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ORIGINAL CONTRIBUTION

Multi-Objective Optimization of Turning for Nickel-Based Alloys Using Taguchi-GRA and TOPSIS Approaches

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Abstract One of the significant challenges faced by industries today is obtaining the best process parameters while meeting the needs of both producers and users. It is necessary to introduce and use optimization strategies to accomplish this aim and satisfy these demands. This paper examines the exploit of Taguchi grey relational analysis (GRA) to optimize the turning process parameters of a nickel-based alloy, considering surface roughness (SR), tool wear rate (TW), and material removal rate (MRR). The approach combines L9 experiments with grey relational analysis, incorporating control parameters such as speed (A) at 300 rpm, 400 rpm, and 500 rpm; feed rate (B) at 0.05 mm/rev, 0.10 mm/rev, and 0.15 mm/rev; and cutting depth (C) at 0.1 mm, 0.3 mm, and 0.5 mm. The optimal parameter values obtained were $A = 300$ rpm, $B = 0.15$ mm/rev, and $C = 0.5$ mm, resulting in the best production outcomes: SR = 1.56 µm, TW = 0.0178 mm, and MRR = 2.14884 cm^3/min. To compare the results, technique TOPSIS, a Multiple Attribute Decision Making technique, was also employed. The optimal parameter values derived from TOPSIS were $A = 500$ rpm, $B = 0.15$ mm/rev, and $C = 0.5$ mm, leading to ideal output parameters: SR = 1.774 µm, TW = 0.0191 mm, and MRR = 3.85226 cm^3/min. The comparative study demonstrates the efficiency of the Taguchi GRA approach in optimizing turning process parameters for nickel-based alloys. Using this approach, we accomplished significant decreases in surface roughness (SR), tool wear rate (TW), and material removal rate (MRR) by 12.6%, 6.81%, and 44.21%, respectively.

Keywords Turning Inconel 718 · Surface roughness · Material removal rate · Tool wear · Multi-Objective Optimization · TOPSIS · Grey relational analysis

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Introduction

Inconel 718, a refractory superalloy rich in nickel and chromium, finds application in aircraft, rocket, and submarine engine parts due to its exceptional attributes. These include high strength, excellent toughness, remarkable fatigue resistance, good corrosion and wear resistance, as well as high-temperature strength [1, 2]. However, due to its less thermal conductivity, it is regarded as intricate to machine in terms of its machining behaviour like rapid tool wear, poor surface integrity, increased cutting forces, and sturdy vibrations [3–5].

As a result of these factors, the Inconel 718 is considered a tough material to manufacture, and due to this reason, the technical area, especially in the field of machining, has shown a significant degree of interest in this refractory alloy [6]. The best machining conditions for this material, which offer straightforward machining, the lowest power, high surface quality, usage, and maximum productivity at low cost, have been the focus of substantial research [7–9].

Rahman et al.'s [10] evaluated the impact of machining conditions on the Inconel 718 machinability, indicating that workpiece wear, roughness, and cutting strength are the important factors for tool life. Deshpande et al. [11] considered the estimation of surface roughness prediction models by taking the parameters like cutting force, thrust force, noise, and vibration to investigate how cutting conditions

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impact surface quality and flank wear performance. The machinability of Inconel 718 was investigated by D'Addona et al. [12] in terms of tool erosion and surface quality in machining at high speeds.

Tebassi et al. [13] observed the correlation among the technical parameters of cutting force and surface roughness during milling by cutting speed, feed rate and depth of cut, process parameters. Behera et al. [14] examined the effectiveness of dry machining Inconel with a coated carbide and uncoated insert; the findings show that the inserts with coating reduce tangential cutting force by 39.79%. While turning Inconel 718, the mechanisms of tool life were investigated by Cantero et al. [15] utilizing various tools like CBN, ceramics, and carbide inserts. The surface integrity of Inconel 718 which has been cut with both ceramic and carbide inserts was examined by Tan et al. [16, 17]. Pereira W.H et al. [17] investigated surface finish, micro-hardness, and residual stresses.

By focusing on morphology, cutting force fluctuation, tool life, heat distribution, and chip formation Xu et al. [18] carried out an quantitative and experimental study of the manufacturing of Inconel 718 with worn tools.

