Analysis of Machining Parameters for Turning Al-SiC (10p) MMC Using ANOVA and Grey Relational Analysis

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Abstract—This study provides the detailed experimental investigation on turning Aluminium Silicon Carbide particulate Metal Matrix Composite (Al-SiC -MMC) using polycrystalline diamond (PCD) 1600 grade insert. Experiments were carried out on medium duty lathe. An overview of experiments, based on the techniques of Taguchi, was performed. Analysis of variance (ANOVA) is used to investigate the machining characteristics of MMC (A356/10/SiCP). The objective was to establish a correlation between cutting speed, feed and depth of cut to the specific power and surface finish on the work piece. The optimum machining parameters were obtained by Grey relational analysis. Finally, confirmation test was performed to make a comparison between the experimental results and developed model and also tool wear analysis is studied.

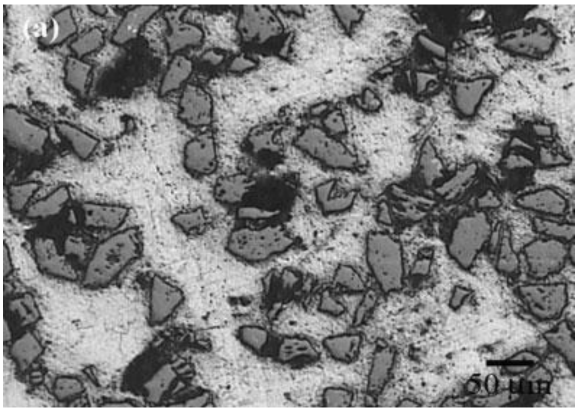
Keywords—Metal matrix composites–Machining–PCD–Surface Roughness–Specific power–Grey relational analysis

I. INTRODUCTION

Metallic matrix composites have found considerable applications in aerospace, automotive and electronic industries1 because of their improved strength, stiffness and increased wear resistance over unreinforced alloys.2 However, the final conversion of these composites in to engineering products is always associated with machining, either by turning or by milling. A continuing problem with MMCs is that they are difficult to machine, due to the hardness and abrasive nature of the reinforcing particles.2 The particles used in the MMCs are harder than most of the cutting tool materials. Most of the researchers reported diamond is the preferred tool material for machining MMCs.3-8 Most of the research on machining MMCs is concentrated mainly on the study of cutting tool wear and wear mechanism.9,10 Heat and Chadwick4,5,8 investigated the performance of polycrystalline diamond (PCD) in machining MMCs which containing aluminum oxide fibre reinforcement. They compared the tool life of cemented carbide with PCD and concluded that sub-surface damage is greater with cemented carbide than that of PCD tools. Lane3 studied the performance of different PCD tools grain size. He reported that, a PCD tool with a grain size of 25µm is better withstand of abrasion wear than tools with grain size 10 µm. He also reported that further increases in the grain size do not have any influence on the tool life but it causes significant deterioration in the surface roughness. The work carried out by Andrewes et al11 characterizes the wear mechanisms of PCD and CVD diamond tools in the machining MMCs. The conclusions can be applied to the design of better diamond tools and optimization of machining process. In the view of above machining problems, the main objective of the present work is to investigate the influence of different cutting parameters on surface finish and specific power criterion. The Taguchi design approach is utilized for experimental planning during turning of Al-SiC –MMC. The results are analyzed to achieve optimal surface roughness and specific power. Grey relational analysis was performed to combine the multiple responses in to one numerical score, rank these scores, and determine the optimal machine parameter settings.12-14 Confirmation tests were performed by using experiments. ANOVA is performed to investigate the more influencing parameters on the surface finish and specific power.

II. EXPERIMENTAL PROCEDURE

Commercially fabricated cylindrical bars using stir casting method of diameter 50 mm and 175 mm long are turned on self centered three jaw chuck, medium duty lathe of spindle power 2 KW. The cutting insert used was Poly Crystalline Diamond (PCD 1600 Grade, average particle size = 4 μm, volumetric percentage of diamond = 90%) of designation CNMA 120408 with zero degree top rake angle and tool holder used was PCLNR 25*25 M 12. Figure 1 shows the microstructure of the work piece. Table 1 shows the chemical composition of the work piece for experimentation. Table 2 shows the physical and mechanical properties of Al- SiC10p-MMC. Parameter such as power consumed by main spindle was measured by using a digital wattmeter (Make-Nippen Electrical Inst.Co, Model 96x96 – dw 34). The machined surface was measured at three different positions and the average surface roughness (R_a) value was taken using a surf test (Make- Mitutoyo– Model SJ-301) measuring instrument with the cutoff length2.5mm.Taguchi method is a systematic application ofdesignand analysis of experiments for the purpose of designingandimproving productquality.[15-17]



