

# Integrated Taguchi and Grey Relational Optimization of CNC Drilling Process Parameters

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## Abstract

The appropriate selection of machining parameters plays a vital role in enhancing productivity, improving surface finish, and reducing machining costs in drilling operations. The present study focuses on optimizing spindle speed, feed rate, depth of cut, and drill diameter to improve Material Removal Rate (MRR) and minimize surface roughness. Experimental investigations were conducted on EN 36 steel using a CNC drilling machine equipped with carbide-coated HSS twist drills, following an L16 orthogonal array based on the Taguchi design. Signal-to-Noise (S/N) ratio analysis was employed to identify the optimal parameter settings for the individual performance characteristics. Analysis of Variance (ANOVA) was subsequently performed to assess the statistical significance and relative contributions of the selected machining parameters. To achieve simultaneous optimization of MRR and surface roughness, Grey Relational Analysis (GRA) was implemented to convert the multiple-response problem into a single Grey Relational Grade (GRG). Based on the GRG analysis, the optimal machining conditions were determined as a spindle speed of 2500 rpm, a feed rate of 100 mm/min, a depth of cut of 15 mm, and a drill diameter of 18 mm. The ANOVA findings indicated that depth of cut was the most significant factor influencing the overall drilling performance, followed by drill diameter, spindle speed, and feed rate. The results demonstrate the applicability of integrating Taguchi methodology, ANOVA, and GRA for optimizing multiple performance characteristics in the drilling of EN 36 steel.

**Keywords:** EN 36 steel, Taguchi method, Analysis of Variance, Grey Relational Analysis, Material Removal Rate, Surface Roughness.

## 1. Introduction

Drilling is one of the most widely used machining operations for producing holes with the required dimensional accuracy and surface integrity in metallic alloys and composite materials. It plays a significant role in manufacturing components for aerospace, automotive, marine, and other engineering applications, where hole quality directly influences component performance, reliability, and service life. However, achieving high-quality drilled holes remains challenging because drilling performance is influenced by several factors, including cutting speed, feed rate, drill diameter, tool geometry, tool material, coating, and cooling conditions. Improper selection of these parameters may lead to increased

thrust force and torque, poor surface finish, dimensional deviations, tool wear, and material damage such as delamination in fibre-reinforced composites. Therefore, systematic investigation and optimization of drilling parameters are essential for improving machining efficiency, product quality, and tool life. Several researchers have investigated drilling performance across different materials using experimental design, statistical analysis, and predictive modelling techniques. Taguchi methods have been widely employed to identify optimal machining conditions with a reduced number of experimental trials, while analysis of variance (ANOVA) has been used to determine the relative significance of individual process parameters. Response surface methodology (RSM) has facilitated the development of mathematical models and the evaluation of interactions between machining variables and performance responses. The following literature review presents the contributions of previous studies by highlighting their investigated materials, adopted methodologies, key process parameters, and major findings.

