Multiresponse Regression Modeling in Face Milling of Al6061 Using Design of Experiments



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1 Introduction

Aluminum and its alloys are utilized in an assortment of uses, for example, making vehicle and aviation segments, rocket parts, stockpiling compartments, marine applications, storage containers, etc., as a result of its low density, fantastic corrosion resistance, and better thermal and mechanical properties. These metals are easy to machine as compared to other metals. With the addition of various kinds of metals, properties of pure aluminum can be enhanced [1]. Nowadays, Al6061 is one of the most significant and widely used materials in the industries from Al 6xxx series alloys. It is created in 1935 and contains Mg and Si as its major alloying parts [2]. It is an easily available metal and has good mechanical properties, exhibits good weldability, commonly extruded. It is mostly used in aircraft, automobiles, boats, and packaging of food and beverage industries [3].

2 Literature Survey

Nowadays due to industrials rivalry, the utilization of reasonable improvement strategies for the right choice of process parameters is amazingly important to stay away from non-esteem included costs. The advancement of process parameters requires deliberate methodologies [4]. As indicated in literature, different conventional methods, for example, geometric programming, goal programming,

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and dynamic programming have been viably applied to improve process parameters [5]. Among the different strategies, the Taguchi-based methodology has created exceptional and remarkable control that appears differently with customary practices. It has demonstrated a wide extent of present-day applications for making the item obtuse toward any wild factors [6].

Niranjan et al. [7]; Rajendra and Deepak [8] streamlined speed, feed rate, and depth of cut in the turning of Al 6061 for surface finish and material removal rate. Kishore et al. [9] considered the impact of cutting parameters on cutting force and surface quality performing CNC turning on Al6061-4 wt% TiC composite. Ugrasen et al. [10] determined the ideal process parameters concerning ultimate tensile strength (UTS) and hardness of the weld joint utilizing the Taguchi technique. Kandpal et al. [11] proposed a multiresponse improvement strategy utilizing the Taguchi approach and utility idea for electrical discharge machining (EDM) of Al6061/10%Al2O3 MMC. MisbahNiamat et al. [12] enhanced electrical discharge machining parameters for electrode wear rate (EWR) and material ejection rate of Aluminum 6061 T6 Alloy utilizing Taguchi plan of assessment. Adalarasan et al. [13] enhanced lesser cutting parameters using the Taguchi-based response surface method.

Shaik and Srinivas [14]; Kumar et al. [15], built up a coordinated framework to demonstrate and improve the processing parameters during end milling of Al 6061. Nghiep et al. [16] examined the mechanism of deflection error, and Tomadi et al. [17] introduced the forecast model in the end milling process. Kondayya and GopalaKrishna [18] introduced a non-dominated sorting genetic algorithm-II for modeling and multi-objective optimization of the CNC end milling process.

Niknam and Songmene [19] utilized Taguchi and ANOVA investigation to streamline burr size and surface finish parameters similarly Palanisamy et al. [20] utilized genetic algorithm by considering machining time as a target for slot milling activity. Shinge and Dabade [21] explored the impact of preparing factors in micro-milling of Al 6063 T6 utilizing Taguchi L16 orthogonal array. Hwan and Sang-Heon [22] endeavored to obtain ideal cutting conditions for burr minimization in faceprocessing tasks. Response surface methodology (RSM) has been utilized by Premnath [23] for finding the ideal machining parameters while milling Al6061/Al₂O₃/Gr. Baharudin et al. [24] utilized the Taguchi strategy to locate the ideal surface roughness for Al6061 face milling. Sukumar et al. [25] utilized an artificial neural network (ANN) model and Taguchi S/N ratio examination for getting the ideal blend of parameters to accomplish a decent surface finish in face milling activity. Nguyen [26] investigated the effects of milling type and various cutting conditions on the surface roughness using Taguchi and ANOVA analysis.

