [5] for cutting force prediction and concluded that artificial neural network has capabilities to capture the high nonlinearities nature of specific cutting energies during helical end-milling of composite materials [5]. Wu et al. [6] have used feed forward back propagation artificial neural network to predict the cutting tool life during milling of stainless steel. A single layer hidden layer with eight neurons was found to be optimum for cutting tool life prediction. Cherukuri et al. [7] uses the artificial neural network to generate the stability lobe diagram for data obtained from the analytical modelling of turning process. They concluded that the accuracy of the prediction depends on the number of hidden layers and the neurons selected per hidden layer. Radhakrishnan and Nandan [8] predicted the cutting force in milling using artificial neural network and concluded that neural network method is more accurate than regression method. Briceno et al. [9]

compared two supervised network for force prediction during milling process and concluded that radial biased network predicts cutting forces more accurately than back-propagation networks. An inclusion of uncertainty in cutting forces modeling can predict the cutting forces with good accuracy but prediction accuracy depends on the accurate capturing of standard deviation in cutting coefficients obtained experimentally [10].

Most of the work carried out for the prediction of cutting forces by using artificial neural network is limited to low spindle speed (<60000 rpm). The selection of single hidden layer with few neurons was found to be predicting the cutting force with good accuracy. However, there is requirement to study the number for hidden layers and required neuron for hidden layers for prediction of cutting forces in high speed micromachining process. Hence, in the present work a neural network architecture has been optimised for accurate prediction of cutting force as a nonlinear function of machining parameters.

2. Methodologies

In the present work cutting force modelling has been carried out using the mechanistic approach. Different experiments have been carried to determine the tangential and radial cutting coefficients. The estimated cutting coefficients have been curve fitted by minimising the least square error to get the nonlinear relationship of cutting coefficients with cutting velocities and chip load. The nonlinear relation of cutting coefficients with cutting velocity and chip load has also been obtained using Artificial Neural Network (ANN) based deep learning method. Finally, the cutting force has been predicted with the predicted cutting coefficients at different cutting velocities and chip loads. The predicted cutting forces has also been compared with the experimentally obtained cutting forces. The methodologies adopted in the present work is shown in Fig. 1.

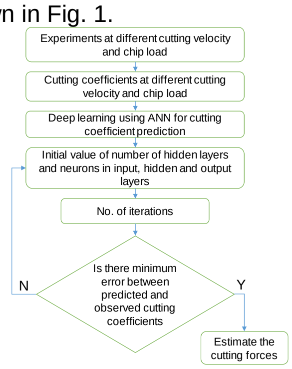


Fig. 1 Methodologies for the force prediction

3. Cutting Force Modelling

A mechanistic approach has been used for the cutting force modelling. The tangential and radial cutting forces on a flute *j* of the cutting tool are directly proportional to cutting area, given as:

$$F_{t,j} = K_{tc} a h(\emptyset_j) \tag{1}$$

$$F_{r,j} = K_{rc} a h(\emptyset_j) \text{ and } F_{r,j} = K_r F_{t,j} \tag{2}$$

where K_{tc} and K_{rc} are the tangential and radial cutting coefficients, respectively. $h(\emptyset_j)$ is the instantaneous chip thickness and *a* being the depth of cut. K_r is the ratio of radial cutting coefficient to tangential cutting coefficient. The overall cutting forces for all N flutes involved in cutting can be obtained as:

$$F_T = \sum_{j=1}^{N} F_{t,j} \quad \text{and} \quad F_R = \sum_{j=1}^{N} F_{r,j} \tag{3}$$

The tangential and radial cutting forces for a flute *j* at any instantaneous position $\emptyset_j$ are obtained from coordinate transformation of the measured X and Y-direction cutting forces (Fig. 3(b)) using below equations.

$$F_{x,j} = -F_{t,j} cos\emptyset_j - F_{r,j} sin\emptyset_j \tag{4}$$

$$F_{y,j} = F_{t,j} sin\emptyset_j - F_{r,j} cos\emptyset_j \tag{5}$$

The cutting coefficients have been assumed as a nonlinear function of cutting velocity (V) and chip load, given as:

$$K_{tc} = CV^{\alpha}\bar{h}^{\beta} \text{ and } K_{rc} = DV^{\gamma}\bar{h}^{\delta} \tag{6}$$

where C and D are the constant. α, β, γ and δ are the exponents which depends on the machining process parameters, material and geometry of workpiece and cutting tool. $\bar{h}$ is the average chip load which is obtained as;

$$\bar{h} = \frac{2}{\pi} f_t \tag{7}$$

A nonlinear regression fitment has been used using least square minimization equation given as below to obtain the constants and exponents of Eq. (6).

