Application of Grey Relation Analysis for Multi Optimization during Turning of Al/SiC-Gr MMC

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***Abstract*:-** The objective of the present research work is to multi optimize the turning conditions for minimum surface roughness and maximum metal removal rate using Taguchi methodology with grey relation analysis during the turning of Al 6063/ SiC-Gr metal matrix composites. An Attempt has also been made to investigate the effect of turning conditions on surface roughness and metal removal rate. The % wt SiC-Gr particulates, feed, cutting speed and depth of cut have been found significant terms that's affects the surface roughness and MRR. Also, the surface roughness continuously increased with increase in feed and depth of cut while decreased with increase in cutting speed while MRR increased with increase in % wt SiC-Gr, feed, depth of cut and cutting speed. On the other hand, the best performance characteristics which simultaneously optimized surface roughness and MRR has been obtained at the 1st level of SiC-Gr, 4th level of feed, 1st level of cutting speed and 4th level of depth of cut.

Keywords: MMC, aluminium, SiC, Gr, Grey Taguchi, optimization

1. Introduction

In the present scenario, automobiles, recreational industries and aerospace applications require materials that have high strength, hardness, wear resistance and strength to weight ratio and less expensive. It is very difficult to achieve these properties in any monolithic material (Tjong, 2014). Metal matrix composites (MMCs) materials have been noted to offer such tailored property (Alaneme and Bodunrim, 2011). Among all the alloys, Aluminium is the most utilized metallic alloy as matrix material in the development of MMCs (Alaneme and Bodunrin, 2013).

Now days, due to global competitiveness, manufacturing industries are more concerned about the quality of their products at high production rate and at minimum cost (Pal and Chakraborty, 2005). The surface roughness is considered to be a measure of the technological quality of a product (Nalbant et al., 2006). The surface finish and MRR are greatly influenced by the cutting conditions, tool geometry, tool material, machining process, chip form, workpiece material, tool wear and vibration during machining (Ghani et al., 2002). In order to manufacture machine parts with required surface finish at desirable MRR, the machining conditions should be elected carefully (Yang and Chuang, 2008). Therefore, an optimal selection of manufacturing parameters is very important in order to obtain high precision parts. In the past, so many studies have been reported to optimize machining parameters for desire responses.

Davim and Antonio (2001) optimized the process parameters for minimum cutting forces, minimum tool wear and minimum surface finish during the machining of aluminium matrix composites using PCD tool. Manna and Bhattacharayya (2002) investigated the effect of speed, feed rate, depth of cut, inclination angle of the tool holder, types of tool, cutting time and length of machining on the tool wear and surface roughness during the turning of Al/SiC/MMC. Manna and Bhattacharyya (2004) used 3 level full factorial design to optimize cutting parameters for minimum surface roughness indicators during the turning of Al/SiC-MMC using a fixed rhombic tooling system. Singh et al (2004) used Taguchi methodology with grey relational analysis (GRA) to optimize the multi-response characteristics of electrical discharge machining during machining of Al-10%SiCp composites. Kilickap et al (2005) studied the influence of machining parameters on tool wear and surface roughness during the machining AlSiCp MMC. Kok (2005) experimentally investigated the effect of machining conditions on responses during turning of silicon carbide particulate aluminium MMC using uncoated carbide tool.

