Green Machinability Study of Al 6061 in CNC End Milling using Box Behnken Design and Grey Relational Analysis

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Abstract - Green Machining (GM), a step towards addressing the means and ways to minimize environmental impact has found inevitable stand among researchers involved in machinability studies. Several means and techniques are being followed and tested with an aim of reducing the adverse effect on environment caused by different manufacturing operations without compromising on quality aspects. The major area focused here is the study of the coolant impact on the process and the environment. Specifically, when the used coolant is disposed without proper treatment causes adverse effect to the health and environment. By considering the environment's effects into account, green machining strategies like dry machining (DM), minimum quantity lubrication (MQL), ice-jet machining, cryogenics etc. are employed for minimizing the usage of coolant along with high quality deliverables. This study focuses on the dry machinability study during the operation and function of end milling on Al6061. The entire experimental analysis were executed as per box-Behnken design (BBD) and grey relational analysis (GRA). The study involved spindle speed (S_s), depth of cut (D_c), and feed rate (F_r) as controlling parameters and responses as average roughness (R_a), material removal rate (M_{rr}), and power consumption (P_c). A total of 27 experimental runs based on BBD were performed and the responses were analyzed for prediction of optimal solutions.

Keywords - Roughness **(**R_a), Material Removal Rate (M_{rr}), Power Consumption (P_c), Box-Behnken Design (BBD), Grey Relational Analysis (GRA).

I. INTRODUCTION

Reddy et. al. [1] made an experimental analysis on the impact of actual geometric tool (including nose radius and also with along radial rake angle) and all the necessary parameters (S_s and F_r) on machining performance in the required dry milling along with the use of actual solid TiAlN-coated carbide end mill cutters. The study helped in predicting R_a by generating a useful mathematical model with the help of various other surface methods. The model thus created was validated for its reliability and used for optimization using genetic algorithms (GA). The result showed satisfactory result of the model developed. Wibowo et. al. [2] described a method for estimating the exact optimal values of the three parameters namely F_r for estimating minimum R_a by hybridization of kernel principal component analysis (KPCA) based nonlinear regression and radial rake angle, S_s, and GA. For building a good nonlinear regression, KPCA based regressions were widely used which also helps in managing and prevention of the impact of several multi-linearity in the prediction model. The precise prediction compared to standard linear regression was clearly shown in the study also showed reduction of R_a from 45.3% to 54.2% when compared to RSM and experimental data [3].

Another model linking the R_a and M_{rr} along with the machining factors was performed for optimisation using RSM and DOE in the study. Since the responses R_a and M_{rr} are contradictory in nature, arriving at the optimal solution was complex and therefore, pareto-optimal collection of solutions was followed using the non-domination sorting genetic algorithm-II. Rudrapati et. al. [4] made an experimental analysis on machining parameters affecting vibration and S_r during transverse cut cylindrical grinding. The study was actually done and performed on a stainless-steel material. Input factors considered were S_s, F_r, longitudinal feed, for the BBD matrix. For mathematical modeling, to identify relationships between inputs and responses, RSM was employed followed by application of ANOVA for analysis of significance. In order to demonstrate how several output reactions fluctuate and differs as the parameters used for machining are modified, vibration and surface roughness contour and surface plots have been constructed accordingly. In the end, vibrations and roughness of the surface have been optimised concurrently with the multi-objective genetic algorithm (MOGA). The expected parametric condition were verified by confirmatory experiments, which is the last step. The suggested optimization approach (RSM cum MOGA) seems useful for evaluating and improving the workflow when multiple input factors influence several important output responses throughout a manufacturing process.

Saglam et. al. [5] the research was done on how the parameters for cylindrical grinding affected the R_a and roundness error. Various factors, including wheel material used, loading and dressing nature of wheel, material employed, mechanism used in drive, clamping techniques, lubricants opted, F_r, and S_s, etc had a huge direct effect on the performance and quality of machining. The proposed research solely looks at the effects of the three variables D_c, F_r, and S_s. The grinding experimentation has been set up using Taguchi's orthogonal arrays with the objective to optimize roundness error and R_a. The findings from the experiment were analyzed statistically through ANOVA. The results revealed that the roundness feature was highly influenced by S_s, P_c, and D_c, while R_a was influenced by F_r and S_s.

Neşeli et. al. [6] did a field study using the Taguchi technique (TM) and RSM for reducing vibrations (V_b) and Ra. L 27 orthogonal array served as the foundation for the layout of the experiment. The V_b and R_a of the surfaces were the results, and the three parameters used for input were a S_s, F_r, and D_c. The study finally proposed two optimized designs by means of computer-aided single-objective optimization. Hou et. al. [7] arrived at the best milling parameters and functionality using Taguchi design (TD), RSM, and genetic algorithm (GA). A relevant orthogonal array test is carried out to gather responses and values at a cost-effective rate. With the help of the main impact plot and ANOVA, the ideal setting for parameters is selected in order to locate and identify the key variables associated with it. The RSM technique was used to draw the relationship among the input variables and the output responses and to act as the function of fitness for determining the fitness value of the GA method. The experimental findings demonstrate that, in the wet milling of nano-particles, the integrated approach does identify the best parameters that produce extremely good output responses.

Sivasakthivel et. al. [8] analyzed end milling machining factors such as F_r, S_s, cutter helix angle, and axial and radial D_c on temperature rise. Using response surface methods, a temperature rise prediction model was created. Al 6063 investigations employing high-speed steel end mill cutters were performed using CCD with 32 tests. K-type thermocouples was employed for recording temperature rise. ANOVA was used to verify the model appropriateness. The model analyzed both the individual and combined effects of the machining settings on the increase in temperature. To ensure a low-temperature increase, the machining process characteristics have been optimized using genetic algorithms. The optimization procedure was executed using the C program code that was developed. The obtained optimal machining settings resulted in an approximate value of 0.173 °C for the lowest rise in temperature.

