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Multi-response optimization for milling AISI 304 Stainless steel using GRA and DFA

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Abstract. The objective of the present work is to optimize process parameters namely, cutting speed, feed rate, and depth of cut in milling of AISI 304 stainless steel. In this work, experiments were carried out as per the Taguchi experimental design and an L_{27} orthogonal array was used to study the influence of various combinations of process parameters on surface roughness (Ra) and material removal rate (MRR). As a dynamic approach, the multiple response optimization was carried out using grey relational analysis (GRA) and desirability function analysis (DFA) for simultaneous evaluation. These two methods are considered in optimization, as both are multiple criteria evaluation and not much complicated. The optimum process parameters found to be cutting speed at 63 m/min, feed rate at 600 mm/min, and depth of cut at 0.8 mm. Analysis of variance (ANOVA) was employed to classify the significant parameters affecting the responses. The results indicate that depth of cut is the most significant parameter affecting multiple response characteristics of GFRP composites followed by feed rate and cutting speed. The experimental results for the optimal setting show that there is considerable improvement in the process.

Keywords: AISI 304 stainless steel; end milling; surface roughness; MRR; GRA; DFA

1. Introduction

Austenitic stainless steels are grades of chromium-nickel steels exhibiting a very high corrosion resistance in addition to a wide range of excellent mechanical properties not offered by any other alloy. Austenitic stainless steels cannot be hardened by traditional heat treatment processes but they can be strengthened by cold working (Peckner and Bernstein 1977). AISI 304 steel is hard to machine due to their high strength, high ductility and low thermal conductivity, high tensile strength, high fracture toughness and high work hardening rate. Machining operations of austenitic stainless steels are usually accompanied by a number of difficulties such as irregular wear and built-up-edge on the tool flank face and crater face, respectively (Kosa 1989, Groover 1990). The present of built-up-edge will cause an increase in tool wear rate and deterioration of the surface integrity of the work.

The surface roughness (Ra) and material removal rate (MRR) have been identified as quality

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attributes and are assumed to be directly related to performance of machining process, productivity and production costs. Several experimental investigations have been carried out over the years in order to study the effect of cutting parameters, tool geometries and cutting fluids on the workpiece surface integrity using several workpiece materials.

Thangarasu *et al*. (2012) established a relationship with the basic parameters to the responses namely surface roughness and material removal rate for AISI 304 stainless steel using Box-Behnken Response Surface Methodology, and multi-objective optimization of CNC milling process was carried out using Genetic Algorithm. Nalbant *et al*. (2007) used Taguchi method to find optimum cutting parameters for surface roughness in turning of AISI 1030 carbon steel bars using TiN coated tools by considering three cutting parameters namely, insert radius, feed rate, and depth of cut. They recommended, use of greater insert radius, low feed rate and low depth of cut to achieve better surface roughness for the specific test range. The Influence of cutting fluids on tool wear and surface roughness during turning of AISI 304 with carbide tool was carried out by Anthony Xavior *et al*. (2009). The study of surface roughness and tool wear on milling of AISI 304 stainless steel using different cooling conditions was done by Chockalingam *et al*. (2012). Kaladhar *et al*. (2010) studied surface roughness in turning of AISI 202 austenitic stainless steel using CVD coated cemented carbide tools. They have observed feed is the most significant factor that influences the surface roughness followed by nose radius. Bhattacharya *et al*. (2009) presented Taguchi and ANOVA techniques to analyse the effect of cutting parameters on surface finish and power consumption during high speed machining of AISI 1045 steel. They reported that cutting speed is the most significant factor on the surface roughness and power consumption, while the other parameters did not substantially affect the responses. The influence of machining parameters on the performance measures, surface roughness and flank wear in turning of AISI 304 austenitic stainless steel with a two layer Chemical vapour deposition(CVD) coated tool was attempted by Kaladhar *et al*.(2013). Ghani *et al*. (2004) applied Taguchi method to find optimum cutting parameters for surface roughness and cutting force in end milling when machining hardened steel AISI H13 with TiN coated P10 carbide insert tool under semi-finishing and finishing conditions of high speed cutting. Yang *et al*. (1998) have used Taguchi method to optimize the turning operation of S45C steel bars using tungsten carbide cutting tools and reported that cutting speed, feed rate, and depth of cut are the significant cutting parameters on surface roughness. El-Tamimi and El-Hossainy (2008) investigated the machinability of austenitic AISI 302 stainless steel under oblique cutting. They have studied the surface roughness at different cutting conditions and nose radius. Philip Selvaraj and Chandramohan (2010) brought out the influence of cutting parameters like cutting speed, feed rate and depth of cut on the surface roughness of AISI 304 austenitic stainless steel bars during dry turning.

