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Optimization of Machining Parameters using ANOVA and Grey Relational Analysis while Turning Aluminium 7075

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Abstract: In this research a detailed study is carried out on machining parameters for turning operation on aluminium 7075 with high speed steel. This grade of aluminium is known for its applications in aerospace industry and research about its machining parameters will lead to more developments in the field of production. Aim of this work is to optimize turning operation. Machining parameters viz. speed, feed and depth of cut are taken as input parameters. Material removal rate (MRR), tool wear (TWR), surface roughness (SR) are taken as output parameters and the set of optimized parameters means reduction in total production cost. The experiments are planned using Taguchi's L9 orthogonal array. Grey relational analysis (GRA) is used for multi objective optimization using grey relational grades. Application of analysis of variance(ANOVA) helps in the identification of most prominent parameters among speed, feed and depth of cut.

Index Terms: Aluminium 7075, Grey Relational Analysis, MRR, TWR, SR.

I. INTRODUCTION

Current day's research in the fields like transport engineering focuses on lightweight materials with the primary goal of saving fuel. Even though various synthetic composite materials replaced metals in this field, the classical low density- high strength metal viz aluminum is used for many components of an automobile. Also in other fields, aluminum is chosen over other metals due to its numerous favorable properties. Of all the heat, treatable aluminum alloys 7075 aluminum alloy is the most adaptable one. Apart from high corrosion resistance it also showcases different mechanical properties that are useful for a broad range of applications [1]. For achieving higher profits, it is important either to minimize the production cost or maximize the productivity by choosing optimum machining parameters [2].

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Properties like fatigue strength, corrosion resistance and creep strength are heavily influenced by surface roughness. These properties influence the mean life of components. This work explores the relationship between the tool material (stainless steel), workpiece material (aluminum 7075) and the machining parameters for achieving best possible surface roughness with minimum cost [3-4].

In manufacturing, while using contemporary machines material removal rate is a major concern [5-6]. Tool wear rate is another concern when it comes to automation of any machining process. Monitoring tool wear is always a difficult task when the manufacturing process is in progress [7]. Hence if the process is optimized, one can precisely control tool wear, surface roughness and material removal rate. GRA is an optimization technique that converts an optimization problem with multiple outputs into a single output problem effectively. The Grey Relation Coefficients provide the relationship between the process and the factors considered for the optimization problem [8-9]. Statistical analysis of variance (ANOVA) is utilized to understand the influence of input parameters on the output responses [10-11]. In this work, ANOVA is used to understand the individual contributions of machining parameters to the output responses through f-test. In case of multiple objective optimization, the results of GRA can be used and in case of single objective optimization, results of ANOVA are used.

II. EXPERIMENTATION

The experimentation was performed on the Al-7075 alloy as shown in Fig. 1, widely used in mold tool manufacturing, transport engineering etc., because of its strength, good fatigue strength, average machinability and low density in comparison to many steels. Table. I give the composition of 7075 aluminium alloy.

Table. I Chemical composition of 7075 aluminium alloy

Element	% of Composition
Zinc	5.6–6.1
Magnesium	2.1–2.5
Copper	1.2–1.6
Silicon, Iron, Manganese, Titanium, Chromium	< 0.5

The turning operation was done on NAGMATI Lathe using cutting tools made of high speed steel. The selected machining parameters are show in Table.

II. In Minitab v17 software L9 orthogonal array (as shown in Table. III) is generated for setting up of design of experiments (DoE). Machining is done at various speeds(S), feeds (f) and depths of cut (d). The surface roughness(SR) of the workpieces is measured using Talysurf as show in Fig. 2, tool wear (TWR) is measured using tool maker's microscope as shown in Fig. 3, and the material removal rate (MRR) is calculated. ANOVA studies the influence of design parameter on MRR, TWR and SR. In GRA, experimental results are normalized (between 0 and 1) and are tabulated. The result of the process is known as grey relational generation. Then these normalized experimental results are used to calculate the Grey Relational Coefficient (GRC). Hence GRC gives the relationship between the actual experimental results and desired output.

