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Optimization of Multiple Performance Characteristics for CNC Turning of Inconel 718 Using Taguchi–Grey Relational Approach and Analysis of Variance

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Abstract: The optimization of machining processes is a deciding factor when increasing productivity and ensuring product quality. The response characteristics, such as surface roughness, material removal rate, tool wear, and cutting time, of the finish turning process have been simultaneously optimized. We used the Taguchi-based design of experiments L9(3^4) in this study to test and find the best values for process parameters like cutting speed, feed rate, depth of cut, and nose radius. The Taguchi-based multi-objective grey relational approach (GRA) method was used to address the turning problem of Inconel 718 alloy to increase productivity, i.e., by simultaneously minimizing surface roughness, tool wear, and machining time. GRA and the S/N ratio derived from the Taguchi approach were utilized to combine many response characteristics into a single response. The grey relational grade (GRG) produces results such as estimations of the optimal level of input parameters and their proportional significance to specific quality characteristics. By employing ANOVA, the significance of parameters with respect to individual responsibility and the overall quality characteristics of the cutting process were ascertained. The single-objective optimization yielded the following results: minimal surface roughness of 0.167 µm, tool wear of 44.65 µm, minimum cutting time of 19.72 s, and maximum material speed of 4550 mm^3/min. While simultaneously optimizing the Inconel 718 superalloy at a cutting speed of 100 m/min, depth of cut of 0.4 mm, feed rate of 0.051 mm/rev, and tool nose radius of 0.4 mm, the results of the multi-objective optimization showed that all investigated response characteristics reached their optimal values (minimum/maximum). To validate the results, confirmatory experiments with the most favorable outcomes were conducted and yielded a high degree of concurrence.

Keywords: single; multi; optimization; Taguchi; GRA; prediction

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1. Introduction

The high-strength material Inconel 718 is a member of the class of nickel-based heat-resistant alloys. Its great strength and creep resistance at high temperatures, among other mechanical and physical attributes, make it a popular material in the aircraft industry for parts that are used in the hot region of turbine engines [1]. Inconel 718 is regarded as a difficult-to-machine material as it exhibits low heat conductivity as well as the capacity to be strain-hardened [2]. It can be difficult to achieve the necessary dimensional precision and surface finishing when machining this alloy. When turning, suitable cutting parameters and specialized tools can be used to affect the precision and roughness of the measured dimensions [3]. The geometry of the cutting edge, the feed rate, the cutting speed, and the depth of cut all have a significant impact on performance measures like surface roughness, cutting force, tool wear, and residual stress on the machined surfaces of Inconel 718 alloy [4]. Prior research has documented that an increased nose radius has a favorable impact on

surface roughness [5,6]. Thus, in their study of the machining of Inconel 718 [5], found that with an increase in tool nose radius, the tool–workpiece friction increased. Therefore, the cutting temperature increased due to friction and resulted in thermal softening on the machined surface, which reduced the degree of work hardening on the machined surfaces of Inconel 718 alloy [4].

The importance of these parameters is considerable in industries such as automotive, aerospace, and machine and mold manufacturing as they serve as a critical indicator of surface stability throughout the assembly process [7]. To remain competitive with mass production, industries desire a material removal rate (MRR) that is high enough to ensure that product quality is not compromised within a short time. Quality cutting tools with a high resistance to wear (VB) are, therefore, required to facilitate a shorter machining time and a prolonged tool life of the cutting tool [8]. Scientific techniques based on Taguchi have been developed to optimize a single performance feature to reduce these machining issues; multiple performance optimization is not applicable for these techniques [9]. The methodology generates optimal operating conditions for each response variable when multiple response variables are associated with the same conditions as independent variables; however, these conditions may vary among one another [10]. Consequently, an enhancement in one performance attribute could potentially result in a decline in another performance attribute.

Therefore, the process of optimizing multiple performance characteristics is inherently more complex than optimizing a single characteristic [11,12]. The interrelation among multiple factors in a complex process like machining is often ambiguous. Grey systems are frequently used to refer to those that provide inaccurate, insufficient, and ambiguous data [13]. To address this type of issue, grey relational analysis (GRA) is an essential technique. Deng [14] introduced the utilization of GRA in addressing engineering challenges by demonstrating its efficacy in managing information that is inadequate, insufficient, and ambiguous. GRA is used to effectively resolve the intricate interrelationships between numerous performance characteristics.

The following were the primary goals of the current study:

- Determining the minimum or maximum required values of individual characteristics such as surface roughness, tool wear, cutting time, and material removal rate using a single-objective function, which involved setting the best possible combinations of levels of process control parameters for the Inconel 718 superalloy during finished turning in a CNC machine.
- Determining the optimal combination of control factor levels to evaluate the performance of the characteristics in a scenario where both (minimum and maximum) are simultaneously considered for optimization.
- Identifying the most important machining parameters and the impact of each process parameter on the machining process's performance attributes.

The structure of this paper is illustrated in Figure 1, which shows the process flow diagram and experimental setup used to carry out the investigation.

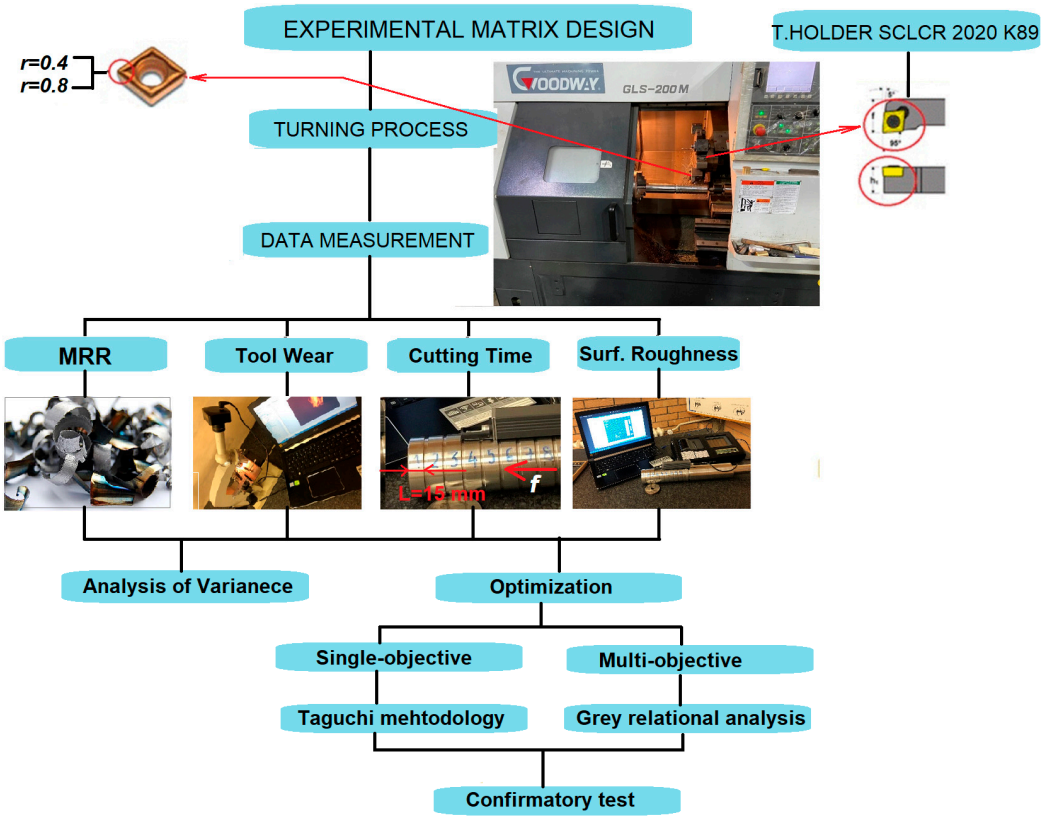


Figure 1. Process flowchart used to conduct the research.

