JJMIE

Volume 17, Number 4, December. 2023
ISSN 1995-6665
Pages 489– 499
https://doi.org/10.59038/jjmie/170404
Editor-in-Chief: Prof. Ali M. Jawarneh

Jordan Journal of Mechanical and Industrial Engineering

Application of Taguchi Method and Response Surface Methodology on Machining Parameters of Al MMCs 6063-TiO_2

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Received 23 May 2023 *Accepted 16 Aug 2023*

Abstract

The goal of this project is to use CNC end milling operations to process AL 6063 composites reinforced with varying weight percentages of Nano TiO_2 (1, 3 and 5). The composites are made using the stir casting technique in an electric melting furnace. Due to their superior wear and corrosion resistance, low density, and outstanding mechanical qualities as compared to other metals and alloys, aluminum alloys are utilized extensively in the aerospace and automotive sectors.

For study and optimization using Taguchi's method, analysis of variance (ANOVA) was used to determine the importance of process factors on the response variable. Cutting forces and surface roughness are the factors that are taken into consideration during machining. Cutting forces and surface roughness have been examined for the CNC end milling study parameters, which include rotating speed, cutting speed, TiO_2 addition content, end mill cutting edges number, depth of cut, and feed rate under dry lubrication conditions. To develop mathematical models for all parameters as functions of significant process factors, Response Surface Methodology (RSM) is applied. The results of analyses of variance indicate that the cutting force is best at the center level of rotating speed (25 m/min), low level of cutting speed (500 rpm), center level of the number of flutes on the cutting edges, and highest levels of feed rate and depth of cut.

In accordance with the determined optimal level, experimental data is gathered, interest-area mathematical models are developed, and process model optimization is performed.

Keywords: ANOVA,Stir casting, Taguchi method, Surface roughness, CNC,metal matrix composites.

1. Introduction

One of the most significant advancements in material engineering in recent years is the use of composite materials. MMCs are presently employed in a wide range of technical applications, including automotive, aerospace, marine, and turbine compressors. Their low weight, strong strength, high rigidity, and high temperature resistance are their key advantages [1-6]. Many types of Metal matrix materials exist such as magnesium, aluminum, zinc and copper. The hard reinforcement can be (SiC), titanium oxide (TiO_2) and aluminum oxide (Al_2O_3). Many polymeric matrix materials in different fields have been developed using Nano fillers as materials [7-10].Metal matrix materials come in many varieties, including those made of magnesium, aluminum, zinc, and copper. The hard reinforcement can be made of silicon carbide (SiC), titanium oxide (TiO_2), or aluminum oxide (Al_2O_3). Numerous researchers have looked into the importance of improving processing parameters, as choosing effective processing parameters is a top priority in the manufacturing sector and operational efficiency is crucial in today's cutthroat marketplace. Modern production relies heavily on Computer Numerical Control (CNC) devices because of its These machines—as well as the CNC machinists trained to use them—are quick, precise, and versatile, and they are essential to many significant sectors in the state. Typically[11].Al and its alloys are used to make MMC. Aluminum and its alloys have drawn the greatest attention as the matrix material in MMCs in most technical applications owing to its exceptional mechanical qualities,

superior ductility, and strong corrosion resistance [12-13]. Figure 1 shows how AL-MMCs are used. The utilization of AL-MMCs for diverse industrial applications is significantly influenced by their mechanical characteristics.

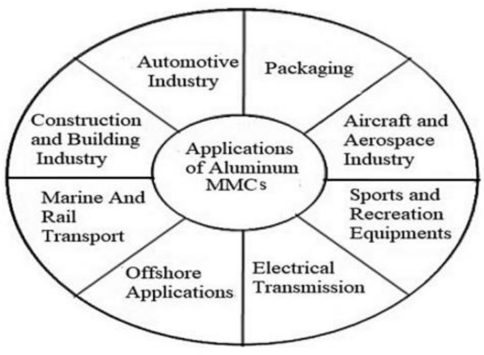

Figure 1. Different Applications of AL-MMC's [13]

