Journal of Manufacturing Engineering, September, 2012, Vol. 7, Issue. 3, pp 176-183

OPTIMIZATION OF PROCESS PARAMETERS DURING MACHINING OF Al-SiC COMPOSITES

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ABSTRACT

This study presents an experimental investigation of the effects of cutting speed, feed rate, depth of cut and volume fraction of SiC particles on surface roughness and material removal rate in turning of Al-SiC composites. A plan of experiments based on Taguchi method was implemented for machining of Al-SiC composites using tungsten carbide tool. Analysis of Variance was employed to find out the contribution and influence of each parameter on surface roughness and material removal rate. In addition to ANOVA, the multiple performance characteristics were also analyzed using Grey relational approach and Taguchi response table by determining grey relational coefficients and grades. The optimum level of parameters setting in machining of Al-SiC composites for minimum surface roughness and maximum material removal rate was obtained at 200 m/min of cutting speed (level 3), 0.1 mm/rev of feed rate (level 2), 1 mm of depth of cut (level 2) and 10% of volume fraction of SiC (level 2).

Keywords: Al-SiC Composites, Turning, Surface Roughness, Material Removal Rate and Optimization.

1. Introduction

Composite materials provides interesting opportunities for new product design because of higher specific properties of strength and stiffness, increase in wear resistance, lower coefficient of thermal expansion, dimensional stability at higher temperature when compared to unreinforced monolithic alloys. Metal matrix composites (MMC) are developed since 1970s for the aerospace industry, but other application in the automotive industry are found during middle of 1980s. The matrix materials normally used in MMC are aluminium, magnesium, titanium and some super alloys reinforced with a disperse phase in the form of particles, short fibers (whiskers) or long fibers of the ceramic material [1]. Even though particulate metal matrix composites having excellent mechanical and thermal properties, these materials are very much complicated to machine. The hard reinforcement particles like SiC, Al_2O_3 acts as abrasive medium between cutting tool and work piece finally ensuing in high tool wear and more power consumption [2]. The fabrication of particulate metal matrix composites (PMMC) is easier, large volume production, inexpensive than the fiber reinforced MMCs and in addition PMMC are of special significance of high ductility and lower anisotropic properties [3]. Though the many engineering components are manufactured to near net shape through casting and forming process, they subsequently require machining for preferred dimensions, shape and surface texture [4]. The necessity of accurate machining of composites is increased in diverse fields; therefore selecting most suitable machining condition is essential to reduce the machining cost, produce superior quality and to improve the efficiency of machining. In this study, the effects of the process parameters and their level of significance on the performance characteristics of minimum surface roughness and maximum material removal rate are statistically evaluated by analysis of variance (ANOVA). Grey relational analysis was also used to optimize the parameters for the multi performance characteristics of minimum surface roughness and maximum material removal rate in machining of Al-SiC particulate composites.

2. Literature Survey

Sahin investigated machinability of MMCs containing 20 wt.% SiC and 10 wt.% SiC particles using different coatings of cutting tools, chip breaker and geometry of cutting tools. The build up edge formation (BUE) was appeared at lower cutting speeds for the lower weight fraction of composite [5]. Paulo