2. Experimental Methodology

2.1. Machining Conditions

Machine tool: The trials were carried out under dry cutting conditions using a CNC lathe machine (Goodway, Type GLS-200 M) with a spindle power of 7.5 kW and a maximum spindle speed of 4000 rpm.

Workpiece material: A molded round bar with a test specimen length of 500 mm and a diameter of 63.5 mm, hardened to 411 HBW after heat treatment, was utilized as the workpiece material for the cutting and turning tests. The hardened Inconel 718 alloy was produced in the UK and it complied with EN 10204-3.1/ISO 9001/EN/AS/JISQ 9100. Special Metals Wiggin Limited certified the material; its inspection certificate number is 433803 v1, dated 28 August 2020. Table 1 lists its chemical composition and Table 2 lists mechanical properties. To conduct a set of nine trials using Taguchi's method, the sample was divided into nine equal areas of 15 mm length, each separated by a slit 4 mm wide and 2 mm deep.

Table 1. Chemical composition of Inconel 718.

C	Si	Mn	Al	Co	Cr	Fe	Mo	Nb	Ni	Ti	Se
0.03	0.06	0.07	0.49	0.25	19.3	17.3	3.3	5.28	52.9	0.96	≤3

Table 2. Mechanical properties of Inconel 718.

Tensile Strength (Mpa)	Yield Strength (Mpa)	Young's Modulus (Mpa)	Density (Kg/m^3)	Melting Point (°C)	Hardness (HBW)	Hardness after Heat Treatment (HBW)	Thermal Conductivity (W/Mk)
1197	1248	205 × 103	819	1290	245	411	11.20

Carbide tool inserts as per ISO specification CCMT09T308N-SU (Sumitomo, grade AC5005S, and coated using a PVD ultra multi-layer thin-layer AlTiSiN process) were used for the finish turning tests of the Inconel 718 alloy.

Surface roughness measurement: A Mitutoyo 2D SJ-310 surface roughness tester was used to calculate the arithmetic mean of the profile deviation (Ra) of the machined surface in accordance with EN-ISO 4287-1998 requirements. The measurement parameters used for the measurement were evaluation length (12.5 mm), cut-off length (0.8 mm), sampling length (4 mm), and driving speed (0.5 mm/s). All roughness values were measured three times and only average values were calculated to minimize experimental errors. For more information, the theoretical expression below defines the relationship between the surface roughness and the nose radius [15]:

$$\mathrm{Ra} = \frac{\mathrm{f}^2}{32\mathrm{r}} \tag{1}$$

where Ra is the average surface roughness, mm; f is the feed rate, mm/rev; and r is the nose radius, mm.

The positive impact of a greater snout radius on the Ra (mm) is highlighted in Equation (1).

Tool wear measured process: After the experimental test was finished, the flank wear (VB) of the cutting tool insert was measured using a Carl Zeiss optical microscope with 15 × 8 magnification. An AmScope MU1403B digital camera equipped with Windows software (XP/Vista/7/8/10 (32 × 64 bit), Mac OS, Linux.) was mounted on the microscope. Flank wear measurements were obtained based on (ISO 3685,1993), which specifies a maximum flank wear width of 0.38 mm for finishing turning.

Calculation of the material removal rate: The quantity of material removed per unit of time during the turning process is known as the material removal rate and it is expressed in mm^3 per minute. The material removal rate, which can be computed using expression (2), is most frequently utilized as a criterion to maximize the production rate during the turning process [16].

$$\mathrm{MRR} = \mathrm{v} \times \mathrm{f} \times \mathrm{d} \times 1000 \tag{2}$$

where v is the cutting speed (m/min), f is the feed rate (mm/rev), and d is the depth of cut (mm).

Calculation of machining time: The formula to process time is expressed according to Equation (3) [17]:

$$\mathrm{T} = \frac{\mathrm{L}}{(\mathrm{n} \times \mathrm{f})} \tag{3}$$

where L is the cutting length (mm), f is the feed speed (mm per rotation), and n is the number of rotations (rpm).

2.2. Control Factor Selection and Levels

Despite copious studies on process optimization problems, there is no universal input–output and in-process parameter relationship model that is applicable to all kinds of metal cutting processes [18].

As the guidelines for the selection of the control input parameter ranges, which are based on the recommendations of the tool maker and data in the database, are not always adequate, extensive preliminary testing was conducted on the workpiece material and cutting tool inserts utilized in this study to define the limit values and the level of machining parameters, as shown in Table 3.

2.3. Selection of Response Variables

Surface roughness (Ra), material removal rate (MRR), cutting time (CT), and tool wear (VB) were the four response variables that were monitored. The goals were to minimize surface roughness, tool wear, and cutting time and to maximize the material removal rate.

Table 3. Machining parameters and their levels.

Cutting Parameters	Notation	Unit	Levels		
			1	2	3
Cutting speed	S	m/min	60	80	100
Feed rate	F	mm/rev	0.051	0.071	0.091
Depth of cut	D	mm	0.2	0.3	0.4
Nose radius	R	mm	0.4	0.8	0.4

3. Results and Discussion

The experimental testing was performed using a GOODWAY CNC lathe in compliance with the DOF analysis and using the input parameters chosen in Table 3. The 3D design of the workpiece model was created using SolidWorks CAD software (https://www.solidworks.com/). The cutting path for the tests was then found using AZ-CAM software (https://azcam.readthedocs.io/en/latest/). The tests were based on nine different trials or Taguchi's experimental design L9(3^4) with a standard orthogonal array. The workpiece that was produced following the machining process was checked for the material removal rate, tool flank wear, surface finish parameter, and cutting time, as indicated in Table 4.

Table 4. Coded experimental and natural matrix layout using an L9 orthogonal array for R_a and MRR.

Exp. No.	Coded Matrix				Natural Matrix				Responses			
	Abbreviation				S	F	D	R	Ra	VB	MRR	CT
	Unit				m/min	mm/rpm	mm	mm	µm	µm	mm^3/min	s
1	1	1	1	1	60	0.051	0.2	04	0.198	61	306	58.64
2	1	2	2	2	60	0.071	0.3	0.8	0.225	65	1278	42.12
3	1	3	3	3	60	0.092	0.4	0.4	0.237	67	2730	32.87
4	2	1	2	3	80	0.051	0.3	0.4	0.198	90	1224	43.98
5	2	2	3	1	80	0.071	0.4	0.4	0.221	98	2840	31.59
6	2	3	1	2	80	0.092	0.2	0.8	0.179	63	728	24.65
7	3	1	3	2	100	0.051	0.4	0.8	0.211	111	2550	35.19
8	3	2	1	3	100	0.071	0.2	0.4	0.175	113	710	25.27
9	3	3	2	1	100	0.092	0.3	0.4	0.195	108	2730	19.72

3.1. Taguchi-Based Single-Objective Optimization

The Taguchi method is a relatively new and extensively implemented engineering design optimization technique that rapidly reduces the costs of existing processes and products while concurrently enhancing their quality, with minimal development man-hours and engineering resources. The Taguchi method accomplishes this by rendering variations in factors such as materials, manufacturing equipment, workmanship, and operating conditions "insensitive" to the performance of the product or process. As the Taguchi method ensures the robustness of a process or product, it is also referred to as robust design [19].

Single-objective optimization (SOO) is a powerful method used to achieve the "best" solution by maximizing or minimizing a single objective [20]. Depending on the objective of the experiment, the individual response characteristics are optimized based on the signal-to-noise (S/N) ratios using the following technique [21]:

"Larger-the-better", to maximize the positive characteristics:

$$S/N = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \quad (4)$$

"Smaller-the-better", to minimize the non-negative with a target value of zero:

$$S/N = -10\log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \quad (5)$$

where n is the number of repetitions of the experiment, y_i is the response of the process.