Adem Cicek, Turgay Kivak et al. [1] optimised AISI 316 stainless steel drilling using Taguchi L8 design and regression analysis, demonstrating the effectiveness of deep cryogenic treatment in improving surface quality and roundness. A. Navanth and T. Karthikeya Sharma [2] optimised Al 2014 drilling parameters using Taguchi and ANOVA to improve surface roughness and hole diameter accuracy. M. A. Amrana et al. [3] applied RSM to investigate the effects of spindle speed, feed rate, and drill diameter on hole surface roughness and texture. Murthy B. R. N. et al. [4] combined Taguchi and RSM to evaluate the effects of drilling parameters on thrust force and torque during GFRP composite drilling. S. Madhavan et al. [5] compared HSS, carbide, and PCD drills for CFRP drilling and developed an RSM model to predict thrust force. Yogendra Tyagi et al. [6] applied Taguchi methodology to investigate the influence of spindle speed, feed rate, and depth of cut on surface roughness and MRR. S. Jayabal et al. [7] developed a mathematical model to analyze the effects of spindle speed, feed rate, and drill point angle on thrust force and torque during GFRP drilling. B. Ramesh et al. [8] used Taguchi and ANOVA to optimize drilling parameters for minimizing surface roughness and delamination in GFRP composites. A. Navanth and T. Karthikeya Sharma [9] optimised Al 2014 drilling parameters using Taguchi methodology to improve hole surface roughness and diameter accuracy. Vishwajeet N. et al. [10] applied Taguchi and ANOVA to optimize drilling parameters for minimizing surface roughness and maximizing tool life in hardened boron steel. Evren Kabakli et al. [11] investigated the influence of hole geometry, feed rate, and cutting speed on dimensional accuracy, perpendicularity, and cylindricity in drilling. Biren Desai et al. [12] identified spindle speed and feed rate as important parameters for controlling circularity and hole size during defect-free drilling. Godfrey C. Onwubolu et al. [13] developed an RSM-based mathematical model to predict axial force and torque during aluminium alloy drilling. Erol Kilickap et al. [14] examined the effects of cutting speed, feed rate, and cutting environment on surface roughness during AISI 1045 steel drilling. P. Venkataramaiah et al. [15] developed an ANN model combined with Taguchi optimization to predict multiple drilling responses, including torque, cutting force, surface roughness, MRR, and power. P. Venkataramaiah et al. [16] developed an ANN model to predict multiple responses during drilling of EN8 steel using coated tools. N. Keerthi et al. [17] integrated Taguchi methodology and ANN to predict and optimize drilling performance in EN8 steel. Indumathi V. et al. [18] applied desirability function analysis to optimize spindle speed, feed rate, and cone radius ratio during thermo-mechanical form drilling of AA1100 aluminium sheets. Bhemappa S. et al. [19] investigated the effects of cutting speed, feed rate, and drill type on thrust force and torque in particle-filled glass fabric-reinforced epoxy composites. K. Giasin et al. [20] examined drilling forces in GLARE fibre-metal laminates using TiAlN-coated carbide drills and evaluated the influence of feed rate, spindle speed, and fibre orientation.

J. Pradeep Kumar and P. Packiaraj [21] used Taguchi, ANOVA, and regression analysis to evaluate drilling parameters affecting surface finish, tool wear, and MRR in OHNS steel. Reddy Sreenivasulu [22] combined Taguchi methodology and ANN to optimize drilling parameters for minimizing surface roughness in Al 6061. Yogendra Tyagi, Vedansh Chaturvedi et al. [23] applied Taguchi L9 design to optimize spindle speed, feed rate, and depth of cut for improving MRR and surface finish during mild steel drilling. M. Sundeeep, M. Sudhahar et al. [24] investigated AISI 316 stainless steel drilling using Taguchi L9 design and identified the influence of spindle speed on surface finish and MRR. Nisha Tamta and R. S. Jadoun [25] applied Taguchi and ANOVA to optimize spindle speed, feed rate, and drilling depth for surface roughness in aluminium alloy 6082. A. Munia Raj et al. [26] used RSM to optimize drilling parameters for minimizing surface roughness in Al6061/SiC/graphite hybrid composites. Kapil Kumar Goyal et al. [27] applied RSM and ANOVA to optimize abrasive-assisted drilling of SS304, demonstrating improved surface finish using abrasive slurry. C. C. Tsao et al. [28] combined Taguchi methodology and ANN to predict thrust force and surface roughness during composite drilling, demonstrating the effectiveness of radial basis function networks. Kadam Shirish and M. G. Rathi [29] applied Taguchi methodology to optimize cutting speed, feed rate, and hole depth for improved surface roughness and tool life in EN24 steel. Turgay Kivak, Gurcan Samtas et al. [30] used Taguchi L16 design and ANOVA to assess the effects of coated and uncoated drills, cutting speed, and feed rate on AISI 316 drilling performance. B. Shivapragash, K. Chandrasekaran et al. [31] combined Taguchi and grey relational analysis to optimize drilling parameters for improved surface finish in Al-TiB<sub>2</sub> composites. Nalawade P. S. and Shinde S. S. [32] applied Taguchi, ANOVA, and regression analysis to optimize cutting parameters for improved surface finish and hole accuracy in dry-drilled EN31 steel. Samar Singh and Mukesh Verma [33] applied Taguchi L27 design and ANOVA to optimize electrical discharge drilling parameters for maximizing MRR in Al7075. Sathish Rao U. and Lewlyn L. R. Rodrigues [34] used Taguchi, ANOVA, and regression analysis to evaluate the effects of drilling parameters on tool wear in GFRP composites under dry conditions. Sonbaty et al. [35] investigated the influence of cutting speed, feed rate, drill diameter, and fibre volume fraction on thrust force, torque, and surface roughness during fibre-reinforced composite drilling.