The information on heat generation during Inconel processing and its effect on diverse output machining variables was thoroughly reviewed by Mahesh et al. [19]. While cutting Nickel alloy 718 in dry and wet turning, Zeilmann et al. [20] were fascinated in finding the primary wear processes with different ceramic tools. A comparison between wet and dry machining of nickel-based alloy 718 utilizing coated carbide tools in moderately finished turning was conducted by Devillez et al. [21, 22] and Park et al. [23] measured cutting tool wear under various lubricating oils while milling of nickel alloy 718.

The experimental trials were planned using the Taguchi technique, which is extensively worn in the field of industrialized process optimization, particularly for the turning process. The main goals of the optimization were to enhance tool life and improve surface quality [24].

Many researchers are using multi-objective optimization techniques for machining. These techniques enable the resolution of paradoxical issues and produce intriguing outcomes [25–27]. Among the optimization techniques, the most widely used technique is the grey relation analysis (GRA), which is especially used widely in segment manufacturing. This approach has demonstrated its efficacy in identifying the ideal machining parameters for the responses [28]. In contrast to numerous alternative optimization techniques, the grey relational analysis (GRA) method demands fewer trial runs, a particularly advantageous aspect when conducting physical tests that are resource-intensive or time-consuming. This efficiency is made possible by Taguchi's fractional factorial designs, which allow for a thorough exploration of parameter space while conserving resources. GRA excels in multi-objective optimization, which involves balancing competing goals. This is achieved through grey relational analysis, a process that simplifies the multi-objective challenge into a single-objective framework. By assigning priority to objectives based on their relative significance, GRA streamlines decision-making and facilitates the discovery of compromise solutions that enhance all objectives concurrently.

To optimize the process parameters for electric discharge machining of Ti6Al4V and steel (316L), Sahu et al. [29] employed the GRA approach for abrasive waterjet cutting of EN31 steel; Kant and Dhami [30] used the GRA approach to know the optimized parameters for multi-response machining. To reduce hardness and surface roughness while machining AISI 1045 steel, Kant et al. [31] conducted research to find out the ideal cutting parameters when using the GRA technique. Hong, T.T. et al. [32] attained optimum EDM machining parameters for multi-response turning of the 90CrSi steel. To enhance the cutting factors for the machining of Al-SiC by using the GRA process, Ramanujam et al. [33] employed the GRA technique, while for end milling of hybrid mixtures by various reinforcements, Rajeswari et al. [34] used the GRA technique.

Karsh and Sanghvi [35, 36] employed the GRA approach for managing the factors for the multi-response problem of milling nickel-based alloy. Alsoruji et al. [37] utilized the Taguchi analysis coupled with the GRA technique to produce the best cutting parameters for Inconel 718 laser beam drilling that satisfies high (MRR), decreased taper angle, and low roughness. The GRA technique was also employed by Lin et al. [38] to identify the optimal welding parameters needed to enhance the Inconel 718 alloy. Vikram et al. [39] evaluated the process factors for milling of low machinability materials in both wet and dry conditions using GRA.

Touggui et al. [40] performed single and multi-response optimizations for dry-turning AISI 316L grade steel using the Taguchi-based TOPSIS approach to identify the ideal set of cutting conditions. The optimal machining parameters for machining EN25 with coated carbide cutting tools were similarly determined by Singaravel et al. [41] using the TOPSIS technique, at the same time optimizing hardness at the microlevel, machining exterior quality, and enhancing MRR.

Singh et al. [42] combined the Taguchi methodology with the TOPSIS several response optimization techniques to develop a further dependable design process to optimize several surface quality factors of machined mixtures of polyester. While turning Inconel 718, Thirumalai et al. [43] optimized the cutting conditions using the TOPSIS technique. They used a Taguchi L27 design to convert this metal into cylindrical rods. Sanghvi et al. [36] employed the GRA, fuzzy logic, and TOPSIS, as three multi-objective optimization techniques to reduce surface finish and enhance the MRR in the machining operations of Inconel 825.

In addition to conduct a multi-response optimization which could be observed in the industry, other optimization techniques were also performed and compared. For the EDM of AISI D2 steel, Pradhan and Hanif et al. [44, 45] employed the GRA and RSM procedures to optimize the variables. Furthermore, Chaudhari et al. [46] determined the best parameters for EDM on pure titanium by combining the PCA approach with the two techniques: response surface methodology & GRA. The methods were effectively applied by Yaser and Shunmugesh [47] to find the best milling parameters for a glass fibre-reinforced polymer (GRA & DF).

