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Retraction

Retracted: Green Machining Characteristics Study of Al-6063 in CNC Milling Using Taguchi Method and Grey Relational Analysis

Advances in Materials Science and Engineering

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] R. Suresh Kumar, S. Senthil Kumar, K. Murugan, and S. M. Hailegiorgis, "Green Machining Characteristics Study of Al-6063 in CNC Milling Using Taguchi Method and Grey Relational Analysis," *Advances in Materials Science and Engineering*, vol. 2021, Article ID 4420250, 12 pages, 2021.

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Research Article

Green Machining Characteristics Study of Al-6063 in CNC Milling Using Taguchi Method and Grey Relational Analysis

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Green machining strategies in the manufacturing sector help to maintain the product value by considering the environmental impacts. Also, improvisation in the quality contribution of the parts can minimize the environmental consequences by improving resource efficiency, specifically in terms of coolants used in machining. Certain hazardous impacts have been witnessed because of longer exposure to such a machining environment. To address it, many researchers have concentrated on providing a healthy machining environment either by introducing dry machining or by minimum quantity lubrication (MQL). The proposed study addresses this context. The influence of these tactics on the attained surface quality of Al-6063 is quantified in this paper in terms of surface integrity (R_a) and removal rate of material (MRR). The study involves single-response optimization using the Taguchi design and multiresponse optimization using grey relational analysis (GRA). The results reveal that the depth of cut (D_c) and spindle speed (S_s) have the greatest impact on R_a and MRR. The machinability of Al-6063 is examined by considering the key machinability parameters, such as the spindle speed (S_s), feed rate (F_r), and the depth of cut (D_c), to arrive at the best possible surface roughness and removal rate of the material. As a typical Taguchi approach cannot perform multiresponse optimization, grey relational analysis is used. The grey relational analysis combined with Taguchi gives a novel methodology for multi-optimization. The entire study is performed in dry condition and under minimum quantity lubrication. The results suggest that the responses are highly influenced by the depth of cut and spindle speed.

1. Introduction

Advancements in nonconventional machining technologies are now widely employed to address a variety of challenges in machining processes, such as machining high-strength materials, improving surface integrity, achieving high levels of precision, reducing surplus material, and shortening production time. CNC end milling is one of the most versatile machining processes in which a desired output can be achieved with reliability and accuracy. Many industries and researches are employing different techniques to understand the behavior of alloy materials during machining by monitoring R_a, MRR, etc. Many investigations and studies are performed using optimization techniques to determine the effect of R_a, MRR, etc. on the machining performance of both brittle and ductile materials. Such studies usually incorporate the application of numerical and statistical models combined with the design of experiment (DoE). Generally, the surface roughness of the CNC end milling parameters is predicted using a mathematical model followed by the application of regression analysis for predicting the results. Such results are validated with the experimental values. The researcher used DoE to evaluate the R_a and MRR of the aluminum metal matrix composites. The quality achieved postmachining is compared with the projected values. The results attained are found to be increased [1–7] based on Taguchi's prediction involving improvisations in the efficiency of resource management, energy consumption, parameter settings, and energy efficient systems. A study of machining factors is performed for estimating MRR by considering the spindle speed, coolant flow, and the depth of cut in a combination set framed by the central composite rotatable design [8].

Helu et al. [9, 10] proposed a process time reduction model. The model provides the total cost analysis based on the experimental data involving the tool wear and service costs. Derflinger et al. [11] investigated and found that the alloys of aluminum or steel, when subjected to dry machining, achieved positive results. Also, the test results depict that the tool coated with the hard and lubricant layers can significantly improve the tool's lifetime. Dry machining characteristic studies on aluminum alloys were performed on Al-5052 by Tatsuya et al. [12]. In this study, a cemented carbide cutting tool is used for machining aluminum alloys. In a few studies, MQCL (Minimum Quantity Cooled Lubrication) model was implemented [13–16]. The study employed biodegradable vegetable oil as a coolant. The result revealed a 1.57-time increase in the tool's life. The study used ceramic-bound cutting materials and CBN. The study revealed that the CBN tools are associated with high thermal conductivity compared to ceramics. Moreover, CBN effectively dissipated heat, and finally, the study concluded that CBN is highly suited for the dry machining of cast irons. These studies also emphasized the impact of dry machining on high-speed machining.

The impact of dry machining [17–22] studied by various researchers also provides a positive platform toward eco-friendly machining, involving studies on cutting forces, chip formations, heat dissipation, etc. Various simulation models [23–26] are developed for estimating the minimum energy consumption, minimum R_a, and maximum productivity. The study involved a minimum energy formulation by looking at the tactics and constraints for lowering the machine tool energy consumption, while maintaining the tool's life and parts' quality. While the approach seems to be beneficial in increasing the utilization of resource efficiency, they rarely consider component quality or different production outputs as alternatives for the improvisation of resource efficiency and ensuring successful marketable goods. Few researches on micro-milling also employed the application of optimization techniques in addressing effective utilization of resources [27–31]. Jawahir et al. [32] put forth an insight toward the research perspective that merely spotlighted the formulation of the predictive and measuring methods for surface integrity. The consistent study toward sustainability and machining with environmental consciousness [33, 34] is visible in such articles that aim to find solutions with the least impact on environmental issues. The parameter optimization for attaining required roughness R_a using different tools and techniques in machining aluminium and its alloys are elucidated with commendable outcomes [35–39]. The previous attempts made by researchers toward the implementation of green machining strategies and their impacts on the machining processes are commendable. As a result, an attempt has been made on the application of green machining strategy on Al-6063, which is one of the most successful architectural materials in today's scenario.