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Davim analyzed the influence of cutting speed, feed rate and cutting time on turning MMCs (A356/20SiCp-T6) using PCD cutting tools based on Taguchi techniques. The correlation between cutting speed, feed rate and cutting time with tool wear, power consumed and surface roughness are established. The cutting velocity has the highest statistical influence on tool wear and surface finish [6]. Palanikumar and Karthikeyan examined the factors influencing surface roughness on the machining of Al-SiC particulate composites using tungsten carbide tool inserts (K10). They concluded that the surface roughness of the composite was highly influenced by the feed rate, cutting speed and volume fraction of SiC particles [7]. Basheer et al. developed a model to envisage surface roughness in precision machining of metal matrix composites using PCD tools by varying the factors such as size and volume of reinforcement, tool nose radius, feed rate and depth of cut. They have concluded that roughness of the machined surfaces significantly influenced by the size of reinforcements and its magnitude is comparable to that of the feed rate and tool nose radius [8]. Lin et al. experimented the machining of Al359/SiC/20p using centre lathe with different cutting speeds of 300, 500 and 700 m/min, feed rates of 0.1, 0.2 and 0.4 mm/rev and depth of cut as constant at 0.5mm. He observed that material removal rate was more at higher feed rate and lower cutting speed. Surface finish of the machined samples does not vary extensively with the change of cutting speed but deteriorates with increasing feed rates [9]. The existence of uniformly dispersed SiC particles leads to discontinuous chip formation. Build up edge formation was observed at low cutting speeds, while at high cutting speeds low specific power consumption and very good surface finish could be achieved during continuous turning of composite rods [10]. Kannan and Kishawy deliberated the mechanisms of tool wear, surface roughness and chip formation under both dry and wet turning of Al-SiC particulate composites with tungsten carbide tool. The wet turning has less favorable effect over surface roughness when compared to dry turning conditions due to flushing away of particulates over the machined surface, thus produces voids and pit holes [11]. Narahari et al. evaluated that tungsten carbide tools had a longer tool life than HSS under different machining conditions of eutectic Al-Si (LM6) and hypoeutectic Al-Si (LM25) alloys reinforced with 10, 15, and 20% SiC particles. The tool life of WC/HSS tool with cutting fluid is only about 10 to 20% of that without cutting fluid while machining composites [12]. The HSS tools are incapable of machining with Al-SiC composites. Tungsten carbide tools are chosen for rough machining in order to reduce the machining cost and PCD tools could be preferred for finish machining operations [7].

3. Experimental Procedures

The composites were fabricated from a molten metal of aluminium alloy using an electric induction furnace. The aluminium alloy LM25 was the matrix phase and SiC particles with an average size of 25μm were used as the reinforcement material. Aluminium alloy LM25 contains silicon content between 7 to 15% which will inhibit the formation of reaction product Al_4C_3 from SiC [13]. The chemical composition of LM25 aluminium alloy is 7%Si, 0.35%Mg, 0.45%Fe, 0.13%Cu, 0.08%Zn, 0.01%Ni, 0.16%Mn, 0.01Pb, 0.05%Ti, Al-balance.

The melting process was carried out in a crucible made from graphite. For manufacturing of MMCs, 5 wt.%, 10 wt.% and 15 wt.% of SiC particles were used. The SiC particles was added and mixed homogeneously in aluminium matrix by continuous mechanical stirring. Figure 1 shows the production of Al-SiC composites using stir casting technology. The size of the casting produced was 30mm diameter and 80mm length which is shown in Fig. 2. The specifications of the machining details are given in Table 1. All the tests were performed without coolant in ACE LT2 type of CNC lathe as per the levels indicated in Table 2.

Fig. 1 Production of Al-SiC Composites

Fig. 2 Al-SiC Composite Specimens

Table 1: Specifications of Machining Details

Work piece material	Al-SiC composites of 5%, 10%, 15% of SiC particles
Machine	CNC Lathe
Tool holder	MTJNL 2525M16
Tool insert	TNMG 120408, nose radius – 0.8mm, Tungsten Carbide
Coolant	Dry turning

Table 2: Factors and their Levels used for Turning Operations

Control factors	Level 1	Level 2	Level 3
Cutting speed A (m/min)	100	150	200
Feed rate B (mm/rev)	0.075	0.1	0.125
Depth of cut C (mm)	0.5	1	1.5
Volume fraction of SiC D (%)	5	10	15

In this study, Taguchi tool was used to determine optimal machining parameters in turning of Al-SiC metal–matrix composites. Taguchi's orthogonal array is the most competent method of experimental planning to find out the optimum level of control factors on the performance variable [14]. Based on the number of parameters and levels, an experimental plan of Taguchi L9 orthogonal array has been selected. The surface roughness (Ra) was measured by using Mitutoyo Surfest SJ-201 contact profilometer with cutoff length of 0.8mm and traverse length of 5 mm.

