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# Modeling and Optimization of Process Parameters for Surface roughness and Cutting Forces on End Milling using RSM and Taguchi Method

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Abstract

End milling is one of the most used machining techniques for removing metal from objects and milled surfaces. It is widely used in tools, aerospace, automotive, machine design, and production for joining other parts. Surface roughness is a crucial indicator of a product's technological excellence and a component that significantly affects manufacturing costs. The effects of several factors of the milling process, such as rotational speed, cutting speed, depth of cut, number of cutting edges and feed rate, find their influence on the surface finish. Surface roughness, cutting forces, and material removal rate were chosen as process responses. Taguchi method and the RSM in the evaluation and optimization of the machining parameters of end milling for the machining of Al 6063/$SiO_2$ by using Minitab 19. The vertical milling machine was used to perform experiments based on the Taguchi $L_{27}$ orthogonal array. The rotational speed, cutting speed, weight percentages of Nano $SiO_2$ (1, 3 and 5), number of cutting edges, feed rate, and depth of cut were considered machining parameters.

According to ANOVA results, additions and cutting speed are the factors that have the greatest impact on the model metal removal rate.

## 1. Introduction

Aluminum alloys are the appropriate choice for most cases technical engineering applications due to their low density and excellent mechanical and thermal properties [1, 2]. Due to automation, improved dimension accuracy, faster machining, and the ability to optimize manufacturing settings, CNC technology is favored [3]. The most significant issue for machine operations is the inaccuracy induced by high cutting forces. The cutting force model has become a crucial step in understanding the behavior of cutting processes to secure the stability of the machining system and optimize the process parameters. [4]

Composite materials are often more difficult to machine than conventional materials because they are non-homogeneous and contain a highly abrasive component. How these materials are machined depends on a variety of criteria, including the percentage composition and properties of the reinforcing elements, the characteristics of the base or matrix material, and the primary machining factors. The major goals of this study are to ascertain the relationship between input control variables and output response as well as the best end-milling parameter combination for a variety of output performances [5,6]. A few researchers have applied the Design of Experiments (DOE) to reduce the number, time, and cost of experiments. To improve the quality characteristics of the answers, process parameters must be optimized. Turning is the most used operation in the manufacturing industry. Therefore, optimization is urgently needed. The Taguchi method, genetic algorithms, fuzzy logic, and other optimization approaches can be used to increase the efficiency of industrial operations. [7].

Ozben et al. [8] For different volume fractions, Al/SiCp composite surface roughness and tool wear effects of machining settings were examined. It was discovered that increasing the amount of reinforcement added resulted in increased mechanical properties (hardness and impact toughness). They also investigated the machinability qualities and discovered that greater reinforcement of SiCp enhanced tool wear and that surface roughness was mostly determined by cutting speed, and feed rate. Ömer Seçgin et al. [9] For the milling of AL 6061-T6, it was determined using Taguchi methodology that the optimal levels of optimization parameters for the surface roughness were "4000 rev/min for the rotational speed of the cutting tool, 0.4 mm for the depth, and the optimal value for the feed rate 500 mm/min. Alagarsamy et al. [10] studied the effects of the CNC end milling process parameters cutting speed, feed rate and depth of cut on the material removal rate and surface roughness of AA 7075-15 wt% B4C metal matrix composites were studied using the Taguchi method. The metal matrix composite was successfully produced using the stir-casting process. Sesharao, Y., et al. [11] investigated how reinforced metal matrix composites affected aluminium alloys. The core of this work is the fabrication of the AA6066 composite with HSS and Cu, the continuous execution of machining tests and the evaluation of surface roughness, tool wear and shear force of the stir cast samples. The aluminum composite is 90 percent AA6066 alloy reinforcement, 6 percent high-speed steel and 4 percent cast copper alloy. M A Țîțu et al. [12] employed the Taguchi optimization approach to identify the best cutting parameters for end-milling. The $L_{27}$ orthogonal matrix served as the foundation for an experimental strategy. Both longitudinally and transversely in the cutting direction, the surface roughness was measured. The aluminum alloy 7136 is the subject of an experimental study. Wiciak-Pikuła et al. [13] For milling DuralcanTM Composite, a model based on an artificial neural network (ANN) based vibration and a model based on experimental design were established to analyze the effects of machining parameters such as cutting speed, spindle speed, and feed rate, axial infeed depth, and radial infeed depth. Layatitdev Das et al. [14] Input machining parameters (cutting speed, tool feed, and cutting depth) and their effects on machining forces, MRR, and surface roughness during milling are studied in the creation of Ti6Al4V metal matrix composites. According to the results of the ideal test, Ra should be minimized, MRR should be maximized, and machining forces should be kept to a minimum.

