ANNALS of Faculty Engineering Hunedoara – International Journal of Engineering
ISSN: 1584 - 2673

A COUPLED ARTIFICIAL NEURAL NETWORK AND RESPONSE SURFACE METHODOLOGY MODEL FOR THE PREDICTION OF AVERAGE SURFACE ROUGHNESS IN END MILLING OF PREHEATED Ti6Al4V ALLOY

Md. Anayet U. PATWARI[1,2], A.K.M. Nurul AMIN[2], Turnad L. GINTA[2]

[1] Mechanical and Chemical Engineering Department, IUT, Dhaka, BANGLADESH
[2]Department of Manufacturing and Materials Engineering, IIUM, MALAYSIA

ABSTRACT:
In this work, a surface roughness model was developed by coupling artificial neural network (ANN) with response surface methodology for the investigation and prediction of the relationship between cutting parameters, work-piece preheated temperature and surface roughness during high speed end milling of Ti6Al4V. For this interpretation, advantages of statistical experimental design technique, experimental measurements, artificial neural network were exploited in an integrated manner. Cutting experiments are designed based on small centre composite design technique to develop a response surface mode. The input parameters of the model are the cutting parameters: cutting speed, feed, and work-piece preheated temperature. The output parameter of the model was surface roughness. This response surface model was coupled with artificial neural network for the surface roughness model. A predictive model for surface roughness was created using a feed-forward back-propagation neural network exploiting experimental data. The network was trained with pairs of inputs/outputs datasets generated when end milling Ti6Al4V alloy with WC-Co insert. The model can be used for the analysis and prediction for the complex relationship between cutting conditions and the surface roughness in metal-cutting operations for efficient and economic production.
Key words: Surface Roughness, Response surface methodology, preheating, Artificial Neural Network

1. INTRODUCTION

Surface roughness is one of the important factors for evaluating work-piece quality during the machining process because the quality of surface roughness affects the functional characteristics of the work-piece such as compatibility, fatigue resistance and surface friction. Surface roughness is expressed as the irregularities of material resulted from various machining operations. In quantifying surface roughness, average surface roughness definition, which is often represented with Ra symbol, is commonly used. In workshop practice, cutting parameters are selected from machining databases or specialized handbooks, but the range given in these sources are actually starting values, and are not the optimal values. To ensure the quality of machining products, and to reduce the machining costs and increase the machining effectiveness, it is very important to select the machining parameters. A machinability model may be defined as a functional relationship between the input of independent cutting variables (speed, feed, depth of cut) and the output known as responses (tool life, surface roughness, cutting force, etc) of a machining process [1].

The factors that affect the surface roughness during the end milling process include tool geometry, feed rate, depth of cut and cutting speed. Several researchers have studied the end milling process in the recent years. The researchers also used response surface methodology (RSM) to explore the effect of cutting parameters as cutting speed, feed rate and axial depth of cut. Alauddin et al. [2] developed a mathematical model to predict the surface roughness of steel after end milling. The prediction model was expressed via cutting speed, feed rate and depth of cut. Fuh and Hwang [3] used RSM to construct a model that can predict the milling force in end milling operations. Sundaram and Lambert [4 -5] considered six variables i.e speed, feed, depth of cut, time of cut, nose radius and type of tool to monitor surface roughness. But it is very important to investigate the effect of work-piece preheated temperature on the surface roughness along with the other major cutting parameters effects considering nonlinearity and time variant. Compared to traditional computing methods, the artificial neural networks (ANNs) are robust and global. ANNs have the characteristics of universal approximation, parallel distributed processing, hardware implementation, learning and adaptation, and multivariable systems [6]. ANNs have been extensively applied in modeling many metal-cutting operations such as turning, milling, and drilling [7-9]. However, this study was inspired by the very limited work on the application of ANNs in modeling the relationship between cutting conditions, work-piece preheating temperature and the surface roughness during high-speed end milling of Titanium alloy.

