The Eurasia Proceedings of Science, Technology,
Engineering & Mathematics (EPSTEM)
ISSN: 2602-3199

The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM), 2023

Volume 23, Pages 338-348

ICRETS 2023: International Conference on Research in Engineering, Technology and Science

Single Objective Optimization of Cutting Parameters for Surface Roughness in Turning of Inconel 718 Using Taguchi Approach

Fatlume Zhujani
University of Pristina

Georgi Todorov
Technical University of Sofia

Konstantin Kamberov
Technical University of Sofia

Abstract: The majority of work in cutting machining processes is focused on choosing the parameters that will result in the greatest rate of material removal and the least amount of surface roughness, cutting temperatures, cutting pressures, vibrations, etc., which are the main quality responses. Surface roughness is one of the most precise quality criteria that affects how machined parts work. By choosing the appropriate cutting settings, it should be possible to get a greater surface finish and a longer service life for the machined parts. The link between changes in surface roughness caused by turning operations with respect to different machining settings is investigated in this study using the Taguchi method L9(3^3). The orthogonal array, signal-to-noise ratio, and analysis of variance are utilized to examine the performance characteristics when turning Inconel 718 bars with CCMT09T308N-SU coated cemented carbide insert tools. The optimal setting of cutting parameters to lessen surface roughness is chosen using the Taguchi method. Speed, feed rate, and cut depth are the three cutting parameters. Experimental results are given to illustrate the effectiveness of this strategy.

Keywords: Taguchi, Turning, Inconel 718, S/N ratio.

Introduction

The aerospace and aeronautical engineering sectors predominantly use the heat-resistant nickel-based superalloy Inconel 718. Due to its peculiar mechanical and thermal properties, the material is referred to as being challenging to cut. From the past to the present, research has been done to improve the machinability of nickel-based alloys (Wassila Frifita, 2020).

The surface roughness of machined parts is a crucial product quality characteristic that pertains to the deviation from the nominal surface. The significance of surface roughness is evident in numerous applications, including but not limited to precision fits, fastener holes, aesthetic specifications, and components that are exposed to fatigue loads. The selection of cutting parameters and machine tools during the process development is significantly constrained by surface roughness, as noted in reference (Abhang & Hamedullah, 2010). The act of turning is a fundamental procedure utilized in the majority of industrial production activities. The surface finish of turned components holds significant sway over the overall quality of the final product. The surface finish during turning operations is subject to the influence of several factors, including but not limited to feed rate, work material properties, workpiece hardness, unstable built-up edge, cutting speed, depth of cut, cutting time, tool nose radius, tool cutting edge angles, machine tool and workpiece setup stability, chatter, and use of cutting fluids (Palanikumar, 2006).

The evaluation of a machining operation's efficacy is often predicated on the surface finish of the machined parts, which is considered a crucial criterion. Furthermore, the surface finish is a crucial attribute that can potentially govern the functional specifications of numerous constituent parts. Components with good surface finish offer numerous advantages when compared to those with poor surface finish (Mallampati & Chittaranjan Das , 2012).

The degree of surface roughness plays a crucial role in the effectiveness and excellence of subsequent surface coatings for all materials, as stated in reference (Thomas, 2014). Among the various techniques available for preparing metal surfaces, machining is one of the most commonly employed methods due to its ability to achieve low levels of surface roughness (Benardos, 2003). For optical applications, machining can yield surface roughness values of approximately 50 nm (Guenther et al., 1984).

Optimizing machining parameters is imperative for enhancing cutting efficacy, minimizing expenses, and ensuring superior product quality. The primary focus of contemporary machining industries centers on attaining superior quality with regards to work piece dimensional accuracy and surface finish. The term "surface roughness" pertains to the minute irregularities present in the surface texture, which encompasses the feed marks produced during the machining operation (Kumar, 2013).

Typically, the selection of optimal parameters is based on the operator's expertise or design data books. However, this approach can result in decreased productivity due to suboptimal utilization of machining capabilities, leading to increased machining costs and reduced quality. Therefore, the implementation of statistical design of experiments and statistical/mathematical models is utilized to reduce both machining cost and time, as stated in reference (Raykar, 2014). The Taguchi experimental design method is a widely recognized and effective approach for enhancing the quality of products or processes. The application of this technique is prevalent in the analysis of experimental data and in the resolution of optimization problems. Taguchi has devised a factorial experimental design known as an orthogonal array, which encompasses the complete parametric space with a reduced number of experiments (Kanlayasiri & Boonmung, 2007).