From the earlier work done and literature, it shows that the surface quality (surface roughness) and material removal rate is strongly dependent on cutting parameters, tool geometry and cutting forces. Therefore this paper focuses on the effect of cutting speed, feed rate, and depth of cut on multiple responses using grey relational analysis (GRA) and also using desirability function approach with an aim to minimize Surface roughness and maximize material removal rate. To identify the significant parameters affecting the multiple response characteristic for milling AISI 304 stainless steel, ANOVA was applied.

2. Grey relational analysis (GRA)

GRA is a measurement technique in grey system theory that analyzes the degree of relation in a discrete sequence. GRA had been used for optimization of multiple response characteristics in machining variety of materials, and this method for the optimization of the multi-response problems is a very useful tool for converting multi-responses into single response problem. The step-by-step procedure followed by Gopalsamy *et al.* (2009) for converting multi-responses into single response problem is used for the analysis:

Step 1: Data preprocessing

Grey data processing must be performed before grey correlation coefficients are calculated. A series of various units must be transformed to be dimensionless. In order to find grey relational grade usually, each series is normalized by dividing the data in the original series by their average. Let the original reference sequence and sequence for comparison be represented as x_i (k) and y_i (k), i=1, 2….m; k=1, 2,….n, respectively, where m is the total number of experiments to be considered, and n is the total number of responses. Data preprocessing converts the original sequence to a comparable sequence. Several methodologies of preprocessing data can be used in GRA, depending on the characteristics of the original sequence. If the target value of the original sequence is "the-smaller-the-better", then the original sequence is normalized with Eq. (1).

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{1}$$

If the target value of the original sequence is "the-larger-the-better", then the original sequence is normalized with Eq. (2).

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

Step 2: Grey relational coefficients

Following the data preprocessing, a grey relational coefficient can be calculated with the Eq. (3) using the pre-processed sequences.

$$\chi_i(k) = \frac{\Delta_{\min} + \xi\,\Delta_{\max}}{\Delta_{0i}(k) + \xi\,\Delta_{\max}} \tag{3}$$

Where,

$\Delta_{0i}(k) = |x_0(k) - x_i(k)|$ = difference of absolute value $x_0(k)$ and $x_i(k)$;

ξ = the distinguishing coefficient $0 \leq \xi \leq 1$;

$\Delta_{\min} = \forall j^{\min} \in i\,\forall k^{\min} |x_0(k) - x_i(k)|$ = The smallest value of Δ_{0i}; and

$\Delta_{\max} = \forall j^{\max} \in i \forall k^{\max} |x_0(k) - x_i(k)|$ = The largest value of Δ_{0i}.

Step 3: Grey relational grade (GRG)

The grey relational coefficient values are used to find the grey relational grade. The grey relational grade for each experimental run can be obtained by accumulating the grey relational coefficient of each quality characteristic. The average grey grade for the i^{th} experimental run for all 'n' responses is given by Eq. (4).

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \chi_i(k) \qquad (4)$$

where n is the number of process responses and $\chi_i(k)$ is the grey relational coefficient of k^{th} response in i^{th} experiment.

