Experimental Investigation of Parameters of CNC Turning by Taguchi based Grey Relational Analysis

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Abstract
The AISI H13, a chromium based hot work tool Steel has a wide variety of applications in aluminum casting and extrusion dies, forging dies, hot nut tools, hot header dies, extrusion mandrels, plastic molds, cores, die holder blocks, hot press dies and specially hot work punches etc. In this study, the optimization of two response parameters (Surface roughness and Material Removal Rate) by three machining parameters (cutting speed, feed rate and depth of cut) is investigated in high speed turning of H13 in dry conditions. Taguchi's L'18 orthogonal array and analysis of variance (ANOVA) are used for individual optimization. The simultaneous optimization is done by Grey Relational Analysis approach. The different levels of all machining parameters are used and experiments are done on HMT STALLION-100 HS CNC lathe machine. The optimum condition for combined effects was found V5-F1-D1 and the optimal value of the surface roughness (Ra) comes out to be 0.85 (µm) and of MRR is 488.8 (mm^3/sec). The optimum results are also verified with the help of confirmation experiments.

Keywords: CNC Turning, Optimization, ANOVA, MRR, Surface Roughness (Ra), Taguchi Method, Grey Relational Analysis, GRG.

1. Introduction
Quality plays a major role in today's manufacturing market. From Customer's viewpoint quality is very important because the quality of products affects the degree of satisfaction of the consumers during usage of the product. It also improves the goodwill of the company.

High speed turning operation is done on CNC lathe. The quality of the surface plays a very important role in the performance of dry turning because a good quality turned surface surely improves fatigue strength, corrosion resistance and creep life. Surface roughness also affects on some functional attributes of parts, such as, contact causing surface friction, wearing, light reflection, ability of distributing and also holding a lubricant, load bearing capacity, coating and resisting fatigue.

As we know in actual machining there are many factors which affect the surface roughness and material removal rates i.e. cutting conditions, tool variables and work piece variables. Cutting conditions includes speed, feed and depth of cut. The tool variables includes tool material, nose radius, rake angle, cutting edge geometry, tool vibration, tool overhang, tool point angle etc. The work piece variables include hardness and mechanical properties of the material. It is very difficult to take all the parameters that control the response parameters for a particular manufacturing process. In a turning operation, it is very difficult to select the cutting parameters to achieve the high surface finish with optimal material removal rate. This study would help the operator to select the cutting parameters.

The hot work tool steels have the ability to resist softening under hot working conditions and after numerous exposures to elevated operating temperatures. Hot work material used for the present study is H13 steel. The nominal chemical compositions are {Chromium (5%), Vanadium (1%), Molybdenum (1.5%), Carbon (0.4%), Maganese (0.35%)}. This H13 tool steel is suitable for forging dies, forging die inserts, hot gripper dies, hot nut tools, hot header dies, brass forging and pressing dies, aluminum base dies, aluminum casting and extrusion dies, zinc die casting dies, extrusion mandrels, plastic molds, cores, die holder blocks, hot press dies and hot work punches etc.

This paper is about experimentally investigating and optimizing the machining parameters for Material Removal Rate (MRR) and Surface Roughness in CNC turning by Taguchi method and grey relational analysis approach.. Taguchi's orthogonal arrays are highly fractional designs, used to estimate main effects using very few experimental runs. These designs are not only applicable for two level factorial experiments, but also can investigate main effects when factors have more than two levels. Designs are also available to investigate main effects for some mixed level experiments where the factors included do not have the same number of levels.

For example, a four-level full factorial design with five factors requires 1024 runs while the Taguchi orthogonal array reduces the required number of runs to 16 only.

Ojel, T. et al. (2004) has studied the effects of cutting edge geometry, work piece hardness, feed rate and cutting speed on surface roughness and resultant forces in the finish hard turning of AISI H13 steel. Cubic Boron Nitrite inserts with two distinct edge preparations (chamfered and honed) and through hardened AISI H13 steel bars were used. The honed Edge geometry and lower work piece surface hardness resulted in better surface roughness.

