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Optimization of machining parameters of Al6061 composite to minimize the surface roughness – modelling using RSM and ANN

S Jeyakumar[a]*, K Marimuthu[b] & T Ramachandran[a]

[a]Department of Mechanical Engineering, PSNA College of Engineering and Technology, Dindigul 624 622, India

[b]Department of Mechanical Engineering, Coimbatore Institute of Technology, Coimbatore 641 014, India

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The Al6061/SiC_p metal matrix composites are most frequently used for automobile and aerospace applications and the end milling operations are performed to achieve the better surface roughness of these composites. It is difficult to achieve required surface roughness on these composites due to their hardness. By considering the spindle speed (*s*), feed rate (*f*), depth of cut (*d*) and nose radius (*r*) and as predominant parameters and are optimized to achieve required surface roughness. In this regard, a versatile prediction model is required to determine the surface roughness of the composite considering the effect of machining parameters. In this research work, the response surface method (RSM) and an artificial neural network (ANN) based prediction models are developed to determine the surface roughness (R_a) of Al6061/SiC_p and the performance of the RSM and ANN models are compared with experimental results for their effectiveness. The genetic algorithm (GA) based optimization of machining parameters for the RSM and ANN models are also carried out to minimize surface roughness. The results of the GA optimal parameters are analyzed for the convergence of various crossover and mutation probabilities and also to find the better prediction model.

Keywords: Al6061, Surface roughness, Response surface method, Artificial neural network, Genetic algorithm

The metal matrix composite (MMC) of particle-reinforced aluminum alloy is one of the significant composite among the MMCs. MMCs have extensive potential for various applications like automotive and aerospace industries due to their superior properties compared with conventional alloys. The hard reinforced particles in MMCs give higher wear resistance and detriment to the cutting tools. This cause early failure of the cutting tool and increase in the cutting tool wear sternly involves the quality and veracity of the machined surface. The surface roughness plays an important role in measuring and evaluating the surface quality of the machined product and signifies the functional characteristics of products in wear resistance friction, fatigue, lubrication and material coatings. The end milling operation is associated with surface roughness due to some requirements such as machining efficiency, high-quality surfaces, dimensional accuracy, and the process reliability[1]. The many factors such as machining parameters, tool geometry, work-piece material, chatter, and cutting fluids are considered as the factors for the surface roughness. Most of the researches have been performed on the determination of the surface roughness in end milling operation and its effect on the regular materials like steel and aluminum and few researches only made to obtain the minimum surface roughness using GA in machining of Al6061 material. Huang and Chen[2] investigated the uncontrollable factors of the end milling operation for surface roughness through the cutting parameters. Some investigation had also been performed to predict surface roughness using ANN and the model indicates the machining parameters in turning and end milling processes. Huang *et al.*[3] studied the neural network-based surface roughness using Pokayoke system and maintained the roughness in a desired level by in-process method of the end-milling process for Al6061 material. Zhong *et al.*[4] developed an ANN model to determine the surface roughness in turning of copper and aluminum materials using TiAlN-coated carbide tools. Basheer *et al.*[5] fabricated Al-2124/SiC_p composite material through powder metallurgy process. They developed ANN model such that surface roughness was determined by the machining parameters feed rate, depth of cut, reinforcement sizes and nose radius. The greatest surface quality was achieved at low feed-rates,

*Corresponding author (E-mail: kmk_ jai@yahoo.com)

smaller size of particle and larger nose radius. Azlan Mohd Zaina *et al.*[6] formulated standard mathematical model to predict the minimum surface roughness in the end milling process. The model uses experimental data of the R_a in the regression analysis and ANN to predict surface roughness. The responses obtained from the regression and ANN models are found to be minimum in R_a.