Kittur et. al. [9] examined how well pressure die-casting technique models performed. A type of experimental design was actually put into place to gather data from the experiments. The output-input correlations were established using the response surface strategy. The most suitable and ideal parameters for the procedure were chosen using the desirability factor. In accordance with the results of the trials, a pair of nonlinear frameworks using a central composite structure and Box-Behnken design are currently being produced. Both of these models have separately been assessed in terms of statistical appropriateness and predictive capability using ANOVA and a number of actual test situations. The CCD has been demonstrated to deliver results more effectively than BBD, while the latter type of design is proven to execute higher than the earlier one for the surface response hardness and porosity. Performance evaluation is carried using the average absolute percent variance in predicting the replies. R_a, H_b, and p of the responses are found to have definitive percentage variance with values of 5.95, 1.29, and 63.94, correspondingly, in CCD. The comparable numbers in BBD, on the other hand, turn out to be 14.19, 3.04, and 4.94. Additionally, an attempt was made to reduce the p and R_a whilst increasing the H_b of the die-cast component.

Kilickap et. al. [10] examined how actually drilling AISI 1045's roughness of the surface was impacted by machining variables. The experimental conditions matrix consisted of S_s, F_r, and machining environment. A predictive model based on numerical framework for R_a was constructed using RSM. The effect of drilling settings on the R_a was assessed, and the best machining circumstances for lowering it were found, using RSM and evolutionary techniques. As a result, it showed a strong connection between both the actual and predicted values, validating the developed model for calculating R_a with accuracy. The expense of the finished item and the amount of time required for machining are significantly decreased through employing this kind of model.

Celep et. al. [11] analyzed experimentally the effects of ultra-fine grinding. For a 3 level BBD, RSM and quadratic programming (QP) was implemented to define and optimize certain operational settings in ultra-fine grinding. Grinding experiments were carried out in a pin-type vertical stirred mill sized for the laboratory. Through the use of empirical model equations, the predictive model was generated and evaluated. A strong coefficient of determination for the analysis of variance (R 2 = 0.9698) ensured that the second-order regression model would be a reasonable fit. QP was employed for optimizing the model's formula the aim towards minimizing and precisely reduced 80 size within the boundaries of the studied experimental range. Utilizing the appropriate amount of control over variables, three confirmation tests were conducted to verify the increase in grinding efficiency. 3.37 m was the outcome for d 80, which was lower than the findings obtained in the original tests.

Mukherjee et. al. [12] investigated and studied the outcomes and findings of several optimization methods and techniques available in the process of metal cutting. The process and functionality of metal cutting are completely necessary in order to efficiently respond to fierce competition and expanding market demand for high-quality goods for the production unit. Choosing the appropriate cutting conditions and modelling the correlation between several output-input and in-process parameters are two optimization strategies that are frequently employed in the process of absolute metal cutting and are crucial instruments for enhancing output quality in goods and processes. The ideal cutting conditions can be determined using inexpensive mathematical models, but this is a difficult research topic. Modelling and optimization techniques have advanced and become more sophisticated over time.

Due to the intricacy of the welding process [13], the welding conditions have been established using empirical and experimental data. Both of genetic algorithms (GA) and RSM approaches are being suggested as answers to such problems and might be used to find the ideal welding circumstances. In the beginning, near-optimal conditions were created all over a substantial area using a GA. The perfect conditions for welding were then determined across a reasonably small area encompassing such nearly perfect circumstances applying response surface techniques. A desirability function strategy was utilized to determine distinct objective function values based on whether the optimization problem's target value had a positive or negative response.

Suresh et. al. [14] studied the manufacturing demands trustworthy layouts, frameworks and models and methodologies to perfectly find the resulting performance of several machining process because of heavy usage of fully automated machine in the current industry. Process planning greatly benefits from the finding and forecasting of the ideal machining settings and circumstances for optimum surface quality and dimensional accuracy. In the current work, R_a prediction layout for machining mild steel is studied and created to work on utilizing the RSM. Mild steel components were machined throughout the experiments utilizing TiN-coated cutting tool. A second-order mathematical model was developed for R_a estimation using RSM. The factor effects of the various process parameters are provided by this model. Also, an attempt has been made to use GA to improve the desired definitive function or method of the R_a prediction model. The least and highest values of R_a as well as the corresponding ideal machining conditions are provided by the GA software.

Pradhan et. al. [15] studied the findings of an axisymmetric two-dimensional, coupled thermal-structural in EDM process reflecting the R_a of an EDM surface. For a single spark heat flux input, transient thermal analysis with Gaussian distribution was performed. It is investigated how current affects temperature distribution. In the succeeding structural study, the thermal stresses resulting from temperature field non-uniformities are examined under the assumption of elastic-perfectly flexible material behaviour. Based on the findings of the FEM study, the real residual stresses was studied during the EDM operation. The work piece's residual tensile stresses are negligible following a single heat flux, but they might build up over numerous spark cycles and result in damage to the surface like small cracks. Both the temperature dispersion and the residual stress have been found to be in excellent accord with past research.

Krajnik et. al. [16] examined the results of process optimisation and experimental simulation for plunge centerless grinding. Evaluation of the micro geometric aided by measurements of R_a was collected after processing. Grinding factors are created using RSM, which includes experimental design, regression modelling to fit a model for optimisation. The RSM was used to develop an initial R_a simulation. The model was fully created by establishing using regression coefficients and the basic structure of the model. The single-objective optimization with computer assistance is carried out using genetic algorithms and non-linear programming.

II. BBD

BBD is a response surface methodology experimental design developed by E. P. Box and Donald Behnken in 1960. This design aims to achieve three equally spaced values for each variable, with a minimum of three levels required. The design is quadratic, with terms consisting of squares, products of two factors, intercepts, and linear terms. The ratio between the number of experimental points and coefficients should be between 1.5 to 2.6. Compared to other design tools such as CCD and Dohlert Design, BBD is considered the most powerful because it has better coverage of non-linear design space and corners. The number of blocks added to the design depends on the number of factors or parameters. Every design includes orthogonal blocks, and BBD or RSM requiring atleast 3 levels. These designs are created by combining 2 level factorial designs with the necessary statistical properties. Blocking options are usually available with these designs, allowing for the generation of runs to be multiplied by the number of factor level combinations.