2. Aluminum Alloy Al-6063

Al-6063 contains magnesium and silicon as the main alloying elements. The composition standardization of the alloys is maintained by The Aluminum Association. Al-6063 possesses good mechanical properties and is heat treatable and weldable. Table 1 details the chemical composition of the selected material. This alloy is most commonly used for extrusions as complex shapes can be formed much easily. Few applications include window frames, door frames, roofs, and sign frames. The extensive use of the material in architectural applications elicited the idea of performing a study on providing a suitable solution for the machining of Al-6063 with the least effect on the environment, irrespective of demand. For this study, a rectangular work material of dimensions 75 mm × 30 mm × 12 mm is taken for machining. Based on the literature survey, the TiCN end mill cutter is taken as the cutting tool material with a Rockwell hardness of 88. The cutter selected is of 20 mm diameter with a total length of 74 mm. To avoid the effect of vibration and chatter while machining, an overhung length of 20 mm is maintained throughout the process.

3. Experimental Design

The experiments are based on Taguchi Robust Design. The L9 Orthogonal array is selected for the experimental run pattern with respect to the parameters and their levels assigned. In this study, three controllable factors are considered to study the pattern of behavior on two uncontrollable parameters, as shown in Table 2. The controllable parameters considered are the spindle speed (rpm), the depth of cut (mm), and the feed rate (mm/min). Each parameter is subjected to a three-level test as the parameters are multilevel factors. The responses considered for the analyses are surface roughness (R_a) and materials removal rate (MRR). In the machining process, the surface roughness is measured based on the outer profile texture attained. The attainment of the surface texture is commonly measured in terms of the arithmetic average of profile heights for the length under evaluation and is represented by the average surface roughness (R_a). The three levels for each factor are represented as S_s, F_r, and D_c, as given in Table 2. The response outputs for the experimentation are represented as R_a and MRR. Figure 1 shows the experimental runs conducted in a 3-axis vertical milling center. The surface tester Mitutoyo is employed for measuring the roughness of the machined. The surface tester has a resolution varying from 0.01 microns to 0.3 microns. The average roughness value (R_a) is considered for the analysis.

The machining process is performed in dry conditions and is also performed with the minimum quantity lubrication (MQL) method. The results of the experimental runs for both dry and MQL are depicted in Table 3.

4. Results and Discussion

The following sections provide an insight into the parametric influence of the machining parameters on the responses

Table 1: Chemical composition.

Si	Fe	Cu	Mn	Mg	Cr	Zn	Ti	Others	Al
1.12	0.15	0.04	0.01	0.53	0.01	0.03	0.06	0.05	98

Table 2: Machining parameters and their levels.

Control factors	Unit	Code	Levels		
			1	2	3
Spindle speed	rpm	S_s	1500	2300	3000
Feed rate	mm/min	F_r	10	20	30
Depth of cut	mm	D_c	0.4	0.5	0.6

Figure 1: Measurement of roughness.

Table 3: Experimental runs and responses.

Exp	Machining parameter levels			Dry run		MQL	
	S_s (rpm)	D_c (mm)	F_r (mm/min)	R_a (μm)	MRR (IPM)	R_a (μm)	MRR (IPM)
1	1500	0.4	10	0.91	0.787	0.76	0.779
2	1500	0.5	20	1.59	1.293	1.13	1.311
3	1500	0.6	30	2.28	2.038	2.14	2.042
4	2300	0.4	20	0.88	0.632	0.78	0.643
5	2300	0.5	30	1.63	1.378	1.42	1.412
6	2300	0.6	10	2.05	1.987	1.98	1.923
7	3000	0.4	30	0.76	0.236	0.71	0.265
8	3000	0.5	10	0.79	0.345	0.73	0.330
9	3000	0.6	20	1.49	0.989	1.37	1.115

considered. The capability of the function is also validated by the analysis of variance (ANOVA).

4.1. Surface Roughness (R_a). Figures 2 and 3 depict the parametric interactions of the S/N ratios on R_a in the dry run conditions and the MQL method. The objective function is taken as smaller-the-better. From the graph, it is evident that in the dry runs and the MQL method, D_c is the most significant parameter governing R_a, followed by S_s and F_r, respectively. On careful observation, it is notable to record that the application of coolant in the minimum level improvises R_a.

