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Sustainable Optimization of Drilling Parameters for AA2017/AlN Composite Materials: A Grey Relational Analysis Approach

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Abstract. Modern engineering materials have seen remarkable development. Because conventional materials can no longer meet the needs of modern applications, numerous composites are being employed as viable alternatives. Drilling is the most important production step for most uses, and the resulting holes are high-stress zones that must be handled carefully. Scientists and engineers have long been interested in the challenge of finding the best combination of drilling settings for cutting-edge composite materials. As part of this research, AA2017/AlN composites with matrices made of AA2017 aluminium alloy and reinforcements made of 5, 10, and 15 wt % AlN were produced using stir casting. By experimenting with different input parameters, we were able to utilise the L9 OA to determine the best machining arrangement for drilling materials. The investigation focused on critical drilling characteristics, including burr height (H), thrust force (T), and surface roughness (SR), with a keen emphasis on sustainability.By considering the burr height (H), thrust force (T) and surface roughness (SR) and this work used grey relational analysis (GRA) to establish the optimum cutting parameters for drilling holes in the cutting-edge composite AA2017/AlN. The significance of different machining settings and their effect on the typical characteristics of the drilling were analysed using GRA. However, a confirmation experiment was conducted to ensure the highest quality outcomes. Test results and GRA indicate that the best grey relational grade is achieved with the following parameters: spindle speed (S) of 3500 rpm, feed rate (F) of 60 m/s, drill material (D) of Tungsten Carbide, and reinforcement (R) of 10%.. Analysis of variance (ANOVA) revealed statistically significant impacts on GRG from the drill material (29.08%), the feed rate (24.24%), and the spindle speed (19.52%). The error term was a function of the reinforcement

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percent and its interactions with all other parameters; however, the influence of the interaction between feed rate and drill material on GRG was small. The GRG is 0.856, which is higher than the prediction of 0.824. The calculated and measured values agree quite well and 3.7% is a negligible margin of error. The mathematical models for all reactions depending on the drill bits employed was also constructed.

Keywords: Drill material; feed rate; spindle speed; Reinforcement; thrust force; surface roughness.

1 Introduction

Incorporating sustainability into the discussion of materials like aluminium matrix composites (AMCs) involves considering their environmental impact, resource efficiency, and potential for recycling. While AMCs offer significant advantages in terms of performance, it's essential to assess their sustainability aspects. Several researchers have found that Al alloy, used in aluminium matrix composites (AMCs), may compensate for the drawbacks of ferrous metals while still providing the greatest spec'd performance values [1]. Low-density, high-stiffness, and medium-strength materials like AMCs are widely used because they can fulfil the stringent requirements of technological applications [2]. AMCs are composite materials that improve upon the metal characteristics of matrix alloys by incorporating ceramic reinforcements. Authors [3–5] proposed using a two-dimensional array and the GRA approach to achieve optimal drilling performance while working with Al/SiC composites. Drilling parameters and their effect on MWCNTs hybrid polymer composites was investigated by authors [6]. GRA was used to find the best values for the cutting parameters so that the T, SR, and H of drilled holes could all be optimised at the same time[7]. Composites of hybrid aluminium metal matrices were drilled with the optimal machining settings using the grey-fuzzy approach [8]. Three levels of the OA L9 are employed in the tests. While authors [9] made MMC using a hot press, they analysed the impacts of the output factors on the T and R of composites with an analysis of variance (ANOVA).

