

# MULTI-RESPONSE OPTIMISATION OF TURNING PROCESS PARAMETERS WITH GRA AND TOPSIS METHODS

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## Abstract

The research deals with the optimisation of CNC turning process parameters to determine the optimal parametric combination that provides the minimal surface roughness ( $R_a$ ) and maximal material removal rate. The experiment was conducted by the CNC turning process of S355J2 carbon steel. Data from the Taguchi design of experiments were the subject of analysis with Grey Relational Analysis (GRA) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). In the present study, three process parameters, such as cutting speed, feed rate and depth of cut, were chosen for the experimentation. It was found that 250 m/min cutting speed, 0.10 mm/rev feed rate and 1.8 mm depth of cut presented the optimal parametric combination by both used multi-objective optimisation methods. Analysis of variance (ANOVA) at a 95 % confidence level was used to determine the most significant parameters. Finally, the accuracy of GRA and TOPSIS results were validated by confirmation experiments.

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**Key Words:** Turning, Cutting Parameters, Optimisation, Grey Relational Analysis, TOPSIS

## 1. INTRODUCTION

Cutting parameters' optimisation is one of the technological problems which is motivated by productivity and quality. Turning is the most common cutting process, and is, therefore, also one of the most researched and optimised processes. Despite this, because of the new part and tool materials and occurrence of new optimisation techniques, the number of published researches from this topic is still rising. Historically the first focus was on the increase of productivity and tool longevity, which is essential for rough turning. Increase of productivity or decrease of tool cost increase the process profitability, but it is usually degrading the quality, which is represented by accuracy and surface quality. Therefore, at the finishing stage of cutting, not only the cost is considered, but also the quality, and, consequently, the multi-criteria optimisation should be proceeded. When analysing manufacturing processes, experimental design is required to be evaluated with a limited number of experiments, in which the input parameters have a significant impact on the process performances, and how to select the appropriate level of inputs and appropriate multi-criteria optimisation techniques to achieve the best result.

The presented work deals with the optimisation of the turning process regarding the maximal material removal rate and minimal average surface roughness. After the introduction, the state-of-the-art of the multi-criteria cutting process follows. Experiments were based on the Taguchi orthogonal array of experiments to minimise the number of experiments, which were purposely chosen as small as possible. The collected data were used for optimisation by Grey Relational Analysis (GRA) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) respectively. The verification and conclusion were made after the analysis.

## **2. STATE-OF-THE-ART**

State-of-the-art of multicriteria optimization of process parameters presented here is focused to the study of cutting parameters' for turning. Design of experiments was made by the Taguchi method, which is a popular choice in the domain of Optimisation of Manufacturing Processes [1, 2], and especially for the turning process [3]. Yang and Tarng made one of the key researches of cutting parameters by the Taguchi method [4]. This research proved the Taguchi method to be a useful tool for design of experiments in the domain of Cutting Parameters Optimisations. The separate goals were to improve the surface quality and maximise tool life. Optimisation of surface quality is one of the most researched optimisation goals for the turning process [4, 5] and also for other processes [6, 7]. Proceeding researches researched various combinations of workpiece and tool materials, including tool coatings. Choice of materials ranges from the most common engineering metals like steels and aluminium alloys, where the goal is the optimisation of material removal rate, surface roughness, cutting force, accuracy [8] or combination of the above mentioned. Similar procedures were used for the optimisation of cutting parameters for machining of materials which are difficult to machine [9], such as various metal matrix composites [10, 11] or magnesium alloys [11, 12]. One of the motivations for such investigation is also enabling the machining technology with cutting parameters out of the most common intervals [13]. Gok researched the optimisation of cutting parameters according to the surface quality and cutting force [5]. Savicevic et al. analysed the impact of cutting parameters on surface roughness and cutting forces in turning of hard steel using CBN cutting tool [14]. The research was based on a Taguchi experiment and made by TOPSIS and multi-objective GRA [5]. The TOPSIS method was also used for optimisation of the dimensional accuracy of turning [8]. The influence factors' analysis was made by ANOVA, which is typical for many conducted researches. Sterpin Valic et al. [15] utilized Taguchi based entropy weighted GRA to obtain the optimal combination of turning parameters such as cutting speed, feed, depth of cut and cooling method on surface roughness, tool life and material removal rate as output responses. Ramanujam et al. used for the optimisation of cutting parameters GRA for turning of an Aluminium Silicon Carbide particulate Metal Matrix Composite [16]. Research made by Viswanathan et al. [11] for turning of magnesium alloy added Principal Component Analysis (PCA). Previous work from this group researched turning of magnesium alloy and employed GRA and TOPSIS [12]. The same combination of methods for minimisation of cutting force, temperature and surface roughness in end milling of challenging to cut magnesium hybrid metal matrix composite was also used by other researchers [17]. A similar methodology was also used by other authors for optimisation of surface roughness by turning of 15-5PH stainless steel [18]. The presented approach proved itself also usable for optimisation of other technologies, such as EDM [19, 20] or incremental sheet forming [21]. Response surface analysis is an additional method which proved itself in some researches [22, 23].

