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Multi-Response Optimization on the Effect of Wet and Eco-friendly Cryogenic Turning of D2 Steel Using Taguchi-Based Grey Relational Analysis

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Abstract

Material removal processes, including turning and milling, are still commonly used operations for manufacturing most of mechanical components in modern industry. Apart from the cutting parameters, the cooling method has the great impact on the technological effects and, above all, on the environmental friendliness of production. In this study, multi-response optimization on the effect of wet and cryogenic machining is performed during the turning of AISI D2 steel samples. Spindle speeds, feed rates, depths of cut, and cutting fluid types varied in a Taguchi mixed design L16 orthogonal array. Statistics, such as an analysis of variance (ANOVA) and a regression model, were applied to the obtained data on the metal removal rate and surface roughness. By employing a grey relational analysis, the best cutting factors for a set of several responses were determined. Among the many factors influencing the rate at which material is removed, analysis of variance revealed that the feed rate was the most influential factor (46.67%), followed by spindle speed (46.65%). Analysis of the factors influencing surface roughness pointed to the feed, cutting condition, and spindle speed as the most essential at 56.66%, 26.04%, and 11.7%, respectively. ANOVA of grey relational analysis shows that speed followed by cutting conditions are the most predominant factor, with a percentage contribution of 71.9% and 14.14%, respectively. From grey relational analysis, a level setting of 4-4-1-2 was identified as the best possible combination of multi-response process parameters. A close agreement is observed between the predicted value of GRG 0.7927 and the experimental validation value of GRG 0.8031. Moreover, the validation test reveals that the percentage error in estimating material removal rate, surface roughness, and GRG, respectively, are 4.33%, 9.09%, and 1.29%, from predicted values. A study on metallographic observations revealed that parts after wet machining have more tool marks on the treated surface than parts after cryogenic machining.

Keywords: Cryogenic machining, GRA, Material removal rate, Surface roughness, Taguchi method

1. Introduction

Turning is one of the most commonly used manufacturing processes utilized for the production of mechanical components. This machining operation is a subtractive technique to remove the material allowance using controlled predictive variables. The volume of the material removed through this technique depends on the duration of the processing time and involved predictive variables [1]. The cutting power is converted to heat while conducting turning operation, and cooling techniques, whether wet and cryogenic, are used to reduce the effect of this heat on the part surface quality [2].

Wet machining utilizes common cutting fluids such as water-mixed types containing complex petrochemical elements and vegetable oil based types like castor, sesame, sunflower, and canola oil. Flooding of cutting fluid at approximately 100 l/h into the cutting zone is a common industrial practice to provide an effective cooling effect and lubrication. This flooding, negatively impacting the environment, is crucial for effective chip removal and heat transfer from the cutting zone [3, 4]. Eco-friendly cryogenic machining utilizes nitrogen or carbon dioxide in the form of a liquid or gas acting directly on the tool or directly delivered to the cutting zone. This cooling technique is greener and better at preventing tool defects and refining the machining process. It also has a significant superiority when machining composites and other non-metals due to ease of chip breaking, low tool wear, superior quality score, and reduced chip contact length [5].

Many investigators studied the effect of wet and cryogenic cutting fluids during turning challenging to cut materials through the quality score of cutting force, tool wear, material removal rate, specific cutting energy, and surface roughness. A cryogenic cutting condition showed 20%

better surface roughness than an equivalent weight condition of flood or wet cooling technique during turning operation employed on AISI 316 austenitic stainless steel [6] and Ti-6Al-4V [7]. To minimize surface roughness and the tool wear during processing Ti-6Al-4V, a Taguchi-based grey relational analysis was performed to examine the impact of predictive variables. The ANOVA result displayed that the feed rate followed by the cutting fluid contributed more to the total variation in simultaneous objective functions. The suggested optimal machining setting improved surface roughness, tool wear, and specific cutting force in 22%, 30%, and 4%, respectively [8].

Younas et al. [9] integrated grey relational analysis with the analytical hierarchy process to optimize and model a multi-objective function. Turning quality scores, surface roughness, tool wear, specific cutting energy, and material removal rate were selected for multi-response optimization during turning Ti-6Al-4V material with uncoated H13 carbide insert in dry turning condition. A response surface method was employed in their study to determine the optimal machining setting. ANOVA results showed that the interaction of feed to speed contributed more in affecting grey relational grade for the simultaneous objective function. Optimal turning setting increased tool life by 7% and material removal rate by 34%, whereas surface roughness and specific cutting force diminished by 2% and 6%, respectively [9].

In research performed by Sharma et al. [10] on AA6262T6 aluminium alloy dry turning conditions and an uncoated tool with a carbide insert were employed. The study considers the depth of cut, cutting speed, and feed rate as predictive variables and uses grey relational analysis for multi-response optimization. The predicted results showed a boost of 14.55% for the material removal rate and a diminished 8.9% for surface roughness [10]. Ranjith et al. [11] analysed AA6063 turning at cryogenic and room temperature by utilizing an L16 orthogonal array design with grey relational analysis to determine the effect of machining parameters on the response surface roughness and material removal rate. The results proved that cryogenic turning is superior to room temperature by lessening the material removal rate and improving surface roughness [11].

The experimental study presented in [12] was conducted on AISI L6 difficult-to-cut material to investigate the effect of liquid nitrogen cutting fluid in turning operation and to optimize the response quality scores such as surface roughness, cutting energy, tool wear, and material removal rate. Taguchi-based grey relational analysis with L9 orthogonal array adapted for optimization identified optimal input settings as speed 160 m/min and feed 0.16 mm/rev [12]. The effect of predictive variables and Al_2O_3 Nanofluid during turning of Incoloy 800H steel using AlTiN coated carbide tool inserts and L9 Taguchi design was presented in [13]. Results showed that 0.25% concentration of Al2O3 Nanofluid in coconut oil, along with a speed of 100 m/min and 0.14 mm/rev feed rate have a better quality score to minimize the roughness, tool wear, and cutting force. The crystallographic plane, surface roughness, microhardness, and microstructure were some of the quality scores examined on AZ31C magnesium alloy in both dry and cryogenic environments [14]. Cryogenic conditions showed better surface quality and an increase in microhardness from 53.7 HV to 98 HV.

D2 steel tested in this study is used in high-tech applications that require long-run tooling, where surface quality is critical. This applies, for example, to applications such as the production of thread rolling dies, blanking dies or forming dies. Deteriorated surface and rapid tool wear have been noted as hypercritical damage induced during the turning process [15]. Accordingly, optimal set of turning parameters and cooling conditions under which surface roughness is reduced and material removal rate increases plays a significant role in manufacturing industries. To achieve this goal, a comparative method was used to study the occurrence of tool wear through surface texturing on the flank face of the coated carbide tool. Turning AISI D2 steel with a hardness of 45 HRC using a textured and non-textured coated carbide tool and eight tests with three predictive factors are studied. The result showed that the flank wears more in the non-textured cutting tool than in the textured one. Research presented in [16] focused on comparative study of machining conditions on material removal rates, and with the limited study on the effect of the cutting fluid effect due to its inadequacy of the observed results [16]. In the studies presented in [15], it was found that the feed contributes more to the dry-turning process than all other predictive variables. The study was focused on investigating the effects of dry turning operation having predictive machining parameters such as tool material, tool geometry, speed, feed, and depth of cut. In contrast, in the conducted experiments, the study of the effect of cutting fluids on the response quality factor has not been investigated.

Much research has been conducted to optimize the machining process of D2 steel, which is often used in modern industrial applications. Apart from the cutting parameters, the cooling method has the great impact on the technological effects and, above all, on the environmental friendliness of production. Previous research presented in other works, focused mainly on either dry or wet turning processes with parametric consideration of only speed, feed, and depth of cut. Early studies on the effects of cutting fluids, such as wet and cryogenic, were inadequate and insufficient for performing turning on D2 steel. This limitation related to the cutting fluids has not allowed to find optimal machining conditions for the D2 steel turning process so far. Machining with optimal process parameters plays a vital role for increased quality scores, increasing productivity, and lowering the costs of production. The main of this study is to find the set of optimal parameters, including the cooling method which has not yet been studied in detail. A Taguchi-based grey relational analysis [17-20] was applied to investigate the effect of wet and cryogenic cutting fluids during turning D2 steel to obtain the optimal machining conditions. In addition, a study on metallographic observations revealed that parts after wet machining have more tool marks on the treated surface than parts after cryogenic machining.

2. Materials and Methods

2.1. Materials

Figure 1 shows samples with a diameter and a length of 40 mm and 200 mm, respectively, prepared from a round bar of D2 steel. The results of the analysis of the elemental composition of the samples performed with the JASCO FT/IR-6700 spectrometer are presented in Table 1. The experiments were conducted under the wet and cryogenic conditions of machining using a welded tungsten carbide tool with the following specification: P30 grade, 5° rake angle, 140 mm x 20 mm dimensions and 0.4 mm nose radius.