2. EXPERIMENTAL SETUP

Cutting tests was conducted mainly on Vertical Machining Center (VMC ZPS, Model: 1060) powered by a 30 KW motor with a maximum spindle speed of 8000 rpm. Figure 1 show the preheating set up used in vertical machining centre for preheated machining.

Surface measuring instrument (SURFTEST) SV-500 was used to measure the surface roughness (R_a) are shown in Figure 2.

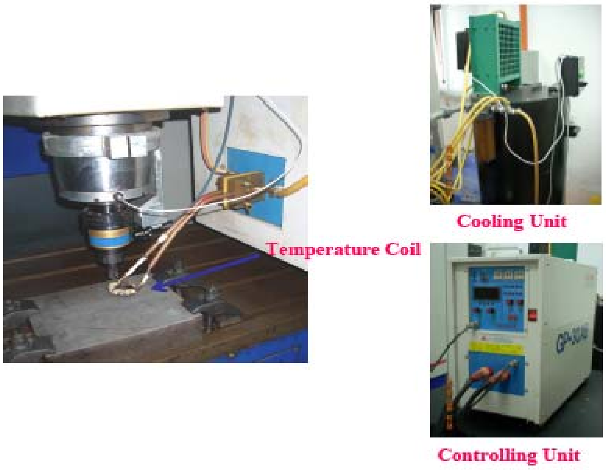


Figure 1. Experimental setup of the preheated machining

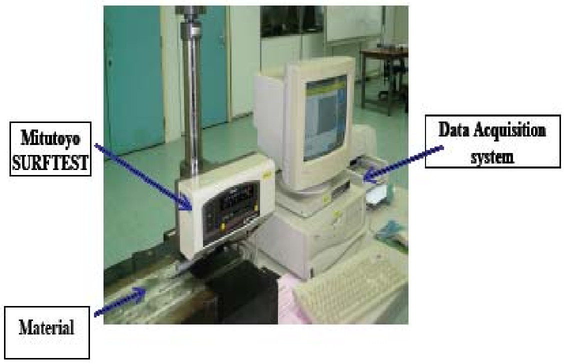


Figure 2. Surface Roughness Measurement Apparatus

2.1 Work-piece materials Used

The work-piece material used in all experiments was titanium based alloy Ti-6Al-4V with ($\alpha + \beta$) phases. The microstructure of this work-piece is presented in Figure 3. The microstructure consists of both coaxial and columnar alpha phase and inter-granular beta phase. The mechanical and physical properties of Titanium alloy are shown in Table 1.

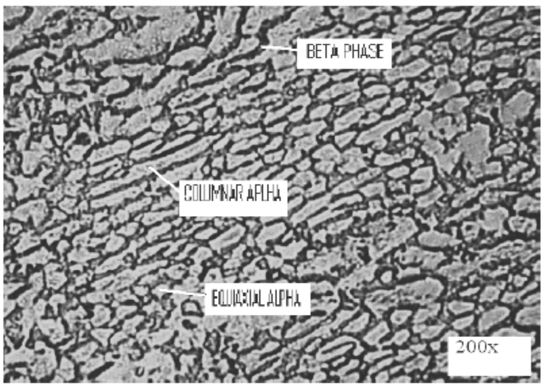


Figure 3 Microstructure of Ti-6Al-4V with equi-axed and columnar alpha grains (light) with inter-granular beta phase (dark); Etchant: 10% HF, 5% HNO3, 85% H2O

Table 1. The mechanical and physical properties of Titanium Alloy Ti-6Al-4V

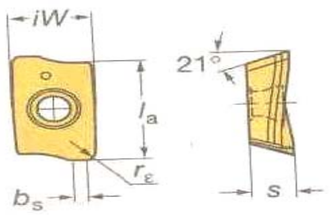
Properties	
Ultimate tensile strength	897 MPa
Elongation	10 %
Elastic Modulus	114 GPa
Hardness	320 HV
Density	4.42 g/cm^3
Melting point	1649 °C ±15 °C

2.2 Tool (inserts)-SANDVIK grade PM1030

Insert code: R390- 11 T3 08E- PL, Insert coating material: carbide, Working condition: light to medium milling. Insert geometries are given below in Table 2.