In the present study case, we had conflicting objective functions of individual responses, i.e., maximization for material removal rate and minimization for surface roughness, tool wear, and cutting time.

3.2. Parametric Influence on Machining Characteristics

An estimation of the impact of individual input variable values on the characteristics of machining responses was performed utilizing Equations (4) and (5) of the Taguchi technique. The resulting values are displayed in Tables 5–8. Figure 2a–d illustrate the results of Taguchi's approach for the machining characteristics Ra, VB, MRR, and CT.

Table 5. Response table for Ra.

Factors	**Mean of Means**				**Mean of S/N Ratio**			
Level	S	F	D	R	S	F	D	R
1	0.2133	0.1980 *	0.1780 *	0.2023	13.46	14.07 *	15.00 *	13.92
2	0.1967	0.2037	0.2027	0.1980 *	14.17	13.87	13.87	14.11 *
3	0.1927 *	0.2010	0.2220		14.33 *	14.01	13.09	
Delta	0.0207	0.0057	0.0440	0.0043	0.87	0.21	1.91	0.19
Rank	2	3	1	4	2	3	1	4

* Indicates significant term.

Table 6. Response table for VB.

Factors	**Mean of Means**				**Mean of S/N Ratio**			
Level	S	F	D	R	S	F	D	R
1	64.33 *	87.33	79.00 *	89.50	−36.16 *	−38.57	−37.58 *	−38.81
2	83.67	92.00	87.67	79.67 *	−38.30	−39.05	−38.67	−37.72 *
3	110.67	79.33 *	92.00		−40.88	−37.73 *	−39.08	
Delta	46.33	12.67	13.00	9.83	4.72	1.32	1.50	1.09
Rank	1	3	2	4	1	3	2	4

* Indicates significant term.

Table 7. Response table for MRR.

Factors	**Mean of Means**				**Mean of S/N Ratio**			
Level	S	F	D	R	S	F	D	R
1	1438.0	1360.0	581.3	-	60.19	59.87	54.66	62.50
2	1597.3	1609.3	1744.0	-	62.69	62.74	64.20	62.50
3	1996.7 *	2062.7 *	2706.7 *		64.63 *	64.90 *	68.64 *	
Delta	558.7	702.7	2125.3	-	4.44	5.03	13.98	0.00
Rank	3	2	1	4	3	2	1	4

* Indicates significant term.

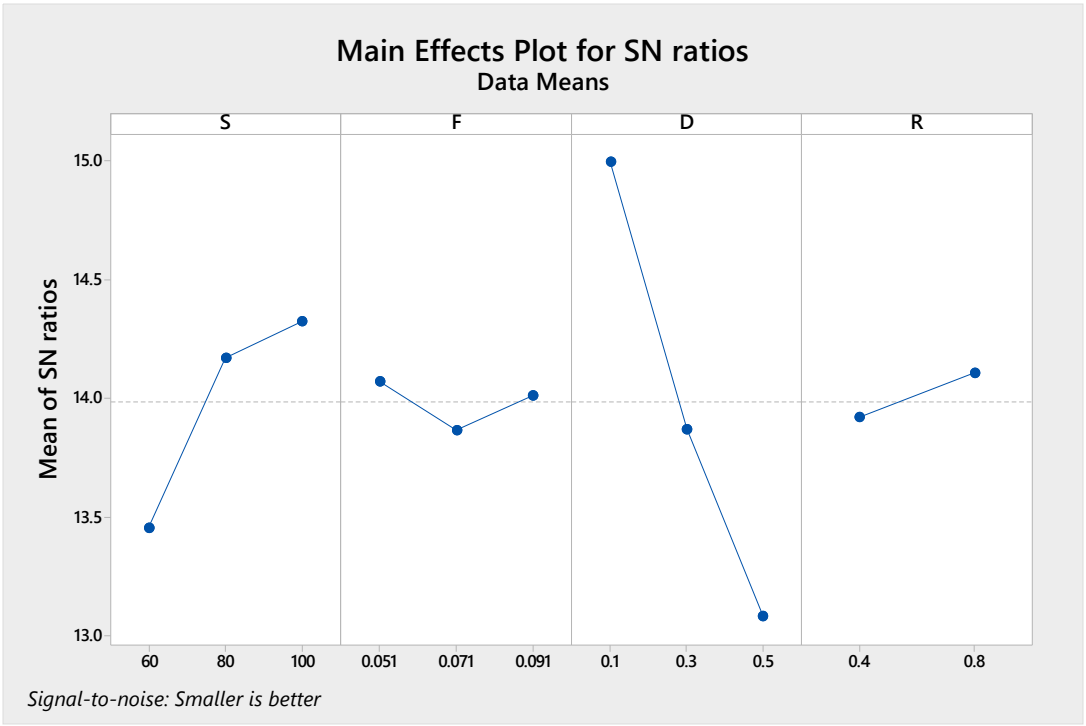
Table 8. Response table for CT.

Factors	**Mean of Means**				**Mean of S/N Ratio**			
Level	S	F	D	R	S	F	D	R
1	44.54	45.94	-	-	−32.73	−33.05	−30.42	−30.42
2	33.41	32.99	-	-	−30.23	−30.18	−30.42	−30.42
3	26.73 *	25.75 *	-		−28.29 *	−28.02 *	−30.42	
Delta	17.82	20.19	-	-	4.44	5.03	0.00	0.00
Rank	2	1	3	4	2	1	3	4

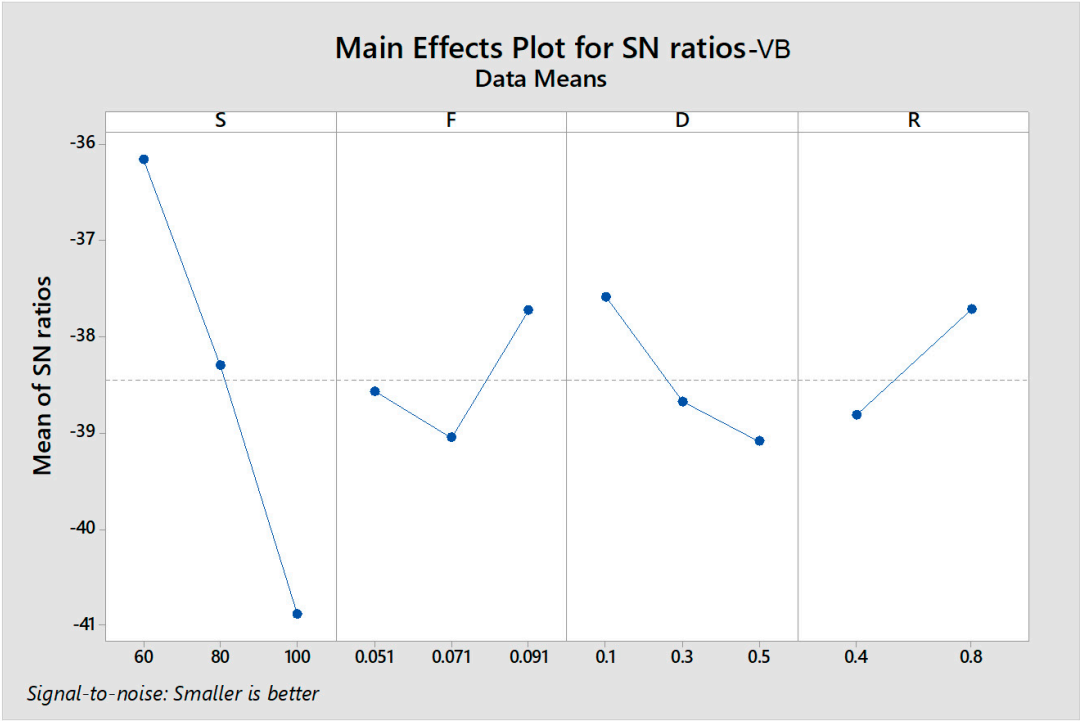
* Indicates significant term.