Taking into account the information provided, this study may be summed up in three ways:

First, it was determined how the CNC turning of the Inconel 718 alloy with PVD AlTiSiN-coated carbide inserts affected the surface roughness and rate of material removal. For the studies, Taguchi's L9 (33) orthogonal-array was utilized. To find the best cutting parameters (cutting speed, feed rate, and depth of cut) for the lowest surface roughness Taguchi's signal-to-noise ratio was applied. The significant cutting parameters impacting the Ra were then identified using an analysis of variance (ANOVA).

Second, using regression analysis, a linear first-order mathematical model was created to estimate the results of varying amounts of input parameters. Finally, validation experiments were carried out to confirm that the developed models were accurate.

Experimental Design and Procedure

Machining Conditions

Machine Tool

The study involved conducting experiments in a dry cutting environment using a CNC lathe machine of the GOODWAY brand, specifically the GLS-200 M model, which boasts a spindle power of 7.5 kW and a maximum spindle speed of 4000 rpm, as illustrated in (Figure 1).

Workpiece Material

The test specimen utilized for the cutting turning tests is a molded round bar of Inconel 718 alloy that has undergone hot treatment. The dimensions of the test specimen are 63.5mm in diameter and 500mm in length, with a post-treatment hardness of 411 HBW. The Inconel 718 alloy is of British origin and has been subjected to certification by Special Metals Wiggin Limited. The material has been issued a certificate of inspection bearing the number 433803 v 1, dated 28th August 2020, in accordance with the EN 10204-3.1/ISO 9001/EN/AS/JISQ

9100 standard. Table 1 displays the chemical composition of material and Table 2 displays the mechanical properties.

Figure 1. CNC Lathe Machine GLS-200 M

The specimen was partitioned into nine uniform segments, each measuring 15 mm in length and separated by a 4 mm wide and 2 mm deep slit. This was done to conduct a set of nine experiments using Taguchi's L9 orthogonal array design, with the objective of minimizing the impact of wear on the results. Prior to each test, a fresh cutting edge was employed.

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 Modulus (MPA)	Density (KG/M^3)	Melting Point(˚C)	Hardness (HBW)	Hardness After Heat Treated (HBW)	Thermal Conductivity (W/MK)
1197	1248	205×10^3	819	1290	245	411	11.20

Cutting Inserts

The finish turning tests of the Inconel 718 alloy were conducted using carbide tool inserts that conform to the ISO specification CCMT09T308N-SU. These inserts were coated with the PVD ultra multi-layer thin layer AlTiSiN process, utilizing Sumitomo grade AC5005S. The tool inserts are affixed in a fixed manner to a toolholder with the designation SCLCR 2020 K89, as illustrated in Figure 2.

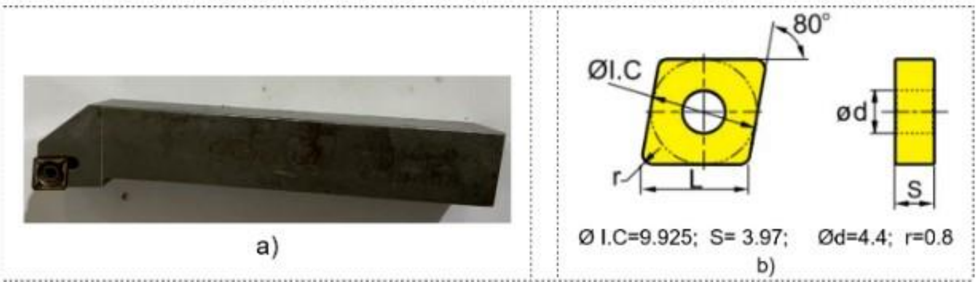


Figure 2. a) Toolholder SCLCR 2020 K89 – Techno Takim, b) Cutting insert CCMT 09T308N

Surface Roughness Measurement

The surface roughness of the machined surface was evaluated using the Mitutoyo 2D SJ-310 surface roughness tester in accordance with the EN-ISO 4287-1998 standards, and the arithmetic mean of the profile deviation (Ra) was determined. The experimental surface tester utilized in the study is illustrated in (Figure 3).