Oktem[7] determined the surface roughness by multiple regression analysis and ANN and optimized the machining parameters using GA in end milling operation of steel with TiAlN solid carbide tool. Song *et al.*[8] proposed a systematic experimental investigation method to optimize the heat treatment of 7175 aluminum alloy, by integrating ANN equation with and GA optimization method. Zain *et al.*[9] optimized the machining process by new method using soft computing approaches to find the optimal result of the cutting parameters for minimum R_a value in the turning operation. The results were compared with the techniques used in previous studies, genetic algorithm (GA), simulated annealing (SA), Tabu search (TS), ant colony optimization (ACO), and the new method for the optimal cutting conditions for machining problems. Suresh *et al.*[10] developed a prediction model to find the surface roughness of the machining process in mild steel using RSM. The testing was performed with TiN-coated tungsten carbide tools in various machining conditions and the optimum conditions were obtained through GA. It was also found that the R_a increases with an increase in the nose radius and depth of cut. Oktem *et al.*[11] developed RSM model to find the optimum machining conditions like feed rate, cutting speed, axial depth of cut and radial depth of cut for minimum R_a in milling operation. Palanisamy *et al.*[12] used GA as optimization technique to reduce the R_a value on mild steel material at various machining conditions like cutting speed, feed rate, and depth of cut. Saravanan *et al.*[13] compared the GA and SA models in optimizing the cutting parameters in turning process with carbide tools. In the optimization the constraints were considered in the variables cutting force, power constraint, and tool-tip temperature. Bhushan *et al.*[14] developed the regression model using experimental data of AA7075 composites in turning process. The model was optimizes in GA and optimal result of machining conditions were determined for minimum value of R_a. Ramachandran and Padmanaban[15] have used GA to optimize the balancing disc parameters to minimize the engine vibration displacements at the engine block. It was found that the GA made good convergence towards the optimal results such that the displacements are minimum.

Deris *et al.*[16] successfully applied the support vector machine (SVM) techniques as mathematical tool for modelling the machining operations as regression functions. Out of different kernel functions like linear, polynomial, radial basis function (RBF), sigmoid and Gaussian kernel for training the parameters in SVM the authors used the RBF kernel function as it was most widely applied in SVM. Norfadzlan Yusup *et al.*[17] reviewed the recent evolutionary optimization techniques that are used in optimization of machining parameters to minimize the surface roughness and also they compared each method with others in different aspects. Apart from GA, SA, PSO, ACO and ABC, they identified that GA was most widely used by researchers in optimizing the machining process parameters. Yusup *et al.*[18] detailed the PSO methodology in optimizing the machining process parameters for the traditional and modern machining processes. They explained the PSO process to optimize the parameters such as cutting speed, depth of cut and radial rake angle to improve the machining performance and production costs. Zain *et al.*[19-21] integrated the meta-heuristic optimization methods SA and GA to determine the optimized abrasive water jet machining (AWJ) process parameters to improve the performance of the machining. They used two integrated methods SA–GA-type1 and SA–GA-type2 and investigations were carried out with six modules, which are experimental data, regression modeling, SA, GA, SA–GA-type1 and SA–GA-type2. The optimized results of the process were compared with the experimental results and are found in good agreement with each other. The results showed that the computational methods used were well managed to estimate the optimal process parameters in improving the machining performance compared with the result of experimental results.

In this study, empirical models for the prediction of surface roughness in end milling are developed using RSM and ANN and their results are compared with experimental results. The RSM and ANN models are also integrated with GA based optimization to determine the best combinations of machining parameters that lowers the surface roughness during end milling process of Al6061/SiC_p composite with carbide tool insert at dry conditions. The optimal parameters of both the models are also compared and the better model is chosen for the experimental simulation and the optimized parameters validated for the least surface roughness.

Design of Experiments

The design of experimentation has an important role on the number of experiments required to form the experimental replica of the performance parameter. The machining experiments should be well-designed and performed preciously such that the experimental errors will be avoided. The experiment is designed in 3-level response surface method of central composite design with 31 runs to obtain the measured surface roughness values of Al/SiC_p composite material. The machining parameters cutting speed (*s*), feed rate (*f*), depth of cut (*d*), nose radius (*r*) are the design variables for the experimental runs of end milling of Al/SiC work-pieces. The levels for the experiment are designed in the coded values within the range of design variables. The coded levels of design variables are shown in Table 1**.** The corresponding design conditions are carried out in the end milling machine with the Al/SiC_p.

