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Artificial neural network modeling for surface roughness prediction in cylindrical grinding of Al-SiC$_p$ metal matrix composites and ANOVA analysis

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A B S T R A C T

In the present work, surface roughness prediction model in cylindrical grinding of LM25/SiC/4$_p$ metal matrix composites (MMC) was developed using artificial neural network (ANN) methodology. The independent input machining parameters considered in the modeling were wheel velocity, feed, work piece velocity and depth of cut. The neural network architecture 4-12-1 with logsig transfer function was found optimum with 94.20 % model accuracy. The analysis of variance (ANOVA) was carried to study influence of the machining parameters on surface roughness. The study revealed higher *F*-ratio for wheel velocity and it found to be the most influencing parameter in prediction of surface roughness. The percentage of contribution for wheel velocity was 32.47 %, feed was 26.50 % and work piece velocity was 25.08 %. The depth of cut was found to have least effect on surface roughness with 13.22 % contribution. The independent and combined effect of process parameters on predicted value of surface roughness was studied using two-dimensional graphs and surface plots. The study showed that surface roughness increases as feed increases while it decreases with increase in wheel velocity. It was also observed that minimum surface finish could be obtained at high wheel and work piece velocities, and low feed and depth of cut.

A R T I C L E I N F O

Keywords:
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1. Introduction

Metal matrix composites (MMC) having aluminium (Al) in the matrix phase and silicon carbide particles (SiC$_p$) in reinforcement phase, i.e. Al-SiC$_p$ type MMC, have gained popularity in the recent past. In this competitive age, manufacturing industries strive to produce superior quality products at reasonable price. This is possible by achieving higher productivity while performing machining at optimum combinations of process variables. The low weight and high strength MMC are found suitable for variety of components demanding high performance, especially in the automotive, aerospace, military, and medical applications [1]. The MMC provide advantages of higher specific strength and modulus over monolithic metals (steels and aluminium). Though the MMC can be produced to net-near shape, subsequent machining is found essential to bring them to the desired shape and size with proper surface integrity [2]. This is achieved by either of the machining processes viz. turning, milling or grinding. However, due to the hard and abrasive reinforcement used, MMC exhibit poor machinability resulting in accelerated tool wear and increased manufacturing cost. Thus, higher machining cost has remained a major concern which has impeded significant use of MMC components [3, 4].

Surface roughness (R_a) is one of the main attributes of a machined component that characterizes surface topography. It is evidently influenced by cutting parameters, work-tool material, tool geometry and statistical variation during machining. Surface roughness predominantly describes the quality of finish and plays a crucial role in various engineering applications. Reasonable surface finish is always desirable to improve tribological aspects and aesthetic appearance where as excessive surface finish involves higher machining cost. Surface finish of a machined component is defined as the degree of smoothness of surface as a result of roughness, waviness and flaws generated due to machining. Among various methods available, center line average (CLA) method is most commonly used for the measurement of surface roughness. In this method, surface roughness is measured as the average deviation from the nominal surface and mathematically expressed as in Eq. 1.

$$R_a = \frac{1}{L} \int_{0}^{L} |Y(x)| \, dx \qquad (1)$$

where, R_a is arithmetic average deviation from the mean line, L is sampling length, and Y is ordinate of the roughness profile.

Modeling of surface roughness prediction has been attempted using multiple regression analysis, response surface methodology (RSM), fuzzy logic (FL), and artificial neural network (ANN). The study of influence of cutting parameters on surface roughness in MMC machining has been the focused area in academia. The soft computing techniques viz. ANN and FL found effective to model machining processes which are complex in nature.

