SURFACE ROUGHNESS MODELLING AND OPTIMIZATION IN CNC END MILLING USING TAGUCHI DESIGN AND NEURAL NETWORKS

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Abstract: A Neural Network modelling approach is presented for the prediction of surface texture parameters during end milling of aluminium alloy 5083. Eighteen carbide end mill cutters were manufactured by a five axis grinding machine and assigned to mill eighteen pockets having different combinations of geometry parameters and cutting parameter values, according to the L_{18} (2^1x3^7) standard orthogonal array. A feed-forward back-propagation NN was developed using data obtained from experimental work conducted on a CNC milling machine center according to the principles of Taguchi's design of experiments method. It was found that NN approach can be applied easily on designed experiments and predictions can be achieved, fast and quite accurately.

1 INTRODUCTION

Aluminium 5083 is generally supplied as a flat rolled product in plate form and it has the highest strength of the non-heat treatable alloys. Although there is no specific machinability data the Al 5083 is machinable by conventional means.

The machinability of an engineering material denotes its adaptability to machining processes with regard to factors such as cutting forces, tool wear and surface roughness. Surface roughness plays an important role on the product quality and is a parameter of great importance in the evaluation of the machining accuracy (Kechagias *et al.*, 2009; 2010).

The surface roughness of parts produced by material removal processes is affected by various factors such as material properties, tool geometry, cutting parameters, etc. Thus parameter design for a material is useful in order to have the best performance and consequently decrease the quality loss of a process (Phadke, 1989).

A number of attempts, which study surface quality, cutting forces, tool wear, and cheap morphology, during end milling, are reported in the literature. Most of these studies refer to specific cutting conditions, such as the tool-workpiece material and the cutting tool geometry (Engin and Altintas, 2001; Yun and Cho 2000).

The current research work studies the influence of the cutting parameters and the end cutter geometry parameters during end milling of Al alloy 5083 on the surface texture parameters; arithmetical mean roughness (R_a), maximum peak (R_y), and ten-point mean roughness (R_z).

The two-flute end cutter geometry parameters tested are the core diameter (%), flute angle (^{o}), rake angle (^{o}), peripheral 1st relief angle (^{o}) and peripheral 2nd relief angle (^{o}). The core diameter is measured as a percentage of the end mill cutter diameter. End mill cutter geometry parameters can be seen in Figure 1.

The above parameters were combined with cutting depth (mm), cutting speed (rpm) and tool feed (mm/flute) using an L_{18} (2^1x3^7) orthogonal matrix experiment and the results were used to built a NN model in order to predict/estimate the surface roughness indicator response according to the

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geometry and cutting parameters of the end milling process.

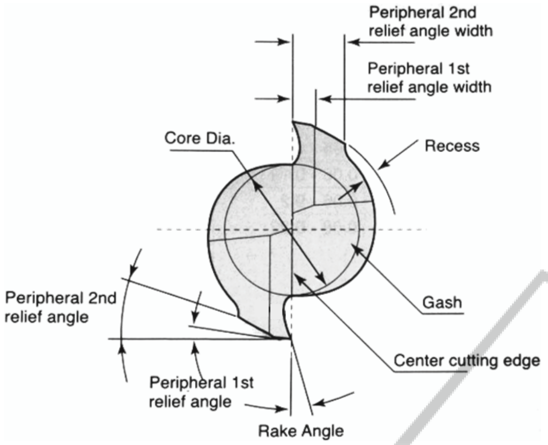

Figure 1: Two flute end mill cutter geometry (front view).

NNs have also been effectively used in the past not only for modelling and optimization of manufacturing processes but also in case of highly non-linear non-manufacturing problems (Chryssolouris et al., 2004; Kechagias and Iakovakis, 2009; Markopoulos *et al.*, 2006).

2 EXPERIMENT

Aluminum alloy 5083 is a non-heat treatable alloy. It has very good corrosion resistance; it is easily welded and is of high strength.

End milling pockets were performed on a DECKEL MAHO DMU 50V-monoBLOCK 5-axis universal high speed machining center. The max power of the machine tool and the max spindle speed were 18,9 kW and 14.000 r/min respectively. The two flute carbide end mill cutters were manufactured using the five axis Hawemat 2001 grinding machine. NAMROTO CAM program was used to simulate the grinding process in order to avoid collision among machine components.

Table 2 was designed using the Taguchi methodology (Phadke, 1989) and corresponds to the standard L_{18} (2^1x3^7) orthogonal array. In this method, the main parameters, which are assumed to have an influence on the process results, are located in different rows in a designed orthogonal array and the results can be analyzed using an analysis of means and analysis of variance, in a similar way as a full factorial design, were conducted.