Then the GRCs corresponding to each and every response are averaged to yield the overall Grey Relational Grade (GRG). For a process with more than one response parameters, GRG represents the overall performance characteristic. The parametric combination associated with the highest GRG is considered to be optimum and is then evaluated. Taguchi method is employed for achieving best combination of parameters which would result in the maximum GRG. In Grey relational generation, Higher-the-better criterion is applied on the normalized MRR data as shown in "(1)", while the Lower-the-better criterion is applied on the TWR and SR data as shown in "(2)".

$$y_i^*(p) = \frac{y_i^0(p) - \min\ y_i^0(p)}{\max y_i^0(p) - \min y_i^0(p)} \qquad (1)$$

$$y_i^*(p) = \frac{\max\ y_i^0(p) - y_i^0(p)}{\max\ y_i^0(p) - \min\ y_i^0(p)} \qquad (2)$$

$$\epsilon_i(p) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(p) + \zeta\Delta_{max}} \qquad (3)$$

$$\Delta_{oi} = \|y_0^*(p) - y_i^*(p)\| \qquad (4)$$

$$\Delta_{min} = \underset{\forall\, j\, \in\, i}{min}\ \underset{\forall\, k}{min} \|y_o^*(p) - y_j^*(p)\| \qquad (5)$$

$$\Delta_{max} = \underset{\forall\, j\, \in\, i}{max}\ \underset{\forall\, k}{max} \|y_o^*(p) - y_j^*(p)\| \qquad (6)$$

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \zeta_i(p) \qquad (7)$$

Where $y_0^*(p)$ reference is sequence and $y_i^*(p)$ is comparability sequence. ζ is the identification coefficient which lies between [0, 1]. ζ = 0.5 is widely used and the smaller value of ζ points at higher distinguished ability.

Fig. 1 Al 7075 and HSS Steel

Fig. 2 Surface Roughness Tester

Fig. 3 Toolmakers Microscope

Table. II Machining Parameters

S No.	Stage	Spindle Speed (RPM)	Feed Rate (mm/rev)	DOC (mm)
1	1	325	0.05	0.2
2	2	770	0.10	0.4
3	3	1200	0.15	0.6

Table. III Design of experiments L9 array

S.No.	Cutting speed (rpm)	Feed (mm/rev)	Depth of cut (mm)
1	325	0.05	0.2
2	325	0.10	0.4
3	325	0.15	0.6
4	770	0.05	0.4
5	770	0.10	0.6
6	770	0.15	0.2
7	1200	0.05	0.6
8	1200	0.10	0.2
9	1200	0.15	0.4

III. RESULTS AND DISCUSSION

A. Analysis of ANOVA

Table. IV exhibits the results of the MRR, TWR and SR

Table. IV Experimental results

Cutting Speed	Feed	Depth of cut	MRR (kg/min)	Tool Wear (mm)	Surface Roughness (µmm)
325	0.05	0.2	02	0.070	1.076
325	0.10	0.4	11	0.165	1.281
325	0.15	0.6	14	0.265	1.724
770	0.05	0.4	10	0.285	1.103
770	0.10	0.6	11	0.295	1.517
770	0.15	0.2	06	1.080	1.340
1200	0.05	0.6	28	0.845	1.186
1200	0.10	0.2	11	0.555	3.214
1200	0.15	0.4	43	0.315	3.987

Table. V Analysis of Variance for Means(MRR)

Source	DF	Adj SS	Adj MS	%contri bution	Rank
Speed	2	672.22	336.11	55.87	1
Feed	2	164.22	82.11	13.63	3
DOF	2	366.89	183.44	30.50	2
Error	2	73.56	36.78		
Total	8	1276.89			

Table. VI Analysis of Variance for Means(TWR)

Source	DF	Adj SS	Adj MS	%contri bution	Rank
Speed	2	0.31387	0.15694	58.06	1
Feed	2	0.07354	0.03677	13.54	3
DOF	2	0.15369	0.07684	28.38	2
Error	2	0.34877	0.17439		
Total	8	0.88987			

