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Optimization of multi-response characteristics in CNC turning of Inconel 625 using Taguchi-grey relational analysis, weighted grey relational analysis, and analysis of variance methods

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ABSTRACT

In experimental design, the classical Taguchi method is often used to improve the processes that have only one main outcome. However, in real manufacturing, particularly during machining, it is often necessary to consider several important characteristics simultaneously. This study used a combination of the Taguchi method and grey relational analysis (GRA) to improve the CNC dry turning of Inconel 625. The goal was to make the process more efficient while also ensuring better surface quality, which are two goals that often work against each other. The approach uses the data from Taguchi designs to calculate signal-to-noise ratios (S/N) and combines them with GRA to create a single measure of overall performance. To understand how each process setting affects the final result, an analysis of variance (ANOVA) is performed. The best settings found were a depth of cut of 1.0 mm, a cutting speed of 80 m/min, and a feed rate of 0.08 mm/rev. These settings give the best balance between removing material quickly and keeping the surface smooth. The tests done to examine these results confirmed that the method works well, with the actual results matching the expected outcomes closely.

Keywords: Taguchi method, turning, multi-response optimization, grey relational analysis, weighted grey relational analysis, analysis of variance.

INTRODUCTION

Nickel-chromium alloys are notoriously difficult to manufacture due to their low heat conductivity, poor work hardening, and strong chemical activity [1]. When machining these alloys, properties like high strength, hardness, ductility, and tendency to harden at high temperatures make cutting forces high and chip breakage difficult. However, because of their strength and thermophysical qualities, they are frequently employed for components in the aerospace, chemical, and medical industries [2, 3]. The productivity of a manufacturing process depends heavily on input machining parameters. Therefore, optimizing these parameters helps improve performance and machinability. Optimization methods offer new opportunities for finding better solutions by helping find the best input parameters, which in turn increases productivity [4]. Industries look for a material removal rate (MRR) that is high enough to preserve product quality in a short amount of time to remain competitive in mass manufacturing. Surface roughness (Ra), which indicates the state of the surface following machining and the efficiency of the cutting process, is a crucial parameter for assessing the quality of a machined surface [5].

Single objective Taguchi-based techniques have been used to solve machining problems and optimize specific performance aspects, but they are not suitable for optimizing multiple performance factors at once. When multiple responses depend on the same input conditions, the method helps to identify the best settings for each response variable. However, it can be difficult to improve one performance feature without negatively affecting another because these conditions often change [6]. Therefore, compared to single-performance optimization, optimizing multiple-performance characteristics is inherently more complex [7]. The interactions between many components in a complex process like machining can be confusing [8]. The challenge is to keep the surface roughness low, while also making the process efficient by keeping high MRR. This trade-off has been studied a lot. Using support vector regression and NSGA-III, it was found that dry turning of AISI 4340 can lead to better machining results when MRR is optimized and Ra is controlled [9].

Similarly, the optimization of dry hard turning parameters for Inconel 625 was conducted using the Taguchi–grey relational approach (T-GRA), with the objective of minimizing surface Ra and cutting force (Fc), while maximizing the MRR. This study highlights the importance of balancing conflicting performance indicators in multi-objective optimization processes [10]. Deng's GRA is widely acknowledged for its ability to handle partial or ambiguous information in engineering situations. It excels in resolving complex relationships between different performance parameters by analyzing similarities between data series, especially when dealing with ambiguous or incomplete data [11]. While the Taguchi-GRA technique has been widely employed in the literature for multi-response optimization, the majority of research uses either equal weights for response qualities or subjectively stated weighting schemes with no good scientific foundation [12–14]. Such methods can undermine the credibility of optimization findings by failing to appropriately reflect the relative importance of each parameter. Dry machining of difficult materials, such as Inconel 625, has frequently employed this technique [15]. In recent years, researchers have enhanced the T-GRA technique by including fuzzy logic and weighted models to better reflect the importance of each performance factor [16], [17]. These methods improve the accuracy of optimization and help with better decision-making in multi-criteria situations, especially in dry turning (e.g., Inconel 625), where both surface quality and productivity are important. This research used a more objective and data-based weighting method that employs all the gray relational coefficients (GRC) to close this gap. The main goal of this study was to prove that the proposed method is effective and suitable by comparing the optimization results with other weighting methods, as well as to evaluate the system's stability and method validity using confirmation experiments.