4. Results and Discussion

The optimal combination of parameters level can be determined more accurately by using ANOVA. In Taguchi method, the deviation between the experimental value and the desired value is represented as loss function. This obtained loss function is further converted into a signal-to-noise (S/N) ratio. Experimental work normally has three possibilities in calculation of signal-to-noise ratio which depends on the type of quality characteristics; smaller-the-better, larger-the-better or normal-the-better [15].

4.1 Surface roughness

The lower surface roughness (Ra) is the indication of better performance in turning process. Therefore, optimum machining performance characteristic for the surface roughness "smaller the better" was selected and its loss function (L) is calculated as follows,

Smaller the better $L_{ij} = (1/n)\ \Sigma\ y_{ij}^2$ (1)

The S/N ratio for the i^{th} performance characteristic in the j^{th} experiment can be expressed as:

S/N ratio = -10 log (L_{ij}) (2)

The surface roughness of each experiment based on orthogonal array and its corresponding signal-to-noise (S/N) ratio is listed in Table 3. The greater S/N ratio value corresponds to a better performance, in spite of category of the performance characteristics.

Table 3: Experimental Results for Surface Roughness and S/N Ratio Values

Exp	Control factors				Ra µm	S/N dB
	A	B	C	D		
1	1	1	1	1	3.16	-9.99
2	1	2	2	2	2.81	-8.97
3	1	3	3	3	3.94	-11.91
4	2	1	2	3	1.87	-5.44
5	2	2	3	1	3.25	-10.24
6	2	3	1	2	3.32	-10.42
7	3	1	3	2	2.24	-7.00
8	3	2	1	3	1.46	-3.29
9	3	3	2	1	3.54	-10.98

Table 4: ANOVA Results for Surface Roughness

Factor	S/N ratio (dB)			Sum of square	%
	Level 1	Level 2	Level 3		
A	-10.29	-8.70	-7.09[a]	15.38	23.51
B	-7.48[a]	-7.50	-11.10	26.14	39.97
C	-7.90[a]	-8.46	-9.72	5.19	7.93
D	-10.40	-8.80	-6.88[a]	18.70	28.59
Total				65.40	100

a – Optimum results of minimum Ra

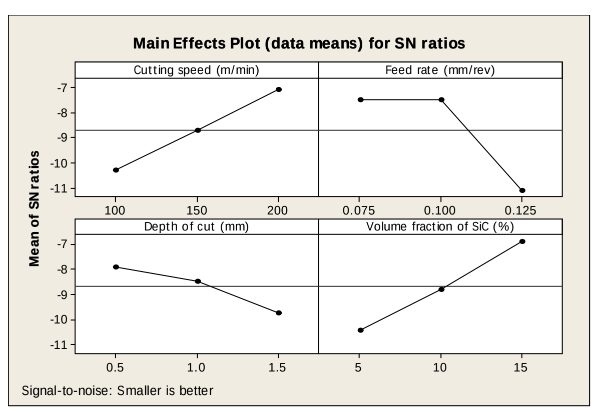

Fig. 3 Mean S/N Graph for Surface Roughness

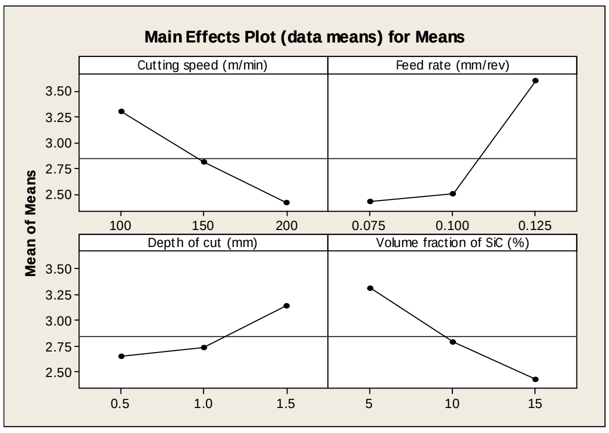

Fig. 4 Mean Graph for Surface Roughness

The machining characteristics are mostly affected by the build-up edge formation (BUE). The increase in volume fraction of SiC promotes brittleness of the composites and subsequently disappearance of BUE occurs. This results in good surface finish of the machined component. At low speeds, the BUE is formed and also the chip fracture readily producing the surface roughness. As the speed increases, the BUE vanishes, chip fracture decreases and hence the roughness decreases. The increase in depth of cut induces high normal pressure and seizure on the rake face of the tool, which promotes the BUE formation [7].

