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Multi Response Optimization during Machining of Magnesium Matrix Nanocomposite Reinforced with TiN Nanoparticulates

Ganesh Radhakrishnan[1]*, Sivakumar Vaithilingam[2], V. D. Tamilarasan[3] and M. Manikandan[4]
[1]Mechanical and Industrial Section, Engineering Department, University of Technology and Applied Sciences, Nizwa, Oman
[2]Department of Mechanical Engineering, Ramco Institute of Technology, Rajapalayam, Tamil Nadu, India.
[3]Department of Automobile engineering, Dr. Mahalingam College of Engineering and Technology, Pollachi, Coimbatore, Tamil Nadu India
[4]Department of Mechanical Engineering, Nandha Engineering College, Erode, Tamil Nadu, India.
*Corresponding author (e-mail: ganesh.radhakrishnan@utas.edu.om)

The present investigation is all about multiple process parameters optimization in the milling of TiN nanoparticulate reinforced magnesium matrix composite, which was carried out using Taguchi based Grey Relational Analysis (GRA). The parameters considered during the end milling process were the weight fraction of TiN in the composite, feed rate and depth of cut. Spindle speed was maintained constant at 1000 rpm. The performance parameters considered in the study include cutting force, material removal rate and surface roughness of the machined surface. The milling process was carried out in normal atmospheric conditions and at room temperature. An end mill cutter made of polycrystalline diamond (PCD) coated carbide was used in the work. L9 orthogonal array was used in the design of experiments and optimization process. The results of the optimization revealed that the combination of process parameters is A3B2C1, corresponding to 5-wt.% TiN, 10 mm/min feed rate and 0.15 mm depth of cut respectively, ranked top with respect to Grey Relational Grade (GRG), which was an indicator of optimization for the machinability of Mg-TiN nanocomposite. The predicted combination of optimized process parameters was confirmed theoretically and experimentally again and found that the combination of process parameters was A1B1C1, corresponding to 1.5 wt.% TiN, 5 mm/min feed rate and 0.15 mm depth of cut respectively for being achieved minimum cutting forces, maximum material removal rate and least surface roughness on the machined surface. The main effect and interaction effect plots confirmed the fact that the effect of process parameters on machinability performance was appreciably significant in the order: depth of cut, feed rate and weight fraction of TiN nanoparticles and complemented with normal probability, surface, and residual plots.

Keywords: Optimization; milling; process parameters; cutting forces; surface roughness; Taguchi

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In recent times, consistent innovation is visible in materials engineering. Particularly, with the metal matrix composites, slowly and gradually, lightweight aluminium is replaced by many other lightweight and high strength-to-weight ratio materials such as magnesium and hybrid alloys targeting variety of applications such as transportation, structural and even biomedical applications. Compared to that aluminium, magnesium has many attractive features such as being very lightweight, having high wear and corrosion resistance etc. Despite its high inflammability, its biodegradable property expanded widely its application in biomedical sectors. In recent years, bio-implants are mainly fabricated by pure magnesium or magnesium-based alloys or composite. Tailor-made composites with magnesium-based alloy as matrix and hard ceramic crystalline material as reinforcement have been developed to a larger extent to satisfy the desired qualities expected in the engineering fields. Hard ceramic reinforcements like silicon carbide (SiC), titanium oxide (TiO_2), titanium nitride (TiN), boron carbide (B_4C) etc. have been used in the development of magnesium matrix composites. Nanoparticulates have higher performance than that micro-sized particulates due to their high surface area and better grain boundary strength. However, different fabrication processes are available to fabricate metal matrix composites such as liquid casting, solid processing, and in-situ processing etc., solid processing like powder metallurgy technology become more popular and suitable for magnesium-based materials because of its inflammability property.