Among the gamut of soft computing techniques, ANN and FL are the two important methods effectively applied for modelling and optimization of machining processes. Number of researchers has used these tools to develop predictive models in various machining processes. In the area of machining, ANN modelling techniques have been commonly used for the prediction of surface roughness, cutting forces, tool wear, tool life and dimensional deviation [5]. Recently, gravitational search algorithm (GSA) was applied for modelling of a turning process with multiple responses (main cutting force, surface roughness and tool life) by Hrelja et al. [6]. The coefficients of the polynomial model for each of the responses were optimized iteratively using PSO algorithm. The optimized model for cutting force was reported to be most accurate with 1.75 % average error (maximum error: 6.3 %) followed by prediction model for surface roughness (average error: 5.85 %, maximum error: 43 %) and tool life (average error: 24.5 %, maximum error: 60 %). The higher values of error were attributed to fewer datasets used in the knowledge base during the learning phase. The ANN and FL techniques were used to develop knowledge based system for prediction of surface roughness in turning process [7]. The knowledge based system consisted of a ANN module which is used to generate large data set to form if-then rules of the fuzzy model. A methodology that requires small size data set for ANN modeling is presented by Kohli and Dixit [8]. Risbood et al. [9] developed a multilayer perceptron (MLP) model for prediction of multiple responses (surface roughness and dimensional deviation) in wet turning of steel with HSS tool with four input parameters. The error in surface roughness prediction was reported nearly 20 %.

Routara et al. [10] applied RMS to develop the second order mathematical models for surface roughness prediction. The models were further optimized by genetic algorithm (GA) to find the optimum cutting parameters.

Sonar et al. [11] used radial basis function neural network (RBFN) for prediction of surface roughness in turning process with same accuracy in shorter computational time. Contrarily, the surface roughness prediction using neural network (NN) model was found less accurate than FL and regression models in hard turning of AISI 4140 steel [12]. The RBFN found more accurate than multi variable regression analysis in the prediction of thrust force and surface roughness in drilling of carbon fiber reinforced polymer (CFRP) composite materials [13]. The NN and FL models reported to predict multiple responses, i.e. material removal rate, tool wear and radial over cut with agreeable accuracy (prediction error 4.94-16.22 %) in electrical discharge machining of AISI D2 steel [14]. Optimization of machining parameters using ANN was found effective in comparison with analysis of variance (ANOVA) by Muthukrishan and Davim [15] in turning of Al-SiC$_p$ MMC. The influence of machining parameters on surface roughness in drilling [16] and in end milling [17] of Al-SiC$_p$ MMC has been studied using RSM. The surface roughness is predominantly influenced by feed rate and cutting speed. The depth of cut reported to have least effect.

Thiagarajan et al. [18] have carried out experimental investigation of surface integrity during cylindrical grinding of LM25/SiC$_p$ MMC and reported that wheel velocity, job velocity and feed are the main influencing factors. The NN prediction models based on two different training algorithms viz., scaled conjugate gradient (SCG) and Levenberg-Marquardt (LM) compared with multiple regression models in turning of AISI 1040 steel [19]. Both the NN models found better in prediction than regression model. A similar work was carried out by Pare et al. [20] for cutting force prediction in turning of titanium alloy. The ANN model prediction found superior to RSM. Edwin Raja Dhas and Somasundaram [21] found ANN technique and fuzzy logic to accurately predict weld residual stress. Devarasiddappa et al. [22] developed ANN model for predicting the surface roughness in end milling of Al-SiC$_p$ MMC using small set of experimental data sets. The predictive performance of the model was found highly encouraging with average error of 0.31 % as against 0.53 % for the RSM published result.

Number of researchers has carried out the experimental study and modeling of different machining processes by employing both conventional and soft computing based methodology. Recently, ANN is used as popular and promising technique for prediction surface roughness in machining process. Though, a large number of research publications are available on MMC machining, few publications are available in MMC grinding. In this paper, development of ANN based model for prediction of surface roughness during cylindrical grinding of Al-SiC$_p$ MMC has been attempted. The various machining parameters and their influences on job surface roughness were studied. The development of ANN predictive model and analysis of process parameters is detailed out in subsequent sections.

2. Development of surface roughness prediction model

In order to improve machining process, surface roughness prediction model is developed. There are four common techniques for the development of a prediction model: 1) multiple regressions, 2) physics based modeling, 3) ANN, and 4) FL based models. ANN is one of the most widely used artificial intelligent techniques and has been successfully employed by researchers. It has ability to learn the mapping between a set of input and output values.