BBD Steps

- The design has specified points where factors are positioned.
- Each factors have three levels.
- A quadratic model is used to estimate the design.
- Strong coefficient estimates are found **exactly at the centre point** of the design space, while weaker coefficients are **positioned** at the corners of the cube.
- Missing data and runs can lead to inaccuracies in the results, making the Box-Behnken method not recommended.
- The Central composite design is preferred as it includes more initial runs and is better suited for solving problems.

III. GRA

Normalization

In the data preparation stage, the selection of an objective function determines the approach used. If the aim is to maximize a parameter, Equation (1) is applied for normalization, while if the goal is to minimize a parameter, Equation (2) is utilized. Normalization is a statistical method that reduces variance and simplifies analysis by transforming data into a consistent scale. In the data preparation stage, the selection of an objective function determines the approach used. If the aim is to maximize a parameter, Equation (1) is applied for normalization, while if the goal is to minimize a parameter, Equation (2) is utilized. Normalization is a statistical method that reduces variance and simplifies analysis by transforming data into a consistent scale.

$$Zj(q) = \tag{1}$$

$$Zj(q) = \frac{maxzi(q) - zi(q)}{maxzi(q) - minzi(q)} \tag{2}$$

Where, j= 1, ... m;
q = 1 ..... n. m is the experimental data
Zi(q) represents the value after data pre-processing.
zi(q) is the original sequence data.
max zi (q) - largest value of zi (q).
min zi (q) - the minimal value

Deviation Sequence
In the stage, the following options were fixed:
smaller-the -better option is selected for R_a,
larger-the-better option is chosen for M_{rr}

Grey Relational Coefficients (GRCs)
GRC is calculated using equation (3) as shown below, which involves the use of the GRC Ɛi(z).The minimum and maximum values indicate the absolute difference, while the lowest and highest values are also considered. Typically ranging between 0 and 1, the differentiating coefficient is 0.5.

$$Ɛi(z) = \frac{\Delta min + \Psi \Delta max}{\Delta oi(z) + \Psi \Delta max} \tag{3}$$

Grey Relational Grade (GRD)
In this stage, GRD is calculated using the correlation between the reference and comparison sequences. In this stage, all equations involving multi-analysis are brought under as a single objective function enabling easy computation and interpretation.

Optimal Parameters
In this stage, the rank of each group of values is determined. Based on the achieved rank, the optimal level can be easily computed, which consolidates all responses to identify the best alternative.

Optimized set of Parameters using GRA
In order to observe the optimal set of parameters, the values are ranked in this stage. GRA is used to calculate the correlation between the observations, M_{rr} and R_a, and obtain a ranked grade for the best possible outcome of the parameter combination. The highest ranked grade is selected to obtain the optimal results.

IV. EXPERIMENTAL WORK

Material
In the present work, Al 6061 is selected as the material of choice. Common uses of Al 6061 include aircraft and automotive parts, bicycle frames, marine application due to its strength-to-weight ratio, screws, and bolts. **Table 1** highlights the material composition.

Table 1. Material Composition (Chemical)

Si	**Fe**	**Cu**	**Mg**	**Cr**	**Zn**	**Ti**	**Others**	**Al**
0.6	0.28	0.2	0.01	1.0	0.04	0.1	0.1	0.15

Machine and Tools
The machining process was performed on a 3-Axis CNC End Mill, and HSS tool of 12 mm diameter was employed having 4 flutes with overhanging length maintained at 22 mm to avoid any chatter while machining. BBD matrix is followed for conducting experimental runs with assigned parameters as enlisted in **Table 2** with their levels assigned.

Table 2. Parameters, Notations & Levels

Parameters	**Symbol**	**Levels**		
		1	**2**	**3**

Spindle Speed, (rpm)	S_s	2500	2750	3000
Depth of Cut, (mm)	D_c	0.5	0.75	1.0
Feed Rate, (mm/min)	F_r	800	880	960

Experimental Runs
The experimental runs performed are recorded in the **Table 3** with their responses as per BBD matrix.

Table 3. Experimental Runs with Responses

S_s	D_c	F_r	R_a (microns)	M_{rr} (IPM)	P_c (HP)
2750	0.5	800	3.293	0.349	0.27
2750	1	960	3.986	1.405	1.47
2500	0.75	800	3.62	0.895	0.813
3000	0.75	960	3.659	0.859	0.927
3000	0.75	880	3.624	0.737	0.697
2500	0.75	960	3.816	0.976	1.088
2750	0.75	880	3.639	0.877	0.87
2750	0.5	880	3.454	0.308	0.315
2750	0.75	880	3.639	0.877	0.87
2750	0.75	880	3.639	0.877	0.87
2500	0.5	880	3.469	0.448	0.488
3000	0.75	880	3.498	0.9	0.881
2750	0.5	880	3.328	0.471	0.499
3000	1	880	3.809	1.306	1.252
2500	0.75	880	3.655	1.017	1.042
2750	1	800	3.79	1.324	1.195
2750	0.75	800	3.604	0.755	0.64
2750	0.75	960	3.675	0.999	1.099
2750	0.75	800	3.478	0.918	0.824
2500	1	880	3.966	1.423	1.413
2500	0.75	880	3.781	0.854	0.858
3000	0.5	880	3.312	0.331	0.327
2750	1	880	3.825	1.446	1.424
2750	0.5	960	3.489	0.43	0.545
2750	0.75	880	3.639	0.877	0.87
2750	1	880	3.951	1.283	1.24
2750	0.75	880	3.639	0.877	0.87
2750	0.75	960	3.801	0.836	0.915
3000	0.75	800	3.463	0.778	0.652

Surface Tester
Mitutoyo surface tester was used for measuring the average value for roughness (R_a). The average R_a value is taken for the analysis purpose.