Yazid and Razak [1] had used ANOVA to study the level of influence of process parameters during minimum quantity lubrication (MQL) machining of Mg alloy. It was found from the study that better surface finish was obtained at maximum cutting speed

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and minimum feed rate. MQL had helped in efficient lubricant penetration during machining and observed that feed force was higher than radial force irrespective of the cutting conditions. Shi et. al [2] have used Taguchi based Grey Relational Analysis (GRA), one of the optimization techniques for the multiple process parameter optimization during milling of Ti alloy. It was revealed from the study that the cutting depth was more significant than other parameters influencing more on the surface integrity and wear. The process parameters of friction stir welding of magnesium alloy using Taguchi based Grey Relational Analysis was carried out by Sahu and Pal [3]. It was concluded from the study that the process parameters, shoulder diameter and welding speed were significantly influencing the machining performance and the study was also proved to be more feasible for the effective estimation of optimized process parameters. In general, machinability is considered more challenging in metal matrix composites compared to that homogeneous metals because of the inclusion of hard ceramic reinforcement. This ceramic reinforcement affects the tool life significantly in addition to affecting the machinability and surface integrity of the materials under machining. The scientific contribution of the concepts, theories, models etc. being developed every day in magnesium composites provide a wide scope to undergo a detailed investigation on the machinability of magnesium-based nanocomposite so that a consistent scientific outcome, an identified research gap from the literature review could be expected at the end of the study.

MATERIALS AND METHODOLOGY

Pure Magnesium particulates of average size ranging between 55 to 300 microns is used as matrix and the reinforcement is TiN nanoparticles with an average particle size of 20 nm. The nanocomposite is prepared by a powder metallurgy process, which involves initially blending of Mg and TiN powders using a mechanical alloying technique followed by cold compaction and hot extrusion as secondary processing. Cold compaction is done in a 100 T hydraulic press under an iso-static pressure of 300 MPa at room temperature. After the compaction, the green nanocomposite specimens are taken to sintering in a box furnace at a temperature of 550°C for 4 hours followed by hot extrusion using an extrusion die maintained at a constant temperature of 500°C with an extrusion ratio of 2.25:1. [4,5] The nanocomposite fabricated contains various levels of weight fraction such as 1.5, 2.5, and 5% of TiN. Milling process was done in a CNC machining center. The end mill made of PCD-coated solid carbide is used for milling the nanocomposites. The present work is to investigate the effects of process parameters on the machining performance of nanocomposite and also to optimize the multiple process parameters of the machining. [6-8]. The process parameters considered for this study are weight fraction of TiN (%), spindle speed, feed rate and depth of cut. Cutting forces, material removal rate and surface roughness are considered for performance indicators [9]. Spindle speed is kept constant during the study, whereas the feed rate and depth of cut are varied. The properties of Mg and TiN are listed in Table 1. The parameters chosen with their levels are shown in Table 2. Multi objective optimization for the machinability of Mg-TiN nanocomposite was carried out using Taguchi based Grey Relational Analysis (GRA). Grey Relational Analysis is most popularly used tool for solving optimization process involving multiple responses. [10-12] In this approach, a grey relational grade is obtained for analyzing the correlation among the multiple responses. L_9 orthogonal array is used in this study, which will be more appropriate for three process parameters with three levels. The procedure of Grey Relational Analysis (GRA) used in this study was explained as follows.

Step 1: Transform the experimental responses into S/N ratios. In this study, the output measures such as cutting force, and surface roughness were minimized and therefore the smaller-the-better type of quality characteristic was used, whereas the other output measure, material removal rate to be maximized and therefore larger-the-better type of quality characteristic was used. "i" refers to experiments and "j" refers to responses. The S/N ratios are calculated using the equation 1 for smaller-the-better type and equation 2 for larger-the-better type.

$$\boldsymbol{S/N = -10\ log\left[\frac{1}{n}\sum_{i=1}^{n} Y_i^2\right]} \tag{1}$$

$$\boldsymbol{S/N = -10\ log\left[\frac{1}{n}\sum_{i=1}^{n} \frac{1}{Y_i^2}\right]} \tag{2}$$

Step 2: Normalize the term, Y_{ij} as N_{ij} ($0\leq N_{ij}\leq 1$) using the formula applicable for the quality characteristic, smaller-the-better type.

$$N_{ij} = \frac{\max(Yij, i=1,2\ldots\ldots,n) - Yij}{\max(Yij, i=1,2\ldots\ldots,n) - \min(Yij, i=1,2\ldots\ldots,n)} \tag{3}$$

Step 3: Calculate deviation sequences using the formula.