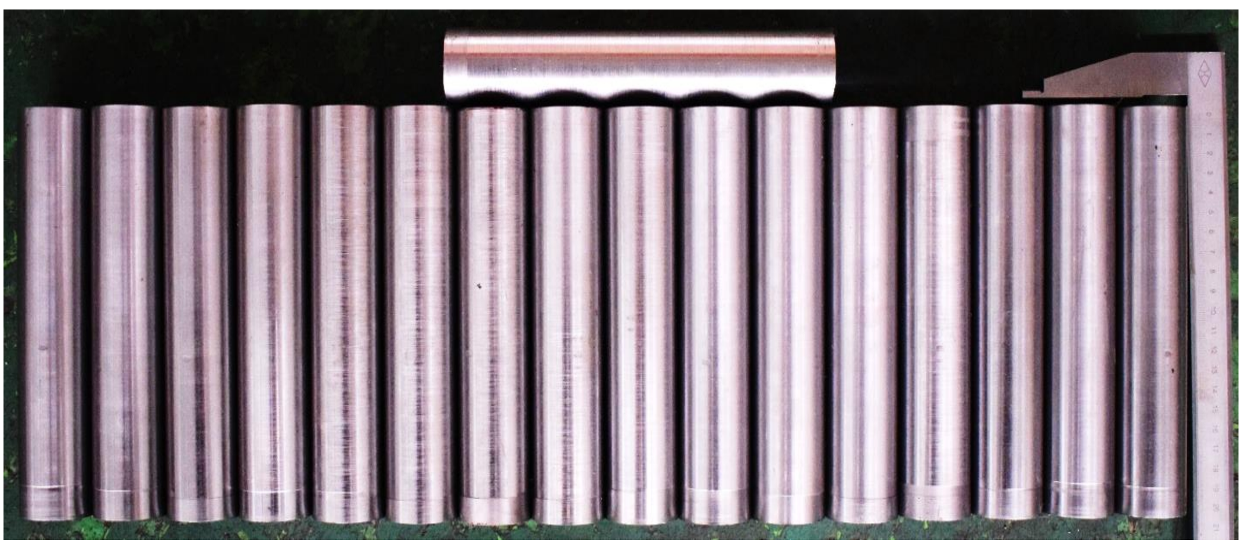


Figure 1. Samples of D2-steel before wet and cryogenic machining

Table 1. Elemental composition of D2 steel used in wet and cryogenic machining, in %

V	C	Mo	Cr	Si	S	T	Mn
0.90	1.50	0.80	12	0.30	0.030	0.460	0.340

2.2. Design of experiment

Tool makers recommend to maintain a relatively low cutting speed to reduce heat generation and prevent premature tool wear during turning of D2-steel. According to West Yorkshire steel Ltd. the recommended cutting speeds for D2 steel using a carbide tip cutting tool and employing water based cutting fluid is typically ranges from 800 to 1200 (rpm) and 1200 to 2500 (rpm) for rough and fine turning respectively. Table 2 shows four selected levels of predictive variables, i.e. spindle speed, feed and depth of cut within the acceptable operating range and two levels of categorical variables, i.e. the type of the cooling method, as the input factor. Table 3 displays selected Taguchi L16 orthogonal arrays with different mixed-level designs, corresponding to 16 turning experiments conducted on the samples of D2 steel.

Table 2. Input factors with the assumed levels

Factors	Unit	Symbol	Levels			
			1	**2**	**3**	**4**
Spindle speed	rpm	A	650	1250	1850	2450
Feed	mm/rev	B	0.06	0.12	0.18	0.24
Depth of cut	mm	C	0.3	0.6	0.9	1.2
Cutting fluid	--	D	Wet	Cryogenic	----	----

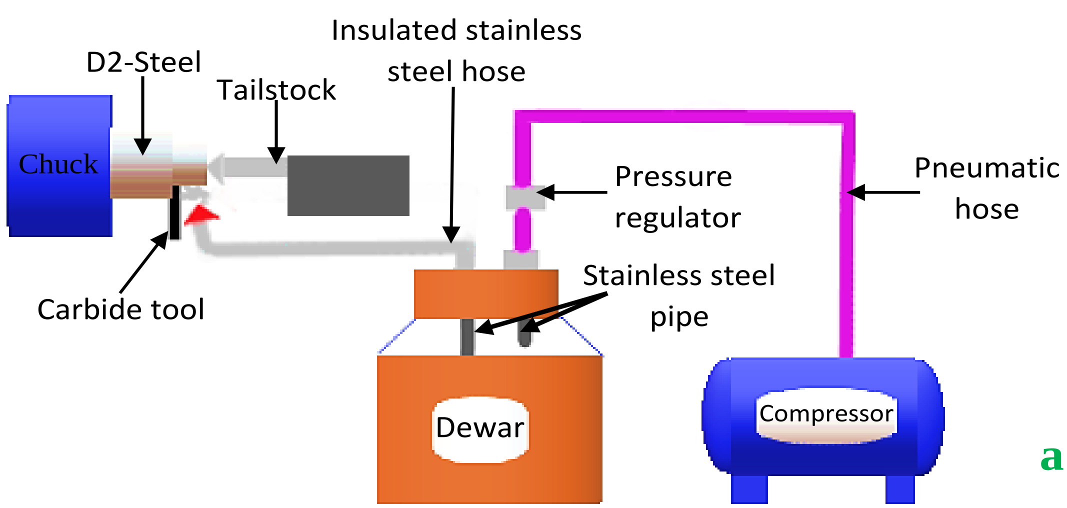
Table 3. L16 Orthogonal array design matrix for wet and cryogenic turning

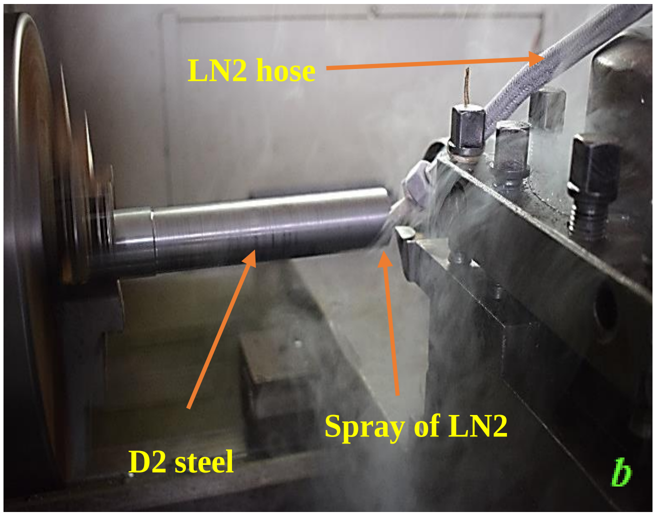
Experimental Run	Spindle speed	Feed	Depth of cut	Cutting fluid
1	1	1	1	1
2	1	2	2	1
3	1	3	3	2
4	1	4	4	2
5	2	1	2	2
6	2	2	1	2
7	2	3	4	1
8	2	4	3	1
9	3	1	3	1
10	3	2	4	1
11	3	3	1	2
12	3	4	2	2

13	4	1	4	2
14	4	2	3	2
15	4	3	2	1
16	4	4	1	1

2.3. Experimentation

Cryogenic machining requires an additional supply system of the cooling medium, as shown in Figure 2a. A dewar with a capacity of 25 liters was used as a special container for the cryogenic liquid to safely maintain its temperature. It is combined with the air compressor to control the pressure and flow rate of the liquid nitrogen (LN2). The workpiece is mounted rigidly in a three-jaw chuck on a CNC lathe. An insulated stainless steel hose was attached to the CNC machine tool to deliver LN2 to the rake face of a cutting tool while maintaining its temperature at -181^{o}C and pressure at 2 bar, as shown in figure 2b. Figure 2c shows a built-in machine system with a pipe to deliver the conventional fluid from the coolant tank to the rake face of a tool face, under the flood conditions. A tank was filled with a bio-stable water-soluble Shell Dromus B cutting oil. The CNC lathe of Dalian machine tool group corp. with a machine model number CKE6150Z was used for the experiments.





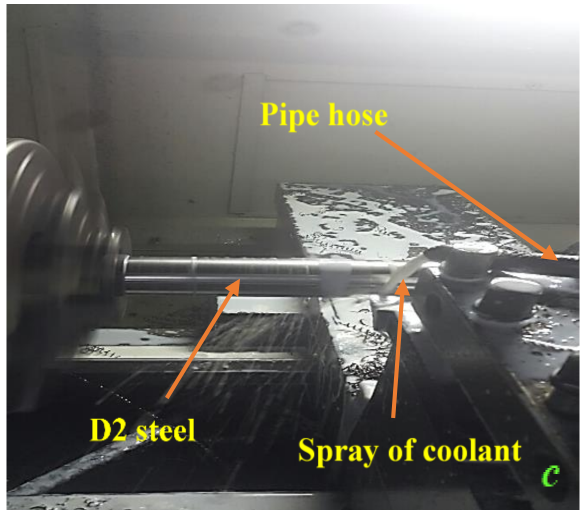


Figure 2. Schematic illustration of the supply system of the liquid nitrogen cooling medium (a) and real cooling systems with liquid nitrogen (b) and conventional coolant (c) during turning experiments

2.4. Measurement of surface roughness and materials removal rate

The surface roughness of the workpieces was assessed using a Vogel surface roughness tester in the direction of the longitudinal feed of the tool. Three separate readings of the surface roughness parameter are taken and averaged for the study. Each D2 steel sample was weighed before and after machining on a CSS balance to estimate the material removal rate in mm^3/min using Equation 1 [1, 21]:

$$MRR = \frac{W_i - W_f}{\rho * T_m} \quad (1)$$

where: W_i is the initial weight in kilograms, W_f is the final weight in kilograms, T_m is the machining time in minutes, and ρ is the density of D2 steel, which is 7700 kg/m^3.