3 Research Gaps and Problem Definition

Al 6061-T6 is a typical alloy that is utilized in different modern applications for some reason since it has prevalent mechanical properties. At present, numerous endeavors are being attempted to improve different handling parameters utilizing the genetic algorithm, response surface methodology, regression analysis, neural network, grey relational analysis (GRA), Taguchi strategy, etc. In the present date, necessity of industry is to make items having high quality at low cost as well as high productivity, less machining, and production time. This paper will fulfill the industries need to deliver excellent items with minimal effort. Problem definition of underlying paper is to improve the processing parameters, for example, speed, feed rate, and cutting depth on surface roughness (Ra) and material removal rate (MRR) in the face milling process by utilizing Taguchi plan of experiment and multiresponse regression analysis.

4 Research Objectives and Research Methodology

The main objective of this paper is to investigate the optimum setting of machining parameters (speed, feed rate, and depth of cut) in face milling of Al6061-T6 alloy to accomplish the minimal surface roughness and high material removal rate utilizing the Taguchi plan of an experiment. Figure 1 shows the research methodology flowchart. Experimentation is done according to the L27 orthogonal array with 03 control factors and 03 levels for each factor. Further examination is completed using signal-to-noise (S/N) ratio investigation and analysis of variance (ANOVA), to figure out which process parameters are measurably noteworthy. At long last, a confirmation test is done to examine the improvement in optimization. Finally, a multiresponse regression examination is performed to study the combined impact of the two responses.



		1			2				
Elements	Cr	Fe	Si	Mg	Mn	Cu	Zn	Ti	Al
Percentages	0.1	0.35	0.5	0.08	0.04	0.28	0.02	0.01	Balance

Table 1 Chemical composition of Al6061 T6 alloy

Table 2	Levels of	of inpu	ıt
paramete	rs used i	in this	study

Input parameters	Level 1	Level 2	Level 3
Spindle speed (RPM)	1000	1500	2000
Feed rate (mm/min)	200	400	600
Depth of cut (mm)	0.4	0.8	1.2

5 Experimental Work

5.1 Material

In this paper, blocks of Al 6061 T6 alloy with a size 50 mm * 60 mm * 50 mm are used for experimentation. The chemical composition of the Al 6061 T6 alloy is given in Table 1.

5.2 Machining Parameters

Cutting speed (v), feed rate (f), and cutting depth (d) are chosen as input parameters similarly surface roughness and material removal rate are chosen as output factors for the examination. According to suggestions of the cutting instrument maker and the limit of the machine device, the levels of these input parameters were chosen as appeared in Table 2.

5.3 Experimental Setup and Procedure

For performing face milling, a Cosmos 05-axis vertical milling machine with a rotational speed of 8000 rpm and motor power of 11 kW was utilized as appeared in Fig. 2. A carbide face milling cutter having a diameter 63 mm, 05 inserts, and sixteen cutting edges for each insert manufactured by Tungaloy has been used as cutting tools. The impact of the selected milling input parameters on output factors and ideal settings of the parameters has been practiced utilizing Taguchi's L27 orthogonal array.



Fig. 2 Setup of vertical milling machine

5.4 Measurement of Output Factors

Surface roughness (Ra) is estimated by surface roughness analyzer SRT-6210. Three readings for surface roughness were taken for every surface, and its average is considered as a final value, to minimize the error. Material removal rate (MRR) is determined with the help of formula, [Material Removal Rate = Width of cut (mm) * Depth of cut (mm) * Feed Rate (mm/min)].

5.5 Taguchi Signal to Noise Ratio Analysis

Analysis of experimental data of surface finish (Ra) and material removal rate (MRR) is finished by utilizing the Taguchi plan in Minitab-19 software and the estimated S/N ratio values. From Fig. 3, it can presume that as rotational speed and cutting depth builds, surface roughness value diminishes, while feed rate diminishes at first up to 400 mm/min, over that it is incremented. Smaller the better trademark was utilized to decide the surface quality. Table 3 shows that speed at position 1, feed rate at position 3, and cutting depth at position 1 are the best estimations of parameters for surface finish. In Table 3, position 1, position 2, and position 3 are given to feed rate, cutting speed, and depth of cut, respectively, which demonstrates that the feed rate is having a most elevated effect on the S/N proportions of surface quality because of its delta worth and rank, and later, this is trailed by the cutting speed and depth of cut, respectively. Table 4 shows that speed at 1000 rpm, feed rate at 600 mm/min, and depth of cut at 0.4 mm ideal values of parameters for surface finish.

