Development of an Artificial Neural Network Algorithm for Predicting the Surface Roughness in End Milling of Inconel 718 Alloy

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Abstract

In this work, an artificial neural network (ANN) model was developed for the investigation and prediction of the relationship between cutting parameters and surface roughness during high speed end milling of nickel-based Inconel 718 alloy. The input parameters of the ANN model are the cutting parameters: cutting speed, feed, and axial depth of cut. The output parameter of the model was surface roughness. 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 statistical three-level full factorial experimental design technique. 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 Inconel 718 alloy with single-layer PVD TiAlN coated carbide inserts. A very good predicting performance of the neural network, in terms of concurrence with experimental data was attained. 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 and for the optimization of the surface roughness for efficient and economic production.

I. Introduction

Surface roughness is one of the important factors for evaluating workpiece quality during the machining process because the quality of surface roughness affects the functional characteristics of the workpiece such as compatibility, fatigue resistance and surface friction. 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. [1] 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 [2] used RSM to construct a model that can predict the milling force in end milling operations. But as the machining process is nonlinear and time-dependent, it is difficult for the traditional identification methods to provide an accurate model. 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 [3]. ANNs have been extensively applied in modeling many metal-cutting operations such as turning, milling, and drilling [4-6]. However, this study was inspired by the very limited work on the application of ANNs in modeling the relationship between cutting conditions and the surface roughness during high-speed end milling of nickel-based, Inconel 718, alloy.

II. 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 Figure1. It was designed using MATLAB Neural Network Toolbox [7]. The network consists of one input, 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_c), feed (f) and axial depth of cut (a). Output layer corresponds to surface roughness (R_a).

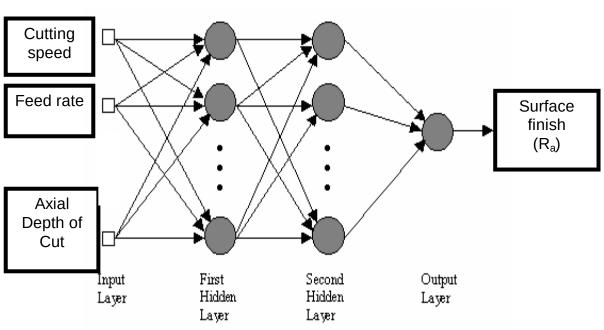


Figure 1. ANN architecture designed

III. EXPERIMENTAL DATA FOR TRAINING THE ANN

A. Experimental Set-up

A typical range of machining parameters is selected and experimental data over this whole range is conducted and identified as training and testing data sets for the neural network. For the experimentation, Vertical Machining Center (VMC ZPS, Model: MLR 1040) was used for end milling process, which was carried out with a constant redial depth of cut (a_r) 5 mm under dry conditions. TiAlN coated carbide insert of model ML2031 of CoroMill 390 end mill with 20 mm diameter was selected from the Sandvik Coromant tool catalogue [8]. The surface roughness of Inconel 718 was measured by Mitutoyo SURFTEST SV-500.

In this work, down milling method was employed in end milling process due to some advantages such as better surface finish, less heat generation, larger tool life, better geometrical accuracy and compressive stresses favourable for carbide edges [9].

B. Cutting Parameters and Sets of Experiments

Cutting conditions were chosen by an appropriate selection of cutting parameter values within specific ranges as recommended by the technical guide of Sandvik coromant [10]. Of these parameters, spindle speed, feed and axial depth of cut have been varied in current experiments and surface roughness was recorded. Other parameters such as radial depth of cut, rake angle, tool diameter, etc. were kept constant for the scope of the study. Three values were selected for each parameter and three-level full factorial design of experiments (DOE) was used, which gave 27 (3^3) experiments. The details of these selected values of the parameters are given below:

1. Cutting Speed (mm/min): 20, 30 and 40.
2. Feed (mm/tooth): 0.04, 0.075 and 0.11.
3. Axial Depth of cut (mm): 0.4, 0.6 and 0.8,

Redial Depth of cut was kept constant at 5 mm (quarter immersion) throughout this study. The experimental results for all the 27 experiments are given in Table 1.