The ANOVA results and contribution of each parameter towards surface roughness are shown in Table 4. The feed rate is the most dominant parameter on the performance characteristics of surface roughness, with the contribution ratio of 39.97%. The effect of other parameters on surface roughness is as follows, 28.59% of volume fraction of SiC, 23.51% of cutting speed and 7.93% of depth of cut. The S/N response table indicates that superior surface finish can be achieved at increase in cutting speed and higher volume fraction of SiC reinforcement. The optimal machining performance for the surface roughness based on the analysis of S/N ratio was obtained at 200 m/min of cutting speed (level 3), 0.075 mm/rev of feed rate (level 1), 0.5 mm of depth of cut (level 1) and 15% of volume fraction of SiC (level 3) settings. The process parameters with its level and corresponding signal-to-noise (S/N) ratio of surface roughness are shown in Fig. 3. The mean graph for surface roughness Fig. 4 represents the surface roughness increases with increase in feed rate, depth of cut and decreases with increase in cutting speed and volume fraction of SiC particles.

4.2 Material removal rate

The material removal rate (MRR) was determined from the amount of material worn during the period of machining in minutes. The high precision digital balance meter was used for weighing the samples, thereby eliminating the possibility of errors while calculating the MRR in machining operation. The higher material removal rate is the indication of better performance in turning process. Therefore, optimum machining performance characteristic for the material removal rate "larger the better" was selected and its loss function (L) is calculated using equ. 3.

$$L_{ij} = (1/n)\,\Sigma\,(1/\,y_{ij}^{2}) \qquad (3)$$

The material removal rate of each experiment based on orthogonal array and its corresponding signal-to-noise (S/N) ratio is listed in Table 5. The ANOVA results are tabulated in Table 6, which represents the significant effect of each input parameter towards the performance characteristics of MRR. The inclusion of SiC in metal matrix is reported to increase the hardness, tensile strength and heat resistant of the aluminium alloy. The rate of change of these properties depends on the volume fraction of SiC added to the aluminium alloy. The increase in % of SiC results in increase in hardness of Al-SiC composites. The higher % of SiC induces more flank wear of the tool and simultaneously offers less material removal rate [7,10].

Table 5: Experimental Results for Material Removal Rate and the S/N Ratio Values

Exp	Control factors				MRR gm/min	S/N dB
	A	B	C	D		
1	1	1	1	1	8.28	18.36
2	1	2	2	2	19.24	25.68
3	1	3	3	3	25.05	27.98
4	2	1	2	3	16.41	24.30
5	2	2	3	1	45.29	33.12
6	2	3	1	2	24.16	27.66
7	3	1	3	2	26.79	28.56
8	3	2	1	3	10.90	20.74
9	3	3	2	1	50.81	34.12

Table 6: ANOVA Results for Material Removal Rate

Factor	S/N ratio (dB) Level 1	Level 2	Level 3	Sum of square	%
A	24.01	28.36^{b}	27.81	33.71	15.75
B	23.74	26.52	29.92^{b}	57.44	26.84
C	22.26	28.03	29.89^{b}	95.02	44.40
D	28.53^{b}	27.30	24.34	27.86	13.02
Total				214	100

