

Multi-Response Optimization of Machining Parameters For Hybrid Aluminium Matrix Composites Using Grey Relational Analysis

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Abstract

Composite materials are beginning to find a foothold in the modern industrial environment owing to their ever increasing applications. In this research work, LM-13 Aluminium alloy matrix was reinforced with Fly ash (5 wt.%) and varying percentage of Silicon Carbide particulates (0 wt.%, 5 wt.% & 10 wt.%) to fabricate the hybrid composites with the help of Stir casting equipment. The composites were subjected to continuous turning in a CNC lathe with the help of carbide inserts and the experiments were conducted based on the L₂₇ Taguchi orthogonal array design. The turning operation was

conducted at various levels of cutting parameters such as depth of cut, feed and speed. The effect of these machining parameters on Material Removal Rate (MRR) and Surface Roughness (SR) of the hybrid composites was studied using Taguchi Method. Signal-to-noise (S/N) ratio analysis and Grey Relational Analysis were performed to determine the optimal setting of machining parameters that result in maximum MRR and minimum SR. Analysis of Variance (ANOVA) was used to study the influence of process parameters and their interactions on the multiple responses, which showed that feed was the most significant factor influencing the responses.

Keywords: Hybrid Aluminium Matrix Composites, Material Removal Rate, Surface Roughness, Design of Experiments, Taguchi, Grey Relational Analysis.

Introduction

The term “composite” refers to a material system which constitutes distinct constituents (reinforcements) dispersed in a continuous phase (matrix). The composite material has characteristics that are different from the characteristics of its constituents [1]. In Aluminium Matrix Composites (AMCs), one of the constituent is aluminium/aluminium alloy, which functions as the matrix phase and the other constituent which is dispersed in the matrix is the reinforcement. The reinforcements are in the form of particulates or fibres. The major advantages of AMCs are improved strength, improved stiffness, reduced density, improved thermal conductivity, controlled thermal expansion coefficient and improved abrasion and wear resistance [1]. AMCs are being used increasingly in numerous structural, non-structural and functional applications in different engineering sectors. They give both improved performance and also have economic and environmental benefits. Industries which are currently enjoying the added benefits of AMCs are the automotive and aerospace sector. They are especially used in hot reciprocating parts such as pistons where hot strength and resistance to thermal stresses are a prerequisite. The unique thermal properties of AMCs such as metallic conductivity with coefficient of expansion that can be tailored down to zero, add to their prospects in aerospace and avionics [2].

LM-13 Aluminium alloy is mainly used for applications where thermal stresses are high since it can withstand higher temperatures and loads and has good wear resistance properties. AMCs which are reinforced with Silicon Carbide (SiC) have enhanced specific strength, lower thermal expansion coefficient, higher thermal conductivity and higher wear resistance compared to the matrix material [3,4]. Fly ash which mainly consists of refractory oxides like silica, alumina, and iron oxides has low density. It can be mixed with aluminium alloy to reduce overall weight and density of the composites [5]. The cost of fly ash is also much lower than most other reinforcing materials and as well as the matrix aluminium. Therefore the usage of the low cost fly ash particulates in aluminium alloy has the potential to reduce the cost of hybrid AMC products. The incorporation of fly ash also increases the hardness and wear resistance of composites [5]. The incorporation of several different types of

reinforcements into a single matrix has led to the development of hybrid composites. The reason for using stir casting method to fabricate composites was to achieve uniform distribution of reinforcements and also due to the fact that it is economical [6,7].

Since AMCs contain certain amount of hard and abrasive ceramic reinforcements, they are considered to be one of the most difficult materials to machine [8,9]. Improving the machinability of AMCs and developing machining data are the most promising ways to convince designers and manufacturers to use AMCs in their applications. The prominent quality indicator for machined products is Surface Roughness (SR). In many critical applications, achieving the desired surface quality is of great importance for the effective use of the product [10]. Material Removal Rate (MRR) is a key indicator of productivity in the turning operation. Another major challenge in turning of AMCs is the lack of machining data for all possible combination of reinforcements. Investigation of mechanical and machinability properties of SiC particle reinforced AMCs was conducted by many researchers [11,12,13,14]. It has been reported in the literature that during turning process, parameters like Depth of Cut (DOC), feed and cutting speed, influence the MRR and SR [15,16,17].