Δ = difference between Y_{ij} and Y_{oj}, where Y_{oj} is the optimum performance value.

Table 1. Physical properties of Mg and TiN.

S. No	Description	Mg	TiN
1	Particle Size	55-300 µm	~20 nm
2	Purity level	>98%	>99%
3	Mass density	1.75 g/cm^3	5.4 g/cm^3
4	The shape of the crystal	Hexagonal	Face Centered Cubic
5	Melting point	650°C	2930°C
6	Thermal conductivity	156 W/mK	4.92 W/mK
7	Modulus of Elasticity	40-45 GPa	251 Gpa
8	Coefficient of thermal expansion	25 µ/k	9.35 µ/k

Table 2. Process parameters with their levels.

Parameters	Levels		
	-1	0	1
Weight % of TiN	1.5	2.5	5
Feed rate, mm/min	5	10	15
Depth of cut, mm	0.15	3	0.45

Step 4: Calculate the Grey relational coefficient using the formula.

$$GC_{ij} = \frac{\Delta min + \lambda\, \Delta max}{\Delta ij + \lambda\, \Delta max} \quad (4)$$

where, λ is the distinguishing factor, with range 0 ≤ λ ≤ 1.

Step 5: Calculate the Grey relational grade (G_i) using the formula.

$$G_i = \frac{1}{m} \sum GC_{ij} \quad (5)$$

Step 6: Using ANOVA, optimum levels are found for a maximum grey relational grade.

Step 7: Calculate the predicted Grey relational grade ($G_{i\text{-predicted}}$).

$$G_{i\text{-predicted}} = \text{Mean } G_i + \sum_{i=1}^{q} maximum\ G_i - \text{Mean } G_i \quad (6)$$

Where q is the number of factors affecting the responses.

Table 3. Responses and their S/N values.

S.No.	Factors			Responses				S/N of responses			
	A	B	C	F_x	F_y	MRR	SR	F_x	F_y	MRR	SR
1	1.5	5	0.15	10.55	12.31	1.6479	0.302	-20.465	-21.805	-4.339	10.400
2	1.5	10	0.3	10.13	11.45	6.2464	0.28	-20.112	-21.176	-15.913	11.057
3	1.5	15	0.45	10.63	11.23	13.113	0.198	-20.531	-21.008	-22.354	14.067
4	2.5	5	0.3	10.23	12.43	3.1855	0.389	-20.198	-21.889	-10.064	8.201
5	2.5	10	0.45	10.46	12.1	9.2497	0.339	-20.391	-21.656	-19.323	9.396
6	2.5	15	0.15	9.94	12.27	4.4518	0.27	-19.948	-21.777	-12.971	11.373
7	5	5	0.45	10.3	11.35	4.6217	0.731	-20.257	-21.100	-13.296	2.722
8	5	10	0.15	10.01	12.07	2.8936	0.478	-20.009	-21.634	-9.229	6.411
9	5	15	0.3	11.28	12.23	9.4389	1.141	-21.046	-21.749	-19.498	-1.146

