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Prediction of Optimum Cutting Parameters to obtain Desired Surface in Finish Pass end Milling of Aluminium Alloy with Carbide Tool using Artificial Neural Network

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***Abstract*—**End milling process is one of the common metal cutting operations used for machining parts in manufacturing industry. It is usually performed at the final stage in manufacturing a product and surface roughness of the produced job plays an important role. In general, the surface roughness affects wear resistance, ductility, tensile, fatigue strength, etc., for machined parts and cannot be neglected in design. In the present work an experimental investigation of end milling of aluminium alloy with carbide tool is carried out and the effect of different cutting parameters on the response are studied with three-dimensional surface plots. An artificial neural network (ANN) is used to establish the relationship between the surface roughness and the input cutting parameters (i.e., spindle speed, feed, and depth of cut). The Matlab ANN toolbox works on feed forward back propagation algorithm is used for modeling purpose. 3-12-1 network structure having minimum average prediction error found as best network architecture for predicting surface roughness value. The network predicts surface roughness for unseen data and found that the result/prediction is better. For desired surface finish of the component to be produced there are many different combination of cutting parameters are available. The optimum cutting parameter for obtaining desired surface finish, to maximize tool life is predicted. The methodology is demonstrated, number of problems are solved and algorithm is coded in Matlab®.

***Keywords*—**End milling, Surface roughness, Neural networks.

I. Introduction

In basic machining processes 'milling' is one of the most widely used metal removal processes in industry and milled surfaces are largely used to mate with other parts in die, particularly in aerospace, automotive, and manufacturing Industries. Manufactured part qualities are determined by their 'form errors' and 'surface finishes' produced by the manufacturing processes. Surface roughness is one of the important attribute on quality of manufactured product since affects the functional characteristics of component. The component with good surface finish improves the tribological properties, fatigue strength, wear resistant, light reflection, heat transmission, and aesthetic appearance of the product. However, excessively better surface finish may involve higher manufacturing cost. Hence much attention has been paid to estimate the surface finish of the manufactured component and optimum selection of cutting parameters. 'Center line average (CLA)' is one of the universally recognized and the most commonly used for the measurement of surface roughness. It is expressed as:

$$R_a = \frac{1}{L}\int_1^L \left|Y(x)\right| dx \tag{1}$$

where R_a is the arithmetic average deviation from the mean line, L is the sampling length, and Y is the ordinate of the roughness profile. For the prediction of R_a three modeling techniques viz., experimental models, analytical models and Artificial Intelligence (AI) based models are commonly employed [1]. The soft computing based on ANN model is preferred over conventional statistical regression technique due to its ability to predict high accuracy rate.

In this work an experimental investigation of end milling process is performed to study the effect of three machining parameters viz. spindle speed, feed rate and depth of cut, on the surface roughness of the machined surface. The effect of these parameters are analysed on three dimensional surface plots. ANN model is established for obtaining the relationship between the surface roughness and the input cutting parameters. The network predicts surface roughness for unseen data and found that the result/prediction is better. For desired surface finish of the component to be produced the optimum cutting parameters are obtained among different combination of cutting parameters are available. The paper is organized as follows. The review of previous literature is presented in Section 2. Section 3 demonstrates experimental study on surface roughness and ANN model is presented in Section 4. The optimization procedure for obtaining optimum

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cutting parameters to achieve desired surface roughness is explained in Section 5. Conclusions are presented in Section 6.

II. Literature Review

Modeling of manufacturing process and optimization are two major issues in metal cutting optimization. In order to develop surface roughness model and optimizing the process it is essential to review the published literature for understanding current status of work in this area. Hasmi et al. [2] used the RSM model for assessing the influence of the workpiece material on the surface roughness on steel specimen. They establish the relationship between surface roughness and cutting parameters viz cutting speed, feed and depth of cut. Alauddin et al. [3] established a mathematical model for predicting the surface roughness of 190 BHN steel using end milling process. They developed the prediction model using response surface methodology (RSM) to predict surface roughness in term of cutting speed, feed rate, and depth of cut. Reddy and Rao [4] studied the influence of tool geometry during end milling of medium carbon steel using RSM and the model is optimized with genetic algorithm to obtain minimum surface roughness and the corresponding cutting conditions.

