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Optimization of Machining Parameters in Mild Steel Turning Operation by Response Surface Methodology

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Abstract:
A lot of process variables affect the surface roughness obtained in turned machine parts. One of these variables is bearing clearance. However, there is limited information on the influence of bearing clearance on surface integrity. This paper is an optimization study in which the surface roughness of AISI 1018 mild steel is minimized with the aid of the response surface methodology. In this paper, the effect of process parameters like cutting speed, feed, depth of cut, and bearing clearance is analyzed to ascertain how the surface finish properties of mild steel can be improved. The design of the experiment used for this study involves a rotatable central composite system. This design is used to find the experimental results of machining. The analysis of variance (ANOVA) was used to determine the statistical significance of the improved quadratic model developed. The numerical and graphical optimization carried out determined the optimum values of each of the parameters used in different ways. From the ANOVA, it was revealed that the most significant factor in the model was the depth of cut. This factor was closely followed by spindle speed, bearing clearance, and feed, respectively. Numerical optimization results employing the desirability function showed optimum values to be at bearing clearance of 70um, depth of cut of 2.5mm, feed of 0.01mm/rev, and a spindle speed of 450rpm. The result obtained using the graphical optimization option was similar to the results from the other options. The variation of surface roughness with the process parameters chosen for the experiment was mathematically modeled. The model developed used the response surface methodology, and it was validated with a set of experimental values. The result from the exercise undertaken revealed that the predicted values of the surface roughness were very close to measured values. The average percentage deviation of 6.20% for all sample data utilized showed that the model developed was in close agreement with the experimental results.

Keywords: *Bearing clearance, ANOVA, rotatable central composite design, numerical optimization*

1. Introduction

One of the basic metal machining operations widely used in the metal cutting industry or in the various industries that require the services of or expertise in metal cutting is the turning operation (Kumar, 2013). A turning operation involves feeding a high-precision single-point cutting tool, which is rigidly held in a tool post, past a rotating work-piece. This feeding is done at a constant rate, in a parallel direction to the axis of rotation of the work-piece. The waste materials from the process, which are unwanted materials chipped off from the work-piece, are removed in the form of chips. A turning operation gives rise to a cylindrical and more complex profile (Trent & Wright, 2010). The operation, which is carried out in a lathe machine, can either be manually operated under human supervision or automatically operated with a controlling computer program. The latter minimizes the need for human supervision. In a lathe, the power required for an operation is usually transmitted to the spindle pulley or to the gears. On the tool end of the spindle, where there is a heavy combined load, it is critical to have a high degree of rigidity and a high load-carrying capacity. This operational requirement is necessary because the unexpected failure of spindles in operation can lead to severe part damage and costly machine downtime. Such a hitch would adversely affect the overall outcome in production, logistics, and productivity (Hassan & Hussain, 2009). With the design and strength of bearings in machine tool spindle systems playing an essential role in the performance of the machine, there is a need to pay very close attention to bearings. The bearing has an internal clearance called 'initial clearance.' This initial clearance is technically used to capture the amount of clearance that a bearing has before it is installed on a shaft or any housing.

When one of the rings of a bearing, the inner ring or the outer ring, is fixed and the other ring is free to move, displacement could occur either in an axial or radial direction. When displacement occurs, the amount of such displacement gives the value of the internal clearance, while the direction of the displacement determines whether it is called the radial internal clearance or the axial internal clearance. Under normal operating conditions, the internal clearance of a bearing, termed 'effective clearance,' is usually smaller than the initial clearance of the same bearing. This disparity can be attributed to the bearing fit, the difference in temperature between the inner and outer rings, and many other variables. Since the operating clearance of a bearing has an effect on the bearing's life, heat generation, vibration, noise, and other machine parts and operational variables, there is a need for utmost care to be taken in the selection of the most suitable bearing operating clearance.

The quality of the finished products and the ability of the machine to manufacture products that meet the required specifications depend on the performance of the turning process. Surface roughness (Ra) is the index used to determine surface quality in turning operations. This index is a measure of the smoothness attained on a machined surface. Many lifelong attributes of a product are determined by how well the integrity of the surface finish is maintained. Available examples of activities for which it may be necessary to specify the surface roughness are painting or coating adherence, surface reflectivity, and frictional requirements. When the surface roughness requirement of a product is not met, a defect is said to have occurred (Mandara De Roy, 1999). However, the major variables are usually controlled independently during operation to attain the desired surface roughness. For optimum results, conventional machining approaches often rely on human skills and expertise for their design, control, and maintenance. Machining has become increasingly complex as technology advances as it incorporates new technology. This technological advancement has resulted in an increased awareness of the importance of optimization by both researchers and industrialists. Optimization is a science that makes it possible to get the most excellent results from a process that is subjected to a number of resource constraints (Sharma, Murtaza, and Garg, 2010). Optimization is a necessity with the contemporary challenges faced by organizations in their bid to:

- Meet up with the detailed quality specifications of their customers, Outperform their competitors, and
- Retain or increase their market share

It is a tool that is of utmost importance to all organizations and researchers who seek to meet the growing demand for improved product quality, lower production costs, and faster production rates (Sharma et al., 2010).

The statistical design of experiments is used extensively in process optimization systems. This type of design method refers to the planning of the experiments in such a manner that the data gathered from them can be analyzed by statistical methods, which gives credibility to the validity and objectivity of the findings or conclusions (Montgomery, 1997). The uptake of new methodologies like the Response Surface Methodology (RSM), the Factorial Designs, and other similar methods has actively replaced the erstwhile experimental approach, which utilized one factor at a time and was more costly as well as time-consuming (Noordin, Venkatesh, Chan, and Abdullah, 2001), lends weight to this argument. The RSM is practical, economical, and relatively easy to use. It has been deplored by various researchers in experiments that model machining processes (Hasegawa, Seireg, and Lindberg, 1976; Box & Draper, 1987; El Baradie, 1993; Sundaram & Lambert, 1981). The RSM can model the responses of significant parameters and the interactions and square terms of the parameters. These features are not provided by other techniques. Wu and Matsumoto (1990) were the researchers who pioneered the use of the RSM in tool life testing. While Reen (1977) noted that the tool life, surface finish, and power consumed during cutting must be considered for an accurate rating of machinability, Shaw (1986) expressed the same views. However, using the RSM approach (Taraman, 1975) returned a prediction of surface roughness. In a survey of surface roughness prediction models carried out by Mital and Mehta (1988), the researchers found that most of the models available and surveyed were developed for steel. The turning operation is governed by both geometric factors and machining factors. Boothroyd (1975) and El Baradie (1993) investigated the effect of speed, feed, and depth of cut on steel and gray cast iron and used their findings to underscore the use of the RSM in developing a surface roughness prediction model.