It has been observed from the literature that researchers used different multi-objective optimisation techniques to find the optimal input parameters concerning surface roughness and material removal rate in the turning process of various materials. It has been observed that different combinations of optimal parameters were obtained when analysing the same case and when using different multi-criteria optimisation techniques. However, this study has shown that, by selecting the input parameters properly and selecting their values appropriately with a reduced number of experiments, the same optimal combination of parameters can be obtained from several of the multi-criteria optimisation techniques used.

## **3. EXPERIMENT**

In this study, a CNC lathe machine, Doosan Puma (model: GT-2600M), was used for the experiment. A round bar of carbon steel S355J2 with a diameter of 50 mm and length of

150 mm was used as work material for turning. In each cut, the machining length was 90 mm. The work material was cut and cleaned before the actual turning machining. Turning experiments were conducted by using the external machining cutting tool with inserts, type DNMG 150604-TF IC907. For each experimental run, a new cutting insert was used, to eliminate the effect of tool wear. Fig. 1 shows the experimental setup.



Figure 1: Experimental set up.

The three input parameters were selected i.e. cutting speed, feed rate and depth of cut, varying at three levels. Input parameters and corresponding levels are given in Table I. The process parameter levels were chosen according to the recommendation of the cutting tool manufacturer. Taguchi experimental design with L9 orthogonal array was performed to find out the optimal setting parameters on the performance of the turning process. These methods were used to reduce the number of experiments to reach the optimal conditions. The experimental results with nine runs are presented in Table II.

Table I: Process parameters and corresponding levels.

Parameter	Unit	Symbol	Level 1	Level 2	Level 3
Cutting speed	m/min	$v$	150	200	250
Feed rate	mm/rev	$f$	0.10	0.15	0.20
Depth of cut	mm	$a$	0.6	1.2	1.8

Table II: Experimental results on surface roughness and *MRR*.

No.	$v$ (m/min)	$f$ (mm/rev)	$a$ (mm)	Surface roughness, $R_a$					Average $R_a$ ( $\mu\text{m}$ )	<i>MRR</i> ( $\text{cm}^3/\text{min}$ )
				$R_{a1}$	$R_{a2}$	$R_{a3}$	$R_{a4}$	$R_{a5}$		
1	150	0.10	0.6	1.150	1.117	1.108	1.073	1.080	1.106	9
2	150	0.15	1.2	2.069	2.067	2.057	2.056	2.032	2.056	27
3	150	0.20	1.8	3.464	3.506	3.248	3.478	3.481	3.435	54
4	200	0.10	1.2	1.137	1.063	1.137	1.155	1.086	1.116	24
5	200	0.15	1.8	3.619	3.302	3.067	3.510	3.537	3.407	54
6	200	0.20	0.6	3.365	3.238	3.391	3.325	3.350	3.334	24
7	250	0.10	1.8	0.859	0.814	0.821	0.832	0.808	0.827	45
8	250	0.15	0.6	1.850	1.808	1.847	1.845	1.805	1.831	22.5
9	250	0.20	1.2	3.526	3.619	3.571	3.529	3.570	3.563	60