Experimental investigation

The experiments are performed on the HMT FNIU milling machine with tungsten carbide end mill cutter at dry condition. The specimen, Al6061 alloy of 100×100×30 mm size, reinforced with silicon carbide particle of 15% weight fraction, is produced from the stir casting method. The TE 90AX 220 with ISO specifications of the tool cutters and AXMT 0903 PER EML TT 8020 tungsten carbide tool insert is used in the milling operation. While the condition of the certain design matrix, the machining operation carried out in a random fashion to avoid systematic errors. The experimental observations corresponding to the specific design conditions are tabulated and will be used in the RSM runs.

Surface roughness measurement

The most practical way in determining the surface quality of a machined product is surface roughness and it is the implication of permanent irregularities remained on the machining surface. For the measurement of surface roughness, TR100 model roughness is used and the measurement is carried out along the feed direction. The measurements on the machined surface are obtained at different locations and the surface roughness in each location is average of three successive measurements and is recorded as R_a.

Modeling of response surface equation

Response surface method (RSM), a statistical technique, is used to develop an analytical prediction model to determine the surface roughness from a set of predetermined experiments of four factor central composite design (CCD). The model developed is a second-order one such that the surface roughness is a response and the machining parameters are the design variables. The Eq. (1) represents the model of machining response.

$$Y=b_o+\sum_{i=1}^{4} b_i x_i+\sum_{i=1}^{4} b_{ii} x_i^2+\sum_{i<j}^{4} b_{ij} x_i x_j \qquad \ldots (1)$$

Where, b_0 is constant, x_i is coded variable, b_i, b_{ii} and b_{ij} are linear, quadratic, interaction coefficients, respectively.

$$\begin{aligned} Y(R_a) = {} & 2.41390 - 0.04324 x_1 + 0.01410 x_2 \\ & + 0.09974 x_3 + 0.08858 x_4 \\ & + 0.00031 x_1^2 - 0.00021 x_2^2 \\ & + 1.00739 x_3^2 - 0.02120 x_4^2 \\ & + 0.00014 x_1 x_2 - 0.01455 x_1 x_3 \\ & - 0.00330 x_1 x_4 - 0.00578 x_2 x_3 \\ & + 0.00187 x_2 x_4 + 0.30952 x_3 x_4 \end{aligned} \qquad \ldots (2)$$

The analysis of RSM model equation (Eq. 2) is performed to reveal the fitness with the experimental values[17]. The results of the surface roughness equation are presented in Table 2. The correlation coefficient R^2 is calculated as be 0.9961. When R^2 approaches 1 the investigational measurement excellently fits with experimental results. Analysis of variances (ANOVA) (Table 3) is carried out to find the effect of machining parameters on the surface roughness and its statistical importance on machining parameters.

Table 1—The levels of machining parameters

Parameter	Unit	Symbol	Levels		
			-1	0	1
Cutting speed	m/min	*s*	30	60	90
Feed	mm/min	*f*	50	75	100
Depth of cut	mm	*d*	0.75	1	1.25
Nose radius	mm	*r*	0.4	0.8	1.2

The *F* test is also carried out for these parameters and the probability values are found to be less than 95% confidence level and inferred that machining parameters have a significant effect on the surface roughness.

Artificial Neural Network

ANN is nonlinear mapping systems in artificial intelligence which has the capability to solve several problems with modeling, predicting and measuring in experimental knowledge. ANN formation is commonly designed by multi-layers such as input layer, hidden layer and output layer. Three layer ANN topology for surface roughness is shown in Fig. 1. The processing elements (neurons) are connected in weighed interconnections, which are similar to the strength of bioelectricity transmitting between the neuron cells in actual network. The functional relationship creating between the input and outputs in the model of problems with ANN trains and the learning process is carried out using back-propagation (BP) method. In BP learning algorithm, it has a gradient descent method for minimizing the mean square error (MSE) among the desired and network outputs. A multilayered ANN based on the BP learning algorithm can be formed effectively by employing the Eq. (3)

$$net_j = \sum_{i=1}^{n} W_{ji} X_i \quad \dots (3)$$

Where, net_j , w_{ji} are the weight of outputs and the link connecting neuron *j* to *i*. In neural network, every neuron accepts entire input from all of the neurons in the previous layer. In the next layers, the tangent hyperbolic activating function (f_a) is used to calculate the output (O_j) of the j^{th} neuron Eq. (4).

