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Effect of Cryogenic Cooling on Surface Integrity in Turning of Hard Alloy Steel

KEYWORDS: Cryogenic cooling; Hard steel; Surface integrity; Grey relational analysis; Optimization

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ABSTRACT *Surface roughness and micro-hardness which are the constituents of surface integrity (SI) of the machined components generally get affected by cutting parameters such as the cutting speed, the feed rate, the depth of cut, etc. This paper presents a study that investigates the effect of the CNC hard turning parameters on the surface roughness average (Ra) and the micro-hardness (µh) of hard steel (AISI 52100) under cryogenic cooling conditions. Nine experimental runs based on an orthogonal array of Taguchi method are performed and grey relational analysis method is then applied to determine an optimal combination of the cutting parameter setting. Further, the Grey relational grade matrix obtained by analyzing the data is used to represent the degree of influence for each controllable process factor onto individual quality targets. From the results, the feed rate is found to have the most influence on the roughness average and also on the micro-hardness. In addition, the analysis of variance (ANOVA) is also employed to identify the most significant factor; the cutting speed is the most significant controlled factors for affecting the SI in the cryogenically cooled turning operations according to the weighted sum grade of the surface roughness average and micro-hardness.*

1. Introduction

Components made of hard steel such as AISI 52100 are used by numerous industries e.g. automotive, gear, bearing, tool and die making industries. Manufacturing of high quality products with low cost and reduced time is the major objective of today's industries and to achieve this they employ automated and flexible manufacturing systems along with computerized numerical control (CNC) machines. Recently, hard turning of steel has attracted researchers involved in industrial production and scientific research owing to a number of potential advantages, including lower equipment costs, shorter setup time, high accuracy, fewer process steps, and greater part geometry flexibility offered by the turning process. According to an estimate, hard turning used to fabricate complex parts, could save manufacturing costs by up to 30 times [1, 2]. It has been observed that in wet hard machining, conventional cutting fluid used during machining fails to penetrate the chip–tool interface and thus, the heat generated is not dissipated efficiently. The application of cutting fluid does not effectively reduce the cutting temperature and thus, it does not improve the tool life. Consequently, researchers have recently employed cryogenic cooling by liquid nitrogen in hard machining of some commonly used steels. Cryogenic cooling provides less cutting forces, reduces the cutting temperature, improves tool life and also results in better surface finish as compared to both dry as well as wet machining [3, 4]. Cryogenic cooling has recently been found to be an innovative technique to improve tool wear resistance [5- 8].

Hard turning processes are characterized by a high level of accuracy in terms of the form and size, high quality of surface finish and surface integrity (SI) in workpieces [9-11]. In order to establish adequate machining guidelines, study of several factors (roughness, hardness, residual stresses, micro-structural changes, etc.) that define the surface integrity generated in the part by a machining operation is required. Maintaining SI in the machined components is one of the most critical requirements, as functional behaviour and reliability of the components such as fatigue life and wear resistance depend to a great extent on the SI of the components when they are put to use. [12-14]. It is important to select the optimum combination of cutting parameters such as cutting speed, feed rate, depth of cut and cutting fluid as these parameters have impact on multi performance characteristics like surface roughness, strain hardening, micro-hardness and microstructure which are indeed constituents of SI [15] and they also affect high production rate of the products with an acceptable quality level and SI. Among the several SI parameters, surface roughness (R_a) and the micro-hardness (µh) are very important as they correlate with the surface profiles in order to better characterize the different machining processes. Recently, studies have been conducted to investigate the effect of cryogenic machining on the surface integrity. It has been found that the cryogenic machining performed with a large edge radius tool led to enhanced surface integrity [16, 17]. It has been also found that the surface roughness gets reduced when machining with cryogenic cooling [18].

Umbrello et al. [19] determined the effects of cryogenic cooling on surface integrity in orthogonal machining of hardened AISI 52100 bearing steel. They performed experiments under dry and cryogenic conditions using chamfered CBN tool inserts. Their results showed the benefits and the future potential of cryogenic cooling for surface integrity enhancement to achieve improved product's functional performance in hard machining. Grzesik et al. [20] studied the applicability of cryogenic hard machining for improving surface integrity produced in turning operations on parts made of high-strength, low alloy 41Cr4 steel with hardness of 57±2 HRC. The aim of their research was to quantify the surface roughness and the mechanical properties of the sublayer produced under practical working conditions. Their results indicated that the hard machining produced surfaces with acceptable surface roughness. Further, they also mentioned that using cryogenic hard cutting operations can partly eliminate grinding operations in cases when white layer is not produced.

