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Research Paper

PREDICTION OF SURFACE ROUGHNESS IN CNC MILLING MACHINE BY CONTROLLING MACHINING PARAMETERS USING ANN

Ravikumar D Patel[1]*, Nigam V Oza[1] and Sanket N Bhavsar[2]

*Corresponding Author: Ravikumar D Patel, ✉ ravіengineer2007@gmail.com

By optimization of various parameters of CNC milling process like spindle speed, feed rate and depth of cut, Improvement can be achieved in surface finishing. Various methods are used for predict surface roughness in CNC milling machine. Here Artificial Neural Network has been implemented for better and nearest result. By using this paper, mathematical model can be developed easily for milling process. Number of experiments have been done by using Hy-tech CNC milling machine. Conclusion from Taguchi method, Surface roughness is most influenced by Feed rate followed by spindle speed and lastly depends on depth of cut. Predicted surface roughness has been obtained, average percentage error is calculated by ANN method. The mathematical model is developed by using Artificial Neural Network (ANN) technique shows the higher accuracy is achieved which is feasible and more efficient in prediction of surface roughness in CNC milling. The result from this paper is useful to be implemented in manufacturing industry to reduce time and cost in surface roughness prediction.

Keywords: CNC milling, ANN, Surface roughness

INTRODUCTION

Higher quality is mainly goal of modern machining industries. CNC milling is a very commonly used machining process now in industry. High production rate with good surface finish and low machining time is the main criteria for industries today. To achievement for higher surface finishing, machining parameters like spindle speed, feed rate and depth of cut should be properly controlled. The ability to control the process for better surface finishing of the final product is most importance. The mechanism for the generation of surface roughness in CNC milling process is very complicated, and process parameters dependent. In CNC milling machining process, some of the parameters can be controlled like Spindle speed, Feed,

[1] Government Polytechnic College, Nr. Shankhalpur Talav, Vadnagar, Mehsana, Gujarat, India.

[2] Mechatronics Department, G H Patel College of Engineering & Technology, Vallabh Vidyanagar 388120, Anand, Gujarat, India.

Depth of Cut, by choosing particular drill cutting tool with required angle and flute, number of pass etc. Sometimes, machine operators are using 'trial and error' method to set-up milling machine for cutting workpiece. This method is not effective and efficient. It is a repetitive and very time consuming method. Thus, a mathematical model using statistical method provides a better solution.

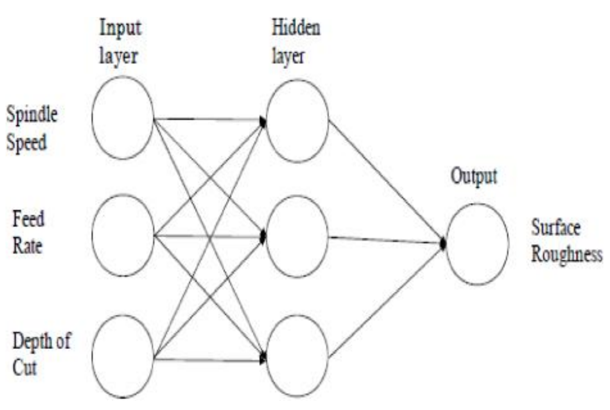
Multiple regression analysis is suitable to find the best combination of independent variables (Like spindle speed, feed rate and the depth of cut) in order to achieve desired surface roughness. Unfortunately, multiple regression model is obtained from a statistical analysis which require to collect large number of sample data.

Artificial Neural Network (ANN) is state of the art. Artificial intelligent method is the best method to prediction of surface roughness. This paper will present the application of ANN to predict surface roughness for CNC milling process.

LITERATURE REVIEW

Ghani *et al.* (2004) outlined the Taguchi optimization methodology, which was applied

Figure 1: Artificial Neural Network (ANN)