RESULTS AND DISCUSSIONS

The responses of the machinability study and their computed S/N ratios are shown in Table 3. The S/N ratios are normalized and their deviation sequences are calculated using equations 3 and 4 respectively. The normalized S/N ratios and deviation sequences are shown in Table 4. Grey Relational Coefficient (GRC) is estimated for each process parameter in all the experiment runs using equation 5. The predicted Grey Relational Grade (GRG) is calculated for each run using equation 6. The GRG values are equivalent to multiple response performance index and therefore ranked from highest to lowest. The GRC and GRG values are shown in Table 5. The ideal process parameters combination of Rank 1 in the GRG corresponds to the 8th experiment run A3B2C1. According to Table 6, the mean GRG computed for each factor at all the levels conclude that the predicted process parameters combination based on the maximum value of GRG for each factor corresponds to A1B1C1. The predicted process parameters combination, computed using equation 6 was repeated experimentally and found that there is a consistency observed in the optimum process parameters in the machinability of the nanocomposite. Mean Grey Relational Grade versus (a) Level of control factor (b) Experiment run and the main effect plot or S/N ratio of GRG are shown in Figure 1 and 2 respectively. The main effect plot drawn for GRG values at each level of the process variable confirms that the effect i.e., the influence of each control factor on the performance is significant. It is also noticed from the interaction plot, shown in Figure 3 that a significant interaction between the process variables exists. [13-16] The dependency between the variables is observed to be significant and contributes appreciably on the overall performance of the investigation from the interaction plot. Similarly, Normal Probability of GRG plot, residual fit for GRG and residual order for GRG plotted in Figure 4 and surface plot for GRG with various process parameters shown in Figure 5 The normal probability plot releals the fact that all the points are very closer to the fitted line and ensures the accuracy of the optimization procedure being used in this study. Also, it was found that the error data points plotted in the residual plots confirms that the distribution is purely random and doesn't fall in any pattern, which once gain complements the accuracy obtained in other plots.The profile of the surface plots obtained for GRG reveals the fact that there is a significant interaction between the control factors in influencing the performance.

Table 4. Normalized S/N and Deviation Sequences.

S.No.	Factors			Normalized S/N				Deviation Sequences			
	A	B	C	F_x	F_y	MRR	SR	F_x	F_y	MRR	SR
1	1.5	5	0.15	0.230	0.000	1.000	1.117	0.770	1.000	0.000	-0.117
2	1.5	10	0.3	0.713	0.628	0.599	1.119	0.287	0.372	0.401	-0.119
3	1.5	15	0.45	0.138	0.788	0.000	1.126	0.862	0.212	1.000	-0.126
4	2.5	5	0.3	0.598	-0.088	0.866	1.110	0.402	1.088	0.134	-0.110
5	2.5	10	0.45	0.333	0.153	0.337	1.114	0.667	0.847	0.663	-0.114
6	2.5	15	0.15	0.931	0.029	0.755	1.120	0.069	0.971	0.245	-0.120
7	5	5	0.45	0.517	0.701	0.741	1.080	0.483	0.299	0.259	-0.080
8	5	10	0.15	0.851	0.175	0.891	1.102	0.149	0.825	0.109	-0.102
9	5	15	0.3	-0.609	0.058	0.320	1.044	1.609	0.942	0.680	-0.044

Table 5. Grey Relational Coefficient, Grey Relational Grade and their ranks.

S.No.	Factors			Grey Relational Coefficient				Grey Relational Grade (GRG)	Rank
	A	B	C	F_x	F_y	MRR	SR		
1	1.5	5	0.15	0.565	0.500	1.000	1.133	0.799	5
2	1.5	10	0.3	0.777	0.729	0.714	1.135	0.839	3
3	1.5	15	0.45	0.537	0.825	0.500	1.145	0.752	7
4	2.5	5	0.3	0.713	0.479	0.882	1.123	0.799	6
5	2.5	10	0.45	0.600	0.542	0.601	1.129	0.718	8
6	2.5	15	0.15	0.935	0.507	0.803	1.137	0.846	2
7	5	5	0.45	0.674	0.770	0.794	1.087	0.831	4
8	5	10	0.15	0.870	0.548	0.902	1.114	0.858	1
9	5	15	0.3	0.383	0.515	0.595	1.046	0.635	9

Table 6. Mean GRG for each factor.

Factors	Level			Delta	Rank
	1	2	3		
A	0.796	0.787	0.774	0.022	3
B	0.809	0.805	0.744	0.065	2
C	0.834	0.757	0.767	0.077	1

