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Taguchi based Utility and Grey Relational Approaches to optimize Bi-Objective Machining of AISI 202 Stainless Steel

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Abstract: ***To optimize single response problems traditional Taguchi approach is widely used. Performance evaluation of the manufacturing process is often determined by several quality characteristics. Under such circumstances, multi-characteristics response optimization is the solution to optimize multi-objective quality characteristics. In the present work, bi-objective characteristics response optimization model based on Taguchi based Grey relational analysis and Utility approach is used to optimize process parameters, cutting speed, depth of cut, feed and nose radius on two different performance characteristics namely surface roughness (Ra) and material removal rate (MRR) during dry turning of austenitic stainless steel AISI 202 with cemented carbide tipped tool. Both approaches are analysed using Taguchi's L8 orthogonal array (OA) and found that both approaches predicted the same experimental settings, higher levels of cutting speed, depth of cut, nose radius and lower level of feed are critical to achieve low surface roughness and high material removal rate simultaneously.***

Index Terms: Utility approach, Grey relational analysis

I. INTRODUCTION

Austenitic stainless steels are two types, 200-series and 300-series. 300-series stainless steel is most widely used around the world. But in Asian countries, 200 series stainless steels have become more common in view of rise in nickel prices. AISI 202 stainless belongs to the low nickel and high manganese stainless steel which contains below 0.25% Nickel and manganese 7.5 to 10%. AISI 202 stainless steel is known for its high temperature strength than 18-8 steel at 800°C, with good oxidation resistance. This steel is widely used in architectural decoration, guard rail, hotel facilities, shopping malls etc.

Manufacturing industries focus their attention on surface finish and dimensional accuracy. To obtain ideal cutting parameters, they depend on the information available in machining handbooks and experience of the operator to fulfil their requirements of surface finish and dimensional accuracy. These traditional approaches lead to inadequate surface finish and reduced productivity due to sub-optimal use of machining capability. This leads to high manufacturing cost and low product quality [1]. Both material removal rate (MRR) and surface roughness are important performance characteristics in turning operation. Hence, there is a need to optimize the process parameters in an efficient way to achieve the requirements of two response characteristics by means of design of experiments and other statistical tools.

Taguchi's design of experiments (DOE) is one of the most important and proven tool in the industry to design robust experimental designs at reduced cost. These designs help to reduce the large number of experimental trials especially when the number of process parameters are more. But Taguchi's DOE approach is designed to optimize only single response problems. We can't use this technique directly to optimize multi-response problems. Most of the works published so far focused on single response performance characteristic optimization using Taguchi approach [2]. As the performance of product/process is often evaluated by several quality characteristics, it is required to consider multi-response optimization. Many researchers proposed various methods to solve multi-response optimization problems by converting it as single response optimization problem [3]..

M.Kaladhar et al [4] published their work on multi-response optimization of AISI 202 austenitic stainless steel for smaller surface roughness and larger material removal rate during turning. They have proposed Taguchi based Utility approach technique to find the best combination of the machining parameters like cutting speed, feed, depth of cut and nose radius of the cutting tool to accomplish minimum surface roughness and maximum MRR simultaneously. Confirmation tests were conducted and validated the results.

Present work is an extension of the research work published by M.Kaladhar et al [4]. Here, grey relational grade is calculated to find the best combination and results are compared with utility approach based predictions of M. Kaladhar et al. Process parameters and their levels used in the experiment are given in Table 1

Table 1 Process parameters and their levels

Code	Factors	Low level (-1)	High level (+1)
A	Cutting speed(m/min)	111	200
B	Depth of cut (mm)	0.25	0.75
C	Feed (mm/rev)	0.15	0.25
D	Nose radius (mm)	0.40	0.80

Finding the degree of freedom (DOF) of the system is the first step in Taguchi experimental design.

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Minimum number of experiments should be greater than or equal to the system degree of freedom as per Taguchi.
DOF = 1 + No. of Factors*(Levels-1) = 1 + 4(2-1) =5

As most of the Taguchi designs are fractional factorial designs, as per full factorial designs, total number of experiments required are (levels) Factors , which is 24 = 16. Fractional factorial designs possible are 8 or 4. As it should be greater than the DOF 5, L8 orthogonal array is selected for the experimental design. Responses surface roughness(Ra) and material removal rate(MRR) calculated are presented in Table 2.

