ARTIFICIAL NEURAL NETWORK MODEL TO PREDICT THRUST FORCE IN DRILLING OF HYBRID METAL MATRIX COMPOSITES

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Abstract

This paper presents, a neural network based on back-propagation (BP) algorithm with hidden layers are used for the modeling of Thrust force 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 TiN coated carbide drill 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 Thrust force of Al 356/Sic_p-mica composites. The result shows that the well trained neural network model can precisely predict the thrust force in drilling of Al 356/SiC-Mica composites. Validation results reveal that the neural network model is suitable for predicting the thrust force in drilling hybrid composites. It was found that the maximum error obtained in training of ANN system when comparing the experimental results is less than 5.0%. The efficiency of the system can be improved by using more number of data point.

Keywords: Hybrid composites; ANN; drilling; thrust force

I. INTRODUCTION

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 mach inability is the main drawback to their substitution to other metallic parts. 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]. Feed rate is the main factor, which is influencing the thrust force in Al/SiC composites. Rubensten [4,5] established drilling models to predict Thrust forces. Barnes et al.[6] has shown that softer as-extruded and solution treated materials produced less wear and lower thrust forces than the harder aged materials. However, the height of the burrs produced during drilling was found to be greater with the softer materials and the quality of the drilled surface was also inferior. The incorporation of 3% graphite in Al/SiCp composite will reduce up to 25% of the thrust force for the range of parameters studied.[7]

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 bymany researchers for machining process. Caydas and Hascalik [8] 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.[9] 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 for the modeling of thrust force in drilling Al/SIC-Mica composites.

II. EXPERIMENTAL

A. 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[7].

B. 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. The machining parameter chosen for the experiment are (i) Spindle speed (ii) feed rate (iii) wt % Mica. Table 2 indicates the factors and their level. 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.

C. Experimental procedure:

Drilling is one of the important operations. In 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 schematic arrangement of experimental set-up is presented in Figure 1.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 150 mm $\times$ 150 mm $\times$ 10 mm blocks for each material. The TiN coated carbide drill bits of 6 mm diameter were used. All the drilling operations were carried out under dry cutting conditions. Each experiment was repeated three times and and Schematic representation is shown in Figure 1.

The computer controlled data acquisition system was used to collect and record the data of the experiments. The Kirsler dynamometer was used to record the thrust force in drilling of hybrid metal matrix composites. The dynamometer is connected to a 3-channel charge amplifier type through a connecting cable, which in turn is connected to the PC by a 37-pin cable from the A/D board. The thrust force in drilling of Al/SiC-Mica composites is measured directly from the dynamometer.

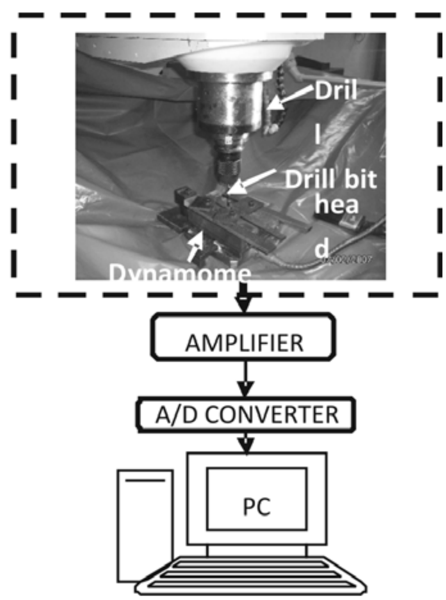

Fig. 1. Schematic representation of experimental set-up

III. 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 [10, 11]. 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 theneuron. 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 [12]. 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 [13] (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.

A. IMPLEMENTATION OF ANN MODEL FOR PREDICTION OF THRUST FORCE

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.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 optimisation tool Neurointelligence evaluation software is used. The model with 9-4-1 architecture is found to be the most suitable for the wear loss prediction problem. It consists of 9 neurons in input layer,four neurons in hidden layer, and one neuron in output layer corresponding to the thrust force 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 optimisation 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 1-3.

IV. 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. 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 details of the architecture used and the results are given in Table 4. Models developed to predict the thrust force of hybrid Al356/SiC-Mica MMCs is compared with experimental results. Comparison of experimental measurements with predicted results from ANN is shown in Figure 4. The influence of different parameters on thrust force is analyzed by using analysis of variance. Table 5 illustrates the analysis of results to be used for finding the significance of the three factors, its square effects and their interactions affecting the wear loss of the Al/SiC-Mica composites. From the table it can be asserted that feed rate (35.44%) is the main factor which influences the thrust force of Hybrid Metal matrix composite, followed by weight % of Sic and speed.

