Taguchi integrated Grey Relation based Multi-Performance Optimization for Productivity and Surface Quality in Dry Machining of SS304

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Abstract

Stainless steel has numerous applications in medical, engineering and industrial fields. It is recognized as difficult to machine (DTM) material. Conventional machining is challenging and also environmentally-unfriendly. Therefore, in the present work, SS304 has been attempted to machine using coated carbide tools under dry environment. This paper reports the investigation conducted on analysis of the effects of machining parameters such as cutting speed, feed rate, and depth of cut on productivity (material removal rate) and surface quality (average surface roughness); and optimization of machining parameters for the best values of these machinability indicators. Taguchi L9 orthogonal array based experimentation has been done. ANOVA has also been conducted to verify the statistical fitness and significant parameters. Grey relational technique has been used for optimization. Dry machining of SS304 at optimum combination of machining parameters i.e. cutting speed: 70m/min; feed: 0.1mm/rev; depth of cut: 1mm resulted in the optimized values of machinability indicators i.e. material removal rate- 116.67 mm^3/s and average surface roughness- 1.99 µm.

Keywords
Dry machining, Machinability, Optimization, Stainless steel, Surface quality

1. Introduction

Stainless steel 304 is used in various biomedical, marine, automobile, precision manufacturing and chemical processing applications. It possesses special properties such as excellent corrosion resistance, biocompatibility, and good recrystallization [1-3]. In order to manufacture parts and components to be used in the aforementioned applications, stainless steel has to undergo extensive machining operations. Conventional machining of stainless steel is challenging due to its high work-hardening, low thermal conductivity and high toughness properties [4]. It results in poor work surface quality, extreme tool wear, and high consumption of energy etc. These overall results in high consumption of cutting fluids, escalated machining cost and environmental footprints. Machining without coolant or lubricant i.e. dry machining which is the environmentally-benign machining technique can be a good and affordable substitute of the conventional wet/flood cooling based machining to enhance the machinability of stainless steels. Coated carbide tools can also effectively contribute in that [5].
Material removal rate (MRR) and surface roughness are two most important machinability indicators that determine productivity and surface quality respectively. It is always desirable to achieve high productivity along with good surface quality. For that machining at optimum parameters is required to be done specifically for a particular material. It requires significant analysis and optimization efforts.
There have been some past attempts made by the researchers to optimize the machining parameters and machining performances for various DTM materials [6-8]. But, SS304 machining requires some more exploration to find novel ways of machining at optimum conditions. In the present work, an attempt has been made to optimize the machining parameters (CS, f and DoC) according to the response variable (MRR and Ra) simultaneously using Taguchi and Grey relational analysis.

2. Experimental Details

A total of nine experiments with two replications each have been conducted on a manual lathe machine where turning of SS304 material has been done using TiN/AlTiN coated carbide tools. The machining was done for 5min and 30s considering the factor of tool failure. ISO recommendations have been followed where maximum flank wear value 6 mm is considered as tool failure or end of tool life. Figure 1 presents the actual picture of the experimental setup and sequence of tasks performed for this research work. The process parameters and their respective levels used in present work are depicted in Table 1.

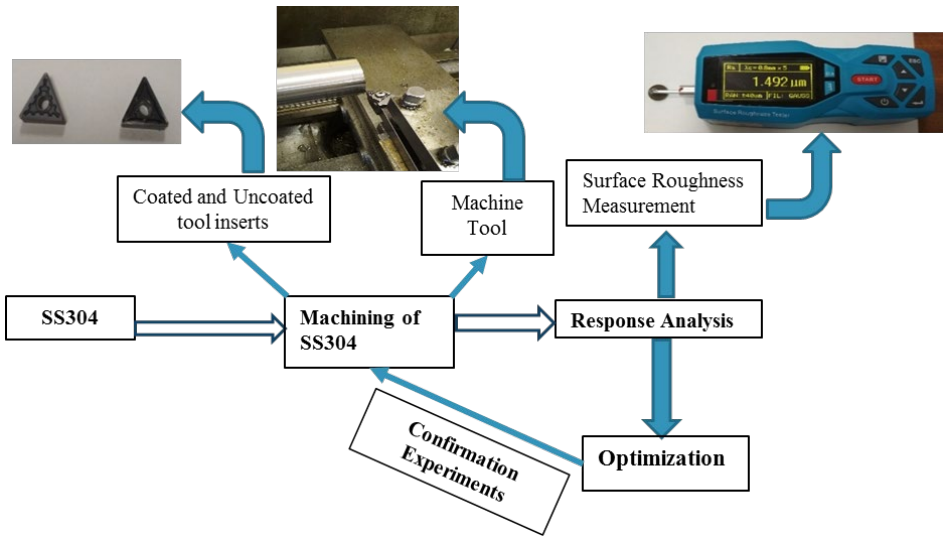


Fig. 1 Experimental setup and sequence of tasks

Table 1: Process parameters and their levels

Sr. No	Process parameter	Units	Level 1	Level 2	Level 3
1	**Cutting speed**	**m/min**	70	120	170
2	**Feed**	**mm/rev**	0.1	0.15	0.20
3	**Depth of cut**	**mm**	0.5	1.0	1.5

