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OPTIMIZATION OF END MILLING PARAMETERS FOR AL/SIC BY GENETIC ALGORITHM

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ABSTRACT

For industrial applications, the ceramics composites are machined in large scale using end milling process. Due the abrasive reinforcement particle of composite, the failure in tool life and surface quality are possible. This research work focuses on developing the mathematical models of cutting force (F_R), Metal Removal Rate (MRR) and surface roughness (Ra) and to optimize it. The composite design with L_{31} empirical model is used for conducting the basic trials on Al/SiC composites of various compositions. The XRD, EDS, optical microscopic images of Al/SiC composites are analyzed. The models developed for predicting responses were tested by analysis of variance (ANOVA) to evaluate its adequacy. The optimal configuration of machining parameters is identified which yields 31.9326mm^3/s, 1.4443µm and 41.4364N of MRR, Ra and F_R respectively.

Keywords: Milling, Optimization, Aluminium Matrix Composites, Polycrystalline Diamond Tool.

I. INTRODUCTION

Generally, the ceramic composites are aluminium based composites [1] which are reinforced with ceramic particles like Si_3N_4 [2], $A1_2O_3$ [3], B_4C [4], TiC [5], etc. The Al/SiC composites are most preferable for the industrial applications due to its low density and high strength [6].

The machining of ceramic composites was difficult because of its non-homogeneous, anisotropic and reinforced by abrasive materials [7]. The machined composite may experience a significant damage and high wear rate on the cutting tools. The machining of composite materials was depending on several conditions like material properties, relative content of the reinforcement and the response to the machining process [8].

Fei *et al.* [9] studied the compound machining of the engineering materials to increase the efficiency of the machining method. It was concluded that the machine can be suggested based on the efficiency of output parameters but optimizing all the outputs in a single machine mode was tedious.

End milling is a vital and common machining process because of its flexibility and capability to produce various profiles even with the curved surfaces. It has the ability to remove material with good surface quality and the milled surfaces are largely used to mate the aerospace, automobile, biomedical and manufacturing industries applications [10]. It has wide use in these industries because of its good performance in processing difficult-to-machine materials [11].

The major aims of the machining process are improving the surface roughness quality and maximizing the material removal rate (MRR) with optimal cutting force. Traditionally, trial-and-error and heuristic approaches were employed to obtain the optimal machining parameters. It was well recognized that these methods were time consuming and lead to long machining periods with large machining cost [12].

Design of Experiments (DOE) is a powerful analysis tool for modelling and analyzing the influence of control factors on output performance. The traditional experimental design is difficult to be used especially when dealing with large number of experiments and when the number of machining parameters increased [13]. The most important stage in the design of experiment lies in the selection of the control factors [14].

Oktem *et al.* [15] had focused on the development of an effective methodology to determine the optimum cutting conditions leading to minimum surface roughness (Ra) in milling by coupling the Response Surface Methodology (RSM) with the developed genetic algorithm (GA). Afazov *et al.* [16] studied the micro milling conditions which influence the cutting force for optimizing the process stability. Later, Emel *et al.* [17] had done a work to optimize the cutting fluids and the cutting parameters in end milling process using DOE. As a result, a new machining method with minimal machining cost and without environmental impacts was developed.

The optimization of all the output parameters of end milling process was a tedious. This research work focuses on developing the mathematical models of cutting force (F_R), Metal Removal Rate (MRR) and surface roughness (Ra) and to optimize it. And also the adequacies in predicting the responses by the developed models were analyzed along with experimental results and the deviation from the optimal configuration was evaluated.

II. MATERIALS AND METHODS

2.1 Materials

The end milling tests were conducted with BATIBOI-NOMO universal milling machine (Fig. 1 (a)). In the milling experiments, Al 6061/SiC composite material were used as the work piece with varying reinforcement wt. % of 5, 10 and 15, which had the dimension of $100*100*10mm^3$. Using the stir casting method, the Al/SiC composites were manufactured with the SiC particle size of 37µm. For machining these composites for good machinability, the Poly Crystalline Diamond (PCD) tools were selected [18].The PCD coated tool (Fig. 1 (b)) of thickness 0.6mm and 12mm in diameter was used.

