International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 6 Issue 07, July - 2017

Taguchi Based Grey Relational Analyses for Multi Objective Optimization of Response Variables in CNC Turning of Aluminum 7075 Alloy

Navneet Saini [1]
PG Student, Industrial and Production Engineering
Modern institute of Engineering and Technology,
Mohri, Ambala, India

Jitender Panchal [2]
Assistant Professor, Mechanical Engineering Department,
Modern Institute of Engineering and Technology,
Mohri, Ambala, India

Abstract - **High speed turning has emerged as a key manufacturing technology in machining of different metals and alloys. Turning at high speed is performed on the order of five to ten times the conventional cutting speed. It is advantageous in many ways like reduction in cutting forces and temperature, low power consumption, improvement in surface finish, high MRR, better dimensional accuracy and better part quality [1, 2]. In order to achieve the quality output, it is necessary to optimize the process parameters (like speed, feed, depth of cut, nose radius) during the high speed machining of alloy. To achieve this goal, the current research work is aimed at optimizing the input parameters of CNC turning. The study applies Taguchi's design of experiment methodology and grey relational analysis to optimize the process parameters in turning aluminum alloy AA7075-T6 material, a high strength aluminum alloy used for aerospace application using coated carbide insert under dry environment condition and having four type insert nose radius such as 0.2, 0.4, 0.8, 1.2 mm. Experiment have been carried out based on L16 standard orthogonal array design with four process parameters namely cutting speed, feed rate , Depth of cut and nose radius for surface roughness and Material removal rate[3, 4].The data was analyzed using Grey Relational Analysis (GRA) coupled with Principal Component Analysis (PCA). Analysis of S/N ratio was done to obtain the optimum combination of input parameters. The Grey Relational Grade (GRG) at optimum setting of the input parameters was obtained by Regression analysis. The experimental results were validated by comparing the experimental value of GRG with that of the predicted value and the comparison shows a good relationship between them.**

Keywords: Nose radius, MRR, surface roughness, grey relational analysis, Taguchi approach

I. INTRODUCTION

The increase of consumer needs for better quality metal cutting related products in terms of more precise tolerance and better surface finish has driven the metal cutting industry to continuously improve quality control of the metal cutting processes. Surface Roughness quality is an important requirement of the finished work pieces in the machining operations. This parameter is of great importance in automotive, aerospace, die and mould manufacturing application.[3]. At the same time, higher material removal rate (MRR) is desired by the industries to cope up with mass production without sacrificing product quality in short span of time. Higher MRR is achieved by optimizing the process parameters like cutting speed, feed and depth of cut. However, very high cutting speed induces the larger power which may exceed the power available in the machine tool. Also it is disadvantageous to both the tool and the product as it causes dimensional inaccuracies by thermal deformation, the machined surface is also affected due to thermal defects and built-up-edge formation and damages the tool sharpness and causes vibration [2]. So, it is necessary to select appropriate process parameters for the effectiveness, efficiency and overall economy of manufacturing by machining to achieve these objectives (higher MRR and product quality).

Optimization is the science of getting excellent results subjected to several resource constraints. In the present world scenario, optimization is of the utmost importance for organizations and researchers to meet the growing demand for improved product quality along with lesser production costs and faster production [4]. To cope up with global manufacturing industries, high functional work piece are required in view of the machining operation is considered as important manufacturing process that contributes in economic and best quality manufacturing. Surface roughness and material removal rate plays a very vital role in deciding the productivity in global manufacturing. Surface roughness is one of the important quality control parameter for evaluating of production process, Efficiently turned component improves many functional attributes like desired tolerance, lesser tool wear, fatigue strength, load bearing capacity, corrosion strength and contact friction etc. The present study uses cutting speed, feed, and depth of cut and nose radius as the machining parameters and the objective is to optimize these parameters so as to find the minimum surface roughness and maximum material removal rate (MRR).

II. EXPERIMENTAL DETAILS AND METHODOLOGY

A. Experimental set up

The setup used for experimentation in the present study consists of computer numerical control M-TAB company machine. In CNC system a dedicated computer is used to perform all the basic functions as per the executive program stored in the computer memory. The system directs commands to servo drives to drive the servo motor & other output devices like relays, solenoids etc. to initiate the operations such as motor starting & stopping, coolant on & off, tool changing, pallet changing etc. All the operations of CNC machine are monitored continuously with appropriate feedback devices.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 6 Issue 07, July - 2017

Table 1: Specification of CNC lathe (M TAB) machine

Make	M TAB Chennai
Chuck size	100 mm
Max. turning diameter	32 mm
Max. turning length	120 mm
Spindle speed range	150-3000 rpm
Feed rate	0-100 m/min

Fig.1: M TAB CNC Lathe Machine

In addition to CNC machine a surface roughness tester SJ-201 was used to directly measure the average surface roughness (Ra) value after performing the turning operation at each work piece at different combination of control parameters designed by Taguchi methodology of DOE.