$$error\ (e) = \sum_{i=1}^{n} \sum_{p=1}^{m} (F_{expi,p} - F_{theo})^2 \tag{8}$$

where n is the numbers of run at each feed and velocity and m is the number of samples selected for the fitment. F_{exp} and F_{theo} are the root mean square value of experimental and fitted force, respectively.

4. Deep Learning Method

Artificial neural network (ANN) method of deep learning uses a different hidden layers to establish a relationship between the output and the input. The weight which is multiplied to each neurons of a layers before it can be fed to other layers has to be optimised to obtain the accurate relationship between the output and the input. The use of feedback loop is necessary to optimise the weight and hence, a feedforward back propagation neural network has been used in the present work.

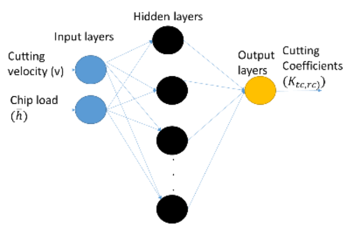


Fig. 2 ANN modelling

The selection of activation functions for input and the hidden layers has been carried out by minimising the error between the predicted and the observed cutting coefficients. The minimisation of error is obtained by minimising the cost function given as:

$$J(w) = \frac{1}{2} \sum_i (K_{tc}^{(i)} - \Phi(z^{(i)}))^2 \tag{9}$$

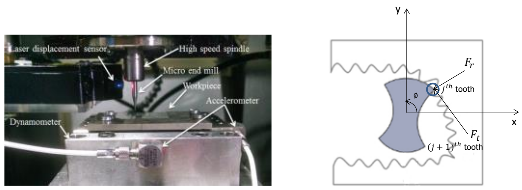
where w is the weight and $z^{(i)}$ is the input to the layers *i* obtained from the activation function. The rectilinear (ReLU) activation has been found to be following the trend of the cutting coefficients and is given as:

$$\Phi(z) = \max(0, z) \tag{10}$$

where z is the net input to a layer. The number of neurons in the hidden layers and the number of hidden layers have to be optimised to minimise the error between the observed and the predicted cutting coefficients. The number of iteration (Epoch) for weight optimization has also be varied to select the optimum epoch for minimizing the prediction error. The optimum epoch is highly desirable as there can be increase in the computational time due to large epoch.

5. Experiments

The experiments have been carried out at developed high speed micromachining center in machine tools lab of IIT Bombay. The spindle of three axes high speed micromachining can rotate up-to 140000 rpm with maximum torque of 4.3 N-cm. The stacked X and Y- axes linear stages are driven by brushless DC servo motor with accuracy of ±1 µm and resolution of 0.5 µm. The Z-axis is equipped with counter balancing pneumatic cylinder for providing the depth of cut. The Z-axis is driven by brushless DC servo motor with accuracy of ±0.3 µm and resolution of 0.5 nm. The experimental set-up is shown in Fig. 3(a).



(a) (b)

Fig. 3(a) Experimental set-up; (b) Micromilling process modeling

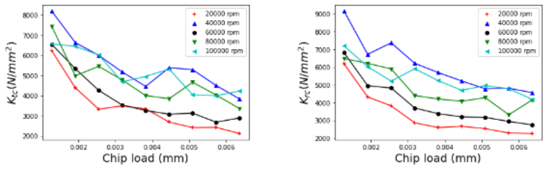
All the experiments have been carried out with two fluted uncoated tungsten carbide micro-end mill of diameter 500 µm without any lubrication. Different slots have been machined on Ti6Al4V workpiece having thickness of 3 mm. The machining has been carried out at spindle speed varying from 20000 to 100000 rpm at an interval of 20000 rpm. The feed rate used for machining has been varied from 2 µm/flute to 10 µm/flue at an interval of 1 µm/flute. Depth of cut of 30 µm is kept constant for all the experiments. X-and Y-direction cutting forces have been measured using Kistler dynamometer (Model:9256C1) and both tangential and radial cutting coefficients have been obtained from the tangential and radial cutting forces. 80% data has been used for training the ANN and 20% data has been used for testing of the ANN model. The testing conditions for ANN modelling is given in table 1.