Design of Experiments (DOE) is a powerful analysis tool for modelling and analysing the influence of multiple control factors on the performance output. DOE approach using Taguchi technique can be used for process optimization and to determine the optimal combination of factors for a given response [18]. Taguchi's Signal-to-Noise (S/N) ratios, which are logarithmic functions of desired output, serve as objective functions for optimization, help in data analysis and prediction of optimum results [19]. It helps in predicting the extent to which the parameters affect the response. Analysis of Variance (ANOVA) is used to determine the influence of individual machining parameters on the responses and as well as their interactions.

Taguchi method is designed to optimize single response characteristic. The higher-the-better performance for one factor may affect the performance because another factor may demand lower-the-better characteristics. Hence, multi-response optimization characteristics are complex. Grey relational analysis [20] is an efficient tool for such multi-response analysis. Grey relational analysis owes its origin to grey system theory. Grey system theory formulated by Deng [20,21] is used to study the unascertained problems with limited data but poor information. In Grey Relational Analysis, black represents having no information and white represents having all information. A grey system has a level of information between black and white. This analysis can be used to represent the grade of correlation between two sequences so that the distance of two factors can be measured discretely. When the experiments are ambiguous or when the experimental method cannot be carried out exactly, grey analysis helps to compensate for the shortcomings in statistical regression. Grey Relation Analysis is an effective means of analyzing the relationship between sequences with less data and can analyze many factors that can overcome the disadvantages of statistical methods [22].

Based on the literature review, LM-13 Aluminium alloy was chosen as the matrix in this research work. SiC and fly ash particulates were chosen as reinforcements.

However, limited information is available regarding the optimization of process parameters in turning Aluminium-SiC-fly ash hybrid composites using statistical methods. In this investigation, the Taguchi approach followed by Grey Relational Analysis is applied to solve the multi-response optimization in turning Aluminium-SiC-fly ash hybrid composites. ANOVA was used to determine the contribution of each parameter and their interactions on the turning process.

Experimental Details

Materials

LM-13 Aluminium alloy (Al-Si12Cu) has been used as the matrix material in this investigation. LM-13 alloy is generally used for piston, pulleys (sheaves) and for other engine parts operating at elevated temperatures. It has the advantage of good resistance to wear, good bearing properties, a low coefficient of thermal expansion and good machinability. The alloy has a density of 2.7 g/cm³. The chemical composition of LM-13 aluminium alloy is listed in Table 1. SiC and fly ash particulates were used as reinforcements. SiC particulates were used owing to better strength and thermal properties, and fly ash was used for its lower density and hardness improvement properties. The spherical fly ash particles contain both solid precipitators and hollow cenospheres. The particle density of SiC and fly ash were 3.21 g/cm³ and 2.04 g/cm³, respectively. Fly ash particles with a size range of 53-75 μ m were used. The average particle size of the reinforcement SiC was 30 μ m.

Table 1: Chemical Composition of LM-13 Aluminium Alloy

Element	Cu	Fe	Pb	Mg	Mn	Ni	Si	Sn	Ti	Zn	Al
% by weight	0.7-1.5	1.0	0.1	0.8-1.5	0.5	1.5	10.0-13.0	0.1	0.2	0.1	Remainder

Fabrication of Hybrid Composites using Stir Casting

The hybrid composite was prepared with the help of stir casting equipment as shown in the Figure 1. The reinforcement particles were first preheated at a temperature of 600-800°C for a few hours so that the volatile substances were removed. The LM-13 alloy was placed in the crucible at the bottom of the furnace and melted by heating it to around 750°C. The melt was agitated with a stirrer and Magnesium ribbons were added to remove the slag. Fly ash and SiC particles were then added and stirred for duration of 10 minutes until the particles were homogeneously distributed in the matrix. The molten mixture was then poured into the moulds which were also preheated and allowed to cool down and solidify. The composite samples were removed after solidification.



Figure 1: Stir Casting Equipment

Hybrid composite sample which are cylindrical in shape were cast with varying weight percentage of SiC (0 wt.%, 5 wt.% and 10 wt.%) and a fixed weight percentage (5 wt.%) of fly ash. Table 2 shows the composition of the various composite samples. The samples were machined to produce cylindrical specimens each measuring 75mm in length and 20mm in diameter. A total of 9 specimens for each composition was fabricated using stir casting equipment so that they could be utilized for the 27 different experiments.

