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Grey-Fuzzy Based Optimisation of Machining Parameters in Turning of AA 7068/TiC MMCs

Syed Altaf Hussain[1]*, Sudhamadhuri K[1], Upendra Rajak[1], and Abhishek Dasore[2]

[1]Department of Mechanical Engineering, Rajeev Gandhi Memorial College of Engineering & Technology, 518501 Nandyal, Andhra Pradesh, India

[2]Department of Computer Science and Engineering, SR University, Ananthasagar, Hasanparthy, 506371 Warangal, Telangana, India

ABSTRACT

With the growing applications of Metal Matrix Composites in several engineering fields, it is necessary to develop appropriate machining technology to process them efficiently. The turning process is generally used across all industries. In this research, an effort has been made to determine optimum values of process parameters for turning of AA7068/TiC metal matrix composites (MMCs) using the Grey Fuzzy Approach. The selected process parameters are the % weight of particle reinforcement, cutting speed, feed and depth of cut. Experiments have been designed according to CCD and conducted on an all-geared lathe machine with a carbide (K-30) cutting tool insert. The responses considered are cutting force, surface roughness and metal removal rate (MRR). To optimise the machining responses simultaneously, grey relational analysis combined with fuzzy logic is employed to determine the grey-fuzzy reasoning grade. The optimum combination of process parameters that generated the highest GFRG value (0.6083) was found to be a wt% reinforcement of 2%, a cutting speed of 50 m/min, a feed of 0.06 mm/rev, and a depth of cut of 0.2 mm. From the ANOVA, the wt% of TiC reinforcement was the only statistically significant linear factor at the 95% confidence level in the multi-response optimisation. Confirmation test under optimum conditions led to a reduction in cutting force by 4.00% from 129.45 N to 124.27 N, an improvement in surface roughness by 3.04% from 0.493 μm to 0.478 μm, and an increase in MRR by 5.99% from 136.37 mm^3/s to 144.55 mm^3/s.

Keywords: AA7068/ TiC MMCs, carbide (K-30) cutting tool, grey-fuzzy logic, optimisation

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E-mail addresses:
syedaltafhussain@rgmcet.edu.in (Syed Altaf Hussain)
ksmadhurime@gmail.com (Sudhamadhuri K)
upendrarajak86@gmail.com (Upendra Rajak)
dasore.abhishek@sru.edu.in (Abhishek Dasore)
* Corresponding author

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INTRODUCTION

The aluminium alloy AA7068 finds use in numerous applications owing to its unique properties such as corrosion resistance, high electrical and thermal conductivity, and good fatigue and wear resistance (Ashraf & Shibli, 2009; Cerik, 2017; Heinz et al., 2000; Shin et al., 2017; Teimouri et al., 2017). Major applications include those where alloys are preferred over conventional materials such as steels and cast irons owing to their lightweight yet high-strength mechanical properties, and composites based on aluminium alloys, known as aluminium metal matrix composites (MMCs). Turning these MMCs is an important step in the machining process.

Good corrosion resistance, along with a high strength-to-weight ratio, is exhibited by the first-generation aluminium-based MMCs reinforced with ceramics (Gururaja et al., 2013). The effect of various machining parameters on tool wear and BUE formation during the turning of Al-SiC MM Cs using a rhombic uncoated carbide tool. The formation of a less built-up edge was observed at lower cut depths and high speeds (Manna & Bhattacharyya, 2005). A two-dimensional array was developed using GRA to optimise process parameters while drilling Al/SiC MMCs (Haq et al., 2008). A sensitivity-based multi-criteria optimisation method aimed at minimising the cutting force and maximising material removal while machining unidirectional glass fibre reinforced polyester rods (Isik & Kentli, 2009). The influence of cutting parameters on temperature, thrust force, and surface roughness (SR) during drilling of AA6351/B4C composite materials was presented (Samy & Kumaran, 2017). To minimise tool wear and specific cutting pressure, and maximise the material removal rate, the grey relational grade and Taguchi method were implemented in the turning process of glass fibre/epoxy composites using a carbide (K-10) tool (Palanikumar et al., 2006).

Application of grey fuzzy logic to optimise the drilling process parameters of composite plates comprising carbon fibre-reinforced plastic (Krishnamoorthy et al., 2012). Employed the Grey Fuzzy algorithm in the process of optimising the machining parameters while drilling the hybrid aluminium metal matrix composites (Rajmohan et al., 2013). Adoption of response surface methodology (RSM) to optimise the machining parameters of LM 25 Al/SiC specimen while performing the turning process (Palanikumar & Karthikeyan, 2006). The Taguchi and GRA combination approach has been extensively utilised to optimise objectives such as surface finish, cutting force, tool life, flank wear, and MRR (Jangra et al., 2012; Nalbant et al., 2007; Sahoo et al., 2013). To meet the desired output responses such as high SR, low tool wear, and shorter time intervals, GA has been employed to optimise process parameters (Chen et al., 2014; Ganesan & Mohankumar, 2013). Application of fuzzy logic to predict the output responses (MRR, TWR, and SR), while the desirability method was used for optimising process parameters in EDM of Inconel 718 (Sengottuvel et al., 2013).

The multi-objective optimisation technique based on fuzzy TOPSIS was applied to enhance the EDM surface integrity and the dimensional accuracy of AISI P20 tool steel (Dewangan et al., 2015). Furthermore, there is significant potential for GRA to enhance the performance of fuzzy logic in multi-objective optimisation problems. In the current case, the complex multi-response optimisation problem could be easily converted into a single GFRG optimisation. An approach through a fuzzy logic controller that estimates the shape of the weld bead of a weld joint using the TIG welding process. Eventually, it was mentioned that the developed fuzzy logic model was tested several times to ensure sufficient precision (Narang et al., 2011). The use of the fuzzy interface system, along with the Taguchi method, to optimise the parameters of the TIG welding process for A387 Grade 11 Class 2 steel.

Finally, it was found that the critical input parameter for the TIG welding process is arc voltage, whereas the second one is the welding cutting (Prajapati et al., 2020). Various methods can be used to address multi-objective optimisation problems, such as fuzzy logic, ANN, GA, GRA, and RSM (Krishnaiah & Shahabudeen, 2012). Applications of a fuzzy logic-based approach are in environments with significant uncertainty and hesitation. Multi-criteria decision-making (MCDM) systems based on fuzzy logic have become popular in current research on optimising manufacturing processes.