2.1 Artificial neural network modeling

The ANN is a data processing system consisting of a large number of simple and highly interconnected processing elements resembling biological neural system. It can be effectively used to determine the input-output relationship of a complex process and is considered as a tool in nonlinear statistical data modeling. A multilayer NN that works on back propagation learning algorithm was used in the present work. The ANN model was trained initially using experimental data so as to predict response variable(s) for unknown input datasets within reasonable accuracy.

In the present work, ANN model was developed for predicting surface roughness in cylindrical grinding of Al-SiC$_p$ MMC (i.e., LM25/SiC/4$_p$) using vitrified-bonded white aluminium oxide grinding wheel. The independent input machining parameters considered were (a) cutting speed of the grinding wheel, V_s (m/min), (b) cutting speed of the work piece, V_w (m/min), (c) feed, f (m/min), and (d) depth of cut, d (μm). For training the neural network, real life datasets obtained through machining experimentation from experimental result of Thiagarajan et al. [19] were used. The four process parameters at three different levels were considered for experimentation. The level of the parameters considered is given in Table 1.

Table 1 Levels of parameters used for experimentation

Parameters	Level 1	Level 2	Level 3
V_s (m/min)	1414	2026	2639
V_w (m/min)	6.11	12.72	26.72
f (m/min)	0.06	0.09	0.17
d (μm)	10	20	30

2.2 Network architecture and training

A typical multilayer ANN model consists of input, hidden and output layers. The ANN architecture consisting of an input layer with four neurons each representing one input variable, one hidden layer (12 neurons) and an output layer with one neuron having purelin processing function was employed in the present work. The model was trained using 20 experimental datasets given in Table 2 including corner datasets of each variable. The five datasets given in Table 3 were used for testing the model during training. The source code was written in MATLAB version 7.8.

Table 2 Experimental datasets used for ANN model training

Sl. No	V_s (m/min)	V_w (m/min)	f (m/min)	d (μm)	R_a (μm)
1	1414	6.11	0.06	10	0.40
2	1414	6.11	0.06	30	0.58
3	1414	6.11	0.17	10	0.67
4	1414	12.72	0.06	10	0.34
5	1414	12.72	0.09	30	0.72
6	1414	12.72	0.17	20	0.78
7	1414	12.72	0.17	30	0.86
8	1414	26.72	0.06	10	0.25
9	2026	6.11	0.09	10	0.46
10	2026	6.11	0.17	30	0.80
11	2026	12.72	0.09	20	0.43
12	2026	26.72	0.06	10	0.19
13	2026	26.72	0.09	20	0.34
14	2026	26.72	0.17	30	0.42
15	2639	6.11	0.09	20	0.43
16	2639	6.11	0.17	30	0.52
17	2639	12.72	0.06	30	0.29
18	2639	26.72	0.06	10	0.18
19	2639	26.72	0.17	10	0.19
20	2639	26.72	0.17	30	0.38

The Fig. 1 depicts the two layer feed forward NN used in this work. The input layer consists of 4 neurons as wheel speed, workpiece speed, feed and depth of cut being the control parameters. The output layer consists of one neuron having purelin processing function. The NN training was performed for desired error goal of 0.0001 by varying hidden layer neurons from 5-20 for two different transfer functions – tansig and logsig.

The number of neurons in the hidden layer plays a vital role in deciding the optimal architecture of the model. If less number of neurons are taken, the network may not be able learn the input-output relationship properly and the error in prediction will be higher. Increasing the number of neurons in the hidden layer gives more flexibility to the network because the network has more parameters it can optimize and hence learning can be more accurate.