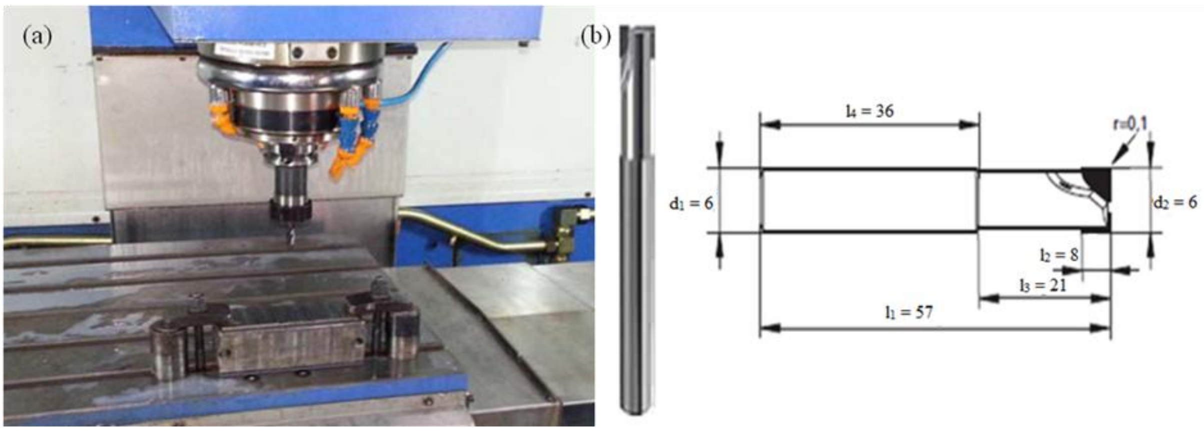

Fig. 1 (a) Universal milling machine (b) PCD coated tool

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2.2 Measurements

The MRR was calculated using the equation (1) and the cutting forces was measured using the 3-axis milling tool dynamometer- Kistler 9257B (Fig. 2 (a)). The force data were acquired via DAQ card and an amplifier, and it was processed by Dynoware software. Using this force setup, three force components (F_x, F_y and F_z) were measured simultaneously and its resultant (F_R) was calculated using equation (2). The Surface roughness (Ra) of the machined surface was measured using ROGOSOFT 90G Profilometer (Fig. 2 (b)) with the accuracy of 0.001µm.

$$MRR = \frac{l * b * DOC}{Time} \quad (1)$$

$$F_R = \sqrt{F_x^2 + F_y^2 + F_z^2} \quad (2)$$

Where, l = length of the plate

b = breath of the plate

DOC = depth of cut

F_R = Resultant cutting force

F_x, F_y and F_z = Cutting force along x, y and z-axis respectively.