Fig.2: Surface Roughness Tester SJ-201

B. Selection of cutting tools

The cutting tool selected for present work is coated carbide inserts with four level of nose radius

Fig. 3: Inserts of Different Nose Radius

C. *Selection of work piece material*

The work piece material used for current work is Aluminium Alloy AA 7075-T6, a high strength aluminum alloy used for aerospace application A total of sixteen circular bars of diameter 25.4 mm and length 50mm were turned at different combination of control parameters according to the array designed.

Fig. 4:Work pieces of AA 7075 T6 Alloy

III. METHODOLOGY

In CNC machine, the turning operation can be easily done by rotating the work piece in the spindle located at the head stock. This can be done by loading the work piece at the magnetic chuck located at the headstock. High precision single point cutting tool (insert) fixed in a tool holder is held rigidly at a tool post and is fed past a rotating work piece in a direction parallel to the axis of the rotation of the work piece at a constant rate, and unwanted material is removed in the form of chips. A tool holder fixed at the tool post has such a arrangement where inserts of different nose radius can be fixed and removed easily. Spindle speed, feed rate and depth of cut can be controlled by feeding specific values in the program stored in the computer memory [5, 6]. The values of each control parameter (Speed, Feed rate, DOC and Nose Radius) were changed according to the design of experiment to obtain different values of response variables (MRR and Ra).

IV. EXPERIMENTATION AND ANALYSIS

The number of input parameters/control factors and their levels involved in a study helps to decide the design of experiment (DOE) to be adopted according to which the experiments are conducted. In the present experiment L_{16} array is designed by using Taguchi technique and then further process is advanced accordingly. Additionally, the robustness of the selected design is also ensured. A robust design is one which has minimum effect of the noise/uncontrollable factors on the response variables. Details of experiment and analysis technique used in the present study for multi-response optimization is described in the following sections

A. Selection of Control Parameters

In the present study four control/input parameters namely, spindle speed (V), feed rate (f), depth of cut (DOC) and nose radius (NR) are selected. Each parameter has four levels. The parameters and their levels were selected based on the literature review and the rationale behind their selection and their levels are given below:

B. Speed: The speed at which the spindle and work piece moves is known as spindle speed as it is taken in RPM in the present experiment for optimization purpose

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

C. Feed Rate: Feed always refers to the cutting tool, and it is the rate at which the tool advances along its cutting path [7, 8].

$$F_m = f.\ N \qquad \text{mm/min.} \qquad (1)$$

Here Fm is the feed in mm/minute, f is the feed in mm/rev and N is the spindle speed in RPM. [10]

D. Depth of Cut: It is the thickness of the layer being removed (in a single pass) from the work piece or the distance from the uncut surface of the work to the cut surface, expressed in mm [7, 8].

$$D\text{-}d = 2 \times DOC \qquad \text{in mm} \qquad (2)$$

Here D and d represent initial and final diameter (in mm) of the job respectively.

E. Nose Radius: It is the rounded tip on the cutting edge of a single point tool. A zero degree nose radius creates a sharp point of the cutting tool. its value normally varies from 0.4mm to 1.6mm, depending upon several factors like depth of cut, amount of feed, type of cutting, type of tool (solid or with insert) etc [1 ,8].

Table 2: Control/Input Parameters and their Levels

Input Parameters	Symbol	Unit	Level 1	Level 2	Level 3	Level 4
Speed	V	rpm	300	400	500	600
Feed rate	F	mm/min	20	30	40	50
Depth of cut	DOC	mm	0.2	0.4	0.6	0.8
Nose radius	NR	mm	0.2	0.4	0.8	1.2

F. Response variables

Two response variables namely, material removal rate (MRR) and surface roughness (Ra) were measured. The objective was to maximize material removal rate (MRR) and to minimise the surface roughness (Ra).Selected response variables along with their abbreviations and units are given in Table 3.

Table 3: Response Variables

S. No.	Response Variables	Abbreviation	Unit
1.	Material Removal Rate	MRR	mm^3/min
2.	Surface Roughness	Ra	µm

G. Material Removal Rate:

The material removal rate (MRR) is the volume of material removed per unit time is expressed in mm^3/min. In turning operation, for each revolution of the work piece, a ring-shaped layer of material is removed, whose cross- sectional area is product of the distance the tool travels in one revolution (feed) and depth of cut [7,8].

$$MRR = \frac{\text{Initial weight} - \text{Final weight}}{\text{Density x time}} \qquad (4)$$

Where Initial and Final weight were measured using Digital weighing machine and Density of AL 7075 T6 was taken as 2.81 g/cm^3 and time taken for turning of specimen was taken in minutes.