Figure 2a shows that increasing the cutting speed and nose radius improved surface roughness until it deteriorated with an increase in the depth of cut and feed rate up to a certain value; it then improved.

As illustrated in Figure 2b, an increase in cutting speed and depth of cut resulted in an increase in tool arm wear.

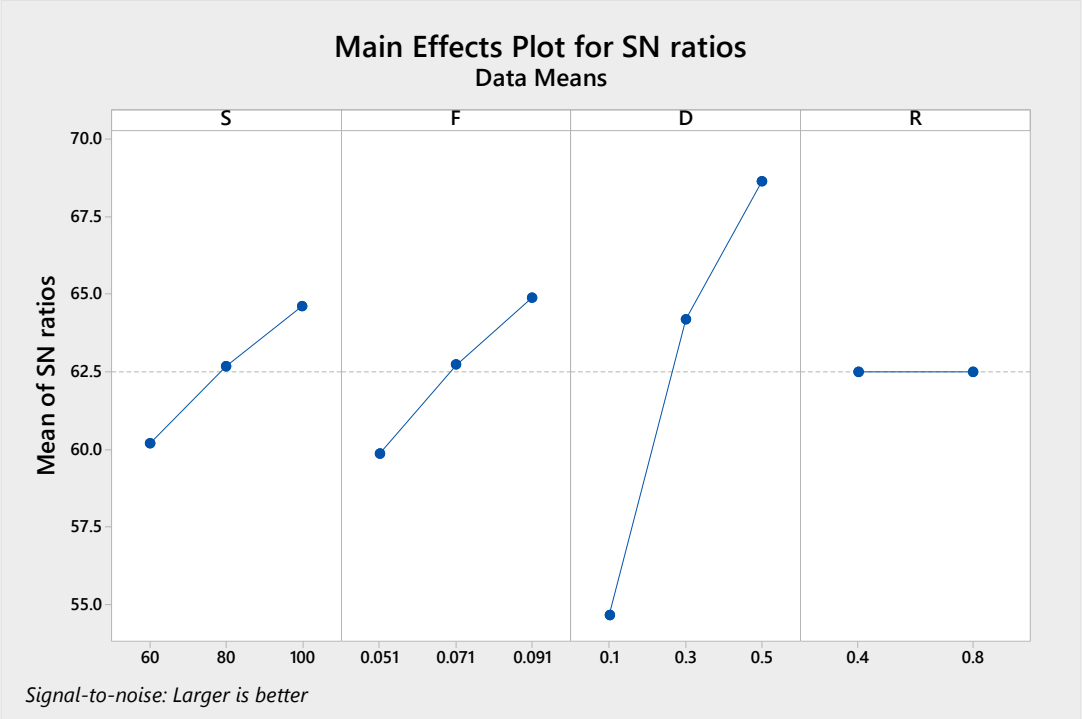


(**a**)

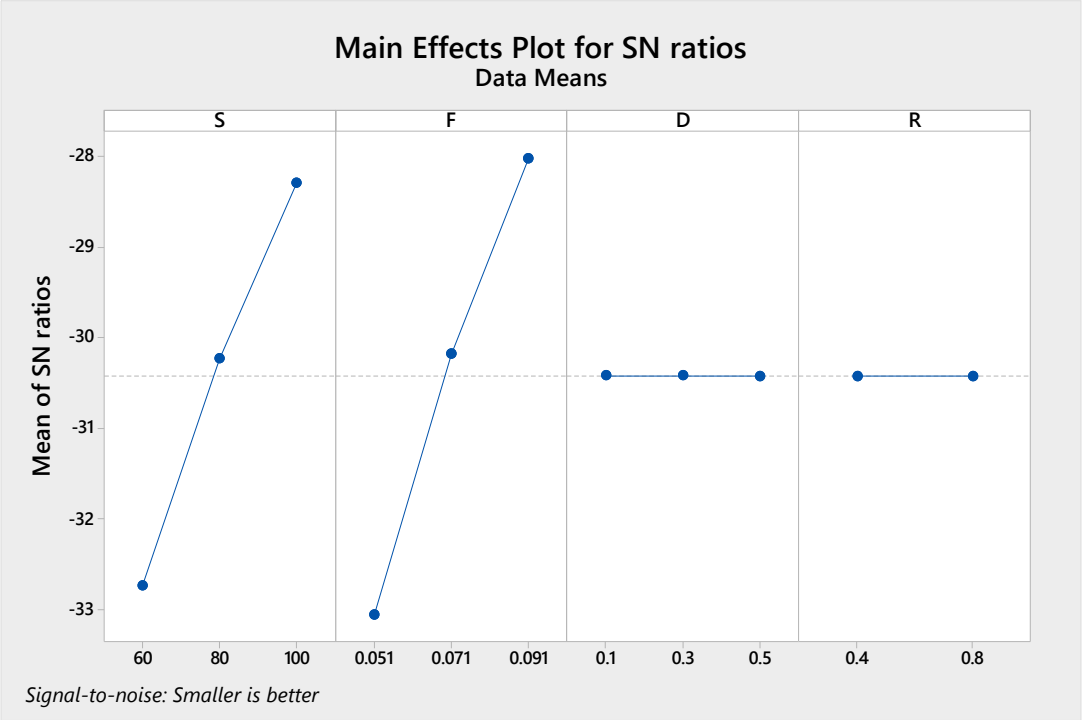


(**b**)

Figure 2. *Cont.*



(**c**)



(**d**)

Figure 2. Main effects plot for S/N ratios: (**a**) surface roughness, (**b**) tool wear, (**c**) material removal rate, and (**d**) cutting time.

Furthermore, it was observed that tool wear decreased as the tool nose radius grew and increased with feed rate up to a certain point before declining.

The material removal rate increased in tandem with each input variable, excluding the tool radius, which remained constant, as shown in Figure 2c.

Figure 2d demonstrates that although the cutting time decreased with an increase in feed rate and cutting speed, it was unaffected by changes in the depth of cut or nose radius.

3.3. Analysis of Variance (ANOVA)

Using ANOVA as a statistical technique, one can ascertain whether the value of an observable feature for an element under investigation has a statistically significant impact on the value of a random variable for that element [22].

Through it, key parameters can be determined to quantify error variances and determine the key process parameters that most affect performance metrics such as surface roughness, tool wear, material removal rate, and cutting time. Using ANOVA, it was possible to estimate the percentage contribution of each control factor to the identified output factors and find the R-squared values that indicated good results [23]. The investigation included both fixed and adjustable R-squared values to assess the suitability of the data.

The ANOVA findings are displayed in Tables 9–12 and were calculated using the statistical program Minitab 18.

