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Analysis in Drilling of Al6061/20%SiCp Composites using Grey Taguchi based TOPSIS (GT-TOPSIS)

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Abstract: Drilling is an important metal removal process for the final fabrication stage particularly in cases of components joined by mechanical fasteners. The selection of drilling parameters like drill bit speed, feed and the cutting point angle is vital, while drilling holes in ceramic based composites. The objective of research work is to perform drilling on Al6061/20%SiCp compositeand observe the responses like surface finish and drilling induced thrust force. Taguchi's L_9orthogonal arrayis used to conduct the machining trials and a new integrated approach of the grey Taguchi based technique for order performance by similarity to ideal solution (GT-TOPSIS) is disclosed to predict the optimal drilling conditions. The confirmation experiment is conducted at the best input setting identified by the proposed algorithm for demonstrating the accuracy of the approach.Feed rate is identified as the prime factor affecting the quality of drilled holes.
Keywords: Al/SiCp composite;Optimization; Drilling; Grey relational analysis;TOPSIS; Taguchi; Surface finish.

1 Introduction

Aluminium based composites find wide applications in the aerospace and automotive partsand particularly those reinforced with ceramic particles offer many advantages, exhibitingan isotropic mechanical behaviour. The growing industrial application demands a structured study of their drilling characteristics, as it is an important metal removal process for the final fabrication stage prior to application. However the presence of a secondary ceramic phase like silicon carbide increases the difficulty in machining,causing an excessive tool wear [1]. Wide spread applications of these composites are practically impossible without solution to the drilling problems. Hence a drilling database with optimal input parameters becomes essential to find a solution to multi criteria decision making (MCDM) problem involving responses like tool wear, cutting forces and surface finish.

While turning Al/SiC composites tool wear was observed to be higher at the elevated cutting speed and feed rate [2]. The effect of various input parameters could be clearly seen in the quality of machined surfaces [3]. Taguchi's optimization approach was used to obtain the optimal parameters for better quality characteristics in different manufacturing processes [4,5]. However the method was effective only in single response optimization,while a practical situation demands simultaneous optimization of multiple responses. An approach based on Taguchi design and ANN was used to form a model. It was further optimized using genetic algorithm in machining of Al/SiC composites [6]. During the drilling of aluminium based composites,carbide tipped drills were observed to show acceptable levels of drill forces and hole quality in dry conditions. It was found that the feed rate and cutting point angle play an important role in affecting the responses. It was also found that the

HSS tools are not so effective in handling aluminium based composites as the tool wear was found to be more, along with poor finish of the machined surfaces [7, 8]. Taguchi based simulated annealing could be used for parameter design to achieve better responses [9].

A deterministic decision making approach adopted to study the drilling operations on the CNC machines had proved that a global solution was possible with a clearly defined approach [10]. The response surface methodology (RSM) based on grey theory was used tominimize the surface roughness in non-traditional cutting processes,but it was observed that the method losses its power in irregular regions and requires tedious computational efforts as well [11, 12]. A hybrid model of artificial neural network-simulated annealing (ANN-SA) and artificial neural network-genetic algorithm (ANN-GA) could predict as well as optimize the machining characteristics. However training of back propagation network was found to be difficult and it was also observed that GA cannot scale well with complexity [13, 14].

Hence many methods were suggested for multi response optimization including grey relational analysis (GRA), principal component analysis (PCA), data envelopment analysis and neural networks [15]. Technique for order performance by similarity to ideal solution(TOPSIS) was used for ranking the responses with respect to several criteria parameters and was found to be effective in multi response optimization [16, 17]. Itwas a MCDM technique with fewest rank reversals, which can be successfully applied to solve selection problems with a finite number of options. Its intuitive nature allows easy understanding and implementation [18]. GRA was applied for optimizing the input parameters in a pure format or in an integrated format with other techniques and was found to improve the quality characteristics significantly [19, 20]. A hybrid approach for optimization using GRA and PCA was found to take the advantages of the techniques adopted and could predict an optimal solution [21].Taguchi's experimental design and further analysis using desirability method or RSM was observed to be economical because of a reduced number of experimentations [22-24].