Where D= diameter of work piece in mm, DOC= depth of cut in mm and Fm=feed rate in mm/min.

H. Surface Roughness:

Surface roughness most commonly refers to the average variation in the height of the surface relative to a reference plane [8].

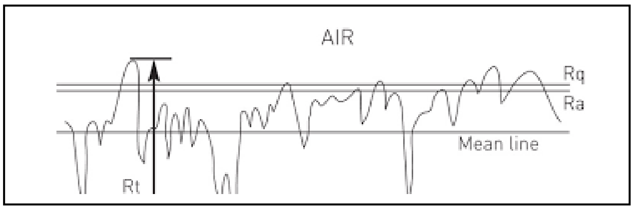

Fig.5: Surface Roughness Parameters

I. Selection of Orthogonal Array- Taguchi Method

An orthogonal array (OA) Designed by using Taguchi method can be used to investigate the effect of input parameters of a system or process on the response variables with lesser number of experiments. OA is selected on the basis of number of input parameters and their levels involved in the experimentation. The number of parameters and their levels, helps us to deicide the minimum number of experimental runs required for investigation which is obtained from the relation (L-1) P + 1, where L is the number of levels and P is the number of input parameters. In the present study, since L = 4 and P = 4, therefore, minimum number of experiments required to be performed is (4-1) x 4 + 1 = 13. Therefore, in the present study L_{16} orthogonal array was selected as shown in Table 4 [11]. Standard statistical software such as Minitab can be used to select standard OA and to perform the data analysis and in the present study Minitab 17 was used for this purpose.

Table 4: Shows orthogonal array designed by Taguchi Method

S.NO.	Speed	Feed	DOC	NR
1	300	20	0.2	0.2
2	300	30	0.4	0.4
3	300	50	0.6	0.8
4	300	40	0.8	1.2
5	400	20	0.4	0.8
6	400	30	0.2	1.2
7	400	40	0.8	0.2
8	400	50	0.6	0.4
9	500	20	0.6	1.2
10	500	30	0.8	0.8
11	500	40	0.2	0.4
12	500	50	0.4	0.2
13	600	20	0.8	0.4
14	600	30	0.6	0.2
15	600	40	0.4	1.2
16	600	50	0.2	0.8

J. Analysis of S/N Ratio

For MRR larger-the-better criterion was used as the objective was to maximize it and S/N ratio was calculated using Eq. (1). Similarly, for surface roughness (Ra) smaller-the-better criterion was used as the objective was to minimize it and S/N ratio was computed using Eq. (2).

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 6 Issue 07, July - 2017

The S/N ratio for larger-the better characteristic is expressed as:

$$= -10log\left[\frac{1}{r}\sum_{i=1}^{r}\frac{1}{y_i^2}\right] \qquad (5)$$

where y_i is the mean of the measured values of the response variable of i^{th} experiment and r is the number of experiments at a particular level of control factor in an orthogonal array. The negative sign ensures that the largest value gives an optimum value of the response variable.

Table 5: Shows Experimental MRR and S/N ratios for MRR

Speed	Feed	DOC	NR	MRR	S/N Ratio for MRR
300	20	0.2	0.2	355.8	51.02
300	30	0.4	0.4	1070.2	60.58
300	50	0.6	0.8	2669.0	68.52
300	40	0.8	1.2	2846.9	69.08
400	20	0.4	0.8	711.7	57.04
400	30	0.2	1.2	535.1	54.56
400	40	0.8	0.2	2846.9	69.08
400	50	0.6	0.4	2669.0	68.52
500	20	0.6	1.2	1067.6	60.56
500	30	0.8	0.8	2140.5	66.61
500	40	0.2	0.4	711.7	57.04
500	50	0.4	0.2	1779.3	65.00
600	20	0.8	0.4	1423.4	63.06
600	30	0.6	0.2	1605.4	64.11
600	40	0.4	1.2	1423.4	63.06
600	50	0.2	0.8	889.6	58.98

Similarly, the S/N ratio for smaller-the-better characteristic is given as:

$$= -10log\left[\frac{1}{r}\sum_{i=1}^{r}y_i^2\right] \qquad (6)$$

where y_i is the mean of the measured values of the response variable of i^{th} experiment and r is the number of experiments at a particular level of control factor in an orthogonal array. The negative sign ensures that the largest value gives an optimum value of the response variable.