Metal matrix materials come in many varieties, including those made of magnesium, aluminum, zinc, and copper. Aluminum oxide ($Al_2O_3$), titanium oxide ($TiO_2$), and silicon carbide (SiC) can all be used as the hard reinforcement. Nano fillers have been used as materials in the development of numerous polymeric matrix materials in various fields[15-20].

The goal of this article is to explore the effects of several CNC machining milling process factors on surface roughness, cutting forces, and material removal rate (MRR), including rotating speed, cutting speed, feeding rate, nano percentage content, and depth of cut.

## 2. Taguchi method

A strong analytical technique for predicting and studying the impact of control parameters on performance output is the design of experiments. The use of the conventional experimental design is challenging, particularly when dealing with a high volume of tests and when the number of machining parameters rises [21]. The choice of the control parameters is the most crucial step in the design of an experiment [22]. As a result, the Dr. Genichi Taguchi-created Taguchi method is presented as an experimental approach that enables the reduction of experimental numbers by employing orthogonal arrays and minimizing the effects outside of control parameters [21]. The Taguchi approach consists of a plan of experiments with the goal of gathering data in a controlled manner, conducting these experiments, and analyzing the data to learn more about the behavior of the given process [23,24,25].

The three steps of Taguchi's design process, as seen in Fig. 1, are system design, parameter design, and tolerance design [26]. The elements influencing quality features in the manufacturing process may be determined via parameter design, which is regarded as the most crucial step. Selecting the appropriate orthogonal array (OA) in accordance with the controllable factors (parameters) is the first stage in Taguchi's parameter design. After that, trials are conducted in accordance with the OA established before, and the experimental data is assessed to determine the ideal circumstance. Following the identification of the ideal circumstances, confirmation runs are conducted using the determined ideal values for each parameter [26].

In Taguchi's methodology, parameter design is an engineering technique that focuses on choosing the parameter settings that provide the optimum levels of a quality characteristic with the smallest sum of fluctuation for a product or process. Making products that are resilient to all noise elements is the primary goal of quality engineering [21]. To integrate as many elements as feasible into the control factor selection step and to quickly identify nonsignificant variables, Taguchi developed the standard orthogonal array. Signal-to-noise (S/N) ratio was employed by Taguchi as a metric for the choice's qualitative attributes. This demonstrates that engineering systems may work in a way that allows the production factors that have been altered to be separated into three groups [21]:

1. Controlling variables (variables that have an impact on the process variability as shown by the S/N ratio).

2. Signal elements (elements that have no impact on S/N ratio or process mean).

3. Elements (elements that have no bearing on S/N ratio or process mean)

Signal-to-noise (S/N) ratios are then created from the experimental findings. Taguchi chose the signal-to-noise (S/N) ratio as the quality criterion, and there are several S/N ratios available depending on the type of performance criterion [22]. When the features are continuous, the S/N ratio may be divided into three categories:

Larger the better characteristics:

$$\textbf{SNR } (\boldsymbol{\eta}) = -10 \log \left( \frac{1}{N} \sum_{i=1}^{N} \frac{1}{Y_i^2} \right) \qquad \textbf{(1)}$$

Nominal is the best characteristic:

$$\textbf{SNR } (\boldsymbol{\eta}) = -10 \log \left( \frac{1}{N} \sum_{i=1}^{N} Y_i^2 \right) \qquad \textbf{(2)}$$

Smaller the better characteristics:

$$\textbf{SNR } (\boldsymbol{\eta}) = -10 \log \left( \frac{\bar{y}}{\sigma^2} \right) \qquad \textbf{(3)}$$

where '$\bar{y}$' is the average observed data, '$\sigma^2$' the variance of 'y', 'n' the number of observations, and 'y' the observed data. For each type of characteristic, a higher or lower value of S/N ratio indicates the better result value [27].