Table 2. Cutting tool material and geometry data

Tool material	Dimension(mm)					Number of cutting edge
	l_a	iW	s	b_s	r_ε	
Uncoated WC-Co insert (R390-11 T3 08E-NL H13A)	11	6.8	3.59	1.5	0.8	2



3. DEVELOPMENT OF QUADRATIC RESPONSE SURFACE MODEL

The design of experiment has a major effect on the total number of required experiments. A well planed experimental design can reduce the number of experiments quite substantially. For this reason, a small CCD with 2 blocks and 4 replication of centre point in each factorial block was selected to design the experiments. This ultimately resulted in 14 experiments, with 4 other factorial points and 6 axial points. This experimental design provides 5 levels for each of the independent variables. The cutting variables with different cutting conditions are given below:

- x_1, Cutting speed, V (m/min): 30.6, 39, 70, 126, 160.6
- x_2, Feed, f_z (mm/tooth): 0.05, 0.06, 0.088, 0.128, 0.15
- x_3, Preheating temperature (°C): 315°C, 350°C, 450°C, 580°C, 650°C

From the experimental results, empirical equation (1) was developed to predict the surface roughness and the significant parameters involved using response surface methodology. From the analysis of variance (ANOVA) and fit and summary test results it has been observed that quadratic model is more significant for the prediction of surface roughness. The second-order model (1) for surface roughness in its transformation state with the transforming equation of each individual variable is:

$$\begin{aligned}\hat{y} = -1.55 - 0.11x_1 + 0.25x_2 + 0.056x_3 - 0.03x_2^2 + 0.085x_3^2 \\ + 0.052x_1x_2 + 0.16x_1x_3 - 0.068x_2x_3\end{aligned} \quad (1)$$

$$x_1 = \frac{\ln V - \ln 70}{\ln 126 - \ln 70};\quad x_2 = \frac{\ln f_z - \ln 0.088}{\ln 0.128 - \ln 0.088};\quad x_3 = \frac{\ln \theta - \ln 450}{\ln 580 - \ln 450}$$

4. ARTIFICIAL NEURAL NETWORK DESIGN

Supervised neural network was developed in this study for the prediction of surface roughness in end milling process and its performance was tested. The network was back propagation neural network (BP) with log-sigmoid transfer function in hidden layers and linear transfer functions in the output layers. The neural network architecture used in this study is shown in Figure 4. It was designed using MATLAB Neural Network Toolbox [10]. The network consists of input layer, two hidden and one output layers. Hidden layers have 15 neurons each, whereas input and output layers have three and one neurons, respectively. Neurons in the input layers correspond to cutting speed (V), feed (f_z) and preheated temperature (θ). Output layer corresponds to surface roughness (R_a).The developed RSM model based on design of experiment for the prediction of surface roughness are coupled with the ANN model for the data generation. Since only a limited number of experiments are representative of the feasible parameter space, it is important that the ANN realizes each set fully [11]. All the data sets are taken with in the ranges of -1 to +1 for feasible parameter space.

