Multi-objective Optimization of Turning Titanium Alloy by Grey Rational Analysis

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ABSTRACT

In order to optimize the turning operation on titanium alloy, one needs to understand how different parameter combinations serve under varied conditions and needs. It is critical to compare single and multiple objectives in optimization. This study focused on single and multi-objective optimization evaluations for the primary performance responses of surface roughness (SR) and tool flank wear (TW), aiming for optimal turning process parameters. To examine the effects of feed rate (f), cutting speed (R), depth of cut (d), cutting angle (X), and mist inlet pressure (P) on the responses of both SR and TW, Taguchi L27 orthogonal arrays were used in this study. Moreover, analysis of variances (ANOVA) and grey relational analysis (GRA) have been incorporated in this study, where the former was used to study the influence of each parameter on SR and TW while the latter was used to determine the best combinations for the multi-objective optimization process. The results revealed that for single-objective optimization of SR, the optimal values for f, R, d, X, and P were found to be 0.3 mm/rev, 250 rpm, 1.5 mm, 100 degrees, and 1 bar mist inlet pressure, respectively. For single-objective optimization of TW, the optimal values for f, R, d, X, and P were found to be 0.20 mm/rev, 250 rpm, 0.5 mm, 50 degrees, and 3 bar mist inlet pressure, respectively. Meanwhile, for multi-objective optimization, the optimal values for f, R, d, X, and P were found to be 0.30 mm/rev, 500 rpm, 2.0 mm, 75 degrees, and 1 bar mist inlet pressure, respectively. These optimal combinations of turning parameters resulted in the lowest SR and TW simultaneously.

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Introduction

Machining a low heat conductivity, low elastic modulus, and work-hardening Titanium provides an increasingly challenging task [1]. Numerous industries, including aerospace, maritime industries and medical devices use Titanium-grade-5 alloy. While these alloys are tough to process, there has been extensive study done on how to manufacture them sustainably while considering technical, financial, and environmental considerations. For Titanium alloy machining, adopting the proper process parameters is critical to attaining optimal machining efficiency [2]. Surface roughness and tool wear are important variables in machining operations that affect the final products quality as well as the productivity of the process [3]. Optimizing manufacturing processes requires an understanding of their significance and their relationship to machining parameters. Surface roughness has a direct impact on machined components use and appearance [4]. Roughness differences can have an impact on performance even in small applications, such as sealing, friction, or appearance. Surface roughness can affect wear characteristics, fatigue life, and corrosion resistance in precision components, as those found in medical or aeronautical systems. The cost and lead time of additional finishing procedures might be affected by determining if the desired surface finish can be achieved. The efficiency and cost of production are directly impacted by tool wear. Early wear can result in more frequent tool replacements, downtime for replacements, and higher tooling costs. Dimensional accuracy and surface finish may deteriorate with tool wear, impacting item quality and raising the possibility of scrap or rework [5]. Excessive tool wear can compromise the machining process predictability and dependability by causing vibration, a poor surface finish, and even tool breakage. Higher cutting speeds typically result in increased tool wear in response to machining parameters because they generate higher temperatures and frictional forces [6]. On the other hand, by encouraging effective chip removal and cutting dwell time, ideal speeds can lessen tool wear. If proper cutting speeds and cut depths are not achieved, higher feed rates may result in greater tool wear. To preserve tool life and achieve specified surface finishes, proper feed rates are essential. Particularly in harder materials, deeper cuts can result in more tool wear. Effective material removal without undue tool wear requires balancing the depth of cut with other parameters.

The turning process is affected by several aspects that greatly influence the quality and efficiency of the procedure. These considerations include cutting speed, feed rate, tool geometry, tool wear, the characteristics of the workpiece material, such as thermal diffusivity and hardness, and the use of coolants [7]. Additionally, the depth of cut, feed speed, and the nose radius of the cutting insert are highlighted as key parameters determining the *SR* and dimensional accuracy of the machined component [8]. Vibration during the machining process can significantly influence the quality of the treated materials and potentially cause damage to the tool and machine [9]. The application of multi-objective optimization techniques, such as the Taguchi method, has been proven to be successful in optimizing process parameters and boosting the surface quality of machined components [10]-[11]. This current study, based on existing literature, intends to analyze the influential parameters of *f*, *R*, *d*, *X*, and *P*.

