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# Influence of Speed, Feed and Depth of Cut on Multiple Responses in CNC Turning

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***Abstract***

*This paper presents the multi objective optimization of material removal rate (MRR) and surface roughness ($R_a$) in dry turning of AA7075 using tungsten carbide insert and also finds correlations. The experiments have been conducted as per Taguchi's L9 orthogonal array design with three process parameters, namely speed, feed and depth of cut. Taguchi based grey relational grade method has been applied to optimize the multiple responses. Multiple linear regression analysis was used to find the correlations. Based on the signal-to-noise (S/N) ratios of the grey relational grade the optimal parametric combination of multi responses (material removal rate and surface roughness) is found at v3-f1-d3 i.e. speed at 2000 rpm, feed at 0.2 mm/rev and depth of cut at 1 mm. The feed is found to be the most significant parameter in effecting the multi responses at 95% confidence level followed by the depth of cut and speed has the least significance from Analysis of variance (ANOVA) study. Mathematical models have been developed for the responses using regression analysis. The regression models developed are statistically significant and adequate because of higher $R^2$ (MRR = 96.2%, $R_a$ = 98.1) value. The normal probability plot vs. residuals of the model shows that the residuals are lying close to a straight line implying that the terms mentioned in the model are significant. The predicted values from the models are compared with the experimental values and they found very close to each other showing significance of the models developed.*

***Key words:*** *AA7075, Material Removal Rate (MRR), Surface Roughness ($R_a$), Taguchi, ANOVA, Grey Analysis, Regression Analysis*

## 1. Introduction

The manufacturing industries are continuously challenged in achieving a high material removal rate and good surface quality in order to remain competitive in the market. Higher material removal rate is desired by the industry to cope up with mass production and it can be achieved through increasing the cutting parameters like speed, feed and depth of cut. [1-5] But, with an increase in cutting parameters cutting temperature will increase. This increase in temperature causes dimensional inaccuracies by thermal deformation and damages the tool. So, selection of appropriate cutting parameters and cutting tool play important roles in the effectiveness, efficiency and overall economy of manufacturing by machining to achieve a higher material removal rate and low surface roughness. Tungsten carbide tools have been developed to meet high speeds for maximum productivity and good surface quality. Carbide tools have properties like high hardness, high elastic modulus, thermal conductivity and low thermal expansion, *etc*. [6-7] In case of machining, surface quality is the most important requirements of the customer. Surface roughness also influences the properties such as appearance, corrosion resistance, wear resistance, fatigue resistance, lubrication, initial tolerance, ability to hold pressure, load

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carrying capacity, noise reduction in case of gears, *etc.*, surface roughness mainly depends on the factors like material of the workpiece, type of machining, rigidity of the system consisting of machine tool, fixture cutting tool and work, type and material of cutting tool, cutting conditions *i.e.*, speed, feed and depth of cut and type of coolant used *etc.* [8-11]

As the material removal rate and surface roughness depend on several factors, it is impossible to consider all the factors for conducting the experiment. The number of experiment increases with increase of process parameters and takes lots of time and cost. To solve this problem Denichi Taguchi has proposed a design called an orthogonal array. OA covers the entire parametric space with the least number of experiments. [12-18] Taguchi method can be used for single objective problems only, for the multi objective optimization Taguchi based grey method was invented by deng. It is useful for dealing the problems with poor, insufficient and uncertain information. Grey theory is a powerful optimization tool to analyze the process with multiple output characteristics. The theory does not attempt to find the best solution, but provides techniques for determining a good solution. From grey analysis, we will obtain a single parametric combination that optimizes the overall process. It can also be used to identify the most influencing factors affecting the output characteristics. In grey analysis a multi objective optimization problem can be converted into a single objective problem in terms of grey relational grade. [19-22] In case of production to maximize the gain of manufacturer, process parameters such as speed, feed and depth of cut needs to be optimized for individual and multi performance characteristics. The theoretical model for surface roughness is $R_a = f^2/32r$ where $R_a$ is surface roughness in microns, f is feed in mm/rev and r is nose radius in mm. This model only describes the effect of feed and nose radius on surface roughness. It does not provide any information about the effect of speed and depth of cut. Thus to improve the efficiency of the turning process, the mathematical model needs to be developed for complete understanding of the prediction of responses and their effect on variables. [23-24] The present work includes.

- Study on effect of speed, feed and depth of cut on material removal rate and surface roughness in turning of AA7075 alloy with tungsten carbide insert under dry environment using Taguchi’s standard L9 orthogonal array.
- Simultaneous optimization of material removal rate and surface roughness using the grey relational grade method.
- ANOVA has been done to find the significant factors.
- Development of mathematical models for the responses using regression analysis.

## 2. Experimental Procedure

### 2.1. Workpiece Material and Cutting Tool

The work material selected for the study is AA7075 alloy shown in Figure 1. The work specimens are of cylindrical shape having dimensions 30 mm diameter and 60 mm length. AA7075 has a wide range of applications in the field of manufacturing and aerospace applications. The chemical composition and mechanical properties of AA7075 alloy are given in the Tables 1 and 2. The cutting tool plays an important role in achieving better surface quality. In the present study, tungsten carbide insert having ISO designation DNMG160404 has been used for the experiments. Cutting tool was inserted in a tool holder having ISO designation PDJNL2525M16 as shown in Figure 2.