From the available literature, it was understood that not enough work has been done on decision making associated with the drilling of composites. Hence the present work is focussed towards developing a new methodology (GT-TOPSIS), which combines the merits of Grey Taguchi and TOPSIS to identify the optimal drilling condition for the Al/SiCp composites.

2 Experimental Design and Observation

The Al6061 aluminium alloy was reinforced with silicon carbide (SiC) particlesof size 10µm (20% weight fraction). The work material (Al/SiCp plate) was fabricated using the process of stir casting, by dispersing SiC particles in the liquid aluminium alloy. The work samples used for the experimental trial consists of two square plates, each of side 100mm and thickness 15 mm, which were ground to avoid surface asperities during the drilling process. A radial drilling machine was employed to carry out the process using taper shank twist drill (carbide tipped) of diameter 10 mm and a new tool was used during different trials under dry drilling conditions.

The input parameters taken for the study includes the spindle speed, feed rate and cutting point angle.These inputs were varied during various trial runs and their levels were identified based on available literature [6, 7, 8]and it was ensured that the experiments would not end up in poor values of responses. The number of input parameters and their levels chosen for the workare indicated in Table 1. The flow diagram representing the study is indicated in Figure 1.

Table 1 Drillingparameters and their levels

Symbol	Input Parameters	unit	Level 1	Level 2	Level 3
A	Feed rate	mm/rev	0.12	0.16	0.20
B	Spindle speed	rpm	900	1120	1330
C	Cutting Point angle	deg	90	118	135

Taguchi L_9 orthogonal array was used to conduct the experimentsand one hole was drilled for each parameter combination, on two plates separately (two replicates). The responses observed were the drilling induced thrust force and surface roughness (SR). The setup used for measuring the thrust force involves a strain gauge transducer in half bridge configuration (model: FT 100) to which the drilled plates were rigidly fastened. An amplifier unit connected to transducer could measure the values of thrust force in the range of 0-10 KN digitally. The holes were drilled with uniform gaps between them during different trials and well away from the plate edges. The surface finish was studied by using a Talysurf III recorder using a cut-off length of 0.8 mm to characterize the surface quality. The surface roughness (Ra) is measured at four places around the circumference of hole, midway along the thickness of the plate and the average value of eight readings was used in analysis. The responses obtained during the trials are listed in Table 2.The trials were conducted randomly to average out the effects of extraneous factors which may be present during experimentation.

