ISSN: 0974-5823 Vol. 7 No. 4 April, 2022

International Journal of Mechanical Engineering

Experimental Investigation and Optimization of Cutting Parameters of Dry Turning EN-8 Steel for Enhanced Surface Finishing

Kirubel Tadele Weldgbrel[1], Moera Gutu Jiru[2] , Balkeshwar Singh[3]

[1,2,3]Department of Mechanical Design and Manufacturing Engineering

Adama Science and Technology University, Adama City, Ethiopia

Abstract: This research focuses on the development of optimization models to analyze the influence of machining parameters on surface roughness and to obtain the optimal machining parameters leading to minimum surface roughness during the turning of EN-8 steel using cemented carbide cutting tools. Data analysis has been done using Design-Expert version 11 and Minitab 19 software. The developed models have been compared using relative error and the results have been validated using the experimental confirmation tests. The minimum surface roughness at optimum tuning parameters in this research has been obtained. The result of variance indicates that the contribution of cutting speed, feed rate, and depth of cut has 3.11%, 7.69%, and 76.36%, respectively. It has been found that the predictive model provides optimum machining parameters. The results of the proposed model provide improvement in surface roughness over the best experimental run. The 3D surface and contour plots constructed during the research has been used for choosing the optimal machining parameters to obtain particular surface roughness values. The optimal machining parameters indicate that the depth of cut is the most significant machining parameter followed by the cutting speed and feed rate in surface roughness. The confirmation experiments has been performed to facilitate the verification of the obtained feasible optimal machining parameters (v = 375 m/min, f = 0.287 mm/rev and d = 1 mm) for the surface roughness and the optimized surface roughness obtained is (Ra) 5.113 µm. The results reveal that the developed predictive models provide a close relationship between the predicted values and the experimental surface roughness values.

Keywords: Response Surface Methodology, Surface Roughness, EN-8 steel

1. INTRODUCTION

Surface finish is one of the most important quality characteristics in manufacturing industries, which influences the performance of mechanical parts as well as production cost. In recent times, modern industries are trying to achieve high-quality products in a very short time with less operator input. For that purpose, the computer numerically controlled machine tools with automated and flexible manufacturing systems have been implemented. In the manufacturing industries, various manufacturing processes are adopted to remove the material from the workpiece. Out of these, turning is the first most common method for metal cutting because of its ability to remove materials faster with reasonably good surface quality [1]. Producing good quality, appropriate surface finish, and geometry is essential for the machined work piece. The surface finish or surface texture based on ASME, 1985[2] is defined as geometrical irregularities of solid materials surface while surface roughness is defined as the more delicate irregularities of the surface texture, usually resulting from the inherent action of the assembly process, such as feed marks produced during machining.

A lot of research has been done in past and a survey on critical controllable tuning parameters for the lathe machines such as cutting speed, feed, depth of cut, tool geometry, tool, and work piece material, which affect the desired output including, surface finish, tool wear, tool life and performance are studied. But a little research has been done on optimization of surface roughness on cutting parameters of different EN carbon steel grades and a few works are available for different materials to show contrasting results – few authors observed that cutting speed is the most significant factor followed by the depth of cut[3][4][5]. Other authors observed that the depth of cut is the significant factor followed by cutting speed [6][7]. Therefore, more studies need to be carried out to observe the influence of machining parameters on performance characteristics. A generalized relationship between the machining parameters and the process performance is hard to model accurately mainly largely due to the nature of the challenging stochastic process mechanisms in machining.

This work is an attempt to fill this gap in the research. Machining is still an open field of research after the last some years of research mainly because of the changes in machining technology, materials, and the advancement in the modeling and optimization techniques as well as the advancements in computational technology.

This research aims to investigate the effects of cutting parameters on the resulting surface roughness in the turning operation of EN-8 steel material. The specific products from this steel are shafts, cam, bolt, stud, gear, so on. It is essential to optimize this material due to the quick-wear of components under dynamic load. In the present work, models are developed to predicate the surface roughness with the assistance of Response surface methodology, Design of experiments [8]. The response surface methodology (RSM) may be practical, accurate, and straightforward for implementation. The study of the most important variables affecting the quality characteristics and a plan for conducting such experiments is called the design of experiments [9].