Lou and Chen [5] studied the effect of spindle speed, feed rate and depth of cut on the surface roughness of end milling processes. They used in-process surface roughness recognition (ISRR) and a neural fuzzy system for predicting workpiece surface roughness. Chiang et al. [6] developed a scheme for evaluation of optimal cutting condition using two different kinds of neural networks. They used a neural network that works on back propagation algorithm, having three inputs and four outputs to simulate the machining process. The second network is used to calculate the optimal cutting parameters to achieve the goal of maximizing the material removal rate. Luo et al. [7] developed a neural network to simulate the cutting force and contour error in an end milling process. The NN is used to make corrections to the feed rate components with parametric interpolation algorithm so as to minimize the contour error caused by the dynamic lag of the closed-loop servo systems used to control the table feed drives. Rangwala and Dornfeld, Kohli and Dixit and many others used artificial neural network models for predicting surface roughness in a turning process with different network training methodology and input parameters, etc [8], [9]. Zain et al.[10] also used ANN model for predicting surface roughness in the milling process. In this work, neural network model based on multi layer perceptron network is used as a surface roughness prediction technique from the obtained experimental data sets.

Survey of previous research on surface roughness prediction in end milling process reveals that most of the researchers used mathematical model, multiple regression method, response surface methodology (RSM), the fuzzy-set-based technique and neural network are various popular prediction techniques [11], [12]. Chandrasekaran et al. [13] carried out the review of previous research about the application of soft computing methods on parameter prediction such as surface roughness, tool life and tool wear, cutting force, etc., including process optimization for four common machining processes. Among this, neural network modelling seems to be more promising method for predicting surface finish with reasonable accuracy with lesser computational time.

III. Experimental Study on Surface Roughness

For developing models on the basis of experimental data three main machining parameters are considered to predict surface roughness of aluminium alloy using carbide tool in dry cutting condition. The available literature reveals that spindle speed, feed rate and axial depth of cut are primary machining parameters on which surface roughness depends. These factors are considered for experimentation and analysis of present study. Considering three levels with three parameters, varying one factor at a time, 3^3=27 experiments were conducted. End mill cutter with 20 mm diameter having two flutes with carbide tipped is used for machining aluminium alloy work piece. Among the range of spindle speed, feed, and depth of cut (axial) available/possible in the machine the following three levels are considered as shown in table I.

The machining was carried out on Vertical milling machine, HMT model available at Central workshop, IIT Guwahati. The cutter is held on the spindle of the machine and rotates in vertical axis. The aluminium work piece is clamped on vice mounted on the table of the machine. Figure 1(a) & (b) shows the machining process and work tool motion of the end milling process respectively.

The machining is carried out by selecting proper spindle speed and feed rate during each experimentation. The depth of cut remains constant during each pass. However, similar experiment was carried out by varying the depth of cut. On completion of each pass the surface roughness is measured on the work piece at four locations. The evaluation length is considered as 2.4 mm. CLA values of surface roughness are directly obtained from 'Pocket Surf'. The average values of surface roughness measured at four different locations approximately at equal interval along the length of the

TABLE I
Levels of experiment

Sl. No.	Parameter	Unit	Symbol	Level-1	Level-2	Level-3
1	Spindle speed	RPM	*N*	500	1000	1400
2	Feed rate	mm/min	*F*	16	25	40
3	Depth of cut	mm	*D*	0.05	0.1	0.2

machining is considered as 'actual surface roughness' value of those particular cutting conditions. Table II shows the experimental result.