The impact of process parameters was examined on machining characteristics such as surface roughness and Material Removal Rate (*MRR*). The surface roughness, with a sampling length of 0.8 mm on the machined surface, was measured using the Mitutoyo SJ-301 Surftest. The average roughness ( $R_a$ ) was used for the evaluation of the surface roughness, because it is

one of the most commonly used parameters in research, and in industry. The surface roughness was measured at five different places throughout the length of the machined surface.

The *MRR* was calculated using the following Eq. (1):

$$MRR = v \cdot f \cdot a \left[ \frac{\text{cm}^3}{\text{min}} \right] \tag{1}$$

where *v* is the cutting speed in m/min, *f* is the feed rate in mm/rev and *a* is the depth of cut in mm.

## 4. RESULTS AND DISCUSSION

### 4.1 Impact of process parameters on surface roughness and Material Removal Rate

The most common optimisation goal of the machining process is between productivity and quality. A multi-criteria optimisation has a goal to get a maximum *MRR* with minimum surface roughness at the same time. The impact of cutting speed, feed rate and depth of cut on surface roughness and *MRR* in a CNC turning process of steel S355J2 is illustrated in Figs. 2 and 3, respectively.

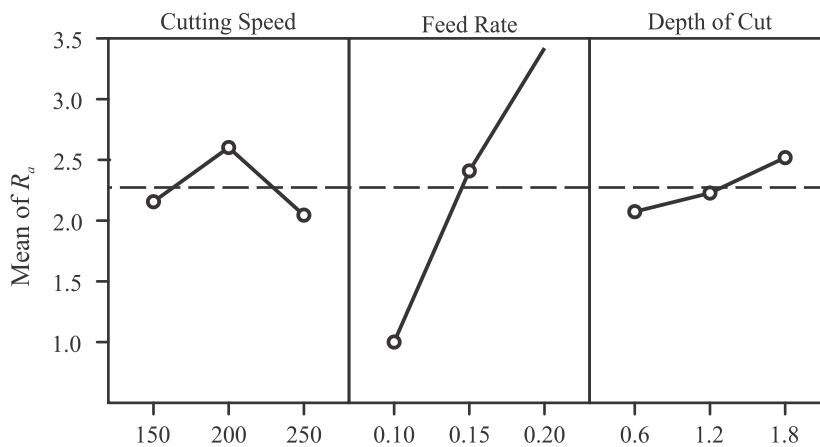


Figure 2: Mean of  $R_a$  at different levels of turning parameters.

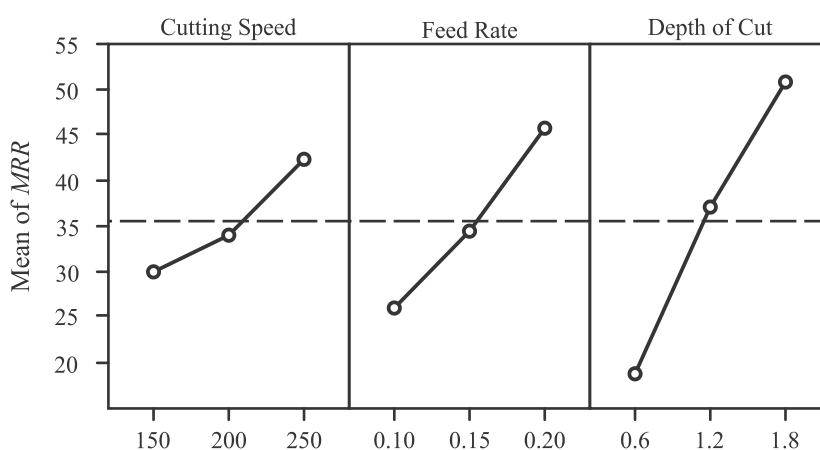


Figure 3: Mean of  $MRR$  at different levels of turning parameters.

