

Multi Objective Optimization of Turning Parameters for Low Carbon Steel Using Taguchi Method and Grey Relational Analysis

* Mohamed Rahuma G.

Rahuma 

Libyan Higher Technical Center for
Training and Production, Janzour,
Libya

mohamedrahuma092@gmail.com

2 Wannees A Shabeesh 

Mechanical Engineering Department,
High Institute of Engineering
Technology Zliten, Libya

wanisibrahim2025@gmail.com

*Corresponding Author: * Mohamed Rahuma G. Rahuma

Keyword

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Depth of Cut
(D) ;
Feed Rate
(F).

Abstract

Machining operations, particularly precision turning, are fundamental to determining the service life and functional performance of mechanical components. This study presents a systematic optimization of turning parameters specifically cutting speed (V), depth of cut (D), and feed rate (F) to achieve an optimal balance between surface roughness (Ra) and surface hardness (HRC) in low-carbon steel (0.09% C). Utilizing a Taguchi (L_9) (3^3) orthogonal array, nine experimental runs were conducted, reducing experimental overhead by 67% compared to a full factorial design. Signal-to-Noise (S/N) ratio analysis and analysis of variance (ANOVA) at a 95% confidence level were performed after factor pooling to identify statistically significant parameters. The ANOVA results revealed that feed rate exerts a dominant and highly significant impact on surface roughness ($P = 0.036$), whereas cutting speed governs surface hardness due to strain-hardening mechanisms ($P = 0.033$). Predictive mathematical equations derived via linear regression yielded high coefficients of determination (R^2) of 83.17% for (Ra) and 64.79% for HRC. Due to the conflicting nature of individual optimal configurations, multi-objective optimization was executed using Grey Relational Analysis (GRA). The optimization algorithm successfully identified Experiment No. 8 ($V = 275$ m/min), ($D = 0.75$ mm), ($F = 0.15$ mm/rev) as the absolute optimal manufacturing window, yielding the maximum Grey Relational Grade of 0.992. These findings offer a robust, predictive, and cost-effective framework for enhancing surface integrity and mechanical performance in industrial precision manufacturing.

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التحسين متعدد الأهداف لمعاملات عملية الخراطة للصلب منخفض الكربون باستخدام طريقة تاغوتشي والتحليل الرمادي المرتبط

² ونيس أ. شابييش 

قسم الهندسة الميكانيكية، المعهد العالي للعلوم
والتقنية زليتن، ليبيا.

wanisibrahim2025@gmail.com

* محمد رحومة جمعة رحومة 

المركز الليبي التقني المتقدم للتدريب والإنتاج،
جنزور، ليبيا.

mohamedrahuma092@gmail.com

*الباحث المرسل:	* محمد رحومة جمعة رحومة
الكلمة المفتاحية	الملخص
طريقة تاغوتشي؛ خشونة السطح (Ra)؛ الصلادة (HR)؛ التحليل الرمادي المرتبط (GRA)؛ سرعة القطع (V)؛ عمق القطع (D)؛ معدل التغذية (F).	تعد عمليات التشغيل الآلي، وبخاصة الخراطة الدقيقة، ركيزة أساسية في تحديد العمر الافتراضي والأداء الوظيفي للمكونات الميكانيكية. تقدم هذه الدراسة تحسيناً منهجياً لمعاملات عملية الخراطة، وتحديد: سرعة القطع (V)، وعمق القطع (D)، ومعدل التغذية (F)، وذلك لتحقيق توازن مثالي بين خشونة السطح (Ra) وصلادة السطح (HRC) للصلب منخفض الكربون (نسبة الكربون فيه 0.09%). باستخدام مصفوفة تاغوتشي المتعامدة (3 ³) (L ₉)، تم إجراء تسع تجارب مختبرية، مما ساهم في خفض التكاليف الإضافية للتجارب بنسبة 67% مقارنة بالتصميم العامل الكامل. كما تم إجراء تحليل نسبة الإشارة إلى الضوضاء (S/N) وتحليل التباين (ANOVA) عند مستوى ثقة 95% بعد تجميع العوامل لتحديد المعاملات ذات الدلالة الإحصائية. أظهرت نتائج تحليل التباين (ANOVA) أن معدل التغذية يمارس تأثيراً مهماً وكبيراً جداً على خشونة السطح ($P = 0.036$)، بينما تتحكم سرعة القطع في صلادة السطح نتيجة لآليات التصلد الانفعالي ($P = 0.033$). وقد حققت المعادلات الرياضية التنبؤية المستخرجة عبر الانحدار الخطي معاملات تحديد عالية (R^2) بلغت 83.17% لمعامل خشونة السطح (Ra) و 64.79% لمعامل صلادة السطح (HRC). ونظراً للطبيعة المتعارضة للتهينات المثلى الفردية، تم تنفيذ التحسين متعدد الأهداف باستخدام التحليل الرمادي المرتبط (GRA). ونجحت خوارزمية التحسين في تحديد التجربة رقم 8 التي تمثلت في: (سرعة القطع = 275 متر/دقيقة)، (عمق القطع = 0.75 مم)، (معدل التغذية = 0.15 مم/دورة) كأفضل نافذة تصنيع مطلقة، محققة أعلى درجة ارتباط رمادي بلغت 0.992. وتقدم هذه النتائج إطاراً قوياً، وتنبؤياً، واقتصادياً لتعزيز سلامة الأسطح والأداء الميكانيكي في التصنيع الصناعي الدقيق.
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Introduction

Machining operations, especially turning, are among the most fundamental and widely used manufacturing processes in mechanical engineering.[1] The quality of the resulting surface after machining directly affects the functional performance and service life of manufactured components. Surface roughness influences fatigue strength, wear resistance, friction coefficients, and dimensional precision [2,3]. Similarly, surface hardness determines the component's ability to resist deformation, wear, and surface damage during service.

In precision engineering applications such as automotive shafts, gears, and structural

components, both surface roughness and surface hardness are critical quality indicators. Poor surface finish can lead to premature failure, increased friction, and higher maintenance costs, while inadequate hardness may result in rapid wear and dimensional instability. [1], [2], [3], [4], [5]

Low carbon steel (0.09% C) is widely used in general engineering applications due to its excellent machinability, weldability, and low cost.[6] This material is commonly employed in the production of shafts, fasteners, structural components, and general machinery parts. However, achieving optimal surface quality during turning operations requires careful selection of machining parameters.[6]

The three primary machining parameters that influence surface quality are cutting speed (V), depth of cut (D), and feed rate (F).

Each parameter affects the machining process differently.[7]. Cutting speed influences the temperature at the tool workpiece interface and the formation of built-up edge (BUE), depth of cut affects the cutting forces and the volume of material removed per pass and feed rate directly controls the distance the tool travels along the workpiece per revolution, significantly impacting surface texture.