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Production of high quality products with low cost requires optimum setting of the machining parameters and Taguchi method can be effectively used for the optimization of process parameters with minimum number of experiments. Researchers have extensively used the Taguchi method to plan experiments for the purpose of optimization of process and design parameters due to the several advantages offered by the Taguchi method [21, 22]. Sharma et al. [23] applied Taguchi method to find the optimal cutting parameters for surface roughness in turning of AISI-410 steel using TiN coated inserts. Saini et al. [24] used Taguchi method together with the analysis of variance (ANOVA) to optimize the wire electrical discharge machining (WEDM) parameters for cutting composite material Al6061/SICP.

The Grey relational analysis method is used for measuring the degree of approximation among the sequences using a Grey relational grade. It is a new technique for performing prediction, relational analysis, and decision making in many areas. Theories of the Grey relational analysis have attracted considerable interest among researchers [25]. Some researchers have also performed the optimization of process parameters using Grey relational analysis. For example, Tzeng et al. [26] performed the optimization of CNC turning operation parameters for SKD11 alloy tool steel using Grey relational analysis method. Taguchi method based Grey relational was applied by Sharma and Bhambri [27] for the optimization of two response parameters (surface roughness and material removal rate) by three cutting parameters (cutting speed, feed rate and depth of cut) during high speed turning of AISI H13 under dry conditions. Abhang and Hameedullah [28] used Grey relational analysis coupled with factorial design for optimizing the cutting parameters i.e. cutting speed, feed rate, tool nose radius, and concentration of solid–liquid lubricants (minimum quantity lubricant) for the workpiece surface roughness and the chip thickness.

It appears from the literature presented above that not much work has been done to investigate the effect of cutting parameters during turning using cryogenic cooling , in general, and hard turning in particular on SI in terms of surface roughness and micro-hardness of the machined surface. Keeping this in view, the present work is aimed at investigating the effect of three cutting parameters (cutting speed, feed rate and depth of cut) on SI during CNC hard turning of AISI 52100 alloy steel under cryogenic cooling condition. The Taguchi L9 (33) design is employed for experimental planning for this purpose. The Grey relational analysis is then applied to examine how the turning operation factors influence the quality targets of surface roughness and micro-hardness. An optimal parameter combination was then obtained. Through analyzing the Grey relational grade matrix, the most influential factors for individual quality targets of turning operations can be identified. Additionally, the ANOVA is performed to investigate the more influencing parameters on the SI.

2. Grey relational analysis
2.1. Data preprocessing
Normally the range and the unit in one data sequence are different from those in another sequence. Thus, it is necessary that a series of various units must be transformed to be dimensioless and to achieve this data preprocessing is required. Data preprocessing involves the transfer of the original sequence to a comparable sequence.

Let the original reference sequence and comparability sequence be represented as $x_0^{(O)}(k)$ and $x_i^{(O)}(k)$, i = 1,2,...., m; k = 1,2,...., n, respectively, where m is the total number of experiment to be considered, and n is the total number of observation data . Data preprocessing converts the original sequence to a comparable sequence. Several methodologies of preprocessing data can be used in Grey relation analysis, depending on the characteristics of the original sequence [26; 29-30]. If the target value of the original sequence is "the-larger-the-better", then the original sequence is normalized as follows:

$$x_i^*(k) = \frac{x_i^{(O)}(k) - \min(x_i^{(O)}(k)}{\max(x_i^{(O)}(k) - \min(x_i^{(O)}(k)} \qquad (1)$$

When "the-smaller-the-better" is a characteristic of the original sequence, then the original sequence should be normalized as follows:

$$x_i^*(k) = \frac{\max(x_i^{(O)}(k) - x_i^{(O)}(k)}{\max(x_i^{(O)}(k) - \min(x_i^{(O)}(k)} \qquad (2)$$

However, if a defined target value, OB, exists, then the original sequence is normalized in the form:

$$x_i^*(k) = 1 - \frac{\left|x_i^{(O)}(k) - OB\right|}{\max\left\{\max(x_i^{(O)}(k)) - OB, OB - \min(x_i^{(O)}(k))\right\}} \qquad (3)$$

Alternatively, the original sequence can be normalized using the simplest methodology in which the values of the original sequence is divided by the first value of the sequence, $x_i^{(O)}(1)$, viz

$$x_i^*(k) = \frac{x_i^{(O)}(k)}{x_i^{(O)}(1)} \qquad (4)$$

where, $x_i^{(O)}(k)$: the original sequence, $x_i^*(k)$: the sequence after the data preprocessing, $\max x_i^{(O)}(k)$: the largest value of $x_i^{(O)}(k)$, and $\min x_i^{(O)}(k)$: the smallest value of $x_i^{(O)}(k)$.

