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Multi-objective optimization using Grey Relational Analysis (GRA) for the high-speed orthogonal turning of heat-treated alloy steel

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KEYWORDS

Surface roughness
Tool life
Grey relation analysis
Multi-response optimization

ABSTRACT

This study concerns the high-speed machining of heat-treated AISI 4340 alloy steel using multi-layer coated carbide tools in dry condition. Taguchi L_{18} experimental design is selected to accommodate the machining parameters, which includes coated carbide tool type (T=Physical vapor deposition (PVD) and Chemical Vapor Deposition (CVD), cutting speed (V=300-400m/min), feed rate (F=0.05-0.15mm/rev), and depth of cut (DOC=0.1-0.3mm). The study examined how input variables affect tool life and surface roughness using the Taguchi signal-to-noise (S/N) ratio. Additionally, Grey Relation Analysis (GRA), a multi-objective optimization method, was used to identify the best parameter settings for improved machining performance. The results showed that the CVD tool achieved the highest tool life of 14.75 minutes, while the PVD tool delivered the lowest surface roughness of 0.276 µm. Using the GRA method, the optimal machining parameters (T=CVD, V=300 m/min, F=0.05 mm/rev, DOC=0.1 mm) were identified and validated through confirmation tests. ANOVA on the grey relation grade (GRG) revealed that feed rate had the greatest impact on tool life and surface roughness, followed by tool type, cutting speed, and depth of cut.

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1.0 INTRODUCTION

Hardened steels have widespread applications in metal industry owing to its great hardness, wear resistance and shock absorbing capability (Radzman et al., 2023) . Many commercial components including, engine mounting, landing gears, fuel injectors, crank shafts, and power transmission links are produced with hardened steel (Ahmad et al., 2021). These components require close tolerances and excellent surface characteristics for better functional performance. In this respect, hard turning is becoming an attractive machining alternative, gaining popularity owing to its shorter setup time, lower machining costs, high material removal rate, and ability to demonstrate high product quality compared to the conventional grinding process (Mir & Wani, 2017). Reportedly, the performance characteristics of hard turning process is highly dependent on input variables which includes nose radius, tool material, machining speed, feed rate, and depth of cut (Bartarya & Choudhury, 2012). Since, machining heat-treated material induced high thermal and mechanical stresses, which resulted in increased cutting force, material softening, pre-mature tool failure and deteriorated surface integrity. Hence, it is crucial to carefully choose the cutting variables for enhanced machinability. According to Zenjanab et al. (2022), ceramic tools at V=250m/min, F=0.1mm/rev, and DOC=0.6mm demonstrated the lowest surface roughness during high-speed machining of AISI 4340 alloy steel. Ochengo et al. (2022) performed the high speed turning (V(m/min)=320-575, F(mm/rev)=0.1-0.26) using coated and uncoated carbide inserts to evaluate the surface quality and cutting power. It was found that machining speed with highest contribution rate of 70.53% and 93.61% influenced the surface roughness and cutting power, respectively. Bag et al. (2022) also reported the highest contribution (71.93%) of feed rate on surface roughness, while the effect of machining speed was identified to be most dominant on flank wear, with a contribution percentage of 66.06% in dry cutting of AISI 4340. Literature also reported the performance of different types of tool coating in turning high-strength steel. For instance, Abd Rahman et al. (2021) explored the wear behavior of TiAlN-PVD coated carbide tools in machining D2 tool steel. Butt et al. (2021) presented the wear characterization of TiCN/Al_2O_3/TiN-PVD and CVD coated tools in hard turning of AISI 4340 material considering the following machining scheme cutting speed in the range between 50-200 m/min, feed per tooth between 0.051-0.101 mm/rev, and cutting depth between 0.2-0.6 mm. The statistical analysis on surface roughness and tool flank wear revealed that PVD tool exhibited best performance at low machining parameters while CVD tools outperformed at high machining parameters. Moreover, Sahoo et al. (2023) utilized TiN/TiCN/Al_2O_3-CVD coated inserts in turning high-strength AISI 4340 steel, reported turning speed being the most governing variable effecting the tool wear in dry environment, while depth of cut exhibited the dominating effect under MQL environment.

Most of the published literatures have devised many scientific methods such as ANOVA, Taguchi signal-to-noise (S/N) ratio, response surface methodology (RSM), and grey relation analysis (GRA) to determine the optimal parametric settings in machining various heat-treated materials. Mia et al. (2017) applied GRA approach to optimize the machine speed, feed per revolution, and minimum quantity lubrication (MQL) flow rate in milling AISI 4140 steel to attain considerably low cutting force and surface roughness. As per their results, V at 32 m/min, F at 22 mm/min, and MQL flow rate at 150 ml/min is best parametric combination for better surface quality with less force. In a subsequent study on heat-treated AISI 1060 steel, Mia et al. (2018) performed Taguchi S/N ratio and recognized that machine setting at V=90m/min, F=0.2mm/rev, and DOC=1.5mm is best for better surface finish and high material removal rate, while V=60 m/min, F=0.2 mm/rev, and DOC=1 mm machining setting is favorable for lowest tool flank wear.