to optimize cutting parameters in end milling when machining hardened steel AISI H13 with TiN coated P10 carbide insert tool under semi-finishing and finishing conditions of high speed cutting. The milling parameters evaluated was cutting speed, feed rate and depth of cut. An orthogonal array, Signal-to-Noise (S/N) ratio and Pareto analysis of variance (ANOVA) were employed to analyze the effect of these milling parameters. Wattanutchariya and Pintasee (2006) attempted to optimize the metallic milling parameters for surface finishing. The two controlled parameters were spindle speed and feed rate. Three materials: aluminum, brass and cast iron were tested. The research methodology concerned the Response Surface Methodology (RSM) by Central Composite Design (CCD). Then, the Al 2072, brass with 10% zinc and cast iron (A287) were tested in order to investigate the relationship between the controlled parameters. Gopalsamy (2009) applied Taguchi method to find optimal process parameters for end milling while hard machining of hardened steel. An orthogonal array, signal-to-noise ratio and ANOVA were applied to study performance characteristics of machining parameters (cutting speed, feed, depth of cut and width of cut) with consideration of surface finish and tool life. Chipping and adhesion were observed to be the main causes of wear. Multiple regression equations were formulated for estimating predicted values of surface roughness and tool wear. Ginta *et al.* (2009) focused on developing an effective methodology to determine the performance of uncoated WC-Co inserts in predicting minimum surface roughness in end milling of titanium alloys Ti-6Al-4V under dry conditions. Central composite design of response surface methodology was employed to create an efficient analytical model for surface roughness in terms of cutting parameters: cutting speed, axial depth of cut, and feed per tooth. Ab. Rashid *et al.* (2009) presented the development of mathematical model for surface roughness prediction before milling process in order to evaluate the fitness of machining parameters; spindle speed, feed rate and depth of cut. Multiple regression method was used to determine the correlation between a criterion variable and a combination of predictor variables. It was established that the surface roughness was most influenced by the feed rate. Alwi (2010) studied the optimum of surface roughness by using response surface method. The experiments were carried out using CNC milling machine. All the data was analyzed by using Response Surface Method (RSM) and Neural Network (NN). The result showed that the feed gave the more affect on the both prediction value of Ra compare to the cutting speed and depth of cut. Routara *et al.* (2010) highlighted a multi-objective optimization problem by applying utility concept coupled with Taguchi method through a case study in CNC end milling of UNS C34000 medium leaded brass. Rashid and Abdul Lani (2010) Derive the nearest result for predict surface roughness by Comparision between Multiple Regression Analysis and Artificial Neural Network for predict surface roughness.

Moaz Ali and Basim (2013) developed Finite Element Modeling (FEM) to predict the effect of feed rate on surface roughness with cutting force during face milling of titanium alloy. In this paper, focus is on the effect of feed rate (f) on surface roughness (Ra) and cutting force components (Fc, Ft) during the face-milling operation of the titanium alloy (Ti-6Al-4V) and several tests are performed at several feed rates (f) while the axial depth of the cut and cutting speed remain constant in dry cutting conditions. Results showed that one could predict the surface roughness by measuring the feed cutting force instead of directly measuring the surface roughness experimentally through using the finite element method to build the model and to predict the surface roughness from the values of the feed cutting force. The accuracy of both values of the cutting force for the experimental and predicted model was about 97%.

METHODOLOGY

Artificial Neural Networks (ANNs) are one of the most powerful techniques, currently being used in various fields of engineering for complex relationships which are difficult to describe with physical models. The input and output data set of the ANN model is generated to predict surface roughness. The input parameters of the artificial neural network are Spindle Speed, Feed rate and Depth of Cut. The output of this ANN model is Surface Roughness.

For this study, the network is given a set of inputs and corresponding desired outputs, and the network tries to learn the input-output relationship by adapting its free parameters. The activation function $f(x)$ used here is the sigmoid function which is given by:

$$f(x) = \frac{1}{1 + \exp(-x)}$$

Between the input and hidden layer:

$$x = \sum_{i=1}^{m} \mu_{ji} u_i + {}^{-}_{j} \qquad j = 1 \text{ to } n$$

and between hidden layer and output layer:

$$x = \sum_{j=1}^{m} \mu_{kj} u_j + {}^{-}_{k} \qquad k = 1 \text{ to } i$$

where

m = Number of input nodes

n = Number of hidden nodes

i = Number of output nodes

u = Input node values

v = Hidden node values

µ = Synaptic weight

¯ = Threshold

In back-propagation neural network, the learning algorithm has two phases. One, a training input pattern is indicated to the network input layer. The network then propagates the input pattern from layer to layer until the output pattern is generated by the output layer. If this pattern is different from the desired output, an error is calculated and then propagated backwards through the network from the output layer to the input layer.

And Second, a back-propagation one is determined by the connections between the neuron (Network's architecture), the activation function used by the neurons, and the learning algorithm (or learning law) that specifies the procedures for adjusting weights.

Typically, a back-propagation network is multilayer network that has three or four layers. The layers are fully connected, that is, every neuron in each layer is connected to every other neuron in the adjacent forward layer. The neural network computational model coding is built using MATLAB software.

EXPERIMENTAL SETUP

Aluminium 80 x 80 x 20 mm piece is machined by HSS CNC milling cutter is used. Here three types of spindle speeds, three types of feed and three types of depth of cut are taken and achieve surface roughness for each case.

Figure 2: CNC Milling Machine

MACHINE TECHNICAL SPECIFICATION

Axes: Longitudinal Traverse 250 mm

Cross Traverse 150 mm

Vertical Traverse 200 mm

Spindle Speed: 200 to 2500 rpm

Minimum increment: 0.005 mm

Tool Offset: 12 sets

Table 1: Input Parameters for CNC Milling Machining

Variables	Levels		
	Low	Medium	High
Spindle Speed (rpm)	950	1300	1600
Feed (mm/min)	150	400	600
Depth of Cut (mm)	0.25	0.75	1.25

RESULTS

By controlling three input data (independent variables) in this paper are spindle speed, feed