The geometry parameter values of each of the eighteen two-flute end mill cutters are shown in columns A to E of Table 2. All of the eighteen carbide cutters have a diameter of 8 mm. The cutting parameter values during eighteen pockets are shown in columns F to H of Table 2, too.

Each of the eighteen end mill cutters cut a pocket of 100 mm x 64 mm and 15 mm in depth on the two faces of an Al 5083 plate of 500 mm x 280 mm and 60 mm in depth. The two faces were finished with a face mill cutter, 50 mm in diameter, and two recesses were constructed in order to fix the Al plate on to the machine center chuck. The cutting parameter values for each pocket are depicted in columns F, G, and H of Table 2. The surface texture parameters measured were the arithmetical mean roughness (R_a), maximum peak (R_y) and ten-point mean roughness (R_z).

Figure 2: Surface roughness measurements.

Surface roughness measurements were taken using a RUGOserf tester. Each surface roughness parameter (R_a, R_y, and R_z) was measured three times, parallel to the arrows (Figure 2), and an average of each was calculated for each of the eighteen pockets (see last three columns of Table 2).

3 TAGUCHI DESIGN OF EXPERIMENTS

The Taguchi design method is a simple and robust technique for optimizing the process parameters. In this method, the main parameters, which are assumed to have an influence on the process results, are located in different rows in a designed orthogonal array. With such an arrangement randomized experiments can be conducted. In the case of the surface quality indicators (R_a, R_y, R_z), lower values are desirable. Table 1 summarises the parameter values (levels) used in the orthogonal matrix experiment in Table 2.

An analysis of means and variance on the experimental results show that the optimum values for the geometry parameters are: core diameter (50%), flute angle (38^o), rake angle (22^o), relief angle 1st (22^o), and relief angle 2nd (30^o).

Table 1: Parameter levels.

		Levels		
	Parameters	1	2	3
A	Core diameter (%)	48	50	-
B	Flute angle (°)	38	45	50
C	Rake angle (°)	18	20	22
D	Relief angle 1st (°)	20	22	25
E	Relief angle 2nd (°)	25	28	30
F	Cutting depth (mm)	0.5	1.0	1.5
G	Cutting speed (rpm)	5000	6000	7000
H	Feed (mm/flute)	0.05	0.08	0.10

Table 2: Parameter design according to L_{18} (2^1x3^7) orthogonal array and performance measures.

No.	Columns								Perform. Measures		
	A	B	C	D	E	F	G	H	R_a	R_y	R_z
1	48	38	18	20	25	0.5	5000	0.05	0.08	0.93	0.73
2	48	38	20	22	28	1.0	6000	0.08	0.17	1.27	1.17
3	48	38	22	25	30	1.5	7000	0.10	0.18	1.30	1.07
4	48	45	18	20	28	1.0	7000	0.10	1.66	5.73	6.83
5	48	45	20	22	30	1.5	5000	0.05	0.12	1.47	0.90
6	48	45	22	25	25	0.5	6000	0.08	0.19	2.10	1.13
7	48	50	18	22	25	1.5	6000	0.10	0.22	1.80	1.27
8	48	50	20	25	28	0.5	7000	0.05	1.33	12.13	7.10
9	48	50	22	20	30	1.0	5000	0.08	0.19	1.27	1.27
10	50	38	18	25	30	1.0	6000	0.05	0.13	1.20	0.93
11	50	38	20	20	25	1.5	7000	0.08	0.19	1.47	1.23
12	50	38	22	22	28	0.5	5000	0.10	0.17	1.27	1.10
13	50	45	18	22	30	0.5	7000	0.08	0.11	1.03	1.10
14	50	45	20	25	25	1.0	5000	0.10	0.13	1.27	1.03
15	50	45	22	20	28	1.5	6000	0.05	0.14	0.77	0.70
16	50	50	18	25	28	1.5	5000	0.08	0.22	1.37	1.10
17	50	50	20	20	30	0.5	6000	0.10	0.15	1.20	0.97
18	50	50	22	22	25	1.0	7000	0.05	0.16	1.37	0.90

4 MODELLING FRAMEWORK

In the frame of this modelling work a NN was developed in order to predict the surface roughness parameters (R_a, R_y, and R_z) during end milling on the surface texture of Al alloy 5083. The eight (8) factors studied were used as input parameters of the NN model.