The higher value of grey relational grade corresponds to intense 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, higher grey relational grade means that the corresponding parameter combination is closer to the optimal. The optimum level of the process parameters is the level with the highest grey relational grade.

3. Desirability function analysis (DFA)

Desirability function analysis (DFA) is one of the most extensively used methods for the optimization of multi-responses problems. DFA is used to change the multi-responses problems into single response problems. As a result, optimization of the complicated multi-response problems could be converted into optimization of a single response problem termed composite desirability (Naveen Sait 2009).

Step 1. Individual desirability function (d_i) for the corresponding responses has to be determined. For the smaller-the-better, the desirability function can be expressed as in Eq. (5). The value of $\hat{y}$ is expected to be the smaller-the-better while $\hat{y}$ is less than a particular criterion value, the desirability value will be equal to 1; if the $\hat{y}$ exceeds a particular criterion value, the desirability value will be equal to 0.

$$d_i = \begin{cases} 1, & \hat{y} \le y_{min} \\ \left(\dfrac{\hat{y} - y_{max}}{y_{min} - y_{max}}\right)^r, & y_{min} \le \hat{y} \le y_{max}, \quad r \ge 0 \\ 0, & \hat{y} \ge y_{max} \end{cases} \qquad (5)$$

where the y_{min} represents the lower tolerance limit of $\hat{y}$, the y_{max} represents the upper tolerance limit of $\hat{y}$ and r refers to the weight.

For the-larger-the better, the value of $\hat{y}$ is expected to be the larger the better. When the $\hat{y}$ exceeds a particular criteria value, which can be viewed as the requirement, the desirability value equals to 1; if the $\hat{y}$ is less than a particular criteria value, which is unacceptable, the desirability value equals to 0. The desirability function of the larger- the better can be written as given in Eq. (6)

$$d_i = \begin{cases} 0, & \hat{y} \le y_{min} \\ \left(\dfrac{\hat{y} - y_{min}}{y_{max} - y_{min}}\right)^r, & y_{min} \le \hat{y} \le y_{max}, \quad r \ge 0 \\ 1, & \hat{y} \ge y_{min} \end{cases} \qquad (6)$$

Table 1 Chemical composition of AISI 304 Stainless Steel

Element	C	Mn	Si	Cr	Ni	P	S
Wt %	0.02	1.31	0.32	16.38	12.17	0.3	0.2

where, y_{min} represents the lower tolerance limit of $\hat{y}$, y_{max} represents the upper tolerance limit of $\hat{y}$ and r represents the weight.

Step 2. The index of individual desirability for entire responses can be united to form a single value named composite desirability (dG) by Eq. (7)

$$dG = \sqrt[w]{(d_1^{w_1} * d_2^{w_2} \dots\dots\dots\dots..* d_i^{w_i})} \tag{7}$$

where d_i is the individual desirability of the property Y_i, w_i refers to the weight of the property "Y_i" in the composite desirability, and w is the summation of the individual weights.

Step 3. At last, the optimal parameter and its level of combinations are to be determined: The higher the composite desirability value implies better product quality. Thus, on the basis of the composite desirability (dG), the parameter effect and the optimum level for each parameter are estimated.

4. Experimental details

The experimental investigation presented here was carried out on a CNC milling (KENT Ind. Co. Ltd., Taiwan) with 7.5 kW power and maximum spindle speed of 8000 rpm. The work material selected for the study was AISI 304 stainless steel with high strength, high ductility and low thermal conductivity. The selection of the AISI 304 stainless steel was made taking into account its use in almost all industrial applications for approximately 50% of the world"s stainless steel production and consumption. The important characteristics responsible for the commercial popularity of this material are its ability to resistance to corrosion and staining. Low maintenance, relatively low cost and familiar lustre make it an ideal base material for a host of commercial