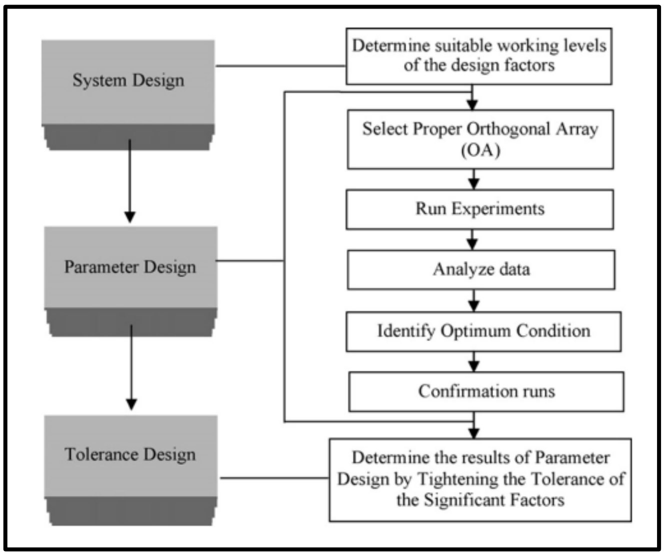



**Figure (1):** Taguchi design procedure [26].

## 4. Experimental Details

The experiments were performed in rectangular (100 × 100 × 50 mm) of Al-MMc be prepared using the stir casting method with $SiO_2$ nanoparticle additions of 1, 3, and 5 wt.% used as reinforcing material in the preparation of composites Table 1. The machine tool used for end milling is a 4-axis CNC vertical milling machine with a maximum spindle speed is 8000 rpm (SINUMERIK 802D-CNC machine). End mills with varied numbers of cutting edges have been used for dry cutting. Input parameter values for rotating speed, cutting speed, $SiO_2$ addition content, number of cutting edges, depth of cut, and feed rate are displayed in Table 2 for the parameters. Surface roughness and cutting force are the responses. The orthogonal array $L_{27}$ is employed for testing. The root mean square value parameter (Ra) is used for evaluating surface roughness using the Surface Roughness Tester (TAYLOR-HOBSON-SURTRONIC). Cutting forces are measured using a KISTLER dynamometer of type (5806 A). While the end mill tool used is an HSS with an 8 mm diameter.

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

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

**Table (2) :** Input process parameters and levels used in the designed experiments.

| Symbol | Input parameters | Unit | L 1 | L 2 | L 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 |

Figure (2): depicts the experimental setup and the experimental arrangement's schematic design.

The process's output parameters would be impacted by milling variables. Each of them, namely rotational speed cutting speed, additions, number of cutting edges, feed rate, and axial depths of cutting, was altered in various levels in complete factorial table 3 way to examine their impact on the milling process perfectly. As a result, 27 experiments were devised and conducted in this research. The experiment design levels are displayed in Table 3. It should be mentioned that both the author's experience and a review of the literature were used to create the experimental design.