Fig. 2 shows that the surface roughness ( $R_a$ ) first increased with an increase in the cutting speed from 150 m/min to 200 m/min, and then decreased from 200 m/min to 250 m/min with the cutting speed. It also shows that the  $R_a$  increased with an increase of feed rate from 0.10 mm/rev and 0.20 mm/rev, and with an increase in depth of cut from 0.6 mm to 1.8 mm. In

Fig. 3 it can be observed that the *MRR* increased with increases in cutting speed, feed rate and depth of cut.

### 4.2 Grey Relational Analysis

GRA is the most suitable multi-objective optimisation technique to get the optimal process parameters. Optimisation of multi-response characteristics can be converted into an optimisation single-response characteristic based on calculating Grey Relational Grade (*GRG*). The highest *GRG* is assigned the optimal state.

The first step in the GRA is the normalisation of the process responses. The objective of this study is to minimise the *R<sub>a</sub>*, hence, "the smaller is better" type was chosen, and the expression is given in Eq. (2):

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

*MRR* was maximised, hence "the higher is better" type was chosen and depicted in Eq. (3):

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

where,  $y_i(k)$  is the  $i^{\text{th}}$  experimental result for the  $k^{\text{th}}$  process response,  $\max y_i(k)$  is the maximum value of  $y_i(k)$ ,  $\min y_i(k)$  is the minimum value of  $y_i(k)$ , and  $x_i(k)$  is the normalised value of  $y_i(k)$ .

The normalised values of process responses calculated by Eqs. (2) and (3) are presented in Table III. After normalisation, the deviation sequences are calculated by Eq. (4):

$$\Delta_{0i}(k) = |x_0(k) - x_i(k)| \tag{4}$$

where,  $\Delta_{0i}(k)$  is the difference in the absolute value between  $x_0(k)$  and  $x_i(k)$ , and  $x_0(k)$  is the reference sequence of the  $k^{\text{th}}$  process response.

Table III: Normalised values and deviation sequences of process responses.

No. Ex.	Normalised values of responses, $x_i(k)$		Deviation sequences of responses, $\Delta_{0i}(k)$	
	<i>R<sub>a</sub></i>	<i>MRR</i>	<i>R<sub>a</sub></i>	<i>MRR</i>
1	0.8981	0.0000	0.1019	1.0000
2	0.5507	0.3529	0.4493	0.6471
3	0.0466	0.8824	0.9534	0.1176
4	0.8945	0.2941	0.1055	0.7059
5	0.0570	0.8824	0.9430	0.1176
6	0.0838	0.2941	0.9162	0.7059
7	1.0000	0.7059	0.0000	0.2941
8	0.6330	0.2647	0.3670	0.7353
9	0.0000	1.0000	1.0000	0.0000

Grey Relational Coefficient (*GRC*) calculated by Eq. (5) is depicted in Table IV:

$$\varepsilon_i(k) = (\Delta_{min} + \varepsilon \cdot \Delta_{max}) / (\Delta_{0i}(k) + \varepsilon \cdot \Delta_{max}) \tag{5}$$

where  $\Delta_{min}$  is the minimum value of  $\Delta_{0i}(k)$ ,  $\Delta_{max}$  is the maximum value of  $\Delta_{0i}(k)$ , and  $\varepsilon$  is the identification coefficient ranging within zero to one. It is usually considered to be 0.5. The *GRC* is used to estimate the *GRG*. It is expressed as:

$$\alpha_i = \frac{1}{n} \sum_{k=1}^n \varepsilon_i(k) \tag{6}$$

where  $n$  is the number of process responses.

The *GRC* and *GRG* are calculated by Eqs. (5) and (6), respectively, and presented in Table IV.