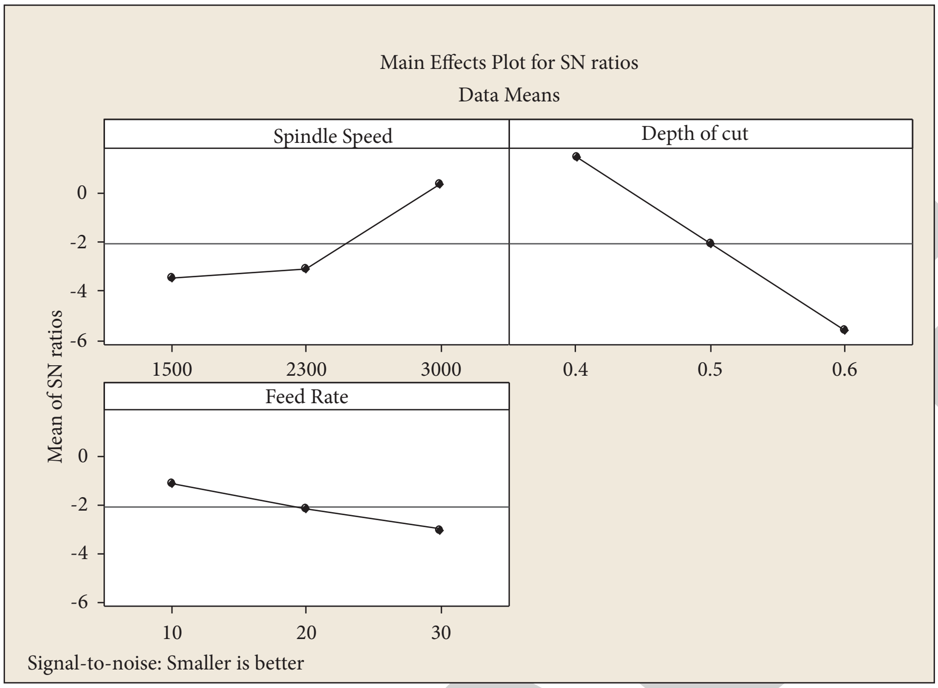

Figure 2: S/N ratio plot for R_a-dry runs.

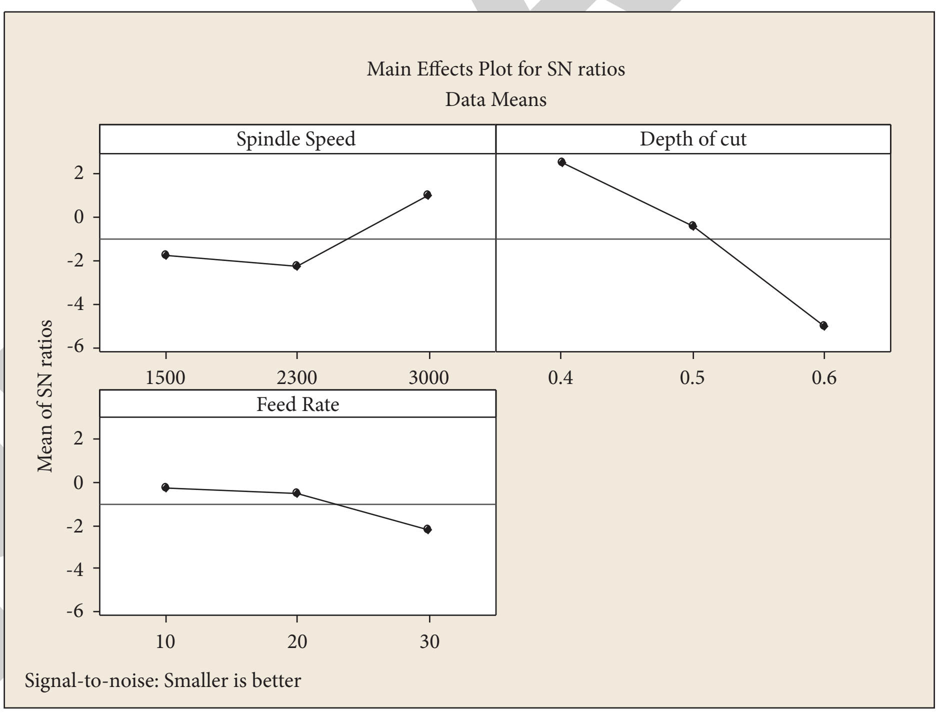

Figure 3: S/N ratio plot for R_a-MQL.

4.1.1. Parameter Interaction Effects on Dry Runs and MQL. Figures 4 and 5 highlight the parametric interaction of the means on R_a in the dry run condition and the MQL method. From the graph, it is clearly evident that in the dry runs and the MQL method, D_c is the most influencing parameter governing R_a, followed by S_s and F_r, respectively.

4.1.2. ANOVA for Roughness under Dry Run. The relevance of the desirability function is confirmed by the "F-value" of 27.60 and the "P value" of 0.035 as shown in Table 4. If the values are more than 0.10, the function is said to be insignificant. In other words, there is a 0.01% chance that the noise will cause an insignificant effect. Furthermore, the

