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ANN MODEL TO PREDICT SURFACE ROUGHNESS IN DRILLING HYBRID COMPOSITES

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Abstract:
Metal matrix composites are materials which combine a tough metallic matrix with a hard ceramic reinforcement. The inclusion of an additional reinforcement phase makes them hybrid composites. Most industries are usually looking for replacement of ferrous components with lighter and high strength alloys like Aluminium metal matrix composites. Despite the superior mechanical and thermal properties of particulate metal matrix composites (PMMCs), their poor machinability is the main drawback to their substitution to other metallic parts. Artificial neural network (ANN) in artificial intelligence is an implementation of an algorithm inspired by research in to the brain.

This paper presents a neural network based on back-propagation (BP) algorithm with hidden layers are used for the modeling of surface roughness in drilling of hybrid metal matrix composites. Materials used for the present investigation are Al 356- aluminum alloy reinforced with silicon carbide of size 25 microns and Mica of size 45 microns which are produced through stir casting route. Experiments are conducted on a vertical CNC machining centre using carbide drills of 6 mm diameter. The parameters considered for the drilling experiments are spindle speed, feed rate and wt % SiC. The data for training and testing have been taken from experiments conducted as per design of experiments.

An empirical model has been developed for predicting the surface roughness of hybrid composites. The result shows that the well trained neural network model can precisely predict the surface roughness in drilling of hybrid composites. Validation results reveal that the neural network model is suitable for predicting the surface roughness in drilling hybrid composites. The efficiency of the system can be improved by using more number of data points. It was found that the maximum error obtained in training of ANN system when comparing the experimental results is less than 5.0%. The influence of different parameters on surface roughness is analyzed by using analysis of variance (ANOVA) and it can be asserted that feed rate is the main factor which influences the surface roughness of hybrid Metal matrix composite.

Key Words: Hybrid Composites, Artificial Neural Network (ANN), Drilling, Surface Roughness

1. INTRODUCTION

Hybrid metal matrix composites find diverse applications in many engineering fields. Applications of these composite materials are among the most important developments in materials engineering in recent years [1]. Ramulu et al. reported that the alumina particulates caused extremely rapid flank wear in drilling tools, when machining Al_2O_3 particulate reinforced aluminum-based MMC. Among the three tool materials studied, polycrystalline diamond (PCD) drills possessed the highest resistance to tool wear and they are recommended for finish machining operations under most cutting conditions. The carbide tipped drill also showed acceptable drilling forces and hole quality. In this case, carbide tipped drills can be used under compromised conditions. HSS drills are unsuitable for drilling of ceramic reinforced metal matrix composites because of very high tool wear, poor hole quality and higher drilling forces induced [2,3]. Several studies are carried out on the machining of metal matrix composites. Reduction in tool wear and improving surface finish during machining of metal composites has been the bone of contention of researchers worldwide. HSS tools are reported as not the viable option for machining metal composites. Tool wear is excessive and surface finish inadmissible in most cases. PCD, CBN, and coated tools are suitable at certain levels of cutting speed and feed rates with satisfactory surface finis[4,5] Monaghan and OReily [6] used coated and uncoated high speed steel, carbide and PCD-tipped drills and solid carbide drills in the drilling tests. The results indicate that the hardness of the tool material has a significant influence on cutting edge wear and on the drilling-torque, surface finish and thrust-forces. Surface finish is an important parameter in machining process. Surface roughness has received serious attention for many years. It has formulated an important design feature in many situations such as parts subject to fatigue loads, precision fits, fastener holes and aesthetic requirements. In addition to tolerances, surface roughness imposes one of the most critical constraints for selection of machines and cutting parameters in process planning [7].

Taguchi technique is a powerful tool for the design of high quality systems. It provides a simple, efficient and systematic approach to optimize design for performance, quality and cost. The methodology is valuable when design parameters are qualitative and discrete. Taguchi parameter design can optimize the performance characteristics through the setting of design parameters and reduce the sensitivity of the system performance to the source of variation [8-9]. In order to get good surface quality and dimensional properties, it is necessary to employ optimization techniques to find optimal cutting parameters and theoretical models to do predictions. Taguchi and response surface methodologies can be conveniently used for these purposes. Suresh [10] used the response surface method and genetic algorithm for predicting the surface roughness and optimizing the process parameters.