Figure 3. Surface roughness measurements with Mitutoyo SJ-310

Selection of Factors and Their Levels

Extensive preliminary tests were conducted on the work piece material and the inserts of the cutting tools utilized in this research. These tests established the limit values of the processing parameters, specifically the range of input variables. Table 3 displays the machining parameters that will be examined, including cutting speed, feed rate, and depth of cut, along with their respective levels.

Table 3. Machining parameters and their levels

Cutting parameters	Notation	Unit	Levels		
			1	2	3
Cutting speed	v	m/min	60	80	100
Feed rate	f	mm/rev	0.05	0.071	0.092
Depth of cut	d	mm	0.2	0.3	0.4

Experimental Design and Optimization

In the realm of experimental design, the Taguchi method is a widely recognized approach. The Taguchi design, alternatively referred to as an orthogonal array, is a method utilized for constructing experiments that generally necessitates a reduced number of total factorial combinations (C., 2021). Consequently, it is possible to assess each factor in isolation, without any impact on the evaluation of the other factors. Orthogonal arrays have the ability to reduce the number of tests considerably by minimizing the impact of uncontrollable variables. Furthermore, it provides a clear, efficient, and organized approach for determining the ideal machining parameters in the course of the production procedure. The Taguchi methodology ascertains the disparity between the actual values obtained from experiments and the target values by employing a loss function. The loss function is utilized to generate the signal-to-noise (S/N) ratio.

The signal data (S) is comprised of the intended impact on the test outcomes, while the noise data (N) encompasses the unintended impact on the test outcomes. Optimal performance is achieved when the signal-to-noise ratio is at its maximum. There exist three discrete methodologies for computing signal-to-noise ratios. The three approaches under consideration are the smaller-the-better, the nominal-is-best, and the larger-the-better.

The current investigation employed the smaller-the-better options of the signal-to-noise (S/N) quality characteristic to determine the optimal combination for achieving low surface roughness (Ra). The concept of the smaller-the-better is articulated as follows, as documented in reference (Saeheaw, 2022).

Smaller-the-better (minimize):

$$S/N_{Ra} = -10log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (1)$$

In the context of machining experiments, the variable "y_i" denotes the observed outcomes of a given machining characteristic under a specific trial condition repeated "n" times. The presence of a negative sign in Eq. (1) serve the purpose of indicating the quality characteristic of smaller-the-better.

Experimental Work

The experimental tests were conducted on the GOODWAY CNC lathe, utilizing the parameters and levels as presented in (Table 3). The workpiece model was designed in SolidWorks CAD software in 3D, and the cutting path for the tests was calculated using AZ-CAM software, employing Taguchi's experimental design. A total of nine trials were conducted using the standard orthogonal array L9 to machine the workpiece. The resulting surface finish parameter (Ra) were evaluated and recorded in Table 4.

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

Exp.No.	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Ra (μm)
1	1	1	1	0.18
2	1	2	2	0.24
3	1	3	3	0.25
4	2	1	2	0.17
5	2	2	3	0.22
6	2	3	1	0.24
7	3	1	3	0.15
8	3	2	1	0.16
9	3	3	2	0.22

Table 5. Experiment results and STN ratio for Ra

Exp. No.	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Ra (μm)	S/N Ratio
1	60	0.050	0.2	0.14	17.077
2	60	0.071	0.3	0.18	14.895
3	60	0.092	0.4	0.22	13.152
4	80	0.050	0.3	0.14	17.077
5	80	0.071	0.4	0.17	15.391
6	80	0.092	0.2	0.18	14.895
7	100	0.050	0.4	0.13	17.721
8	100	0.071	0.2	0.14	17.077
9	100	0.092	0.3	0.17	15.391

The Taguchi methodology was employed to assess the surface roughness by utilizing an orthogonal array for every permutation of the experimental variables, and the signal-to-noise (S/N) ratios were utilized to optimize the process parameters. (Table 5) presents the signal-to-noise ratios that were calculated based on the experimental outcomes utilizing the equation denoted as Eq1. (1). Subsequently, the data underwent further examination to ascertain the impact of cutting parameters on surface roughness. The generation of main effect plots was carried out utilizing Minitab-18 software, as depicted in (Figure 5).

