

## Optimization of machining parameters in drilling hybrid aluminium metal matrix composites

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**Abstract:** Taguchi method with grey relational analysis was used to optimize the machining parameters with multiple performance characteristics in drilling hybrid metal matrix Al356/SiC-mica composites. Experiments were conducted on a computer numerical control vertical machining centre and  $L_{18}$  orthogonal array was chosen for the experiments. The drilling parameters namely spindle speed, feed rate, drill type and mass fraction of mica were optimized based on the multiple performance characteristics including thrust force, surface roughness, tool wear and burr height (exit). The results show that the feed rate and the type of drill are the most significant factors which affect the drilling process and the performance in the drilling process can be effectively improved by using this approach.

**Key words:** hybrid composites; Grey relational analysis; Taguchi method

### 1 Introduction

Metal matrix composites (MMCs) have become a large leading material in composite materials, and particle reinforced aluminium MMCs have received considerable attention due to their excellent engineering properties. 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 [1]. The application fields of MMCs include aerospace, defense and automotives [2]. Hybrid MMCs were obtained by reinforcing the matrix alloy with more than one type of reinforcements having different properties [3]. The Al-based hybrid composites, with 20% SiC whiskers and 0, 2%, 5%, 7% SiC nano particles, were fabricated by squeeze casting route [4]. In the view of the growing engineering applications of these composites, a need for detailed and systematic study of their machining characteristics is envisaged. The efficient and economic machining of these materials is required for the desired dimensions and surface finish [5].

Taguchi technique is a powerful tool in experiment design. It provides a simple, efficient and systematic approach for optimization, quality and cost [6]. The methodology is valuable when the design parameters are qualitative and discrete [7]. Optimum machining condition in turning A356/SiC/20p metal matrix composites for minimizing the surface roughness was determined using desirability function approach [8]. UDAY et al [9] presented an elaborative experimentation using Taguchi methods on four Al/SiC composites to analyze the effects of size (15 and 65  $\mu\text{m}$ ) and volume fraction (20% and 30%) of the reinforcements in the composites on machining forces and machined surface roughness. KREMER et al [10] investigated the effect of SiC content in the Al/SiC particulate metal-matrix composites on the machinability. Artificial neural networks (ANN) based model was used for the prediction of the surface roughness during the machining of composite material using back propagation algorithm [11]. The effect of machining parameters on the surface roughness was evaluated and optimum machining conditions for maximizing the metal removal rate and

minimizing the surface roughness were determined using response surface methodology in the turning of particulate MMCs [12].

For the practical MMC materials, it is necessary to determine the optimal machining parameters to achieve better performance such as less tool wear and good surface finish. In the grey system theory, the grey relational analysis (GRA) is a method used to analyze the relationship between sequences, using less data and multi-factor. It is considered to be more advantageous than the statistical regression analysis. The GRA was successfully applied for the manufacturing process [13]. Taguchi-grey relational method was used to study the boro-carburizing and boronizing of AISI 1015 steel on the tensile strength [14]. Taguchi method with GRA was used for the optimization of PTA-processing in hard facing of WC/W<sub>2</sub>C-reinforced Ni-based MMC, considering multiple quality characteristics of the microstructure parameters relevant to abrasion resistance [15]. Using grey relational analysis, the multi-criteria weighted average was proposed in decision-making process to rank the materials with respect to several criterias [16].

The optimum combination of various input factors, including type of abrasive slurry, their size and concentration, nature of tool material and power rating of the machine for the ductile chip formation in the machining of Stellite 6, was determined by applying the Taguchi multi-objective optimization technique and F-test [17]. The design of experiments was utilized to create a model of the ironing process [18].

TOSUN [19] used GRA in optimizing the drilling parameters. KUO et al [20] applied Taguchi method and GRA for optimizing the multi-response simulation problems. KAO and HOCHENG [21] used the GRA for optimizing the electro polishing of 316L stainless steel with multiple performance characteristics like surface roughness and passivation strength. RAMAKRISHNAN and KARUNAMOORTHY [22] used ANN model and multi-response optimization technique to predict performance characteristics, namely material removal rate and surface roughness, to select the best cutting parameters of wire electro-discharge machining of Inconel 718. Analysis of variance (ANOVA) was also employed to identify the level of importance of the machining parameters on the multiple performance characteristics. CHIANG and CHANG [23] implemented GRA for optimizing the wire electric discharge machining process of Al<sub>2</sub>O<sub>3</sub> particle-reinforced material (6061 alloy) with multiple performance characteristics. GRA and the principal component analysis are applied to evaluate the optimal combination of cutting parameters and weighting values corresponding to various performance characteristics in high-speed end milling on

SKD61 tool steel [24]. The basic idea of GRA is to find a grey-relational grade (GRG), which can be used for optimizing the conversion from a multi-objective case to a single-objective case. GRG was also used to estimate the parameter effects on the overall performance response [25]. TZENG et al [26] investigated the optimization of CNC turning operation parameters for SKD11 (JIS) using the grey relational analysis method.

Mica is a lamellar solid which requires more energy than graphite to shear over the laminar planes [27]. Traditionally, mica is a natural lubricant which eases the machining operation. A review of literatures indicates that the study on machining of Al/SiC–mica composites is very limited. This study presented the optimization in drilling of Al/SiC–mica composites to minimize the thrust force, surface roughness, burr height and tool wear using Taguchi method with grey relational analysis (TGRA) considering multiple performance characteristics. Eighteen experimental runs based on Taguchi orthogonal array were conducted to determine the best factor level combination. The influence of the control factors such as the mass fraction of mica, drill type, spindle speed and feed rate were studied by assessing the single weighted GRA.