Artificial neural network (ANN) in artificial intelligence is an implementation of an algorithm inspired by research in to the brain. They are a technology in which computers learn directly from data, there by assisting in classification, function estimation, data compression and similar tasks. ANN can be viewed as computing elements, simulating the structure and function of the biological neural network. They are successfully used to solve variety of complex engineering and scientific problems. The ANN can be used by many researchers for machining process. Caydas and Hascalik [11] used ANN in the study of abrasive water jet machining process. They have successfully applied ANN for estimation of surface roughness in water jet machining with less number of experiments. Hayajneh et al.,[12] studied the effect of cutting speed, cutting feed, and volume fraction of the reinforced particles of self-lubricated aluminum/alumina/graphite hybrid composites on the thrust force and cutting torque using experimental techniques and ANN In view of the above reason, in this study ANN is used to predict surface roughness in drilling of hybrid composites.

2. EXPERIMENTALS

2.1 Materials and methods

Aluminum alloy Al56 was used as a matrix material. The silicon carbide particles of size 25 microns and Mica of average size 45 microns were used as the reinforcement materials. The composites were fabricated with 5-15 weight % of the Sic particles and a fixed quantity of 3 weight % of Mica. The composites were fabricated by stir casting method which was used by the other researchers [5].

2.2 Experimental Design

The experiments were conduct as per the standard orthogonal array. The selection of the orthogonal array is based on the condition that the degrees of freedom for the orthogonal array should be greater than or at least equal sum to those of drilling parameters. In the present investigation an L27 orthogonal array was chosen, which has 27 rows and 13 columns as shown in Table I.The machining parameter chosen for the experiment are (i)Spindle speed (ii)feed rate(iii) wt % Sic. Table II indicates the factors and their levels. The experiment consists of 27 tests (each row in the L27 orthogonal array) and the columns were assigned with parameters. The first column was assigned to Speed (V), second column was assigned to Feed rate (F),fifth column was assigned to wt % SiC (R) and the remaining columns were assigned to their interactions.

Table I: L_{27} Orthogonal array used for experimentation.

Column numbers													
	V	*F*	*V x F*	*V x F*	*R*	*V x R*	*V x R*	*F x R*	-	-	*F x R*	-	-
Trial No.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	2	3
5	1	2	2	2	2	2	2	3	3	3	1	3	1
6	1	2	2	2	3	3	3	1	1	1	2	1	2
7	1	3	3	3	1	1	1	3	3	3	2	3	2
8	1	3	3	3	2	2	2	1	1	1	3	1	3
9	1	3	3	3	3	3	3	2	2	2	1	2	1
10	2	1	2	3	1	2	3	1	2	3	1	3	1
11	2	1	2	3	2	3	1	2	3	1	2	1	2
12	2	1	2	3	3	1	2	3	1	2	3	2	3
13	2	2	3	1	1	2	3	2	3	1	3	1	3
14	2	2	3	1	2	3	1	3	1	2	1	2	1
15	2	2	3	1	3	1	2	1	2	3	2	3	2
16	2	3	1	2	1	2	3	3	1	2	2	2	2
17	2	3	1	2	2	3	1	1	2	3	3	3	3
18	2	3	1	2	3	1	2	2	3	1	1	1	1
19	3	1	3	2	1	3	2	1	3	2	1	2	1
20	3	1	3	2	2	1	3	2	1	3	2	3	2
21	3	1	3	2	3	2	1	3	2	1	3	1	3
22	3	2	1	3	1	3	2	2	1	3	3	3	3
23	3	2	1	3	2	1	3	3	2	1	1	1	1
24	3	2	1	3	3	2	1	1	3	2	2	2	2
25	3	3	2	1	1	3	2	3	2	1	2	1	2
26	3	3	2	1	2	1	3	1	3	2	3	2	3
27	3	3	2	1	3	2	1	2	1	3	1	3	1