Table 2. Responses of Taguchi L8 experimental design

A	B	C	D	Ra (µm)	MRR (cm3/min)
111	0.25	0.15	0.4	1.32	4.162
111	0.25	0.25	0.8	1.56	6.937
111	0.75	0.15	0.8	0.813	12.487
111	0.75	0.25	0.4	2.736	20.812
200	0.25	0.15	0.8	0.7	7.5
200	0.25	0.25	0.4	1.713	12.5
200	0.75	0.15	0.4	1.3	22.5
200	0.75	0.25	0.8	1.683	37.5

II. METHODOLOGY

As per Taguchi's approach responses are optimized individually, that is one response at a time. First surface response is optimised and then material removal rate is optimized. Predicted settings are analysed. In the next stage multi objective optimization using utility approach and grey relational analysis are carried out by converting the multi objective problem into single parameter optimization problem. Predicted settings are compared in both the cases.

2.1.Surface roughness Ra: It should be as small as possible. In Taguchi method, quality characteristic used is Signal-to-Noise ratio(S/N). For smaller the better, S/N of Ra is calculated using the formula -10 log10 [Ra2]. S/N values are presented in table 3 and S/N at different levels and their importance in terms of rank is presented in table 4. Main effects of S/N are shown in figure 1.

Figure.1 Main effects plot for SN ratios of Surface roughness

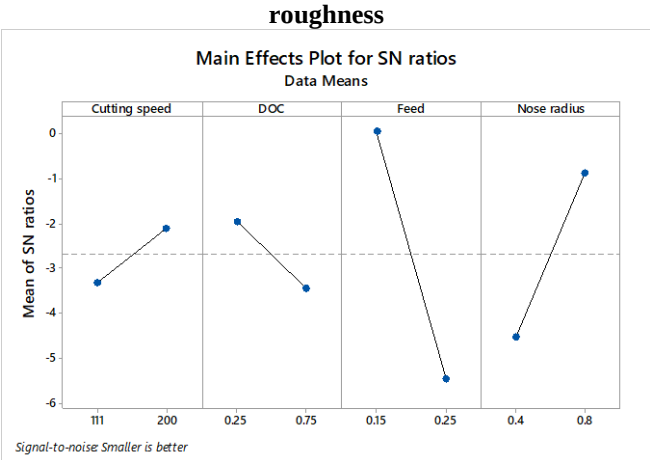

Table 3. Signal to Noise ratio of Surface roughness

A	B	C	D	Ra	S/N (Ra)
111	0.25	0.15	0.4	1.32	-2.41148
111	0.25	0.25	0.8	1.56	-3.86249
111	0.75	0.15	0.8	0.813	1.798189
111	0.75	0.25	0.4	2.736	-8.74232
200	0.25	0.15	0.8	0.7	3.098039
200	0.25	0.25	0.4	1.713	-4.67515
200	0.75	0.15	0.4	1.3	-2.27887
200	0.75	0.25	0.8	1.683	-4.52168

Table 4. Response table of S/N of surface roughness

Level	A	B	C	D
1	-3.30453	-1.96277	0.05147	-4.52695
2	-2.09441	-3.43617	-5.45041	-0.87199
Delta	1.21011	1.4734	5.50188	3.65497
Rank	4	3	1	2

From table 4, Feed and nose radius are influencing surface roughness as expressed empirically f2/8R, where f is feed and R is nose radius of the tool. Signal -to-noise ratio should be maximum for any quality characteristic. From S/N plot shown in figure 1, it is suggested that cutting speed at level2, Depth of cut at level1, Feed at level1 and Nose radius at level2 are best settings for less surface roughness. At these settings(A2B1C1D2), Predicted mean value of Ra is 0.460125.

Confidence Interval (CI) is calculated using the equation 1.

$$CI = \sqrt{\frac{F_{95\%,1,dof_{error}} * V_{error}}{n_{efficiency}}} \quad (1)$$

Where F 95%,1, dof of error is F-ratio for 95% confidence level and dof of numerator 1 and dof of denominator is degree of freedom of error 3, is F(1,3) at 95% confidence = 10.13 from F-distribution table.

From ANOVA table 5, Verror = Error mean square = 0.0711

n efficiency = N/(1+DOF of parameters allied to that level)

Where N= Total number of runs =8 and DOF=Levels-1

So n efficiency = 8/(1+1+1+1) =1.6

Therefore CI=±0.671

Predicted Mean value – CI ≤ Mean value at predicted levels ≤ predicted Mean value + CI

Predicted mean value at A2B1C1D2 is 0.46012. So, actual confirmation experiment mean value (observed mean) of Ra should be within 0.21 to 1.13

Prediction error = Predicated mean – Observed mean, and the prediction error should be within the confidence interval(CI) ±0.671

To find more accurately the influence of each parameter and to find the confidence interval, ANOVA is performed and percentage contribution of each factor is analysed as given in table 5.