Basavarajappa et al. (2007) investigated the effect of drilling parameters and different tools on surface roughness of the drilled holes during the drilling of Al2219 - 15%SiCp and Al2219/15%SiCp- 3% Graphite (hybrid) composites. Kurt et al (2008) investigated the effect of different coating, point angle, cutting parameters on the hole quality during the drilling of Al 2024 alloy. Jailani et al. (2009) used L9 orthogonal array based Taguchi methodology with grey relation analysis to optimize the sintering process parameters of Al-Si (12%) alloy/fly ash composite for multi-response characteristics. Khanna et al. (2009) experimentally investigated the generate forces and the changes in the microstructure of the matrix during turning. Przestacki (2009) compared the laser-assisted machining with conventional machining during the turning of A359/20SiCp material using cubic boron nitride (CBN) and sintered carbide inserts. Tsao (2009) used the Grey - Taguchi method for the optimization of milling parameters for desire of multiple performance characteristics during the drilling of A6061P-T651 aluminium alloy. Bhushan et al. (2010) investigated the effect of cutting speed, depth of cut, and feed rate on surface roughness during the turning of 7075 Al alloy and 10 wt.% SiC particulate metal-matrix composites using tungsten carbide and polycrystalline diamond (PCD) inserts. Ramanujam et al. (2011) used Taguchi methodology with grey relation analysis to optimize multiple performance characteristics during the turning of Aluminium Silicon Carbide particulate Metal Matrix Composite (Al-SiC –MMC) using polycrystalline diamond (PCD) 1600 grade insert. Bhardwaj et al. (2013a) developed surface roughness prediction in terms of feed, speed, depth of cut and nose radius model using response surface methodology based on center composite rotatable design with Box–Cox transformation in turning of AISI 1019 steel. Bhardwaj et al. (2013b) experimentally investigated the effect of end milling parameters on surface roughness during milling of AISI 1019 steel using carbide inserts. Bhardwaj et al. (2014a) investigated the influence of cutting speed, feed, depth of cut and nose radius on surface roughness during wet turning of EN 353 steel using tungsten carbide inserts. Bhardwaj et al. (1014b) employed RSM with Box-Cox transformation for the formulation of relationship between the surface roughness and turning conditions during the turning of EN 353 steel. Karabulut, (2015) optimized the milling parameters for minimum surface roughness and minimum cutting forces using Taguchi methodology during the milling of AA7039/Al2O3 metal matrix composite. Lijay et al. (2016) fabricated AA6061/TiC AMCs using in situ reaction of inorganic salt K2TiF6 and SiC with molten aluminum.

Literature survey reveals that a lot of work has been carried out to optimize machining parameters in turning using Taguchi methodology, response surface methodology, artificial neural network etc on different materials. However, fewer efforts have been made for multi response optimization using grey relational analysis with Taguchi methodology. In the present research grey relational analysis with Taguchi methodology was selected for optimization of machining parameters for minimum surface roughness and maximum material removal rate during turning of Al−SiC−Gr composite.

2. Experimentation &Measurement

In the present work AA 6063 /SiC/Gr metal matrix composites in different percentages of SiC-Gr have been fabricated using manual stir casting method. The aluminium alloy AA 6063 has been used as a matrix material while SiC-Gr particulates as reinforcement.

All the turning experiments have been carried out on CNC turning center (PUSHKAR-200 manufacture by HMT) using carbide inserts. The turning length 30 mm has been selected for all specimens. The surface roughness of finished workpieces has been measured using surf coder while MRR have been measured using equation 1.

Then material removal rate =(V/T) (1)

Where, V is the difference between the initial and final volume of the work piece while T is the machining time.

3. Selection of turning conditions and levels

Among the all turning conditions, the main parameters affecting the surface roughness and metal removal rate are cutting speed, depth of cut and feed. These three are the primary parameters governing the performance of any basic machining operation. The machine operator has complete control over these parameters (Bhardwaj et al. 2014). On this basis, in the present work, feed in mm/rev, cutting speed in m/min and depth of cut in mm have been selected as turning conditions along with SiC-Gr particulates in %wt. The range of turning conditions has been decided according to past published literature.

Table 1 Turning conditions and levels of turning conditions

Cutting conditions	Levels			
SiC-Gr % wt	2.5%	5 %	7.5 %	10%
Cutting speed	50	100	150	200
Feed	0.05	0.1	0.15	0.2
Depth of Cut	0.25	0.5	0.75	1

The levels of turning conditions have been decided according to L_{16} orthogonal based Taguchi methodology. Table 1 shows the turning conditions and levels of turning conditions according to L_{16} orthogonal based Taguchi methodology. Table 2 shows the design matrix for experimentation in actual form along with measured values of surface roughness and calculated values of MRR.

4. Multi-objective optimization using grey relational analysis

Grey relational grade is used to convert optimization problem from a multi-objective to a single-objective (Emel and Babur, 2013). The aim of the present work is to determine the optimal combination of turning conditions that simultaneously minimize surface roughness and maximize the material removal rate. Therefore, grey relational analysis (GRA) has been used in the present work. The implementations of steps of GRA are as follows:

Step 1 Calculation of S/N ratio

The aim of the present work is to minimize the surface roughness and maximize the MRR. Therefore, smaller is better signal to noise ratio (S/N) has been used for surface roughness while larger is better S/N ration has been used for material removal rate. The S/N ratio smaller is better and larger is better have been calculated using equations 2 and 3 respectively.