Larger the better trademark was utilized to determine the material removal rate. From Fig. 4, it can be seen that as feed rate and cutting depth build MRR increments,



Fig. 3 Main effect plot of S/N ratios for surface roughness

Table 3Surface roughnessS/N ratio for each level ofcontrol parameters

Level	Speed (Rpm)	Feed rate (mm/min)	Depth of cut (mm)
1	5.785	6.186	5.517
2	4.312	-2.161	3.947
3	1.371	7.443	2.005
Delta	4.413	9.603	3.512
Rank	2	1	3

Bold values are the highest values, which shows the intensity of particular level on the effect of parameters

Table 4Optimum controlparameter values for surfaceroughness S/N ratio analysis

S. No.	Parameters	Optimum value
1	Speed (Rpm)	1000
2	Feed rate (mm/min)	600
3	Depth of cut (mm)	0.4

whereas MRR is consistent for all estimations of speed. Table 5 shows that feed rate and depth of cut at level 3 are the best values of cutting parameters for MRR. From Table 5, feed rate and depth of a cut have an equivalent impact on the S/N proportions of MRR because of its delta worth and rank. Cutting speed has no impact on the material removal rate because to calculate the MRR we have consider the formula, MRR = Depth of cut * Width of cut * Feed rate. Table 6 presumes that any value of speed, feed rate at 600 mm/min, and cutting depth at 1.2 mm is the ideal benefit of preparing parameters for MRR.



Fig. 4 Main effect plot of S/N ratios for material removal rate

Table 5Material removalrate S/N ratio for each level ofcontrol parameters

Level	Speed (Rpm)	Feed rate (mm/min)	Depth of cut (mm)
1	84.00	78.81	78.81
2	84.00	84.83	84.83
3	84.00	88.35	88.35
Delta	0.00	9.54	9.54
Rank	3	1.5	1.5

Bold values are the highest values, which shows the intensity of particular level on the effect of parameters

Table 6Optimum controlparameter values for materialremoval rate S/N ratioanalysis

S. No.	Parameters	Optimum value
1	Speed (Rpm)	Any value
2	Feed rate (mm/min)	600
3	Depth of cut (mm)	1.2

6 Analysis of Variance (ANOVA)

ANOVA is performed on the surface roughness and material removal rate to explore the impact of process parameters.

From the *F*-value shown in Table 7, it is clear that the commitment of feed rate is high for the surface finish, and later, this was trailed by cutting speed and cutting depth, respectively. *P*-estimation of feed rate is under 0.05, so this parameter is noteworthy to get the best quality surface, while the *P*-estimation of other parameters is more prominent than 0.05, so these are not critical.

Source	DF	Adj SS	Adj MS	F-value	P-value
Speed	2	1.5153	0.7576	1.58	0.230
Feed rate	2	3.5400	1.7700	3.70	0.043
Depth of cut	2	0.5951	0.2976	0.62	0.547
Error	20	9.5648	0.4782		
Total	26	15.2152			

Table 7 ANOVA table for surface roughness

Table 8 ANOVA table for material removal rate

Source	DF	Adj SS	Adj MS	F-value	P-value
Speed	2	0	0	0.00	1.000
Feed rate	2	1,658,880,000	829,440,000	60.00	0.000
Depth of cut	2	1,658,880,000	829,440,000	60.00	0.000
Error	20	276,480,000	13,824,000		
Total	26	3,594,240,000			

From Table 8, it is clear that for material removal rate, the involvement of feed rate and cutting depth is large, and cutting speed has no impact on it. *P*-value of feed rate and depth of cut is under 0.05, so these parameters are critical to getting the high material removal rate, while the *P*-value of cutting speed is more noteworthy than 0.05, so this is not huge.

7 Confirmation Test

A confirmation test is a critical and last piece of the Taguchi strategy. In this paper, optimal combination of parameters and their levels coincidently coordinate with one of the investigations in the orthogonal array (OA), in this manner confirmation test is not required.