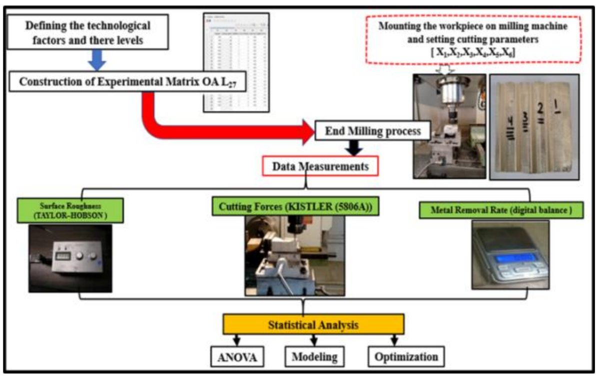



**Figure (2):** Experimental set-up

| Exp. run | Control Factors $L_{27}$OA $X_1$ | $X_2$ | $X_3$ | $X_4$ | $X_5$ | $X_6$ | Ra S/N ratio | MRR S/N ratio | Cutting Forces S/N ratio | $Ra_{mean}$ (μm) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | -13.810 | 25.274 | 145.20 | 4.90 |
| 2 | 1 | 1 | 2 | 2 | 2 | 1 | -13.237 | 25.617 | 139.84 | 4.59 |
| 3 | 1 | 1 | 3 | 3 | 3 | 1 | -12.462 | 25.855 | 152.87 | 4.20 |
| 4 | 1 | 2 | 1 | 2 | 3 | 2 | -12.786 | 27.914 | 157.34 | 4.35 |
| 5 | 1 | 2 | 2 | 3 | 1 | 2 | -11.121 | 27.761 | 170.18 | 3.59 |
| 6 | 1 | 2 | 3 | 1 | 2 | 2 | -14.086 | 28.206 | 187.73 | 4.99 |
| 7 | 1 | 3 | 1 | 3 | 2 | 3 | -11.272 | 28.090 | 206.1 | 3.66 |
| 8 | 1 | 3 | 2 | 1 | 3 | 3 | -13.626 | 26.841 | 158.77 | 4.80 |
| 9 | 1 | 3 | 3 | 2 | 1 | 3 | -10.908 | 27.823 | 174.94 | 3.50 |
| 10 | 2 | 1 | 1 | 1 | 1 | 2 | -13.090 | 28.156 | 173.77 | 4.51 |
| 11 | 2 | 1 | 2 | 2 | 2 | 2 | -10.361 | 26.455 | 197.52 | 3.29 |
| 12 | 2 | 1 | 3 | 3 | 3 | 2 | -8.334 | 27.377 | 199.72 | 2.59 |
| 13 | 2 | 2 | 1 | 2 | 3 | 3 | -10.939 | 28.137 | 203.04 | 3.50 |
| 14 | 2 | 2 | 2 | 3 | 1 | 3 | -7.521 | 27.660 | 209.82 | 2.37 |
| 15 | 2 | 2 | 3 | 1 | 2 | 3 | -11.561 | 26.985 | 204.84 | 3.78 |
| 16 | 2 | 3 | 1 | 3 | 2 | 1 | -12.764 | 27.615 | 223.72 | 4.34 |
| 17 | 2 | 3 | 2 | 1 | 3 | 1 | -12.388 | 27.123 | 176.6 | 4.13 |
| 18 | 2 | 3 | 3 | 2 | 1 | 1 | -11.870 | 26.643 | 219.02 | 3.92 |
| 19 | 3 | 1 | 1 | 1 | 1 | 3 | -13.360 | 27.296 | 232.37 | 4.65 |
| 20 | 3 | 1 | 2 | 2 | 2 | 3 | -12.782 | 27.660 | 227.97 | 4.35 |
| 21 | 3 | 1 | 3 | 3 | 3 | 3 | -11.356 | 26.072 | 214.19 | 3.69 |
| 22 | 3 | 2 | 1 | 2 | 3 | 1 | -8.051 | 27.892 | 235.91 | 2.52 |
| 23 | 3 | 2 | 2 | 3 | 1 | 1 | -7.098 | 27.264 | 235.93 | 2.26 |
| 24 | 3 | 2 | 3 | 1 | 2 | 1 | -8.090 | 27.113 | 264.49 | 2.53 |
| 25 | 3 | 3 | 1 | 3 | 2 | 2 | -11.020 | 27.406 | 278.93 | 3.55 |
| 26 | 3 | 3 | 2 | 1 | 3 | 2 | -7.250 | 27.143 | 298.14 | 2.30 |
| 27 | 3 | 3 | 3 | 2 | 1 | 2 | -8.797 | 27.538 | 318.41 | 2.75 |

**Table (3) :**$L_{27}$OA Design layout and experimental results

## 5. Results and discussion

ANOVA is a statistical method that, after analyzing experimental data, offers significant results. This method is excellent for demonstrating the level of importance of a factor's or a factor's interaction with a factor's effect on a specific response.

The figures, diagrams, and graphs provided below were created using Minitab 19 Statistical Software to illustrate the findings for the experimental settings.

The Orthogonal Array Design L27 (313) was created using Taguchi design. Based on the six components with three levels each, 27 experimental tests were obtained. The effects of cutting forces, surface roughness, and metal removal rate on each factor individually (X1,X2,X3,X4,X5,X6), as well as on how they interact (X1.X2, X1.X3 and X12), were observed.

**Table (4) :**Analysis of Variance for the Cutting Forces [a].

| Source | Seq. SS | Df | Adj. MS | $F_{calculated}$ | $P$ (%) |
|---|---|---|---|---|---|
| Rotational speed ($X_1$) | 37375.5 | 2 | 18687.8 | 255.33 | 69.96 |
| Cutting Speed ($X_2$) | 7654.1 | 2 | 3827.1 | 52.29 | 14.33 |
| Additions ($X_3$) | 846.4 | 2 | 423.2 | 5.78 | 1.58 |
| No. of Edge ($X_4$) | 140.4* | 2 | | | |
| Feed rate ($X_5$) | 1024.4 | 2 | 512.2 | 6.99 | 1.92 |
| Depth of Cut ($X_6$) | 131.6* | 2 | | | |
| $X_1 . X_2$ | 3396.2 | 4 | 849.1 | 11.60 | 6.36 |
| $X_1 . X_3$ | 279.8* | 4 | | | |
| $X_1 . X_4$ | 2393.7 | 4 | 598.4 | 8.18 | 4.48 |
| Error | 7654.1 | 10 | | | 1.37 |
| Total | 53424.3 | 26 | | | 100 |

[a] Df: degrees of freedom; SS: sum of squares; MS: Variance; $P$: percent contribution. * Pooled, Tabulated $F$- ratio at 99% confidence level: $F_{0.01,\ 2,\ 10} = 7.56$.

