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Multi-Objective Optimization of High Speed Turning Parameters of Hybrid Aluminium Matrix Composite Reinforced with Silicon Carbide and Coconut Shell Ash

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Keywords： LM24 aluminum alloy. silicon carbide particles. coconut shell ash. Taguchi based grey relational analysis

ABSTRACT

In any machining process, the vital part is determination of optimum values for the process parameters for attaining the highest desired quality at lower machining cost. This paper mainly focuses on machining parameters optimization in turning operation of hybrid aluminum metal matrix (LM24-SiCp-coconut shell ash) composite through Taguchi based grey relational analysis. All composite samples for the study were prepared by optimal squeeze casting parametric condition and the experimental trials were selected based on L9 $(3)^4$ orthogonal array. The main response considered in this study were surface roughness (SR) and material removal rate (MRR) and machining parameters such as cutting speed, feed rate, depth of cut and tool nose radius were chosen. The optimum machining conditions were obtained through Taguchi based grey relational analysis (GRA) and checked through the confirmation experiments. The machining parameters were cutting speed (51.31%) and feed rate (23.45%) most significant factors which affect the output response. The confirmation experiment results at optimal parameter combination show that the SR was reduced from 0.45 to 0.39 µm and the MRR was improved from 1.73 g/min to 2.12 g/min. The grey relational grade from the measured performance measures based on the confirmation experiment was found to be 0.7887. It was also observe that, surface roughness of the turned surface was decreased in 13.33% and material removal rate was increased in 22.54% with the Taguchi based GRA optimum setting conditions.

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INTRODUCTION

The process of selecting the most suitable materials for the engineering applications becomes more tedious as the engineering society keeps on enlarging the materials library. The current global market pushes the research activities in the direction of composite materials rather than unreinforced alloys. Composite materials are highly capable to replace the existing monolithic materials in the specific engineering applications in aviation, automobile, and marine fields, especially Metal matrix composites (MMCs), the matrix materials are of aluminum, magnesium, copper and their alloys are preferred much as they exhibit the excellent mechanical properties such as high wear and corrosion resistance, improved tensile strength, toughness, and impact strength etc., Aluminum based MMCs are gaining much attention among others for the reasons of compatibility with all kind of hard as well as soft reinforcements (Manjunath Patel G C et al. 2016; Adalarasan et al. 2015; Ramnath et al. 2014; Lal S et al. 2014).

However, the cost of aluminum metal matrix composites (AMCs) is comparatively high as the reinforcements are slightly expensive than the conventional alloys. Singh, S et al (2017) and Bello, S.A et al. (2017) have been carried out to reduce the cost of AMC; one method is of reinforcing the easily available inexpensive materials such as rice husk ash (RHA), bamboo leaf ash, groundnut shell ash (GSA), coconut shell ash etc. but which alters desirable properties. Dwivedi et al. (2015); Toptan, F et al. (2012) studied the the low-cost reinforcements led to attempts for the usage of industrial and agro wastes. Usually, MMCs are fabricated through any one of the following techniques, such as solid-state processing (powder metallurgy), liquid state processing (stir casting, squeeze casting, compo casting) and infiltration technique. The most commonly preferred technique for processing of al based MMCs is of stir casting as it is more economical and simple in operation. But the major setbacks encountered in the stir cast parts are of formation porosity, poor wettability and lack of homogeneous dispersion of the reinforcements and these issues are addressed through the squeeze casting method (Dhanasekaran et al. 2016; Kumar, R et al. 2015).

The surface roughness is being considered as one of the most significant quality attributes to any of the machined components as it directly contributes to the functioning or operational performance. Jan Linder et. al. (2006) has reported that the fatigue failures of the machining components begin from the surface and the poor surface characteristics are highly vulnerable to fatigue failures. Because the maximum stress for the loads like bending and torsion is induced at the surface. Kök, M et al. (2011); Murthy, K.S et al 2009; Muthukrishnan, N et al. (2012) investigated that the machining of aluminum-based MMC's, especially the composite reinforced with hard particles which cause in the poor surface finish and rapid tool wear due to the abrasive of nature of reinforcement. In general, the presence of hard ceramic particles makes them extremely difficult to machine such they lead to rapid tool wear and also need good surface finish is essential for many components. The machining operations in aluminum metal matrix composite reinforced with the hard carbide particles such as SiCp, B4Cp, TiCp, and WCp etc., lead to more complexes in achieving the good surface finish. This problem is usually addressed by adding soft particles such as organic reinforcements like coconut shell ash, rice husk ash with hard ceramics particles (Palanikumar, K et al. 2008, 2014; Premnath, A.A et al. 2012).