Table IV: Grey Relational Coefficient and Grey Relational Grade.

No. Ex.	<i>GRC</i>		<i>GRG</i>	Rank
	$R_d$	<i>MRR</i>		
1	0.8307	0.3333	0.58202	4
2	0.5267	0.4359	0.48130	8
3	0.3440	0.8095	0.57678	6
4	0.8257	0.4146	0.62017	3
5	0.3465	0.8095	0.57801	5
6	0.3530	0.4146	0.38384	9
7	1.0000	0.6296	<b>0.81481</b>	<b>1</b>
8	0.5767	0.4048	0.49073	7
9	0.3333	1.0000	0.66667	2

From Table IV it can be observed that experiment no. 7 had the highest *GRG* among the nine experiments. The means of the *GRG* for each level of process parameters were calculated based on the *GRG* values shown in Table IV and are presented in Table V. Total mean *GRG* was achieved from the mean of all the *GRGs*, whose value is 0.5771.

Table V: Response table for the mean *GRG*.

Parameter	Grey Relational Grade			Delta	Rank
	Level 1	Level 2	Level 3		
Cutting speed, $v$	0.5467	0.5273	<b>0.6574</b>	0.1301	3
Feed rate, $f$	<b>0.6723</b>	0.5167	0.5424	0.1557	2
Depth of cut, $a$	0.4855	0.5894	<b>0.6565</b>	0.1710	1
Total mean <i>GRG</i> is 0.5771					

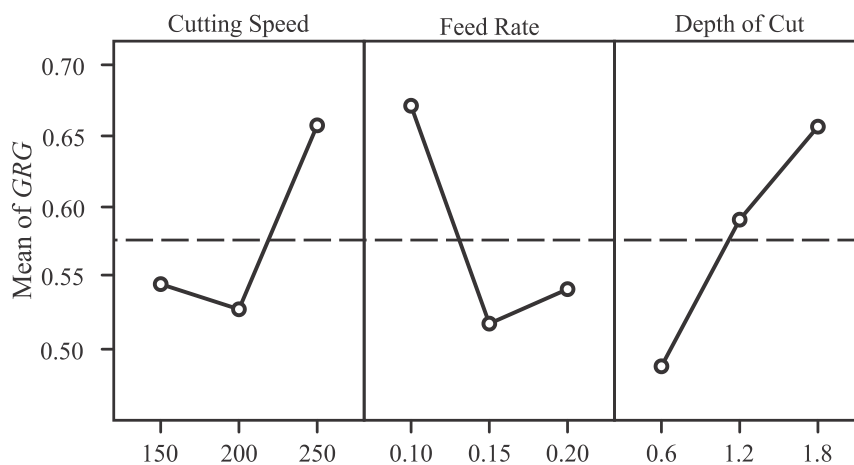


Figure 4: Main effects plot for *GRG*.

The most critical impact is indicated by the highest variation of the mean *GRG* value. Hence, the depth of cut has the most significant impact on the process performance, followed by feed rate and then the cutting speed. By considering the highest values of the mean *GRG* in Table V, the optimal parametric combination is  $v$  – level 3,  $f$  - level 1, and  $a$  – level 3. So, it was found that 250 m/min cutting speed, 0.10 mm/rev feed rate and 1.8 mm depth of cut presented the optimal parametric combination for carbon steel S355J2 turning, and it is shown in Fig.4.

### 4.3 ANOVA of Grey Relational Analysis

Analysis of variance (ANOVA) was applied to identify which turning parameters influenced the multi-response characteristics significantly by using the Grey Relation Grade value. Based on the ANOVA results in Table VI, it was found that the percentage contribution of cutting speed, feed rate and depth of cut affecting the multi-response characteristics was 24.54 %, 34.69 % and 36.99 %, respectively. The highest percentage contribution of ANOVA was obtained for a depth of cut, suggesting its maximum impact on the process performances, followed by the feed rate.

Table VI: ANOVA results for *GRG*.