2.5. Surface topography

Regular machining marks are typical for turning with the specific distance between the scratches corresponding to the feed rate. A micrographic observation was conducted using the Guangzhou LISS inverted metallurgical microscope to observe the scratch lines, also called as feed marks, and to evaluate the surface topography, i.e. spacing between the scratch lines, number of scratch lines within a given area, and deviations from the ideal structure influencing the surface quality, such as surface tearing.

2.6. Analysis of responses

The impact of turning settings on responses was analyzed statistically using a Minitab 18 software. In the analysis, opting higher is better for MRR, and lower is better for surface roughness. The signal-to-noise ratio for MRR and surface roughness may be determined using Equation 2 and Equation 3:

$$\frac{S}{N} = -10 \log\left(\frac{1}{k}\right) \sum_{i=1}^{k} \left(\frac{1}{y2}\right) \tag{2}$$

$$\frac{S}{N} = -10 \log\left(\frac{1}{k}\right) \sum_{i=1}^{k} y2 \tag{3}$$

where: *k* is the number of replication and *y* is the response value.

2.7. Multi-response optimization

Execution of multi-response optimization requires utilizing an appropriate technique or algorithm. This work uses grey relational analysis technique to determine the optimal machining parameters for maximizing MRR while minimizing surface roughness. This procedure has a few steps [8, 22], and the first is normalizing the responses to the value zero-one.

For MRR, 'higher is better' is utilized to normalize the response using Equation 4:

$$x_{ijk} = \left[\frac{y_{ij} - \min(y_{ij})}{\max(y_{ij}) - \min(y_{ij})}\right] \tag{4}$$

, and lower is better for surface roughness using Equation 5:

$$x_{ijk} = \left[\frac{\max(y_{ij}) - y_{ij}}{\max(y_{ij}) - \min(y_{ij})}\right] \tag{5}$$

The response variables i are given below for each replication k = 1, 2, 3… r., min (y_{ij}) and max (y_{ij}) are intended to be the minimum and maximum of each response variable. Equation 6 is used to determine the maximum of normalized values:

$$x_{oj} = Max\left(x_{ijk}\right) \tag{6}$$

Regardless of the response variables, the absolute difference between each normalized value and the reference value x_{ij} is estimated using equation 7:

$$\Delta_{ij} = \left|x_{oj} - x_{ijk}\right| \tag{7}$$

Grey relational coefficient γ (x_{0j}, x_{ij}) was calculated using Equation 8, ξ is distinguishing coefficient ranges from 0 to 1 (0.5 widely accepted) [8, 9]. ξ is used to expand and compress the grey relational coefficient. The formula of Equation 8 is:

$$\gamma(x_{oj}, x_{ij}) = \left[\frac{\Delta_{min} + \xi\,\Delta_{max}}{\Delta_{ij} + \xi\,\Delta_{max}}\right] \tag{8}$$

The grey relational coefficient leads to finding the grey relational grade for each experimental run using Equation 9:

$$\Gamma\left(x_{oj}, x_{ij}\right) = \frac{1}{k * i}\sum_{i=1}^{n}\gamma\left(x_{oj}, x_{ij}\right) \tag{9}$$

3. Results and Discussion

3.1 Responses character with an experimental run

Table 4 shows the responses measured in this experimental study which were material removal rate and surface roughness. After turning D2-steel in wet and cryogenic conditions as shown in Figure 3, the material removal rate is calculated using Equation 1. The surface roughness was measured three times on the longitudinal feed direction, typically as in turning,

Figure 3. Samples of D2-steel after machining

Table 4. Response value of material removal rate (MRR) and surface roughness (Ra)

Exp. Runs	**Control Parameters**				**Response Value**			
	Speed (rpm)	**Feed (mm/rev)**	**DOC (mm)**	**Cutting fluid**	**MRR (mm^3/min)**	**Ra (μm)**		
						Rep1	**Rep2**	**Rep3**
1	650	0.06	0.3	Wet	2851	0.79	0.82	0.76
2	650	0.12	0.6	Wet	4947	0.84	0.86	0.82
3	650	0.18	0.9	LN2	17100	0.84	0.85	0.86
4	650	0.24	1.2	LN2	27228	1.09	1.08	1.1
5	1250	0.06	0.6	LN2	6697	0.60	0.64	0.62
6	1250	0.12	0.3	LN2	9746	0.58	0.55	0.61
7	1250	0.18	1.2	Wet	35375	0.97	0.98	0.99
8	1250	0.24	0.9	Wet	41422	1.18	1.2	1.16
9	1850	0.06	0.9	Wet	13428	0.76	0.74	0.78
10	1850	0.12	1.2	Wet	34892	0.83	0.81	0.82
11	1850	0.18	0.3	LN2	48701	0.73	0.75	0.77
12	1850	0.24	0.6	LN2	57720	0.8	0.79	0.81
13	2450	0.06	1.2	LN2	25688	0.41	0.45	0.49
14	2450	0.12	0.9	LN2	50134	0.55	0.52	0.58
15	2450	0.18	0.6	Wet	50226	0.88	0.85	0.91

16	2450	0.24	0.3	Wet	57296	1.02	0.99	0.96

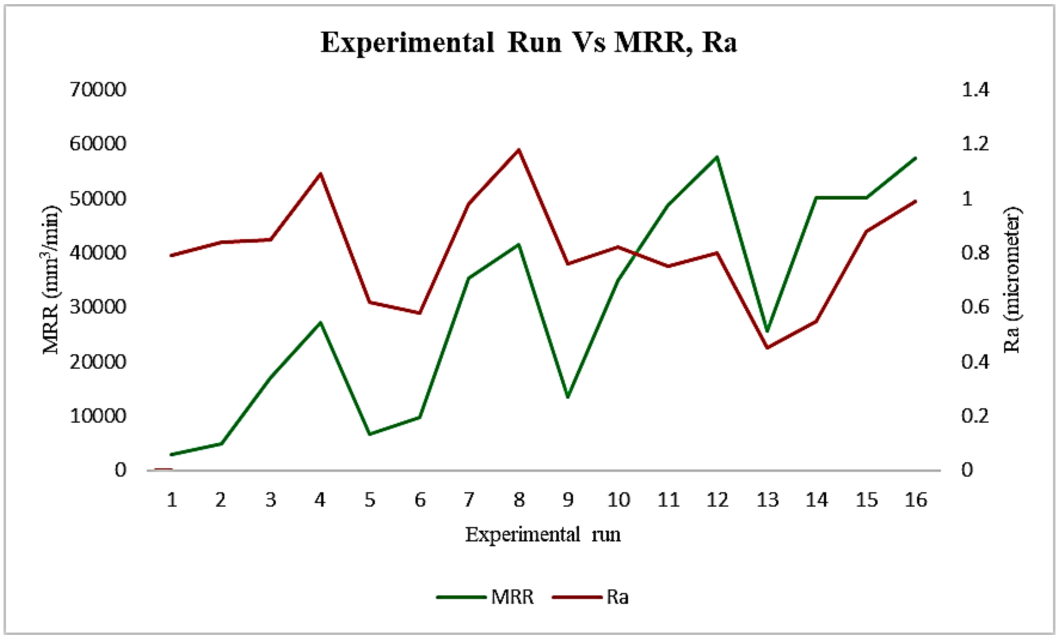


Figure 4. Responses for consecutive experimental runs

Responses behaviour for consecutive experimental runs is shown in Figure 4. The surface roughness value increases as the material removal rate rises and diminishes as the material removal rate falls. Comparing results from several stages of the experiment it can be found that the rate of material removal behaved in an incremental approach, while surface roughness varied between relatively stable values.

3.2 Analysis of the material removal rate and surface roughness

The MRR and Ra were analyzed by Signal-to-Noise ratio, with higher being better and lower being better criterion, as indicated in Equations 2 for MRR and in Equation 3 for the surface roughness. A higher MRR has a higher SN ratio, and the better surface finish with lower surface roughness has a higher SN ratio. Figure 5a shows how a rise in the spindle speed, depth of cut, feed, and machining with liquid nitrogen accelerates the material removal rate. The material removal rate is to be linearly controlled by feed and spindle speed, according to the research conducted in [22]. A higher material removal rate is also observed during cryogenic machining. Figure 5b illustrates how various turning factors affect the surface roughness of the response. A higher SN ratio corresponds to a best response (lower surface roughness) and a lower SN ratio corresponds to a bad response (higher surface roughness). Tool manufacturers recommend to perform turning operations within the limits of relatively lower spindle speed while employing wet cutting fluids in order to protect the surface being machined from deterioration, but here the result demonstrates that cryogenic condition and increase in the spindle speed improves the surface roughness significantly. The roughness increases with the increase in depth of cut and the feed rate. The feed rate is directly related to the surface roughness, as described in [12, 23-24].