Table 2: Composition of the Hybrid Composite Samples

Sample Number	LM-13 Aluminium alloy (wt.%)	Fly ash (wt.%)	Silicon Carbide (wt.%)
1	95	5	NIL
2	90	5	5
3	85	5	10

Turning of Hybrid Composites and Design of Experiments (DOE)

These hybrid composite specimens were then subjected to turning operation in a CNC lathe at various levels of DOC, feed and speed for a constant duration of 2 minutes and 45 seconds. Carbide tipped tool was used for turning operation, because the composites are comparatively harder than conventional materials and also due to the fact that these tools have the capacity to withstand the high temperatures encountered during the high speed turning operation. The experimental setup for turning of hybrid

composites using CNC lathe is shown in Figure 2. The sequence in which the experiments were to be conducted was determined based on Taguchi's Method. This is essentially a 4-Factor and 3-Level design as it has 4 input variables and with 3 different levels. The input variables are composition, DOC, feed, speed and the responses are MRR and SR. The various levels of input parameters are shown in Table 3. An L27 orthogonal array was selected for this work and it has 27 rows and 13 columns. The photomicrograph of the cylindrical hybrid composite specimens after the turning operation is shown in Figure 3.



Figure 2: Experimental setup for Turning Hybrid Composites using CNC Lathe



Figure 3: Photomicrograph of the Hybrid Composite Specimens after Turning operation

Measurement of MRR and SR

MRR and SR of the machined samples are the performance characteristics which are used to evaluate the machining quality in this study. The initial mass of the samples was measured using an accurate weighing scale and the final mass was measured after the turning operation. The machining time was kept constant for all the samples at 2 minutes and 45 seconds. The difference between the initial and final mass gave the mass loss in gram. MRR is defined as the ratio of mass of the work material removed to the machining time. MRR for each experiment was calculated using the following expression:

$$MRR = \frac{(\text{Initial mass} - \text{Final mass})}{\text{Machining Time}} \quad (1)$$

The unit in which MRR is measured is g/min.

SR was measured in micrometers (μm) with the help of a surface roughness meter as shown in Figure 4.

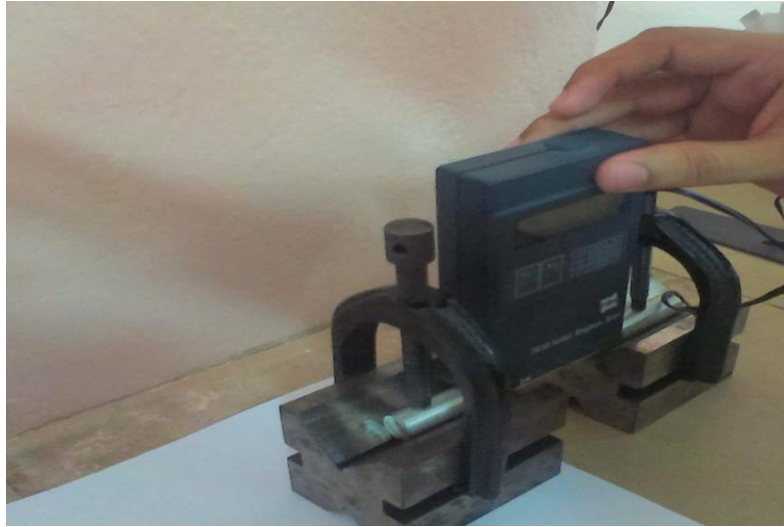


Figure 4: Measurement of Surface Roughness using Surface Roughness Tester

S/N Analysis, Grey Relational Analysis and ANOVA

S/N ratio measures how the response varies relative to the nominal or target value under different noise conditions. The objective of determining S/N ratio is to develop processes that are insensitive to noise. The S/N ratio characteristics can be classified into three categories, namely, 'smaller is better', 'larger is better' and 'nominal is best' characteristic.

For MRR, 'Larger is Better' characteristic is chosen to determine S/N Ratio:

$$\frac{\bar{s}}{N} = -10 \log \left[\frac{1}{n} \left(\sum \frac{1}{y^2} \right) \right] \quad (2)$$

where y is the observed data (MRR) and n is the number of observations.