2.2. Grey relational coefficients and Grey relational grades
Following the data preprocessing, a grey relational coefficient can be calculated using the preprocessed sequences. The grey relational coefficient is defined as follows:

$$\tilde{a}(x_0^*(k)\ x_i^*(k)) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}(k) + \zeta\Delta_{\max}} \text{ and } 0 < \tilde{a}(x_0^*(k)\ x_i^*(k)) \le 1 \qquad (5)$$

where $\Delta_{0i}(k)$ is the deviation sequence of the reference sequence $x_0^*(k)$ and comparability sequence $x_i^*(k)$; namely

$$\Delta_{0i}(k) = \left|x_0^*(k) - x_i^*(k)\right|,$$

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \left|x_0^*(k) - x_j^*(k)\right|$$

$$\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} \left|x_0^*(k) - x_j^*(k)\right|$$

With ζ : distinguishing coefficient, $\zeta \in [0,1]$.

A grey relational grade is a weighted sum of the grey relational coefficients, and is defined as follows:

$$\tilde{a}(x_0^*, x_i^*) = \sum_{k=1}^{n} \beta_k \tilde{a}(x_0^*(k)\ x_i^*(k))$$

where $\sum_{k=1}^{n} \beta_k = 1$ (6)

The grey relational grade $\tilde{a}(x_0^*, x_i^*)$ represents the level of correlation between the reference and comparability sequences. The value of the grey relational grade equals one when the two sequences are identical. The grey relational grade also indicates the degree of influence exerted by the comparability sequence on the reference sequence. Consequently, if a particular comparability sequence is more important to the reference sequence than other comparability sequences, the grey relational grade for that comparability

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sequence and the reference sequence will exceed that for other grey relational grades. The grey relational analysis is actually a measurement of the absolute value of data difference between the sequences, and can be used to approximate the correlation between the sequences.

3. Experimental procedures and test results

3.1. Materials

In this study, AISI 52100 hardened alloy steel, widely used in the automotive, gear, bearing and die industry, etc. was used as workpiece material. The chemical composition of AISI 52100 is shown in Table 1.

Table1: Chemical composition of AISI 52100 alloy steel

C	Si	Mn	S	P	Ni	Cr	Mo	Cu	Fe
0.98	0.28	0.39	0.024	0.023	0.141	1.302	0.081	0.042	Rest

3.2. Schematic of machining

The experiments were carried out under cryogenic cooling condition using liquid nitrogen (LN_2) on a rigid CNC lathe machine (LEADWELL T-6) with a 7.5 KW spindle motor at 4500 rpm. Fig.1 shows Nozzle for LN_2. Application in CNC lathe machine. CNMG 120408-TN7105 coated carbide insert (TiN-TiCN-AL2O3-TiN) having nose radius of 0.8 mm was used as cutting tool. The turning length and diameter of the workpiece were fixed to 150 mm and 45 mm respectively as shown in the schematic diagram (Fig. 2).