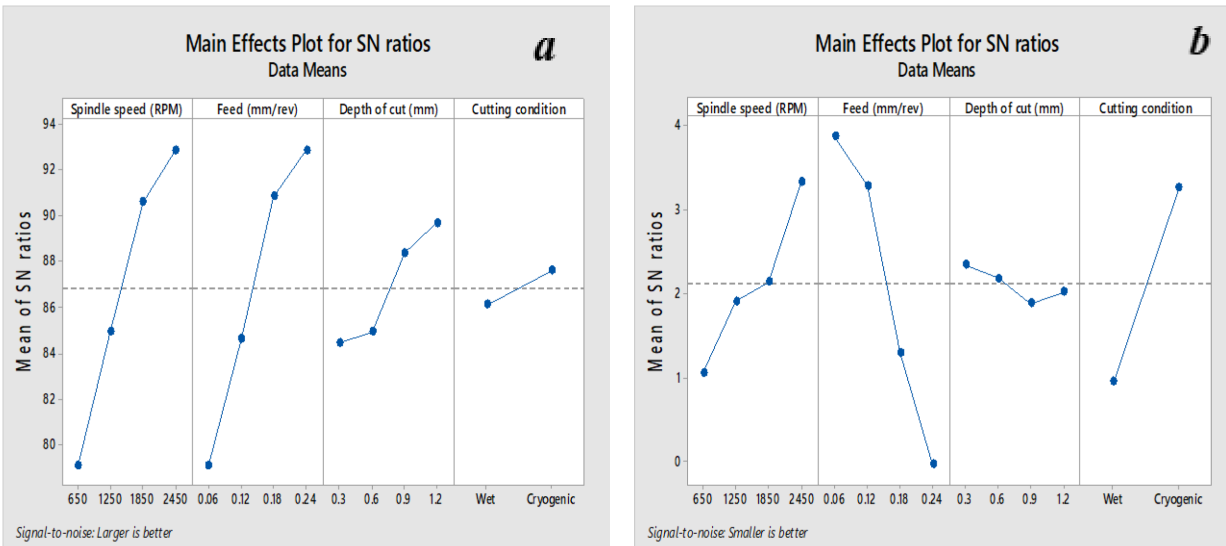
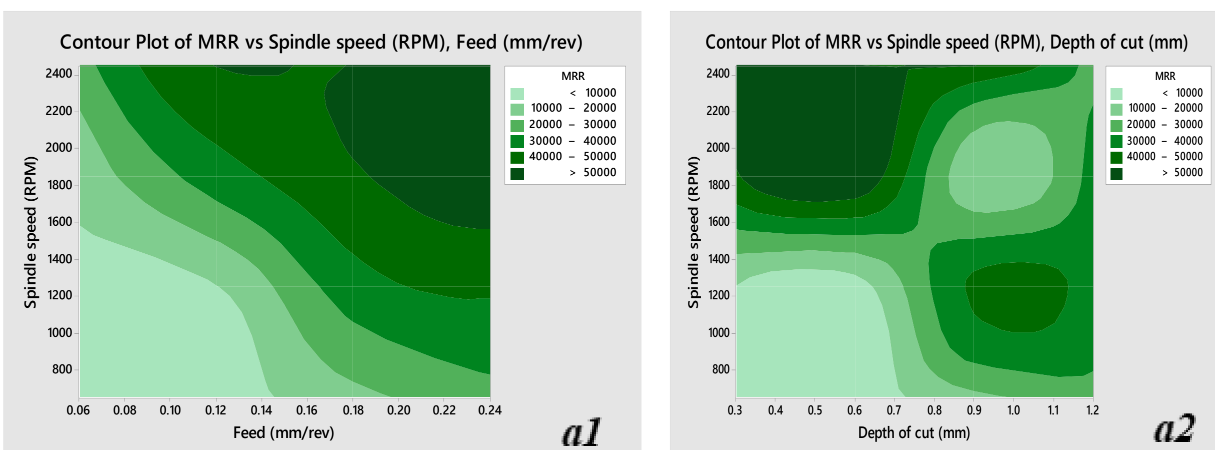


Figure 5. Main effect plot for Signal-to-Noise ratio for: a) material removal rate, b) surface roughness



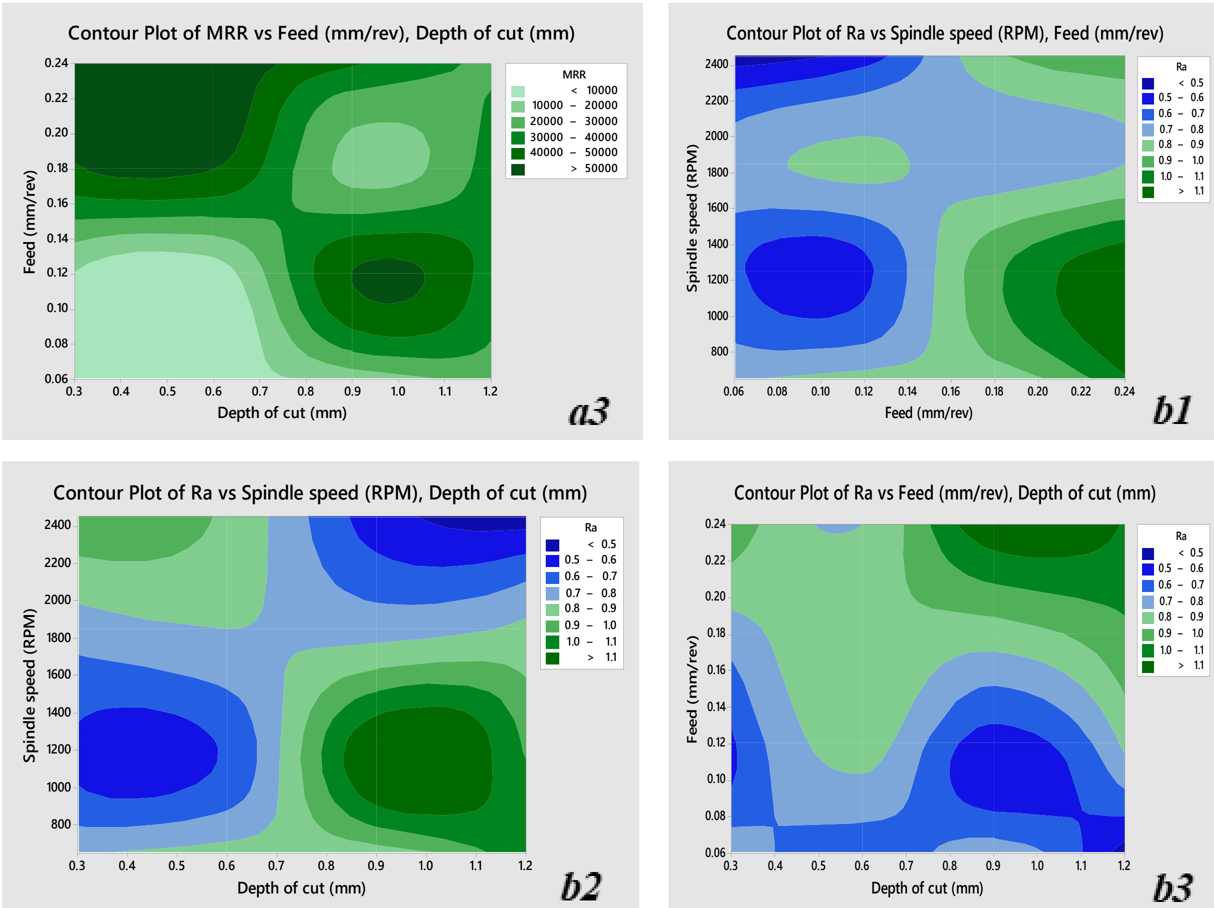


Figure 6. Contour plots for responses of: a) material removal rate, b) surface roughness

Increased material removal rates were obtained from high speed to high feed, high speed to low depth, and high feed to the low depth of cut, as shown in Figure 6 (a1-a3) contour plots. This occurs due to the increased feed rate and reduced friction in the cutting zone between the workpiece and the cutting tool. According to the study results of other researchers, the interaction of higher predictive variables increases the material removal rate. The combination of lower feed with higher speed, the lower speed with a lower depth of cut, the higher speed with a greater depth of cut, and lower feed with lower to higher depth results in a good quality score or lesser roughness, as shown in contour plots presented in Figure 6 (b1-b3). This is due to the reason that when the depth of cut is low, the surface roughness is highly sensitive to cutting speed and higher cutting speeds with increasing depth of cut reduce the value of surface roughness [25].

Table 5 and Table 6 show the analysis of variance for material removal rate and surface roughness, carried out at a confidence level of 95%. The largest significant source or term associated with the material removal rate is feed which contributes 46.67% of the total variation. The next largest significant contribution comes from the spindle speed of 46.65%. This shows that changes in these variables are associated with changes in the response variable. Depth of cut contributed 0.06% and cutting fluid 0.0076%, which are not statistically significant, or there is a lower association with material removal rate and 6.60% error contribution.