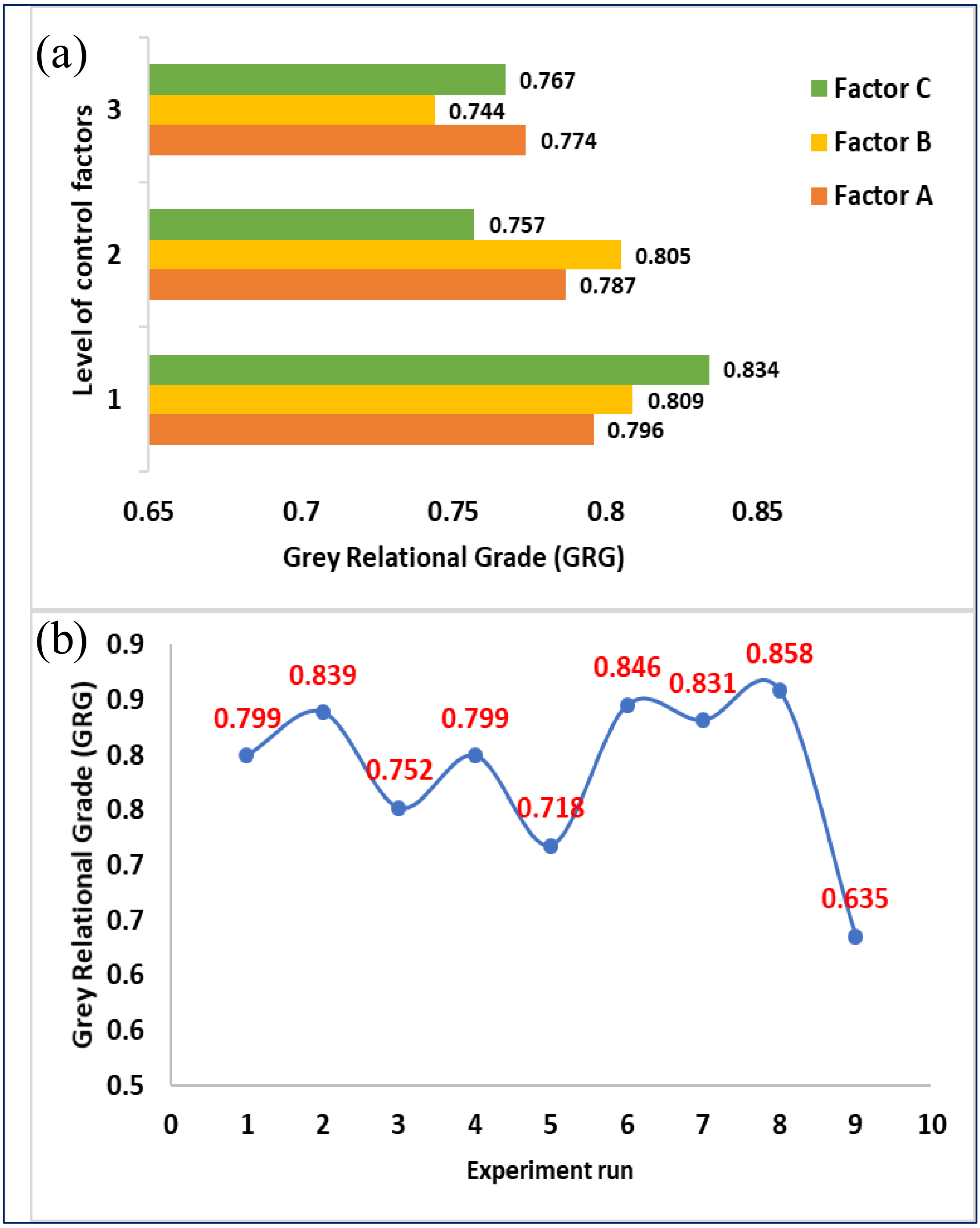

Figure 1. Mean Grey Relational Grade versus (a) Level of control factor (b) Experiment run.