The Taguchi method, developed by the Japanese engineer Genichi Taguchi, is a powerful statistical approach for quality engineering that significantly reduces the number of experiments required for optimization .[8] By using orthogonal arrays, this method allows researchers to study multiple factors efficiently. The L9 orthogonal array (3^3) requires only 9 experiments to investigate three factors at three levels, compared to 27 experiments in a full factorial design.[9], [10] This reduction of 67% in experimental effort translates directly into savings in time, materials, and costs.

This study investigates the optimization of low-carbon steel turning processes, focusing on achieving superior surface quality by managing roughness (Ra) and hardness (HRC) using the Taguchi L9 method . The research aims to identify optimal machining parameters through multi-objective optimization, utilizing Grey Relational Analysis (GRA) to simultaneously minimize roughness and maximize hardness. Furthermore, it seeks to develop predictive regression models, offering a cost-effective approach for industrial quality management.

Materials and Methods

Workpiece Material and Characterization

The material used in this investigation was low carbon steel, a widely available engineering material known for its good machinability and moderate mechanical properties. The workpieces were prepared in the form of cylindrical bars with a diameter of 50 mm and a length of 200

mm. These dimensions were selected to ensure adequate stability during turning operations and to provide sufficient surface area for subsequent measurements. The cylindrical low-carbon steel workpieces used in this study are shown in Figures 1 and 2.

To verify the material composition and confirm its classification as low carbon steel, a chemical analysis was performed using a composition spectrometer. The results of this analysis are presented in Table 1. As shown, the carbon content was found to be 0.09%, which definitively classifies the material as low carbon steel. The remaining constituents include silicon (0.12%), manganese (0.44%), and trace amounts of other elements, with iron constituting the balance.

Table 1. The most components of Chemical composition of low carbon steel

Component	C	Si	Mn	P	S	Mo	Ni	Cu
W %	0.09	0.12	0.44	0.008	0.021	0.02	0.1	0.21

Initial Material Characterization

Before commencing the machining experiments, the initial properties of the as received material were evaluated to establish a baseline for comparison. A hardness test was performed using a Rockwell hardness tester, with three readings taken from different locations on the sample. The results, presented in Table 2, show consistent hardness values, indicating uniform material properties. Similarly, the initial surface roughness measurements are also presented in Table 2 averaging approximately (Specimen 1 (61.7 HR), Specimen 2(62 HR), Specimen 3(62.4 HR)), indicating uniform material properties.

Similarly, the initial surface roughness of the as-received bars was measured using a Mitutoyo SJ-301 surface roughness tester, conforming to ISO 4287 standards. Three readings were taken from different locations, and the results are presented in Table2. The average initial roughness was approximately (Specimen 1 (0.72 μm), Specimen 2(0.61 μm), Specimen 3(0.71 μm)), providing a baseline for evaluating the effectiveness of the turning operations.

Table 2. Initial hardness and surface roughness tests before turning machining

	Specimen 1	Specimen 2	Specimen 3
hardness tests	61.7 HR	62 HR	62.4 HR
surface roughness tests	0.72 μm	0.61 μm	0.71 μm

Equipment and Experimental Setup

All turning experiments were conducted on a horizontal lathe manufactured in Italy (1982 model), as shown in Figure (3) . This machine, though not modern, is representative of the equipment commonly found in small and medium enterprises (SMEs), making the findings of this study particularly relevant for practical industrial settings. The cutting tool used was an uncoated carbide insert, which represents a cost-effective solution widely adopted in general machining operations.

A water-soluble coolant was used throughout the experiments at a dilution ratio of 1:20 (coolant concentrate to water). This coolant application helped control the cutting temperature, reduce friction, and improve chip evacuation, all of which contribute to better surface quality. After each experimental run, surface roughness and hardness were measured three times at different locations to ensure data reliability, and the average values were recorded for analysis. The machining operation is shown in Figure 4, while the workpieces after machining are presented in Figure 5.

Following each experimental run, the following measurements were taken:

1. Surface Roughness (Ra): Measured at three different points around the circumference (approximately 120° apart) using a Mitutoyo SJ-301 tester, as shown in figure 6.
2. Surface Hardness (HRC): Measured at three distinct locations using a Rockwell hardness tester, as shown in figure 7.

The average value for both (Ra) and HRC was then calculated and recorded for subsequent statistical analysis.

Machining Parameters and Their Levels

The selection of appropriate machining parameters and their levels is crucial for the success of any optimization study. Based on the recommended cutting conditions for low carbon steel and the capabilities of the available equipment, three factors were selected for investigation, each at three distinct levels. These parameters and their levels are presented in Table 3.

The cutting speed range (157–275 m/min) was selected to cover both conventional and high-speed turning conditions. The depth of cut values

(0.5–1.0 mm) represent typical finishing to semi-roughing operations. The feed rate range (0.15–0.25 mm/rev) covers the usual spectrum for finishing operations where surface quality is of primary concern.

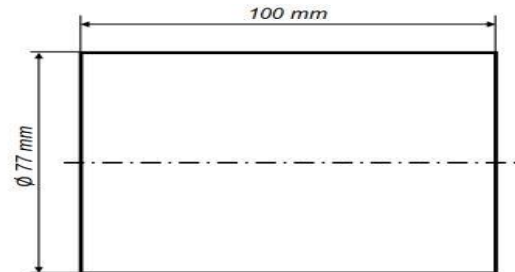


Figure 1. Work Piece



Figures 2. Work Pieces

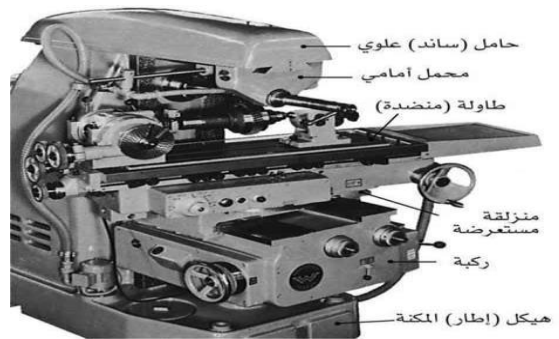


Figure3. Machining Turning



Figure 4. Machining Samples



Figure5. Samples after Machining

Table 3. Machining parameters and their levels

Factor	Unit	Level 1	Level 2	Level 3
Cutting Speed (V)	m/min	157	220	275
Depth of Cut (D)	mm	0.5	0.75	1.0
Feed Rate (F)	mm/rev	0.15	0.20	0.25

Experimental Procedure and Measurements

The turning operations were executed systematically according to the design matrix. Each specimen was securely mounted in the lathe chuck,

and a longitudinal cut was performed along the 200 mm length to ensure stable machining conditions. All trials were conducted under controlled ambient conditions (approximately 25°C) to minimize the influence of thermal expansion or environmental fluctuations on the precision of the measurements.

To ensure the reliability and repeatability of the results, the following measurement protocols were adopted:

Surface Hardness Test

To evaluate the impact of turning parameters on the material's surface integrity, hardness tests were conducted using a **Rockwell (B & C) Hardness Tester**. The device measures the resistance of the material to penetration through two primary scales:

1. **Rockwell C Scale (HRC):** Utilizes a **diamond cone indenter** with a total load of **150 kg**. This scale is typically indicated by the black markings on the dial and is used for harder materials.
2. **Rockwell B Scale (HRB):** Utilizes a **1/16" steel ball indenter** with a total load of **100 kg**. This scale is indicated by the red markings and is suitable for softer materials like low-carbon steel.