Table 1: Testing conditions for ANN

Condition no.	Feed rate (µm/flute)	Cutting Velocity (mm/sec)
0	2	523.34
1	5	523.34
2	2	1046.67
3	3	1570
4	5	1570
5	2	2616.67
6	5	2616.67
7	8	2616.67
8	10	2616.67

6. Results & Discussion

First the tangential and radial forces are obtained through the coordinate transformation of measured X and Y-direction cutting forces. The tangential and radial cutting coefficients are obtained from the tangential and radial forces using Eq. 1 & 2. The tangential and radial cutting coefficients are found to increasing with a decrease in chip load (Fig. 4(a) and (b)). The increase in cutting coefficients is attributed to increase in specific cutting energy at low chip load and hence shows the phenomenon of size effect in micromilling process.



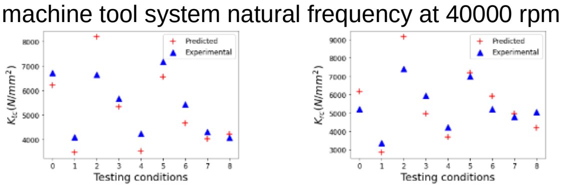
(a) (b)

Fig. 4 (a)Tangential and (b) radial cutting coefficients at different cutting velocities and chip loads

A machining process like macro milling process induces a thermal softening in material which reduces the cutting forces and maintains the uniform cutting coefficients at higher velocity. However, during high speed micromilling process; there is increase in cutting coefficients with the increase in cutting velocity (Fig. 4). The increase in cutting coefficients with velocity is because of the strain hardening owing to low thermal diffusivity of the Ti6Al4V.

6.1 Cutting Coefficients Prediction

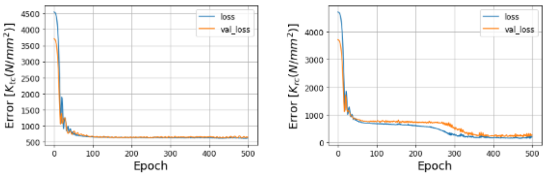
The experimentally measured cutting coefficients has been trained with the ANN method of deep learning. The cutting coefficients were trained as a nonlinear function of cutting velocity and chip load with different hidden layers. Two input layers consists of cutting velocity vector and chip load vector has been used for training along with tangential and radial cutting coefficients as the output layers. The hidden layers have been varied from one to five with different neurons for minimising the predicted cutting coefficients. Three hidden layers with five hundred neurons has been found to be giving the minimum error for the predicted cutting coefficient as shown in Fig. 5. The training of the neural network has been carried out with both sigmoid and ReLu activation function. The activation function ReLu is found to be giving less error than Sigmoid. The error at different testing conditions (table 1) with three hidden layers is found to be lying within 20% for tangential and radial cutting coefficients (Fig. 5(a)& (b)). The large prediction error is observed at condition 2 (Fig. 5) i.e. at velocity 1046.67 mm/sec (40000 rpm) attributed to machine tool system natural frequency at 40000 rpm.



(a) (b)

Fig. 5 Testing data prediction with ANN model

The selection of number of iteration (Epoch) is critical steps for minimising the prediction error. Note that increasing the epoch will increase the computational time and hence training the cutting coefficients with different epochs has been carried out. Figure 6(a) and 6(b) shows the error with increasing epoch for training of tangential and radial cutting coefficients. The optimum epoch has been selected as 400 for prediction of cutting forces.

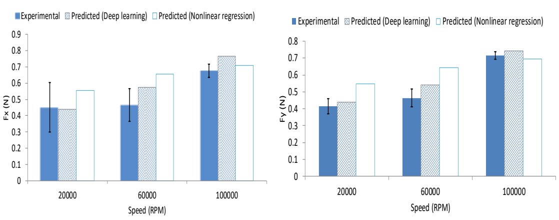


(a) (b)

Fig. 6 Error in tested data at different epoch (a) Tangential cutting coefficient (b) radial cutting coefficients

