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Artificial Neural Network Modeling for Predicting Surface Roughness in End Milling of Al-SiC$_p$ Metal Matrix Composites and its Evaluation

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Abstract: In the present study surface roughness prediction model for end milling of Al-SiC$_p$ metal matrix composites using artificial neural network is developed. The SiC percentage in the metal matrix composites is considered as one of the input parameters in addition to three prominent variables i.e., spindle speed, feed rate and depth of cut for predicting surface roughness being the output variable. A multi layer perception network having 4-14-1 architecture is found to be optimum network. The network is trained with 25 data sets and the trained network predicts the surface roughness for the interpolated values of input parameters. The result shows that the prediction performance of the neural network model is highly encouraging with an average percentage error being 0.31%. While response surface model predicts an average percentage error of 0.53%. The surface roughness is mainly affected by feed rate followed by other parameters spindle speed, SiC percentage and depth of cut.

Key words: Metal matrix composite, artificial neural network, surface roughness, feed rate, spindle speed

INTRODUCTION

Due to increased competition, the industries are facing the challenging issue of meeting the performance of components/systems which is getting more and more demanding as the days roll out. The composites materials in general and Metal Matrix Composites (MMCs) in particular have emerged as the promising alternatives to the conventional materials for the industries such as automotive, aerospace, electronics, military etc. (Lin *et al*., 2003). This is because of the potentially attractive properties the MMCs offer high specific strength and stiffness, increased wear resistance, etc. Despite of these merits, the applications of MMCs is not fully realized in commercial sense for the common man use which can be attributed to some of the following reasons (Cramer *et al*., 2002; Golzar and Poorzeinolabedin, 2010):

- High cost of manufacture of MMCs
- Higher manufacturing cost involved in producing a component from a MMC
- Lack of experience and knowledge in how to design with advanced composites
- Lack of affordable process for producing advanced composites parts in high volume suitable to industry standards (ex. automotive production standards)

It is observed that the high cost involved in producing a component is one of the main reasons hindering the widespread use of MMCs. Though it is possible to produce the MMCs components to near net shape, the final conversion of these parts into applicable engineering components is always associated with machining either by turning or milling to the desired shape, size, dimensions and surface finish (Ramanujam *et al*., 2010). The main reason for higher cost in producing a part from MMCs can be attributed to their poor machinability. This is due to hard and abrasive nature of the reinforcement used in MMCs.

Surface roughness is an important attribute of job quality. A good surface finish is essential for improving the tribological properties, aesthetic appeal of the product, etc. The production of excessively better surface finish involves higher cost of manufacturing. Therefore researchers have attempted to develop prediction model and identify suitable cutting parameters using different

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methodologies viz., the multiple regression technique, Response Surface Methodology (RSM), Neural Network (NN) and fuzzy set based modelling. Artificial Neural Network (ANN) modeling has been found very effective for surface roughness prediction (Abburi and Dixit, 2006). Kohli and Dixit (2005) have presented an artificial neural network based methodology which requires a small sized data set for the network training.

Neural networks and fuzzy set theory are two popular soft computing techniques apart from many other techniques available. Artificial neural networks are a humble attempt to model biological neural networks. An artificial neuron determines its output by calculating the weighted sum of the inputs to represent the total strength of the input signals and applying a suitable activation (threshold) function to the sum.

Number of researchers has used these tools to develop prediction models in various machining process. Chandrasekaran *et al*. (2010) have reviewed research work spanning over two decades on the application of these methods in modeling and optimization of various machining processes. In the area of machining, neural network modeling techniques have been commonly used for the prediction of surface roughness, cutting forces, tool wear, tool life and dimensional deviation. Risbood *et al*. (2003) developed a Multi Layer Perception (MLP) neural network for the prediction of surface roughness and dimensional deviation in wet turning of steel with a High Speed Steel (HSS) tool. The input layer has four neurons correspond to feed (f), cutting speed (v), depth of cut (d) and acceleration of radial vibrations (a) of the tool. They obtained the error in prediction of surface roughness less than 20%. The Radial Basis Function (RBF) neural network used by Sonar *et al*. (2006) predicts almost same accuracy in a shorter computational time. Akkus and Asilturk (2011) have used the ANN, fuzzy logic and regression model to predict the surface roughness in hard turning of AISI 4140 steel and compared the result. With least mean squared error (MSE) they found the fuzzy logic model to be the best prediction model followed by the regression model and the ANN model. Pradhan and Biswas (2010) also used neural network and fuzzy logic to predict various responses (material removal rate, tool rate wear and radial over cut) in electrical discharge machining of AISI D2 steel.