(i) Smaller- the- better

$$S/N\ ratio = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_{ij}^{2}\right) \qquad (2)$$

(ii) Larger- the- better

$$S/N\ ratio = -10\ log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_{ij}^{2}}\right) \qquad (3)$$

Where, n is the number of replications; y_{ij}^2 is the observe response value; i= 1,2, …n; j= 1,2,...k. The table 3 shows the S/N ratio for surface roughness and MRR.

Table 2 Design matrix for experimentation in actual form

S. No.	Sic-Gr (wt%)	Feed (mm/rev.)	Cutting speed (m/min)	Depth of cut (mm)	Surface roughness (microns)	MRR (mm^3/min)
1	2.5	0.05	50	0.25	3.448	488
2	2.5	0.1	100	0.5	3.746	5870
3	2.5	0.15	150	0.75	3.969	11851
4	2.5	0.2	200	1	4.773	17757
5	5	0.05	100	0.75	2.9	7507
6	5	0.1	50	1	5.005	9476
7	5	0.15	200	0.25	3.237	9870
8	5	0.2	150	0.5	3.823	9897
9	7.5	0.05	150	1	1.51	10870
10	7.5	0.1	200	0.75	1.593	11397
11	7.5	0.15	50	0.5	2.785	6707
12	7.5	0.2	100	0.25	1.955	8176
13	10	0.05	200	0.5	2.054	7976
14	10	0.1	150	0.25	2.504	5507
15	10	0.15	100	1	4.375	15897
16	10	0.2	50	0.75	4.6	10870

Table 3Actual and normalizeezd value of S/N ratio for surface roughness and MRR

S.No.	Surface roughness			Metal removal rate		
	Experimental values	SN ratio	Normalized value (X_{ij} (k))	Experimental values	SN ratio	Normalized value (X_{ij} (k))
1	3.448	-10.7516	0.69	488	53.76919	1.00
2	3.746	-11.4707	0.76	5870	75.3724	0.31
3	3.969	-11.9727	0.81	11851	81.4751	0.11
4	4.773	-13.5761	0.96	17757	84.98752	0.00
5	2.9	-9.24913	0.54	7507	77.50962	0.24
6	5.005	-13.9887	1	9476	79.5325	0.17
7	3.237	-10.2023	0.64	9870	79.88613	0.16
8	3.823	-11.6483	0.78	9897	79.91006	0.16
9	1.51	-3.57872	0	10870	80.72439	0.14
10	1.593	-4.04664	0.04	11397	81.1358	0.12
11	2.785	-8.89649	0.51	6707	76.53089	0.27
12	1.955	-5.82429	0.22	8176	78.25082	0.22
13	2.054	-6.25131	0.26	7976	78.03571	0.22
14	2.504	-7.97256	0.42	5507	74.8187	0.33
15	4.375	-12.8199	0.89	15897	84.0263	0.03
16	4.6	-13.2547	0.93	10870	80.72439	0.14

Step 2 Normalization of S/N ratio

In this step, a normalization of the S/N ratio is carried out to prepare raw data for the analysis where, the original data is transferred to a comparable data. Linear normalization is usually required since the range and unit in one data sequence may differ from the others. The normalization of S/N ratio is carried out using following formulas 4 and 5.

(i) For larger- the- better characteristics

$$X_{ij}(k) = \frac{y_{ij} - \min(y_{ij}, i = 1,2, \dots n)}{max(y_{ij}, i = 1,2, \dots .n) - \min(y_{ij}, i = 1,2, \dots .n)} \quad (4)$$

(ii) For smaller the better

$$X_{ij}(k) = \frac{\max(y_{ij}, i = 1,2, \dots n) - y_{ij}}{max(y_{ij}, i = 1,2, \dots .n) - \min(y_{ij}, i = 1,2, \dots .n)} \quad (5)$$

The table 3 shows the normalized value of S/N ratio for surface roughness and MRR.