Analysis and Assessment of Experimental Results

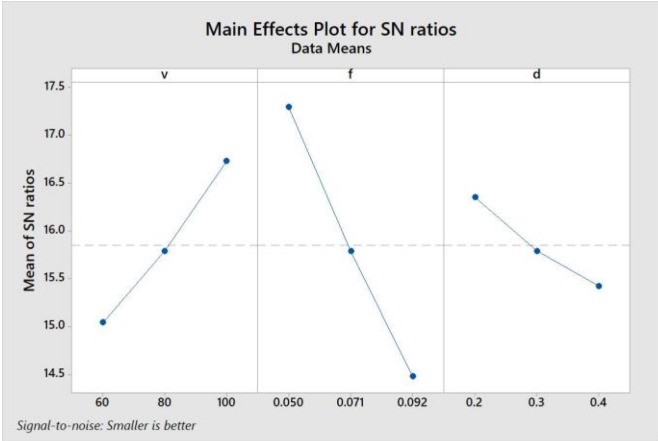
Analysis of the Signal-to-Noise (S/N) Ratio

The analysis of process parameters, including cutting speed, feed rate, and depth of cut, was conducted using a S/N response table generated through the Taguchi technique. This can be observed in (Tables 6). The authors illustrate the signal-to-noise ratio (S/N) for every level of the control factors and its variation as the control factors settings are modified from one level to another (Basmacı, et al., 2023).

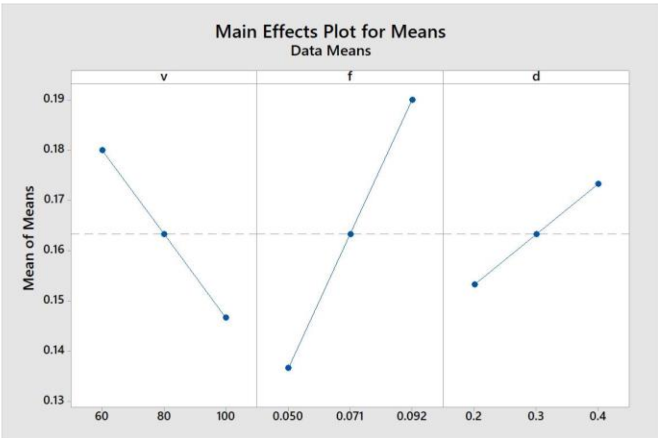
Figure 5 illustrates the relationship between surface roughness and diverse process parameters. A negative correlation was observed between cutting speeds and Ra. The observed phenomenon can be attributed to the thermal softening of the workpiece and the consequent reduction of spread materials on the machined surface, which are caused by elevated cutting temperatures in the machining zone that are directly proportional to the increase in cutting speed (Agari, 2022). Elevating the feed rate leads to an augmented Ra value. The impact of each control element's magnitude can be observed through the graphical representation of the S/N ratio effects, as illustrated in Figure 5. Specifically, the slope of the line connecting the levels provides insight into the extent of the effect.

Table 6. Response table for surface roughness (Ra)

	Control Factors					
	S/N ratio			Means		
	v	f	d	v	F	d
Level 1	15.04	17.29	16.35	0.1800	0.1367	0.1533
Level 2	15.79	15.79	15.79	0.1633	0.1633	0.1633
Level 3	16.73	14.48	15.42	0.1467	0.1900	0.1733
Delta	1.69	2.81	0.93	0.0333	0.0533	0.0200
Rank	2	1	3	2	1	3



a)



b)

Figure 5. Main effects plot for Ra: a) for S/N ratio and b) for Means

Empirical evidence suggests that the feed rate is the most significant factor affecting surface roughness, as it holds the topmost (rank 1). In contrast, cutting speed holds a lower rank (rank 2) in terms of its impact on surface roughness. Additionally, the depth of cut holds the least influence (rank 3), as evidenced by the gentle slope of the lines.

Analysis of Variance (ANOVA)

The utilization of analysis of variance (ANOVA) is a computational technique employed to assess error variance and determine significant process parameters that have the greatest impact on performance characteristics, such as surface roughness. The ANOVA results were obtained and displayed in (Tables 7) using the statistical software Minitab 18. The Fisher's ratio, also known as the F-value, is employed in the analysis of variance (ANOVA) to ascertain the significant impact of a given parameter on the chosen surface roughness.

If the value of the calculated F-stat test is greater than the critical F- stat at α=0.05, derived from the null hypothesis i.e. $F_{\alpha,1,2}$=18.513, a statistically significant relationship can be inferred between the factors and the outcome variable. A probability value (P-value) below 0.05 indicates statistical significance of the parameters at a confidence level of 95%, as stated in reference (Neha Makwana, 2023).