## 2 Experimental

### 2.1 Material

The matrix material used for the fabrication of composites was aluminum alloy Al356 and its chemical composition is presented in Table 1. The reinforcing materials used were silicon carbide and mica. The silicon carbide particles size used was 25 μm and the average size of mica used was 45 μm. The composites were fabricated with 0 and 3% (mass fraction) mica. The silicon carbide particles used for fabricating the composites was fixed at 10%.

**Table 1** Composition of Al 356 alloy (mass fraction, %)

Cu	Si	Mg	Mn
<0.0005	7.27	0.45	<0.002
Fe	Ti	Zn	Al
0.123	0.08	0.005	Bal.

The composites were fabricated by stir casting method as it ensured the uniform distribution of the reinforcements [28]. In the process of preparing the composites, the Al 356 aluminium alloy in the form of ingot was cut into small pieces to accommodate in the silica crucible. The aluminum alloy was melted in an electric muffle furnace with crucible. Mica and SiC preheated at about 620 °C were added to the molten metal at 750 °C and stirred continuously. The stirring

was done at 500 r/min for 5–7 min. Magnesium was added in small quantity during stirring to increase the wetting. The melt with reinforcement was poured into permanent metallic mould to get the required shape and size of the work piece.

## 2.2 Experimental design

Taguchi method which is a powerful tool in parameter design was used for conducting the experiments.  $L_{18}(2^1 \times 3^7)$  orthogonal array with 18 rows (corresponding to the number of experiments) was used for the experiment. It provided a simple, efficient and systematic approach to optimize the design for performance, quality and cost. The methodology is valuable when the design parameters are qualitative and discrete [7]. Table 2 lists the drilling parameters used as control factors and the levels.

**Table 2** Machining parameter and levels

Control parameter	Symbol	Level		
		1	2	3
Content of mica/%	A	0	3	–
Drill type	B	Carbide	TiN coated carbide	Polycrystalline diamond
Spindle speed/ ( $r \cdot \text{min}^{-1}$ )	C	1000	2000	3000
Feed rate/ ( $\text{mm} \cdot \text{min}^{-1}$ )	D	50	100	150

## 2.3 Experimental procedure

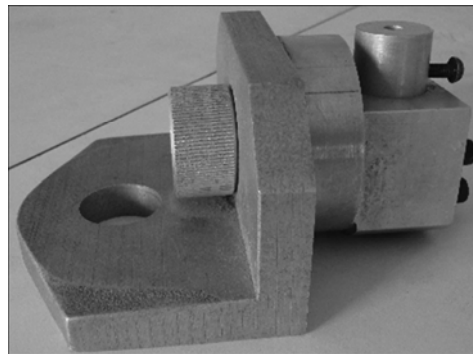
The drilling experiments were conducted on a computer numerical control (CNC) vertical machining centre (VMC 100), manufactured by ARIX CNC machine Co. Ltd., Taiwan, China. The dimensions of the work piece samples used for conducting the experiments were 100 mm×100 mm×10 mm. The drill size was 6 mm in diameter and its helix angle was 30°, the point angle used was 118°. The drills used were carbide, TiN coated carbide and polycrystalline diamond (PCD) manufactured by SANDVIK (India). The hardness of the drill material was HRC 72, 80 and 90, respectively.

The thrust force in drilling of the composite materials was captured by using computer controlled data acquisition system. The dynamometer used for capturing the thrust force signals in drilling was Kistler made. The dynamometer was connected to a 3-channel charge amplifier through a connecting cable, which in turn was connected to the computer by a 37-pin cable from the A/D board. The signals were captured and stored in a computer for analysis. The surface roughness of the work piece hole was measured by using Mitutoyo portable SurfTest SJ-201 P/M contact profilometer with a cut-off value of 2.4 mm. The measurements were taken

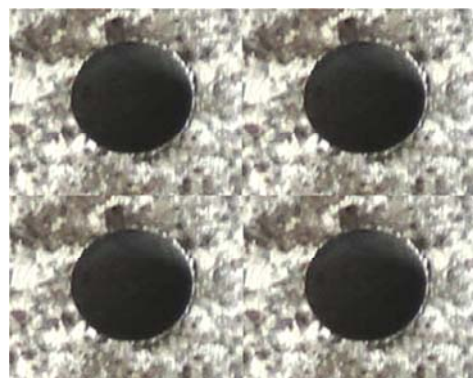
perpendicularly to the circumference of the hole [28]. The surface roughness values given in this study were the mathematical average of two measurements taken from the same hole surface.

One of the biggest challenges in burr research was burr measurement. The burr height has been measured by several methods such as contact method, optical microscope method, optimal CMM method and rubber casting method. In the present study, the burr height (exit) of the drilled holes was measured with the help of coordinate measuring machine (CMM), BROWN and SHARP made. The burr heights were measured at 4 different places. In each measurement, the distance of the highest peak to the deepest valley was measured, then the average value was taken for analysis.

After drilling 10 through holes for each experimental run, the degree of flank wear was measured by using optical microscope Metzer 1395A. Measurement of tool wear in drill was comparatively more difficult than measurement of the wear of a single point tool. A special fixture was designed and fabricated to measure the flank wear, as presented in Fig. 1. The drill tool was supported by a bush in the fixture to determine the degree of flank wear. In addition, the damage and the wear features of the drill wear were investigated using scanning electron microscope (SEM). The experimental results are summarized in Table 3. The photographs of the machined samples are presented in Fig. 2.



