OPTIMIZING CUTTING PARAMETERS FOR ENHANCED MATERIAL REMOVAL RATE IN TURNING ALUMINIUM ALLOY-6082: A TAGUCHI APPROACH

Abstract

Nowadays, metal cutting industries are in search of a process which can significantly reduce machining time. In this context, a possibility was attempted to increase the Material Removal Rate (MRR), (mm^3/sec) by varying three independent input parameters. The present experimental study is centred on determination of the optimal cutting parameters for turning Aluminium Alloy-6082, a medium-strength alloy known for its outstanding corrosion resistance. Three input parameters of Spindle speed (mm/min), Feed rate (mm/min) and Depth of Cut (mm) of three levels each was used. Experiment was performed on CNC Lathe using a Carbide tipped high speed steel tool. The experimental design plan utilized the Taguchi L_{27} orthogonal array to conduct the experiments. Reduction in Variance was accomplished by optimizing the Signal to Noise ratio (S/N ratio) in Minitab software. Based on confirmation tests, it was observed that Taguchi analysis identified the optimal process parameters leading to a notable enhancement in turning performance during machining. From Analysis of Variance (ANOVA), it was inferred that MRR was appreciably influenced by Depth of Cut. Furthermore, Multivariate Polynomial Regression models were developed in MATLAB software to predict the MRR value.

Keywords: Materials Removal Rate, Taguchi's optimization, Multivariate polynomial regression.

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I. INTRODUCTION

In the ever-changing world of contemporary production, sustainable practices, involving efficiency, resource efficiency and environmental concerns are becoming more and more important. Researchers and practitioners are delving into the modelling and optimization of sustainable manufacturing processes. This has been further reiterated by usage of Computer Numerical Control (CNC) machines during manufacturing processes, such as machining of aluminium and its alloys.

Aluminium is an essential material in many different industries because of its well-known lightweight qualities, resilience to corrosion and ability to be recycled. A key tool in precision machining, the CNC lathe machine is essential for shaping and perfecting aluminium components. In order to minimize waste, energy consumption and environmental effect, this manufacturing process must incorporate sustainability concepts.

In an experimental study by Aryan et al.[1], optimization of input variables for obtaining minimum surface roughness and maximum material removal rate was performed during turning of aluminium alloy 6082 using Taguchi design of experiment. S/N Ratio was used and ANOVA was utilized to study the individual effect of each input factors. Chowdhury et al. [3] carried out the study on Fuzzy MCDM methods to effectively optimize CNC turning of Al 6082-T6, identifying ideal parameters while handling uncertainty and validating robustness.

Kartal et al.[3] investigated the impact of machining parameters like nozzle feed rate, abrasive flow rate, spindle speed and standoff distance on surface roughness and surface characteristics during water jet turning operation on Al-6082 T6 alloy. Pump pressure of 350 MPa, abrasive size of 120 mesh and nozzle diameter of 0.75 mm were kept constant. Results suggested that smoother surface was obtained at increased spindle speed, decreased nozzle feed rate, increased abrasive flow rate and lower standoff distance.

Kumar et al.[4] studied the impact of cutting speed, feed rate and depth of cut on machining time, surface roughness, and material removal rate (MRR) during CNC turning of aluminum alloy Al-6082 T6, employing a tungsten carbide tool. Through Taguchi design of experiment process, grey relational analysis (GRA) and Principal Component Analysis (PCA), they optimized response variables. Experimental results highlighted the statistical significance of speed and feed, while depth of cut was deemed insignificant.

Lakshmanan et al.[5] investigated the influence of cutting parameters (speed, feed rate, depth of cut) on surface roughness and material removal rate (MRR) of Al7075 alloy during turning process, using a tungsten carbide tool under both dry and wet conditions. Grey Relational Analysis (GRA) and ANOVA were used to find the influence of input parameters on responses. Results revealed that depth of cut and speed had the greatest influential followed by feed rate. Majumder et al. [6] effectively optimizes the turning of ASTM A588 steel by identifying ideal parameters, outperforming TOPSIS-PCA in multi-objective machining decision-making. Meanwhile, Patel et al.[7] investigated the influence of spindle speed, feed rate, depth of cut, and nose radius on material removal rate and surface roughness in turning Aluminum Alloy (Al 6082) on a conventional lathe machine. They determined optimal process variables to maximize material removal rate and minimize roughness of surface using an L_8 orthogonal array, ANOVA, and the signal-to-noise ratio. Spindle speed, depth of cut, and feed rate emerged as significant factors respectively.