 

**Figure 1. AA7075 Workpiece**

**Table 1. Chemical Composition of AA7075 Steel**

| element | Al | Zn | Cu | Cr | Fe | Mg | Mn |
|---|---|---|---|---|---|---|---|
| Wt % | 87.1-91.4 | 5.1-6.1 | 1.2-2.0 | 0.18-0.28 | 0.5 max | 2.1-2.9 | 0.3 max |

**Table 2. Mechanical Properties of AA7075 Steel**

| parameter | Ultimate Tensile Strength (psi) | Yield Strength (psi) | Brinell (BHN) | Rockwell | Density ($gm/cm^3$) |
|---|---|---|---|---|---|
| Value | 83000 | 73000 | 150 | 1387 | 2.8 |

**Figure 2. Cutting Tool and Tool Holder**

### 2.2. Machine Tool Setup and Surface Roughness Measurement

The turning experiments were carried out on a CNC (Computer Numerical Control) lathe (DX 200, JOBBER XL) under dry environment. The setup for CNC turning is as shown in Figure 3. The surface roughness measurements were done by using Mitutoyo SJ301 (Measuring range: 350μm, Tip radius: 5μm, shape stylus: Diamond) as shown in Figure 4.

 

**Figure 3. Machine Tool Setup**

**Figure 4. Surface Roughness Measurement Setup**

### 2.3. Plan of Experiments

Taguchi's L9 orthogonal array (OA) for three factors at three levels was used for the experiments. L9 array design with actual values is given in the Table 3. Table 4 indicates the factors selected and their levels. The L9 OA has 3 columns and 9 rows. The plan of experiments is made of 9 tests, where the first column was assigned to the cutting speed. Similarly, second and third columns are assigned to feed and depth of cut respectively. The outputs studied were material removal rate and surface roughness.

 

**Table 3. L9 Orthogonal Array with Actual Parameters**

| Run no. | Factor (v) | Actual (v) rpm | Factor (f) | Actual (f) mm/rev | Factor (d) | Actual (d) mm |
|---|---|---|---|---|---|---|
| 1 | 1 | 1000 | 1 | 0.2 | 1 | 0.5 |
| 2 | 1 | 1000 | 2 | 0.3 | 2 | 0.75 |
| 3 | 1 | 1000 | 3 | 0.4 | 3 | 1 |
| 4 | 2 | 1500 | 1 | 0.2 | 2 | 0.75 |
| 5 | 2 | 1500 | 2 | 0.3 | 3 | 1 |
| 6 | 2 | 1500 | 3 | 0.4 | 1 | 0.5 |
| 7 | 3 | 2000 | 1 | 0.2 | 3 | 1 |
| 8 | 3 | 2000 | 2 | 0.3 | 1 | 0.5 |
| 9 | 3 | 2000 | 3 | 0.4 | 2 | 0.75 |

**Table 4. Selected Parameters with Their Levels**

| Parameter | units | Level-1 | Level-2 | Level-3 |
|---|---|---|---|---|
| Speed (v) | rpm | 1000 | 1500 | 2000 |
| Feed (f) | mm/rev | 0.2 | 0.3 | 0.4 |
| Depth of cut (d) | mm | 0.5 | 0.75 | 1 |

## 3. Grey Taguchi Optimization

In the present study, Taguchi based grey relational analysis has been used for the optimization of multi responses. The grey theory was proposed by Deng in 1982. In recent years, grey relational analysis has become a powerful tool for optimization of multiple responses. In grey analysis, experimental data are first normalized ranging from zero to one. This process is known as a grey relational generation. Next, based on normalized data, grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then the overall grey relational grade is determined by averaging the grey relational coefficients of responses. The overall performance characteristic of the multiple response process depends on the calculated grey relational grade. This method converts a multiple response optimization problem into a single response optimization problem, with the objective function as an overall grey relational grade. The optimal parametric combination is then evaluated by maximizing the overall grey relational grade.

### 3.1. Grey Relational Analysis

The experimental results of material removal rate and surface roughness values were given in the Table 5. The first step in grey analysis is to normalize the experimental data ranging from zero to one. For normalizing, Larger-the-better and Smaller-the-better characteristics were selected for material removal rate and surface roughness respectively and the values were given in the Table 6.

$$\text{Larger-the-better} = \frac{y_i(I) - \min y_i(I)}{\max y_i(I) - \min y_i(I)}$$

$$\text{Smaller-the-better} = \frac{\max y_i(I) - y_i(I)}{\max y_i(I) - \min y_i(I)}$$

Where, min $y_i(I)$ is the least value of $y_i(I)$ and max $y_i(I)$ is the highest value of the $I^{th}$ response where I = 1,2,3,4 for various output responses considered in a sequence.

 

**Table 5. Experimental Results of MRR and $R_a$**

| S.No. | Experimental results | |
|---|---|---|
| | MRR | $R_a$ |
| 1 | 9.21 | 2.11 |
| 2 | 24.85 | 5.023 |
| 3 | 32.57 | 9.17 |
| 4 | 20.57 | 2.036 |
| 5 | 39 | 7.16 |
| 6 | 24.85 | 11.59 |
| 7 | 41.14 | 3.35 |
| 8 | 27 | 7.25 |
| 9 | 39.85 | 11.75 |

**Table 6. Grey Relational Generation**

| S.No. | Grey relational generation | |
|---|---|---|
| | MRR (Larger-the better) | $R_a$ (Smaller-the-better) |
| 1 | 0 | 0.9923 |
| 2 | 0.4898 | 0.6925 |
| 3 | 0.7316 | 0.2655 |
| 4 | 0.3557 | 1 |
| 5 | 0.9329 | 0.4725 |
| 6 | 0.4898 | 0.01647 |
| 7 | 1 | 0.86473 |
| 8 | 0.557 | 0.4632 |
| 9 | 0.9595 | 0 |

The second step in grey analysis is evaluation of $\Delta_{oi}$ for each of the responses for calculation of grey relational coefficients. $\Delta_{oi}$ denotes the absolute values of the difference between $x_0(k)$ and $x_i$ (k) and the values are given in the Table 7.

$$\Delta_{oi} = \| x_o(k) - x_i(k) \|$$

**Table 7. Loss Function ($\Delta_{oi}$)**

| S.No. | Loss function | |
|---|---|---|
| | MRR | $R_a$ |
| 1 | 1 | 0.0077 |
| 2 | 0.5102 | 0.3075 |
| 3 | 0.2684 | 0.7345 |
| 4 | 0.645 | 0 |
| 5 | 0.068 | 0.5275 |
| 6 | 0.511 | 0.984 |
| 7 | 0 | 0.136 |
| 8 | 0.4429 | 0.537 |
| 9 | 0.041 | 1 |