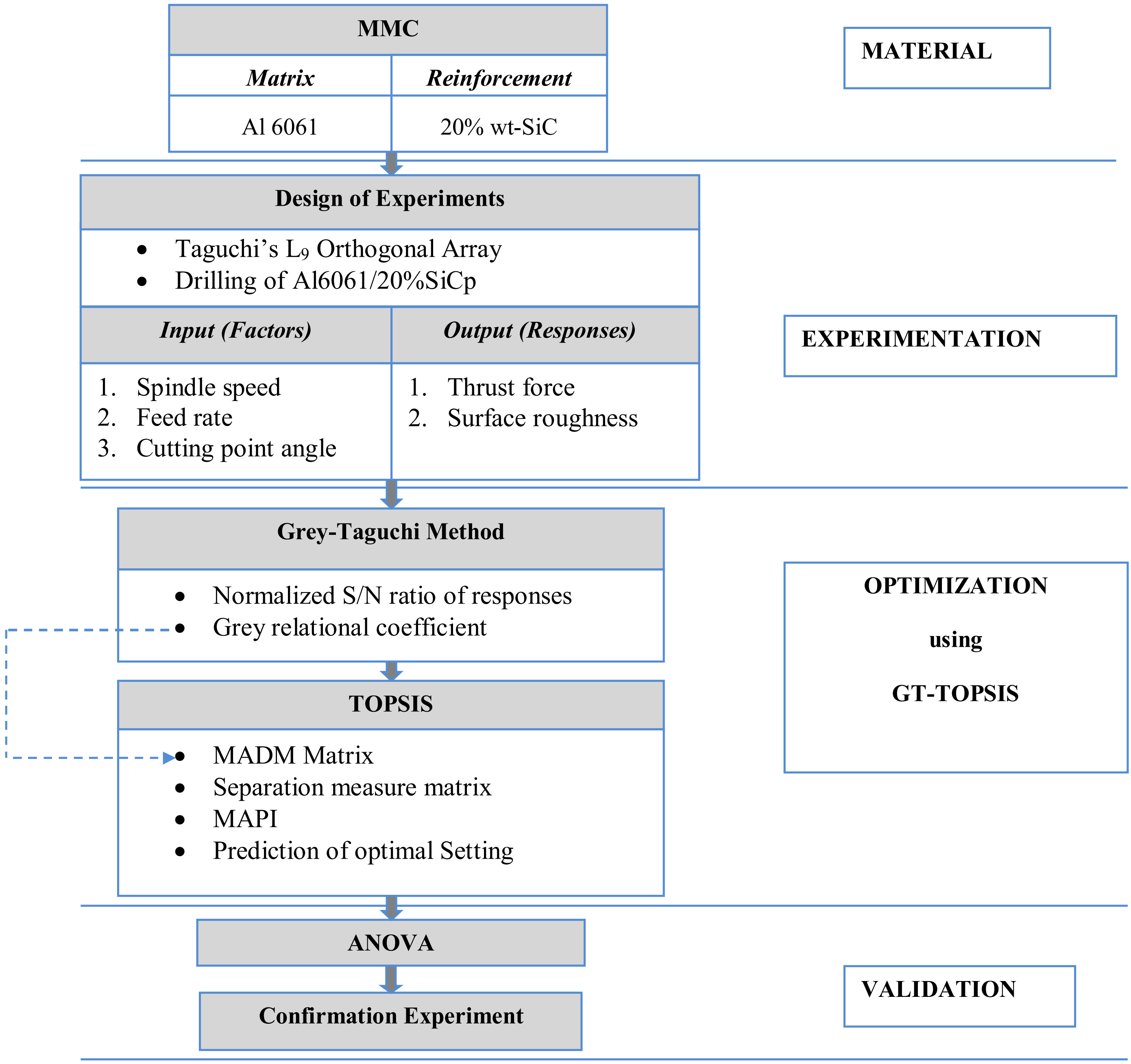

Figure 1 Flow diagram of the study

Table 2 L_9 array showing the combination of process parameters and the responses obtained

Trial	Parameters and their levels			Responses	
	A	B	C	Ra (µm)	F_T(N)
1	1	1	1	2.42	281.31
2	1	2	2	2.12	129.33
3	1	3	3	1.79	182.11
4	2	1	2	2.94	330.31
5	2	2	3	2.85	235.64
6	2	3	1	1.91	401.32
7	3	1	3	3.01	675.77
8	3	2	1	2.96	458.61
9	3	3	2	2.05	535.97

3 Methodology of Grey Taguchi based TOPSIS (GT-TOPSIS)

In grey relational analysis, black represents a state with no information and white represents astate with all the data. A grey system has a level of information between the two [19]. GRA helps in compensating the shortcoming of statistical regression and identifies the relations between the elements based on the degree of similarity or difference of development trends among those elements. The measure of performance in the grey theory is the signal-to-noise ratio (S/N ratio), according to which each performance characteristic would have a target value. The algorithm for the GT-TOPSISwas discussed in two phases (section 3.1 and section 3.2).

3.1. Phase I: Grey Relational Analysis

Step 1: Calculate the S/N ratio (y_{ij}) for the responses using the appropriate formula based on the quality characteristic [27]. A quality characteristic is one which determines the outcome of a process and will have a target which may be *smaller-the-better or larger-the-better.*

Smaller-the-better

The target of *smaller-the-better* characteristic is 0 (zero). Minimization of such a characteristic is desired in the *smaller-the-better type* problems. The S/N ratio (y_{ij}) for such a characteristic is calculated by usingEquation(1).

$$S/N\ Ratio(\eta) = -10\log_{10}\left(\frac{1}{r}\cdot\sum_{i=1}^{r} y_{ij}^2\right) \tag{1}$$

Where

r = number of replications, y_{ij} = observed response values, i = 1,2,3… r and

j = 1,2,…m, m is the number of trials.