Numerous studies were made on optimization of parameters for turning operations across various materials. Sakthivelu et al.[8] investigated the machining attributes of Aluminum Alloy 7075 T6 in CNC milling, employing cutting tools of High-Speed Steel and utilizing Taguchi method for parameter optimization. Through experimental design, they determined the optimal variables to minimize surface roughness (Ra = 0.76 µm) and maximize material removal rate (MRR = 538.899 mm3/min). Similarly, Singh et al.[9] utilized Response Surface Methodology (RSM) and Central Composite Design (CCD) to optimize CNC turning parameters for Al-7020 alloy. Their study aimed to strike a balance between maximizing material removal rate (MRR) and minimizing surface roughness (Ra). They recognized cutting speed and feed as more influential than depth of cut in non-ferrous machining. On the other hand, Singh et al.[10] explored the Taguchi Experimental Design application to optimize surface roughness on a CNC lathe machine. They identified speed as the most effective variable, then feed rate, while depth of cut had minimal impact. The study by Solanki et al.[11] focused on experimental investigation and optimization of cutting parameters for turning Aluminum-6082, utilizing various methods including Taguchi, SNR, ANOVA, TOPSIS, and GRA. Cutting speed, feed rate and depth of cut were the input factors, while material removal rate and surface roughness were the output responses. Signal to noise ratio and mean values were plotted to find optimal level of input factors. Results revealed the efficacy of Chemical Vapour Deposition (CVD) coated carbide inserts with Enklo-68 cutting oil and identified optimal process parameters for MRR and surface roughnessThis experimental research aimed to investigate optimal control parameter settings to achieve maximum material removal rate (MRR) during turning of Aluminium Alloy-6082, applying Taguchi analysis.

A comparative table of prior studies which include material, method, optimum MRR and technique is displayed in Table 1.

Table 1: Comparative table of prior studies (material, method, optimum MRR and technique)

Study	Material	Method/Tool	Technique	Optimum MRR (mm³/min)
Aryan et. Al.[1]	Al Alloy 6082	Turning in conventional lathe using High Speed Steel (HSS) tool, carbide tool and cobalt tool (5% carbon content).	Taguchi, ANOVA, SN Ratio	2.929 for HSS tool, 1.513 for carbide tool, 3.323 for cobalt tool
Kartal et. Al.[3]	Al-6082 T6 alloy	Abrasive water jet turning	Variance analysis, Regression analysis	An increase in the abrasive jet penetration increases the amount of material removal rate
Kumar et al.[4]	Al Alloy 6082 T6	CNC Turning with carbide	Taguchi L9, GRA, PCA	526.8
Lakshmanan et al.[5]	Al Alloy 7075	Tungsten carbide, dry/wet	GRA, ANOVA	565.5
Patel et al.[7]	Al Alloy 6082	Conventional lathe	Taguchi L8, ANOVA, S/N	510.80
Sakthivelu et al.[8]	Al Alloy 7075 T6	High Speed Steel (HSS) in CNC milling	Taguchi	538.899
Singh et al.[9]	Al Alloy 7020	CNC Turning	RSM, CCD	632.78
Singh et al.[10]	Aluminium (unspecified)	CNC Turning	Taguchi	475.30
Solanki et al.[11]	Al Alloy 6082	CVD carbide, cutting oil	Taguchi, ANOVA, SNR, TOPSIS, GRA	563.52

Literature reviews on turning aluminium alloys, have suggested few investigations using Taguchi L_{27} design. Specifically, none have been performed on Aluminium alloy 6082 and for the sole purpose of maximizing MRR. This study addresses that gap by providing a systematic parametric analysis focusing on improving machining efficiency for sustainable manufacturing.

II. MATERIALS AND METHODS

1. **Experimental Details:** Machine specification: Fanuc 3.7/5.5 KW / Siemens 3.7/5.6 KW; Tool holder: VDI tool holders.

   Calculation of Material Removal Rate (MRR):

   Material Removal Rate (MRR) = Volume/Time

   = $[\Pi/4*(D^2 - d^2) * h]$/Time, (mm^3/sec)…………(1), where,D= Initial diameter (mm);

   D= Final diameter) mm);h= Length of cut (mm).

   Time was measured using a stop watch.

   This experimental investigation used Taguchi L_{27} orthogonal array as the design of experiment, where three factors of three levels each were chosen to perform twenty-seven (27) unique experimental runs. The order of twenty-seven experimental runs was randomized prior to execution of the experiments. This was done to mitigate the influence of any uncontrolled variables or systematic biases (e.g., machine warm up, tool wear, or environmental variability). No repeated trials were conducted.

2. **Steps Involved: The Current Study Progressed through Several Phases**
   - Calculation of Material Removal Rate (MRR) based on observation data.
   - Identification of Response Variable (Material Removal Rate) for analysis.
   - Identification of Control Factors (Spindle Speed, Feed Rate, Depth of Cut) which influence the Response Variable.
   - Determination of Control Factor ‘Levels’ (various values) and their potential interactions with the Response Variable.
   - Selection of an appropriate Orthogonal Array (OA) and allocation of factors at their respective levels within the OA.
   - Optimization of cutting conditions for aluminium utilizing Taguchi’s design of experiment.
   - Analysis of experimental results by Signal-to-Noise ratio (S/N) and Analysis of Variance (ANOVA).
   - Development of a predictive turning performance model through Regression Analysis.

2.1 Parameter and Range Selection

In this investigation, Taguchi L_{27} orthogonal array was chosen due to its appropriateness to handle three-level problems. Three factors of three levels each, were selected based on Taguchi design of experiment method and an L_{27} array was constructed to compute the

Material Removal Rate (MRR). The three factors with their corresponding three levels are depicted in Table 2.