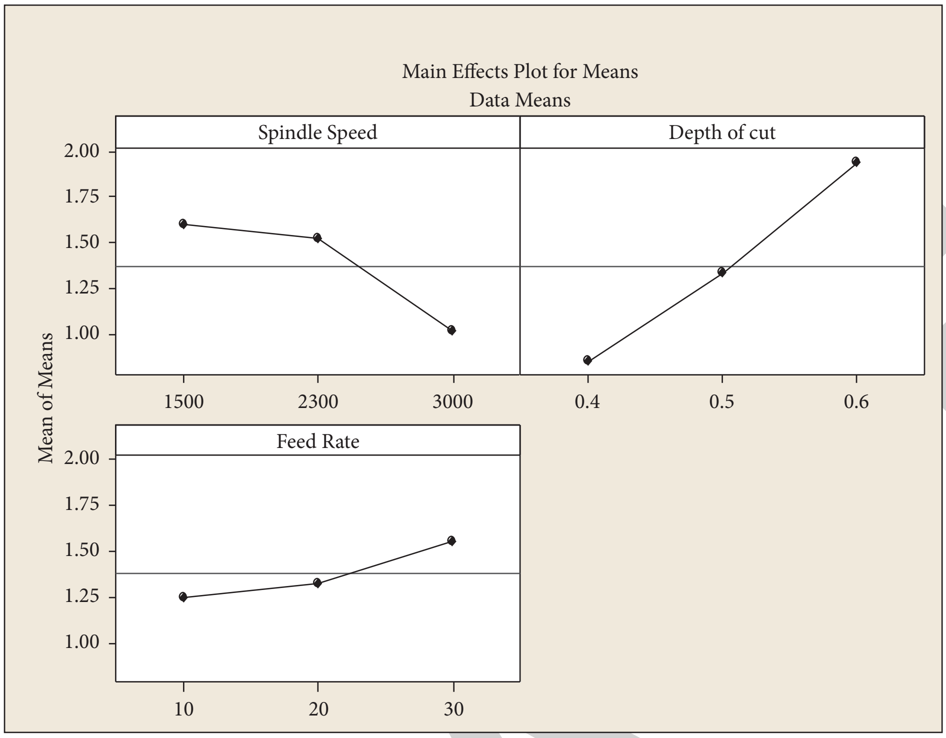

Figure 4: Means plot for R_a-dry runs.

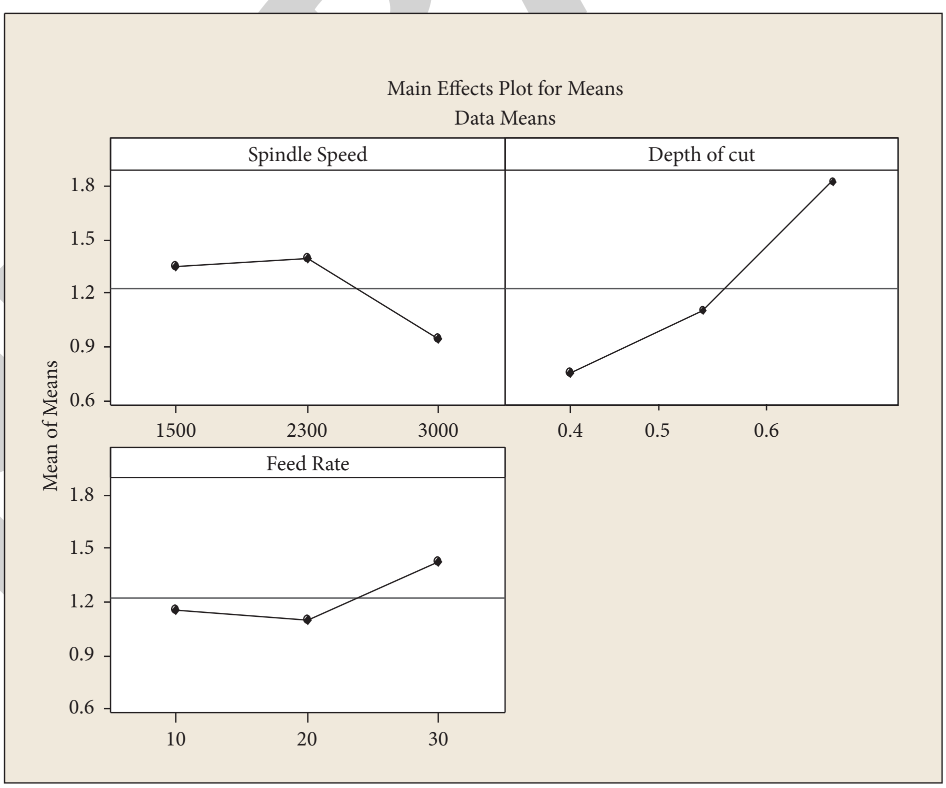

Figure 5: Means plot for R_a-MQL.

Table 4: ANOVA for S/N ratios (R_a-dry runs).

Response surface linear model						
Analysis of variance for S/N ratios-dry run						
Source	Df	Seq. SS	Adj. SS	Adj. Ms	F-value	P value
A	2	26.257	26.257	13.128	9.70	0.093
B	2	74.701	74.701	37.350	27.60	0.035
C	2	5.329	5.329	2.664	1.97	0.337
Residual error	2	2.707	2.707	1.353		
Total	8	108.993				
Standard deviation	1.163 (%)					
R^2	97.5					
Adj R^2	90.1					

Table 5: ANOVA for S/N ratios (R_a-MQL).

Response surface linear model						
Analysis of variance for S/N ratio-MQL						
Source	Df	Seq. SS	Adj. SS	Adj. Ms	F-value	P value
A	2	18.503	18.5028	9.2514	19.55	0.049
B	2	87.980	87.9796	43.9898	92.98	0.011
C	2	6.719	6.7186	3.3593	7.10	0.123
Residual error	2	0.946	0.9463	0.4731		
Total	8	114.147				
Standard deviation	0.6878					
R2	99.2%					
Adj R2	96.7%					

values of R^2 and Adj R^2 indicate a favorable trend toward a higher efficacy.

4.1.3. ANOVA for Roughness under MQL. Table 5 shows a similar data of ANOVA comparison for R_a under the MQL condition. Here, we can find that the "F-value" of 92.98 and the P value of 0.011 show the significance level. Also, the values of R^2 and Adj R^2 indicate a favorable trend toward a higher efficacy.