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Due to the determination of the quality parameter, it is vital and crucial to optimize the process parameters [14–15]. Metal removal techniques include the use of end mills and face mills. Surface roughness and material removal rate are factors in the end milling process because of the high-quality surfaces, machining efficiency, process dependability, and dimensional correctness [16–17]. When producing pockets, slots, and precise molds and dies, end milling is employed in a few industrial sectors, including aerospace and automotive [18-19].Nowadays, the word surface roughness is increasingly being replaced by the Ra parameter when studying theprocessing of novel materials or when managing intricate machine parts[20]. The ideal feed rate that provided a maximum material removal rate under the provided surface roughness restriction may be chosen via a bisection approach, according to research by Dae Kyun Baeket et al. [21] utilizing a surface roughness model, M.S. A genetic algorithm was used by Shunmugam et al. [22] to examine the selection of ideal circumstances in multi-pass face-milling.According to Arokiadas R et al. [23], metal matrix composites can be made using a variety of techniques that are divided into solid-state, semisolid-state, and liquid state depending on the types of materials used, the required strength, the shape of the finished product, and the size of the reinforced particle. Although liquid state procedures are more cost-effective and have a closer net shape, solid-state approaches provide the greatest mechanical qualities. The most popular approach for optimization in design of experiments (DOE) methods, which save money, time, and resources, is the Taguchi method, according to Ting-Cheng Chang et al. [24]. Dynamic experiments are a straightforward, systematic, and more effective way of determining the ideal machining settings. To produce nano-crystalline structured chips from High Carbon Steel (HCS), Ilangkumaran M. et al. [25] examined the impact of machining settings on the machining parameters. The machining process with multi-response performance characteristics is studied using an orthogonal array, multi-response performance index, signals-to-noise ratio, and analysis of variance. When Dwivedi et al. [26] used the Taguchi robust design technique to examine how the surface roughness of an A356/SiC composite material affected the electromagnetic stir casting process, they found that the procedure significantly enhanced the microstructure. The feed, cutting speed, and depth of cut were discovered to affect surface roughness, and the ideal combination of the parameters was established to produce the surface roughness of 3.15 m. When turning AISI 52100 bearing steel with a CBN tool.S. A. Hussain et al. [27] they discover that the model may be utilized for predicting the surface roughness (Ra) of turning GFRP composites. By using Design of Experiments (DOE) L25 orthogonal array on an all-geared lathe. The cutting parameters considered were the cutting speed, feed, depth of cut, and workpiece (fiber orientation).Varaprasad et al. [28] In the hard turning of AISI D3 steel, the effects of the cutting speed, feed rate, and depth of cut on the surface roughness were examined. A mixed ceramic tool was used to process AISI D3 steel that had been hardened to 62 HRC. Response Surface Methodology (RSM) was used to develop mathematical models for surface roughness. A Central Composite Design (CCD) is utilized as the experimental design. Twenty tests were performed using a mixed ceramic tool of Al_2O_3/TiC with a corner radius of 0.8 mm and six center points.Khamel et al. [29] investigated the effects of speed, feed, and depth of cut on tool life, surface roughness, and cutting forces. Using ANOVA, they examined how process restrictions affected performance attributes. They concluded that feed rate and cutting speed significantly affect tool life and surface roughness. In high-speed ball-end milling of Al2014-T6.Mithilesh K. Dikshit et al. [30] created empirical mathematical models for cutting forces and surface roughness under the influence of axial depth of cut, feed, radial depth of cut, and cutting speed. Based on the response surface approach, central composite design has been used to organize ball-end milling trials. To improve surface roughness, we employed coated carbide tools and the Taguchi approach for machining characteristics optimization while milling GFRP at high speeds. The L9 orthogonal array has process parameters including feed, speed, and the surface roughness response parameter. Analyzing the results of the optimization process using the S/N ratio. ANOVA results show that feed rate significantly affects surface roughness. The GFRP milling method enhanced its performance in terms of surface roughness by 90.3%[31].Tomov et al. [32] Using DOE to validate a close relationship between the primary, waviness, and roughness profiles in a reliable hard turning process. The models were created based on empirical data gathered with a CNC lathe to manufacture special rings made of steel EN C55 (AISI 1055) with a hardness of 53.1 HRC.Through extensive experimentation, Xu et al. [33] investigated the comprehensive effects of milling process parameters and robot posture on machining results. Based on their findings, they successfully decreased the cutting forces to improve the surface quality of the milling process.Numerous engineering problems based on modelling and optimization impacted by experimental factors can be resolved using the RSM collection of statistical techniques. To determine the best performance for the situation, this technique concurrently examines the effects of many parameters and the relationship between variables [34,35,36].Parameter optimization techniques are critical to improve the efficiency and effectiveness of machining processes. In recent years, several studies have been conducted to examine and improve these techniques[37].

2. MATERIALS AND EXPERIMENTAL WORK

The 6063 Al-alloy matrix material was utilized in this work. Table1 lists the chemical make-up of the matrix material. Figure 2 shows a scanning micrograph of TiO_2 nanoparticles, and Table 2 lists the supplier's specifications for nanoparticles. TiO_2 nanoparticle additions of 1, 3, and 5 wt% are used as reinforcement materials. Stir casting is used to create the composites. In an electric melting furnace, the aluminum alloy is melted for 40 minutes at a temperature of 785^{o}C. The molten aluminum alloy is then progressively combined with hot Nano powder that has reached temperatures of up to 450^{o}C, and the combination is then agitated for five minutes at a speed of 300 rpm to achieve homogeneity. The liquid is put into a metal mold that has been preheated to 350 to 400^{o}C and agitated with a 500^{o}C stirrer.

Table 1. Chemical composition of Al-6063 alloy (wt. %)

Element	Mg	Si	Fe	Zn	Ti	Mn	Cr	Cu	Al
Present%	0.45-0.9	0.2-0.6	0.35	0.10	0.10	0.10	0.10	0.10	Balance

Molds measuring 100 mm x 100 mm x 50 mm are filled with molten material. The experimental setup together with the schematic diagram of the experimental setup is represented in Figure 3. The 4-axis vertical **SINUMERIK 802D** CNC machine was used for all studies Figure 4. The blades are made of HSS. End mills have been used for dry cutting with varying numbers of cutting edges. The values of the input parameters are shown in Table 3 for rotational speed, cutting speed, TiO_2 addition content, number of cutting edges, depth of cut, and feed rate. The responses are cutting force and surface roughness. For testing, the orthogonal array L27 is used. When measuring surface roughness using the Surface Roughness Tester (TAYLOR-HOBSON-SURTRONIC), the root mean square value parameter (Ra) is employed. A **KISTLER** dynamometer type (5806 A) is used to measure cutting forces.

For slot machining, end-mill cutting tools with two, three, and four flutes made of HSS are employed. Figure 5 provides an illustration of the study work's technique. In the present work, then the resultant cutting force (R_{cf}) for the forces (F_x, F_y, and F_z) is determined as follows.

$$\boldsymbol{RCF} = \sqrt{F_x^2 + F_y^2 + F_z^2} \quad (1)$$

3. TAGUCHI METHODOLOGY

In the 1980s, Genichi Taguchi created a three-stage technique [39,40]. Systems design, parameter design, and tolerance design are the three phases. The study methodology is shown in Figure 5. The Taguchi method based L_{27} orthogonal array is used for the studies. L_{27} (3^{13}) contains 13 columns at three levels and 27 rows with the same number of levels as tests (26 degrees of freedom). The experiment consists of 27 tests, with the first column representing rotational speed (rpm), the second column representing cutting speed (m/min), the third column representing addition percentage, the fourth column representing the number of cutting edges, the fifth column representing feed rate of cut (mm/min), the sixth column representing depth of cut (mm), and the remaining tests being interactions between these variables, as shown in Figure 6. The Taguchi technique is used to reduce the 81 trials to only 27. At three levels, six criteria are used. Table 3 lists the parameters that were examined and the levels that were given to them.