Many methods are being adopted by researchers around the world, for the systematic way of determining the optimum machining parameters. For achieving the desired output of any process, it is necessary to identify the optimum process parameters which influence the expected outcome. A quite number of techniques are being adopted for optimizing the process parameters and they may be categorized as conventional tools (Taguchi method, response surface method, grey relationship analysis) and soft computing tools (genetic algorithm, artificial neural network, particle swarm optimization, fuzzy logic) (Senthilkumar, C et al. 2011). The conventional tools are used to develop the regression models based on the experimental results and the soft tools are applied for an exact optimum solution. The surface quality of the machined components is majorly affected by the machining process parameters such as cutting conditions, tool variables and work piece variables. Suresh et al (2014) studied the influence of machining parameters such as feed rate, cutting speed and mass fraction of Sic particles on machining of Al-SiCp-Gr hybrid composite. Arokiadass et al (2012) have investigated the machining characteristics of hybrid aluminum matrix composites (Al356/SiCp-mica composites). The results revealed that spindle speed and SiCp are the dominant parameters, whereas the other parameters such as depth of cut and feed rate do not influence the machining operation. They have also optimized the machining parameters of a drilling operation in Al356/SiC-mica composites for minimizing the surface roughness. The optimum condition of machining parameters was determined the electrochemical machining of Al/15% SiCp composite using the genetic algorithm. In the grey system approach, the grey relational analysis (GRA) is a multi-objective optimization tool is used to estimate the relationship between sequences, using fewer data and multi-factor (Senthil, P et al. 2012, 2014; Rao, R V et al. 2014). Patel G M et al. 2014 examined that GRA is used to find a grey relational grade (GRG), which can be applied for multi-objective response to a single objective response. GRG was also applied to find the effects of parameters on the response characteristics. Several investigators are mainly focused that tribological properties of different types of tool materials based on process parameters and surface roughness while machining of aluminum-based composites reinforced with hard and soft particles was examined. The effects of machining parameters like cutting speed, feed rate depth of cut and tool nose radius were studied. From the literature survey, a research gap was found in the direction of multi-response optimization of turned hybrid metal matrix (LM24/SiCp/coconut shell ash) composite using Taguchi based GRA has not been investigated.

The purposes of the present study have been carried out to investigate the effect of high speed turning parameters like cutting speed, feed rate, depth of cut and tool nose radius on the surface roughness and material removal rate of hybrid aluminum metal matrix composites. Taguchi based grey relational analysis has been used to predict the optimum turning conditions for obtaining the minimization of surface roughness (SR) and maximization of material removal rate (MRR) on the turned hybrid composite components.

MATERIAL AND THEIR CHARACTERISTICS

Materials Used

LM24 aluminum alloy was used as the matrix material and its chemical composition is shown in Table 1. The average particles size of SiC_p (150 µm) and coconut shell ash particles (150 µm) were used as reinforcement materials. The chemical composition of coconut shell ash particle shown in Table 2. The hybrid metal matrix composite of a fixed percentage of reinforcement was fabricated with 2.5% of coconut shell ash particle and 7.5% of SiC_p. In addition to that, the percentage of reinforcement particles which results decreased in mechanical properties (Arulraj, M et al. 2018). The mechanical property of hybrid metal matrix (LM24/SiC_p/coconut shell ash) composite is given in Table 3.

Table 1. Chemical elements of LM24

Element	Si	Fe	Cu	Mn	Mg	Cr	Ni	Zn	Al
JIS (wt %)	7.5-9.5	≤ 3	3.0-4.0	≤ 0.5	≤ 0.3	≤ 0.5	≤0.5	≤ 3	Bal.
Ingot (wt%)	7.943	0.686	3.723	0.28	0.18	0.030	0.039	1.276	85.84

Table 2. Chemical elements of coconut shell ash

SiO_2	MgO	Al_2O_3	Fe_2O_3	CaO	K_2O	Na_2O	ZnO	MnO
44.05	17.2	14.6	13.4	0.67	0.42	0.35	0.4	0.22

LM24 aluminum alloy ingot was melted in electric furnace its heating capacity limit up to 1200°C. The reinforcement particles 2.5% of coconut shell ash and 7.5% of SiC_p were preheated at 500°C in the separate crucible furnace. By using hexachloroethane (C_2Cl_6) tablets was degassed in the molten metal. Perhaps the most common method of degassing in foundry applications is the use of hexachloroethane (C_2Cl_6) tablets. Even though it may be the oldest technique, normally C_2Cl_6 tablet would provide effective degassing in the case of less quantity of aluminum melt. The preheated reinforcement particles were gradually added to the pure molten metal when maintaining constant stirring speed at 500 rpm for 10 minutes ((Senthil, P et al. 2012, 2014; Arulraj, M et al. 2018). The optimum squeeze casting parametric conditions are given in Table 4.