Using S/N ratio method, the optimal value for each output parameter may be calculated [10–12]. The results showed that at both feed rates, the R of the MMCs was most heavily dependent on the fraction of extra phase materials. According to the published works, the T and R values improved when the F was raised through the machining process. The T and R values in this MMC system, however, dropped as the feed rate rise, making this study more unique. Drilling parameters for GFRP composites were optimized using GRA by authors [13, 14], who based their calculations on the values of R and T. The experiment uses the Taguchi L9 three-level OA. Using the GRA-obtained GRG, they determined the optimal values for many performance metrics. Authors [15] investigated how adjusting a single process parameter affected the surface quality of turned parts. Planned and executed experiments on controlled machining of workpieces under preset cutting circumstances were based on Taguchi's techniques. Multiple linear regressions were used to uncover the connections [16]. Finally, the findings of the theory were compared to the predicted results based on the correlations, using confirmation tests. Drilling operations affect the temperature, T, and R of AA6351/ B_4C composite materials, as determined by the researchers [17, 18]. Titanium nitride coated carbide drill bits were used at various angles, from 90 degrees to 118 degrees and even 135 degrees. To attain this significantly lower temperature, spindle speeds and feed rates must be reduced. However, when point angles aren't optimised, tool wear and surface roughness rise. The generation of thrust force is also affected by the machining variables. Drilling at an angle of 135^o produces less thrust power but more delamination [19].

Multiple impressive physical and mechanical features of SiCp/Al matrix composite materials [20]. The objective of this analysis is to determine what aspects of working with SiCp/Al composites accelerate the wear of diamond drill bits. The machining process of the AA6063/ silicon carbide particles composite was evaluated by measuring drilling forces and hole reliability [21]. Wear processes resulting from mechanical action and chemical graphification permitted by thermodynamics both appear to play a substantial role in SiCp/Al6063 drilling, as evidenced by the results. While working with composites, diamond-coated Carbide drills are recommended due to their durability, minimum wear rate, and aptitude to achieve adequate machining efficacy even when drilling a large number of holes [22, 23]. As cutting speed and feed rate are increased, machine time increases but surface roughness values drop. The machine-ability was improved by the discovery and validation of optimal process parameters. The machinability of the coconut oil medium was enhanced by increasing the speeds and feeds. Drilling AA2219/TiB_2/ZrB_2 hybrid composites was analysed for its effects on surface roughness (R) [24]. By controlling for other factors, exploratory research can isolate the effect of a particular variable in a process. Carbide twist drills were used to drill Al/10 B_4C and Al/10B_4C/5Gr composites at varying S and F under dry cutting circumstances, and the effects on thrust force (T), surface roughness, dimensional accuracy, and burr height (H) were studied by the authors [25]. Using analysis of variance, we calculated how much each process variable impacted final product quality. Finally, statistical models were devised to assess various quality characteristics. The second phase material Al/10B_4C/5Gr, which contains 5% graphite, reduced the composites' T and H, leading to a higher quality surface.

Drilling Al2219/8 % boron Carbide (B_4C) composite and Al2219/8 % B_4C/3 % Gr hybrid composites were studied by authors [26]. Analyzing the impacts of the T and SR at varying speeds and feeds, the researchers found that the T and SR increased with increasing FR. Graphite's lubricating qualities make hybrid composites' thrust weaker and its surface rougher. The effects of feed, spindle speed, and drilling material tip angle on Thrust force, Surface roughness, and circularity error were studied by authors [27], who drilled SA182 work material. Orthogonal array and RSM were used in the study's design to shed insight on the relationship between machinability and hole quality. The viability of the provided models for the required outcomes using an ANOVA. The response surface analysis showed that the circularity error decreased at high cutting speeds and feeds, whereas all other responses decreased with rising spindle speeds. The circularity inaccuracy was reduced and the surface was smoothed down by increasing the point angle. This research aims to attain minimum values for T, SR, and H of AA2017/AlN.
The mechanical characteristics of the produced nanocomposites, as well as the effect of drilling parameters on chips and burr development, were investigated. The drill tool's material, feed, and speed were the input parameters that were chosen for the study. The drilling of the NMMC was done using drill bits composed of HSS and TiN coated HSS[28]. Composite by doing two things: (1) identifying the factors that have an effect on these variables, and (2) doing multi-objective optimization of drilling process parameters.

2 Materials and Methods

2.1 Materials

Aluminum nitride (AlN) was selected as the reinforcing material, while AA2017 aluminium alloy was used as the matrix, because both are readily available. The alloy is shaped into fine polish regions where relatively significant corrosion resistance from seawater or marine atmospheres is necessary, as well as in the manufacturing of equipment used in the food and chemical sectors. They are well-known for both their aesthetically pleasing and functional casts, which are used in a variety of industries, including the food-handling dairy industry, chemical and naval plumbing, and shipbuilding and decoration. The chemical composition of AA2017 is determined by optical emission spectrometry, and the results are listed in Table 1.