## 2. Methodology

The use of Taguchi method with grey relational analysis to optimize drilling parameters with multiple process response characteristics includes the following steps:

- Identify the performance characteristics and cutting parameters to be evaluated.
- Determine the number of levels for the process parameters.
- Select the appropriate orthogonal array and assign the cutting parameters to the orthogonal array.
- Conduct the experiments based on the arrangement of the orthogonal array.
- Normalize the experiment results.
- Perform grey relational generating and calculate the grey relational coefficient.
- Calculate the grey relational grade by averaging the grey relational coefficient.
- Analyze the experimental results using the grey relational grade and statistical ANOVA.
- Select the optimal levels of cutting parameters.

In grey relational analysis, experimental data i.e. measured features of quality characteristics are first normalized ranging from zero to one. The process is known as grey relational generation. Next, based on

normalized experimental data, grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses. The overall performance characteristic of the multiple response process depends on the calculated grey relational grade. This approach converts a multiple response process optimization problem into a single response optimization situation with the objective function is overall grey relational grade. The optimal parametric combination is then evaluated which would result into highest grey relational grade. The optimal factor setting for maximizing overall grey relational grade can be performed by Taguchi method.

## Data Pre-Processing:

In grey relational analysis, the data pre-processing is the first step performed to normalize the random grey data with different measurement units to transform them to dimensionless parameters. Thus, data pre-processing converts the original sequences to a set of comparable sequences. Different methods are employed to pre-process grey data depending upon the quality characteristics of the original data. If the original sequence data has quality characteristic as 'larger-the-better' then the original data is pre-processed as 'larger-the-best':

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}$$

If the original data has the quality characteristic as 'smaller-the better', then original data is pre-processed as 'smaller-the-best':

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}$$

Here  $x_i(k)$  is the value after grey relational generation,  $\min y_i(k)$  is the smallest value of  $y_i(k)$  for the  $k^{\text{th}}$  response, and  $\max y_i(k)$  is the largest value of  $y_i(k)$  for the  $k^{\text{th}}$  response.

## Deviation Sequencing:

Deviation sequencing is calculated for the obtained pre-processing data by considering ideal value 1. Deviation sequencing can be calculated by using the following formula

$$\Delta_{0i} = 1 - x_i(k),$$

Where  $\Delta_{0i}$  = Deviation sequencing for the  $k^{\text{th}}$  pre-process data and  $x_i(k)$  =  $k^{\text{th}}$  pre-process value.

## Grey Relational Coefficient [ $\xi_i(k)$ ]

In the next step coefficient  $\xi_i$  is calculated for all the obtained deviational sequencing data individually, Grey relational coefficient  $\xi_i(k)$  is calculated using the formula:

$$\xi_i(k) = \frac{\Delta_{\min} + \psi \Delta_{\max}}{\Delta_{0i}(k) + \psi \Delta_{\max}}$$

Where  $\psi$  is the distinguishing coefficient  $0 \leq \psi \leq 1$ , therefore  $\psi$  is take as 0.5

$\Delta_{0i}(k)$  = Deviation sequencing of  $k^{\text{th}}$  value

$\Delta_{\max}$  = Maximum deviation value form the  $k^{\text{th}}$  deviation values

$\Delta_{\min}$  = Minimum deviation value form the  $k^{\text{th}}$  deviation values

## Grey Relational Grade:

After obtaining the grey relational coefficient in final step relational grade is calculated by the following formula. Here n is the number of process responses.