Table 6: S/N Ratio for Surface Roughness (Smaller the better)

Speed	Feed	DOC	NR	Ra	S/N ratio for Ra
300	20	0.2	0.2	1.29	-2.21
300	30	0.4	0.4	1.43	-3.10
300	50	0.6	0.8	1.51	-3.57
300	40	0.8	1.2	1.16	-1.28
400	20	0.4	0.8	1.72	-4.71
400	30	0.2	1.2	0.55	5.19
400	40	0.8	0.2	1.66	-4.40
400	50	0.6	0.4	1.59	-4.02
500	20	0.6	1.2	0.57	4.88
500	30	0.8	0.8	0.95	0.44
500	40	0.2	0.4	1.21	-1.65
500	50	0.4	0.2	2.15	-6.64
600	20	0.8	0.4	1.17	-1.36
600	30	0.6	0.2	1.14	-1.13
600	40	0.4	1.2	0.74	2.61
600	50	0.2	0.8	1.07	-0.58

V. MULTI OBJECTIVE OPTIMIZATION TECHNIQUE

As two response parameters are considered to be optimized simultaneously so we have adopted a multi objective optimization technique. In present experimental work we are taking grey and Taguchi for optimization of process parameters and then based on its grade it is finally optimized by Taguchi technique.

A. Grey Relational Technique

Grey relational technique is a method to convert two or more quality parameters in to single quality parameter so that Multi objective can be converted in to a single objective quality parameter and optimization technique like Taguchi used for single objective optimization can be utilized. This is done by obtaining grey relational grade from grey relational analysis. It is characterized by less data and multifactor analysis, where these two characteristics can overcome the disadvantage of statistical regression analysis. Grey relational grade is used as a performance characteristic in this single objective optimization technique. This step by step procedure of grey relational analysis with result is shown below [15].

B. Methodology of Grey Relational Analysis

The procedure of GRA follows the steps described below.

C. Normalization of S/N ratios:

The first step in Taguchi based grey relational analysis is normalization of the S/N ratio to prepare initial data for the analysis where the original sequence is transferred to a comparable sequence. Normalization of the S/N ratio transforms the data in the range between zero and unity which is also known as the grey relational generation .In this investigation larger the better criterion is used for MRR and “smaller the-better” criterion is used for normalization of surface roughness by using the equations which are mentioned in Eq. 1 and 2 respectively [1, 2].

Larger the better

$$u_i(p) = \frac{z_i(p) - \min z_i(p)}{\max z_i(p) - \min z_i(p)} \qquad (7)$$

Smaller the better

$$u_i(p) = \frac{\max z_i(p) - z_i(p)}{\max z_i(p) - \min z_i(p)} \qquad (8)$$

Where, $u_i(p)$ is the value obtained by grey relational generation, min $z_i(p)$ is the smallest value of S/N ratio, $z_i(p)$ for the p^{th} response and max $z_i(p)$ is the largest value of $z_i(p)$ for the p^{th} response. The normalized data is given in Table(10)

Table 7: Normalized value of S/N Ratio for MRR and Ra

SPEED	FEED	DOC	NR	$U_i(p)$ FOR MRR	$U_i(p)$ FOR RA
300	20	0.2	0.2	0.00	0.55
300	30	0.4	0.4	0.48	0.62
300	50	0.6	0.8	0.78	0.65
300	40	0.8	1.2	1.00	0.48
400	20	0.4	0.8	0.30	0.74
400	30	0.2	1.2	0.18	0.00

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

400	40	0.8	0.2	0.90	0.71
400	50	0.6	0.4	0.88	0.69
500	20	0.6	1.2	0.48	0.02
500	30	0.8	0.8	0.78	0.35
500	40	0.2	0.4	0.30	0.51
500	50	0.4	0.2	0.70	0.88
600	20	0.8	0.4	0.60	0.49
600	30	0.6	0.2	0.65	0.47
600	40	0.4	1.2	0.60	0.19
600	50	0.2	0.8	0.40	0.43

D. Determination of Deviation Sequence

The deviation sequence Δ_{oi} is the absolute difference between the reference sequence $\mathbf{y_o(p)}$ and $\mathbf{y_i(p)}$ the comparability sequence after normalization [1]. It is determined using Eq. 3 as:

$$\text{Calculate } \Delta_{oi} = |y_o(p) - y_i(p)| \qquad (9)$$

Table 8: Shows Deviation Sequence for MRR and Ra

SPEED	FEED	DOC	NR	Δ_{oi} for MRR	Δ_{oi} for Ra
300	20	0.2	0.2	1.00	0.45
300	30	0.4	0.4	0.52	0.38
300	50	0.6	0.8	0.22	0.35
300	40	0.8	1.2	0.00	0.52
400	20	0.4	0.8	0.70	0.26
400	30	0.2	1.2	0.82	1.00
400	40	0.8	0.2	0.10	0.29
400	50	0.6	0.4	0.13	0.31
500	20	0.6	1.2	0.52	0.98
500	30	0.8	0.8	0.22	0.65
500	40	0.2	0.4	0.70	0.49
500	50	0.4	0.2	0.30	0.12
600	20	0.8	0.4	0.40	0.51
600	30	0.6	0.2	0.35	0.53
600	40	0.4	1.2	0.40	0.81
600	50	0.2	0.8	0.60	0.57