$$\left(O_j\right) = fa\left(net_j\right) = \frac{1-e^{(-net_j)}}{1+e^{(-net_j)}} \quad \dots (4)$$

BP learning algorithm updates the network trains and weights until the mean square error (Eq.(5)) coverage to a smallest value among the desired and network outputs.

$$MSE = \sum_{m=1}^{m} \sum_{k=1}^{K} (D_{mk} - O_{mk})^2 \quad \dots (5)$$

Where, D_{mk} and O_{mk} are the desired output and the network output, *k* is the number of output neutron, *m* is the overall number of dataset. The adjustment of the weights can be defined as in the Eq. (6).

$$w_{ij}(t) = \eta \delta_j x_i + \alpha w_{ij}(t-1) \quad \dots (6)$$

Table 2—Regression analysis co-efficient for surface roughness (R_a)

Symbol	Surface roughness (R_a)µm	
	Coefficient	*P* value
Constant	2.41390	0.000
x_1 (s)	-0.04324	0.000
x_2 (f)	0.01410	0.000
x_3 (d)	0.09974	0.000
x_4 (r)	0.08858	0.003
x_1^2	0.00031	0.000
x_2^2	-0.00021	0.000
x_3^2	1.00739	0.029
x_4^2	-0.02120	0.899
$x_1 x_2$	0.00014	0.000
x_1x_3	-0.01455	0.000
$x_1 x_4$	-0.00330	0.002
$x_2 x_3$	-0.00578	0.004
$x_2 x_4$	0.00187	0.095
$x_3 x_4$	0.30952	0.010
S = 0.042255	R^2 = 99.61%	Adjusted R^2 = 99.27%

Table 3—ANOVA results for surface roughness

Source	Surface roughness (R_a)				
	DOF	Sum of square	Adjusted mean square	*F* value	*P* value
Regression	14	7.3546	0.525327	294.22	0
Linear	4	6.4982	0.120591	67.54	0
Square	4	0.4266	0.10665	59.73	0
Interaction	6	0.4298	0.071636	40.12	0
Residual Error	16	0.0286	0.001785		
Lack-of-fit	10	0.0246	0.00246	3.72	0.061
Pure error	6	0.004	0.000662		
Total	30	7.3832			