**Fig. 1** Photo of fixture used for determining drill wear



**Fig. 2** Photograph of machined composites

**Table 3** Experimental results using  $L_{18}$  orthogonal array

No.	Content of mica/%	Drill type	Spindle speed/ ( $r \cdot \text{min}^{-1}$ )	Feed rate/ ( $\text{mm} \cdot \text{min}^{-1}$ )	Thrust force/ N	Surface roughness/ $\mu\text{m}$	Tool wear/ mm	Burr height/ mm
1	0	Carbide	1000	50	565	4.5	0.158	0.165
2	0	Carbide	2000	100	650	5.1	0.225	0.284
3	0	Carbide	3000	150	735	3.7	0.315	0.345
4	0	Coated	1000	50	585	4.2	0.145	0.185
5	0	Coated	2000	100	675	4.2	0.215	0.302
6	0	Coated	3000	150	755	3.5	0.3	0.365
7	0	PCD	1000	100	585	4.1	0.132	0.194
8	0	PCD	2000	150	690	4.2	0.182	0.315
9	0	PCD	3000	50	590	2.75	0.274	0.2
10	3	Carbide	1000	150	680	5.6	0.14	0.312
11	3	Carbide	2000	50	560	4.35	0.2	0.183
12	3	Carbide	3000	100	635	3.4	0.285	0.306
13	3	Coated	1000	100	730	5.1	0.125	0.225
14	3	Coated	2000	150	745	4.5	0.201	0.345
15	3	Coated	3000	50	625	3.35	0.285	0.325
16	3	PCD	1000	150	600	5.1	0.113	0.205
17	3	PCD	2000	50	520	3.4	0.168	0.118
18	3	PCD	3000	100	605	3.75	0.241	0.185

### 3 Grey relational analysis

Grey theory is one of the important theories and can be used for analyze the uncertainty, multi-input and discrete data. A grey system has a level of information between black and white. The grey relational analysis is a measurement of the absolute value of the data difference between sequences, and is also used to measure an approximate correlation between sequences. It is an effective means of analyzing the relationship between the sequences with less data and can analyze many factors [13]. In the present investigation, the problem has four performance characteristics that need to be minimized by choosing appropriate processing conditions. The performance characteristics used are thrust force, surface roughness, tool wear and burr height. The grey relational analysis deals with the ranks and not with the real value of the grey relational grade.

#### 3.1 Analysis approach

The experiments were conducted according to Taguchi's orthogonal array in 18 different experiments. For GRA, these 18 experiments became 18 subsystems. The influence of these subsystems on the response variable was analyzed by using GRA technique. The drilling process (system) was assessed by conducting 18

experiments (subsystems) and each experiment was termed as comparability sequence. The parametric conditions corresponding to the highest weighted GRG gave minimum values of the thrust force, surface roughness, tool wear and burr height. In this manner, the multi-objective problem was converted into single objective optimization using GRA technique.

#### 3.2 Formulation of problem

PAWADE and JOSHI [29] reported the steps involved in the formulation of the multi objective problem i.e., the multi-objective optimization problem under investigation can be stated as the minimization of  $f$  (thrust force, surface roughness, tool wear and burr height), subject to independent decision variables as: content of mica, drill type, spindle speed and feed rate. Furthermore, the above multi-objective problem can be converted into a single optimization problem using GRG, such as the maximization of GRG,  $0 \leq \text{GRG} \leq 1$ , subjected to independent decision variables.

#### 3.3 Methodology

GRA involves the following steps [13–24]: 1) compute S/N ratio of the quality characteristics; 2) normalize the S/N ratio of the quality characteristics; 3) calculate the grey relational coefficient; 4) calculate the GRG by averaging the grey relational coefficient; 5)

analyze the experimental results using the GRG and the statistical analysis of variance; 6) select the optimal levels of process parameters; and 7) verify the optimal parameters through the confirmation experiment.

3.3.1 S/N ratio to compute quality characteristics

During the drilling of hybrid metal matrix composites, thrust force, surface roughness, tool wear and burr height have been considered as smaller-the-better type. These considerations have been made with respect to greater quality characteristics of interest. Hence, the S/N ratio  $\eta$  of the quality characteristics (smaller-the-better type) are computed as:

$$\eta = -10 \lg \left[ \frac{1}{n} \sum_{i=1}^n y_{ij}^2 \right] \tag{1}$$

where  $n$  is the number of replications;  $y_{ij}$  is the observed response value, and  $i=1, 2, \dots, n; j=1, 2, \dots, k$ .

3.3.2 Normalize S/N ratio of quality characteristics (data pre-processing)

In the GRA, S/N ratio of quality characteristics is normalized first to reduce the variability. This known data pre-processing is normally required because the range and the unit in one data may differ from others. Data pre-processing is a means of transferring the original sequence to a comparable sequence, so the data is normalized between 0 and 1. Depending on the characteristics of the data sequence, there are various methodologies of data pre-processing available. If the target value of the original sequence is infinite, then it has a characteristic of higher-the-better. The original sequence can be normalized as [13–24]:

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{2}$$

When the lower-the-better characteristic of the original sequence is considered, then the original sequence should be normalized as:

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{3}$$

However, if there is a definite target value (desired value) to be achieved, the original sequence can be normalized as:

$$x_i^*(k) = 1 - \frac{|x_i^0(k) - x_i^0|}{\max x_i^0(k) - x_i^0} \tag{4}$$

Or the original sequence can be simply normalized by the most basic methodology, i.e. the values of original sequence can be divided by the first value of the sequence as:

$$x_i^*(k) = \frac{x_i^0(k)}{x_i^0(1)} \tag{5}$$

where  $x_i^0(k)$  is the original sequence;  $x_i^*(k)$  is the sequence after the data pre-processing;  $x_i^0(1)$  is the first value of the sequence;  $\max x_i^0(k)$  is the largest value of  $x_i^0(k)$ ;  $\min x_i^0(k)$  is the smallest value of  $x_i^0(k)$  and  $x_i^0$  is the desired value.