Material removal rate (MRR) has been calculated using Equation 1. Average surface roughness (Ra) has been measured by handheld surface roughness tester of TMtech make having resolution ±0.001µm. It is measured three time and their mean is used as final value for further analysis.

$$\text{MRR} = \text{Cutting speed} \times \text{Feed} \times \text{Depth of cut} \quad (1)$$

3. Results and Discussion

Table 2 presents all nine experimental combinations and corresponding values of responses (average values of replications) with their S/N ratios.

Table 2: Experimental combinations of process parameters with corresponding results

Exp. No	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	MRR	Ra	S/N (dB) for MRR	S/N (dB) for Ra
1	70	0.1	0.5	58.33	1.975	35.317	-5.911
2	70	0.15	1	175	2.4	44.86	-7.604
3	70	0.2	1.5	350	3.07	50.881	-9.742
4	120	0.1	1	200	2.312	46.02	-7.279
5	120	0.15	1.5	450	2.82	53.064	-9.004
6	120	0.2	0.5	200	2.771	46.02	-8.852
7	170	0.1	1.5	425	3.765	52.567	-11.515
8	170	0.15	0.5	212.5	3.337	46.547	-10.467
9	170	0.2	1	566.66	4.171	55.066	-12.404

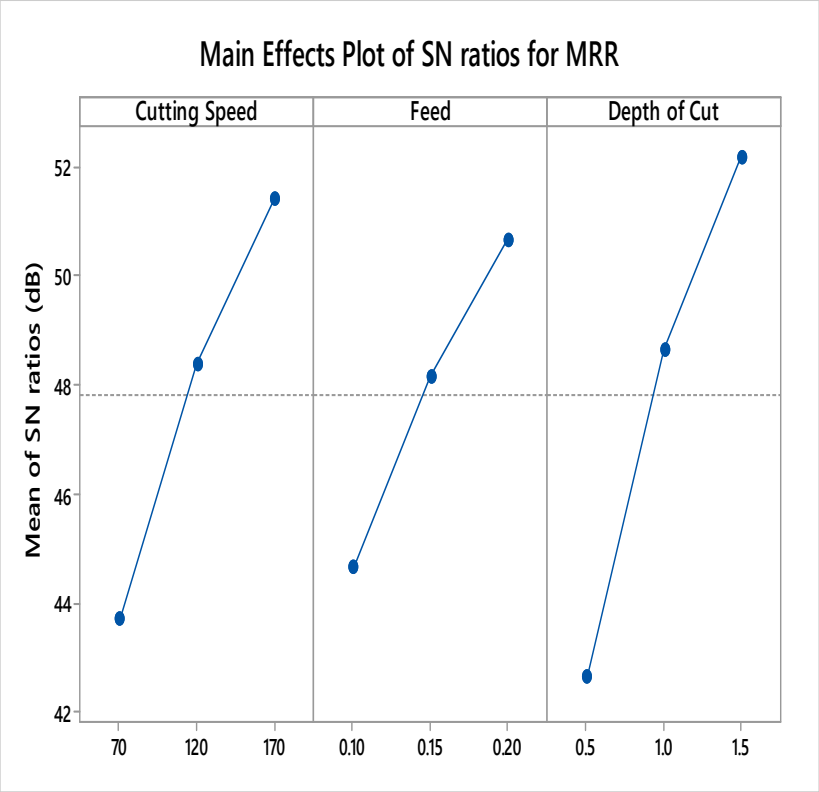
ANOVA of S/N ratio for MRR is given in Table 3. The statistical summary depicts that DoC have the maximum contribution (49%) for the calculation of S/N ratio of MRR followed by CS (31.74%) and f (19.26%). These percentage contributions have been investigated using the sum of square (SS) values, where as the mean square (MS) values were computed by dividing the SS to corresponding degree of freedom (DF).