b – Optimum results of maximum MRR

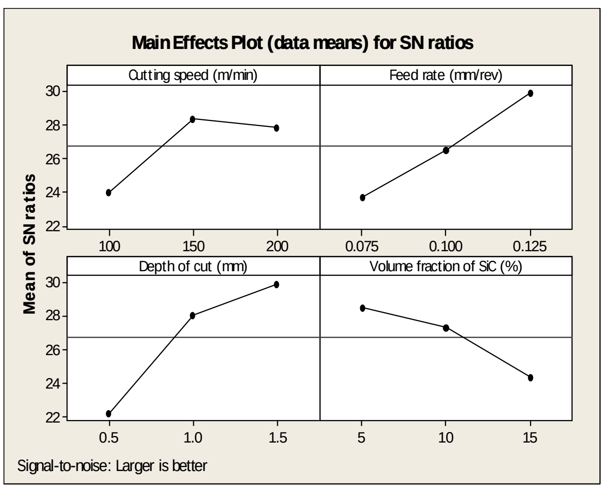

Fig. 5 Mean S/N Graph for MRR

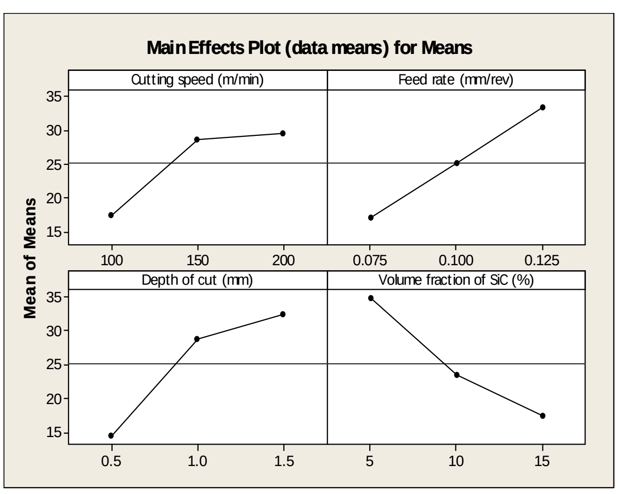

Fig. 6 Mean Graph for MRR

Aluminium and silicon carbide have very different mechanical properties: young's moduli of 70 and 400 GPa, coefficients of thermal expansion of 24×10^{-6} and 4×10^{-6} / ^{0}C and yield strengths of 35 and 600 MPa, respectively. By combining these materials of 17% SiC, an MMC with a young's modulus of 96.6 GPa and yield strength of 510 MPa can be produced [13].

The depth of cut is the fundamental parameter which influences the material removal rate with about 44.40%, followed by feed rate with 26.84%, cutting speed with 15.75% and volume fraction of SiC particles with 13.02% of the contribution ratio. The optimum performance characteristics of higher material removal rate as per Taguchi response table is $A_2B_3C_3D_1$ with cutting speed of 150 m/min, feed rate of 0.125 mm/rev, depth of cut 1.5 mm and 5% volume fraction of SiC. The mean graph of S/N ratio Fig. 5 shows that the material removal rate increases with increase in feed rate, depth of cut and with lower volume fraction of SiC reinforcement.

4.3 Optimum parameters with multiple performance characteristics

In the grey relational analysis, data preprocessing is done to normalize the raw data. When the range of series is too large or the optimal value of a quality characteristic is too high, it will influence some factors to be ignored. Therefore the original experimental data are to be normalized to eliminate such effect. When the characteristics of original sequence is "higher the better" it can be normalized as follows [14],

$$x_{ij} = \frac{\eta_{ij} - \min_j \eta_{ij}}{\max_j \eta_{ij} - \min_j \eta_{ij}} \quad (4)$$

When the "lower the better" is a characteristic feature of the original sequence, it can be normalized as follows [14],

$$x_{ij} = \frac{\max_j \eta_{ij} - \eta_{ij}}{\max_j \eta_{ij} - \min_j \eta_{ij}} \quad (5)$$