C. Data Pre-processing

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]. This is achieved by normalizing the data as follows,

$$N = \frac{(R - R_{\min}) \times (N_{\max} - N_{\min})}{(R_{\max} - R_{\min})} + N_{\min} \quad (1)$$

Where, N: normalized value of the real variable; N_{min} and N_{max}: minimum and maximum values of normalization, respectively; R: real value of the variable; R_{min} and R_{max}: minimum and maximum values of the real variable, respectively.

IV. ANN MODEL DEVELOPMENT

A. 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,

$$Input_i = \begin{bmatrix} CuttingSpeed \\ FeedRate \\ AxialDepthofCut \end{bmatrix}$$

And the corresponding target vector,

$$Target_i = [SurfaceRoughness]$$

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 27 experimental results, which are shown in Table 1, were used for this training. TRAINLM updates weights so as to minimize the mean square error (MSE) between the network prediction and training data set.

TABLE 1: EXPERIMENTAL RESULTS TO TRAIN THE ANN MODEL

no.	Cutting speed (mm/min)	Feed (mm/tooth)	Axial DoC (mm)	Surface finish (Ra)
1	20	0.04	0.4	0.045
2	20	0.04	0.6	0.031
3	20	0.04	0.8	0.020
4	20	0.075	0.4	0.077
5	20	0.075	0.6	0.077
6	20	0.075	0.8	0.066
7	20	0.11	0.4	0.110
8	20	0.11	0.6	0.138
9	20	0.11	0.8	0.134
10	30	0.04	0.4	0.084
11	30	0.04	0.6	0.057
12	30	0.04	0.8	0.038
13	30	0.075	0.4	0.087
14	30	0.075	0.6	0.090
15	30	0.075	0.8	0.076
16	30	0.11	0.4	0.092
17	30	0.11	0.6	0.118
18	30	0.11	0.8	0.122
19	40	0.04	0.4	0.103
20	40	0.04	0.6	0.071
21	40	0.04	0.8	0.046
22	40	0.075	0.4	0.080
23	40	0.075	0.6	0.080
24	40	0.075	0.8	0.070
25	40	0.11	0.4	0.069
26	40	0.11	0.6	0.087
27	40	0.11	0.8	0.089

When the network training was successfully finished, the network was tested with additional test data.

B. *Adapting and Testing of the Developed model*

In order to further assess the predicting efficiency of the developed ANN model, 18 more random experiments were conducted. First 10 experimental results from that were utilized to further adapt the developed ANN model and the remaining 8 experimental results for different surface roughness values were compared with the ANN model predicted values and the error was found less that 12%. It was considered reasonable, taking into account that there is inherent randomness in metal cutting process.

V. 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.

A. *Effect of cutting speed on surface roughness*

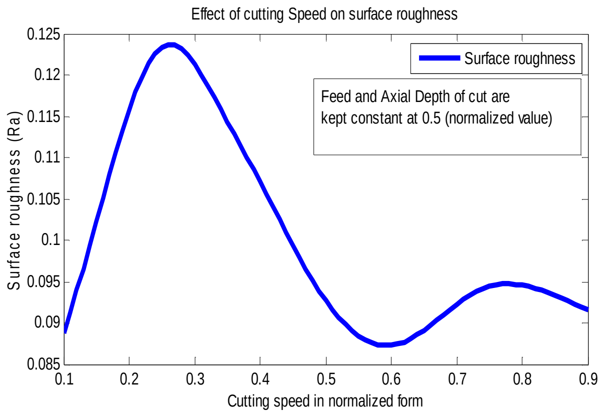
Cutting speed is one of the most important cutting parameters in metal-cutting operations and it is very influential on surface roughness as shown in Figure 3(a). At a very low cutting speed it has a adverse effect on surface finish, but after a certain speed the surface finish improves with cutting speed. But if cutting speed is increased further then at high speed it does not have much effect on surface roughness. At very low speed the cutting force is very high because of low cutting temperature which may have an adverse effect on surface finish. At high cutting speed the cutting temperature goes up and which eventually reduces the cutting force drastically. That is the cause for better surface finish at higher cutting speed. So, too low cutting speed should be avoided in end milling operation in Inconel 718 for its adverse effect on surface finish.