Ghani, M.U. et al. (2007) has presented results of an investigation into the tool life and the tool wear behaviour of low content CBN cutting tools used in hard turning of hardened H13 tool steel using finite element thermal modeling. It involved measuring the cutting forces, cutting temperatures, tool wear and the contact area. Using the measured cutting forces and the contact area in the orthogonal cutting model, he calculated the heat flux on the tool. The heat partition into the tool was estimated to be around 21–22% for conventional speeds, 14% for high-speed turning. The tool wear, however, was found to be dominated by chipping for both cutting speeds and could be reduced considerably by reducing the amount of heat entering the tool.

Jaharah, A.G. et al (2009) has studied the effect of uncoated carbide tool geometries in turning AISI 1045 using finite element analysis. This paper presents the application of Finite element method (FEM) in simulating the effect of cutting tool geometries on the effective stress and temperature increased in turning. The tool geometries studied were various rake (α) and clearance (β) in the different ranges. The minimum effective stress of 1700MPa is achieved using rake and clearance angles of 5° and 5° respectively with cutting speed of 300mm/min, and feed rate of 0.25mm/rev.

Chakradhar, D. and Venu Gopal, A. (2011) has done the multi objective optimization of electrochemical machining of EN-31 steel by grey relational analysis. The process parameters considered are electrolyte concentration, feed rate and applied voltage and are optimized with considerations of multiple performance characteristics including material removal rate, over cut, cylindricity error and surface roughness. With the help of Analysis of variance (ANOVA) it was observed that feed rate is the significant process parameter that affects the ECM robustness.

Hassan, K. et al. (2012) has done the experimental investigation of material removal rate (MRR) in CNC turning of C34000 using Taguchi method using L'27 array. When the MRR is optimized alone the MRR comes out to be 8.91. The optimum levels of process parameters for simultaneous optimization of MRR have been identified. Optimal results were verified through confirmation experiments. It was concluded that MRR is mainly affected by cutting speed and feed rate.

2. Design of Experiment

The experiments are designed using Taguchi method so that effect of all the parameters could be studied with minimum possible number of experiments. Using Taguchi method, Appropriate Orthogonal Array has been chosen and experiments have been performed as per the set of experiments designed in the orthogonal array. Signal to Noise ratios are also calculated for analyzing the effect of machining parameters more accurately. The results of the experimentation are analyzed analytically and graphically as well. ANOVA is used to determine the percentage contribution of all factors upon each response individually.

3. Taguchi Method

The traditional experimental design methods are very complicated and difficult to use. Additionally, these methods also require a large number of experiments when the number of process parameters increases. In order to minimize the number of tests required, Taguchi experimental design method, a powerful tool for designing high-quality system, was developed by Taguchi. Taguchi method uses a design of orthogonal arrays to study the entire parameter space with small number of experiments only. Taguchi recommends analyzing the mean response for each run in the array, and he also suggests to analyze variation using an appropriately chosen signal-to-noise ratio (S/N). There are 3 Signal-to-Noise ratios of common interest for optimization of static problems:

1. **Smaller The Better**
$$\frac{S}{N} = -10\log\left(\frac{(\Sigma Yi^2)}{n}\right)$$

2. **Larger The Better**
$$\frac{S}{N} = -10\log((\Sigma\frac{1}{yi^2})/n)$$

3. **NOMINAL-THE-BEST**
$$\frac{S}{N} = 10\log(\frac{y^2}{s^2})$$

Where,

Yi - ith observed value of the response,
n - Number of observations in a trial,
y - Average of observed values (responses)
s - Variance.

Regardless of the category of the performance characteristics, the higher S/N ratio corresponds to a better performance. Therefore, the optimal level of the process parameters is the level with the highest S/N value. The statistical analysis of the data is performed by analysis of variance (ANOVA) to study the contribution of the various factors and interactions and to explore the effects of each process on the observed values.

4. Experimentation

In this study, three machining parameters were selected with different levels as given in Table 1. The experimental design was according to an L'18 array based on Taguchi method. A set of experiments designed and conducted to investigate the relation between the process parameters and response factor. Minitab 16 software is used for optimization and graphical analysis of obtained data.