Step 3 Calculation for grey relation coefficient for surface roughness and MRR

Equation 6 is used to calculate the grey relation coefficients for the normalized S/N ratio values. The value of Δ max, Δ min is taken as 1 and 0 respectively. Since all the parameters have equal weighting, on this basis the value of ζ is taken as 0.5. The grey relation coefficients for each experiment values of surface roughness and MRR is shown in table 4 and 5 respectively.

$$\gamma\, (y_0(k)\, , y_i(k)) = \frac{\Delta \min + \zeta\Delta \max}{\Delta_{oj}(k) + \zeta\Delta \max} \quad (6)$$

Where, $\Delta_{oj}(k) = x_o(k) - x_{ij}(k)$

$x_o(k)$= Reference sequence which is equal to 1

Table 4 Grey relation coefficient for surface roughness

Surface roughness						
Normalized values	reference sequence $x_o(k)$	deviation sequence $x_0(k) - x_{ij}(k)$	ζ	Δ_{min}	Δ_{max}	Grey relation coefficient
0.69	1	0.31	0.5	0	1	0.6173
0.76	1	0.24	0.5	0	1	0.6757
0.81	1	0.19	0.5	0	1	0.7246
0.96	1	0.04	0.5	0	1	0.9259
0.54	1	0.46	0.5	0	1	0.5208
1	1	0	0.5	0	1	1.0000
0.64	1	0.36	0.5	0	1	0.5814
0.78	1	0.22	0.5	0	1	0.6944
0	1	1	0.5	0	1	0.3333
0.04	1	0.96	0.5	0	1	0.3425
0.51	1	0.49	0.5	0	1	0.5051
0.22	1	0.78	0.5	0	1	0.3906
0.26	1	0.74	0.5	0	1	0.4032
0.42	1	0.58	0.5	0	1	0.4630
0.89	1	0.11	0.5	0	1	0.8197
0.93	1	0.07	0.5	0	1	0.8772

Table 5 Grey relation coefficient for MRR

Metal removal rate						
Normalized values	reference sequence $x_o(k)$	deviation sequence $x_0(k) - x_{ij}(k)$	ζ	Δ_{min}	Δ_{max}	Grey relation coefficient
1	1	0	0.5	0	1	1.0000
0.31	1	0.69	0.5	0	1	0.4202
0.11	1	0.89	0.5	0	1	0.3597
0	1	1	0.5	0	1	0.3333
0.24	1	0.76	0.5	0	1	0.3968
0.17	1	0.83	0.5	0	1	0.3759
0.16	1	0.84	0.5	0	1	0.3731

0.16	1	0.84	0.5	0	1	0.3731
0.14	1	0.86	0.5	0	1	0.3676
0.12	1	0.88	0.5	0	1	0.3623
0.27	1	0.73	0.5	0	1	0.4065
0.22	1	0.78	0.5	0	1	0.3906
0.22	1	0.78	0.5	0	1	0.3906
0.33	1	0.67	0.5	0	1	0.4274
0.03	1	0.97	0.5	0	1	0.3401
0.14	1	0.86	0.5	0	1	0.3676

Table 4.11 Grey relation grades and order of grades

S.No.	Grey relation coefficient for surface roughness	Grey relation coefficient for material removal rate	Grey relational grade	Order
1	0.6173	1	0.80865	**1**
2	0.6757	0.4202	0.54795	**6**
3	0.7246	0.3597	0.54215	**7**
4	0.9259	0.3333	0.6296	**3**
5	0.5208	0.3968	0.4588	**10**
6	1	0.3759	0.68795	**2**
7	0.5814	0.3731	0.47725	**9**
8	0.6944	0.3731	0.53375	**8**
9	0.3333	0.3676	0.35045	**16**
10	0.3425	0.3623	0.3524	**15**
11	0.5051	0.4065	0.4558	**11**
12	0.3906	0.3906	0.3906	**14**
13	0.4032	0.3906	0.3969	**13**
14	0.463	0.4274	0.4452	**12**
15	0.8197	0.3401	0.5799	**5**
16	0.8772	0.3676	0.6224	**4**

Step 4. Generation of grey relational grade

In this step, grey relation grade is calculated using the equation 7. The table 6 represents the grey relation grade along with order.

$$\bar{\eta_j} = \frac{1}{k}\sum_{i=1}^{m}\gamma_{ij} \qquad (7)$$

where $\bar{\eta_j}$ is the grey relation grade for jth experiment and k is the number of responses.