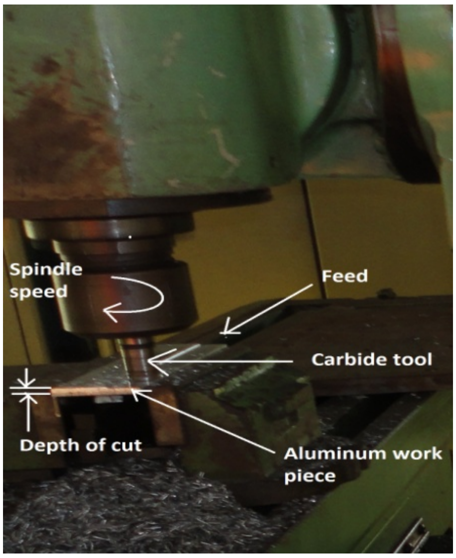

Fig. 1 (a) End Milling – Machining process

TABLE II
EXPERIMENTAL RESULTS

Expt. No.	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	CLA Surface roughness (µm)
1	500	16	0.05	0.312
2	500	16	0.1	0.320
3	500	16	0.2	0.334
4	500	25	0.05	0.392
5	500	25	0.1	0.394
6	500	25	0.2	0.406
7	500	40	0.05	0.410
8	500	40	0.1	0.420
9	500	40	0.2	0.431
10	1000	16	0.05	0.280
11	1000	16	0.1	0.284
12	1000	16	0.2	0.311
13	1000	25	0.05	0.352
14	1000	25	0.1	0.368
15	1000	25	0.2	0.392
16	1000	40	0.05	0.396
17	1000	40	0.1	0.406
18	1000	40	0.2	0.414
19	1400	16	0.05	0.286
20	1400	16	0.1	0.276
21	1400	16	0.2	0.286
22	1400	25	0.05	0.326
23	1400	25	0.1	0.338
24	1400	25	0.2	0.346
25	1400	40	0.05	0.382
26	1400	40	0.1	0.386
27	1400	40	0.2	0.394

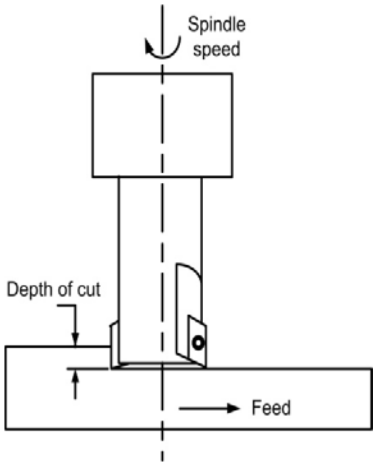

Fig. 1 (b) End Milling – Work-tool motion

A. Effect of the machining parameters on surface roughness

The effect of cutting parameters such as spindle speed, feed and depth of cut are analyzed through three-dimensional surface plots. The surface plots are useful to visualize the effect of the response and to have idea about the functional relationship between the response (i.e., surface roughness) and the experimental factors (i.e., spindle speed, feed and depth of cut). From the result, the surface roughness is highly depends on spindle speed followed by feed rate. Depth of cut has least effect on surface roughness produced. The variation of surface roughness with spindle speed, feed rate and depth of cut obtained from the experimental are described below.

Figure 2 shows the surface plot of surface roughness with spindle speed and feed while depth of cut is kept constant. The increase on spindle speed reduces the surface roughness value. On the other hand, in case of feed the value of surface roughness increases as feed increases. The plot shows the effect for the depth of machining of 0.1 mm.

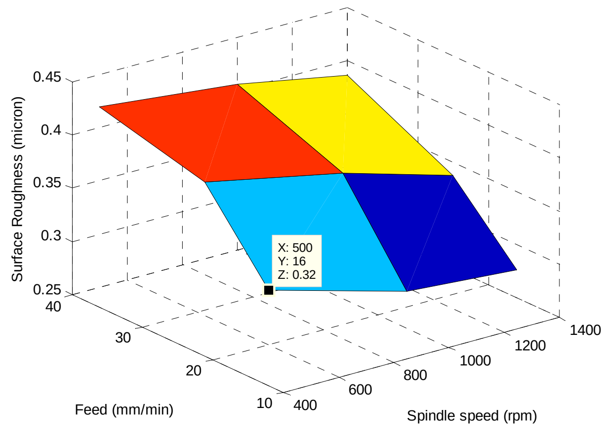

Fig. 2 Surface plot of 'spindle speed' and 'feed'

Figure 3 shows the surface plot of surface roughness with spindle speed and depth of cut while feed is kept constant. The plot reveals that the increase in spindle speed reduces the surface roughness value. On the other hand, in case of depth of cut, the value of surface roughness increases as depth of cut increases but the effect in least. The plot shows the effect for feed (table feed) of 25 mm/min.

