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Modeling and optimization of parameters for minimizing surface roughness and tool wear in turning Al/SiCp MMC, using conventional and soft computing techniques

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A B S T R A C T

Aluminium alloy with silicon carbide particulate (Al/SiCp) reinforced metal matrix composite (MMC) are used within a variety of engineering applications due to their excellent properties in comparison with non-reinforced alloys. This presented work attempted the development of predictive modeling and optimization of process parameters in the turning of Al/SiCp MMC using a titanium nitride (TiN) coated carbide tool. The surface roughness R_a as product quality and tool wear *VB* for improved tool life were considered as two process responses and the process parameters were cutting speed *v*, feed *f*, and depth of cut *d*. Two modeling techniques viz., response surface methodology (RSM) and artificial neural network (ANN) were employed for developing R_a and *VB* predictive models and their predictive capabilities compared. Four different RSM models were tried out viz., linear, linear with interaction, linear with square, and quadratic models. The linear with interaction model was found to be better in terms of predictive performance. The optimum operating zone was identified through an overlaid contour plot generated as a response surface. Parameter optimization was performed for minimizing R_a and *VB* as a single objective case using a genetic algorithm (GA). The minimum R_a and *VB* obtained were 2.52 μm and 0.31 mm, respectively. Optimizations of multi-response characteristics were also performed employing desirability function analysis (DFA). The optimal parameter combination was obtained as v = 50 m/min, f = 0.1 mm/rev and d = 0.5 mm being the best combined quality characteristics. The prediction errors were found as 4.98 % and 3.82 % for R_a and *VB*, respectively, which showed the effectiveness of the method.

A R T I C L E   I N F O

Keywords:
Metal matrix composite
Surface roughness
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1. Introduction

The application and use of metal matrix composites (MMC) in manufacturing industries have now become increased due to its improved properties viz., high strength, low weight, high wear resistance, low heat of thermal expansion, etc. [1]. The matrix phase and reinforcement design of the material is responsible for the desired property of MMC. Among different types of MMC available, aluminium based SiC particulate (SiCp) reinforced MMC have found useful application as engineering material [2]. The conversion of these materials into an engineering part or component is obtained by machining through common conventional machining processes like turning, milling, drilling, and grinding. Turning is considered as foremost common machining method because of its ability to machine cylindrical surfaces faster with reasonably good surface finish. Due to hard and abrasive characteristic of reinforcement materials used in MMC the machinability study, development of predictive modeling and optimizing the process parameters have attracted the researchers. Most of the research on MMC machining is concentrated on investigation of cutting tool wear, surface roughness of the machined product, delamination factor of drill holes produced, and metal removal rate during machining.

Yuan and Dong [3] studied on surface finish in precision turning of MMCs using diamond tool. They considered spindle speed, feed rate, cutting angle, volume percentage of reinforcement material as investigating parameters. Davim [4] used Taguchi's orthogonal array and analysis of variance (ANOVA) to investigate the cutting characteristics of MMC (A356/20/SiCp-T6) in turning using polycrystalline diamond (PCD) cutting tool. Cutting velocity, feed rate, and cutting time are considered as input parameters and found that the cutting velocity has the highest physical and statistical influence on the tool wear and cutting power. Feed have high influence on the surface roughness of the component. Muthukrishnan and Davim [5] also conducted an experimental study on turning of Al/SiCp (20 %) MMC using the PCD tool for prediction of the surface roughness and found that the feed rate is a highly influencing parameter. Palanikumar and Karthikeyan [6] have studied on surface roughness using Taguchi method combined with RSM for minimizing the surface roughness in machining GFRP composites with PCD cutting tool. They concluded that fiber orientation and machining time are more influencing parameters on machining for obtaining better surface roughness. Rajasekaran et al. [7] also investigated the influence of surface roughness in turning CFRP composite using cubic boron nitride (CBN) cutting tool and applied fuzzy logic technique for modeling. They found that feed has the greater impact on surface roughness and fuzzy logic model predicts better. The influence of tool wear on machining glass fibre-reinforced plastics (GFRP) composites was investigated by Palanikumar and Davim [8] conducting series of experiments. They used ANOVA technique to assess the influencing parameters.

Chandrasekaran and Devarasiddappa [9] used fuzzy logic for developing surface roughness model for end milling of Al/SiCp metal matrix composite with carbide cutter. They found that the model predicts with an average prediction error of 0.31 % when compared with experimental data. The surface roughness is influenced by feed rate and spindle speed while depth of cut has less influence. In comparing the performance of ANN model with RSM they found that ANN outperforms. Arokiadass et al. [2] also developed surface roughness prediction model for end milling of LM25Al/SiCp MMC using RSM technique. They also have taken influencing parameters as feed rate, spindle speed, depth of cut and SiCp percentage and found that feed rate is the most dominant parameter and depth of cut is of least influence on the surface roughness.