For SR, 'Smaller is Better' characteristic is chosen to determine S/N Ratio:

$$\frac{\bar{s}}{N} = -10 \log \left[\frac{1}{n} (\sum y^2) \right] \quad (3)$$

where y is the observed data (SR) and n is the number of observations.

Multi-response optimization of machining parameters for the hybrid composites was performed using Grey Relational Analysis. The overall evaluation of the multiple process responses (MRR and SR) is based on the grey relational grade. The relative contribution of each control factor on the overall measured multiple responses is obtained by ANOVA. Basically, ANOVA compares two types of variances: the variance within each sample and the variance between different samples. It uses a mathematical technique known as the sum of squares to quantitatively examine the deviation of the average mean of the factors that affect the response from the overall experimental mean response. MINITAB 15.2 software was used for the analyses of the experimental data.

Results and Discussion

S/N Analysis using Taguchi Method

Taguchi method uses a special set of arrays called orthogonal arrays which stipulate the way of conducting the minimal number of experiments that would give the full information of all the factors that affect the performance parameter. The experiments were conducted based on the L_{27} Taguchi orthogonal array design. The system has 4 parameters and each of them has 3 levels. Table 3 shows the list of parameters and their levels. Testing all the possible combinations of these parameters will result in a set of $81(3^4)$ test cases. However instead of testing the system for each combination of parameters, one can use an orthogonal array to select only a subset of these combinations. A total of 27 experiments (turning operations) were carried out with different combinations of input parameters by utilizing Taguchi's orthogonal array.

Table 3: Turning Parameters and their Levels

Level	Composition (Wt. % of SiC)	Depth of Cut (mm)	Feed (mm/rev)	Speed (rpm)
1	0	0.5	0.125	500
2	5	0.75	0.250	750
3	10	1.00	0.375	1000

MRR was calculated using the equation 1 for all the 27 experiments. SR was measured in micrometers (μm) with the help of a surface roughness meter after the turning operation. The experimental results for MRR and SR are shown in Table 4. The experimental results were then converted to S/N Ratios so that the effects of various parameters on the responses could be found out. The S/N ratios for a given response were calculated using the equations 2 and 3 and the values are listed in Table 4. A process parameter setting with the highest S/N ratio always yields the optimum quality with minimum variance.

Table 4: Orthogonal Array and Experimental Result

Expt. No.	Composition (Wt.% of SiC)	Depth of Cut (mm)	Feed (mm/rev)	Speed (rpm)	MRR (g/min)	S/N for (dB)	Ratio MRR	SR (μm)	S/N for (dB)	Ratio SR
1	0	0.5	0.125	500	2.992	9.519232		1.8466	-5.32746	
2	0	0.5	0.25	750	8.2413	18.31991		4.8666	-13.7445	
3	0	0.5	0.375	1000	14.6594	23.32232		7.88	-17.9305	
4	0	0.75	0.125	750	6.1814	15.82174		2.02	-6.10703	
5	0	0.75	0.25	1000	15.0234	23.53536		6.62	-16.4172	
6	0	0.75	0.375	500	12.0974	21.65384		5.86	-15.358	
7	0	1	0.125	1000	10.9176	20.76254		1.8766	-5.46743	
8	0	1	0.25	500	10.8804	20.7329		4.972	-13.9306	
9	0	1	0.375	750	19.18109	25.65747		7.7933	-17.8344	
10	5	0.5	0.125	500	3.0589	9.711306		1.78	-5.0084	
11	5	0.5	0.25	750	8.5342	18.62326		2.96	-9.42583	
12	5	0.5	0.375	1000	13.8179	22.80884		6.085	-15.6852	
13	5	0.75	0.125	750	6.3743	16.08865		1.6766	-4.48859	
14	5	0.75	0.25	1000	14.0307	22.94159		3.7866	-11.565	
15	5	0.75	0.375	500	12.0815	21.64242		5.89	-15.4023	
16	5	1	0.125	1000	11.3597	21.10734		1.66	-4.40216	
17	5	1	0.25	500	10.8626	20.71868		3.8533	-11.7167	
18	5	1	0.375	750	19.6184	25.85327		6.6233	-16.4215	
19	10	0.5	0.125	500	5.9699	15.51934		2.16	-6.68908	
20	10	0.5	0.25	750	14.5175	23.23784		3.3266	-10.44	
21	10	0.5	0.375	1000	14.7835	23.39555		4.8933	-13.792	
22	10	0.75	0.125	750	7.7964	17.83788		2.2066	-6.87447	
23	10	0.75	0.25	1000	13.5175	22.61793		3.91	-11.8435	
24	10	0.75	0.375	500	11.455	21.1799		4.9933	-13.9678	
25	10	1	0.125	1000	10.7706	20.6448		2.3	-7.23456	
26	10	1	0.25	500	10.7587	20.6352		3.9633	-11.9611	
27	10	1	0.375	750	19.3498	25.73353		4.9466	-13.8861	