In recent years, researchers have successfully implemented the grey relational approach to address interdependencies among multiple objectives across various manufacturing fields (Ahilan et al., 2009; Chiang & Chang, 2006; Hsiao et al., 2008; Krishnamoorthy et al., 2012; Lin & Lin, 2005). A genetic algorithm (GA) integrated with PCA and grey relational analysis (GRA) for optimisation of machining parameters to obtain better surface quality with minimum cutting force without any increase in specific power consumption during the turning of MMCs (Khandey et al., 2017). The use of GRA, along with fuzzy logic, for the optimisation of wire EDM of AISID2 steel to minimise surface roughness and layer thickness (Soepangkat & Pramujati, 2013). The use of TOPSIS together with the Taguchi method to arrive at the optimal settings of machining parameters in the turning of GFRP composite (Hussain et al., 2025). The use of grey fuzzy logic to optimise CNC milling parameters for Al-4.5% Cu-TiC MMCs with multiple performance measures (Das et al., 2016). Several optimisation methods have been efficiently implemented in many manufacturing operations, most of which were carried out under uncertainty (Yang & Huang, 2012). Various objectives related to different issues in materials science have been achieved using evolutionary algorithms and other machine learning techniques (Giri et al., 2013).

Optimisation on a multi-objective basis for the tribological properties of the hybrid composite material based on aluminium alloy A356 containing SiC has been done using the ‘Block-on-Disc’ tribometer system, where the input parameters have been taken as load, sliding velocity, and graphite content. The output parameters have been measured as

the coefficient of friction and wear rate. The multi-objective optimisation was performed using GRA and verified with TOPSIS (Gajević et al., 2024). Efforts have been made to minimise the frictional wear properties of aluminium 2024-TiB2 metal matrix composites (MMCs) using the grey fuzzy optimisation technique. The effectiveness of the new grey fuzzy optimisation approach for solving multiple-response tribological problems has been successfully tested (Dey et al., 2023). Polyvinyl Alcohol's improved mechanical performance, thermal stability, and reduced moisture absorption have been achieved through crosslinking with varying weight percentages of fumaric acid and graphite particles modified with sulfuric acid.

The grey-fuzzy optimisation technique has been used to achieve a trade-off between competing objectives related to mechanical and physical properties (Kafaltiya et al., 2024). AVOA-SVM regression models were used to predict and analyse machining responses, such as surface roughness and MRR, during the machining of 7068 alloy using a graphite nanofluid (Shrotriya et al., 2026). A grey-Fuzzy approach was used to identify the optimal combination of tribological parameters to minimise wear and friction in Al2024-TiB2 MMCs (Dey et al., 2023). Optimum drilling parameters for machining CFRP by combining the grey relation coefficient with the combined compromise solution (Grey-CoCoSo) for the machining responses like MRR, surface roughness, and delamination factor (DF) (Shunmugesh et al., 2025). A hybrid grey-based fuzzy algorithm was used to determine the optimum results of a combination of factors such as cutting speed, feed rate, cutting depth and cutting path strategy for the machining responses like surface quality, MRR and production time (Engin et al., 2026). AA8011 AMC reinforced with 9 wt% SiO2 particles was fabricated using the stir-casting technique, and tribological responses, such as the coefficient of friction and frictional forces, were optimised using the Grey-fuzzy approach (Bhowmik et al., 2026).

Limited work has been reported on the influence of turning variables on various machining responses. So, this work was undertaken to optimise the process parameters for machining AA7068/TiC particulate metal matrix composites using the Grey-Fuzzy logic approach. The primary machining responses considered are Fz (cutting force), Ra (surface roughness), and MRR (metal removal rate). An optimised set of input machining parameters is required to reduce machining responses.

MATERIALS AND METHODS

In this study, AA7068/TiC Metal Matrix Composites with reinforcement percentages of 2-10% (in increments of 2%) are fabricated using a stir casting technique, in which AA7068 is placed in a crucible and heated to 850ºC. Once the matrix had melted, magnesium ribbons were introduced into the molten metal to clean it and increase the wettability of AA7068, and 2% TiC was added to the molten metal, which was preheated to 300ºC. In the meantime, the molten metal was stirred at 300 rpm for 15 minutes to ensure

uniform mixing of the matrix and reinforcements. The experimental setup is shown in Figure 1. Specimens of dimension Ø 22 × 190 mm are cast. Experiments have been planned to use a central composite design and conducted on a lathe machine with a cutting tool insert made of Carbide K-30. A four-factor central composite design (CCD) is chosen since it provides an efficient experimental design for investigating the effects of multiple continuous machining parameters on the response while still estimating the behaviour of the response within the experimental design region. The current CCD comprises 31 experimental runs, as shown in Table 1.

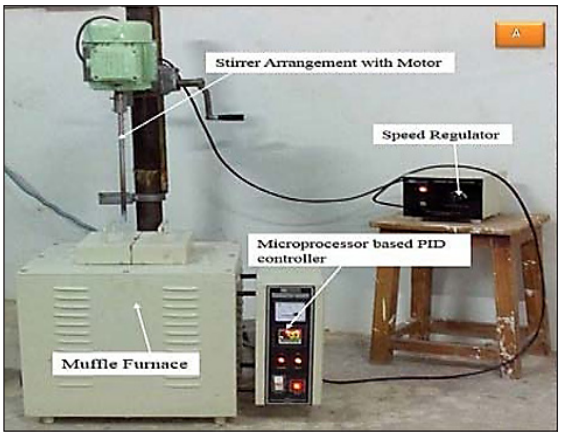


Figure 1. Stir casting setup

Table 1
Observation table

Sl. No.	Weight Percentage of TiC, (wt. %)	Cutting Speed (V), m/min	Feed (f), mm/rev	Depth of Cut (d), mm	Observed Responses		Calculated Responses
					Cutting Force (Fz), N	Surface Roughness (Ra), µm	Material Removal Rate (MRR), mm^3/sec
1	4	40	0.07	0.5	129.45	0.493	136.37
2	8	40	0.07	0.5	167.82	0.643	94.56
3	4	60	0.07	0.5	144.02	0.506	137.59
4	8	60	0.07	0.5	182.39	0.716	116.10
5	4	40	0.09	0.5	131.15	0.566	147.70
6	8	40	0.09	0.5	164.56	0.737	89.15
7	4	60	0.09	0.5	145.22	0.552	138.82
8	8	60	0.09	0.5	164.86	0.706	104.88
9	4	40	0.07	1.1	128.64	0.556	146.23
10	8	40	0.07	1.1	167.33	0.687	87.43
11	4	60	0.07	1.1	144.26	0.516	140.51
12	8	60	0.07	1.1	170.68	0.662	111.54
13	4	40	0.09	1.1	156.89	0.598	150.22
14	8	40	0.09	1.1	179.45	0.786	105.96

Table 1 (*continued*)