Table 6 Grey relation grades and order of grades

S.No.	Grey relation coefficient for SR	Grey relation coefficient for MRR	Grey relational grade	Order
1	0.6173	1	0.80865	**1**
2	0.6757	0.4202	0.54795	**6**
3	0.7246	0.3597	0.54215	**7**
4	0.9259	0.3333	0.6296	**3**
5	0.5208	0.3968	0.4588	**10**
6	1	0.3759	0.68795	**2**
7	0.5814	0.3731	0.47725	**9**
8	0.6944	0.3731	0.53375	**8**
9	0.3333	0.3676	0.35045	**16**
10	0.3425	0.3623	0.3524	**15**
11	0.5051	0.4065	0.4558	**11**
12	0.3906	0.3906	0.3906	**14**
13	0.4032	0.3906	0.3969	**13**
14	0.463	0.4274	0.4452	**12**
15	0.8197	0.3401	0.5799	**5**
16	0.8772	0.3676	0.6224	**4**

Step5. Determination of optimum combination of levels

For the further analysis, calculated grey relation grade for each experiment is considered as response. The higher grey relational grade implies the better quality characteristic, since a larger value indicates the better performance of the process. Therefore, on the basis of higher grey relational grade, the optimal level for each controllable factor can also be determined.

The result has been presented in table 7. On the basis of highest grade for each parameter in the table, the optimal combination of the parameters has been identified as first level of SiC-Gr, fourth level of feed, first level of cutting speed and fourth level of depth of cut. It is also clear from figure 1, which represent the plot between grade values and level of parameters.

Step 6. Analysis of variance based on grey relation grade

The main purpose of the analysis of variance (ANOVA) is to calculate the percentage contribution of each factor on the process result. The table 8 represents the ANOVA for grey relation grade.

Table 7 Response table for grey relation grades

Level	Sic-Gr	Feed	Cutting speed	Depth of cut
1	**0.6321**	0.5037	**0.6437**	0.5304
2	0.5394	0.5084	0.4943	0.4836
3	0.3873	0.5138	0.4679	0.4939
4	0.5111	**0.5441**	0.464	**0.562**
Delta	0.2448	0.0404	0.1797	0.0784
Rank	1	4	2	3

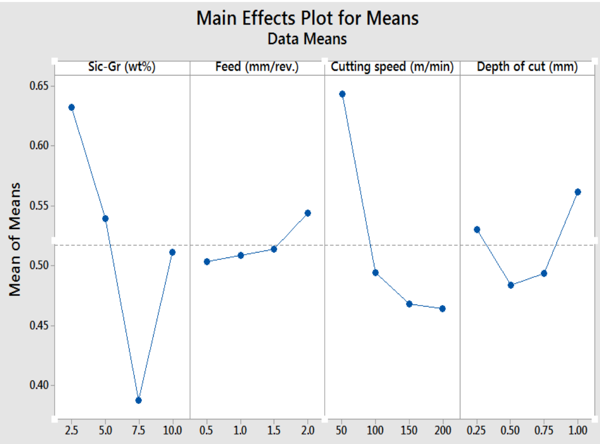

Figure 1 Plot between grade values and level of parameters

Table 8 ANOVA for grey relation grade

Source	DOF	sum of square	Mean square	F-value	% contribution
SiC-Gr	3	0.1224	0.0408	8.6935	53.4716
Feed	3	0.0040	0.0013	0.2825	1.7378
Cutting speed	3	0.0871	0.0290	6.1886	38.0642
Depth of cut	3	0.0154	0.0051	1.0936	6.7265
Residual error	3	0.0141	0.0047		
Total	15	0.2430			

From the table 8 it has been revealed that SiC- Gr has maximum effect on grey relation grade with 53.47 % contribution followed by cutting speed (with 38.06 % contribution), depth of cut (with 6.72 % contribution) and feed (with 1.73 % contribution).

5. Effect of turning conditions on surface roughness

The influence of turning conditions on surface roughness is shown in figure 2. From the figure it has been revealed that the surface roughness decreases with increase in SiC-Gr percentage of from 2.5 % to 7.5% after that surface roughness increase with increase in SiC-Gr percentage of from 7.5 % to 10%. The minimum surface roughness is achieved with 7.5 % of SiC-Gr. The graphite acts as solid lubricants which decrease friction between the workpiece and tool, which further decrease the cutting force, due to this surface roughness decreases. On the other hand SiC particles acts as a abrasive particles which increase tool wear, which increase surface roughness. The effect of Gr in SiC-Gr is predominant up to 7.5% wt after that SiC particle in SiC-Gr exhibits main effect. Therefore surface roughness decreases up to 7.5 wt % after that it increases.