MATERIALS AND METHODS

Figure 1 depict the structure of the study, as well as the experimental apparatus, process flow diagram, and optimization tools and methods used. The workpiece materials were round bars that were 180 mm long and 62 mm in diameter. The work material used in this experiment is Inconel 625. German-made Inconel 625 has a certificate of inspection in accordance with EN 10204-3.1 and is certified by Deutsche Nickel GMBH. Table 1 shows the chemical composition of components utilized in the workpiece.

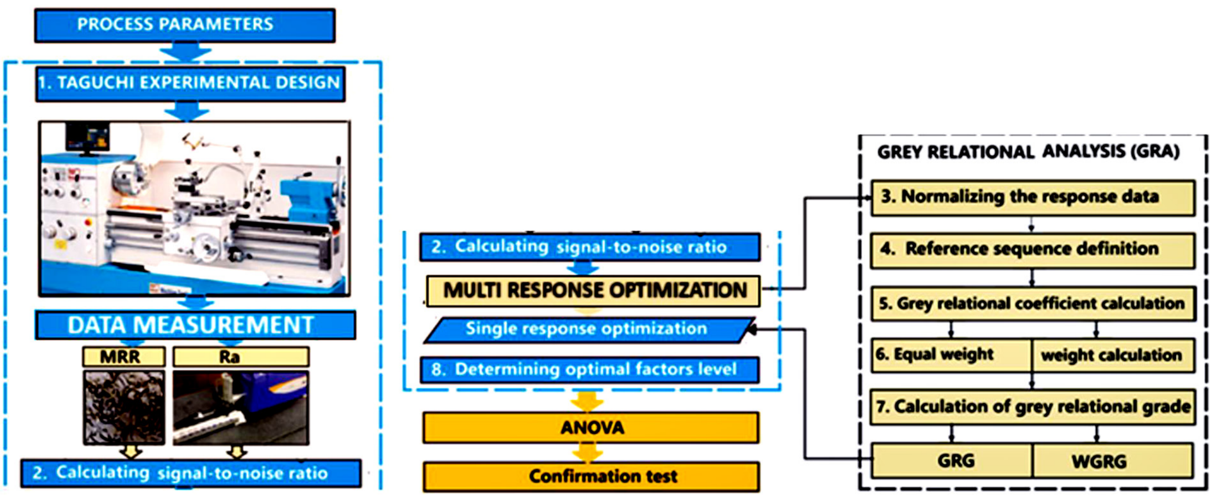

Figure 1. a) Experimental setup, b) process flow and Taguchi-GRA framework

Table 1. Chemical composition and mechanical properties

Chemical composition						Rm	HB
Ni [%]	Cr [%]	Mo [%]	Nb [%]	Fe [%]	Co [%]	N/mm^2	N/mm^2
59.64	22.34	9.20	3.57	4.20	0.032	470	223.229

The CNC lathe, Pico Turn V-Turn 410, has the following specifications: P = 5.5 kW, speed range 550–3000 rpm/min, and feed rate ranges; X-axis 0.025 mm/R – 0.85 mm/R, Z-axis 0.05 mm/R – 1.7 mm/R, turning-Ø over support 255 mm, center width 1500 mm, center height 205 mm, turning diameter over bed 380 mm and overall dimensions (length x width x height) 2.44 × 1 × 1.32 m.

Dry cutting conditions were used for the research and a CNMG 120408NN cutting insert with a TiN/TiCN PVD coating was used. Since Inconel 625 is difficult to manufacture, the PCLNR 2525 12A toolholder from the reliable business ISCAR was selected for the turning operations, as seen in Figure 2.

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Taylor Hobson's Talysurf portable surface roughness analyzer was utilized to test workpiece surface Ra, as demonstrated in Figure 3. It operated at a speed of 0.5 mm/s and used a cut-off interval of 4.8 mm. After taking three surface roughness measurements, the average roughness parameters of the workpiece surfaces were calculated. Although the measurement setup itself is conventional, it is included to illustrate the uniform procedure followed for each trial, ensuring data reliability and repeatability in surface roughness evaluation.