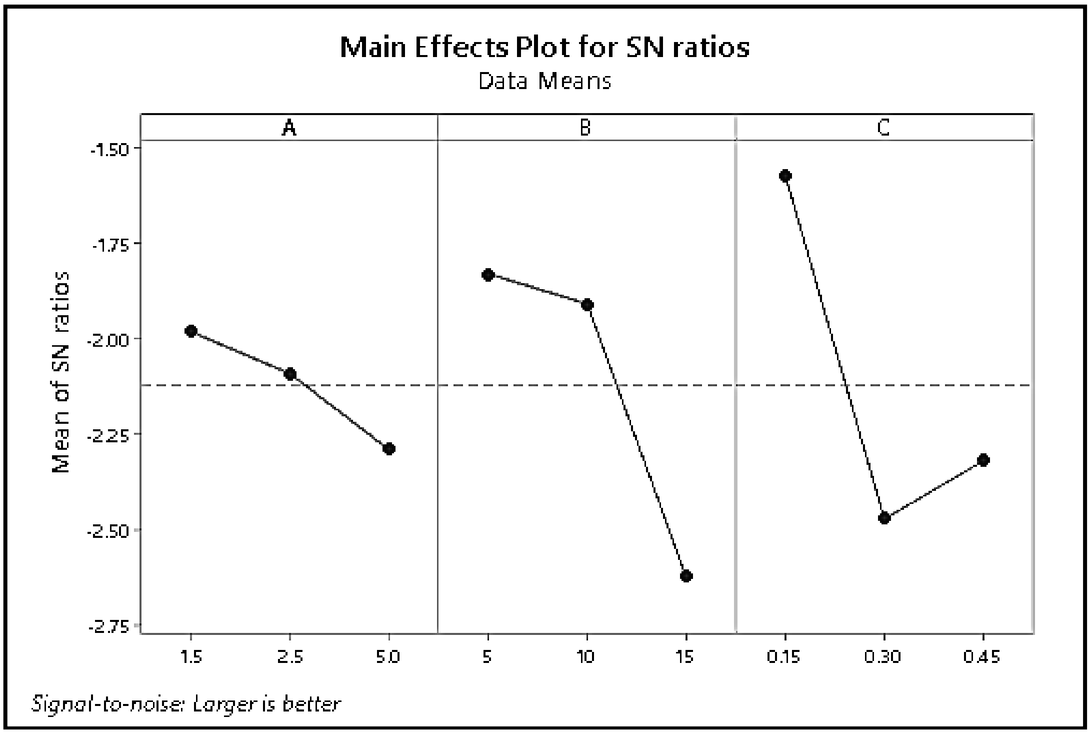

Figure 2. Main effect plot for S/N ratio of GRG.