Optimal turning performance has been linked to specific machining parameters, such as *R*, *f*, and *d* [12]. This association highlights the critical role of these parameters in achieving optimal performance in turning operations. In addition, lathe machining parameters like *R*, *f*, and *d* have been found to accelerate tool wear and affect surface finishing [13]. This finding emphasizes the need to control and optimize these parameters to ensure the longevity and surface finish quality of tool. Not just that, the cutting tool rake angle has been identified as a significant parameter affecting the main cutting force, along with machining parameters such as *R* and *f* [14]. This finding provides valuable insights into how the cutting tool rake angle and other machining parameters affect the cutting force in the lathe process.

The impact of *f* and *R* on *SR* during the machining of stainless steel has been highlighted, indicating their significant effect on the turning process [15]. This finding emphasizes the significance of these parameters in ensuring the quality of the final product, particularly when machining stainless steel. Likewise, in common turning processes, performance traits have been closely linked with cutting parameters like the rate of feed, speed of cutting, and cut depth [16]. This correlation highlights the significance of these parameters in determining the performance characteristics of turning operation.

Additionally, increasing cutting feed rates and spindle speeds has been shown to improve the processing efficiency of remanufactured lathes, consequently reducing processing time [17]. This finding highlights the potential benefits of increasing cutting feed rates and spindle speeds for enhancing processing efficiency and reducing processing time. In short, these parameters have been extensively studied and shown to have a significant impact on various aspects of the turning process, including vibration, SR, TW, and processing efficiency. This illustrated the complexity of the turning operation, as well as the need for continuous research and optimization in this field.

In order to understand how different solutions perform under various conditions and needs, it is important to compare single and multiple goals optimization in turning titanium alloy. Through single and multi-objective optimization, the primary goal of this work is to thoroughly examine and optimize each machined SR and TW's process parameters. The goal of the study is to improve knowledge of how important process variables like *f*, *R*, *d*, *X*, and *P* relate to the final machining response characteristics. By employing the Taguchi method and Grey Relational Analysis (GRA), the goal is to develop optimized conditions for turning Titanium alloy that ensure superior turning performance.

The Taguchi technique has been widely applied in manufacturing to enhance processes with single performance criteria by selecting the best process parameters. However, multi-objective optimization is outside the scope of the conventional Taguchi approach. Thus, the Taguchi approach is combined with GRA to assist this matter. A more complex multi-performance characteristics optimization may be successfully solved using the normalizing assessment approach known as GRA [18]. The raw data is then converted into SN ratio values for the Taguchi analysis. The "lower-the-better" rule applies to SR and TW responses, as Equation (1);

$$\mathrm{SN}_{\mathrm{ratio}} = -10\log_{10}\left(\frac{1}{n}\right)\sum_{i=1}^{n} y_{ij}^{2} \tag{1}$$

where, n is the number of replications, y_{ij} is the observed response value for $i = 1, 2, 3, \ldots, m$ and $j = 1, 2, 3\ldots, n$

GRA is introduced for the optimization of multi-performance characteristics. The GRA was founded on a linear normalization of the data in the range of zero to one. To prevent the impact of using various units and to lessen unpredictability, the y_{ij} is normalized as $z_{ij}\,(0 \le z_{ij} \le 1)$. The normalized experimental data z_{ij} may be written as Equation (2) and (3):

$$z_{ij} = \frac{\left(y_{ij},\, i = 1, 2, 3, \ldots, n\right) - \min\left(y_{ij},\, i = 1, 2, 3, \ldots, n\right)}{\max\left(y_{ij},\, i = 1, 2, 3, \ldots, n\right) - \min\left(y_{ij},\, i = 1, 2, 3, \ldots, n\right)} \tag{2}$$

$$z_{ij} = \frac{\max\left(y_{ij},\, i = 1, 2, 3, \ldots, n\right) - \left(y_{ij},\, i = 1, 2, 3, \ldots, n\right)}{\max\left(y_{ij},\, i = 1, 2, 3, \ldots, n\right) - \min\left(y_{ij},\, i = 1, 2, 3, \ldots, n\right)} \tag{3}$$

The ideal normalized results should equal one, the greater the normalized results, the better the performance. Next, in order to measure the degree of correlation between the optimal (most advantageous) and actual normalized experimental results, the gray relational coefficient is calculated. Equation (4) can be used to express the grey relationship coefficient.