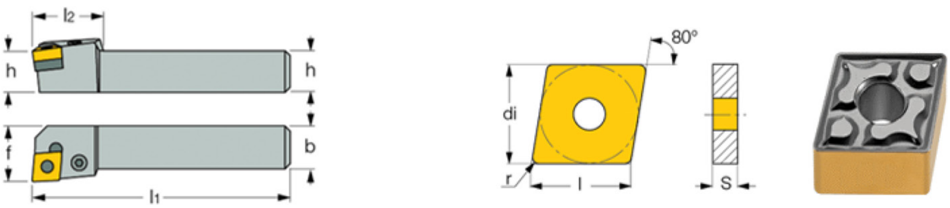
When looking at how productive the optimized settings are, the main thing to check is the material removal rate (MRR). MRR shows how much material is taken away in a minute during the turning process, and it is a key measure of how efficient the turning is. This study used this formula to calculate MRR, as mentioned in [18].

$$MRR = v \times f \times d \text{ [mm}^3\text{/min]} \quad (1)$$

where: v is the cutting speed (m/min), f is the feed rate (mm/rev), and d is the depth of cut (mm).

DESIGN OF EXPERIMENT

To find out how the different input variables affect the results, an approach called design of experiment (DOE) can be used. One type of DOE is the Taguchi design, also called an orthogonal array (OA), which uses only some of the possible



a) b)

Figure 2. a) Tool holder PCLNR 2525 12A, b) cutting insert CNMG 120408 NN

Figure 3. Measuring surface roughness using Talysurf, Taylor Hobson

combinations of settings [19, 20]. The effect of one factor does not affect the way another factor is measured because each can be studied on its own [18].

Choosing control factors and their levels

Even though a lot of research has been done on process optimization, there is not a single model that shows how input, output, and in-process factors are connected for all kinds of metal cutting [21]. Advice from toolmakers and existing data is not always enough to find the best ranges for the input parameters. Therefore, the authors conducted detailed initial tests on the workpiece material and cutting tool inserts to find the limits and the right levels for the parameters, as shown in Table 2. The study looked at two results: surface roughness (Ra) and material removal rate (MRR).

The goal was to make the surface as smooth as possible while removing least material. After checking three levels and three factors of degrees of freedom (DOF), the standard OA L9 (3^3) was chosen for this study [12]. The workpiece was tested for surface finish, as it is shown in Table 3.

The T-GRA method combines Taguchi's experimental design with GRA to allow for multi-response optimization. In this study, the S/N ratios for material removal rate and surface roughness were calculated using "larger-the-better" and "smaller-the-better" criteria, respectively [22, 23]. Normalization was performed, followed by the calculation of GRC and GRG, both equally and unequally weighted, to determine the best parameter values [24, 26]. Weight factors were calculated using the range of influence across responses, as described in the linked literature [26].

RESULTS AND DISCUSSION

The Taguchi L9 (33) orthogonal array was employed to produce both experimental and calculated results. Minitab 18, software for designing experiments and analyzing data, was used to evaluate the outcomes. The Taguchi method and ANOVA were then used to determine the best conditions for optimizing individual responses and assessing their contributions. In practical engineering problems, different responses hold varying levels of significance. The GRG can fluctuate notably when responses are assigned unequal weights, highlighting the critical role of weight allocation in achieving optimal results. Therefore, to accurately assign values to multiple responses during optimization, it is essential to establish an objective and fair method for calculating weight factors [24, 27, 28]. The proposed weighting method, which is based on the quantitative influence degree of each response, was chosen due to its impartiality and simplicity in describing experimental response sensitivity. Unlike information-theory-based methods like entropy or CRITIC, which rely on correlation or data dispersion, the current method directly displays the relative influence of responses resulting from experimental variability. This guarantees that the statistical contribution of each response is aligned with the optimization target.

Answers to engineering problems vary in their importance. GRG varies dramatically when the different responses have unequal weight, indicating the relevance of weight considerations for the best results. This work utilized Taguchi-based grey relational analysis (T-GRA) and weighted GRA to improve response variables, focusing on optimizing both MRR and surface Ra. The

Table 2. Process parameters and their levels

Cutting parameters	Notation	Unit	Levels		
			1	2	3
Cutting speed	S	m/min	50	65	80
Feed rate	F	mm/rev	0.04	0.06	0.08
Depth of cut	D	Mm	0.4	0.7	1.0

Table 3. The coded experimental and natural matrix of the orthogonal array L9 for Ra, MRR, and S/N ratio