Table 2. Specification of TiO_2 Nano particles [38]

Property	Value
Assay	≥99.9%
Form	Nano particles
Particle size	50 nm (TEM)
Surface area	20-40 m^2/g
Density	4.23 g/cm3
Color	white
Melting point	1850 °C

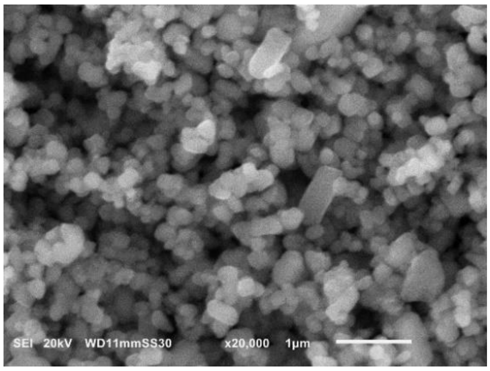

Figure 2.SEM micrographs of TiO_2 Nano particles

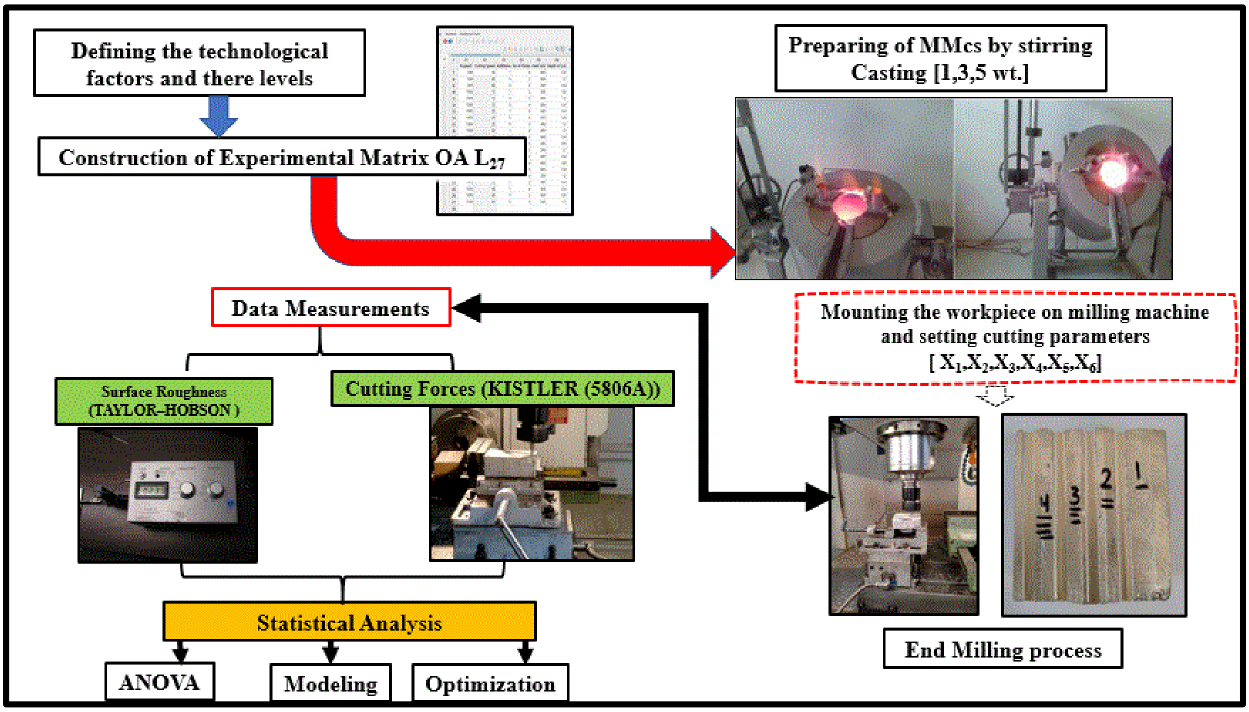

Figure 3. Experimental setup

Figure 4.CNC milling machine set up

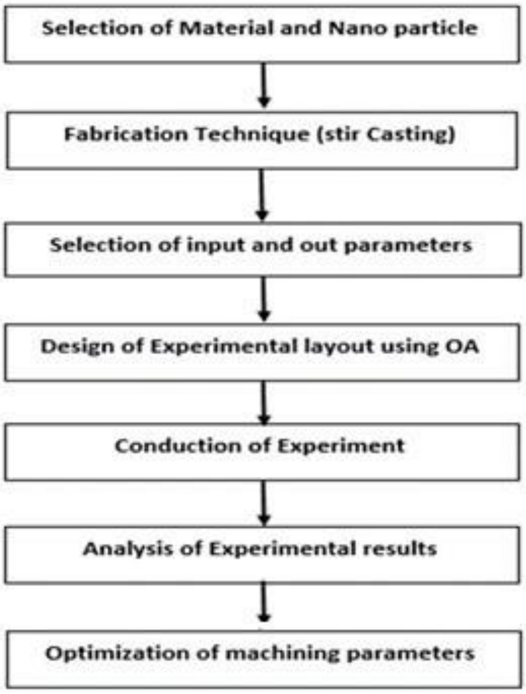

Figure 5. Methodology of the research work

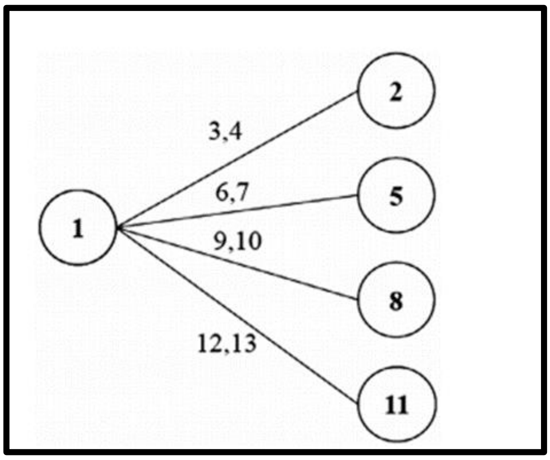

Figure 6. Search graph for L_{27} OA [41]

Table 3 displays the numerical values of these characteristics. During one cutting operation, the roots mean square values of three variables are measured.