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$$\gamma = \left(x_{oj}, x_{ij}\right) = \left(\Delta_{\min} + \zeta\Delta_{\max}\right) \Big/ \left(\Delta_{ij} + \zeta\Delta_{\max}\right) \tag{4}$$

for $i = 1, 2, 3, \ldots, m$ and $j = 1, 2, 3, \ldots, n$

where, $\Delta_{ij} = \left|x_{oj} - x_{ij}\right|$

$\Delta_{\min} = \min \Delta_{ij},\ i = 1, 2, 3, \ldots, m;\ \ j = 1, 2, 3, \ldots, n$

$\Delta_{\max} = \max \Delta_{ij},\ i = 1, 2, 3, \ldots, m;\ \ j = 1, 2, 3, \ldots, n$

$\zeta =$ distinguishing coefficient, $\zeta \in (0,1)$

The value of ζ is set to 0.5. The weighted sum of the grey relational coefficients for a certain experiment is used to calculate the grey relational grade, using Equation (5),

$$\Gamma\left(X_0, X_i\right) = \sum_{j=1}^{n} w_j X \gamma\left(x_{oj}, x_{ij}\right) \quad \text{for } i = 1, 2, 3, \ldots, m \tag{5}$$

The grey relational grade, $\Gamma\left(X_o, X_i\right)$, represents the level of similarity between the comparability sequence, X_i and reference sequence X_o. Additionally, the sum of the weights $\sum_{j=1}^{n} w_j = 1$, ensures that the weights add up to one. Equation (6) can be used to obtain the estimated grey relational grade, γ when the optimal level of the machining parameters is utilized.

$$\dot{\gamma} = \gamma_m + \sum_{i=1}^{n}\left(\dot{\gamma}_i - \gamma_m\right) \tag{6}$$

The variable γ_m represents the overall average of the grey relational grade, $\dot{\gamma}_i$ represents the average of the grey relational grade at the optimal level, and n represents the number of the machining parameters that have a substantial impact on numerous performance aspects.

Multi-objective optimization in the turning of titanium alloys is necessary to simultaneously address conflicting objectives like productivity, tool wear, surface finish, and thermal effects. By finding a balance between these factors, the overall machining process can be made more effective, economical, and suitable for the demanding needs of titanium in industry by striking a balance between these elements. In the present study, the wear of the tool and the roughness of the machined surface are used to evaluate the machining capabilities of Titanium grade-5 alloy. Turning studies were performed using SANDVIK CNMG carbide inserts utilizing vegetable oil-based under lowest quantity lubrication. This work has attempted to ascertain the effects of four process parameters in order to identify the ideal parametric combination for obtaining the best SR with the least amount of TW. Two responses, namely, the SR and TW have been directly integrated utilizing the Taguchi technique in conjunction with GRA. Thus, this technique may greatly reduce the optimization of the complex multiple performance characteristics into a single objective optimization problem. The parameter that significantly impacts the multi-performance characteristics is determined using ANOVA. An optimal set of conditions was employed to conduct a confirmation experiment to validate the study.

Experimental

All the tests were performed on Colchester Harrison Tornado T4 CNC Lathe, having an integrated vegetable oil-based under minimum quantity lubrication. Fresh implants with good adhesion and flank wear resistance (SANDVIK GC1205 PVD-coated carbide grades) were utilized in all tests in accordance with manufacturer instructions. Titanium Alloy (TI-6Al-4V) grade 5 was used as the workpiece material in all tests, with 20 mm in diameter and 300 mm in length. Figure 1 shows the experimental setup for turning operation. Key physical/mechanical parameters and chemical composition of the workpiece materials are specified in Table1 and Table 2 accordingly.

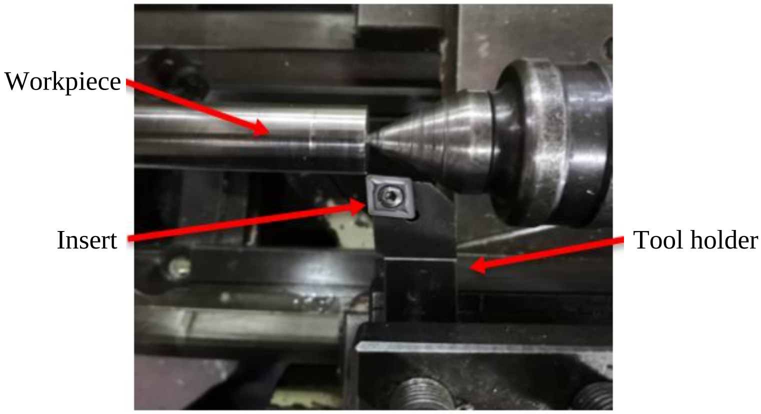

Figure 1 : Experimental setup for turning operation

Table 1: Physical properties of Titanium grade 5 [19]