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Table 5. ANOVA table for Ra

Source	DOF	Sum of Squares (SS)	Mean SS	F-Value	% contribution
Cutting speed	1	0.1334	0.1334	1.88	4.78%
DOC	1	0.1919	0.1919	2.7	6.87%
Feed	1	1.5833	1.5833	22.26	56.73%
Nose radius	1	0.6687	0.6687	9.4	23.96
Error	3	0.2134	0.0711		7.64%
Total	7	2.7907			

2.2 Material Removal Rate (MRR): MRR should be high. So, the quality characteristic is larger the better. Signal to noise ratio for larger the better is -10 log10 [1/(MRR)2]. S/N values calculated are presented in table 6. S/N at different levels and their importance in terms of rank is presented in table 7.

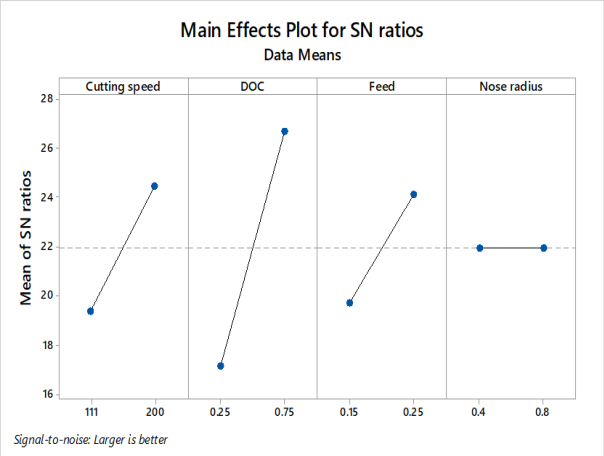
Table 6. Signal to noise ratio of Material Removal Rate

A	B	C	D	MRR (cm3/min)	S/N
111	0.25	0.15	0.4	4.162	12.3860415
111	0.25	0.25	0.8	6.937	16.8234339
111	0.75	0.15	0.8	12.487	21.9291622
111	0.75	0.25	0.4	20.812	26.3662763
200	0.25	0.15	0.8	7.5	17.5012253
200	0.25	0.25	0.4	12.5	21.9382003
200	0.75	0.15	0.4	22.5	27.0436504
200	0.75	0.25	0.8	37.5	31.4806254

Table 7. Rank allocation

Level	A	B	C	D
1	19.38	17.16	19.72	21.93
2	24.49	26.70	24.15	21.93
Delta	5.11	9.54	4.44	0.00
Rank	2	1	3	4

Main effects plot for S/N ratios is presented in Figure 2.
Figure 2: Main effects plot for S/N ratios for MRR



Signal-to-noise ratio should be high for any quality characteristic. Hence for large material removal rate(MRR) settings A2-B2-C2-D1 or D2 is suggested. Predicted mean value of MRR at these settings is 32.2188 cm3/min.

Confidence Interval (CI) is calculated using equation (1)

Where F 95%,1, dof of error is F-ratio for 95% confidence level and dof of numerator 1 and dof of denominator is degree of freedom of error 3, is F(1,3) at 95% confidence = 10.13 from F-distribution table.

From ANOVA table 8, Verror = Error mean square = 26.577

n efficiency = N/(1+DOF of parameters allied to that level)

Where N= Total number of runs =8 and DOF=Levels-1

So n efficiency = 8/(1+1+1+1) =1.6 ; On substitution, CI = ±12.9712

Predicted Mean value – CI ≤ Mean value at predicted levels ≤ predicted Mean value + CI

Predicted mean value of MRR at A2B2C2D2 is 32.2188. So, actual confirmation experiment mean value (observed mean) of MRR should be within 19.24 and 45.19.

Prediction error = Predicated mean – Observed mean, and the prediction error should be within the confidence interval(CI) ±12.9712.