Larger-the-better

A *larger-the-better* characteristic has a target of infinity and the maximization of such a quality characteristic is achieved by finding the S/N ratio using Equation(2).

$$S/N\ Ratio(\eta) = -10\log_{10}\left(\frac{1}{r}\right)\sum_{i=1}^{r}\frac{1}{y_{ij}^2} \tag{2}$$

Step 2: Calculate the normalized S/N ratio (Z_{ij}) using Equation(3) to avoid the effect of variability among the S/N ratio [19, 20]. The normalized S/N ratio varies as $0 \leq Z_{ij} \leq 1$.

$$Z_{ij} = \frac{y_{ij} - \min(y_{ij}, i = 1,2,.....,n)}{\max(y_{ij}, i = 1,2,.....,n) - \min(y_{ij}, i = 1,2,.....,n)} \quad (3)$$

*Step 3***:** Compute the grey relational coefficient (GRC (γ))to express the relationship between the best and the actual normalized experimental results from normalized S/N ratio using Equation(4).

$$\gamma_i^j = \frac{\Delta \min + \xi \Delta \max}{\Delta_{oj}(i) + \xi \Delta \max} \quad (4)$$

$\Delta_{oj} = \left\| z_o(i) - z_j(i) \right\|$ is the absolute value of the difference between $z_o(i)$ and $z_j(i)$, $z_o(i)$ is the reference sequence ($z_o(i)$=1; i=1,2,…,n), $z_j(i)$ is the specific comparison sequence, $\Delta \min = \min\limits_{\forall j \in i} \min\limits_{\forall i} \left\| z_o(i) - z_j(i) \right\|$ is the smallest value of $z_j(i)$, $\Delta \max = \max\limits_{\forall j \in i} \max\limits_{\forall i} \left\| z_o(i) - z_j(i) \right\|$ is the largest value of $z_j(i)$ and ξ is the distinguishing coefficient, whose value is taken to be 0.5 for analysis.

3.2. Phase II: TOPSIS

TOPSIS is an attractive ranking technique requiring a limited subjective input [25,26].The advantage of TOPSIS lies in its ability to identify the best alternative faster. The grey coefficients are used to form the decision making matrix in TOPSIS which is further analysed as follows.

*Step 4:*Establish the matrix [A]for multiple attribute decision making [26].

$$A = \begin{bmatrix} \gamma_1^1 & \gamma_2^1 & .. & .. & \gamma_n^1 \\ \gamma_1^2 & \gamma_2^2 & .. & .. & \gamma_n^1 \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \gamma_1^m & \gamma_1^m & .. & .. & \gamma_n^m \end{bmatrix}$$

Where n is the number of variables and γ_i^j is the value of GRC.

*Step 5:*Normalize the matrix [A] to form matrix A_N [25].This is done to transform the various attribute dimensions into non-dimensional attributes, allowing for the comparison across the attributes.

Where $x_i^j = \frac{\gamma_i^j}{\sqrt{\sum_{j=1}^{m} \left(\gamma_i^j\right)^2}}$ (5) x_i^j is the normalized valueof the GRC (γ_i^j).

*Step 6:*Determine the distance of the j_{th} alternative from the ideal and negative-ideal solutions.The distance of j_{th} alternative from ideal solution (separation measure I) is calculated using Equation(6).

$$d_j^+ = \sqrt{\sum_{i=1}^{n} \left(x_i^j - x_i^+\right)^2}, \text{ for } i=1, 2\ldots n \quad (6)$$

The distance of j_{th} alternative from negative-ideal solution (separation measure II) is calculated using Equation(7).

$$d_j^- = \sqrt{\sum_{i=1}^{n} \left(x_i^j - x_i^-\right)^2}, \text{ for } i=1, 2\ldots n \quad (7)$$