Table 3 Testing datasets used for ANN model development

Sl. No	V_s (m/min)	V_w (m/min)	F (m/min)	d (μm)	R_a (μm)
1	1414	6.11	0.09	20	0.69
2	1414	6.11	0.17	20	0.80
3	1414	12.72	0.06	30	0.48
4	1414	26.72	0.09	10	0.33
5	2639	26.72	0.06	30	0.23

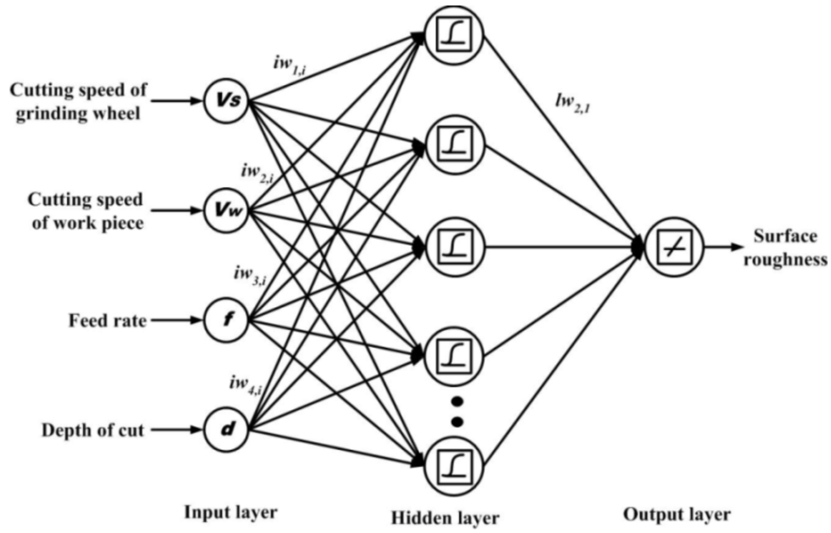


Fig. 1 Typical two layer NN architecture used

However, if the hidden layer neurons are too large, it might cause the problem to be under-characterized since the network has to optimize more parameters than there are data vectors to constrain these parameters. Thus the generalization capability of the network and hence its performance is compromised with large number of neurons in the hidden layer. The selection of suitable transfer function is also equally important. The transfer function is used to calculate the output from the input parameters. In the present work, the log sigmoid (logsig) transfer function found suitable for the hidden layer. The Eq. 2 and Eq. 3 represent logsig and purelin transfer functions, respectively,

$$a = logsig\ (n) = \frac{1}{1 + e^{-n}} \tag{2}$$

$$a = purelin\ (n) = n \tag{3}$$

where n is net weighted input to the neuron.

The neural network was trained with different number of neurons (varying from five to twenty) and different transfer functions in the hidden layer. The maximum number of epochs allowed in each run is 25000. The code was run five times at each network topology with different initial random weights. The network configurations giving average percentage error in training and testing data set within 15 % were recorded. A properly trained NN gives nearly equal training and testing error. A network having smaller training error exhibits poor generalization capability and thus predicts poorly for new datasets. The detail of training and testing error for different network topology is presented in Table 4 and its graphical representation is depicted in Fig. 2.

Table 4 Network training result for different architectures

Sl. No.	NN architecture	Average percentage error		Effective error (%)
		Training	Testing	
1	4-6-1 (tansig)	8.66	12.12	3.46
2	4-15-1 (logsig)	11.93	8.53	3.40
3	4-17-1 (tansig)	11.32	14.59	3.27
4	4-18-1 (logsig)	11.79	14.38	2.59
5	4-11-1 (tansig)	3.83	5.73	1.90
6	4-12-1 (logsig)	10.55	9.35	1.20