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Table 2: Factors with corresponding levels

Parameters	Symbol	Level		
		Low	Medium	High
Spindle Speed (mm/min)	S	750	1000	1250
Depth of Cut (mm)	D	0.05	0.075	0.10
Feed Rate (mm/min)	F	50	75	100

3. **Observation Table:** Twenty-seven number of experimental runs were conducted combining the factors of spindle speed, feed rate and depth of cut based on Taguchi L_{27} design of experiment. The corresponding values of Material removal rate (MRR) is depicted in Table 3.

Table 3: Observed values of MRR for L_{27} Orthogonal Array

Exp. No	**Spindle Speed (rpm)**	**Depth of Cut (mm)**	**Feed Rate (mm/min)**	**MRR (mm^3/sec)**
1	750	0.05	50	3.71492
2	750	0.05	75	3.13706
3	750	0.05	100	2.89628
4	750	0.075	50	4.84846
5	750	0.075	75	4.20768
6	750	0.075	100	3.96690
7	750	0.1	50	6.12068
8	750	0.1	75	5.51908
9	750	0.1	100	5.27830
10	1000	0.05	50	4.08729
11	1000	0.05	75	3.63903
12	1000	0.05	100	2.87981
13	1000	0.075	50	5.68592
14	1000	0.075	75	4.19121
15	1000	0.075	100	3.95043
16	1000	0.1	50	6.67684
17	1000	0.1	75	5.86183
18	1000	0.1	100	5.02105
19	1250	0.05	50	3.64278
20	1250	0.05	75	2.62256
21	1250	0.05	100	2.38178
22	1250	0.075	50	4.80230

23	1250	0.075	75	3.69318
24	1250	0.075	100	3.45240
25	1250	0.1	50	6.41589
26	1250	0.1	75	5.00458
27	1250	0.1	100	4.76380

III. RESULTS AND DISCUSSION

1. Signal to Noise Ratio

The Signal-to-Noise (S/N) ratio is employed as a metric to evaluate quality characteristics and to determine the influence of the chosen factors on the responses. S/N ratios are primarily of three types: lower-the-better, higher-the-better, and nominal-the-better. Here, S/N ratio calculations were conducted using Minitab software to assess the effect of control variables on Material Removal Rate (MRR) as well as to identify optimal settings to maximize MRR. Specifically, "Larger-the-Better" performance characteristic was used in the S/N ratio analysis. The S/N ratio with a larger-the-better characteristic is represented in equation (2):

$$\boldsymbol{\eta}_{ij} = -10 \log\left(\frac{1}{n}\sum_{j=1}^{n}\frac{1}{y_{ij}^2}\right) \qquad (2)$$

Where, y_{ij} stands for the i^{th} experiment at the j^{th} test, n stands for the total number of the tests, and s stands for the standard deviation.

Table 4: Response Table for Signal to Noise Ratios (Larger the Better).

Level	Spindle Speed	Depth of Cut	Feed Rate
1	12.67	10.04	13.96
2	13.11	12.60	12.22
3	11.84	14.95	11.41
Delta	1.27	4.92	2.56
Rank	3	1	2

Table 5: Response Table for Means.

Level	Spindle Speed	Depth of Cut	Feed Rate
1	4.410	3.222	5.111
2	4.666	4.311	4.208
3	4.087	5.629	3.843
Delta	1.27	2.407	1.267
Rank	3	1	2

The response tables for S/N Ratio (Larger the better) and Means are depicted in Table 4 and Table 5 respectively. The Main Effects Plot for Means as shown in Figure 1, depicts that at cutting speed of 1000 rpm, depth of cut of 0.1 mm and feed rate of 50 mm/min, the MRR value is optimized, i.e., larger the better. The same conclusion is observed for the Main Effects Plot for S/N Ratio as in Figure 2.