Table 5. ANOVA for material removal rate

Source	DF	Adj SS	Adj MS	F-Value	P-Value	C %	Hypothesis
Spindle speed	3	2634152917	878050972	11.78	0.011	46.65%	Significant
Feed	3	2634849886	878283295	11.78	0.011	46.67%	Significant
Depth of cut	3	3410533	1136844	0.02	0.997	0.06%	Not significant
Cutting fluid	1	415058	415058	0.01	0.943	0.0076%	Not significant
Error	5	372671938	74534388			6.60%	
Total	15	5645500331				100	

The feed is the largest significant parameter with a better association with measure response related to the surface roughness, contributing 56.66% of the total variation. Higher feed rate increases the surface roughness, and the lower one has a better quality score lowering the surface roughness. The report from experimental study which has been conducted on D2-steel under a dual nozzle MQL environment proved that feed has a larger effect on surface roughness with contribution of 66.71% from the total variation [26].

The next significant contribution comes from the cutting fluid which was 26.04%, then the spindle speed at 11.79%. Depth of cut contributed about 2.02% of the total variation, which is not statistically significant for the surface roughness, and the contribution of error was 3.49%. Similar experimental study results showed that the feed was the most significant parameter, followed by cutting fluid, speed and depth of cut [1, 27].

Table 6. ANOVA for surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value	C %	Hypothesis
Spindle speed	3	0.06802	0.022673	5.63	0.046	11.79	Significant
Feed	3	0.32687	0.108956	27.06	0.002	56.66	Significant

Depth of cut	3	0.01167	0.003890	0.97	0.477	2.02	Not significant
Cutting fluid	1	0.15016	0.150156	37.29	0.002	26.04	Significant
Error	5	0.02013	0.004026			3.49	
Total	15	0.57684				100	

3.2.1 Regression modeling for material removal rate and surface roughness

The relationship between the predictive variables, the response material removal rate, and surface roughness was modeled by multiple linear regressions for both categorical variables, as shown in Equations 10-13. The following equations are used to predict the output performance measure of the material removal rate and surface roughness for a given predictive variable:

$$\boldsymbol{Wet} \qquad MRR = -28900 + 18.96A + 190287B + 1355C \tag{10}$$

$$\boldsymbol{Cryogenic} \qquad MRR = -28578 + 18.96A + 190287B + 1355C \tag{11}$$

$$S = 6361.41 \quad R - sq = 92.12\% \quad R - sq(adj) = 89.25\% \quad R - sq(pred) = 81.48\%$$

$$\boldsymbol{Wet} \qquad Ra = 0.6880 - 0.000097A + 2.079B + 0.0742C \tag{12}$$

$$\boldsymbol{Cryogenic} \qquad Ra = 0.4942 - 0.000097A + 2.079B + 0.0742C \tag{13}$$

$$S = 0.0585225 \quad R - sq = 93.47\% \; R - sq\ (adj) = 91.09\% \quad R - sq\ (pred) = 86.28\%$$

where: MRR-Material removal rate, Ra-Roughness, A-Spindle speed, B-Feed, C-Depth of cut

3.2.2 Prediction on optimal setting for material removal rate and surface roughness

Figure 7 and 8 illustrates the optimal turning prediction plot for material removal rate and surface roughness, respectively. The response surface goal was to maximize the material removal rate and minimize surface roughness. The resulting predicted optimal variable settings for material removal rate are: spindle speed 2450 rpm, feed rate 0.24 mm/rev, depth of cut 1.20 mm, and cryogenic liquid nitrogen used as the cutting fluid with the predicted response value of 65181 mm^3/min. The optimal parametric setting for surface roughness: spindle speed 2450 rpm, feed rate 0.06 mm/rev, depth of cut of 0.3 mm, and cryogenic liquid nitrogen also used as the cutting fluid of. Using the predicted parametric values, the estimated response for surface roughness is 0.4034 µm.

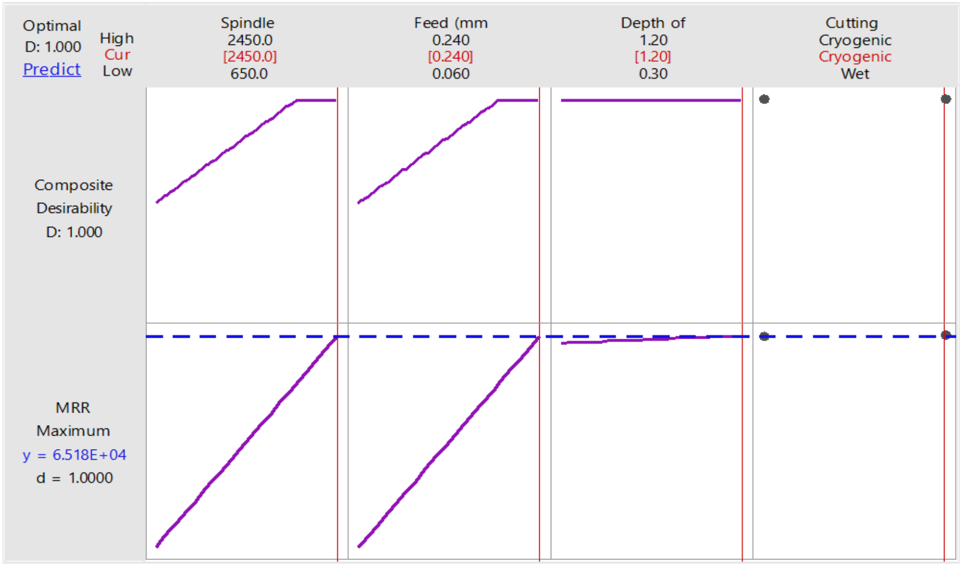


Figure 7. Response surface optimization plot for material removal rate

Figure 8. Response surface optimization plot for surface roughness

3.3 Multi-response optimization

3.3.1 Necessity for multi-response optimization

The statistical analysis of the single response result highlights that two different responses, material removal rate and surface roughness, are optimized to varying values of input variables. Table 7 shows how each response becomes best and worst at different input variables. This different situation necessitated a balance between all responses by multi-response optimization.

Table 7. Necessities for MRO

Input parameters	Responses			
	MRR (mm^3/min)		Ra (µm)	
	Best	Worst	Best	Worst
Spindle speed (rpm)	2450	650	2450	650
Feed (mm/rev)	0.24	0.06	0.06	0.24
Depth of cut (mm)	1.2	0.3	0.3	1.2
Cutting fluid	2	1	2	1

3.3.2 Evaluating for grey relational grade

Table 8 shows the overall calculated results of the grey relational analysis. The first is calculating the values of the responses to normal values ranging from zero to one. The average response surface roughness is used to proceed with the grey relational analysis. The normalized values for material removal and surface roughness are calculated using Equation 4 and Equation 5, respectively. Based on normalized values, the maximum and minimum of these normalized values are selected regardless of the response using Equation 6. The absolute difference between every normalized value is computed using this normalized experimental data with Equation 7. The grey relational coefficient was calculated using Equation 8 to represent the correlation between the desired and actual experimental data. The total sum of the grey relational coefficient of both responses was calculated regardless of their replications. The overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses by using Equation 9.

The overall performance characteristic of the multiple-response processes depends on the calculated grey relational grade, and this operation converts a multiple-response process optimization problem into a single-response optimization situation, with the objective function being the overall grey relational grade.

Table 8. Analysis of Grey relational grade

Ex. Run	Normalized value		Absolut difference		GRY coefficient		Total of GRC	GRG
	MRR	Ra	MRR	Ra	MRR	Ra		

1	0	0.534246575	1	0.465753425	0.333333333	0.517730496	0.85106383	0.425531915
2	0.038200077	0.465753425	0.961799923	0.534246575	0.342044073	0.483443709	0.825487782	0.412743891
3	0.259691265	0.452054795	0.740308735	0.547945205	0.403125436	0.477124183	0.880249619	0.44012481
4	0.444276367	0.123287671	0.555723633	0.876712329	0.473608797	0.36318408	0.836792877	0.418396438
5	0.070094224	0.767123288	0.929905776	0.232876712	0.34967339	0.682242991	1.031916381	0.51595819
6	0.125662943	0.821917808	0.874337057	0.178082192	0.363811772	0.737373737	1.101185509	0.550592755
7	0.592757295	0.273972603	0.407242705	0.726027397	0.551120441	0.407821229	0.95894167	0.479470835
8	0.702965244	0	0.297034756	1	0.627325216	0.333333333	0.960658549	0.480329275
9	0.19276823	0.575342466	0.80723177	0.424657534	0.382487644	0.540740741	0.923228385	0.461614192
10	0.58395451	0.493150685	0.41604549	0.506849315	0.545824422	0.496598639	1.042423061	0.521211531
11	0.835626674	0.589041096	0.164373326	0.410958904	0.752588915	0.54887218	1.301461095	0.650730548
12	1	0.520547945	0	0.479452055	1	0.51048951	1.51048951	0.755244755
13	0.416209517	1	0.583790483	0	0.461343782	1	1.461343782	0.730671891
14	0.861743425	0.863013699	0.138256575	0.136986301	0.783384018	0.784946237	1.568330254	0.784165127
15	0.863420146	0.410958904	0.136579854	0.589041096	0.785447414	0.459119497	1.244566911	0.622283455
16	0.992272504	0.260273973	0.007727496	0.739726027	0.984780229	0.403314917	1.388095146	0.694047573

3.3.3 Selecting optimal settings

The best experimental run is obtained in experiment #14 with the value of GRG 0.784165 with the input parameters (4-2-3-2) of speed 2450 rpm, feed 0.12 mm/rev, and depth of cut 0.9 mm under cryogenic fluid. This setting has a good quality score compared to the rest 15 experimental runs. The final step in the grey relational analysis is selecting and setting multi-response optimized input values for each predictive variable level. Based on the calculated GRG and writing it against to orthogonal array the average grey relational grades were obtained and illustrated in table 9.