The 18 experimental data samples (Table 2), were separated into three groups, namely the training, the validation and the testing samples. Training samples are presented to the network during training and the network is adjusted according to its error. Validation samples are used to measure network generalization and to halt training when generalization stops improving. Testing samples have no effect on training and so provide an independent measure of network performance during and after training (confirmation runs).

Nine (9) samples (50%) were used for training, four (4) samples (20%) for validation and five (5) samples (30%) for testing purposes. The samples that were used for ANN training were selected following the L_9 Taguchi orthogonal array (i.e. experiments 1-3, 7-9, and 13-15). For the validation process were used the samples 4, 12, 16, and 18. The remaining ones (i.e. 5-6, 10-11, and 17) were used for testing purposes.

There are many possible types of architecture for ANN. In this work, the feed-forward with back-propagation learning (FFBP) architecture has been selected to predict the surface roughness. These types of networks have an input layer of X inputs, one or more hidden layers with several neurons and an output layer of Y outputs. In the selected ANN, the transfer function of the hidden layer is hyperbolic tangent sigmoid, while for the output layer a linear transfer function was used. The input vector consists of the eight process parameters of Table 2. The output layer consists of the performance measures, namely the R_a, R_y and R_z. In order to compute the best number of neurons and hidden layers, several trial and errors have taken place for the initial learning phase. It was found that network architecture (8-7-5-4-3) with three hidden layers of seven (7) neurons in the first hidden layer, five (5) neurons in the second hidden layer and four (4) neurons in the third hidden layer exhibits a minimal error between the output values estimated by the NN and the data samples provided by the experimental data.

Back-propagation NNs are prone to the overtraining problem that could limit their generalization capability (Tzafestas *et al.*, 1996). Overtraining usually occurs in ANNs with a lot of degrees of freedom (Prechelt, 1998) and after a number of learning loops, in which the performance of the training data set increases, while the performance of the validation data set decreases.

The performance of the network is measured by the MSE of the estimated output with regards to the values of the experimental data. Mean Squared Error is the average squared difference between network output values and target values. Lower values are better. Zero means no error. The best validation performance is equal to 0.0069 when the training of the ANN stops, which means very good network efficiency. Another performance measure for the network efficiency is the regression (R). Regression values measure the correlation between output values and targets. The acquired results show a very good correlation between output values and targets during training (R=1), validation (R=0.89) and testing procedure (R=0.93).

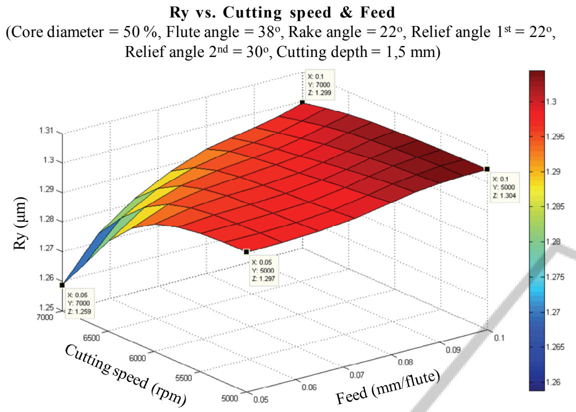

Figure 3: Response surface diagram of R_y in relation to the cutting speed and feed, while cutting depth is 1,5 mm.

The trained NN model can be used for the optimization of the surface roughness parameters during CNC end milling. This can be done by testing the behaviour of the response variables (R_a, R_y and R_z) under different variations in the values of geometry and cutting parameters. In order to ensure accurate prediction of the surface roughness parameters, the values concerning the eight input parameters should be inside the range of values that are defined during the experimental setup.

Figure 3 presents an example of a surface response diagram for the roughness parameter R_y while cutting speed and feed rate vary within their range of values. In this diagram all the geometry parameters were kept constant at their optimum values. This figure shows that when the cutting speed increases, as well as in the case of feed rate reduction, the response variable (surface roughness, R_y) decreases.

5 CONCLUSIONS

A FFBP-NN model was built to estimate the surface roughness indicator response according to the geometry and cutting parameters of the process. The performance of the network was found to be efficient providing very good correlation between outputs and targets during training (R=1), validation (R=0.89) and testing procedure (R=0.93).

Furthermore, the response surface diagram in Figure 3 shows that when the geometry parameters take their optimum values, the increase of cutting speed, as well as the decrease of feed rate, results in deduction of the surface roughness, which is also in accordance with the machining theory. Multi-parameter investigation of the process according to other quality indicators will be studied and analyzed in future work.

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