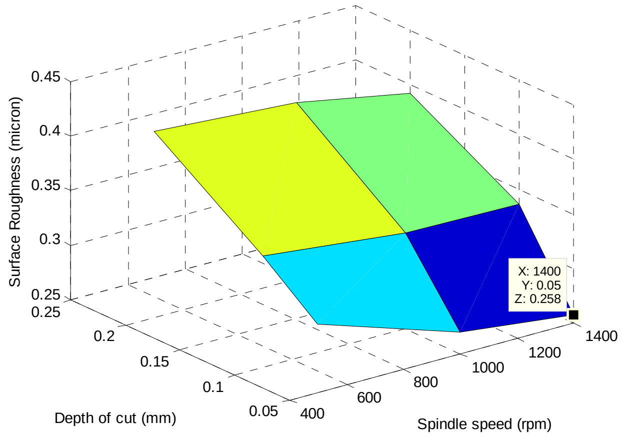

Fig. 3 Surface plot of 'spindle speed' and 'depth of cut'

IV. Neural Network Modelling

Neural network is a highly flexible modeling tool with the ability to learn the mapping between input and output parameters [14]. An artificial neural network (ANN) is capable of learning from an experimental data set to describe the nonlinear and interaction effects more effectively. The network consists of an input layer used to present data, output layer to produce ANN's response, and one or more hidden layers in between. The network is characterized by their topology, weight vectors, and activation function that are used in hidden and output layers of the network. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. The knowledge is presented by the interconnection weight, which is adjusted during the learning stage using the back propagation learning algorithm to minimize the mean square between the actual output of the network and the desired output pattern. Here it is used to develop surface roughness prediction model for end milling process.

From 27 experiments were conducted 24 experimental datasets are used to train the network. Before applying the neural network for modeling the architecture of the network has to be decided; i.e. the number of hidden layers and the number of neurons in each layer and transfer function for each layer. As there are 3 inputs to produce one output, the number of neurons in the input and output layer has to be set to 3 and 1 respectively. Considering one hidden layer the number of neurons in the hidden layer is optimized. A procedure was employed to optimize the hidden layer neurons and selection of transfer function for which a program was generated in MATLAB.

Accordingly, an experimental approach was adopted, which involves testing the trained neural network against another 3 set of data from 27 experimental dataset that were drawn randomly. However, the set of combinations was different from one used for training the network. The established verification and predicted outputs for different number of neurons have been compared. In all cases, maximum error tolerance was kept constant. It was observed that average prediction error was minimized with 12 neurons and the transfer function combination of tansig-tansig-tansig. Prediction error has been defined as follows:

$$Prediction\_Error\% = \left| \frac{(Verification\_Result - Predicted\_Result)}{Verification\_Result} \right| \times 100 \quad (2)$$

Hence, 3-12-1 is the most suitable neural network for the task under consideration. The transfer functions used in this are Tan Sigmoid. The training function employed is TRAINGDM. Figure 4 shows the configuration of the neural network. The neural network can provide the result for any arbitrary value of input data set.

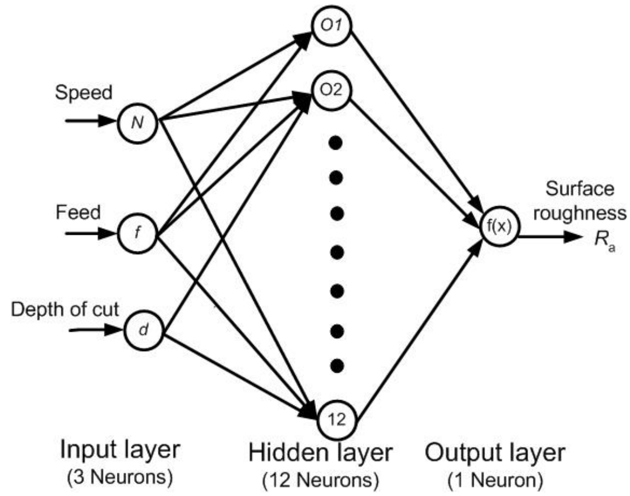

Fig. 4 Configuration of the Neural Network

TABLE III
Comparison of ANN predictions with experimental data

Machining Parameters			Experimental Response	ANN Model Prediction	Prediction error (%)
Spindle Speed (RPM)	Feed rate (mm/min)	Depth of cut (mm)	CLA Surface roughness (μm)	CLA Surface roughness (μm)	
500	40	0.1	0.42	0.4226	0.62
1000	16	0.1	0.284	0.3191	12.36
1400	40	0.2	0.394	0.3039	0.01
Average prediction error (%)					4.33

Table III shows the established verification result and the NN model prediction. It was observed that the prediction based on an ANN model is quite close to the established observation. The average prediction error for data set is found to be 4.33% and maximum prediction error is 12.36%.