Table 7. Analysis of variance for means of Ra

Source	DF	SS	MS	F	P	Contributtion (%)
v	2	0.00167	0.00083	25.00	0.038	25.30
f	2	0.00427	0.0021	64.0	0.015	64.70
d	2	0.00060	0.0003	9.00	0.100	9.09
Error	2	0.00007	0.00035			1.06
Total	8	0.00660				100

Table 7 presents the ANOVA results, which reveal that the feed rate variable has the greatest impact on the total variance in surface roughness, explaining 64.7% of the variance. The variable of cutting speed accounts for 25.30% of the contribution, whereas the variable of depth of cut displays a comparatively lower level of significance, contributing only 9.09% to the overall variance. The calculated percentage of error for Ra was determined to be 1.06%, which suggests a noteworthy degree of precision.Upon analyzing (Table 7), it can be inferred that the P-values for the cutting speed (0.038) and feed rate (0.015) are both below the predetermined significance level of $\alpha = 0.05$, thereby indicating a confidence level of 95%.

Thus, it can be inferred that the aforementioned two factors exert a notable impact on the surface roughness. On the other hand, the statistical analysis indicates that the depth of cut is not significant, as its P-value of 0.1 exceeds the predetermined level of significance. The aforementioned discovery is consistent with the corresponding F-value of 9.0, which exhibits a lower value than the F-statistic obtained from the null hypothesis ($F_{\alpha,1,ferr}=F_{0.05,1,2}$)=18.513). Based on the analysis conducted, it can be inferred that the F-critical value and P-value lead to a consistent outcome, which is the presence of a significant correlation between the dependent variables and at least two independent variables.

Development and Analysis of Regression Model

Regression analysis has been a frequently employed statistical technique in numerous scientific investigations to establish a correlation between independent variables and experimental outcomes. The Minitab 18.0 software tool was utilized to create mathematical predictive models for Ra and MRR based on cutting speed (v), feed (f), and depth of cut (d). The regression statistics for these models can be found in (Tables 8).

Table 8. Regression statistics and coefficients for linear regression of Ra

Regression statistics		Coefficients	
Multiple R	0.960373	Intercept	0.158333
R-sq	0.922316	Cutting speed	-0.00117
R-sq (adj)	0.875706	Feed rate	1.666667
Standard error	0.01354	Depth of cut	0.066667

The linear prediction equation indicated in Eq. (2) is obtained through regression statistic for Ra presented in (Table 8).

$$Ra = 0.158333 - 0.00117 * v + 1.66667 * f + 0.066667 * d \tag{2}$$

The correlation coefficient, as indicated by multiple R values, is approximately 0.96 for Ra. This indicates that the regression model that was fitted provided an explanation for over 96% of the variability observed in surface roughness.

The expected R-squared metric indicates the degree of precision with which a regression model predicts the response of new observations. Existing literature proposes that the coefficient of determination (R-squared) should fall within the range of 0.8 to 1 (Davide Chicco et al., 2021).

The coefficient of determination, denoted as R-sq, was found to be 0.92 for Ra in this study. This value indicates a strong level of significance for the proposed model.

A graphical method was employed to investigate the residual of the model. The adequacy of the models was assessed by scrutinizing the residuals. The statistical soundness of the models was evaluated through examination of specific diagnostic charts pertaining to the model.

The residuals in typical residual plots exhibit a linear pattern, indicating a uniform distribution of errors, as depicted in (Figure 6). This presents empirical support for the significance and precision of the developed model.

The coefficient of determination, denoted as R-sq, has been calculated to be 0.92 for Ra in this study. This value indicates a strong correlation and underscores the significance of the proposed model. A graphical method was employed to investigate the residual of the model. The adequacy of the models was assessed by scrutinizing the residuals. The statistical soundness of the models was evaluated through the examination of specific diagnostic charts pertaining to the model. The residuals in conventional residual plots exhibit a linear pattern, indicating that the errors are uniformly distributed, as depicted in (Figures 6). This indicates that the developed model holds significance and precision.