Eshpande et al. [48] used the ANN strategy for turning Inconel 718, estimating roughness in dry-cutting conditions. Sivalingam et al. [49] used two approaches ARAS & CODAS, to enhance the optimal parameters. Zahoor et al. [50] investigated three optimization techniques for Inconel 718 milling to decrease SR. The results indicate that the particle swarm optimization performs the competitors GRA & DF. In the interest of evaluating the efficacy of the GRA & TOPSIS procedures, Gopal et al. [51] considered the enhancement of the cutting strength, surface finish, and heat for the milling of a magnesium composite.

The extensive literature review has revealed that manufacturing industries are actively seeking optimal input parameters for output responses in the turning process of various materials. However, limited attention has been given to the investigation of nickel, specifically, using different multi-objective optimization techniques. This indicates a gap in the existing research and highlights the need for further exploration in this area. There are many different multi-response optimization techniques, which can make it difficult to decide. To determine the effectiveness of each strategy and its scope of use, a study of such different approaches is necessary.

Therefore, this research endeavour introduces a unique approach by employing a dual methodology involving grey relational analysis (GRA) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This approach is specifically tailored for nickel-based alloys, and a comparative investigation is initiated to showcase its exceptional effectiveness in optimizing machining parameters. By presenting an innovative outlook on multi-objective optimization within machining processes, this study makes a meaningful contribution to the progression of knowledge in this domain. Its findings hold the promise of providing valuable insights to both researchers and industry professionals alike.

To ensure an efficient experimental design and maintain statistical validity, a strategic approach is adopted to reduce the number of experiments conducted. This approach leverages the Taguchi orthogonal array of experiments, which provides a systematic and organized framework for selecting the most informative set of experiments.

Section 2 of the paper provides a comprehensive description of the equipment and material specifications used in the study. It also outlines the experimental setup and the specific processes involved in the turning of the nickel alloy.

Part 3 of the paper is divided into three sub-sections, each contributing to the consolidation and explanation of the findings. The first sub-section presents the experimental observations, highlighting the variations in performance parameters based on different combinations of cutting conditions.

The subsequent sub-section focuses on the application of GRA and TOPSIS for multi-response optimization. Both techniques are employed to recognize the optimal combination of cutting conditions that lead to the desired performance parameters. GRA utilizes to assess the connection between input parameters and performance measures, while TOPSIS determines the relative preference of different parameter combinations based on their similarity to the ideal solution.

The final sub-section of Part 3 compares and contrasts the outcomes obtained from GRA and TOPSIS. This comparative analysis provides insights into the strengths and limitations of each technique in achieving the desired optimization goals.

The conclusions drawn from the findings are summarized in the final section of the paper. This section highlights the significance of the study, discusses the implications of the results, and suggests potential avenues for potential research in optimizing the performance parameters of nickel alloys in the turning process.

Experimental Methodology

Materials Used for Machining

A cylindrical bar with a 35 mm dia and 350 mm length was employed as the Inconel 718 specimen; the Inconel 718 chemical composition is listed in Table 1. The CNC

Table 1 Inconel 718 chemical constituents: [21]

Component	%Wt	Component	%Wt
Nickel + cobalt	50–55	Manganese	0.35
Chromium	17–21	Titanium	0.3
Niobium + tantalum	4.75–5.5	Copper	0.2–0.8
Molybdenum	2.8–3.3	Boron	0.006
Cobalt	1.0	Phosphorus	0.015
Carbon	0.08	Sulphur	0.015
Aluminium	0.65–1.15	Iron	Remaining
Silicon	0.35		

lathe machine with model name LOKESH-L200 utilized for the experiment, which was housed in CITD, was of the Simple Turn type and was made by LOKESH Machines Ltd as shown in Fig. 1. The CNC was given the codename LOKESH TL200. The cutting inserts for the experimentation are cemented carbide with a TiCN–Al_2O_3 coating [52], which has outstanding adhesion and uniform draught wear. A tool holder developed by SANDVIK with ISO number TNMG 160408-MT has inserts attached to it. The cutting fluid used in the turning process is ISO VG68 [53]. The key components are paraffin mineral oils which have antiwear additives, antioxidants, anti-rust, anti-corrosion, and foam inhibitors because of the utilization of zinc dialkyl dithiophosphate (ZDDP) [54].