Table 1. Chemical composition of AA2017

Copper	Magnesium	Silicon	Manganese	Iron	Titanium	Zinc	Aluminium
4.5	0.8	0.8	0.4	0.7	0.15	0.25	Balance

AlN is a ceramic material composed of aluminium nitride, a white crystalline oxide of aluminium. Aluminum nitride production requires the collection and elimination of waste materials and byproducts. Because of its stability at high temperatures, AlN ceramics are frequently used to join ceramics and steel together. Another terrible combination of characteristics is low heat conductivity and high strength.

2.2. Manufacturing of AA2017/AlN Composites

The composite is made in a C-type closed furnace equipped with a stir casting apparatus. The chuck built into the stirrer makes swapping out the shaft quick and easy. The high-chromium steel impeller of the fan is made up of four individual blades. The AA2017 alloy was first melted by heating tiny ingots to temperatures of roughly 850°C in the crucible. The AlN powder is dried in a muffle furnace for 20 minutes at 200°C to remove moisture from the reinforcement. The stirrer was gradually introduced to the molten metal, causing a vortex to form. The stirrer speed was maintained at 600 rpm while the warmed AlN, with a mean particle size of 70 to 90μm, was gradually incorporated into the liquid metal. The churning proceeded for a further 7 minutes after the particle feeding stopped. Before putting the slurry into the mold, three minutes were spent injecting it with argon gas to minimize porosity. The melting point was set at 750 ºC. Before putting the slurry into the mold, it was heated to 650 ºC for 30 minutes to ensure a consistent solidification. Using this method, we reinforced AA2017 with 5, 10, and 15 % of AlN particles, yielding three distinct composites.

2.3 Drilling of AA2017/AlN Composites

Composite material holes are drilled with a Kistler peizo-electric dynamometer, attached to a vertical machining centre (VMC). Specimen 1 is AA2017 with 5% AlN added, Specimen 2 is AA2017 with 10% AlN added, and Specimen 3 is AA2017 with 15% AlN added. The T produced during drilling, which is the primary factor in the quality of the hole, was measured with a piezo-electric dynamometer. Vision Measuring System (VMS) was used to measure H, whereas a surf corder was used to measure SR [28]. In this study, the performance of High Speed Steel (HSS), Tungsten carbide (WC), and Boron nitride (BN) coated cutting tools were compared. Each of the three drills has a helix angle of 30 ^{0}, a point angle of 118 ^{0}, and a diameter of 6 mm. The experiment's processing factors and its levels are listed in Table 2.

Table 2. Drilling processing factors and its levels

Parameters	Units	Code	Level		
			1	2	3
Feed Rate	(mm/min)	F	60	120	180
Spindle speed	(rpm)	S	1500	2500	3500
Drill Material		D	High speed steel	Tungsten Carbide	Boron Nitride
Reinforcement	(%)	R	5	10	15

2.4. Grey Relational Analysis

As a result of its success in optimising many performance metrics simultaneously in intricate procedures, GRA has found widespread use. Proven effectiveness in employing grey system theory to address issues of missing, skewed, or unclear information. In grey relational analysis, the terms black, white, and grey all have distinct meanings. There is no information in a black system, all the information is in a white system, and there is some information in a grey system. The goal of this method is to enhance the responsive characteristics of existing machining systems [29, 30]. The initial phase of grey relational analysis is data pre-processing, during which the experimental data for T, SR, and H are normalised such that they fall within the range 0–1. Pre-processing of data is frequently required due to discrepancies in range and unit across individual data sets. Data pre-processing is the process of making a sequence that is consistent with the original. GRA can use a variety of data pre-processing techniques, each of which is tailored to the specifics of a given data set. If the goal value is infinite, the "greater is better" quality applies. In order to normalise the sequence, we use the formula (1):

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

The following formula (2) can be used to normalise the original sequence when it exhibits a "lower is better" characteristic:

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

where the original reference sequence (i), (i, k= 1, 2,. 3.., m, n respectively) and the preprocessed data (k) are shown. The notation $x_i{*}(k)$ stands for the normalized value, $x_i^{(0)}$ for the desired sequence, min $x_i(^{0)}(k)$ for the smallest value in the sequence, and max $x_i^{(0)}(k)$ for the highest value in the sequence. There are m experiments, but only n total observations.

