Multi Response Optimization of Process Parameters Using Grey Relational Analysis for Turning of Al-6061

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Abstract: Al-6061 is one among the most useful material used in manufacturing of products. The major qualities of Aluminium are reasonably good strength, corrosion resistance and thermal conductivity. These qualities have made it a suitable material for various applications. While manufacturing these products, companies strive for reducing the production cost by increasing Material Removal Rate (MRR). Meanwhile, the quality of surface need to be ensured at an acceptable value. This paper aims at bringing a compromise between high MRR and low surface roughness requirement by applying Grey Relational Analysis (GRA). This article presents the selection of controllable parameters like longitudinal feed, cutting speed and depth of cut to arrive at optimum values of MRR and surface roughness (Ra). The process parameters for experiments were selected based on Taguchi’s L9 array with two replications. Grey relation analysis being most suited method for multi response optimization, the same is adopted for the optimization. The result shows that feed rate is the most significant factor that influences MRR and Surface finish.

Keywords: Al-6061, ANOVA, Grey relation analysis, MRR, Surface roughness, Spindle speed

Nomenclature

| A       | Linear Cutting speed (m/min) |
|---------|-----------------------------|
| ANOVA   | Analysis of variance        |
| B       | Longitudinal Feed (mm/rev)  |
| C       | Depth of cut (mm)           |
| Ra      | Surface roughness (µm)      |
| DF      | Degrees of freedom          |
| GRA     | Grey relational Analysis    |
| GRC     | Grey relational coefficient |
| GRG     | Grey relational grade       |
| SS      | Sum of squares              |
| MS      | Mean sum of squares         |
MRR  Material removal rate  
F   Fisher’s Number  
i   Number of attributes  
j   Number of trials  
k   Number of replications  
T   Overall average GRG  
n_{eff}  Effective sample size  

1. INTRODUCTION  
Aluminum alloys have high demand in many engineering applications because of their excellent mechanical properties. Any production activity is performed with main objectives of good surface quality and higher production rate. Machinability of the material refers to the ease of machining which is indicated by output parameters like tool wear rate, surface finish, MRR and power consumption (Songmene et al., 2011), etc. In addition to the longitudinal feed, cutting speed and depth of cut, geometry of the tool and stability of machine tool also influences the surface finish. MRR is another important output parameter which controls the productivity. Simultaneously achieving the low surface roughness and higher settings of material removal rate is difficult as they are two conflicting attributes. MRR can be increased at the cost of surface finish. In such situations GRA is the popular statistical tool which helps to set optimum input process parameters.

Influence of shape and cutting edge materials in turning operation of die-cast aluminum alloys studied by Horváth et al (2015). Among the studied materials, the harder hyper-eutectic alloy was found to produce lower surface roughness. Using desirability function, multi-objective optimization was performed by the authors to increase MRR and reduce surface roughness. Further, Raykar et al. (2015) adopted GRA to select process parameters to optimize the surface finish, power consumption, MRR and machining time. Rahul Dhabalea (2014) applied non-dominated sorted generic algorithms to optimize the turning parameters of AlMg1SiCu. Jayaram et al. (2014) carried out the multi response optimization of machining parameters of Al6063 T6 using GRA. Camita (2013) optimized turning of Al6061-T6. The work was intended to decide the process parameters that would reduce power consumption (single objective optimization). It was found that higher feed rate reduces the power consumption, but adversely affect the surface finish. Surendra et al. (2014) have shown that Taguchi-Fuzzy method give acceptable result in deciding factors that result in optimum setting for multi-objective response in turning of Al8081 alloy. Feed rate exhibited most influencing effect on the chosen responses followed by the depth of cut and the cutting speed. Mukesh et al. (2009) have developed a regression model for the prediction the surface finish for different feed, speed and depth of cut while turning Al6061-T4 with coated carbide tool.

Many researchers have strived to modify the quality of work material either developing composites or aging and to predict the influence of these factors on optimum machining condition. Ravindra Kumar et al (2015) conducted experiments on Al7075/ 7075 hybrid composites using artificial neural network and response surface methods. The results depicted that, feed rate is significant than spindle speed and approach angle on the output response i.e.,
Halil et al. (2009) investigated the influence of ageing on the output response for the machining conditions on Al-6061 alloy in as cast, aged and solution treated alloys. The results have indicated that, aging (at 1800°C) and cutting speed have influence on surface finish. The cutting force was not influenced by these parameters except for solution treated work pieces which have lower hardness. Rao et al (2013) studied the effect of machining parameters on the cutting force and surface finish in turning of AISI 1050 steel with ceramic (Al2O3 and TiC) tool. The results revealed that feed rate is significant parameter in controlling cutting force as well as surface finish. The authors have arrived at model for optimum combination of cutting force and depth of cut which results in minimum power consumption.