Properties	Value
Density	4.43 x 103 kg/m^3
Hardness, Rockwell C	33 HRC
Modulus of Elasticity	120 GPa
Thermal Expansion (20 °C)	8.6 x 10^{-6} °C^{-1}
Specific Heat Capacity	526.3 J/kg-°C
Thermal Conductivity	6.7 W/m-°C
Fracture Toughness	43 Mpa-$m^{1/2}$
Tensile Strength (MPa)	900 - 1160
Melting Point (°C)	650
Machinability	Low

Table 2 : Weightage alloy in the Ti-6Al-4V

Component	Wt. %
Al	6.2
Fe	0.25 (max)
O	0.2 (max)
Ti	90
V	4.1

To get an understanding of the fundamental operating parameters to turn TI-6Al-4V and their impact on tool performance, an initial series of exploratory tests was conducted. Digimizer image analysis software was used to measure and perform pre- and post-machining inspections on each insert tool. To remove any impurities based on hydrocarbons or detergents, as well as any adhering particles, all inserts were thoroughly cleaned in an acetone ultrasonic solution. To the greatest extent practical, the tests were carried out in conformance with ISO 3685:1993(en) Tool-life testing with single-point turning tools requirements.

All the tests were conducted utilizing the Taguchi design of experiment (L27 orthogonal arrays), which took into consideration five parameters that were modified at three distinct levels. A number of important parameters have been considered to ensure a robust and effective optimization strategy. The process parameters and their values are listed in Table 3 based on manufacturer recommendations, prior research experience, and trial-and-error experiments. With a portable Marsurf surface profilometer, the machined SR was averaged over three points (15 mm apart, the middle and the opposite ends) for each turning test. The measurement recorded follows the guideline from ISO 4288 standards. After that, the flank wear of the cutting tools for each turning test was analyzed using a Mitutoyo Insert Maker. The Taguchi method was used to maximize each objective response through single objective optimization.

Then, all objective functions were simultaneously optimized using the Taguchi-based GRA technique. These procedures determined parameter settings for the best and worst values of each objective function. The results were confirmed through additional calculations. Additionally, a formula was established to determine each parameter's contribution ratio to the outcomes. Lastly, further confirmatory tests are undertaken to establish the optimal parameter combination.

Table 3 : Process parameters and their levels

Process Parameter	***f***	***R***	***d***	***X***	***P***
	mm/rev	rpm	mm	deg	bar
Level 1	0.20	250	0.5	50	1
Level 2	0.25	500	1.5	75	2
Level 3	0.30	1000	2.0	100	3

Results and Discussion

Taguchi analysis was performed to identify the effects of each component on each response. The most relevant criteria were chosen for each objective. The contribution ratios of all parameters were determined numerically to express the significance of parameters. Subsequently, GRA was undertaken to achieve multi-objective optimization research attempting to satisfy every objective.

Single objective optimization on SR

Based on identified machined SR on 27 experiment tests, the mean of SR was from 2.220 to 6.844 µm. Figure 2 illustrates the Pareto chart of the SR standardized effects. The x-axis standardized impact reveals how much of an influence each parameter has on the response or outcome, in this instance SR. The greater the standardized effect, the more of an impact the parameter has on the result. Furthermore, $\alpha = 0.05$, the significance level, is illustrated by the red dashed line. This implies that a bar has a statistically significant impact on the result if it goes beyond this line. The strongest effect is feed rate (*f*), followed by cutting speed (*R*), mist inlet pressure (*P*), cutting angle (*X*) and depth of cut (*d*), even if none of them passed the line. Table 4 demonstrates analysis of variance (ANOVA) for SR response. It demonstrates that the P-value is smaller than the normal significance level of 0.05, thus implying that the *f* has a statistically significant impact on the SR response, accounting for 63.6% of the response variation. As the *f* grows, SR also rises. This is because, when *f* is elevated, helicoids furrows are created owing to the movement of the tool with respect to the workpiece and the tool shape. These furrows develop deeper and larger as *f* increases [20].