Sl. No.	Weight Percentage of TiC, (wt. %)	Cutting Speed (V), m/min	Feed (f), mm/ rev	Depth of Cut (d), mm	Observed Responses		Calculated Responses
					Cutting Force (Fz), N	Surface Roughness (Ra), µm	Material Removal Rate (MRR), mm^3/sec
15	4	60	0.09	1.1	172.11	0.588	156.00
16	8	60	0.09	1.1	190.73	0.675	118.14
17	2	50	0.08	0.8	114.45	0.426	179.32
18	10	50	0.08	0.8	209.00	0.815	77.04
19	6	30	0.08	0.8	148.86	0.659	105.00
20	6	70	0.08	0.8	167.20	0.546	135.23
21	6	50	0.06	0.8	141.46	0.594	106.25
22	6	50	0.10	0.8	179.88	0.716	132.50
23	6	50	0.08	0.2	150.54	0.549	109.75
24	6	50	0.08	1.4	180.86	0.689	135.89
25	6	50	0.08	0.8	132.08	0.624	129.45
26	6	50	0.08	0.8	138.69	0.621	127.86
27	6	50	0.08	0.8	138.78	0.661	125.52
28	6	50	0.08	0.8	142.34	0.618	126.35
29	6	50	0.08	0.8	138.52	0.594	126.46
30	6	50	0.08	0.8	144.13	0.646	126.52
31	6	50	0.08	0.8	145.36	0.609	126.75

This is comprised of factorial/axial points and repeat centre points. Experiments 25-31 represent the repeat centre points that involve 6 wt.% TiC, 50 m/min cutting speed, 0.08 mm/rev feed rate and 0.8 mm depth of cut, resulting in 7 centre points for the estimation of experimental/pure error. This tool insert conforms to ANSI standards. It has the same ISO geometry as that of SNMG 120408. The cutting tool inserts are attached to a PSBNR-2525M12 WIDAX tool holder. Input parameters used for conducting experiments are tabulated in Table 2, and output responses obtained from experiments are tabulated in Table 1. The cutting force generated during the turning of MMC bars is measured using the Kistler Dynamometer model 9257B. The surface finish obtained on the machined specimens is measured using a 'Talysurf' tester supplied by Metasonic Private Ltd. The metal removal rate is evaluated using Equation 1. Figure 2 illustrates the experimental setup.

The percentage of variation in the density of the MMCs due to variation in the amount of reinforcement added is very small and was ignored.

$$\text{MRR} = \frac{wtb - wta}{Machining\ \ Time\ (t) * Density\ (\rho)} \quad \frac{mm^3}{sec} \qquad [1]$$

Where

wtb = Wt. of w/p before machining

wta = Wt. of w/p after machining

T = Time, Sec

ρ = Density, g/mm^3

Table 2
Process parameters for AA7068/TiC machining

S.No	Parameters	Notation	Levels				
			1	2	2	4	5
1	The weight percentage of TiC,	wt%	2	4	6	8	10
2	Velocity of cutting, m/min,	V	30	40	50	60	70
3	Feed (f), mm/rev	f	0.06	0.07	0.08	0.09	0.1
4	Depth of Cut mm	d	0.2	0.5	0.8	1.1	1.4

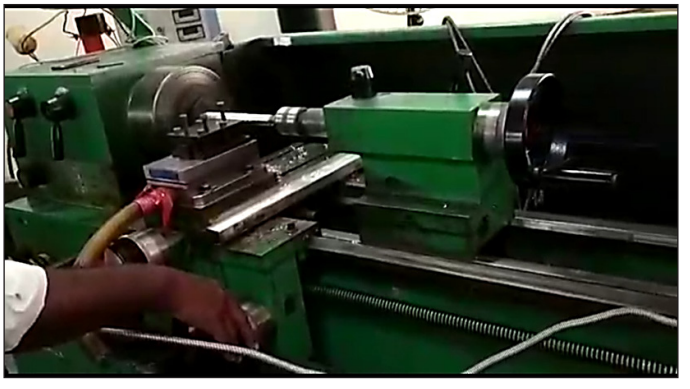
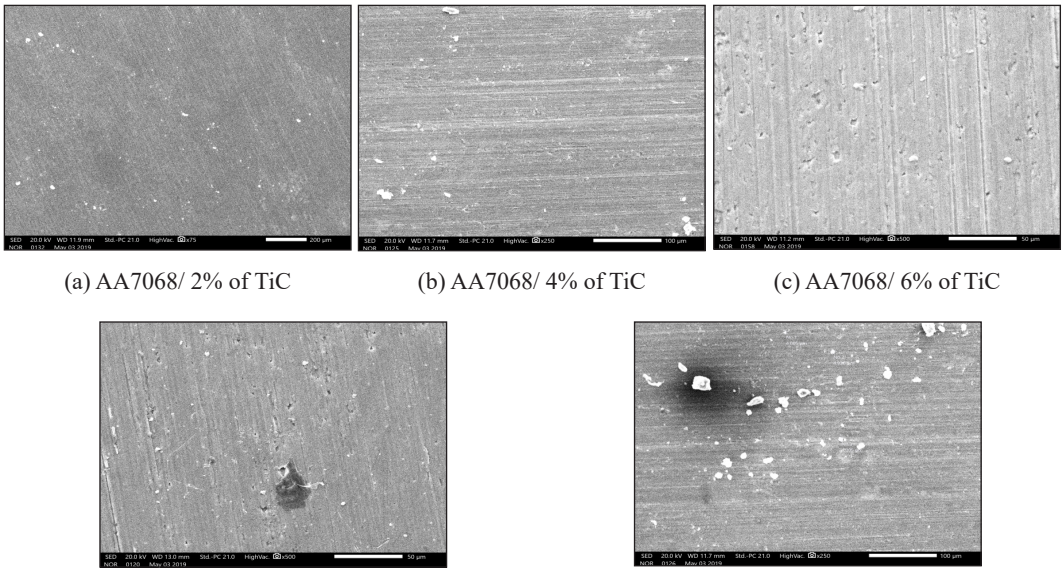


Figure 2. Photograph of the original experimental setup

SEM images are taken to investigate the surface characteristics of developed composite materials (AA7068/TiC MMCs). The images show uniform dispersion of TiC reinforcement particles in the AA7068 matrix. There is no agglomeration of reinforcement particles found in the composite material. Thus, a stirring speed of 300 rpm is appropriate for AA7068/ TiC MMCs. The SEM images are shown in Figure 3a to 3e.