Neseli, Yaldiz, and Turkes (2011) found out that the nose radius has the most significant effect on surface roughness when they used an RSM method that employed the nose radius, approach angle and rake angle as input variables. Speed, feed, and depth of cut were found to be the three primary machining parameters in a basic turning operation that was adjustable in the turning operation. It is the combination of the speed, feed, and depth of cut that produces the material removal (Halim, 2008). However, a review of the existing literature revealed that only a few studies included bearing clearance as a critical cutting parameter in their modeling approaches. In fact, Dahbi, El Moussami, and Ezzine (2015) noted that bearing clearance and its interaction with the three main cutting parameters on surface roughness was a study that had not been established or, better put, undertaken. Therefore, the integration of the bearing clearance parameter as an input of the RSM would as undertaken in this research, take the main and interaction effects of the bearing clearance into account to model the three cutting parameters with high accuracy.

2. Materials and Method

2.1. Materials

AISI 1018 mild/low carbon steel was employed as the work-piece material for the turning experiments. Physical and Mechanical properties of the AISI 1018 mild steel are given in tables 1 and 2, respectively.

Alloying Elements	Carbon	Silicon	Manganese	Sulphur	Phosphorous	Chromium	Molybdenum
Handbook of Percentage composition	0.14	0.26	0.96	0.019	0.023	0.11	0.007
Experimental Percentage composition	0.14	0.26	0.95	0.018	0.023	0.10	0.007

Table 1: Chemical Composition of AISI 1018 Mild Steel Specimen

Property	Density	Yield Strength	Ultimate Strength	Hardness	Shear Strength	Fatigue Strength	Poission's Ratio
Handbook Values	7.858g/cc	370MPa	440MPa	126BHN	80GPa	140GPa	0.29
Experimental Values	7.788g/cc	367MPa	439MPa	127BHN	81GPa	142GPa	0.28

Table 2: Mechanical Properties/ Physical Properties

2.1.1. Cutting Tool

A cemented carbide-tipped tool with the following characteristics was used as a cutting tool:

- Cutting speed range – 60–200m/min
- Temperature – 1000°C
- Hardness – up to HRC 90

The machine used for dry machining is a Conventional lathe of Colchestar student lathe Model 630 with the following technical specification:

Figure 1: Model 630 Colchester Lathe Machine

Centres	Height	167mm
Swing	Over Bed	330mm
	Over Cross Slide	210mm
	In Gap Diameter	480mm
Spindle	Bored to pass	48mm
	Nose	No. 4-D1
Speeds	Number	12
	Range	40 to 2500 r.p.m
Motor	(1500 r.p.m @50Hz)	2.2 Kw
Leadscrew	Diameter	28mm
	Thread	6mm pitch or 4 TP
Threads	39 Metric Pitches	From 0.2 to 14mm Pitch
	35 English Pitches	From 2 to 56 TPI
	18 Module Pitches	From 0.3 to 3.5 MOD
	18 Diametral Pitches	From 8 to 56 DP
Feed	16 Metric (R.10 Series)	From .01 to 1mm/rev
Cross Slide	Width	140mm
	Travel	190mm
Top Slide	Width	82mm
	Travel	92mm
Tool	Max. Section	16 x 20mm
Tailstock	Quill-Diameter	42mm
	Travel	110mm
Weight	630mm Model	
	630mm (25") Cts.	583kg

Table 3: Technical Specification of Lathe Machine

2.1.2. Measurement of Surface Roughness

Surface roughness was measured with the help of an SRT6210 Roughness Tester.

Figure 2: Surface Roughness Testing Machine and Accessories

Display	**4 digits, 10 mm LCD, with Blue Backlight**
Measuring Range	Ra, Rq: 0.005-16.00µm Rz, Rt: 0.020-160.0µm

Table 4: Technical Specification of SRT 6210 Surface Roughness Tester

2.2. Method

2.2.1. Cutting Condition

For the experimentation process, a dry-cutting environment was used. Given the fact that cutting fluids have corrosive effects and are not environmentally friendly, the use of the dry-cutting process not only reduces the machining cost but also addresses the issue of environmental unfriendliness. Cylindrical roller bearings of bore diameter 50 mm with varying clearances of 60 m, 70 m, 80 m, 90 m, and 110 m were used in the experiment on the lathe machine based on the manufacturer's catalog shown in Appendix I. Radial clearance is classified on a C2, CN, C3, C4, and C5 scale, with clearance increasing toward the highest number, which is C5.

2.2.2. Experimental Procedure

The turning experiments were carried out under dry-cutting conditions using a Colchester student center lathe. It has a maximum spindle speed of 2500 rpm and a spindle power of 2.2 kW. Work-pieces of diameter 30 mm and length 100 mm were held in the chuck; the tool overhang was kept at 20 mm to increase the rigidity of the machining system. The experiments involved turning the work-piece with the feed direction toward the chuck of the lathe, which is referred to as the 'left feed direction.' This is often the case during conventional turning. A randomized experimental run has been carried out to minimize the error due to the machining setup. The levels of cutting parameters, such as bearing clearance, depth of cut, feed rate, and spindle speed for the experiments, have been listed in table 5.

Control Variable	**Levels**					
	Units	**-2**	**-1**	**0**	**1**	**2**
Bearing clearance (A)	µm	60	70	80	90	110
Depth of cut (B)	Mm	1	1.5	2	2.5	3
Feed (C)	rev/mm	0.005	0.01	0.015	0.02	0.025
Spindle Speed (D)	Rpm	250	350	400	450	500

Table 5: Control Factors and Range of Setting for Experiment

The design of the experiment employed was basically a rotatable central composite design, which was based on the RSM. The design was developed using the Design Expert 7.0 Statistical Software Package, which produced sets of combinations of these parameters. A total of 30 experiments were performed. The turning operations performed on the work-pieces were performed with different combinations of the parameters engaged. The parameters engaged were: bearing clearance, depth of cut, feed, and spindle speed. Bearings of various clearances were installed for different combinations of cutting parameters as specified in the experimental design matrix in table 6. After machining, the surface roughness of each work-piece was measured using the surface roughness tester. The data collected showed the average value of three readings of surface roughness values (Ra) corresponding to different combinations of parameters. Based on the design of the experiment, an analysis of variance (ANOVA) module of RSM was applied to the collected data. The DESIGN EXPERT 7.0 STATISTICAL SOFTWARE PACKAGE was used in this analysis. With this, the level of significance of each parameter in achieving low surface roughness was obtained. In addition, a statistical model that relied on regression analysis was developed. This model used the regression coefficient estimates of the various operational-based parameters. The experimental data obtained are summarized in table 6.