Rajasekaran *et al*. (2011) have applied the fuzzy logic for prediction of surface roughness in turning of Carbon Fiber Reinforced Polymer (CFRP) composite using the Cubic Boron Nitride (CBN) cutting tool. Barman and Sahoo (2009) have applied ANN for modeling fractal dimension in CNC turning of aluminium, brass and mild steel using coated carbide tool (titanium nitrate coating) and compared with response surface model. They have concluded that the ANN models predict fractal dimension with better accuracy than the RSM models. Very few researchers have worked on prediction and optimization of process parameters in machining of MMCs (particularly Al-based MMC).

Basavarajappa *et al*. (2007) studied the variation of surface roughness on the drilling of metal matrix composites using carbide tool and found that the surface roughness decreases with the increase in cutting speed and increases with the increase in feed rate. Arokiadass *et al*. (2011) have used response surface model to predict surface roughness in end milling of Al-SiC_p MMC. It is reported that R_a is mainly influenced by feed rate and spindle speed. Apart from conventional modeling neural network based prediction modeling becomes popular and found effective. In this study a surface roughness prediction model for end milling of Al-SiC_p MMCs using artificial neural network and its evaluation is carried out.

DESCRIPTION OF THE PROBLEM

Apart from composites manufacturing, modeling and optimization of machining of composite materials is gaining importance among researchers. Much attention is paid for the development of prediction model for surface roughness during the machining process such as turning and milling. Among the different prediction strategies neural network modeling has been found effective for surface roughness prediction. In this work, an artificial neural network based surface roughness prediction model for end milling of MMCs having LM25 Aluminium alloy matrix reinforced with Silicon Carbide (SiC) milled with carbide tool is developed and results are compared with response surface model. Also the effect of various parameters is studied. In addition to the three basic machining parameters viz. spindle speed, N (rpm), feed rate, f (mm. rev^{-1}) and depth of cut, d (mm) another variable SiC percentage, S (% wt) is considered in the study. The level of the parameters considered is given in the Table 1. The experimental data sets of

Table 1: Levels of parameters

	Coding of levels				
Factors	-2	-1	0	1	2
X_1	2000	2500	3000	3500	4000
X_2	0.02	0.03	0.04	0.05	0.06
X_3	0.5	1.0	1.5	2.0	2.5
X_4	5	10	15	20	25

X_1: Spindle speed, N (rpm), X_3: Depth of cut, d (mm), X_2: Feed rate, f (mm. rev^{-1}), X_4: SiC content, S (%wt)

Arokiadass *et al.* (2011) are used in this work for ANN modeling. The surface roughness depends on spindle speed, N (rpm), feed rate, f (mm. rev^{-1}) and depth of cut, d (mm) and SiC percentage, S (% wt).

DEVELOPMENT OF ANN MODEL

Neural network or artificial neural network is network/combination of a number of interconnected processing elements/units/nodes called the neurons. The ANN can be used to determine the input and output relationship of a complex process. It is therefore, considered as the non linear statistical data modeling tool. The neural network system can thus acquire, store and utilize the knowledge gained from the experience. ANN models motivated from the working of human brain can be trained with the experimental data to describe the non linear and interaction effects of the process variables on the response. A properly trained neural network can predict the response parameter value for unknown input variables with reasonable accuracy.