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k)$$

The higher value of grey relational grade corresponds to intense relational degree between the reference sequence  $x_0(k)$  and the given sequence  $x_i(k)$ . The reference sequence  $x_0(k)$  represents the best process sequence; therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal. The mean response for the grey relational grade with its grand mean and the main effect plot of grey relational grade are very important because optimal process condition can be evaluated from this plot. For getting the contribution of each parameter ANOVA is performed by using Statistical tool and Taguchi analysis is done to find out S/N ratio, for each grey relational grade value. Optimal process parameters and their predicted values are calculated. And confirmatory test is carried out to compare the S/N ratio of obtained with the predicted S/N ratio.

## 3. Experimentation

EN36 steel was selected as the workpiece material for the present investigation. The mechanical properties and chemical composition of EN36 steel are presented in Tables 1 and 2, respectively. The drilling experiments were conducted using a CNC AGNI BMV 45 T20 machine, following Taguchi's L16 orthogonal array (OA) experimental design. Four machining parameters, namely spindle speed, feed rate, depth of cut, and drill diameter, were considered as the process variables, each at four different levels. The L16 orthogonal array was employed to systematically design the experimental trials and evaluate the influence of these machining parameters on the selected performance responses while minimizing the number of experiments required.

**Table 1: Mechanical Properties of EN 36**

| Density (g/cm <sup>3</sup> ) | Tensile Strength (N/mm <sup>2</sup> ) | Yield Strength (N/mm <sup>2</sup> ) | Elongation (%) | Hardness (BHN) |
|------------------------------|---------------------------------------|-------------------------------------|----------------|----------------|
| 7.8                          | 1100                                  | 950                                 | 15             | 341            |

**Table 2: Chemical Composition of EN 36**

| Element    | Carbon       | Manganese    | Silicon      | Nickel       | Chromium     | Sulphur & Phosphorous |
|------------|--------------|--------------|--------------|--------------|--------------|-----------------------|
| Weight (%) | 0.12 - 0.18% | 0.30 - 0.60% | 0.10 - 0.35% | 3.00 - 3.75% | 0.60 - 1.10% | 0.00 - 0.05%          |



**Figure 1: CNC Machine AGNI BMV 45 T20**

**Table 3: Process Parameters and their levels**

| Parameter          | Units  | Level-1 | Level-2 | Level-3 | Level-4 |
|--------------------|--------|---------|---------|---------|---------|
| Spindle Speed (n)  | rpm    | 1000    | 1500    | 2000    | 2500    |
| Feed rate (fr)     | mm/min | 50      | 150     | 200     | 250     |
| Depth of cut (d)   | mm     | 6       | 8       | 12      | 15      |
| Drill diameter (D) | mm     | 10      | 12      | 15      | 18      |

**Table 4: L16 Orthogonal array with Control factors**

| Experiment No. | Spindle Speed | Feed rate | Depth of cut | Drill Dia |
|----------------|---------------|-----------|--------------|-----------|
| 1              | 1000          | 50        | 6            | 10        |
| 2              | 1000          | 100       | 9            | 12        |
| 3              | 1000          | 150       | 12           | 15        |
| 4              | 1000          | 200       | 15           | 18        |
| 5              | 1500          | 50        | 9            | 15        |
| 6              | 1500          | 100       | 6            | 18        |
| 7              | 1500          | 150       | 15           | 10        |
| 8              | 1500          | 200       | 12           | 12        |
| 9              | 2000          | 50        | 12           | 18        |
| 10             | 2000          | 100       | 15           | 15        |
| 11             | 2000          | 150       | 6            | 12        |
| 12             | 2000          | 200       | 9            | 10        |
| 13             | 2500          | 50        | 15           | 12        |
| 14             | 2500          | 100       | 12           | 10        |
| 15             | 2500          | 150       | 9            | 18        |
| 16             | 2500          | 200       | 6            | 15        |

#### 4. Results and Discussion

Taguchi analysis method can optimize a single objective function; it cannot solve multi-objective optimization problem. So, MRR and Surface roughness can be optimized individually by using this Taguchi technique. But it may so happen that, the optimal setting for a response variable cannot ensure other response variables within acceptable limits. So, one should go for such an optimal parameter setting so that all the objectives should fulfill simultaneously; (maximum MRR, and minimum Surface roughness). These will be achieved using grey based Taguchi method as discussed below. This method can convert several objective functions into an equivalent single objective function (representative of all desired response characteristics of the product/process), which would be maximized next. Table 5 shows the process responses of experiment trials.