Table 9. Analysis of variance for Ra.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value	Contribution (%)
S	2	0.000721	0.000360	60.07	0.091	19.32
F	2	0.000048	0.000024	4.02	0.333	1.29
D	2	0.002918	0.001459	243.19	0.045	78.21
R	1	0.000038	0.000038	6.26	0.242	1.02
Error	1	0.000006	0.000006	-	-	0.16
Total	8	0.003731	-	-	-	100

Table 10. Analysis of variance for VB.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value	Contribution (%)
S	2	3249.56	1624.78	1083.19	0.021	82.19
F	2	246.22	123.11	82.07	0.078	6.23
D	2	262.89	131.44	87.63	0.075	6.65
R	1	193.39	193.39	128.93	0.056	4.89
Error	1	1.50	1.50		-	0.04
Total	8	3953.56	-	-	-	100

Table 11. Analysis of variance for MRR.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value	Contribution (%)
S	2	496,963	248,481	1.39	0.419	5.91
F	2	761,419	380,709	2.13	0.32	9.05
D	2	6,795,563	3,397,781	18.98	0.05	80.78
Error	2	358,112	179,056			4.26
Total	8	8,412,056				100.00

Table 12. Analysis of variance for CT.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value	Contribution (%)
S	2	486.08	243.041	34.98	0.003	42.58
F	2	627.68	313.84	45.17	0.002	54.98
Error	4	27.79	6.948	-	-	2.43
Total	8	1141.55	-	-	-	100

The F-value and *p*-value were used to assess the machining factors' influence. The ANOVA analyses were conducted at a 95% confidence level. At a 95% confidence level, the *p*-value for a significant influence on the chosen response should not be greater than

0.05% [24]. Depth of cut had the highest F-value and the lowest *p*-value in the ANOVA findings, as shown in Table 9, suggesting that it was the most important influencing factor, with a dominant contribution of 78.21%. As indicated in Table 9, the cutting speed was the next most important factor affecting input components, accounting for 19.32% of the Ra, while the nose radius was the least influential. A contribution error of 0.16% was attained, demonstrating that the current data could be used to estimate future results with a low degree of inaccuracy.

Table 10 displays a statistical analysis using ANOVA, which demonstrates that only the cutting speed had a significant influence on VB, with a *p*-value for each variable of less than 0.05 and an 82.19% contribution. A small contribution mistake of 0.04% was discovered, demonstrating that the current data could be used to produce future estimates with low inaccuracy.

An examination of MRR through an analysis of variance (ANOVA) is presented in Table 11. The results indicated that the only depth of cut had a significant impact on MRR, with a *p*-value of 0.05 and an equal of 0.05, accounting for 80.78% of the variance. It was determined that the current data contributed a negligible amount of error (4.26%), suggesting that they may be utilized to generate estimations in the future with minimal error.

An examination of CT through an analysis of variance (ANOVA) is presented in Table 12. The results indicated that the input variables of cutting speed and feed rate, with *p*-values of 0.03 and 0.02, respectively, were both less than 0.05. Furthermore, with respective contributions of 42.58% and 54.98%, these variables had a significant impact on the cutting time. It was determined that the current data contributed a negligible amount of error (2.43%), suggesting that they may be utilized to generate estimations in the future with minimal error.

3.4. Determining the Optimal Levels

As shown in Figure 2a–d, obtaining optimal levels involves computing the average values of the S/N ratios for each response characteristic at each level. By selecting the highest S/N ratio for each cutting condition, the optimal levels of machining conditions with the lowest surface roughness, tool wear, and cutting time as well as the highest material removal rate values could be determined. As Figure 2a–d show, S3F1D1R2 for Ra, S1F3D1R2 for VB, S3F3D3 for MRR, and S3F3 for CT were the optimal parameter combinations for a single-response characteristic. Table 13 displays the appropriate predictive optimal values for these parameters and the contour plots in Figures 3–6 show their optimal zones. The optimal areas for Ra, VB, and CT are dark blue, while the dark green area represents the optimal area for MRR.

Based on this analysis, different optimal combinations were determined for individual characteristic responses (Ra, VB, MRR, and CT). Therefore, the presence of more than one single-response characteristic necessitated the optimization of the entire system with diverse and competing goals via a suitable multi-objective technique, which was far more involved than that for a single-quality characteristic [25].

To determine the best combination of input components for all machining characteristics with various and competing aims, an appropriate multi-objective optimization was required, as Section 3.5 illustrates.

Table 13. The predicted and confirmed values at single optimal setting.

Machining Characteristic	Optimal Parameter Combination	Optimal Predicted Values	Experimental Values	Prediction Error (%)
Surface roughness, µm	S3F1D1R2	0.169	0.167	1.18
Tool wear, µm	S1F3D1R2	43.67	44.65	2.24
Cutting time, s	S3F3	19.72	19.72	0
Material removal rate, mm^3/min	S3F3D3	4550	4550	0

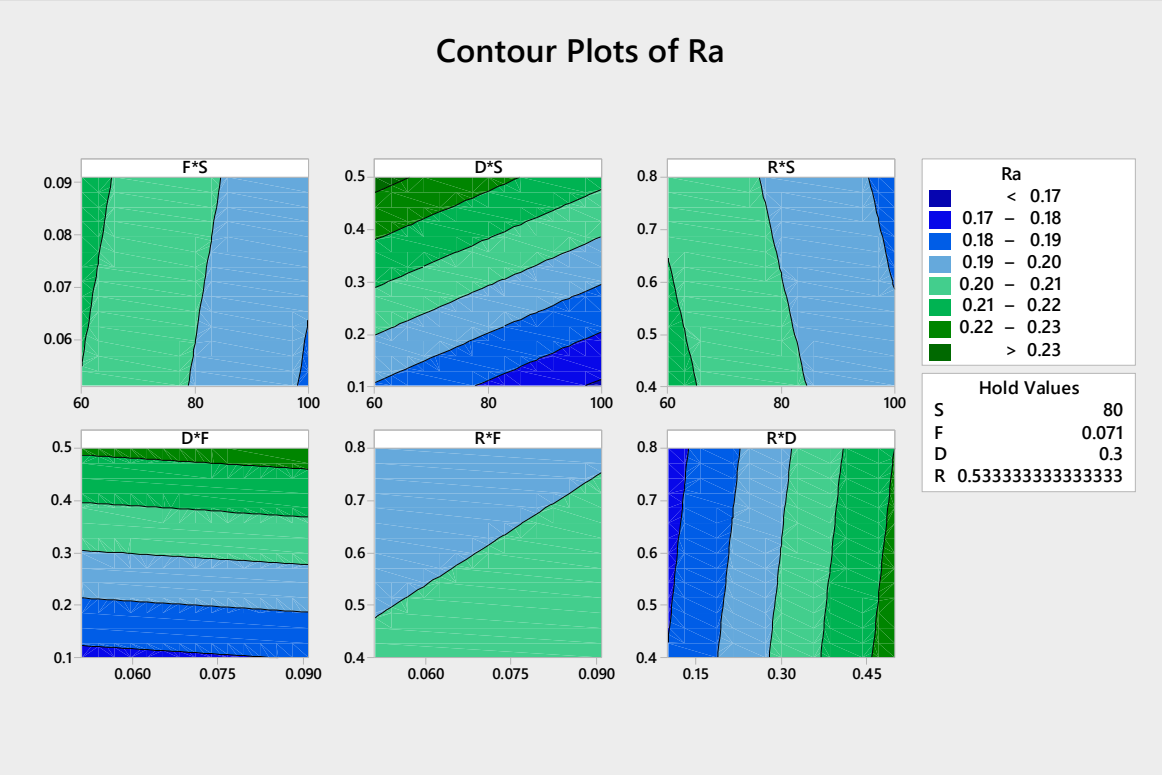


Figure 3. Contour plots for surface roughness.