Similarly, Agebo et al. (2023) employed Taguchi based grey relation method to determine the influence of flood and cryogenic cooling while the turning of D2 steel to identify the optimal cutting conditions in respect to surface roughness and material removal rate and realized 2.43% improvement with optimized machine setting.

In a most recent study on Hastelloy C276, Sen & Bhowmik, (2024) utilized TiAlN-TiN-PVD carbide tools to validate the predicted results of multi-objective response surface methodology (MORSM). In their work the highest 0.912 desirability score, signifies the effectiveness of MORSM in optimizing machining variables for favorable machinability. Bag et al. (2023) attempted to improve the productivity and surface quality for hardened AISI 4340 cylindrical material using Taguchi TOPSIS optimization and observed an enhancement in the closeness coefficient to 0.237 at V=80 m/min, F=0.05 mm/rev, and DOC=0.3 mm. Li et al. (2023) adopted a new method of fractal and multi-fractal features to characterize the surface morphology of high-strength steel AISI 4340, considering the high speed regime (V=280-440 m/min). Moreover, multi-objective optimization was performed considering the most crucial surface roughness and fractural features, which resulted in notable reduction of 4.9% in R_a of 31.45% improvements in machining efficiency, and 2.52% reduction in machining cost when compared with non-optimized state. Al Awadh et al. (2023) using grey-crow search hybrid optimization technique found TiAlSiN-PVD^2 coated carbide tool at V=220m/min and F=0.04mm/rev with 32 HRC AISI 4340 material produced the enhanced surface finish and material removal rate. Alok et al. (2021) used the desirability function and suggested optimized parametric setting for lowest cutting, axial, and radial forces, as well as lower surface roughness, and tool wear at V=249.99m/min, F=0.08 mm/rev, and DOC=0.06mm in turning 52 HRC AISI 4340 steel with HSN^2 coated carbide tool.

Based on the reviewed literature, it was determined that most of the optimization studies on hardened steel, particularly AISI 4340 alloy steel have been carried out at low cutting speeds using carbide tools. Very few studies have been reported on high machining speeds and simultaneous optimization of surface roughness and tool life. Therefore, this study aims to identify the optimal machine settings for hardened AISI 4340 alloy steel considering the high cutting speed using coated carbide tools in dry environment. It is expected that this study will benefit the academicians and machinists to adopt cost-effective coated carbide tools in high-speed hard turning of steel alloy.

2.0 EXPERIMENTAL PROCEDURE

For this study cylindrical workpieces of AISI 4340 alloy steel are machined on a CNC lathe center under dry environment. Before the actual experimentations, the workpieces were heat-treated to attain 50 HRC Rockwell hardness. The experimental design as per Taguchi L_{18} methodology was selected to accommodate two levels of tool type (H-grade TiAlN/AlCrN PVD and P-grade Al_2O_3/TiCN CVD), three levels each of cutting speed (300, 350,400 m/min), feed rate (0.05,0.1,0.15 mm/rev), and depth of cut (0.1,0.2,0.3 mm). The selection of input parameters were based on Zenjanab et al. (2022), who utilized flood machining with nanoparticle additives in high-speed machining of AISI 4340 alloy steel using ceramic tools. The cutting tools was coated carbide with 0.4 mm nose radius, -6° rake angle, and 95° cutting edge angle. To obtain the experimental data for this study, surface roughness tester "Mitutotyo Surfest SJ-301" and optical microscope "Zeiss Stemi 2000-C model" are used for the measurement of tool life (TL) and surface roughness (R_a), respectively. Furthermore, an average tool life criteria Vb=0.3mm is considered as per ISO 3685 standard for tool life evaluation. The quality of the machined surfaces was evaluated by measuring the mean arithmetic roughness (R_a), according to the ISO 4288. Figure 1 shows the experimental scheme and Table 1 shows the controllable variables and their levels.