Exp. No.	Coded matrix			Natural matrix			Responses			
	Abbreviation			S	F	D	Ra	MRR	Ra	MRR
	Unit			m/min	mm/rev	mm	μm	mm^3/min	S/N	S/N
1	1	1	1	50	0.04	0.4	0.911	0.8	0.810	-1.94
2	1	2	2	50	0.06	0.7	1.595	2.10	-4.055	6.44
3	1	3	3	50	0.08	1.0	1.573	4.00	-3.935	12.04
4	2	1	2	65	0.04	0.7	1.174	1.82	-1.393	5.20
5	2	2	3	65	0.06	1.0	1.542	3.90	-3.762	11.82
6	2	3	1	65	0.08	0.4	2.092	2.08	-6.411	6.36
7	3	1	3	80	0.04	1.0	0.884	3.20	1.071	10.1
8	3	2	1	80	0.06	0.4	1.355	1.92	-2.639	5.67
9	3	3	2	80	0.08	0.7	2.345	4.48	-7.403	13.03

multi-response characteristics were transformed into a single response using GRA, and the signal-to-noise ratio (S/N) was computed using the Taguchi method [29]. Table 4 shows the calculated GRC and GRG for equal weight (GRGEW) and weighted (GRGW) for MRR and Ra scale according to [9, 25, and 26].

This procedure entails allocating weights depending on the quantitative influence degree of each performance answer. The weights ratio (0.52:0.48) was calculated as the average total of the GRC range [21]. Table 4 reveals that experimental run 9 has the highest GRew and GRGw, equal to 1. A GRG of 1 means that the process or product of the system perfectly meets the target values for all performance criteria [16]. Next, the average of GRGEW and GRGW with identical parameter levels in each column of the orthogonal set is determined using the Taguchi analysis response table, as shown in Table 5.

When the ratio of weights between the two responses in the considered case (e.g., Ra and MRR) is 52% to 48%, and these weights are compared to an equal ratio (50:50) in the GRG, the significance of this change can be interpreted as a small fluctuation but indicating a tendency towards one of the responses (Ra). Since GRG remains almost constant, this trend suggests that even with a small uneven distribution between Ra and MRR, the overall system is stable. This stability can be interpreted as evidence for the robustness of the chosen method. To determine the optimal level of factors (V, F, D) from Table 5 and GRG main effects graphs shown in Figure 4, it is necessary to define the optimization objectives. If the objective is to maximize average response, larger values are better, or minimize if smaller values are desired [29, 30]: V = 80 (consistent with the SN ratio and the mean), F = 0.08 (consistent with the SN ratio and the mean), D = 1.0 (highest SN ratio, but the mean reaches D = 0.7).

In this case, the goal was to maximize the response with the least variability, so the SN ratio was prioritized (minimizing variability, D

Table 4. Results of grey relational analysis $GRGE_W$, and GRG_W

Exp. No.	GRC_{MRR}	GRC_{Ra}	GRG_{EW}	SNR_{GRGEW}	RANK	GRG_W	SNR_{GRGW}	RANK
1	0.33	0.34	0.34	-9.45174	9	0.34	-9.44798	9
2	0.53	0.56	0.55	-5.26875	6	0.55	-5.25983	5
3	0.88	0.55	0.72	-2.8953	3	0.71	-2.98	2
4	0.49	0.41	0.45	-6.91417	8	0.45	-6.94445	8
5	0.86	0.54	0.70	-3.10642	2	0.69	-3.19053	3
6	0.53	0.81	0.67	-3.48413	5	0.68	-3.40827	4
7	0.72	0.33	0.53	-5.58022	4	0.52	-5.71399	6
8	0.50	0.47	0.49	-6.24116	7	0.49	-6.25362	7
9	1.00	1.00	1.00	0	1	1.00	0	1

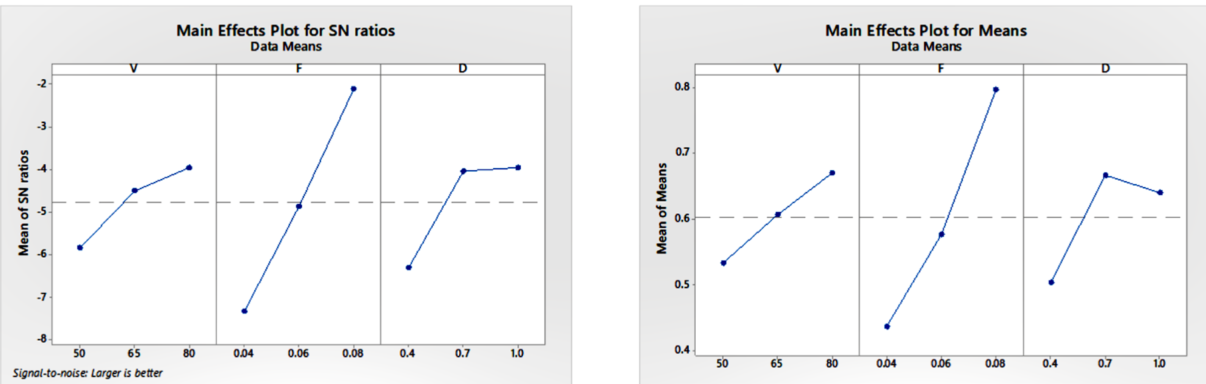
Table 5. Average values, ranking of parameters, and optimal level of GRG_{EW}, and GRG_W