In the present study, ANN predictive model is developed using 25 data sets and given in the Table 2. The ANN is modeled using Neural Network toolbox available in MATLAB® version 7.8 to predict the surface roughness as a function of four input parameters viz., spindle speed, feed rate, depth of cut and SiC percentage.

Table 2: Experimental design matrix and experimental values of R_a

Expt. No.	Coded values X_1	X_2	X_3	X_4	Surface roughness R_a (µm)
1	-1	-1	-1	-1	4.406
2	1	-1	-1	-1	3.812
3	-1	1	-1	-1	6.034
4	1	1	-1	-1	5.229
5	-1	-1	1	-1	4.472
6	1	-1	1	-1	3.802
7	-1	1	1	-1	6.032
8	1	1	1	-1	5.312
9	-1	-1	-1	1	4.978
10	1	-1	-1	1	4.395
11	-1	1	-1	1	6.789
12	1	1	-1	1	5.945
13	-1	-1	1	1	5.071
14	1	-1	1	1	4.402
15	-1	1	1	1	6.804
16	1	1	1	1	6.054
17	-2	0	0	0	6.202
18	2	0	0	0	4.638
19	0	-2	0	0	3.679
20	0	2	0	0	7.008
21	0	0	-2	0	5.062
22	0	0	2	0	5.299
23	0	0	0	-2	4.334
24	0	0	0	2	5.639
25	0	0	0	0	5.183
26	0	0	0	0	5.177
27	0	0	0	0	5.221
28	0	0	0	0	5.163
29	0	0	0	0	5.155
30	0	0	0	0	5.199
31	0	0	0	0	5.229

A MLP with one hidden layer having fourteen neurons with logsig transfer function is used in the present work. Four input neurons, each representing one input variable constitute the input layer while the output layer consists of one neuron with purelin activation function, corresponding to one response variable i.e., surface roughness. Figure 1 shows architecture of two-layer feed forward neural network used in the present study. Figure 2 shows the graphical representation of the transfer functions used in building the network.

Table 3 shows the testing error and the corresponding MSE obtained in arriving at optimum number of neurons and transfer function used in hidden layer. Optimum number of neurons and transfer function for the hidden layer is selected based on the least MSE in

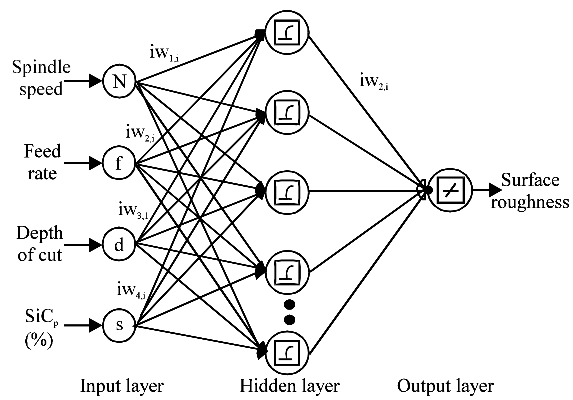

Fig. 1: Typical two-layer feed forward neural network architecture

Table 3: Optimal number of neurons and transfer function for the hidden layer

Hidden layer neurons	Transfer function: Logsig Testing error*	Logsig MSE	Tansig Testing error*	Tansig MSE
5	1.408	0.006766	1.662	0.014504
6	3.799	0.077062	1.502	0.006420
7	1.899	0.007145	2.576	0.031618
8	1.046	0.003151	0.715	0.001809
9	0.651	0.002563	1.585	0.016941
10	1.750	0.015857	4.347	0.132081
11	1.706	0.010682	2.368	0.015968
12	3.064	0.070898	4.085	0.051785
13	1.758	0.012079	1.689	0.009199
14	0.453	0.001128	3.015	0.029706
15	2.354	0.040292	1.863	0.019076
16	1.419	0.006021	1.009	0.003262
17	2.025	0.014323	1.986	0.017452
18	1.722	0.016170	0.669	0.002245
19	4.478	0.047198	1.953	0.019752
20	2.199	0.021294	2.301	0.015690