Where

$$x_i^+ = \max \left\{x_i^j, \text{for } j = 1,2,...,m\right\} \ \forall x_i^j \left(i = 1,2,...,n, j = 1,2,...,m\right)$$

$$x_i^- = \min \left\{x_i^j, \text{for } j = 1,2,...,m\right\} \ \forall x_i^j \left(i = 1,2,...,n, j = 1,2,...,m\right)$$

Step 7: Calculate the relative closeness of various alternatives to ideal solution[26] using Equation(8).It is considered as the multi-attribute performance index (MAPI). The MAPI value lies between 0 and 1.

$$MAPI_j = \frac{d_j^-}{d_j^+ + d_j^-} \tag{8}$$

*Step 8:*Determine the optimal level of the parameters based on MAPI. The main effect (ε_i) of the control factors was calculated using Equation(9) to determine the optimal level.

$$\varepsilon_i = \max\left(MAPI_{ij}\right) - \min\left(MAPI_{ij}\right) \tag{9}$$

The best level j^* of the controllable factor 'i' is selected asj^* = max ($MAPI_{ij}$)

Step 9: Calculate the predicted S/N ratio ($\overline{\eta}$) at the selected optimal levelsof the parameter using Equation(10).

$$\overline{\eta} = \eta_m + \sum_{i=1}^{f}\left(\overline{\eta_i} - \eta_m\right) \tag{10}$$

Where η_m = Average S/N ratio,f = Number of control factors and $\overline{\eta_m}$ = Average S/N ratio corresponding to the i_{th} factor on the f_{th} level.

Step 10: Perform ANOVA to predict the significant parameters and their contribution. Conduct the confirmation experiment at the identified optimal process parameters setting for validation.

4. Results and Discussion

4.1 S/N ratio and grey relational coefficient

A linear normalization of the experimental results was performed for the responses (R_a and F_T) and the grey relational coefficients (GRC) were calculated using Equation(4). These values are listed in Table 3. The $R_a$and $F_T$weretreated as the *smaller-the-better* characteristics with the target for them remaining to be zero. The S/N ratio was taken as themeasure of performance in the grey theory and a higher value of S/N ratio was desired, irrespective of the nature of quality characteristic [24].

Table 3 S/N ratio, normalized S/N ratio and GRC of responses

Trial	S/N ratio		Normalized S/N ratio		GRC (matrix A)	
	Ra	F_T	Ra	F_T	Ra	F_T
1	-7.676	-48.984	0.420	0.530	0.463	0.515
2	-6.527	-42.234	0.674	1.000	0.606	1.000
3	-5.057	-45.207	1.000	0.793	1.000	0.707
4	-9.367	-50.378	0.045	0.433	0.344	0.469
5	-9.097	-47.445	0.105	0.637	0.358	0.579
6	-5.621	-52.070	0.875	0.315	0.800	0.422
7	-9.571	-56.596	0.000	0.000	0.333	0.333
8	-9.426	-53.229	0.032	0.234	0.341	0.395
9	-6.235	-54.583	0.739	0.140	0.657	0.368

4.2. Effect of parameters on responses

After calculating the S/N ratio corresponding to each experimental trial, the parameter effect at any level can be found out by taking the average of all S/N ratios at the same level. A graphical representation of the effect of various parameters at different levels isshown in Figure (2-4)for the various responses. The level corresponding to a maximum average S/N ratio for a parameter could produce better responses [24].It was seen that lesser value of feed rate (0.12 mm/rev) is desired for minimal thrust forces and roughness(Figure 2). The improvement in finish could be attributed to lower wear rate and lesser distortion of the carbide tip. From Figure3, it was observed that an increase in spindle speed produces better finish of the surface, while a moderate value of spindle speed (1120 rpm) was desired for keeping the drilling induced thrust forces at a minimal level. From Figure4, it was found that the variation in S/N ratio (for surface roughness) at different levels of cutting point angle was less.However the thrust forces were observed to be lesser at a point angle of 118^{o}.