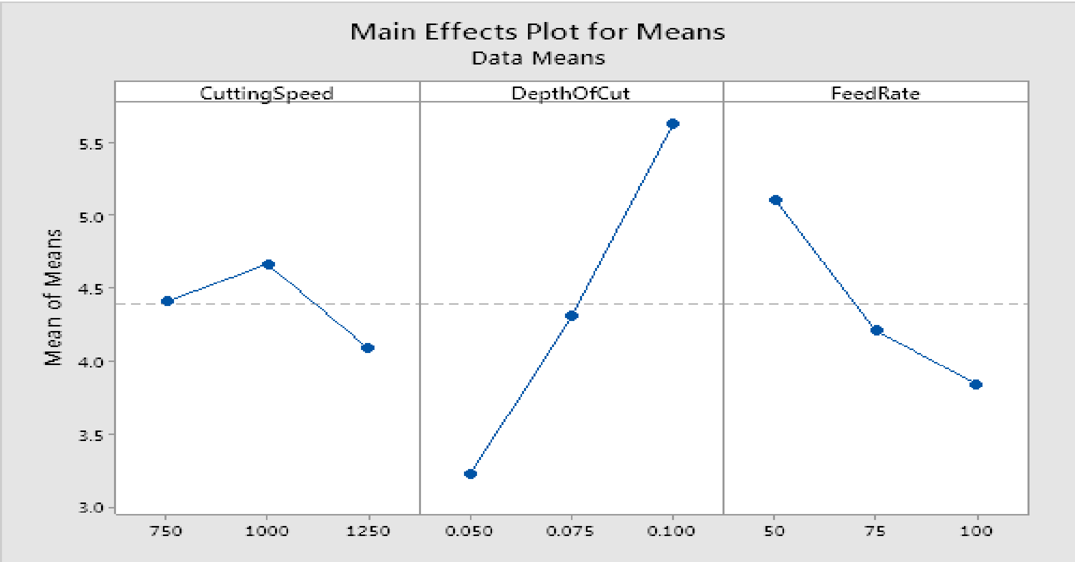

Figure 1: Main Effects Plot for Means.

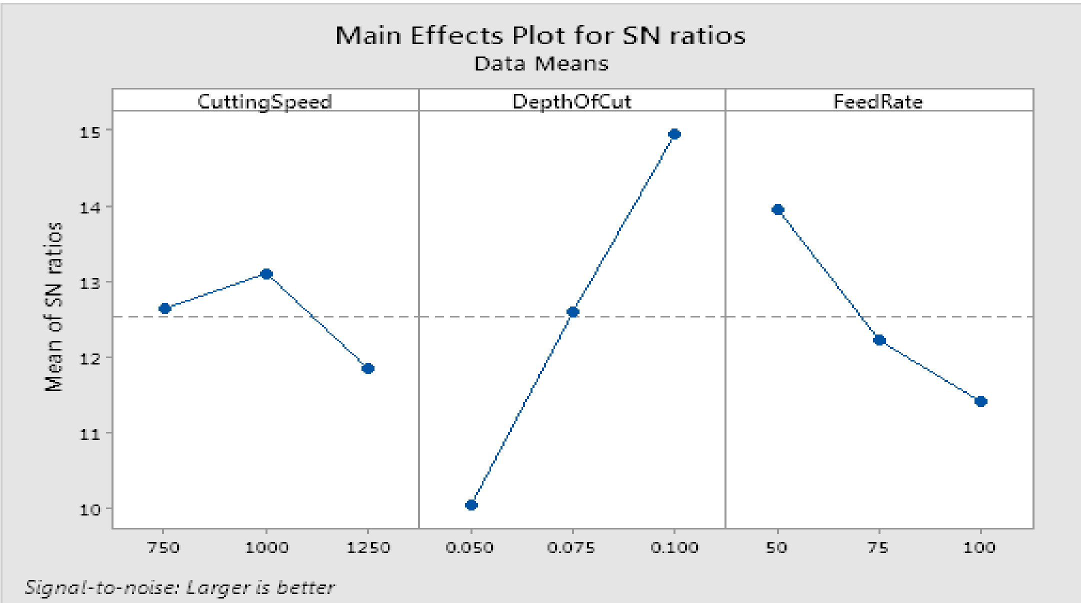

Figure 2: Main Effects Plot for S/N ratios.

Residual plots aided to analyze the importance of the coefficients in the predicted model. A straight-line residual plot indicated that residual errors in the model are normally distributed and that the coefficients in the model are notable. The residual plots for Material Removal Rate (MRR) are illustrated in Figure 3 and Figure 4, respectively.