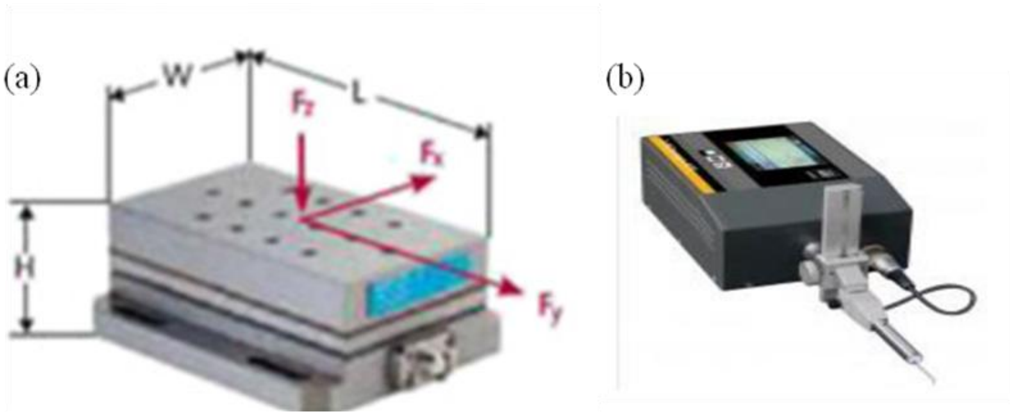

Fig. 2 (a) 3-axis dynamometer - Kistler 9257B (b) Profilometer - ROGOSOFT 90G

III. CHARACTERIZATION

3.1 X-ray diffraction analysis

The X-ray diffraction (XRD) (Model: X'per PRO) pattern of the Al/SiC composite was shown in Fig. 3 and it matches with the JCPDS file #04-0787 [19]. It exhibits strong orientation of (111) plane at 38.33° and weak orientation of (311) peak at 77.91°. An osbornite phase was identified; and as a result of (111) plane and (220) plane intensity ratio; it was almost similar to the preferred orientation of Al [20]. It can be seen that the higher full width half maximum (FWHM) appeared along the (200) plane at 44.56°, resulting in the calculated crystalline size of about 44.9 nm. The unit cell of the Al/SiC composite exhibits a hexagonal structure with a = b = 4.063460 Å and c = 4.068095Å of lattice.

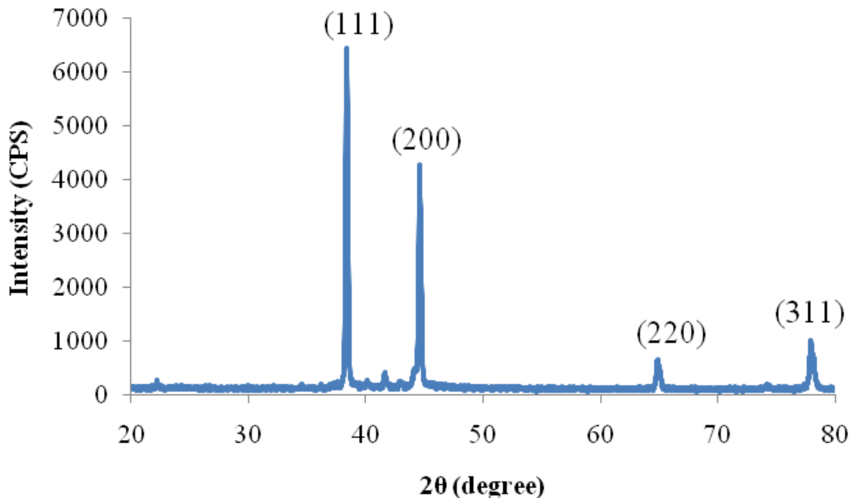

Fig. 3 XRD pattern of Al/SiC composite

3.2 Energy Dispersive Spectrum analysis

The Energy Dispersive Spectrum (EDS) analysis of Al/SiC composite was shown in Fig. 4 which reveals the presence of Al, Si and C elements in it.

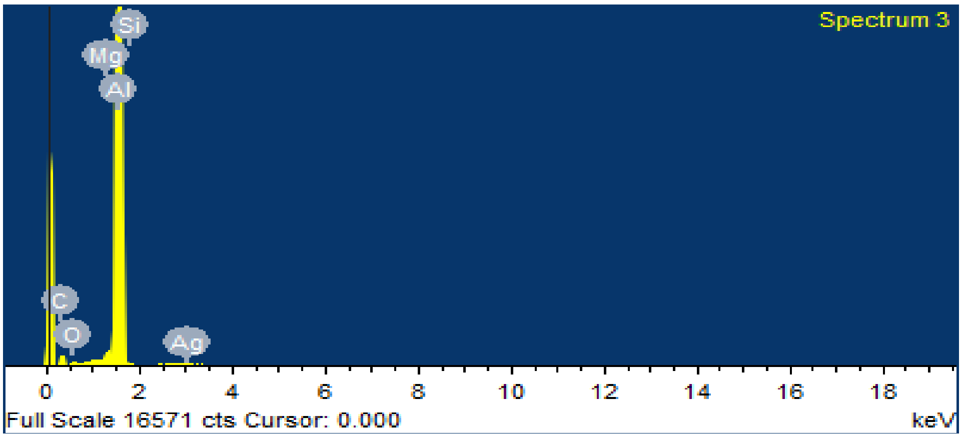

Fig. 4 EDS image of Al/SiC composite

3.3 Structural analysis

The optical microscopic images of the Al/SiC composites with varying reinforcement wt. % of 5, 10 and 15 were shown in Fig. 5 (a-c). The arrangement of SiC particles were clear and uniform on the Al matrix was evidenced from optical microscopic images. The presence of SiC increases homogeneously with an increase in SiC wt. % which was confirmed through the black spot on the matrix.