2.3 Experimental Procedure

In the important operation drilling cutting tools or work pieces are rotated relative to each other. It uses a multi-point rotating, fluted, end cutting tool called drill bit. It may produce coarse, helical feed marks on the work piece depends on the machining parameters (feed, speed, tool geometry, coolant, etc.). Drilling may affect the mechanical properties of the work piece by creating low residual stresses around the hole opening and a very thin layer of highly stressed and disturbed material on the newly formed surface. This causes the work piece to become more susceptible to corrosion at the stressed surface. The drilling experiments are carried out in computer numerical control (CNC) Vertical Machining Centre (VMC 100). The machining samples were prepared in the form of 100mm×100mm×10mm blocks for each material. The solid carbide drill bits of 6mm diameter were used. All the drilling operations were carried out under dry cutting conditions. The surface roughness of the work piece was measured with a Mitutoyo portable Surftest SJ-201 P/M contact profilometer. An average of three measurements was used to characterize the surface roughness at each cutting condition and Schematic representation is shown in Figure1.

Table II: Machining parameter and levels.

Control parameters	symbol	Level		
		1	2	3
Speed rpm	*V*	1000	2000	3000
Feed rate mm/min	*F*	50	100	150
Wt fraction of Sic %	*R*	5	10	15

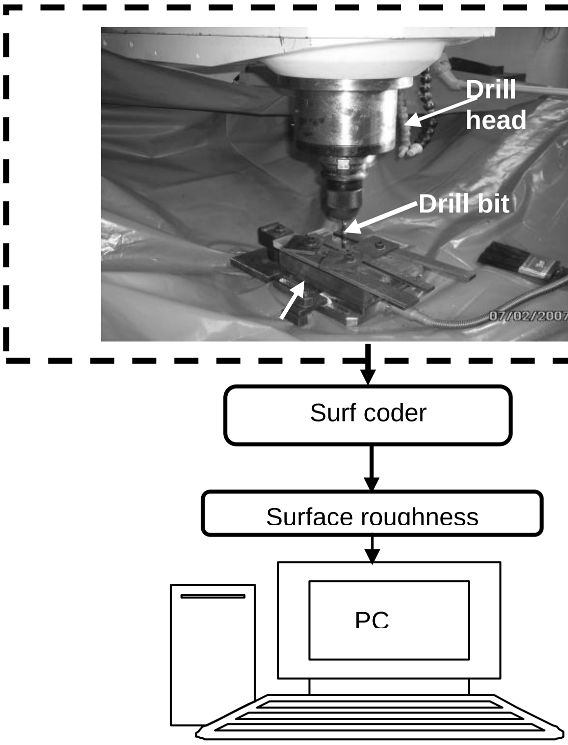

Figure 1: Schematic representation of experimental set-up.

3. NEURAL NETWORKMODEL

A neuron is the basic element of neural networks, and its shape and size may vary depending on its duties. Analyzing a neuron in terms of its activities is important, since understanding the way it works also helps us to construct the ANNs. An ANN may be seen as a black box which contains hierarchical sets of neurons (e.g., processing elements) producing outputs for certain inputs. Each processing element consists of data collection, processing the data and sending the results to the relevant consequent element. The whole process may be viewed in terms of the inputs, weights, the summation function, and the activation function [13, 14].According to the figure, we have the following.(1) The inputs are the activity of collecting data from the relevant sources.(2) The weights control the effects of the inputs on the neuron. In other words, an ANN saves its information over its links and each link has a weight. These weights are constantly varied while trying to optimize the relation in between the inputs and outputs.(3) Summation function is to calculate of the net input readings from the processing elements. (4) Transfer (activation) function determines the output of the neuron by accepting the net input provided by the summation function. There are several transfer functions like summation function. Depending on the nature of the problem, the determination of transfer and summation function is made. A transfer function generally consists of algebraic equations of linear or nonlinear form [15].The use of a nonlinear transfer function makes a network capable of storing nonlinear relationships between the input and the output. A commonly used function is sigmoid function because it is self-limiting and has a simple derivative. An advantage of this function is that the output cannot grow infinitely large or small [16] (5) Outputs accept the results of the transfer function and present them either to the relevant processing element or to the outside of the network. The functioning of ANNs depends on their physical structure. An ANN may be regarded as a directed graph containing a summation function, a transfer function, its structure, and the learning rule used in it. The processing elements have links in between them forming a layer of networks. A neural network usually consists of an input layer, a number of hidden layers, and an output layer.