Source	DF	Adj SS	Adj MS	F-value	p-value	Contribution (%)
Cutting speed	2	0.029547	0.014773	6.5	0.133	24.54
Feed rate	2	0.041767	0.020883	9.19	0.098	34.69
Depth of cut	2	0.044536	0.022268	9.79	0.093	36.99
Error	2	0.004547	0.002274			3.78
Total	8	0.120397				100.00

### 4.4 GRA confirmation experiment

After setting of the optimal parameter level, the verification test should be carried out to check the analysis accuracy. The estimated *GRG* was evaluated from the optimal level parameter as:

$$\gamma_i = \gamma_m + \sum_{i=1}^p (\bar{\gamma}_i - \gamma_m) \quad (7)$$

where  $\gamma_m$  is the total mean *GRG*,  $\bar{\gamma}_i$  is the mean *GRG* at the optimal level, and  $p$  is number of major variables.

Table VII: Results of GRA confirmation test.

Level	Initial factor setting	Optimal set	
	$v1 f1 a1$	Predicted $v3 f1 a3$	Experimental $v3 f1 a3$
Cutting speed (m/min)	150		250
Feed rate (mm/rev)	0.10		0.10
Depth of cut (mm)	0.6		1.8
$R_a$ ( $\mu\text{m}$ )	1.106		0.827
<i>MRR</i> ( $\text{cm}^3/\text{min}$ )	9		45
<i>GRG</i>	<b>0.58202</b>	<b>0.83198</b>	<b>0.81481</b>
Improvement in <i>GRG</i> is <b>0.23279</b>			

Table VII shows that *MRR* was improved from 9  $\text{cm}^3/\text{min}$  to 45  $\text{cm}^3/\text{min}$ , and  $R_a$  was also improved from 1.106  $\mu\text{m}$  to 0.827  $\mu\text{m}$  considering the initial set. Thus, it is shown clearly the significantly improved multi response characteristics in the turning of the examined steel in the *GRG* of 0.23279.

### 4.5 TOPSIS method

The basic principle of the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method is that the selection of a solution should be closest to a positive ideal solution, and farthest from a negative ideal solution. The primary goal is to find a solution according to the relative closeness coefficient between the achievable solution and the ideal solution.

The TOPSIS method was used to optimise the multi-response characteristics, such as  $R_a$  and  $MRR$ . The surface roughness  $R_a$  should be minimised, and  $MRR$  should be maximised. The following steps involved in TOPSIS are presented below.

*Step 1:* The first step in the TOPSIS method is to determine a normalised matrix using Eq. (8):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \tag{8}$$

where,  $x_{ij}$  is the actual value of the  $i^{\text{th}}$  experimental result for the  $j^{\text{th}}$  process response, and  $r_{ij}$  is the corresponding normalised value.

*Step 2:* The weighted normalised decision matrix is calculated as:

$$a_{ij} = w_j \cdot r_{ij} = w_j \cdot \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \tag{9}$$

where,  $\sum_{j=1}^n w_j = 1$  and  $w_j (j = 1, 2, \dots, n)$  are the weights per attribute.

The normalised matrix and the weighted normalised matrix calculated by Eqs. (8) and (9) respectively are listed in Table VIII.

Table VIII: Normalised matrix and weighted normalised matrix.

Exp. No.	Normalised matrix		Weighted normalised matrix	
	$R_a$	$MRR$	$R_a$	$MRR$
1	0.1452	0.0763	0.0726	0.0381
2	0.2701	0.2288	0.1351	0.1144
3	0.4513	0.4576	0.2256	0.2288
4	0.1465	0.2034	0.0733	0.1017
5	0.4476	0.4576	0.2238	0.2288
6	0.4379	0.2034	0.2190	0.1017
7	0.1086	0.3813	0.0543	0.1907
8	0.2405	0.1907	0.1203	0.0953
9	0.4680	0.5085	0.2340	0.2542