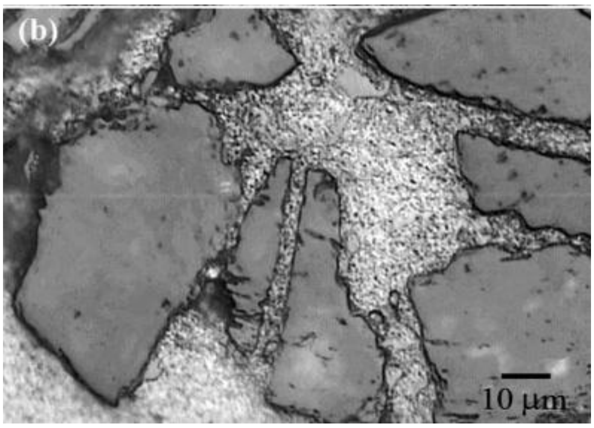


Fig. 1 Microstructure of the work piece

Table 1 Chemical composition of Al-SiC (10p) –MMC

Type of MMC	Reinforce-ment	%SiC	%Si	%Mg	%Fe	%Cu	%Mn	%Zn	%Ti	%Al
Particulate MMC	SiC -54 μm	10.00	7.77	0.63	0.15	0.16	0.09	0.08	0.10	Balance

Table 2 Physical and Mechanical properties of Al-SiC –MMC

Material	Density (gms/cm^3)	Tensile Strength (Mpa)	Hardness (BHN)	Modulus of Elasticity (Gpa)	%of Elongation
A 356 10 SiC$_p$	2.65	280	100	90	1.3 – 1.9

Table 3 Machining parameter and their levels

Symbol	Machining parameter	Unit	Level 1	Level 2	Level 3
A	Cutting Speed	m/min	75	120	180
B	Feed	mm/rev	0.1	0.2	0.3
C	Depth of cut	mm	0.3	0.6	0.9

UsingL27orthogonalarray, threemachining parameters are considered as controlling factors (cuttingspeed, feed rateanddepthofcut) andeachparameterhasthreelevels.Table3 shows the cutting parameters and their levels asconsideredfor experimentation.Table4showstheexperimentallayoutusingL2 7 orthogonal array and corresponding results. The Table4 showsthree columns of the L27 orthogonal array leads to the mainfactors only (machining parameters).

A. *GREYANALYSIS*

The grey analysis was first proposed many decades ago but it has been extensively applied only in last decade.[18] Grey analysis has been applied in evaluating the performance of a complex project with meager information. In the grey relational analysis, data preprocessing is first performed in order to normalize the raw data for the analysis. In the present study, a linear normalization of the experimental results for surface roughness and specific power consumption as shown in Table 5 were performed in the range between zero and one, which is also called grey relational generating. The normalized experimental results X_{ij}can be expressed as:

Table 4 Experimental Layout using an L27 orthogonal array and corresponding response values

Group No.	Machining Parameter A Cutting Speed	B Feed	C Depth of cut	Response(s) Surface Roughness (Ra) in Microns	Specific power (Sp) in Pascal (10^{-6})
1	1	1	1	5.22	10.93
2	1	1	2	5.17	6.40
3	1	1	3	5.50	4.62
4	1	2	1	7.63	6.93
5	1	2	2	9.97	4.93
6	1	2	3	4.92	5.02
7	1	3	1	10.57	5.78
8	1	3	2	8.64	4.04
9	1	3	3	5.93	3.17
10	2	1	1	6.65	8.5
11	2	1	2	7.37	6.33
12	2	1	3	7.07	5.67
13	2	2	1	5.95	5.33
14	2	2	2	5.36	3.67
15	2	2	3	4.57	4.33
16	2	3	1	5.64	4.94
17	2	3	2	6.39	4.22
18	2	3	3	7.44	1.37
19	3	1	1	7.86	9.00
20	3	1	2	2.98	6.00
21	3	1	3	4.03	5.48
22	3	2	1	4.79	5.28
23	3	2	2	4.43	4.09
24	3	2	3	3.06	3.75
25	3	3	1	7.22	4.33
26	3	3	2	7.08	3.19
27	3	3	3	6.57	2.37

$$x_{ij} = \frac{y_{ij} - \min_j y_{ij}}{\max_j y_{ij} - \min_j y_{ij}} \qquad (1)$$