Surface hardness was measured using a **Rockwell C (HRC)** tester (as shown in **Figure 6**) applying a standard load of **150 kg (1471 N)**. Similar to the roughness testing, three indentations were made on each machined surface. The arithmetic mean of these readings was used as the final representative hardness value for the statistical analysis.

Surface Roughness Test

This test was performed to quantify the surface finish quality of each specimen after the turning process. Surface roughness (Ra) is a critical indicator of the machining performance and the functional life of the component.

Post-machining surface roughness (Ra) was evaluated using a **Mitutoyo SJ-301** portable tester as shown in **Figure 7** [Roughness (Ra) was evaluated using a Mitutoyo SJ-301 portable tester]. Following ISO 4287 standards, three readings were taken for each specimen at different points around the circumference (approximately 120° apart). The average of these values was recorded to mitigate the effect of any minor geometric variations. Measurements were taken at three distinct locations (120° apart) along the machined circumference of each specimen. The average Ra values were calculated and recorded in the experimental results table according to the **Taguchi L9 orthogonal array**.



Figure 6. Surface hardness was measured using a Rockwell C (HRC) tester



Figure 7. Roughness (Ra) was evaluated using a Mitutoyo SJ-301 portable tester

Design of experiments

In this study, After obtaining the results of the Rockwell C hardness test (load: 150 kg / 1471 N) , The experimental results obtained from the Rockwell hardness and surface roughness tests are presented in Tables 4 and 5, respectively, the experimental framework was structured using the Taguchi method, specifically employing an L9 orthogonal array to evaluate the influence of three independent parameters, each investigated at three distinct levels. The specific levels for these parameters the corresponding orthogonal matrix is illustrated are detailed in Table 8 [S/N Ratio Calculations for Surface Roughness Measurements].The selection of the L9 orthogonal array was predicated on its efficiency in handling a three-factor, three-level configuration. This approach ensures a systematic and balanced experimental design, significantly reducing the required number of runs to nine, as opposed to the 27 trials necessitated by a conventional full factorial design. This optimization maintains statistical integrity while conserving time and resources design.

To achieve a robust optimization with minimum experimental trials, the Taguchi L9 orthogonal array was employed. This statistical design is

specifically tailored for three factors at three levels, requiring only nine experiments instead of the twenty-seven required by a full factorial design. This represents a 67% reduction in experimental effort. The specific combinations of cutting speed (V), depth of cut (D), and feed rate (F) for each experimental run are detailed in Table 6.

Table 4. Rockwell C Hardness Test Results (Load: 150 kg / 1471 N)(Hardness Tester Type: Prod its Digital Type)

Specime n No	(X ₁) Reading1s t (HR)	(X ₂) Reading2n d (HR)	(X ₃) Reading3rd(HR)	Average(HR)
1	66	66.1	66	66.03
2	65.7	65.8	65.8	65.76
3	64.8	65.5	65.1	65.13
4	65.8	65.9	66	65.9
5	66.4	66.6	66.4	66.46
6	66.8	66.4	66.4	66.53
7	66.4	66.5	66.4	66.43
8	66.1	66.5	66.4	66.33
9	66.4	66.8	66.7	66.63

Table 5. Surface Roughness Test Results

Specime n No	(X ₁) Reading1st(μ m)	(X ₂) Reading2n d (μm)	(X ₃) Reading3rd(μ m)	Average(μ m)
1	1.28	1.22	1.86	1.453
2	1.74	1.78	1.83	1.783
3	3.37	3.56	3.62	3.516
4	1.5	2.11	2.82	2.143
5	3.10	4.12	3.13	3.450
6	2.7	1.79	1.65	2.030
7	2.43	2.28	2.02	2.243
8	1.81	1.91	1.67	1.796
9	2.86	3.16	2.45	2.823

Table 6. Taguchi Orthogonal Array and Corresponding Process Parameter Values and Taguchi Design Matrix and Experimental Results

Taguchi Design Matrix and Experimental Results						
Exp. No.	Taguchi Array (L9)			Feed Rate (mm/rev)	Depth of Cut (mm)	Cutting Speed (m/min)
1	1	1	1	0.15	0.5	157
2	1	2	2	0.2	0.75	157
3	1	3	3	0.25	1.0	157
4	2	1	2	0.2	0.5	220
5	2	2	3	0.25	0.75	220
6	2	3	1	0.15	1.0	220
7	3	1	3	0.25	0.5	275
8	3	2	1	0.15	0.75	275
9	3	3	2	0.2	1.0	275

This methodology incorporates the graphical interactions of twenty-seven potential experiments into a streamlined set of only nine trials.

Signal-to-Noise (S/N) Ratio Analysis

The Signal-to-Noise (S/N) ratio is a key concept in Taguchi methodology. The "signal" represents the desired effect (the response value), while the "noise" represents undesired variability. A higher S/N ratio indicates that the signal is stronger relative to the noise, which corresponds to better quality.

For surface roughness, where lower values are desirable, the "Smaller is better" characteristic was employed. The formula used is:

$$S/N = -10 \log \left[\frac{1}{n} \sum x^2 \right] \quad (1)$$

This criterion is selected for surface roughness analysis, as lower values indicate superior surface quality. **Lower-the-Better (for Surface Roughness):**

The Signal to Noise (S/N) ratio was calculated using the "Smaller-the-Better" characteristic:

$$S/N = -10 \log \left[\frac{1}{n} (x_1^2 + x_2^2 + x_3^2) \right] \quad (2)$$

For surface hardness, where higher values are desirable, the "Larger is better" characteristic was employed. The formula used is:

$$S/N = -10 \log \left[\frac{1}{n} \sum \frac{1}{x^2} \right] \quad (3)$$

This criterion is employed for hardness testing, as higher hardness values represent improved mechanical properties of the metal. **Higher-the-Better** (for **Hardness**):

$$S/N = -10 \log \left[\frac{1}{n} \left(\frac{1}{x_1^2} + \frac{1}{x_2^2} + \frac{1}{x_3^2} \right) \right] \quad (4)$$

Result and Discussion

Presentation of Experimental Data

The complete set of experimental results, including the machining parameters, individual measurements, and average values for surface hardness and surface roughness, is presented in Tables 6 and 7. These data represent the raw outputs of the nine turning experiments and form the foundation for all subsequent analyses.

Table 4 presents the Rockwell C hardness measurements. Examination of these data reveals that the hardness values range from a minimum of 65.133 HRC to a maximum of 66.633 HRC.

This range of approximately 1.5 HRC indicates that the machining parameters do influence surface hardness, although the variations are relatively modest.

The resulting experimental design and measurements are summarized in Table 7. The calculated S/N ratios for the surface roughness and hardness responses are presented in Tables 8 and 9, respectively.