This suggests that the parameter with the greatest influence will be the one for which the line is inclined the most. The main effects figure in this study makes it abundantly evident that parameter $X_1$ (Rotational speed), followed by parameter $X_2$ (Cutting speed), had the greatest impact on Fc, but parameters $X_4$ (No.of cutting edge) and $X_6$ (Depth of cut) have insignificant impact. The process parameter combination with the best results for everyone's greatest mean S/N ratio and Fc is $X_{11}$,$X_{21}$,$X_{32}$,$X_{41}$,$X_{53}$,$X_{61}$ according to figure3.

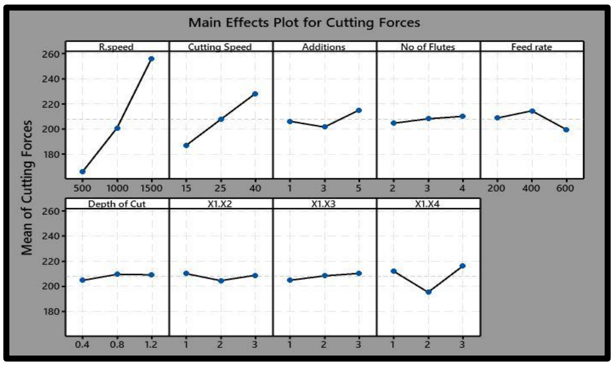



**Figure 3.** Plot of control factors effects (S/N ratios) for ($F_c$)

### 5.2 For the MRR

ANOVA results for the MRR (table 5) show that cutting speed is the most factor effect on MRR at contributes 30.02 % and the addition is the second factor effect at contributes 8.00 %. The factors X2, and X1.X2 are statistically significant at 90%, 95% and 99% confidence levels. Table 6 shows how different operating factors affect the MRR's S/N ratio. It is evident that the rotational speed at level 2 (1000 rpm), cutting speed at level 2 (25 m/min), additions at level 1 (1 wt.%), number of cutting edges at level 2 (2 flutes), feed rate at level 1 (200 mm/min), and depth of cut at level 1 (0.4 mm) are the best levels for various control factors to achieve maximize Ra

**Table (5):** Analysis of Variance for the MRR[a].

| Source | Seq. SS | Df | Adj. MS | $F_{calculated}$ | *P* (%) |
|---|---|---|---|---|---|
| Rotational speed ($X_1$) | 0.45496 | 2 | 0.2275 | 255.33 | 2.77 |
| Cutting Speed ($X_2$) | 4.9316 | 2 | 2.4658 | 52.29 | 30.02 |
| Additions ($X_3$) | 1.3136 | 2 | 0.6568 | 5.78 | 8.00 |
| No. of Edge ($X_4$) | 0.1347* | 2 | | | |
| Feed rate ($X_5$) | 0.0676* | 2 | | | |
| Depth of Cut ($X_6$) | 0.2461* | 2 | | | |
| $X_1$. $X_2$ | 5.5054 | 4 | 1.3763 | 9.24 | 33.51 |
| $X_1$. $X_3$ | 1.5136 | 4 | 0.3784 | 2.54 | 9.21 |
| $X_1$. $X_4$ | 1.5170 | 4 | 0.3793 | 2.55 | 9.23 |
| Error | 1.1927 | 8 | | | 7.26 |
| Total | 16.4297 | 26 | | | 100 |

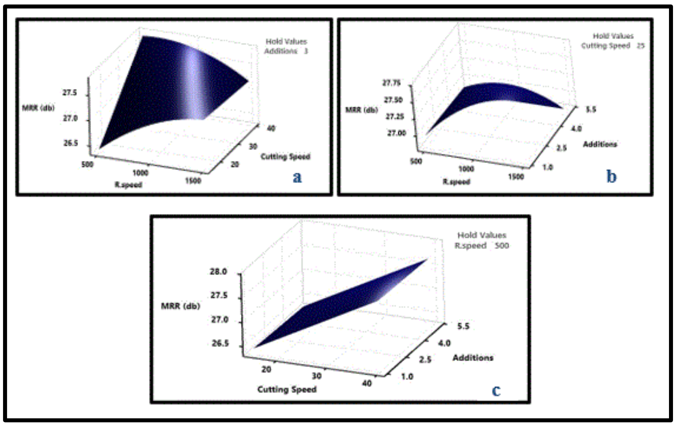
[a] Df: degrees of freedom; SS: sum of squares; MS: Variance; *P*: percent contribution. * Pooled, Tabulated *F*- ratio at 99% confidence level: $F_{0.01,\,2,\,8} = 8.65$.