3.3.3 Grey relational coefficient and grey relational grade

The grey relational analysis is used to measure the relevancy between two systems. The sequences used in the grey relational analysis are called a grey relational coefficient. The grey relational coefficient ( $k$ ) can be calculated as:

$$\xi_i(k) = \frac{\Delta_{\min} + \xi \Delta_{\max}}{\Delta_{0_i}(k) + \xi \Delta_{\max}} \tag{6}$$

where  $\Delta_{\min}$  is the smallest value of  $\Delta_{0_i}(k)$ ,  $\Delta_{\max}$  is the largest value of  $\Delta_{0_i}(k)$ .

$$\Delta_{\min} = \min_i \min_k \|x_0^*(k) - x_i^0(k)\| \tag{7}$$

$$\Delta_{\max} = \max_i \max_k \|x_0^*(k) - x_i^0(k)\| \tag{8}$$

$\Delta_{0_i}$  is the absolute value of the difference between  $x_i^0(k)$  and  $x_i^*(k)$  and it is also known as the deviation sequence and  $\xi$  is the distinguishing coefficient. The value of  $\xi$  can be adjusted with the systematic actual need and defined in the range between 0 and 1,  $\xi \in [0, 1]$ . If the value of the  $\xi$  is smaller, then the distinguished ability is larger. In general,  $\xi = 0.5$  is used.

$$\Delta_{0_i} = \|x_0^*(k) - x_i^0(k)\| \tag{9}$$

$$\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} \|x_0^*(k) - x_j^*(k)\| \tag{10}$$

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \|x_0^*(k) - x_j^*(k)\| \tag{11}$$

where  $x_0^*(k)$  is the ideal normalized S/N ratio;  $x_i^0(k)$  is the normalized comparability sequence.

After the Grey relational coefficient is derived, the average value of the grey relational coefficient is taken as the GRG. The GRG is defined as:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \tag{12}$$

However, in a real engineering system, the importance of various factors in the system varies according to the real condition of an unequal weight being carried out by various factors. The GRG in Eq. (12) is extended and defined as:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n w_k \xi_i(k) \tag{13}$$

where  $w_k$  denotes the normalized weight of factor  $k$ . If  $w_k$  is same for all the factors then, Eqs. (11) and (12) are

equal. The GRG indicates the degree of influence by the comparability sequence over the reference sequence. If a particular comparability sequence is more important than the other comparability sequences to the reference sequence, then the GRG for that comparability sequence and reference sequence are higher than other GRG.

It is known that, lower thrust force, surface roughness, tool wear and burr height provide better quality of the machined surface. Thus, the data sequences of responses have smaller-the-better characteristics. The smaller-the-better methodology as expressed in Eq. (1) is used for determining the S/N ratio. The S/N ratio values of the response variables are shown in Table 4. The S/N ratio values are normalized using Eq. (3). The minimum thrust force, surface roughness, tool wear and the burr height are set as a reference sequence  $x_i^{(0)}(k)$ , and the results of the 18 experiments have the comparability sequences  $x_i^{(0)}(k)$ ,  $i=1-18$ ,  $k=1-4$ . All the sequences after normalization are denoted as  $x_0^*(k)$  (ideal normalized S/N ratio) for reference sequence and  $x_i^*(k)$  comparability sequence. The larger value of normalized results can indicate the better performance characteristics, and the best-normalized results are equal to 1. Then, the deviation sequences,  $\Delta 0_i(k) = |x_0^{(0)}(k) - x_i^*(k)|$  are determined using Eq. (9) and are listed in Table 5.

**Table 4** S/N ratio of experimental results

No.	S/N ratio of responses/dB			
	Thrust force	Surface roughness	Tool wear	Burr height
1	-55.04096896	-13.0643	16.02686	15.65032
2	-56.25826713	-14.1514	12.95635	10.93363
3	-57.32574678	-11.364	10.03379	9.243618
4	-55.34311732	-12.465	16.77264	14.65657
5	-56.58607546	-12.465	13.35123	10.39986
6	-57.55893903	-10.8814	10.45757	8.754143
7	-55.34311732	-12.2557	17.58852	14.24397
8	-56.77698181	-12.465	14.79857	10.03379
9	-55.41704023	-8.78665	11.24499	13.9794
10	-56.65017825	-14.9638	17.07744	10.11691
11	-54.96376054	-12.7698	13.9794	14.75098
12	-56.05547451	-10.6296	10.9031	10.28557
13	-57.2664572	-14.1514	18.0618	12.95635
14	-57.44312545	-13.0643	13.93608	9.243618
15	-55.91760035	-10.5009	10.9031	9.762333
16	-55.56302501	-14.1514	18.93843	13.76492
17	-54.32006687	-10.6296	15.49381	18.56236
18	-55.63510749	-11.4806	12.35966	14.65657

**Table 5** Data of 18 comparability sequences

Experiment run (comparability sequence)	Deviation sequence $\Delta 0_i(k) =  x_0^{(0)}(k) - x_i^*(k) $			
	Thrust force, $\Delta 0_1(k)$	Surface roughness, $\Delta 0_2(k)$	Tool wear, $\Delta 0_3(k)$	Burr height, $\Delta 0_4(k)$
1	0.777422	0.307508	0.673028	0.703102134
2	0.401582	0.131511	0.328206	0.222210669
3	0.071998	0.582753	0	0.049904624
4	0.684134	0.404522	0.75678	0.601783447
5	0.300371	0.404522	0.372552	0.167789763
6	0	0.660892	0.047592	0
7	0.684134	0.438406	0.848404	0.559716675
8	0.241429	0.404522	0.53509	0.13046675
9	0.66131	1	0.136019	0.532742832
10	0.280579	0	0.791009	0.138941195
11	0.80126	0.355178	0.443096	0.611409332
12	0.464194	0.701652	0.097625	0.156137322
13	0.090304	0.131511	0.901553	0.428437387
14	0.035757	0.307508	0.438231	0.049904624
15	0.506762	0.722485	0.097625	0.10279035
16	0.616237	0.131511	1	0.510875727
17	1	0.701652	0.613166	1
18	0.593982	0.563878	0.261197	0.601783447