Table 3 Mechanical properties of hybrid metal matrix (LM24/SiC_p/coconut shell ash) composite

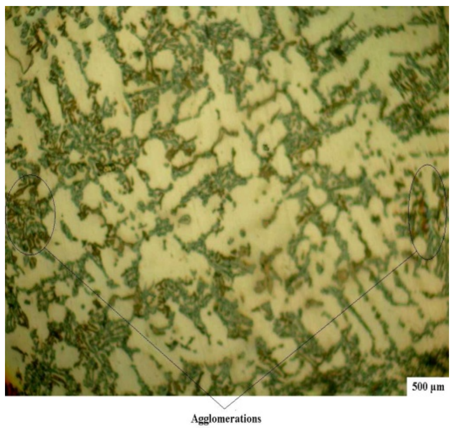
Property	Value
Density	2.91 g/cm^3
Tensile strength	384 MPa
Elongation	1.56 %
Charpy impact strength	4.15 N-m
Brinell hardness number	101.4 BHN
Shear strength	221 MPa

Table 4 squeeze casting process parameters

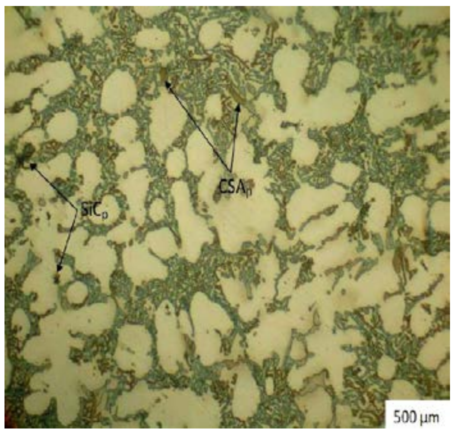
Parameter	Value
Squeeze pressure	150 MPa
Pouring temperature	690ºC
Die preheating temperature	500ºC
Mould temperature	211ºC
Pressure duration	45 seconds

Microstructure Analysis

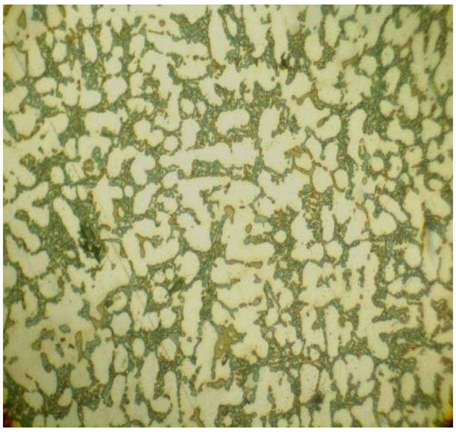
The specimen was prepared for microstructure analysis; they were polished and cleaned the surface with Keller's reagent. The casting sample was obtained from optimal squeeze casting parametric condition showed the uniform distribution of reinforcement particles in the matrix phase and good wettability. The quality of castings determined in terms of porosity, agglomeration of reinforcement, shrinkage defects etc., they are not visible in the micro-examination of the specimens, which expose the quality of castings. The castings obtained for the squeeze cast optimum condition showed better grain refinement in the microstructure and nearly than the castings obtained for gravity die casting condition and pressure die casting condition ((Senthil, P et al. 2012, 2014). Due to applying for high squeeze load, heat transfer raised significantly between the melt and the mold, which led to enhance in solidification time. High heat transfer or cooling was the cause for good grain refinement in the microstructure. The different casting sample microstructures were shown in Fig. 1.



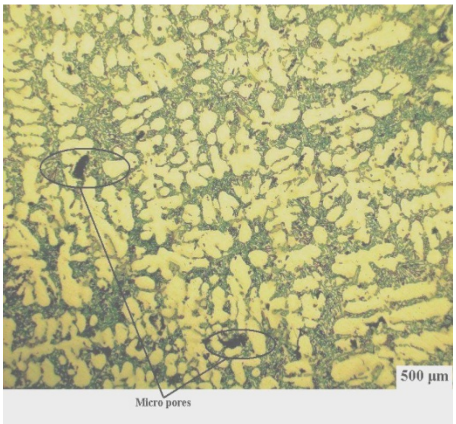
a) Pressure die cast condition



b) Squeeze cast at optimum condition



c) Gravity die cast condition



d) Low squeeze pressure cast with micro pores

Fig. 1 Optical microstructure of LM24 /SiC$_p$/coconut shell ash composite

High Speed Turning

High-speed turning operation was performed on the casting samples using computer numerical control (CNC) turning center (ECOTURN-25) manufactured by Geedee Weiler Pvt ltd., Coimbatore, India. The dimension of the casting samples was 25 mm diameter and 150 mm length used for conducting the turning operation. The tool holder PDJNL 1616H11 and cutting tool as uncoated carbide insert 332-SF H13A was used in the turning operations. The turning operation was conducted in the dry environment condition. The surface roughness (SR) of the turned casting samples was measured with help of a surface roughness tester (Mitutoyo SJ-210). Material removal rate (MRR) is a ratio between mass loss and time taken for machining. MRR is one of the most important performance characteristics while carried out machining, with a high rate considered in any machine operations. MRR was determined from the amount of material worn during the period of machining. The high precision digital balance meter was used to weigh the samples, thus ruling out the possibility of errors.