(a) AA7068/ 2% of TiC (b) AA7068/ 4% of TiC (c) AA7068/ 6% of TiC

(d) AA7068/ 8% of TiC (e) AA7068/ 10% of TiC

Figure 3. SEM images of AA7068/TiC MMCs at different wt% of TiC

Grey Relational Analysis

A good method for analysing sequence groups is GRA, which requires that all sequence values be comparable in the absence of dimensionality, scaling, or polarisation characteristics (Deng, 1989). The first step in the GRA process is to normalise all experimental data to the range 0 - 1. As different responses have varying ranges, the requirement for normalisation arises. In case of a higher-is-better nature of response, the data are normalised using Equation 2.

$$x^{*}i\ (k) = \frac{x_i\ (k) - \min x_i(k)}{\max x_i - \min x_i(k)} \qquad [2]$$

If the 'Lower-the-better' criterion is to be followed, then the following Equation 3 is to be used for normalising the corresponding data.

$$x^{*}i\ (k) = \frac{\max xi\ (k) - x_i\ (k)}{\max x_i - \min x_i(k)} \qquad [3]$$

Where $x^{*}{}_{\mathrm{I}}$ (k) and $x_i\ (k)$ are the normalised data and observed data, respectively, for the ith experiment using the kth response. After normalising the responses, the next step

is to calculate the grey relation coefficient (GRC). GRC is denoted for k[th] response. It is calculated by using Equation 4.

$$\zeta_i\ (k)=\frac{\Delta_{min}\ -\zeta\Delta_{max}}{\Delta_i(k)+\zeta\Delta_{max}} \quad [4]$$

Where $\Delta_i\ (k) = \|x_0\ (k) - x_i\ (k)\|$ is the difference of absolute value between $x_0\ (k)$ and $x_i\ (k)$, ζ = distinguishing coefficient (0 ~ 1), ζ = 0.5 commonly used, Δ_{min} = minimum value of the deviational sequence, Δ_{max} = maximum value of the deviational sequence.

In the present study, the distinguishing coefficient was set to ζ=0.5 because it is commonly used in GRA and provides balanced discrimination among experimental sequences. The GRC equation used in the study explicitly defines ζ (zeta) as a parameter in the range 0-1 and states that 0.5 is the commonly used value.

Fuzzy Rule-Based Modelling

In GRA, the application of higher-the-better, lower-the-better, and nominal-the-better performance measures reveals some vagueness in the results achieved. This kind of vagueness can be successfully resolved through the application of fuzzy logic (Tzeng & Chen, 2007). A complex multi-response optimisation problem can be solved by combining GRA and fuzzy logic techniques.

The fuzzy logic system (also referred to as the Mamdani system) consists of a fuzzifier, a membership function, a fuzzy rule-based inference engine, and a defuzzifier. In the present study, the three grey relational coefficients (GRCs) for cutting force (Fz), surface roughness (Ra), and material removal rate (MRR) were used as inputs to a Mamdani fuzzy inference system. The GRCs were first normalised, and the resulting values were fuzzified using five overlapping triangular linguistic membership functions: Low (L), Low-Medium (LM), Medium (M), High-Medium (HM), and High (H). 31 fuzzy rules were generated, with maximum–minimum composition and defuzzification in MATLAB.

Steps in the Grey-Fuzzy Logic Approach

The step recommended for the grey-fuzzy-logic approach is given in Figure 4 and is explained as follows:

- The cutting force (Fz), surface roughness (Ra) and metal removal rate (MRR) obtained experimentally are first normalised between 0 and 1.
- Grey relational coefficient (GRC) for each response is then computed.
- The fuzzification step follows, where the fuzzifier uses the membership function to convert the GRC of the machining response.

- The next step involves generating fuzzy rules (if –then control rules). After that, defuzzifier converts fuzzy predicted values into GFRC.
- The last step involves determining optimal settings for the machining parameters using the main effects plot of GFRC.

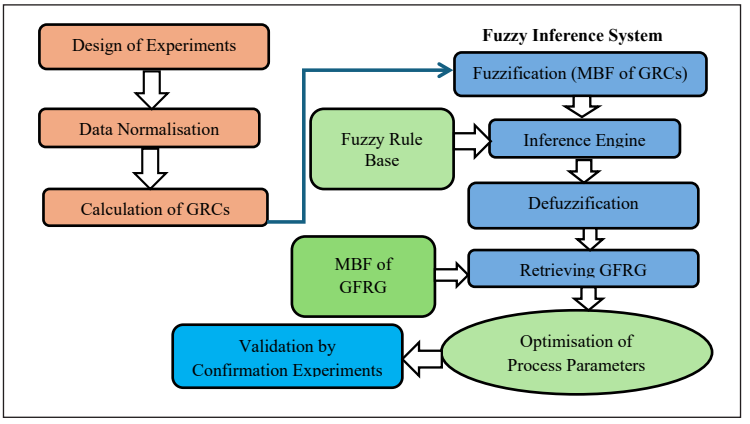


Figure 4. Suggested grey-fuzzy-logic approach

RESULTS AND DISCUSSIONS

Calculation of Grey Relational Coefficient (GRC)

The experimental data are preprocessed to calculate the grey relational coefficients for each response, as shown in Table 3. For responses like cutting force (F_z) and surface roughness (R_a), the 'lower the better' criterion is used, while the 'higher the better' criterion is used for metal removal rate (MRR). The grey fuzzy logic approach is used here to calculate the grey fuzzy relational grade (GFRG) to minimise the ambiguity in the data.

Table 3
Data pre-processing, computing GRC and grey fuzzy reasoning grade (GFRG)

Exp. No.	Normalised Values of Machining Responses			Grey Relational Coefficient (GRC)			GFRG
	Fz	Ra	MRR	Fz	Ra	MRR	
1	0.8414	0.8278	0.5801	0.7591	0.7438	0.5435	0.5000
2	0.4355	0.4422	0.1713	0.4697	0.4727	0.3763	0.4500
3	0.6873	0.7943	0.5920	0.6152	0.7086	0.5507	0.5000
4	0.2814	0.2545	0.3819	0.4103	0.4014	0.4472	0.3420
5	0.8234	0.6401	0.6908	0.7390	0.5815	0.6179	0.5000
6	0.4700	0.2005	0.1184	0.4854	0.3848	0.3619	0.3830
7	0.6746	0.6761	0.6040	0.6057	0.6069	0.5581	0.5000
8	0.4668	0.2802	0.2722	0.4840	0.4099	0.4072	0.3770

Table 3 (*continued*)