*Step 3:* Determine the positive ideal solution ( $A_j^+$ ) and the negative ideal solution ( $A_j^-$ ). The positive ideal solution is for the best possible value, and the negative ideal solution the worst value of every process response from the weighted decision matrix. Positive ideal and negative ideal solutions are determined as:

$$A^+ = \{A_1^+, \dots, A_n^+\},$$

where  $A_i^+ = \{\max(A_{ij}), \text{if } j \in J; \min(A_{ij}) \text{ if } j \in J^*\}$  (10)

$$A^- = \{A_1^-, \dots, A_n^-\},$$

where  $A_i^- = \{\min(A_{ij}), \text{if } j \in J; \max(A_{ij}) \text{ if } j \in J^*\}$  (11)

where  $J^*$  is a set of cost attributes and  $J$  is a set of beneficial attributes. In this case, the positive ideal solution for  $R_a$  is the minimum value, and for the  $MRR$  is the maximum value for each experimental result.

*Step 4:* The separation of positive ideal ( $S^+$ ) and negative ideal ( $S^-$ ) solutions calculated as:

$$S^+ = \sqrt{\sum_{j=1}^n (a_{ij} - A_j^+)^2} \tag{12}$$



$$S^- = \sqrt{\sum_{j=1}^n (a_{ij} - A_j^-)^2} \tag{13}$$

Step 5: The Relative Closeness Coefficient (*RCC*) is determined by using Eq. (14):

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{14}$$

The *RCC* of each experimental run is determined by the TOPSIS method, and their corresponding rank order is presented in Table IX.

Table IX: Relative Closeness Coefficient with the respective rank.

Exp. No.	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Closeness coefficient	Rank
1	150	0.1	0.6	0.42669	7
2	150	0.15	1.2	0.43625	6
3	150	0.2	1.8	0.52423	5
4	200	0.1	1.2	0.52932	3
5	200	0.15	1.8	0.52702	4
6	200	0.2	0.6	0.22540	9
7	250	0.1	1.8	<b>0.78764</b>	<b>1</b>
8	250	0.15	0.6	0.42533	8
9	250	0.2	1.2	0.54595	2

From Table IX it can be seen experiment no. 7 had the highest *RCC* among the nine experiments. The means of the *RCC* for each level of process parameters were calculated based on the *RCC* values presented in Table IX, and given in Table X.

Table X: Response table for the mean *RCC* with respective rank.

Parameter	Grey Relational Grade			Delta	Rank
	Level 1	Level 2	Level 3		
Cutting speed, <i>v</i>	0.4624	0.4272	<b>0.5863</b>	0.1591	2
Feed rate, <i>f</i>	<b>0.5812</b>	0.4629	0.4319	0.1494	3
Depth of cut, <i>a</i>	0.3591	0.5038	<b>0.6130</b>	0.2538	1

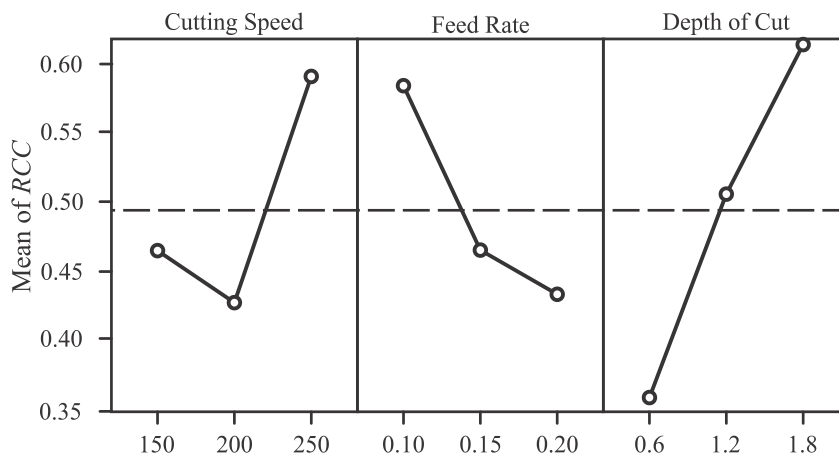


Figure 5: Main effects plot for *RCC*.