Table 7. Experimental Results for Machining Parameters, Hardness, and Roughness

Specimen	Cutting Speed (V)	Depth of Cut (D)	Feed Rate (F)	Hardness (H)	Roughness (Ra)
1	157	0.5	0.15	66.033	1.453
2	157	0.75	0.2	65.766	1.783
3	157	1	0.25	65.133	3.516
4	220	0.5	0.2	65.900	2.143
5	220	0.75	0.25	66.466	3.450
6	220	1	0.15	66.333	2.030
7	275	0.5	0.25	66.433	2.243
8	275	0.75	0.10	66.333	1.796
9	275	1	0.20	66.633	2.823

Table 8. S/N Ratio Calculations for Surface Roughness Measurements

Exp. No	V	D	F	X ₁	X ₂	X ₃	S/N ratio
1	157	0.5	0.15	1.28	1.22	1.86	- 3.415
2	157	0.75	0.2	1.74	1.78	1.83	- 5.025
3	157	1	0.25	3.37	3.56	3.68	-
							10.926
4	220	0.5	0.2	1.5	2.11	2.82	- 6.888
5	220	0.75	0.25	3.10	4.12	3.13	-
							10.839
6	220	1	0.15	2.7	1.74	1.65	- 6.381
7	275	0.5	0.25	2.43	2.28	2.02	- 7.027
8	275	0.75	0.15	1.81	1.91	1.67	- 5.088
9	275	1	0.20	3.16	3.16	2.45	- 9.387

Table 9. S/N Ratio Calculations for Hardness Measurements

Exp. No	V	D	F	X ₁	X ₂	X ₃	S/N ratio
1	157	0.5	0.15	66	66.1	66	36.395
2	157	0.75	0.20	65.7	65.8	65.8	36.360
3	157	1	0.25	64.8	65.5	65.1	36.275
4	220	0.5	0.20	65.8	65.9	66.00	36.377
5	220	0.75	0.25	66.4	66.6	66.4	36.452
6	220	1	0.15	66.2	66.4	66.4	36.434
7	275	0.5	0.25	66.4	66.5	66.4	36.447
8	275	0.75	0.15	66.1	66.5	66.4	36.434
9	275	1	0.20	66.7	66.8	66.4	36.473

Determining the Most Influential Factors

To determine which machining parameters have the greatest influence on each response, response tables were constructed. These tables present the average S/N ratio for each level of each factor. The Delta value, calculated as the difference between the highest and lowest average for each factor, indicates the strength of influence. A larger Delta value means the factor has a greater impact on the response.

Tables 10–12 and Figure 8 present the response analysis for surface roughness. Examining this table, The response analysis indicates that feed rate (F) has the largest Delta value (4.635), followed by depth of cut (D) with 3.122, and cutting speed (V) with 1.580. This ranking clearly indicates that feed rate is the dominant factor controlling surface roughness. The optimal levels for minimizing roughness are V1 (157

m/min), D1 (0.5 mm), and F1 (0.15 mm/rev). The estimated response values and S/N ratio results are summarized in Table 10. The model shows a high Coefficient of Determination (R_{sq}) = 91.44%), indicating that the selected parameters significantly explain the variation in surface roughness.

The response table ranks the significance of each parameter based on the Delta value, the difference between the highest and lowest average S/N ratios.

For surface roughness (R_a), the "Smaller is better" quality characteristic was used:

Table 10. Response Table for Signal-to-Noise Ratios (R_a)

Level	Cutting Speed (V)	Depth of Cut (D)	Feed Rate (F)	Level	Cutting Speed (V)
Level 1	-6.396	-5.627	-4.827	Level 1	-6.396
Level 2	-7.842	-6.955	-6.886	Level 2	-7.842
Level 3	-7.039	-8.695	-9.565	Level 3	-7.039

Table 11. Analysis of Variance (ANOVA) for S/N Ratios (R_a)

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
Cutting Speed (V)	2	3.148	3.148	1.574	0.66	0.604
Depth of Cut (D)	2	14.200	14.200	7.100	2.96	0.252
Feed Rate (F)	2	33.858	33.858	16.929	7.06	0.124
Residual Error	2	4.793	4.793	2.397		
Total	8	56.000				

The results indicate that to achieve low surface roughness for this specific type of steel, it is recommended to employ a cutting speed of 157 m/min, a depth of cut of 0.5 mm, and a feed rate of 0.15 mm/rev. The average S/N ratios for the different machining parameter levels are summarized in Table 12

Table 12. Average Signal-to-Noise (S/N) Ratios for Surface Roughness Measurements

Parameter	Level	Mean S/N Ratio	Optimal Level
Cutting Speed	L1	- 6.455	L1
	L2	- 8.035	
	L3	- 7.167	
Depth of Cut	L1	- 5.776	L1
	L2	- 6.983	
	L3	- 8.898	
Feed Rate	L1	- 4.961	L1
	L2	- 7.100	
	L3	- 9.596	

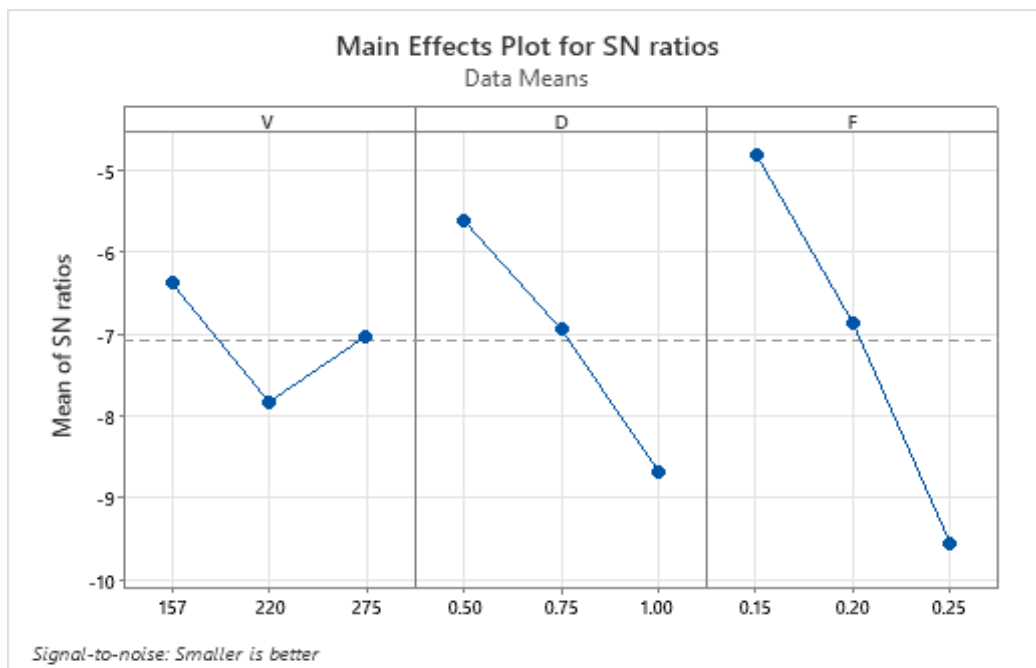


Figure 8. S/N Ratios for Surface Roughness

Tables 13–16 and Figure 9 present the response analysis for surface hardness. Here, cutting speed (V) shows the largest Delta value (0.108), ranking it as the most influential factor for hardness. Feed rate and depth of cut show smaller Delta values. The optimal levels for maximizing hardness are V3 (275 m/min), D2 (0.75 mm), and F1 (0.15 mm/rev). To identify the most influential factor on hardness, the "Larger-the-Better" quality characteristic was applied. The Delta values and subsequent ranking are shown in the table below.