The optimized parametric setting for multi-response optimization is set as (4-4-1-2) with a spindle speed of 2450 rpm, feed of 0.24 mm/rev, depth of cut 0.3 mm, and a liquid nitrogen (LN2) as a cutting fluid.

Table 9. Average grey relational grade

Factors	**Average Grey Relational Grade**			
	Spindle-speed	**Feed**	**Depth of cut**	**Cutting fluid**
Level 1	0.424199263	0.533444047	**0.580225697**	0.512154083

Level 2	0.506587764	0.567178326	0.576557573	**0.605735564**
Level 3	0.597200256	0.548152412	0.541558351	
Level 4	**0.707792012**	**0.58700451**	0.537437674	

3.4 Analysis for grey relational grade

Figure 9 illustrates the effect of used machining parameters on the simultaneous quality scores. From the main effect plot, we can understand that the grey relational grade increases with the increase of spindle speed. Regarding the feed rate, it increases for two first values, then decreases for the third value and increases again with the last feed value. GRG increases with a decrease in the depth of cut, and cryogenic machining is preferred over wet machining in terms of better multi-response GRG. Generally, this cryogenic (LN2) cutting fluid has changed the thought which is recommended by tool manufacturers to perform turning operations on D2-steel at a lower cutting speeds employing wet condition. Turning of D2-steel at a higher spindle speed results with better response (lower roughness and higher material removal rate) if we incorporate LN2 as a cutting medium.

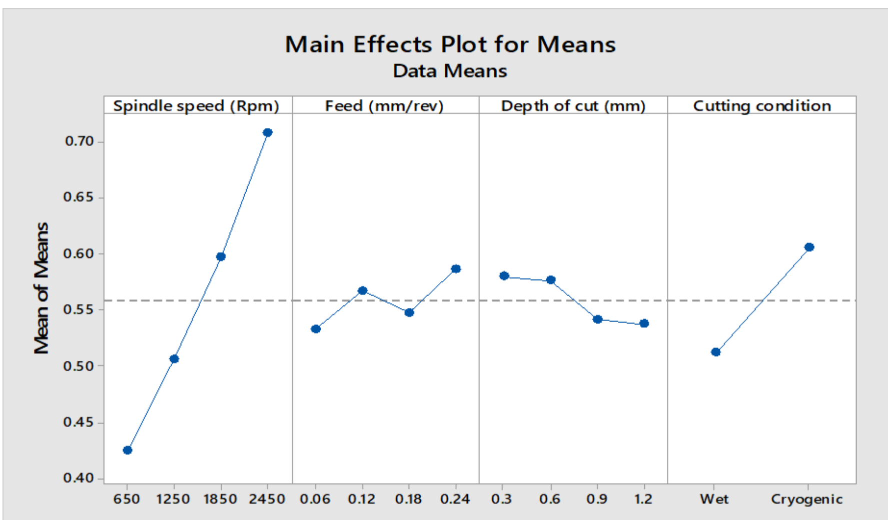


Figure 9. Main effect plot for GRG means

The relationship between predictive variables to the response grey relational grade are shown in Figure 10. Figure 10a illustrates relationship between spindle speed and feed rate, and the darker green regions of the contour indicate higher quality of production (lower Ra and higher MRR). These higher response values seem to form a ridge running from the graph's upper right to the upper left. The valleys in the graph's darker blue sections represent spindle speed-feed combinations that result in under-quality of production (higher Ra and lower MRR). As seen in

Figure 10b for the relationship between spindle speed and cut depth, the contours darker green regions indicate higher production quality (higher MRR and lower Ra). These higher response values seem to form a ridge running from the graph's upper left to the upper right. The valleys in the graph's dark blue regions represent spindle speed-depth of cut combinations that result in under-quality production (higher Ra and lower MRR). Figure 10c illustrates the relationship between feed and depth of cut with the darker green regions of the contour indicating a higher quality of production (lower Ra and higher MRR). These higher response values seem to form a ridge running from the graph's upper left to the lower right. The valleys in the graph's dark blue region represent feed-depth of cut combinations that result in under-quality production (higher Ra and lower MRR).

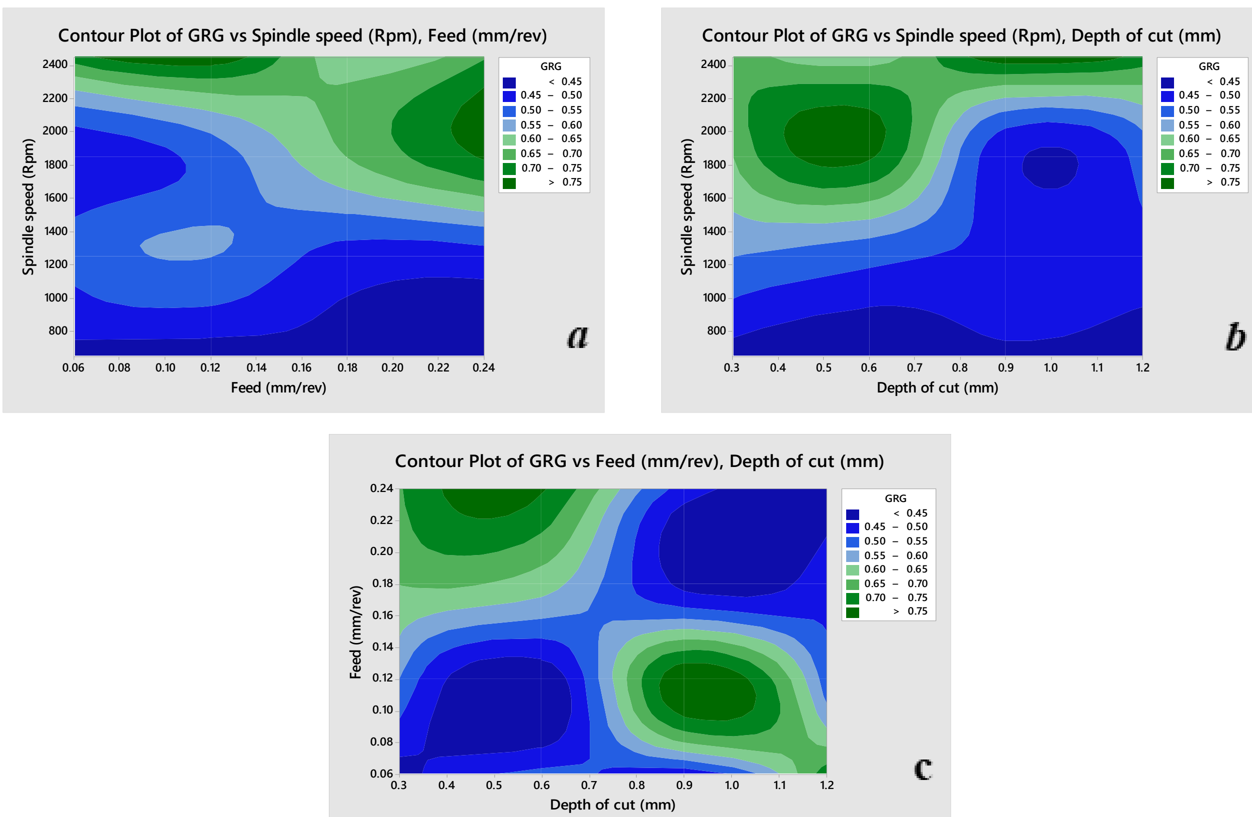


Figure 10. Contour plot for GRG (a) Speed-Feed, (b) Speed-Depth of cut, (c) Feed-Depth of cut

The analysis of variance was conducted for a confidence level of 95%. A factor with a P-value less than 0.05 are considered as statistically significant to the quality score. Results in Table 10 show that the largest significant parameter for GRG is spindle speed with a 71.9% degree of influence from the total variation. The next significant degree of influence comes from the cutting fluids as

14.14%, and then from the feed rate as 2.62%, and from the depth of cut as 2.47%, which are not statistically significant. The error contribution was 8.87%.

Table 10. Analysis of Variance for GRG

Source	DF	Adj SS	Adj MS	F-Value	P-Value	C %	Hypothesis
Spindle speed	3	0.178066	0.059355	13.43	0.008	71.9 %	Significant
Feed	3	0.006488	0.002163	0.49	0.705	2.62 %	Not significant
Depth of cut	3	0.006112	0.002037	0.46	0.722	2.47 %	Not significant
Cutting fluid	1	0.035030	0.035030	7.93	0.037	14.14 %	Significant
Error	5	0.022098	0.004420			8.87 %	
Total	15	0.247794				100	

3.4.1 Prediction of optimal GRG using response surface method

A predicted parametric input results shown in Figure 11 illustrate that the optimal parametric setting has an optimized quality. A prediction set as a fourth level of spindle speed of 2450 rpm, a fourth level of feed of 0.24 mm/rev, the first level of depth of cut 0.3 mm, and a second level of cutting fluids of LN2 could have a GRG of 0.7927. The predicted optimal setting is obtained through a response surface optimization technique, proving the optimized settings obtained by grey relational analysis.