Fig. 1 Experimental setup on CNC vertical machining center

applications. The chemical composition of the work piece material is given in Table 1. The dimension of the work piece used in the experiment was 460 mm×100 mm×10 mm. The cutting tool used was tungsten carbide end mill with 4 flutes of 10 mm diameter. A schematic diagram of

Table 2 Machining parameters and levels

Parameters	Variables	Level 1	Level 2	Level 3
Cutting speed (m/min)	A	63	79	95
Feed rate (mm/min)	B	600	700	800
Depth of cut (mm)	C	0.4	0.6	0.8

Table 3 Experimental design using L_{27} orthogonal array and their responses

Trial No.	Variables			Surface roughness, Ra (µm)	Material removal rate, MRR (mm^3/min)
	A	B	C		
1	1	1	1	0.32	120
2	1	1	2	0.30	150
3	1	1	3	0.34	160
4	1	2	1	0.39	140
5	1	2	2	0.42	165
6	1	2	3	0.32	180
7	1	3	1	0.56	115
8	1	3	2	0.47	150
9	1	3	3	0.46	170
10	2	1	1	0.38	140
11	2	1	2	0.44	180
12	2	1	3	0.46	200
13	2	2	1	0.57	160
14	2	2	2	0.60	180
15	2	2	3	0.52	200
16	2	3	1	0.64	145
17	2	3	2	0.56	155
18	2	3	3	0.57	170
19	3	1	1	0.49	160
20	3	1	2	0.58	165
21	3	1	3	0.61	200
22	3	2	1	0.70	140
23	3	2	2	0.74	170
24	3	2	3	0.59	210
25	3	3	1	0.88	135
26	3	3	2	0.73	180
27	3	3	3	0.75	200

the experimental set-up used in this study is shown in Fig. 1.

The responses considered in this study are surface roughness and material removal rate. The surface roughness was evaluated using stylus type profilometer Mitutoyo SJ-201. The surface roughness used in this study is the arithmetic mean average surface roughness value (Ra), which is mostly used in industries. The experiments are repeated for three times and average values are used for the analysis. Material removal rate is used to evaluate a machining performance. Material removal rate is expressed as the amount of material removed under a period of machining time and is calculated using the Eq. (8).

$$MRR = \frac{Volume\ of\ material\ removed\ from\ work\ piece(mm^3)}{Machining\ time(min)} \tag{8}$$

where, Volume of material removed from work piece (mm^3) = Depth of cut (mm) * breadth of the work piece (mm) * groove width (mm).

To perform the experimental design, three levels of machining parameters cutting speed, feed rate, and depth of cut are selected and are shown in Table 2. To select an appropriate orthogonal array for the experiments, the total degrees of freedom need to be computed. The degrees of freedom for the orthogonal array should be greater than or equal to those for the process parameters. In this study, an L_{27} orthogonal array is used because it has 26 degrees of freedom more than the 6 degrees of freedom in the machining parameters. The experimental combinations of the machining parameters using the L_{27} orthogonal array are presented in Table 3. Based on the designed orthogonal array, twenty seven milling operations are performed on AISI 304 stainless steel.

4. Results and discussion

4.1 Multiple response optimizations using GRA

The Taguchi experimental design for various combination of machining parameters and experimental results for the surface roughness and MRR are tabulated in Table 3. Basically, the surface roughness belongs to the "smaller-the-better" methodology and the MRR belongs to the "larger-the-better" methodology that in Eqs. (1-2) which are employed for data preprocessing. The values of the surface roughness and MRR are set to be the reference sequence x_i (k), k=1,2. Moreover, the results of twenty seven experiments are the comparability sequences y_i (k), i=1,2….27, k=1,2. Table 4 lists all of the sequences after implementing the data preprocessing using Eqs. (1-2). Then the deviation sequences, $\Delta_{0i}(k) = |x_0(k) - x_i(k)|$, $\Delta_{max}(k)$ and $\Delta_{min}(k)$ for i=1-27, k=1, 2 can be calculated. The distinguishing coefficient ξ can be substituted for the grey relational coefficient in Eq. (3). If all the performance characteristics have equal weightage, ξ is set to be 0.5. The grey relational grade is calculated based on the Eq. (4). Table 5 lists the grey relational coefficients and the grade for all twenty seven comparability sequences. The higher grey relational grade represents that the corresponding experimental result is closer to the ideally normalized value.