Table 1 Turning parameters and levels

Levels	CS (m/sec)	F (mm/rev)	DOC (mm)
1	150	0.1	0.5
2	180	0.2	1
3	210	0.3	1.5
4	240		
5	270		
6	300		

The work material selected for this experiment is H13 of Ø 32 mm, length 70 mm in the present study. The chemical composition of H13 sample can be seen in Tables 2.

Table 2 Chemical composition of H13 sample

Ele-ments	C	Cr	V	Mo	SI	S	P
%	0.36	4.9	0.9	1.4	1.04	0.03	0.03

The turning tests were carried out to determine the Material Removal Rate and Surface Roughness under various turning parameters. A HMT STALLION-100 HS CNC lathe machine is used for experimentation.
Roughness is measured using stylus type surface roughness tester 'Surftest SJ-201' made of Mitutoyo, Japan. The cut-off length (λ) was chosen as 0.8cm for each roughness measurement. An average of 5 measurements of the surface roughness was taken to use in the multi-criteria optimization.
The Material Removal Rate, MRR (mm³/ min) was calculated using formula:

$$MRR = \frac{Wi - Wf}{\rho s\ t} mm^3/sec$$

Where, Wi = Initial weight of work piece in *gm*
Wf= Final weight of work piece in *gm*
t = Machining time in seconds
ρs= Density of mild steel (7.9 x 10^{-3} *gm/mm³*).

5. Results and Discussions

In high speed turning operation, surface roughness is an important criterion. The purpose of the analysis of variance (ANOVA) is to investigate which design parameter significantly affects the surface roughness. Based on the ANOVA, the relative importance of the machining parameters with respect to material removal rate and surface roughness was investigated to determine the optimum combination of the machining parameters.

A series of turning tests are conducted to assess the effect of turning parameters on surface roughness in turning of H13. The Material Removal Rate calculations and experimental results of the surface roughness for turning of H13 with different turning parameters are shown in Table 3.

Table 3 Design of experiment and calculations

S. No.	Weight before turning (gm)	Weight after turning (gm)	Machining Time (sec.)	Means of Material Removal Rate (mm³/sec)
1	454.1	425.2	12.0	304.85
2	425.2	406.7	7.0	334.53
3	406.7	386.7	5.7	444.14
4	456.4	424.2	10.4	391.91
5	424.2	399.4	8.0	392.40
6	399.4	380.9	5.5	425.77
7	456.2	421.2	10.1	438.65
8	421.2	399.3	6.4	433.14
9	399.3	382.9	5.2	399.22
10	454.0	415.9	9.6	502.37
11	415.9	392.2	6.2	483.87
12	392.2	377.4	3.9	480.36
13	452.0	418.8	8.5	494.41
14	418.8	390.1	7.2	504.57
15	390.1	372.9	4.4	494.82
16	457.0	424.4	8.5	483.99
17	424.4	402.7	6.5	422.59
18	402.7	384.4	4.9	459.82

Table 4 Design of experiment and calculations

Ex. No.	CS (m/ min)	F (mm/ rev)	D (mm)	MRR (mm³/ sec)	Ra (μm)
1	150	0.1	0.5	304.85	0.57
2	150	0.2	1.0	334.53	0.96
3	150	0.3	1.5	444.14	1.04
4	180	0.1	0.5	391.91	0.59
5	180	0.2	1.0	392.40	0.88
6	180	0.3	1.5	425.77	1.09
7	210	0.1	1.0	438.65	0.81
8	210	0.2	1.5	433.14	0.86
9	210	0.3	0.5	399.22	0.81
10	240	0.1	1.5	502.37	0.97
11	240	0.2	0.5	483.87	0.84
12	240	0.3	1.0	480.36	0.94
13	270	0.1	1.0	494.41	0.92
14	270	0.2	1.5	504.57	1.06
15	270	0.3	0.5	494.82	1.04
16	300	0.1	1.5	483.99	1.06
17	300	0.2	0.5	422.59	1.02
18	300	0.3	1.0	459.82	0.98