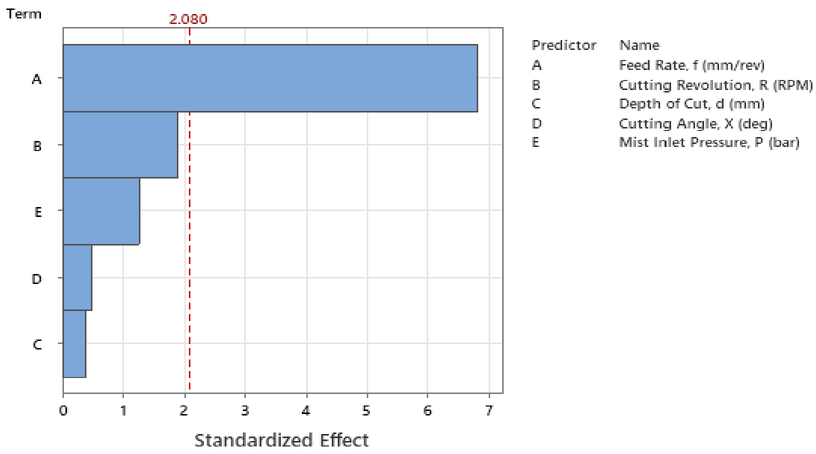

Figure 2 : Pareto chart for SR response (μm), $\alpha = 0.05$

Table 4 : ANOVA for SR response at $\alpha = 0.05$

Source	**DOF**	**% Contrib.**	**Adj SS**	**Adj MS**	**F-value**	**P-value**
f (mm/rev)	2	92.00%	52.7221	26.361	3760.13	0.000
R (rpm)	2	5.00%	2.8040	1.4020	199.98	0.000
d (mm)	2	0.0%	0.1429	0.0715	10.190	0.001
X (deg)	2	0.0%	0.3786	0.1893	27.00	0.000
P (bar)	2	2.00%	1.1492	0.5746	81.96	0.000
Error	16	0.0%	0.1122	0.007		
Total	26	100.00%				

The *R* also appeared to have a substantial effect on the reaction with a contribution of 4.89%. On the other hand, other parameters such as *d*, *X*, and *P* do not appear to have a substantial effect on the outcome, as their P-values are rather high. This shows that adjustments in these parameters do not significantly alter the variance in the outcome. Figure 3 displays the primary effect plot of SN ratio for each parameter to machined SR. It clearly shows a sharp increase in the average SR with increasing *f*, less noticeable variations in SR at different *R* levels, a relatively constant SR at different *d*, some variations in SR with changing of *X*, and a slight decrease in SR with increasing of *P*. It can be determined that, for the sole purpose of decreasing machined SR (2.220 µm), the turning parameters must be 0.30 mm/rev for *f*, 250 rpm for *R*, 1.5 mm for *d*, 100° for *X*, and 1 bar or *P* accordingly.

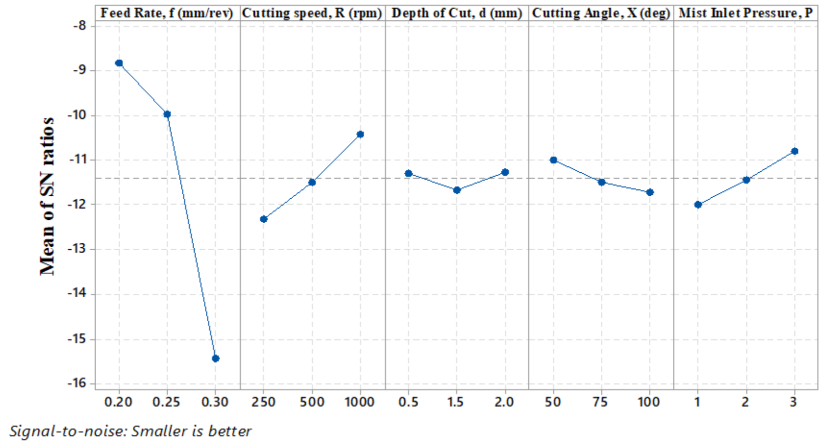

Figure 3: Main effect plot of SN ratios for *SR*

Single objective optimization on TW

Based on measured TW on 27 experiment tests, the TW ranged from 0.101 to 0.301 mm. Figure 4 displays, the Pareto chart of the TW response with standardized effects. It demonstrates that F(A) has a significant effect, followed by cutting speed (*B*), depth of cut (*C*), and mist inlet pressure (*E*). cutting angle (*D*) however, does not appear to have major influence since the bar is below the dashed line.