E. Determination of Grey Relational Coefficient

GRC for all the sequences expresses the relationship between the ideal (best) and actual normalized S/N ratio If the two sequences agree at all points, then their grey relational [1, 2]. Co-efficient is 1. The grey relational coefficient GRC can be expressed by Eq. 3.

$$x_i(p) = \frac{\Delta_{\min} + \Psi\Delta_{max}}{\Delta_{oi}(p) + \Psi\Delta_{max}} \qquad (10)$$

Where, $\Delta_{oi} = |y_o(p) - y_i(p)|$ = difference of absolute $y_o(p)$ and $y_i(p)$. Ψ is distinguishing coefficient whose value lies in the range of 0 to 1 i.e. $0 < \Psi < 1$ but it is generally taken as 0.5. In the present study, the value of Ψ is also taken as 0.5. Δ_{min} is the smallest value of Δ_{oi} and Δ_{max} is the largest value of Δ_{oi}.

Table 9: shows Grey Relational Coefficient for MRR and Ra

SPEED	FEED	DOC	NR	GRC $x_i(p)$ FOR MRR	GRC $x_i(p)$ FOR RA
300	20	0.2	0.2	0.33	0.53
300	30	0.4	0.4	0.49	0.57
300	50	0.6	0.8	0.69	0.59
300	40	0.8	1.2	1.00	0.49
400	20	0.4	0.8	0.42	0.66
400	30	0.2	1.2	0.38	0.33
400	40	0.8	0.2	0.84	0.64
400	50	0.6	0.4	0.80	0.61
500	20	0.6	1.2	0.49	0.34
500	30	0.8	0.8	0.69	0.44
500	40	0.2	0.4	0.42	0.50
500	50	0.4	0.2	0.62	0.81
600	20	0.8	0.4	0.56	0.49
600	30	0.6	0.2	0.59	0.49
600	40	0.4	1.2	0.56	0.38
600	50	0.2	0.8	0.45	0.47

F. Principal Component Analysis (PCA)

Principal component analysis (PCA) was first introduced by Karl Pearson in 1901 as an analogue of the principal axis theorem in mechanics. The origins of PCA lie in multivariate data analysis. PCA is one of the most important results from applied linear algebra which reduces the original data set, which may have large number of variables in just a few variables (the principal components) [17,18].

From Table 10, it can be seen that the variance contribution for the first principal component is as high as 69.10% and for the second principal component it is only 30.90%. Hence the squares of its corresponding eigenvectors are selected as the weighting values of the related performance characteristic and are shown in Table 12. The obtained weights are used in the calculation of grey relational grades given in Table 13.

Table 10: Eigen Values and Explained Variation

Principal component	Eigen value	Explained variation (%)
PC-1	1.3829	69.10
PC-2	0.6171	30.90

Table 11: Eigen Vectors for Principal Components

Response variables	Pc-1	Pc-2
MRR	0.707	0.707
SR	0.707	-0.707

Table 12: Response Variables and their Weight

Response Variable	Weights
MRR	0.50
SR	0.50

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 6 Issue 07, July - 2017

G. Determination of Grey Relational Grade and Rank

The overall evaluation of the multiple performance characteristics is based on the Grey Relational Grade (GRG). The grade with highest value is assigned highest rank. The next step of grey relational analysis is the calculation of grey relational grade on which the overall evaluation of the multiple-performance characteristic is based and it is calculated using Eq. (4) given below [1, 2]:

$$\delta_i = \sum_{p=1}^{n} w_p \, x_i(p) \qquad (11)$$

Where, *n* is the number of response variables, w_p is the weighing factor for each grey relational coefficient. The total sum of weighing factors for all the response variables should be unity. The weighing factor assigned to each response variable is determined using principal component analysis (PCA) as discussed in the previous section.

Table 13: Shows Grey Relational Grade and Rank

SPEED	FEED	DOC	NR	GRG	RANK
300	20	0.2	0.2	0.43	14
300	30	0.4	0.4	0.53	9
300	50	0.6	0.8	0.64	5
300	40	0.8	1.2	0.75	1
400	20	0.4	0.8	0.54	8
400	30	0.2	1.2	0.36	16
400	40	0.8	0.2	0.74	2
400	50	0.6	0.4	0.71	4
500	20	0.6	1.2	0.41	15
500	30	0.8	0.8	0.57	6
500	40	0.2	0.4	0.46	12
500	50	0.4	0.2	0.72	3
600	20	0.8	0.4	0.52	10
600	30	0.6	0.2	0.55	7
600	40	0.4	1.2	0.47	11
600	50	0.2	0.8	0.44	13

VI. RESULTS AND DISCUSSIONS

A. Taguchi Analysis: GRG versus Speed, Feed, DOC, NR

It is clear from figure that as spindle speed increases S/N ratio decreases. But in case of feed rate and DOC increase in these parameters S/N ratio also increases it can also be seen that with the increase in nose radius S/N ratio decreases. It can be estimated from the figure that spindle speed at level 1, feed rate at level 4, DOC at level 4 and nose radius at level 1 means **V1-F4-D4-N1** will provide the optimum combination of output parameters (MRR and surface roughness) simultaneously.