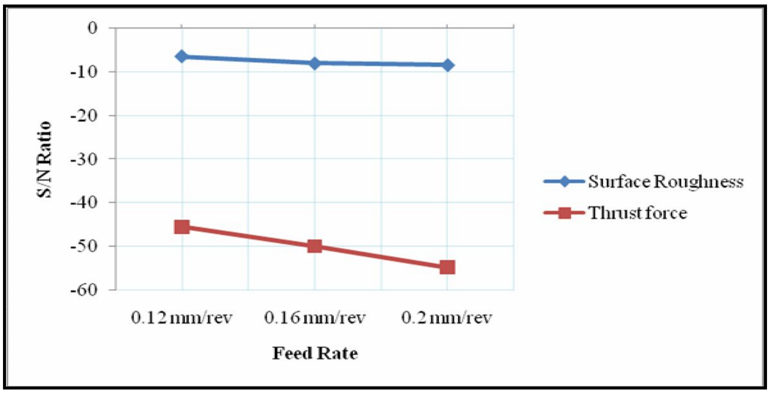

Figure2 Effect of feed rate on the responses

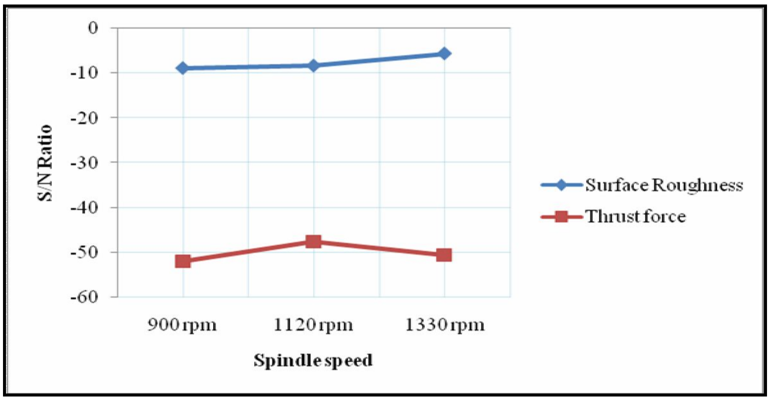

Figure3 Effect of spindle speed on the responses

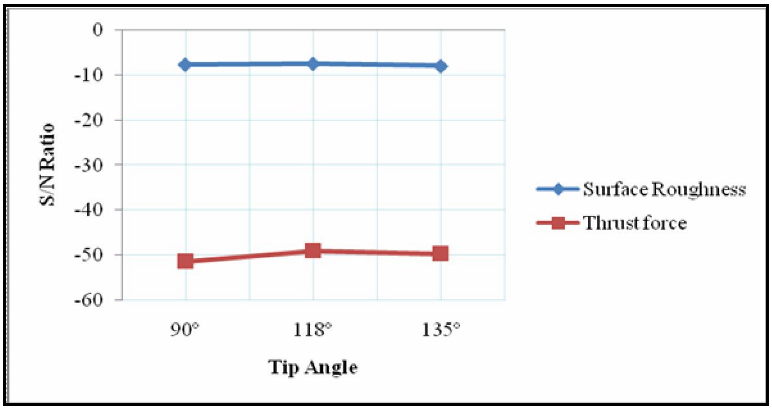

Figure4 Effect of cutting point angleon the responses

4.3 Calculation of MAPI

The normalized matrix (A_N)and the separation measure matrix were formed and the relative closeness of various alternatives to the ideal solution, considered as a function of MAPI value is listed in Table 4.

Table 4 Separation measure matrix and MAPI values.