To investigate further, ANOVA is performed for MRR and tabulated as shown in Table 8

Table 8. ANOVA of MRR

Source	DOF	Sum of Squares (SS)	Mean SS	F-Value	% contribution
Cutting speed	1	158.438	158.438	5.96	18.74 %
DOC	1	483.605	483.605	18.20	57.22 %
Feed	1	120.901	120.901	4.55	14.3%
Nose radius	1	2.475	2.475	0.09	0.29%
Error	3	79.732	26.577		9.43%
Total	7	845.151	845.151		

From ANOVA, DOC and Cutting speed are most significant factors for high material removal rate, as calculated using the formula MRR(cm3/min) =DOC(mm) x Feed(mm/rev) x Cutting speed(m/min)

2.3.Multi response optimization using utility approach: The ideal combination of process parameters for low surface Roughness(Ra) and high Material Removal Rate(MRR) simultaneously is obtained by the mean values of multi-response S/N ratio of the overall utility value. From Utility approach, the multi-response S/N ratio of the overall utility value is

(S/N) multi = W1 * (S/N) of Ra + W2 * (S/N) of MRR

Where W1 & W2 are the weights assigned to Ra and MRR, based on experience of engineers, customers' requirements and their priorities. Here equal importance is given for both Ra and MRR, therefore W1 and W2 =0.5. Overall S/N ratio and considering (S/N)overall as response, (S/N) value for this response considering larger the better quality characteristic are presented in table 9.

Now treating (S/N)overall as response we have to analyse above Taguchi design for larger the better characteristic, as the problem is converted as single response optimization as described in previously.

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Signal to noise ratio for larger the better(LTB) is -10 log10 [1/(S/N)2overall]

Then we have to find the optimum levels from the main effects plot for (SN)LTB as shown in figure 3. At these levels identified in figure 3, we have to predict the mean value. Optimum levels of process parameters for the multi response optimization are A2-B2-C1-D2 as shown in figure 3 and response table for S/N ratios of larger the better(LTB) case at different levels of parameters are presented in table 10.

Table 9. S/N values as per utility approach

A	B	C	D	(S/N) for Ra	(S/N) for MRR	(S/N)overall	(S/N)LTB
1	1	1	1	-2.41148	12.386042	4.987281	13.95728
1	1	2	2	-3.86249	16.823434	6.480472	16.23213
1	2	1	2	1.798189	21.929162	11.86368	21.48439
1	2	2	1	-8.74232	26.366276	8.811978	18.90147
2	1	1	2	3.098039	17.501225	10.29963	20.25643
2	1	2	1	-4.67515	21.9382	8.631525	18.72175
2	2	1	1	-2.27887	27.04365	12.38239	21.85609
2	2	2	2	-4.52168	31.480625	13.47947	22.59346

Figure3: Main effects plot for overall S/N as per utility approach

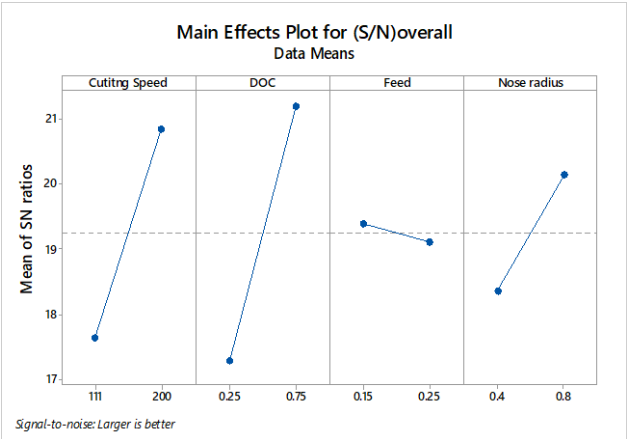

Table 10: Response Table of (S/N)LTB

Level	A	B	C	D
1	17.64	17.29	19.39	18.36
2	20.86	21.21	19.11	20.14
Delta	3.21	3.92	0.28	1.78
Rank	2	1	4	3

From experiments at A2-B2-C1-D2, we can calculate (S/N)overall by transforming the real values into S/N values.

(S/N)overall = W1 x (S/N) of Ra + W2 x (S/N) of MRR

Where S/N of Ra = -10 log (Ra2) and S/N of MRR = -10 log [1/(MRR)2]

Confidence Interval of (S/N)overall at 95% confidence for the predicted mean on confirmation experiment is calculated using the equation (1)

Where F 95%, 1, 3 = From F-distribution, F-ratio at 95 %

Numerator DOF is 1 and Denominator DOF is 3, so F(1,3)= 10.13

From ANOVA table11, Error Variance = V error = 0.3886

nefficiency = N/ (1 + Total DOF of parameters allied to that level)

Where N= Total Number of runs = 8 +1(confirmation)=9

Total DOF = (Levels-1) of each factor =1+1+1+1=4 (for 4 factors)

nefficiency = 9/(1 + (4)) =9/5= 1.8

On substitution CI = ±0.6233

Predicted Mean value – CI ≤ Mean at predicted level ≤ predicted Mean value + CI

14.3955 – 0.6233 < μ A2B2C1D2 < 14.3955 + 0.6233

Or 13.772 < μ A2B2C1D2 < 15.01

So at A2-B2-C1-D2, Ra and MRR values are transformed to (S/N)overall value and it should be with the range of 13.772 and 15.01

To investigate further, ANOVA is performed for (S/N)overall and tabulated in table 11.