Thiagarajan and Sivaramakrishnan [10] conducted an experimental study for investigating the grindability of Al/SiCp MMC in a cylindrical grinding process. They considered wheel velocity, work piece velocity, feed, depth of cut and SiCp volume fraction percentage as input parameters. They observed that the improved surface roughness and damage free surfaces are obtained at high wheel and workpiece velocity while using white Al_2O_3 grinding wheels. A numerical model based GA optimization methodology has been applied by Davim et al. [11] for determination of optimal drilling conditions in A356/20/p metal matrix composites. The experimental study inferred that the surface finish of the drilled holes increase with increase in feed rate but does not change significantly with variation in cutting speed. Basavarajappa et al. [12] have studied the variation of surface roughness on the drilling of metal matrix composites using carbide tool. They also found that the surface roughness decreases with the increase in cutting speed and increases with the increase in feed rate. Chandrasekaran and Devarasiddappa [13] developed a surface roughness prediction model using artificial neural network (ANN) for grinding of MMC components. The input parameters are wheel velocity, feed, work piece velocity and depth of cut. They found that surface roughness is highly influenced by feed and wheel velocity but least effected by depth of cut. Hocheng and Tsao [14] compared the RSM and radial basis function network (RBFN) for core-center drilling of composite materials. They concluded that for evaluating thrust force RBFN is more practical and predict better than the RSM method. Drilling CFRP composites have investigated by Tsao and Hocheng [15] using Taguchi and neural network methods. They conducted an experiment using Taguchi L_{27} orthogonal array of experiments with feed rate, spindle speed and drill diameter as input parameters. Thrust force and surface roughness produced were output parameters and it has been found that the feed rate and drill diameter are most significant factors for predicting the thrust force. They also confirmed that RBFN model is found to be more effective than multiple regression analysis in predicting the output responses, i.e. surface roughness and thrust force. From review of above literatures the machining investigation on turning Al/SiCp MMC was performed by the researchers. They were mainly considered mainly single response and simultaneous modeling and optimization of surface roughness and tool wear were not attempted. These responses are important for manufacturing industries on the basis of job quality and longer tool life.

In the area of modeling and optimization the researchers were carried out by a number of traditional and soft computing techniques. Application of GA found successful by number of researchers, Mukherjee and Ray [16], and Wang and Jawahir [17]. Öktem et al. [18] used RSM coupled with GA to optimize the cutting conditions for obtaining minimum surface roughness in milling of mold surfaces. For optimizing multi-response characteristics, various researchers use GRA as useful tool. The method does not require mathematical computation and can be applied easily for multi-response problems. Pawade and Joshi [19] have attempted to optimize the high-speed turning of Inconel 718 to optimize machining parameters using grey relational analysis considering cutting speed, feed, depth of cut and edge geometry as input parameters and surface roughness and cutting force as responses. Sahoo and Pradhan [20] carried out an experiment study based on Taguchi L_9 orthogonal array in turning Al/SiC MMC using uncoated carbide tool. Three cutting parameters viz., cutting speed v, feed rate f and depth of cut d were optimized to obtain minimum flank wear and surface roughness. Low and high cutting speed was found as optimum parameter for VB and R_a, respectively. They also developed a linear mathematical model for VB and R_a and found statistically significant as P-value is less than 0.05. In another attempt, Sahoo et al. [21] performed turning experiments on Al/SiC MMC (10 % weight) produced by traditional casting process. Multi-layer coated carbide tool was used to investigate tool wear and surface roughness. They found that cutting speed is the most influencing machining parameter on flank wear and feed rate on surface roughness. They also carried out multi-objective optimization using grey relational grade and found optimum combination as cutting speed at 180 m/min, feed at 0.1 mm/rev, and depth of cut at 0.4 mm. Gopalakannan and Thiagarajan [22] investigated on Al/SiCp MMC using EDM process. Pulse current, gap voltage, pulse on time and pulse off time were considered as input parameters and metal removal rate, electrode wear rate and surface roughness were output parameters. The developed RSM models show good predictive capability. The parameters were optimized using desirability analysis for multiple objectives.

The present work is envisaged to develop a modeling and optimization of machining parameters on the performance characteristics in turning of Al/SiCp MMC using TiN coated cutting tool. Predictive modeling was developed for surface roughness R_a and tool wear VB using RSM and ANN techniques. Machining parameters are optimized for single- and multi-objective case using GA and DFA for minimize R_a and VB or both simultaneously.

2. Development of RSM mathematical model

The statistical tools such as multiple regression analysis, response surface methodology and Taguchi method are widely used for development of conventional predictive modeling. RSM is a collection of mathematical and statistical techniques for empirical model building. It is used for the problems in which an output parameter is influenced by several input parameters and the objective is to optimize the output response. In this work RSM model is developed in order to investigate the influence of machining parameters (i.e., cutting speed v, feed rate f, and depth of cut d on the surface roughness R_a and tool flank wear VB in turning Al/SiCp MMC. All the machining parameters were chosen as independent input variables while desired responses are assumed to be affected by the cutting parameters. The predicted surface roughness (response surface) of turning process can be expressed in term of the investigating independent variables as

$$R_a = C v^x f^y d^z \tag{1}$$

where R_a is the predicted surface roughness in µm, v is the cutting speed in m/min, f is the feed in mm/rev, and d is the depth of cut in mm. C is the constant and x, y, and z are the exponents to be estimated from experimental results. Eq. 1 is linearized using logarithmic transformation and can be expressed as

$$\ln R_a = x \ln v + y \ln f + z \ln d \tag{2}$$

Eq. 2 is re-expressed into generalized linear model as:

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 = \beta_0 + \sum_{i}^{3} \beta_i x_i \tag{3}$$

where y is true (measured) response surface on logarithmic scale, x_0 is dummy variable and its value is equal to 1, and x_1, x_2, and x_3 are logarithmic transformation of input variables, i.e. cutting speed, feed, and depth of cut, respectively. β_0, β_1, β_2, and β_3 are the parameters to be estimated. If ε is the experimental error between estimated response y' and measured response y then

$$y' = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 \tag{4}$$

where the b values are the estimate of β parameters. The linear model of Eq. 4 is extended as second-order polynomial response surface model (i.e., quadratic model) and is expressed as

$$\begin{aligned} y' = y - \varepsilon = {} & b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_{11} x_1^2 + b_{22} x_2^2 + b_{33} x_3^2 + b_{12} x_1 x_2 + b_{13} x_1 x_3 \\ & + b_{23} x_2 x_3 \end{aligned} \tag{5}$$

or

$$y' = b_0 + \sum_{i=1}^{3} b_i x_i + \sum_{i=1}^{3} b_{ii} x_i^2 + \sum_{i=1}^{2} \sum_{j=2}^{3} b_{ij} x_i x_j \tag{6}$$

where b_0 is constant or free term, b_i, b_{ii}, and b_{ij} represent the coefficients of linear, quadratic, and cross product (i.e., interaction) terms. The Eq. 5 can be written as to build the relationship between turning parameters and responses (i.e., surface roughness and tool wear) as

$$y_{R_a} = b_0 + b_1 v + b_2 f + b_3 d + b_{11} v^2 + b_{22} f^2 + b_{33} d^2 + b_{12} x_1 x_2 + b_{13} x_1 x_3 + b_{23} x_2 x_3 \tag{7}$$

$$y_{VB} = b_0 + b_1 v + b_2 f + b_3 d + b_{11} v^2 + b_{22} f^2 + b_{33} d^2 + b_{12} x_1 x_2 + b_{13} x_1 x_3 + b_{23} x_2 x_3 \tag{8}$$

Where b_0 is constant or free term, b_i, b_{ii}, and b_{ij} represent the coefficients of linear, quadratic, and cross product (i.e., interaction) terms. The experimental work carried out by Kılıçkap et al. [23] in turning Al/SiCp MMC using K10 TiN coated cutting tool for investigating surface roughness and tool wear is used in this work. For modeling and analysis of machining parameters RSM model is developed using MINITAB 15® statistical software. Table 1 show various machining parameters used at three levels.

The RSM predictive model is developed using 20 data sets selected based on central composite design (CCD). The CCD experimental design matrix and responses are given in the Table 2. It is used for analyzing the measured response and determining the mathematical model with best fits. The fit summary for surface roughness and tool wear suggests that the quadratic relationship where the additional terms are significant and the model is not aliased.

Table 1 Assignment of levels and parameters

Factor	Units	Symbol	Levels		
			-1	0	1
Cutting speed	m/min	v	50	100	150
Feed	mm/rev	f	0.1	0.2	0.3
Depth of cut	mm	d	0.5	1.0	1.5

Table 2 Experimental result

Sl. No	Cutting speed, v (m/min)		Tool feed, f (mm/min)		Depth of cut, d (mm)		Experimental responses	
	Code (A)	Actual value	Code (B)	Actual value	Code (C)	Actual value	Surface roughness, R_a (μm)	Tool wear, VB (mm)
1	-1	50	1	0.3	1	1.5	4.13	0.601
2	1	150	1	0.3	1	1.5	3.17	1.050
3	-1	50	1	0.3	1	1.5	3.95	0.447
4	0	100	-1	0.1	0	1.0	3.21	0.603
5	0	100	1	0.3	0	1.0	4.03	0.702
6	1	150	1	0.3	-1	0.5	3.47	0.902
7	-1	50	-1	0.1	1	1.5	3.34	0.502
8	0	100	0	0.2	-1	0.5	3.47	0.630
9	0	100	0	0.2	0	1.0	3.40	0.651
10	-1	50	-1	0.1	-1	0.5	3.24	0.327
11	1	150	0	0.2	0	1.0	3.27	0.896
12	0	100	0	0.2	0	1.0	3.40	0.651
13	0	100	0	0.2	0	1.0	3.40	0.651
14	1	150	-1	0.1	0	1.0	3.17	0.623
15	0	100	0	0.2	1	1.5	3.43	0.698
16	1	150	-1	0.1	1	1.5	3.14	0.602
17	0	100	0	0.2	0	1.0	3.40	0.651
18	0	100	0	0.2	0	1.0	3.40	0.651
19	0	100	0	0.2	0	1.0	3.40	0.651
20	-1	50	0	0.2	0	1.0	3.68	0.477

Four different types of RSM mathematical models viz., linear, linear with interaction, and quadratic are obtained for prediction of surface roughness y_{Ra} and tool wear y_{VB} were obtained.