*Average percentage error

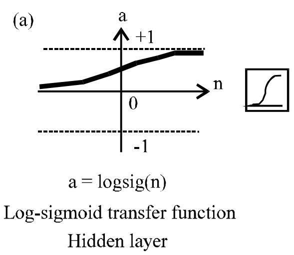

Fig. 2(a-b): Transfer functions used; (a) Hidden layer and (b) Output layer

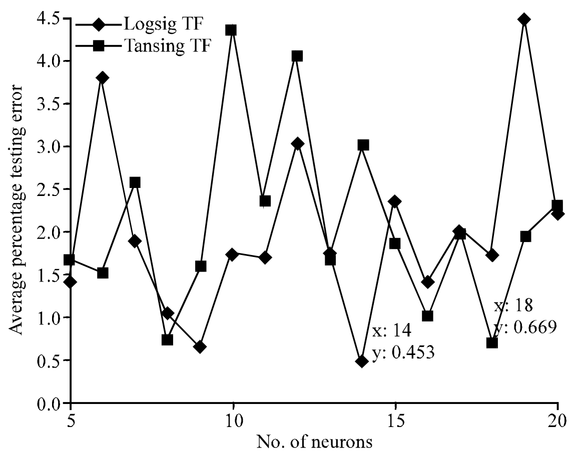

Fig. 3: Average percentage testing error vs. No. of neurons in the hidden layer

the testing data sets after training network until one of the stopping criteria is achieved. The testing error and MSE of the network are recorded starting from minimum five (05) neurons and number of neurons is increased gradually in steps of one till a maximum of twenty (20) neurons. The fourteen neurons with logsig transfer function giving least average percentage testing error of 0.453% (MSE = 0.001128) is found to be optimum in the present work. Figure 3 and 4 show the plot of average percentage testing error and MSE recorded for different number of neurons used with logsig and tansig transfer function.

In the present study, the total number of data sets available is limited to 25 only. As in early stopping, dividing these data sets into three subsets would result in only 15 data sets for training; 5 data sets each for validation and testing. With this division of data sets, the trainlm (Levenberg-Marquardt back propagation) training function did not produce a network with good generalization performance with absolute testing error recording as high as 35% and the average testing error being close to 20%.

Therefore, the network is trained with trainbr (Bayesian regulation back propagation) training function