TAGUCHI METHOD

Taguchi method is a powerful statistical tool which is widely applied for improving the performance of machining process with an extensive reduction in time for conducting experiments, a considerable laceration in machining cost and improvement in the desired quality. Optimization of machining parameters is a statistical approach in the Taguchi method to obtaining the desired quality at minimum cost. Several researchers are conducted in many experiments when the increasing process parameters. Taguchi method is used a special design of orthogonal arrays to investigate the effect of machining parameters with a minimum number of experiments. The developing orthogonal array for the set of experiments and the importance of signal to noise (S/N) ratio which together determined how the average value (signal) of the input variables has been attained and the amount of variability (noise) has been examined.

Design of Experiments

The most influence parameters affect on surface roughness namely cutting speed (A), feed rate (B), depth of cut (C) and tool nose radius (D) are considered and their levels are given in the Table 5.

Table 5. Experimental parameters and their levels

Parameter	Notation	Level		
		1	2	3
Cutting speed (rpm)	A	3250	3500	3750
Feed rate (mm/rev)	B	0.1	0.15	0.2
Depth of cut (mm)	C	0.1	0.2	0.3
Tool nose radius (mm)	D	0.4	0.8	1.2

Grey Relational Analysis

Optimizations of multiple performance characteristics are very difficult to optimize the process parameters using Taguchi approach. Grey relational analysis (GRA) is used to predict the optimal parameters for the multiple performance characteristics. In this study, The application of Taguchi method with grey relational analysis to determine the optimal turning parameters conditions when considering multiple performance characteristics such as surface roughness (SR) and material removal rate (MRR). Flowchart for the grey relation analysis steps are shown in Fig. 2.

S/N ratio to compute quality characteristics

A signal-to-noise (S/N) ratio was used to determine the difference between the observed value and predicted value. In general, there are three types of the quality characteristic in the estimation of the S/N ratio such as, lower the better, nominal the better and larger the better. The S/N ratio for each level of parameters was evaluated based on the range of the S/N ratio. The surface roughness was treated as an output response with the category of quality characteristics “smaller-the-better”. The material removal rate was treated as an output response with the category of quality characteristics “larger-the-better”.

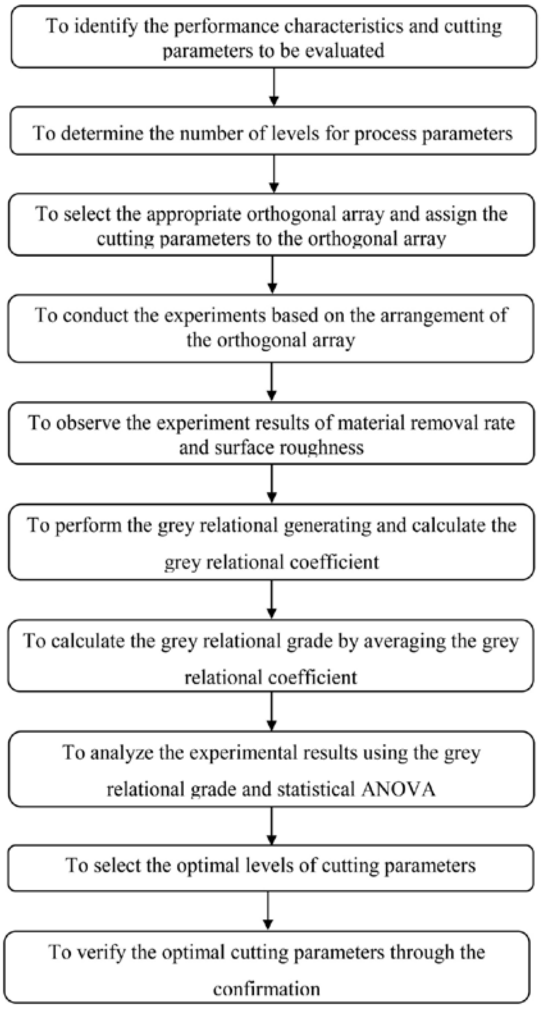


Fig. 2 Flow chart for grey relation analysis steps

In present work, two types of S/N ratio has been used; Higher-the-better for MRR and lower-the-better for SR.The S/N ratio for the SR and MRR were estimated by using Equation (1) and (2) for each experimental condition and their values are given in Table 6.

The S/N ratio with lower-the-better characteristic that can be expressed as follows,

$$S/N(dB) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} SR^2\right)$$

The S/N ratio with higher-the-better characteristic that can be expressed as follows,

$$S/N(dB) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{MRR^2}\right)$$

where i = 1,2,…, n (here n = 4) and SR and MRR were the response value for an experimental condition. Mean value ($\overline{Y}$) of S/N ratios was also calculated using Equation (2) and is given in Table 6.

$$\text{Mean}, \overline{Y} = \frac{1}{N}\left(\sum_{j=1}^{N} Y_j\right)$$

where j = 1,2… N (here N = 9) and Yj is S/N ratio for jth parametric setting.