The Taguchi parameters design approach is utilized in this work to identify the best machining parameters for reducing cutting forces (Fc) and surface roughness (Ra). Six control elements are taken into consideration: X_1, X_2, X_3, X_4, X_5, and X_6, as well as certain squared terms and interaction terms like $X_1.X_1$, $X_2.X_3$, $X_1.X_4$, $X_2.X_3$... and X_1^2 interactions [40]. The experimental findings are further translated into a lower S/N ratio, which is better for measuring surface roughness. The S/N ratio also expresses the dispersion around the goal value; the smaller the scatter, the higher the S/N ratio value. Other quality traits could exist, depending on the experiment's goals. It is preferable to have a smoother surface. For LB type features, the Surface Roughness Mean Square Deviation (MSD) from the target value may be stated as [42].

$$\boldsymbol{MSD} = -10Log\left({}^{1}/_{n}\right)\left(\sum 1/y_i^2\right) \quad (2)$$

Where ***n*** is the number of observations

y is the observed data.

Based on up mention equation it is found that the better surface roughness at the higher the S/N ratio.

Table 3. Input process parameters and levels used in the designed experiments.

Symbol	Input parameters	Unit	Level 1	Level 2	Level 3
X_1	Rotational speed	rpm	500	1000	1500
X_2	Cutting speed	m/min	15	25	40
X_3	Additions	wt.%	1	3	5
X_4	Cutting edges	No.	2	3	4
X_5	Feed rate	mm/min	200	400	600
X_6	Depth of cut	mm	0.4	0.8	1.2

4. RESULTS AND DISCUSSIONS

4.1. ANALYSIS OF EXPERIMENTAL RESULTS

A statistical method known as analysis of variance (ANOVA) is used to quantitatively estimate the proportional contribution of each control factor to the total measured response. F-ratios or percentage contributions are often used to express the relative importance of factors [41]. The goal of this study's design was to link the effect of control variables to each response that was assessed. The influence of variables and their interactions are determined by analyzing experimental data, which also helps to establish optimal levels and validate experimental findings using the signal-to-noise ratio. Analysis of variance and mean (ANOM). Table 4 displays the results of cutting forces and average surface roughness responses (three repeated values).

Table 4. Experimental design using L_{27}OA.

L_{27} (3^{13})	Experimental Control FactorsL_{27}OA									Cutting Forces (N)			Ra (µm)		
	X1	X2	X3	X4	X5	X6	X1. X2	X1. X3	X1. X4	F_X	F_y	F_z	1st trial	2nd trial	3rd trial
1	1	1	1	1	1	1	1	1	1	21.95	73.74	137.01	4.25	4.12	4.63
2	1	1	2	2	2	1	2	2	2	89.55	81	119.15	4.21	4.09	4.42
3	1	1	3	3	3	1	3	3	3	73.3	61	116.49	4.66	4.02	4.42
4	1	2	1	2	3	2	1	2	3	44.97	55.96	123.89	3.99	3.89	3.93
5	1	2	2	3	1	2	2	3	1	69.3	87	121.44	4.44	4.05	4.02
6	1	2	3	1	2	2	3	1	2	92.06	71.03	102.75	4.04	4.34	4.16
7	1	3	1	3	2	3	1	3	2	59.96	87.36	105.56	2.35	2.84	2.74
8	1	3	2	1	3	3	2	1	3	94.54	101.12	65.89	2.22	2.63	2.80
9	1	3	3	2	1	3	3	2	1	86.42	98.5	90.34	2.78	2.94	2.92
10	2	1	1	1	1	2	2	2	2	94.21	65.21	84.97	3.94	4.10	4.05
11	2	1	2	2	2	2	3	3	3	79.21	68.3	90.92	4.08	3.96	4.13
12	2	1	3	3	3	2	1	1	1	45.03	74.15	86.43	4.29	4.11	4.24
13	2	2	1	2	3	3	2	3	1	65.32	85.1	92.75	2.62	2.52	2.47
14	2	2	2	3	1	3	3	1	2	94.81	81.6	91.09	2.71	2.51	2.64
15	2	2	3	1	2	3	1	2	3	60.94	65.21	80.54	2.85	2.63	2.77
16	2	3	1	3	2	1	2	1	3	88.85	67.78	90.76	3.98	4.10	4.16
17	2	3	2	1	3	1	3	2	1	103.59	96.97	96.98	4.32	4.11	4.42
18	2	3	3	2	1	1	1	3	2	76.09	65.34	88.09	4.42	4.22	4.30
19	3	1	1	1	1	3	3	3	3	87.21	74.05	96.38	2.88	3.12	3.06
20	3	1	2	2	2	3	1	1	1	84.97	76.87	100.44	2.90	3.25	3.15
21	3	1	3	3	3	3	2	2	2	102.97	97.98	86.98	3.41	3.13	3.12
22	3	2	1	2	3	1	3	1	2	94.8	86.75	67.98	2.31	2.22	2.38
23	3	2	2	3	1	1	1	2	3	101.41	81.1	96.17	2.72	2.16	2.50
24	3	2	3	1	2	1	2	3	1	95.61	105.17	109.18	2.71	2.33	2.49
25	3	3	1	3	2	2	3	2	1	56.78	98.04	108.67	2.43	2.21	2.32
26	3	3	2	1	3	2	1	3	2	67.57	98.26	95.98	2.13	2.34	2.30
27	3	3	3	2	1	2	2	1	3	97.95	113.3	108.9	2.08	2.30	2.28

4.1.1. SURFACE ROUGHNESS

There are many variable factors that affect the surfaceproperties in CNC milling [43]. Based on S/N ratios and ANOM values, respectively, Tables 5 and 6 provide the ANOVA results for surface roughness. Rotational speed, cutting speed, addition, and $X_1.X_2$ interaction are important variables impacting S/N ratio at 99% confidence level when using surface roughness and S/N ratio transformation. At whatever degree of confidence, the interactions $X_1.X_3$ and $X_1.X_4$ have no meaningful impact. According to mean values and surface roughness as the response, rotating speed, cutting speed, additions, and $X_1.X_2$ are all statistically significant at 99%. At any degree of confidence, the variables edge count, feed rate, depth of cut, $X_1.X_3$ and $X_1.X_4$ are not significant. Several characteristics are shown to be unimportant while making a sizable contribution to the statistical sum of squares overall.