**Table 5: Process Responses**

| Exp. No | MRR<br>mm <sup>3</sup> /min | Average Surface roughness R <sub>a</sub> (μm) |
|---------|-----------------------------|-----------------------------------------------|
| 1       | 471                         | 7.33                                          |
| 2       | 1017                        | 4.97                                          |
| 3       | 2120                        | 4.96                                          |
| 4       | 2200                        | 3.93                                          |
| 5       | 1300                        | 3.8                                           |
| 6       | 1526                        | 5.13                                          |
| 7       | 1178                        | 4.25                                          |
| 8       | 1200                        | 4.89                                          |
| 9       | 3052                        | 6.06                                          |
| 10      | 1900                        | 3.76                                          |
| 11      | 678                         | 7.25                                          |
| 12      | 707                         | 6.39                                          |
| 13      | 1696                        | 3.92                                          |
| 14      | 800                         | 4.73                                          |
| 15      | 2000                        | 3.9                                           |
| 16      | 1060                        | 5.68                                          |

#### Grey Relational Analysis

**Step 1: Pre-processing data:** The obtained process responses are pre-processes in the first step as explained. Table 6 shows the Pre-processing data for each individual response.

**Table 6. Pre-processing data**

| Exp. No | MRR<br>mm <sup>3</sup> /min | Average Surface roughness R <sub>a</sub> (μm) |
|---------|-----------------------------|-----------------------------------------------|
| 1       | 0.0000                      | 0.0000                                        |
| 2       | 0.2117                      | 0.6611                                        |
| 3       | 0.6387                      | 0.6639                                        |
| 4       | 0.6699                      | 0.9524                                        |
| 5       | 0.3212                      | 0.9888                                        |

|    |        |        |
|----|--------|--------|
| 6  | 0.4088 | 0.6162 |
| 7  | 0.2737 | 0.8627 |
| 8  | 0.2824 | 0.6835 |
| 9  | 1.0000 | 0.3557 |
| 10 | 0.5537 | 1.0000 |
| 11 | 0.0803 | 0.0224 |
| 12 | 0.0912 | 0.2633 |
| 13 | 0.4745 | 0.9552 |
| 14 | 0.1275 | 0.7283 |
| 15 | 0.5924 | 0.9608 |
| 16 | 0.2281 | 0.4622 |

**Step 2: Sequencing deviation ( $\Delta_{oi}$ ):** Deviation sequencing is calculated for the obtained pre-processing data by considering ideal value 1. Results of sequencing deviation are shown in the Table 7.

**Table 7. Sequencing deviation ( $\Delta_{oi}$ ) Ideal Value=1**

| Exp. No | MRR<br>mm <sup>3</sup> /min | Average Surface roughness $R_a$<br>( $\mu$ m) |
|---------|-----------------------------|-----------------------------------------------|
| 1       | 1.0000                      | 1.0000                                        |
| 2       | 0.7883                      | 0.3389                                        |
| 3       | 0.3613                      | 0.3361                                        |
| 4       | 0.3301                      | 0.0476                                        |
| 5       | 0.6788                      | 0.0112                                        |
| 6       | 0.5912                      | 0.3838                                        |
| 7       | 0.7263                      | 0.1373                                        |
| 8       | 0.7176                      | 0.3165                                        |
| 9       | 0.0000                      | 0.6443                                        |
| 10      | 0.4463                      | 0.0000                                        |
| 11      | 0.9197                      | 0.9776                                        |
| 12      | 0.9088                      | 0.7367                                        |
| 13      | 0.5255                      | 0.0448                                        |
| 14      | 0.8725                      | 0.2717                                        |
| 15      | 0.4076                      | 0.0392                                        |
| 16      | 0.7719                      | 0.5378                                        |

**Step 3: Grey relational coefficient ( $\xi_i(k)$ ):** In the next step coefficient  $\xi_i$  is calculated for all the obtained deviational sequencing data individually, Grey relational coefficient  $\xi_i(k)$  is calculated. Grey Relational Coefficients are shown in the Table 8.