Table 5 ANOVA Table for means of MRR

V	DF	SS	MS	F	P	C
CS	5	41373	8274.7	11.83	0.002	73.79 ***
F	2	1526	762.9	1.09	0.381	2.7 2*
D	2	7566	3783.2	5.41	0.033	13.49 **
E	8	5598	699.7			9.98
T	17	56064				100

Table 6 Response Table for means of MRR

Level	CS	F	DOC
1	361.2	436.0	416.2
2	403.4	428.5	433.4
3	423.7	**450.7**	**465.7**
4	488.9		
5	**497.9**		
6	455.5		
Delta	136.8	22.2	49.5
Rank	**1**	**3**	**2**

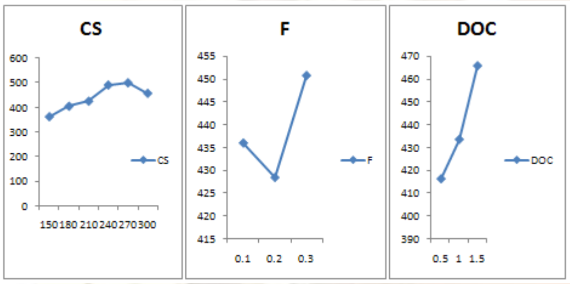

Fig 1 Main effect plot for means of MRR

Table 7 ANOVA Table for means of Ra

V	DF	SS	MS	F	P	C
CS	5	0.10327	0.0206	2.32	0.139	27.08 **
F	2	0.08493	0.0424	4.77	0.043	22.27 *
D	2	0.12203	0.0610	6.86	0.018	31.99 ***
E	8	0.07117	0.0088			18.66
T	17	0.38140				100

Table 8 Response Table for means of Ra

Level	CS	F	DOC
1	0.8567	**0.8200**	**0.8117**
2	0.8533	0.9367	0.9150
3	**0.8267**	0.9833	1.0133
4	0.9167		
5	1.0067		
6	1.0200		
Delta	0.1933	0.1633	0.2017
Rank	**2**	**3**	**1**

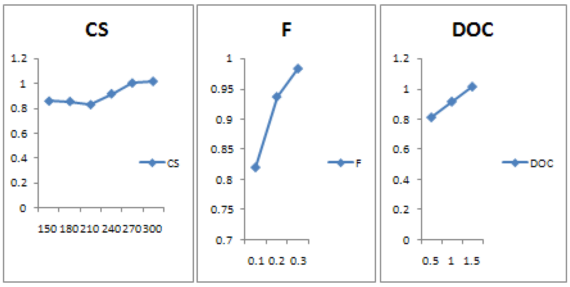

Fig 2 Main effect plot for means of Ra

Here,

V-Variable,	CS-Cutting Speed,
F-Feed Rate,	D-Depth Of Cut,
SR-Surface Roughness,	E-Error,
T-Total,	DF-Degree of Freedom,
SS-Sum of Squares,	MS-Mean of Squares,
F-a statistical parameter,	P-Percentage,
C-% Contribution.	

Here *** & ** represents most significant and significant parameters and * as less significant.

6. Grey Relational Analysis

In the Grey relational analysis the quality characteristics are first normalized, ranging from zero to one. This process is known as Grey Relational Generation. Then the Grey Relational Coefficient based on normalized experimental data is calculated to represent the correlation between the desired and the actual experimental data. Then overall Grey Relational Grade (GRG) 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 GRG. This Grey relational approach converts a multiple response process optimization problem into a single response optimization problem. The optimal parametric combination is then evaluated, which would result in the highest Grey relational grade. The optimal factor setting for maximizing the overall Grey relational grade can be performed using the Taguchi method.

In Grey relational generation, the normalized MRR should follow the smaller-the-better (SB) criterion, which can be expressed as:

$$xi(k) = \frac{\max yi(k) - yi(k)}{\max yi(k) - \min yi(k)}$$

The normalized Ra should follow the larger-the-better (LB) criterion which can be expressed as:

$$xi(k) = \frac{yi(k) - \min yi(k)}{\max yi(k) - \min yi(k)}$$

Where, $x_i(k)$ and $x_j(k)$ are the value after Grey Relational Generation for LB and SB criteria. Max $y_i(k)$ is the largest value of $y_i(k)$ for k^{th} response and min $y_i(k)$ is the minimum value of $y_i(k)$ for the k^{th} response.