4.1.2. CUTTING FORCES

The sole significant component for the rotating speed is X_1, which accounts for 32.87% of the entire variance, according to the ANOVA findings for cutting forces (Table 7). With 38.78%, $X_1.X_3$ is the contributor who comes in second. The quantity of cutting edges, the depth of cut, and $X_1.X_4$ all contribute at considerably lesser levels.

4.2. OPTIMUM LEVELS

Table 8 and Figure 7 depict the impact of various operational parameters on the S/N ratio, which makes up the Ra. It is obvious that the rotational speed at level 3 (1500 rpm), cutting speed at level 3 (40 m/min), additions at level 1 (1 wt.%), number of cutting edges at level 2 (2 flutes), feed rate at level 3 (600 mm/min), and depth of cut at level 3 (1.2 mm) are the best levels for various control factors to achieve minimum Ra. The response graph of the S/N ratio for the process parameters and the three levels shows the rotating speed (X_{11}, X_{12}, X_{13}), cutting speed (X_{21}, X_{22}, X_{23}), addition (X_{31}, X_{32}, X_{33}), number of flutes (X_{41}, X_{42}, X_{43}), feed rate (X_{51},X_{52},X_{53}), and depth of cut (X_{61},X_{62},X_{63}). According to the graph, the ideal settings for rotating speed, cutting speed, addition, number of flutes, feed rate, and depth of cut are level 3, level 2, level 1, level 2, and level 3, respectively. The major impact of interactions on the Ra is shown in Figure 7 by the S/N ratio.

Table 5. Analysis of Variance (ANOVA) for the surface roughness[a].

Source	Seq. SS	Df	Adj. MS	$F_{calculated}$	*P* (%)
Rotational speed (X_1)	50.441	2	25.221	423.88	39.81
Cutting Speed (X_2)	8.407	2	14.204	238.72	22.42
Additions (X_3)	0.85	2	0.418	7.03	0.66
No. of Edges (X_4)	0.128*	2			
Feed rate (X_5)	0.116*	2			
Depth of Cut (X_6)	0.304*	2			
$X_1.X_2$	46.074	4	11.518	193.58	36.36
$X_1.X_3$	0.109*	4			
$X_1.X_4$	0.248*	4			
Error	0.9517	16			0.75
Total	**126.720**	**26**			**100**

[a] Df: degrees of freedom; SS: sum of squares; MS: Variance; *P*: percent contribution. * Pooled, Tabulated *F*-ratio at 99% confidence level: $F_{0.01,\,2,\,16} = 6.23$.

Table 6. Analysis of Means (ANOM) for the surface roughness[a]

Source	Seq. SS	Df	Adj. MS	$F_{calculated}$	*P* (%)
Rotational speed (X_1)	6.9530	2	3.3410	498.66	39.19
Cutting Speed (X_2)	3.7064	2	1.8148	270.86	20.89
Additions (X_3)	0.1195	2	7.67	7.67	0.67
No. of Edges (X_4)	0.0147*	2			
Feed rate (X_5)	0.0081*	2			
Depth of Cut (X_6)	0.0462*	2			
$X_1.X_2$	6.8521	4	1.6779	250.43	38.63
$X_1.X_3$	0.0161*	4			
$X_1.X_4$	0.0176*	4			
Error	0.1077	16			0.62
Total	**17.3795**	**26**			**100**

[a] Df: degrees of freedom; SS: sum of squares; MS: Variance; *P*: percent contribution. * Pooled,

Table 7. Analysis of Variance (ANOVA) for the Cutting Forces [a]

Source	Seq. SS	Df	Adj. MS	$F_{calculated}$	*P* (%)
Rotational speed (X_1)	195.06	2	975.53	19.73	32.87
Cutting Speed (X_2)	3.7064	2	94.00	1.9	3.17
Additions (X_3)	0.1195	2	223.09	4.51	7.52
No. of Edges (X_4)	0.0147*	2			
Feed rate (X_5)	0.0081*	2	103.87	2.10	3.50
Depth of Cut (X_6)	0.0462*	2			
$X_1.X_2$	6.8521	4	86.486	1.75	5.83
$X_1.X_3$	0.0161*	4	575.47	11.64	38.78
$X_1.X_4$	0.0176*	4			
Error	0.1077	10			8.33
Total	**5935.54**	**26**			**100**

[a] Df: degrees of freedom; SS: sum of squares; MS: Variance; *P*: percent contribution. * Pooled,

Table 8. Effect of factors on S/N (Ra) [a]

Symbol	Factors	S/N ratios (dB)		
		Level 1	**Level 2**	**Level 3**
X_1	Rotational speed	11.188	11.063	8.228[a]
X_2	Cutting speed	11.610	9.457	9.412[a]
X_3	Additions	9.967[a]	10.120	10.392
X_4	No. of Edges	10.175	10.069[a]	10.235
X_5	Feed Rate	10.214	10.198	10.067[a]
X_6	Depth of Cut	10.304	10.124	10.051[a]