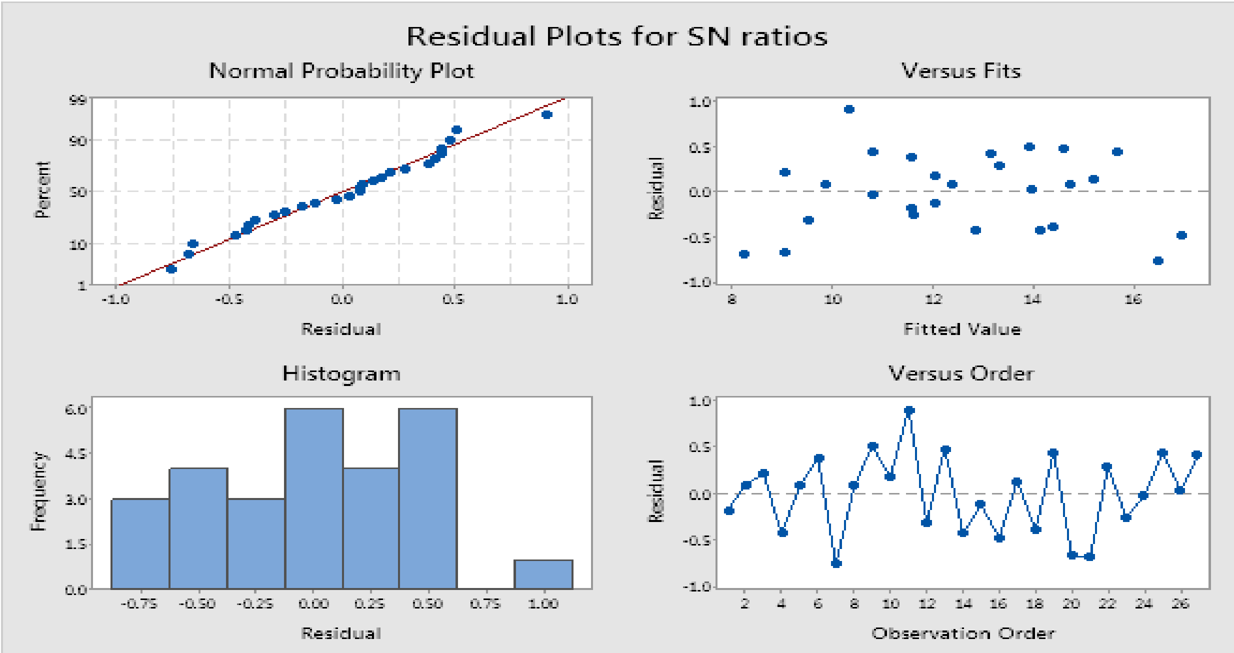

Figure 3: Residual Plots for S/N ratios: Normal Probability Plot, Versus Fits, Histogram,Versus Order

The plot shown in Figure 3, presents Residual Plots for S/N (Signal-to-Noise) Ratios, typically utilized in regression analysis to verify assumptions and validity of a model. Residuals are differences between predicted and observed values.

Here is the description of each of the four subplots:

1. **Normal Probability Plot (Top Left)**
   Purpose: To verify whether residuals are normally distributed.
   Interpretation: The points lie close to the straight line, indicating that the residuals are close to normally distributed. This confirms the normality assumption in regression.

2. **Residuals vs. Fitted Values (Top Right)**
   Purpose: To identify non-linearity, unequal error variances, and outliers.
   Interpretation:The residuals look randomly dispersed about the horizontal zero line.
   No discernible pattern indicates good model fit with no serious problems such as heteroscedasticity (non-constant variance).

3. **Histogram of Residuals (Bottom Left)**
   Purpose: To visually check the distribution of residuals.
   Interpretation:The histogram is approximately normal-shaped and symmetric. This again indicates that the residuals are approximately normally distributed.

4. **Residuals vs. Observation Order (Bottom Right)**
   Purpose: To verify patterns over time or observation order (e.g., autocorrelation).
   Interpretation:The residuals randomly vary around zero with no systematic trend. This indicates that the residuals are independent over time/order.

The model seems to meet the important assumptions of regression:

Normality of the residuals,Constant variance (homoscedasticity), Independence of errors,No obvious non-linearity.

The residual plots therefore support the use of the regression model to analyze S/N ratios.

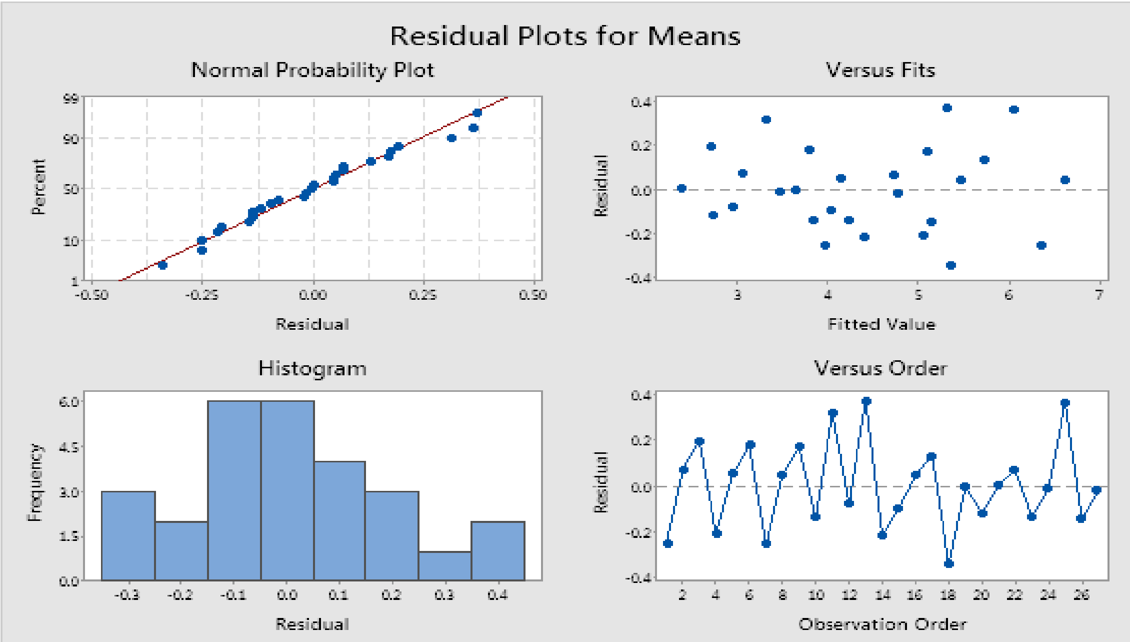

Figure 4: Residual Plots for Means: Normal Probability Plot, Versus Fits, Histogram, Versus Order

Residual Plots for Means are shown in Figure 4. They are used in regression or ANOVA to check if the assumptions of the model (such as normality, constant variance, and independence of residuals) for the mean responses hold.