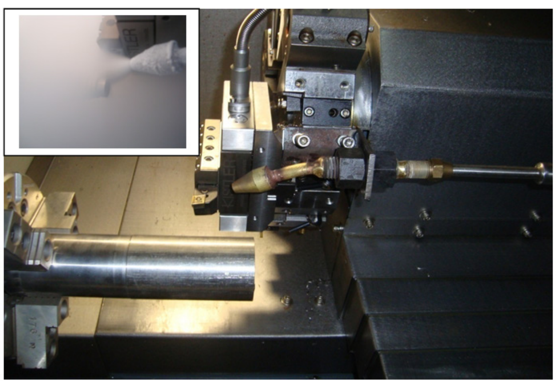

Fig.1: Nozzle for LN2 Application

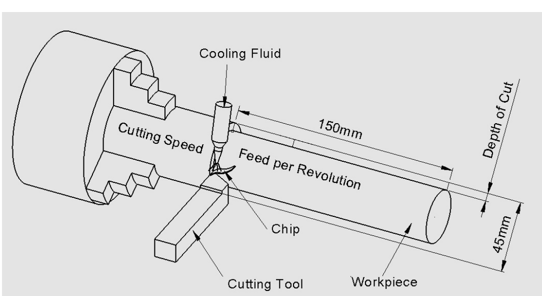

Fig.2: Schematic of turning operation

3.3. Experimantal parameters and design

The experiments are conducted with three controllable 3-level factors and two response variables. Nine experimental runs based on the orthogonal array L_9 (3^3) are required. Table 2 presents three controlled factors of the cutting speed (i.e., A (m/min)), the feed rate (i.e., B (mm/rev)), and the depth of cut (i.e., C (mm)) with three levels for each factor. Table 3 shows the nine cutting experimental runs according to the selected orthogonal table. After turning, two quality objectives of the workpieces are chosen, including the surface roughness (i.e., Ra (μm)) and micro-hardness (i.e., μh (hV)). Typically, small values of surface roughness and target values of micro-hardness are desirable for the surface integrity in turning operations.

Table 2: Experimental factors and their levels

Factor	Symbol	Unit	Level-1	Level-2	Level-3
Cutting speed	A	m/min	100	175	250
Feed rate	B	mm/rev	0.1	0.16	0.22
Depth of cut	C	mm	0.2	0.6	1

Table 3: Orthogonal array L9 (33) of the experimental runs

Exp. No.	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	3
5	2	2	1
6	2	3	2
7	3	1	2
8	3	2	3
9	3	3	1

3.4. Measuring apparatus

The R_a values were measured by the surface roughness tester (model: SURFTEST, SV-2100; make: Mitutoyo, Japan). The micro-hardness tester (model: MitroWizard; make: Mitutoyo, Japan) was used to get μh values.

4. Results and discussion

4.1 Best experimental run

The experimental results for the surface roughness (R_a) and micro-hardness (μh) are listed in Table 4.

Table 4: Orthogonal array L_9 (3^3) of the experimental runs and results

Run no.	A	B	C	R_a (μm)	μh (hV)
1	1	1	1	1.549	307.233
2	1	2	2	2.261	326.133
3	1	3	3	2.737	326.4
4	2	1	3	0.405	322.6
5	2	2	1	0.937	328.633
6	2	3	2	2.209	340.9
7	3	1	2	0.592	327.6
8	3	2	3	0.906	344.833
9	3	3	1	1.907	323.833

Typically, smaller values of the R_a and target values of μh are desirable for surface integrity of the machined surface. It may be noted that the average μh value of the workpiece material before machining was 352.4 hV. Thus, the data sequences have a "the-smaller-the-better characteristic" for Ra and therefore, Eq. (2) was employed for data preprocessing. Similarly, Eq. (3) was used for data preprocessing for μh. The values of the Ra and the μh are set to be the reference sequence $x_0^{(O)}(k)$, k = 1, 2. Moreover, the results of nine experiments were the comparability sequences $x_i^{(O)}(k)$, i = 1, 2, ...,9, k = 1, 2. Table 5 listed all of the sequences after implementing the data preprocessing using Eq. (2) and Eq. (3). The reference and the comparability sequences were denoted as $x_0^*(k)$ and $x_i^*(k)$, respectively. Also, the deviation sequences Δ_{0i}, $\Delta_{max}(k)$ and $\Delta_{min}(k)$ for i = 1, 2, ..., 9, k = 1, 2 can be calculated.

Table 5: The sequence after data preprocessing

Reference/Comparability sequence		R_a	μh
Reference sequence		1.0000	1.0000
Comparability sequences	No. 1	0.4906	1.0000
	No. 2	0.7959	0.5816
	No. 3	1.0000	0.5756
	No. 4	0.0000	0.6598
	No. 5	0.2281	0.5262
	No. 6	0.7736	0.2546
	No. 7	0.0802	0.5491
	No. 8	0.2148	0.1675
	No. 9	0.6441	0.6325

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The distinguishing coefficient ζ can be substituted for the grey relational coefficient in Eq. (5). If all the process parameters have equal weighting, ζ is set to be 0.5. Table 6 listed the grey relational coefficients and the grade for all nine comparability sequences.

Table 6: The calculated grey relational coefficient and grey relational grade for nine comparability sequences.

Experimental run (Comparability sequences)	Orthogonal array L_9 (3^3)			Grey relational Coefficient		Grey relational grade
	A	B	C	R_a	μh	
1	1	1	1	0.5048	0.4450	0.4749
2	1	2	2	0.3858	0.6172	0.5015
3	1	3	3	0.3333	0.6206	0.4770
4	2	1	3	1.0000	0.5756	0.7878
5	2	2	1	0.6867	0.6505	0.6686
6	2	3	2	0.3926	0.8846	0.6386
7	3	1	2	0.8618	0.6363	0.7490
8	3	2	3	0.6995	1.0000	0.8497
9	3	3	1	0.4370	0.5894	0.5132

This investigation employs the response table of the Taguchi method to calculate the average Grey relational grades for each factor level, as illustrated in Table 7.