The experimental data is used to develop mathematical models for second-order models using regression methods. Analysis of variance is used to verify the validity of the model. RSM optimization procedure has been used to optimize the output responses of surface roughness. On selected material, a different trial with different parameters level carried experiment, and finally, to verify the predicted value, a confirmation test is conducted based on an experiment. The research has completed a fractional experiment design that allows considering different levels of cutting parameters (cutting speed, feed rate, depth of cut) on the measured dependent variable (surface roughness). The ability to control the process for the better quality of the product is significant [10].

In this research work, variation of surface roughness with varying parameters (cutting parameters has been investigated. Experimental investigation of surface roughness of EN-8 steel material using turning operation and the variation of surface roughness with response variables has been done. The models have been developed to predicate the surface roughness with the assistance of Response surface methodology, Design of experiments.

2. MATERIALS AND METHODOLOGIES

2.1 Experimental setup

A conventional lathe machine was used for experimental study for cutting parameters on surface roughness. The turning machine with the model of URSUS 200 was used for this study. The sample material for the research was EN-8 steel. The work piece was estimated by using a surface roughness analyzer (Profilo-meter) and it was used to measure average roughness. The detailed information on chemical composition and mechanical properties and specification of EN-8 steel is provided in Table 1 and Table 2 respectively. A round bar with 50 mm diameter and 280 BHN was used.

Table 1 Chemical composition of EN 8 steel [11]

Element	**Standard (wt%)**	**Actual (wt%)**
Sulfur, S	0.045	0.04
Phosphorus, P	0.045	0.04
Molybdenum, Mo	0.10	0.10
Carbon, C	0.36	0.44
Silicon, Si	0.40	0.40
Chromium, Cr	0.40	0.25
Nickel, Ni	0.40	0.25
Manganese, Mn	0.65	0.60

Table 2 Mechanical properties of EN-8 steel [12]

Sample ID	Solid, Round
Diameter (mm)	50
Area (mm^2)	1,963.495
Yield Stress MPa	280
Tensile Stress MPa	550
Hardness	152/207

2.2 Machining parameters and their levels

The choice of machining parameters was made by taking into account the capacity/limiting cutting conditions of the turning, tool manufacturer's catalog, experimental time and cost into account, and the values taken by researchers in the literature. Cutting speed, feed rate, and depth of cut are the input parameters chosen for the research. The cutting speed (A) [rev/min] is the rotational speed of the lathe machine spindle or the work-piece. Feed rate (B) [mm/rev] is the speed of the cutting tool relative to that of the work-piece as the tool takes a cut along the axis of the work-piece. The depth of cut (C) [mm] is the thickness of the material removed in one pass of the work under cutter. The performance characteristic chosen to investigate the effect of machining parameters is surface roughness. Cutting parameters for EN-8 steel were selected depending on the recommended cutting parameters, which are given in Table 3, and the range was taken to get accurate results since the maximum difference was at the maximum range.

Table 3 Machining parameters and their levels

Factor	**Symbol**	**Level 1**	**Level 2**	**Level 3**
Cutting speed (m/min)	v	220	292	375
Feed rate (mm/min)	f	0.1	0.2	0.3
Depth of cut (mm)	d	1	1.5	2

2.3 Response variables

The surface roughness was selected for response variable. The surface roughness, as a measure of surface texture, was the vertical deviations of a real surface from its ideal form. A significant deviation was taken as a rough surface; while a small deviation was taken as a smooth surface. Thus, surface roughness seen as the high frequency, short wavelength component of surface measured, which determines how a real object was interact with its environment. Rough surfaces wear faster and have a higher coefficient of friction than smooth surfaces. Again, the roughness of a surface [micron, µm, or µmm] may form nucleation sites for cracks or corrosion, promote adhesion, and may be very expensive to control in manufacturing.