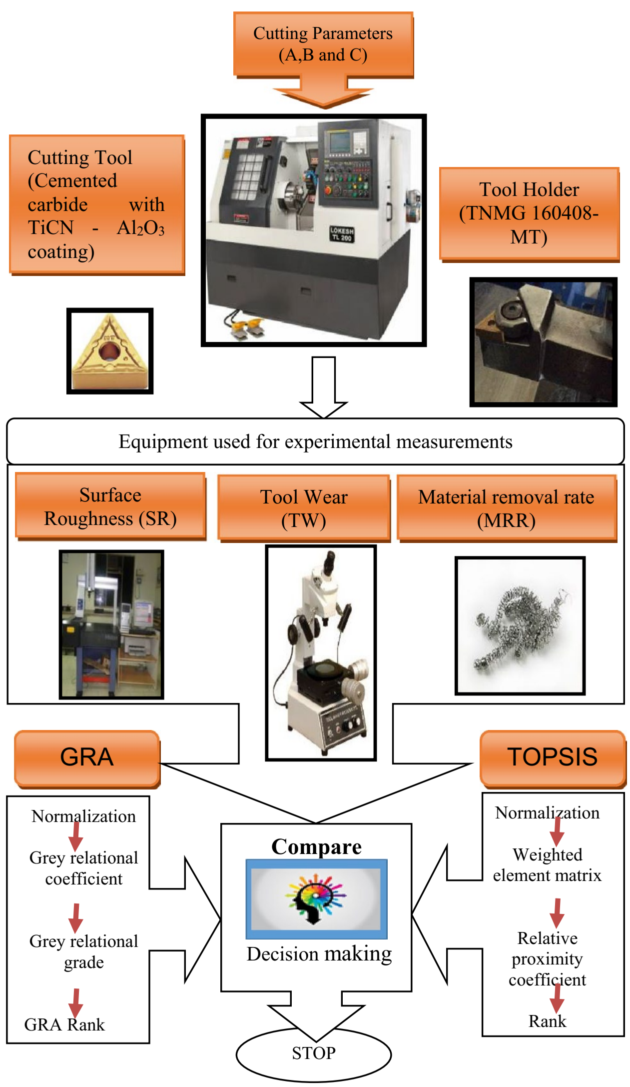

Fig. 1 Methodology of current work

Measurement Tools

Using a MITUTOYO Crysta-Plus M776 Coordinate Measuring Machine (CMM), surface roughness was measured. The work item was flipped through a 120° angle three times throughout the measuring process, and the average of the three measurements was measured. The TM 60 Monocular Advanced Tool Makers Microscope is made per international standards and has multiple applications, and is used to determine tool wear. Its features include dimensional angle, and contour measurements of tiny parts as well as inspection of mechanical surfaces, erect images, and more. The productivity metric selected was the material rate of removal which is calculated by using Eq. 1.

$$\mathrm{MRR} = \mathrm{v\ x\ f\ x\ d\ cm^3/min} \tag{1}$$

Design of Experiment (DOE)

In this study, the optimization of the turning process involved three input parameters like speed (A), feed rate (B), and cutting depth (C), each considered at three different levels. To design the experiments effectively, the Taguchi design of experiments (DOE) approach utilizing the L9 orthogonal array was employed. The software Minitab-19 was utilized for this purpose.

The cutting depth levels of 0.1 mm, 0.3 mm, and 0.5 mm were investigated, along with speed levels of 300 rpm, 400 rpm, and 500 rpm, and feed rate levels of 0.05 mm/rev, 0.10 mm/rev, and 0.15 mm/rev. These combinations resulted in a total of nine experimental conditions. Table 2 provides a summary of the cutting conditions and their corresponding levels, facilitating a clear understanding of the experimental setup.

Results and Discussion

Experimentation Outcomes

Values of the output parameters for the SR, TW, and MRR and output parameters are provided in Table 3. Calculations of the S/N proportion are used to build a gradient descent

Table 2 Investigational variables and their magnitudes

Parameter	Symbol	Units	Level 1	Level 2	Level 3
Speed	A	rpm	300	400	500
Feed rate	B	mm/rev	0.05	0.10	0.15
Cutting depth	C	mm	0.1	0.3	0.5

