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Trade Off Among Conflicting Multi Objectives of CNC End Milling Process for LM6 Al/SiC$_p$

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Abstract: ***This research work focuses on trade off among conflicting multi objectives of CNC End Milling process for metal matrix composite (MMC$_s$). Experiments were designed and conducted based on L$_{27}$ orthogonal array. The controllable parameters for end milling are weight percentage of SiC$_P$ in the metal matrix, cutting speed, depth of cut, feed & cutter diameter. The study provided to minimizing surface roughness (R$_a$) and maximizing material removal rate (MRR) occurring during end milling process for composite material LM6 AL/SiC$_p$. A statistical approach "Grey-Taguchi Method" is used for combining the orthogonal array (OA), design of experiments (DOE) with grey-relational analysis (GRA), which enables to optimizing multiple objectives problem of CNC end milling. The results show that semi finishing process of milling is best among 27 experiments. Regression modelling validate grey-taguchi methodology by obtaining best value of grey relational grade.***

Keywords: CNC End Milling, Composite material, Taguchi method, Grey relational analysis.

1. Introduction with Literature Review

Quality and productivity are the challenging two main objectives for growth of manufacturing industries. It can be seen that these two are conflicting to each other, thus quality increases then productivity tends to decrease, or vice-versa. But manufacturing industries require optimizing both quality and productivity simultaneously. The product being machined has to have the minimum surface roughness in order to obtain high surface quality processing time has to be compromised which directly affects the productivity [1]. The quality of the product mainly depends upon the material and process parameters [2]. Among various types of milling processes, as shown in Figure-1, end milling is the most important and common metal cutting process used for machining parts because of its capability to producing complex geometric surfaces at faster rate with reasonable accuracy and surface finish [3].

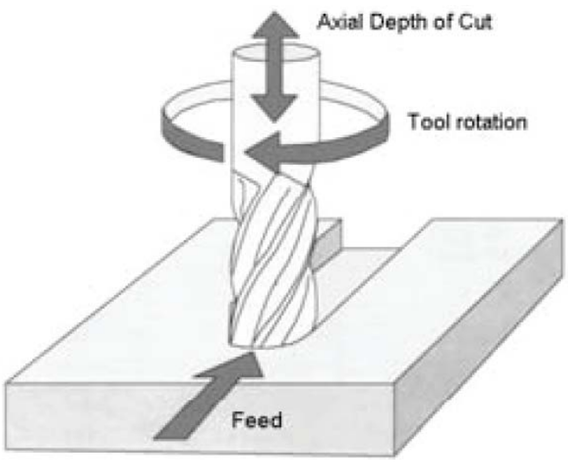

Figure-1: End Milling Operation [4]

Also, it is capable of producing a variety of configurations including aerospace and automotive sectors, where surface quality is an important response factor in the production of slots, pockets, precision moulds and dies [4]. Computer numerically controlled (CNC) machine tools provide greater improvements in productivity, and enhance the surface quality of the machined parts and require less operator input. For these reasons, CNC end milling process is very versatile and useful machining operation in most of the modern manufacturing industries [6].

Composites are one of the most widely used materials in engineering due to their outstanding mechanical properties. aluminum matrix composite (AMCs) have become a large leading material in composite materials because of their superior properties such as lightweight, high strength, hardness, stiffness, and greater wear resistance [7]. In recent times, aluminum matrix composites (AMCs) refer to the class of lightweight high-performance aluminum centric material systems which is highly sought after in the automotive and aircraft industry [8]. These materials are known as the difficult-to-machine materials, because of the hardness and abrasive nature of reinforcement element like silicon carbide (SiC) particles [9]. In the view of extensive using composites in manufacturing industries, a detailed and systematic study is required for investigate their machining characteristics.

In this present study, composite LM6 Al/SiC$_p$ with different percentage 5%, 10% and 15% of weight of SiC$_p$ were fabricated by stir casting technique and machined on CNC end milling. The experiment designs were determined by using Taguchi's experimental design method. Grey relational analysis was applied to obtain the optimum values of the control parameters among 27 experiments for formation of straight rectangular slots of 100 mm length. The control parameters such as weight percentage of SiC$_p$, cutting speed, feed, depth of cut and cutter diameter of end mill cutting tool were optimized with the considerations of conflicting multiple objectives such as material removal rate and surface roughness value on the work material. This study may be helpful to the manufacturers for getting good surface quality with high productivity.