Grey Relational Analysis

In the Grey Relational Analysis, S/N ratios for MRR and SR were first normalized in the range between zero and one, which is termed the grey relational generation. The relationship between the desired and actual experimental data is expressed through the grey relational coefficient, which is calculated from the normalized experimental data. The mean of the grey relational coefficients corresponding to each process response is calculated, which corresponds to the grey relational grade. The overall evaluation of the multiple process responses is based on the grey relational grade. As a result, optimization of complicated multiple process responses can be converted into optimization of a single grey relational grade. The optimal level of the process parameters is the level with the highest grey relational grade.

After grey relational generation, the deviation sequence is calculated as:

$$\Delta_{oi} = \|x_o(k) - x_i(k)\| \quad (4)$$

The reference sequence and comparability sequence are denoted by $x_o(k)$ and $x_i(k)$ respectively. Then, the grey relational coefficient $\xi_i(k)$ for the k^{th} performance characteristics in the i^{th} experiment is calculated as:

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{oi}(k) + \zeta \Delta_{\max}} \quad (5)$$

$0 < \xi_i(k) \leq 1$; ζ is known as the distinguishing coefficient and it is defined in the range $0 \leq \zeta \leq 1$, and therefore a value of $\zeta = 0.5$ is used.

The average value of the grey relational coefficients is the grey relational grade. Therefore, the grey relational grade is calculated as follows:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k), \quad (6)$$

where n is the number of process responses. The grey relational grade γ_i represents the level of correlation between the reference sequence and the comparability sequence. A higher value of the grey relational grade implies that the corresponding process parameter is closer to the optimal one.

The grey relational generation was carried out and the normalized S/N ratio values are listed in Table 5. In general, the larger normalized S/N ratio corresponds to the better performance. The deviation sequence Δ_{oi} is calculated using equation 4 as follows:

$$\Delta_{02}(1) = |x_o(1) - x_2(1)| = |1.0000 - 0.53879| = 0.46121$$

$$\Delta_{02}(2) = |x_o(1) - x_2(1)| = |1.0000 - 0.30942| = 0.69058$$

The same calculation method is used for all experiments ($i = 1$ to 27), and the results of all deviation sequences are listed in Table 5. $\Delta_{\max}$ and $\Delta_{\min}$ obtained from Table 5 are as follows:

$$\Delta_{\max} = \Delta_{01}(1) = \Delta_{03}(2) = 1.00$$

$$\Delta_{\min} = \Delta_{18}(1) = \Delta_{16}(2) = 0.00$$

Table 5: S/N Ratios, Normalized S/N Ratios and Deviation Sequences

Expt. No.	S/N Ratios		Normalized Ratios		S/N Deviation Sequences	
	MRR	SR	MRR	SR	MRR	SR
1	9.519232	-5.32746	0	0.93160	1	0.0684
2	18.31991	-13.7445	0.53879	0.30942	0.46121	0.69058
3	23.32232	-17.9305	0.84505	0	0.15495	1
4	15.82174	-6.10703	0.38585	0.87397	0.61415	0.12603
5	23.53536	-16.4172	0.85809	0.11186	0.14191	0.88814
6	21.65384	-15.358	0.7429	0.19015	0.2571	0.80985
7	20.76254	-5.46743	0.68833	0.92125	0.31167	0.07875
8	20.7329	-13.9306	0.68652	0.2956	0.31348	0.7044
9	25.65747	-17.8344	0.9880	0.00718	0.0120	0.99282
10	9.711306	-5.0084	0.01175	0.95518	0.98825	0.04482
11	18.6236	-9.42583	0.55738	0.62865	0.44262	0.37135
12	22.86884	-15.6852	0.81361	0.16597	0.18639	0.83403
13	16.08865	-4.48859	0.40219	0.9936	0.59781	0.0064
14	22.94159	-11.565	0.82174	0.47053	0.17826	0.52947
15	21.64242	-15.4023	0.7422	0.18688	0.2578	0.81312
16	21.10734	-4.40216	0.70944	1	0.29056	0
17	20.71868	-11.7167	0.68565	0.45931	0.31435	0.54069
18	25.8532	-16.4215	1	0.11154	0	0.88846
19	15.51934	-6.68908	0.3673	0.83095	0.63267	0.16905
20	23.23789	-10.44	0.83988	0.55368	0.16012	0.44632
21	23.39555	-13.792	0.84953	0.30591	0.15547	0.69409
22	17.83788	-6.87447	0.5092	0.81724	0.4908	0.18276