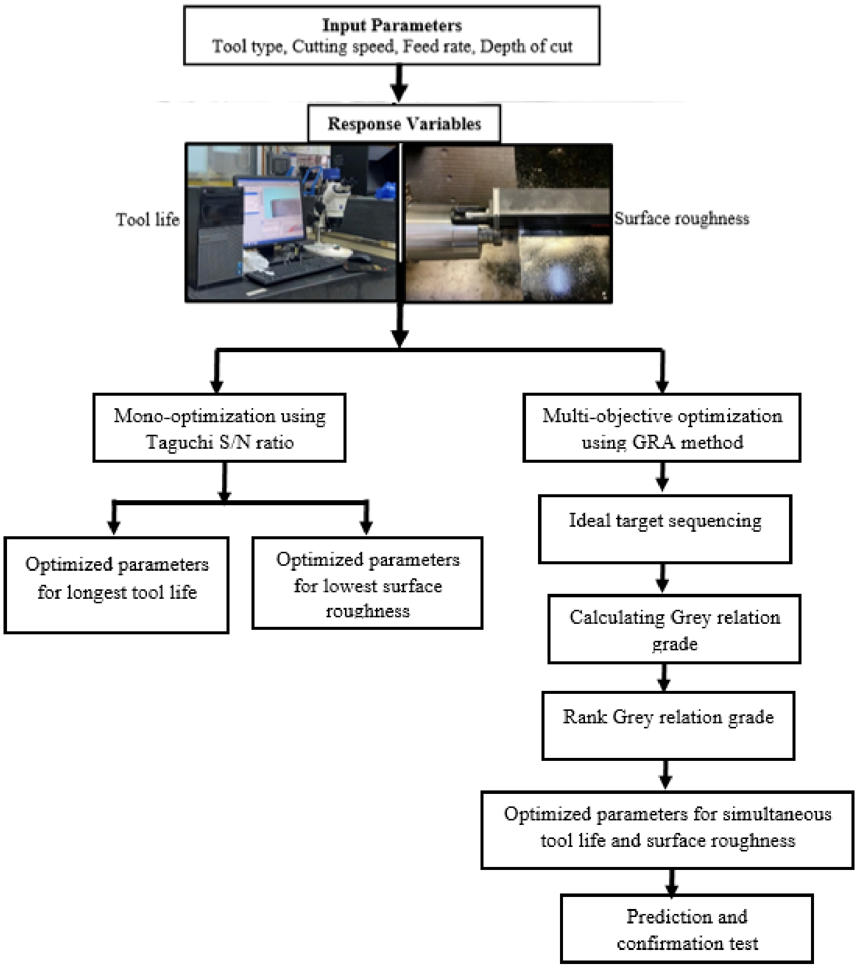


Figure 1: Experimental scheme employed for hard turning process.

Table 1: Controllable variables with their levels.

Control Factors	**Levels**		
	1	**2**	**3**
Tool type (T)	PVD	CVD	-
Cutting/machining speed (V)	300	350	400
Feed rate/ (F)	0.05	0.1	0.15
Depth of cut (DOC)	0.1	0.2	0.3

3.0 RESULTS AND DISCUSSION

3.1 Analysis of Response Variables Using Taguchi (S/N) Ratio

Taguchi is a most reliable design technique that is used to reduce the number of experiments and screen significant factors (Hamran et al., 2023). This technique is also utilized to determine the optimal parametric settings to achieve the highest quality characteristics by minimizing the existing variation in the process. Taguchi uses signal-to-noise ratio (S/N) for three quality characteristics, "nominal the better", "larger the better", and "smaller the better" as shown in equation (1), (2), and (3), respectively. In this present work, two quality characteristics are used to compute Taguchi S/N ratios; "larger the better" for longest tool life and "smaller the better" for lower surface roughness. Subsequently, the effective order of input variables is determined against each response factor by computing the delta value, which denotes the difference between the highest and lowest mean values of the S/N ratio. The corresponding S/N values against each L_{18} experimental setting is shown in Table 2.

$$\text{Quality characteristic based on Nominal is better, } \frac{S}{N} = 10\log\frac{\bar{x}}{{S_x}^2} \qquad \text{(Eq 1)}$$

$$\text{Quality characteristic based on Smaller is better, } \frac{S}{N} = -10\log\frac{1}{n}\left(\sum x^2\right) \qquad \text{(Eq 2)}$$

$$\text{Quality characteristic based on larger is better, } \frac{S}{N} = \log\frac{1}{n}\left(\sum x^2\right) \qquad \text{(Eq 3)}$$

Whereas x represents the response, $\bar{x}$ represents the average value of x, and S_x represents the variation in response factor.

Based on the tool life results illustrated in the response Table 3, it was established that feed rate (F) and cutting speed (V) are the most influential variables for tool life as they exhibited largest delta values 11.97 and 10.37, respectively. However, the tool type (T) and depth of cut (DOC) with less delta values are found to be the least influential parameters in relation to tool life. The main effect graph in Fig. 2a also presents similar conclusions, as can be seen the broader spread of feed rate and cutting speed in comparison to other input parameters. These results were unexpected because, generally the machining speed is considered as a governing variable for tool life/tool wear (Muhamad et al., 2022). The prevalent results in this study indicate that the variation in the tool-workpiece contact area caused by changing the feed rate has more significant influence on tool wear than the temperature variation induced by cutting speed. López-Luiz et al. (2018) in machining high-strength AISI D2 steel also reported highest influence of feed rate on tool wear with coated carbide tools. According to their findings, an increase in feed rate caused an increase in the tool-chip contact area, which resulted in higher friction force and increased loading on the cutting edge. These conditions significantly accelerated flank wear due to the involvement of high thermal stresses. Moreover, in a recent study Fedai, (2023) carried out turning of AISI 4340 and observed feed rate to be more influencing variable effecting the flank wear compared to cutting speed.

Surface roughness (R_a) results were also analyzed based on Taguchi S/N ratio. From Table 3, feed rate, demonstrating the highest delta value of 11.61, continues to be the most significant factor affecting surface roughness. This is followed by machining speed, depth of cut, and tool type each exhibiting relatively low delta values of 3.35, 2.28, and 1.87, respectively, suggesting their lesser influence on surface roughness. These results are corroborated by the main effect plot in Figure 2b, which displays that the machining speed, tool type, and depth of cut graphs show comparatively narrower spreads when compared to feed rate. Moreover, the stated findings are consistent with reference (Mia et al., 2018), who reported feed rate followed by cutting speed being the most influential variable for surface roughness in the turning process of AISI 1060 steel. The critical reason for this behavior is that a raise in feed rate causes the chip volume and thrust force to rise, which in turn promotes tool vibration, consequently affecting the surface quality.