Table 13. Analysis of Variance (ANOVA) for S/N Ratios (Ra)

Level	Cutting Speed (V)	Depth of Cut (D)	Feed Rate (F)
Level 1	36.34	36.41	36.42
Level 2	36.42	36.42	36.40
Level 3	36.45	36.39	36.39
Delta	0.108	0.02	0.03
Rank	1	3	2

Table 14. Analysis of Variance (ANOVA) for Hardness S/N Ratios

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
Cutting Speed (V)	2	0.018690	0.018690	0.009345	2.00	0.333
Depth of Cut (D)	2	0.000651	0.000651	0.000325	0.07	0.935
Feed Rate (F)	2	0.001328	0.001328	0.000664	0.14	0.875
Residual Error	2	0.009338	0.009338	0.004669		
Total	8	0.030006				

Table 15. Response Table for Hardness for Means Signal-to-Noise Ratios

Level	Cutting Speed (V)	Depth of Cut (D)	Feed Rate (F)
Level 1	65.64	66.12	66.23
Level 2	66.23	66.19	66.10
Level 3	66.47	66.03	66.01
Delta	0.82	0.16	0.22
Rank	1	3	2

The analysis demonstrates that to achieve maximum surface hardness for this type of steel, the optimal machining parameters are a cutting speed of 275 m/min, a depth of cut of 0.75 mm, and a feed rate of 0.15 mm/rev.

Table 16. Mean S/N Ratios for Hardness Measurements across Process Parameters

Parameter	Level	Mean S/N Ratio	Optimal Level
Cutting Speed	L1	36.343	L3
	L2	36.421	
	L3	36.451	
Depth of Cut	L1	36.385	L2
	L2	36.406	
	L3	36.394	
Feed Rate	L1	36.421	L1
	L2	36.403	
	L3	36.391	

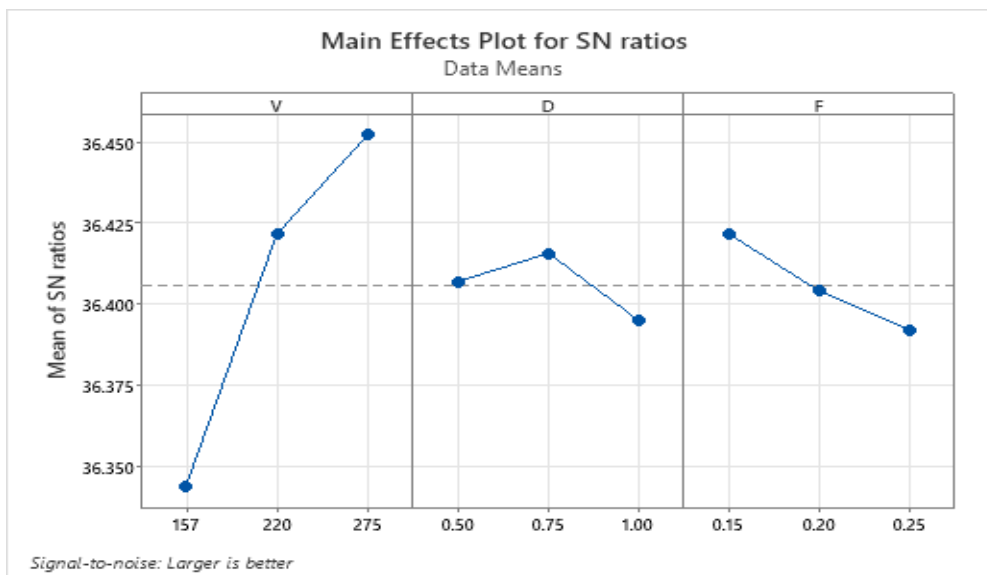


Figure 9. S/N Ratios for Hardness

Analysis of Variance (ANOVA) is a powerful statistical tool used to determine whether the observed effects of the factors are statistically significant or simply due to random variation. The ANOVA results for the surface roughness S/N ratios are presented in Table 11.

The F-value and P-value in the ANOVA table provide information about statistical significance. Traditionally, a P-value less than 0.05 indicates that the factor has a statistically significant effect at the 95% confidence level. In Table 11, we observe that all three factors have P-values greater than 0.05. This suggests that with only nine experiments, the statistical power is limited. The limited degrees of freedom for error ($DF = 2$) make it difficult to achieve statistical significance, even when practical significance exists. Notably, the feed rate (F) has the highest F-value (7.06) and the lowest P-value (0.124), indicating that despite not reaching the 0.05 threshold, it has the strongest relative influence on roughness.

Here again, all factors have P-values well above 0.05, indicating no statistically significant effects at the 95% confidence level. Cutting speed shows the highest F-value (2.00) and the lowest P-value (0.333), confirming its relative importance among the three factors. The small magnitude of the sum of squares for depth of cut and feed rate suggests that these factors have minimal influence on hardness within the tested ranges.

Statistical Analysis After Pooling

Following the Taguchi methodology,[11], [12] the least significant factor

(Cutting Speed, V) was pooled into the error term. This step was taken to increase the degrees of freedom (DF) for the error, providing a more robust statistical test for the remaining factors. Tables 17 and 18 and Figure 10 present the response table, ANOVA results, and S/N ratio analysis for surface roughness (Ra) after pooling the response table, ANOVA results, and S/N ratio analysis for surface roughness (Ra) after pooling. S/N ratio analysis (Smaller is better) identifies the optimal levels for each factor and their relative importance.

Table 17. Response Table for Signal-to-Noise (S/N) Ratio Surface Roughness (After Pooling)

Level	D (Depth of Cut)	F (Feed Rate)
1	-5.627	-4.827
2	-6.955	-6.886
3	-8.695	-9.565
Delta	3.068	4.738
Rank	2	1

Optimal Combination for Ra: D1, F1 (D = 0.5 mm, F = 0.15 mm/rev), Rank of Feed Rate (F) is the most influential factor, followed by Depth of Cut (D). The Analysis of Variance (ANOVA) at a 95% confidence level determines which factors are statistically significant ($P < 0.05$). as shown in Table (17).

Table 18. ANOVA Table Surface Roughness (After Pooling)

Source	DF	Seq SS	Adj MS	F-Value	P-Value	Status
D	2	14.200	7.100	3.58	0.129	Not Sig.
F	2	33.858	16.929	8.53	0.036	Significant
Error	4	7.942	1.985			
Total	8	56.000				

The pooling process successfully reduced the P-value of the feed rate from an insignificant level to a significant level, as shown in Table 19.