Normalizing S/N ratio of quality characteristics

In the GRA analysis, S/N ratio of the quality characteristics is normalized first to reduce the variability. This is first steps in GRA called as data pre-processing. Data pre-processing is also essentially required as the range and unit in one data may differ from others. Data pre-processing is a way of transferring the original series of value to an equivalent series of value, so the data is normalized to set between zero and one. There are various methodological data pre-processing available depending on the quality characteristics of a data sequence

If the objective of the original sequence is unbounded, then it has a quality characteristic of larger-the-better.the original sequence should be normalized as:

$$x_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)}$$

When the quality characteristics considered as lower-the-better of the original sequence, then the original sequence can be normalized as:

$$x_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)}$$

However, the original sequence for definite objective (desired value) will be normalized in the form:

$$x_i(k) = \frac{|x_i(k) - x_0(k)|}{\max x_i(k) - x_0(k)}$$

Where $x(k)$ is the sequence of after the data pre-processing; $x_i(k)$ is the original sequence; $x_0(k)$ is the desired value of sequence; $\max x_i(k)$ is the highest value of $x_i(k)$; $\min x_i(k)$ is the lowest value of $x_i(k)$.

Grey relational coefficient and grey relational grade

After the data pre-processing is carried out, determine the grey relational coefficient. The distinguishing coefficient p is between 0 and 1. Generally, the distinguishing coefficient p is set to 0.5. Grey relational coefficient ξ can be expressed as follows:

$$\xi_i(k) = \frac{\Delta\min + p\Delta\max}{\Delta x_i(k) + p\Delta\max}$$

where $\Delta\min$ is the lowest value of $\Delta x_i(k)$, $\Delta\max$ is the highest value of $\Delta x_i(k)$.

After the Grey relational coefficient is computed, the average value of the grey relational coefficient is taken as the Grey relational grade (GRG). The GRG value is to obtain the following form:

$$r_i = \sum [w(k)\xi(k)]$$

Where ξ is the Grey relational coefficient, $w(k)$ denotes the normalized weightage of factor k. In a real engineering system, the importance of factors with unequal weightage being carried by various factors. Varying the weightages for the machinability indices will indicate different combinations of control parameters. In this study of composites, the surface roughness and material removal rate were assigned for different responses: $w(1)$ (SR) = 0.5 and $w(2)$ (MRR) = 0.5.

RESULTS AND DISCUSSION

Grey relation generation

The grey relational analysis was carried out to change in form the untidy the experiment results into a systematic sequence to get the relationship between the different factors. The responses observed for surface roughness (SR) was taken as the smaller-the-better characteristics with a target value set as one. The responses observed for material removal rate (MRR) was taken as the larger-the-better characteristics with a target value set as zero. Preprocessed data values and calculated value of GRC and GRG are shown in the Table 7 and Table 8, respectively.

Table 6 Experimental results using L9 orthogonal array and S/N ratio value

Ex. No.	Parameters and their levels				Surface roughness (SR) (μm)		Material removal rate (MRR) (g/min)	
	A	B	C	D	SR	S/N Ratio (dB)	MRR	S/N Ratio (dB)
1	1	1	1	1	2.15	-6.65	0.85	-1.41162
2	1	2	2	2	1.65	-4.35	2.32	7.30976
3	1	3	3	3	1.85	-5.34	1.95	5.80069
4	2	1	2	3	1.13	-1.21	2.11	6.48565
5	2	2	3	1	1.24	-1.94	1.89	5.52924
6	2	3	1	2	0.45	2.50	1.73	4.76092
7	3	1	3	2	2.54	-8.13	2.84	9.06637
8	3	2	1	3	1.94	-5.80	1.68	4.50619
9	3	3	2	1	1.75	-4.86	2.29	7.19671
$\bar{Y}$						**-3.975**		**5.471**

Table 7 Preprocesses data and corresponding deviation sequences

MRR (g/min)		SR (μm)		Data pre-processing		Deviation sequences	
MRR	(S/N ratio)-MRR	SR	(S/N ratio)-SR	MRR	SR	Delta1-MRR	Delta2-SR
0.85	-1.411	2.15	-6.65	0	0.096	1	0.904
2.32	7.309	1.65	-4.35	0.832	0.249	0.167	0.751
1.95	5.802	1.85	-5.34	0.688	0.183	0.311	0.817
2.11	6.484	1.13	-1.21	0.753	0.468	0.246	0.532
1.89	5.521	1.24	-1.94	0.662	0.414	0.337	0.586
1.73	4.760	0.45	2.50	0.589	1	0.410	0
2.84	9.066	2.54	-8.13	1	0	0	1
1.68	4.506	1.94	-5.80	0.564	0.156	0.435	0.844
2.29	7.196	1.75	-4.86	0.821	0.215	0.178	0.785

Table 8 Calculated values of GRC and GRG

Grey relation coefficient (GRC)		Grey relation grade (GRG)	Rank
MRR (g/min)	SR (μm)		
0.333	0.356	0.3445	9
0.748	0.399	0.5735	4
0.616	0.380	0.4980	7
0.669	0.484	0.5765	3
0.596	0.460	0.5280	6
0.548	1	0.7740	1
1	0.333	0.6665	2
0.534	0.372	0.4530	8
0.736	0.389	0.5625	5