2.4.1. Grey Relational Coefficient (GRC)

The GRC is a criterion in GRA for comparing the interchangeability of two systems. The grey relational coefficient, represented by Eqn (3), is employed in GRA to demonstrate the degree of similarity between the sequences $x_0(k)$ and $x_i(k)$.

$$\gamma x_0(k), x_i^* = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{0i}(k) + \zeta \Delta_{\max}} \tag{3}$$

where$\Delta_{0i}(k)$ sequence deviation and imitates the variations among $x_0(k)$ and $x_i^*(k)$.

$$\Delta_{0i}(k) = x_0(k) - x_i^*(k), \quad (4)$$

$\Delta_{\min}$ minimum value of $\Delta_{0i}(k)$,
$\Delta_{\max}$ maximum value of $\Delta_{0i}(k)$
ζ distinctive coefficient.

2.4.2 Grey Relational Grade (GRG)

In most cases, the GRG may be computed from the mean value of the GRC. In order to assess features of multiple responses, GRG is employed. It is written as an equation (4), which is as follows:

$$\tau_i = \frac{1}{n}\sum_{i=1}^{n}(\gamma(x_0(k), x_i^*(k)) \quad (5)$$

where

n no of processing responses

τ_i GRG.

The higher the GRG, the more closely the corresponding experimental result matches the normalised ideal value.

In the Taguchi design of experiments, the optimal values of each ingredient are used to predict the best replies, and then those predictions are confirmed by more trials. Experimental conditions are optimised to either minimum or maximum the response.

3 Results and Discussions

The goal of this GRA-based multi-objective optimization effort was to concurrently reduce production costs for T, SR, and H. The trial results, including GRC, GRG, and rankings, are shown in Table 3.

Table 3. Results of a GRA (AA2017/AlN)

S. No	**Feed**	**Speed**	**Drill Material**	**Reinforcement**	**GRC results**			**GRG**	**Rank**
Units	**(mm/min)**	**(rpm)**		**(wt %)**	**T**	**SR**	**H**		
1	60	1500	HSS	5	0.3333	1.0000	0.3333	0.556	3
2	60	2500	WC	10	0.3727	0.7594	0.3727	0.502	6
3	60	3500	BN	15	0.5127	0.4879	0.5127	0.504	5
4	120	1500	WC	15	0.4024	0.6601	0.4024	0.488	8
5	120	2500	BN	5	0.4529	0.5580	0.4529	0.488	9
6	120	3500	HSS	10	0.6433	0.4089	0.6433	0.565	2
7	180	1500	BN	10	0.4698	0.5344	0.4698	0.491	7
8	180	2500	HSS	15	0.6048	0.4262	0.6048	0.545	4
9	180	3500	WC	5	1.0000	0.3333	1.0000	0.778	1

Trials are evaluated based on their GRG ratings. Figure 4 indicates that at the first F level, the third S level, and the second D and R percent A1B3C2D2 levels, GRG is obviously enhanced.

Fig. 1. Main effect plot for GRG

Table 4 displays the average ratings for factorial level. D has the greatest impact on the grey relational grade, followed by Feed rate, Spindle speed, and Reinforcement in that order of importance. With a 95% degree of certainty, the actual experimental plan was assessed. ANOVA results are shown in Table 5. An R^2 of 80.47 % was calculated for GRG. There is a statistically significant relationship between F, S, and D and the GRG ($p \pm 0.05$).