The Grey relational coefficient $\xi_i(k)$ can be calculated as:

$$\xi_i(k) = \frac{\Delta\min + \Psi\,\Delta\max}{\Delta\, o_i(k) + \Psi\,\Delta\max}$$

And $\Delta\, o_i = \| x_o(k) - x_i(k) \|$

Where $\Delta\, o_i$ is the difference between absolute value $x_o(k)$ and $x_i(k)$. Ψ is the distinguishing coefficient $0 \leq \Psi \geq 1$. Δ min and Δ max are the minimum and maximum value among the $\Delta\, o_i$ for corresponding k^{th} response.

Now the Grey Relational Grade (GRG) can be calculated as :

$$\gamma i = \frac{1}{n}\sum_{k=1}^{n} \xi_i\,(k)$$

Where *n* is the number of process responses.

The higher value of the GRG corresponds to a relational degree between the Reference Sequence $x_o(k)$ and the given sequence $x_i(k)$. The Reference Sequence $x_o(k)$ represents the best process sequence. Therefore, a higher GRG means that the corresponding parameter combination is closer to the optimal. The mean response for the GRG and the main effect plot of the GRG are very important because the optimal process condition can be evaluated from this plot.

Table 9 S/N Ratio Calculation for MRR and Ra

S. No.	**Mean Values**		**S/N Ratios**	
Xo	**MRR**	**Ra**	**MRR**	**Ra**
1	304.85	0.57	49.681	4.882
2	334.53	0.96	50.488	0.354
3	444.14	1.04	52.950	-0.340
4	391.91	0.59	51.863	4.582
5	392.40	0.88	51.874	1.110
6	425.77	1.09	52.583	-0.748
7	438.65	0.81	52.842	1.830
8	433.14	0.86	52.732	1.310
9	399.22	0.81	52.024	1.830
10	502.37	0.97	54.020	0.264
11	483.87	0.84	53.694	1.514
12	480.36	0.94	53.631	0.537
13	494.41	0.92	53.881	0.724
14	504.57	1.06	54.058	-0.506
15	494.82	1.04	53.888	-0.340
16	483.99	1.06	53.696	-0.506
17	422.59	1.02	52.518	-0.172
18	459.82	0.98	53.251	0.175
Max.	304.85	0.57	49.681	4.882
Min.	504.57	1.09	54.058	0.354

Table 10: Grey Relational Analysis Calculations

S. N.	**GRGC**		**RSDC**		**GRCC**	
	MRR	**Ra**	**MRR**	**Ra**	**MRR**	**Ra**
xo	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
1	0.000	1.000	1.000	0.000	0.333	1.000
2	0.148	0.250	0.852	0.750	0.369	0.400
3	0.697	0.096	0.303	0.904	0.622	0.356
4	0.431	0.962	0.569	0.038	0.467	0.929
5	0.438	0.404	0.562	0.596	0.470	0.456
6	0.605	0.000	0.395	1.000	0.558	0.333
7	0.669	0.519	0.331	0.481	0.601	0.519
8	0.642	0.442	0.358	0.558	0.582	0.472
9	0.472	0.538	0.528	0.462	0.486	0.519
10	0.988	0.231	0.012	0.769	0.976	0.394
11	0.896	0.481	0.108	0.519	0.822	0.490
12	0.878	0.288	0.122	0.712	0.803	0.412
13	0.949	0.327	0.051	0.673	0.907	0.426
14	1.000	0.058	0.000	0.942	1.000	0.346
15	0.951	0.096	0.049	0.904	0.910	0.356
16	0.896	0.058	0.104	0.942	0.827	0.346
17	0.589	0.135	0.411	0.865	0.548	0.366
18	0.775	0.212	0.225	0.788	0.689	0.388