Next, the grey relational coefficient is calculated. In this study, all the machining parameters influence the responses equally. Considering equal weight, the distinguishing coefficient  $\zeta=0.5$  is substituted in Eq. (6). Then, the weighted GRG is determined by Eq. (12). Table 6 lists the grey relational coefficient and weighted grey relational grade for each experiment using the  $L_{18}$  orthogonal array. A higher weighted GRG indicates that the corresponding S/N ratio is closer to the ideally normalized S/N ratio. It is observed from the results that the experiment number 17 has the highest weighted GRG; therefore, it can be considered as a best experimental sequence for multiple performance of the process.

The GRA is further analyzed by using response tables and response graphs. For example, considering the first column in the orthogonal array, the runs No. 1–9 are the experimental runs, in which factor A is set at level 1. The average sum of these values corresponds to the average response value at that level. The mean response table for the overall GRG is listed in Table 7 and represented graphically in Fig. 3. The steep slope of GRG graph (means plot) indicates more influence of machining parameters in the performance characteristics. In the present case, the effects of feed rate and drill have greater influence as can be seen from their steep slope. A horizontal line in this figure is the value of the overall

mean of the weighted GRG. Basically, the larger the grey relational grade is, the better the multiple performance characteristics are. From the GRG graph, the optimal parametric combination is determined. The optimal factor setting is  $A_2 B_3 C_1 D_1$ , i.e., the mass fraction of mica at level 2 (3%), drill type at level 3 (PCD), spindle speed at level 1 (1000 r/min), and feed rate at level 1 (50 mm/min).

## 4 Results and discussion

### 4.1 Effect of content of mica on grey relational grade

The mechanism in drilling of metal matrix composite is due to the application of thrust by the drill on the composite materials. The mechanism of drilling depends on the content of reinforcement particles embedded in the matrix, type of drill used, cutting conditions used, etc. The increase in mica content increases the surface roughness for all cutting conditions. Less dense mica compared to SiC acts as a weak spot region. When the tool passes over these regions, the crushed mica particles form a deep gorge and hence increase the surface roughness of the material. Similar result was given by MURALIKRISHNAN and RAJA [30]. The removed mica particles get smeared on the machined surface, this smeared mica layer also

**Table 6** Calculated grey relational coefficient and weighted GRG for 18 comparability sequences

Experiment run (comparability sequence)	Grey relational coefficient				Weighted GRG
	Thrust force, $\Delta 0_1(k)$	Surface roughness, $\Delta 0_2(k)$	Tool wear, $\Delta 0_3(k)$	Burr Height, $\Delta 0_4(k)$	
1	0.691967	0.41929	0.604615	0.627433	0.5858262
2	0.4552	0.365366	0.426696	0.391301	0.4096409
3	0.35014	0.545109	0.333333	0.344805	0.39334678
4	0.612846	0.456422	0.672748	0.556659	0.57466844
5	0.416796	0.456422	0.443479	0.375316	0.42300321
6	0.333333	0.595871	0.344256	0.333333	0.40169831
7	0.612846	0.47099	0.767346	0.531755	0.59573416
8	0.397276	0.456422	0.518183	0.365088	0.43424211
9	0.596168	1	0.366574	0.516926	0.61991687
10	0.410031	0.333333	0.705227	0.367361	0.45398814
11	0.715574	0.436749	0.47308	0.562689	0.54702291
12	0.482716	0.626294	0.356538	0.372062	0.45940232
13	0.354686	0.365366	0.835496	0.466608	0.50553938
14	0.341473	0.41929	0.470912	0.344805	0.39412016
15	0.503404	0.643074	0.356538	0.357856	0.46521809
16	0.565763	0.365366	1	0.505498	0.60915672
17	1	0.626294	0.563803	1	0.79752429
18	0.551865	0.534118	0.403616	0.556659	0.51156452

**Table 7** Response table for grey relational grade

Symbol	Machining parameter	Grey relational grade		
		Level 1	Level 2	Level 3
A	Content of mica/%	0.493	0.527*	–
B	Drill	0.474	0.46	0.594*
C	Speed/(r·m <sup>-1</sup> )	0.554*	0.5	0.475
D	Feed rate/(mm·min <sup>-1</sup> )	0.6*	0.499	0.447