The most important impact was indicated by the highest variation of the mean *RCC* value. Thus, it can be observed that the depth of cut has the most significant impact on the considered process performance, followed by the cutting speed and then the feed rate. By considering the

highest values of the mean *RCC* in Table X, optimal parametric combination was:  $v$  – level 3,  $f$  – level 1, and  $a$  – level 3. Namely, it was found that 250 m/min cutting speed, 0.10 mm/rev feed rate and 1.8 mm depth of cut presented the optimal parametric combination for carbon steel S355J2 turning, and it is illustrated in Fig. 5.

#### 4.6 ANOVA of TOPSIS method

ANOVA was applied to identify which turning parameters influenced the multi-response characteristics significantly by using the *RCC* value. Based on the ANOVA results in Table XI, it was observed that the percentage contribution of cutting speed, feed rate and depth of cut affecting the multi-response characteristics were 23.69 %, 21.08 % and 55.00 %, respectively. The highest percentage contribution of ANOVA was obtained for a depth of cut, suggesting its maximum impact on the process performances, followed by the cutting speed and then the feed rate.

Table XI: ANOVA results for *RCC*.

Source	DF	Adj SS	Adj MS	F-value	p-value	Contribution (%)
Cutting speed	2	0.041891	0.020946	98.05	0.01	23.69
Feed rate	2	0.037278	0.018637	87.25	0.011	21.08
Depth of cut	2	0.097267	0.048634	227.67	0.004	55.00
Error	2	0.000427	0.000214			0.24
Total	8	0.176861				100.00

#### 4.7 TOPSIS confirmation experiment

The verification test was performed using the most appropriate combination of process parameters to check the accuracy of the analysis.

Table XII: Results of *RCC* confirmation test.

	Initial set	Optimal set - experimental
Level	$v1 f1 a1$	$v3 f1 a3$
Cutting speed (m/min)	150	250
Feed rate (mm/rev)	0.10	0.10
Depth of cut (mm)	0.6	1.8
$R_a$ ( $\mu\text{m}$ )	1.106	0.827
<i>MRR</i> ( $\text{cm}^3/\text{min}$ )	9	45
<i>RCC</i>	<b>0.42669</b>	<b>0.78764</b>
Improvement in <i>RCC</i> for an ideal solution is <b>0.36095</b>		

In Table XII, TOPSIS shows that increase in *MRR* with decrease of  $R_a$  obtained the optimal setting. So, it can be concluded that productivity and surface roughness were improved. For the ideal solution, the improvement in *RCC* value by the TOPSIS method was 0.36095.

## 5. CONCLUSION

The present study explains the process parameters' impact on surface roughness ( $R_a$ ) and Material Removal Rate (*MRR*) in the CNC turning process of S355J2 carbon steel. The Taguchi method was used to design the experiments, using L9 orthogonal array by varying the following process parameters, i.e., cutting speed, feed rate and depth of cut at three levels. The Multi-response optimisation GRA and TOPSIS were performed to obtain an optimal parametric combination that provides the minimum  $R_a$  with the maximum *MRR*.

The conclusions from the present experimental investigation are summarised below:

- a) The optimal combination of turning parameters was found to be at  $v3f1a3$ , i.e., at the cutting speed of 250 m/min, the feed rate of 0.10 mm/rev and depth of cut of 1.8 mm from both of the used multi-objective optimisation techniques.
- b) At a 95 % confidence level, based on the percentage contribution of ANOVA, the depth of cut was the most significant parameter for the process characteristics in both used techniques.
- c) The Relative Closeness Coefficient of the multi-response characteristics was improved significantly by 0.36095 through the TOPSIS method, and the GRG was also improved by 0.23279 through the GRA method.

Based on the results of this study, it can be observed that both techniques are suitable for setting the best achievable result for the combination of input parameters.

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