a) Linear model:

$$y_{R_a} = 3.367 - 0.0042v + 2.65f - 0.018d \tag{9}$$

$$y_{VB} = -0.0093 + 0.00344v + 1.045f + 0.1045d \tag{10}$$

b) Linear with interaction models:

$$y_{R_a} = 2.382 + 0.00217v + 8.41f + 0.313d - 0.034vf - 0.00009vd - 1.95fd \tag{11}$$

$$y_{VB} = 0.320 + 0.0018v - 1.63f + 0.127d + 0.018vf - 0.00149vd + 0.612fd \tag{12}$$

c) Linear with square models:

$$y_{R_a} = 3.28 - 0.0026v - 2.13f + 0.88d - 0v^2 + 12.17f^2 - 0.423d^2 \tag{13}$$

$$y_{VB} = -0.053 + 0.0037v + 2.46f - 0.039d - 0v^2 - 3.63f^2 + 0.044d^2 \tag{14}$$

d) Quadratic models:

$$\begin{aligned} y_{R_a} = {} & 2.55 + 0.0022v + 4.086f + 0.737d - 0.000v^2 + 12.84f^2 - 0.227d^2 - 0.035vf \\ & - 0.0009vd - 2.47fd \end{aligned} \tag{15}$$

$$\begin{aligned} y_{VB} = {} & 0.103 + 0.0026v - 0.55f + 0.288d - 4.114f^2 - 0.066d^2 + 0.0203vf - 0.002vd \\ & + 0.877fd \end{aligned} \tag{16}$$

where *v, f*, and *d* are cutting speed, feed and depth of cut, respectively. From these model equations, it is observed that the factor with highest value of coefficient posses the most dominating effect over the response. Feed has most significant effect over surface roughness and tool wear followed by the depth of cut and cutting speed.

2.1 Checking adequacy of the model

The test of significance of all the models was carried out using analysis of variance (ANOVA) and their predictive capability is analyzed. ANOVA find the influence of machining parameters (*v*, *f*, and *d*) on the total variance of the experimental findings. The test is performed by calculating the ratio between the regression mean square and the mean square error (i.e., F-ratio). The ratio measures the significance of the model in respect of variance of the parameters included in the error term for particular level of significance α. The analysis was carried out at 95 % confidence level and the result is presented in Table 3. The adequacy of the model is decided upon the value of S and coefficient of determination R^2. S value being the measurement of error, it is the smaller value that gives better results. If R^2 approaches unity the response model fits better with the actual data and less difference exists between predicted and actual data. To compare, more precisely adjusted R^2 (Adj R^2) is used, which is adjusted for the degrees of freedom. The closeness of the Adj R^2 with R^2 determines the fitness of the model.

The higher value of R^2 is obtained for linear with interaction model. This shows the predictive capability of *linear with interaction* model is found better and is selected among all models. The model equation used for prediction of surface roughness and tool wear is given in Eq. 11 and Eq. 12, respectively.

Table 3 Test of significance of RSM models

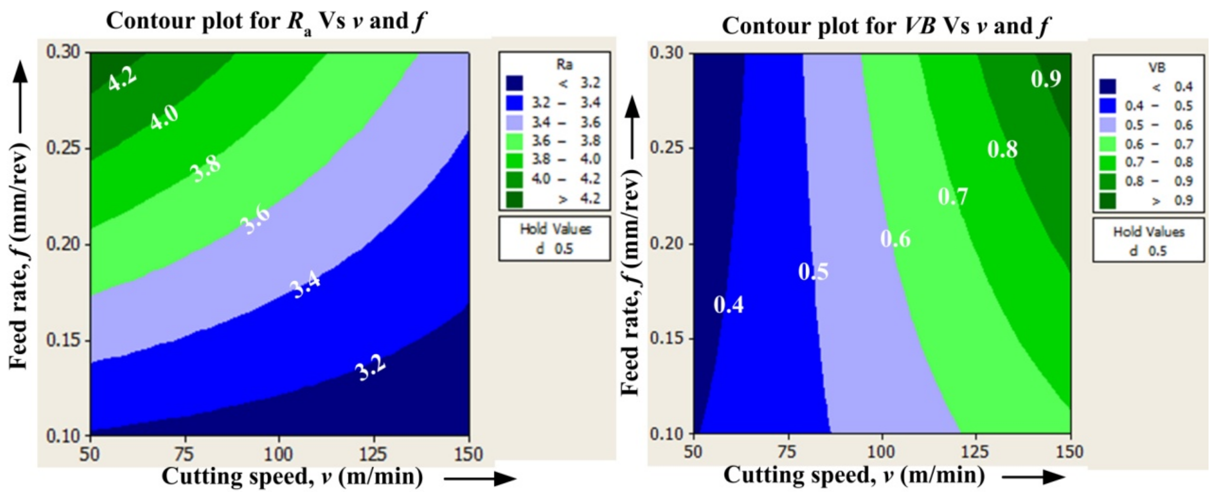
Sl. No.	RSM model	S-Value		R^2		Adj R^2	
		R_a	*VB*	R_a	*VB*	R_a	*VB*
1	Linear	0.15	0.073	76.09	82.51	71.01	79.21
2	Linear with interaction	0.089	0.052	96.00	92.16	94.12	90.00
3	Linear with square	0.15	0.078	80.17	83.59	70.94	76.02
4	Full quadratic	0.089	0.046	94.86	95.63	89.78	91.69

2.2 Contour plots

Fig. 1 shows two dimensional surface plot that shows the effect of influencing parameters on the output responses. Fig. 1(a) reveals that higher cutting speed and lower feed produces better surface finish. Increased feed increases the surface roughness value. This is due to rapid tool movement which deteriorates the quality of the machined surface. The analysis of contour plot shows improved surface roughness is obtained at higher *v* and lower *f*. The combination of parameters with cutting speed at 150 m/min, feed at 0.1 mm/rev, and depth of cut at 0.5 mm produces minimum surface roughness of 3.17 μm.