Here is a detailed logical breakdown of the four residual plots:

1. **Normal Probability Plot (Upper Left)**
   Purpose: To check if the residuals are normally distributed.
   Observations: Points lie very close to the reference line. This implies that the residuals are approximately normally distributed, which supports the assumption of a normal distribution.

2. **Residuals vs Fitted Values (Upper Right)**
   Purpose: To check for non-linearity, non-constant variance (heteroscedasticity), and fit of the model.
   Observations: Residuals are randomly scattered about the horizontal line (y = 0). There is no evidence of a funnel shape or curve.
   This indicates that the model is appropriate and the variance appears constant across fitted values (homoscedasticity).

3. **Histogram of Residuals (Lower Left)**
   Purpose: To check the distribution of the residuals.
   Observations: Histogram is approximately symmetric with a symmetric peak centred near zero. This indicates that the residuals are fairly normally distributed with no significant extreme skew or outliers.

4. **Residuals vs Order of Observation (Lower Right)**
   Purpose: To check for time-based patterns or autocorrelation.
   Review: The residuals oscillate about zero, but show a zig-zag pattern that repeats. This may suggest some potential periodic behaviour or autocorrelation in the residuals, which means that observations may not be fully independent over time/order.

Assumption of normality and constant variance is valid. The model appears to be suitable for comparing means. There is a slight concern with the residual vs order plot, and if dependence in time or order matters then an additional test (e.g. Durbin-Watson) may be warranted. Overall, it seems like a reasonably good model fit with only a very mild suggestion of potential dependence on the order of observations.

1. **Analysis of Variance**: The analysis aimed to ascertain if there is a statistically salient dissimilarity amongst the means of two or more independent samples by comparing the means of the response variable at various factor levels. The test results and Signal-to-Noise (S/N) Ratio were evaluated using Analysis of Variance (ANOVA) for identifying significant factors and their relative contributions to the outcomes. Unlike S/N Ratio alone, ANOVA enabled the assessment of individual parameter effects, allowing for the determination of percentage contribution of each parameter.

Table 6: Analysis of Variance for S/N Ratios

Source	DOF	Seq SS	Adj SS	Adj MS	F	P	Contribution
Spindle Speed	2	7.390	7.390	3.6952	15.75	0.000	4.87%
Depth of cut	2	108.792	108.792	54.3961	231.91	0.000	71.76%
Feed Rate	2	30.716	30.716	15.3582	65.48	0.000	20.26%
Residual Error	20	4.691	4.691	0.2346			
Total	26	151.590					

The ANOVA results of S/N Ratios shown in Table 6, depicts the effect of each factor on the S/N ratios.

It was observed that maximum effect on S/N Ratio was due to depth of cut with 71.76% contribution, followed by feed rate and spindle speed with 20.26% and 4.87% contributions respectively.

Table 7: Analysis of Variance for Means.

Source	DOF	Seq SS	Adj SS	Adj MS	F	P	Contribution
Spindle Speed	2	1.5172	1.5172	0.7586	16.27	0.000	4.18%
Depth Of Cut	2	26.1447	26.1447	13.0723	280.43	0.000	72.11%
Feed Rate	2	7.6581	7.6581	3.8291	82.14	0.000	21.12%
Residual Error	20	0.9323	0.9323	0.0466			
Total	26	36.2523					

The ANOVA table of Means as shown in Table 7, depicts the contribution of each factor on the S/N ratios.

It was observed that depth of cut has maximum effect on Means with 72.11% contribution, followed by feed rate and spindle speed with 21.12% and 4.18% contributions respectively.

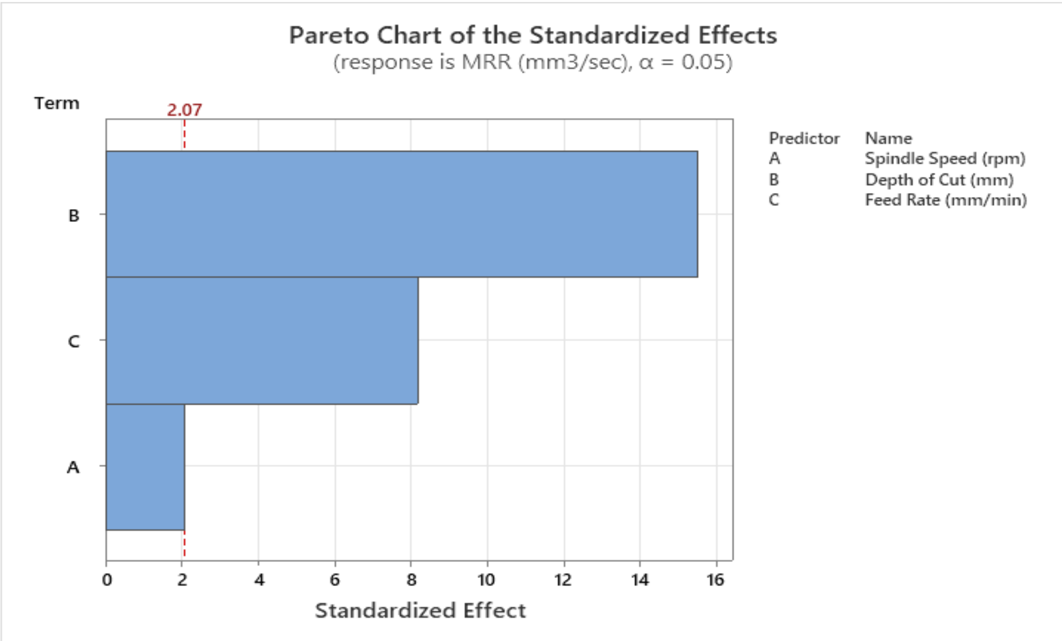

Figure 5: Pareto chart of the standardized effect.