**Table (6):** Effect of factors on S/N (MRR) [a].

| Symbol | Factors | S/N ratios (dB) | | |
|---|---|---|---|---|
| | | L 1 | L 2 | L 3 |
| $X_1$ | Rotational speed | 27.04 | 27.35[a] | 27.26 |
| $X_2$ | Cutting speed | 26.64 | 27.66[a] | 27.36 |
| $X_3$ | Additions | 27.53[a] | 27.06 | 27.07 |
| $X_4$ | No. of Edges | 27.13 | 27.30[a] | 27.23 |
| $X_5$ | Feed Rate | 27.27[a] | 27.24 | 27.15 |
| $X_6$ | Depth of Cut | 27.30[a] | 27.28 | 27.08 |

[a]Optimum level

Response surface plots of the metal removal rate as a function of several process variables are shown in Figures 4(a) through (c). For a three-dimensional surface, metal removal rate values (dB) are calculated as a function of $X_1$, $X_2$, $X_3$, $X_1$.$X_2$, and $X_1$.$X_3$. In each of these figures, one of the three variables is held




**Figure(4):** Effect of studied parameters on the Predicted MRR.

as a function of X1, X2, X3, X1.X2, and X1.X3. In each of these figures, one of the three variables is held constant at the central level. Figure (4a) shows a surface plot showing the relationship between cutting speed, rotational speed, and MRR while considering additions. The assumption is that the addition will always be 3%. Figures (10 b-c) depict the effect of cutting speed and additions on MRR while maintaining a constant rotational speed, in contrast to the surface plot, which demonstrates how cutting speed affects MRR contour at varied rotational speeds. Also observed is the fact that rotational speed at high levels results in relatively high MRR and that, when taking the contour effect into account.

### 5.3 For The surface roughness

ANOVA results for the Ra (table 7) based on S/N ratio show that rotational speed is the most factor effect on Ra at contributes 29.16 % and the cutting speed is the second factor effect at contributes 13.71 %.

**Table (7):** Analysis of Variance for the surface roughness [a].

| Source | Seq. SS | Df | Adj. MS | $F_{calculated}$ | *P* (%) |
|---|---|---|---|---|---|
| Rotational speed ($X_1$) | 36.358 | 2 | 18.1790 | 20.39 | 29.16 |
| Cutting Speed ($X_2$) | 17.090 | 2 | 8.5451 | 9.58 | 13.71 |
| Additions ($X_3$) | 8.671 | 2 | 4.3356 | 4.86 | 6.95 |
| No. of Edge ($X_4$) | 11.389 | 2 | 5.6947 | 6.39 | 9.13 |
| Feed rate ($X_5$) | 4.503 | 2 | 2.2516 | 2.53 | 3.61 |
| Depth of Cut ($X_6$) | 1.4930* | 2 | | | |
| $X_1$. $X_2$ | 30.364 | 4 | 7.5911 | 8.51 | 24.35 |
| $X_1$. $X_3$ | 4.372 | 4 | 1.0930 | 1.23 | 3.51 |
| $X_1$. $X_4$ | 8.376 | 4 | 2.0940 | 2.35 | 6.75 |
| Error | 3.5663 | 4 | | | 2.86 |
| Total | 124.697 | 26 | | | 100 |

The factor $X_1$.$X_2$ is statistically significant at 90% and 95% confidence levels. Table 8 shows that $X_2$, $X_4$ and $X_1$.$X_2$ are statistically significant at 90%, 95% and $X_3$ is statistically significant at 90% confidence levels. $X_6$ and $X_1$.$X_3$ are insignificant at any confidence levels. $X_1$ is statistically significant at all confidence levels. The ANOM results show that the rotational speed and cutting speed are the most important factors influencing Ra. It contributes 28.99 % and 13.65 % respectively. The second factor that influences Ra is No. of cut Edges It contributes 11.70 %.

**Table (7) :**Analysis of Variance for the surface roughness [a].

| Source | Seq. SS | Df | Adj. MS | $F_{calculated}$ | *P* (%) |
|---|---|---|---|---|---|
| Rotational speed ($X_1$) | 36.358 | 2 | 18.1790 | 20.39 | 29.16 |
| Cutting Speed ($X_2$) | 17.090 | 2 | 8.5451 | 9.58 | 13.71 |
| Additions ($X_3$) | 8.671 | 2 | 4.3356 | 4.86 | 6.95 |
| No. of Edge ($X_4$) | 11.389 | 2 | 5.6947 | 6.39 | 9.13 |
| Feed rate ($X_5$) | 4.503 | 2 | 2.2516 | 2.53 | 3.61 |
| Depth of Cut ($X_6$) | 1.4930* | 2 | | | |
| $X_1$. $X_2$ | 30.364 | 4 | 7.5911 | 8.51 | 24.35 |
| $X_1$. $X_3$ | 4.372 | 4 | 1.0930 | 1.23 | 3.51 |
| $X_1$. $X_4$ | 8.376 | 4 | 2.0940 | 2.35 | 6.75 |
| Error | 3.5663 | 4 | | | 2.86 |
| Total | 124.697 | 26 | | | 100 |

[a] Df: degrees of freedom; SS: sum of squares; MS: Variance; *P*: percent contribution. * Pooled, Tabulated *F*- ratio at 99% confidence level: $F_{0.01,\,2,\,4}=18$.