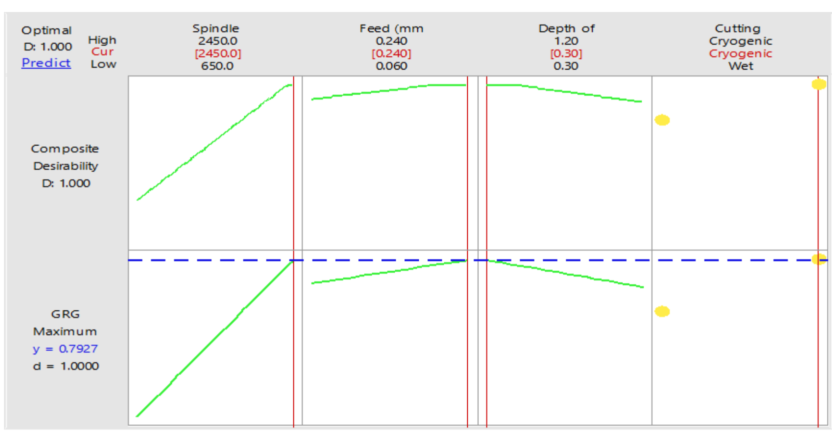


Figure 11. Response surface optimization plot for GRG

3.4.2 Regression modeling for multi-response GRG

Multi-response GRG was modeled by multiple linear regressions using the following equations 14 and 15. These equations can simultaneously predict the multi-responses GRG for material removal rate and surface roughness for two cutting fluids.

$$\boldsymbol{Wet} \qquad GRG = 0.2744 + 0.000157A + 0.236B - 0.0545C \qquad (14)$$

$$\boldsymbol{Cryogenic} \qquad GRG = 0.3680 + 0.000157A + 0.236B - 0.0545C \qquad (15)$$

$S = 0.0487760 \quad R-sq = 89.44\% \quad R-sq\ (adj) = 85.60\% \quad R-sq(pred) = 77.07\%$

3.5 Validation test result and comparison to prediction

Based on the multi-response optimized result obtained using the Taguchi-based grey relational analysis technique, a validation test was conducted and the responses were measured to proof the developed models. Table 11 shows the experiment settings and results obtained from the validation test, the material removal rate and surface roughness were compared to the best experimental run #14.

Table 11. Validation test settings with obtained responses

Experiment	**Parameters**				**Responses**	
Validation test	**Spindle speed (rpm)**	**Feed (mm/rev)**	**Depth of cut (mm)**	**Cutting fluid**	**MRR (mm^3/min)**	**Ra (µm)**
	Level 4	Level 4	Level 1	Level 2	**66,845**	**0.70**
	2450	0.24	0.3	LN2		

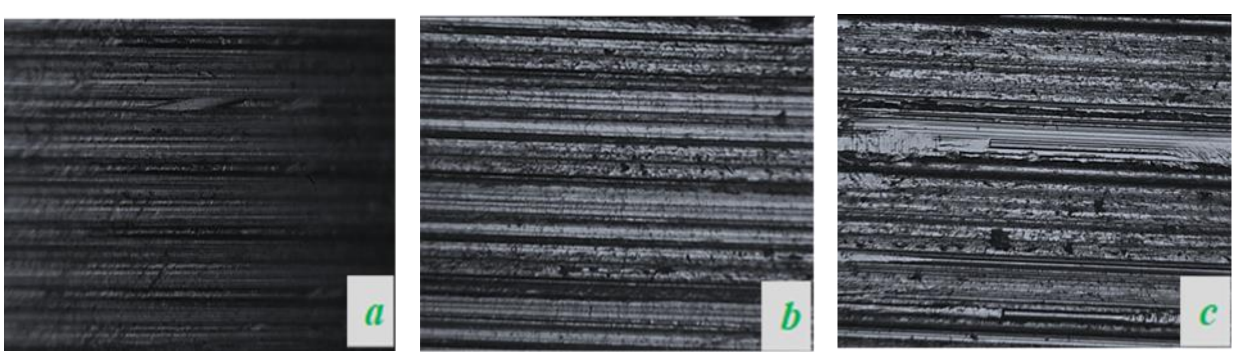
Experimental validation test is conducted in order to confirm the response results of the predicted optimal values with their parametric settings. The same specifications of D2-steel as the sample test were utilized in this validation test and responses were recorded to compare with predictive one. Table 12 shows a close agreement between the predicted value of GRG (0.7927) and the experimental validation value of GRG (0.8031). The increase in grey relation grade observed from the initial best conditions of GRG is 0.7841 to optimal conditions of GRG is 0.8031, and the variation is 2.36%. The validation test also shows that the percentage error between prediction and actual experiment is 4.33%, 9.09% and 1.29% for material removal rate (MRR), surface roughness (Ra) and grey relational grade (GRG), respectively.

Table 12. Comparison of prediction with validation results

Experiment	Parameters				Responses		GRG
	Spindle speed (rpm)	Feed (mm/rev)	Depth of cut (mm)	Cutting fluid	MRR (mm^3/min)	Ra (µm)	
Prediction	2450	0.24	0.3	LN2	**63,949**	**0.77**	**0.7927**
Validation run	2450	0.24	0.3	LN2	**66,845**	**0.70**	**0.8031**
% of error					**4.33**	**9.09**	**1.29**

3.6 Surface morphology

A metallographic study was carried out on a D2-steel after all experimental runs. Figure 12 (a-h) shows the surface of D2-steel after machining under wet conditions. In general, the surface topography is worst when compared to the machining under cryogenic conditions Figure 13(a-i). The lower the spindle speed, the poor surface was obtained during wet machining, and the higher feed also affects the steel surface, as seen in Figure 12(d). The measured surface roughness Ra parameter value of experimental run #8 was of 1.18 µm, and it was the worst surface finish from all wet machined samples. Overall wet machining conditions exhibited more tool marks on the workpiece surface. This is due to using a wet condition cooling technique at the tool-workpiece interface, which results in higher cutting temperatures in the metal cutting region. The higher temperature causes higher adhesion at the tool-workpiece interface. This results in more tool marks on the machined surface and voids, resulting in a poorer surface finish. This result proves the study presented in [28], which concluded that more surface marks are obtained during wet machining with an increased feed rate of machining conditions.



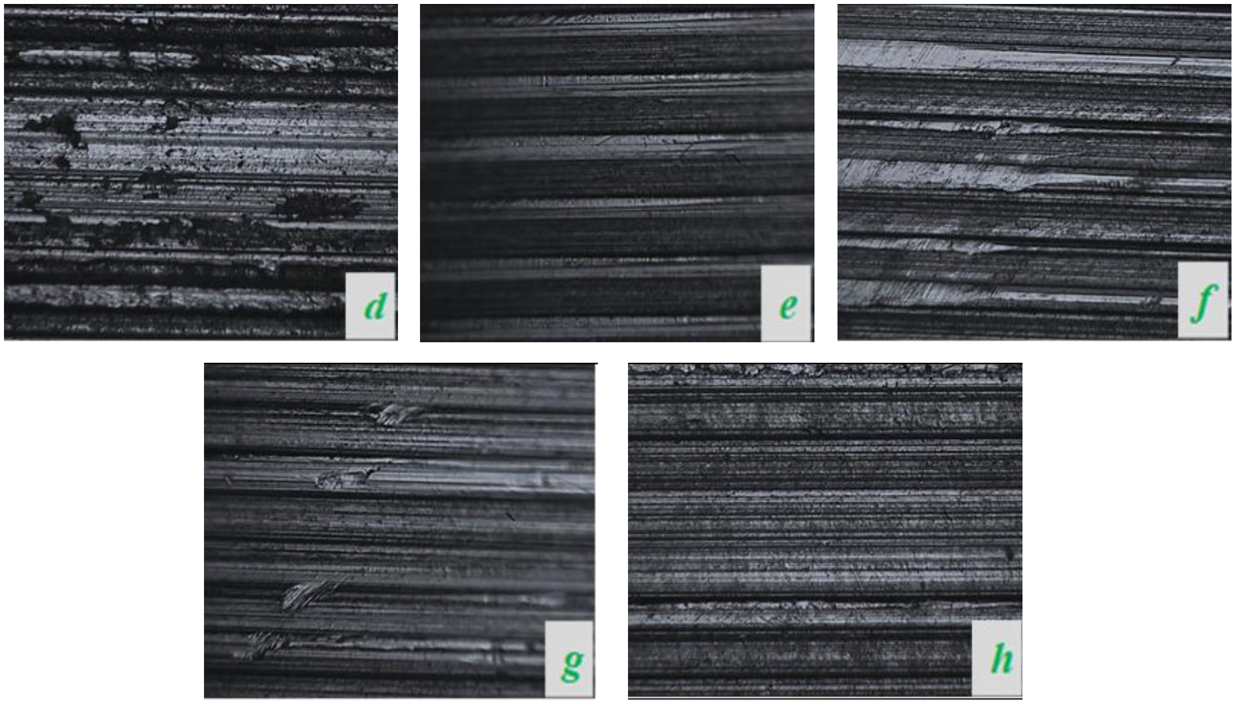


Figure 12. Optical micrographs of parts machined under wet conditions: (a) Experiment 1, (b) Experiment 2, (c) Experiment 7, (d) Experiment 8, (e) Experiment 9, (f) Experiment 10, (g) Experiment 15, (h) Experiment 16

In particular, some surface defects were observed in wet machining conditions, resulting from the built-up edge and have been observed to increase surface roughness and deteriorate surface topography compared with cryogenic cooling conditions. It should be noted that a small difference in cutting parameters made a considerable difference in the surface topography of the D2 steel. However, the measured surface roughness showed a similar behaviour at low-speed machining of D2-steel. The machined work material's surface displayed feed marks that were less visible at high speed, as shown in Figure 13(a-i). With an increased speed, the surface quality of wet and cryogenic machining became better. Deteriorated surface morphology and feed marks were attributed to high cutting temperatures at lower cutting speeds and higher feed than with higher cutting speeds. These results were valid in both the cutting fluid conditions.