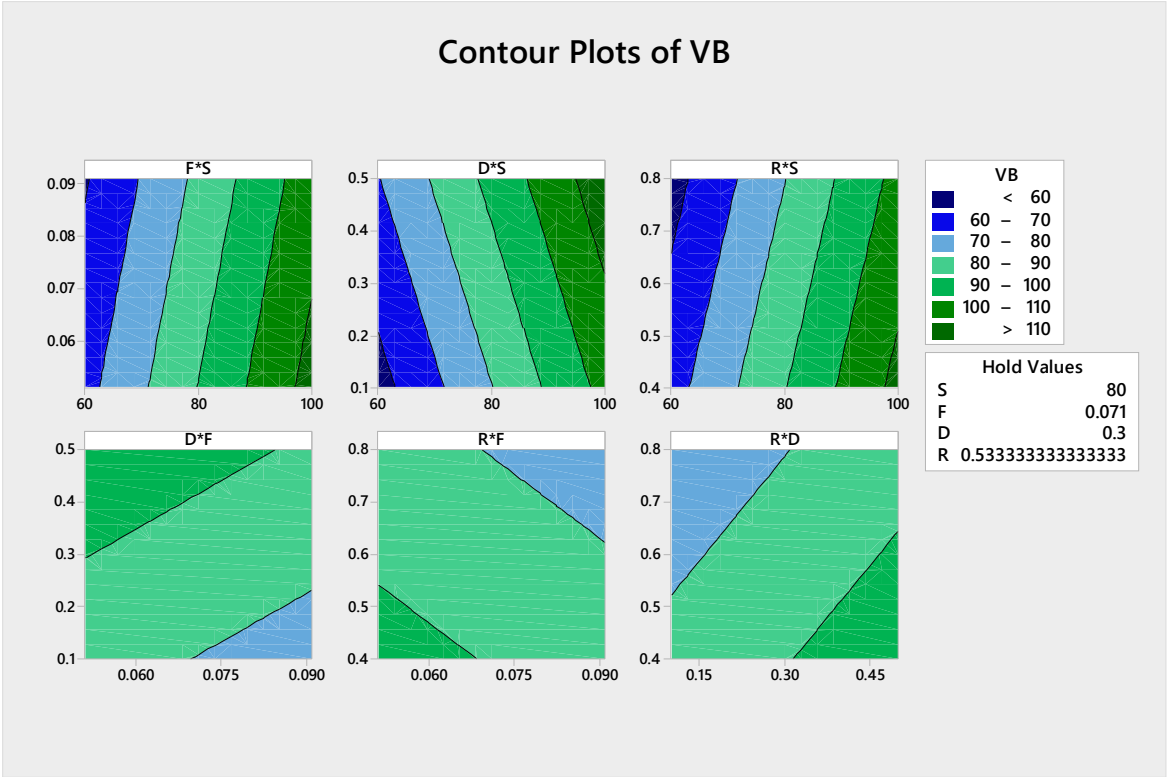


Figure 4. Contour plots for tool wear.

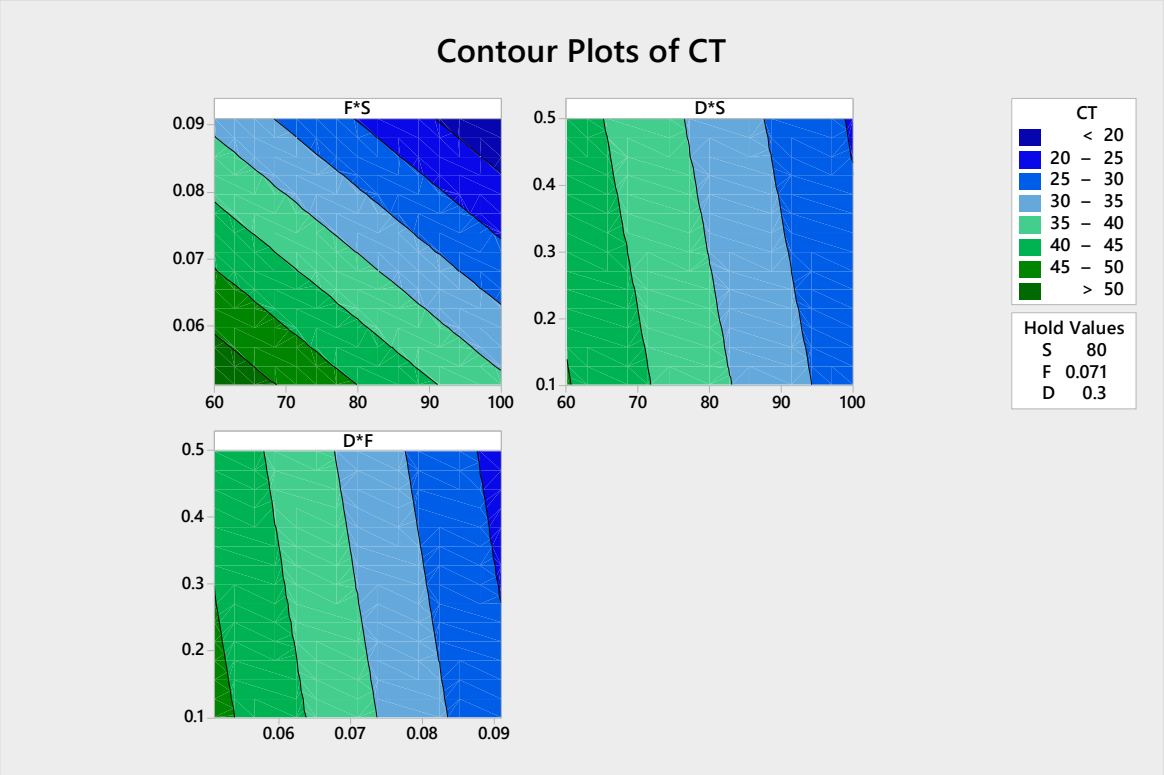


Figure 5. Contour plots for cutting time.

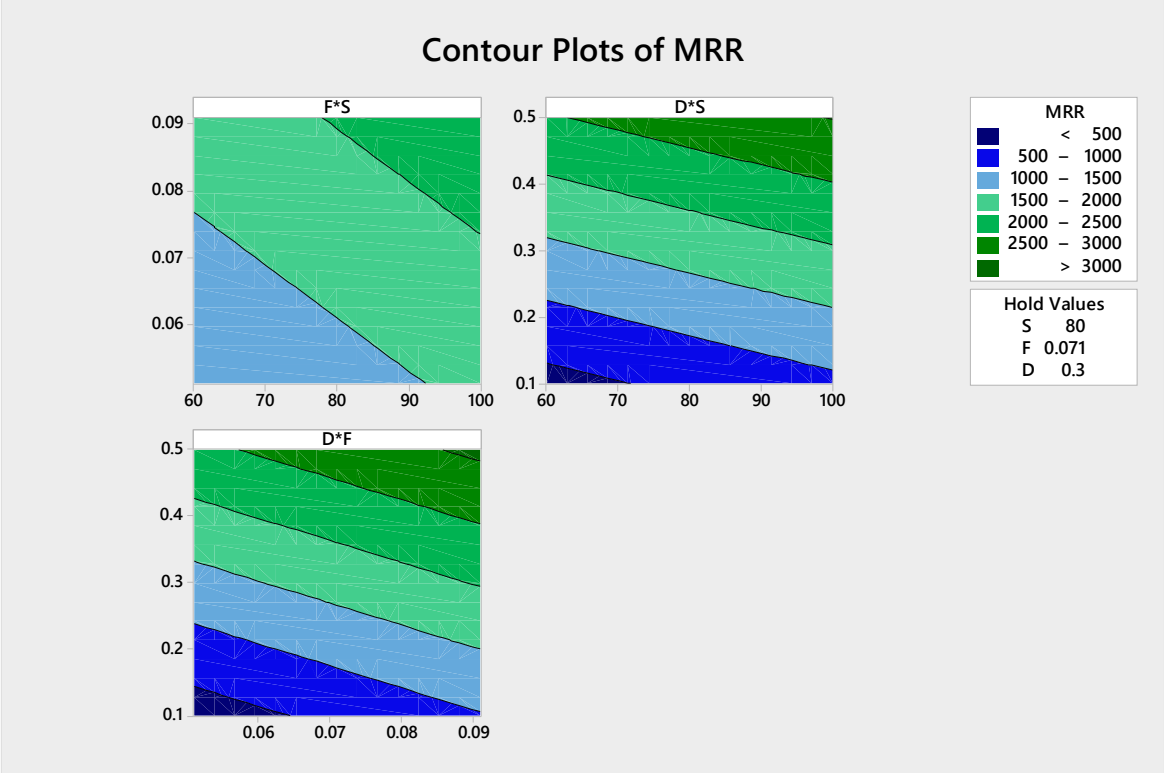


Figure 6. Contour plots for material removal rate.