Trial	Normalized matrix (A_N)		Separation measure I	Separation measure II	MAPI
	Ra	F_T	d_j^+	d_j^-	
1	0.2618	0.3026	0.416	0.130	0.2375
2	0.3425	0.5870	0.223	0.421	0.6535
3	0.5655	0.4152	0.172	0.436	0.7174
4	0.1944	0.2751	0.485	0.080	0.1410
5	0.2027	0.3402	0.439	0.145	0.2486
6	0.4525	0.2477	0.358	0.269	0.4294
7	0.1885	0.1957	0.543	0.000	0.0000
8	0.1926	0.2319	0.515	0.036	0.0662
9	0.3716	0.2159	0.419	0.184	0.3055

The MAPI values represent an overall quality measure for the two responses. The MAPI values plotted for the various trials is shown in Figure5. Higher values of MAPI indicate that the combination of factors in the corresponding trial would produce better responses. The parameter combination close to trial number 3 was found to have higher MAPI value (Figure5). However the effect of the factor levels on the MAPI should be observed (Figure6), before arriving at the optimal setting.

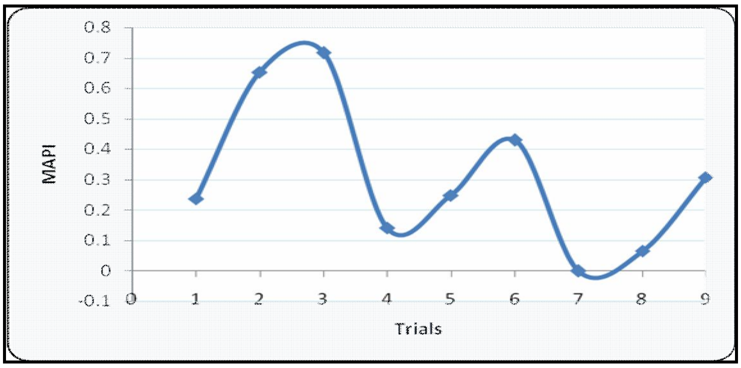

Figure5 Variation of MAPI values for the various trials

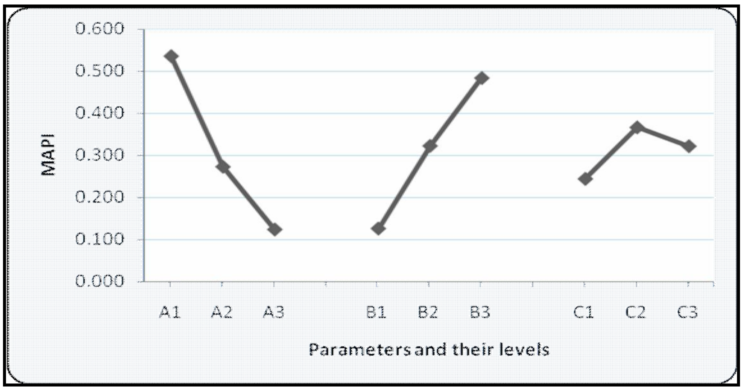

Figure6 Effect of parameter levels on MAPI

The main effect of the various input parameters on the MAPI for each level was calculated and shown in Table5. The best level of each input parameter was identified as the one having the maximum value of average MAPI among the different levels. From Figure 6 and Table 5, the optimal parameter level was identified as $A_1B_3C_2$.

Table 5 Effect of the drilling parameters on MAPI

Parameters	Level 1	Level 2	Level 3	Max-Min
A	**0.5361***	0.2730	0.1239	0.4122
B	0.1262	0.3228	**0.4841***	0.3579
C	0.2443	**0.3667***	0.3220	0.1223

*Best level of each input parameter.

4.4 Results of ANOVA

Using ANOVA (analysis of variance), the significant input parameters for multi response performance and their percentage contribution to the total variation was found out. ANOVA was performed on the MAPI values and the results are listed in Table 6. A pictorial representation of the contribution of various factors is shown in Figure7.

Table 6 Result of ANOVA onMAPI

Source of variation	Sum of square	Degrees of freedom	Mean sum of square	F-ratio	% Contribution
A	0.2614	2	0.1307	18.44	53.21
B	0.1928	2	0.0964	13.60	39.23
C	0.0230	2	0.0115	1.62	4.68
Error	0.0142	2	0.0071		2.89
Total	0.4913	8			100