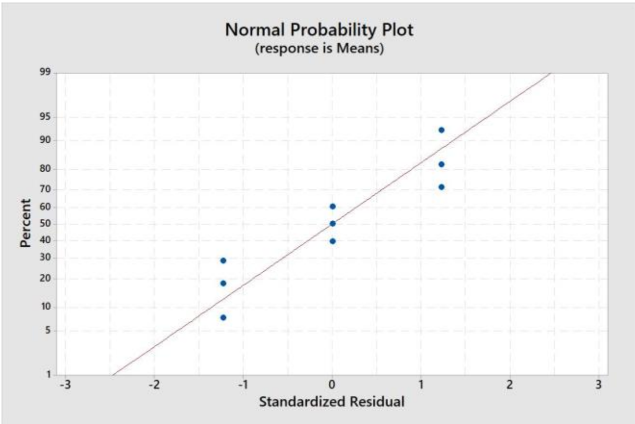


Figure 6. Normal probability charts for surface roughness

Selection of Optimum Cutting Conditions for Ra

The determination of optimal cutting conditions for improved surface quality involves the acquisition of a main effects plot for S/N ratios and mean data means through the utilization of Minitab-18 statistical software, as depicted in Figures 5a and 5b. Irrespective of the category of performance attributes being evaluated, a superior performance is always indicated by a higher signal-to-noise (S/N) ratio. Therefore, the optimal configuration for the process parameters is the configuration that produces the highest signal-to-noise ratio, as stated in reference (Qazi , 2020).

The presented graphs depict the impact of individual parameters on the signal-to-noise ratio and the slope of the line. Additionally, they illustrate the recommended cutoff parameter levels, which are identified as the highest points in Figure 5.a and the lowest points in Figure 5.b. Hence, the Taguchi method was employed to ascertain the most suitable anticipated process parameters that would result in minimal surface roughness. The determined optimal values for the parameters were v = 100 m/min, f = 0.05 mm/rev, and d = 0.2 mm, as highlighted in bold in response (Table 6).

The findings suggest that the most favorable amalgamation was distinguished by factor v at level 3 (v=100 m/min, S/N 16.73 dB, mean: 0.1467 µm), factor f at level 1 (f=0.05 mm/rev, S/N=17.29 dB, mean: 0.1367 µm), and factor d at level 1 (d=0.2 mm, S/N = 16.35 dB, and mean: 0.1533 µm. The optimal combination that has been predicted for surface roughness is denoted as (v3-f1-d1), as illustrated in Table 9.

Table 9. Optimum conditions for surface roughness

Parameter	Notation	Ra (µm) Best level	Value
Cutting speed (m/min)	V	3	100
Feed rate (mm/rev)	F	1	0.05
Depth of cut (mm)	D	1	0.2

Estimation of Optimum Surface Roughness

In the final stage of the Taguchi method, it is necessary to perform a verification experiment in order to validate the precision of the optimization. The experiment for verification was conducted using the optimal levels of the variables that were selected, as presented in Table 6. Consequently, based on the information presented in the (Table 6), the most favorable mean value for quality attributes, specifically surface roughness, is determined to be (v_3-f_1-d_1), as seen in Eq.3.

$$Ra_{popt} = \overline{P_{Ra}} + (\overline{V_3} - \overline{P_{Ra}}) + (\overline{F_1} - \overline{P_{Ra}}) + (\overline{D_1} - \overline{P_{Ra}}) \tag{3}$$

where the variable P_{Ra} represents the mean value of performance attributes, specifically surface roughness, as indicated by all the L9 measurements in (Table 5). The acronym "Ra_{popt}" denotes the anticipated average of the surface roughness rate when subjected to ideal conditions. Meanwhile, the values denoted by "($\overline{V_3}$-$\overline{F_1}$-$\overline{D_1}$)" represent the mean surface roughness values obtained when the process parameters are set to their optimal levels, as presented in Table 6.

The response averages have been computed and the resulting values are presented below. The surface roughness values for P, V3, F1, and D1 are 0.1634 µm, 0.1467 µm, 0.1367 µm, and 0.1533 µm, respectively. Upon incorporation of the aforementioned values into Equation (3), it is projected that the average optimal magnitude of surface roughness will manifest as $R_{apop}t$=0.1099 µm.