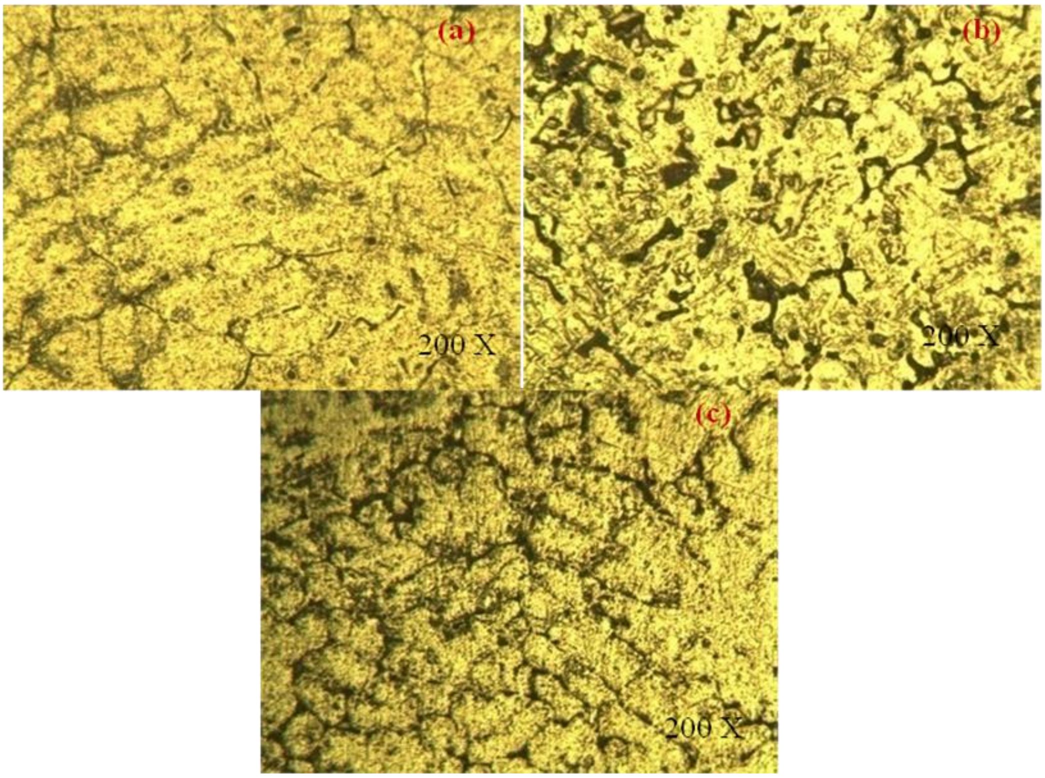

Fig. 5 Microstructure images of Al/SiC composite (a) 5 wt. % (b) 10 wt. % (c) 15 wt. %

IV. STASTICAL ANALYSES

The composite design involves the study about responses based on the combinations, estimating the coefficients, fitting the experimental data, predicting the response and checking the adequacy of the fitted model [21]. Here, the responses are MRR, Ra and FR for the independent variables (input parameters) are reinforcement %, Depth of Cut, and Feed rate, Cutting Speed (Table 1). For this DOE, the two levels design with L_{31} array was done using MINITAB 16. The results of the output parameters after machining process were consolidated for mathematical modelling the input parameters (Table 2). The regression equations were formed for the individual responses based on the controlling parameters. From this mathematical model, the predicted models were estimated and the models are validated through ANOVA [22].