Third step is the calculation of grey relational coefficients $\xi_i$ (k) using the formulae

$$\xi_i(k) = \frac{\Delta_{min} + \psi\,\Delta_{max}}{\Delta_{oi}(k) + \psi\,\Delta_{max}}$$

Where, $\Delta_{oi} = \|x_o(k) - x_i(k)\|$, the difference of the absolute value between $x_o$ (k) and $x_i$ (k). $\Delta_{min}$ and $\Delta_{max}$ are the minimum and maximum values of the absolute differences ($\Delta_{oi}$) of all comparing sequences. $\psi$ is a distinguishing coefficient, $0 \le \psi \le 1$. The turning process parameters are equally weighted and $\psi$ value is taken as 0.5.

Fourth step is the calculation of the grey relational grade $\gamma_i$ using the formulae

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

Where n is the number of process responses. Grey relational coefficients, grade and their order for each performance characteristics have been calculated and given in the table 8. Thus, the multi-response optimization problem has been transformed into a single equivalent objective function *i.e.*, grey relational grade using the combination of taguchi approach and grey relational analysis. The higher the value of grey relational grade, closer is the corresponding factor to the optimal.

**Table 8. GRC, GRG, S/N of GRG and Ranking**

| S.No. | Grey Coefficient | | Grey relational grade | S/N of GRG | Rank |
|---|---|---|---|---|---|
| | MRR | $R_a$ | | | |
| 1 | 0.333 | 0.9848 | 0.6592 | -3.6201 | 4 |
| 2 | 0.4949 | 0.6191 | 0.5571 | -5.0816 | 6 |
| 3 | 0.6507 | 0.405 | 0.5279 | -5.5493 | 7 |
| 4 | 0.4366 | 1 | 0.7185 | -2.8716 | 2 |
| 5 | 0.8802 | 0.4866 | 0.6842 | -3.2961 | 3 |
| 6 | 0.4945 | 0.3369 | 0.4160 | -7.6181 | 9 |
| 7 | 1 | 0.7861 | 0.8935 | -0.9777 | 1 |
| 8 | 0.53022 | 0.4821 | 0.5063 | -5.9119 | 8 |
| 9 | 0.9242 | 0.333 | 0.6293 | -4.0230 | 5 |

A graph is plotted by taking the experimental number on X-axis and grey relational grade on Y-axis and shown in the Figure 5. From the Figure 5, it is observed that seventh experiment gives the best multi performance characteristics among the nine experiments.

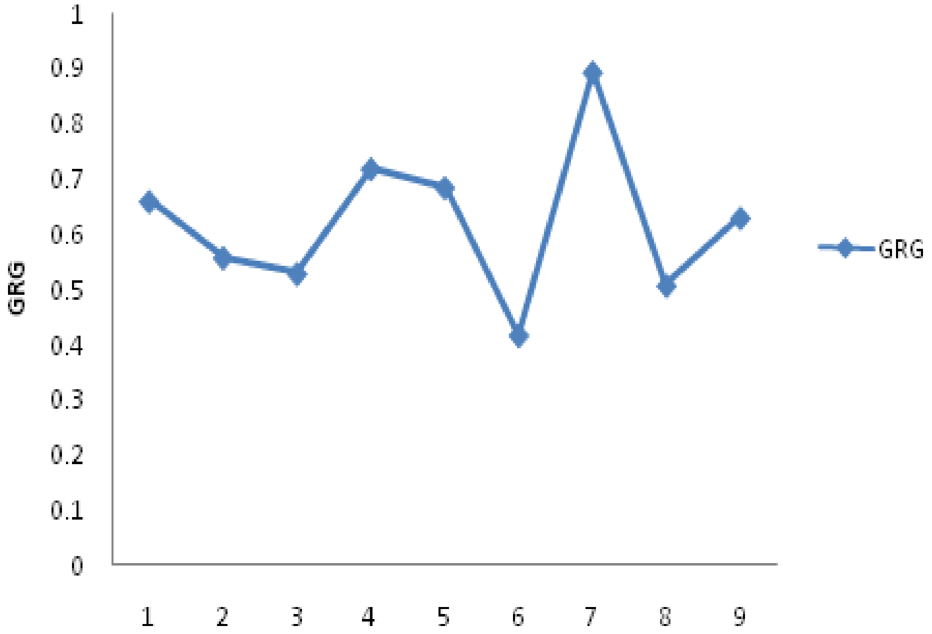


**Figure 5. GRG vs. Experiment Number**

The mean grey relational grade ratio for each level of the process parameters are given in the Table 9. From the Table 9, main effect plots were drawn and shown in Figures 6 and 7. The optimal combination of multiple performance characteristics is found at v3-f1-d3 and the corresponding optimum levels and values were given in the Table 10.