Run	Block	Factor 1 A: Bearing Clearance (um)	Factor 2 B: Depth of Cut(mm)	Factor 3 C: Feed Rate(mm/rev)	Factor 4 D: Spindle Speed (rpm)	Response 1,2,3 Mean Value of Surface Roughness (um)
1	Block 1	90	2.5	0.02	450	3.768
2	Block 1	70	1.5	0.01	450	3.042
3	Block 1	80	2	0.015	400	5.322
4	Block 1	80	2	0.015	400	3.534
5	Block 1	90	1.5	0.01	350	4.662
6	Block 1	70	2.5	0.02	450	3.072
7	Block 1	70	1.5	0.01	350	5.982
8	Block 1	80	2	0.015	250	4.26
9	Block 1	70	2.5	0.01	350	2.502
10	Block 1	70	2.5	0.01	450	2.22
11	Block 1	80	2	0.015	400	4.002
12	Block 1	80	2	0.025	400	2.898
13	Block 1	90	1.5	0.01	450	2.862
14	Block 1	70	2.5	0.02	350	2.478
15	Block 1	80	1	0.015	400	4.74
16	Block 1	90	2.5	0.01	350	3.378
17	Block 1	90	2.5	0.02	450	3.978
18	Block 1	80	2	0.015	400	3.108
19	Block 1	90	1.5	0.015	350	3.078
20	Block 1	70	1.5	0.02	450	4.2
21	Block 1	80	2	0.015	500	3.12
22	Block 1	90	2.5	0.02	350	3.96
23	Block 1	80	2	0.015	400	4.26
24	Block 1	80	2	0.015	400	3.198
25	Block 1	90	1.5	0.02	450	3.924
26	Block 1	60	2	0.02	400	3.726
27	Block 1	110	2	0.015	400	3.792
28	Block 1	80	3	0.015	400	3.84
29	Block 1	80	2	0.005	400	3.87
30	Block 1	70	1.5	0.02	350	3.9

Table 6: Experimental Results Obtained

2.2.3. Analysis and Validation of Results

In order to ascertain the accuracy of the model developed from experimental results, percentage deviation φ_i and average percentage $\bar{\varphi}$ deviation were calculated and used. The percentage deviation is represented by φ_i (Okokpujie et al., 2015);

$$\varphi_i = \left(\frac{R_{a(p)} - R_{a(e)}}{R_{a(e)}}\right) \times 100\,\% \qquad (3.1)$$

Where:

- φ_i: percentage deviation of single sample data
- $Ra_{(e)}$: the experimental values of the surface roughness
- $Ra_{(p)}$: predicted surface roughness generated by a multiple regression equation

In the same vein, the average percentage deviation $\bar{\varphi}_i$ was defined by Okokpujie et al. (2017):

$$\bar{\varphi}_i = \frac{\sum_{i=1}^{n} \varphi_1}{n} \qquad (3.2)$$

Where:

- $\bar{\varphi}_i$: Average percentage deviation of all sample data
- n: the size of sample data

The mathematical model for the surface roughness prediction based on the experimental results is given by equation 3.3. The developed mathematical model to predict surface roughness (Ra) is:

Surface Roughness = 38.58 - 0.176*A -12.40*B - 613* C-0.04795*D +0.09238*A*B + 0.01083* B * D+ 1.487*C *D (3.3)

3. Results and Discussions

3.1. Analysis of ANOVA Results

The results obtained from the experiment were fed into DESIGN EXPERT 7.0 software for further analysis. The analysis of variance (ANOVA) was computed using the Design Expert software, as shown in table 7. This computation was used to study the effect and significance of the cutting parameters on the response variables, i.e., surface roughness.

Source	Sum of Squares	Df	Mean Square	F-value	p-value	prob>F
Model	11.09	7	1.584	3.987	0.005867	Significant
A-Bearing clearance	3.001	1	3.001	7.553	0.01173	Significant
B-Depth of cut	4.780	1	4.780	12.03	0.002184	Significant
C-Feed	2.325	1	2.325	5.851	0.02429	Significant
D-Spindle Speed	3.599	1	3.599	9.057	0.006450	Significant
AB	3.413	1	3.413	8.589	0.007739	Significant
BD	1.174	1	1.174	2.954	0.09970	Not significant
CD	2.213	1	2.213	5.568	0.02758	Significant
Residual	8.743	22	0.3974			
Lack of fit	5.326	17	0.3133	0.4586	0.8954	Not significant
Pure error	3.416	5	0.6832			
Cor Total	19.83	29				

Table 7: ANOVA for Surface Roughness

Table 7 shows a Model F-value of 3.99, which implies that the model is significant. There is only a 0.59% chance that a 'Model F-value' this large could occur solely due to noise. Values of 'Prob > F', which is less than 0.0500, indicate that the model terms are significant. In the case under consideration, A, B, C, D, AB, and CD are significant model terms. Values greater than 0.05 suggest that the model terms are not significant. In this study, the depth of cut has been found to be the most influential parameter of all the parameters studied. Depth of cut affected the surface roughness with the lowest P-value among all four parameters. This performance was followed by spindle speed, bearing clearance, and feed, respectively. The 'Lack of Fit F-value' of 0.46 implies that the Lack of Fit is not significant relative to the pure error. There exists 89.54% chance that a 'Lack of Fit F-value' that is this large could occur as a result of noise. A non-significant lack of fit is good because it is a requirement for the model to fit. The regression coefficients are obtained from the Design Expert 7.0.1 statistical software package. After determining the significant coefficients (95% confidence interval), the final model was developed using only these coefficients. The final estimated regression model using the coded variables is expressed as follows:

Final Equation in Terms of Coded Factors:

Surface Roughness (Ra(p)) = 38.58 - 0.176*A -12.40*B - 613* C-0.04795*D +0.09238*A*B + 0.01083* B * D+ 1.487*C *D (3.3)

3.2. Assessing Surface Roughness Model Adequacy

R-squared (R^2)	0.5592
Adj R-Square	0.4189
Pred R-Squared	0.2221
Adeq Precision	9.419

Table 8: Model Adequacy Values

The adequacy of the model developed was tested with the analysis of variance (ANOVA) tool. The results of the second-order response surface model fitting in the form of analysis of variance (ANOVA) are given in table 8. The coefficient of determination (R^2) indicates the goodness of fit for the model.