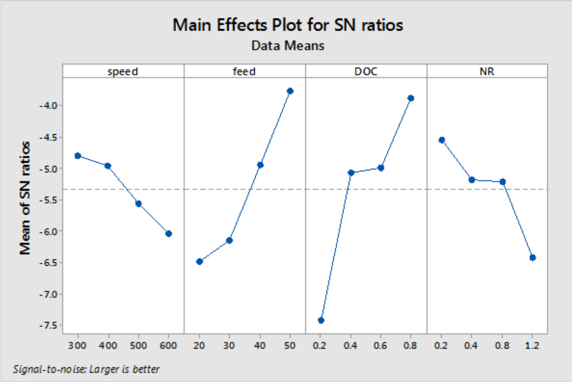

Fig. 6: Main effect plot for S/N ratio of GRG

B. Response Table for Signal to Noise Ratio

Based on the value of rank shown in Table 14, It can be concluded from the response table that control parameters affecting the response variable (GRG) follows the order in descending order as given DOC > Feed rate > Nose radius > Speed

Table 14: Response Table for S/N Ratios (Larger the better)

Level	Speed	Feed	DOC	NR
1	-4.805	-6.485	-7.424	-4.538
2	-4.954	-6.156	-5.070	-5.187
3	-5.556	-4.949	-4.987	-5.214
4	-6.042	-3.768	-3.878	-6.419
Delta	1.237	2.717	3.546	1.881
Rank	4	2	1	3

C. Analysis of Variance for GRG

From ANOVA table of GRG, it can be seen that P Value of the parameters which are below the significant level 0.05 is DOC and feed rate and we can also see that their percentage contribution is also high as it is 43.52% for DOC and 35.35% for feed rate, which means that DOC is the most influencing factor followed by feed rate and the other two factors (nose radius and speed) has 10.32% and 9.21% influence.

Table 15: Analysis of Variance (ANOVA) for GRG

Source	DF	Adj SS	Adj MS	P-Value	% Contribution
Speed	3	0.021425	0.007142	0.083	9.21
Feed	3	0.082225	0.027408	0.013	35.35
DOC	3	0.101225	0.033742	0.010	43.52
NR	3	0.024275	0.008092	0.071	10.43
Error	3	0.003425	0.001142		
Total	15	0.232575			

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

D. Analysis of Mean

The optimal level of the process parameters was determined through the analysis of means (ANOM). As we are optimizing the process parameters under multi objective optimization therefore, the set of input parameters can be seen from ANOM graph for optimization of response variable (GRG) as shown below we have to take the higher values of input parameters under larger the better criteria adopted for optimization of GRG so optimum set of input parameters can be taken as 300 rpm speed, 50 mm/min feed, 0.8 mm depth of cut and 0.2 mm nose radius.

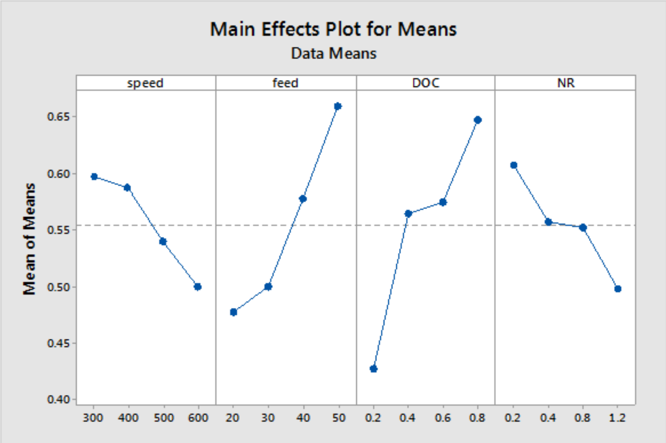

Fig.7: Main effect plot for Mean of Means of GRG

Based on the value of rank shown in Table below, It can be concluded from the response table that control parameters affecting the response variables follows the order in descending order as given DOC > Feed rate > Nose radius > Speed

Table 16: Response table for Means

Level	Speed	Feed	DOC	NR
1	0.5875	0.4775	0.4275	0.6075
2	0.5875	0.5000	0.5650	0.5575
3	0.5400	0.5775	0.5750	0.5525
4	0.5000	0.6600	0.6475	0.4975
Delta	0.0875	0.1825	0.2200	0.1100
Rank	4	2	1	3