Yij for the ith experimental results in the jth experiment. Basically, the larger the normalized results correspond to the better performance and the best-normalized results should be equal to one. Next, the grey relational coefficient is calculated to express the relationship between the ideal and the actual normalized experimental results. The grey relational coefficient ξ ij can be expressed as:

$$\xi_{ij} = \frac{\min_i \min_j \left|x_i^o - x_{ij}\right| + \xi \max_i \max_j \left|x_i^o - x_{ij}\right|}{\left|x_i^o - x_{ij}\right| + \xi \max_i \max_j \left|x_i^o - x_{ij}\right|} \qquad (2)$$

Where xi0 is the ideal normalized results for the ith performance characteristics and ξ is the distinguishing coefficient which is defined in the range 0 ≤ ξ ≤ 1. Then, the grey relational grade is computed by averaging the grey relational coefficient corresponding to each performance characteristics. The overall evaluation of the multiple performance characteristics is based on the grey relational grade, that is:

$$\gamma_j = \frac{1}{m}\sum_{i=1}^{m} \xi_{ij} \qquad (3)$$

Table 5 Evaluated Grey relational coefficients and Grades for 27 groups

Expt. No	Grey relational coefficients		Grey relational Coefficients after weighted		Grey relational grade	
	Ra	Sp	Ra	Sp	Grade	Rank
1	0.705	0.000	0.629	0.333	0.4811	21
2	0.711	0.474	0.634	0.487	0.5607	16
3	0.668	0.660	0.601	0.595	0.5981	13
4	0.387	0.418	0.449	0.462	0.4558	24
5	0.079	0.628	0.352	0.573	0.4625	23
6	0.744	0.618	0.662	0.567	0.6144	10
7	0.000	0.539	0.333	0.520	0.4267	26
8	0.254	0.721	0.401	0.642	0.5215	19
9	0.611	0.812	0.563	0.726	0.6445	9
10	0.516	0.254	0.508	0.401	0.4549	25
11	0.422	0.481	0.464	0.491	0.4772	22
12	0.461	0.550	0.481	0.526	0.5039	20
13	0.609	0.586	0.561	0.547	0.5539	17
14	0.686	0.759	0.615	0.675	0.6449	8
15	0.791	0.690	0.705	0.618	0.6612	6
16	0.650	0.627	0.588	0.572	0.5802	14
17	0.551	0.702	0.527	0.626	0.5766	15
18	0.412	1.000	0.460	1.000	0.7299	3
19	0.357	0.202	0.437	0.385	0.4113	27
20	1.000	0.516	1.000	0.508	0.7540	2
21	0.862	0.570	0.783	0.538	0.6605	7
22	0.762	0.591	0.677	0.550	0.6136	11
23	0.809	0.715	0.724	0.637	0.6804	4
24	0.989	0.751	0.979	0.668	0.8235	1
25	0.441	0.690	0.472	0.618	0.5449	18
26	0.460	0.810	0.481	0.724	0.6025	12
27	0.527	0.895	0.514	0.827	0.6704	5

Where γ_j is the grey relational grade for the jth experiment and m is the number of performance characteristics. Table 5 shows the grey relational grade for each experiment using L27 orthogonal array. The higher grey relational grade represents that the corresponding experimental result is closer to the ideally normalized value. Experiment 24 has the best multiple performance characteristics among 27 experiments because it has the highest grey relational grade. In other words, optimization of the complicated multiple performance characteristics can be converted into the optimization of a single grey relational grade. Since the experimental design is orthogonal, it is then possible to separate out the effect of each machining parameter on the grey relational grade at different levels.19 The mean of the grey relational grade for each level of the machining parameter is summarized and shown in Table 6. In addition, the total mean of the grey relational grade for the 27 experiments is also calculated and listed in Table 6. Figure 2 shows the grey relational grade graph for the levels of the machining parameters. Basically, the larger the grey relational grade, the better is the multiple performance characteristics. However, the relative importance among the machining parameters for the multiple performance characteristics will still need to be known so that the optimal combinations of the machining parameter levels can be determined more accurately. Based on the above results, the optimal machining parameters are the cutting speed at level 3, feed at level 2, and depth of cut at level 3. From Table 6 (Response table), indicates that the depth of cut has the maximum level difference (Max-Min) value of grey relational grade, 0.1538. It is also reconfirmed by using analysis of variance.