In this case, the value of the coefficient of determination (R^2=0.5592) indicates that about 44% of the total variations are not explained by the model. The value of the adjusted coefficient of determination (adjusted R^2=0.4189) is also moderate but is closer to the value of R^2, which indicates that the model is significant. The 'Adeq Precision' measures the signal-to-noise ratio. A signal-to-noise ratio greater than 4 is desirable. So the signal-to-noise ratio of 9.419 obtained indicates an adequate signal. This result obtained means that the model can be used to navigate the design space. That the model is adequate is shown by the fact that it is represented by the points falling on a straight line in the normal probability plot of figure 3. This straight-line plot is an indication that the errors are normally distributed. This is the expectation that the model has a good fit (Correia et al., 2005). The plot of the residuals versus the predicted values of surface roughness is structureless, i.e., it contains no obvious pattern. Hence, it shows no need for transformation and provides proof of constant variance, as shown in figure 4. The plots, as shown in figures 4 and 5, investigate the presence of outliers or influential values. From the information available in these plots, it can be deduced that there is a complete absence or a significant lack of presence of an outlier that will distort the analysis of variance obtained. The value of probability >F in table 7 is less than 0.05. This indicates that the model is significant. All the above consideration indicates excellent adequacy of the regression model.

3.3. Residual Plots

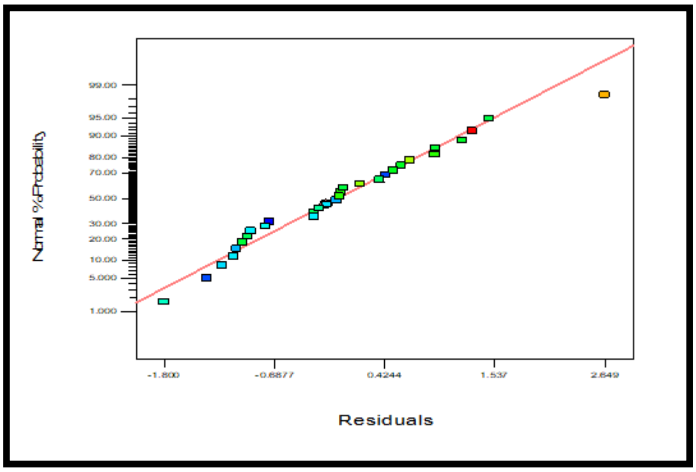

Figure 3: Normal Probability Plot of Residuals

- Interpretation:

Figure 3 shows the plots of the residuals versus their expected values when the distribution is normal. The residual values calculated from the analysis should be normally distributed. In standard practice, for balanced or nearly balanced designs or for data with a large number of observations, moderate departures from normality do not seriously affect the results. So, the normal probability plot of the residuals should roughly follow a straight line. Except for one outlier point, no signs of non-normality and skewness were observed.

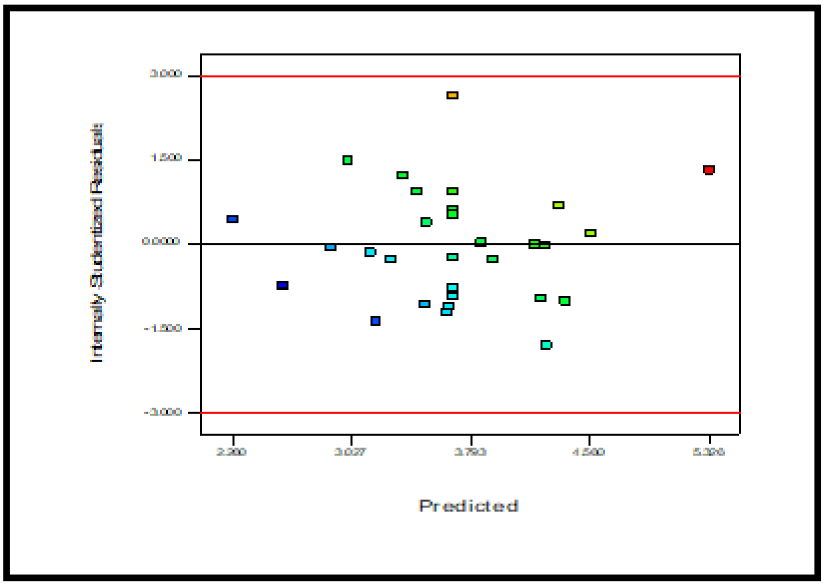

Figure 4: Residuals versus Predicted Values

- Interpretation

Figure 4 shows plots of the residuals versus the fitted values. The residuals should be scattered randomly about zero. Based on this plot, the residuals appear to be randomly scattered about zero- No evidence of the existence of non-constant variance, missing terms, outliers, or influential points.

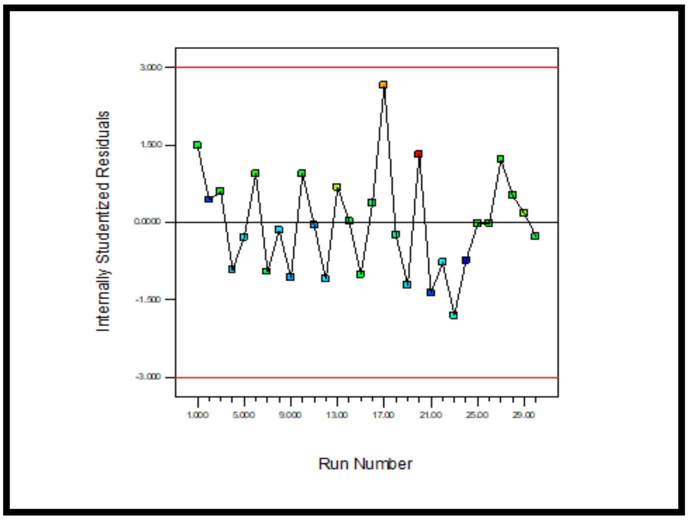

Figure 5: Residual versus Experimental Run Order

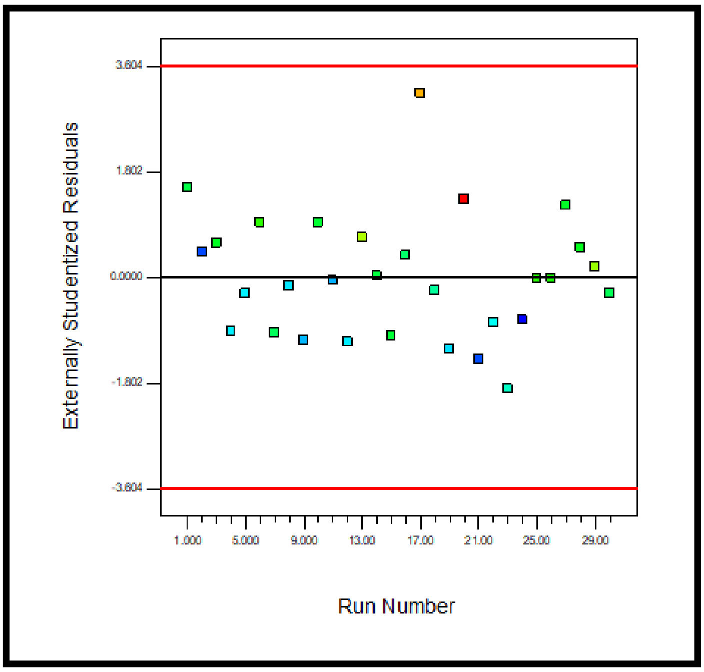

Figure 6: Plot of Residuals

- Interpretation:

Figures 5 and 6 show the plots of residuals in the order of the corresponding observations. These plots check for the existence of any lurking variables that may have influenced the response during the experiment. The plot is expected to depict a random scatter. The plots are examined to see if any correlation exists between error terms that are close to each other. The residuals appear to be randomly scattered about zero. No evidence exists that the error terms are correlated with one another.

3.4. Contour Plots and 3-D Surface Plots

Figures 7 and 8 show the 3D surface plots for surface roughness. It is observed in figure 7 that with the combination of depth of cut and spindle speed, the surface finish can be varied to a minimum value. In figure 8, the combination of bearing clearance and depth of cut also creates a space for minimal surface roughness to be achieved at different values of these factors.

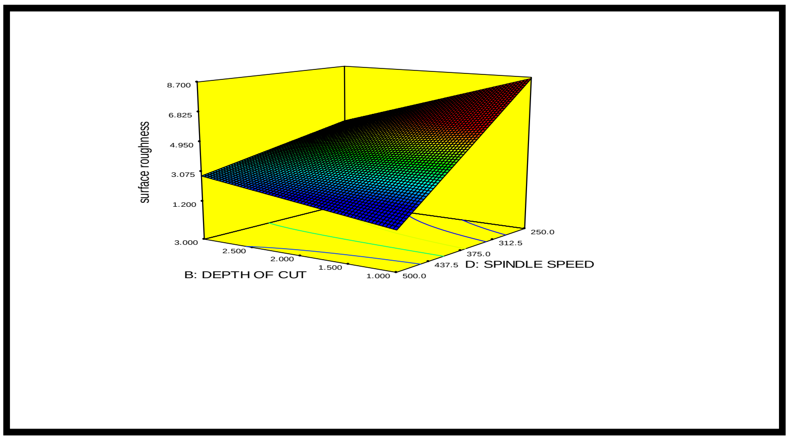

Figure 7: Variation of Surface Roughness with Bearing Clearance and Depth of Cut

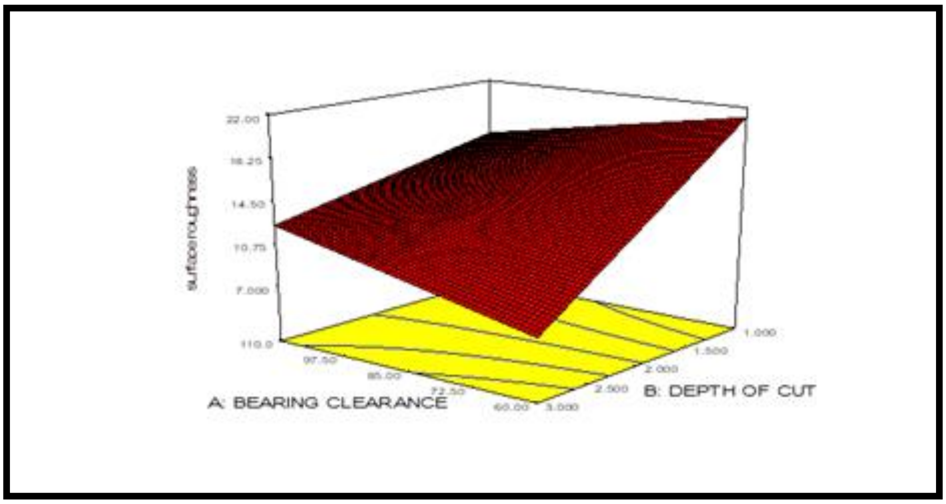

Figure 8: Variation of Surface Roughness with Spindle Speed and Feed

In the present investigation, the process parameters corresponding to the minimum surface finish are considered optimum. Figures 9 and 10 present three-dimensional response surface plots for the response surface roughness obtained from the regression model. The optimum surface roughness is exhibited by the apex of the response surface. The saddle line variation of the surface plot indicates a marked influence of the chosen interactions (AB and CD) on the surface roughness of the mild steel turning.

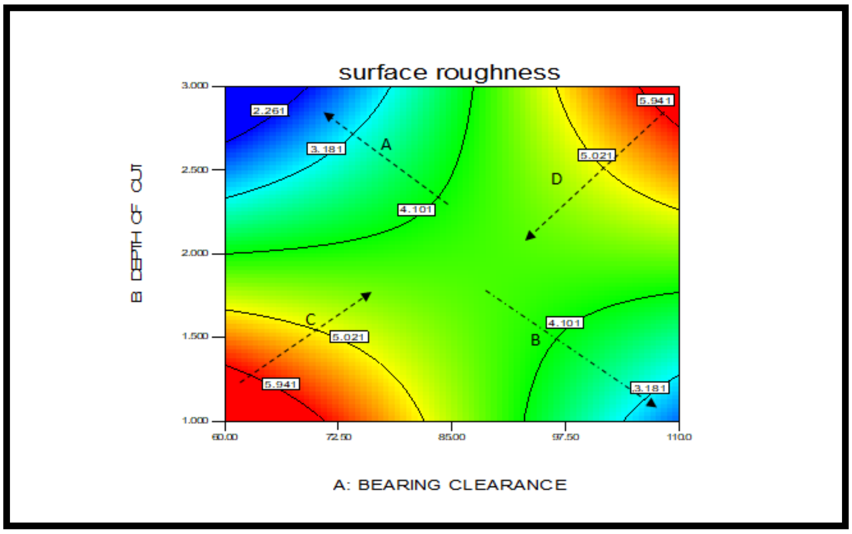

Figure 9: Contour Plot of Surface Roughness in Terms of Bearing Clearance and Depth of Cut