The confidence interval (CI_{Ra}) was determined for the estimated surface roughness through the utilization of Eqs. (4) and (5) as stated by reference (Dvivedi & Kumar, 2007).

$$Cl = \sqrt{F_{\alpha,1,ferr} \cdot V_{er} \cdot \left(\frac{1}{n_{eff}} + \frac{1}{R}\right)} \tag{4}$$

$$n_{eff} = \frac{N}{1+T_{dof}} \tag{5}$$

The equation denoted as (4) provides the F ratio at a confidence level of 95%, where the variables α, f_{err}, V_{err}, R, and neff represent the significance level, degree of freedom of the error, error variance, number of replications for the verification test, and effective number of replications, respectively. The equation denoted as (5) expresses T_{dof} as the aggregate primary factor of the degree of freedom, while N represents the overall quantity of tests conducted. The F-test table indicates that the value of $F_{\alpha,1,2}$ is 18.513. Moreover, as presented in (Table 7), the value of V_{errRa} is 0.00035, while the parameters R, N, and T_{dof} are 3, 9, and 6, respectively. Applying Equation (5), the resulting value of n_{eff} is 1.285. The confidence interval (CI_{Ra}) was computed as ±0.08484987 using equations (4) and (5).

At a confidence level of 95%, the anticipated mean optimal surface roughness is as stated below:

[Ra_{popt} – CI_{Ra}] < [Ra_{opt} <[Ra_{popt} +CI_{Ra}], i:e:; [0.1099- 0.08484987] < Ra_{exp} < [0.1099+ 0.08484987]= 0.025< Ra_{exp} < 0.1947.

The R_{aexp} value derived from the confirmatory trial, as presented in Table 10, falls within the confines of the confidence interval. The Taguchi method was effectively employed to optimize the system at a significance level of 0.05 during the turning of Inconel 718 alloy under varying cutting conditions.

Experimental Validation

Confirmation testing was conducted on the process parameters at optimal and random levels for the Taguchi technique and regression equations. (Table 10) displays the comparison between the test results and the anticipated values obtained through the Taguchi method and regression equation (Eq. 2). The observed outcomes and the anticipated values exhibit a high degree of similarity. According to reference (Columb, & Atkinson, 2016), statistical analysis can only be deemed reliable if the error values remain below 20%.

Hence, the success of this optimization can be deemed valid, as substantiated by the outcomes of the verification tests.

Table 10. Conformation results for Taguchi method and linear regression

	Taguchi method			Linear regression		
Level	EXp	Pred.	Error (%)	EXp	Pred.	Error (%)
$v_3f_1d_1$(Optimum)	0.12	0.11	8.33	0.12	0.1383	15.25
$v_2f_2d_2$ (Random)	0.18	0.163	9.44		0,20	11.11
$v_1f_2d_3$	0.19	0.18	5.26		0.23	21

Conclusion

The current study utilized the Taguchi methodology to determine the most effective machining parameters for the turning process of Inconel 718 alloy, utilizing *CCMT09T308N-SU* PVD coated carbide inserts in the absence of any cutting fluid. ANOVA was utilized to perform statistical analysis on the experimental results. It is conceivable to deduce the ensuing inferences:

The investigation ascertained the most advantageous degrees of control variables with the aim of reducing surface roughness and enhancing material removal rate, employing signal-to-noise ratios. The study determined that the optimal conditions for achieving favorable surface roughness results were determined to be at $v_3f_1d_1$, which corresponds to a cutting speed of 100 mm/min, a feed rate of 0.05 mm/rev, and a depth of cut of 0.2 mm.

The statistical analysis indicated that the feed rate exhibited the most significant level of importance in terms of surface roughness, explaining 64.70% of the variability. The multiple R values obtained have an approximate value of 0.96. The aforementioned results suggest that the fitted regression model exhibited a high level of explanatory capability, with a percentage exceeding 96%, in relation to the surface roughness.

The results suggest that the Taguchi methodology is a reliable technique for reducing machining duration and manufacturing costs in the computer numerical control (CNC) turning procedure of Inconel 718 alloy.

Recommendations

In order to enhance the machinability of Inconel 718 alloy material in CNC turning machines and to place particular emphasis on the quality of the machined surface, the present investigation may be extended in the following manner:

- Additional research can be conducted by incorporating a greater quantity of process parameters and responses.
- The experimentation process can be enhanced by increasing the spindle speed and utilizing diverse cutting tool inserts and conditions.

Furthermore, it is recommended that future research endeavors focus on exploring alternative prediction models for mathematical optimization models of machinability characteristics' cutting parameters, such as second-order and higher-degree models.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Acknowledgements or Notes

* This article was presented as an oral presentation at the International Conference on Research in Engineering, Technology and Science (www.icrets.net) held in Budapest/Hungary on July 06-09, 2023.