In all cases, maximum error tolerance was kept constant. It was observed that the average prediction error was minimized with 12 neurons and the transfer function combination of tansig-tansig-tansig. Hence, 3-12-1 is the most suitable neural network for the task under consideration. The transfer functions used in this are Tan Sigmoid. The training function employed is TRAINGDM. The neural network can provide the result for any arbitrary value of input data set in the interpolation range.

V. Cutting Parameter Optimization

In the past, numerous researchers have studied the influences of cutting variables on surface finish for practical end milling. For the particular value of surface roughness to be produced there are many possible combination of cutting parameters are available. The selection of cutting parameters among all the possible set of cutting parameters which will provide maximum possible 'tool life' is aimed here.

A. Optimization Procedure

Optimization is carried out in two phases. In first phase, the cutting parameters are predicted which produce minimum error between desired surface roughness and NN prediction. The objective functions for the first case is represented as

$$Minimize\_Ra_{Error} = \left| Ra(N, f, d) - Ra_{(\max)} \right| \tag{3}$$

Subjected to

$$N_{\min} \le N \le N_{\max}$$
$$f_{\min} \le f \le f_{\max}$$
$$d_{\min} \le d \le d_{\max}$$

where R_a and $R_{a(max)}$ are NN predicted surface roughness and the desired surface roughness to be achieved respectively. There are number of combination of cutting parameters that produce minimum allowable error, are obtained. The figure 5 flow chart shows the procedure for obtaining various cutting parameter sets for minimum error. The source code is developed in the MATLAB.

In the second phase the cutting parameter is optimized for maximum tool life. The tool life is considered as a function of cutting velocity, feed and depth of cut. Tolouei-Rad and Bidhendi [15] proposed an empirical relation to evaluate tool life T for end milling process as

$$T = \frac{60}{Q}\left(\frac{C\left(0.2d/f\right)^{g}}{\left(df\right)^{w} v}\right)^{1/n}, \tag{4}$$

where T is the tool life in minutes, v is the cutting speed in m/min, C is the constant for 60 min tool life when the area of cut is 1 mm^2, f is the feed in mm/rev, d is the depth of cut in mm, and g, w, and n are exponents for different tool and work material combination. The factor Q is contact proportion of cutting edges with work piece per revolution. . In this work, Cv, g, w, and n are selected as 60, 0.14, 0.28 and 0.3 respectively. This confirms the prescribed range values proposed by Toloei-Rad and Bidhendi [15] for carbide tool and satisfies tool life interaction among cutting variables. A low value of combination provides the highest tool life and variation is studied by three dimensional surface plot.