**Table 8: Grey relational coefficient ( $\xi_i(k)$ )**

| Exp. No | MRR<br>mm <sup>3</sup> /min | Average Surface roughness<br>$R_a$<br>( $\mu$ m) | Grey Relational Grade |
|---------|-----------------------------|--------------------------------------------------|-----------------------|
| 1       | 0.333333                    | 0.333333                                         | 0.333333              |

|    |          |          |          |
|----|----------|----------|----------|
| 2  | 0.388104 | 0.595993 | 0.533323 |
| 3  | 0.580522 | 0.597990 | 0.543537 |
| 4  | 0.602334 | 0.913043 | 0.829528 |
| 5  | 0.424158 | 0.978082 | 0.818929 |
| 6  | 0.458199 | 0.565769 | 0.559102 |
| 7  | 0.407741 | 0.784615 | 0.679230 |
| 8  | 0.410660 | 0.612350 | 0.550679 |
| 9  | 1.000000 | 0.436965 | 0.589097 |
| 10 | 0.528352 | 1.000000 | 0.800524 |
| 11 | 0.352186 | 0.338389 | 0.348060 |
| 12 | 0.354923 | 0.404304 | 0.405055 |
| 13 | 0.487551 | 0.917738 | 0.764198 |
| 14 | 0.364291 | 0.647913 | 0.588084 |
| 15 | 0.550907 | 0.927273 | 0.858483 |
| 16 | 0.393116 | 0.481781 | 0.455350 |

**Step 4: Grey Relational Grade,** from the obtained coefficients in Table 9, the grey relational grade is calculated.

**Step 5: Taguchi for Grey Relational Grade:** In the final step, the obtained Grey relational grade has been analyzed by using Taguchi and ANOVA to obtain the optimal process parameter level.

**Table 9: Response Table for Signal to Noise Ratios**

| Level | Spindle Speed | Feed          | Depth of Cut  | Drill Diameter |
|-------|---------------|---------------|---------------|----------------|
| 1     | -5.480        | -4.552        | -7.648        | -6.341         |
| 2     | -3.832        | <b>-4.264</b> | -4.093        | -5.536         |
| 3     | -5.886        | -4.787        | -4.921        | -3.949         |
| 4     | <b>-3.776</b> | -5.372        | <b>-2.313</b> | <b>-3.149</b>  |
| Delta | 2.110         | 1.109         | 5.335         | 3.192          |
| Rank  | 3             | 4             | 1             | 2              |

Optimal parameters from Table 9, by Taguchi design for Grey relational grade are Spindle speed = 2500 rpm, feed = 100 mm/min, Depth of cut = 15 mm and Drill diameter = 18 mm. The corresponding levels and optimal process parameters are shown in Table 10.

**Table 10: Optimal process parameters for MRR and Surface roughness**

| Parameters     | Level          | Level Description |
|----------------|----------------|-------------------|
| Spindle speed  | A <sub>4</sub> | 2500              |
| Feed           | B <sub>2</sub> | 100               |
| Depth of Cut   | C <sub>4</sub> | 15                |
| Drill diameter | D <sub>4</sub> | 18                |

#### 4.1. Analysis of variance for Grey Relational Grade

From the ANOVA table 11, the most significant factors that affect the both MRR and Surface roughness are in Depth of cut, Drill Diameter, Spindle speed and feed respectively. Based on the percentage of

contribution it can be said that Depth of cut has more affect on MRR and Surface roughness. The percentage contribution of Depth of Cut is 61.47%. The following graph shows in Figure 2 the Taguchi optimal parameters for MRR and Surface roughness. The graph shows the effect of each parameter on the process response.