V. RESULT AND DISCUSSION

ANOVA for R_a

The ANOVA for R_a and its analysis is depicted in the **Table 4** below. From the table, the F-value of 323.14 shows the significance of the model developed. This value represents that the model has only a 0.01% chance of attaining this value due to noise factor considered.

Table 4. ANOVA for R_a

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	1.08	14	0.0768	323.14	< 0.0001	significant
S_s	0.0689	1	0.0689	289.57	< 0.0001	
D_c	0.7854	1	0.7854	3302.93	< 0.0001	
F_r	0.1070	1	0.1070	449.86	< 0.0001	
S_s x D_c	0.0074	1	0.0074	31.10	< 0.0001	
S_sx F_r	0.0066	1	0.0066	27.59	0.0001	
D_c x F_r	0.0178	1	0.0178	74.95	< 0.0001	
S_s^2	0.0049	1	0.0049	20.75	0.0004	
D_c^2	0.0018	1	0.0018	7.62	0.0154	
F_r^2	0.0022	1	0.0022	9.17	0.0090	
Residual	0.0033	14	0.0002			
Lack of Fit	0.0033	10	0.0003			
Pure Error	0.0000	4	0.0000			
Cor Total	1.08	28				

The significance of the parameters can be ascertained by the standard p-value taken at 95% confidence interval. Here in this case P-value (less than 0.0500) shows that the model generated is significant. In this case S_s, D_c, F_r, S_sxD_c, S_SxF_r, DxF, S_s^2, D_c^2, F_r^2 are significant model terms. The governing equation of R_a is given in Eqn 4 below.

$$Ra = 0.376500 - 0.000177 * Ss + 2.49033 * Dc + 0.003231 * Fr + 0.000688 * Ss * Dc + 2.02500E - 06 * Ss * Fr + 2.02500E - 06 * Ss * Fr + 5.00000 - 0.003338 * Dc * Fr - 4.41333E - 07 * Ss^2 - 0.267333 * Dc^2 - 2.86458E - 06 * Fr^2 \tag{4}$$

Parameter Interaction Effects on R_a

The upcoming figures represents the interaction effects of the parameters on to the response R_a. These representation gives a clear understanding on the parametric effect on the responses, which in turn helps to optimize the machining parameter selection based on the objectives assigned. **Fig 1** shows the interaction effect of S_s and D_c on R_a. The graph shows that almost in all levels of S_s minimum R_a can be achieved provided it is influenced by the assigned level of D_c. When the level of D_c is increased from 0.5 mm there is a gradual and significant increase in R_a. However, min R_a is achieved when the level of D_c and S_s is maintained lower and higher level respectively. On careful analysis one can say that min R_a is achievable when S_s is set at 3000 rpm and D_c is maintained between 0.5 to 0.7 mm.

Fig 2 shows the interaction effect of S_s and F_r on R_a. From the graph it is clearly evident that F_r has higher influence on S_s compared to that of D_c. From the graph it is notable to state that the range of achieving minimum Ra is very narrow and it is achievable only when S_s is maintained between 2950 to 3000 rpm and F_r between 800-840 mm/min. Any other combination of these parameters will result in higher R_a.

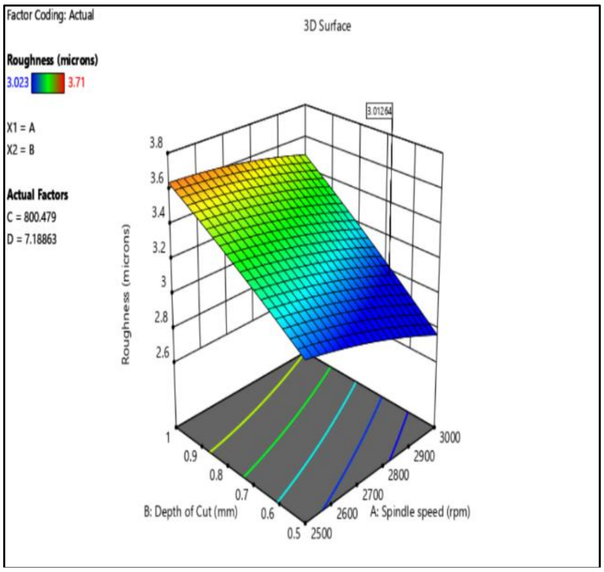


Fig 1. Contour Plot - S_s & D_c on R_a.

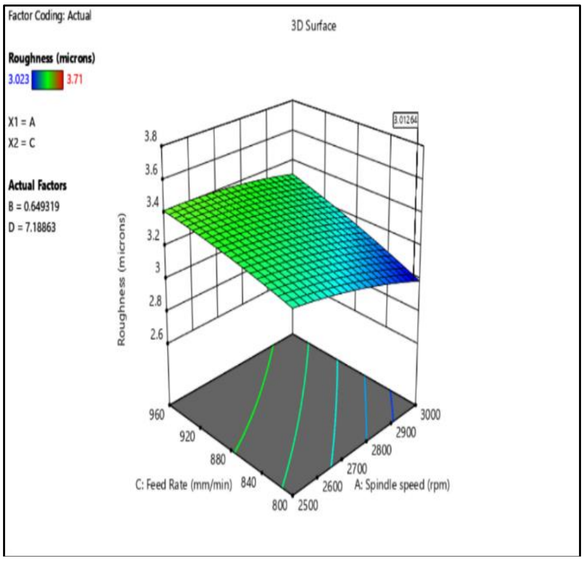


Fig 2. Contour Plot - S_s & F_r on R_a.