Table 3: Analysis of variance of S/N ratio of MRR

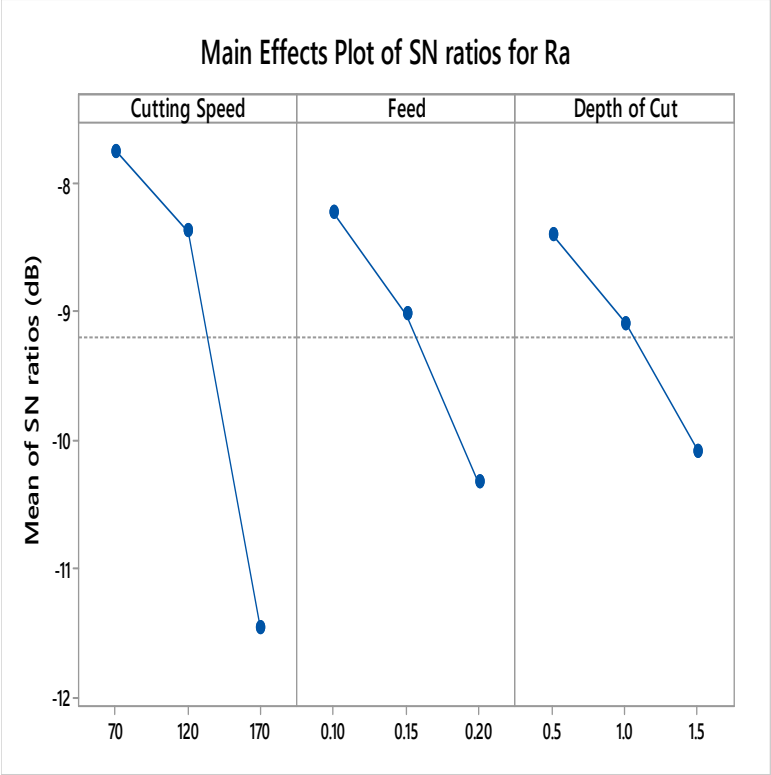
Source	DF	SS	Percentage Contribution	MS	F	P
Cutting Speed	2	90.472	31.74	45.2361	1136430000	0.000
Feed	2	54.897	19.26	27.4487	689572000	0.000
Depth of Cut	2	139.714	49.00	69.8569	1754960000	0.000
Residual Error	2	0.0001		0.00001		
Total	8	285.083				

Figure 2a represent the variation of S/N ratio of MRR at different levels of process parameters. As signal to noise ratio is the ratio of significant factors to non-significant factors. Therefore, this ratio must be higher-the-better type attribute either the response varibales 'smaller the better' type or 'higher the better' type attribute. It was found that for the caluculation of MRR, the third level of CS (170m/min), f (0.2mm/rev) and DoC (1.5mm) suggests the best setting. This is due to the fact that at high value of cutting speed more material was removed from the work-piece. At high value of feed rate, more material was removed with each revoultion of the work-piece. Therefore, high MRR was obtained. From Fig. 2a, it is clear that high value of DoC causes the high MRR.

Fig. 2b depicts the variation of S/N ratio of Ra with the input process parameters. It was observed that first level of CS, f and DoC favous the minimum Ra value.



(a)



(b)

Fig. 2 Variation of S/N ratio with process parameters for (a) MRR (b) Ra

Table 4: Analysis of variance for S/N ratio of Ra

Source	DF	SS	Percentage contribution	MS	F	P
Cutting speed	2	23.6602	68.11	11.8301	310.74	0.003
Feed	2	6.7364	19.39	3.3682	88.47	0.011
Depth of cut	2	4.2666	12.28	2.1333	56.04	0.018
Residual error	2	0.0761	0.22	0.0381		
Total	8	34.7393				

Table 5: Response table for Signal to Noise ratio

Level	MRR			Ra		
	Cutting speed	Feed	Depth of cut	Cutting speed	Feed	Depth of cut
1	43.69	44.64	42.63	**-7.753**	**-8.235**	**-8.410**
2	48.37	48.16	48.65	-8.379	-9.025	-9.096
3	**51.39**	**50.66**	**52.17**	-11.462	-10.333	-10.088
Delta	7.71	6.02	9.54	3.710	2.098	1.677
Rank	2	3	1	1	2	3

Table 4 shows the ANOVA of S/N ratio for Ra and is clear that for the Ra, CS (68.11%) has a significant contribution followed by f (19.39%) and Doc (12.28%). Higher the F-value, higher will be the influence of process parameter and smaller the P-value, higher the contribution of corresponding process parameter on response variables. The results obtained in case of percentage contribution are in-lined with the F-values and P-values. Table 5 gives the response table of S/N ratio for MRR and Ra. It was observed that third levels of CS, f and DoC correspond maximum MRR while on the other hand first level of CS, f and DoC correspond to the minimum Ra values. The rank of each parameter in case MRR and Ra is also provided in Table 5.