Exp. No.	Normalised Values of Machining Responses			Grey Relational Coefficient (GRC)			GFRG
	Fz	Ra	MRR	Fz	Ra	MRR	
9	0.8499	0.6658	0.6765	0.7691	0.5994	0.6071	0.5000
10	0.4407	0.3290	0.1016	0.4720	0.4270	0.3575	0.4110
11	0.6847	0.7686	0.6206	0.6133	0.6837	0.5685	0.5000
12	0.4053	0.3933	0.3373	0.4567	0.4518	0.4300	0.4000
13	0.5511	0.5578	0.7155	0.5269	0.5307	0.6373	0.5000
14	0.3125	0.0746	0.2828	0.4211	0.3508	0.4108	0.3750
15	0.3902	0.5835	0.7720	0.4505	0.5456	0.6868	0.5000
16	0.1932	0.3599	0.4018	0.3826	0.4386	0.4553	0.3530
17	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9200
18	0.0000	0.0000	0.0000	0.3333	0.3333	0.3333	0.3410
19	0.6361	0.4010	0.2734	0.5787	0.4550	0.4076	0.5000
20	0.4421	0.6915	0.5689	0.4726	0.6184	0.5370	0.5000
21	0.7143	0.5681	0.2856	0.6364	0.5366	0.4117	0.5720
22	0.3080	0.2545	0.5422	0.4195	0.4014	0.5220	0.2500
23	0.6183	0.6838	0.3198	0.5671	0.6126	0.4237	0.6170
24	0.2976	0.3239	0.5754	0.4158	0.4251	0.5408	0.2500
25	0.8135	0.4910	0.5124	0.7284	0.4955	0.5063	0.7500
26	0.7436	0.4987	0.4969	0.6611	0.4994	0.4984	0.5000
27	0.7427	0.3959	0.4740	0.6602	0.4529	0.4873	0.6390
28	0.7050	0.5064	0.4821	0.6289	0.5032	0.4912	0.5660
29	0.7454	0.5681	0.4832	0.6626	0.5366	0.4917	0.6250
30	0.6861	0.4344	0.4838	0.6143	0.4692	0.4920	0.6460
31	0.6731	0.5296	0.4860	0.6047	0.5152	0.4931	0.6250

Grey-Fuzzy Reasoning Analysis

In this experiment, a three-input one-output fuzzy-logic system is applied. To generate a fuzzy value, fuzzy reasoning is applied using a fuzzy inference engine (e.g., the Mamdani fuzzy inference system) and fuzzy rules. The fuzzy rules appear as If-Then control rules. The Grey relational coefficients (Cutting force, Surface roughness, and Metal Removal Rate MRR) serve as inputs to the fuzzy logic system. For the fuzzy rules in this case, the membership functions are classified as low, low-medium, medium, high-medium, and high for the grey relational coefficients of the input variables F_z, Ra, and MRR. Similarly, the output grey fuzzy relational grade (GFRG) is represented by very small, small, medium, large, and very large linguistic membership functions. This research applies triangular membership functions, and 31 rules are generated for this analysis, as shown in Figure 5. The generation of a fuzzy output requires maximum-minimum fuzzy reasoning composition. The conversion of the fuzzy output is accomplished using

a defuzzifier in MATLAB R2014a's fuzzy logic toolbox into GFRG, with the resulting values presented in Table 3.

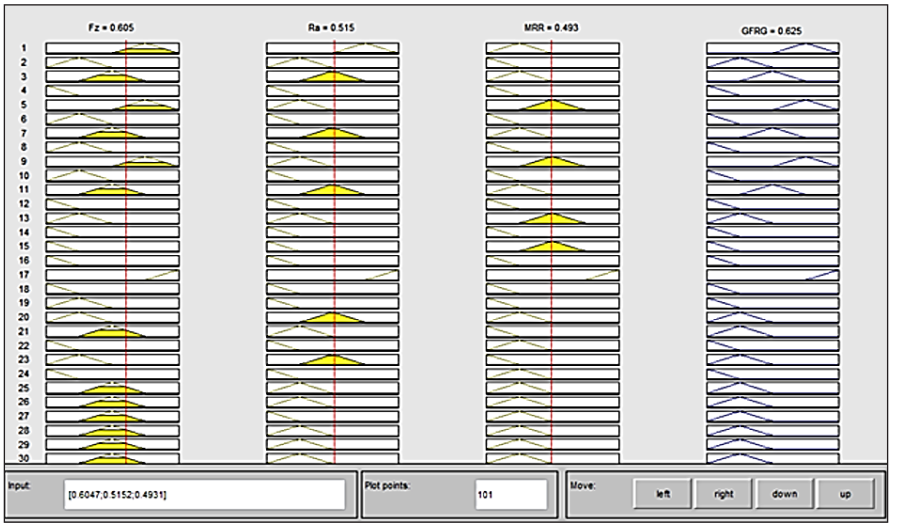


Figure 5. Fuzzy logic rules viewer

Higher GFRG levels are associated with better performance across multiple characteristics. Means analysis is done on GFRG. The response table for GFRG is given as Table 4. From the response table, the weight percentage of reinforcement is the most influential parameter, followed by the depth of cut and the feed rate. The physical reason for the strong effect of TiC is its high hardness and abrasiveness of TiC particles. An increase in TiC concentration increases resistance at the cutting edge and creates intermittent contact between the carbide cutter and hard titanium carbide particles, thereby increasing cutting resistance and adversely affecting the surface generation process. This influence of the experimentally observed parameters can be seen, for example, at the centre of the cutting: with TiC content varying from 2 to 10 wt%, cutting force changes from 114.45 N to 209.00 N, while surface roughness changes from 0.426 to 0.815 μm. An increase in feed rate increases the undeformed chip thickness, thereby increasing material removal per revolution and, consequently, the cutting load. In addition, feed rate influences the geometric component of surface roughness. Figure 6 depicts the main effects plot for GFRP. The optimal settings of process parameters, as identified, are wt% of reinforcement = 2%, Cutting speed (V) = 50 m/min, Feed Rate (f) = 0.06 mm/rev and Depth of cut (d) = 0.2 mm. Table 5 depicts the result of ANOVA for GFRG. ANOVA is used to study the effect of each process parameter on multiple performance characteristics. The fitted linear model for GFRG produced an R^2 of 37.99% and an adjusted R^2 of 31.10%, with an RMSE of 0.1192. The overall model was statistically significant ($F = 3.98$, $p = 0.012$), whereas the

lack-of-fit was statistically insignificant ($F_{table} = 2.84$, $p = 0.100$). These results indicate that the model provides a statistically meaningful representation of the experimental response, although its predictive capability is moderate.