The tool wear contour plots are shown in Fig. 1(b). Cutting speed is the influencing parameter followed by depth of cut and feed. Higher tool wear is noticed at increased *v*. This is due to increased temperature causing flank wear at tool nose. Tool wear plot shows reduced tool wear is obtained at lower values of *v*, *f*, and *d*. The combination of parameters with cutting speed at 50 m/min, feed at 0.1 mm/rev, and depth of cut at 0.5 mm produces tool wear less than 0.4 mm found as minimum.

The comparison of experimental and RSM prediction for the parameters combination that produces minimum surface roughness and minimum tool wear are presented in the Table 4. However, the optimum region for combined minimization of surface roughness and tool wear is obtained by overlaying contour plot presented in the next subsection.



(a) For surface roughness (b) For tool wear

Fig. 1 Contour plots for interaction effect (at d = 0.5 mm)

Table 4 Optimum parameter combination

Sl. No.	Turning parameters (v–f–d)	Expt.	RSM prediction	Error (%)
1	For minimum R_a (150–0.1–0.5)	3.17 µm	3.18 µm	0.32
2	For minimum VB (50 –0.1– 0.5)	0.33 mm	0.38 mm	13.15

2.3 Overlaying contour plot for optimum operating zone

Fig. 2 shows the region for the selection of optimum cutting speed and feed for different value of surface roughness with minimum tool wear. The range of cutting speed as 50-80 m/min and feed as 0.1-0.14 mm/rev with 0.5 mm depth of cut produce surface roughness less than 3.4 µm with tool wear less than 0.5 mm. It may be considered as optimum operating zone. Similar trend have been seen at all values of depth of cut. The method of overlaying contour plot pictorially obtains the optimum operating zone and easy selection of cutting parameters for different values of R_a.

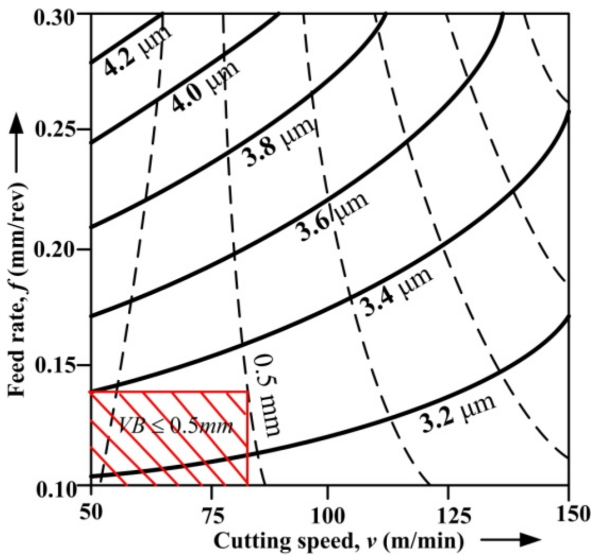


Fig. 2 Optimum operating region

3. Multi-response artificial neural network modeling

Artificial neural network (ANN) is the system that acquire, store and utilize knowledge gained from experience. It is motivated by the biological neurons that work in human brain. Researchers have employed ANN for modeling of machining processes and found that ANN provides reasonable accuracy. The network is built with number of layers (input, hidden and output) having specific number of neurons (also called *nodes*). All the neurons are interconnected with *weights* and *bias* is added at each node. The number of neurons in the input and output layers depend upon input and output parameters of the proposed model. The number of neurons of the hidden layer is decided during network training. The network architecture is trained with the number of real life experimental datasets. Each dataset consists of input parameters and the corresponding output responses. The optimum network is obtained with the selection of appropriate *transfer functions* and number of neurons in the hidden layer. The mean square error between the experimental response and ANN prediction is the criteria for deciding the optimum network architecture. Once network is trained then it is ready for prediction. The trained network is tested with unseen datasets for model validation and the predictive results are compared with experimental results.