**Table (8) :**Analysis of Means for the surface roughness [a]

| Source | Seq. SS | Df | Adj. MS | $F_{calculated}$ | *P* (%) |
|---|---|---|---|---|---|
| Rotational speed ($X_1$) | 5.6154 | 2 | 2.8077 | 17.46 | 28.99 |
| Cutting Speed ($X_2$) | 2.6434 | 2 | 1.3217 | 8.22 | 13.65 |
| Additions ($X_3$) | 1.2902 | 2 | 0.6451 | 4.01 | 6.66 |
| No. of Edge ($X_4$) | 2.2666 | 2 | 1.1333 | 7.05 | 11.70 |
| Feed rate ($X_5$) | 0.5951 | 2 | 0.2976 | 1.85 | 3.07 |
| Depth of Cut ($X_6$) | 0.2490 | 2 | | | |
| $X_1$. $X_2$ | 4.4676 | 4 | 1.1169 | 6.95 | 23.06 |
| $X_1$. $X_3$ | 0.6461 | 4 | | | |
| $X_1$. $X_4$ | 1.2062 | 4 | 0.3016 | 1.88 | 6.23 |
| Error | 1.28629 | 8 | | | 6.64 |
| Total | 19.3719 | 26 | | | 100 |

[a] Df: degrees of freedom; SS: sum of squares; MS: Variance; *P*: percent contribution. * Pooled, Tabulated *F*- ratio at 99% confidence level: $F_{0.01,\,2,\,8}=8.65$.

## 6. Mathematical models

Based on the S/N ratio in Eq. (5), a mathematical model for the cutting forces has been created. According to figure 5, the model deviance ranges from 0.13% to 20.72% (at run number experiment 16 and 17 respectively shown on Appendix ), whereas the average percentage accuracy is 94.07%

$$Fc_{S/N} = 153.6 - 0.0471\,X_1 - 0.070X_2 - 1.36\,X_3 + 2.75\,X_4 - 0.0231X_5 + 5.7\,X_6 + 0.001698\,X_1X_2 + 0.00358\,X_1X_3 + 0.000041X_1^2 \quad (5)$$

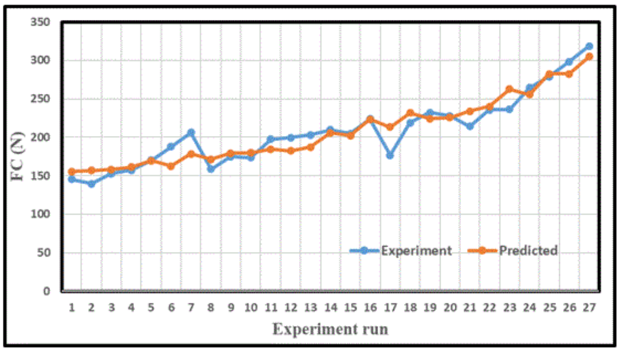



**Figure (5):** Measured Vs. Predicted S/N ratio response (Fc).

Based on the mean response and S/N ratio found in equations (6 and 7) as well as the surface roughness, a mathematical model for surface roughness has been created. The average percentage accuracy of the surface roughness based on S/N ratio data is 86.61%, while the model deviance ranges from 0.33% to 39.92%(at run number experiment 8 and 26 respectively).

$$Ra_{S/N} = -15.4 + 0.00151\,X_1 - 0.0407\,X_2 - 0.047\,X_3 + 0.795\,X_4 + 0.00011\,X_5 - 0.48\,X_6 + 0.000072\,X_1X_2 + 0.000315\,X_1X_3 - 0.000001\,X_1^2 \quad (6)$$

$$Ra_{Mean} = 10.03 - 0.00207\,X_1 - 0.210X_2 - 0.1119X_3 - 0.897X_4 - 0.000102X_5 + 0.248\,X_6 - 0.000025\,X_1X_2 - 0.000544\,X_1X_4 + 0.00396\,X_2^2 \quad (7)$$