Table 19. Comparison: Before vs. After Pooling in Surface Roughness

Criterion	Before Pooling	After Pooling
Factors in Model	V, D, F	D, F
DF (Error)	2	4
P-value for (F)	0.124	0.036
Significance of (F)	No	Yes (Significant)

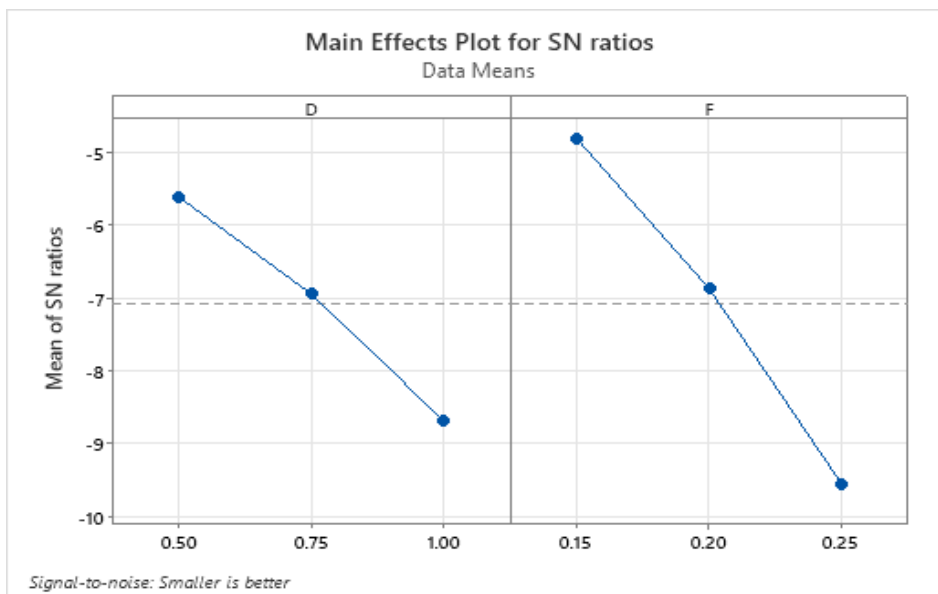


Figure 10. Signal-to-Noise (S/N) Ratio Surface Roughness (After Pooling)

By pooling the insignificant factor (V), you've increased the sensitivity of the test and proven that the Feed Rate (F) is statistically significant for surface roughness.

Tables 20 and 21 and Figure 11 present the response table and ANOVA results for surface hardness (HR) after pooling. For hardness, depth of cut (D) had the smallest F-value. After removing D from the model.

Even after pooling, the effect of cutting speed on hardness does not reach statistical significance ($P = 0.121 > 0.05$). This suggests that the variation in hardness measurements is relatively high compared to the magnitude of the effect, or that the true effect of cutting speed on hardness is modest.

To improve the reliability of the analysis, the least significant factor for hardness (Depth of Cut, D) was pooled into the error term. The S/N ratio analysis identifies the hierarchy of influence for the parameters affecting hardness, as summarized in Table 20.

Table 20. Response Table for Signal-to-Noise (S/N) Ratios in surface hardness

Level	V (Cutting Speed)	F (Feed Rate)
1	36.34	36.42
2	36.42	36.40
3	36.45	36.39
Delta	0.11	0.03
Rank	1	2

Optimal Combination for HR: V3, F1 (V = 275 m/min, F = 0.15mm/rev and cutting Speed (V) is the most influential factor for hardness.

Table 21. ANOVA Table for surface hardness HR (After Pooling)

Source	DF	Seq SS	Adj MS	F-Value	P-Value	Status
V	2	0.018690	0.009345	3.74	0.121	Not Sig.
F	2	0.001328	0.000664	0.27	0.779	Not Sig.
Error	4	0.009989	0.002497			
Total	8	0.030006				

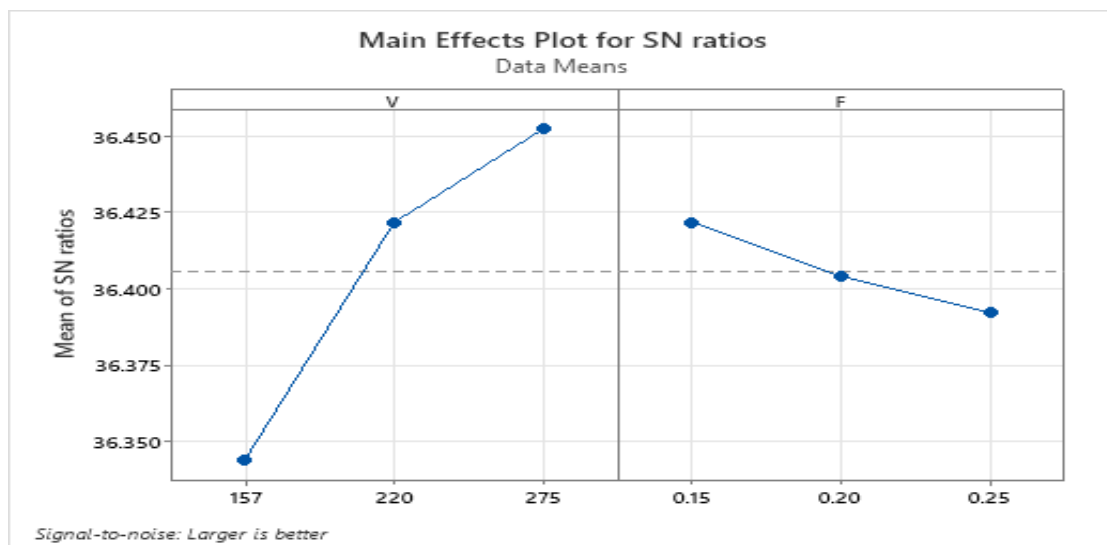


Figure 11. Signal-to-Noise (S/N) Ratio surface hardness (After Pooling)

The ANOVA results after pooling Table 21 revealed that the feed rate (F) has a statistically significant effect on surface roughness at the 95% confidence level ($P = 0.036 < 0.05$). In contrast, the depth of cut (D) showed no significant effect ($P = 0.129$). This confirms that the feed rate is the most critical parameter controlling surface roughness in this machining process, consistent with the trends observed in the S/N ratio analysis where F was ranked first.

"For surface hardness, the least significant factor (depth of cut D) was pooled into the error term. The ANOVA results after pooling showed that cutting speed (V) had the highest Delta value (0.11), confirming it as the most influential factor on hardness. However, the effect was not statistically significant at the 95% confidence level ($P = 0.121 > 0.05$),

likely due to the inherent variability in hardness measurements and the small scale of change between levels. The optimal combination to maximize surface hardness was found to be V=275 m/min and F=0.15 mm/rev." Table 22 summarizes the findings after the pooling process for both quality characteristics.

