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Studies on effect of cutting parameters on surface roughness of Al-Cu-TiC MMCs : An Artificial Neural Network Approach

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Abstract

An artificial neural network model of 'Feed Forward Back Propagation' type is developed for the analysis and prediction of surface roughness, the relationship between cutting and process parameters of Al-4.5Cu-1.5TiC Metal Matrix Composites. The effect of the process parameters namely, Cutting speed, feed, depth of cut upon the responses like: surface roughness parameter R_a, R_z and R_t of Al-4.5Cu-1.5TiC MMC are analyzed during this investigation. The Experiments have been carried out as per Taguchi's L_{25} orthogonal array with five levels defined for each of the factors for developing the knowledge base for ANN training. To have all the data in a same scale the experimental results have been normalized before being used in the Artificial Neural Network model.

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Keywords: ANN; Surface Roughness; turning operations; orthogonal array; Al-Cu based MMCs; Taguchi Method.

1. Introduction

Now a days in various manufacturing sectors turning is the most primary operation. The finished surface prepared by turning operation requires good surface finish. For achieving good surface finish the lathe operators use their own knowledge and experience.

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Greater production cost can be incurred for an improper decision of an operator in turning operation. Thus selection of proper cutting tools and proper input parameters is a very critical and vital task (Nian et al., 1999). Therefore a proper estimation of surface roughness is the focus of study for several years. Surface roughness is the indicator of the quality of the machined surfaces and it influences properties such as fatigue strength, wear resistance, wear rate, coefficient of friction, lubrication, and corrosion resistance of the machined parts (Feng and Wang, 2002).

Because of the complexity of the machining process performing optimization of a machining process is very difficult. Therefore, ANN which is capable of mapping the input/output relationships, and as well as capable of doing computing, have attracted great attention of researchers. To implement the general functions of human brain artificial neural network model is developed. The development of artificial neural network (ANN) is to imitate human brain for the implementation of the functions such as association, self-organization and generalization. It can approximate any functions more efficiently and thus it is suitable for modelling any non-linear process. It is having the learning ability, generalization ability, can capture complex input–output relationships (Kosko, 1994; Schalkoff, 1997). Now a days artificial neural network has been applied for predicting qualities of any machining process.

Rangwala and Dornfeld used a multilayered perception neural network to model the turning process and an augmented Lagrange multiplier method to optimize the material removal rate. Zouaghi and Ichida established a simple neural network model to identify grinding mode and for predicting surface in grinding of silicon nitride. Sathyanarayan et al. for studying creep feed grinding of super alloys developed a neural network model. For predicting tool wear on chamfered and honed CBN cutting tools Ozel and Nadgir (2002) developed a back-propagation type neural network model during orthogonal cutting of hardened H-13 steel. Singh et al. (2006) also studied ANN model for predicting drill wear while drilling of copper workpieces. Xu LiuJie et al. (2007) used a neural network method for studying the effects of pv factor and contact temperature for dry sliding tribological behaviour of 30 wt.% carbon-fiber-reinforced polyetheretherketone composite (PEEK-CF30).

The Al-Cu based composites is studied by a number of researchers and is found to possess high strength and stiffness. It was found that the TiC reinforced composites exhibit higher stiffness and ductility. This may be attributed to the stronger interfacial bonding in the Al-Cu-TiC system because of the increased tendency for nucleation of solid on the particle surfaces [10-12].

Hence, present area of research has been chosen to analyze effects of feed, cutting speed and depth of cut on surface roughness parameters, Centre line average roughness R_a, Average maximum height of the profile R_z, Maximum peak to valley height of the profile R_t by developing ANN models during turning of Al-4.5Cu-1.5TiC Metal Matrix Composite by using cemented carbide tools. First of all, process parameters effecting surface roughness have been screened by using Taguchi Method of design of experiment. The experimental results based on design of experiment have later been used for training of the artificial neural network model. Finally, experimental verifications on the established model and comparison among the experimental and predicted data is conducted.

2. Experimental Set up

The experiment was carried out in a ‘FLEXTURN SIEMENS 802D’ CNC Lathe manufactured by MTAB Engineers Pvt. Ltd. The machining was carried out in dry environment without any cutting fluid. CNC part programs were used for doing the turning operation in CNC Lathe machine. 3D profilometer has been used to measure the surface roughness parameters with 20x magnification with 4.7mm cut off distance.

Fig. 1. Photograph of the CNC Lathe machine used for turning operations

2.1. Design of experiment

Five levels, of equal spacing within the range of the parameters have been selected (table 1) in the present investigation, Taguchi's L_{25} Orthogonal Array design has been taken into consideration for the experimentation.