Table 1 Parameters and Levels in End Milling

S.No	*Variable*	*Parameter*	*Units*	*levels*	
				Low	*High*
1.	A	Material	(Wt. %)	5	15
2.	B	Depth of Cut	(mm)	0.3	0.6
3.	C	Feed	(mm/min)	30	90
4.	D	Cutting Speed	(rpm)	100	1000

Table 2 Analytical table of responses for the independent variables

S. No.	Material (wt. %)	Depth of Cut (mm)	Feed (mm/min)	Cutting Speed (rpm)	MRR (mm^3/s)	R_a (µm)	F_R (N)
1	15	0.3	30	1000	4.5	0.5	36.68
2	10	0.6	60	550	12.44	2.41	264.8
3	10	0.6	60	550	12.44	2.41	264.8
4	10	0.6	60	550	12.44	2.41	264.8
5	15	0.3	90	100	24.28	4.92	314.03
6	10	0.6	30	550	7.2	0.52	94.96
7	10	0.6	60	550	12.44	2.41	264.8
8	10	0.6	90	550	20.57	2.32	25.82
9	5	0.3	90	1000	10.29	0.69	49.33
10	15	0.9	90	1000	36	0.95	88.91
11	15	0.9	90	100	30.86	6.15	501.65
12	5	0.9	90	100	27	9.06	752.12
13	5	0.9	90	1000	31.76	1.24	43.21
14	10	0.6	60	550	12.44	2.41	264.8
15	10	0.9	60	550	11.37	1.13	122.16
16	10	0.6	60	100	12.13	3.51	365.64
17	10	0.6	60	1000	13.12	0.01	44.86
18	10	0.6	60	550	12.44	2.41	264.8
19	15	0.6	60	550	8	1.25	111.07
20	10	0.6	60	550	12.44	2.41	264.8
21	15	0.3	90	1000	8	1.25	111.07
22	10	0.3	60	550	3.6	0.62	88.91
23	15	0.3	30	100	3.6	2.76	35.62
24	5	0.6	60	550	8.37	0.78	51.01
25	5	0.9	30	1000	10.8	2.25	57.81
26	15	0.9	30	100	4.77	4.82	278.14
27	15	0.9	30	1000	4.25	0.78	7.28
28	5	0.3	90	100	1.87	7.57	501.65
29	5	0.3	30	100	2.4	1.84	373.07
30	5	0.3	30	1000	4	0.35	4.87
31	5	0.9	30	100	10.8	2.01	178.72

4.1 Mathematical Models of the Responses

Based on the uncoded data from the given input trails, the mathematical models of the responses were estimated. The MRR in the form of regression equation was stated in equation (3), which states that the factor B influences more compared to other factors. In equation (4) and (5) were the regression equations of Ra and F_R respectively, which also declare that the factors B (depth of cut) influences highly in all the configuration results.

$$MRR = 1.25478 + 1.75719*A + 33.8615*B - 0.688283*C - 0.0103421*D - 0.0749221*A^2 - 28.5895*B^2 + 0.00425216*C^2 + 1.27E-05*D^2 - 1.09583*A*B + 0.0162917*A*C - 7.09E-04*A*D + 0.451806*B*C + 0.00682407*B*D + 2.78E-07*C*D \quad (3)$$

$$Ra = -1.26391 + 0.138958*A + 4.77893*B + 0.0573958*C - 0.00338567*D + 0.000519467*A^2 - 1.41126*B^2 + 0.00046443*C^2 + 0.00000374314*D^2 - 0.0154167*A*B - 0.0030125*A*C + 0.0000347222*A*D - 0.0132639*B*C - 0.00138426*B*D - 0.0000763426*C*D \quad (4)$$

$$F_R = 45.5807 + 2.53377*A + 50.2841*B + 10.8129*C - 0.653551*D - 1.23815*A^2 - 71.7649*B^2 - 0.0573376*C^2 + 0.000460524*D^2 + 11.2092*A*B - 0.03355*A*C + 0.0210617*A*D + 2.39389*B*C - 0.22425*B*D - 0.00468241*C*D \quad (5)$$

4.2 Adequacy of model

The adequacy of the responses were tabulated in Table 3 with R^2 and $R^2_{(adj)}$ values. These indicate that the model fits the data well and R^2 was in agreement with $R^2_{(adj)}$ which supports the prediction capacity of the model. In all the models, both the values were good and above 80% which makes a fitness in predicting solutions [23].

Table 3 Adequacy of the models

S. No.	Response	Std. Deviation	R^2	$R^2_{(adj)}$
1.	MRR	3.308	92.7%	86.4%
2.	Ra	1.069	86.6%	84.9%
3.	F_R	108.9	89.4%	81.4%

4.3 ANOVA

The ANOVA for MRR, Ra and F_R is tabulated in Table 4. In all forms of regression, the P values of the responses were less than the F value and also it was less than 0.05 i.e. the level of significant was 95%. It confirms that the developed models were adequate, and the predicted values were in good agreement with the measured data.