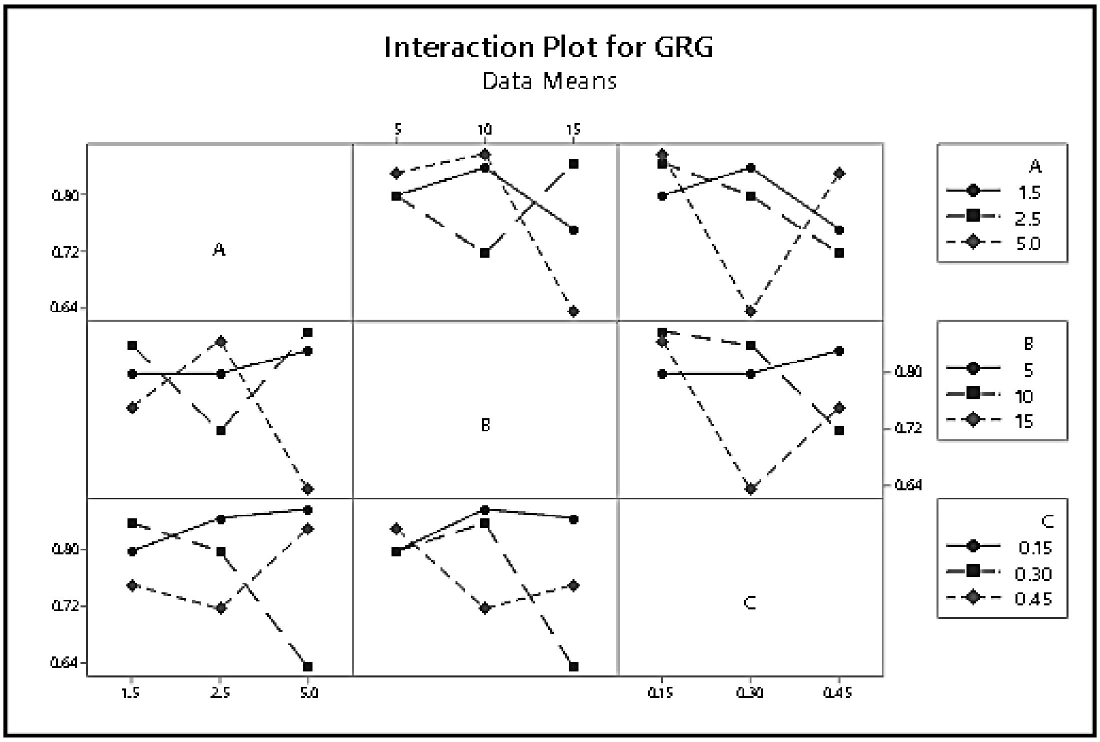

Figure 3. plot for GRG with process parameters at all levels.

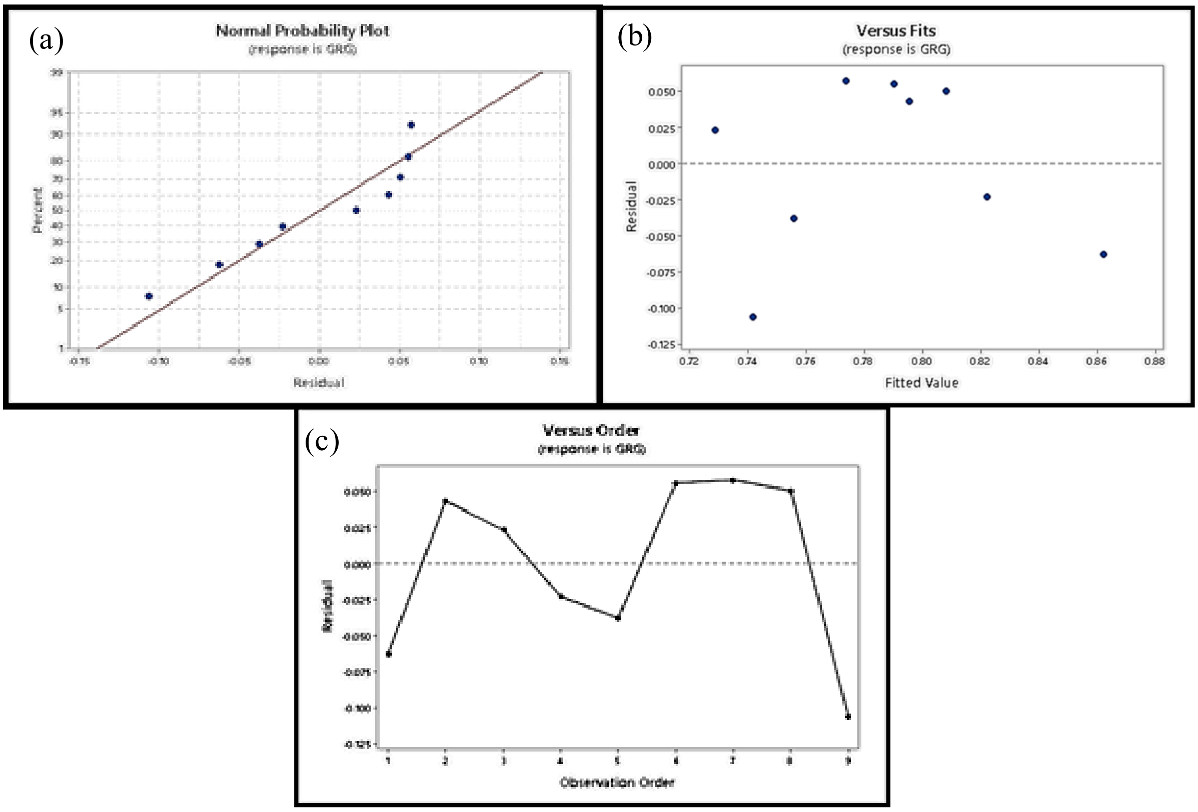

Figure 4. (a) Normal probability plot of GRG (b) Residual fit for GRG (c) Residual order for GRG.