2. Composite Materials and Fabrication Method

The fabrications of metal matrix composites LM6 Al/SiC$_p$ with different percentage of weight SiC$_p$ were carried out by stir casting technique. The composition of LM6 is tabulated in Table 1.

Table 1: Chemical composition (LM6)

Elements	Al	Si	Cu	Mn	Mg	Fe	Zn	Cr
%age	87.33	10.41	0.14	0.35	0.28	0.98	0.38	0.02
Elements	Ni	Ti	Ca	Pb	V	P	As	
%age	0.01	0.02	0.01	0.01	0.01	0.001	0.008	

A measured amount of LM6 aluminium base alloy ingots were taken into a graphite crucible and melted in an electrical furnace. A measured amount (5%, 10%, and 15%) of laboratory tested moisture free ‘silicon carbide particles’ with mesh 200 µm were added to the melt. After that, the melt was stirred at an average mixing speed of 400 rpm to make a vortex in order to disperse the particles in the melt. After through stirring the melt was poured into sand moulds and result out in the form of as shown in Figure 2, three workpiece samples of 100 mm different amount of SiC (5%, 10%, and 15%) with dimension length, 100 mm width and 10 mm thickness.

Figure 2: Casted composite materials after stir casting

3. Experimental Set Up

The following equipment’s were used in this experimental works:

- CNC Vertical Milling Machine
- End Milling Cutters
- Surface Roughness Tester
- Digital Vernier Caliper

3.1 CNC Vertical Milling Machine

As shown in Figure 3, CNC vertical machining center (Jyoti VMC 430) was used to perform the end milling. It is installed in AVTS Hi-Tech Training Centre, Tarsali, Vadodara.

Figure 3: Experimental set up for end milling operation

3.2 End Mill Cutters

The tool used for performing end milling operation are made up of coated solid carbide tool of different diameters (6 mm, 8 mm and 10 mm diameter) as shown in Figure 4. Tools with four flutes are selected for better surface quality.

Figure 4: Solid carbide end mill with different diameters

3.3 Surface Roughness Tester

The machining length was of 100mm. After performing the machining process, the machined surface was checked at three position by using a surface roughness tester as shown in Figure 5 (Make: HOMMEL surf test at MS university, vadodara) and it given average surface roughness (R$_a$) measurement value that was recorded in micron meter.

Figure 5: Set up for HOMMEL surface roughness tester

3.4 Digital Vernier Caliper

As Shown in Figure 6, digital vernier Caliper of resolution 0.01 was used to measure the dimension (Length × Width × Depth) of the machined straight rectangular slots on work pieces after the machining process.

Figure-6: Digital Vernier Caliper

4. Response Objectives Parameters

There are two response objective parameters include:

- Surface Roughness (R_a)
- Material Removal Rate (MRR)

4.1 Surface Roughness

Roughness is often a good predictor of the performance of a mechanical component, since irregularities in the surface may form nucleation sites for cracks or corrosion [10]. Roughness is quantified by the vertical deviations of a real surface from its mean line. If these deviations are large, the surface is rough; if small, the surface is smooth [11]. There are various roughness parameters such as average roughness (R_a), smoothening depth (R_p), root mean square (R_q), and maximum peak-to-valley height (R_t). In this work, the average surface roughness (R_a), was adopted and measurements were carried at three different positions of the machined surface using a HOMMEL Surftest. It measured average surface roughness by comparing all the peaks and valleys to the mean line, and then averaging them all over the entire cut-off length.

4.2 Metal Removal Rate (MRR)

In this research work, material removal rate (MRR) is used as another performance measure to evaluate a machining performance. Material removal rate is expressed as the amount of material removed under a period of machining time and is expressed in mm^3/min.

$$\text{MRR in } mm^3/\text{min} = \frac{L \times D \times W}{t}$$

Where *L* is the machining length, *D* is the depth of cut and *W* is the width of cut, and these dimension are measured with digital vernier caliper. In the above MRR relationship, *t* is the machining time in minute.

5. Grey – Taguchi Method: Proposed Methodology

Grey – Taguchi method is of combining the orthogonal array (OA) design of experiments (DOE) with grey relational analysis (GRA) which enables the determination of the optimal combination of CNC end milling process for multiple objectives response [12]. The use of Taguchi method with grey relational analysis to optimize the end milling process with multiple performance characteristics includes the following procedure as shown in Figure 7.