Table 1. Selected levels for cutting

Parameter	Notation	Unit	Level of factors				
			Level 1	Level 2	Level 3	Level 4	Level 5
Cutting Speed	N	rpm	500	700	900	1100	1300
Feed	f	mm/min	15	25	35	45	55
Depth of Cut	d	mm	0.05	0.10	0.15	0.20	0.25

3. Designing of Artificial Neural Network

In this present investigation a Feed Forward neural network is developed for predicting the Ra, R_a, R_z and R_t of Al-4.5Cu-1.5TiC Metal Matrix Composite. The network developed is a Back Propagation Neural Network (BP) with one hidden layer apart from one input and one output layer. The neural network is developed for 3 (three) input variables namely: Cutting speed, feed, depth of cut along with 3 (three) output variables i.e. R_a, R_z and R_t Al-4.5Cu-1.5TiC Metal Matrix Composite.

3.1. Back Propagation Neural Network

[13] Back Propagation type artificial neural networks consist of inputs and processing units known as neurons or nodes. The neurons in every layers are interconnected by different connection strengths called weights, along with the architecture of the network; which stores the knowledge of a trained network. A bias neuron is

connected to each processing unit in the hidden layer and output layer. Depending on the size and nature of the dataset the hidden layers number and neurons in each layer varies.

Back Propagation type artificial neural networks are neural networks with supervised learning rules. Feed forward refers to the direction of information flow from the input layer to the output layer. Back Propagation type artificial neural networks are the most common multi-layered network used in almost 80% of all applications.

3.2. Data Preprocessing

It is always convenient to bring the data to a uniform scale for input to any soft computing methods and this has been achieved by normalizing using Equation 1 for a range varying from 0.1 to 0.9 as there is a considerable variation in the input data range in terms of numerical value,

$$y = 0.1 + 0.8\left(\frac{x - x_{min}}{x_{max} - x_{min}}\right) \tag{1}$$

Where, x = actual value,

x_{max} = maximum value of x,

x_{min} = minimum value of x,

y = normalized value corresponding to x.

All the experimental data have been normalized using Equation 1.1 in the range of 0.1 to 0.9 and are tabulated in the Table 2.

Table.2. Normalized Values of the Experimental Data

Experiment No.	Input variables in actual data scale			Input variables in normalized scale			Output variables in actual data scale			Output variables in normalized scale		
	Cutting Speed	Feed	Depth of Cut	Cutting Speed	Feed	Depth of Cut	R_a	R_z	R_t	R_a	R_z	R_t
1	500	15	0.05	0.10	0.10	0.10	2.02	2.63	3.57	0.61	0.62	0.90
2	500	25	0.10	0.10	0.30	0.30	2.06	1.97	3.00	0.63	0.38	0.73
3	500	35	0.15	0.10	0.50	0.50	1.98	2.12	2.93	0.60	0.43	0.71
4	500	45	0.20	0.10	0.70	0.70	1.83	3.40	3.25	0.54	0.90	0.81
5	500	55	0.25	0.10	0.90	0.90	2.16	2.17	1.91	0.67	0.45	0.41
6	700	15	0.10	0.30	0.10	0.30	2.01	2.03	1.79	0.61	0.40	0.37
7	700	25	0.15	0.30	0.30	0.50	1.69	2.15	2.04	0.48	0.44	0.45
8	700	35	0.20	0.30	0.50	0.70	1.51	2.31	2.46	0.41	0.50	0.57
9	700	45	0.25	0.30	0.70	0.90	1.99	3.24	1.08	0.60	0.84	0.16
10	700	55	0.05	0.30	0.90	0.10	1.71	2.28	1.57	0.49	0.49	0.31
11	900	15	0.15	0.50	0.10	0.50	0.72	1.76	1.21	0.10	0.30	0.20
12	900	25	0.20	0.50	0.30	0.70	1.87	2.21	2.02	0.56	0.47	0.44
13	900	35	0.25	0.50	0.50	0.90	2.24	2.29	0.86	0.70	0.49	0.10
14	900	45	0.05	0.50	0.70	0.10	1.92	2.02	1.00	0.58	0.40	0.14
15	900	55	0.10	0.50	0.90	0.30	2.03	1.73	1.38	0.62	0.29	0.25
16	1100	15	0.20	0.70	0.10	0.70	1.62	2.21	2.67	0.46	0.47	0.63
17	1100	25	0.25	0.70	0.30	0.90	1.73	1.21	1.76	0.50	0.10	0.37
18	1100	35	0.05	0.70	0.50	0.10	2.01	3.21	1.34	0.61	0.83	0.14
19	1100	45	0.10	0.70	0.70	0.30	2.74	3.02	2.90	0.90	0.76	0.70