This investigation employs the response table of the Taguchi method to calculate the average grey relational grade for each factor level, as illustrated in Table 6 and is represented graphically in

Table 4 The data preprocessing of the each individual quality characteristic

Trial No.	Ra	MRR
Reference sequence	1.0000	1.0000
1	0.9655	0.0526
2	1.0000	0.3684
3	0.9310	0.4737
4	0.8448	0.2632
5	0.7931	0.5263
6	0.9655	0.6842
7	0.5517	0.0000
8	0.7069	0.3684
9	0.7241	0.5789
10	0.8621	0.2632
11	0.7586	0.6842
12	0.7241	0.8947
13	0.5345	0.4737
14	0.4828	0.6842
15	0.6207	0.8947
16	0.4138	0.3158
17	0.5517	0.4211
18	0.5345	0.5789
19	0.6724	0.4737
20	0.5172	0.5263
21	0.4655	0.8947
22	0.3103	0.2632
23	0.2414	0.5789
24	0.5000	1.0000
25	0.0000	0.2105
26	0.2586	0.6842
27	0.2241	0.8947

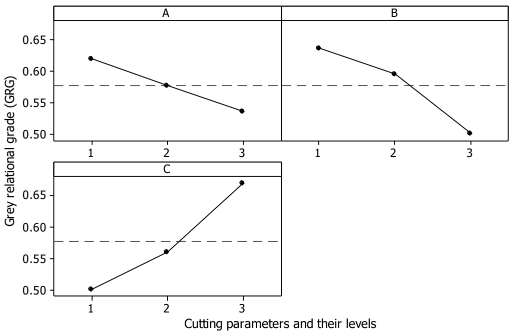

Fig. 2 Effect of milling parameters on grey relational grade (GRG)

Table 5 Grey relational coefficient of responses and grey relational grade (GRG)

Trial No.	Grey relational coefficient		Grey relational grade (GRG)
	Ra	MRR	
1	0.9355	0.3455	0.6405
2	1.0000	0.4419	0.7209
3	0.8788	0.4872	0.6830
4	0.7632	0.4043	0.5837
5	0.7073	0.5135	0.6104
6	0.9355	0.6129	0.7742
7	0.5273	0.3333	0.4303
8	0.6304	0.4419	0.5361
9	0.6444	0.5429	0.5937
10	0.7838	0.4043	0.5940
11	0.6744	0.6129	0.6437
12	0.6444	0.8261	0.7353
13	0.5179	0.4872	0.5025
14	0.4915	0.6129	0.5522
15	0.5686	0.8261	0.6974
16	0.4603	0.4222	0.4413
17	0.5273	0.4634	0.4953
18	0.5179	0.5429	0.5304
19	0.6042	0.4872	0.5457
20	0.5088	0.5135	0.5111
21	0.4833	0.8261	0.6547
22	0.4203	0.4043	0.4123
23	0.3973	0.5429	0.4701
24	0.5000	1.0000	0.7500
25	0.3333	0.3878	0.3605
26	0.4028	0.6129	0.5078
27	0.3919	0.8261	0.6090

Table 6 Response table for GRG

Parameter	Level-1	Level-2	Level-3	Optimum levels
A	**0.6192**	0.5769	0.5357	A1
B	**0.6365**	0.5948	0.5005	B1
C	0.5012	0.5608	**0.6697**	C3

Fig. 2. Since the grey relational grades represent the level of correlation between the reference and the comparability sequences, the larger grey relational grade means the comparability sequence exhibiting a stronger correlation with the reference sequence

Based on this study, a combination of the levels can be selected so that it can provide the largest average response. In Table 6, the combination of A1, B1, and C3 shows the largest value of the grey relational grade for the factors A, B, and C respectively. Therefore, it is observed that the cutting speed at 63 m/min, feed rate at 600 mm/min, and depth of cut at 0.8 mm is the optimal parameter combination of the milling AISI 304 stainless steel.