From Figure 3 CVD tools demonstrated longest tool life (14.75 min) in experiment 10, while PVD tool demonstrated lowest surface roughness of 0.26 µm in experiment 4. However, most effective results for both response variables have been achieved with CVD coated tools, though the depth of cut was comparatively high with CVD tools at low machining speed and feed value. The micrographic view of flank wear land for both PVD and CVD tools at V=300 and F=0.05 in Figure 4 also supports this finding. Though abrasion and adhesion identified to be the dominating on tool wear mechanisms in both tools, excessive chipping and greater damage to the tool cutting edge indicate that TiAlN/AlCrN coating remained ineffective to shield the tool against thermal-mechanical stresses. Conversely, comparatively stable cutting geometry were witnessed for CVD tool demonstrated the effectiveness of Al_2O_3/TiCN coating, that prevented the cutting tool from thermal-mechanical variation. This retention of the cutting-edge geometry resulted in prolonged tool life and enhanced surface finish. According to Bjerke et al. (2022) the outer layer of the Al_2O_3 coating can successfully produce an aluminum oxide protective layer, giving the cutting edge thermal stability and favorable resistance to abrasion. It is due to this critical reason the surface roughness results are 66.6% improved in comparison to PVD tools.

Taguchi S/N ratio is also a useful method for mono-optimization, means to determine the optimal machining setting for favorable individual response factors (tool life and surface finish for this study). Thus, from the main effect graph in Figure 2, the optimal level of response variable is determined from the point where the S/N ratio was highest for respective input factor. For instance, for longest tool life, the optimal combination is achieved with CVD-coated tool at low cutting speed (300m/min), low feed rate (0.05mm/rev), and moderate depth of cut (0.2mm). However, for the lowest surface roughness, the favorable parametric setting is obtained with CVD-coated tool at highest cutting speed (400m/min), lowest feed rate (0.05mm/rev), and lowest depth of cut (0.1mm).