Average response table for grey relational grade

The GRG value was noted for the sixth experimental condition, the corresponding input parameters condition was set the initial parametric condition. In order to find optimum level of the process parameters, average grey relational grade was calculated for every level of the parameters and the corresponding details are given in Table 9. Based on the highest value of average GRG, an optimum level for each parameter (A: 2nd level; B: 3rd level; C: 2nd level; D: 2nd level) was noted. Thus the optimum parametric setting $A_2B_3C_2D_2$ (cutting speed: 3500 rpm, feed rate:0.2 mm/rev, depth of cut:0.2 mm and tool nose radius: 0.8 mm) was obtained for the output response.

Table 9 Average response table for grey relational grade

Symbol	A	B	C	D
Turning parameter	Cutting speed (rpm)	Feed rate (mm/rev)	Depth of cut (mm)	Tool nose radius (mm)
Level1	0.4720	0.5291	0.5238	0.4783
Level2	**0.6261***	0.5181	**0.5708***	**0.6713***
Level3	0.5606	**0.6115***	0.5641	0.5091

Optimum	A2	B3	C2	D2

*Levels for optimum GRG

GRG response graph

The GRG response graph has shown in Fig. 3 described the variation of each process control parameter on the output response. From the response graph, the peak points were selected as the optimum level of machining parameters i.e. cutting speed at second level (0.621), feed rate at third level (0.6115), depth of cut at second level (0.5708) and tool nose radius at second level (0.6713).

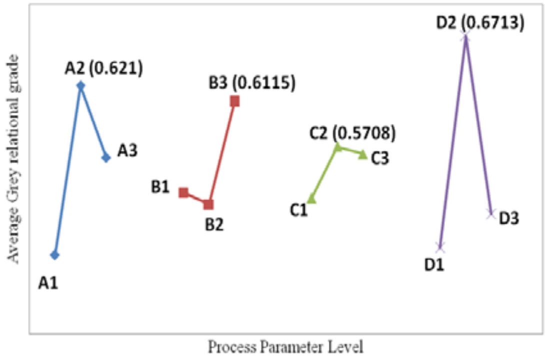


Fig. 3 GRG response graph

ANOVA for grey relational grade

Using MINITAB 17 software, Analysis of Variance (ANOVA) test was performed to determine the relative influence of factors on the machinability characteristics. The results of ANOVA for grey relational grade values with the control factors are shown in Table 10.From the observations, it is noted that all the four factors are significant at 95% confidence level. The percentage of contribution (PC %) of each variable in the total variation indicating their degree of influence on the response. From percentage of contribution analysis graph shown in Fig. 4, the cutting speed (51.31%) has greater influence on the output response (SR and MRR) followed by feed rate (23.45%), depth of cut (15.43%) and tool nose radius (9.81%).

Table 10 ANOVA for grey relational grade

Parameters	Sum of squares	DOF	Mean sum of squares	F-ratio	PC (%)
Cutting speed (A)	0.0897	2	0.0448	4.503	51.31
Feed rate (B)	0.0410	2	0.0205	2.751	23.45
Depth of cut (C)	0.0270	2	0.0135	2.925	15.43
Tool nose radius (D)	0.0171	2	0.0085	3.576	9.81
Total	0.1748				100

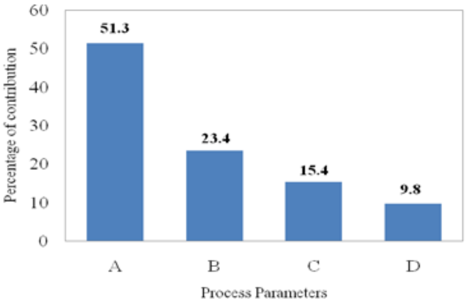


Fig. 4 Percentage of contribution

Confirmation Experiments

A confirmation experiment was conducted to validate the Taguchi based GRA implemented for optimization. The initial process parameter (Experimental condition 6) for which the quality characteristics with highest value of GRG (0.7740) was chosen as the initial process parameter setting. The SR and MRR value was estimated for the initial parameter setting was compared with observe value of optimum setting by Taguchi based GRA shown in the Table 11. The confirmation experiment results at optimal parameter combination ($A_2B_3C_2D_2$) show that the surface roughness was reduced from 0.45 to 0.39µm, the material removal rate is improved from 1.73 g/min to 2.12g/min. The grey relational grade from the measured performance measures based on the confirmation experiment was found to be 0.7887. It was also observe that, surface roughness of the turned surface was decreased in 13.33% and material removal rate was increased in 22.54% with the Taguchi based GRA setting. From the confirmation experiments, it is proved that Taguchi based GRAwould give better result in the aspect of surface quality and also indirectly in the aspects of energy savings and production time.