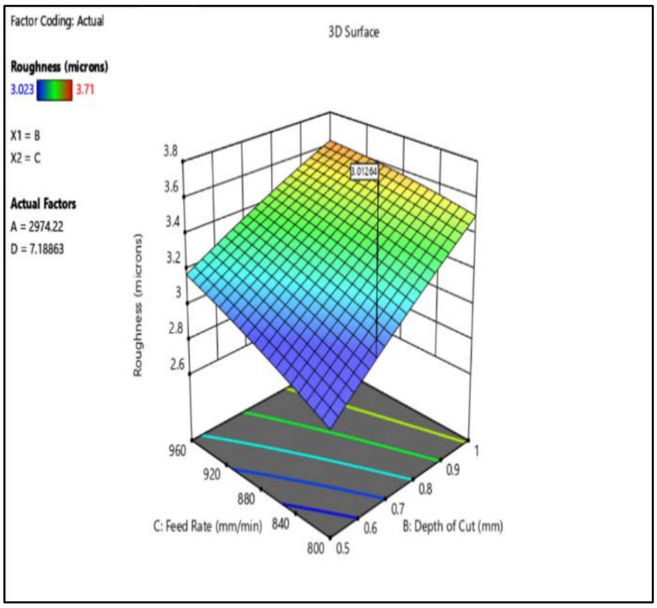


Fig 3. Contour Plot - D_c & F_r on R_a.

Fig 3 displays the impact of D_c and F_r on R_a. In this case, these two parameters D_c and F_r plays a prominent role in identification of optimum settings. These two parameters has a dynamic relation governing the response and varies according to the level assigned for S_s. F_r between 800-850 mm/min and D_c between 0.5 to 0.6 mm assists in attaining minimum R_a.

Predicted Optimum Parameter for R_a

The below **Table 5** displays the predicted optimized value for R_a

Table 5. Optimized Value - R_a

Runs	S_s	D_c	F_r	R_a
1	2974.222	0.649	800.479	3.013

Prediction of M_{rr}

Table 6 shows the ANOVA for M_{rr} and the F-value (6233.68) shows the significance of the created and developed model. This value represents that the layout or model has only a 0.01% chance of attaining this value due to noise factor considered.

Table 6. ANOVA for M_{rr}

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	2.99	14	0.2137	6233.68	< 0.0001	significant
S_s	0.0370	1	0.0370	1078.09	< 0.0001	
D_c	2.85	1	2.85	83179.69	< 0.0001	
F_r	0.0227	1	0.0227	662.29	< 0.0001	
S_s x D_c	0.0000	1	0.0000	0.0000	1.0000	
S_s x F_r	0.0001	1	0.0001	4.20	0.0596	
D_c x F_r	0.0000	1	0.0000	0.0000	1.0000	
S_s^2	0.0004	1	0.0004	12.11	0.0037	
D_c^2	0.0002	1	0.0002	4.73	0.0473	
F_r^2	0.0004	1	0.0004	12.11	0.0037	
Residual	0.0005	14	0.0000			
Lack of Fit	0.0005	10	0.0000			
Pure Error	0.0000	4	0.0000			
Cor Total	2.99	28				

The significance of the parameters can be ascertained by the p-value at 95% confidence interval. Here in this case P-value (less than 0.0500) shows that the model generated is significant. In this case S_s, D_c, F_r, S_s^2, D_c^2, F_r^2 are significant model terms. The governing equation of M_{rr} is given in Eqn 5 below.

$$Mrr = -3.55200 + 0.000746 * Ss + 2.07000 * Dc + 0.003569 * Fr + 9.18904E - 18 * Ss * Dc - 3.00000E - 07 * Ss * Fr - 4.81535E - 20 * Dc * Fr - 1.28000E - 07 * Ss^2 - 0.080000 * Dc^2 - 1.25000E - 06 * Fr^2 \tag{5}$$

Parameter Interaction Effect on M_{rr}

The following figures represents the interaction effects of the parameters on M_{rr}. This set of representation gives a clear understanding the parametric effect on the result and outcome, which in turn helps to optimize the machining parameter selection based on the objectives assigned.

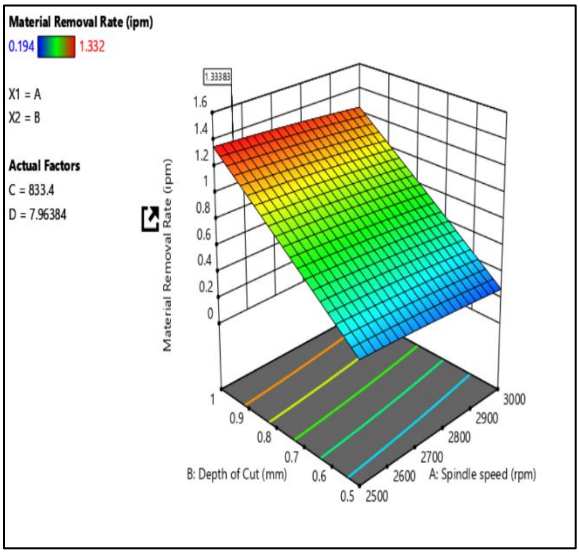


Fig 4. Contour Plot - S_s & D_c on M_{rr}

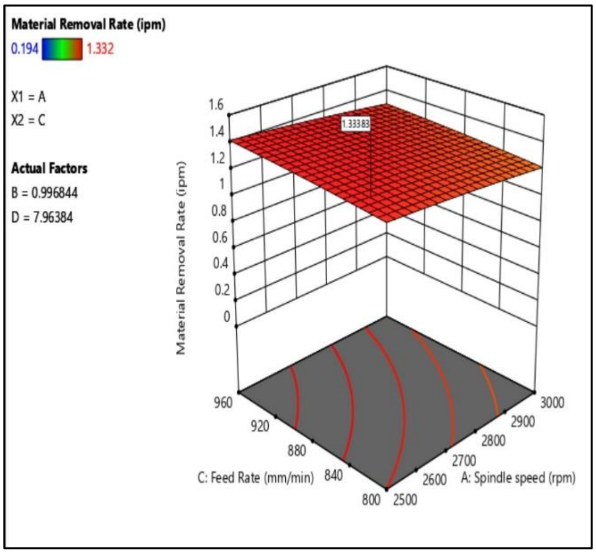


Fig 5. Contour Plot - S_s & F_r on M_{rr}.