Table 4
Response table for GFRG

Process Parameter	Level 1	Level 2	Level 3	Level 4	Level 5	Δ (Max-Min)	Rank
wt%	0.9200	0.5000	0.4729	0.3864	.3410	0.5790	1
V	0.5000	0.4524	0.5102	0.4340	0.500	0.0762	4
f	0.5720	0.4504	0.5357	0.4360	0.2500	0.3220	3
d	0.6170	0.4440	0.5292	0.4424	0.2500	0.3670	2

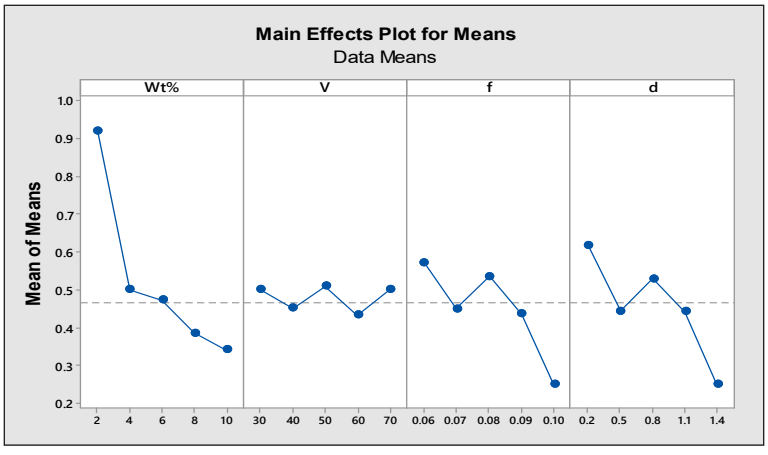


Figure 6. Response graph for every level of process parameter

Table 5
ANOVA for GFRG

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	4	0.226175	0.056544	3.98	0.012
Linear	4	0.226175	0.056544	3.98	0.012
wt%	1	0.178020	0.178020	12.54	0.002
V	1	0.000900	0.000900	0.06	0.803
f	1	0.024003	0.024003	1.69	0.205
d	1	0.023250	0.023250	1.64	0.212
Error	26	0.369183	0.014199		
Lack-of-Fit	20	0.333898	0.016695	2.84	0.100
Pure Error	6	0.035286	0.005881		
Total	30	0.595358			

Confirmation Test

Once the optimal value for the process parameter has been obtained, the results will be validated through a confirmation test. Table 6 displays the results of the confirmation test on machining responses of AA7068/TiC MMCs using a K30 cutting tool insert. Machining with an optimal parameter combination will reduce cutting force (Fz) from 129.45 N to 124.27 N, surface roughness (Ra) from 0.493 µm to 0.478 µm, and increase MRR from 136.37 mm^3/sec to 144.55 mm^3/sec. The value of Y at the optimal process parameter level can be estimated using the following Equation 5:

$$Y = Y_m + \sum_{i=1}^{q} Y_i - Y_m \quad [5]$$

Where Y_m is the mean of GFRG for all the experimental runs, and Y_i is the mean of GFRG values at the optimum level of input parameters. Table 6 indicates that machining with the optimum setting would improve GFRG from 0.9200 to 0.9395 for the experimental and predicted values, respectively.

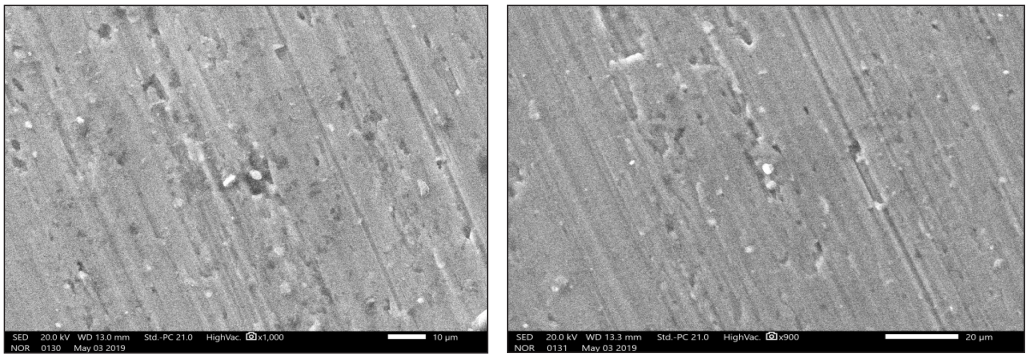
The confirmation experiment demonstrated simultaneous improvements in cutting force, surface roughness, and MRR under the optimised conditions. However, since the present confirmation test was performed as a single experimental verification, experimental standard deviations and confidence intervals were not determined. Therefore, the observed improvements are considered evidence of practical validation rather than formal statistical significance.

Table 6
Comparison of the results obtained for the initial and optimum machining conditions

Levels	Initial Machining Parameters Level	Optimal Machining Parameters Level		Improvement
	wt% = 4, V = 40 m/min, f = 0.07 mm/rev, d = 0.5 mm	wt% =, V = 50 m/min, f = 0.06 mm/rev, d = 0.2mm		
		Predicted	Experimental	
Cutting force (Fz), N	129.45		124.27	4.00% reduction
Surface Roughness (Ra), µm	0.493		0.478	3.04% reduction
Metal Removal Rate (MRR), mm^3/sec	136.37		144.55	5.99% increase
GFRG	0.5000	0.9395	0.9200	2.07% error
Improvement in the GFRG	0.0195			

Hence, the current study proves the effectiveness of the Grey-Fuzzy logic technique for optimisation of multi-response surface finishing of AA7068/TiC metal matrix

composites. Figures 7a to 7b depict the microscopic photographs of the machined surface after verification experiments.



(a) (b)

Figure 7. Machined surfaces of the AA7068/TiC MMCs before and after confirmation experiments

CONCLUSION

The grey-fuzzy approach was effectively used to evaluate cutting force, surface roughness, and MRR simultaneously during the turning of AA7068/TiC MMCs. In the experimental investigation, four process parameters were considered: TiC reinforcement ratio, cutting speed, feed rate and depth of cut.

The optimum condition obtained through the GFRG response analysis was 2 wt% TiC, 50 m/min cutting speed, 0.06 mm/rev feed rate and 0.2 mm depth of cut.

The TiC reinforcement content was the dominant factor in the GFRG response analysis, with a response range of (0.5790), followed by depth of cut (0.3670), feed rate (0.3220) and cutting speed (0.0762).

Confirmation test under optimum conditions led to a reduction in cutting force by 4.00% from 129.45 N to 124.27 N, an improvement in surface roughness by 3.04% from 0.493 µm to 0.478 µm, and an increase in MRR by 5.99% from 136.37 mm^3/s to 144.55 mm^3/s.

The calculated GFRG is 0.9395, while the experimentally obtained GFRG is 0.9200, yielding an absolute prediction error of 2.07%.

ANOVA shows that TiC content has a significant effect on GFRG ($p = 0.002$), but the effects of cutting speed, feed, and depth of cut are not significant individually ($p > 0.05$). The overall linear model is significant ($p = 0.012$), with R^2=37.99%, adjusted (R^2=31.10%) and a non-significant lack-of-fit (p=0.100).