Table 4. Response table for Grey relational Grade (AA2017/AlN)

Level	**F**	**S**	**R**	**D**
1	0.5205	0.5117	0.6071	0.5553
2	0.5138	0.5116	0.5194	0.5892
3	0.6048	0.6158	0.5127	0.4946
Delta	0.0910	0.1042	0.0944	0.0947
Rank	4	1	3	2

Table 5. ANOVA for GRG (AA2017/AlN)

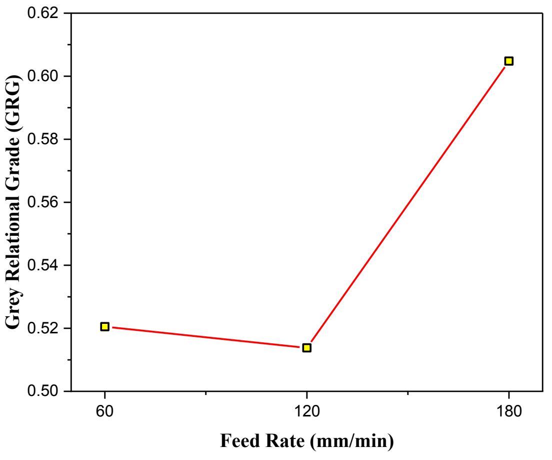
Source	**DoF**	**Seq SS**	**Contribution**	**Adj SS**	**Adj MS**	**F-Value**	**P-Value**
Feed Rate	2	0.01285	19.01%	0.01542	0.007709	7.86	0.003
Spindle speed	2	0.02059	30.47%	0.02169	0.010844	9.54	0.004
Drill Material	2	0.01110	16.42%	0.01380	0.006901	6.54	0.001
Reinforcement	2	0.01324	19.59%	0.01666	0.008330	7.91	0.002
Error	8	0.00982	14.51%				
Total	16	0.06757	100.00%				

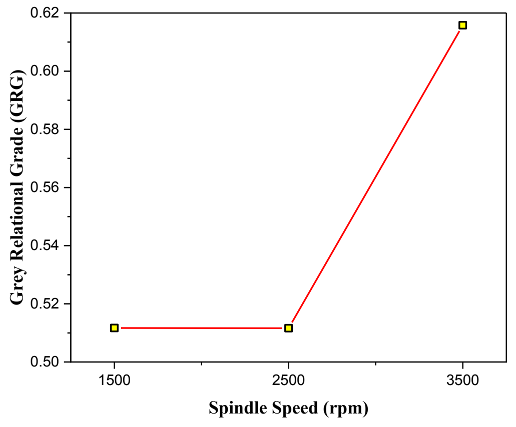
Table 5 makes it clear that F, S, and D all have a considerable effect on GRG since their tested values are higher than the F-tabled value. The values obtained from the F test for R percent and for interactions with other variables are less than what is given. D's impact on the GRG was found to be the highest (30.47%), followed by F's and finally S's. Since F has a little effect on GRG, the response variable R percent and all of its interactions with other factors are now part of the error term.

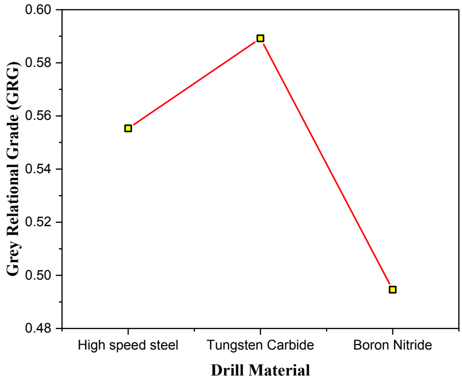
3.1. Confirmation on Experiments

The experimental value of GRG was found to be 0.856, whereas the expected value was 0.824. The error is only 3.7 %, indicating that the anticipated and experimental results coincide well.

The GRG is an accurate representation of all replies and so includes the T, SR, and H options. The effects of these variables on the GRG are shown in Figure 2. As seen by the highest point on the GRG response graph, drilling variables had a greater impact on machinability characteristics [31]. Maximum GRG value was achieved with process settings of 60 mm/min, 3500 rpm, Tungsten Carbide drilling material, 10 wt % of reinforcement during drilling.