Table 3 Performance parameter findings from experiments

S.No	A	B	C	SR (μm)	TW (mm)	MRR (cm^3/min)
1	300	0.05	0.1	1.18	0.0219	0.14514
2	300	0.10	0.3	1.26	0.02	0.86519
3	300	0.15	0.5	1.56	0.0178	2.14884
4	400	0.05	0.3	1.167	0.0181	0.57679
5	400	0.1	0.5	1.933	0.0184	1.91008
6	400	0.15	0.1	1.25	0.0171	0.58056
7	500	0.05	0.5	1.42	0.0192	1.9938
8	500	0.1	0.1	1.21	0.0188	0.4838
9	500	0.15	0.3	1.397	0.0192	2.16298

that proceeds the volatility considering the preferred reference value [59]. S/N proportions are tabulated in Table 4. According to the kind of output variable, three potential types might be developed for this report: the smaller is the best, the larger is the best, and the nominal is the best. In the pursuit of minimizing surface roughness (SR) and tool wear (TW), the preferred options will be those that result in smaller values, as smaller values are optimal for SR and TW. Conversely, when aiming to maximize material removal rate (MRR), the favoured choices will involve larger values, as larger values are optimal for MRR. Equations (2) and (3) are used in to calculate the S/N ratios for the investigational data for SR, TW, and MRR. [60].

Minimum is the best:

$$\frac{S}{N}_{(SR,TW)} = -10 * \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (2)$$

Maximum is the best:

$$\frac{S}{N}_{(MRR)} = -10 * \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \quad (3)$$

Multi-Response Optimization

Generally speaking, the appeal of multi-response optimization is primarily in satisfying the needs of the manufacturing, which calls for clarifications that reflect a compromise between opposing objectives [61]. For instance, improving output and maximizing surface finish present a truly contradictory scenario in the field of machining that necessitates multi-objective optimization research to concurrently meet both competing aims. Many multi-response optimization strategies have been established and used in the areas of manufacturing mechanical components to alter the functional cutting conditions for competitiveness in machining [62]. To find the optimal responses, the GRA and TOPSIS approaches, which are among these processes, have been applied in the current work. These techniques mostly rely on looking at the signal-to-noise ratio.

Procedure of GRA

A multi-response optimization technique can be effectively reduced to a single response via grey relational analysis. It makes it possible to get the perfect combination of input parameters, which concurrently improves the outputs. The following actions are included [7]:

Table 4 S/N values of L9 orthogonal array

S.No	A	B	C	S/N_{SR}	S/N_{TW}	S/N_{MRR}
1	300	0.05	0.1	– 1.4376	33.1911	– 16.764
2	300	0.1	0.3	– 2.0074	33.9794	– 1.2577
3	300	0.15	0.5	– 3.8624	34.9916	6.64411
4	400	0.05	0.3	– 1.3414	34.8464	– 4.7795
5	400	0.1	0.5	– 5.7246	34.7036	5.62106
6	400	0.15	0.1	– 1.938	35.34	– 4.7229
7	500	0.05	0.5	– 3.0457	34.3339	5.99365
8	500	0.1	0.1	– 1.6557	34.5168	– 6.3065
9	500	0.15	0.3	– 2.9039	34.3339	6.70107

Table 5 Normalization, delta values

S.No	Normalization			Delta		
	SR	TW	MRR	SR	TW	MRR
1	0.978	0	0	0.022	1	1
2	0.848	0.367	0.661	0.152	0.633	0.339
3	0.425	0.838	0.998	0.575	0.162	0.002
4	1	0.77	0.511	0	0.23	0.489
5	0	0.704	0.954	1	0.296	0.046
6	0.864	1	0.513	0.136	0	0.487
7	0.611	0.532	0.97	0.389	0.468	0.03
8	0.928	0.617	0.446	0.072	0.383	0.554
9	0.644	0.532	1	0.356	0.468	0

Step 1 Responses are normalized to produce transformed values in the middle of 0 and 1

$$X_{ij}^{*}=\frac{X_{ij}\text{ - Min}(X_{ij})}{\text{Max}(X_{ij})\text{ - Min}(X_{ij})}$$

where

X_{ij} = Normalized assessment for *i*th response variable of the *j*th trail,

q = the number of runs, j = 1, 2,3, …q.

Step 2 Reference value is calculated, which is the greatest of the normalized value and absolute difference between each normalized value

$$R = \text{Max}(X_{ij}^{*})$$

$$\Delta_{ij} = \left|X_{ij}^{*} - R\right|$$

Step 3 Use the following equation to determine the GRC for each of the normalized values:

$$\xi_{ijk} = \frac{\text{Min}(\Delta_{ijk}) + [\varsigma * \text{Max}(\Delta_{ijk})]}{\Delta_{ijk} + [\varsigma * \text{Max}(\Delta_{ijk})]}$$

where

ξ_{ij} = grey correlation coefficient for the *j*th trial's *i*th response variable.