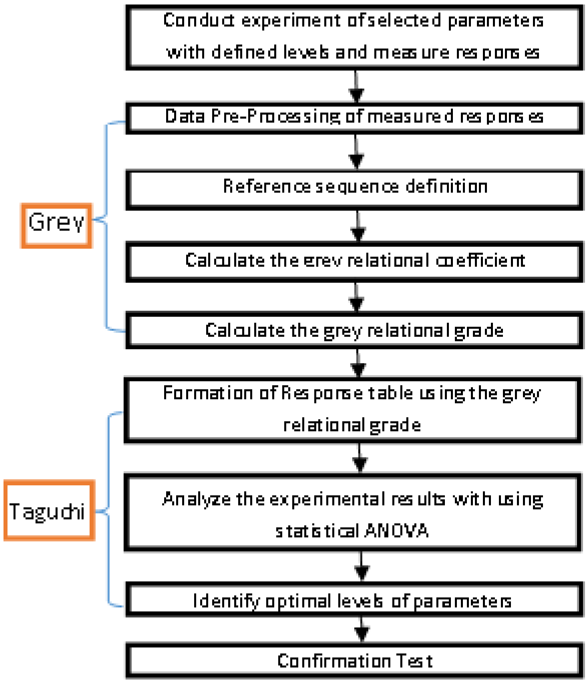

Figure 7: Taguchi- Grey Relational Analysis

5.1 Design of Experiment

The design of experiments technique is a very powerful tool, which allows us to carry out the modeling and analysis of the influence of controllable variables on the response variables. The response variable is an unknown function of the controllable variables, which are known as design factors [13]. The Design of experiment includes five controllable milling parameters at three levels are tabulated with their performance characteristics in Table 2. The three level parameters include weight percentage of SiC_p (A), cutting speed (B), feed (C), Depth of cut (D) and cutter diameters (E). Orthogonal array L_{27} with sample size two has been considered to conduct experiments and investigate the interrelationships of parameters within experimental design. The Orthogonal array (OA) has 5 columns and 27 rows. Each end milling parameter was assigned to a column, according to standard methodology of OA [14].

All experiments were carried out on vertical milling machine. The workpiece material used for the purpose was LM6 Al/SiC_p as described earlier and the dimensions of the workpiece were 100mm×10mm×10mm. The objective was to obtain optimal levels of the controllable parameter for end milling machining process.

Table 2: Experiment design with measurable results

Trial No.	SiC% (A)	SPEED (B) (rpm)	FEED (C) (mm/m)	DEPTH OF CUT(D) (mm)	Cutter Dia (E) (mm)	Ra (μm)	MRR (mm3/min)
1	5	2500	50	0.5	6	1.4479	140.69
2	5	2500	50	0.5	8	1.5757	225.81
3	5	2500	50	0.5	10	1.5736	293.63
4	5	3500	75	1	6	1.3014	631.32
5	5	3500	75	1	8	1.9957	698.68
6	5	3500	75	1	10	1.8114	1036.04
7	5	4500	100	1.5	6	1.4450	862.64
8	5	4500	100	1.5	8	2.0786	1243.16
9	5	4500	100	1.5	10	1.5657	1532.85
10	10	2500	75	1.5	6	2.3793	758.63
11	10	2500	75	1.5	8	2.0700	962.17
12	10	2500	75	1.5	10	1.3714	1255.25
13	10	3500	100	0.5	6	2.6186	344.01
14	10	3500	100	0.5	8	2.2000	424.67
15	10	3500	100	0.5	10	1.5164	580.96
16	10	4500	50	1	6	1.2036	399.03
17	10	4500	50	1	8	1.3407	367.57
18	10	4500	50	1	10	1.4564	548.03
19	15	2500	100	1	6	2.8821	611.18
20	15	2500	100	1	8	2.7593	945.18
21	15	2500	100	1	10	1.4157	1128.63
22	15	3500	50	1.5	6	1.6664	430.06
23	15	3500	50	1.5	8	1.9843	615.56
24	15	3500	50	1.5	10	1.6857	798.08
25	15	4500	75	0.5	6	1.8314	229.36
26	15	4500	75	0.5	8	2.1329	403.03
27	15	4500	75	0.5	10	1.5129	513.48

5.2 Grey-Relational Analysis

Grey relational analysis was proposed by Deng in 1989 [15]. The word grey used for indicating between black (with no information) and white (with full and complete certain information) [16].