Parameter	GRG_{EW}			GRG_W		
Level	S	F	D	S	F	D
1	0.5329	0.4380	0.4980	0.5333	0.4367	0.5033
2	0.6067	0.5773	0.6654*	0.6067	0.5767	0.6667*
3	0.6712*	0.7954*	0.6473	0.670*	0.7967*	0.6400
Delta	0.1383	0.3574	0.1675	0.1367	0.3600	0.1633
Range	3	1	2	3	1	2
GRGm		0.60			0.60	

Note: * Indicates the optimal level of GRG.

= 1.0); as a result, the optimal level chosen is V3S3D3, which represents the best performance for multiple quality characteristics, such as surface roughness and material removal rate. As it can be seen, the determined optimal levels of the process parameters S3V3D3 are not consistent with any of the nine tests shown in Table 3. As a result, optimal response values must be found experimentally, through verification testing or using Taguchi prediction or linear regression. [31, 32]. These strategies allow researchers to enhance their processes and increase product quality by methodically finding the variables that have a substantial impact on outcomes. Organizations can use these statistical tools to make more informed decisions that increase efficiency and minimize variability in their operations. The ANOVA method calculates the proportions for multiple inputs based on the variability of the response variable. The main goal of this approach is to estimate how much each factor (V, F, D) contributes to the total variance and to determine the statistical significance of each source. According to the ANOVA results shown in Tables 6 and 7, none of the factors analyzed showed a significant impact on the GRG values at a 95% confidence level ($p \leq 0.05$) [24, 33]. To identify the factors affecting the GRGE and GRGW responses, ANOVA analysis was applied [34]. Table 6 presents the analysis of variance for GRGE, showing that different factors (V, F, D) contribute to the total variance. Depth of cut (D) has the highest weight with 54.21%, suggesting that it is the most influential factor. It is followed by feed rate with 30.61%, indicating a medium influence, while cutting speed contributes less with 10.26%. The error accounts for 4.92% of the total variance, which is a low value, suggesting that the model fits perfectly and has little unexplained variance.

Similarly, in Table 7 for GRGW, feed rate (F) has the highest influence, contributing 66.40% of the total variance. The p-value of 0.116, on the other hand, shows that this effect is not statistically significant at the 0.05 level. Depth of cut (D) represents 15.48% of the variance, while cutting speed (V) has the lowest contribution with 9.43%. The error accounts for 8.69% of the total variance, indicating that some of the variability



a) b)

Figure 4. Main impact plots of GRG a) S/N ratios b) Means

Table 6. Analysis of variance for GRG_E

Source	DF	Adj SS	Adj MS	F-ratio	P-value	Contribution (%)
V	2	1.2600	0.6300	2.08	0.324	10.26
F	2	3.7608	1.8804	6.22	0.139	30.61
D	2	6.6600	3.3300	11.01	0.083	54.21
Error	2	0.6048	0.3024	-	-	4.92
Total	8	12.2856	-	-	-	100.00

remains unexplained by the main factors. The F-ratio value for feed rate (F) is 7.64, suggesting a possible effect but not enough to reach statistical significance.

CONFIRMATION EXPERIMENT

A confirmatory test is necessary to verify the findings of the investigation, since the determined optimal level of process parameters S3V3D3 did not match any of the nine tests presented in Table 3. To check the veracity of the conclusions drawn by T-GRA optimization, confirmation experiments were carried out with the various optimal parameter choices given in Table 8.

Table 8 provides a summary of the data values obtained during the confirmation experiments. The next phase involved forecasting and validating that the performance characteristics would improve when compared to Experiment #6, which had an arbitrarily chosen initial parameter configuration. The estimation of GRG was carried out as per the method described in [35, 36] employing Equation 1 and the specified parameters. To evaluate the quality attributes of the Inconel-625 alloys machined through the turning process, the optimal variable factors within their selected range were validated, according to Equation 2 [37].

$$\eta_{pred} = \eta_{mean} + \sum_{i=1}^{p} (\eta_i - \eta_{mean}) \quad (2)$$

where: η_{pred} represents the predicted response, η_{mean} is the average of all response values from the L9 studies, p represents the total number of main process parameters that have a significant impact on performance attributes, and ηi indicates the optimal response values for each parameter.