[a] Optimum level

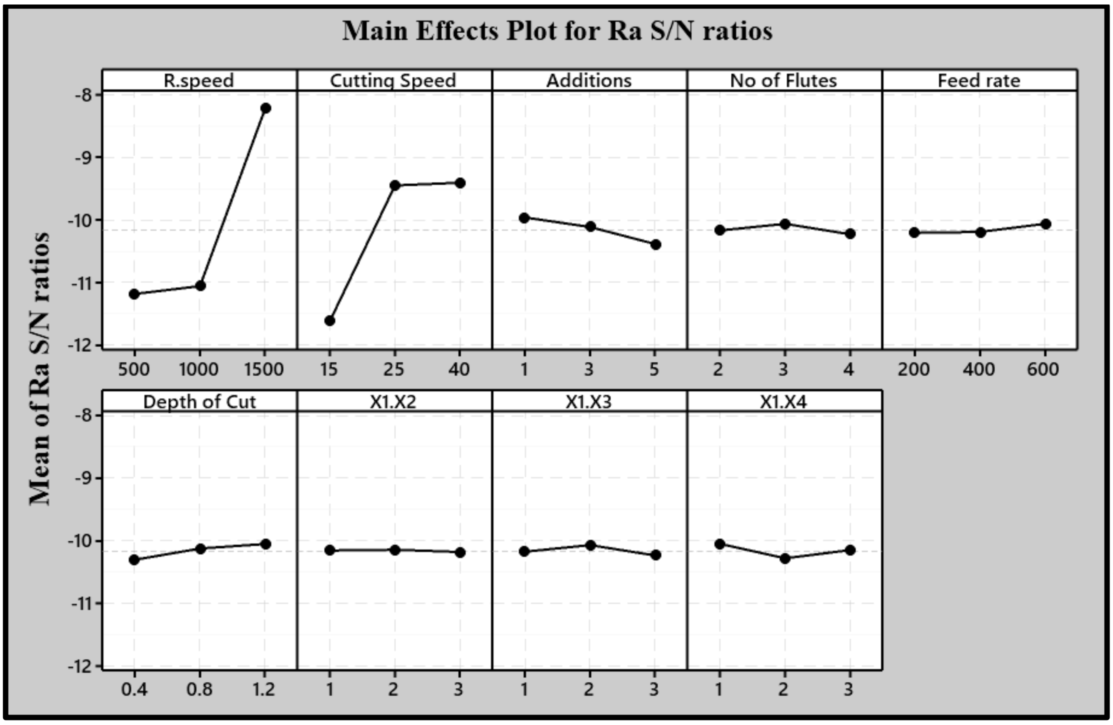

Figure 7. Main effect of CNC machine parameters and Interactions on S/N ratios (Ra)

Overall, while it may be tempting to ignore interactions between variables [34,44,45,46], doing so can result in incomplete and potentially misleading conclusions others have ignored their effects. Careful consideration of interactions can help to reveal important relationships between variables and lead to a more complete understanding of the phenomenon under study. The interaction effects appear to be so negligible as to be ignored. Consequently, it is safe to investigate the primary storyline[47].

4.3. VERIFICATION OF EXPERIMENTAL RESULTS

Once the optimal level of design parameters has been selected, the next stage is to check the improvement of quality characteristics using those parameters. The estimated optimum set of parameters is determined using the formula:

$$Y_{predicted} = Y_{mean} + \sum [Yi - Y_{mean}] \quad (3)$$

Where:

Y_i is the overall mean (S/N ratio and mean) response.

Y_{mean} is the optimal mean (S/N ratio and mean) response.

Tables 9 and 10 compare the projected and actual cutting forces and average surface roughness for the primary design elements determining the quality characteristics. There is evidently good agreement between the expected and observed (S/N ratio and mean) responses. The answer for surface roughness varies most from mean and S/N ratio responses.

Tables 9 and 10 show that, given the cutting forces under consideration, the experimental and projected responses are both extremely similar. Based on mean response and S/N ratio response, a comparable degree of agreement is shown. Average surface roughness results from experiments and predictions are similar.

Table 9. Results of the confirmation experiment for S/N ratios values

Cutting Forces		
	Prediction	Experiment
Optimal levels	X_{12}, X_{21} X_{31}, X_{53}	X_{12}, X_{21}, X_{31}, X_{53}
Cutting Forces S/N ratio (dB)	159.77	159.16
Surface roughness		
Optimal levels	X_{31}, X_{23}, X_{31}	X_{31}, X_{23}, X_{31}
Surface roughness S/N ratio (dB)	-12.38	-12.49

Table 10. Results of the confirmation experiment for mean values

Surface roughness		
	Prediction	Experiment
Optimal levels	X_{22}, X_{41}	X_{22}, X_{41}
Surface roughness mean values	4.12	4.21

5. RESPONSE SURFACE METHODOLOGY (RSM)

Response Surface Methodology is utilized to examine how independent factors affect responses. A mathematical model's objective is to link process responses to process variables. The typical mathematical model for the process responses is shown as [33]:

$$\boldsymbol{Y} = F (X_1, X_2, X_3 \ldots, Xn) + \varepsilon, \quad (4)$$

Where X_1, X_2 . . . X_n are process parameters

ε is the error term

Which is normally distributed about the observed response Y. RSM-based coefficients of process parameters are shown as:

$$[B] = \text{Inverse } ([Z]^T * [Z]) * [Z]^T * [F] \quad (5)$$

Where [B]: array of coefficients of process parameters

[Z]: orthogonal of the array values of selected process parameters

[F]: array of the measured response

$[Z]^T$: transpose array of [Z].

To determine to which level the anticipated model is accurate, Deviation percentage φ_i and average deviation percentage $\varphi^{\wedge}$ are defined as:

$$\varphi_I = [(\text{Absolute }[R\text{ measured} - R\text{ predicted}]) / (R\text{ measured})] X100 \quad (6)$$

Where φ_I: percentage deviation of single sample dataand R measured: measured response. R predicted: predicted response.

$$\varphi^{\wedge} = \sum \varphi_I / n \quad (7)$$

Where $\varphi^{\wedge}$ is average percentage deviation of all sample data n is the size of sample data.