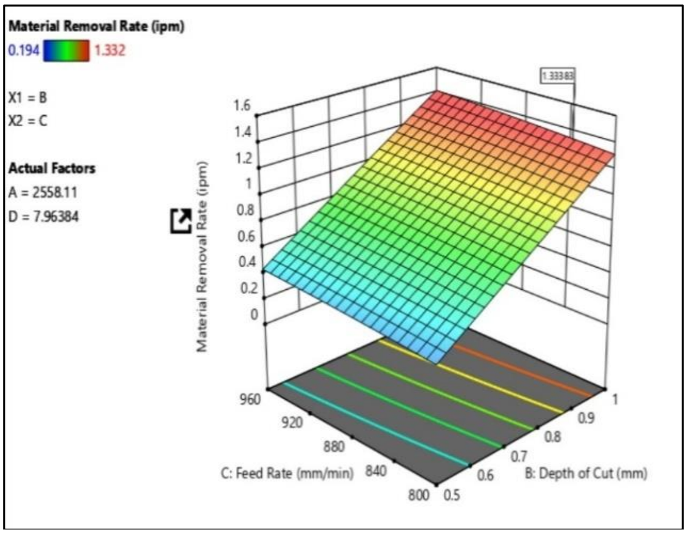


Fig 6. Contour Plot - D_c & F_r on M_{rr}.

Fig 4 displays the interaction effect of S_s and D_c on M_{rr}. The graph shows that almost in all levels of S_s maximum M_{rr} can be achieved provided it is influenced by the assigned level of D_c. When the level of D_c is increased from 0.7 to 1 mm there is a gradual and significant increase in M_{rr}. However, maximum M_{rr} is achieved when the level of D_c and S_s is maintained higher and lower level respectively. On careful analysis one can say that maximum M_{rr} is achievable when S_s is set between 2500 to 2600 rpm and D_c is maintained between 0.9 to 1 mm. **Fig 5** neatly depicts and displays the interaction effect of S_s and F_r on M_{rr}. With the help of graph, it is clearly understandable that F_r has higher influence on S_s compared to that of D_c. From the graph it is notable to state that F_r contributes to maximum M_{rr} almost in all its levels irrespective of the S_s assigned. **Fig 6**

Predicted Optimum Parameter for Mrr

The below **Table 7** shows the predicted optimized value for M_{rr}

Table 7. Optimized Value - M_{rr}

Runs	**S_s**	**D_c**	**F_r**	**M_{rr}**
1	2500.86	0.966	912.941	1.334

Prediction of P_c

Table 8 shows the ANOVA for P_c and the F-value (631.13) shows the significance of the developed and created model. The value represents that this layout or model has only a 0.01% chance of attaining this value due to noise factor considered.

Table 8. ANOVA for P_c

Source	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**p-value**	
Model	2.95	14	0.2106	631.13	< 0.0001	significant
S_s	0.1102	1	0.1102	330.27	< 0.0001	
D_c	2.48	1	2.48	7444.92	< 0.0001	
F_r	0.2280	1	0.2280	683.20	< 0.0001	
S_s x D_c	0.0020	1	0.0020	6.07	0.0273	
S_s x F_r	4.000E-06	1	4.000E-06	0.0120	0.9144	
D_c x F_r	0.0000	1	0.0000	0.0000	1.0000	
S_s^2	0.0076	1	0.0076	22.91	0.0003	
D_c^2	0.0132	1	0.0132	39.51	< 0.0001	
F_r^2	0.0210	1	0.0210	62.79	< 0.0001	
Residual	0.0047	14	0.0003			
Lack of Fit	0.0047	10	0.0005			
Pure Error	0.0000	4	0.0000			
Cor Total	2.95	28				

The significance of all the parameters can be ascertained by the p-value at 95% confidence interval. Here in this case P-value (less than 0.0500) shows that the layout or model generated is very necessary and important. In such scenarios S_s, D_c, F_r, S_s x D_c, S_s^2, D_c^2, F_r^2 are absolutely crucial and important model terms. The governing equation of R_a is given in Eqn 6 below.

$$Pc = -11.40167 + 0.002054 * Ss + 1.91200 * Dc + 0.017215 * Fr + 0.000360 * Ss * Dc + 5.00000E - 08 * Ss * Fr + 8.79239E - 18 * Dc * Fr - 5.49333E - 07 * Ss^2 - 0.721333 * Dc^2 - 8.88021E - 06 * Fr^2 \quad (6)$$

Parameter Interaction Effect

The following figures represents the parameters' interactions' influence on P_c. This set of representation gives a clear understanding of the parametric effect on the result and outcome, which in turn helps to optimize the machining parameter selection based on the objectives assigned.

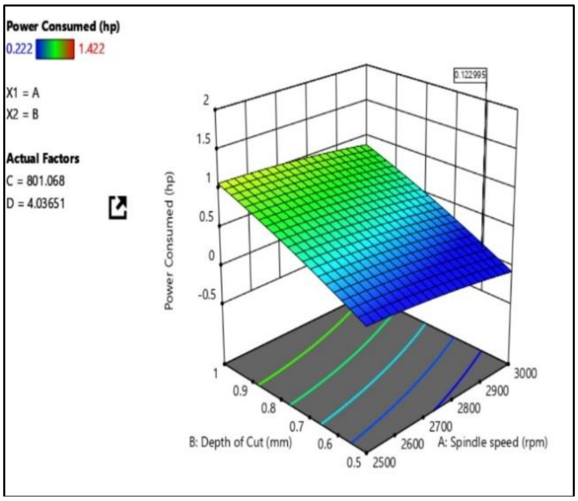


Fig 7. Contour Plot - S_s & D_c on $\mathbf{P_c}$ **.**

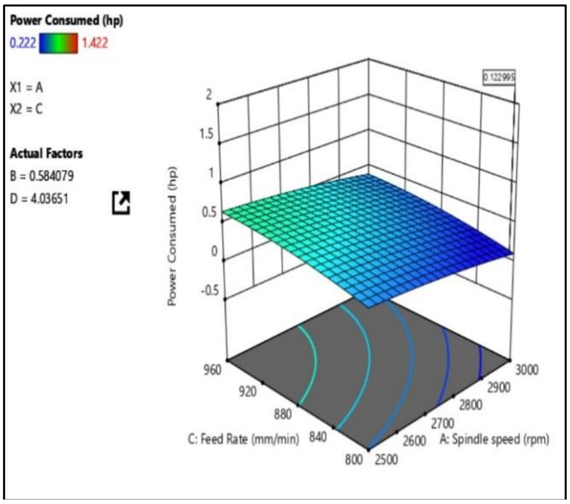


Fig 8. Contour Plot - S_s & F_r on P_c.