Where, η_{ij} and x_{ij} represents original sequence and comparability sequence, max η_{ij} and min η_{ij} represents the largest and smallest value of original sequence η_{ij}, $i = 1,\ldots,m$; m is the number of response variable and $j = 1,\ldots,n$; n is the number of experimental runs. The grey relational coefficient is calculated to express the relationship between ideal and normalized data. The grey relational coefficient ξ_{ij} for the i^{th} performance characteristic in the j^{th} experiment can be determined as [14],

$$\xi_{ij} = \frac{\min_i \max_j |x_i^0 - x_{ij}| + \zeta \max_i \max_j |x_i^0 - x_{ij}|}{|x_i^0 - x_{ij}| + \zeta \max_i \max_j |x_i^0 - x_{ij}|} \qquad (6)$$

Where, x_i^0 is the ideal normalized data for the i^{th} performance characteristic and ζ is identification coefficient which lies between 0 and 1. ζ = 0.5 is used normally because the value is smaller and distinguish ability is larger. The overall evaluation of the performance characteristics is based on the grey relational grade which is determined by the average sum of grey relational coefficient of response variables in each experiment [14],

$$\gamma_j = \left(\frac{1}{m}\right) \sum_{i=1}^{m} \omega_i \xi_{ij} \qquad (7)$$

Where γ_j is the grey relational grade for the j^{th} experiment, ω_i the weighing factor for the i^{th} performance characteristic, assume that $\omega_1=\omega_2=1$. Table 8 shows the grey relational grade for each experiment using L9 orthogonal array.

Table 7: Normalized Values for Each Individual Response

Exp	Comparability sequence		Deviation sequence	
	R_a	MRR	R_a	MRR
1	0.3145	0.0000	0.6855	1.0000
2	0.4556	0.2576	0.5444	0.7424
3	0.0000	0.3943	1.0000	0.6057
4	0.8347	0.1912	0.1653	0.8088
5	0.2782	0.8704	0.7218	0.1296
6	0.2500	0.3733	0.7500	0.6267
7	0.6855	0.4352	0.3145	0.5648
8	1.0000	0.0614	0.0000	0.9386
9	0.1613	1.0000	0.8387	0.0000

Table 8: Grey Relational Grade and its Order

Exp	Grey relational coefficient		Grey relational grade	Order
	R_a	MRR		
1	0.4218	0.3333	0.3776	9
2	0.4788	0.4024	0.4406	6
3	0.3333	0.4522	0.3928	8
4	0.7515	0.3820	0.5668	4
5	0.4092	0.7941	0.6017	3
6	0.4000	0.4438	0.4219	7
7	0.6139	0.4696	0.5417	5
8	1.0000	0.3476	0.6738	2
9	0.3735	1.0000	0.6867	1

Table 9: ANOVA Results for Grey Relational Grade

Factor	S/N ratio (dB)			Sum of square	%
	Level 1	Level 2	Level 3		
A	0.40	0.53	0.61^C	0.07	37.89
B	0.50	0.67^C	0.50	0.08	42.28
C	0.49	0.56^C	0.51	0.01	5.09
D	0.44	0.56^C	0.54	0.03	14.75
Total				0.18	100

c – Optimum results of multi performance characteristics

In grey relational analysis, original sequence data were first transformed into comparability sequence and subsequently the grey relational coefficient, grey relational grades, orders were determined for all experiment runs. When compared to all grey relational grades in Table 8, the highest grade value is obtained for 9^{th} experimental run. This specifies that the machining parameters in the experimental run 9 produce the optimum state for the better performance of minimum surface roughness and maximum MRR among all 9 runs and its surface texture of the machined specimen is shown in Fig. 7.

The parameter setting combination $A_1B_1C_1D_1$ of the experiment no.1 of orthogonal array represents lowest grade and its SEM micrograph of the machined surface is shown in Fig.8. In the machining condition $A_1B_1C_1D_1$, because of low speed produces high surface roughness and also the material removal rate is less in this low level of parameters setting. Based on grey relational approach and Taguchi response Table the optimum performance of machining Al-SiC composites was attained at $A_3B_2C_2D_2$ settings and its SEM micrograph at optimum machining conditions is shown in Figure 9.