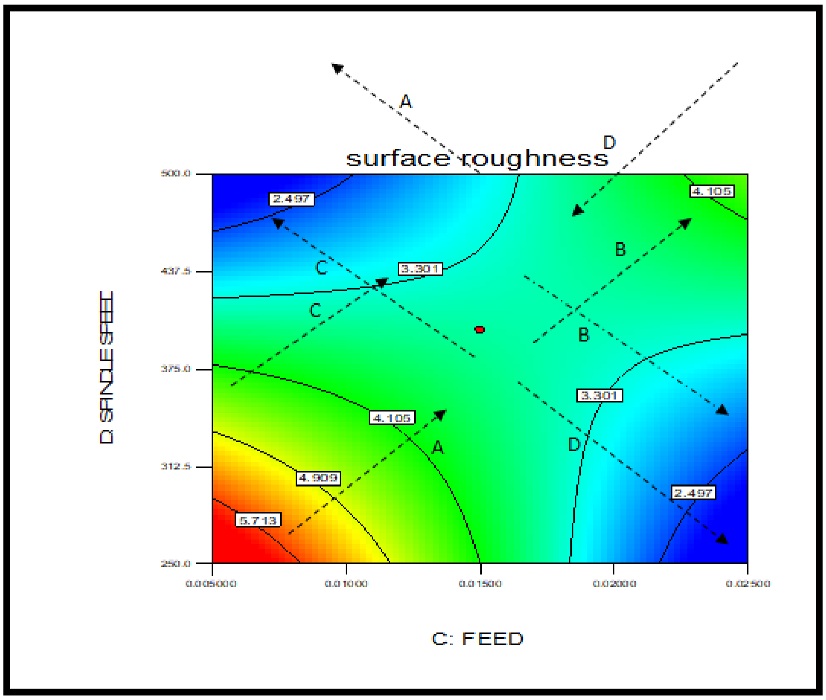

Figure 10: Contour Plot of Surface Roughness in Terms of Spindle Speed and Feed

Figure 9 shows a saddle-shaped contour plot for surface roughness considering the two-factor interaction of depth of cut and bearing clearance. Dotted lines are drawn at 45° and 135° to the horizontal to show regions of minimum surface roughness. At a lower depth of cut, the surface roughness will be minimized as we go down the 'B' arrow. At a higher depth of cutline, 'A' describes the minimum surface roughness. Figure 10 shows a contour plot for surface roughness considering two-factor interactions of spindle speed and feed. Dotted lines at angles of 45° and 135° to the horizontal depict regions of minimum surface roughness.

At lower spindle speed, surface roughness becomes minimal as we go down the 'D' arrow. At higher spindle speeds, line 'C' describes the minimum surface roughness.

3.5. Numerical Optimization

The assignment of a weighted value to a goal functions to adjust the shape of its particular desirability function. On the other hand, the 'importance' of a goal affects the way optimization proceeds. In this dissertation, an identical weight one (1) and importance of three (3) are values assigned to all the parameters and responses, as shown in table 9.

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
Bearing clearance (μm)	Is in range	60	110	1	1	3
Depth of cut (mm)	Is in range	1	3	1	1	3
Feed (mm/rev)	Is in range	0.005	0.025	1	1	3
Spindle speed(rpm)	Is in range	250	500	1	1	3
Surface roughness (μm)	Minimize	2.22	5.982	1	1	*3*

Table 9: Optimization Constraints for the Response

The numerical optimization had thirty (30) solutions, from which the first three were chosen considering the optimization condition and the desirability value. A desirability of 1 was obtained, indicating that the first three solutions are the best solutions in terms of desirability, as shown in table 10. A desirability value close to 1 is accepted as a criterion for determining the optimum response.

Number	Bearing Clearance (μm)	Depth of Cut (mm)	Feed (mm/rev)	Spindle Speed (rpm)	Surface Roughness (μm)	Desirability
1	70	2.5	0.01	450	2.173	1
2	66.67	2.63	0.0147	459.6	2.235	1
3	70	2.5	0.02	350	2.673	1

Table 10: First Three Solutions of the Numerical Optimization Using Criterion 1

Figure 12 shows the ramp plot for the first solution for easier interpretation. The colored dot on each ramp reflects the factor settings or response prediction for the solution. The height of the dot shows how desirable it is. For this solution, bearing clearance and feed are designed to be at a minimum while the depth of cut and spindle speed is designed to be maximum to achieve a minimum surface roughness with a desirability of 1. The desirability plot for this solution is shown in figure 11. The surface roughness plot (Figure 11) shows that at a high depth of cut (2.5mm) at a bearing clearance of 70um, a minimal surface roughness of 2.17µm can be achieved.