23	22.61793	-11.8435	0.80192	0.44994	0.19808	0.55006
24	21.1799	-13.9678	0.71388	0.29291	0.28612	0.70709
25	20.6448	-7.23456	0.68112	0.79063	0.31888	0.20937
26	20.6352	-11.9611	0.68054	0.441251	0.31946	0.558749
27	25.73353	-13.8861	0.99267	0.2989	0.00730	0.70110

The grey relational coefficients and the grey relational grade for each experiment were calculated using the equations 5 and 6 respectively. The average value of the grey relational coefficients is the grey relational grade. The calculated values and the ranks of coefficients and grades are listed in Table 6. The 18th experiment with a grey relational coefficient value of 1.000 for MRR had the highest rank. This indicates that the optimal setting of control parameters for maximum MRR are 5 wt.% SiC (level 2), 1 mm DOC (level 3), 0.375 mm/rev Feed (level 3) and 750 rpm Speed (level 2). The 16th experiment had the highest grey relational coefficient value of 1.000 for SR and therefore the optimal setting of control parameters for minimum SR are 5 wt.% SiC (level 2), 1 mm DOC (level 3), 0.125 mm/rev Feed (level 1) and 1000 rpm Speed (level 3). This indicates that the machined surface obtained after 16th experiment is very smooth in nature in comparison to other experiments and has the optimum surface finish. The 3rd experiment had the lowest grey relational coefficient of 0.3333 for SR which indicates that the machined surface obtained after this experiment is very rough in comparison to others.

Ranks of grey relational grade for all the experiments are listed in Table 6. It can be clearly observed from the table that the 16th experiment with a grey relational grade value of 0.8162 had the highest rank. This indicates that the optimal parameter combination for the multiple responses are 5 wt.% SiC (level 2), 1mm DOC (level 3), 0.125 mm/rev Feed (level 1) and 1000 rpm Speed (level 3). Based on the Grey Relational Analysis, the optimal combination of parameters for obtaining the highest MRR and lowest SR during turning operation of LM-13 Aluminium/SiC/fly ash hybrid composites is given in Table 7.

Table 6: Grey Relational Coefficient and Grey Relational Grade

MRR			SR			MRR and SR		
Expt. No.	Grey Relational Coefficient	Rank	Expt. No.	Grey Relational Coefficient	Rank	Expt. No.	Grey Relational Grade	Rank
18	1.0000	1	16	1.000	1	16	0.8162	1
27	0.9856	2	13	0.9873	2	7	0.7399	2
9	0.9765	3	10	0.9177	3	13	0.7214	3
5	0.7789	4	1	0.8796	4	27	0.7009	4
3	0.76341	5	7	0.8639	5	18	0.6800	5

21	0.7628	6	4	0.7986	6	25	0.6577	6
20	0.7574	7	19	0.7473	7	9	0.6557	7
14	0.7371	8	22	0.7323	8	20	0.6429	8
12	0.7284	9	25	0.7048	9	10	0.6268	9
23	0.7162	10	11	0.5738	10	4	0.6237	10
6	0.6604	11	20	0.5283	11	22	0.6184	11
15	0.6598	12	14	0.4856	12	14	0.6114	12
24	0.6360	13	17	0.4804	13	1	0.6064	13
16	0.6324	14	23	0.4761	14	23	0.5962	14
7	0.6160	15	26	0.47225	15	19	0.5943	15
8	0.6146	16	2	0.4199	16	21	0.5907	16
17	0.6139	17	21	0.4187	17	5	0.5695	17
25	0.6105	18	27	0.4162	18	11	0.5521	18
26	0.6101	19	8	0.4151	19	12	0.5516	19
11	0.5304	20	24	0.4142	20	3	0.5483	20
2	0.5201	21	6	0.3817	21	17	0.5472	21
22	0.5046	22	15	0.3807	22	26	0.5412	22
13	0.4554	23	12	0.3748	23	24	0.5251	23
4	0.4487	24	5	0.3601	24	6	0.5210	24
19	0.4414	25	18	0.3601	25	15	0.5202	25
10	0.3359	26	9	0.3349	26	8	0.5148	26
1	0.3333	27	3	0.3333	27	2	0.4700	27