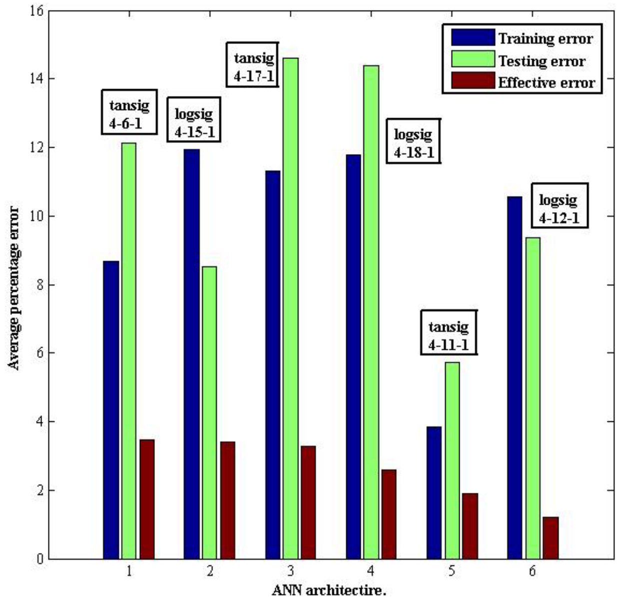


Fig. 2 Selection of optimal NN architecture

The NN was trained using trainbr (Bayesian regulation back propagation) training function which uses Bayesian regularization. The training datasets of the converged network are given in Table 2. The testing datasets of the converged network are presented in Table 3. The network was trained with a different data set (80 %) each time, which were randomly selected. The testing datasets (20 %) were also selected randomly. The network converged at 362nd iteration. The weights and biases as well as sum squared weights of converged network remains constant. The sum squared error (SSE) during testing recorded approximately 0.1311 and remained constant. The SSE during training was found to be 0.4269. The mean squared error in training and testing datasets of the converged NN model was found to be 0.0025 and 0.0031 respectively.

The optimum number of neurons and the selected transfer function that produce minimum effective error found as best network architecture. The ANN architecture 4-12-1 with logsig transfer function giving effective error of 1.20 % was found optimum in this work. At optimum network, weights and bias were saved and used to predict surface roughness for unknown datasets.

2.3 Network prediction performance

Accuracy of the NN predictive model was tested for 10 randomly selected experimental datasets. The model predicted R_a values were compared with experimental values and percentage error was calculated. The results are presented in Table 5.

The maximum and minimum percentage error recorded as 14.71 % and 0.0 %, respectively. The average percentage error (APE) and mean squared error (MSE) was computed using Eq. 4 and Eq. 5, respectively,

$$APE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|t_i - y_i|}{t_i}\right) \times 100 \tag{4}$$

$$mse = \frac{1}{n}\sum_{i=1}^{n}(t_i - y_i)^2 \tag{5}$$

where t_i is target value for data set i, y_i is predicted value for data set i, and n is the total number of data sets.

Table 5 Validation result of neural network model

Sl. No.	Datasets used				R_a (µm)		Procentage error	Prediction accuracy
	V_s (m/min)	V_w (m/min)	f (m/min)	d (µm)	Exp.	ANN		
1	1414	6.11	0.06	20	0.54	0.51	5.56	94.44
2	1414	6.11	0.09	10	0.52	0.57	9.62	90.38
3	1414	6.11	0.17	30	0.88	0.89	1.14	98.86
4	1414	26.72	0.09	30	0.5	0.46	8.00	92.00
5	2026	12.72	0.06	20	0.34	0.31	8.82	91.18
6	2026	26.72	0.06	30	0.29	0.29	0.00	100.00
7	2026	26.72	0.09	30	0.34	0.39	14.71	85.29
8	2639	6.11	0.06	20	0.34	0.36	5.88	94.12
9	2639	12.72	0.17	30	0.52	0.51	1.92	98.08
10	2026	6.11	0.06	20	0.42	0.41	2.38	97.62

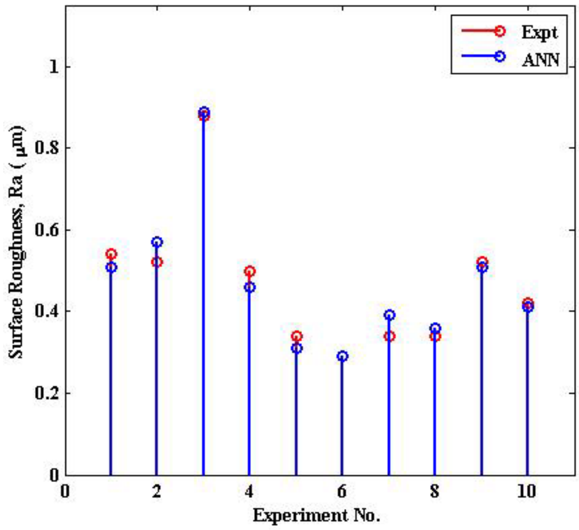


Fig. 3 Validation result of NN model

The average percentage error and MSE was found to be 5.80 % and 0.00091 respectively. The graphical representation of the NN prediction for validation data set is depicted in Fig. 3.