4.1.4. Response Table for S/N Ratios for R_a. Table 6 is the response for S/N ratio for R_a and its influence. From the table, we can find that D_c is the major significant parameter influencing R_a, followed by S_s and F_r in the dry run condition and the MQL method. The delta values in both cases (dry runs and MQL) are found to be closer, which shows the capability of machining to attain the desired outcome in either condition.

Table 6: Response table for S/N ratios (R_a).

	Dry runs			MQL		
	Response table-S/N ratios			Response table-S/N ratios		
Level	S_s	D_c	F_r	S_s	D_c	F_r
1	−3.4558	1.4377	−1.1228	−1.762	2.5056	−0.272
2	−3.1228	−2.0747	−2.1271	−2.2737	−0.4579	−0.546
3	0.3225	−5.6192	−3.0062	0.9913	−5.092	−2.2264
Delta	3.7788	7.0569	1.8834	3.265	7.5976	1.9544
Rank	2	1	3	2	1	3

4.2. Material Removal Rate (MRR)

4.2.1. Parameter Interaction Effects on Dry Runs and MQL. Figures 6 and 7 depict the parametric interaction of the S/N ratios on MRR in the dry run condition and the MQL method. The objective function is taken as larger-the-better. From the graph, it is evident that in the dry runs and the MQL method, D_c is the most influencing parameter governing MRR, followed by S_s and F_r, respectively. However, the presence of coolant enhances the desirability function.

Figures 8 and 9 highlight the parametric interaction of the means on MRR in the dry run condition and the MQL method. From the graph, it is evident that in the dry runs and the MQL method, D_c is the most influencing parameter governing R_a, followed by S_s and F_r, respectively.

4.2.2. ANOVA for MRR under Dry Run. The relevance of the desirability function is confirmed by the "F-value" of 16.69 and the "Pvalue" of 0.057 as shown in Table 7. If the values are more than 0.10, the function is said to be insignificant. In other words, there is a 0.01% chance that noise will cause an insignificant effect. Furthermore, the values of R^2 and Adj R^2 indicate a favorable trend toward a higher efficacy.

4.2.3. ANOVA for MRR under MQL. Table 8 shows a similar data on ANOVA comparison for MRR under the MQL condition. Here, we can find that the "F-value" of 11.25 and the P value of 0.082 show a significance level. Moreover, the R^2, Adj R^2, and Pred R^2 values indicate a positive approach toward its higher efficacy, and the values are close to 1.

4.2.4. Response Table for S/N Ratios for MRR. Table 9 is the response for the S/N ratio of MRR and its influence. From the table, we can find that D_c is the major significant parameter influencing R_a, followed by S_s and F_r in the dry run condition and the MQL method. The delta values in both cases (dry runs and MQL) are found to be closer, which shows the capability of machining to attain the desired outcome in either condition.

4.3. Optimized Parameters. The optimized set of machining parameter is given in Table 10.

5. Grey Relational Analysis (GRA)

The steps followed to arrive at the optimal solutions are as follows.

5.1. Normalization. The preprocessing of data is done in this step based on the chosen objective function. If the normalization or data preprocessing is based on "larger-

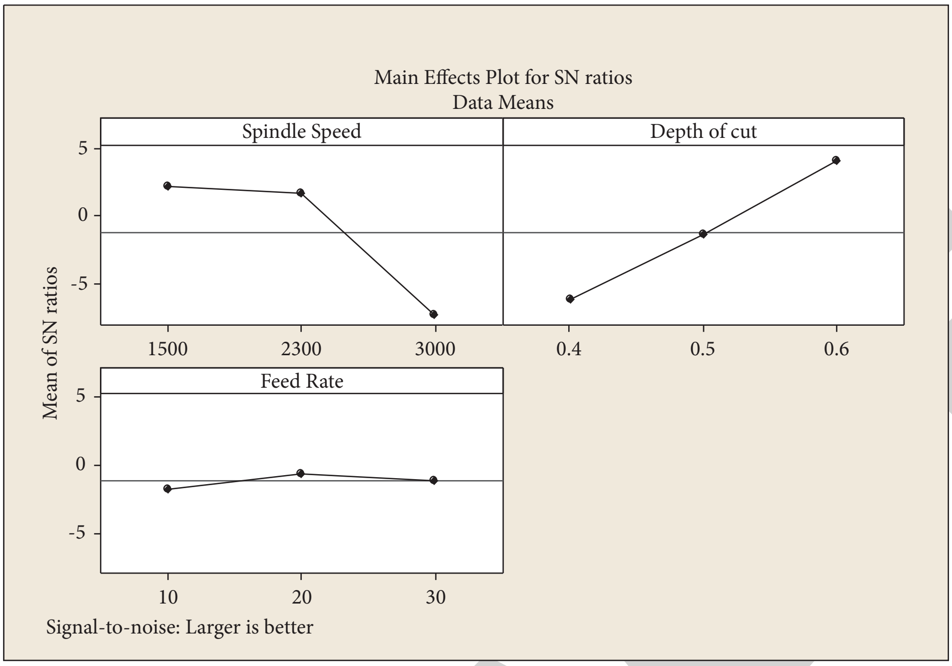

Figure 6: S/N ratio plot for MRR-dry runs.