6.2 Cutting Force Prediction

The cutting forces have been predicted using the cutting coefficients obtained from the training of ANN model. The predicted cutting forces have also been compared with the cutting force predicted with nonlinear regression fitment of velocity and chip load with cutting coefficients. The prediction error at 20000 rpm, 8 µm/flute feed and 30 µm depth of cut compared to experimentally measured cutting force is 2.4% and 5.1% for X-direction and Y-direction cutting forces, respectively with ANN trained model while the predicted error is 23.3% and 33.7% for X-direction and Y-direction cutting forces, respectively with nonlinear regression based model (Fig. 7(a) & (b)). The prediction error for X-direction cutting force at 60000 rpm, 8 µm/flute feed and 30 µm depth of cut is reduced to 16% with ANN model compared to 38.8% error achieved with nonlinear based regression model. However, the prediction error at 100000 rpm, 8 µm/flute feed and 30 µm depth of cut in Y-direction cutting force is found to be 4% with ANN model while the error is 2.7% with nonlinear regression based model as shown in Fig. 7(b).



(a) (b)

Fig. 7. Cutting force prediction at different spindle speed, 8 µm feed rate and 30 µm depth of cut (a) F_X(b) F_Y

7. Conclusions

In the present work, deep learning based ANN has been used to predict the velocity and chip load dependent cutting coefficients. Furthermore, cutting forces have been predicted using the estimated cutting coefficients from the training of ANN model at different machining conditions. The cutting force has also been predicting using the nonlinear regression based fitment of velocity and chip load with cutting coefficients. Finally, predicted cutting forces have been compared with the measured cutting forces. Following conclusions can be made from the present work:

- Three hidden layers with ReLU activation function have been found to be training the cutting coefficients with good accuracy.
- Optimum no. of iterations (Epoch) was found to be 400 for minimum error of prediction of cutting coefficients.
- The error in predicted X-direction cutting forces was 38.8% with nonlinear regression based modelling of cutting coefficients while error achieved with ANN model is 16% at 60000 rpm, 8 µm/flute feed and 30 µm depth of cut.
- Similarly, the error in predicted Y-direction cutting forces was 2.72% with nonlinear regression based modelling of cutting coefficients while error achieved with ANN model is 4% at 100000 rpm, 8 µm/flute feed and 30 µm depth of cut.
- The cutting force predicted with ANN model based cutting coefficient predicts cutting forces more accurately than nonlinear regression based model.

Acknowledgements

Authors gratefully acknowledge the support of BITS-Pilani-Research Initiation Grant (BITS/GAD/RIG/2019/H0698).

References

[1] Jin, Xiaoliang, and Yusuf Altintas. "Chatter stability model of micro-milling with process damping." J. Manuf. Sci. Eng., 2013, 135.3.

[2] Afazov, S. M., et al. "Chatter modelling in micro-milling by considering process nonlinearities." Int. J. Mach. Tools Manuf., 2012, 56: 28-38.

[3] Singh, Kundan K., V. Kartik, and Ramesh Singh. "Modeling of dynamic instability via segmented cutting coefficients and chatter onset detection in high-speed micromilling of Ti6Al4V." J. Manuf. Sci. Eng., 2017, 139.5.

[4] Liu, Ziye, and Yuebin Guo. "A hybrid approach to integrate machine learning and process mechanics for the prediction of specific cutting energy." CIRP Ann., 2018, 67.1: 57-60.

[5] Kalla, Devi et al., "Prediction of cutting forces in helical end milling fiber reinforced polymers." Int. J. Mach. Tools Manuf., 2010, 50.10: 882-891.

[6] Wu, Dazhong, et al. "A comparative study on machine learning algorithms for smart manufacturing: tool wear prediction using random forests." J. Manuf. Sci. Eng., 2017, 139.7.

[7] Cherukuri, Harish, et al. "Machining chatter prediction using a data learning model." J. manuf. Mater, 2019, 3.2: 45.

[8] Radhakrishnan, T., and Uday Nandan. "Milling force prediction using regression and neural networks." J. Intell. Manuf., 2005, 16.1: 93-102.

[9] Briceno, Jorge F., et al., "Selecting an artificial neural network for efficient modeling and accurate simulation of the milling process." Int. J. Mach. Tools Manuf., 2002, 42.6: 663-674.

[10] Singh, Kundan K., and Ramesh Singh. "Process Mechanics Based Uncertainty Modeling for Cutting Force Prediction in High Speed Micromilling of Ti6Al4V." Procedia Manuf., 2020, 48: 273-282.