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ANN Based Prediction of Effect of Reinforcements on Abrasive Wear Loss and Hardness in a Hybrid MMC

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Abstract: Problem statement: The reinforcements added to an alloy lead to variation in properties. The content and size of the reinforcement influences the properties of composites. Very little research has been carried out in hybrid composites. Work on hybrid LM6 aluminium alloy metal matrix composites (MMC) with flyash and SiC has been initiated here. The effect of the four parameters, size and weight of the reinforcements on the hardness and wear loss has been studied. **Approach***:* Artificial neural networks, from the artificial intelligence family, is a type of information processing system, based on modeling the neural system of human brain. The effect of the parameters was investigated using ANN. Central composite rotatable method of design of experiments was used to arrive at the combination and the number of specimens. The specimens were prepared using the liquid metallurgy route and tested. Pin-on-disc apparatus was used for determining wear. Rockwell hardness on C scale was determined. The data from the experiments were used for training and testing the network. **Results***:* The accuracy in ANN prediction was appreciable with the error estimated for wear loss and hardness being less than 2%. **Conclusions/Recommendations***:* The ANN prediction is quick and economical way of estimating the properties.

Key words: LM6 Aluminium alloy, SiC, Flyash, Dry sliding wear

INTRODUCTION

Metal Matrix Composites possess high specific strength, better stiffness and wear resistance in addition to high service temperatures. With particle reinforcements, metal matrix composites exhibit isotropic properties. Aluminium alloys with various reinforcements have been considered for applications in automotive components. The hardness and wear resistance of alloys improve with the addition of hard reinforcement like SiC. The wear resistance of Aluminium alloys with SiC particles has been studied in detail[1]. However the addition of reinforcement leads to increase in the cost of the product. Flyash which is a waste coal combustion byproduct from thermal power plants has been used as a filler material or functional extender in plastics, paints, resins and adhesives. The addition of flyash is also found to be effective in improving the resistance to wear of Al alloys[2]. Moreover the addition of flyash reduces the density of the composite[3], leading to structural applications where weight saving is of importance. Increase in percentage by weight of flyash leads to reduction in wear rate[3]. Increase in volume percentage of SiC reduces weight loss in aluminium alloys[4]. The wear loss in aluminium alloy composite was found to reduce with the size of SiC particle reinforcement[5].

Not much work has been done on hybrid composites, with SiC and flyash as reinforcements. In the present investigation, an attempt has been made to predict the effect of addition of SiC and flyash on the dry sliding wear behavior of LM6 aluminium alloy. The effect of the size and percentage by weight of the reinforcements has been considered in the wear study. Powder metallurgy[6], stir casting[7], pressure infiltration[8], squeeze casting[9] are the techniques used in the manufacture of MMCs. Stircasting is the economical way of getting good distribution of reinforcements.

Neural networks have been successfully used to predict tensile and density properties[10], as also the wear and surface roughness in metal matrix composites[11].

MATERIALS AND METHODS

Preparation of specimens: The flyash for the study has been procured from Raichur thermal powerplant in Karnataka. Aluminium alloy was first melted in an electric furnace. Flyash and SiC, preheated to a

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temperature of about 600ºC, were added to the molten metal at 720ºC and stirred continuously. The stirring was done at 600 rpm for 5-7 min. Magnesium was added in small amounts during stirring to increase the wetting. The melt with reinforcement was poured into permanent metallic mould. Cylindrical pins of length 30 mm and diameter 10 mm were machined.

Wear testing: The wear specimens were tested on Ducom, Bangalore make Pin-on-disc apparatus. The specimen pin was pressed against a rotating EN32 steel disc (Fig. 1.) having hardness of 65 HRC by a constant 8 kg force. The load has to be given at the other end of the arm that carries pin. The speed and distance travelled were maintained constant at 1 m sec^{-1} and 1500 m. The specimens were weighed in a single pan weighing machine having a least count of 0.0001 g. After sliding wear test the specimen were cleaned with acetone and then weighed. The difference in weight before and after the wear test gives the loss of material. The indicator for the wear in microns of the apparatus should indicate zero. This will ensure proper loading of the arm.