The grey relational analysis (GRA) can be clearly broken down into four steps, namely, data pre processing (also known as grey relational generation) with reference sequence generation, grey relational coefficient calculation and grey relational grade calculation. These steps are further explained:

Step-1: *Data Pre Processing* (GRG)
Data pre processing is a normalization process where all performance attributes are processed into a comparable sequence. Data Pre-Processing is normally required, since the range and unit in one data sequence may differ from others.
It is also necessary when the sequence scatter range is too large, or when the directions of the target in the sequences are different [17].

1. If the expectancy of the response is larger-the-better, then it can be expressed by

$$X_{ij} = \frac{Y_{ij} - \min_i Y_{ij}}{\max_i Y_{ij} - \min_i Y_{ij}} \quad (1)$$

2. If the expectancy of the response is smaller-the-better, then it can be expressed by

$$X_{ij} = \frac{\max_i Y_{ij} - Y_{ij}}{\max_i Y_{ij} - \min_i Y_{ij}} \quad (2)$$

Where Y_{ij} is the i^{th} performance characteristic in the j^{th} experiment. $\max_i Y_{ij}$ and $\min_i Y_{ij}$ are the maximum and minimum values of ith performance characteristic for alternate j, respectively.

Step-2: *Reference sequence generation* (RSG)
In comparability sequence all performance values are scaled to [0, 1]. For a response *j* of experiment *i*, if the value x_{ij} which has been processed by data pre-processing procedure is equal to 1 or nearer to 1 then the value for any experiment, then the performance of experiment *i* is considered as best for the response *j*. The reference sequence *X is defined as* $(x_1, x_2, \ldots, x_j, \ldots, x_n) = (1, 1, \ldots, 1, \ldots, 1)$, where x_j is the reference value for j^{th} response and it aims to find the experiment whose comparability sequence is closest to the reference sequence.

Step-3: *Grey relational coefficient* (GRC)
Grey relational coefficient is used for determining how close x_{ij} is to x_j. The larger the grey relational coefficient, the closer x_{ij} and x_j are. The grey relational coefficient can be calculated by using following equation.

$$\gamma_{ij} = \frac{(\Delta_{min} + \zeta * \Delta_{max})}{(\Delta_{ij} + \zeta * \Delta_{max})} \quad (3)$$

For $i = 1, 2 \ldots m$ and $j = 1, 2 \ldots n$
Where, γ = the grey relational coefficient between x_{ij} and x_{0j}

$$\Delta_{min} = \min_{ij} |X_j - X_{ij}|$$
$$\Delta_{max} = \max_{ij} |X_j - X_{ij}|$$
$$\Delta_{ij} = |X_j - X_{ij}| \quad (4)$$
$$\zeta = \text{Distinguishing coefficient}, \zeta \in (0,1)$$

Distinguishing coefficient (ζ) is also known as the index for distinguish ability. The smaller distinguishing coefficient is, the higher is its distinguishing ability. It represents the equation's "Contrast Control". The purpose of distinguishing coefficient is to expand or compressed the range of the grey relational coefficient. Different distinguishing coefficient may lead to different solution results. Decision makers should try several different distinguishing coefficients and analyze the impact on GRA results. Considering value of distinguishing coefficient is 0.5 (Generally used).

Step-4: *Grey relational grade (GRG)*
The measurement formula for quantification in grey relational space is called grey relational grade. A grey relational grade (grey relational degree) is a weighted sum of grey relational coefficients and it can be calculated using following equation.

$$\gamma i = \sum_{j=1}^{n} w_j . \gamma ij \quad i = 1, 2 \ldots m \text{ and } j = 1, 2 \ldots n \quad (5)$$

In above equation γ_i is the grey relational grade between comparability sequence X_i and reference sequence X_n. It represents correlation between the reference sequence and the comparability sequence. w_j is the weight of response surface *j* and depends on decision maker's judgment.

6.Analysis and discussion of Experimental Results

In the present study, Grey relational analysis was used to make a trade off among conflicting multi objectives namely surface roughness and material removal rate by considering two type of machining cut like semi-finishing and finishing with five controllable parameters. The values of the parameter level in 27 experimental runs as per orthogonal array (L_{27}) are set to be the comparability sequences for five controllable parameters as shown in Table 3. Data pre-processing was calculate from Equation 1 & 2 for material removal rate & surface roughness respectively, and the normalized results were tabulated in Table 3. The deviation sequences were calculated using the same method above with the help of Equation (4).