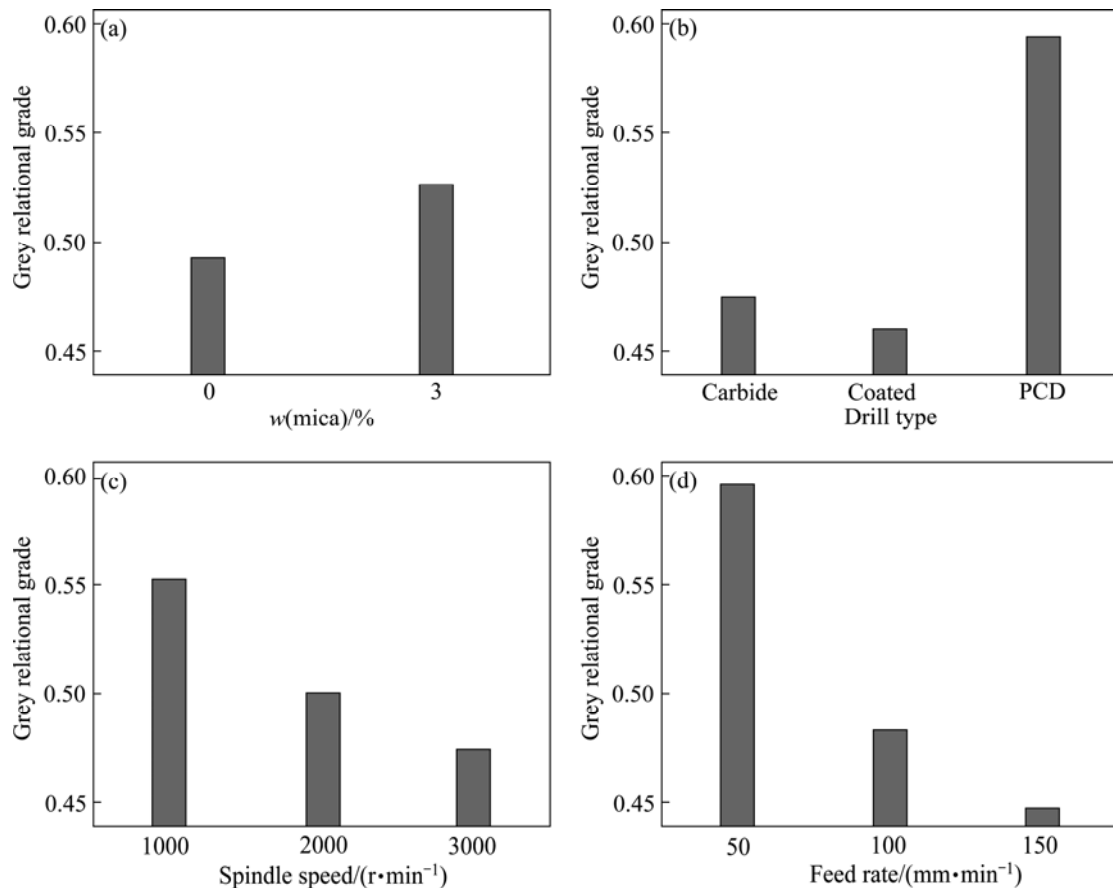
\*Levels for optimum GRG

lowers the coefficient of friction. Also the buffing effect of the trapped SiC is reduced when mica is encountered at the surface of the material [28]. The addition of 3% mica reduces the thrust forces significantly, and is attributed to the solid lubricating property of the mica particles. The mica particles reduce the interfacial friction between the tool and the work piece, and lower the shear flow stress. The addition of mica in Al 356/10SiC composite increases the tool life and decreases the flank wear, this is mainly because of the lubricating properties of the mica. From the results, it is understood that mica may act as a lubricant like graphite [31], mica may form a thin lubricating film at the interface between the surface of work pieces and the tool

thus reduces the amount of heat generated in the cutting zone. This reduces the softening of the tool material, resulting in lower flank wear. The addition of mica to Al356/SiC helps in reducing the burr height. When drilling Al356/SiC–mica is at low feed rate, the thrust force encountered by the material is less and leads to reduced plastic deformation. When the plastic deformation takes place, the mica particle smears before the bending of the material due to the low interfacial bond strength and the cutting is prolonged. As the drill advances and when SiC or mica particle forms the pivot point, a burr of reduced height is formed [28]. Thus, the overall machining performance is higher and reflects in the higher value of the weighted grey related grade at 3% of mica.

#### 4.2 Effect of drill materials on grey relational grade

PCD drills exhibit better surface finish in the machining of hybrid MMCs compared to carbide and coated carbide drills. This is due to the increase in drill hardness which decreases the surface roughness of the drilled surface [32]. Carbide and coated carbide drills exhibits more build up edge than the PCD drills, which contributes to rougher surface. RAMULU et al [33] has also published similar results. Moreover, SiC cannot

**Fig. 3** Response graphs of content of mica (a), drill type (b), spindle speed (c) and feed rate (d) on grey relational grade



micro cut the PCD tool, but in other cases, SiC particles can micro cut the tool materials. Therefore, the machining performance is improved when the PCD drill is used, which can be seen in the GRG graphs.

#### 4.3 Effect of spindle speed on grey relational grade

The increase in spindle speed reduces the surface roughness in the drilling of hybrid Al 356/SiC-mica composites. At high spindle speed, the force induced in cutting is increased which in turn cuts the hybrid MMCs smoothly and produces less surface roughness than at slow speed. The burr height is increased with increasing feed rate predominantly and the increase in burr height with the increase in spindle speed is less. This is mainly due to the thrust force generated. It indicates that at higher cutting speed, burr height may slightly decrease. As the speed increases, flanks wear increases for all the tool materials. A general trend of increase of flank wear with the increase in speed is attributed to the increase in temperature of the cutting zone. The increase of cutting speed increases the action between tool and work piece, which increases the abrasive wear on the tool. Also, as the cutting speed is increased, the recrystallization of the highly strained material of the BUE reduces the hardness and stability of the BUE, and the tool face is exposed leading to increased flank wear. It can also be observed that there is no predominant variation in thrust force on the increasing spindle speed at all the feed rates considered [33]. Thus, the overall machining performance is better at the GRG of 1000 r/min.

#### 4.4 Effect of feed rate on grey relational grade

The results indicate that low feed rate is preferred in the drilling of hybrid Al356/SiC-mica MMC. The increase in feed rate increases the thrust force and torque, and it leads to poor surface finish. Also, the increase in feed rate increases the heat generation during drilling, which increases the surface roughness. The increase in feed rate increases the thrust force in the drilling of composites. This increase in thrust force bends the material to a larger extent before interfacial bond cracking progresses, resulting in larger burr formation.