Table 5 indicates an ANOVA for TW response. The regression model in the ANOVA table displays the overall variation in the result that the model can be accounted for. It reveals that the model explains 97.27% of the variance in the result. The effect of f on the TW response is statistically significant with variance of 66.60% in the response. The *R* parameter contributes 23.43% to the total variance with an F-value of 179.98. Moreover, *d* parameter has a smaller but still substantial influence at 4.94% with an F-value of 37.94. The *X* parameter and *P* have minor impacts on variance at only 0.11% and 2.19% respectively, reflected in their low F-values. However, the P-value for *X* was at 0.378 whereas for *P* was at 0.001, demonstrating that the former had minor impact on the TW whilst the latter was statistically significant.

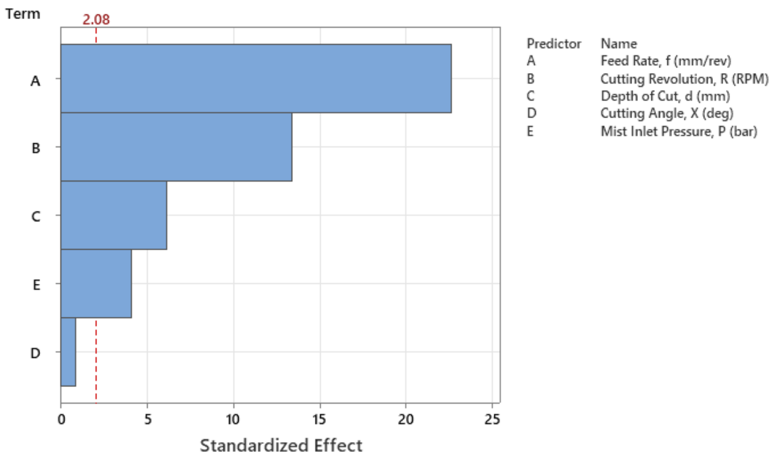

Figure 4: Pareto chart for TW (mm) response, at $\alpha = 0.05$

Figure 5 displays the major effect plot of SN ratio for each parameter in TW response. The research showed that the *f* greatly affected the TW, with an increase in *f* corresponding to a large increase in mean of TW [21]. The *R* indicated a small drop in the TW as it rose. However, the delta value was rather minor, demonstrating that the *R* had negligible effect on the TW compared to other components. The *d* showed considerable fluctuation with the TW, indicating that the *d* might not have had a substantial effect on the TW. Moreover, the *P* and *X* appeared to be reasonably stable throughout different levels suggesting low impact onto the TW for signal to noise ratio. It may be deduced that, for the single purpose of minimizing TW, the turning parameters must be 0.20 mm/rev for *f*, 250 rpm for *R*, 0.5 mm for *d*, 50° for *X*, and 3 bar for *P*.

Table 5: ANOVA for TW response

Source	**DOF**	**% Contrib.**	**Adj SS**	**Adj MS**	**F-Value**	**P-Value**
f (mm/rev)	2	73.00%	0.080655	0.040327	1753.710	0.000
R (rpm)	2	20.00%	0.022003	0.011001	478.420	0.000
d (mm)	2	4.00%	0.00519	0.002595	112.850	0.000
X (deg)	2	0.0%	0.000061	0.000003	1.330	0.293
P (bar)	2	1.00%	0.001445	0.000723	31.430	0.001
Error	16	2.00%	0.002299	0.000109		
Total	26	100%				

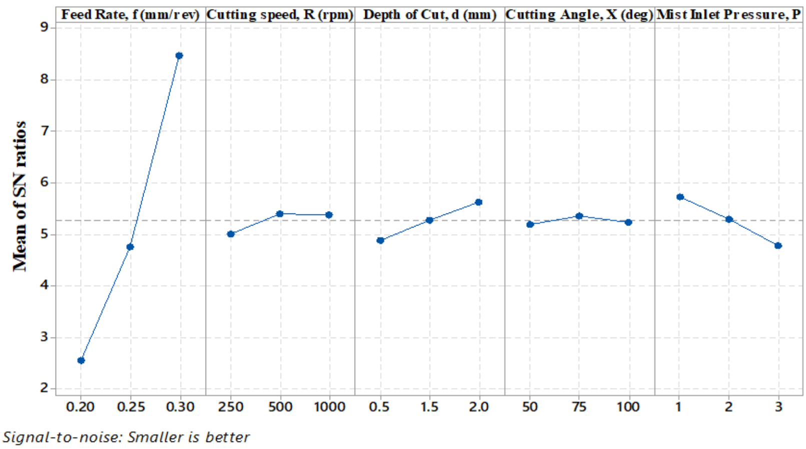

Figure 5: Main effect plot of SN ratio for *TW*

Multi-objective optimization

Table 6 highlights the details of the grey relational generation. The table was divided into multiple columns, each representing a different component of the analysis. These columns contained normalization of SR and TW, deviation sequence of SR and TW, grey relation coefficient for SR and TW and grey relation grade value with rank. Each column comprised numerical data, precise up to four decimal places, which were the outcome of painstaking calculations and measurements.