**Table 9. Mean Values of Grey Relational Grade Ratios**

| Level | v | f | d |
|---|---|---|---|
| 1 | 0.5814 | 0.7571 | 0.5272 |
| 2 | 0.6062 | 0.5825 | 0.6350 |
| 3 | 0.6764 | 0.5244 | 0.7019 |
| Delta | 0.0950 | 0.2327 | 0.1747 |
| Rank | 3 | 1 | 2 |

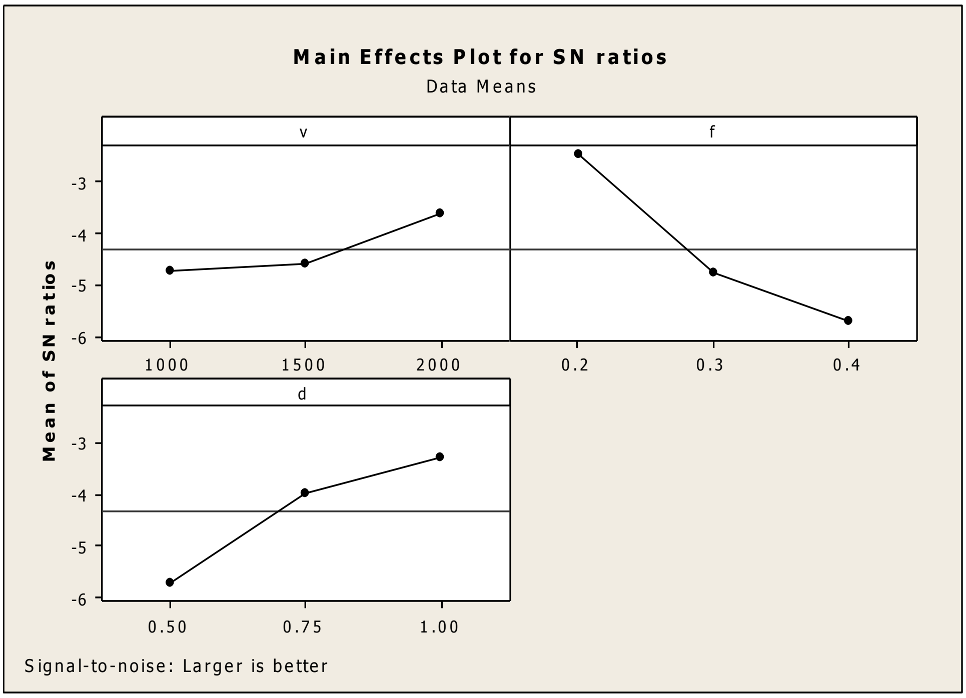


**Figure 6. Main Effects Plot for S/N Ratios of GRG**

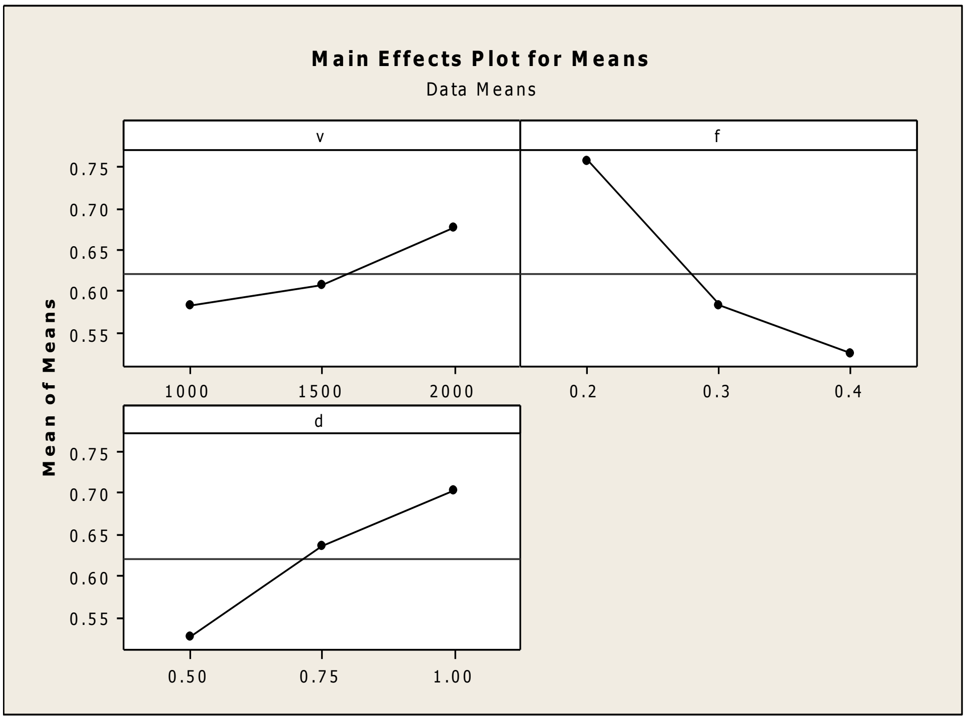


**Figure 7. Main Effect Plot for Means of GRG**

**Table 10. Optimal Combination of Parameters**

| Process parameter | Best level | Value |
|---|---|---|
| Speed (rpm) | 3 | 2000 |
| Feed (mm/rev) | 1 | 0.2 |
| Depth of cut (mm) | 3 | 1 |

### 3.2. ANOVA of Grey Relational Grade

The ANOVA table is performed taking data of grey relational grade and given in the table 11. Analysis was carried out for a significance level of $\alpha = 0.5$ *i.e.*, for a confidence level of 95%. From the table it is concluded that feed is the most significant factor for material removal rate and surface roughness together as F value is 10.90.

**Table 11. Analysis of Variance for Grey Relational Grade**

| Source | DOF | SS | MS | F | P |
|---|---|---|---|---|---|
| v | 2 | 0.014562 | 0.007281 | 1.80 | 0.357 |
| f | 2 | 0.087980 | 0.043990 | 10.90 | 0.084 |
| d | 2 | 0.046628 | 0.023314 | 5.78 | 0.148 |
| Error | 2 | 0.008070 | 0.004035 | | |
| Total | 8 | 0.157240 | | | |

### 3.3. Contour Plots of Grey Relational Grade

Figures 8 and 9 shows contour plots for Grey relational grade against speed (v), feed (f) and depth of cut (d). The dark green portion of the plots shows the maximum value of GRG and it is observed that the GRG found maximum at a high level of speed, low level of feed and high level of depth of cut.