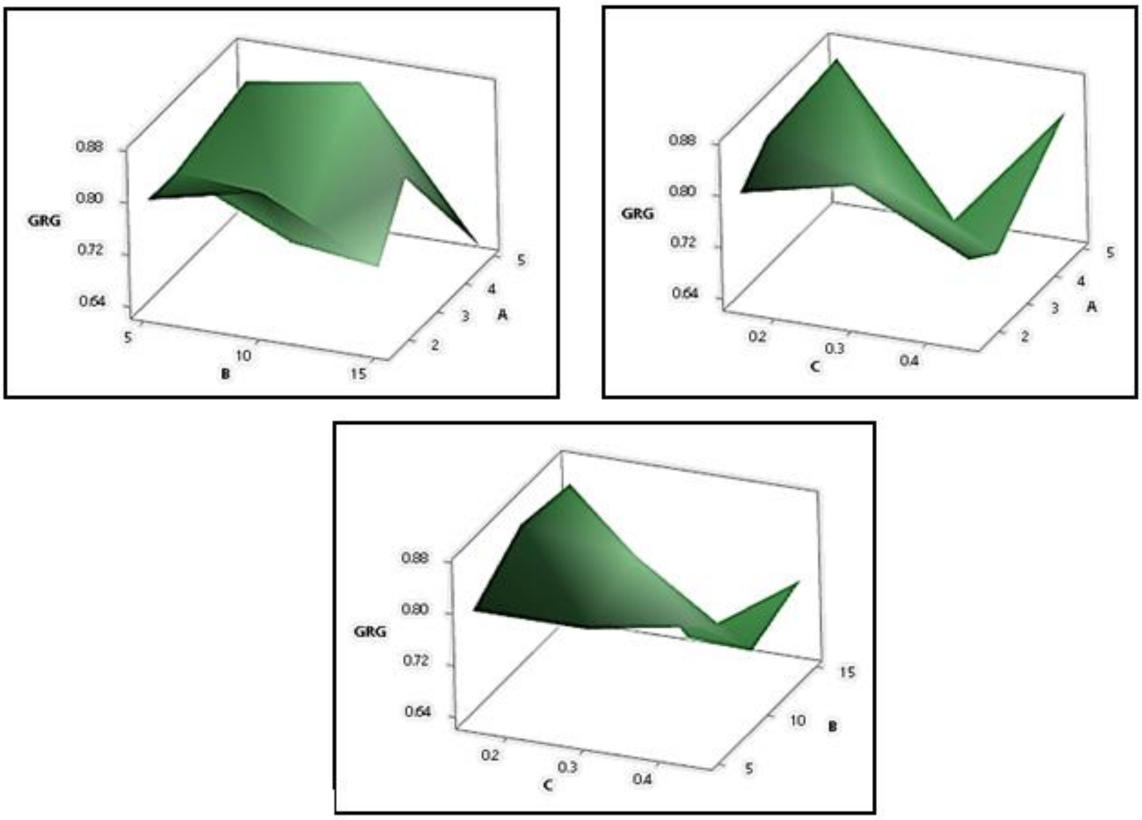

Figure 5. Surface plot for GRG with various process parameters.

The second-order regression equation for GRG is given by the equation,

$$GRG = 0.4804 + 0.1008A + 0.05480B + 0.2668C + 0.001108A^2 - 0.001253B^2 - 1.410C^2 - 0.01197AB + 0.01822AC$$

The optimized combination of multiple parameters in the study will be an asset for the future researchers to work on the optimization of process parameters with appropriate selection of parameters and levels so that the investigation will result in useful scientific outcomes with efficient utilization of resources available targeting for many real time applications in the field of advanced materials, and its characterization.

CONCLUSIONS

In this study, Grey Relational Analysis (GRA) was applied for the multi process parameters optimization and derived the conclusions as follows.

- The influence of individual parameters considered in the machining process and their interations are significant on the machining performance.
- The predicted and experimentally verified combination of optimized process parameters are same corresponding to A1B1C1, confirming the consistency and accuracy of the optimization procedure used.
- Minimum weight fraction, 1.5% of TiN nano particles, feed rate of 5 mm/min and 0.15 mm depth of cut resulted in optimized machining performance.

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