Model accuracy (MA) was computed as the average of individual accuracy on confirmation data set [23]. It is expressed by Eq. 6. The model accuracy of the developed model based on its predictive capability was found to be 94.20 %.

$$MA = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{|t_i - y_i|}{t_i}\right) \times 100 \tag{6}$$

3. Analysis of process parameters

The NN predicted surface roughness values were analysed to study the effect of process parameters. ANOVA technique was used to determine the significant control parameters affecting surface roughness.

3.1 Analysis of variance

ANOVA is a method of portioning variability into identifiable sources of variation and the associated degree of freedom in the model. Four control parameters were considered in the present study. Each factor affects the response to a varying degree. There were 3 levels (low, medium, and high) on four control parameters having 3^4 factorial designs of 81 experimental cutting conditions (datasets). The surface roughness for these datasets was predicted from the developed NN model.

ANOVA is used to decompose the total variability to quantify the effect machining parameters on surface roughness. The percentage contribution of machining parameters was estimated based on the sum of squares of responses. The grand total sum of squares (SS_{grand}) was evaluated using the Eq. 7.

$$SS_{grand} = \sum_{i=1}^{81} R_{ai}^2 \tag{7}$$

The SS_{grand} is decomposed into sum of squares due to mean (SS_{mean}) and total sum of squares (SS_{total}) using Eq. 8 and Eq. 9, respectively,

$$SS_{mean} = 81 \times R_{am}^2 \tag{8}$$

$$SS_{total} = \sum_{i=1}^{81} (R_{ai} - R_{am})^2 \tag{9}$$

where R_{am} is mean of responses. The sum of squares due to a factor is equal to its total squared deviation from the overall mean. In the present study, there were 27 experiments for each factor at each level. The sum of squares due to factor A (SS_A) was computed using the Eq. 10,

$$SS_A = 27(R_{aA1} - R_{am})^2 + 27(R_{aA2} - R_{am})^2 + 27(R_{aA3} - R_{am})^2 \tag{10}$$

where, R_{aA1}, R_{aA2}, and R_{aA3} are the mean of R_a at the level 1, 2, and 3 of the factor A, respectively. The relative importance of factor A influencing the surface roughness was computed as the percentage contribution (PC_A) using Eq. 11.

$$PC_A = \frac{SS_A}{SS_{total}} \times 100 \tag{11}$$

Similarly, the total sum of squares due to factor B (SS_B), C (SS_C) and D (SS_D) and their respective percentage contribution PC_B, PC_C, and PC_D were computed as detailed above. Table 6 shows the results of ANOVA for surface roughness. The degrees of freedom (DF), sum of squares (SS), mean of squares (MS), F-ratio and PC associated with each factor is also presented. This analysis was carried out at 5 % significance level, i.e. at 95 % confidence level.

The calculated values of the F-ratio showed high influence of the wheel velocity, feed and work piece velocity on surface roughness. The contributions of all the control parameters including error are presented pictorially in the pie chart shown in Fig. 4.

The cutting speed of the grinding wheel has the highest influence both in NN model as well as statistically on the surface roughness. Feed and cutting speed of work piece has almost equal influence on the surface roughness. However, the value of surface roughness is inversely proportional to work piece velocity but directly proportional to the feed. The error associated with the ANOVA analysis found minimum as 2.73 %.