References

Abhang L.B., & Hamedullah, M. (2010). Chip-tool ınterface temperature prediction model for turning process. *International Journal of Engineering Science and Technology*, *2*(4), 382-393.

Agari, S. R. (2022). Wear and surface characteristics on tool performance with CVD coating of Al2O3/TiCN inserts during machining of Inconel 718 alloys. *Archive of Mechanical Engineering*, *69*(1), 59-75.

Basmacı, G., Kayacan, M. Y., Ay, M., & Etyemez, A. (2023). Optimization of cutting forces and surface roughness via ANOVA and grey relational analysis in machining of In718. *Open Chemistry*, *21*(1).

Benardos, P., & Vosniakos, G. C. (2003). Predicting surface roughness in machining - review. *International Journal of Machine Tools and Manufacture, 43*(8), 833-844.

Columb, M. O., & Atkinson, M. S. (2016). Statistical analysis: sample size and power estimations. *BJA Education*, *16*(5), 159-161.

Davide Chicco, M. J., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Comput Science,7.* e623.

Dvivedi, A., & Kumar, P. (2007). Surface quality evoluation in ultrasonic drilling through the Taguchi techniques. The *International Journal of Advanced Manufacturing Technology,34,*131-140.

Guenther, K. H., Wierer, P. G., & Bennett, J. M. (1984). Surface roughness measurements of low-scatter mirrors and roughness standards. *Applied Optics*, *23*(21).

Hamzacebi, C. (2021). Taguchi method as a robust design tool . *Intelligent Manufacturing, Robust Design and Charts*, 1-19.

Kanlayasiri, K & Boonmung, S. (2007). Effects of wire- EDM machining variables on surface roughness of newly developed DC 53 die steel: Design of experiments and regression model. *Journal of Materials Processing Technology*, *192*, 459-464

Kumar, U., & Narang, D. (2013). Optimization of cutting parameters in high speed turning by grey relational analysis. *Business, Materials Science*, *3*(1), 832-839.

Mallampati, M., & Chittaranjan Das, V. D. (2012). Optimization of cutting parameters as speed, feed & depth of cut based on surface roughness in turning process using genetic algorithm (Ga) and particle swarm Optimization (pso). *International Journal of Engineering Research & Technology (IJERT)*, *1*(7). 1-11.

Neha Makwana, A. K. (2023). Optimisation of cutting parameters by using Annova method. *Journal of Emerging Technologies and Innovative Research* (*JETIR)*, *10*(5), d748-d760.

Palanikumar, L. K. (2006). Assessment of factors influencing surface roughness on the machining of glass – reinforced polymer composites. *Materials & Design, 27*(10), 862-871.

Qazi M., R. , Akhtar, R., Abas, M., Khalid, Q.S.,Babar, A. R., & Pruncu, C. I. (2020). An integrated approach of GRA coupled with principal component analysis for multi-optimization of shielded metal arc welding (smaw) process. *Materials*, *13*(16), 3457.

Raykar, S., & D'Addona, D. M. (2014). Analysis of surface topology in dry machining of EN-8 steel. *Procedia Material Science*, *6,* 931-938

Saeheaw, T. (2022). Application of integrated CRITIC and GRA-based Taguchi method for multiple quality characteristics optimization in laser-welded blanks. *Heliyon, 8*(11). https://doi.org/10.1016/j.heliyon.2022.e11349

Thomas, T. (2014). Roughness and function. *Surface Topography. Metrology and Properties.* 2(1), 014001

Wassila Frifita, S. B. (2020). Optimization of machining parameters in turning of Inconel 718 Nickel-base super alloy. *Mechanics & Industry 21*(2), 203.

Author Information

Fatlume Zhujani
University of Pristina
Street Agim Ramadani, Kosovo
Contact e-mail: *Fatlume.zhujani@uni-pr.edu*

Georgi Todorov
Technical University of Sofia
Sofia 1000, 8 Kl. Ohridski Blvd, Bulgaria

Konstantin Kamberov
Technical University of Sofia
Sofia 1000, 8 Kl. Ohridski Blvd, Bulgaria

To cite this article:

Zhujani, F. & Todorov, G. & Kamberov, K. (2023 Single Objective Optimization of Cutting Parameters for Surface Roughness in Turning of Inconel 718 Using Taguchi Approach. *The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM), 23,* 338-348