As the feed rate increases, the flank wear increases for both the composites. This can be attributed to the increase in the temperature at high feed rates, which causes the softening of the tool material. The increase in feed rate increases the thrust force and torque and it leads to poor surface finish. Also, the increase in feed rate increases the heat generation during drilling, which increases the surface roughness [12]. Thus, the machining performance is better at lower feed rate of 50 mm/min.

#### 4.5 Analysis of variance for grey relational grade

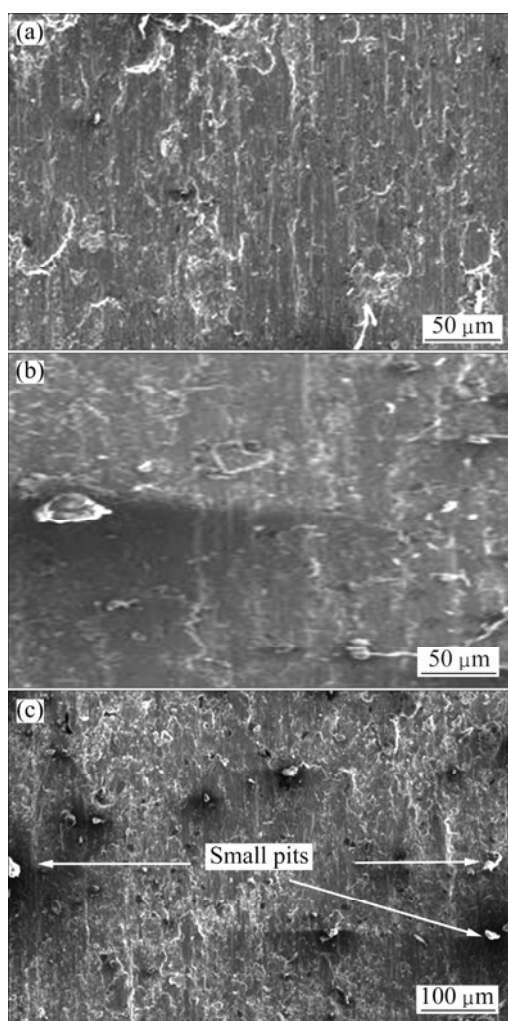
The GRG obtained using Eq. (12) is analyzed using ANOVA and the analysis of means (ANOM). ANOVA is used to reveal the level of significance of influence of factors on a particular response. This is accomplished by separating the total variability of the GRG, which is measured by the sum of the squared deviations from the total mean value of the GRG into contributions by each turning process parameters and the errors. The response table of Taguchi method was employed here to calculate the average GRG for each factor level. The grouping of the grey relational grades was done initially by the factor level for each column in the orthogonal array and then by averaging them. The result of ANOVA (Table 8) indicates that the feed rate is highly influential parameter (percentage contribution 38.37%) followed by drill type (33.67%).

#### 4.6 Surface morphology

Scanning electron microscope (SEM) is used to observe and analyze the machined surface. The SEM micrographs of the drilled surface are given in Figs. 4(a)–(c). During the drilling operation, the mutual rubbing of abrasive particles in the drilled hole surface improves the surface finish. Careful examination of the worn surface reveals that a high feed causes an extensive surface damage in composites due to higher contact pressure. Higher feed rate increases the temperature at the tool-work surface. This leads to the softening by plastic deformation. Al356/SiC–mica composites exhibit voids and cracks at the SiC and mica particle/Al matrix

**Table 8** Results of ANOVA for grey relational grade

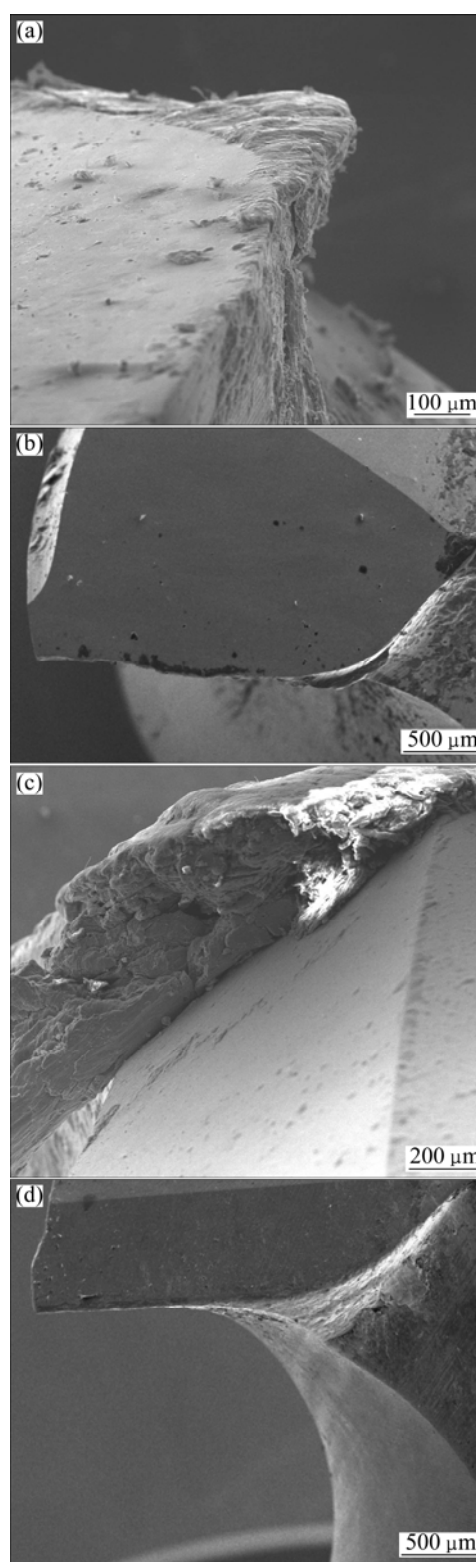
Factor	Degree of freedom	Sum of squares	Mean squares	<i>F</i> value	Prob> <i>F</i>	Contribution/%
A	1	0.005184	0.005184	1.766476	0.2133	2.68
B	2	0.065016	0.032508	11.07812	0.0029	33.67
C	2	0.01946	0.00973	3.315839	0.0786	10.08
D	2	0.074102	0.037051	12.62616	0.0018	38.37
Error	10	0.029345	0.002934			15.20
Total	7	0.193107				100