Where,
GRGC- Grey Relational Generation Calculation,
RSDC- Reference Sequence Definition Calculation,
GRCC- Grey Relational Coefficient Calculation

Table 11 GRG calculation

S. No.	**GRG**		**Rank**
	Mean	**S/N Ratio**	
1	0.6665	-3.5240	5
2	0.3845	-8.3020	18
3	0.4890	-6.2138	14
4	0.6980	-3.1228	1
5	0.4630	-6.6883	15
6	0.4455	-7.0230	17
7	0.5600	-5.0362	10
8	0.5270	-5.5637	12
9	0.5025	-5.9772	13
10	0.6850	-3.2861	2
11	0.6560	-3.6619	6
12	0.6075	-4.3290	8
13	0.6665	-3.5240	4
14	0.6730	-3.4397	3
15	0.6330	-3.9719	7
16	0.5865	-4.6346	9
17	0.4570	-6.8016	16
18	0.5385	-5.3762	11

Table 12: ANOVA table for means of GRG

V	DF	SS	MS	F	P	C
CS	5	0.06541	0.0130	3.38	0.062	40.87***
F	2	0.05077	0.0253	6.55	0.021	31.72**
D	2	0.01288	0.0064	1.66	0.249	8.04*
E	8	0.03099	0.0038			19.37
T	17	0.16005				100

Table 13: ANOVA table for S/N ratio of GRG

V	DF	SS	MS	F	P	C
CS	5	16.240	3.248	3.00	0.081	39.95***
F	2	12.563	6.282	5.81	0.028	30.91**
D	2	3.200	1.600	1.48	0.284	7.87*
E	8	8.650	1.081			21.27
T	17	40.653				100

Table 14 Response Table for means of GRG

Level	CS	F	DOC
1	0.5133	**0.6438**	**0.6022**
2	0.5355	0.5267	0.5367
3	0.5298	0.5360	0.5677
4	0.6495		
5	**0.6575**		
6	0.5273		
Delta	0.1442	0.1170	0.0655
Rank	**1**	**2**	**3**

Table 15 Response Table for S/N Ratio of GRG

Level	CS	F	DOC
1	-6.013	**-3.855**	**-4.510**
2	-5.611	-5.743	-5.543
3	-5.526	-5.482	-5.027
4	-3.759		
5	**-3.645**		
6	-5.604		
Delta	2.368	1.888	1.033
Rank	**1**	**2**	**3**