In practical machining terms, the optimum condition offers a reasonable compromise among low cutting force, good surface finish and high material removal rate. Therefore, the results demonstrate the effectiveness of the grey-fuzzy approach in multi-response

decision-making within the machining range, rather than its universal superiority over other optimisation methods.

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LIST OF ABBREVIATIONS

Term	-	Definition
MMCs	-	Metal Matrix Composites
TiC	-	Titanium Carbide
GRA	-	Grey relational analysis
GFRG	-	Grey Fuzzy relational grade
MCDM	-	Multi-Criteria Decision Making
MRR	-	Metal Removal Rate
ANOVA	-	Analysis of Variance

REFERENCES

Ahilan, C., Kumanan, S., & Sivakumaran, N. (2009). Multi-objective optimisation of CNC turning process using grey based fuzzy logic. *International Journal of Machining and Machinability of Materials, 5*(4), 434-451. https://doi.org/10.1504/ijmmm.2009.026902

Ashraf, P. M., & Shibli, S. M. A. (2009). Development of cerium oxide and nickel oxide-incorporated aluminium matrix for marine applications. *Journal of Alloys and Compounds, 484*(1-2), 477-482. https://doi.org/10.1016/j.jallcom.2009.04.134

Bhowmik, A., Sen, B., Patel, D., Beemkumar, N., Alhazaa, A., Magibalan, S., Romanovski, V., Kumar, R., & Bukate, B. B. (2026). Tribological performance enhancement of SiO_2 reinforced AA8011 composites through grey fuzzy based optimization. *Scientific Reports, 16*(1), Article 21881. https://doi.org/10.1038/s41598-026-52951-4

Cerik, B. C. (2017). Damage assessment of marine grade aluminium alloy-plated structures due to air blast and explosive loads. *Thin-Walled Structures, 110*, 123-132. https://doi.org/10.1016/j.tws.2016.10.021

Chen, X., Ma, L., Li, C., & Cao, X. (2014). Experimental study and genetic algorithm-based optimization of cutting parameters in cutting engineering ceramics. *The International Journal of Advanced Manufacturing Technology, 74*(5-8), 807-817. https://doi.org/10.1007/s00170-014-5979-0

Chiang, K.-T., & Chang, F.-P. (2006). Application of grey-fuzzy logic on the optimal process design of an injection-molded part with a thin shell feature. *International Communications in Heat and Mass Transfer, 33*(1), 94-101. https://doi.org/10.1016/j.icheatmasstransfer.2005.08.006

Das, B., Roy, S., Rai, R. N., & Saha, S. C. (2016). Application of grey fuzzy logic for the optimization of CNC milling parameters for Al–4.5%Cu–TiC MMCs with multi-performance characteristics. *Engineering Science and Technology, an International Journal, 19*(2), 857-865. https://doi.org/10.1016/j.jestch.2015.12.002

Deng, J. L. (1989). Introduction to grey system theory. *The Journal of Grey System, 1*(1), 1-24.

Dewangan, S., Gangopadhyay, S., & Biswas, C. K. (2015). Study of surface integrity and dimensional accuracy in EDM using fuzzy TOPSIS and sensitivity analysis. *Measurement, 63*, 364-376. https://doi.org/10.1016/j.measurement.2014.11.025

Dey, D., Bhowmik, A., & Biswas, A. (2023). A grey-fuzzy based multi-response optimisation study on the friction and wear characteristics of titanium diboride reinforced aluminium matrix composite. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 237*(14), 2227-2239. https://doi.org/10.1177/09544054221147973

Engin, K. E., Eşme, U., & Külekci, M. K. (2026). Optimization of vertical machining parameters of DIN 1.0038 steels using hybrid Taguchi based grey-fuzzy algorithm in CNC pocket milling process. *Çukurova Üniversitesi Mühendislik Fakültesi Dergisi, 41*(1), 115-128. https://doi.org/10.21605/cukurovaumfd.1706626

Gajević, S., Marković, A., Milojević, S., Ašonja, A., Ivanović, L., & Stojanović, B. (2024). Multi-objective optimization of tribological characteristics for aluminum composite using Taguchi grey and TOPSIS approaches. *Lubricants, 12*(5), Article 171. https://doi.org/10.3390/lubricants12050171

Ganesan, H., & Mohankumar, G. (2013). Optimization of machining techniques in CNC turning centre using genetic algorithm. *Arabian Journal for Science and Engineering, 38*(6), 1529-1538. https://doi.org/10.1007/s13369-013-0539-8

Giri, B. K., Pettersson, F., Saxén, H., & Chakraborti, N. (2013). Genetic programming evolved through bi-objective genetic algorithms applied to a blast furnace. *Materials and Manufacturing Processes, 28*(7), 776-782. https://doi.org/10.1080/10426914.2013.763953

Gururaja, S., Ramulu, M., & Pedersen, W. (2013). Machining of MMCs: A review. *Machining Science and Technology, 17*(1), 41-73. https://doi.org/10.1080/10910344.2012.747897

Haq, A. N., Marimuthu, P., & Jeyapaul, R. (2008). Multi response optimization of machining parameters of drilling Al/SiC metal matrix composite using grey relational analysis in the Taguchi method. *The International Journal of Advanced Manufacturing Technology, 37*(3-4), 250-255. https://doi.org/10.1007/s00170-007-0981-4

Heinz, A., Haszler, A., Keidel, C., Moldenhauer, S., Benedictus, R., & Miller, W. S. (2000). Recent development in aluminium alloys for aerospace applications. *Materials Science and Engineering: A, 280*(1), 102-107. https://doi.org/10.1016/s0921-5093(99)00674-7

Hsiao, Y. F., Tarng, Y. S., & Huang, W. J. (2008). Optimization of plasma arc welding parameters by using the Taguchi method with the grey relational analysis. *Materials and Manufacturing Processes, 23*(1), 51-58. https://doi.org/10.1080/10426910701524527

Hussain, S. A., Panchal, M., Meshram, K., Srinivas, R., Rajak, U., Kumar, R., & Gupta, M. (2025). Turning GFRP composites with multi-response optimisation using TOPSIS method. *International Journal on*

Interactive Design and Manufacturing (IJIDeM), 19(2), 1327-1339. https://doi.org/10.1007/s12008-024-01762-w

Isik, B., & Kentli, A. (2009). Multicriteria optimization of cutting parameters in turning of UD-GFRP materials considering sensitivity. *The International Journal of Advanced Manufacturing Technology, 44*(11-12), 1144-1153. https://doi.org/10.1007/s00170-009-1927-9

Jangra, K., Grover, S., & Aggarwal, A. (2012). Optimization of multi machining characteristics in WEDM of WC-5.3%Co composite using integrated approach of Taguchi, GRA and entropy method. *Frontiers of Mechanical Engineering, 7*(3), 288-299. https://doi.org/10.1007/s11465-012-0333-4

Kafaltiya, S., Agrawal, P. K., Sharma, P., Singh, V. K., Bhaskar, J., Chauhan, S., & Verma, A. (2024). Multi-response optimization of characteristics for graphite reinforced biodegradable PVA-fumaric acid cross-linked composite: A gray-fuzzy logic-based hybrid approach. *Journal of Vinyl and Additive Technology, 30*(5), 1190-1206. https://doi.org/10.1002/vnl.22112

Khandey, U., Ghosh, S., & Hariharan, K. (2017). Machining parameters optimization for satisfying the multiple objectives in machining of MMCs. *Materials and Manufacturing Processes, 32*(10), 1082-1093. https://doi.org/10.1080/10426914.2017.1279312

Krishnaiah, K., & Shahabudeen, P. (2012). *Applied design of experiments and Taguchi methods*. PHI Learning.