E. Prediction of Taguchi result

The optimized Taguchi result was predicted by the Minitab 17 software which is illustrated in table below. It was observed that spindle speed of 300 rpm, feed rate of 50 mm/min, DOC of 0.8 mm and nose radius of 0.2 mm will provide optimum combination of MRR and Surface Roughness

Table 16: Factor level for Prediction

Speed	Feed rate	DOC	Nose radius	S/N ratio	GRG
300	50	0.8	0.2	-1.50149	0.84125

F. Regression Analysis

For computing GRG for the response variables at the optimum input parameter settings, it is required to perform the experiment at these settings. But GRG cannot be determined by performing only one experiment. For calculating GRG, the experiments for the whole array of the experiment design are required to be performed as done in the previous section of GRA. Therefore, to determine the experimental values of grey relational grades at optimum input parameter settings, the regression analysis was done and the regression equations were obtained using the data given in Table 10.

G. Regression Equation

$$\mathrm{GRG} = 0.369 - 0.000310\mathrm{V} + 0.00625\mathrm{F} + 0.3350\mathrm{D} - 0.0953\mathrm{N} \qquad (12)$$

Where V= speed, F= feed rate, D= depth of cut and N= Nose Radius

H. Confirmatory Test Result

The final step is to confirm the validity of the optimization technique and verify the improvement of the performance characteristics with predicted optimum level setting. That means experimental value of GRG at spindle speed of 300 rpm, feed rate of 50 mm/min, DOC of 0.8 mm and nose radius 0f of 0.2 mm was calculated using regression analysis and then compared with the predicted value of GRG suggested by Taguchi with the help of Minitab 17 software. We found the value of experimental GRG with the help of regression equation which is 0.83744 and predicted value of GRG to be 0.84125.

I. COMPARISON OF RESULTS

Analyzing experiment result we found that experimental value of GRG obtained by regression analysis at optimum input parameter settings and the values predicted by Taguchi method are very close which revealed good relation between them and confirms that control parameters at **V1-F4-D4-N1** will provide the optimum combination of response variables (MRR and surface roughness) simultaneously.

Table 17: Predicted and Experimental Values

Predicted		Experimental	
S/N Ratio	GRG	S/N Ratio	GRG
-1.50149	0.84125	-1.54092	0.83744

J. Calculation of Error

$$\text{Percent Error} = \frac{\text{Predicted GRG} - \text{Experimental GRG}}{\text{Predicted GRG}} \text{x}100$$

From the above formula it can be estimated that percentage error between experimental GRG and predicted GRG is 0.45% which is within the limits of acceptable level of 5% error. Therefore, it confirms that the results obtained by the above method are acceptable and well within the limits

K. Experimentation at the optimum Input parameters

After the confirmation of experimental and predicted values of GRG to be close enough to each other we can perform the experiment at the combination of input parameters suggested by the optimization results obtained by the Taguchi and grey relational analysis and these set of parameters can be used as optimum parameters to get the best possible combination of MRR and surface roughness at the same time. So we perform

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

the experiment at 300 rpm speed, 50 mm/min feed rate, 0.8 mm depth of cut and 0.2 mm nose radius insert and calculated the value of MRR and surface roughness given below

Shows value of Response variables at Input Parameters suggested by Taguchi

Optimum input parameters	MRR (mm^3/min)	Surface roughness (μm)
V1-F4-D4-N1	3558.71	1.24

VII. CONCLUSION

Multi-objective Optimization for High Speed Turning of Al 7075 using Grey Relational Analysis is discussed in this paper. Based on the analysis following conclusions can be made.

- Grey Relational Analysis is very effective technique for optimization of machining processes which involves multiple responses.
- It can be concluded from the response table that control parameters affecting the response variable (GRG) follows the order in descending order as given DOC > Feed rate > Nose radius > Speed
- The recommended cutting parameters for high speed turning of Al 7075 are 300 rpm Speed, 50 mm/min feed rate, 0.8 mm DOC and 0.2 mm NR, with coated carbide insert and under dry machining conditions.
- Confirmation test revealed good agreement between predicted and experimental values of the GRG at set of the input parameters suggested by optimization technique.