Table 11 Confirmation test results

Parameter setting	GRG	Response	
		SR (µm)	MRR (g/min)
Initial setting	0.7740	0.45	1.73
Optimal setting using Taguchi based GRA	0.7887	0.39	2.12
Improvement	0.0147	0.06	0.85
Improvement rate (%)	1.899	13.33	22.54

CONCLUSION

(i) Taguchi based grey relational analysis was used with different turning parameter settings for predicting the machinability characteristics such as surface roughness (SR)and Material removal rate (MRR) in the high-speed turning of LM24/SiC$_p$/coconut shell ash hybrid metal matrix composite.

(ii) The optimum turning condition was noted for minimizing the surface roughness and maximizing the MRR as $A_2B_3C_2D_2$ (cutting speed: 3500 rpm, feed rate: 0.2 mm/rev, depth of cut: 0.2 mm and tool nose radius: 0.8 mm).

(iii) From the percentage contribution analysis, it was noted that cutting speed (51.31%) and feed rate (23.45%) were the most important influence parameter on surface roughness. depth of cut (15.43%) and tool nose radius (9.81%) were least influence on surface roughness and MRR.

(iv) The optimal settings of high speed turning process parameters can be used wherever aluminium metal matrix composites require high degree of surface finish with increasing the rate of MRR.

(v) From the confirmation experiments, it is noted that Taguchi based GRA would give enhanced result on the part of surface quality and also ultimately in the aspects of energy savings and production rate.

REFERENCES

Adalarasan, R. and Sundaram, A.S., "Parameter design in friction welding of Al/SiC/Al_2O_3 composite using grey theory based principal component analysis (GT-PCA)," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 37, No.5, pp.1515-1528 (2015).

Arokiadass, R., Palaniradja, K. and Alagumoorthi, N., "Prediction and optimization of end milling process parameters of cast aluminium based MMC," *Transactions of Nonferrous Metals Society of China*, Vol. 22, No.7, pp.1568-1574 (2012).

Arulraj, M. and Palani, P.K., "Parametric optimization for improving impact strength of squeeze cast of hybrid metal matrix (LM24–SiCp–coconut shell ash) composite," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 40, No.1, p.2 (2018).

Bello, S.A., Raheem, I.A. and Raji, N.K., "Study of tensile properties, fractography and morphology of aluminium (1xxx)/coconut shell micro particle composites," *Journal of King Saud University-Engineering Sciences*, Vol.29, No.3, pp.269-277 (2017).

Dey, A., Debnath, S. and Pandey, K.M., "Optimization of electrical discharge machining process parameters for Al6061/cenosphere composite using grey-based hybrid approach," *Transactions of Nonferrous Metals Society of China*, Vol. 27, No. 5, pp.998-1010 (2017).

Dhanasekaran, S., Sunilraj, S., Ramya, G. and Ravishankar, S., "SiC and Al_2O_3 Reinforced aluminum metal matrix composites for heavy vehicle clutch applications," *Transactions of the Indian Institute of Metals*, Vol. 69, No.3, pp.699-703 (2016).

Dwivedi, S.P., Sharma, S. and Mishra, R.K., "Microstructure and mechanical behavior of A356/SiC/Fly-ash hybrid composites produced by electromagnetic stir casting," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 37, No.1, pp.57-67 (2015).

Kök, M., "Modeling and assessment of some factors that influence surface roughness for the machining of particle reinforced metal matrix composites," *Arabian Journal for Science and Engineering*, Vol. 36, No.7, pp.1347-1365 (2011).

Kumar, R. and Chauhan, S., "Study on surface roughness measurement for turning of Al 7075/10/SiCp and Al 7075 hybrid composites by using response surface methodology (RSM) and artificial neural networking (ANN)," *Measurement*, Vol. 65, pp.166-180 (2015).

Lal, S., Kumar, S., Khan, Z.A. and Siddiquee, A.N., "Wire electrical discharge machining of AA7075/SiC/Al_2O_3 hybrid composite fabricated by inert gas-assisted electromagnetic stir-casting process," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 36, No. 2, pp.335-346 (2014).

Linder, J., Axelsson, M. and Nilsson, H., "The influence of porosity on the fatigue life for sand and permanent mould cast aluminium," *International Journal of Fatigue*, Vol. 28, No.12, pp.1752-1758 (2006).

Manjunath Patel G C., Krishna, P. and Parappagoudar, M.B., "An intelligent system for squeeze casting process—soft computing based approach," *The International Journal of Advanced Manufacturing Technology*, Vol. 86, No. 9-12, pp.3051-3065 (2016).

Manjunath patel, G C., Krishna, P., Parappagoudar, M.B. and Vundavilli, P.R., "Multi-objective optimization of squeeze casting process using evolutionary algorithms," *International Journal of Swarm Intelligence Research*, Vol. 7, No. 1, pp.55-74 (2016).

Murthy, K.S. and Rajendran, I., "A study on optimisation of cutting parameters and prediction of surface roughness in end milling of aluminium under MQL machining," *International Journal of Machining and Machinability of Materials*, Vol. 7, pp.112-128 (2009).