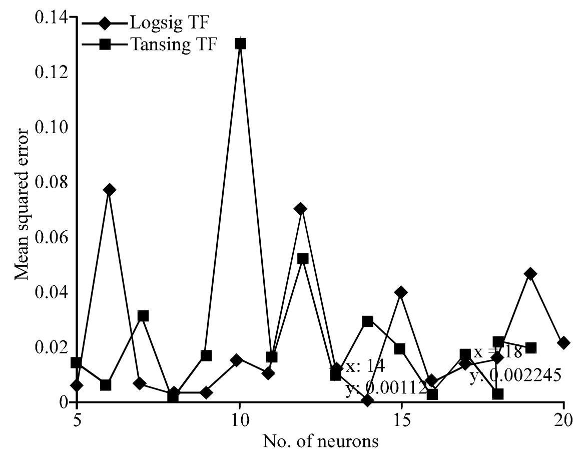

Fig. 4: Mean squared error vs. No. of neurons in the hidden layer

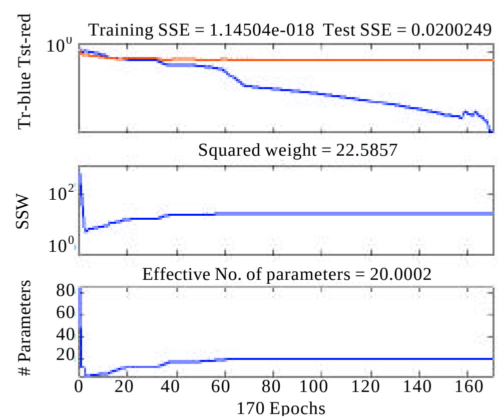

Fig. 5: Network performance parameters of the converged network

that uses the Bayesian regularization. The inputs and outputs are scaled to lie in the range (-1 1) using mapminmax function. A different data set (80%) randomly selected using dividerand function is presented to the network every time it is initialized and trained. The training is continued until specified stopping criteria is achieved. The network is tested with data sets (20%) which are also randomly selected. The effective number of parameters (weight and biases), Sum Squared Error (SSE) and Sum Squared Weights (SSW) are recorded at the end of each training. The network is considered as converged with effective number of parameters and SSW remaining constant at 20 and 22.5857, respectively over 110 epochs. The testing SSE recorded approximately 0.0200249 remained constant over the entire range of iterations. The SSE during training is found to be very small (1.14504×10^{-18}). Figure 5 shows the network performance parameters of the converged network.

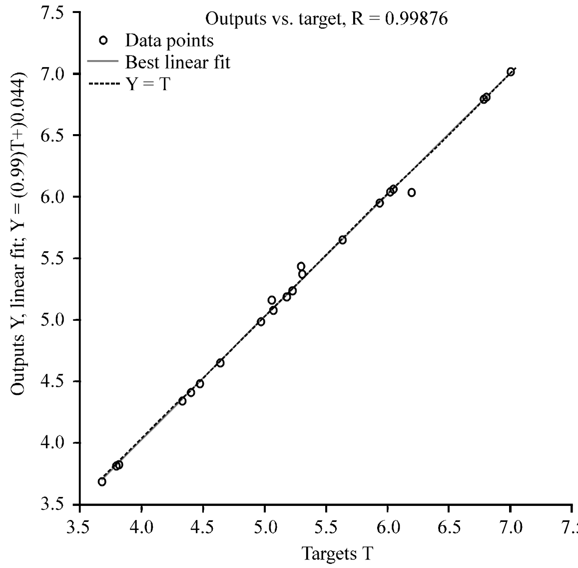

Fig. 6: Predictive performance of ANN model

The post training analysis of the ANN model shows that the model prediction exhibits close relationship with the experimental result with the correlation coefficient R = 0.9988. Figure 6 shows the predictive performance of ANN model.

RESULTS AND DISCUSSION

The predicted values of surface roughness from the ANN model are compared with the experimental result and also with the surface roughness predicted by response surface model. The comparison of prediction performance of both the models with the experimental result is given in Table 4. The response surface model developed by Arokiadass *et al*. (2011) using second order polynomial equation found that the model is statistically significant with 95% confidence level. It is also reported that the input parameter feed rate has more influence on the response followed by spindle speed, SiC_p percentage and depth of cut.

The maximum absolute percentage error in ANN model prediction is 2.31% while for the RSM it is 1.39%, when compared with the experimental result. However, the average percentage error in ANN prediction is 0.31% and is less than that involved in RSM prediction which is 0.51%. The neural network based surface roughness prediction model is found better than the response surface model in end milling of Al-SiC_p metal matrix composites using carbide tool. The graphical representation of the predicted values of R_a from both the ANN model and RSM is shown in the Fig. 7. The prediction of both ANN model and RSM show high correlation with the experimental result.

Table 4: Performance comparison of ANN model and RSM with experimental result

	Surface roughness (R_a), µm			Percentage error	
Expt. No.	Expt.	RSM	ANN	RSM	ANN
1	4.406	4.418	4.406	0.272	0.000
2	3.812	3.768	3.812	1.154	0.000
3	6.034	6.035	6.034	0.017	0.000
4	5.229	5.234	5.229	0.096	0.000
5	4.472	4.468	4.472	0.089	0.000
6	3.802	3.823	3.802	0.552	0.000
7	6.032	6.098	6.032	1.094	0.000
8	5.312	5.301	5.3623	0.207	0.947
9	4.978	4.998	4.978	0.402	0.000
10	4.395	4.334	4.3956	1.388	0.014
11	6.789	6.773	6.789	0.236	0.000
12	5.945	5.958	5.945	0.219	0.000
13	5.071	5.070	5.071	0.020	0.000
14	4.402	4.410	4.402	0.182	0.000
15	6.804	6.857	6.804	0.779	0.000
16	6.054	6.046	6.054	0.132	0.000
17	6.202	6.143	6.0296	0.951	2.780
18	4.638	4.682	4.638	0.949	0.000
19	3.679	3.709	3.679	0.815	0.000
20	7.008	6.962	7.008	0.656	0.000
21	5.062	5.103	5.1529	0.810	1.796
22	5.299	5.242	5.4214	1.076	2.310
23	4.334	4.316	4.334	0.415	0.000
24	5.639	5.641	5.639	0.035	0.000
25	5.183	5.189	5.183	0.116	0.000