Krishnamoorthy, A., Rajendra Boopathy, S., Palanikumar, K., & Paulo Davim, J. (2012). Application of grey fuzzy logic for the optimization of drilling parameters for CFRP composites with multiple performance characteristics. *Measurement, 45*(5), 1286-1296. https://doi.org/10.1016/j.measurement.2012.01.008

Lin, J. L., & Lin, C. L. (2005). The use of grey-fuzzy logic for the optimization of the manufacturing process. *Journal of Materials Processing Technology, 160*(1), 9-14. https://doi.org/10.1016/j.jmatprotec.2003.11.040

Manna, A., & Bhattacharyya, B. (2005). Influence of machining parameters on the machinability of particulate reinforced Al/SiC–MMC. *The International Journal of Advanced Manufacturing Technology, 25*(9-10), 850-856. https://doi.org/10.1007/s00170-003-1917-2

Nalbant, M., Gökkaya, H., & Sur, G. (2007). Application of Taguchi method in the optimization of cutting parameters for surface roughness in turning. *Materials & Design, 28*(4), 1379-1385. https://doi.org/10.1016/j.matdes.2006.01.008

Narang, H. K., Singh, U. P., Mahapatra, M. M., & Jha, P. K. (2011). Prediction of the weld pool geometry of TIG arc welding by using fuzzy logic controller. *International Journal of Engineering, Science and Technology, 3*(9), 77-85. https://doi.org/10.4314/ijest.v3i9.6

Palanikumar, K., & Karthikeyan, R. (2006). Optimal machining conditions for turning of particulate metal matrix composites using Taguchi and response surface methodologies. *Machining Science and Technology, 10*(4), 417-433. https://doi.org/10.1080/10910340600996068

Palanikumar, K., Karunamoorthy, L., & Karthikeyan, R. (2006). Multiple performance optimization of machining parameters on the machining of GFRP composites using carbide (K10) tool. *Materials and Manufacturing Processes, 21*(8), 846-852. https://doi.org/10.1080/03602550600728166

Prajapati, V., Dinbandhu, Vora, J. J., Das, S., & Abhishek, K. (2020). Study of parametric influence and welding performance optimization during regulated metal deposition (RMD™) using grey integrated

with fuzzy Taguchi approach. *Journal of Manufacturing Processes, 54*, 286-300. https://doi.org/10.1016/j.jmapro.2020.03.017

Rajmohan, T., Palanikumar, K., & Prakash, S. (2013). Grey-fuzzy algorithm to optimise machining parameters in drilling of hybrid metal matrix composites. *Composites Part B: Engineering, 50*, 297-308. https://doi.org/10.1016/j.compositesb.2013.02.030

Sahoo, A. K., Pradhan, S., & Rout, A. K. (2013). Development and machinability assessment in turning Al/SiCp-metal matrix composite with multilayer coated carbide insert using Taguchi and statistical techniques. *Archives of Civil and Mechanical Engineering, 13*(1), 27-35. https://doi.org/10.1016/j.acme.2012.11.005

Samy, G. S., & Kumaran, S. T. (2017). Measurement and analysis of temperature, thrust force and surface roughness in drilling of AA (6351)-B_4C composite. *Measurement, 103*, 1-9. https://doi.org/10.1016/j.measurement.2017.02.016

Sengottuvel, P., Satishkumar, S., & Dinakaran, D. (2013). Optimization of multiple characteristics of EDM parameters based on desirability approach and fuzzy modeling. *Procedia Engineering, 64*, 1069-1078. https://doi.org/10.1016/j.proeng.2013.09.185

Shin, J., Kim, T., Kim, D., Kim, D., & Kim, K. (2017). Castability and mechanical properties of new 7xxx aluminum alloys for automotive chassis/body applications. *Journal of Alloys and Compounds, 698*, 577-590. https://doi.org/10.1016/j.jallcom.2016.12.269

Shrotriya, A., Nayak, C., Patel, G., Khan, M. I., & Pathak, V. K. (2026). A new method based on AVOA-optimized support vector machine for predicting performance characterisitcs during turning aluminium 7068 under graphene nanofluid. *Scientific Reports, 16*(1), Article 2564. https://doi.org/10.1038/s41598-025-32577-8

Shunmugesh, K., Raphel, A., Kurian, S., Hiremath, S., Anne, G., Murthy, B. R. N., & Vishwanatha, H. M. (2025). A novel way to optimize the process parameters by integrating the grey relational coefficient and the combined compromise solution for machining the CFRP composites. *Scientific Reports, 15*(1), Article 34729. https://doi.org/10.1038/s41598-025-18368-1

Soepangkat, B. O. P., & Pramujati, B. (2013). Optimization of surface roughness and recast layer thickness in the wire-EDM process of AISI D2 tool steel using Taguchi-grey-fuzzy. *Applied Mechanics and Materials, 393*, 21-28. https://doi.org/10.4028/www.scientific.net/amm.393.21

Teimouri, R., Amini, S., & Mohagheghian, N. (2017). Experimental study and empirical analysis on effect of ultrasonic vibration during rotary turning of aluminum 7075 aerospace alloy. *Journal of Manufacturing Processes, 26*, 1-12. https://doi.org/10.1016/j.jmapro.2016.11.011

Tzeng, Y.-F., & Chen, F.-C. (2007). Multi-objective optimisation of high-speed electrical discharge machining process using a Taguchi fuzzy-based approach. *Materials & Design, 28*(4), 1159-1168. https://doi.org/10.1016/j.matdes.2006.01.028

Yang, Y.-S., & Huang, W. (2012). A grey-fuzzy Taguchi approach for optimizing multi-objective properties of zirconium-containing diamond-like carbon coatings. *Expert Systems with Applications, 39*(1), 743-750. https://doi.org/10.1016/j.eswa.2011.07.067