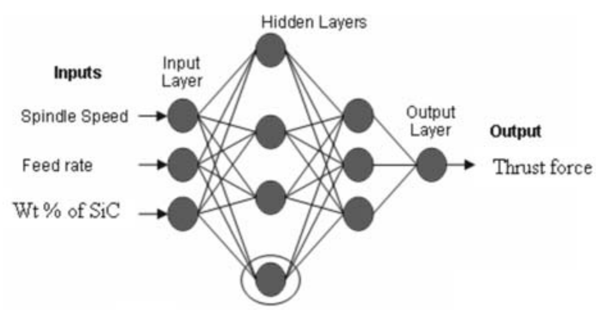

Fig. 2. Neural network architecture used and the principle functioning of the neuron

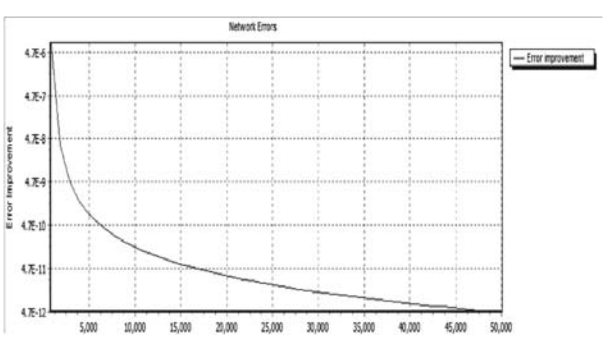

Fig. 3. Error improvements with respect to no of iterations

Table 1 Experimental conditions and results used for training the network

Ex No	Target	Output	AE
1	535	551.4275	16.42747
2	555	558.0492	3.049151
5	575	573.9714	1.028586
6	605	601.1507	3.849329
7	688	685.5938	2.406207
8	710	711.5353	1.535307
9	725	726.5006	1.500639
10	565	566.2099	1.209894
11	590	587.6745	2.325461
14	625	624.9531	0.046911
16	645	646.0456	1.04555
17	700	702.1512	2.151209
19	725	720.5951	4.404872
20	585	579.5089	5.491124
21	598	598.6122	0.612188
22	630	629.5153	0.484747
25	655	657.7756	2.775556
26	675	674.6559	0.344104
27	715	716.5227	1.522659

Table 2 Experimental conditions and results used for Testing the network

Ex no	Target	Output	AE
4	635	648.548	13.54796
13	615	600.0521	14.94792
15	740	725.7915	14.20854
24	735	727.9047	7.095289

Table 3 Experimental conditions and results used for validate the network

Ex no	Target	Output	AE
2	620	619.9995	0.000525
12	550	554.2241	4.224089
13	570	561.4963	8.503697
23	760	733.5858	26.41421

Table 4 ANOVA for Thrust force

Term	DOF	SS	Mean Square	% of contribution
A-Speed	2	4270	2135	3.6
B-Feed	2	10585	52929	90.7
C-Wt of Sic	2	6234	3117	5.3
AB	4	91	22	
AC	4	19	4	
BC	4	40	10	
ABC	8	174	21	
Residuals	0	0		

Table 5 Details of architecture used and results

Network configuration	3-4-3-1
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

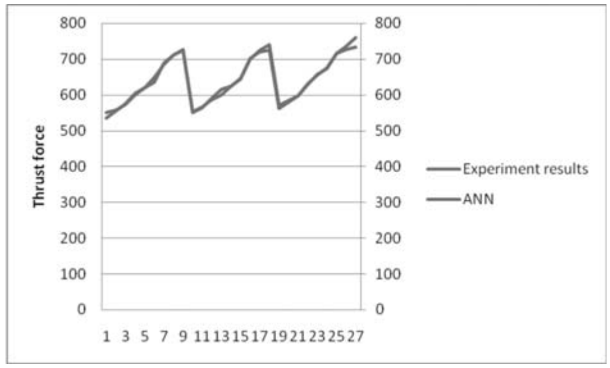

Fig. 4 Comparison of experimental measurement with predicted results from ANN and RSM

V. CONCLUSIONS

- Thrust is the reaction force against the drill's advance into the work piece. The experimental results of thrust forces as a function of cutting parameters in drilling of composites are recorded and analyzed.
- An empirical model has been developed for predicting the Thrust force of Al356/SiC-Mica composites. The result shows that the well trained neural network model can precisely predict the thrust force in drilling of Al 356/SiC-Mica composites.
- The results show that feed rate is the most influential parameter. Validation results reveal that the neural network model is suitable for predicting the thrust force in drilling hybrid composites.
- The efficiency of the system can be improved by using more number of data points.

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