Central composite Rotatable design: A planned way of performing the experiments leads to better results. Design of experiments helps in arriving at the proper combination of the various parameters[12]. It also helps us in arriving at the number of experiments to be conducted. As neural networks are trained, their success depends on the effectiveness of the data used in training. Central composite rotatable design with four factors and five levels was chosen to arrive at the possible combination of variables. Table 1 gives the limits of process parameters. The reinforcements are taken as percentage of weight of base alloy. The size of SiC, the weight fraction of SiC[13], the size and weight fraction[14] of flyash which are bound to influence the wear behavior are the parameters. The reinforcements are sieved and the mean size of the range in microns is used. The limits of the various parameters have been arrived from literature. A high percentage of the reinforcements have been experimentally found to be difficult in fabricating good samples. Also the wear resistance does not improve after a certain percentage by weight as the volume of reinforcement becomes high.

The limits of the process parameters have been arrived from the formula

$$X_i = \frac{2(2X - (X_{max} + X_{min}))}{(X_{max} - X_{min})} \quad (1)$$

where X_i is the required coded value of a variable X, X is any value of the variable from X_{min} to X_{max}, X_{min} is the lower limit of the variable and X_{max} is the upper limit of the variable. The coded values for intermediate values have been calculated using Eq. 1.

The design matrix along with the responses is given in Table 2. The weight loss in material due to wear and Rockwell hardness are the two responses which have been experimentally determined.

Neural network: ANN has been used to model non linear processes in manufacturing. The advantage of ANN is storing samples with distributed coding, forming a trainable non linear system. The data for training and testing have been taken from experiments conducted as per DOE. Data of 18 samples were used for training, while the remaining samples data were used for testing. For training, Levenberg-Marquardt algorithm, though computationally complex, has been used as it is faster[14]. Sigmoid activation function has been used with coded values. The neural network simulation has been done using Matlab. The simple neural network structure used is shown in Fig. 2. The input layer has four neurons, representing the four parameters. The input neurons receive the input from the environment. The output neurons send output out of the system. The output neurons represent the wear loss and hardness. The hidden neurons have the input and output of the system. As there is no method to arrive at the number of neurons in the hidden layer, it has to be found experimentally.

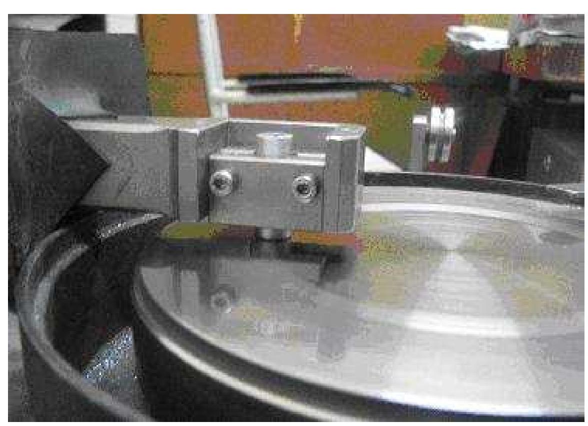

Fig. 1: Pin pressing against rotating steel disc

Table 1: Limits of process parameters

Parameter	Units	Notation	Factor Levels				
			-2	-1	0	+1	+2
Flyash grain size range	µm	F_s	0-40	40-106	106-150	150-180	180-250
SiC grain size range	µm	S_s	0-25	25-40	40-63	63-90	90-106
Flyash weight	%	F	2	4	6	8	10
SiC weight	%	S	2	4	6	8	10

Table 2: Design matrix and responses

Specimen	F_s	S_s	F	S	Response 1: Wear loss (mg)	Response 2: Hardness (HRC)
S1	-1	-1	-1	-1	20.4	117
S2	+1	-1	-1	-1	23.4	132
S3	-1	+1	-1	-1	18.6	128
S4	+1	+1	-1	-1	25.6	134
S5	-1	-1	+1	-1	24.0	120
S6	+1	-1	+1	-1	32.0	135
S7	-1	+1	+1	-1	18.2	150
S8	+1	+1	+1	-1	30.0	130
S9	-1	-1	-1	+1	26.0	105
S10	+1	-1	-1	+1	27.6	126
S11	-1	+1	-1	+1	25.1	123
S12	+1	+1	-1	+1	29.0	145
S13	-1	-1	+1	+1	36.0	102
S14	+1	-1	+1	+1	38.0	118
S15	-1	+1	+1	+1	33.5	137
S16	+1	+1	+1	+1	38.2	125
S17	-2	0	0	0	24.2	128
S18	+2	0	0	0	34.0	175
S19	0	-2	0	0	25.2	102
S20	0	+2	0	0	21.6	136
S21	0	0	-2	0	21.1	120
S22	0	0	+2	0	35.0	108
S23	0	0	0	-2	22.1	129
S24	0	0	0	+2	38.6	125
S25	0	0	0	0	20.0	114