Table 2: Experimental Result

Spindle Speed	Feed	Depth of Cut	Surface Roughness
950	150	0.25	1.961
950	150	0.75	1.95
950	150	1.25	1.942
950	400	0.25	3.145
950	400	0.75	3.141
950	400	1.25	3.09
950	600	0.25	4.02
950	600	0.75	4.01
950	600	1.25	4.016
1300	150	0.25	1.492
1300	150	0.75	1.491
1300	150	1.25	1.485
1300	400	0.25	2.675
1300	400	0.75	2.671
1300	400	1.25	2.658
1300	600	0.25	3.617
1300	600	0.75	3.611
1300	600	1.25	3.605
1600	150	0.25	1.112
1600	150	0.75	1.107
1600	150	1.25	1.092
1600	400	0.25	2.289
1600	400	0.75	2.284
1600	400	1.25	2.278
1600	600	0.25	3.23
1600	600	0.75	3.222
1600	600	1.25	3.216

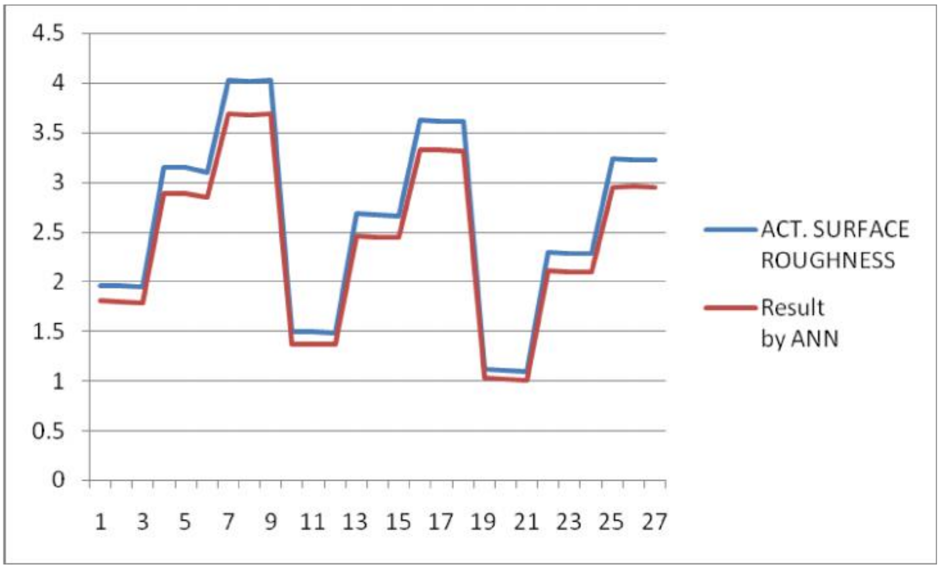
rate and depth of cut while actual surface roughness acted as output. 27 numbers of experimental readings are taken which are shown below.

Artificial neural network has been implemented in this research work. The predicted surface roughness has been calculated using Artificial Neural Network (ANN) in MATLAB. Table shows the predicted surface roughness using this method. The network propagates the input pattern from layer to layer until the output is generated. Then the result output will be compared with the actual surface roughness in this study. Nearest results can be achieved by implementation of

Table 3: Comparision Between Experimental Result and Theoretical Result by ANN

Measured Surface Roughness	Theoretical Result by ANN	% Achieved
1.961	1.809	92.25
1.950	1.791	91.85
1.942	1.782	91.76
3.145	2.891	91.92
3.141	2.889	91.98
3.090	2.845	92.07
4.020	3.692	91.84
4.010	3.684	91.87
4.016	3.691	91.91
1.492	1.372	91.96
1.491	1.369	91.82
1.485	1.364	91.85
2.675	2.460	91.96
2.671	2.454	91.88
2.658	2.445	91.99
3.617	3.325	91.93
3.611	3.325	92.08
3.605	3.315	91.96
1.112	1.025	92.18
1.107	1.015	91.69
1.092	1.005	92.03
2.289	2.110	92.18
2.284	2.100	91.94
2.278	2.100	92.19
3.230	2.950	91.33
3.222	2.965	92.02
3.216	2.955	91.88

Figure 3: Comparision of Actual Surface Roughness and Theoretical Result by ANN



ANN. surface roughness is calculated and propagated back through network. Then, the weight will be changed and the same process repeated until the smallest error is achieved. The plot of predicted surface roughness (output) against the actual surface roughness (target) is indicated in figure.

CONCLUSION

The main purpose of this paper is to provide an nearest result for predict surface roughness in CNC end milling. The model developed is reliable to predict surface roughness with respect to all previous research. Artificial neural network is a feasible technique in engineering field. This technique provides a brand new perspective in engineering field and in surface roughness prediction to be precise.

Back-propagation neural network had been implemented to prepare a predict model of surface roughness. From result, various reading indicates in table which is to minimize the error during surface roughness prediction. The result of the prediction is favorable with 8.06% average percentage of error, means 91.94% accurate. So conclusion, Artificial Neural Network (ANN) provided better accuracy to predict surface roughness in CNC milling process.

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