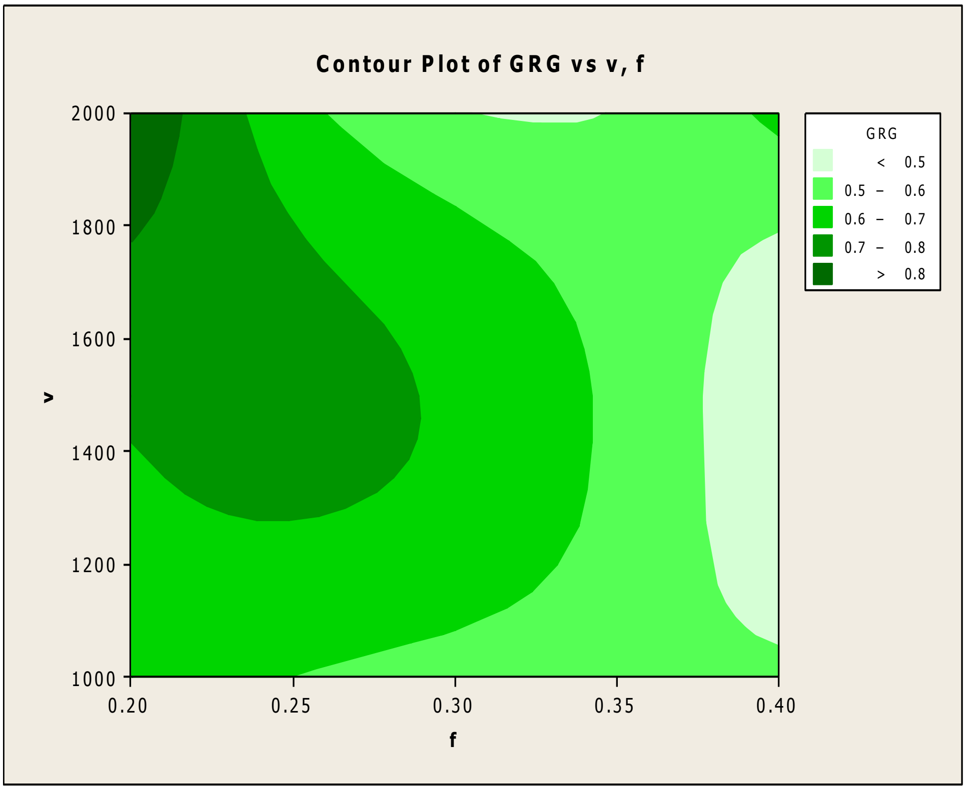


**Figure 8. Contour Plot of GRG vs Speed, Feed**

 

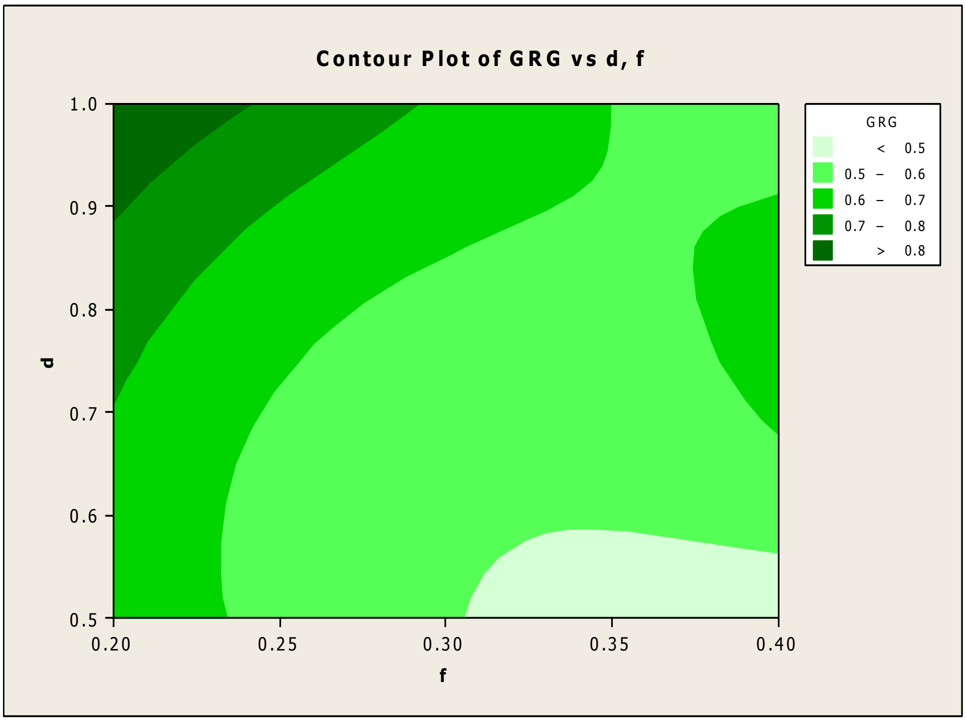


**Figure 9. Contour Plot of GRG vs. Depth of Cut, Feed**

### 3.4. Regression Analysis

From the experimental data, mathematical models for the material removal rate and surface roughness have been developed using multiple linear regression analysis. The dependent variable material removal rate (MRR) and surface roughness ($R_a$) can be conceived as a linear combination of the independent variables, cutting speed, feed and depth of cut. The data were analyzed by MINITAB-16 software. The adequacy of the model has been checked using correlation coefficient ($R^2$) and acceptance was based on high to very high coefficients of correlation. Developed models can be used for predict values of material removal rate and surface roughness from any combinations within the range of variable studied.

Material removal rate (MRR) model

When a regression analysis is employed applying the least squares method to the experimental data in order to obtain the coefficients of the equation, the following equation is attained for material removal rate.

$$MRR = -30.9 + 0.0138\ v + 43.9\ f + 34.4\ d$$
$R^2 = 96.2\%$, $R^2(Adj) = 94.0\%$

ANOVA is used for identifying the level of significance of the model developed. The F-test was used to determine the significance of the process parameters. If the calculated value of F-ratio is higher than the tabulated value of F-ratio, then the model is significant at desired α level. Depending on F-value P-value can be calculated. If the P-value for a term appears less than 0.05 (for 95% confidence level) then it can be concluded that the model is significant. Results of ANOVA of material removal rate are given in the Table 12. From the linear model, regression is significant as P-value (P = 0.001) is less than 0.05. The coefficient of determination, $R^2$ value is 96.2% indicating that the goodness of the fit of the model and high significance of the model.