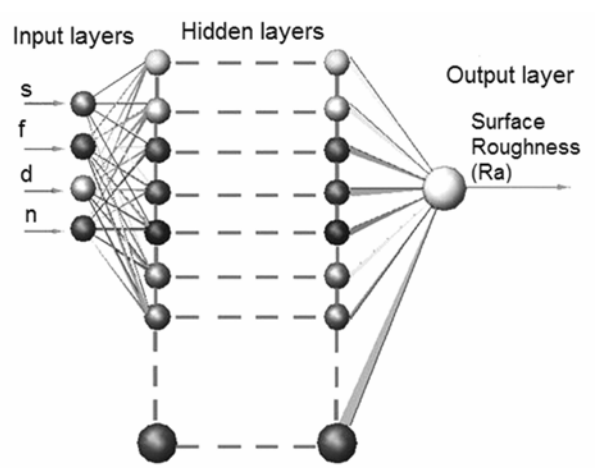

Fig. 1—Three layer ANN topology for surface roughness

Table 4—Weights of different layers of ANN model-for 0.9915 convergence

Layer 1, IW(1,1)				
1	1.0e+003 *-0.0367722	1.0e+003 * 0.0468952	1.0e+003 * -0.1999990	1.0e+003 *-2.0921508
2	1.0e+003 * -0.0171951	1.0e+003 * 0.0042610	1.0e+003 *-0.2590854	1.0e+003 *-2.8437643
3	1.0e+003 * 0.0069999	1.0e+003 * 0.0011847	1.0e+003 * -0.1709124	1.0e+003 *-1.9997525
4	1.0e+003 *0.0059471	1.0e+003 *0.0001632	1.0e+003 *-0.1337775	1.0e+003 *3.4933949
Layer 2, LW(2,1)				
1	-0.000357024	1.121015564	-0.001389157	-0.002045371
2	-8.237610691	-0.989738543	-6.105861096	-14.03545447
3	0.140129903	-7.71669794	-26.12886205	-10.66409647
4	0.175993905	-4.9403696	11.67414305	-19.15724892
Output, LW(3,2)				
1	2.065886521	-0.001007288	0.007536565	-0.001765818

Where, η is learning rate controlling the stability, α is momentum rate and t is itration.

Table 5—Biases of different layers of ANN model for 0.9915 convergence

	Bias 1 for layer 1	Bias 2 for layer 2	Bias 3 for output
1	1.010681475	-0.856407031	-0.526876149
2	10.82780712	0.394153764	
3	0.571152865	-7.794724716	
4	-2.298198776	-7.618056301	

Training and testing of the network

In training stage, cutting parameters such as spindle speed, feed rate, depth of the cut and nose radius were given as input layer and the corresponding results of surface roughness values are used in the output layer. The training of the ANN was performed with predefined R_a values, experimental results, using MATLAB Code. For determining the stability and the rate of convergence, the learning rate is selected as 0.0005 and finally the weights and bias of ANN model considered for convergence towards the 0.9915, which is given in Tables 4 and 5. The MSE of the network is used to verify the performance and is found to be 0.0085. The prediction accuracy of trained ANN can be determined by Eqs (5) and (6).

$$RSME = \sqrt{\frac{1}{2m}\left[\sum_{m=1}^{m}\sum_{k=1}^{k}(D_{mk} - O_{mk})^2\right]} \quad \ldots (7)$$

$$APE(\%) = \left[\frac{(M_{value} - P_{value})}{M_{value}} * 100\right] \quad \ldots (8)$$

The root mean squared error (RSME) is also an important criterion in evaluating results of ANN model and the APE calculates the average percentage of error between the predicted and measured values of R_a.

Comparison of ANN and RSM models

The predicted performance of RSM and ANN models are verified using correlation coefficient (R^2), mean absolute error and root mean square error (RSME) which are shown in Table 6**.** It reveals that in all the cases the ANN models have shown better convergence than RSM model. Figure 2 shows relationship between the experimental and predicted values of R_a for RSM and ANN models. The R^2 value for different R_a responses of ANN and RSM model are found to be 0.9999 and 0.9961 respectively. For all these models, the co-efficient of determination is almost equal to 1. This confirms the goodness of fit for RSM and ANN models. In the case the design data for ANN model ensured better R^2 value as compared to RSM model.

Optimization of Machining Parameters

Genetic algorithm

The genetic algorithm (GA) is a heuristic optimization tool in solving problems in the engineering, mathematics and the other fields. The GA is mostly expected with exposure for universal optima than conventional optimization technique. Because they are searching from a population of points and based on probabilistic rules. In general, the conventional optimization techniques are based on deterministic hill-climbing method, which can obtain local optima. The GA expects for coverage on the most excellent results from changing them during some generations. This technique starts with a possible solution to altering them during several generations. This technique starts with a possible solution of chromosomes is in the structure of binary