The Pareto Chart of the Standardized Effect as shown in Figure 5, also reiterates that the depth of cut has the highest contribution for MRR optimization.

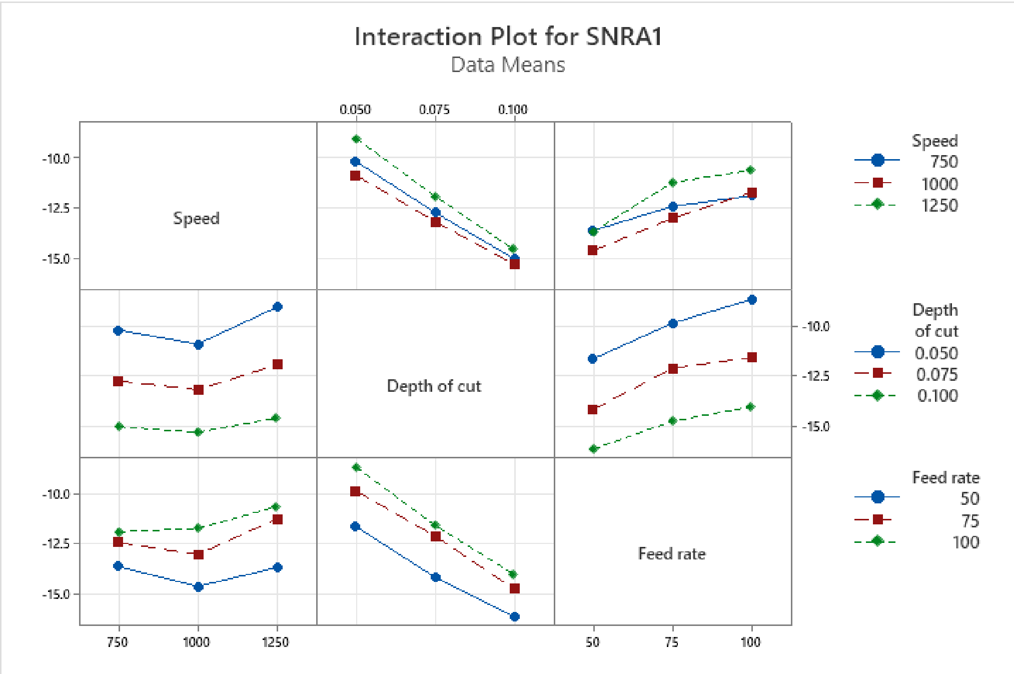

Figure 6: Interaction Plot for S/N Ratio

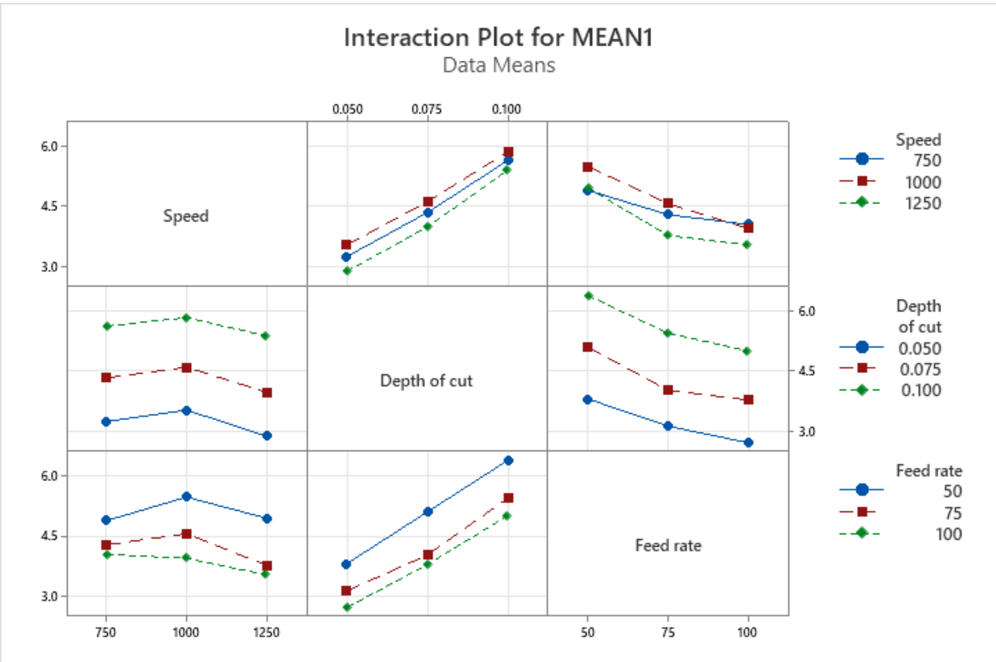

Figure 7: Interaction Plot for Mean

In interaction plot, non-parallel lines and overlapping lines mean more interaction. So, the combined effect of speed and feed rate on MRR will be more. In other words, depth of cut has less effect on MRR.