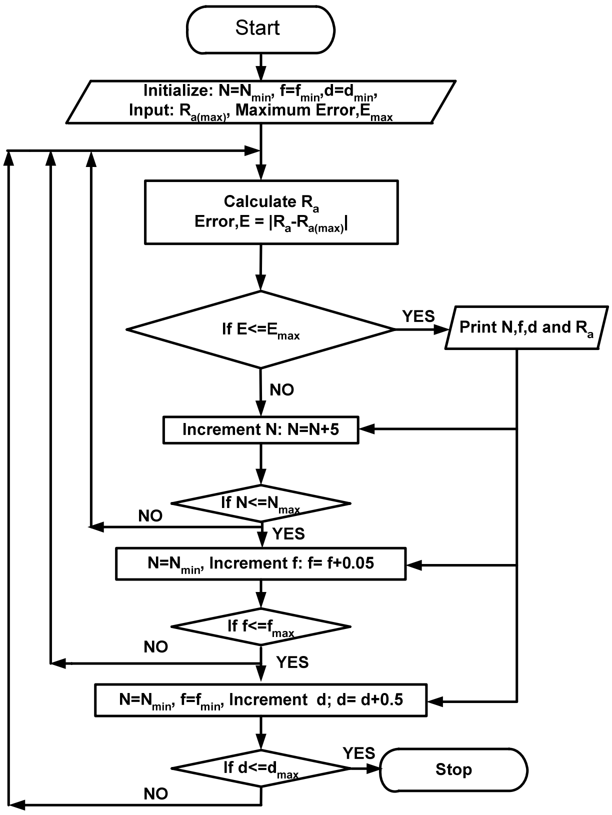

Fig. 5 Flow chart for finding out the desired surface roughness

B. Problem Illustration

To illustrate the methodology number of different problems are solved. During finish pass milling as depth of cut remains constant the optimum value of other cutting parameters (i.e., speed and feed) are obtained for achieving desired surface roughness. For depth of machining as 0.05 mm to achieve desired surface roughness value of 0.35 micron there are 5 different combination of cutting parameters (N, f) viz., (1070,22.6), (1060,22..5), (1050,22.4), (865,22.5) and (735,19.1) are obtained. The predicted surface roughness are within the maximum error of 0.01 micron and maximum tool life achieved 2.14 $x10^{13}$ min. Thus the optimum cutting parameter obtained as (735, 19.1). Similarly number of problems having depth of machining varying from 0.05 to 0.2 mm to obtain different value of desired surface roughness, are solved. The cutting conditions that satisfy the desired surface roughness are many and the optimum cutting parameters that have maximum tool life are shown in Table IV.

TABLE IV
OPTIMUM MACHINING PARAMETERS

Sl. No.	Problem data (d, $R_{a(max)}$) (mm, µm)	Spindle speed, N (rpm)	Feed, f (mm/min)	NN prediction (µm)	Tool life , T (min)
1	**(0.05,0.35)**	1070	22.6	0.35	8.19×10^{12}
		1060	22.5	0.35	8.39×10^{12}
		1050	22.4	0.35	8.60×10^{12}
		865	22.5	0.34	1.41×10^{13}
		735	**19.1**	**0.35**	$\mathbf{2.14 \times 10^{13}}$
2	**(0.1, 0.3)**	1365	17.4	0.30	5.29×10^{11}
		1140	16.2	0.30	8.29×10^{11}
		1120	**16.0**	**0.29**	$\mathbf{8.65 \times 10^{11}}$
3	**(0.15, 0.35)**	1380	36.7	0.34	3.9×10^{10}
		1070	34.0	0.35	7.11×10^{10}
		940	36.9	0.34	8.14×10^{10}
		940	**20.3**	**0.35**	$\mathbf{1.88 \times 10^{11}}$
4	**(0.2, 0.4)**	1330	27.6	0.39	1.09×10^{10}
		1320	38.3	0.39	1.34×10^{10}
		1250	**26.5**	**0.40**	$\mathbf{2.50 \times 10^{11}}$

The results show that the reduction in speed increases the tool life. How ever in order to satisfy the desired surface finish the feed rate either increase or decrease. The neural network used to predict the surface roughness is better with average prediction error for data set is found to be 4.33%.

VI. CONCLUSIONS

In this work an experimental investigation on surface roughness of end milling of aluminium alloy with carbide tool under dry cutting condition is carried out. The surface roughness mainly depends upon / could be predicted effectively with spindle speed, feed rate and depth of cut. The increase in spindle speed produces better surface finish (i.e., surface roughness reduces). On the other hand, for increased feed rate and depth of cut the value of surface roughness increases. However the effect of depth of cut is least in comparison with feed rate. In the first phase the ANN technique is used for development of surface roughness model to predict the surface finish under different unseen cutting conditions. The ANN predicts surface roughness effectively in comparison with other conventional methods in terms of speed, simplicity, accuracy, etc. In the next phase, the optimum cutting condition to achieve desired value of surface finish for maximum tool life is obtained. For the required value of surface roughness many different combination of process parameters could be obtained. The selection of correct combination cutting parameters for maximum tool life should be aimed to obtain economy in machining.

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