Table 7: Optimal Combination of Parameters for Turning Hybrid Composites

Composition	90 wt.% LM-13 Aluminium Alloy, 5 wt.% SiC and 5 wt.% Fly ash
Depth of cut	1.00 mm
Feed	0.125 mm/rev
Speed	1000 rpm

Analysis of Variance (ANOVA) and Significance of Parameters

The relative contribution of each parameter to multiple responses was identified with the help of ANOVA. A confidence level of 95% was used for the analysis, that is for significance level of $\alpha = 0.05$. The ratio of individual sum of squares of a particular independent variable to the total sum of squares of all the variables gives the percentage contribution of the independent variable on the response. The significance of the individual control factors is quantified by comparing the variance between the control factor effects against the variance in the experimental data due to random experimental error, and this is given by the F-test.

ANOVA was performed with grey relational grade as response to determine the relative contribution of each parameter to the overall measured multiple responses. Pairs of the factors in an experiment may also interact with one another to provide synergistic effect on the response. Therefore the three important interactions, namely Composition*DOC, Composition*Feed and Composition*Speed were also included for this analysis. MINITAB 15.2 was used to calculate the total sum of squares and adjusted sum of squares for all the factors and their interactions and all the results are listed in Table 8. Using the software, degrees of freedom, mean squares, and the F-test ratios were also found out for all the factors and their interactions.

Percentage contribution of the independent variables and their interactions to the multiple responses was also calculated. Table 8 shows the percentage contribution of the factors and their interactions to the multiple responses, MRR and SR. This indicates the degree of influence on the results. When the P-value for this model is less than 0.05, then the parameter or interaction can be considered as statistically significant. From the table, it can be noted that feed (33.64%), followed by speed (20.67%) and DOC (17.26%) exert significant influences on the turning responses of hybrid composites. The most dominant parameter was feed, as it had the highest percentage contribution to the multiple responses. This is in agreement with the results obtained by Pushpendra Kumar Jain, et al. during the machining of AMCs [17]. Composition exerts a negligible effect (4.86%), and since its P-value > 0.05, it can be considered as statistically insignificant. Similarly, the interaction terms Composition*Feed, Composition*DOC and Composition*Speed have a P-value > 0.05, and hence are statistically insignificant.

Table 8: ANOVA for MRR and SR (Grey Relational Grade)

Source variation of	DF	Seq SS	Adj SS	Adj MS	F-test	P-value	Percentage Contribution
Composition (Wt.% of SiC)	2	0.007973	0.007973	0.003986	2.76	0.142	4.86
DOC (mm)	2	0.028281	0.028281	0.014140	9.77	0.013	17.26
Feed (mm/rev)	2	0.055130	0.055130	0.027565	19.05	0.003	33.64
Speed (rpm)	2	0.033880	0.033880	0.016940	11.71	0.008	20.67
Composition* DOC	4	0.006812	0.006812	0.001703	1.18	0.408	4.16
Composition* Feed	4	0.017317	0.017317	0.004329	2.99	0.112	10.57
Composition* Speed	4	0.005824	0.005824	0.001456	1.01	0.473	3.55

Error	6	0.008681	0.008681	0.001447			5.29
Total	26	0.163898					100

Notes: DF, Degrees of freedom; Seq SS, Sequential sum of squares; Adj SS, Adjusted sum of squares; Adj MS, Adjusted mean squares; F-test, Fisher's test.