Table 7 shows the results of ANOVA for the grey relational grade. From the Table 7, it is observed that the depth of cut (Percentage contribution, P = 42.45 %) is the most significant machining parameter followed by feed rate (P = 28.23%), and cutting speed (P = 10.13%) affecting the multiple performance characteristics for AISI 304 stainless steel.

4.2 Multi-response optimization using DFA

For every response, the individual desirability (d_i) is calculated depending upon the required quality characteristics. For data pre-processing in the desirability function analysis process, surface roughness is taken as the “smaller is better” and material removal rate is taken as the “larger is better”. The calculated individual desirability for each quality characteristics with Eqs. (5)-(6), is shown in Table 8. With Eq. (7), composite desirability values (dG) are calculated. Finally, these values are taken for optimization of multi-response parameter design problem. The results are shown in Table 9. The effect of process parameters on composite desirability is graphically shown in Fig. 3. Considering the maximization of composite desirability value, the optimal parameter condition is obtained as A1B1C3 for milling AISI304 stainless steel.

Table 7 Results of the ANOVA for GRG

Parameter	Sum of square (SS)	Degree of freedom	Mean square (MS)	F- test	% Contribution
A	0.031385	2	0.015693	5.28	10.13
B	0.087431	2	0.043715	14.71	28.23
C	0.131472	2	0.065736	22.11	42.45
Error	0.059453	20	0.002973		19.19
Total	0.309741	26			100
R-Sq = 80.81% R-Sq(adj) = 75.05%					

Table 8 Individual desirability (d_i) and composite desirability (dG)

Trial No.	Individual desirability (di)		Composite desirability (dG)
	Ra	MRR	
1	0.9655	0.0526	0.5091
2	1.0000	0.3684	0.6842
3	0.9310	0.4737	0.7024
4	0.8448	0.2632	0.5540
5	0.7931	0.5263	0.6597
6	0.9655	0.6842	0.8249
7	0.5517	0.0000	0.2759
8	0.7069	0.3684	0.5377

Table 8 Continued

9	0.7241	0.5789	0.6515
10	0.8621	0.2632	0.5626
11	0.7586	0.6842	0.7214
12	0.7241	0.8947	0.8094
13	0.5345	0.4737	0.5041
14	0.4828	0.6842	0.5835
15	0.6207	0.8947	0.7577
16	0.4138	0.3158	0.3648
17	0.5517	0.4211	0.4864
18	0.5345	0.5789	0.5567
19	0.6724	0.4737	0.5730
20	0.5172	0.5263	0.5218
21	0.4655	0.8947	0.6801
22	0.3103	0.2632	0.2868
23	0.2414	0.5789	0.4102
24	0.5000	1.0000	0.7500
25	0.0000	0.2105	0.1053
26	0.2586	0.6842	0.4714
27	0.2241	0.8947	0.5594

Table 9 Response table for composite desirability (dG)

Parameter	Level-1	Level-2	Level-3	Optimum levels
A	**0.5999**	0.5941	0.4842	A1
B	**0.6404**	0.5923	0.4455	B1
C	0.4151	0.5640	**0.6991**	C3