3.1 Implementation Of ANN Model For Prediction of Surface Roughness

The experimental database is divided into training data set, testing data set and validating data set. The training data set is used to modify the weights between the interconnected neurons, until the desired error level is reached. There are many learning algorithms have been used such as Hebb net, the perceptron learning rule, delta rule etc. It is therefore necessary to choose an appropriate one for the practical application here. Then the network is evaluated by using the testing data set. Training is accomplished by presenting a sequence of training vectors, or data set, each with an associated target output vector. The weights are then adjusted according to a learning algorithm known as supervised learning. Training of the ANN model was performed using experimental results presented in Table III. The network training function updates the weight and bias values so as to minimize the error between the training data set and network prediction. There are 19 data sets used for training the network from the experimental results. For training the network, the TRAIN function of Neurointelligence evaluation software package was used. The function works on batch back propagation algorithm. To find out the suitable architecture of the network for the present problem optimization tool in Neurointelligence evaluation software is used. The model with 9-4-1 architecture is found to be the most suitable for the surface roughness prediction problem. It consists of 9 neurons in input layer, four neurons in hidden layer, and one neuron in output layer corresponding to the surface roughness of composites. The optimized learning rate used is 0.5 and the momentum coefficient used is 0.25. The optimal values of learning rate and momentum coefficient are achieved through optimization tool box in the software used. The principle functioning of neuron is presented in Figure 2.

Experimental conditions and results used for testing and validating the network was shown in Table IV & V. The details of the architecture used is given in Table VI.

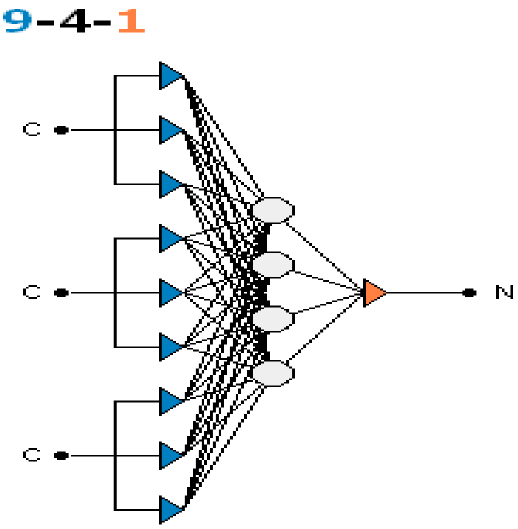

Figure 2: Neural network architecture used and the principle functioning of the neuron.

Table III: Experimental conditions and results used for training the network.

Experiment no	Target	Output
1	2.4	2.43
2	2.1	2.06
3	1.8	1.83
4	3.8	3.80
5	3.4	3.39
8	4.3	4.27
9	4	4.01
10	2	1.96
11	1.8	1.79
14	3	3.02
15	2.7	2.69
16	4	3.99
17	3.7	3.72
18	1.6	1.64
21	1.5	1.60
22	2.8	2.80
25	3.6	3.61
26	3.2	3.20
27	2.76	2.75

Table IV: Experimental conditions and results used for Testing the network.

Experiment no	Target	Output
6	3.2	3.26
12	1.5	1.69
18	3.4	3.36
23	2.5	2.40

Table V: Experimental conditions and results used for validate the network.

Experiment no	Target	Output
7	4.8	4.37
13	3.3	3.51
19	1.7	1.70
24	2.25	2.19

Table VI: Details of architecture used and results.