Table 6 Result of ANOVA

Control factors	DF	SS	MS	F-ratio	PC
A: Wheel velocity	2	71.77	35.88	358.88	32.47
B: Job velocity	2	55.44	27.72	277.2	25.08
C: Feed	2	5858	29.29	292.9	26.50
D: Depth of cut	2	29.20	14.60	146.0	13.22
E: Error	72	6.03	0.1		2.73
Total	80	221.02			100.00

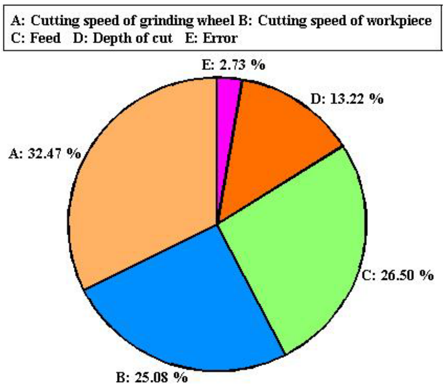
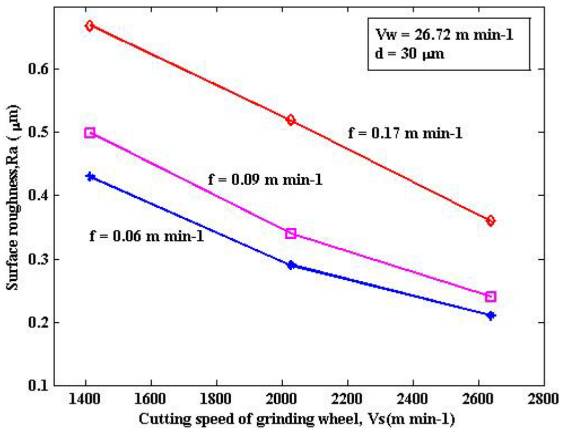


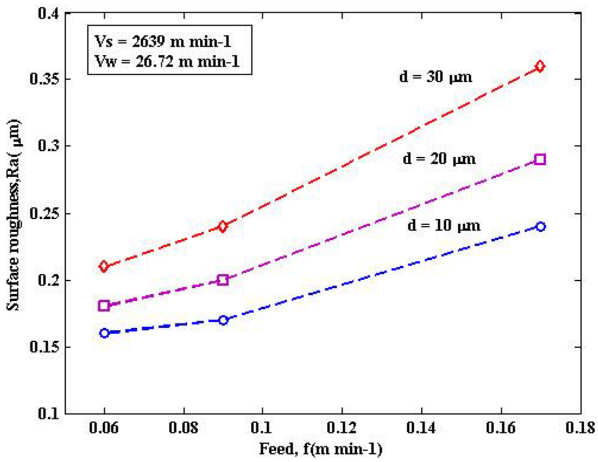
Fig 4 Contribution of control parameters

3.2 Study on influence of process parameters

The performance of the NN based predictive model for predicting the surface roughness was found very encouraging with 5.80 % average percentage error when compared with the experimental results. Based on model prediction, the influence of the process parameters on surface roughness was studied. The effect of these parameters was plotted graphically and is shown in Fig. 5a and Fig. 5b. The increase in wheel speed and workpiece speed improves the surface finish (i.e. surface roughness value reduces) of the job. The value of surface finish deteriorates as work feed increases. The surface finish improves at lower depth of cut as the cutting load lowers at low feed and low depth of cut.