Figure 5 shows the variation of the responses from the mean values through residual plots. Violation of the basic assumptions and model adequacy was investigated by examination of residuals. Residual plots were generated to examine the goodness of model fit. Normal probability plot was used to detect non-normality. If the model is adequate, residuals should be structure less, that is, they should contain no obvious and unusual patterns. From the normal probability plot of the residuals for MRR and SR in Figure 5, it can be observed that the residuals generally fall on a straight line. This indicates that the residuals are normally distributed and thus a goodness-of-fit is obtained. Residual versus observation order plot were used to detect time-dependence of residuals (Figure 5). This plot shows random patterns on both sides of zero line. No clear time-dependent pattern was exhibited by the residuals which show that the data was normally distributed and the equality of variance was not violated. Thus the examination of residuals proved that the model to be fully adequate to represent the relationships between the multiple responses and the independent variables.

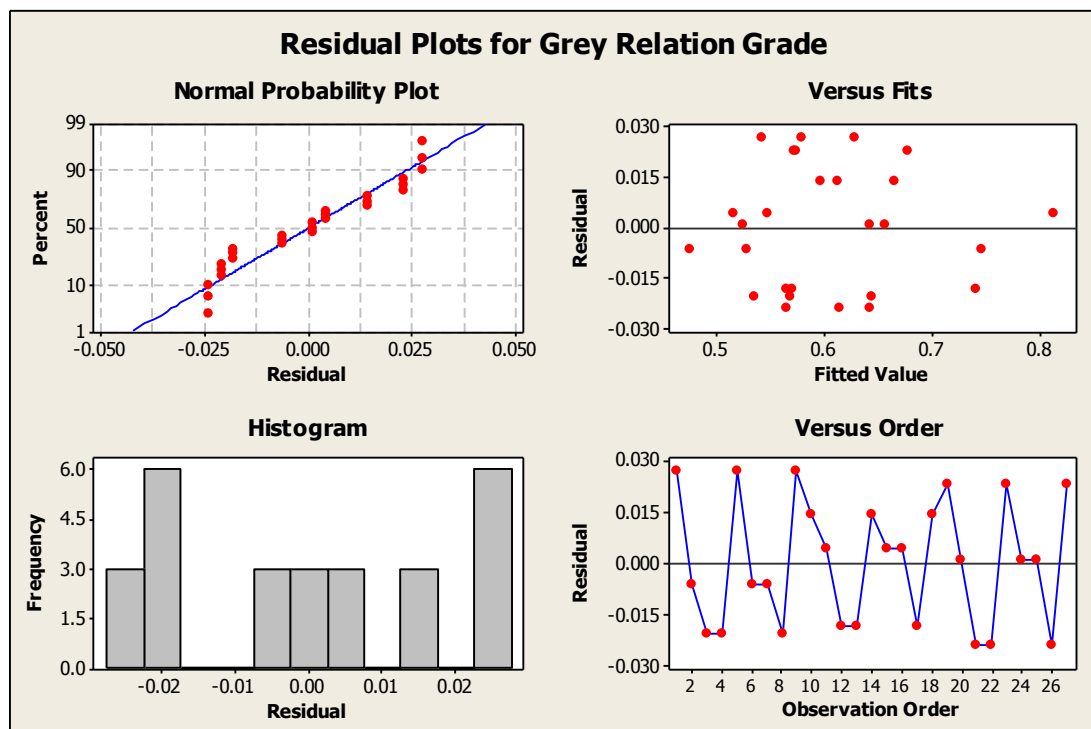


Figure 5 Residual Plots for MRR and SR (Grey Relational Grade)

Conclusions

1. Based on the Grey Relational Analysis, the optimal combination of factors for obtaining the highest MRR and lowest SR during turning operation of LM-13 Aluminium/SiC/Fly ash hybrid composites are: Composition = 5 wt.% SiC & 5 wt.% Fly ash, DOC = 1.00 mm, Feed = 0.125 mm/rev and Speed = 1000 rpm.
2. It was determined based on ANOVA that feed (33.64%) has the predominant influence on the multiple responses MRR and SR, followed by Speed (20.67%) and DOC (17.26%). Composition, Composition*Feed, Composition*DOC and Composition*Speed exert a negligible effect on the multiple responses and hence they are statistically insignificant.
3. The examination of residuals proved that the model to be fully adequate to represent the relationships between the multiple responses and the independent parameters. The usage of optimal parameter combination will lead to an improved MRR and good surface finish during continuous turning operation of hybrid aluminium composites.

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