ζ = a separation factor between 0 and 1, with 0.5 being the accepted value.

Step 4 The resulting equation is considered to determine the grey relationship grade for each trail:

$$\gamma_j = \frac{\sum_{i=1}^{p}\sum_{j=1}^{r}\xi_{ijk}}{n}$$

Table 6 GRG, rank

S.No	GRG			GRG	Rank
	SR	TW	MRR		
1	0.958	0.333	0.333	0.542	9
2	0.767	0.441	0.596	0.601	8
3	0.465	0.755	0.995	0.738	2
4	1	0.685	0.505	0.73	3
5	0.333	0.628	0.916	0.626	7
6	0.786	1	0.507	0.764	1
7	0.563	0.516	0.943	0.674	5
8	0.875	0.566	0.474	0.638	6
9	0.584	0.516	1	0.7	4

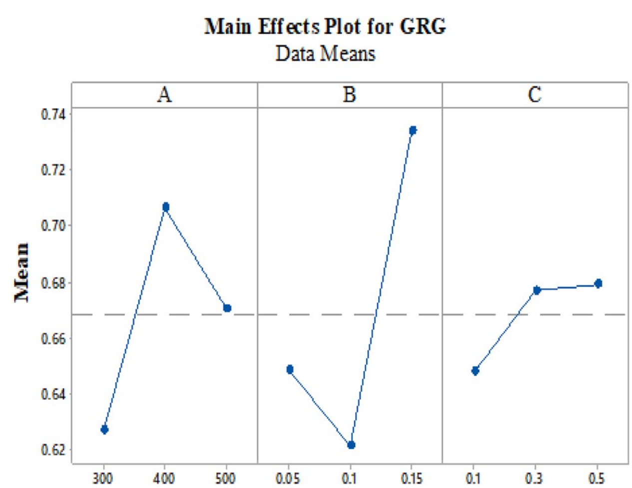

Fig. 2 Main effect plots for GRG

Table 7 Response table for GRG

Level	A	B	C
1	0.62710269	0.64859267	0.64802818
2	**0.70670213**	0.62178479	0.6772051
3	0.67081421	**0.73424158**	**0.67938575**
Delta	0.07959944	0.11245679	0.03135756
Rank	2	1	3

where n = no of responses.

Step 5 The (GRG) values are arranged in ascending order.

Tables 5 and 6 display the outcomes of the (GRA) approach's application to the S/N_{SR}, S/N_{TW}, and S/N_{MRR}. According to an examination of the findings shown, Experiment 6 corresponds to the GRG value with the greatest value, which is 0.764.

The (GRG) mean values are illustrated by the main effects plot in Fig. 2, and a response table is shown in Table 7. The output parameter, which agrees with $A = 300$ rpm, $B = 0.15$ mm/rev, and $C = 0.5$ mm, can be shown to combine the 1st level of A, 3rd level of C, and 3rd level of B. B has the highest impact on the GRG, followed by A and C in that order.

Moreover, any increase in speed causes (GRG) values to expand before starting to decline at the second level. On the other hand, an increase in feed (B) causes a reduction in GRG, which is followed by an increase from the second level. Moreover, a rise in R_i value results from a deeper cut.

Methodology to TOPSIS

The TOPSIS, a multi-response optimization process, reduces multi-response problem to single-response problem. The chosen option should be the farthest from the favourable optimal situation and the closest to the negative optimal situation, according to the theory behind it. The optimal input parameters may be chosen using this multi-criteria judgment procedure. The procedures for calculating it are listed below [56–61]:

Step 1 Constructing the decision matrix that combines 'm' options and 'n' responses:

$$D_m = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{nm} \end{bmatrix}$$

Step 2 Using the following equation, normalize the values of the attributes to get a normalized choice matrix:

$$N_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_i^2}}$$

Step 3 Using the equation, one may compute the weighted components of the normalized decision matrix.

$$W_{ij} = w_j \times N_{ij}$$

where w_j indicates the importance of each measurement result.