Network configuration	9-4-1
No of iterations	5000
Absolute error for training	0.0138
Absolute error for validation	0
Training speed.ite/Sec	847
Training algoritham	Online back propagation
Learing rate	0.5
Momentum	0.25
R-Squared for training the network	0.92
R-Squared for testing the network	0.90
R-Squared for validating the network	0.95

4. RESULTS AND DISCUSSION

Hybrid composite materials are important materials, and are finding increased applications in many engineering components. These composites have abrasive particles. These abrasive particles pose big problems during machining. Spindle speed, feed rate and wt % of SiC are the major drilling parameters that are considered in the experiments. The Surface roughness reduction in drilling is one of the important areas of research. For studying and analyzing the product quality of manufactured parts, mathematical models are used. In this study ANN is used to predict the surface roughness in drilling of hybrid composites. Modeling on of artificial neural network model requires less computational time by Neurointelligence package. The ANN model requires a number of iterative computations and selection of learning rate, momentum and weight randomization range will decide the accuracy of the results. The adequacy of the developed model can be verified by using R^2 value after estimating sum of squares (SS) and mean squares (MS). The quantity R^2 called coefficient of determination, is used to judge the adequacy of regression model developed, $0 \leq R^2 \leq 1$.The R^2 value is the variability in the data accounted for by the model in percentage.

$$R^2 = 1 - SS_{error} / SS_{Total} \tag{1}$$

The coefficient of determination is calculated using the above expression and does more than 95% for the present investigation for thrust force and surface roughness, which shows that there is highcorrelation that exists between the experimental and predicted values. Good agreement is observed between the predictive model values and experimental value.

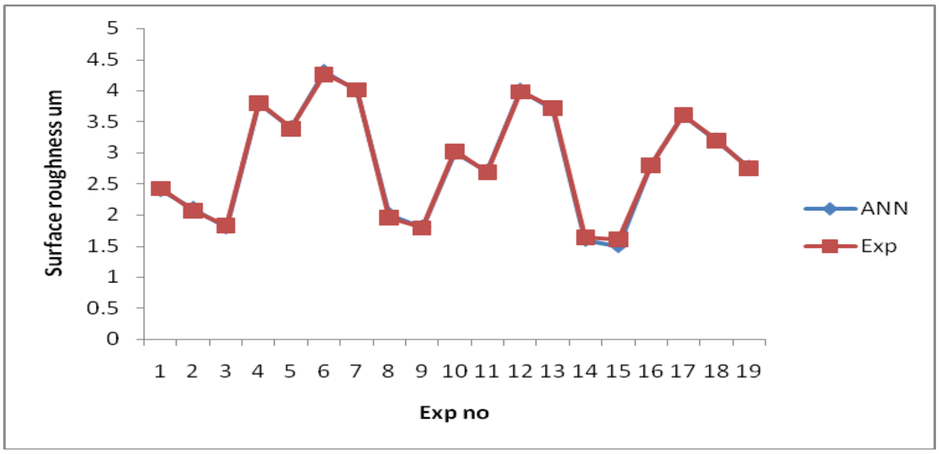

Figure 3: Target and ANN predicted data for training data sets.

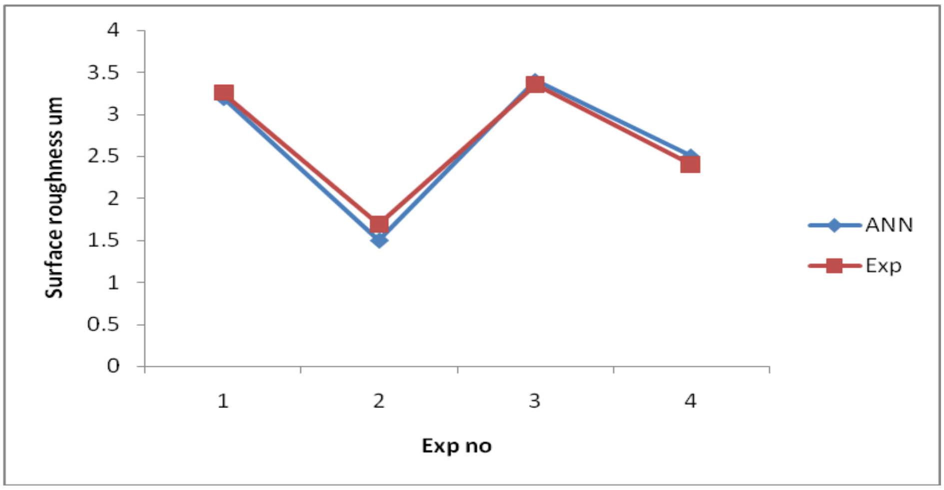

Figure 4: Target and ANN predicted data for validating data sets.