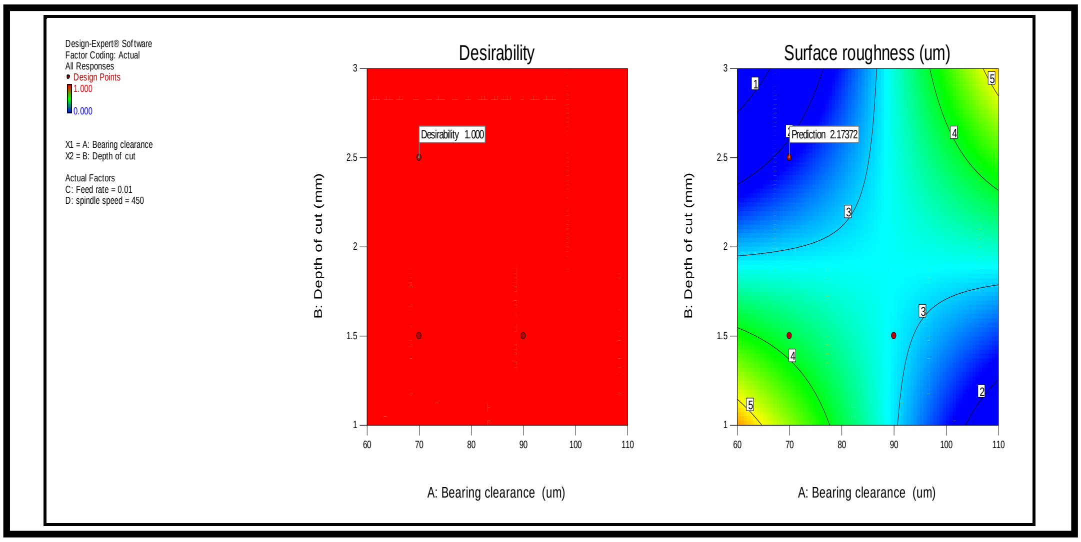

Figure 11: Desirability and Surface Roughness Plot

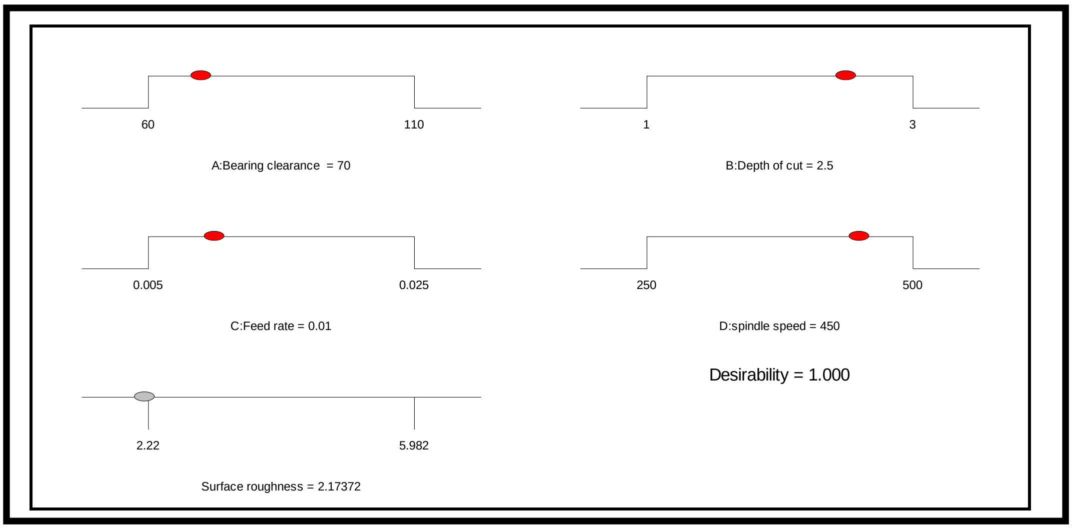

Figure 12: Ramp Plot of First Optimum Solution

From figures 11 and 12, it can be seen that the desirability-based optimization has been carried out. The initial minimum parameters were set to 60 µm bearing clearance, 1 mm depth of cut, 0.005 mm/rev feed, and 250 rpm spindle speed. Each iteration aimed at achieving the initial minimum parameters for minimum surface roughness, but this was not achievable. Considering the ramp plot and the values of the first optimum solution based on the desirability plot, the obtained optimum parameters from RSM were a bearing clearance of 70 µm, a depth of cut of 2.5 mm, a feed of 0.01 mm per rev, a spindle speed of 450 rpm. This reveals that the four machining parameters have significant effects on the surface roughness during machining.

It also reveals that as the spindle speed increases, the surface roughness decreases. This result is in agreement with the observations made by Okonkwo et al. (2015) and Okokpujie and Okonkwo (2015). At these parameter levels, the minimum surface roughness is 2.17372 m, and the desirability is equal to one (D = 1). This observation may be attributed to the simultaneous effects of the four variables.

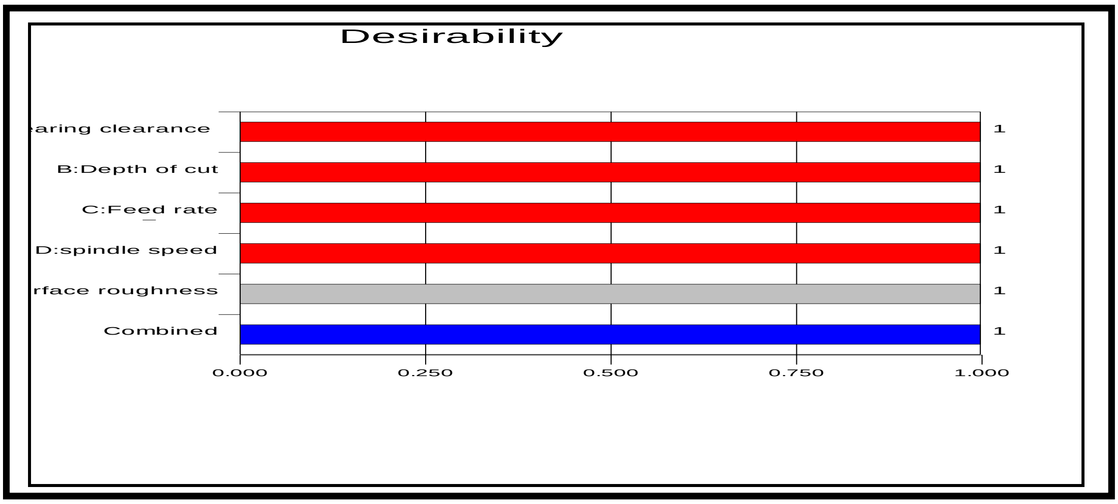

Figure 13: Bar Plot of First Optimum Solution at High Depth of Cut

Figure 13 is a bar plot of the first solution showing the desirability of all the parameters involved in the optimization. All the process parameters have a desirability of 1. The surface roughness response for this solution has a desirability of 1.

3.6. Graphical Optimization

Graphical Optimization Graphical optimizations are graphical tools that show a broader operating window of satisfactory solutions around the optimum point deduced in numerical optimization. On each contour plot, the undesirable area is greyed-out. The colored (yellow) area that remains defines the final optimal factor settings. Figure 14 shows the overlay plot for the optimization of the surface roughness.

From this graphical analysis, it can be found that the optimum value of surface roughness is 2.17372 µm. Since the residuals are low, it can be inferred that the optimization performed undertaken in this study is accurate and usable. For the case considered above, the predicted interval lies between 3.697µm and 0.6501µm. This indicates that predicted surface roughness within this interval can be achieved by considering the factors within the region at the bearing clearance (70µm).

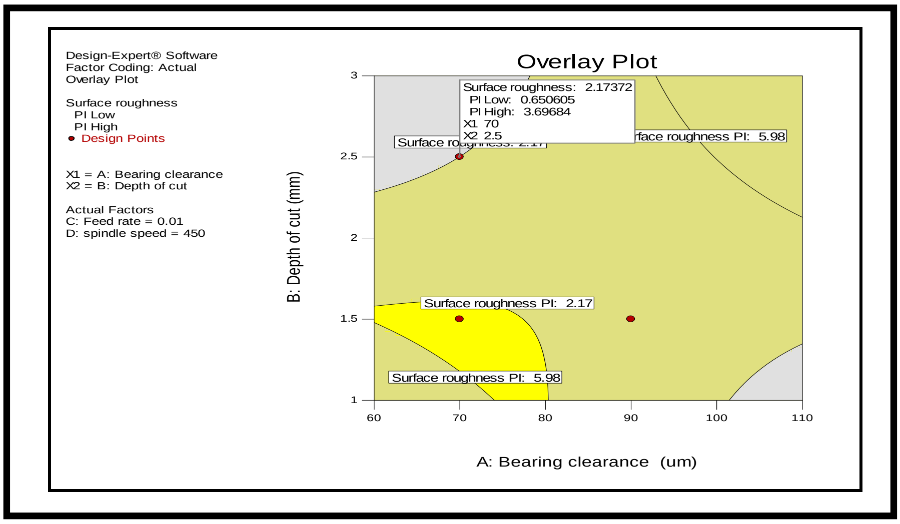

Figure 14: Desirability of Overlay Plot

3.7. Results of Empirical Model Validation

Equation (3.3) is the empirical model that was developed for the prediction of the values of the surface roughness. The predicted values of surface roughness from the developed model and the experimental values are shown in figure 15 and table 11. The comparison of predicted and measured values shows an average percentage deviation of 6.20%. This means that the statistical model could predict surface roughness with about 93.8% accuracy for the given training data set.