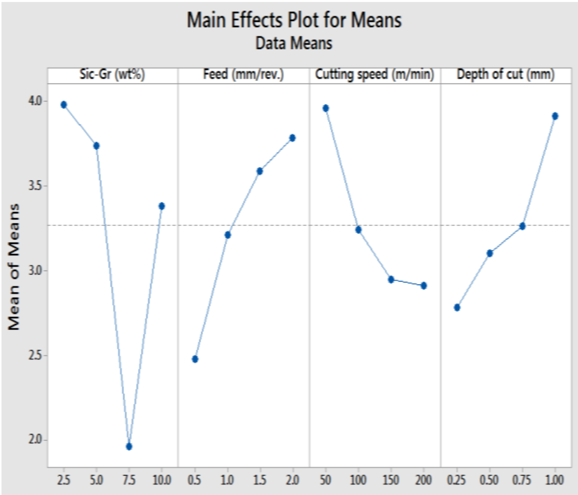

Figure 2 Effect of turning conditions on surface roughness

The surface roughness continuously increases with increase in feed. This is due to the fact that at higher feed rate, tool traverses the workpiece too fast, resulting in deteriorated surface quality and also high feed increase the chatter, which leads to higher surface roughness. The minimum surface roughness is achieved at minimum level of feed. Also, surface roughness decreases with increasing cutting speed due to increase in temperature during cutting, which softens the material to enhance the cutting performance leading to reduced surface roughness (Bhardwaj et al 2013a). The minimum surface roughness is achieved at higher level of cutting speed. On the other hand surface roughness continuously increases with increase in depth of cut due to increase in cutting force and tool vibration. The minimum surface roughness is achieved at lower level of depth of cut.

6. Effect of turning conditions on MRR

The effect of turning conditions on MRR is shown in figure 3. From the figure it has been revealed that MRR increases with increase in % wt SiC-Gr. The maximum MRR is achieved at 4^{th} level of SiC-Gr% wt.

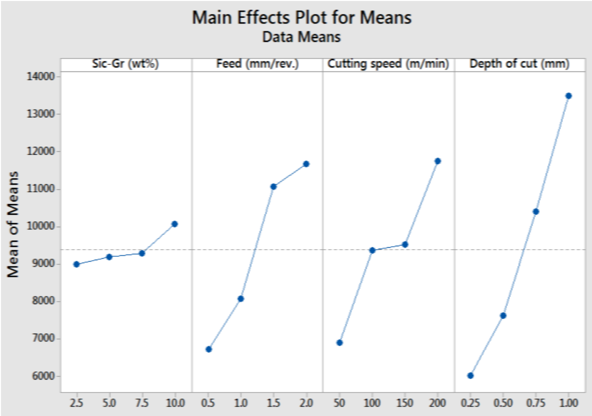

Figure 3 Effect of turning conditions on MRR

The MRR continuously increases with increase in feed. This is due to the fact that as feed increases, the tool traverses the work piece too fast, resulting high MRR with results increase in MRR. The maximum MRR is achieved at higher level of feed. Also as the cutting speed increase, the MRR also increases. With increase in cutting speed, the tool traverses the work piece rapidly, resulting higher MRR. The maximum MRR is achieved at higher level of cutting speed. On the other hand, MRR increase with increase depth of cut. This is due to the fact that as the depth of cut increases, the maximum chip thickness also increased, hence MRR also increases. The maximum MRR is achieved at higher level of depth of cut.

7. Conclusion

The following conclusions have been drawn from the present study:

1. The % wt SiC-Gr particulates, feed, cutting speed and depth of cut have been found significant terms that's affects the surface roughness and MRR.
2. The best performance characteristics has been obtained at the 1st level of SiC-Gr, 4th level of feed, 1st level of cutting speed and 4th level of depth of cut.
3. The % wt SiC- Gr has been found most significant condition that simultaneously affect the surface roughness and MRR with 53.47 % contribution followed by cutting speed (with 38.06 % contribution), depth of cut (with 6.72 % contribution) and feed (with 1.73 % contribution).
4. The surface roughness decreases with increase in SiC-Gr percentage of from 2.5 % to 7.5% after that surface roughness increase with increase in SiC-Gr percentage of from 7.5 % to 10%.
5. The surface roughness continuously increases with increase in feed and depth of cut while decreases with increase in cutting speed.
6. The MRR increases with increase in % wt SiC-Gr, feed, depth of cut and cutting speed.

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