Table 7: The response table for grey relational.

Levels	Factors		
	A	B	C
1	0.4845	0.6706	0.5522
2	0.6983	0.6733	0.6297
3	0.7040	0.5429	0.7048

Since the Grey relational grades represented the level of correlation between the reference and the comparability sequences, the larger Grey relational grade means the comparability sequence exhibiting a stronger correlation with the reference sequence. Based on this study, one can select a combination of the levels that provide the largest average response. Fig. 3 shows the mean value of Grey relational grade at different levels of each turning process parameters. The dashed line in this figure is the value of the total mean of the Grey relational grade. In Table 7 and Fig. 3, the combination of A_3, B_2, and C_3 shows the largest value of the Grey relational grade for the factors A, B, and C, respectively. Therefore, $A_3B_2C_3$ with a cutting speed of 250 m/min, a feed rate of 0.16 mm/rev, and a depth of cut of 1 mm is the optimal parameter combination of the turning operations.

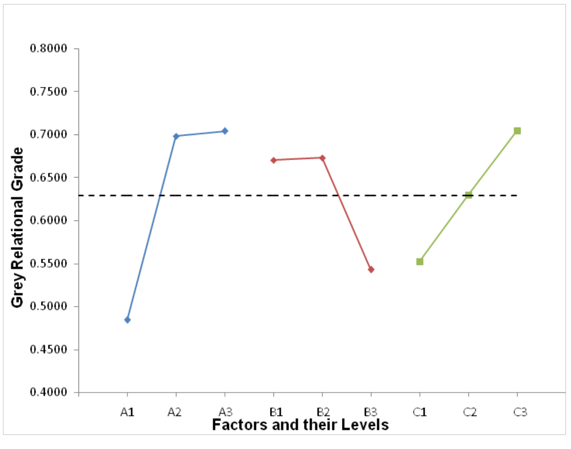

Fig. 3: Grey relational grade graph

4.2 Most influential factor

In this study, the Grey relational analysis is applied to examine how the turning operation parameters influence the quality targets of workpieces. The values of the factor level in nine experimental runs are set to the comparability sequences for three controllable factors. Table 8 listed all of the sequences.

Table 8: The sequence after data preprocessing for the reference sequences and comparability sequences

Experimental run	Comparability sequences			Reference sequences	
	A	B	C	R_a	μh
1	1	1	1	1.00	1.00
2	1	1.6	3	1.46	1.06
3	1	2.2	5	1.77	1.06
4	1.75	1	5	0.26	1.05
5	1.75	1.6	1	0.60	1.07
6	1.75	2.2	3	1.43	1.11
7	2.5	1	3	0.38	1.07
8	2.5	1.6	5	0.58	1.12
9	2.5	2.2	1	1.23	1.05

Data preprocessing was performed based on Eq. (4), and Table 8 listed the normalized results. Subsequently, the deviation sequences were calculated using the method mentioned above. The deviation sequences and the distinguishing coefficient then were substituted into Eq. (5) to obtain the Grey relational coefficients. Additionally, the Grey relational coefficients are averaged using an equal weighting to obtain the Grey relational grade. Table 9 listed the Grey relational coefficients and the grade of the R_a of the reference sequence and comparability sequences. Table 10 gives the Grey relational coefficients and the grade of the μh for the reference sequence and the comparability sequences.

Table 9: The calculated grey relational coefficient and grey relational grade for experimental factors to experimental result of the R_a

	A	B	C
Grey relational coefficient	1.0000	1.0000	1.0000
	0.8375	0.9441	0.6060
	0.7555	0.8455	0.4229
	0.6141	0.7624	0.3333
	0.6742	0.7042	0.8571
	0.8797	0.7538	0.6009
	0.5280	0.7932	0.4751
	0.5530	0.7001	0.3492
	0.6512	0.7098	0.9111
Grey relational grade	0.7215	0.8014	0.6173

Table 10: The calculated grey relational coefficient and grey relational grade for experimental factors to experimental result of the μh