Table 3: Calculated data pre processing and its deviations

Trial No.	Data Pre Processing		Deviation	
	x_{Ra}	x_{MRR}	Δ_{R_a}	Δ_{MRR}
1	0.8544	0.0000	0.1456	1.0000
2	0.7783	0.0611	0.2217	0.9389
3	0.7795	0.1099	0.2205	0.8901
4	0.9417	0.3524	0.0583	0.6476
5	0.5281	0.4008	0.4719	0.5992
6	0.6378	0.6431	0.3622	0.3569
7	0.8561	0.5186	0.1439	0.4814
8	0.4787	0.7919	0.5213	0.2081
9	0.7842	1.0000	0.2158	0.0000
10	0.2995	0.4439	0.7005	0.5561
11	0.4838	0.5901	0.5162	0.4099
12	0.9000	0.8006	0.1000	0.1994
13	0.1570	0.1461	0.8430	0.8539
14	0.4064	0.2040	0.5936	0.7960
15	0.8136	0.3163	0.1864	0.6837
16	1.0000	0.1856	0.0000	0.8144
17	0.9183	0.1630	0.0817	0.8370
18	0.8493	0.2926	0.1507	0.7074
19	0.0000	0.3380	1.0000	0.6620
20	0.0732	0.5779	0.9268	0.4221
21	0.8736	0.7097	0.1264	0.2903
22	0.7242	0.2079	0.2758	0.7921
23	0.5349	0.3411	0.4651	0.6589
24	0.7127	0.4722	0.2873	0.5278
25	0.6259	0.0637	0.3741	0.9363
26	0.4463	0.1884	0.5537	0.8116
27	0.8157	0.2678	0.1843	0.7322

To obtain the grey relational coefficients, the deviation sequences and the distinguishing coefficient were substituted in Equation (3). The grey relational grade can be calculated by using equation (5) which is the overall representative of both the responses which is shown for semi-finishing and finishing machining cut in Table 4.

Table 4: Calculated grey relational grade (GRA) and its Rank in optimization process

Trial No.	γ_{Ra}	γ_{MRR}	*Semi-Finishing (w_{Ra} = 0.5 & w_{MRR} = 0.5)*		*Finishing (w_{Ra} = 0.7 & w_{MRR} = 0.3)*	
			Grade	*Rank*	*Grade*	*Rank*
1	0.7745	0.3333	0.5539	14	0.6422	9
2	0.6928	0.3475	0.5201	17	0.5892	14
3	0.6940	0.3597	0.5268	15	0.5937	12
4	0.8955	0.4357	0.6656	5	0.7576	4
5	0.5144	0.4549	0.4847	19	0.4966	20
6	0.5799	0.5835	0.5817	10	0.5810	15
7	0.7766	0.5095	0.6430	6	0.6964	7
8	0.4896	0.7061	0.5978	8	0.5545	17
9	0.6985	1.0000	0.8493	1	0.7890	3
10	0.4165	0.4734	0.4450	23	0.4336	24
11	0.4920	0.5495	0.5208	16	0.5093	18
12	0.8333	0.7149	0.7741	2	0.7978	2
13	0.3723	0.3693	0.3708	27	0.3714	26
14	0.4572	0.3858	0.4215	25	0.4358	23
15	0.7284	0.4224	0.5754	11	0.6366	10
16	0.9999	0.3804	0.6902	4	0.8141	1
17	0.8595	0.3740	0.6167	7	0.7138	6
18	0.7684	0.4141	0.5913	9	0.6621	8
19	0.3333	0.4303	0.3818	26	0.3624	27
20	0.3504	0.5422	0.4463	22	0.4080	25
21	0.7982	0.6326	0.7154	3	0.7485	5
22	0.6445	0.3870	0.5157	18	0.5672	16
23	0.5181	0.4314	0.4748	20	0.4921	21
24	0.6351	0.4865	0.5608	13	0.5905	13
25	0.5720	0.3481	0.4601	21	0.5049	19
26	0.4745	0.3812	0.4279	24	0.4465	22
27	0.7307	0.4058	0.5682	12	0.6332	11

According to the performed experiment design it is clearly observed from Table 4 that the semi finishing of end milling process having parameters setting of experiment no. 9 has the highest grey relational grade and finishing process experiment no. 16 has highest grey relational grade. In this work, considering trade off among conflicting multi-objectives then experiment no. 9 is given best compromising result because GRA is high for experiment no. 9 in comparison of experiment no. 16, another thing is that experiment no. 9 has good value of surface roughness with high value of material removal rate. Therefore, surface roughness is compromised in increasing value of material removal rate. Thus the experiment 9 gives the best compromising multi performance characteristics among the 27 experiments.