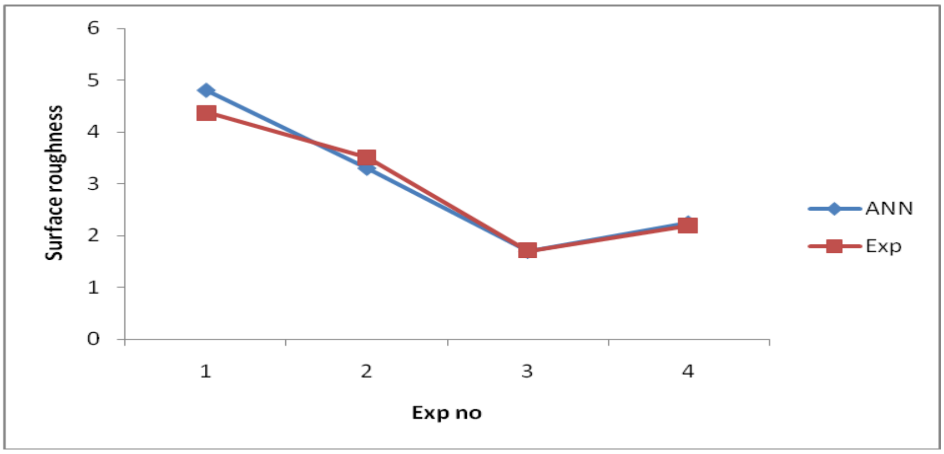

Figure 5: Target and ANN predicted data for testing data sets.

The influence of different parameters on surface roughness is analyzed by using analysis of variance (ANOVA). Table VII illustrates the analysis of results to be used for finding the significance of the three factors affecting the surface roughness of the Al/SiC-Mica composites. From the table it can be asserted that feed rate(77.6 %) is the main factor which influences the surface roughness of hybrid Metal matrix composite, followed by speed and % of Sic. The increase in feed rate increases the thrust force and it leads to poor surface finish. Also, the increase in feed rate increases the heat generation during drilling which in increases the surface roughness. The increase in wt % of SiC decreases the surface roughness.

Table VII: ANOVA for surface roughness.

Source	DOF	Sum of Square	Mean Square	F value	%of contribution
Speed	2	12.019	6.010	18.56	9.9
Feed	2	94.137	47.06	145.38	77.6
Wt % Sic	2	8.872	4.436	13.70	7.27
Error	20	6.475	0.324		
Total	26	121.5			

5. CONCLUSIONS

Experiments were conducted for the analysis of surface roughness in drilling of Al356/SIC-Mica composites. The parameters considered for the experimentation was spindle speed, feed rate and Wt % of SiC. Back propagation ANN model was developed for reducing the surface roughness in drilling of composites. Based on this investigation, the following conclusions can be drawn:

- Neural network configuration is optimized and 9-4-1 structure was selected for the training of 19 set of data sets. Using the weights obtained during training, fresh data sets were tested and the solutions obtained by the ANN are validated with that obtained by experimental values. The number of test data used in this work is only limited. The increase in test data will improve the result further.
- The effect of machining parameters on the surface roughness in drilling of hybrid composites is evaluated using ANOVA. The results show that feed rate is the most influential parameter.
- The results indicated that precision holes are obtained at reasonable spindle speed, low feed rate.
- Validation results reveal that the BP neural network model is suitable for predicting the surface roughness in drilling composites. The efficiency of the system can be improved by using more number of data points.

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