Table. VII Analysis of Variance for Means (SR)

Source	DF	Adj SS	Adj MS	%contri bution	Rank
Speed	2	4.2394	2.1197	58.10	1
Feed	2	2.4081	1.2040	33.00	2
DOF	2	0.6417	0.3209	8.89	3
Error	2	1.4412	0.7206		
Total	8	8.7304			

Speed is ranked one for better MRR, TWR and surface roughness (SR) from the tables of analysis of variance for means (Table. V, Table. VI and Table. VII). Percentage contributions of the machining parameters reveal that the influence of cutting speed is significantly higher than the depth of cut and feed for achieving higher material removal rate (MRR). Also, from Table. VI and Table. VII, the percentage contributions of machining parameters reveal that the influence of cutting speed is significantly higher than the depth of cut and feed for lower TWR and SR.

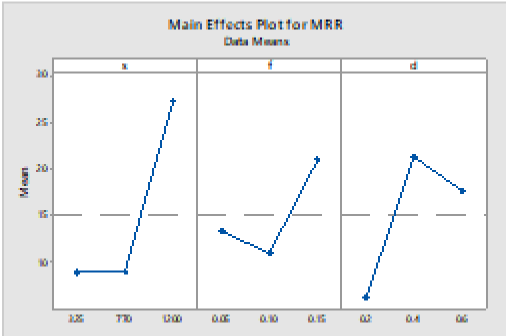

Fig. 4 Main Effects Plot for MRR

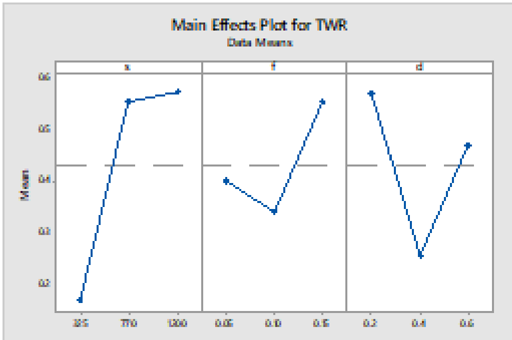

Fig. 5 Main Effects plot for TWR

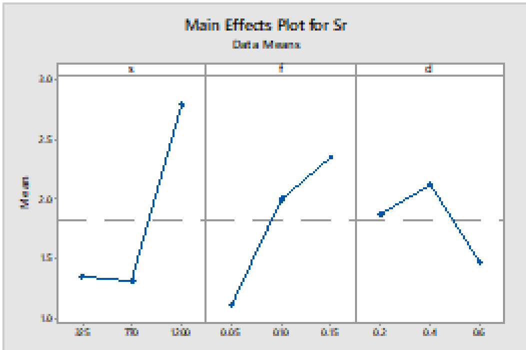

Fig. 6 Main Effects Plot for Mean SR

From Fig. 4, the mean (which is MRR in this case) increases with the increase in speed. Whereas for feed, the mean decreases and then increases and for depth of cut it increases and then decreases. For better MRR, the selection of parameters is as follows: speed at stage 3, feed at stage 3 and depth at stage 2. From Fig. 5, the mean (which is TWR in this case) increases with the increase in speed. Whereas for feed, the mean decreases and then increases and for depth of cut it decreases and then increases.

For better tool wear rate, the selection of parameters is as follows: speed at stage 3, feed at stage 3 and depth at stage 1.From Fig. 6, the mean (which is surface roughness in this case) first decreases and then increases with the increase in speed. Whereas for feed, the mean keeps on increasing and for depth of cut it increases first and then decreases.
For better surface roughness, the selection of parameters is as follows: speed at stage 3, feed at stage 3 and depth at stage 2.