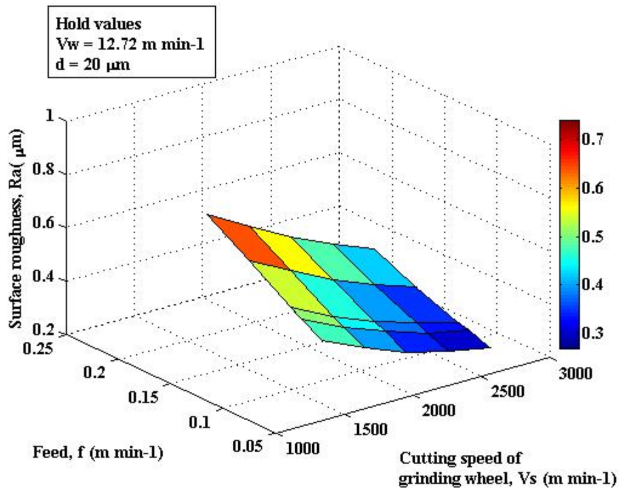


a. Effect of V_s on R_a

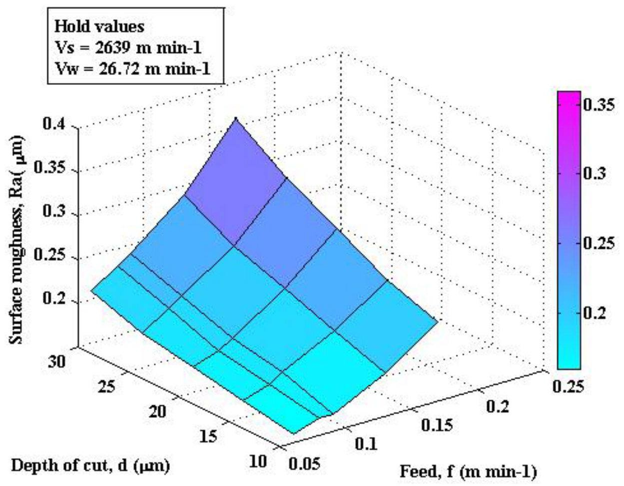


b. Effect of f on R_a

Fig 5 Effect of process parameters on surface roughness



a. Surface plot of R_a with f and V_s



b. Surface plot of R_a with d and f

Fig. 6 Surface plots for combined effect of process parameters on R_a

The Fig. 6a shows the surface plot of surface roughness with feed and wheel velocity when work piece velocity and depth of cut are kept constant. The increase in wheel velocity reduces the surface roughness value. On the other hand, in case of feed, the value of surface roughness increases as feed increases. The plot shows the effect these parameters for the workpiece velocity of 12.72 m/min and depth of machining of 20 μm. The same effect was seen on work piece velocity and feed verses surface roughness. The minimum surface roughness was obtained at low depth of cut. The Fig. 6b depicts the surface plot of surface roughness with feed and depth of cut when wheel velocity and work piece velocity are held constant. The plot reveals that the minimum surface roughness value can be obtained at low feed and low depth of cut. With the combination of all parameters improved surface finish was obtained at high wheel velocity and work piece velocity. However, in case of feed and depth cut, the improved surface finish obtained at low feed and depth of cut due to reduced cutting load.

4. Conclusion

In the present work, the ANN model for prediction of surface roughness in cylindrical grinding of Al-SiC_p MMC was developed. For NN modeling, the datasets were obtained from experimental result presented in [18]. The surface roughness value for different combination of process parameters was obtained and analyzed. The wheel velocity, work piece velocity, feed and depth of cut were considered as process parameters. The ANN architecture 4-12-1 with logsig transfer function giving effective error of 1.20 % was found optimum in the present work. The predictive model was validated with confirmation datasets. Based on NN prediction model and analysis of the parameters, the following conclusions were drawn.

- The proposed neural network modeling was found easy and promising technique to develop predictive model for mapping input and output parameters. The developed model predicted surface roughness accurately for unseen data with 94.20 % model accuracy.
- The result of ANOVA showed highest *F*-ratio for wheel velocity and is the most significant influencing parameter for prediction of surface roughness. The percentage of contribution for wheel velocity was 32.47 %, feed was 26.50 %, and work piece velocity was 25.08 %. The depth of cut was found have least effect on surface roughness with 13.22 % contribution.
- The investigations on this study indicate that the process parameters wheel velocity, work piece velocity, feed and depth of cut are the primary influencing factors which affect the surface roughness of ground MMC component.
- The NN prediction revealed that better surface finish could be obtained at high wheel velocity and high work piece velocity. This is due to development of low grinding force at high speed of operation. The surface finish deteriorates at high feed and depth of cut as it increases the grinding load. The minimum surface finish was obtained with the combination of high wheel and workpiece velocity and low feed and depth of cut. The neural network predicted 0.16 μm being the minimum surface roughness at V_s = 2639 m/min, V_w = 26.72 m/min, f = 0.06 m/min and d = 10 μm.

The proposed methodology could be effectively employed for prediction of responses in variety of machining processes on different material combinations. The detailed ANOVA presented in this paper could be extended to study the influence of input variables on the response(s) in any of the machining processes effectively. The modeling technique discussed can be integrated with optimization algorithms.

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