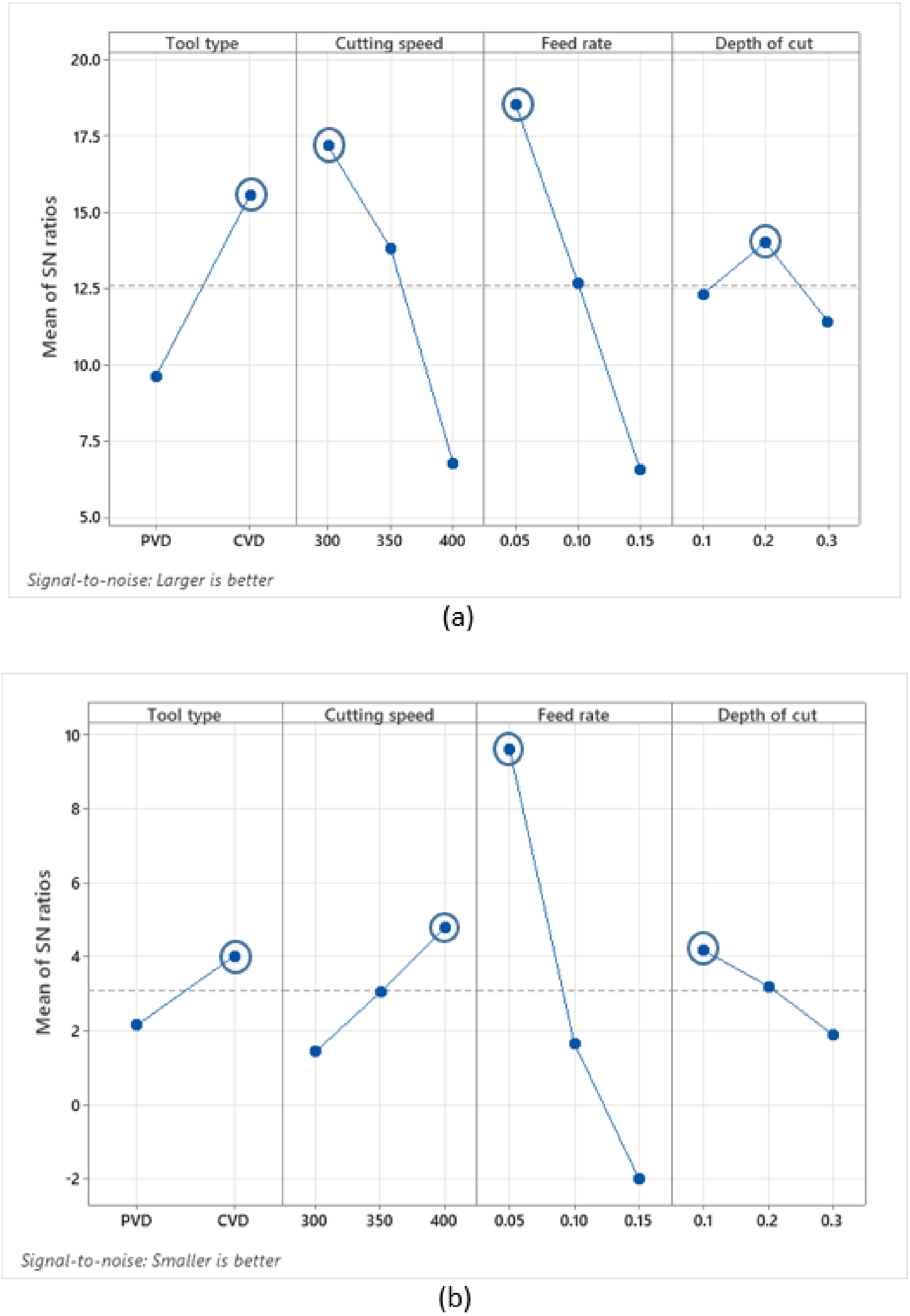


Figure 2: Main effect graph of S/N ratio (a) tool life (b) surface roughness.

Table 2: Surface roughness and Tool life results for different parametric settings.

S.No	**Tool type (T)**	**Cutting speed (V) m/min**	**Feed rate (F) mm/rev**	**Depth of cut (DOC) mm**	**Surface roughness (R_a) µm**	**Tool life (TL) min**	**Surface roughness (S/N ratio)**	**Tool life (S/N ratio)**
1	1	1	1	1	0.3490	10.080	9.144	20.069
2	1	1	2	2	1.0800	6.590	-0.669	16.378
3	1	1	3	3	1.9723	2.980	-5.899	9.484
4	1	2	1	1	0.2755	7.830	11.198	17.875
5	1	2	2	2	1.1660	3.290	-1.334	10.344
6	1	2	3	3	1.7430	1.940	-4.826	5.756
7	1	3	1	2	0.2940	4.530	10.633	13.122
8	1	3	2	3	0.7210	0.943	2.841	-0.509
9	1	3	3	1	1.2060	0.493	-1.627	-6.143
10	2	1	1	3	0.4910	14.750	6.178	23.375
11	2	1	2	1	0.8320	10.570	1.598	20.481
12	2	1	3	2	1.2110	4.540	-1.663	13.141
13	2	2	1	2	0.3050	14.110	10.314	22.990
14	2	2	2	3	0.7190	6.850	2.865	16.713
15	2	2	3	1	0.9920	2.840	0.069	9.066
16	2	3	1	3	0.3070	4.830	10.258	13.678
17	2	3	2	1	0.5820	4.230	4.702	12.526
18	2	3	3	2	0.7940	2.510	2.004	7.993

Table 3: Response table for Taguchi S/N ratio.

Factors	**Level 1**	**Level 2**	**Level 3**	**Delta value**	**Rank**
		Tool life (TL)			
T	9.597	15.552	-	5.955	3
V	17.155	13.791	6.778	10.377	2
F	18.519	12.656	6.550	11.969	1
DOC	12.313	13.995	11.417	2.578	4
		Surface Roughness (R_a)			
T	2.162	4.036	-	1.874	4
V	1.448	3.048	4.802	3.354	2
F	9.621	1.667	-1.990	11.611	1
DOC	4.180	3.214	1.903	2.278	3

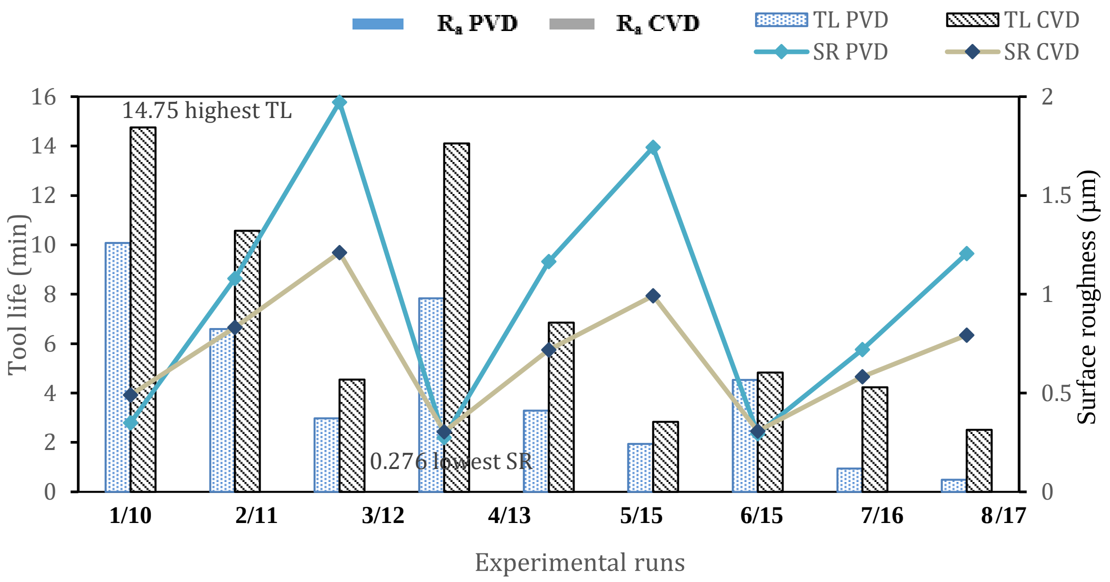
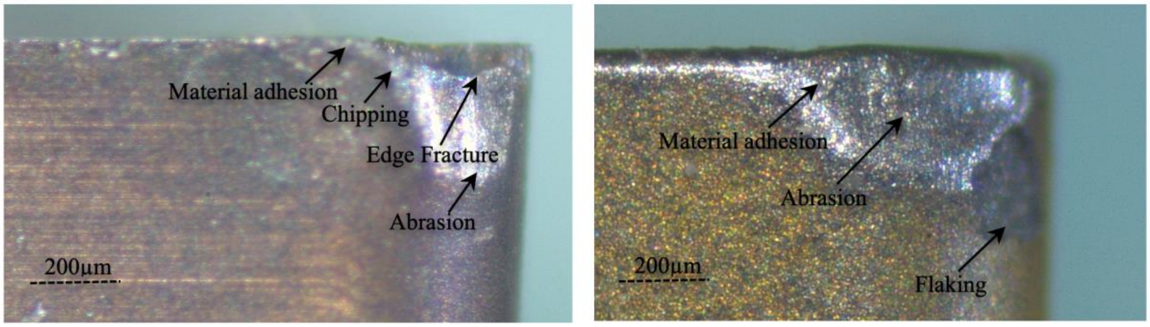