 

**Table 12. Analysis of Variance for MRR Model**

| Source | DOF | SS | MS | F | P | Remarks |
|---|---|---|---|---|---|---|
| Regression | 3 | 845.45 | 281.82 | 42.54 | 0.001 | Significant |
| Residual Error | 5 | 33.13 | 6.63 | | | |
| Total | 8 | 878.57 | | | | |

The Normal probability plot vs. residuals and Versus fits for material removal rate are shown in the Figures 10 and 11, representing that the residuals lie reasonably close to a straight line and the residuals were randomly scattered within a constant variance. The experimental versus predicted values of material removal rate are shown in Figure 12 and they found to be close to each other. Thus the model developed using multiple regression analysis can be used to accurate prediction of the material removal rate.

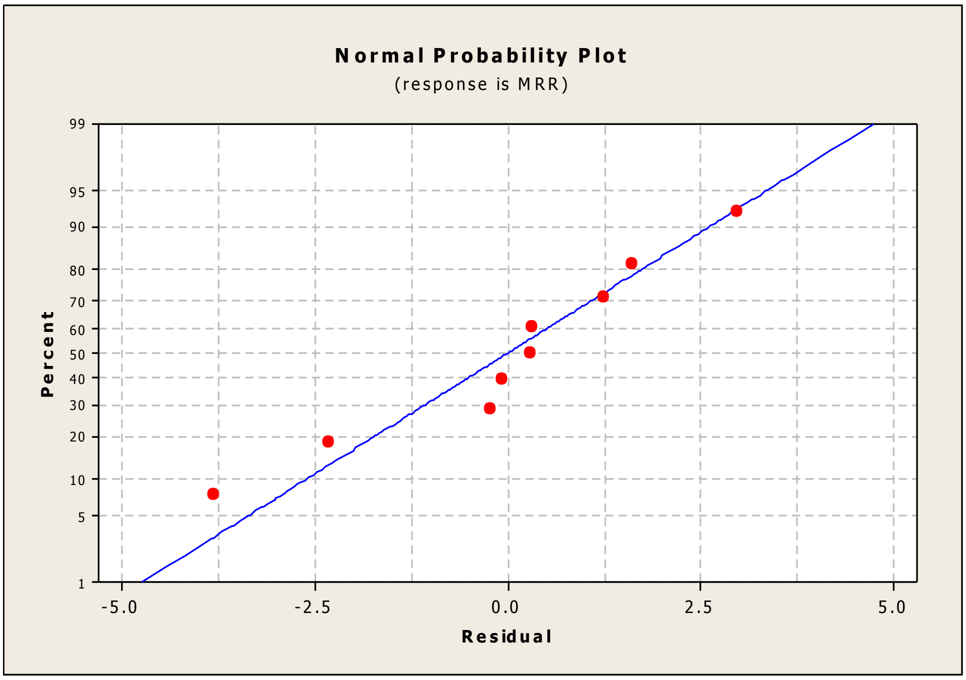


**Figure 10. Normal Probability Plot for MRR**

 