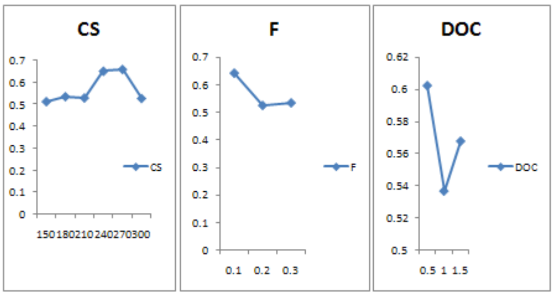

Fig 3 Main effect plot for means of GRG

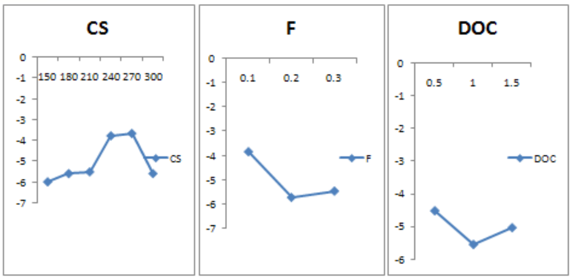

Fig 4Main effect plot for S/N Ratio of GRG

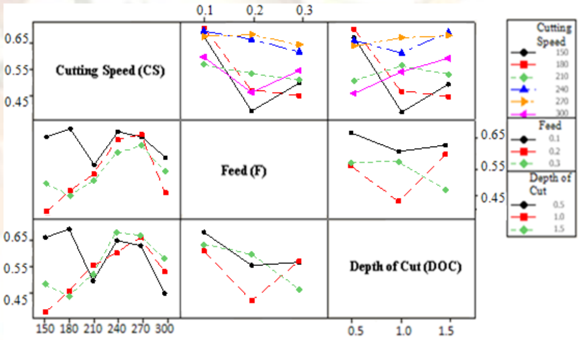

Fig 5 Interaction plot for means of GRG

7. Determination of Optimum Condition:

Both the response and S/N ratio are used to derive the optimum conditions. Since for quality characteristic, Grey Relational Grade larger the better approach is desirable, the largest is the ideal level for a parameter. The S/N ratio is always highest at the optimum condition. The graphs of Figures 2 and 3 are used to determine the optimum process parameters combination. The optimum combination is therefore V5-F1-D1.

7.1 Predictive Equation and Verification:

The predicted values of GRG, MRR and Ra at the optimal levels are calculated by using the relation:

$$\check{n} = nm + \sum_{i=1}^{o} (nim - nm)$$

Where,

ñ - Predicted response value after optimization,

nm - Total mean value of quality characteristic,

nim - Mean value of quality characteristic at optimum level of each parameter and

o - Number of main machining parameters that affect the response parameter.
Applying this relation, predicted values of GRG, MRR and Ra at the optimum conditions are calculated as:

1. ñGRG = 0.5688 + [(0.6575 - 0.5688) + (0.6438 – 0.5688) + (0.6022 - 0.5688)]
   = 0.7659
2. ñRa = 0.9133 + [(1.0067 – 0.9133) + (0.8200 – 0.9133) + (0.8117 – 0.9133]
   = 0.8118 µm.
3. ñMRR = 438.4 + [(497.9 – 438.4) + (436.0 – 438.4) + (416.2 – 438.4)]
   = 473.3 mm³/sec.

The robustness of this parameter optimization is verified experimentally. This requires the confirmation run at the predicted optimum conditions. The experiment is conducted twice at the predicted optimum conditions.

Verifications

1. For Material Removal Rate (MRR)

The calculated value of MRR at the optimum condition (V5-F1-D1) is 488.8 mm³/sec. The error in the predicted optimum value (473.3) and the calculated value (488.8) is only 3.2%.

2. For Surface Roughness (Ra)

The average of two measured values (0.83, 0.87) of the response at the optimum condition (V5-F1-D1) is 0.85 µm. The error in the predicted optimum value (0.8118) and experimental value (0.85) is only 4.7%.

Hence, so good agreement between the actual and the predicted results is observed. Since the percentage error is less than 5%, it confirms excellent reproducibility of the results. The results show that using the optimal parameter setting (V5-F1-D1) a higher material removal rate is achieved with lower surface roughness.

8. Results

The effect of three machining parameters i.e. Cutting speed, Feed rate and Depth of cut and their interactions are evaluated using ANOVA. The purpose of the ANOVA in this study is to identify the important turning parameters in prediction of Material Removal Rate and Surface roughness. Some important results come from ANOVA and plots are given here. Table 16 shown below shows that optimal values of surface roughness and material removal rate that lie between the optimal ranges.

Table 16 Optimal values of machining and response parameters

CP	OV	OL	POV	EOV	OR
CS	270	V5-	MRR= 473.3	MRR= 488.8	473.3 <MRR> 488.8
F	0.1	F1-			
D	0.5	D1	Ra= 0.8118	Ra= 0.84	0.8118 < Ra > 0.84

Where,
CP-Cutting Parameters
OV-Optimal Values of Parameters
OL-Optimum Levels of Parameters
POV-Predicted Optimum value
EOV-Experimental Optimum Value
OR-Optimum Range of MRR and Surface Roughness

9. Conclusions

In this study, the Grey relational based Taguchi method was applied for the multiple performance characteristics of turning operations.
A grey relational analysis of the Material removal rate and the surface roughness obtained from the Taguchi method reduced from the multiple performance characteristics to a single performance characteristic which is called the grey relational grade. Therefore, the optimization of the complicated multiple performance characteristics of the processes can be greatly simplified using the Grey relational based Taguchi method. It is also shown that the performance characteristics of the turning operations, such as the material removal rate and the surface roughness are greatly enhanced by using this method.

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