Table 6 Response table for the grey relational grade

Symbol	Machining parameter	Grey relationalgrade			
		Level1	Level2	Level 3	Max-Min
A	CuttingSpeed	0.5295	0.5759	0.6401*	0.1106
B	Feed	0.5446	0.6123*	0.5885	0.0677
C	Depthofcut	0.5025	0.5867	0.6563*	0.1538

Total Mean Value of the Grey Relational Grade = 0.5881
* Optimum levels

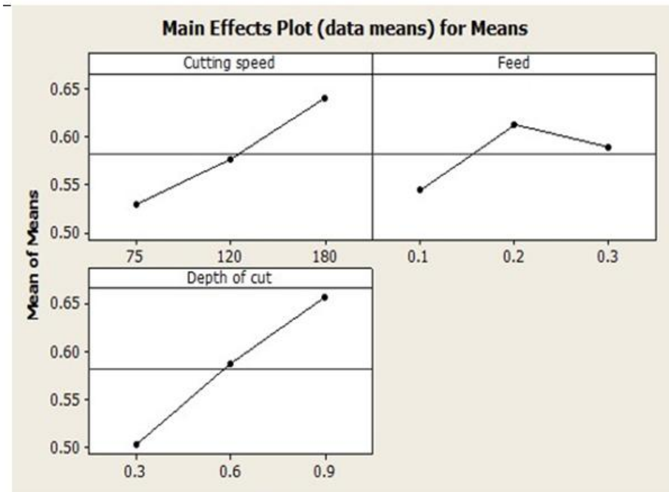


Fig. 2 Grey relational grade graph

B. Analysis of Variance

Analysis of Variance (ANOVA) is a method of apportioning variability of an output to various inputs. Table 7 shows the results of ANOVA analysis. The purpose of the analysis of variance is to investigate which machining parameters significantly affect the performance characteristic.20,21 This is accomplished by separating the total variability of the grey relational grades, which is measured by the sum of the squared deviations from the total mean of the grey relational grade, into contributions by each machining parameter and the error. First, the total sum of the squared deviations SST from the total mean of the grey relational grade γ_m can be calculated as:

$$SS_T = \sum_{j=1}^{p} (\gamma_j - \gamma_m)^2 \qquad (4)$$

Where p is the number of experiments in the orthogonal array and γ_j is the mean grey relational grade for the j th experiment. The total sum of the squared deviations SST is decomposed in to two sources: the sum of the squared deviations SSd due to each machining parameter and its interaction effects and the sum of the squared error SSe. The percentage contribution of each of the machining parameter in the total sum of the squared deviations SST can be used to evaluate the importance of the machining parameter change on the performance characteristic. In addition, the Fisher's F- test22 can also be used to determine which machining parameters have a significant effect on the performance characteristic. Usually, the change of the machining parameters has a significant effect on performance characteristic when F is large.

Table 7 Results of the analysis of variance

Source	Dof	Sum of squares	Mean squares	F_{Cal}	$F_{Critical}$	Contribution %
Cutting Speed (V)	2	0.0555	0.0277	8.97	4.46	19.59
Feed (f)	2	0.0212	0.0106	3.43	4.46	7.48
Depth of Cut (d)	2	0.0913	0.0456	14.74	4.46	32.23
V*f	4	0.0427	0.0106	3.45	3.84	15.07
Vcd	4	0.0323	0.0080	2.61	3.84	11.40
f*d	4	0.0153	0.0038	1.24	3.84	5.40
Error	8	0.0247	0.0030			8.72
Total	26	0.2833				

Table 8 Results of machining performance using initial and optimal machining parameters

	Initial machining parameters	Optimal machining parameters	
		Prediction	Experiment
Setting Level	$A_1B_1C_1$	$A_3B_2C_3$	$A_3B_2C_3$
Surface roughness (Ra)	5.22		3.06
Specific power (Sp)	10.93		3.75
Grey relational grade	0.4811	0.7451	0.8235
Improvement in grey relational grade = 0.3424			

Results of analysis of variance (Table 7) indicate that depth of cut is the most significant machining parameter for affecting the multiple performance characteristics (32.23%).