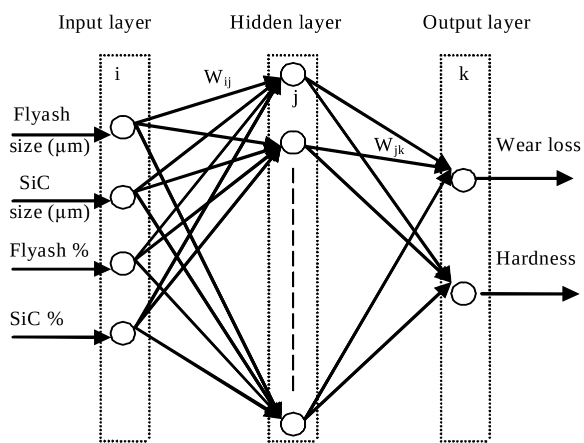

Fig. 2: Structure of the neural network

Table 3: Comparision of predicted with actual values

Specimen	Weight loss (mg)		Hardness (HRC)		Percentage error	
	Actual	Predicted	Actual	Predicted	Wear loss	Hardness
S1	20.4	20.29	117	116.76	0.56	0.200
S2	23.4	23.10	132	130.08	1.29	1.460
S4	25.6	25.57	134	134.03	0.13	-0.020
S7	18.2	18.20	150	148.98	-0.13	0.680
S8	30.0	29.99	130	129.43	0.04	0.440
S14	38.0	38.07	118	118.60	-0.18	-0.500
S16	38.2	38.00	125	125.00	0.53	0.004

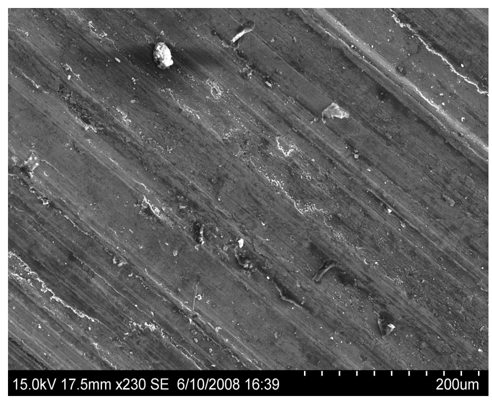

Fig. 3: SEM of the worn surface of pin

RESULTS

A feed forward, multi layer perception neural network has been designed to predict the sliding wear loss and also the hardness of flyash and SiC reinforced LM6 aluminium alloy. The network has a single hidden layer with six neurons. The comparison of the actual values of weight loss due to abrasive sliding wear and the Rockwell hardness for the seven test samples with the predicted ones is shown in Table 3. The MSE for training and validation has been found to be 0.00875092.

DISCUSSION

The values for weight loss and hardness predicted using ANN are in good agreement with the actual values as the error is less than 1.5%. This error for the hybrid composite is similar to the error obtained for wear loss predicted for a metal matrix composite using ANN[11]. The concept of design of experiments used to arrive at the combination of factors has significantly lead to the effectiveness of the modeling using ANN. As the data used for testing is different from that of training, the accuracy of prediction can be greatly appreciated. The SEM (Fig. 3) of the worn surface reveals grooves and debris. The sharp asperities present on the contact surfaces, when coming into contact lead to either plastic deformation or elastic contact. Plastic deformation takes place except at the reinforcements where fracturing takes place. This fracture leads to availability of debris.

CONCLUSION

In this study, a neural network has been designed to predict the effect of the size and percentage by weight of both flyash and SiC reinforcements on the wear loss of LM6 aluminium alloy. The prediction is found to be accurate as can be seen from the verification of test results. Further the time consuming and costly experimental process can be avoided.

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