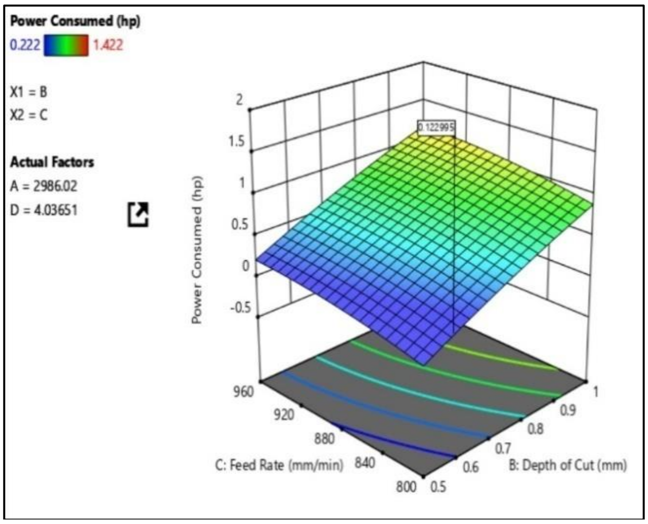


Fig 9. Contour Plot - D_c & F_r on P_c.

Fig 7 displays the interaction effect of S_s and D_c on P_c. The graph shows that almost all levels of S_s assists minimum power consumption but influenced by assigned level of D_c. When the level of D_c is maintained between 0.5 to 0.65 mm, minimum P_c can be achieved. **Fig 8** shows the interaction effect of S_s and F_r on P_c. In the show graph, it is very obvious that F_r has higher influence on S_s compared to that of D_c. From the graph it is notable to state that F_r contributes to minimum P_c when its level is maintained between 800 to 850 mm/min with higher level of S_s. **Fig 9** shows the effect of D_c and F_r on P_c. In this case, these two parameters D_c and F_r plays a prominent role in identification of optimum settings. These two parameters has a dynamic relation governing the response and varies according to the level assigned for S_s. F_r assists in achieving minimum P_c when its levels are maintained between 800 to 880 mm min and D_c between 0.5 to 0.6 mm.

Predicted Optimum Parameter for Power Consumption

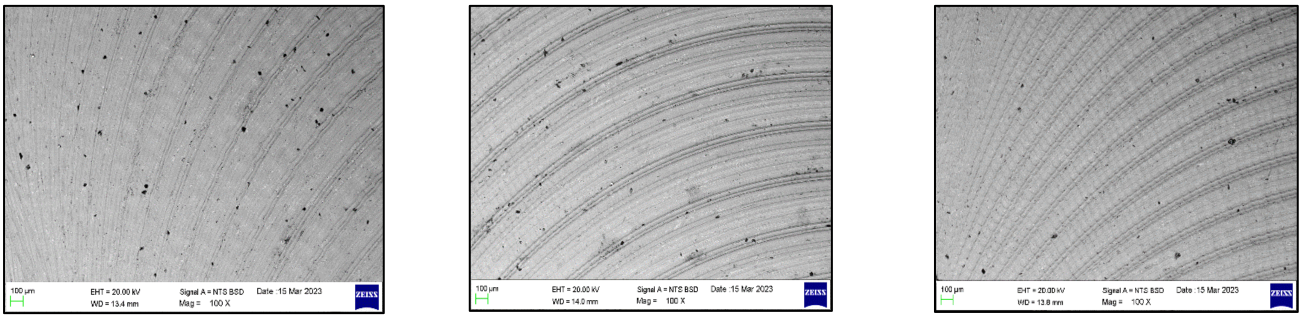
The below **Table 9** displays the predicted optimized value for P_c

Table 9. Optimized Value - P_c

Run	**S_s**	**D_c**	**F_r**	**P_c**
1	2798.766	0.504	806.322	0.203

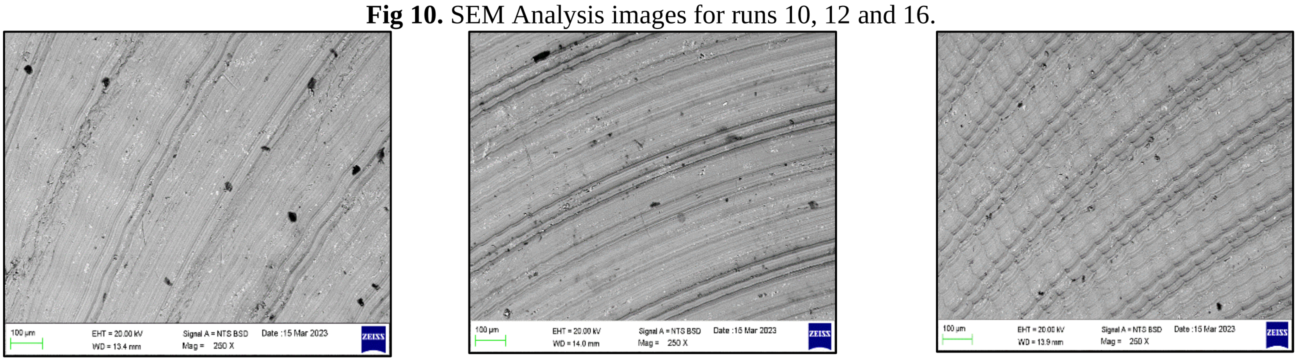
VI. SEM ANALYSIS

The following section provides an explanation of the SEM images taken for the experimental runs conducted to further interpret the surface texture. SEM analysis was performed as shown in the subsequent sections. **Fig 10** and **11** displays the SEM images for runs 10, 12, 16, 17, 18 and 24 at a magnification level of 500X. In all the images, there is evidence of adhered material fragments that develop during plastic deformation while machining. Smeared materials, micro holes, and grooves are also visible in the images, which are formed during the material removal process and are consistently present throughout. The presence of burrs and adhered chip particles is possibly due to thermal distortion or inefficient removal of temperature that arises due to EDM process.



a) b) c)

Fig 10. SEM Analysis images for runs 10, 12 and 16.



a) b) c)

Fig 11. SEM Analysis images for runs 17, 18 and 24.