Figure 3: Results obtained for tool life and surface roughness in different machining runs.



(a) (b)

Figure 4: Microscopic view of tool flank wear at V=300m/min, F=0.05mm/rev (a) PVD tools (b) CVD tool.

3.2 Multi-Objective Optimization Using Grey Relation Analysis (GRA)

GRA has been widely adopted for multi-response optimization problems. This method is useful for three types of optimization objectives (a) maximizing the response factors, (b) minimizing the response factors, and (c) combined maximization and minimization. For this research, multi-objective optimization is performed by using the guidelines (including mathematical equations) provided by Kumar & Davim, (2018). The following are the steps used in the analysis of grey relation analysis.

3.2.1 Normalizing

In the first step, the data is normalized into a scale of 0 and 1 so that raw data is converted into common dimensionless quantity. The data is converted as per the necessity of objective function such as (a) maximizing the better, (b) minimizing the better, and (c) nominal the better. In this scenario, the raw data for tool life is converted into maximizing the better as represented by Eq (4) and surface roughness with minimizing the better Eq (5). The normalized values of tool life and surface roughness are represented in Table 4.

$$y_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \qquad \text{(Eq 4)}$$

$$y_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \qquad \text{(Eq 5)}$$

Whereas $x_i(k)$ denotes the sequence of the terms in original data, $y_i(k)$ is the sequence after normalizing, $\max x_i(k)$ represents the maximum number in the raw data, and $\min x_i(k)$ is the minimum number in the data.

3.2.2 Grey Relation Coefficient

In the following step, the normalized data was utilized to compute the grey relational coefficient by using Eq 6 and Eq 7. This step is performed to define the relation between normalized and standardized data values. The respective values of Grey relation coefficient (GRC) is listed in Table 4.

$$v_i(k) = \frac{\Delta_{min} + \xi\Delta_{max}}{\Delta_{oi}(k) + \xi\Delta_{max}} \qquad \text{(Eq 6)}$$

$$\Delta_{oi}(k) = |y_o(k) - y_i(k)| \qquad \text{(Eq 7)}$$

Whereas ξ in equation 6 is distinctive coefficient, $\Delta_{oi}(k)$ in Eq 7 represents deviation order of reference series $y_o(k)$ and $y_i(k)$ is comparability series in absolute value.

3.2.3 Grey relation grade

In the third step, a dimensionless scale (0-1) is created by computing the grey relation grade (GRG) from the weighted sum of Grey relation coefficient. For this work, an equal weight of 0.5 is assigned to both response variables, surface roughness and tool life, due to their importance in efficient and productive machining. The respective GRG against each experimental run is determined by using Eq 8 (see Table 4).

$$\gamma_i = \sum_{p=1}^{n} (w_p\, \xi(\mathrm{p})) \qquad \text{(Eq 8)}$$

3.2.4 Grey Relation Ranking

In this step, the grey relation grade was ranked in such an order that the computed GRG closer to 1 represents better performance. Table 4 presents the corresponding GRG rankings, assigned in descending order. The graphical representation of GRG in Figure 5 shows experiment 13 (T=CVD coated, V=300m/min, F=0.05mm/rev, DOC=0.1mm with highest GRG value of 0.942 is an optimal combination for multi-response optimization.

In response Table 5, and the variation between each row's highest and lowest values was computed to identify the effective order of input parameters. Thus, the largest delta value, corresponding to feed rate, suggests its highest influence on both tool life and surface roughness, followed by tool type, cutting speed, and depth of cut. Similar results can be seen from the ANOVA in Table 6. It is evident from the P-value that, only the feed rate and tool type demonstrated statistical significance with average GRG.

It is also important to mention that the highest value corresponding to each factor in Table 5, indicates its optimal level. For instance, 0.631(level 2) for tool type, 0.594 (level 1) for cutting speed, 0.790 (level 1) for feed rate, 0.594 (level 1) for depth of cut is the best combination for better tool life and surface quality in turning hardened AISI 4340 alloy steel. Similar inference can be deduced from the main effect graph of the mean of GRG in Figure 6.