Table 6—Comparison of RSM and ANN results with experimental results

Run	Cutting parameter				Surface roughness (R_a) µm				
	s	*f*	*d*	*n*	Experimental value	predicted value in RSM	% of error	predicted value in ANN	% of error
1	90	50	1.25	1.2	1.803	1.809	-0.0033	1.4229	0.2108
2	30	50	0.75	0.4	2.024	1.991	0.0163	2.0240	0.0000
3	90	75	1.00	0.8	1.343	1.35	-0.0052	1.3430	0.0000
4	90	100	1.25	0.4	1.034	1.014	0.0193	1.0340	0.0000
5	90	100	1.25	1.2	1.271	1.28	-0.0071	1.2710	0.0000
6	30	75	1.00	0.8	2.166	2.133	0.0152	2.1660	0.0000
7	60	75	1.00	0.8	1.449	1.464	-0.0104	1.4518	-0.0019
8	30	50	1.25	0.4	2.756	2.748	0.0029	2.7560	0.0000
9	90	50	1.25	0.4	1.615	1.618	-0.0019	1.6150	0.0000
10	60	75	1.00	1.2	1.574	1.583	-0.0057	1.5740	0.0000
11	60	75	0.75	0.8	1.27	1.263	0.0055	1.2700	0.0000
12	60	50	1.00	0.8	1.643	1.681	-0.0231	1.6430	0.0000
13	30	50	1.25	1.2	3.114	3.097	0.0055	3.1140	0.0000
14	60	100	1.00	0.8	1.043	0.979	0.0614	1.0430	0.0000
15	30	100	1.25	1.2	2.153	2.152	0.0005	2.1530	0.0000
16	60	75	1.00	0.8	1.469	1.464	0.0034	1.4518	0.0117
17	60	75	1.00	0.8	1.431	1.464	-0.0231	1.4518	-0.0145
18	30	100	0.75	0.4	1.093	1.116	-0.0210	1.0930	0.0000
19	90	100	0.75	0.4	0.845	0.839	0.0071	0.8450	0.0000
20	90	50	0.75	0.4	1.268	1.298	-0.0237	1.2680	0.0000
21	60	75	1.00	0.4	1.374	1.338	0.0262	1.3740	0.0000
22	60	75	1.00	0.8	1.409	1.464	-0.0390	1.4518	-0.0304
23	60	75	1.00	0.8	1.468	1.464	0.0027	1.4518	0.0110
24	90	50	0.75	1.2	1.435	1.365	0.0488	1.4350	0.0000
25	30	100	1.25	0.4	1.682	1.728	-0.0273	1.6820	0.0000
26	60	75	1.00	0.8	1.485	1.464	0.0141	1.4518	0.0224
27	30	50	0.75	1.2	2.167	2.216	-0.0226	2.3828	-0.0996
28	30	100	0.75	1.2	1.443	1.416	0.0187	1.3929	0.0347
29	60	75	1.25	0.8	1.81	1.791	0.0105	1.6346	0.0969
30	90	100	0.75	1.2	0.942	0.981	-0.0414	1.1316	-0.2013
31	60	75	1.00	0.8	1.456	1.464	-0.0055	1.4518	0.0029

string, which are formed or selected at random. The chromosomes are reproduced by utilizing a fitness condition, while the finest ones are retained and repeated and the others are eliminated. The whole set of these chromosomes develops through many generations. The offsprings are formed using the operators of crossover and mutation such that crossover exchange genes between the pair of chromosomes and the mutation flip the genes between 0 and 1. In this work, uniform crossover and single point flipping of mutation is carried out to drive the offsprings.

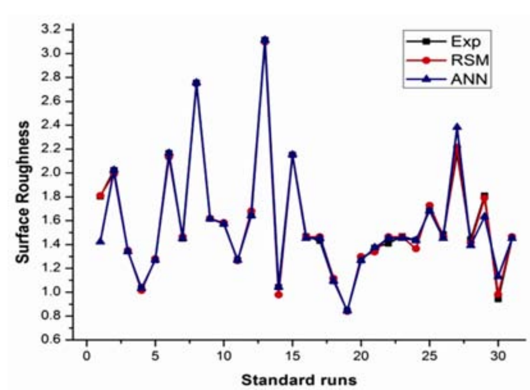

Fig. 2—Surface roughness values of RSM and ANN models

GA control parameters

Reproduction

The simplest way is to reproduce the chromosome by biased roulette wheel where population of every current string has a proportion of roulette-wheel-slot-size to its fitness. In this way the subsequent generation has more greatly fit strings and upper numbers of offspring. When the string can prefer for reproduction an extra model of the string is prepared. Then the string is entered into the mating pool, a provisional new population for additional genetic operator action.