	A	B	C
Grey relational coefficient	1.0000	1.0000	1.0000
	0.9698	0.7858	0.5047
	0.9694	0.6345	0.3340
	0.7383	0.9753	0.3333
	0.7438	0.7883	0.9659
	0.7551	0.6443	0.5109
	0.5794	0.9675	0.5053
	0.5891	0.8053	0.3375
	0.5773	0.6328	0.9734
Grey relational grade	0.7691	0.8038	0.6072

The Grey relational grades in Tables 9 and 10 can be further arranged in a matrix form shown as follows:

$$\gamma = \begin{bmatrix} \gamma(R_a, \mathrm{A}) & \gamma(R_a, \mathrm{B}) & \gamma(R_a, \mathrm{C}) \\ \gamma(\mathrm{hV}, \mathrm{A}) & \gamma(\mathrm{hV}, \mathrm{B}) & \gamma(\mathrm{hV}, \mathrm{C}) \end{bmatrix} \quad (7)$$

$$= \begin{bmatrix} 0.7215 & 0.8014 & 0.6173 \\ 0.7691 & 0.8038 & 0.6072 \end{bmatrix}$$

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By comparing Row 1 and Row 2, some conclusion can be drawn from this matrix. In the first row $\gamma(R_a, \mathrm{B}) > \gamma(R_a, \mathrm{A}) > \gamma(R_a, \mathrm{C})$, it means that the order of importance for the controllable factors to the R_a in sequence, is the factor B, A, and C. Similarly, from the second row $\tilde{a}(\mathrm{hV}, \mathrm{B}) > \tilde{a}(\mathrm{hV}, \mathrm{A}) > \tilde{a}(\mathrm{hV}, \mathrm{C})$, the order of importance for the controllable factors to the µh, in sequence, is the factor B, A, and C.

The most influential factors that affect the output variables are determined by identifying the maximum values in each row. Hence, based on the maximum values in the matrix of the Grey relational $(\gamma(R_a, \mathrm{B}), (HV, \mathrm{B})) = (0.8014, 0.8038)$, it can be found that the factor B, the feed rate, has the most influence on both the R_a and the µh with $\tilde{a}$ value of 0.8014 and 0.8038 respectively.

Additionally, Table 11 gives the results of the analysis of variance (ANOVA) for the R_a and the µh using the calculated values from the Grey relational grade of Table 6 and the response table of Table 7. According to Table 11, the factor A, the cutting speed with 56.43% of contribution, is the most significant controlled parameters for the turning operation; the feed rate is with 19.99% contribution and the depth of cut with 20.97% of contribution if the minimization of the roughness average and micro-hardness is simultaneously considered.

Table 11: ANOVA results for R_a and µh

Factor	Level 1	Level 2	Level 3	Degree of freedom	Sum of squares	Mean square	F value	Contribution (%)
A	0.4845	0.6706	0.5522	2	0.0940	0.0470	21.6856	56.43
B	0.6983	0.6733	0.6297	2	0.0333	0.0166	7.6821	19.99
C	0.7040	0.5429	0.7048	2	0.0349	0.0175	8.0598	20.97
Error				2	0.0043	0.0022	1.0000	2.60
Total				8	0.1665	0.0208		100.00

4.3 Confirmation test

After identifying the most influential parameters, the final phase is to verify the R_a and the µh by conducting the confirmation experiments. The $A_3B_2C_3$ is an optimal parameter combination of the turning process via the grey relational analysis. Therefore, the condition $A_3B_2C_3$ of the optimal parameter combination of the turning process was treated as a confirmation test. The result of the confirmation test gives the surface roughness average and the micro-hardness similar to those given in Table 4.

5. Conclusions

The grey relational analysis based on the Taguchi method's response table was used to optimize the cryogenic machining parameters in the CNC turning process for AISI 52100. Based on the results of the present study, the following conclusions can be drawn:

1. From the response table of the average grey relational grade, it is found that the largest value of the grey relational grade is for the cutting speed of 250 m/min, the feed rate of 0.16 mm/rev, and the depth of cutting of 1 mm. It is the recommended levels of the controllable parameters of the cryogenic machining process as the minimization of the surface roughness average and the micro-hardness are simultaneously considered.
2. The order of the importance for the controllable factors to both the surface roughness average and the micro-hardness, in sequence, is the feed rate, the cutting speed, and the depth of cut.
3. Through ANOVA, the percentage of contribution to the turning process, in sequence, is the cutting speed, the depth of cut, and the feed rate. Hence, the cutting speed is the most significant controlled factor for the turning operation when the minimization of the roughness average and the micro-hardness are simultaneously considered.

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