4. Multi-Performance Optimization

When two or more contradictory responses are optimized simultaneously, then the optimization is termed as multi-response optimization. Taguchi technique is suitable for planning of experiments and single response optimization for maximization or minimization only. The problems for quality and productivity can individually be solved by Taguchi method. But, for multi-response or multi-response optimization, a suitable statistical or soft computing technique is required. Therefore, in the present work, grey relation analysis (GRA) has been used for simultaneous optimization of MRR and Ra.

Grey theory first proposed by Deng [9], calculates the grade values depending upon the raw data or S/N ratio. If raw data was selected for the calculation purposes, then depending upon the quality attribute the lower the better or high the better selected and the normalization of the responses are done. If S/N ratio is selected then it done by selecting higher the better type attributes.

During multi-response optimization the grey relational coefficients for all the responses were calculated and depending upon the number output responses, the mean was evaluated to calculate grade value. Higher grade value corresponding to a setting suggests compromised values of response. The integration of Taguchi with GRA can be easily and effectively used for multiple response optimization.

GRA implementation steps as regards to the present work are described in the following paragraphs.

4.1 Data pre-processing

In data pre-processing, all the responses were normalized in between 0 and 1. This was done due to the fact that all the responses were not in the same range. Some have values in thousands and others are in microns, therefore to maintain symmetry all are normalized in between 0 and 1. Table 6 provides the normalized values of responses.

As in the present work, S/N ratio was used for the GRA, therefore larger the better type quality attribute was used. This larger the better type quality attribute follows equation 2.

$$A_i^*(K) = \frac{A_i(k) - \min A_i(k)}{\max A_i(k) - \min A_i(k)} \tag{2}$$

Where, $A^*_i(k)$ is the sequence after data pre-processing,
$A_i(k)$ is the original sequence.
Where k=1 for MRR and k=2 for Ra;
i=1, 2, 3…, 9 for experimental run 1 to 9.
$A_0^*(k)$ is equal to 1 and is the reference sequence.
The normalized values are given on Table 6 and all values come in between the 0 and 1.

Table 6: Normalized, deviational sequence, Grey relational coefficients and grade value

Exp. No	Normalized values		Deviation sequence		Grey relational coefficients		GRG
	MRR	Ra	MRR	Ra	MRR	Ra	
1	0.000	1.000	1.000	0.000	0.333	1.000	0.667
2	0.483	0.739	0.517	0.261	0.492	0.657	0.574
3	0.788	0.410	0.212	0.590	0.702	0.459	0.581
4	0.542	0.789	0.458	0.211	0.522	0.704	0.613
5	0.899	0.524	0.101	0.476	0.831	0.512	**0.672**
6	0.542	0.547	0.458	0.453	0.522	0.525	0.523
7	0.873	0.137	0.127	0.863	0.798	0.367	0.582
8	0.569	0.298	0.431	0.702	0.537	0.416	0.476
9	1.000	0.000	0.000	1.000	1.000	0.333	0.667

4.2 Calculating the GRC and grade

The deviational sequence was done as per the Equation 3. This was done after normalization and the values obtained the normalization was subtracted from the reference sequence.

$$\Delta_{0i}(k) = \left| A_0^*(k) - A_i^*(k) \right| \tag{3}$$

Where, $\Delta_{0i}(k)$ - deviation sequence,
$A_0^*(k)$ - Reference sequence,
$A_i^*(k)$ - comparability sequence.