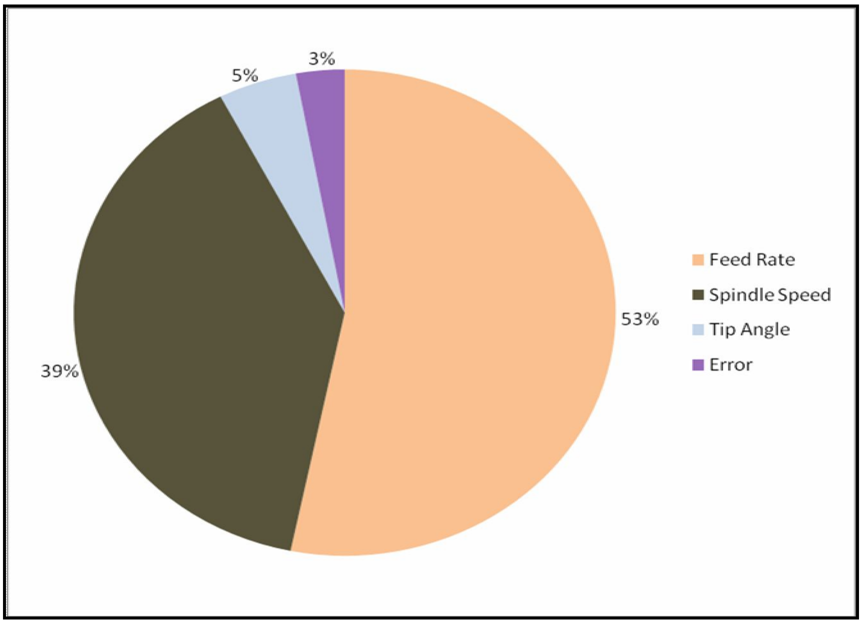

Figure7Contribution chart for the various parameters based on MAPI

4.5 Confirmation experiment

The predicted values of S/N ratio ($\bar{\eta}$) for the responses were calculated using Equation(10).After obtaining the optimal level of the drillingparameters using the hybrid approach of GT-TOPSIS,the confirmation test was conducted to verify the improvement in the performance characteristics. The results of the confirmation experiment conducted with the optimal parameter setting were compared with those obtained with the initial setting of parameters (Table 7).Consequentlythese confirmatory tests gave satisfactory resultsand a significant improvement in the response values was observed.

Table 7 Comparison between the outcome of initial parameter setting and the optimal parameter setting

Responses	Initial parameter Setting		Optimal parameter (GT-TOPSIS)setting		Improvement	
	Observed S/N ratio	Response value	Predicted S/N ratio	Response value	S/N ratio	Response value
Ra (µm)	-5.0571	1.79	-4.1946	1.63	0.8625	0.16
F_T(N)	-45.2067	182.11	-44.9985	172.65	0.2082	9.46
parameter settings	$A_1B_3C_3$		$\mathbf{A_1B_3C_2}$			

5 Conclusion and Future Research

An effective optimization strategy for multi criteria optimization problems is still a challenging task.This paper has presented a new integrated methodology of GT-TOPSIS for predicting the optimal conditions in drilling of Al/SiCp composites. The following conclusions can be drawn.

- The GT-TOPSIS approach had combined the merits of both GRA and TOPSIS. The uncertainty handling capabilities of GRA wascombined with the more realistic form of modelling in TOPSIS, which allows trade-off between the various input parameters. The method requires a relatively simple computational effortin handling multi response problems.
- The optimal combination(spindle speed: 1330 rpm, feed rate: 0.12 mm/rev and cutting point angle: 118^o) predicted by the methodology of GT-TOPSIS has significantly improved the S/N ratio, thereby enhancing the performance characteristics.
- ANOVA was performed on the MAPI value and it was found that the major input parameter affecting the quality characteristics is the feed rate (53.21%), followed by the spindle speed (39.23%) and cutting point angle (4.68%).
- The optimal parameter combination has produced a good surface finish at an acceptable value of thrust force.It is evident that this method could also be applied to solve multi criteria decision making problems in other manufacturing processes as well.

In future, a suitable meta-heuristic algorithms can be identified for MCDM problems, either in an individual or in a combined format and the results of this study may be comparedwith the results of other fuzzy based methods.

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