Step 4 Calculating how far each option is from the optimum solutions, both positive and negative:

Table 8 Normalized and weighted normalization

S.No	Normalization			Weighted normalization		
	SR	TW	MRR	SR	TW	MRR
1	−0.161	0.321	−0.732	−0.054	0.107	−0.244
2	−0.225	0.329	−0.055	−0.075	0.11	−0.018
3	−0.432	0.338	0.29	−0.144	0.113	0.097
4	−0.15	0.337	−0.209	−0.05	0.112	−0.07
5	−0.641	0.336	0.246	−0.214	0.112	0.082
6	−0.217	0.342	−0.206	−0.072	0.114	−0.069
7	−0.341	0.332	0.262	−0.114	0.111	0.087
8	−0.185	0.334	−0.275	−0.062	0.111	−0.092
9	−0.325	0.332	0.293	−0.108	0.111	0.098

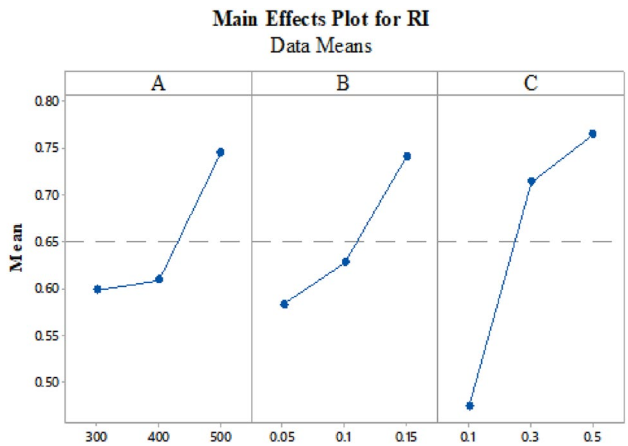

Fig. 3 Main effect plots for R_i

Table 9 Rank of TOPSIS

S.No	S^+	S^-	R_i	Rank
1	0.342	0.16	0.319	9
2	0.119	0.265	0.69	4
3	0.094	0.348	0.787	3
4	0.167	0.24	0.59	6
5	0.165	0.326	0.664	5
6	0.168	0.226	0.574	7
7	0.065	0.346	0.842	2
8	0.19	0.215	0.531	8
9	0.058	0.358	0.861	1

Table 10 Response table for (R_i)

Level	A	B	C
1	0.5986667	0.5836667	0.4746667
2	0.6093333	0.6283333	0.7136667
3	**0.744667**	**0.740667**	**0.764333**
Delta	0.146	0.157	0.2896667
Rank	3	2	1

*The bolded values represent the ideal parameters, ideal levels for each cutting regime component, d ideal regime, respectively

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (W_{ij} - \mathrm{Max}_{w_{ij}})^2}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (W_{ij} - \mathrm{Min}_{W_{ij}})^2}$$

Step 5 The closeness of the relative coefficient is calculated. $R_i(0 < R_i < 1)$ for the best individual response:

$$R_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

Step 6 Sorting the collection of all options according to the relative closeness coefficient's R_i decreasing values.

Table 8 displays the outcomes of applying the TOPSIS approach to the S/N_{SR}, S/N_{TW}, and S/N_{MRR}. According to the classification of R_i, the 9th test, maximum result of 0.861 confirms to the classification of R_i. The primary impacts chart and response table showing the mean values of R_i were utilized to determine the best parameter while accounting for the effects of the cutting parameters on R_i, as shown in Fig. 3 (Table 9).

The output parameters relate to the 3rd level of speed, 3rd level of depth of cut, and 3rd level of feed which accords with $A = 500$ rpm, $B = 0.15$ mm/rev, and $C = 0.5$ mm according to the major effects graph shown in Fig. 3 and response Table 10 exhibiting the R_i mean values. It is evident that the depth of cut has the greatest impact on R_i. The feed and depth of cut come after it, respectively. Moreover, a rise in R_i value results from an increase in all parameters.

Confirmation Test

The (R_i) values for the TOPSIS technique and the GRG values for the GRA method are used to determine the optimum parameters specified by each approach. A confirmation test was conducted for the optimal combination on the workpiece using a CNC lathe, and the findings described in Table 11 are a result of using the two optimization techniques.