Deepak and Rajendra (2015) used Taguchi robust design principles to optimize the process parameters namely longitudinal feed, cutting speed and depth of cut in turning Al6061 alloy for MRR and surface roughness with single objective optimization. Vinod et al. (2014) studied the effect of tool overhang on surface finish. The authors have determined optimum length of overhang that improved the surface roughness. Since, the roughness of the machined surface plays vital role in precision fits, aesthetics and fatigue properties and also, material removal rate is the most predominant factor in improving productivity, the turning parameters requires careful selection so as to obtain optimized values of the multiple attributes. The grey relational analysis can be used for solving such multi responses (Jeyapaul et al. (2005). In GRA method, all response data are normalized and they are reduced to single grade. In the work presented in this paper, the purpose was to optimize the Ra and MRR in turning of Al-6061 material. The method adopted was grey relation analysis. Experimental data is analyzed using ANOVA and optimum combination of process parameters are found to obtain maximum response. Further, confirmation experiments were performed to validate the predicted results.

2. EXPERIMENTAL METHODOLOGY

2.1 Experimental setup

The CNC machine used for the experimental work is shown in Fig. 1. Al-6061 (as cast) alloy in the form of a cylindrical bar, with diameter 40 mm and length 150 mm is used as workpiece in the experiment. The tool used is tungsten carbide insert and coolant used is SAE-40. The composition of the work material is shown by bar chart of Fig. 2.
2.2 Design of Experiments

The value feed, cutting speed and depth of cut are chosen from the pilot study. Three levels of each parameters are considered with two replications. Selection of process parameters follow Taguchi’s L9 array. The value of the input parameters for each level is shown in Table I.

| Factor/Level          | 1   | 2   | 3   |
|-----------------------|-----|-----|-----|
| Cutting speed (m/min) | A   | 308 | 369 | 429 |
| Feed rate (mm/rev)    | B   | 0.05| 0.1 | 0.15|
| Depth of cut (mm)     | C   | 1   | 1.5 | 2   |

2.3 Methodology of Grey Relation Analysis

The experimental data and response for different trials is shown in the Table II. The surface finish is measured using Taylor’s surtronic instrument which directly gives the digital output of Ra value in microns. The material removal rate is determined by reduction volume in cm3 per minute. The results are also listed in Table II. Further, the response data is analyzed using GRA. The procedure involved in multi-response optimization with GRA method is detailed below.
Step 1: Normalized value of surface finish (X1jk*) and MRR (X2jk*) is calculated by following equations

\[ X_{1jk}^* = \frac{X_{1jk} - \text{Min}_jX_{1jk}}{\text{Max}_jX_{1jk} - \text{Min}_jX_{1jk}} \quad \text{for} \; j = 1, 2, \ldots, 9 \; \text{and} \; k = 1, 2 \quad (1) \]

\[ X_{2jk}^* = \frac{\text{Max}_jX_{2jk} - X_{2jk}}{\text{Max}_jX_{2jk} - \text{Min}_jX_{2jk}} \quad \text{for} \; j = 1, 2, \ldots, 9 \; \text{and} \; k = 1, 2. \quad (2) \]

Step 2: The reference value R is the maximum of normalized values and is given by

\[ R = \max(X_i^*), i = 1, 2. \quad (3) \]

Step 3: The difference value \([\gamma]_{ijk}\) is given by

\[ [\gamma]_{ijk} = [X_{ij}^* - R] \quad (4) \]

Step 4: The grey relational coefficient (GRC) \((\xi_{ijk})\)

\[ \xi_{ijk} = \frac{\text{Min}_j[\Delta_{ijk}] + \xi \text{Max}_j[\Delta_{ij}]}{\text{Max}_j[\Delta_{ijk}] + \xi \text{Max}_j[\Delta_{ij}]} \quad ; \xi = 0.5 \quad (5) \]

Step 5: Total GRC is obtained by adding all GRCs

Step 6: Grey relational grades (GRG) is given by taking the average in each row.

\[ \text{GRG}_{ij} = \frac{\sum_{k=1}^{2} \xi_{ijk}}{2x2} \quad (6) \]

3. RESULTS AND DISCUSSION

3.1 Optimization of process parameters using GRA

Table II shows the Ra and MRR corresponding to the experimental conditions. These response values are converted into grey scale coefficient and GRG as shown in the section 2.2. The values of GRG are shown in Table III. Higher GRG shows better response at the respective process settings. The main effect plot of GRG is shown in Fig. 3. The plot indicates the average GRG vs different levels of parameters. The actual values of average GRG is shown in Table IV. The ranking of the process parameters is based on the delta value which is the difference between the maximum and minimum value in each column of Table IV.