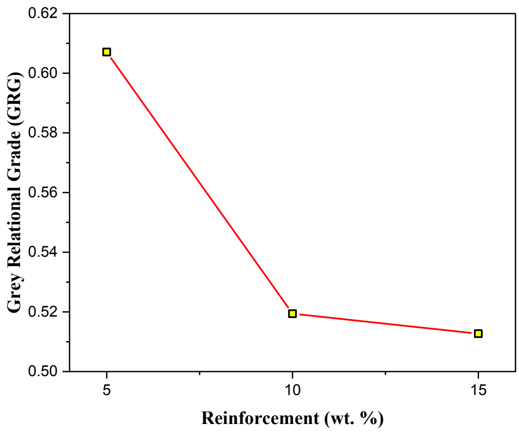


Fig. 2. Impact of drilling processing factors on Grey relational Grade

Minimum F and maximum S had the highest GRG, indicating that low F and high S had the lowest response T, SR, and H. When the drilling temperature is lower, the quality of the surface improves. It was discovered that reducing F led to a decrease in T, which in turn allowed for a passable surface polish at lower F. As the spindle speed increases, the frictional heat generated softens and penetrates the workpiece more easily. GRG values improve with increased spindle speed because less thrust force is used, the workpiece deforms less, and the total time required to complete the cut is reduced. R was lowest for 10% AlN related to the other weight percentages. The T value of the AA2017/AlN composite material improved once AlN was introduced. Increasing the percentage of AlN increases the composite's hardness and hence the T, as AlN is the hardest material. Increases in reinforcing weight percentage reduce R. As F rises, so does the cutting force and the resulting H. The H is maximised in cases of excessive feed rates. As the reinforcing % increases, H decreases in AA2017/AlN composites. Since GRG is calculated as the mean of the experimental GRCs for T, R, and H, it varies from experiment to experiment.

3.2. Mathematical Models

Thrust force (T), surface roughness (R), and burr height (H) for a High speed steel (HSS) drill are modelled mathematically for AA2017/AlN composites in Equations (6)-(11). Equations (9)–(11) show the equations derived for Tungsten Carbide-coated drills, while Equations (12–14) offer the equations derived for Boron nitride-coated drills.

For an High speed steel drill:

$$T = 142.0 + 0.916\ F - 0.05724\ S + 4.45\ R \tag{6}$$
$$SR = 4.094 + 0.03042\ F - 0.00072\ S - 0.0286\ R \tag{7}$$
$$H = 0.0561 - 0.000021\ F - 0.000001\ S - 0.00022\ R \tag{8}$$

For a Tungsten Carbide drill:

$$T = 138.9 + 0.895\ F - 0.05724\ S + 4.45\ R \tag{9}$$
$$SR = 3.674 + 0.03042\ F - 0.000762\ S - 0.0286\ R \tag{10}$$
$$H = 0.0362 - 0.000021\ F - 0.000001\ S - 0.00022\ R \tag{11}$$

For a Boron Nitride drill:

$$T = 132.3 + 0.892\ F - 0.05724\ S + 4.45\ R \tag{12}$$
$$SR = 3.396 + 0.03042\ F - 0.000762\ S - 0.0286\ R \tag{13}$$
$$H = 0.0362 - 0.000021\ F - 0.000001\ S - 0.00022\ R \tag{14}$$

4 Conclusions

Using the inexpensive stir casting technique, the composites in three distinct weight percentages was created. Optical micrographs verified that the reinforcing material (AlN) was evenly dispersed throughout the matrix.

Taguchi's design of experiments (DoE) was employed to conduct drilling tests on AA2017/AlN composites, emphasizing sustainability in the experimental process. Subsequently, a grey relational analysis was utilized to analyze the results sustainably. The following sustainable findings were derived from assessing the impact of drilling factors on AA2017/AlN composites: All specimens' T, SR, and H values went down as the feed rate went down. D is the most notable statistical metric on Grey relational grade, followed by F and S. The experimental value of GRG is 0.856, whereas the anticipated value is 0.824, with a 3.7% margin of error. Confirmation studies show a small margin of error in the results. The anticipated values and the experimental values are in reasonable agreement.

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