	Surface Roughness (Ra) (μm)		
Experimental Runs	**Predicted**	**Experimental**	**Percentage Deviation**
1	4.278	3.768	13.535
2	3.676	3.042	20.842
3	3.712	5.322	-11.462
4	3.712	3.534	5.037
5	4.608	4.662	-1.287
6	3.179	3.072	3.483
7	5.355	5.982	10.481
8	4.302	4.26	0.986
9	3.213	2.502	28.417
10	2.618	2.22	18.829
11	3.712	4.002	-7.246
12	3.530	2.898	21.808
13	2.928	2.862	2.306
14	2.287	2.478	-7.708
15	4.389	4.74	-7.405
16	4.312	3.378	27.649
17	4.278	3.978	7.542
16	3.782	3.108	21.686
19	4.144	3.078	34.633
20	4.237	4.2	0.881
21	3.294	3.12	5.577
22	3.386	3.96	-14.495
23	3.712	4.26	-12.864
24	3.712	3.198	16.073
25	3.489	3.924	-11.086
26	3.446	3.726	-7.515
27	3.975	3.792	4.826
28	3.034	3.84	-20.990
29	3.894	3.87	0.6202
30	4.429	3.9	13.504
			$\sum = 185.908$

Table 11: Comparison between Measure Data and Predicted Data

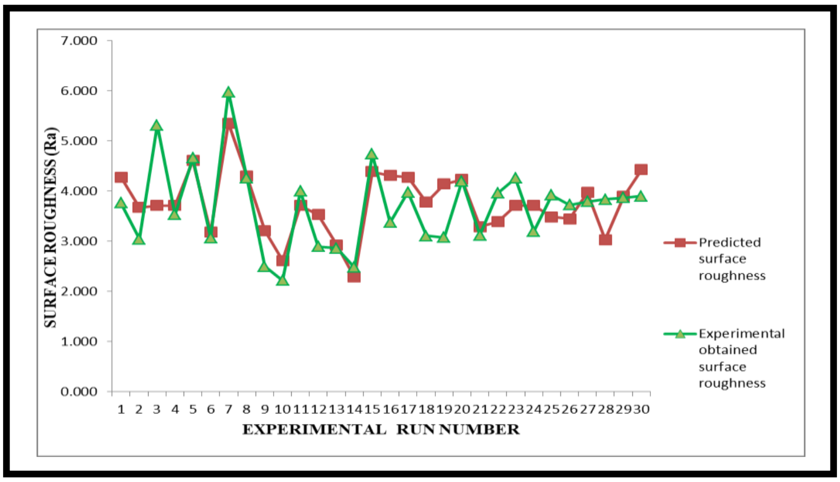

Figure 15: Actual and Predicted Values of the Surface Roughness

4. Conclusion

This study focused on using the response surface methodology to develop empirical models based on three fundamental cutting parameters and a novel process parameter of interest: bearing clearance. In addition to choosing this novel process parameter of interest, bearing clearance, the model undertook an optimization of the turning process using ALSI 1018 mild steel bar specimens.

The rotatable central composite design was used in the experiment to obtain the surface roughness values. A reduced quadratic model for the response variable was applied to the data, and this was presented in the 3D surface plots of figures 7 and 8, along with contour plots of figures 9 and 10. These figures, which were developed during the study, can be used by machine tool manufacturers to provide a range of surface roughness given the interaction effects of bearing clearance and depth of cut, as well as the interaction effects of feed and spindle speed.

The analysis of the numerical optimization values in table 9 revealed that the optimized process conditions during a turning operation occurred at 70μm bearing clearance, 2.5 mm depth of cut, 0.01 revs per minute feed rate, and 450 rpm spindle speed. For these conditions, the minimum surface roughness was 2.173 μm. The graphic optimization based on the overlay plot of figure 14 reveals a broader window of operation for the optimum surface roughness of 2.173, which lies between the intervals of 0.650 and 3.697 at a bearing clearance of 70μm. In the order in which the influential parameters effect the quality of surface finish, the depth of cut was the most significant factor, closely followed by spindle speed and bearing clearance, and the least significant parameter was the feed.

When the developed predictive model's results were compared to the statistically expected values, the surface roughness obtained revealed an average percentage deviation of 6.20% across all sample data. This implies that the statistical model can predict surface roughness with about 93.8% accuracy.

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Appendix

Cylindrical bore bearing Unit μm

Nominal bore diameter d. mm		Clearance									
		C2		CN		C3		C4		C5	
over	up to	min.	max.	min.	max.	min.	max.	min.	max.	min.	max.
–	10	0	25	20	45	35	60	50	75	–	–
10	24	0	25	20	45	35	60	50	75	65	90
24	30	0	25	20	45	35	60	50	75	70	95
30	40	5	30	25	50	45	70	60	85	80	105
40	50	5	35	30	60	50	80	70	100	95	125
50	65	10	40	40	70	60	90	80	110	110	140
65	80	10	45	40	75	65	100	90	125	130	165
80	100	15	50	50	85	75	110	105	140	155	190
100	120	15	55	50	90	85	125	125	165	180	220
120	140	15	60	60	105	100	145	145	190	200	245
140	160	20	70	70	120	115	165	165	215	225	275
160	180	25	75	75	125	120	170	170	220	250	300
180	200	35	90	90	145	140	195	195	250	275	330
200	225	45	105	105	165	160	220	220	280	305	365
225	250	45	110	110	175	170	235	235	300	330	395
250	280	55	125	125	195	190	260	260	330	370	440
280	315	55	130	130	205	200	275	275	350	410	485
315	355	65	145	145	225	225	305	305	385	455	535
355	400	100	190	190	280	280	370	370	460	510	600
400	450	110	210	210	310	310	410	410	510	565	665
450	500	110	220	220	330	330	440	440	550	625	735

Table 12: Radial Internal Clearance of Cylindrical Roller Bearings