Muthukrishnan, N., Babu, T.M. and Ramanujam, R., "Fabrication and turning of Al/SiC/B_4C hybrid metal matrix composites optimization using desirability analysis," *Journal of the Chinese Institute of Industrial Engineers*, Vol. 29, No. 8, pp.515-525 (2012).

Onat, A., Akbulut, H. and Yilmaz, F., "Production and characterisation of silicon carbide particulate reinforced aluminium–copper alloy matrix composites by direct squeeze casting method," *Journal of Alloys and Compounds*, Vol. 436, pp.375-382 (2007).

Palanikumar, K. and Muniaraj, A., "Experimental investigation and analysis of thrust force in drilling cast hybrid metal matrix (Al–15% SiC–4% graphite) composites," *Measurement*, Vol. 53, pp.240-250 (2014).

Palanikumar, K., Muthukrishnan, N. and Hariprasad, K.S., "Surface roughness parameters optimization in machining A356/SiC/20p metal matrix composites by PCD tool using response surface methodology and desirability function," *Machining Science and Technology*, Vol. 12, No.4, pp.529-545 (2008).

Patel, G.M., Krishna, P. and Parappagoudar, M.B., "Optimization of squeeze cast process parameters using Taguchi and grey relational analysis," *Procedia Technology*, Vol. 14, pp.157-164 (2014).

Premnath, A.A., Alwarsamy, T. and Rajmohan, T., "Experimental investigation and optimization of process parameters in milling of hybrid metal matrix composites," *Materials and Manufacturing Processes*, Vol. 27, No.10, pp.1035-1044 (2012).

Puhan, D., Mahapatra, S.S., Sahu, J. and Das, L., "A hybrid approach for multi-response optimization of non-conventional machining on AlSiCp MMC," *Measurement*, Vol. 46, No.9, pp.3581-3592 (2013).

Rajeswari, B. and Amirthagadeswaran, K.S., "Experimental investigation of machinability characteristics and multi-response optimization of end milling in aluminium composites using RSM based grey relational analysis," *Measurement*, Vol. 105, pp.78-86 (2017).

Rajmohan, T., Palanikumar, K. and Kathirvel, M., "Optimization of machining parameters in drilling hybrid aluminium metal matrix composites," *Transactions of Nonferrous Metals Society of China*, Vol. 22, No. 6, pp.1286-1297 (2012).

Ramnath, B.V., Elanchezhian, C., Jaivignesh, M., Rajesh, S., Parswajinan, C. and Ghias, A.S.A., "Evaluation of mechanical properties of aluminium alloy–alumina–boron carbide metal matrix composites," *Materials & Design*, Vol. 58, pp.332-338 (2014).

Rao, R.V., Kalyankar, V.D. and Waghmare, G., "Parameters optimization of selected casting processes using teaching–learning-based optimization algorithm," *Applied Mathematical Modelling*, Vol. 38, No. 23, pp.5592-5608 (2014).

Reihani, S.S.,"Processing of squeeze cast Al6061–30vol% SiC composites and their characterization," *Materials & design*, Vol.27 No. 3, pp.216-222 (2006).

Senthil, P. and Amirthagadeswaran, K.S., "Experimental study and squeeze casting process optimization for high quality AC2A aluminium alloy castings," *Arabian Journal for science and Engineering*, Vol. 39, No. 3, pp.2215-2225 (2014).

Senthil, P. and Amirthagadeswaran, K.S., "Optimization of squeeze casting parameters for non symmetrical AC2A aluminium alloy castings through Taguchi method," *Journal of mechanical science and technology*, Vol. 26, No. 4, pp.1141-1147 (2012).

Senthilkumar, C., Ganesan, G. and Karthikeyan, R., "Parametric optimization of electrochemical machining of Al/15% SiCp composites using NSGA-II," *Transactions of Nonferrous Metals Society of China*, Vol. 21, No.10, pp.2294-2300 (2011).

Seo, Y.H. and Kang, C.G., "The effect of applied pressure on particle-dispersion characteristics and mechanical properties in melt-stirring squeeze-cast SiC_p/Al composites," *Journal of materials processing Technology*, Vol. 55, pp.370-379 (1995).

Singh, S. and Singh, R., "Some investigations on surface roughness of aluminium metal composite primed by fused deposition modeling-assisted investment casting using reinforced filament," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 39, No. 2, pp.471-479 (2017).

Suresh, P., Marimuthu, K., Ranganathan, S. and Rajmohan, T., "Optimization of machining parameters in turning of Al-SiC-Gr hybrid metal matrix composites using grey-fuzzy algorithm," *Transactions of Nonferrous Metals Society of China*, Vol. 24, No.9, pp.2805-2814 (2014).

Toptan, F., Kerti, I. and Rocha, L.A., "Reciprocal dry sliding wear behaviour of B_4C_p reinforced aluminium alloy matrix composites," *Wear*, Vol. 290, pp.74-85 (2012).