Since the Grey relational grades show the level of correlation between the reference and the comparability sequences, the larger Grey relational grade means the comparability sequence exhibiting a stronger correlation with the reference sequence. Based on this study, one can select a combination of the levels that provide the best values for responses.

As per concept of Taguchi method, the statistic delta defined as the difference between the high and the low effect of each parameter, was used. A classification can be done to determine the most significant parameter. When so done, the multiple objective optimization problems are transformed into a single equivalent objective function optimization problem. The higher grey relational grade will be close to the optimal condition. Using the grey relational grade value, the mean of the grey relational grade for each level of different parameters, and the total mean of the grey relational grade is summarized in Table 5.

Table 5: Response table for the mean Grey relational grade

	Grey Grade Analysis for Control Parameter				
Levels	SiC% (A)	SPEED (B) (rpm)	FEED (C) (mm/m)	DEPTH OF CUT(D) (mm)	Cutter Dia (E) (mm)
1	**0.603**	0.5427	**0.5611**	0.4916	0.5251
2	0.5562	0.5168	0.5476	0.5749	0.5012
3	0.5057	**0.6049**	0.5557	**0.5979**	**0.6381**
Delta	0.0969	0.0882	0.0136	0.1063	0.1369
Rank	3	4	5	2	1

(Total mean Grey relational grade = **0.558**)

Then a response graph of the grey relational analysis is obtained by main effect analytic computation, as shown in Figure 8.

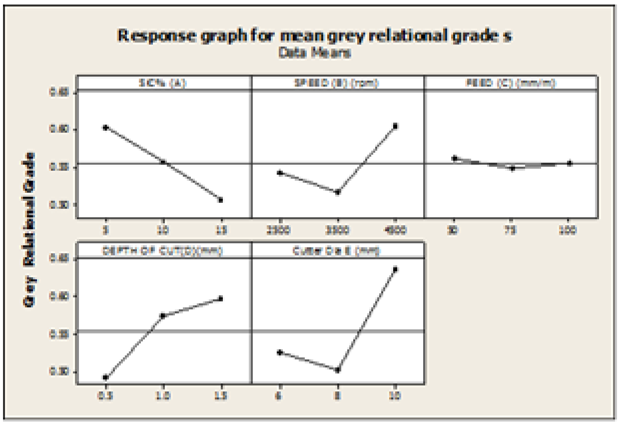

Figure 8: Response graph for mean grey relational grades

From Table 5 and Figure 8, the optimal parameter combination of A_1, B_3, C_1, D_3 and E_3 shows the highest value of the Grey relational grade i.e SiC of 5%, cutting speed of 4500 rpm, feed of 50 mm/min, depth of cut of 1.5 mm and cutter diameter of 10 mm. Therefore compromising surface roughness with high value of material removal rate is obtained for the end milling operation

7. Analysis of Variance

ANOVA is a statistical technique that is used in determining the level of significance of significant parameters. It separates the total variance of the response into contributions rendered by each of parameters. ANOVA was performed for Grey relational grade value to identify the most significant parameters tabulated in Table 6. It is observed that the cutter diameter (27.21%) is most significant parameter.

Table 6: Results of ANOVA

Source	Degree of Freedom (DF)	Adjusted Sum of Squares	Mean Square Value	F_{exp} = MSV/MSV_e	P-Value	% Contribution
SiC%	2	0.042271	0.021136	4.56	0.093	11.95
SPEED	2	0.036959	0.01848	3.99	0.112	10.45
FEED	2	0.000842	0.000421	0.09	0.915	0.24
DEPTH	2	0.056251	0.028126	6.07	0.061	15.90
Cutter Dia	2	0.09628	0.04814	10.39	0.026	27.21
SiC% *Cutter Dia	4	0.017388	0.004347	0.94	0.524	4.91
SPEED *Cutter Dia	4	0.02251	0.005627	1.21	0.428	6.36
FEED *Cutter Dia	4	0.062786	0.015696	3.39	0.132	17.75
Error	4	0.018535	0.004634			5.24
Total	26	0.353823				100

Figure 9 shows the percentile contribution of various input control parameters simultaneously over both surface roughness and material removal rate values.