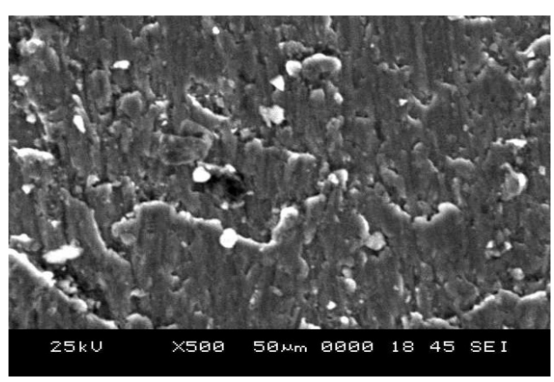

Fig. 7 SEM Image of Machined Surface in Orthogonal Array No. 9 ($A_3B_3C_2D_1$)

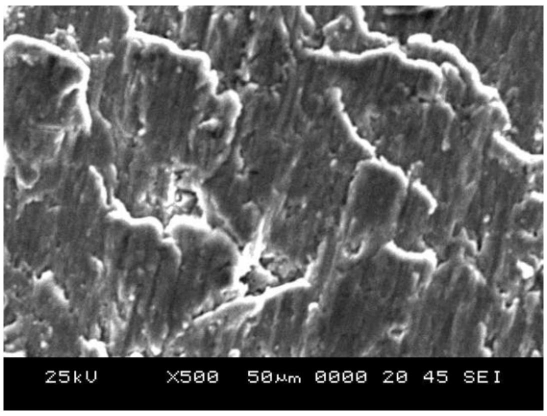

Fig. 8 SEM Image of Machined Surface in Orthogonal Array No. 1 ($A_1B_1C_1D_1$)

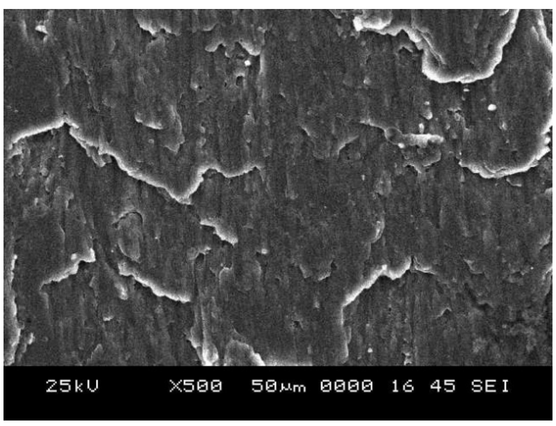

Fig. 9 SEM Image of Machined Surface at Optimum Machining Conditions ($A_3B_2C_2D_2$)

5. Conclusions

The factors influencing surface roughness and material removal rate are analyzed using ANOVA and grey relational analysis based on Taguchi response table and the following conclusions are summarized,

i. The major contribution and influence of the parameters based on Analysis of Variance towards surface roughness is feed rate and followed by volume fraction of SiC, cutting speed and depth of cut.
ii. The optimal machining performance for minimum surface roughness based on the analysis of S/N ratio was obtained at 200 m/min of cutting speed (level 3), 0.075 mm/rev of feed rate (level 1), 0.5 mm of depth of cut (level 1) and 15% of volume fraction of SiC (level 3) settings.
iii. The ANOVA results for material removal rate indicates that depth of cut is the major parameter which influences the material removal rate with about 44%, followed by feed rate with 27%, cutting speed with 16% and volume fraction of SiC with 13% of the contribution ratio.
iv. The significance of controllable factors on the multi performance characteristics is categorized in the order of feed rate, cutting speed, volume fraction of SiC and depth of cut.
v. The optimum factor level of machining Al-SiC composites for minimum surface roughness and maximum MRR within the feasible ranges are cutting speed 200 m/min, feed rate 0.1 mm/rev, depth of cut 1 mm and 10 % volume fraction of SiC.
vi. The variable factors are successfully predicted to reduce set up time and initial cost towards increasing quality and reduce production costs.

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