Table 11: ANOVA table for (S/N) overall as per utility approach.

Source	DOF	Sum of Squares (SS)	Mean SS	F-Value	% contribution
Cutting speed	1	20.0016	20.0016	51.46	32.8
DOC	1	32.5568	32.5568	83.76	53.39
Feed	1	0.5669	0.5669	1.46	0.92
Nose radius	1	6.6797	6.6797	17.19	10.95
Error	3	1.1660	0.3886		1.91
Total	7	60.9709	60.9709		

From ANOVA results, DOC and Cutting speed are highly significant for low surface roughness and high material removal rate. Interaction effect of the process parameters is negligible (1.91%). Predicted mean value at A2-B2-C1-D2 is 14.3955 dB. This mean value is not either Ra or MRR. 14.3955 is combination of both Ra and MRR.

4. Multi response optimization using Grey Relational Analysis(GRA)

Four important steps in grey relational analysis are given below.

1. Responses of experiments are first normalized in a range from zero to one, known as the grey relational generation.
2. Grey relational coefficient is calculated based on the normalized experimental responses to represent the relationship between the desired and actual experimental responses.
3. Grey relational grade is calculated by averaging the grey relational coefficients of the selected responses. This is a measure of the overall performance characteristic of the multiple response process.

For Ra, Lower-the-better quality characteristic is considered and normalised values are found using the equation 2

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \qquad (2)$$

For MRR, Larger-the-better quality characteristic is considered and normalized values are found using the equation 3

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$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \quad (3)$$

Grey relational coefficient is calculated using the equation (4)

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{oi}(k) + \zeta\Delta_{\max}} \quad (4)$$

Where ζ is called as distinguishing or identification coefficient. As Ra and MRR are both are given same priority here ζ is taken as 0.5.

$\Delta_{oi}(k)$ is delta of particular run.

$\Delta_{\min}$ is minimum normalized value = 0

$\Delta_{\max}$ is maximum normalized value =1

From the grey relational coefficient, grey relational grade is calculated by averaging the grey relational coefficients corresponding to each performance characteristic. Higher grey relational grade represents that the corresponding experimental result is closer to the ideally normalized value. From table 12, 8th experiment is having highest grade in the existing eight experimental runs, which will give smaller surface roughness and larger material removal rate.

Since the Taguchi's experimental design(L8) is orthogonal in nature, we can separate out the effect of each machining parameter on the grey relational grade at different levels and highest grade for each factor is the optimum setting for multi objective optimization that is less surface roughness and more material removable rate. From the table 13, that combination is A2-B2-C1-D2. At these levels Taguchi predicted Grey relational grade is 0.7737 and Grey relational grade is enhanced from 0.7543 to 0.7737. Improvement in grey relational grade is 0.0194

Table 12: Calculation of grey relational grade from grey relational coefficients

Exp. No	Ra (Norm)	MRR (Norm)	Delta (Ra)	Delta (MRR)	Grey Coeff (Ra) = 0.5/(Delta+0.5)	Grey coeff (mrr) = 0.5/(Delta+0.5)	Grey Relational Grade
Ref. Sequence	1	1					
1	0.69	0	0.30	1	0.62	0.33	0.47
2	0.57	0.08	0.42	0.91	0.54	0.35	0.44
3	0.94	0.24	0.05	0.75	0.9	0.39	0.64
4	0	0.49	1	0.50	0.3	0.49	0.41
5	1	0.1	0	0.89	1	0.35	0.67
6	0.5	0.25	0.49	0.74	0.5	0.4	0.45
7	0.7	0.55	0.29	0.44	0.62	0.52	0.57
8	0.51	1	0.48	0	0.5	1	0.75

Table 13. Grey relational grades for different levels

	Grey relational Grade	
Factor	Level-1	Level-2
Cutting speed(A)	0.497857	0.61533846
Depth of cut(B)	0.513531	0.59966424
Feed(C)	0.59594	0.51725528
Nose radius(D)	0.480582	0.63261268

CONCLUSIONS

Both Utility approach and Grey Relational Analysis results reveal the same experimental settings (A2/B2/C1/D2) for multi-objective optimization of surface roughness and material removal rate. Hence both approaches can be used to optimize the multi-objective machining problems.

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