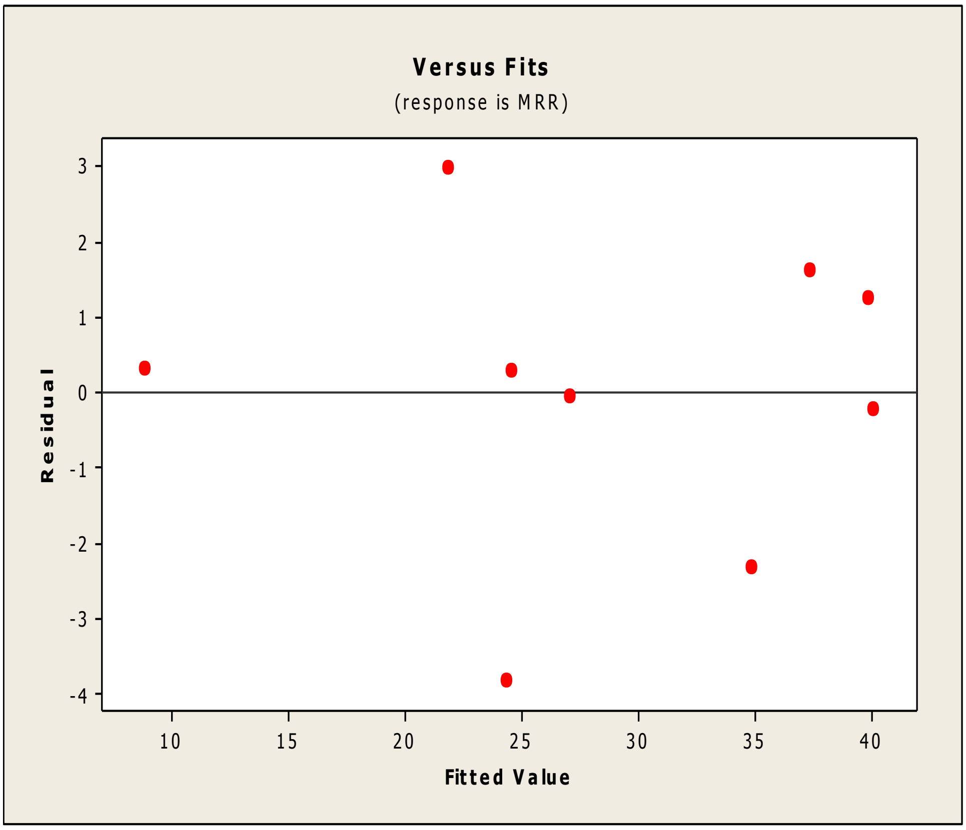


**Figure 11. Versus Fits Plot for MRR**

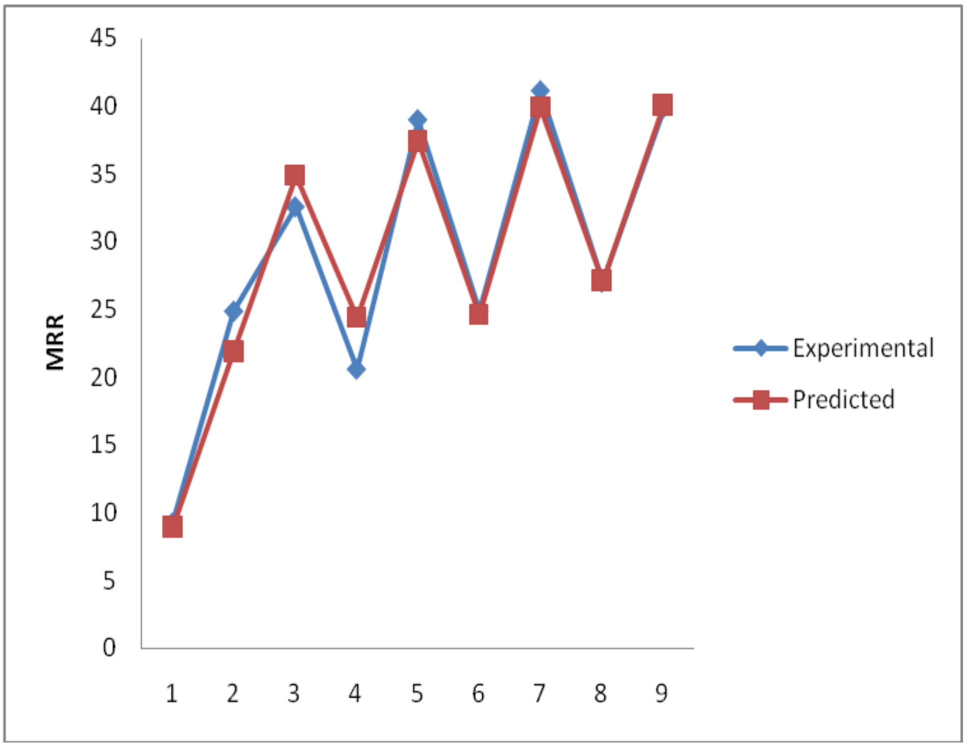


**Figure 12. Comparison of Experimental and Predicted Values of MRR**

Surface roughness ($R_a$) model

$R_a$ = - 8.29 + 0.00202 v + 41.7 f - 0.85 d
$R^2$ = 98.1%, $R^2$(Adj) = 96.9%

From the linear model, regression is significant as P-value (P = 0.000) is less than 0.05. The coefficient of determination, $R^2$ value is 98.1% indicating that the goodness of the fit of the model and high significance of the model. Also, from Normal probability plot vs. residuals and versus fits for surface roughness shown in Figures 13 and 14, representing that the residuals lie reasonably close to a straight line and the residuals were randomly scattered within a constant variance. The experimental versus predicted values of surface roughness are shown in Figure 15 and they found to be close to each other.

**Table 13. Analysis of Variance for $R_a$ Model**

| Source | DOF | SS | MS | F | P | Remarks |
|---|---|---|---|---|---|---|
| Regression | 3 | 110.647 | 36.882 | 85.51 | 0.000 | Significant |
| Residual Error | 5 | 2.157 | 0.431 | | | |
| Total | 8 | 112.803 | | | | |