20	1100	55	0.15	0.70	0.90	0.50	1.20	2.98	3.01	0.29	0.75	0.73
21	1300	15	0.25	0.90	0.10	0.90	1.16	1.56	1.74	0.27	0.23	0.36
22	1300	25	0.05	0.90	0.30	0.10	1.89	2.79	2.09	0.56	0.68	0.46
23	1300	35	0.10	0.90	0.50	0.30	2.05	3.19	1.88	0.63	0.82	0.40
24	1300	45	0.15	0.90	0.70	0.50	2.37	2.06	1.56	0.75	0.41	0.21
25	1300	55	0.20	0.90	0.90	0.70	1.98	1.99	2.56	0.60	0.38	0.60

3.3. Selection of Architecture

The selection of the architecture for the neural network is the most important step for designing a good quality prediction. As there are 3 (three) input variables there will be three neurons in the input layer and to predict three output variables, output layer will consist three neurons. A MATLAB code is used according to the version R2010b to convert the earlier developed ANN model.

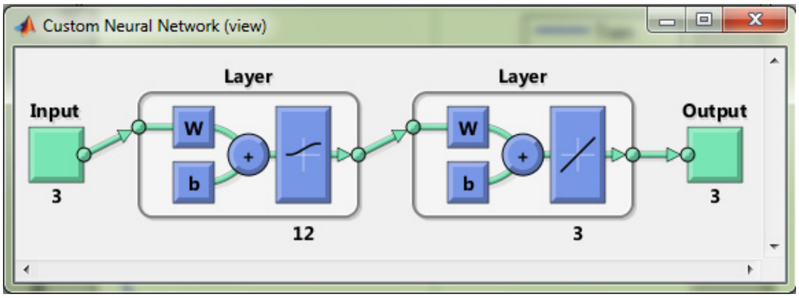

Fig. 2. Schematic view of the neural network used

Table. 3. Shuffled Experimental Data (Normalized) used in input-output patterns

Data group	Experiment No.	Serial on the pattern	Cutting Speed	Feed	Depth of Cut	R_a	R_z	R_t
Training Data Set	1	1	0.10	0.10	0.10	0.61	0.62	0.90
	2	2	0.10	0.30	0.30	0.63	0.38	0.73
	3	3	0.10	0.50	0.50	0.60	0.43	0.71
	4	4	0.10	0.70	0.70	0.54	0.90	0.81
	5	5	0.10	0.90	0.90	0.67	0.45	0.41
	6	6	0.30	0.10	0.30	0.61	0.40	0.37
	7	7	0.30	0.30	0.50	0.48	0.44	0.45
	8	8	0.30	0.50	0.70	0.41	0.50	0.57
	9	9	0.30	0.70	0.90	0.60	0.84	0.16
	10	10	0.30	0.90	0.10	0.49	0.49	0.31
	11	11	0.50	0.10	0.50	0.10	0.30	0.20
	12	12	0.50	0.30	0.70	0.56	0.47	0.44
	13	13	0.50	0.50	0.90	0.70	0.49	0.10
	14	14	0.50	0.70	0.10	0.58	0.40	0.14
	15	15	0.50	0.90	0.30	0.62	0.29	0.25
	16	16	0.70	0.10	0.70	0.46	0.47	0.63
	17	17	0.70	0.30	0.90	0.50	0.10	0.37
	18	18	0.70	0.50	0.10	0.61	0.83	0.14

19	19	0.70	0.70	0.30	0.90	0.76	0.70
20	20	0.70	0.90	0.50	0.29	0.75	0.73
21	21	0.90	0.10	0.90	0.27	0.23	0.36
22	22	0.90	0.30	0.10	0.56	0.68	0.46
23	23	0.90	0.50	0.30	0.63	0.82	0.40
24	24	0.90	0.70	0.50	0.75	0.41	0.21
25	25	0.90	0.90	0.70	0.60	0.38	0.60
Validation Data Set	26	0.32	0.10	0.50	0.17	0.10	0.18
	27	0.55	0.30	0.30	0.20	0.78	0.22
	28	0.77	0.50	0.10	0.13	0.25	0.25
Test Data Set	29	0.32	0.30	0.30	0.27	0.71	0.23
	30	0.55	0.10	0.50	0.13	0.44	0.15
	31	0.77	0.30	0.10	0.13	0.32	0.19

3.4. Performance of Artificial Neural Network model

The performance plot of the trained Artificial Neural Network (ANN) model is shown in Fig. 3. The best validation performance (MSE) of the ANN is found as 0.096503 which can be considered as quite satisfactory.