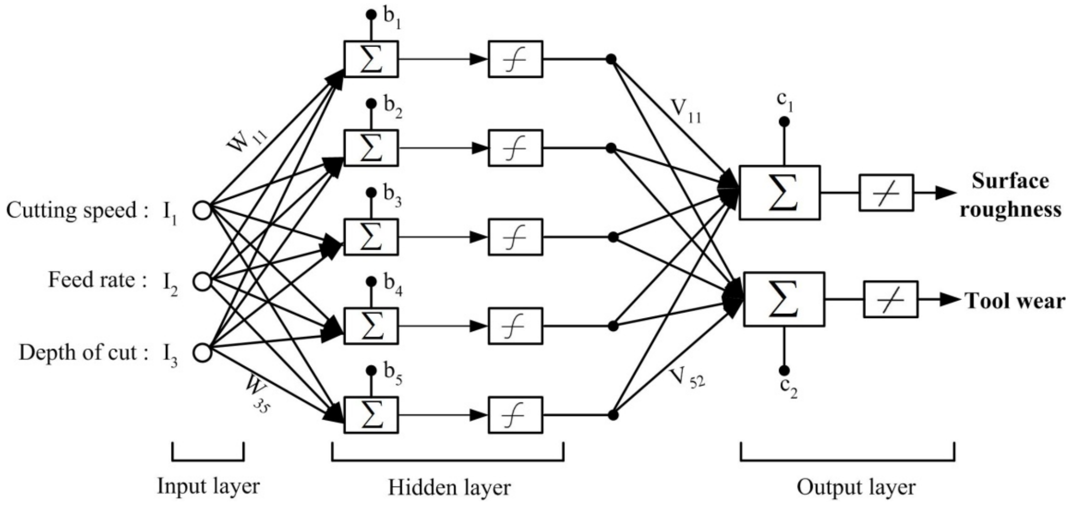
The size and selection of training and testing datasets are very crucial in the design of ANN model. There is no well- established formula for finding out the number of training and testing data [24]. Kohli and Dixit [25] have used 19 datasets for training 9 datasets for testing in developing ANN model used for prediction surface roughness in turning process. Nearly 66 % of total experimental data sets are selected is the training phase. The data sets are selected appropriately including extreme datasets (i.e., $v_{\min}$, $f_{\min}$, and $d_{\min}$; $v_{\max}$, $f_{\max}$, and $d_{\max}$). The remaining 34 % datasets were used in the testing phase. The predictive results of the tested data sets are compared with experimental datasets.

In this work, a soft computing based artificial neural network model for predicting surface roughness and tool wear as a function of three input parameters *viz*., cutting speed, feed, and depth of cut is developed. The multi-layer perceptron (MLP) network comprised of an input layer with three neurons, a hidden layer, and an output layer with two neurons. The networks with neurons (nodes) in each layer are interconnected with nodes of the subsequent and preceding layer with synaptic weights. Additionally a bias is added to each neurons of the hidden and output layer. The output of each neuron is obtained by summing up weighted inputs of neuron in preceding layer and its own bias. The output of each neuron in the hidden or output layer is computed by the equation

$$O_j = f(I) = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \tag{17}$$

where w_{ij} is the associated weights with j^{th} neurons of the layer and i^{th} neurons of the preceding layer, b_j is the bias of j^{th} neurons, n is the total number of neurons of the preceding layer and f is the appropriate transfer function used. In this work, the ANN model is trained with 19 experimental datasets and tested with eight unseen datasets.

Fig. 3 shows the architecture of two layered feed forward neural network system used in this work. The network is modeled with neural network tool box available in MATLAB® that working on back propagation learning algorithm. The algorithm use gradient decent technique and minimize mean square error (MSE) between actual network outputs with desired output pattern.



W_{ij} and b_i are weights and bias of hidden layer, respectively
V_{ij} and c_i are weights and bias of output layer, respectively

Fig. 3 ANN architecture

The network is optimized with varying number of neurons in the hidden layer and activation transfer function used so as to obtain minimum MSE. The network architecture with five hidden layer neurons with *tansig* transfer function obtains least MSE of 0.0001 and is considered as optimum network. The output layer uses *purelin* transfer function to evaluate the estimated outputs of surface roughness and tool wear. The validation of the network is performed by predicting surface roughness and tool wear for unseen data sets and ANN prediction is compared with experimental result.

3.1 Comparison of RSM and ANN model performance

The ANN and RSM predicted values for surface roughness and tool wear is compared with the experimental values. The comparison of predictive performance of both the models with the experimental value is given in Table 5. The prediction accuracy *PA* of each datasets was calculated using Eq. 18.

$$PA = \left[1 - \frac{\mathrm{abs}(Expt\_value_i - \ Model\_pred_i)}{Expt\_value_i}\right] \times 100 \tag{18}$$

Finally, the model accuracy *MA* is computed as the average of individual accuracy on confirmation data set. It is obtained using Eq. 19.

$$MA = \frac{1}{n}\sum_{i=1}^{n}(PA_i) \times 100 \tag{19}$$

The model accuracy of the ANN and RSM model are 95.38 % and 92.90 % for surface roughness and 92.16 % and 91.56 % for tool wear. It can be concluded that the correlation between the prediction of developed models and experimental result is very good. The prediction accuracy in ANN for surface roughness and tool wear is more than 95.00 %. The prediction accuracy for RSM based on linear with interaction model found more than 91.00 % for predicting surface roughness with a maximum PA of 99.69 %. While for tool wear PA is more than 90.0 % with the maximum of 98.64 %. This shows that neural network based prediction model has been found better than the response surface model for turning Al/SiCp metal matrix composite using coated TiN tool.