The data from Taguchi's-based GRA confirmation experiments indicate that the discrepancy between the projected and experimental values, based on optimization methodologies, is equal to or less than 3.22%. As a result, the anticipated values can be considered accurate. The findings of this study are comparable and compatible with those of several reviewed writers. These statistics back up and reinforce their findings, demonstrating that the technique and analyses used are legitimate and dependable. For example, when compared to the works of [14, 24, 27, and 37], the obtained results show great agreement, emphasizing the significance of the common elements examined.

CONCLUSIONS

A three-level Taguchi L9 (3^3) orthogonal array experiment was conducted to determine optimal solutions for contradictory response outcomes during dry CNC turning of Inconel 625 superalloy. The goal was to obtain the maximum quality and productivity. The

Table 7. Analysis of variance for GRG_W

Source	DF	Adj SS	Adj MS	F-ratio	P-value	Contribution (%)
V	2	0.02807	0.01403	1.09	0.480	9.43
F	2	0.19760	0.09880	7.64	0.116	66.40
D	2	0.04607	0.02303	1.78	0.360	15.48
Error	2	0.02587	0.01293	-	-	8.69
Total	8	0.29760	-	-	-	100.00

Table 8. A summary of optimization results obtained through different methodologies

Response	Initial level parameter settings	Experimental optimal level parameter settings		Taguchi-Predicted response	Error (%)
	S2F3D1 (Exp#6)	Multi-objective optimization			
		GRG	GRG		
		-	-		
		S3F3D3	S3F3D3		
MRR	2.08	6.4	6.4	-	0
Ra	2.092	1.78	1.78	0.689	1.40
GRG_{EW}	0.67	0.92	-	0.906	1.52
GRG_{W}	0.68	-	0.93	0.90	3.22
Improvement of GRG		37.31%	36.76		

optimization approach was divided into two stages: first, each answer was optimized as a single objective using the Taguchi method based on signal-to-noise ratio. All replies were then optimized simultaneously as multi-objective functions using the Taguchi methodology using GRG (GRGEw and GRGW).

The following conclusions can be drawn from the outcomes of single- and multi-objective optimization:

- The single-objective optimization yields a minimal surface roughness of 0.699 µm with the following parameters: cutting speed: 50 m/min, feed rate: 0.04 mm, and cut depth: 1.0 mm. When the cutting speed of 80 m/min is combined with a feed rate of 0.08 mm/rev and a depth of cut of 1.0 mm, the maximum material removal rate is 6.4 mm^3/s. Due to scope limits, the single optimization of experimental data was only briefly discussed in the work. This study looked at multi-objective optimization, criteria weighting, and comparing different MCDM techniques. The S3F3D3 combination yields the optimal values for the turning parameters during multi-objective optimization, allowing the desired performance characteristics to be realized.
- Multi-objective optimization results show that, when the Inconel 625 superalloy is turned at a cutting speed of 80 m/min, a feed rate of 0.08 mm/rev, and a depth of cut of 1.0 mm, all investigated response characteristics reach their optimal values (minimize/maximize) during simultaneous optimization. According to the results of multi-objective optimization experiments, standard GRA increased overall quality response characteristics by 37.31% when compared to the initial setup parameters, whereas weighted GRA improved them by 36.76%. The weighted percentages of MRR and Ra values were calculated as 48% and 52%, respectively.
- This study shows that weighting the outcomes does not have a significant effect on the optimization process when using multi-objective optimization approaches. GRG remained largely unchanged, demonstrating that even with unequal distributions between Ra and MRR, the overall system is stable. The ANOVA results in Tables 6 and 7 show that none of the investigated factors had a statistically significant effect on the GRG levels at the 95% confidence level ($p < 0.05$).

The application of adopted single-objective and multi-objective optimization approaches allows for the optimization of well-defined responses throughout the cutting process of different materials under varying situations. However, the ranking of multi-objective optimization strategies may change depending on specific sector criteria, which give different degrees of priority to different responses.

Future research could examine the effects of optimizing the findings using a single multi-criteria decision-making method with a variety of weighting techniques, such as entropy, fuzzy analytical hierarchy process, technique for order preference by similarity to ideal solution, Swara, and so on. Furthermore, process responses such as cutting temperatures and forces, tool life, and other variables could all be used in future studies.

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