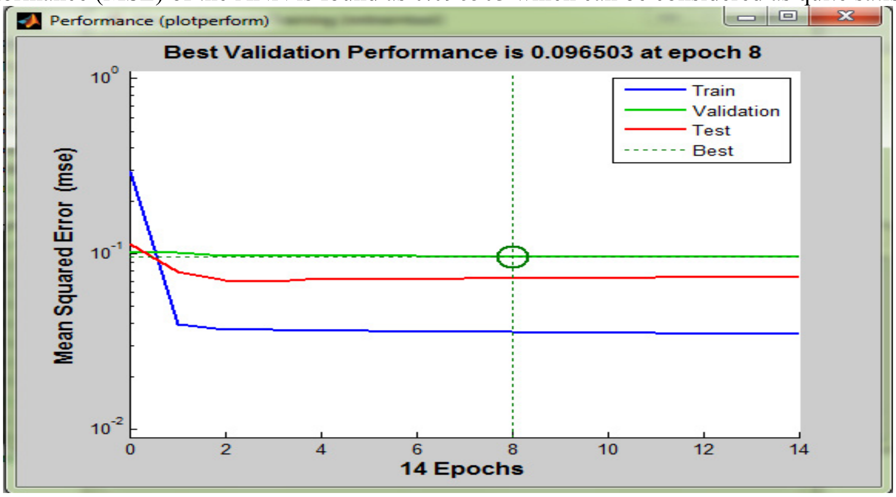

Fig. 3. Performance grah of the neural network after training.

3.5. Simulation Results

Based on the input process variables data, the trained Artificial Neural Network has been simulated to predict the outputs responses. The corresponding simulation results are recorded in the Table 4. As the target data set i.e. the output data set used during training the neural network are in normalized scale, so the predicted outputs are also in the same scale. From the Table 4 it is very clear that all the predicted forecast values are almost equal to the respective experimental values.

Table 4. Artificial Neural Network Predicted Responses in Normalized Scale

Experiment No.	Experimental values in Normalized scale			Simulated Results in Normalized scale		
	R_a	R_z	R_t	R_a	R_z	R_t
1	0.61	0.62	0.90	0.55	0.51	0.44

2	0.63	0.38	0.73	0.56	0.52	0.45
3	0.60	0.43	0.71	0.57	0.53	0.45
4	0.54	0.90	0.81	0.58	0.55	0.45
5	0.67	0.45	0.41	0.59	0.56	0.45
6	0.61	0.40	0.37	0.51	0.47	0.44
7	0.48	0.44	0.45	0.52	0.48	0.44
8	0.41	0.50	0.57	0.56	0.49	0.44
9	0.60	0.84	0.16	0.55	0.51	0.44
10	0.49	0.49	0.31	0.66	0.65	0.46
11	0.10	0.30	0.20	0.48	0.42	0.43
12	0.56	0.47	0.44	0.49	0.44	0.44
13	0.70	0.49	0.10	0.50	0.45	0.44
14	0.58	0.40	0.14	0.63	0.61	0.46
15	0.62	0.29	0.25	0.64	0.62	0.46
16	0.46	0.47	0.63	0.44	0.37	0.43
17	0.50	0.10	0.37	0.45	0.39	0.43
18	0.61	0.83	0.14	0.59	0.57	0.45
19	0.90	0.76	0.70	0.60	0.58	0.45
20	0.29	0.75	0.73	0.61	0.59	0.45
21	0.27	0.23	0.36	0.39	0.32	0.42
22	0.56	0.68	0.46	0.55	0.52	0.45
23	0.63	0.82	0.40	0.56	0.53	0.45
24	0.75	0.41	0.21	0.57	0.54	0.44
25	0.60	0.38	0.60	0.58	0.55	0.44

4. Concluding Remarks

The present paper is on prediction of surface roughness parameters such as Centre line average roughness R_a, Average maximum height of the profile R_z, Maximum peak to valley height of the profile R_t . The analysis was carried out by developing surface roughness models of R_a, R_z and R_t using ANN with cutting speed, feed rate, depth of cut as process parameters. A back propagation type neural neural network is employed for this purpose. The training data set is developed based upon Taguchi's L25 array. In this work, twenty five experiments were conducted according to the design of experiment with four levels of cutting parameters. The following conclusions are drawn.

There exist non-linear relationship between the cutting conditions and surface roughness parameters. This justifies the use of artificial neural network to develop the surface roughness model. Thus Surface roughness of work in turning process can be successfully modelled. This paper has successfully established new process model to predict the surface finish of the work. In different practical applications, values of the process parameters can be controlled better if the process models are employed in different industrial applications.

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