| Trial  | Levels | Ra | MRR |
|--------|--------|----|-----|
| 1      | A 1    | 0.7| 7.41| 9.25|
| 2      | B 2    | 1.1| 22.22| 22.22|
| 3      | C 3    | 2.77| 44.44| 49.99|
| 4      | A 1    | 1.61| 13.33| 15.55|
| 5      | B 2    | 1.91| 35.55| 35.55|
| 6      | C 3    | 2.21| 26.69| 33.36|
| 7      | A 1    | 1.01| 20.74| 20.74|
| 8      | B 2    | 0.66| 20.76| 20.76|
| 9      | C 3    | 1.56| 46.62| 55.56|
Table III Normalized response and GRG

| Trial | Ra  | MRR | GRC | GRG |
|-------|-----|-----|-----|-----|
|       | K=1 | K=2 | K=1 | K=2 |
| 1     | 0.981 | 0.909 | 0.119 | 0.126 | 2.979 | 0.745 |
| 2     | 0.791 | 0.589 | 0.021 | 0.022 | 2.552 | 0.638 |
| 3     | 0.000 | 0.231 | 0.200 | 1.745 | 0.436 |
| 4     | 0.550 | 0.934 | 0.063 | 0.075 | 2.646 | 0.661 |
| 5     | 0.408 | 1.000 | 0.147 | 0.085 | 2.600 | 0.650 |
| 6     | 0.265 | 0.574 | 0.063 | 0.067 | 2.180 | 0.545 |
| 7     | 0.834 | 0.944 | 0.007 | 0.034 | 2.972 | 0.743 |
| 8     | 1.000 | 0.802 | 0.007 | 0.034 | 3.037 | 0.759 |
| 9     | 0.573 | 0.543 | 0.252 | 0.245 | 2.128 | 0.532 |

Table IV Average grey relation grade

| Cutting Speed | Feed rate | Depth of Cut |
|---------------|-----------|--------------|
| Level 1       | 0.6063    | 0.7163       | 0.6830       |
| Level 2       | 0.6187    | 0.6823       | 0.6103       |
| Level 3       | 0.6780    | 0.5043       | 0.6097       |
| Delta         | 0.0717    | 0.2120       | 0.0733       |
| Rank          | 3         | 1             | 2             |

The process parameters which have influence on the response is ranked as feed rate rank –I, depth of cut rate rank –II and cutting speed rate rank –III as shown in Table IV. Further, ANOVA is carried out on GRG to find the significant process parameters. The results are shown in Table V. It is observed that feed rate has most significant effect on the response and its contribution is 79.08 % followed by cutting speed (8.95 %) and depth of cut (10.83 %).

Table V ANOVA of grey relation grade

| Source          | DF | Seq SS   | Adj MS   | F    |
|-----------------|----|----------|----------|------|
| Cutting speed   | 2  | 0.008809 | 0.004404 | 7.97 |
| Feed rate       | 2  | 0.077784 | 0.038892 | 70.41|
| Depth of cut    | 2  | 0.010659 | 0.005329 | 9.65 |
| Residual Error  | 2  | 0.001105 | 0.000552 |      |
| Total           | 8  | 0.098356 |          |      |
3.2 Confirmation experiments

Confirmation experiments were conducted at the identified optimum conditions, i.e., A3B1C1. At this settings predicted GRG is found to be 0.808. The confidence interval (d) is estimated to be 0.04 at 95% confidence level. Hence the expected range of GRG is 0.768 to 0.848. In addition, the observations were confirmed by turning the job at the optimum setting of parameters in which GRG obtained is found within the range established.

\[
T = \frac{\sum \text{Response}}{\text{Total experiments}} = 0.634 \\
\text{GRG}_i = \text{Response at } [A_i + B_i + C_i] - 2T = 0.808 \\
d = \sqrt{F(\text{Error DF}) \frac{\text{MSS}_{\text{Error}}}{n_{\text{eff}}}} = 0.04
\]

Confidence interval = GRG \pm d = 0.808 \pm 0.04 = 0.764 to 0.848

4. CONCLUSION

Turning experiments were conducted on Al-6061 (as cast) as work material. The surface roughness, MRR were measured under different experimental conditions and based on the results, following conclusions are drawn.

1. The feed rate (contribution 79.08%) is the most predominant factor influencing the response followed by DOC and cutting speed. High feed rate leads to broken chips and burrs in the surface of the job.
2. Process parameters are optimized using grey relation analysis and the optimum cutting conditions for maximizing the response is A3B1C1. High cutting speed results in more
MRR and low values of feed and DOC improves surface finish. Combining these factors optimize the output.

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