REFERENCES

[1] S.J. Raykara, D.M. D'Addona, A.M. Manea, "Multi-objective optimization of high speed turning of Al 7075 using grey relational analysis",9th CIRP Conference on Intelligent Computation in Manufacturing Engineering, Procedia CIRP 33 (2015) 293 – 298

[2] P. Jayaramana, L. Mahesh kumar, "Multi-response Optimization of Machining Parameters of Turning AA 6063 T6 Aluminium Alloy using Grey Relational Analysis in Taguchi Method", 12th GLOBAL CONGRESS ON MANUFACTURING AND MANAGEMENT, GCMM 2014, Procedia Engineering 97 (2014) 197 – 204

[3] Rishu Gupta, Ashutosh Diwedi, "Optimization of Surface Finish and Material Removal Rate with Different Insert Nose Radius for Turning Operation on CNC Turning Center", International Journal of Innovative Research in Science,Engineering and Technology, Vol. 3, Issue 6, June 2014

[4] Devendra Singh, Vimanyu Chadha and Ranganath M Singari, "effect of nose radius on surface roughness during cnc turning using response surface methodology", International Journal of Recent advances in Mechanical Engineering (IJMECH) Vol.5, No.2, May 2016

[5] Srinivas Athreya1,Dr Y.D.Venkatesh, "Application Of Taguchi Method For Optimization Of Process Parameters In Improving The Surface Roughness Of Lathe Facing Operation", International Refereed Journal of Engineering and Science (IRJES) ISSN (Online) 2319-183X, (Print) 2319-1821 Volume 1, Issue 3 (November 2012), PP.13-19

[6] Anoop C A, Pawan Kumar, "Application of Taguchi Methods and ANOVA in GTAW Process Parameters Optimization for Aluminium Alloy 7039", International Journal of Engineering and Innovative Technology (IJEIT) Volume 2, Issue 11, May 2013

[7] Puneet Bansal, Lokesh Upadhyay, "Effect of Turning Parameters on Tool Wear, Surface Roughness and Metal Removal Rate of Alumina Reinforced Aluminum Composite", 3rd International Conference on Innovations in Automation and Mechatronics Engineering, ICIAME 2016, Procedia Technology 23 (2016) 304 – 310

[8] Aswathy V, Rajeev, Vijayan, "Effect of machining parameters on surface roughness, material removal rate and roundness error during the wet turning of Ti-6Al-4V alloy", Int. Journal of Applied Sciences and Engineering Research, Vol. 4, Issue 1, 2015

[9] Rusdi Nura, D.Kurniawan, M.Y.Noordinb, S.Izman, "Optimizing power consumption for sustainable dry turning of treated aluminum alloy", 2nd International Materials, Industrial, and Manufacturing Engineering Conference, MIMEC2015, 4-6 February 2015, Bali Indonesia, Procedia Manufacturing 2 (2015) 558 – 562

[10] Azizah Mohamad, Azlan Mohd. Zain, Nor Bahiah Hj. Ahmad, Noordin Mohd Yusof and Farhad Najarian, " Roundness Error Study in Deep Hole Drilling of Cold Mold Steel 718", Indian Journal of Science andTechnology,Vol10(13), April 2017

[11] Feng, C.X. and Wang X, Development of empirical models for surface roughness prediction in finis turning. International Journal of Advanced Manufacturing Technology; 2002, Vol. 20, pp.348-356.

[12] Lambert, B.K.; Determination of metal removal rate with surface finish restriction. Carbide and tool Journal, May – June : 16-19, 1983.

[13] Ho SY , Lee KC, Chen SS, Ho SJ; Accurate Modeling prediction of surface roughness by computer vision in turning operation using an adaptive neuro- fuzzy inference system. Int J Mach Tools Manuf, 2002; 42:1441-1446.

[14] Malakooti B. and Raman V.; An Interactive Multi –Objective artificial neural network approach for machine setup optimization, Journal of Intelligent Manufacturing, 2000, Vol. 111, pp 41-50.

[15] Rasch and Roistadas; Series of finish turning tests under variation of parameters : Material quality ., Tool quality , Tool nose radius , feed speed and cutting time. Journal of material processing technology, 1971, Vol-132, 203-214.

[16] Tian-Syung Lan and Ming-Yung Wang; Competitive parameter optimization of multi-quality CNC turning; The International Journal of Advanced Manufacturing Technology; April 2009, Volume 41, Issue 7-8, pp 820-826

[17] Zhang Xueping, Gao Erwei and C. Richard Liu; Optimization of process parameter of residual stresses for hard turned surfaces; Journal of Materials Processing Technology; Volume 209, Issue 9, 1 May 2009, Pages 4286–4291,Science (IRJES) ISSN (Online) 2319-183X, (Print) 2319-1821 Volume 1, Issue 3 (November 2012), PP.13-19

[18] D'Addona,D.M., Teti, R., 2013, Genetic Algorithm-based Optimization of Cutting Parameters in Turning Processes, Procedia CIRP, Vol. 7, 2013, ISSN 22128271: 323-328

[19] T. K Durga Bhavani , G. S .V Seshu Kumar, Prof. K Satyanarayana, I. Ajit Kumar,Optimization of Material Removal Rate and Surface Roughness in Turning of Aluminum, Copper and Gunmetal Materials using RSM

[20] Lambert, B.K.; Determination of metal removal rate with surface finish restriction. Carbide and tool Journal, May – June : 16-19, 1983.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)