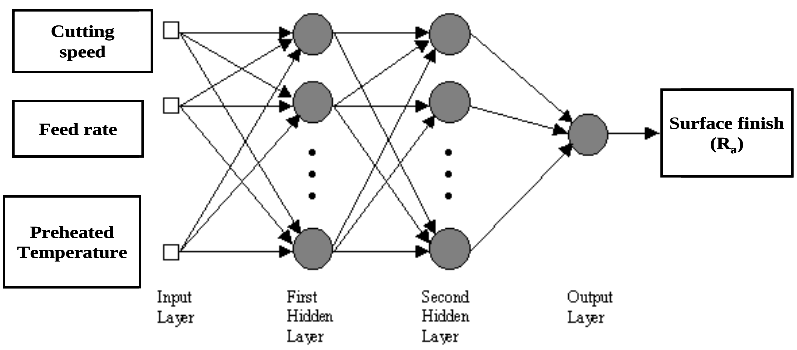


Figure 4. ANN architecture designed for the prediction of surface roughness

4.1. ANN Model Development: Training the ANN model

Before the ANN can be trained and mapping learned, the experimental data was processed into patterns. So Training, validation and testing pattern vector had been formed before the ANN was trained. Each pattern was formed with an input condition vector,

$$\text{Input}_i = \begin{bmatrix}\text{CuttingSpeed} \\ \text{FeedRate} \\ \text{Preheated\_Temperature}\end{bmatrix}$$

And the corresponding target vector,

$$\text{Target}_i = [\text{SurfaceRoughness}]$$

The back-propagation learning algorithm was used for training the network. For training the network, the TRAINLM function of MATLAB was utilized which works on back propagation algorithm [11]. These algorithms iteratively adjust the weights to reduce the error between the experimental and predicted outputs of the network. The 14 experimental results and further 56 generated results from the RSM model were used for this training, prediction and validation of the model. TRAINLM updates weights so as to minimize the mean square error (MSE) between the network prediction and training data set. When the network training was successfully finished, the network was tested with additional test data.

5. SIMULATED RESULTS OF DEVELOPED ANN MODEL

The developed ANN model can predict surface roughness based on the cutting conditions, with a high degree of accuracy within the scope of cutting conditions investigated in the study. Hence, the influence of the cutting conditions on the surface roughness can be studied using the model.

5.1 Effect of Cutting parameters on Surface Roughness

Cutting speed is one of the most important cutting parameters in metal-cutting operations and it is very influential on surface roughness as shown in Figure 5. At a very low cutting speed it has an adverse effect on surface finish, but after a certain speed the surface finish improves with increase of cutting speed.

Feed plays a dominant role on surface finish as shown in the Figure 6. At very low feed it has a sharp adverse effect on surface roughness until a certain feed value. After that surface finish remains somewhat almost constant with feed. But at even higher feed it again affects surface roughness.

Preheated temperature has a small effect on surface roughness as shown in Figure 7. Initially at a very low preheated temperature, it does not have any significant effect on surface roughness. But after certain increases in preheated temperature the surface roughness increases and then again with the further increase the surface roughness shows little improvement.

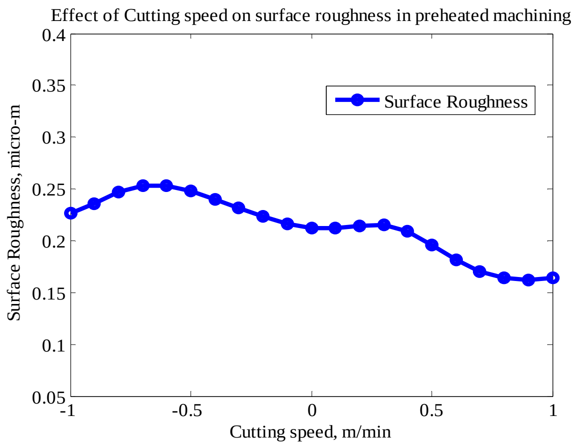


Figure 5. Cutting speed effect on average surface roughness in preheated machining