Table 5 Comparison of ANN and RSM predictive model

Sl. No.	Surface roughness, R_a Expt. (μm)	ANN Pred. (μm)	ANN Pred. acc. (%)	RSM Pred. (μm)	RSM Pred. acc. PA (%)	Tool wear, VB Expt. (mm)	ANN Pred. (mm)	ANN Pred. acc. PA (%)	RSM Pred. (mm)	RSM Pred. acc. PA (%)
1	3.27	3.48	93.96	3.28	99.69	0.508	0.405	79.72	0.45	88.58
2	3.87	4.16	93.02	3.79	97.93	0.400	0.453	88.30	0.35	87.50
3	4.67	4.49	96.15	4.20	89.93	0.521	0.493	94.63	0.43	82.53
4	4.04	3.59	88.86	3.68	91.08	0.799	0.783	97.99	0.81	98.64
5	4.16	4.37	95.88	3.96	95.19	0.685	0.707	96.89	0.63	91.97
6	3.08	3.00	97.40	3.14	98.08	0.653	0.677	96.46	0.66	98.93
7	3.79	3.78	99.74	3.32	87.59	0.750	0.792	94.70	0.81	92.59
8	4.06	4.02	99.01	3.41	83.99	0.951	0.842	88.54	1.04	91.44
Model accuracy			95.50		92.94	Model accuracy		92.15		91.52

4. Optimization of cutting parameters

The selection of best or right combination of cutting parameters for obtaining optimum process response is still the subject of many studies. In this work the parameter optimization for single as well as multiple objectives is carried out. Optimization for minimum R_a and minimum VB are performed using the non-traditional techniques of genetic algorithm (GA). The optimum parameters are also obtained for simultaneous optimization of R_a and VB using desirability function analysis (DFA).

4.1 Single-objective optimization with GA

GA is one of the popular optimization technique performed by the natural evolution process inspired on the principle of survival of fitness [26]. GA works on the mechanism of genetics and evolution and has been found as a very powerful algorithm for obtaining global minima by Chandrasekaran et al. [27]. In GA the different process parameters are represented either binary or decimal numbers, called as *string* or *chromosome*. A set of chromosomes is called *population*. A population is evolved through several generations using different genetic operations such as reproduction, crossover, and mutation. The best chromosome in the population is identified by the closeness of fitness value with the objective function. The process is repeated till the optimization function converges to the required accuracy after many generations and optimum parameter is obtained. Researchers have found GA as powerful optimization tool/procedure to obtain global optima and the mathematical derivative of the function is not required in this procedure.

In this work, the fitness/objective function of the optimization problem is formulated using the best regression model given in Eq. 20 and Eq. 21 for surface roughness and tool wear, respectively. The formulated single-objective optimization function is given as follows:

$$\begin{aligned}&\text{Minimize } R_a(v,f,d)\\&= Min(2.382 + 0.00217v + 8.41f + 3.313d - 0.034vf - 0.00009vd - 1.95fd)\end{aligned} \tag{20}$$

$$\begin{aligned}&\text{Minimize } VB(v,f,d)\\&= Min(0.320 + 0.0018v - 1.63f + 0.127d + 0.018vf - 0.00149vd + 0.612fd)\end{aligned} \tag{21}$$

The variables of the function are limited by its upper and lower bounds and are given as

$$50 \leq v \leq 150 \tag{22}$$

$$0.1 \leq f \leq 0.3 \tag{23}$$

$$0.5 \leq d \leq 1.5 \tag{24}$$

The problem is optimized using the GA parameters: number of population size was 20, maximum number of iterations was 1000, crossover probability was 0.7 and mutation probability was 0.05. Optimization is performed for obtaining minimum R_a and minimum VB within the range of parameters available and it takes 54 and 61 iterations for R_a and VB, respectively.

4.2 Multi-objective optimization with DFA

The concept of desirability function was first introduced by Derringer and Suich [28] in the year 1980. The method is used for optimization of multiple quality characteristics and found popular among manufacturing industries. The desirability function analysis (DFA) evaluates a *composite desirability value* of the various responses from its *individual desirability*. The method makes use of an objective function called the desirability function and transform an estimated response into a scale-free value d_i called *desirability*. The desirability value varies from 0 to 1. A value of 1 represents the ideal case; 0 indicates that one or more responses are outside their acceptable limits. *Composite desirability* is the weighted geometric mean of the individual desirability evaluated against each response. The parameter settings with maximum composite desirability are considered to be the optimal cutting conditions.

In order to optimize the R_a and VB, DFA is adopted. In DFA optimization of multiple response characteristics is converted into single composite desirability grade [29]. The procedure involves: 1) evaluation of individual desirability d_i, 2) evaluation of composite desirability d_G, and 3) ranking of composite desirability. Experimental data sets based on full factorial design, $3^3 = 27$ data sets are used.

In this work, since both the responses are to be minimized, Eq. 25 is used to evaluate the individual desirability d_i

$$d_i = \begin{Bmatrix} 1, y \leq y_{min} \\ \left(\dfrac{y - y_{max}}{y_{min} - y_{max}}\right)^r, y_{min} \leq y \leq y_{max}, r > 0 \\ 0, y \leq y_{max} \end{Bmatrix} \tag{25}$$

where r is weight, y_{min} and y_{max} are the lower and upper value, respectively.