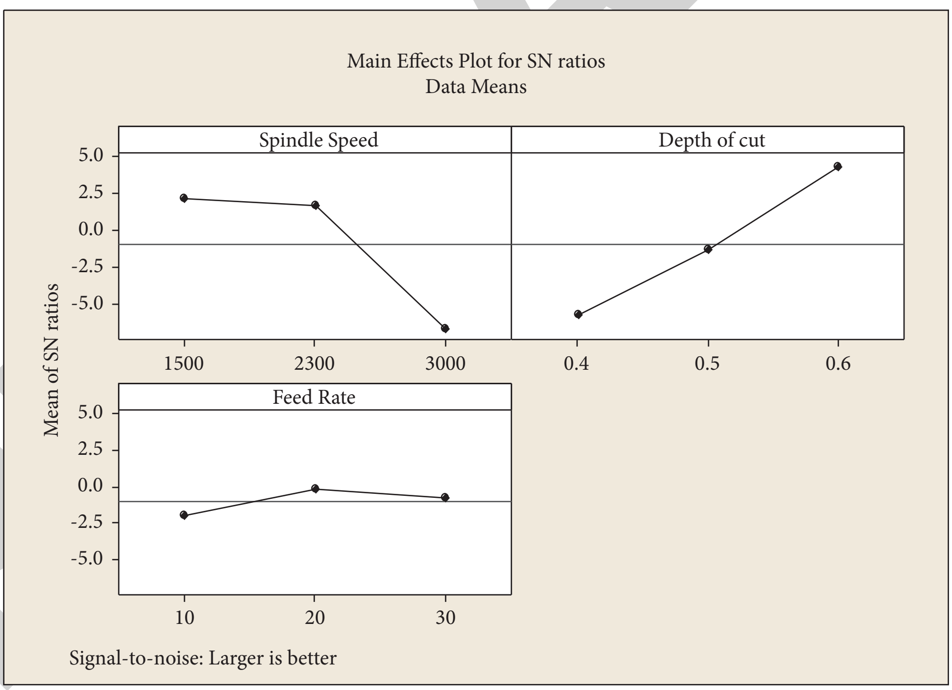

Figure 7: S/N plot for MRR-MQL.

the -better," then equation (1) is used. If the data pre-processing or normalization is based on "smaller-the-better," then equation (2) is used. Normalization is a technique for creating a comparable data set from a larger set of data by lowering the amount of variation for easier analysis.

$$Xi(k) = \frac{xi\ (k) - \min xi\ (k)}{\max xi\ (k) - \min xi\ (k)}. \tag{1}$$

$$Xi\ (k) = \frac{\max xi\ (k) - \ xi\ (k)}{\max xi\ (k) - \min xi\ (k)}. \tag{2}$$

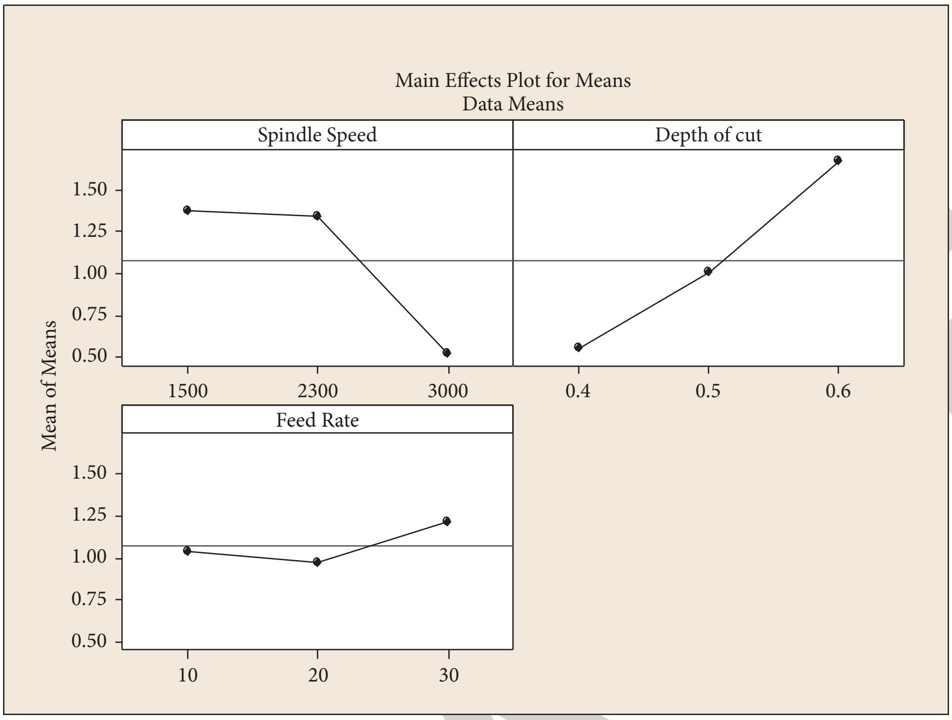

Figure 8: Means plot for MRR-dry runs.