Crossover

The improved strings confidently generated by a crossover operator on the population by selecting the pairs of matting pool. In crossover, the chromosomes exchange genes each other with probability of crossover and is restricted the complete number of participative strings in crossover. The crossover of the chromosomes is shown in Fig. 3

Mutation

Mutation is the infrequent random alteration of the string position value of simple GA. This means flipping of genes (Fig. 4) between 0 and 1 with a small mutation probability of 0.01 to 0.05. A new set of chromosomes are formed at the end of each generation and next generations are continued till the termination condition is attained.

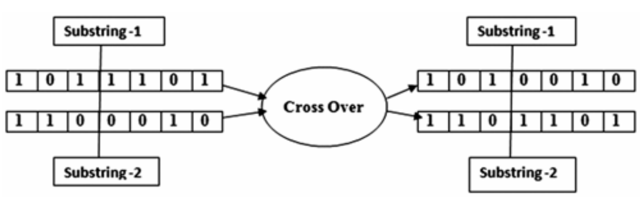

Fig. 3—GA Cross over Process

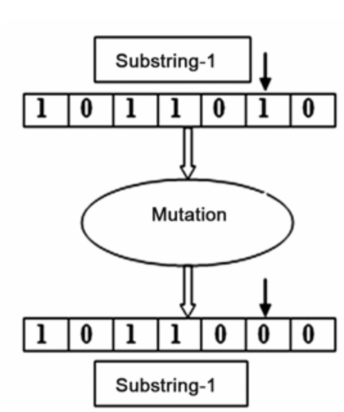

Fig. 4—GA mutation process

Optimization of machining parameters

The objective of the optimization of the machining parameters is to find most favorable machining conditions of process that redound to the minimum value of surface roughness (R_a). To formulate the optimization of this problem the Eq. (1) and Eq. (2) separately is chosen and proposed for optimization for the prediction of least surface roughness. The optimization process consists of process parameters cutting speed, feed rate, depth of cut, and nose radius and the objective function is the surface roughness.

Lower limits of variables [30 50 0.75 0.40];
Upper limits of variables [90 100 1.25 1.20].

A set of 20 random populations, containing the binary strings of variables, are developed and the fitness function (Eq. 2) for each set of machining parameters is determined from the objective function. The experimental range of values (Eq. 9) of cutting parameters are given in Table 1 is used to present the optimization solution.

$$\begin{aligned} &30 \le s \le 90 \text{ m/min} \\ &50 \le f \le 100 \text{ mm/min} \\ &0.75 \le d \le 1.25 \text{ mm} \\ &0.4 \le n \le 1.2 \text{ mm} \end{aligned} \qquad \ldots (9)$$

Generally, the best optimal results attaining depends on various criteria. The major criteria of the optimal result are based on the initial population size, method of reproduction, crossover and mutation probability as they are control parameters of GA. The parameter setting for these criteria is attained by the trial and error process and the most optimal result is estimated using GA when the convergence is reached. Finally, the most favorable combination crossover and mutation probabilities (Table 7) are determined and these combinations will be able to produce the least surface roughness. The convergence of the results of each run is verified through the multi-modal results and the best parameters combination is applied to experimental simulation.

Evaluation of GA results

The response values (31 R_a values) are obtained from the RSM model, for the network training of ANN model using MATLAB. The associations between R_a values are calculated from experiments and those are predictions of RSM and ANN model (Table 9). It is observed from Table 9 that the prediction of R_a values from the RSM and ANN through the number of experiments are closer with

Table 7—Combination of GA parameter rates leading to the optimal solution

S.No.	Probability		Surface roughness (R_a)	
	Cross over	Mutation	RSM	ANN
1	0.65	0.01	0.8046	0.7538
2	0.65	0.02	0.8046	0.7782
3	0.65	0.03	0.8278	0.7666
4	0.65	0.04	0.8278	0.8175
5	0.65	0.05	0.7538	0.7717
6	0.70	0.01	0.7782	0.8090
7	0.70	0.02	0.8046	0.8949
8	0.70	0.03	0.8278	0.7489
9	0.70	0.04	0.7536	0.7840
10	0.70	0.05	0.8278	0.8533
11	0.75	0.01	0.8046	0.8262
12	0.75	0.02	0.7535	0.7929
13	0.75	0.03	0.7620	0.7822
14	0.75	0.04	0.7835	0.8034
15	0.75	0.05	0.8182	0.7547
16	0.80	0.01	0.7740	1.1426
17	0.80	0.02	0.7836	0.7843
18	0.80	0.03	0.8735	0.7822
19	0.80	0.04	0.7589	0.7525
20	0.80	0.05	0.7840	0.7457