For each response, the grey relational coefficients are combined to create the grey relational grade; in contrast, this grade served as a thorough depiction of both SR and TW. By integrating the Taguchi technique and GRA, the multicriteria optimization issue is ultimately reduced to a single equivalent objective function optimization problem. A greater value of the grey relational grade implies that the related parameter combination is reaching the optimal. Table 7 provides the mean answer findings for the overall grey relationship grade.

Figure 6 displays the primary effect plot of means grey relational grade which allows for multi-objective optimization. A higher *f* of 0.30 m/rev, *R* of 500 rpm, *d* of 2.0 mm, *X* of 75°, and *P* of 1 bar are the optimal parameter settings for multi-objective optimization. Thus, at the optimal configuration designated as (*f3*, *R2*, *d3*, *X2*, *P1*) which give response values of 2.911 µm and 0.101 mm for SR and TW, respectively.

Table 6 : GRA on the response of turning process

Normalization		**Deviation Sequence**		**Grey Relation Coefficient**		**Grey Relation Grade**	
SR	TW	SR	TW	SR	TW	Value	Rank
0.7065	0.8914	0.2935	0.1086	0.6301	0.8216	0.7258	6
0.7782	0.9548	0.2218	0.0452	0.6927	0.9170	0.8049	2
0.8542	1.0000	0.1458	0.0000	0.7742	1.0000	0.8871	1
0.7888	0.7240	0.2112	0.2760	0.7030	0.6443	0.6737	8
0.8354	0.7873	0.1646	0.2127	0.7523	0.7016	0.7270	5
0.8736	0.8281	0.1264	0.1719	0.7982	0.7441	0.7712	3
0.9091	0.4570	0.0909	0.5430	0.8461	0.4794	0.6627	9
0.9551	0.4977	0.0449	0.5023	0.9175	0.4989	0.7082	7
1.0000	0.5385	0.0000	0.4615	1.0000	0.5200	0.7600	4
0.6850	0.6290	0.3150	0.3710	0.6135	0.5740	0.5937	12
0.7033	0.5701	0.2967	0.4299	0.6276	0.5377	0.5827	14
0.7635	0.6154	0.2365	0.3846	0.6788	0.5652	0.6220	11
0.7012	0.2670	0.2988	0.7330	0.6259	0.4055	0.5157	18
0.7649	0.3077	0.2351	0.6923	0.6802	0.4194	0.5498	17
0.8088	0.3484	0.1912	0.6516	0.7234	0.4342	0.5788	15
0.8141	0.2262	0.1859	0.7738	0.7290	0.3925	0.5608	16
0.8502	0.2579	0.1498	0.7421	0.7694	0.4026	0.5860	13
0.8932	0.3167	0.1068	0.6833	0.8240	0.4226	0.6233	10
0.0000	0.1493	1.0000	0.8507	0.3333	0.3702	0.3518	27
0.0703	0.2036	0.9297	0.7964	0.3497	0.3857	0.3677	25
0.1357	0.2579	0.8643	0.7421	0.3665	0.4026	0.3845	21
0.1808	0.1267	0.8192	0.8733	0.3790	0.3641	0.3716	24
0.2479	0.1719	0.7521	0.8281	0.3993	0.3765	0.3879	20
0.3429	0.2081	0.6571	0.7919	0.4321	0.3870	0.4096	19
0.2226	0.0000	0.7774	1.0000	0.3914	0.3333	0.3624	26
0.2517	0.0452	0.7483	0.9548	0.4006	0.3437	0.3721	23
0.2952	0.0860	0.7048	0.9140	0.4150	0.3536	0.3843	22

Table 7 : Response table for means of GRA

Level	***f***	***R***	***d***	***X***	***P***
1	0.7467	0.5869	0.5948	0.5614	0.5298
2	0.5751	0.5553	0.5629	0.5620	0.5664
3	0.3769	0.5565	0.5410	0.5753	0.6025
Delta	0.3698	0.0316	0.0538	0.0138	0.0727
Rank	1	4	3	5	2