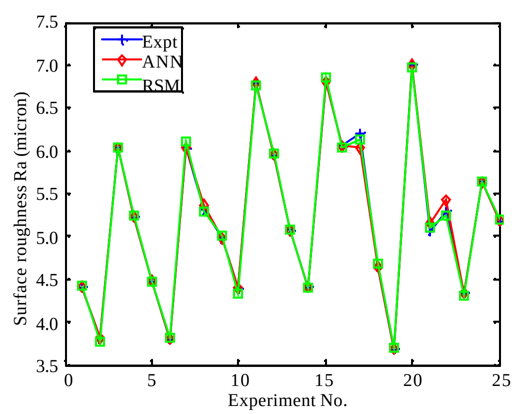

Fig. 7: Correlation between the predicted values of R_a and experimental result

The generalization performance of the ANN predictive model is further examined on completely new 256 hypothetical data sets obtained by taking the average of the two levels of the original parameters as given in Table 5.

The functional dependence of surface roughness for all the possible combinations of input variables is

Table 5: New levels of parameters

	Coding of levels			
Factors	1	2	3	4
X_1	2250	2750	3250	3750
X_2	0.025	0.035	0.045	0.055
X_3	0.75	1.25	1.75	2.25
X_4	7.5	12.5	17.5	22.5

X_1: Spindle speed, N (rpm), X_3: Depth of cut, d (mm), X_2: Feed rate, f (mm. rev^{-1}), X_4: SiC content, S (%wt.)

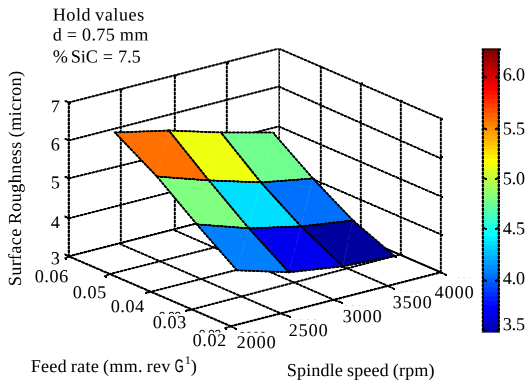

Fig. 8: Surface plot of R_a with spindle speed and feed rate

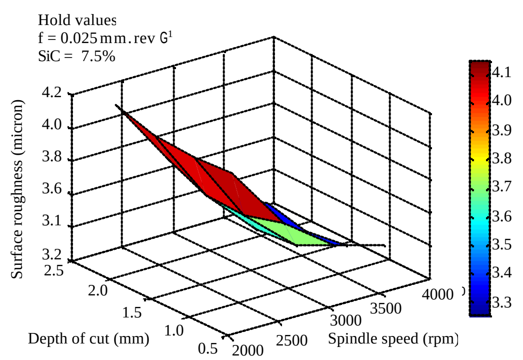

Fig. 9: Surface plot of R_a with spindle speed and depth of cut

analyzed by surface plots. Figure 8 depicts the variation of surface roughness with spindle speed and feed rate for constant values of depth cut (0.75 mm) and SiC percentage (7.5%). It can be inferred from the plot that surface roughness increases as the feed rate increases whereas it decreases with increase in the spindle speed.