5.1. Mathematical models for (Ra)

Based on the mean response and S/N ratio found in equations (8 and 9) as well as the surface roughness, a mathematical model for surface roughness has been created. The observed vs. projected surface roughness based on the S/N ratio are shown in Figure 8. The average percentage accuracy of the surface roughness based on S/N ratio data is 86.81%, while the model deviance ranges from 0.23% to 41.60%.

$$Ra_{S/N} = -12.59 - 0.00614X_1 - 0.1464X_2 - 0.106X_3 - 0.00037X_5 + 0.316X_6 + 0.000065X_1X_2 + 0.000005\,X_1^2 \quad (8)$$

$$Ra_{mean} = 4.38 + 0.00204\,X_1 - 0.0638\,X_2 + 0.058\,X_3 + 0.01\,X_4 - 0.000106\,X_5 - 0.126X_6 + 0.000035\,X_1.X_2 - 0.000017\,X_1.X_3 - 0.000002\,X_1^2 \quad (9)$$

5.2. Mathematical model for (F_c)

Based on the S/N ratio in Eq. (10), a mathematical model for the cutting forces has been created. According to figure 9, the model deviance ranges from 0.38% to 16.28%, whereas the average percentage accuracy is 94.53%.

$$F_{cS/N} = 238.6 - 0.1647\,X_1 - 0.28\,X_2 - 3.96\,X_3 - 0.0166X_5 - 8.27\,X_6 + 0.000536X_1X_2 + 0.00517\,X_1X_3 + 0.00007\,X_1^2 \quad (10)$$

Figures 10(a-j) show response surface plots of surface roughness as a function of various process factors. Surface roughness response values (dB) are computed for a three-dimensional surface as a function of X_1, X_2, X_3, X_5, X_6, and $X_1.X_2$... $X_1.X_5$. Four of the six variables are held constant at the center level in each of these figures. Figure (10a) displays a surface plot for the cutting speed, rotational speed, and Ra relationship while accounting for additions. The feed rate and depth of cut are assumed to be constant at 3%, 400 mm/min, and 0.8 mm, respectively. The surface plot shows that cutting speed affects Ra's contour at various rotational speeds, while Figures (10 b–d) illustrate the impact of additions, feed rate, and depth of cut on Ra while maintaining a constant cutting speed. Additionally, it is noted that rotational speed at high levels results in relatively less surface roughness and that, when taking contour effect into account, Ra response varies greatly at high levels of cutting speed but only slightly at lower levels, relative to additions. In figure (10e), rotational speed, feed rate, and cut depth are all assumed to be constant at 1000 rpm, 400 mm/min, and 0.8 mm, respectively.