This micrographic study presented in Figure 13 shows that machining D2-steel using cryogenic conditions improves the surface quality compared to the wet condition - Figure 12. This is because the concurrent use of LN2 at the tool-workpiece interface lowers the cutting temperatures in the metal cutting region, thus leading to less adhesion at the tool-workpiece interface and creating fewer tool marks on the machined surface. In this manner, a better surface finish was achieved.

The validation test was conducted to confirm the prediction. Here, the micrographic examination of this validation study sample, shown in Figure 13 i, illustrates that machining in cryogenic conditions produces fine surface finish. The study presented in [28, 29] illustrated that surface quality was improved by using cooling/lubricating and at higher cutting speeds. Cryogenic machining generates the best surface quality attributed to less tool wear and less thermal distortion. This result proves that performing turning operation on D2-steel at a higher spindle speed and cryogenic condition results with fine surface finish, and this has an advantages on tool manufacturer's recommendation to perform turning of D2-steel within wet cutting medium and a relative lower cutting speed.

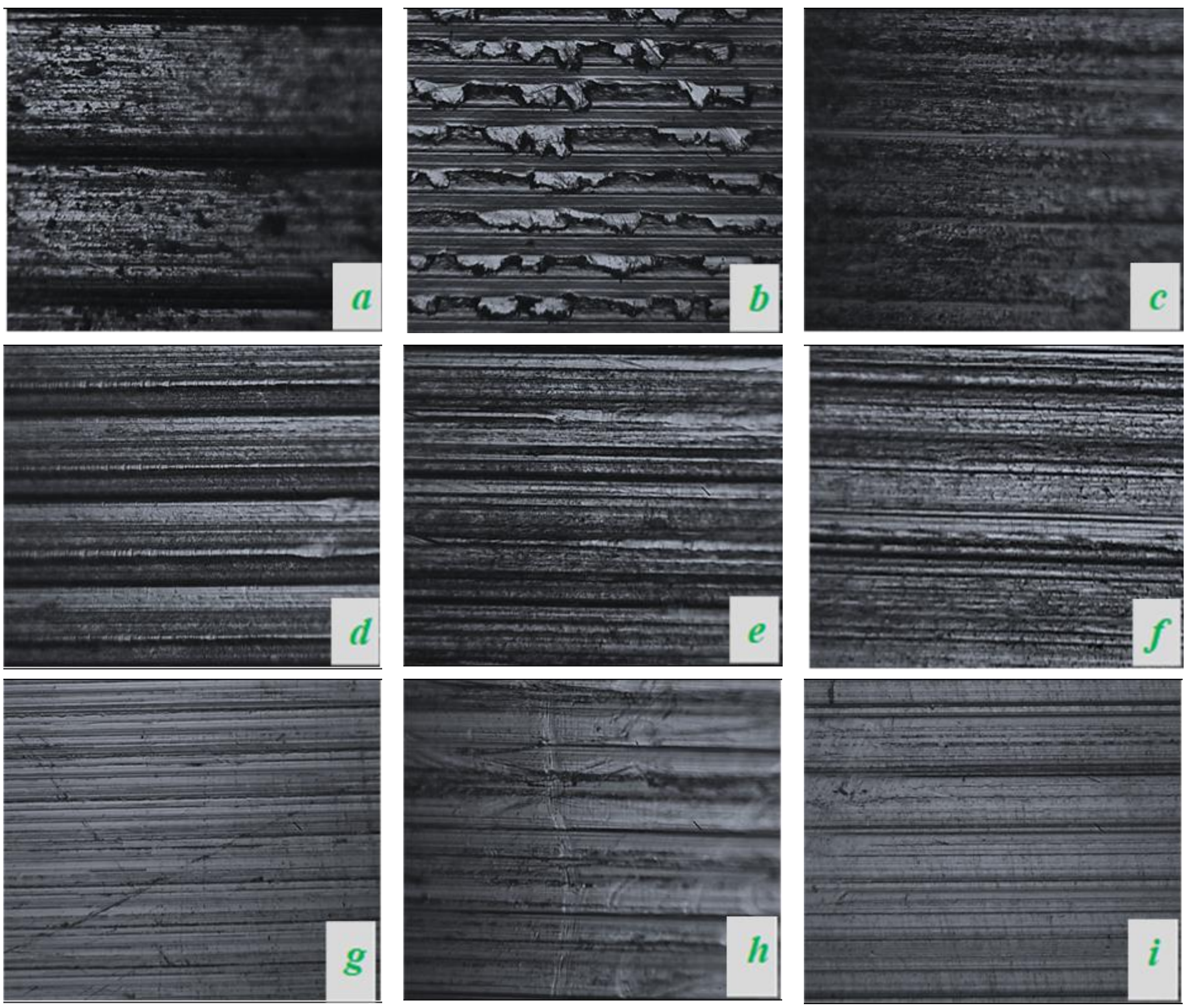


Figure 13. Optical micrographs of LN2 machined parts (a) Experiment 3, (b) Experiment 4, (c) Experiment 5, (d) Experiment 6, (e) Experiment 11, (f) Experiment 12, (g) Experiment 13, (h) Experiment 14, (i) Confirmation experiment

4. Conclusion

Experiments were conducted to determine multi-response optimal turning conditions in wet and cryogenic conditions on D2-steel using Taguchi mixed L16 orthogonal array. Through analysis of the responses of material removal rate and surface roughness, the following conclusions have been drawn:

- Liquid nitrogen used as a cutting fluid in an eco-friendly cryogenic turning of D2-steel allowed the optimization of the machining process regarding surface finish and material removal rate.
- The analysis of variance for material removal rate declares that significant factors associated with response values are feed followed by spindle speed with a percentage contribution of 46.67% and 46.65%, respectively.
- The analysis of variance for surface roughness interprets that significant factors associated with response values are feed, cutting fluid, and spindle speed, with percentage contributions of 56.66%, 26.04%, and 11.79%, respectively.
- Analysis of the variance result reveals that the speed followed by the cutting fluid is the significant process parameter affecting the response GRG with a percentage of contribution of 71.9% and 14.14%, respectively.
- From the experimental tests, experiment #14 with a 4-2-3-2 at a speed of 2450 rpm, feed of 0.12 mm/rev, depth of cut 0.9 mm, and fluid of liquid nitrogen parametric combination resulted in the highest GRG of 0.7841 to get the maximum material removal rate and the minimum surface roughness.
- Surface response optimization exhibits with the new parametric setting 4-4-1-2, and the predicted material removal rate, surface roughness, and GRG are 63,949 mm^3/min, 0.77 µm, and 0.7927, respectively, at a significance level of 95%.
- Grey Relational Analysis determined the actual multiple quality characteristics optimal parameter combination as 4-4-1-2, the same as the predicted setting. The anticipated results were confirmed with the experimental validation result of GRG 0.8031.
- Experimental validated with a parametric combination of 4-4-1-2 at a speed of 2450 rpm, feed of 0.24 mm/rev, depth of cut 0.3 mm, and fluid of liquid nitrogen. Responses measured

for the validation test were material removal rate and surface roughness, and its value is 66,845 mm^3/min and 0.70 µm, respectively.

- The percentage error between prediction and optimal validation experiment is 4.33%, 9.09% and 1.29% for material removal rate, surface roughness and GRG, respectively.
- The final multi-response optimized validation result demonstrated a superior effect from the first best run by 2.36% and 1.29% from the forecast in grade.

Overall, the application of cryogenic liquid nitrogen has resulted in the improvement of AISI D2 steel machinability in terms of surface roughness and material removal rate. As a result, it is suitable for industrial applications involving turning metal machining. The machinability of AISI D2 steel can be researched in the future using a dual nozzle cryogenic supply system. In the future, tool life, cutting force, cutting zone temperature, and chips morphology might all be evaluated in a single and twin nozzle cryogenic environment.

Author contribution

Sisay Workineh conducted experiments and collected data; Sisay Workineh, Mahaboob Patel, and Maruisz Deja analyzed the data; Sisay Workineh wrote the manuscript, and all authors reviewed it.

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Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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