B. *Effect of Feed on surface roughness*

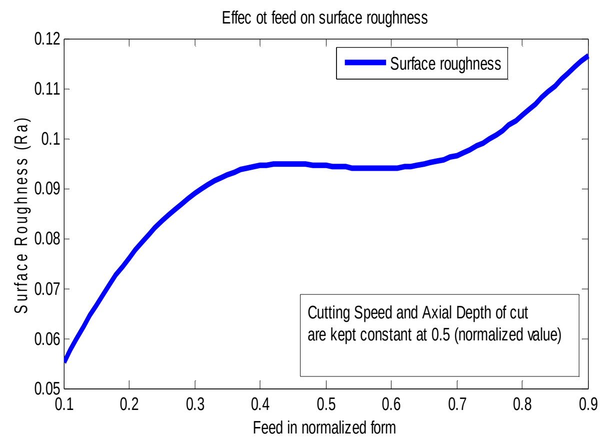
Feed plays a dominant role on surface finish as shown in the fig 3(b). At very low feed it has a sharp adverse effect on surface roughness until a certain feed value. After that surface finish remains somewhat constant with feed. But at even higher feed it affects surface roughness unfavorably. At very low feed the strain hardening effect in Inconel 718 is believed to be very high which might be the reason of poor surface finish at very low feed.

C. *Effect of Axial Depth of Cut on surface roughness*

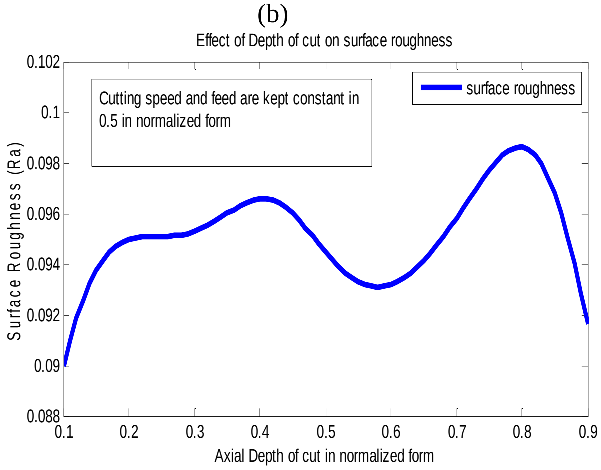
Axial Depth of cut does not have a very significant effect on surface roughness as shown in fig 3(c). Initially at a very low axial depth of cut, it has slightly unfavorable effect on surface roughness. But there is a optimum axial depth of cut for minimum surface roughness. But, in general, Axial Depth of cut does not have that significant effect on surface roughness while end milling of Inconel 718 as the cutting speed and feed have.



(a)



(b)



(c)

Figure 2. Simulation of surface roughness at varying (a) cutting speed,(b) feed, (c) axial depth of cut.

VI. 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. A good performance was achieved with the neural model as the error between the model prediction and experimental values ranging from 1.07% to 8.3%. So this developed ANN model can now be used to analysis and predict the surface roughness for different cutting conditions while end milling of Inconel 718. The surface roughness can be further optimized by coupling this ANN model with Genetic Algorithm (GA) or other optimization methods. Such ANN model can also be developed to predict other process parameters such as cutting force, tool life etc.

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