The next step is to select the parameter combination that will maximize overall desirability d_G using Eq. 26

$$d_G = (d_1 \times d_2 \times d_3 \times \ldots \times d_n)^{1/n} = \left(\prod_{i=1}^{n} d_i\right)^{1/n} \tag{26}$$

where d_i is the individual desirability of the response and n is the number of response in the measure. The desirable ranges from zero to one. If any of the response falls outside the desirability range, the overall function becomes zero. To reflect the difference in the importance of different response the equation can be extended to

$$d_G = d_1^{w1} \times d_2^{w2} \times d_3^{w3} \times \ldots \times d_n^{wn} \tag{27}$$

where the weight w_i satisfies $0 < w_i < 1$, and sum of weights is equal to one. In this work, w_1 *and* w_2 is taken equal as 0.5. Fig. 4 shows the scatter plot of the composite desirability grade for the different set of parameter combination. The larger the grade the better is the multiple performance characteristics. The grade is 0.92 and it corresponds to the first experimental run. The parameter combination as v_1 (50 m/min), f_1 (0.1 mm/rev) and d_1 (0.5 mm) is optimal parameter set. The surface roughness and tool wear predicted by DFA at optimal parameter is 3.24 μm and 0.327 mm, respectively. The confirmation experiments show the surface roughness of 3.41 μm and tool wear of 0.34 mm. The increased surface roughness of 3.24 μm notifies that there is slight loss of quality in simultaneous optimization for multiple responses. However, the confirmation test shows the prediction error percentage is 4.98 % and 3.82 % for R_a and VB, respectively, which shows the effectiveness of the method. Table 6 shows the optimum parameters.

Table 6 Comparison of various optimization techniques

Method	Optimization technique	Optimal parameter combination	Optimal responses
Single-objective optimization	GA	Minimizing R_a: v (134.98 m/min), f (0.1 mm/rev), d (0.5 mm)	R_a = 2.52 μm
		Minimizing VB: v (50 m/min), f (0.21 mm/rev), d (0.5 mm)	VB = 0.31 mm
Multi-objective optimization	DFA	Minimizing R_a and VB: v (50 m/min), f (0.1 mm/rev), d (0.5 mm)	R_a = 3.24 μm VB = 0.327 mm

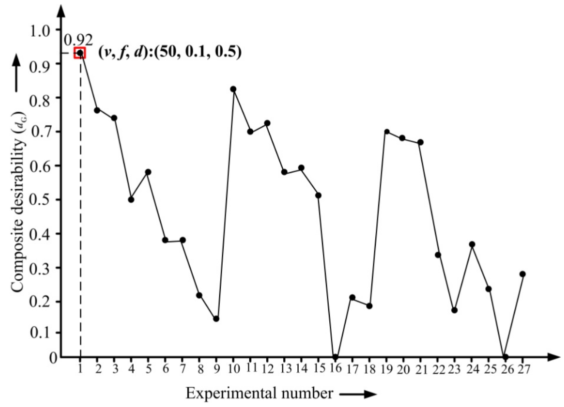


Fig. 4 Scatter plot for composite desirability

5. Conclusion

In this paper the predictive modeling for surface roughness (R_a) and tool wear (VB) in turning Al/SiCp MMC was developed using RSM and ANN. The predictive capability was compared. The three turning parameters viz., cutting speed, feed, and depth of cut are considered as input parameters. The model behavior was analysed through contour plot and optimum operating zone is obtained. The parameters are optimized for single- and multi-response characteristics employing GA and DFA techniques. From the research result the following conclusions are obtained:

1. The surface roughness is highly influenced by feed. Tool wear is influenced by feed and cutting speed. The increase of feed and cutting speed increases VB.
2. Among different RSM models, the linear with interaction model found better in term of predictive performance. The combination of parameters with cutting speed as 150 m/min and feed as 0.1 mm/rev produce minimum surface roughness of 3.3 μm. Minimum tool wear of 0.38 mm is obtained at 50 m/min, feed as 0.1 mm/rev, and depth of cut 0.5 mm. The experimental confirmations show an error of 0.32 % and 13.14 % for R_a and VB, respectively.
3. The response contour plot provides the cutting speed ranges from 50-80 m/min with the feed ranges from 0.1-0.14 mm/rev producing surface roughness less than 3.4 μm with tool wear less than 0.5 mm. It may be considered as the optimum operating zone.
4. Multi-response predictive modeling developed using ANN with 3–5–2 as optimum network architecture providing best prediction accuracy. The model adequacy for surface roughness and tool wear is more than 92 %. On comparison of both RSM and ANN model, the latter is found to be slightly better. ANN shows good generalization ability and found as useful artificial intelligence tool for monitoring machining process.
5. Parameter optimization for single objective using GA obtains minimum R_a and VB as 2.52 μm and 0.31 mm, respectively. DFA based multi-response optimization obtain optimal parameter combination as v_1 (cutting speed, 50 m/min), f_1 (feed, 0.1 mm/rev) and d_1 (depth of cut 0.5 mm) having highest desirability grade of 0.92. Confirmation test shows the percentage of error as 4.98 % and 3.82 % for R_a and VB , respectively, which shows the effectiveness of the method.

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