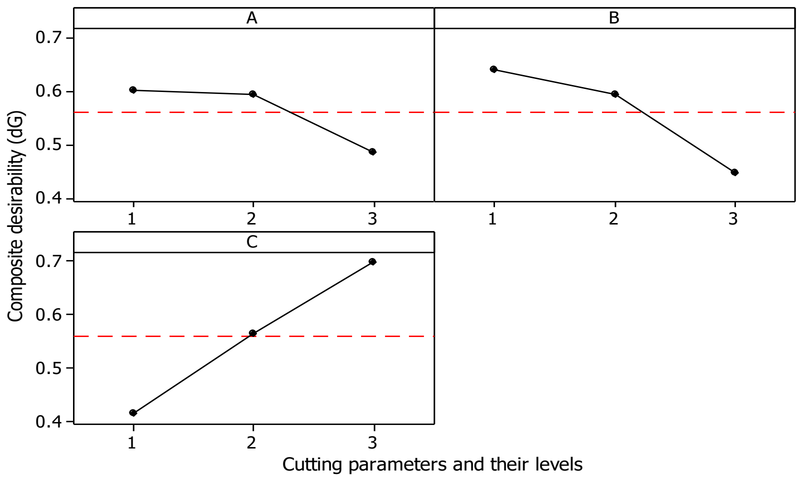

Fig. 3 Effect of milling parameters on composite desirability (dG)

Table 10 Results of the ANOVA for composite desirability

Parameter	Sum of square (SS)	Degree of freedom	Mean square (MS)	F- test	% Contribution
A	0.07647	2	0.03823	6.33	10.25
B	0.18572	2	0.09286	15.37	24.88
C	0.36338	2	0.18169	30.07	48.68
Error	0.12083	20	0.00604		16.19
Total	0.74640	26			100
		R-Sq = 83.81%	R-Sq(adj) = 78.96%		

Table 11 Results of confirmation test

Initial machining parameters		Optimal machining parameters Using GRA		Optimal machining parameters Using DFA	
		Prediction	Experiment	Prediction	Experiment
Levels	$A_1B_3C_1$	$A_1B_1C_3$	$A_1B_1C_3$	$A_1B_1C_3$	$A_1B_1C_3$
Surface roughness (μm)	0.56		0.34		0.34
MRR	115		160		160
Grey relational grade	0.4303	0.7709	0.6830 (improvement in GRG = 0.2527)		-
Composite desirability	0.2759		-	0.8206	0.7024 (improvement in dG = 0.4265)

The results of ANOVA for the composite desirability is shown in Table 10. From the Table 10, it is observed that the depth of cut (Percentage contribution, *P* = 48.68%) is the most significant machining parameter and feed rate (*P* = 24.88%) is the next significant parameter affecting the multiple performance characteristics for AISI 304 stainless steel.

5. Confirmation test

Once the optimal level of the process parameters has been determined, the final step is to verify the improvement of the responses using the optimal level of process parameters. Table 11 shows the comparison of the multi-response for initial and optimal machining parameters using both GRA and DFA. The initial designated levels of machining parameters are A1B3C1 which is the seventh experiment shown in the Table 3. As noted from the Table 11, the surface roughness is decreased from 0.56 μm to 0.34 μm and the MRR is increased from 115 mm^3/min to 160 mm^3/min respectively. The estimated grey relational grade is increased from 0.4303 to 0.6830 and the composite desirability value is increased from 0.2759 to 0.7024, which are shown in Table 11.

6. Conclusions

This present investigation is focused on effective milling of AISI 304 stainless steel using tungsten carbide end mill with multi-response optimization of machining parameters. From this study, using GRA, DFA, and ANOVA, the following results can be concluded:

• Multi-response optimization using GRA and DFA were performed for milling AISI 304 stainless steel and found the optimum setting of cutting speed at 63 m/min, feed rate at 600 mm/min, and depth of cut at 0.8 mm for minimization of surface roughness and maximization of material removal rate.

• From the results of ANOVA, the most significant machining parameters affecting the multiple performance characteristics is the depth of cut followed by feed rate, and cutting speed.

• Confirmation test results proved that the determined optimum condition of milling parameters satisfy the real requirements.

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