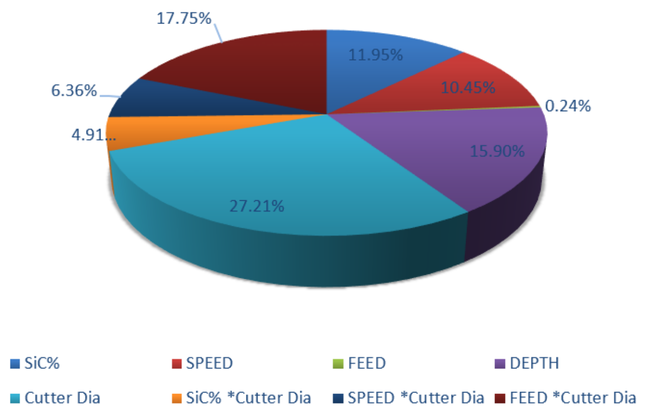

Figure 9: Percentile contribution of parameters

8. Regression Modeling

Regression models can be used to predict the response output behavior by taking different input independent parameters values and grey relational grades associated with each test response results. Equation (6) shows the general form of quadratic regression model.

GRA $= a + b*A + c*B + d*C + e*D + f*E + g*A^2 + h*B^2 + i*C^2 + j*D^2 + k*E^2 + l*A*E + m*B*E + n*C*E + o*D*E$ (6)

In the above formula a, b, c, d, e, f, g, h, i, j, k, l, m, n & o are the regression coefficients to be estimated. In this study, based on the GRA data given in Table 4, the regression model is developed and regression coefficients obtained using DataFit software. The independent variables in model (7) are weight percentage of SiC (A), cutting speed (B), feed rate (C) depth of cut (D) and cutter diameter (E).

GRA $= 2.888836577 - 0.034112223*A - 0.000228111*B - 0.013719556*C + 0.150311112*D - 0.392618750*E - 0.000083778*A^2 + 0.000000057*B^2 + 0.000017369*C^2 - 0.120311111*D^2 + 0.020109722*E^2 + 0.003262500*A*E - 0.000017504*B*E + 0.001375667*C*E + 0.024575000*D*E$
(7)

9. Model validation and ANOVA Results

Analysis of variance (ANOVA) is a mathematical way to determine precision and adequacy of regression modeling. It shows how well the proposed model fits the experimental data and, therefore, represents the actual process under study [18]. It is also a powerful tool in analyzing the variable effects on the process output responses. A summary of ANOVA results for regression model have been presented in Table 7. Based on the statistical analysis results, the coefficient of determination (R^2) for this model is equal to 91.59%. This indicates that the model has good compatibility to the actual data. The p-value of the model is also close to zero which shows the model is good at 95% confidence level. These demonstrate the appropriate compliance of the model with the actual test results.

Table 7: Result of ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio	p
Regression	14	0.3241005	0.02315	9.3467286	0.00021
Error	12	0.0297217	0.0024768		
Total	26	0.3538221			

10. Confirmation Test for Proposed Methodology

The grey relational grade value is 0.6736 at combination $A_1B_3C_1D_3E_3$ was calculated from regression equation (7). This GRA value validate that the proposed grey-taguchi approach is good for trade off among conflicting multi objectives of CNC end milling process for composite material LM 6/Al SiC_p.

11. Conclusion

This research work successfully demonstrated a methodology for making trade off among conflicting multiple objectives of CNC end milling process for composite material LM 6/Al SiC_p and validate that methodology with using the regression models. The conclusions can be drawn from the present work were as follows:

(a) The highest Grey relational grade of 0.849 was observed for the semi-finishing milling process in experiment no. 9, shown in Table 4. So, we can say that experiment no. 9 among performed 27 experiments has best combination $A_1B_3C_3D_3E_3$ for controllable parameters.
(b) Proposed grey-taguchi methodology given best combination $A_1B_3C_1D_3E_3$ which is not in the range of performed 27 experiments.
(c) Regression model validate proposed methodology by obtaining good GRA value.
(d) The most significant parameter in the minimizing surface roughness (R_a) and maximizing material removal rate (MRR), is cutter diameter.

As a result, this methodology can be effectively applied for optimizing multiple objective problem. This methodology also is found efficient for determining the optimal combination of parameter levels.

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