C. CONFIRMATION EXPERIMENT

Once the optimal level of machining parameters is selected the final step is to predict and verify the improvement of the performance characteristics using the optimal level of the machining parameters. The estimated grey relational grade $\hat{\gamma}$ using the optimum level of the machining parameters can be calculated as

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q}(\overline{\gamma}_j - \gamma_m) \qquad (5)$$

Where γ_m is the total mean of the grey relational grade, $\overline{\gamma}_j$ is the mean of the grey relational grade at the optimum level and q is the number of machining parameters that significantly affects the multiple performance characteristics. Based on Eq (5) the estimated grey relational grade using the optimal machining parameters can then be obtained. Table 8 shows the results of the confirmation experiment using the optimal machining parameters. The surface roughness Ra is improved from 5.22 to 3.06 µm and the specific power is greatly reduced from 10.93 to 3.75 Pascal. It is clearly shown that multiple performance characteristics in the Al-SiC (10p) machining process are greatly improved through this study.

D. TOOL WEAR

Tool wear is one of the important factors for analyzing the machinability of Al-SiC-MMC.23,24 Hence the experiment is conducted to study the tool wear and its mechanism. From the confirmation experiment, it is concluded that, optimal machining parameters are A3B2C3. By setting these parameters as constant, tool wear study was carried out for 45 minute duration. It is observed that the main cause of tool failure is due to abrasion nature of hard reinforced SiC particles over tool insert. Hardness of the SiC particles is approximately 50 times greater than PCD insert.25,26 Figure 3 depicts the nose region of a flank of a fresh tool. In Figure 4, 5 and 6, parallel marks are seen on the flank face of the tool after 15, 30 and 45 minutes duration respectively. It is evident that, Parallel marks are due to the hardness of silicon carbide particles presented on the aluminium matrix.2,3,7 Main wear pattern observed on the cutting insert was the flank wear in the nose region.27 Two bodies and three body abrasive wear are also observed. Three body abrasive wear is caused by the released hard particles, entrapped between the tool and the work piece.28-30 The nose region of the flank of the inserts after machining for 15, 30 and 45 minutes at constant cutting speed of 180 m/min with constant feed and depth of cut of 0.2 mm/rev and 0.9 mm respectively are shown in Figures 4, 5 and 6. These figures clearly indicate substantial wear in the nose.

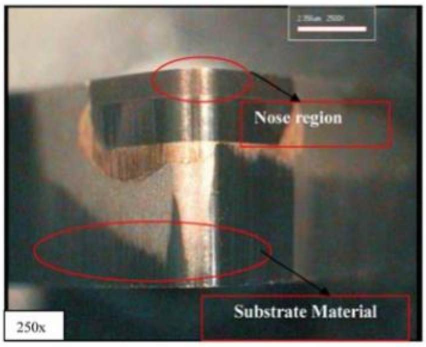


Fig. 3 Flank portion of a fresh tool

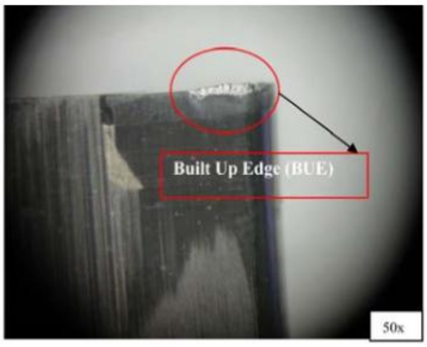


Fig. 4 Flank wear at V= 180 m/min, feed = 0.2 mm/rev, depth of cut -0.9 mm (After 15 min)

E. CONCLUSION

(1) The use of orthogonal array with grey relational analysis to optimize the Al-SiC (10p) machining process with multiple performance characteristics has been reported in this paper. (2) The grey relational analysis of the experimental results of surface roughness and specific power can convert optimization of the multiple performance characteristics in to optimization of the single performance characteristic called the grey relational grade. As a result, optimization of the complicated multiple performance characteristics can be greatly simplified through this approach. (3) It is shown that the performance characteristics of the Al-SiC (10p) machining process such as surface roughness and specific power are improved by using the method proposed by this study. (4) The primary wear mode in the nose region of the flank. The wear is believed due to the abrasive action of hard SiC particles on the tool flank. (5) It is also observed two bodies and three body wear mechanisms plays a major role in the tool failure.

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