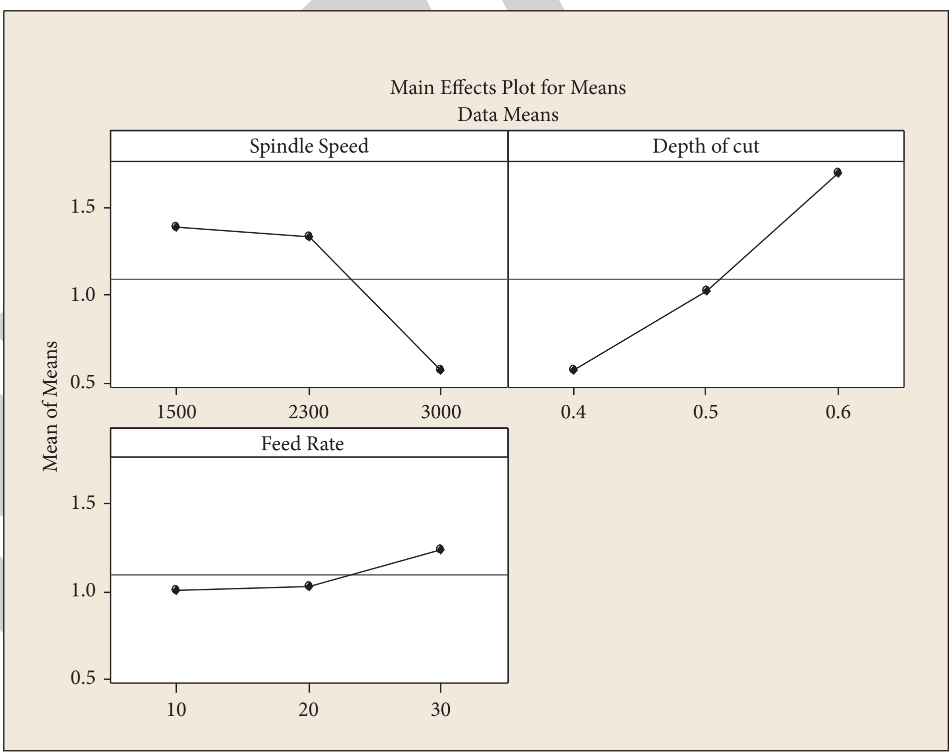

Figure 9: Means plot for MRR-MQL.

Here,, $i = 1$, ... m; $k = 1$ ..... n. m is the number of experimental data. n is the number of responses. $Xi(k)$ represents the value after data preprocessing. $xi(k)$ represents the original sequence data. max xi (k) is the largest value of xi (k). min xi (k) is the minimal value.

Table 7: ANOVA for S/N ratios (R_a-dry runs).

Response surface linear model Analysis of variance for S/N ratios-dry runs						
Source	Df	Seq. SS	Adj. SS	Adj. Ms	F-value	*P* value
A	2	167.624	167.624	83.812	16.69	0.057
B	2	156.871	156.871	78.436	15.52	0.060
C	2	2.054	2.054	1.027	0.20	0.830
Residual error	2	10.045	10.045	5.023		
Total	8	336.595				
Standard deviation				2.241 (%)		
R^2				97.0		
Adj R^2				88.1		

Table 8: ANOVA for S/N ratios (R_a-dry runs).

Response surface linear model Analysis of variance for S/N ratios-MQL						
Source	Df	Seq. SS	Adj. SS	Adj. Ms	F-value	*P* value
A	2	148.679	148.679	74.339	10.82	0.085
B	2	154.508	154.508	77.254	11.25	0.082
C	2	5.410	5.410	2.705	0.39	0.717
Residual error	2	13.740	13.740	6.870		
Total	8	322.337				
Standard deviation				2.621 (%)		
R^2				95.7		
Adj R^2				82.9		

Table 9: Response table for S/N ratios (MRR).

	Dry runs Response table-S/N ratios			MQL Response table-S/N ratios		
Level	S_s	D_c	F_r	S_s	D_c	F_r
1	2.1118	−6.2026	−1.7867	2.1280	−5.8467	−2.0398
2	1.5878	−1.4089	−0.6166	1.6135	−1.4270	−0.1794
3	−7.2938	4.0173	−1.1909	−6.7398	4.2754	−0.7791
Delta	9.4057	10.2200	1.1701	8.8677	10.1221	1.8604
Rank	2	1	3	2	1	3

Table 10: Optimized parameter for both dry run and MQL.

Tool used	Condition	S_s (rpm)	D_c (mm)	F_r (mm/min)
Taguchi	$\mathbf{R_a}$	**3000**	**0.4**	**10**
	MRR	**1500**	**0.6**	**30**

5.2. Deviation Sequence. Based on the responses, smaller-the-better is assigned for R_a, while larger-the-better option is assigned for MRR. The deviation for normalized values is calculated in this phase. The deviation for each response is recorded in relation to the highest normalized value reached.

5.3. Grey Relational Coefficients (GRCs). The grey regression coefficients are determined using equation (3). The grey relational coefficient $\xi i(k)$ is used here. The absolute differences, lowest and maximum values are represented by minimum and maximum values. The difference taken here is 0.5, which is the identifying or distinguishing coefficient that typically varies from 0 to 1.

$$\xi i\ (k) = \frac{\Delta \min +\ \psi \Delta \max}{\Delta oi\ (k) +\ \psi \Delta \max}. \tag{3}$$

5.4. Grey Relational Grade (GRD). The correlation level of the reference and comparison sequences is represented by GRD (γ). A multiobjective function is converted to a single-objective function at this point. The governing equation for achieving grey relational grade is shown as follows:

$$\gamma i = \frac{1}{n \sum_{k=1}^{n} \xi i\ (k)}. \tag{4}$$

5.5. Optimal Parameters. In this stage, the rank of each set of values is determined. The optimized level is readily determined based on the achieved rank, which provides the best solution by combining all responses. Tables 11 and 12 show the grey regression analysis performed on the experimental values.

Table 11: Grey relational analysis-dry runs.