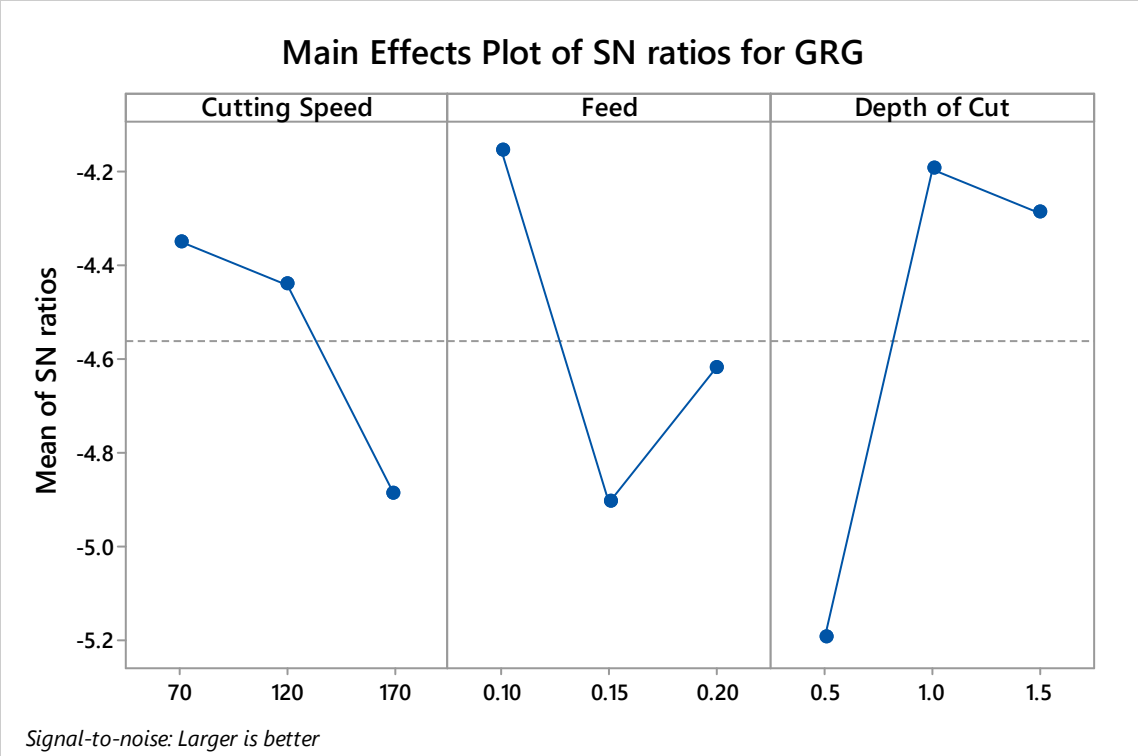


Fig. 2 Variation of S/N ratio with the process parameters for GRG

In the next step GRC was investigated as per Equation 4. It represents the relationship between actual normalized and best values.

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta.\Delta_{\max}}{\Delta_{0i}(k) + \zeta.\Delta_{\max}} \tag{4}$$

Where, Δ_{0i} (k) - deviation sequence,
ζ - identification coefficient. Depending upon the importance of responses, it was decided. In the present work, it is 0.5 to give equal importance to both responses.

The grey relational grade (γ) is calculated after making a mean of all GRC as per Equation 5. The overall evaluation of the multi-responses was dependent upon the grade values.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k) \tag{5}$$

Where γ_i is the grey relational grade for the ith experiment,
n - Number of responses.

Table 6 gives the grade values for all nine experiments. From Table 6 it is clear that trial five, gives the best grade value, therefore it gives compromised values of MRR and Ra. But at the same time, it was comparable to trial one and nine. In the present work, the analysis of grade value was done for simultaneous optimization, and it found first level of CS (70m/min), first level of f (0.1mm/rev) and second level of DoC (1mm) for the best values of MRR and Ra.

Table 7: Results of predicted and confirmation experiment for Multi response optimization

Response	Fifth trial of OA	First trial of OA	Ninth trial of OA	Optimal machining conditions	
				Predicted	Experimental
Setting level	$A_2B_2C_3$	$A_1B_1C_1$	$A_3B_3C_2$	$A_1B_1C_2$	$A_1B_1C_2$
MRR (mm^3/s)	450	58.33	566.66	149.99	116.67
Ra (µm)	2.82	1.975	**4.171**	2.210	1.993
GRG	0.672	0.667	0.667		

Table 7 shows predicted and experimental values of machining parameters and responses for different trials. It is seen that the grade values are very close to the experimental values.

5. Conclusions

In the present research work, dry machining of SS304 is done at different setting of input parameters. Taguchi integrated GRA technique has been used for multi-performance optimization of machining parameters with MRR and Ra as the major responses. The following conclusions can be drawn from this work-

1. The maximum MRR was obtained at CS: 170m/min; f: 0.2mm/rev; DoC: 1.5mm.
2. The minimum roughness was obtained at CS: 70m/min; f: 0.1mm/rev; DoC: 0.5mm.
3. ANOVA study confirms the statistical fitness of the data measured and obtained in the present work.
4. Depth of cut is the most influential factor for MRR and cutting speed for roughness.
5. The values of MRR and Ra after simultaneous optimization are 116.67 mm^3/s and 1.99 µm respectively.
6. For ready industrial use, the values of machining parameters for optimum productivity and surface quality under dry environment are- CS: 70m/min; f:0.1mm/rev; DoC: 0.5mm.

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Biographies

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