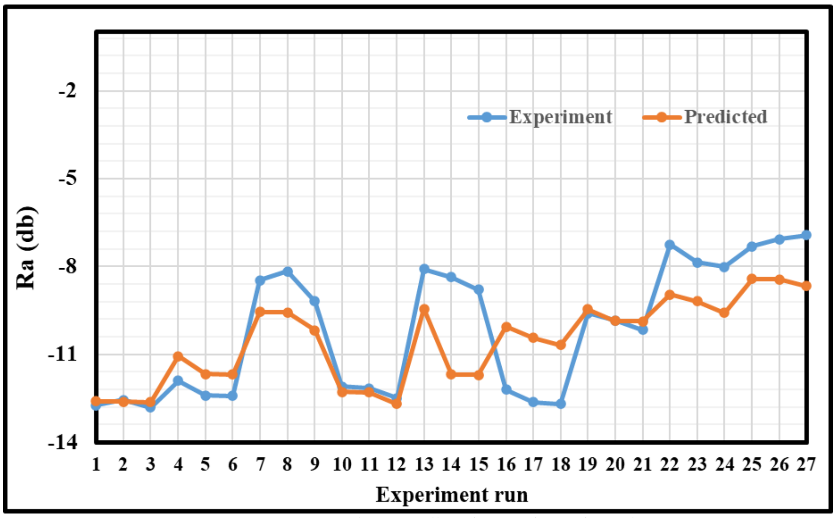

Figure 8. Measured vs. Predicted Ra at low S/N ratio

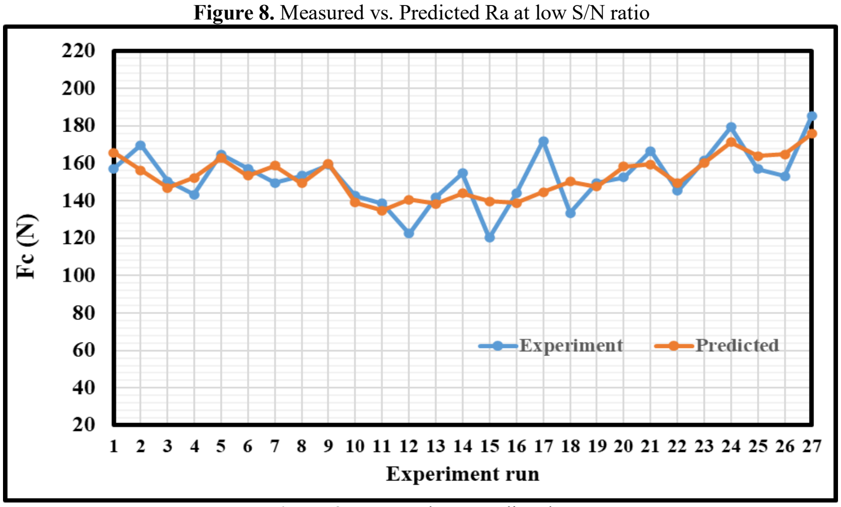

Figure 9. Measured Vs. Predicted F_c

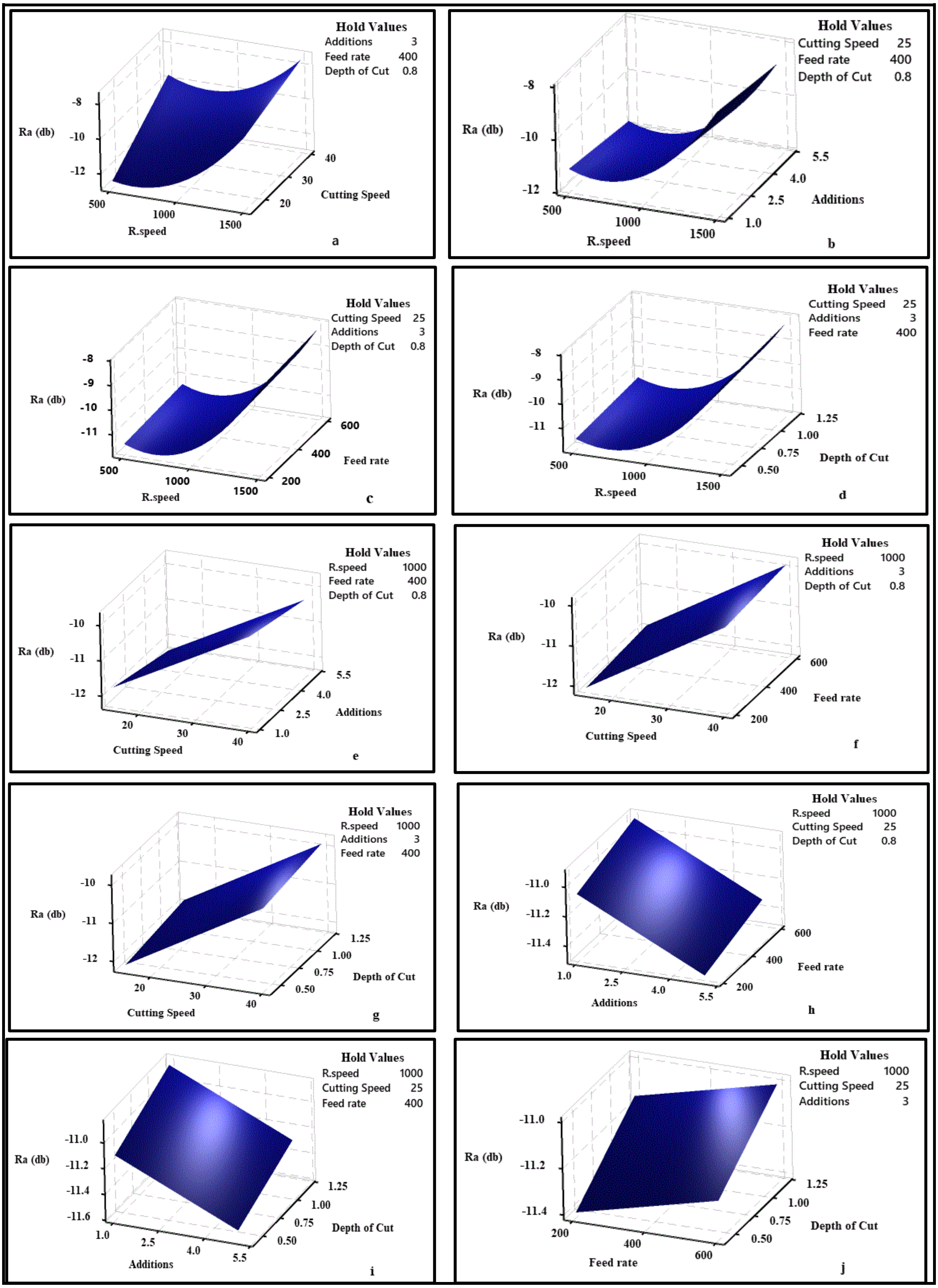

Figure 10. Effect of studied parameters on the Predicted Ra

Examining the 3D graph reveals that Ra gets better with higher cutting speeds while getting worse with higher feed rates. From this vantage point, it is possible to assert that the surface roughness is influenced by the cutting parameters. According to reports, increasing cutting speeds causes surface roughness values to drop [48].

In summary, the Taguchi technique can be effectively utilized as a powerful tool to investigate the effects of CNC process parameters on the mechanical quality of machined parts. By employing this methodology, manufacturers can optimize CNC processes, enhance product quality, and achieve greater efficiency in their manufacturing operations.

6. CONCLUSIONS

The Taguchi experimental design approach was used to evaluate the effects of rotating speed, cutting speed, additives (%wt.), number of edges, feed rate, and depth of cut process parameters on cutting forces and surface roughness during CNC machining of ALMMC/TiO_2. Following were the inferences made from the statistical analysis:

1. According to Taguchi optimization results, the best cutting forces are produced by rotating at 25 m/min, cutting at 500 rpm, adding 1 weight percent, using three cutting edges, feeding at 600 mm/min, and cutting to a depth of 1.2 mm. Additionally, at a rotating speed of 40 m/min, a cutting speed of 1000 rpm, 1 weight percent additions, three edges, a high-level feed rate of 600 mm/min, and a depth of cut of 1.2 mm, the average surface roughness is attained.
2. Based on Taguchi analysis, it is discovered that in the operational range of machine parameters, rotating speed, cutting speed, additions, and feed rate all have a substantial impact on the cutting forces.
3. Rotational speed, cutting speed, and their combined interaction effect are shown to have a considerable impact on average surface roughness.
4. The validation of RSM models reveals that the mean percentage variation in the cutting force value is 5.47%, the mean surface roughness is 13.28%, and the mean surface roughness is calculated using the S/N ratio.
5. To assign X_1, X_2, X_3,X_4,X_5 and X_6 and their corresponding interactions, use search graph approaches[43]. Even though others have neglected their effects, interactions may become significant if carefully examined.
6. Validation of RSM models indicates that the average percentage deviation in cutting forcesand surface roughness ratio, based on S/N ratio values are 5.47 %and 13.19%.
7. Individual and interaction effects should both be included in mathematical models (full models). It is wise to include all terms (individual and interaction effect) in the model creation phase as some studies would include the inconsequential effects as well as interaction effects (Meta models).

Acknowledgements.

Special appreciations are due to Egyptian Aluminum Company, Qena, Egypt for their sincere support with all required materials.

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