Table 4: Calculation of Grey relation analysis.

Exp. No	**Normalized values**		**Grey relation coefficient**		**Grey Relation Grade (GRG)**	**Ranking**
	Tool life (TL)	**Surface roughness (R_a)**	**Tool life (TL)**	**Surface roughness (R_a)**		
1	0.672	0.956	0.604	0.9202	0.762	3
2	0.427	0.525	0.466	0.5137	0.489	12
3	0.174	0	0.377	0.333	0.355	18
4	0.514	1	0.507	1	0.753	4
5	0.196	0.475	0.383	0.488	0.435	15
6	0.101	0.135	0.357	0.366	0.361	17
7	0.283	0.989	0.411	0.978	0.694	5
8	0.0315	0.737	0.3404	0.656	0.498	10
9	0	0.451	0.333	0.477	0.405	16
10	1	0.872	1	0.797	0.898	2
11	0.706	0.672	0.630	0.609	0.617	7
12	0.283	0.448	0.411	0.4755	0.443	14
13	**0.955**	**0.982**	**0.917**	**0.966**	**0.942**	**1**
14	0.4458	0.738	0.474	0.657	0.565	9
15	0.164	0.577	0.374	0.542	0.458	13
16	0.304	0.981	0.4181	0.964	0.691	6
17	0.262	0.819	0.404	0.735	0.569	8
18	0.141	0.694	0.368	0.621	0.494	11

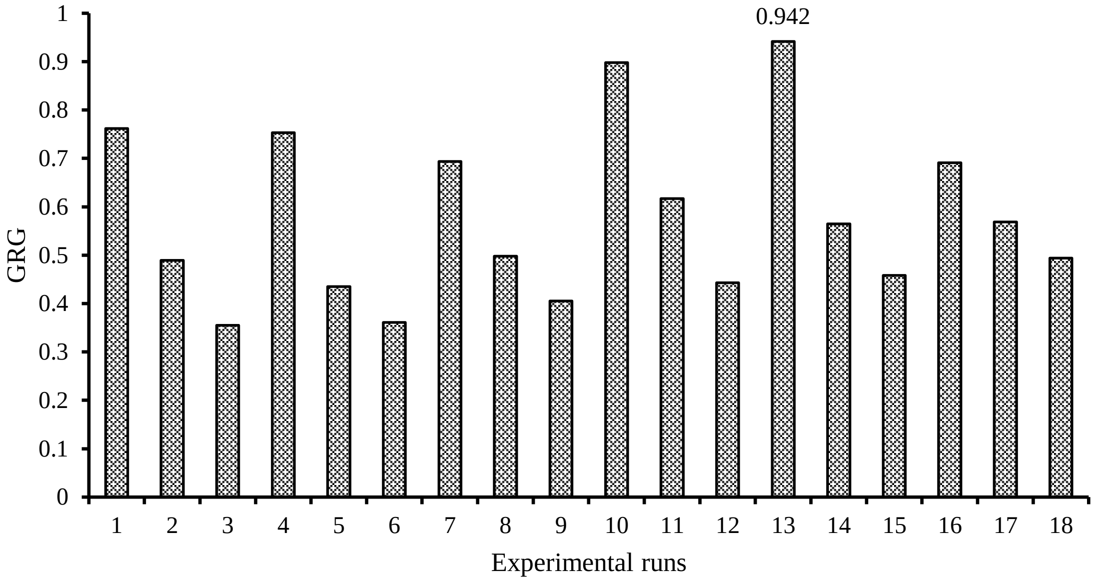


Figure: 5 Grey relation grade corresponding to experimental runs.

Table 5: Response table for mean Grey relation grade.

Parameters	**Levels**			**Delta**	**Rank**
	I	**II**	**III**		
Tool type (T)	0.529	0.631	-	0.1025	2
Cutting speed (V)	0.594	0.586	0.5588	0.0356	3
Feed rate (F)	0.790	0.529	0.419	**0.37071**	**1**
Depth of cut (DOC)	0.594	0.583	0.562	0.0325	4

