Prediction of Ra Value of Al –SiC MMC by Artificial Neural Network

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Abstract— In recent years, the utilization of metal matrix composites (MMC) materials in many engineering fields has increased tremendously. Accordingly the need for accurate machining of composites has also increased enormously. Despite the recent developments in the near net shape manufacture, composite parts often require post-mold machining to meet dimensional tolerances, surface quality and other functional requirements. In the present work, the surface roughness of Al–SiC (20 p) has been studied in this paper by turning the composite bars using coarse grade polycrystalline diamond (PCD) insert under different cutting conditions. Experimental data collected are tested with artificial neural network (ANN) techniques. Multilayer perceptron model has been constructed with back-propagation algorithm using the input parameters of depth of cut, cutting speed and feed. Output parameter is surface finish of the machined component. On completion of the experimental test, ANN is used to validate the results obtained and also to predict the behavior of the system under any condition within the operating range.

I. INTRODUCTION

Metal matrix composites (MMC) materials possess high specific strength and stiffness compare to common structural materials and are extensively used in automobiles, recreational industries and aerospace applications. The most popular type of MMC is aluminium alloy reinforced with ceramics particles. These low cost composites provide higher strength, stiffness and fatigue resistance with a minimal increase in density over the base alloy. Owing to the addition of reinforcing materials, which are normally harder and stiffer than matrix, machining becomes significantly more difficult than those of conventional materials. Attempts had been made to extend the classical metal cutting theory to the machining of MMCs and to find a finite element model-based solution to the issues of machining MMCs. Analytical model extending the classical Merchants Theory, Slip line theory and Griffith's theory of brittle fracture to the machining of ceramic particle reinforced MMCs. This model predicted the cutting forces and was validated experimentally. The authors also contend that the classical metal cutting theories are also, by and large, valid for understanding the machining of MMCs.

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The design of structures and components using newly developed composite materials usually requires extensive (and expensive) testing programs. Ideally, the designer should be able to accurately assess the performance of a new material or an existing material under untested conditions using a relatively small database of test results. For these situations when it is difficult to find an accurate mathematical-based solution and the existing data is incomplete, noisy or complex, the biologically motivated computing paradigm of artificial neural networks (ANN) has emerged as a superior modeling tool.

Artificial neural networks (ANN) have emerged as one of the useful artificial intelligence concepts used in the various engineering applications. Due to their massively parallel structure and ability to learn by example, ANN can deal with non-linear modeling for which an accurate analytical solution is difficult to obtain. ANN have already been used in medical applications, image and speech recognition, classification and control of dynamic systems, among others; but only recently have they been used in modeling the mechanical behavior of fiber-reinforced composite materials.

II.EXPERIMENTAL PROCEDURE

In order to achieve the objective of this experimental work, MMCs of type A356/SiC/20p (aluminium with 7.5% silicon, 2.44% magnesium, reinforced with 20% volume particles of silicon carbide (SiC)) were tested. The silicon carbide particle size ranges from 56 to 185μm. A medium duty lathe with 2 Kw spindle power was used to perform the experiments. The CNMA 120408 inserts with PCLNR 25 X25 M12 tool holder with PCD were used to turn the billets of 48-mm diameter. The used tool geometry was as follows: Top rake angle 0◦, nose radius 0.8mm. The work material is machined at five different cutting speeds ranging from 100 to 600m/min with two feed rates of 0.108 and 0.200mm/rev and depth of cut as 0.25, 0.5 and 0.75mm.. Each experimental trial was carried out for 3min duration. The same experiment was carried out using Titanium nitride coated carbide tool also. The average surface finish (Ra) in the direction of the tool movement was measured in three different places of the machined surface using a surface roughness tester, Mitutoyo Surf test—201 with a cut-off and transverse length of 2.5mm. Finally surface mean roughness (Ra) in microns value of the three locations was considered for the particular trial.

III. EXPERIMENTAL CONDITIONS

Machine Self-centering lathe

Tool insert CNMA 120408, Nose radius—0.8mm (PCD1500 grade coarse grain) and Titanium Nitride coated carbide tool

Holder size 20×20mm

Cutting parameters

Cutting speed: 50, 80, 100, 160and 200 m/min

feed rate: 0.108 and 0.2mm/rev,

DOC: 0.25, 0.50 and 0.75mm

Surface texture equipment:

Surf test—201, Make Mitutoyo

Coolant: Dry machining

Fig 1: CNC lathe used for machining

Fig 2 work piece

Table 1 - Surface texture analysis

Cutting speed (m/min)	Depth of cut (mm)	Feed rate (mm/rev)	Ra (micron) Using PCD	Ra Using TiN coated
50	0.25	0.108	3.32	3.51
50	0.25	0.2	4.01	4.25
50	0.5	0.108	3.48	3.73
50	0.5	0.2	4.35	4.59
50	0.75	0.108	3.83	4.01
50	0.75	0.2	4.57	4.87
80	0.25	0.108	2.61	2.89
80	0.25	0.2	3.02	3.27
80	0.5	0.108	2.92	3.03
80	0.5	0.2	3.28	3.59
80	0.75	0.108	3.09	3.34
80	0.75	0.2	3.67	3.92
120	0.25	0.108	1.94	2.17
120	0.25	0.2	2.38	2.59
120	0.5	0.108	2.25	2.48
120	0.5	0.2	2.38	2.79
120	0.75	0.108	2.41	2.69
120	0.75	0.2	2.82	3.02
160	0.25	0.108	1.33	1.52
160	0.25	0.2	1.68	1.92
160	0.5	0.108	1.51	1.83
160	0.5	0.2	2.08	2.38
160	0.75	0.108	1.82	2.09
160	0.75	0.2	2.34	2.65
200	0.25	0.108	1.02	1.14
200	0.25	0.2	1.28	1.49
200	0.5	0.108	1.18	1.38
200	0.5	0.2	1.38	1.55
200	0.75	0.108	1.32	1.49
200	0.75	0.2	1.52	1.74

IV. BACK-PROPAGATION NETWORK—ALGORITHM

Step 1 Decide the number of hidden layers.

Step 2 Decide the number of neurons for the input layer and the output layer. For input layer, the number of neurons is equal to the number of input variables and for the output layer it is equal to the number of outputs required. Set small number of neurons for the hidden layer.

Step 3 Get the training input pattern.

Step 4 Assign small weight values for the neurons connected in between the input, hidden and output layers.

Step 5 Calculate the output values for all the neurons in hidden and output layers using the following formula.

$Out_i = f\,(net_1) = f(\sum_{wij} out_j + \square_1)$ ……. (1)

where outi is the output of the ith neuron in the layer under consideration; outj is the output of the jth neuron in the preceding layer. f is the sigmoid function can be expressed as:

$f\,(net_1) = 1/(1+e^{-neti/q})$ ……….. (2)

Step 6 Determine the output at the output layer and compare those with the desired output values. Determine the error of the output neurons,

Error = desired output−actual output

Similarly, determine the root mean square error value of the output neurons

$E_p = (\sum(t_{pj} - o_{pj})^2)/2$ ……….. (3)

Step 7 Determine the error available at the neurons of the hidden layer and back-propagate those errors to the weight values connected in between the neurons of the hidden layer and input layer. Similarly, back propagate the errors available at the output neurons to the weight values connected in between the neurons of the hidden layer and output layer using the following formula

Error $\delta_p = (t_{pi} - o_{pi})\, o_{pi} \sum \delta_{pi} w_{ki}$ …..(4)

For hidden neurons

Weight adjustment made as follows

$\delta W_{ji}(n=1) = n\,(\delta_{pi} o_{pi}) = \infty \delta w_{ji}(n)$ …..(5)

Error $\delta_{pi} = (t_{pi} - o_{pi})\, op_i(1-o_{pi})$ ……......(6)

Where n is the learning rate parameter

Step 8 Go to Step 3 and do the calculations up to Step 7. At the end of cycle determine the root-mean-square error value, mean percentage of error and worst percentage of error over the complete patterns. To reach to Step 9 check whether it is of reasonable error or not, if so, go to Step 9 otherwise go to Step 3 and repeat the same from Step 3 to Step 7. Step 9 Stop the iteration and note the final weight values attached to the hidden layer neurons and also to the Output layer neurons.

Step 10 Testing neural network model with the trained weight values, determine the output for the testing pattern and check whether the deviation from desired value is reasonably less or not. If no, try the back propagation with revised network by changing the number of neurons, altering learning rate parameters, altering momentum value and altering temperature value.

V. PREDICTION OF RA VALUE

Ra value is predicted using ANN in MATLAB software and the value obtained is shown in table 2

Table 2 Comparison between actual and predicted Ra value using PCD tool

Spindle speed (rpm)	Depth of cut (mm)	Feed rate (mm/rev)	Predicted Ra value	Actual Ra value	Percentage error
55	0.26	0.19	3.91	3.78	0.033
72	0.48	0.11	3.10	3.28	0.058
89	0.28	0.109	3.08	2.98	0.032
115	0.25	0.109	2.35	2.42	0.029
125	0.72	0.13	2.37	2.24	0.054
139	0.32	0.17	2.35	2.23	0.051
156	0.26	0.12	1.78	1.76	0.011
167	0.66	0.108	1.80	1.68	0.066
188	0.75	0.2	1.29	1.24	0.038
194	0.48	0.178	1.28	1.19	0.070

VI. CONCLUSION

- Experiments were conducted on Lathe using PCD coarse grade cutting insert and Titanium Nitride coated carbide, the data of surface roughness was collected under different cutting conditions for various combinations of cutting speed, feed rate, and depth of cut.
- When comparing PCD insert and Titanium Nitride Coated carbide tool, PCD produced finished surface than Titanium Nitride coated carbide cutting tool.
- ANN has been used to learn the collected data. Neural network configuration was trained. The results of neural network model shows close matching between the model output and the directly measured surface roughness. This method seems to have prediction potentials for non-experimental pattern additionally. ANN methodology consumes lesser time giving higher accuracy

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