VII. GRA OPTIMIZATION

Table 10 shows the GRA optimization.

Table 10. GRA Optimization

Runs	**Normalization**			**Deviation Sequence**			**Grey Relation Coefficients**			**GRG**	**RANK**
	R_a Normalized	**P_c Normalized**	**M_{rr} Normalized**	**R_a**	**P_c**	**M_{rr}**	**R_a**	**P_c**	**M_{rr}**		
1	**1.000**	**1.000**	**0.981**	**0.000**	**0.000**	**0.019**	**1.000**	**1.000**	**0.963**	**0.988**	**1**
2	0.000	0.000	0.101	1.000	1.000	0.899	0.333	0.333	0.357	0.341	29
3	0.529	0.548	0.526	0.471	0.453	0.474	0.515	0.525	0.513	0.518	12
4	0.471	0.453	0.556	0.529	0.548	0.444	0.486	0.477	0.530	0.498	18
5	0.523	0.644	0.658	0.477	0.356	0.343	0.512	0.584	0.593	0.563	9

6	0.245	0.318	0.458	0.755	0.682	0.542	0.398	0.423	0.480	0.434	23
7	0.500	0.500	0.541	0.500	0.500	0.459	0.500	0.500	0.521	0.507	13
8	0.768	0.963	1.015	0.232	0.038	-0.015	0.683	0.930	1.031	0.881	3
9	0.500	0.500	0.541	0.500	0.500	0.459	0.500	0.500	0.521	0.507	13
10	0.500	0.500	0.541	0.500	0.500	0.459	0.500	0.500	0.521	0.507	13
11	0.745	0.818	0.898	0.255	0.182	0.102	0.662	0.733	0.831	0.742	5
12	0.705	0.491	0.522	0.295	0.509	0.478	0.629	0.495	0.511	0.545	11
13	0.950	0.809	0.879	0.050	0.191	0.121	0.908	0.724	0.805	0.813	4
14	0.255	0.182	0.183	0.745	0.818	0.817	0.402	0.379	0.380	0.387	25
15	0.478	0.357	0.424	0.522	0.643	0.576	0.489	0.437	0.465	0.464	21
16	0.284	0.229	0.168	0.716	0.771	0.832	0.411	0.393	0.375	0.393	24
17	0.552	0.692	0.643	0.448	0.308	0.358	0.527	0.619	0.583	0.576	8
18	0.450	0.309	0.439	0.550	0.691	0.561	0.476	0.420	0.471	0.456	22
19	0.733	0.538	0.507	0.267	0.462	0.493	0.652	0.520	0.503	0.559	10
20	0.029	0.048	0.086	0.971	0.953	0.914	0.340	0.344	0.354	0.346	28
21	0.297	0.510	0.560	0.703	0.490	0.440	0.416	0.505	0.532	0.484	19
22	0.971	0.953	0.996	0.029	0.048	0.004	0.946	0.913	0.992	0.950	2
23	0.233	0.038	0.067	0.767	0.962	0.933	0.395	0.342	0.349	0.362	27
24	0.716	0.771	0.913	0.284	0.229	0.087	0.638	0.686	0.852	0.725	6
25	0.500	0.500	0.541	0.500	0.500	0.459	0.500	0.500	0.521	0.507	13
26	0.052	0.192	0.203	0.948	0.808	0.798	0.345	0.382	0.385	0.371	26
27	0.500	0.500	0.541	0.500	0.500	0.459	0.500	0.500	0.521	0.507	13
28	0.268	0.463	0.575	0.732	0.538	0.425	0.406	0.482	0.541	0.476	20
29	0.755	0.682	0.623	0.245	0.318	0.377	0.671	0.611	0.570	0.618	7

Optimized Parameters -GRA

Table 11 shows the optimized parameters.

Table 11. Optimized Parameters - GRA

Run	S_s	D_c	F_r	R_a	M_{rr}	P_c
1	2798.766	0.504	806.322			0.203

VIII. CONFIRMATORY RUNS

Table 12 shown below shows the values recorded by performing the confirmatory runs to validate the accuracy of the optimized levels achieved.

Table 12. Confirmatory Runs

Tool	Type	Predicted			Achieved		
		Dry run R_a	Dry run M_{rr}	Dry run P_c	Dry run R_a	Dry run M_{rr}	Dry run P_c
BBD	Single response (R_a)	3.013	-	-	3.019	-	-
	Single Response (M_{rr})	-	1.334	-	-	1.346	-
	Single Response (P_c)	-	-	0.203	-	-	0.207

GRA	Multi-response	2.987	1.313	0.206	2.989	1.298	0.207

IX. CONCLUSION

The study is performed as single response and multi-response optimization. For single response BBD design is followed and for multi-response GRA is applied. The following are the inferences noted in the entire study and found to be acceptable in accord to the results attained in confirmatory runs:

i) For achieving minimum roughness, B plays the dominant role followed by C and D
ii) The least contributing factor governing roughness in this case, is found to be A
iii) From table 12, minimum R_a achieved is 3.013 microns under single response method
iv) For maximum M_{rr}, C and D played the prominent role
v) In single response, maximum M_{rr} achievable is 1.334 mm^3/min
vi) In single response, minimum power consumption of 0.207 HP is recorded
vii) In case of multi-response optimization, GRA results prediction stands good with minimum R_a of 2.987 microns, maximum M_{rr} of 1.313 mm^3/min and minimum P_c of 0.207 HP

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