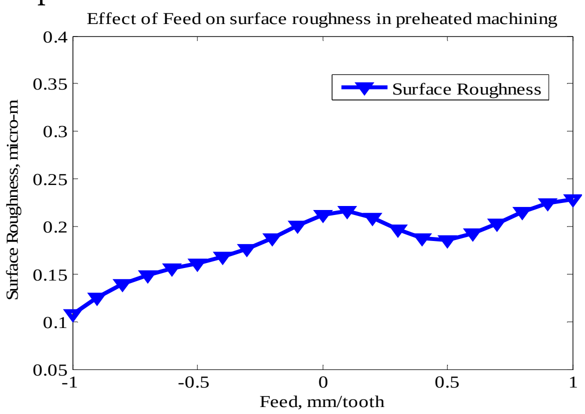


Figure 6. Effect of Feed on average surface roughness

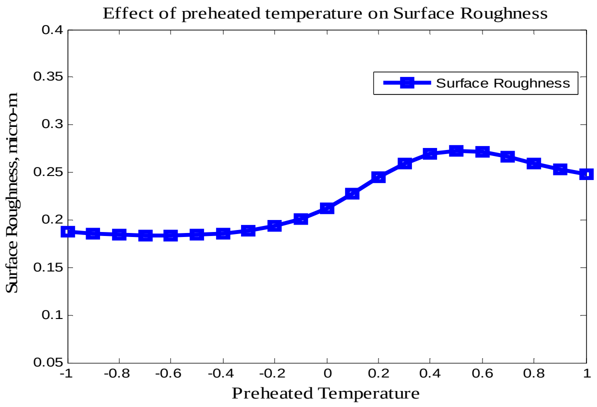


Figure7. Simulation of average surface roughness at varying preheated temperature

6. CONCLUSIONS

The multilayer network with two hidden layers having 15 'log-sigmoid' neurons trained with TRAINLM algorithm was found to be the optimum network for the model developed in this study. From the model it has been observed that increase in feed and preheated temperature increase the surface roughness whereas increase of cutting speed shows improvement of surface roughness. This developed ANN model can now be used to analysis and predict the surface roughness for different cutting conditions while end milling of Ti6Al4V alloy in preheated machining.

REFERENCES

[1] *I.A Choudhury, M.A. El-Baradie, 'Machinability assessment of Inconel 718 by factorial design of experiment coupled with response surface methodology', Journal of Material Processing and Technology 95, pp. 30 – 39, 1999.*

[2] *M. Alauddin, M.A. El Baradie, M.S.J Hashmi, Computer-aided analysis of a surface-roughness model for end milling, J. Mater. Process. Technol. 55(1995) 123-127.*

[3] *K.H. Fuh, R.M. Hwang, Predicted milling force model for high-speed end milling operation, Int. J. Mach. Tools Manuf. 37 (7) (1997) 969-979.*

[4] *R.M. Sundaram and B.K. Lambert , Mathematical models to predict surface finish in fine turning of steel, Part I. International Journal of Production Research 19 (1981), pp. 547–556*

[5] *R.M. Sundaram and B.K. Lambert, Mathematical models to predict surface finish in fine turning of steel, Part II. International Journal of Production Research 19 (1981), pp. 557–564*

[6] *D.E. Dimla Sr., Application of perceptron neural networks to tool-state classification in a metal-turning operation, Eng. Appl. Artif. Intell. 12 (1999) 471-477.*

[7] *H. Z. Li, H. Zeng, X. Q. Chen, An experimental study of tool wear and cutting force variation in the end milling of Inconel 718 with coated carbide inserts,2006, Journal of Materials Processing Technology, 180 (2006) 296-304.*

[8] *Sandvik Coromant, MetalCutting Technical guide, AB Sandvik Coromant 2005.10, printed in Sweden by Elanders.*

[9] *L.H. Tsoukalas, R.E. Uhrig, Fuzzy and Neural Approaches in Engineering, 1997, pp. 191-288.*

[10] *MathWorks Incorporation (2007) MATLAB user manual version 7.4.0 (R2007a). MathWorks Incorporation, Natick, MA.*

[11] *L.H. Tsoukalas, R.E. Uhrig, Fuzzy and Neural Approaches in Engineering, 1997, pp. 191-288.*

ANNALS OF FACULTY ENGINEERING HUNEDOARA
– INTERNATIONAL JOURNAL OF ENGINEERING