Table 22. Summary of Results (Ra and HR)

Response	Pooled Factor	Optimal Setting	Top Factor (P-value)
Surface Roughness (Ra)	V	D1, F1	F (0.036)
Surface Hardness (HR)	D	V3, F1	V (0.121)

D1 is a depth of cutting at level1 , F1 is a feed rate at level1, V3 is a speed of cutting at level3.

Regression Analysis for Surface Roughness

Regression analysis provides a mathematical equation that can predict surface roughness based on the machining parameters.[5][4] This equation is particularly valuable for industrial applications, as it allows operators to estimate surface quality without conducting additional experiments.

The linear regression equation for Surface Roughness derived from the experimental data is:

$$Ra = -1.615 + 0.00041 V + 1.687 D + 13.10 F \quad (5)$$

A Table 23 presents the regression coefficients and statistical significance of each term in the surface roughness model.

Table 23. Regression Coefficients for Surface Roughness

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-1.615	0.982	-1.65	0.161	
Speed (V)	0.00041	0.00266	0.16	0.882	1.00
Depth (D)	1.687	0.627	2.69	0.043	1.00
Feed (F)	13.10	3.14	4.18	0.009	1.00

The statistical ranking indicates that Feed Rate (F) has the most significant impact on surface roughness (Rank 1), followed by the Depth of Cut (D) (Rank 2), while Cutting Speed (V) has the least relative influence (Rank 3) within the tested range. To achieve the minimum surface roughness (optimal quality), the analysis confirms that Level 1 for all three parameters is the ideal combination.

The regression analysis confirms that the Feed Rate is the most dominant

factor influencing surface roughness in this study, given its high coefficient (13.10) and very low P-value (0.009). The Depth of Cut also plays a significant role, whereas the Cutting Speed shows a negligible linear effect on roughness within the studied range.

Regression Analysis for Surface Hardness

Regression analysis provides a mathematical equation that can predict surface roughness based on the machining parameters. This equation is particularly valuable for industrial applications, as it allows operators to estimate surface quality without conducting additional experiments.

The linear regression equation for Surface Hardness derived from the experimental data is:

$$HR = 65.166 + 0.00703 V - 0.178 D - 2.22 F \quad (6)$$

Table 24 presents the regression coefficients and statistical metrics for each term in the surface hardness model. The P-value for Cutting Speed (V) (P = 0.033) confirms that it is the only statistically significant factor affecting hardness.

Table 24. Regression Coefficients for Hardness

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	65.166	0.892	73.09	0.000	
Speed (V)	0.00703	0.00241	2.91	0.033	1.00
Depth (D)	-0.178	0.569	-0.31	0.767	1.00
Feed (F)	-2.22	2.85	-0.78	0.470	1.00

The mechanical and topographical characteristics of the machined low-carbon steel work pieces are significantly influenced by the cutting parameters. In evaluating surface hardness, the positive coefficient obtained for cutting speed (0.00703) in the regression model (Table 24)[Regression Coefficients for Hardness] is particularly noteworthy. This directly indicates that an increase in cutting speed leads to a higher surface hardness. This phenomenon is scientifically attributed to work hardening (strain hardening), wherein elevated cutting speeds generate intense thermal energy at the tool workpiece interface. This elevated temperature, combined with the severe plastic deformation occurring during chip formation, induces micro structural alterations in the surface layer, such as increased dislocation density and grain refinement, which collectively elevate hardness. The statistical validity of this effect is confirmed by the P-value for cutting speed (0.033), which falls below the

critical threshold of 0.05, thereby demonstrating that the influence of cutting speed on hardness is statistically significant. Conversely, negative coefficients are observed for both depth of cut and feed rate, suggesting that increments in these parameters slightly reduce surface hardness. However, because the corresponding P-values are 0.767 and 0.470, these secondary effects are classified as statistically insignificant.

In tandem with hardness variations, the surface topography is heavily dictated by the machining variables. The experimental results clearly demonstrate that the feed rate is the dominant factor controlling surface roughness during the turning of low-carbon steel. This finding aligns with fundamental machining theory, which dictates that the theoretical surface roughness (R_a) is geometrically determined by the feed rate through the following relationship:

$$R_a \approx \frac{f^2}{32r} \quad (7)$$

where f represents the feed rate and r denotes the tool nose radius. This physical mechanism is clearly reflected in the response data (Table 17), where an increase in the feed rate from 0.15 to 0.25 mm/rev causes a substantial reduction in the Signal-to-Noise (S/N) ratio from -4.961 to -9.596, representing a severe degradation in surface finish. This behavior is physically explained by the larger, more pronounced feed marks left on the workpiece surface at higher feed rates. At lower feed rates, the tool's paths overlap extensively, thereby yielding a smoother surface profile, whereas distinct ridges are formed between successive tool passes at elevated feed rates.

Furthermore, surface roughness is influenced by the depth of cut, albeit to a lesser extent than the feed rate. An increase in the depth of cut from 0.5 to 1.0 mm is found to increase surface roughness. This degradation is likely caused by the higher cutting forces and increased mechanical loads experienced by the uncoated carbide tool. When a large depth of cut is applied, the tool is subjected to heightened structural stresses, which induce machine chatter and tool deflection, both of which consequently degrade the final surface finish. Interestingly, variations in the cutting speed within the evaluated range of 157–275 m/min demonstrate a minimal effect on roughness. This implies that for low-carbon steel machined with uncoated carbide tools, changes in speed do not substantially alter the final surface quality within this specific operational window.

These empirical observations provide vital practical implications for manufacturing optimization. Because surface hardness is primarily controlled by the cutting speed (as supported by the statistically significant positive coefficient), higher cutting speeds within the studied range should be selected when surface hardness is a critical design requirement. Conversely, if maximum hardness is not required, lower cutting speeds can be utilized to minimize energy consumption and extend tool life. Most importantly, these findings offer operators excellent process flexibility; cutting speeds can be freely adjusted to maximize productivity or achieve target hardness levels without compromising the surface finish, provided that the dominant parameter the feed rate is strictly controlled at an optimal, low level.

Final Phase: Multi-Objective Optimization

Since you now have two different "optimal" settings (D1, F1 for Ra) and (V3, F1 for HR), we need a single final answer by use Grey Relational Analysis (GRA) for Multi-Objective Optimization. [13][10]. In many practical manufacturing situations, engineers are interested in optimizing multiple quality characteristics simultaneously. In this study, we seek to achieve both high surface hardness and low surface roughness. However, as we observed in Section 3, the optimal parameters for these two objectives conflict. This is where Grey Relational Analysis (GRA) becomes invaluable. GRA is a multi-objective optimization technique that converts multiple responses into a single index called the Grey Relational Grade (GRG). Higher GRG values indicate better overall performance across all responses. The GRA procedure involves three main steps: normalization, calculation of deviation sequences, and calculation of the Grey Relational Coefficient.