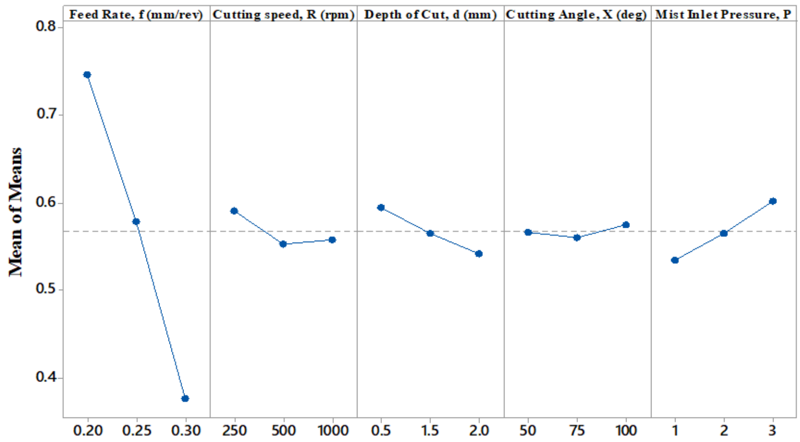

Figure 6: Main effect plot for means of grey relational grade

Confirmatory experiment

Once the optimum settings for the parameters were identified, the second phase involved forecasting the improvement of quality attributes using the optimal combination of parameters. The estimated grey relational grade, which is evaluated based on prior grey relational grade values were generated using Equation (6). An additional confirmatory experiment has been performed to verify this theory. Thus, to validate this prediction, a subsequent confirmation experiment has been carried out. Table 8 demonstrates, the comparison between the experimental and anticipated SR and TW under optimal circumstances, indicating a substantial correlation (improvement in the overall grey relational grade).

Table 8: Comparison between initial level and optimal level

	Initial Turning Parameter	**Optimal Turning Parameter**		
	Orthogonal array	Prediction by Grey Relational analysis	Confirmation experiment	% improvement
Setting Level	*f1, R2, d1, X2, P3*	*f3, R2, d3, X2, P1*	*f3, R2, d3, X2, P1*	
SR (µm)	2.819		2.611	7%
TW (mm)	0.139		0.101	27%
Grey Relational Grade	0.5594		0.8849	58%
Improvement of the grey relation grade = 0.3255				

Conclusions

This research addresses the implementation of orthogonal array in conjunction with grey relational analysis to optimize the responses when turning Titanium alloy grade 5, with its varied performance features. The optimization of numerous performance characteristics may be simplified to the optimization of a single performance characteristic, known as the grey relational grade, using GRA. Thus, this technique can greatly simplify the optimization of the complex multiple performance characteristics. Based on the results, 0.30 mm/rev for feed rate, 250 rpm for cutting speed, 1.5 mm for cut depth, 100° for cutting angle, and 1 bar mist inlet pressure are the optimal values for single objective optimization of SR. However, to achieve the single objective optimization of decreasing TW, the turning parameters need to be set at 3 bar mist inlet pressure, 0.5 mm for depth of cut, 250 rpm for cutting speed, and 0.20 mm/rev for feed rate. Meanwhile, for multiple objectives optimization, the optimal values for f, R, d, X, and P were found to be 0.30 mm/rev, 500 rpm, 2.0 mm, 70°, and 1 bar mist inlet pressure respectively. Comparing single and multiple objectives in optimization is crucial because it helps us understand how different parameter combinations perform under varying conditions and needs. Single-objective optimization often seeks to maximize or minimize a single objective, while multiple-objective optimization simultaneously optimizes numerous objectives. Compare the trade-offs involved in giving one goal priority over another among several goals. In summary, multi-objective optimization enables industries to achieve cost savings, improve efficiency, and uphold quality standards by maximizing multiple competing objectives at once via multi-objective optimization. This approach has a particularly big impact on industries like precision manufacturing, automotive, aerospace, and energy, where productivity, quality, and low costs of materials are key success factors.

Contributions of Authors

The authors confirm equal contributions in each part of this work. All authors reviewed and approved the final version of this work.

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Conflict of Interests

One of the authors, Muhamad Fauzi Othman is an assistant managing editor of the Journal of Mechanical Engineering (JMechE). The author has no other conflict of interest to note.

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