3.5. Multi-Objective Optimization Techniques

Products with single-quality characteristics are the subject of the Taguchi technique, which uses a variety of tests to determine the optimal setting for controllable parame-

ters [26]. However, most of the products include various quality aspects that are of interest. A single setting of a process parameter choice may be optimal for one reaction, but it may be deleterious for other responses. It is vital to consider the application of multi-response optimization while solving various problems in the field of engineering because the performance or quality of products is frequently evaluated by numerous quality characteristics or responses [27]. This study used the grey function approach to optimize multiple responses, considering that four response characteristics were to be simultaneously optimized: Ra, MRR, VB, and CT. Afterwards, the multi-response characteristics were combined into a single response using grey relational analysis, and the signal-to-noise ratio (S/N) was determined using the Taguchi approach [28]. The results of using the Taguchi method on the grey relational grade [29] included predictions of the best level of input parameters and how important each one was for different quality attributes.

3.6. Normalization of S/N Ratio

The initial stage of a grey relational analysis is called grey relational generation, where the experimental data are normalized in the interval of 0 to 1. As the measured amount x_i (k) of various parameters may not have the same units and, hence, cannot be compared, it becomes a requirement to convert these measurements into normalized values, which are of the dimensionless type [30]. Different preprocessing approaches can be used in grey approach analysis depending on the features of the original sequence x_i (k), which converts the original series into a suitable series. To normalize each series, the data in the original series is usually split by its average. Equation (6) demonstrates the "smaller-the-better" criterion, which states that factors with a lower value than the original data produce characteristics of higher quality. In this study, these characteristics corresponded with surface roughness (Ra), tool flank wear (VB), and cutting time (CT).

$$x_i(k) = (\max x_i(k) - x_i(k)) / (\max x_i(k) - \min x_i(k)) \quad (6)$$

The "larger-the-better" criterion, as shown in Equation (7) for the material removal rate (MRR) characteristic, on the other hand, implies that the factor whose value is higher than the original data leads to better characteristics.

$$x_i(k) = (x_i(k) - \min x_i(k)) / (\max x_i(k) - \min x_i(k)) \quad (7)$$

where i = 1, 2, 3, . . ., and m.

Here, m is the number of experimental runs in the Taguchi orthogonal array. In the current work, the L9 (3^4) orthogonal array was chosen, so m = 9, k = 1, 2. . .n. Thus, n is the number of quality characteristics or process responses. In the current work, surface roughness Ra, VB, CT, and MRR were chosen, so n = 4.

The data after the grey relational generation is represented by $x_i(k)$ and the maximum and minimum values of the original sequence factor for the k-th response are represented by maxi(k) and mini(k), respectively. Table 14 displays the normalized and deviation sequence data.

Table 14. Normalized values and deviation sequences of machinability characteristics.

Exp. No	S/N Ratio				Normalized Values				Deviation Sequences			
	Ra	VB	CT	MRR	Ra	VB	CT	MRR	Ra	VB	CT	MRR
1	15.060	−35.707	−35.364	63.046	0.407	0.000	1.000	0.000	0.593	1.000	0.000	1.000
2	13.660	−36.258	−32.490	65.296	0.829	0.103	0.696	0.642	0.171	0.897	0.304	0.358
3	12.439	−36.902	−30.336	67.959	1.000	0.152	0.469	0.982	0.000	0.848	0.531	0.018
4	14.494	−39.085	−32.865	64.629	0.407	0.631	0.736	0.622	0.593	0.369	0.264	0.378
5	13.159	−39.825	−29.991	66.880	0.770	0.769	0.432	1.000	0.230	0.231	0.568	0.000
6	14.457	−40.906	−27.836	69.542	0.075	0.052	0.205	0.389	0.925	0.948	0.795	0.611
7	13.351	−41.727	−30.928	65.968	0.617	0.971	0.531	0.952	0.383	0.029	0.469	0.048
8	15.376	−42.345	−28.052	68.219	0.000	1.000	0.228	0.378	1.000	0.000	0.772	0.622
9	13.906	−41.938	−25.898	70.881	0.357	0.927	0.000	0.982	0.643	0.073	1.000	0.018

3.7. Determination of Deviation Sequence ($\Delta_{0i}(k)$)

According to [31], the deviation sequence $\Delta_{0i}(k)$ represents the absolute difference between the comparability sequence $x_i(k)$ and the reference sequence $x_0(k)$ following normalization. Equation (8) is used to compute it, as follows:

$$\Delta_{0i}(k) = |x_0(k) - x_i(k)| \quad (8)$$

3.8. Grey Relational Coefficient (GRC) Determination

Using a discriminating coefficient between 0 and 1, the grey relational coefficient (GRC) in Equation (9) can be calculated to find the sequence with the lowest deviation. The discriminating coefficient is typically 0.5. For every sequence, GRC establishes the link between the actual normalized S/N ratio and the ideal (optimal). If two sequences agree at every place, their GRC is "1" [32].

$$\xi_i(k) = (\Delta_{min} + \xi \cdot \Delta_{max}) / (\Delta_{oi}(k) + \xi \cdot \Delta_{max}) \quad (9)$$

where ξ is the differentiating coefficient (0.5), ξi(k) is the grey relational coefficient, Δmax is the highest deviation sequence, and Δmin is the lowest deviation sequence.

The computed grey relationship coefficients for Ra, MRR, VB, and CT are shown in Table 15.

Table 15. Grey relational coefficients (GRCs) and GRG.

Exp. No	GRC				GRG	Rank
	Ra	VB	CT	MRR		
1	0.458	0.333	1.000	0.333	0.520	8
2	0.745	0.358	0.622	0.582	0.547	6
3	1.000	0.371	0.485	0.966	0.705	3
4	0.458	0.575	0.654	0.570	0.569	5
5	0.684	0.684	0.468	1.000	0.713	2
6	0.351	0.000	0.386	0.450	0.292	9
7	0.566	0.945	0.516	0.912	0.732	1
8	0.333	1.000	0.393	0.446	0.547	7
9	0.437	0.872	0.333	0.966	0.657	4

3.9. Grey Relational Grade and Rank Determination

Many performance criteria are evaluated using the grey relational grade (GRG). The overall qualities are better the higher the grey relationship grade (i.e., the best compromise between competing quality traits). The computation of the grey relational grade, which serves as the foundation for the comprehensive assessment of multiple performance features, is the next stage of the grey relational analysis. Researchers typically use a weight to subjectively emphasize or de-emphasize a goal that lacks a sound mathematical foundation or they use an equal weight to decide the grey relational grade of numerous responses [33]. Assuming equal effects from the performance variables Ra, MRR, VB, and CT in this case study, each feature had an equal relative weight or relevance. According to [34], the grey relational grade was computed using Equation (10), as follows:

$$\gamma_i = \frac{1}{m} \sum_{k=1}^{n} \omega_k \cdot \xi_i(k) \quad (10)$$

where $\sum_{k=1}^{n} \omega_k = 1$; ω_k is the normalized weight factor for each response characteristic (i = 1, 2, 3, … 9), which is the chosen L9 orthogonal array for the *i*-th experiment; *m* is the total number of replies; and ζi(k) is the grey relational coefficient of the *k*-th response characteristic.

The ideal level of process parameters is the one with the highest grade of grey relation. The association between the reference sequence $x_0(k)$ and the supplied sequence $x_i(k)$

is more intense the higher the grey relational grade score. The grey relational grade produced by Equation (10) is shown in Table 15. Level 1, the highest relational grey grade (i.e., the ideal compromise between conflicting quality characteristics), implies the best overall quality attributes. Therefore, out of the 9 experiments, experiment 7 (i.e., S3F1D3R1) had the best combination of turning parameters for tool wear, material removal rate, and surface roughness. The multi-objective optimization problem was reduced to a single equivalent objective function optimization problem via a grey relational analysis. The Taguchi technique was utilized to determine the optimal set of process parameters according to the grey relational grade, which was the maximum.