The variation of R_a with spindle speed and depth of cut for constant values of f = 0.025 rev. mm^{-1} and SiC = 7.5% is shown in Fig. 9. It shows that the depth of

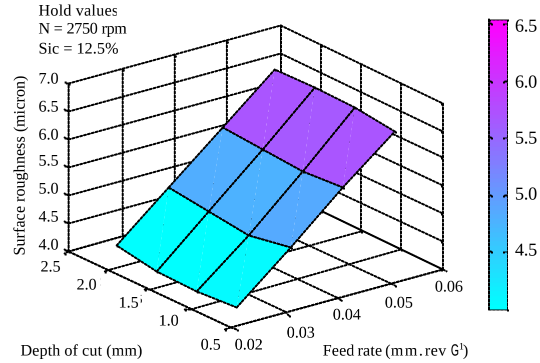

Fig. 10: Surface plot of R_a with feed rate and depth of cut

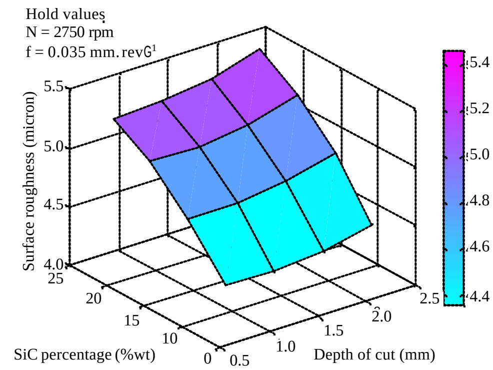

Fig. 11: Surface plot of R_a with depth of cut and SiC percentage

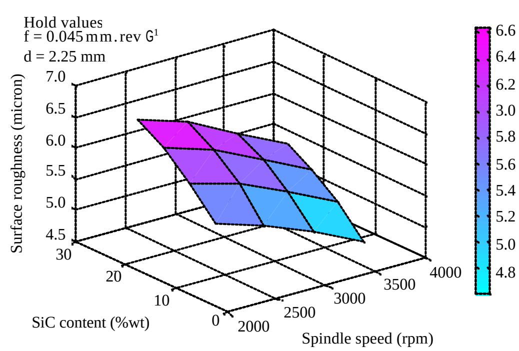

Fig. 12: Surface plot of Ra with spindle speed and SiC percentage

cut has least influence in predicting R_a and it also can be inferred from Fig. 10 and 11. Figure 12 depicts the variation of surface roughness with spindle speed and SiC

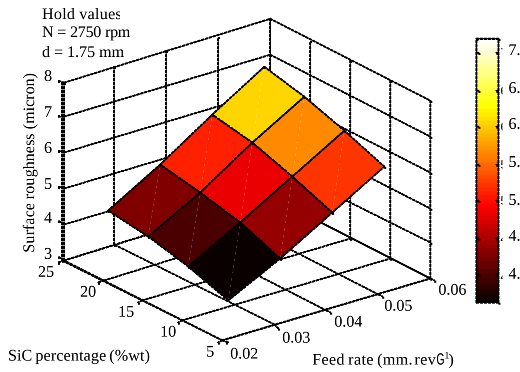

Fig. 13: Surface plot of R_a with feed rate and SiC percentage

percentage for constant values of feed (0.045 mm. rev^{-1}) and depth of cut (2.25 mm). It shows that the variation of R_a is directly proportional to the SiC percentage and it also can be inferred from Fig. 13.

CONCLUSIONS

In the present study, an artificial neural network based surface roughness prediction model for Al-SiC_p MMC milling with carbide tool is developed. The performance of the predictive model is found to be very encouraging with average percentage error being 0.31% when compared with the experimental data sets. The performance of the ANN model is also compared with the response surface model and found that the ANN model outperforms RSM. The surface roughness mainly depends upon feed rate, spindle speed and SiC percentage of Al-SiC_p MMC. It is observed that the depth of cut has least influence on the response variable.

The surface roughness varies directly as the input parameters feed rate and SiC percentage whereas it bears inverse relationship with spindle speed. Thus suitable combination of machining parameters for the desired surface roughness can be obtained. However, improved tool life should be aimed for economical production of MMCs components.

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