**Table 11: Results of ANOVA for Grey Relational Grade**

| Source         | DF | Adj SS  | Adj MS   | F-Value | P-Value | % Contribution |
|----------------|----|---------|----------|---------|---------|----------------|
| Spindle speed  | 3  | 0.05128 | 0.017094 | 2.26    | 0.260   | 12.43%         |
| Feed           | 3  | 0.01079 | 0.003598 | 0.48    | 0.721   | 2.64%          |
| Depth of Cut   | 3  | 0.25293 | 0.084310 | 11.17   | 0.039   | 61.47%         |
| Drill diameter | 3  | 0.10853 | 0.036178 | 4.79    | 0.115   | 26.36%         |
| Error          | 3  | 0.02265 | 0.007550 |         |         |                |
| Total          | 15 | 0.44619 |          |         |         |                |

S = 0.0868882 R-Sq = 94.92% R-Sq (adj) = 74.62%

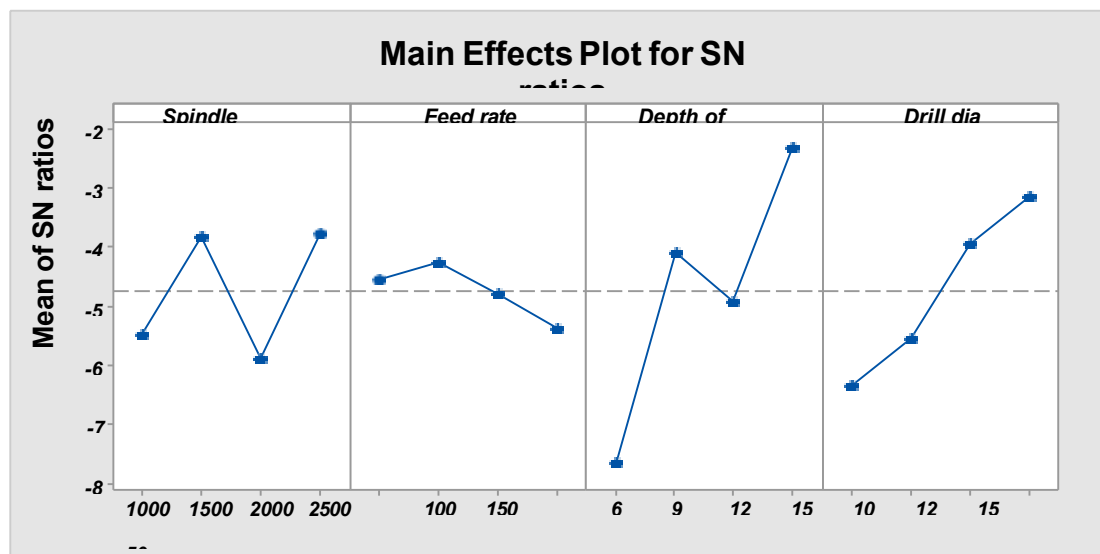


**Figure 2: Main effect plot for Grey relational grade (MRR, Ra, Rq, Rz)**

## 5. Conclusions

Based on the results obtained and discussion made in the earlier chapters the following conclusions are drawn:

- The Optimal combination of the process parameters that enhances the material removal rate is obtained at spindle speed: 2500 rpm, feed rate: 150 mm/min, depth of cut: 15 mm, and drill diameter: 18 mm, respectively.
- ANOVA for MRR revealed that Drill diameter has the greatest influence on MRR (Material removal rate), followed by Depth of cut, Feed rate, and Spindle speed.
- The Optimal combination of the process parameters that enhances the surface roughness is obtained at spindle speed: 1500 rpm, feed rate: 100 mm/min, depth of cut: 15 mm, and drill diameter: 15 mm respectively.

- ANOVA for  $R_a$  revealed that Depth of cut has a stronger influence on Average Surface Roughness ( $R_a$ ), whereas Spindle speed has a medium influence, followed by Drill diameter and feed rate.
- The Optimal combination of the process parameters that attains higher grey relational grade for the multiple responses is found at spindle speed: 2500 rpm, feed rate: 100 mm/min, depth of cut: 15 mm, and drill diameter: 18 mm, respectively.
- ANOVA for the Grey Relational Grade indicated that depth of cut has the greatest influence in the machining process, followed by Drill diameter, Spindle speed, and feed.

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