**Fig. 4** SEM images illustrating drilled surface under different conditions: (a) PCD drill, speed of 2000 r/min, feed rate of 100 mm/min, mica content of 3 %; (b) Carbide drill, speed of 3000 r/min, feed rate of 100 mm/min, mica content of 0%; (c) Coated carbide drill, speed of 2000 r/min, feed rate of 100 mm/min, mica content of 0%

interface and particle pulls out. These cracks are caused by the strain hardening of the material.

SEM observations are also used to investigate the tool wear. In the machining of conventional metals, the cutting tools are abraded by the strain-hardened chips generated in machining process. Since the pressure between the work piece and the cutting tool is very high, much heat is generated. Typical SEM micrographs of wear patterns of carbide, coated carbide and PCD drills are shown in Figs. 5(a)–(d). The figures clearly show the adhesion of material on the flank face of the drill. It can be seen that the flank wear is caused by the abrasive nature of the hard SiC particles presented in the work piece materials. Because of the high pressure generated at the tool-work piece interface, the worn flank encourages the adhesion of the work piece material.



**Fig. 5** SEM micrographs: (a) Carbide drill, speed of 2000 r/min, feed rate of 50 mm/min, mica content of 0%; (b) Coated carbide drill, speed of 3000 r/min, feed rate of 150 mm/min, mica content of 3%; (c) Coated carbide drill, speed of 3000 r/min, feed rate of 50 mm/min, mica content of 0%; (d) PCD drill, speed of 3000 r/min, feed of 100 mm/min mica content of 3%

## 5 Verification of optimal parameters through confirmation experiments

The final step involved in the optimization process is to predict and verify the improvement in the performance characteristic for drilling of Al356/SiC–mica composites with respect to the chosen initial parameters setting. The predicted GRG, using the optimal level of the machining parameters can be calculated as:

$$\xi_{\text{predicted}} = \xi_m + \sum_{i=1}^N (\xi_0 - \xi_m) \quad (14)$$

where  $\xi_m$  is the total mean value of the GRG;  $\xi_0$  is the mean GRG at optimal level and  $N$  is the number of main design parameters that affect the multiple performance characteristics. Table 9 lists the comparison between the predicted and actual machining performance for multiple performance characteristic using the optimal cutting parameters. The confirmation experiment results at optimal level ( $A_2B_3C_1D_1$ ) shows that the thrust force is reduced from 560 to 510 N, the surface finish is improved from 4.5 to 3.4  $\mu\text{m}$ , tool wear is reduced from 0.158 to 0.148 mm and burr height is reduced from 0.165 to 0.118 mm. It is evidently seen from these results that the multiple performance characteristics in the composite machining process is greatly improved through this approach. It is found that an improvement of 10.06 % is observed in the weighted GRG. This ensures the usefulness of grey relational approach in relational analysis to product/process optimization, where multiple quality criteria have to be fulfilled simultaneously.

**Table 9** Comparison between machining performance using initial and optimal level

Machining parameter	Initial machining parameter	Optimal machining parameter	
		Predicted	Experimental
Setting level	$A_1 B_1 C_1 D_1$	$A_2 B_3 C_1 D_1$	
Thrust force	565		510
Surface roughness	4.5		3.4
Tool Wear	0.158		0.118
Burr height	0.165		0.118
Grey relational grade	0.591	0.745	0.820

## 6 Conclusions

1) The recommended levels of drilling parameters for minimizing thrust force, surface roughness, tool wear and burr height (exit) simultaneously are the content of mica at level 2 (3%), drill type at level 3 (PCD), spindle speed at level 1 (1000 r/min) and feed rate at level 1

(50 mm/min). Among the tested parameters, the feed rate shows strongest correlation to the thrust force, surface roughness, tool wear and burr height (exit).

2) An increase in the value of predicted weighted GRG from 0.745 to 0.820 confirms the improvement in the performance of drilling of hybrid metal matrix composites when using the optimal values of process parameters.

3) The experimental results for optimal settings show that there is a considerable improvement in the performance characteristics of machining process. This technique is more convenient and economical to predict the effects of different influential combinations of the parameters within the levels studied.

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## 混合铝基复合材料钻削工艺参数的优化

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**摘要:** 采用 Taguchi 方法和灰色关联分析对 Al356/SiC-云母混合金属基复合材料的钻削工艺参数进行优化。实验采用 L<sub>18</sub> 正交阵列, 在计算机的控制立式机床上进行。考察的钻削性能指标包括轴向力、表面粗糙度、刀具磨损和毛刺高度, 对影响这些性能的钻削工艺参数进行了优化, 包括轴转速、给进速度、钻头类型和云母质量分数。结果表明: 给进速度和钻头类型是影响钻削过程的重要因素, 通过这种方法可以有效地改进钻削工艺的性能。

**关键词:** 混合复合材料; 灰色关联分析; Taguchi 方法

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