3.10. Determination of Optimal Parameters for GRG

The GRG generated for each sequence was used as a response in the subsequent analysis. The analysis was conducted using the "larger-the-better" quality characteristic, which suggested that the process performed better. Analysis of variance (ANOVA) and analysis of means (AOM) plots were used to examine the resulting GRG. The statistical significance of each individual parameter in a given response was determined using an ANOVA. To determine the average GRG for each factor level, Taguchi method's response, as shown in Table 16, was used.

Table 16. Response table for grey relational grade for "larger-the-better".

Factors	**Mean of Means**			
Level	S	F	D	R
1	0.5909	0.6070 *	0.4531	0.6185 *
2	0.5248	0.6025	0.5909	0.5239
3	0.6453 *	0.5515	0.7169 *	
Delta	0.1206	0.0555	0.2638	0.0946
Rank	2	4	1	3

Total mean value of GRG was 0.584; * indicates significant term.

For every column in the orthogonal array, GRGs were first grouped by factor level and subsequently averaged. The corresponding response grade was calculated as the average sum of these values. The mean response table for the entire GRG is provided in Table 16. The AOM plots for GRG are displayed in Figure 7 as well as Table 17, which provides the corresponding F- and *p*-values of the ANOVA for GRG.



Figure 7. Main effects plot for means of GRG.

Table 17. Analysis of variance for GRG.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value	Contribution (%)
V	2	0.021873	0.010936	13.99	0.186	14.52
F	2	0.005706	0.002853	3.65	0.347	3.79
D	2	0.104428	0.052214	66.80	0.086	69.30
R	1	0.017892	0.017892	22.89	0.131	11.87
Error	1	0.000782	0.000782	-	-	0.52
Total	8	0.150681	-	-	-	100.00

As can be appreciated from Figure 7, the highest average values of the input parameters according to the "larger-the-better" criteria were a cutting speed at level (3), i.e., S3 = 100 m/min; a feed rate at level (1), i.e., F1 = 0.051 mm/rpm; a depth of cut at level (3), i.e., D3 = 0.5 mm; and a tool nose radius at level (1), i.e., R1 = 0.4 mm. These represented the combination that simultaneously provided the optimal values of the response characteristics (surface roughness, material removal rate, tool wear, and cutting time).

3.11. Confirmation Experiment

As soon as the best level of the process parameters (S3F1D3R1) was found, the next step was to predict and confirm that the performance characteristics would improve compared with experiment no. 7 (order ranking 1) and experiment no. 4 (order ranking 4), which was chosen at random, as shown in Table 15. The prediction of the gray relational grade was determined according to [35] using Equation (11) and the given parameters.

A validation of the optimal variable factors with their selected range was performed in order to assess the quality attributes of the Inconel 718 alloys machined utilizing the turning method. The greatest grey relational grade value (0.732) was seen in the seventh experiment run (Table 15), indicating that out of nine trials, the best variable set of S3F1D3R2 had the finest performance attributes.

$$\gamma_p = \gamma_m + \sum_{i=1}^{p} (\gamma_i - \gamma_m) \quad (11)$$

where γ_m is the total mean value of GRG, p is the total number of the primary process factors that had a significant impact on the performance characteristics, and γ_i is the mean of the grey relation grade at the optimal level.

3.12. Analysis of Variance

The same method described in the previous section was used to estimate the ideal values of the machining variables. Based on the results of the ANOVA shown in Table 17, none of the controlled factors had a significant effect on the GRG values below the 95% confidence level ($p \leq 0.05$) [29]. From the ANOVA findings displayed in Table 17, it was shown that depth of cut had the highest F-value and the lowest *p*-value, suggesting that it was the primary variable contributing to the GRG at 69.3%. The second most important input factor was feed rate, which was the least influential. Then came cutting speed and nose radius. A minimal contribution error of 0.52% was attained, indicating that future results could be predicted using the existing data with a low degree of inaccuracy.

Improvement of the overall quality characteristic, grey relation grade, is found to be 0.225 (28.34%) at the optimum levels compared with the initial parameter settings. When compared with the best initial parameter settings, the overall quality features improved by 0.062 (7.81%) at optimum levels as seen in Table 18.

To validate the findings, the outcomes of the original experiment and the confirmation experiment were compared. As seen in Table 13, the developed model's prediction performance was good because the expected error percentage was less than 5%.

Table 18. Confirmation results considering initial and optimal parameters of GRG.

Characteristic	Initial Parameter Setting (Random) (Order No. 4)	Optimal Parameter Setting		
		Initial Best Parameters Taguchi–GRA (Order No. 7)	Predicted Optimal Parameters	
			Prediction	Experiment
Factor levels	S2F1D2R3	S3F1D3R2	S3F1D3R1	S3 F1D3R1
Ra (μm)	0.198	0.208	-	0.182
MRR (mm^3/min)	1224	2550	-	2550
VB (μm)	90	111	-	101
CT (s)	43.98	35.19		
GRG	0.569	0.732	0.794	-
Improvement in GRG	0.225	0.062		

4. Conclusions

In this study, surface roughness, tool wear, material removal rate, and cutting time were optimized in terms of cutting speed, feed rate, depth of cut, and tool nose radius at three levels during the turning of an Inconel 718 superalloy. Optimization was achieved in two steps: first, each response was optimized as a mono-objective using the signal-to-noise-ratio-based Taguchi method; then all replies were optimized as multi-objectives using the grey relation grade-based Taguchi methodology.

The following conclusions were drawn based on the single- and multi-objective optimization results:

The following parameters produced minimal surface roughness of 0.167 μm, according to the single-objective optimization results: 100 m/min cutting speed, 0.091 mm feed rate, 0.2 mm depth of cut, and 0.8 mm nose radius. Although the tool wear minimum of 44.65 μm required a 60 m/min cutting speed, 0.091 mm feed rate, 0.2 mm depth of cut, and 0.8 mm nose radius, a minimal cutting time of 19.72 s was obtained when the cutting speed was 100 m/min, the feed rate was 0.091 mm/rev, and the depth of cut was 0.4 mm. Similarly, a maximum material removal rate of 4550 mm^3/min was produced when a cutting speed of 100 m/min, a feed rate of 0.091 mm/rev, and a depth of cut of 0.4 were combined.

The combination indicated as S3F1D3R1 produced the best values for the turning parameters during the multi-objective optimization, allowing for the desired performance characteristics to be realized.

The results of multi-objective optimization showed that when the Inconel 718 superalloy is turned at a cutting speed of 100 m/min, a feed rate of 0.051 mm/rev, a depth of cut of 0.4 mm, and a tool nose radius of 0.4 mm, all investigated response characteristics reached their optimal values (minimum/maximum) during simultaneous optimization.

Thus, an experimental test was conducted to validate this technique. The grey relational grade, or the overall quality characteristic, was found to improve at ideal values by 0.225—i.e., 22.5%—over the initial parameter settings and by 0.062—i.e., 6.2%—over the best initial parameters.

Based on the ANOVA of the GRG results, it was discovered that the most important factor influencing multiple performance characteristics was depth of cut, which contributed 69.30%, followed by cutting speed (14.52%), nose radius (11.87%), and feed rate (3.79%).

The outcomes derived from this study exhibited a high degree of concordance with the findings of the majority of the cited studies.

The utilization of the adopted single-objective and multi-objective optimization techniques may enable the optimization of distinct responses during the cutting process of various materials and under varying conditions.

In future research, we will compare the results produced using GRA with other optimization techniques (e.g., CFD, artificial neural networks, genetic algorithms, etc.).

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