The interaction plots created shows non-parallel and intersecting lines, especially for spindle speed and feed; a clear indication of interaction effect. This means, the effect of feed rate on

MRR is not invariant of spindle speed. Regarding practical implication, the effect of higher spindle speed results in increased material removal and in combination with higher feed rates, more material is removed per unit time leading to a cumulative effect on MRR. Alternatively, at lower spindle speed and increased feed rate, it is unlikely to result in improved MRR because at this cutting condition, same cutting efficiency or tool engagement are not obtained compared to higher spindle speeds.

This interaction is fundamental to process planning. Maximizing one parameter without consideration to the other parameters may not lead to the best outcomes. Therefore, when planning a process, selecting spindle speed and the appropriate feed rate as a set is essential to maximizing MRR.

3. Modelling

In this investigation, Second Order Polynomial Regression Analysis was conducted using MATLAB 16.0 software to construct predictive mathematical models (Table 8) for the dependent variable Material Removal Rate (MRR). Spindle speed, feed rate and depth of cut were considered as predictors. No transformations were applied to the responses. The efficacy of the developed model was examined using the coefficient of determination, R-Square value, which varies between zero and one. A value closer to one signifies a strong fit between the dependent and independent variables. For instance, an R^2 value of 95% suggests that 95% of the variability in new observations can be estimated. In this study, the regression model for MRR demonstrated high R^2 values, reaching 98.31%. Residual plots were employed to ascertain the significance of the coefficients in the predicted model, with a straight line indicating normally distributed residual errors, thus highlighting the importance of the coefficients.

Predicted Regression Equation with MRR as a function of the given three input parameters is shown in Equation 3.

$$MRR= 7\times10^{-3}*S^2+5*S*D-2*S*F+14*S+184*D^2-115*D*F+24*D+0.5*F^2-58*F-1885 \quad \ldots(3)$$

Where,
S= Spindle speed (mm/min); F=Feed rate (mm/min); D=Depth of Cut (mm)

Table 8: Predictive Mathematical Model.

Variable name	Parameter	Coefficients	Parameter var	Parameter std.	DOF	P value	R-sq.	Adj. R sq.	RMSE
S' 'D' 'F'	S*S	-6.6828×10^{-6}	1.5368×10^{-12}	1.2397×10^{-6}	17	4.8787×10^{-5}	0.9831	0.9742	0.1506
	S*D	0.0049	7.684×10^{-5}	0.0088		0.5836			
	S*F	-2.2939×10^{-5}	7.684×10^{-11}	8.765×10^{-6}		0.018			
	S	0.0141	7.0437×10^{-6}	0.0027		5.8517×10^{-5}			
	D*D	183.6978	1.5368×10^{4}	123.9677		0.1567			
	D*F	-0.1151	0.0077	0.0877		0.2067			
	D	24.3133	469.0438	21.6574		0.2772			
	F*F	4.2964×10^{-4}	1.5368×10^{-8}	1.2397×10^{-4}		0.003			
	F	-0.0582	4.6904×10^{-4}	0.0217		0.0156			
	CONST.	-1.8855	3.4221	1.8499		0.3224			

IV. CONCLUSION

This experimental study aimed to determine the optimal combination of Spindle Speed, Depth of Cut and Feed Rate for obtaining maximum Material Removal Rate (MRR). Taguchi's Method was employed to obtain the optimal settings of control variables. Analysis of Variance (ANOVA) was utilized for identifying statistically significant differences in the samples and to assess the impact of control parameters on MRR. The subsequent inferences were concluded from the analysis of the results:

1. Through Taguchi's Signal-to-Noise (S/N) Ratio calculation and graphical analysis, it was deduced that the ideal combination of control parameters for maximizing MRR are as follows: Spindle Speed 1000 rpm, Depth of Cut 0.1 mm, and Feed Rate 50 mm/min.
2. ANOVA revealed that Depth of Cut exerted the maximum impact amongst the control parameters, with a confidence level of 95%.
3. Contribution of each control parameter on MRR as determined by ANOVA analysis, is as follows: a) Spindle Speed: 4.87% b) Depth of Cut: 71.76% c) Feed Rate: 20.26%
4. A Mathematical Model was designed with Multivariate Polynomial Regression Method to predict Material Removal Rate (MRR) based on Spindle Speed, Depth of Cut and Feed Rate. The developed model demonstrated high prediction accuracy.

In this research effort, only performance metric of MRR was conducted. Surface roughness and tool wear were not considered due to limited resources. However, keeping in mind their values, both these parameters will be included for multi-objective optimization in future study.

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