Table 8—Comparison of least R_a values before optimization

Model	Run No.	Speed	Feed	Depth of cut	Nose radius	Surface roughness (R_a)
Experimental value	19	90	100	0.75	0.4	0.8450
RSM value	19	90	100	0.75	0.4	0.8390
ANN value	19	90	100	0.75	0.4	0.8450

Table 9—Comparison of Least R_a values after GA based optimization

S.No	Model	Cutting speed (m/min)	Feed	Depth of cut (mm)	Nose radius (mm)	Surface roughness (R_a) µm
1	RSM	66.8504	100	0.7543	0.4302	0.7535
2	ANN	66.378	100	0.7504	0.4038	0.7457

each other. It is also identified from Table. 9 that the ANN values are very close to the measured values and have a good agreement of R_a values of the experimental and the ANN model.

The associated ANN and RSM models of the problem presented are simulated in GA based optimization. The model variables are represented as 4bit binary string and the length of chromosome is 12bit. A set of binary coded 20 populations are generated and the reproduction, cross over and the mutation operations are performed. After performing the single point cross over and bitwise mutation on the chromosomes the optimal solution of the each generation is stored and process is continued to reach the convergence. After several runs of GA the least surface roughness 0.7457 µm obtained at 0.80 crossover (Pc) and 0.05 mutation (Pm) for the ANN. The estimated optimal values of variable obtained by GA for each machining condition lie within the range of variables of actual machining conditions and also found that the best fitness of the R_a (0.7457 µm) is obtained if the optimal parameters are applied in the experiment.

Conclusions

Prediction models for end milling operation on the Al6061/SiC$_p$ composite is developed using different experimental machining conditions considering the spindle speed (s), feed rate (f), depth of cut (d) and nose radius (r) as machining parameters and the surface roughness as response. Experimental observations are made on the surface roughness during the milling operation with respect to the 31 machining conditions defined by the DEO. The results of 31 runs are simulated in the RSM and trained in ANN using MATLAB. The models are verified for their competency with the experimental results. The prediction equations from the RSM and ANN are used in genetic algorithm to minimize the surface roughness at optimized machining conditions. The cross over and mutation probalities are the control parameters and the termination criteria is the number of generations. The cross over probability is varied from 0.65 to 0.80, the mutation probability is varied from 0.01 to 0.05 and the maximum number of generation is limited to 20. The following conclusions are drawn based on the experimental and prediction results:

(i) From the analysis of RSM, R^2 is found to be 0.9961. and therefore the experimental measurements (R_a values) are adequate to construct the prediction model for surface roughness.

(ii) R_a values predicted ANN model match very well with that of the measured experiments of testing stage and the maximum training error is 0.0085.

(iii) GA based optimization is carried out on both RSM and ANN models and R_a values before and after optimization are found to be 0.7535 and 0.7457 µm respectively.

(iv) The optimized machining parameters with least surface roughness (0.7457 µm) is obtained for ANN model is at 0.80 cross over and 0.05 mutation probabilities. For RSM based model, the optimized machining parameters for the least surface roughness (0.7535 µm) obtained at 0.70 cross over and 0.04 mutation probabilities.

(v) It is concluded that least surface roughness 0.7457 µm is obtained at the optimal machining parameters of 66.378 m/min spindle speed, 100 mm/min, 0.7504 mm and 0.4038 mm.

The prediction accuracy of ANN is found to be better than that of the RSM in finding optimum machining conditions for the minimization of surface roughness. The predictive ANN model was also found to be capable of better prediction of surface roughness the models developed in this study. The GA is well suited and the control parameters are well justified to obtain the better solution in optimization of machining parameters during end milling operation.

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