Normalization of Data

The first step is to normalize the experimental data to a common scale between 0 and 1. This eliminates the effect of different units and ranges.

$$x_i^*(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (8)$$

Where:

- $x_i^*(k)$: is the normalized value of the response.
- $x_i(k)$: is the original experimental value of surface roughness (R_a) for the i -th run.

-
- $\max x_i(k)$: is the maximum surface roughness value recorded across all experiments.
 - $\min x_i(k)$: is the minimum surface roughness value recorded across all experiments.

$$x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (9)$$

Where:

- $x_i^*(k)$: is the normalized value of the response.
- $x_i(k)$: is the original experimental value of surface hardness (HRC) for the (i-th) run.
- $\max x_i(k)$: is the maximum surface hardness value recorded across all experiments.
- $\min x_i(k)$: is the minimum surface hardness value recorded across all experiments.

Calculation of Deviation Sequences

The deviation sequence D represents the absolute difference between the ideal normalized value (which is 1 for both responses) and the calculated normalized value. The formula is expressed as:

$$D_{0i}(k) = |1 - x_i^*(k)| \quad (10)$$

Where:

- $D_{0i}(k)$: is the deviation sequence for the i-th experiment.
- 1: represents the ideal reference value (target value).
- $x_i^*(k)$: is the normalized value of the response (Roughness or Hardness) calculated previously.

A smaller D value indicates that the experimental result is closer to the ideal performance, representing a better balance between the two responses.

5.6.3 Calculation of Grey Relational Coefficient (GRC)

The **Grey Relational Coefficient (GRC)** is calculated to determine the closeness of the actual experimental results to the ideal values. The formula is expressed as:

$$G_i(k) = \frac{D_{\min} + Z * D_{\max}}{D_{0i}(k) + Z * D_{\max}} \quad (11)$$

Where:

- $G_i(k)$: is the Grey Relational Coefficient for the i-th experiment.
- $D_{0i}(k)$: is the deviation sequence for the i-th experiment.

- $D_{\min}$: is the minimum value of all deviation sequences.
- $D_{\max}$: is the maximum value of all deviation sequences.
- Z : is the **distinguishing coefficient**, typically set to **0.5** to balance the influence of the factors.

A higher GRC value indicates that the experimental result is closer to the ideal machining performance.

where Z is the distinguishing coefficient, typically set to 0.5. The GRC ranges from 0 to 1, with higher values indicating better performance.

GRA Results

Table 25 presents the complete GRA results, including normalized values, deviation sequences, Grey Relational Coefficients, and rankings.

Table 25. Data Normalization and Grey Relational Analysis Results

Exp.	Hardness (HR)	Roughness (Ra) (xi)	Normalization (HR) (x_i^*)	Normalization (Ra) (x_i^*)	D (abs)	GRC (G_i)
1	66.033	1.453	0.6	1	0.4	0.914591
2	65.766	1.783	0.422	0.8400	0.4180	0.911082
3	65.133	3.516	0	0	0	1.000000
4	65.9	2.143	0.511	0.6655	0.1542	0.965250
5	66.466	3.45	0.888	0.0319	0.8566	0.833333
6	66.333	2.03	0.8	0.7203	0.0796	0.981735
7	66.433	2.243	0.866	0.6170	0.2496	0.944935
8	66.333	1.796	0.8	0.8337	0.0337	0.992185
9	66.633	2.823	1	0.3359	0.6640	0.865773
MAX	66.633	3.516			0.8566	
MIN	65.133	1.453			0	

Perhaps the most valuable contribution of this study is the identification of a single parameter combination that simultaneously achieves both desirable properties using Grey Relational Analysis.

The GRA results (Table 25) show that Experiment No. 8 ($V=275$, $D=0.75$, $F=0.15$) achieves a GRC of 0.992, making it the optimal practical choice. This combination uses the highest cutting speed to maximize hardness, a medium depth of cut, and the lowest feed rate to minimize roughness.

It is worth noting that Experiment No. 8 does not achieve the absolute best roughness (Experiment 1 is smoother) nor the absolute best hardness (Experiment 9 is harder). However, it achieves an excellent

balance: roughness of 1.796 μm (compared to best of 1.453 μm) and hardness of 66.33 HRC (compared to best of 66.63 HRC). The compromises are minimal while both properties are maintained at high levels.

This balanced optimization is highly valuable for real-world manufacturing, where components typically require both good surface finish and adequate surface strength. The GRA approach provides a systematic, mathematically rigorous method for making such trade-off decisions.

Conclusion

This research successfully employed the Taguchi Method, ANOVA, Regression Analysis, and Grey Relational Analysis to optimize the turning process of low carbon steel. The integration of multiple statistical and optimization techniques provided a robust framework for understanding and improving the machining process. Based on the experimental results and comprehensive analysis, the following conclusions are drawn:

1. the optimal parameter combination for achieving minimum surface roughness ($R_a = 1.453 \mu\text{m}$) is cutting speed of 157 m/min, depth of cut of 0.5 mm, and feed rate of 0.15 mm/rev (Experiment 1). This represents the smoothest surface finish achieved in the study and serves as a benchmark for applications where surface aesthetics or friction reduction are paramount.
2. the optimal parameter combination for achieving maximum surface hardness ($\text{HRC} = 66.63$) is cutting speed of 275 m/min, depth of cut of 0.75 mm, and feed rate of 0.15 mm/rev (Experiment. This configuration maximizes the work hardening effect and is recommended for applications where wear resistance is critical.
3. feed rate (F) is the most influential factor affecting surface roughness, with a Delta value of 4.635 and a rank of 1. After pooling analysis, its effect was confirmed to be statistically significant ($P = 0.036 < 0.05$). This finding has important practical implications: controlling feed rate is the most effective way to manage surface finish quality.
4. cutting speed (V) is the most influential factor affecting surface hardness, with a Delta value of 0.108 and a rank of 1. The regression model showed a positive coefficient (0.00703) with statistical significance ($P = 0.033$), confirming that higher speeds produce harder surfaces.
5. Grey Relational Analysis identified Experiment No. 8 as the optimal multi-objective parameter combination, achieving a Grey Relational Coefficient of 0.992. This combination ($V=275 \text{ m/min}$, $D=0.75 \text{ mm}$,

F=0.15 mm/rev) provides the best overall balance between surface hardness and surface finish quality.

6. the Taguchi L9 orthogonal array successfully reduced the experimental effort by 67% compared to a full factorial design (9 experiments versus 27). This demonstrates the efficiency of the Taguchi method for industrial optimization studies where resources are limited.
7. the developed regression models provide valuable predictive capability for industrial applications. The surface roughness model ($R_a = -1.615 + 0.00041V + 1.687D + 13.10F$) achieved an R^2 value of 83.17%. The surface hardness model ($HR = 65.166 + 0.00703V - 0.178D - 2.22F$) achieved an R^2 value of 64.79%.
8. the methodology developed in this study provides a cost-effective framework that is particularly suitable for small and medium enterprises (SMEs) with limited access to advanced computational tools or extensive experimental facilities. The entire optimization was accomplished using commercially available Minitab software and standard Excel spreadsheets.

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