Based on the S/N ratio in Eq. (8), a mathematical model for the metal removal rate has been created. the model deviance ranges from 0.46% to 4.71% (at run number experiment 9 and 6 respectively), whereas the average percentage accuracy is 94.07%.

$$MRR_{S/N} = 23.83 + 0.00399X_1 + 0.084\,X_2 + 0.091\,X_3 - 0.000059X_1X_2 - 0.000206\,X_1X_3 - 0.000001\,X_1^2 \quad (8)$$

Comparison of experimental and predicted (Fc& Ra& MRR) based on S/N ratio. Shown on table 9 below

**Table (9):** The Comparison of experimental and predicted (Fc& Ra& MRR) based on S/N ratio.

| | The Cutting forces (Fc) | Surface Roughness (Ra) | Metal Removal rate (MRR) |
|---|---|---|---|
| Experimental | 139.84 | -13.626 | 27.823 |
| Predicted | 144.648 | -13.67 | 27.33 |
| Average percentage of Model accuracy % | 94.07 % | 86.61 % | 97.76 % |

## 7. CONCLUSIONS

In the current study, Al6063-$SiO_2$ composites with 1%, 3%, and 5% of $SiO_2$ were made using stir casting equipment and then machined on a CNC end-milling. The following results were then noted:

1. 1.Cutting speed and additives (%wt.) are the significant variables affecting MRR in end milling of the Al6063- $SiO_2$ composites.
2. 2.The optimum conditions obtained from Taguchi method for optimizing of cutting forces in end milling of the Al6063- $SiO_2$ composites under dry condition is rotational speed of 500 rpm followed by depth of cut of 0.4 mm and feed rate of 600 mm/min at 3% additives.
3. 3.According to Taguchi optimization results, the best MRR are produced by rotating speed at 1000 rpm m/min, cutting speed at 25 m/min, adding 1 weight percent, using three cutting edges, feeding at 200 mm/min, and cutting to a depth of 0.4 mm. Additionally, at a rotating speed of 1500 rpm, a cutting speed of 25 m/min , 3 weight percent additions, four edges, a high-level feed rate of 600 mm/min, and a depth of cut of 0.8 mm, the average surface roughness is attained.

4.The cutting speed contributes the most (30.02%), followed by the additives (8.0%), and rotating speed (2.77%), which makes up the least amount of the ideal MRR, according to the MRR ANOVA.

5.The validation of RSM models reveals that the mean percentage variation in the cutting force value is 5.93 %, the mean MRR is 2.24 % the mean surface roughness is 13.39 %, and the mean surface roughness is calculated using the S/N ratio.

## Appendix

Experimental versus predicted for the Cutting Forces (Fc)

| *Run #* | *Experimental response Fc (N)* | *Predicted response Fc (N)* | *%deviation* |
|---|---|---|---|
| 1 | 145.20 | 155.58 | 7.15 |
| 2 | 139.84 | 156.85 | 12.16 |
| 3 | 152.87 | 158.12 | 3.43 |
| 4 | 157.34 | 161.44 | 2.60 |
| 5 | 170.18 | 169.73 | 0.27 |
| 6 | 187.73 | 162.75 | 13.31 |
| 7 | 206.1 | 178.21 | 13.53 |
| 8 | 158.77 | 171.23 | 7.85 |
| 9 | 174.94 | 179.52 | 2.62 |
| 10 | 173.77 | 179.58 | 3.34 |
| 11 | 197.52 | 184.43 | 6.63 |
| 12 | 199.72 | 182.44 | 8.65 |
| 13 | 203.04 | 187.09 | 7.86 |
| 14 | 209.82 | 205.80 | 1.92 |
| 15 | 204.84 | 202.40 | 1.19 |
| 16 | 223.72 | 223.44 | 0.13 |
| 17 | 176.6 | 213.20 | 20.72 |
| 18 | 219.02 | 231.91 | 5.89 |
| 19 | 232.37 | 224.09 | 3.57 |
| 20 | 227.97 | 225.68 | 1.01 |
| 21 | 214.19 | 234.11 | 9.30 |
| 22 | 235.91 | 240.09 | 1.77 |
| 23 | 235.93 | 262.38 | 11.21 |
| 24 | 264.49 | 255.72 | 3.32 |
| 25 | 278.93 | 282.33 | 1.22 |
| 26 | 298.14 | 282.51 | 5.24 |
| 27 | 318.41 | 304.80 | 4.27 |
| **Average Residual (AR)** | | | **160.14** |
| **Average Absolute Residual (AAR)** | | | **5.93 %** |
| **Average percentage of Model accuracy %** | | | **94.07 %** |

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