Table 4 ANOVA for responses

Responses	Source	DF	Seq SS	Adj SS	Adj MS	F	P
MRR	Regression	14	2234.93	2234.93	159.638	14.59	0
	Residual Error	16	175.11	175.11	10.944		
	Total	30	2410.03				
Ra	Regression	14	118.318	118.3183	8.4513	7.39	0
	Residual Error	16	18.293	18.2934	1.1433		
	Total	30	136.612				
F_R	Regression	14	731762	731762	52269	4.41	0.003
	Residual Error	16	189652	189652	11853		
	Total	30	921414				

4.4 Optimization

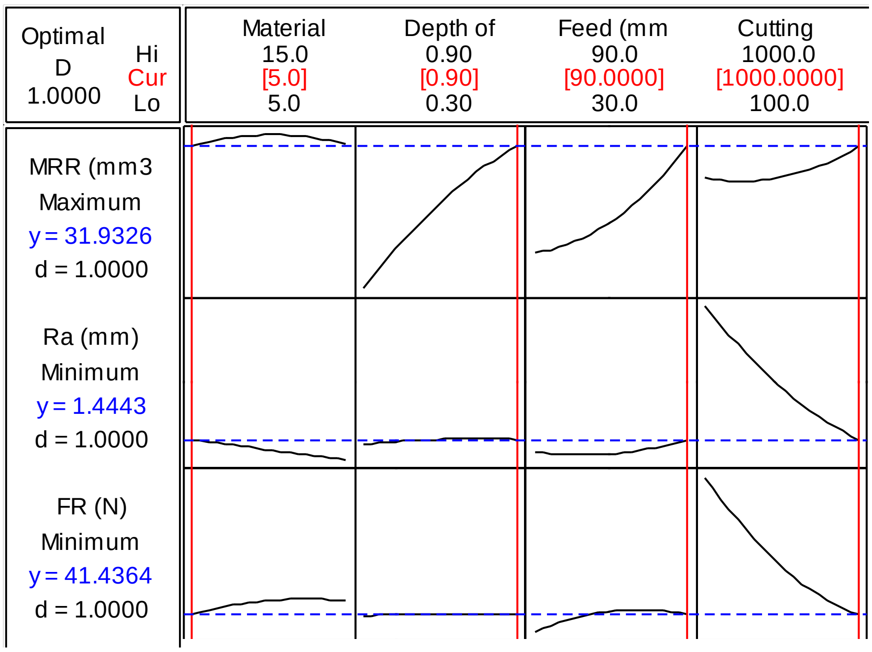

Fig. 6 Optimal configurations for optimal response

The optimal configuration of input parameters and its responses were identified from the Fig. 6. The optimal configuration was 5wt. % reinforced material with machining parameter of high depth of cut 0.9mm, feed rate of 90mm/min and cutting speed 1000rpm which provides the global optimal solution of 31.9326mm^3/s MRR, 1.4443µm surface roughness and 41.4364N of resultant cutting force for desirability of 98.6%, 99.1% and 94.5% respectively. For the same optimal condition, the experimental result was 31.76mm^3/s MRR, 1.24µm Ra and 43.2N F_R which was 0.5%, 14% and 4% deviation from the predicted results which shows the acceptable prediction.

VI. CONCLUSION

The Al/SiC composite with varying reinforcement composition was done to study its machining nature was successful. The Al/SiC composite was characterized using XRD, EDS and optical microscopic images which inferred the structural changes in orientation and surface due reinforcement particle. The influence of machining parameters on the responses was discussed and the effects were evidenced through SEM images. Using RSM, the optimal configuration of machining parameter which provides optimal response was identified. The optimal configuration was 5wt. % reinforced material with machining parameter of high depth of cut 0.9mm, feed rate of 90mm/min and cutting speed 1000rpm which provides the global optimal solution of 31.9326mm^3/s MRR, 1.4443µm surface roughness and 41.4364N of resultant cutting force which shows the acceptable prediction.

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