B. Grey relational analysis

In the present study, the responses taken are Material removal rate, Tool wear and Surface roughness. These response MRR should be maximized and TWR and SR should be minimized. For data processing in GRA, MRR response is assigned with "Higher-the-better" criterion while tool wear and SR are assigned with "Lower-the-better" criterion. Using "(1)" and "(2)", all the sequences are processed and the results are presented in Table. VIII and IX. $y_0^*(p)$ and $y_i^*(p)$ represent reference and comparability sequence, respectively. For obtaining the GRCs the distinguishing coefficient ξ can be substituted into "(4)". Using "(4)", "(5)", "(6)" and "(7)" GRGs of each and every experiment of L9 orthogonal array are evaluated (Table. X).

Table. VIII Comparability Sequence table for responses

Experiment No.	MRR (kg/min)	Tool Wear (mm)	Surface Roughness (µmm)
1	0	1	1
2	0.219	0.906	0.929
3	0.293	0.807	0.777
4	0.195	0.213	0.991
5	0.219	0.777	0.849
6	0.098	0	0.909
7	0.634	0.233	0.962
8	0.219	0.519	0.266
9	1	0.757	0

Table. IX Deviation Sequence table for responses

Experiment No.	MRR (kg/min)	Tool Wear (mm)	Surface Roughness (µmm)
1	1	0	0
2	0.781	0.094	0.071
3	0.707	0.193	0.223
4	0.805	0.787	0.009
5	0.781	0.223	0.151
6	0.902	1	0.091
7	0.366	0.767	0.038
8	0.781	0.481	0.734
9	0	0.243	1

Table. X GRCs and Grey Grades.

Experiment No.	MRR (kg/min)	Tool Wear (mm)	Surface Roughness (µmm)	Grey relational grade
1	0.333	1	1	0.778
2	0.390	0.842	0.876	0.703
3	0.414	0.722	0.692	0.609
4	0.383	0.389	0.982	0.585
5	0.390	0.692	0.768	0.617
6	0.357	0.333	0.846	0.512
7	0.577	0.395	0.929	0.634
8	0.390	0.510	0.405	0.435
9	1	0.673	0.333	0.669

Table. XI Average GRGs

S. No	Factors	Stage-1	Stage-2	Stage-3	Delta	Rank
1	Speed	0.697*	0.571	0.579	0.126	1
2	Feed	0.667*	0.585	0.597	0.082	2
3	DOF	0.575	0.652*	0.620	0.077	3

In this work the outputs are MRR, TWR and SR. In these responses MRR should be maximized, TWR and SR should be minimized. From the analysis of experimental results it is clear that the parameters for machining of Al 7075 achieved highest GRG at run 1(see Table. XI). Hence $v_1f_1d_2$can be considered as optimal parameters for the expected output.

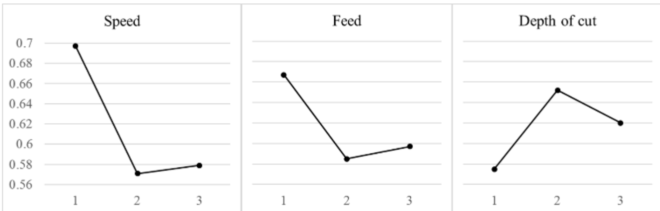

Fig. 7 Average grey grade vs. speed feed and depth of cut

Fig. 7 shows various combinations of machining parameters and the resulting performance (average grey grade). For speed at stage 1, feed at stage 1 and depth of cut at stage 2, the average grey grades are high which means these stages have high influence on the output responses viz., MRR, TWR and SR while turning aluminium.

IV. CONCLUSIONS

The influence of the cutting parameters while turning aluminum 7075 is known through ANOVA and Grey relational analysis. The maximum material removal rate, minimum tool wear and surface roughness are selected as the quality targets. The percentage contribution of cutting speed at stage 1 is ranked one because of its high influence over material removal rate, tool wear and surface roughness. From the response table of the Grey relational analysis, speed is the strongest factor among the other parameters used on the multi performance characteristics. The optimal combination of machining parameters is v1, f1, d2. This study effectively accomplished the grey relational analysis for optimum machining parameters for the turning operation of Aluminum.

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