Table 11 Optimum parameters and responses for GRA and TOPSIS

Process	Optimal parameters			Responses		
	A	B	C	SR	TW	MRR
GRA	300	0.15	0.5	1.56	0.0178	2.1488
TOPSIS	500	0.15	0.5	1.774	0.0191	3.8522

With the exception of speed, it can be shown that the two techniques lead to cutting input parameters with values of B = 0.15 mm and C = 0.5 mm. The reduced surface finish, MRR, and wear rate (SR = 1.56 µm, MRR = 2.1488 cm^3/min, and TW = 0.0178 mm) in the GRA technique instance may be attributed to a speed A = 300 rpm, for TOPSIS A = 500 rpm

Conclusions

In the current work, optimization of the multi-response problem was done by GRA and TOPSIS were investigated, while Inconel 718 is being machined using a TiCN tool coated in Al_2O_3 and cut with ISO VG68. The major goal is to simultaneously increase (MRR) for maximum production and decrease TW and SR to achieve a suitable surface superiority, an extended tool life, and both. The evidence supports the following evaluations:

1. The findings demonstrate that the production bounds vary across a large choice, choosing the best parameters critical for ensuring a compromise between the various responses. Hence, to overcome this problem, many optimization techniques can be used.
2. By combining conflicts between the demands of various responses, the GRA and TOPSIS techniques were able to tackle difficult optimization issues with relatively straightforward MCDM. To do this, the optimization of the multi-response technique is transformed to single-response optimization, which is formerly resolved using the required later techniques.
3. By utilizing the TOPSIS approach, the major impacts graph reveals that the optimal parameters agree with A =500 rpm, B =0.15 mm/rev, and C = 0.5 mm. For the minimizing of SR, TW, and maximizing of MRR, which produced the ideal output parameters such as: SR = 1.774 μm, TW = 0.0191 mm, and MRR =3.85226 cm^3/min, it can be demonstrated that the most important parameter on R_i is the depth of cut.
4. The 2nd level of A, 3rd level of B, and 3rd level of C are the perfect factors for the GRA approach, which is equivalent to A = 300 rpm, B = 0.15 mm/rev, and C = 0.5 mm. For the minimizing of SR, TW, and maximizing of MRR, which produced the best production bounds such as: SR = 1.56 m, TW = 0.0178 mm, and MRR = 2.14884 cm^3/min, it can be demonstrated that the most important parameter on R is the feed rate.
5. Except speed, the two techniques produced cutting comparable factors. The GRA methods favour a speed of v = 300 rpm that resulted in a relatively low roughness SR = 1.56 μm, low tool wear TW = 0.0178 mm, and low material removing rate MRR =2.14884cm^3/min, whereas the TOPSIS method promotes a speed of A = 500 rpm that resulted in a relatively high roughness SR = 1.774 μm, high tool wear TW =0.10191 mm, and high MRR =3.5226 cm^3/min.
6. Examination of the obtained optimal parameters demonstrates that opting for a lower cutting speed led to reductions in SR, TW, and MRR. This observation aligns with Sheheryar, M et al. [63], who similarly highlighted the importance of cutting speed in the context of micro-milling nickel- based alloy Inconel 718 using a Taguchi-Grey relation integrated technique.
7. The outcomes indicate that the Taguchi grey relational analysis yields the most favourable turning process parameters for nickel-based alloys. This finding aligns with Cica, D et.al [64], who similarly suggested optimal levels of process parameters derived through Taguchi-based grey relational analysis for high-pressure jet-assisted turning of Inconel 718. This phenomenon can be attributed to two primary reasons:

I) Through its implementation of orthogonal array design, Taguchi's GRA technique adeptly manages experimental noise within complex production scenarios. Its trial efficiency is particularly suited for resource-intensive tests, where Taguchi's designs enable efficient parameter exploration with fewer resources compared to other techniques.

II)GRA possesses the capability to capture nonlinear correlations between parameters and performance metrics, rendering it suitable for dissecting the intricate impacts of the depth of cut on various objectives. [65]

III)In the realm of multi-objective optimization GRA excels in uncovering optimal compromises by quantifying grey relational grades. This ability proves instrumental in navigating the trade-offs between conflicting objectives. [66]

8. Although the two methods yield differing optimal parameters, the TOPSIS approach has been identified as less intricate. This observation can be attributed to two primary factors:

i) Assigning weights in TOPSIS is a complex process. The significance of objectives can vary in real-world scenarios, and determining weights might involve fluctuations or unavailability. Advanced techniques like AHP or interactive methods offer more adaptable approaches for weight determination. [67]

ii) In the context of multi-objective optimization, TOPSIS might lack a comprehensive perspective on the trade-offs that arise from conflicting objectives. [68]

9. The key benefits of this approach are its ease, flexibility, and fewer steps in the complex equations. As a consequence, it may be used to execute machining optimization by any inexperienced user. Ultimately, the two applicable strategies may be used effectively to resolve further multi-objective optimization issues in different fields.

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