8 Multiresponse Regression Analysis

After analyzing the effect of machining parameters on a single response individually, multiresponse regression analysis is carried out; for this purpose, response optimizer is utilized to recognize the combined impact of input variables on a single or a many output factors and draws an optimization plot. Response optimizer also permits the statistician to perform sensitivity investigation and enhancement in the previous solution. While performing the analysis with a response optimizer, make ensure that stored models should meet the assumptions of the main investigation and setting of variables should be inside the scope of the information that you used to fit the model else it gives erroneous outcomes.

Table 9 demonstrated that the objective for material removal rate is to expand it, and the objective for surface roughness is to limit it. Target value, upper and lower cutoff points, weight, and importance for both responses are also shown in Table 9. The weight decides the distribution of desirability on the interval between the lower (or upper) limit and the objective. The importance decides the impact of each response on the composite desirability. The values of weight and importance are considered from 0.1 to 10 which depict the shape of the desirability function and comparative significance of the response variable, respectively. As per the significance of one response over another, importance values are to be assigned. Higher values related to the most significant responses, lower values to less significant responses. Here both responses have the same importance value. Accordingly, both responses have an equivalent effect on the composite desirability.

Response	Goal	Lower	Target	Upper	Weight	Importance
Material removal rate	Maximum	4800	43,200	43,200	1	1
Surface roughness	Minimum	0.1	0.1	2.7791	1	1

Feed Rat

600.0

Depth of

1.20

 Table 9 Responses and its boundary conditions for multiresponse regression analysis

Speed

2000.0

Optimal

D: 0.8192

High



Fig. 5 Optimization plot of individual and composite desirability for surface roughness and material removal rate

Solution	Speed	Feed rate	Depth of cut	Material removal rate fit	Surface roughness fit	Composite desirability
1	1000	600	1.2	38,400	0.727724	0.819154

 Table 10
 Multiple response prediction table

The optimization plot (Fig. 5) shows the impact of all three input factors on the output parameters or composite desirability. The individual and composite desirability survey how well a blend of factors fulfills the objectives of the output factors. Optimized parameter settings of one and more than that response are assessed by individual and composite desirability, respectively. The value of desirability lies between 0 and 1. One indicates the perfect case; zero demonstrates that some responses are not lies within their adequate cutoff points. An engineer can adjust the values of parameters from the plot to accomplish bigger individual desirability for the response as per the requirement.

Table 10 shows the composite desirability (0.8192) is near to 1, which shows the settings appear to accomplish good outcomes for all responses in general. However, the individual desirability indicates that the settings are more effective at maximizing MRR (0.87500) than at minimizing surface roughness (0.76687). The present variable settings are speed = 1000 rpm, Feed rate = 600 mm/min, depth of cut = 1.2 mm.

Perceptions from the above optimization plot are as per the following:

- 1. Speed: Optimization plot shows that MRR is independent on speed and as speed increases Ra increases.
- 2. Feed rate: As feed rate builds, MRR increments and Ra diminishes.
- 3. Depth of cut: Increasing Depth of cut increments both responses.

9 Conclusion

This research is governed by the Taguchi method to identify the optimal set of parameters such as rotational speed, feed rate, and cutting depth on surface roughness and material removal rate in the face milling process. From Taguchi S/N proportion investigation, it can reason that speed at 1000 Rpm, feed rate at 600 mm/min, and depth of cut at 0.4 mm are the ideal qualities for better surface roughness and any value of speed, feed rate at 600 mm/min, and depth of cut at 1.2 mm are the ideal qualities for material removal rate.

ANOVA examination is recognized that the commitment of feed rate is high on the surface quality then by speed and depth of cut, respectively. On account of material removal rate, the feed rate and depth of cut both are similarly contributed, and cutting speed does not have any impact on MRR.

Multiresponse regression analysis concludes the speed at 1000 rpm, feed rate at 600 mm/min, and depth of cut at 1.2 mm is the ideal characteristics for multiresponse investigation.

10 Limitations and Future Scope

This research is restricted to optimize a couple of parameters including two response factors only. In the future, tool wear rate, tool life, cutting forces, energy consumption, etc., can be considered as a response factor, also tool material, type of workpiece material, type of coolants, coolant flow rate, tool geometry, machine condition, operator skill, environmental condition, costing, etc., can be considered as processing parameters. At the same time, validation and multiple objectives can likewise be accomplished by utilizing other techniques such as genetic algorithm, neural network, etc.

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