Mean GRG is **0.568**

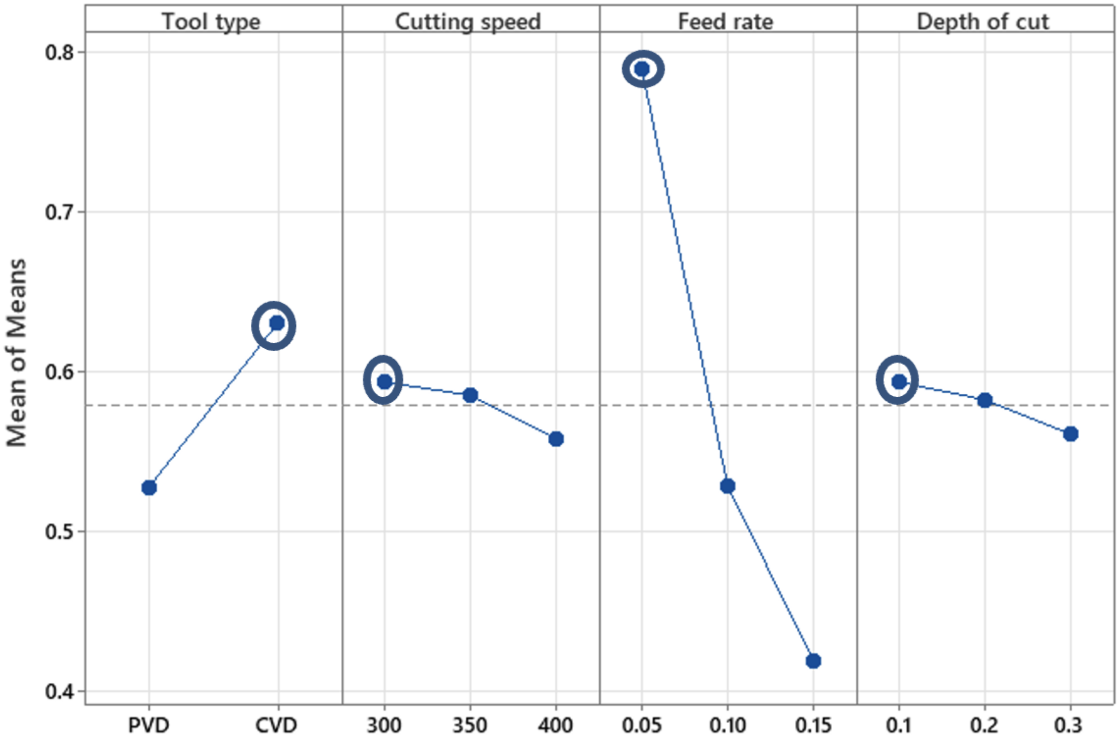


Figure: 6 Main effect graph of GRA.

Table 6: ANOVA on GRG.

Source	DF	Seq SS	Adj MS	F	P	Significance
T	1	0.0475	0.0475	12.39	**0.006***	**Significant**
V	2	0.000414	0.002068	0.545	0.599	Insignificant
F	2	0.43518	0.217592	56.70	**0.000***	**Significant**
DOC	2	0.0032	0.001654	0.43	0.661	Insignificant
Residual Error	10	0.0383	0.003837			
Total	17	**0.5285**				

* Significant factor

3.2.5 Prediction and Confirmation Test

As the optimal parametric setting has been determined for better tool life and surface quality, the last step is to predict and verify the improvements in machining efficiency with respect to initially selected parametric design. The predicted grey relation grade can be determined by emplying Eq (9). Table 7 listed the actual and predicted results and there is 14.57% improvements in grey relation grade after conducting the experiments on optimal parametric setting with CVD tool at V=300m/min, F=0.05mm/rev, and DOC=0.1mm. Thus, it can be state that the actual and predicted results are in good agreement.

$$\gamma_p = \gamma_m + \sum_{i=1}^{n}(\gamma_o - \gamma_m) \qquad \text{(Eq 9)}$$

Whereas γ_p is the expected GRG, γ_m is the average GRG, and γ_0 denotes the maximum of average GRC at optimal levels for each factor.

Table 7: Results of predicted and confirmation test.

Parametric setting		levels	Tool life	Surface roughness	GRG	Improvements in GRG
Initial parametric setting		T1 V1 F1 D1	10.08 min	0.3490 µm	0.762	14.57%
Optimal parametric setting	Predicted	T2 V1 F1 D1			0.8705	
	Experiment	**T2 V1 F1 D1**	19.25 min	0.465 µm	**0.908**	

CONCLUSIONS

This study is focused on Taguchi S/N ratio and grey relation analysis method to optimize the orthogonal hard turning variables for multi-response characteristics (surface quality and tool life). Based on experimental and statistical inference, the following concluding remarks can be drawn:

a. Based on the Taguchi S/N ratio, feed rate and cutting speed are the most influential parameters for tool life, as they exhibited the largest delta values of 11.97 and 10.37, respectively. However, in the case of surface roughness, the feed rate, with the highest delta value of 11.61, remains the most influential parameter, followed by cutting speed, depth of cut and tool type.
b. Based on Taguchi S/N ratio mono-optimization studies, the optimal parametric setting for the longest tool life is achieved at V=300m/min, F=0.05mm/rev, and DOC=0.1mm with a CVD-coated tool. However, for the lowest surface roughness, a high cutting speed V=400 m/min is recommended keeping the remaining settings identical.
c. The highest magnitude of Grey relation grade obtained in experiment run 13 suggested that CVD tool with low machining speed of 300m/min, low feed rate of 0.05mm/rev, and moderate depth of cut of 0.2mm is an optimal parametric setting for both response factors tool life and surface roughness.
d. Moreover, the combined effect of input variable on GRA was analyzed by computing the mean and ANOVA and it was revealed that the two most important factors that concurrently affect surface roughness and tool life are feed rate and tool type. Furthermore, using CVD coated tools, the optimal parametric setting was determined to be V=300m/min, F=0.05mm/rev, and DOC=0.1mm.
e. Lastly, prediction and confirmatory tests were conducted, and 14.57% improvement in GRA was realized, suggesting that the grey relation analysis is an effective tool for multi-objective optimization.

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