Exp	Dry runs		Normalization		Deviation sequence		Coefficients		Grade	Rank
	R_a	MRR	R_a	MRR	R_a	MRR	R_a	MRR		
1	0.91	0.787	0.901	0.694	0.099	0.306	0.835	0.621	0.728	4
2	1.59	1.293	0.454	0.413	0.546	0.587	0.478	0.460	0.469	6
3	2.28	2.038	0.000	0.000	1.000	1.000	0.333	0.333	0.333	9
4	0.88	0.632	0.921	0.780	0.079	0.220	0.864	0.695	0.779	3
5	1.63	1.378	0.428	0.366	0.572	0.634	0.466	0.441	0.454	7
6	2.05	1.987	0.151	0.028	0.849	0.972	0.371	0.340	0.355	8
7	0.76	0.236	1.000	1.000	0.000	0.000	1.000	1.000	1.000	1
8	0.79	0.345	0.980	0.940	0.020	0.060	0.962	0.892	0.927	2
9	1.49	0.989	0.520	0.582	0.480	0.418	0.510	0.545	0.527	5

Table 12: Grey regression analysis-MQL.

Exp	Dry runs		Normalization		Deviation sequence		Coefficients		Grade	Rank
	R_a	MRR	R_a	MRR	R_a	MRR	R_a	MRR		
1	0.76	0.779	0.965	0.711	0.035	0.289	0.935	0.634	0.784	4
2	1.13	1.311	0.706	0.411	0.294	0.589	0.630	0.459	0.545	5
3	2.14	2.042	0.000	0.000	1.000	1.000	0.333	0.333	0.333	9
4	0.78	0.643	0.951	0.787	0.049	0.213	0.911	0.702	0.806	3
5	1.42	1.412	0.503	0.355	0.497	0.645	0.502	0.437	0.469	7
6	1.98	1.923	0.112	0.067	0.888	0.933	0.360	0.349	0.355	8
7	0.71	0.265	1.000	1.000	0.000	0.000	1.000	1.000	1.000	1
8	0.73	0.33	0.986	0.963	0.014	0.037	0.973	0.932	0.952	2
9	1.37	1.115	0.538	0.522	0.462	0.478	0.520	0.511	0.516	6

Table 13: Optimized parameter by GRA.

S_s (rpm)	D_c (mm)	F_r (mm/min)
3000	0.4	30

Table 14: Confirmatory runs.

Tool	Type	Predicted				Achieved	Predicted	Achieved	
		Dry run Ra	Dry run MRR	Dry run Ra	Dry run MRR	MQL Ra	MQL MRR	MQL Ra	MQL MRR
Taguchi	Single response (Ra)	0.76	—	0.81	—	0.71	—	0.73	—
	Single response (MRR)	—	0.236	—	0.255	—	0.265	—	0.302
GRA	Multiresponse	2.28	2.038	2.30	2.054	2.14	2.042	2.11	2.15
% deviation									
Single response (Ra)				5				2	
Single response (MRR)					1.9				3.7
GRA multiresponse				2	1.6			3	4

5.6. Optimized Set of Parameters Using GRA. From Table 13, the highest rank is contributed by the 7th experimental run that includes the combination of parameters as reflected in Tables 11 and 12, which is as follows:

6. Confirmatory Runs

To validate the above, confirmatory runs were conducted, and Table 14 shows the results attained.

The % deviation shown in Table 14 provides a lucid view on the performance of the optimization tool used. It is noteworthy to state that the above approach provides the optimized results satisfactory and within the acceptance limit as the deviation recorded lies within the 10% level of acceptance.

7. Conclusion

This study focused on green machining characteristics while machining Al-6083 in two conditions, i.e., under dry condition and under MQL. The study is performed as single response and multi-response optimization. For single response, Taguchi design is followed, and for multiresponse, GRA is applied. The inferences noted in the entire study and found to be acceptable in accord to the results attained in confirmatory runs are as follows:

(i) For achieving minimum roughness, D_c plays the dominant role followed by S_s.

(ii) The least contributing factor governing roughness in this case is found to be F_r.

(iii) The above two statements stand true irrespective of whether the machining is dry run or MQL. However, it is acceptable that the application of coolant enhances in achieving the minimum roughness.

(iv) From Table 14, minimum R_a achieved under the dry run is 0.76, while in MQL, it is 0.71, which proves that the application of coolant aids in achieving a better finish.

(v) Also, it is evident that the MQL condition is sufficient for achieving the required roughness instead of the flooded machining, depending on the constraints to be considered while machining.

(vi) For maximum MRR, D_c plays a prominent role with S_s assigned at its lower level.

(vii) D_c and S_s are the significant factors in the dry run conditions and the MQL method.

(viii) The presence of coolant also enhances MRR.

(ix) In case of multresponse optimization, GRA results align with the higher level of S_s and the medium level of D_c, followed by F_r.

The % deviation recorded depicts the significance of both dry machining and under MQL. As the deviation level is within 10%, dry machining also fulfills the objective function of achieving a minimum roughness.

From an environmental perspective, green machining is much required for the manufacturing sector. Industries will be required to practice dry machining to comply with environmental laws and health requirements. A few advantages of green machining are that it causes no pollution of the atmosphere, has lower disposal and cleaning cost, and is nontoxic in all aspects (health, skin, allergy).

Data Availability

The data used to support the findings of this study are included within the article.

Disclosure

The study was performed as a part of the Employment of Addis Ababa Science and Technology University, Ethiopia.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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