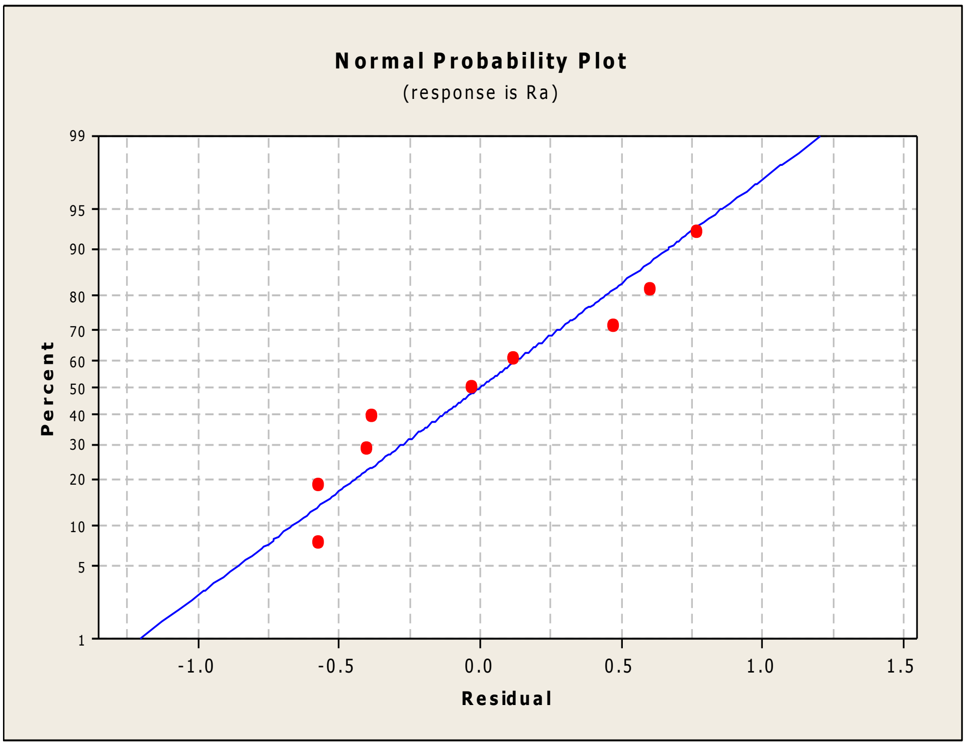


**Figure 13. Normal Probability Plot for $R_a$**

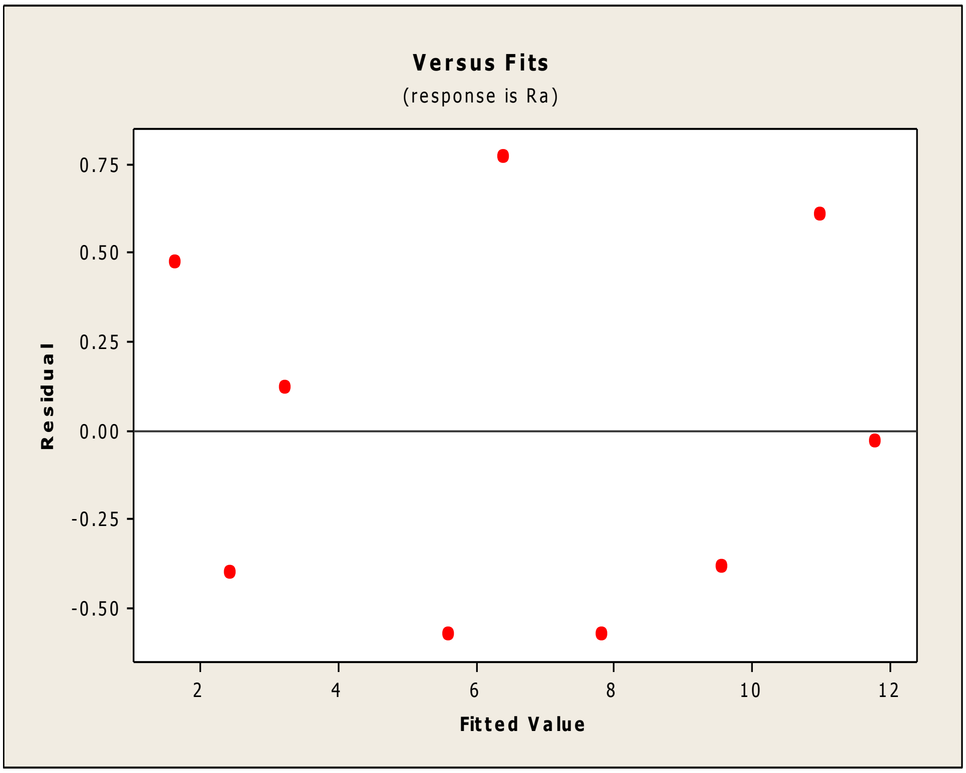


**Figure 14. Versus Fits Plot for $R_a$**

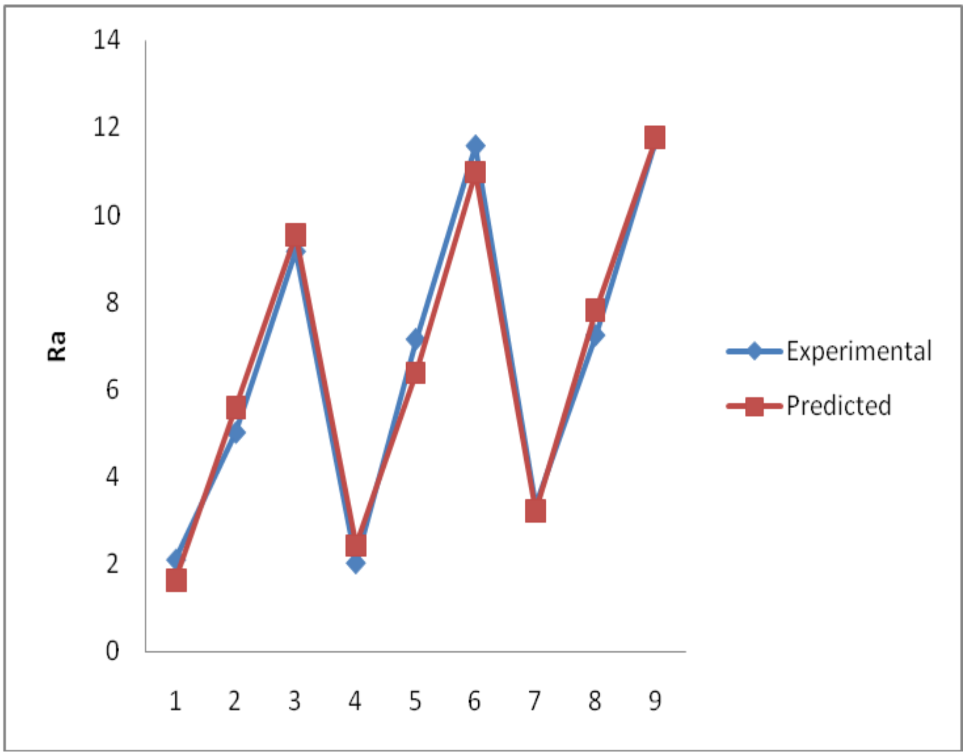


**Figure 15. Comparison of Experimental and Predicted Values of $R_a$**

## 4. Conclusions

Based on the experimental and Regression results obtained by the following conclusions can be drawn

 

- From Grey analysis, the Optimal combination of process parameters is obtained at
  Speed (v): level 3, 2000 rpm
  Feed (f): level 1, 0.2 mm/rev
  Depth of cut (d): level 3, 1 mm.
- From ANOVA results, it is clear that the feed is the most dominant parameter that has high influence on Grey relational grade followed by the depth of cut and speed has very low influence.
- Regression models prepared were statistically significant and adequate because of high $R^2$ values and they can be used for the prediction of both material removal rate and surface roughness.

## 5. Future Scope of Work

- The present work can be analyzed with other optimization methods available.
- The present work can be done with PVD or CVD (single or multi) coated tools.
- The present work can be done by other type of tools like diamond, ceramic *etc*.

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