2.4 Mathematical model

Engineering experiments aim at determining the conditions that can lead to optimum performances. One of the methodologies for obtaining optimum performance is the Response Surface Methodology(RSM). RSM, developed by Box and Draper, 1987[13], is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which several variables influence the response of interest and the objective is to optimize the response. It is a sequential experimentation approach for empirical model building and optimization. RSM is repeatedly applied in the characterization and optimization of processes. In RSM, it is possible to represent independent process parameters in quantitative form as:

$$Y = f(X_1, X_2, X_3, \ldots\ldots X_n) \pm \varepsilon \tag{1}$$

where Y is the response, f is the response function, ε is the experimental error, and X1, X2, X3, ……, Xn are independent parameters. Y is plotted to get the response surface. The form of f is unknown and may be very complicated. Therefore, RSM aims at approximating f by a suitable lower ordered polynomial in some regions of the independent process variables. If the response can be well modeled by a linear function of the independent variables, the function equation (1) can be written as:

$$Y = b_0 + b_{1x1} + b_{2x2} + b_{3x3}, \ldots\ldots b_{nxn} \pm \varepsilon \tag{2}$$

However, if a curvature appears in the system, then a higher-order polynomial such as quadric model (equation (3)) may be used:

$$Y_u = b_0 + \sum_{i=1}^{n} bixi + \sum_{i=1}^{n} bijx^2i + \sum_{i<j}^{n} bijxj \tag{3}$$

where Y is the corresponding response and xi (1, 2, …, n) is the independent input parameters. The terms b_0, b_1, b_2, so on. are the second-order regression coefficients. The second term contributes to the linear effect, the third term contributes to the higher-order effects, and the fourth term contributes to the interactive effects of the input parameters. The values of the coefficients are estimated by using the responses collected (Y1, Y2…, Yn) through the design points (n) by applying the least square technique. This equation can be rewritten in terms of the three variables:

$$Y = b_0 + b_{1x1} + b_{2x2} + b_{3x3} + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 + b_{12x1x2} + b_{13x1x3} + b_{23x2x3} \tag{4}$$

The objective of using RSM is not only to investigate the response over the entire factor space but also to locate the region of interest where the response reaches its optimal or near-optimal value. A careful study of the response surface model provides a combination of factors giving the best response.

2.5 Design of Experiment

In the design of experiment techniques, RSM attempts to minimize the assess experimental error, make a qualitative estimation of parameters, optimize values of parameters, number of runs or trials, and make inferences regarding the effect of parameters on the characteristics of a process. The essential idea of RSM is to use a sequence of designed experiments to obtain an optimal response. To observe the most influential process parameters in the turning process, namely cutting speed, feed, and depth of cut each at three levels was considered in the this research work. For these reasons, RSM, based on CC-DOE, was selected. Therefore, it was used in this work to model, predict, and optimize *Ra*. As a mathematical and statistical technique, it was developed for the treatment of problems involving a response of interest as a function of several variables. This is one of the ways machining process modeling and analysis can achieve to facilitate its optimization. Its application requires machining response *Y* to define as [1]:

$$Y = \varphi\,(x1, x2, \ldots, xi) \pm e \tag{5}$$

where $\varphi\ (x1, x2, \ldots, xi)$ is the response surface function in the form of a polynomial model, *x1* is the process variables and is the residual or experimental error. The second-order polynomial or quadratic model may, therefore, be written as:

$$\varphi = \varphi\,(x_1, x_2, \ldots, X_k)$$

$$= (Y \pm e) \tag{6}$$

$$= b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} {x_i}^2 + \sum_{i=1}^{k} b_{ij} x_i x_j$$

Equation (6) is a multiple regression model. In this form, it has constant, linear, square, and cross-product terms. It can, satisfactorily, be used to correlate dependent variables, φ_j, with independent variables, x_i. Several techniques for DOE are available for use to estimate the coefficients of the regression models.

The Central Composite (CC) was selected for the design of the turning experiment. Analysis of variance (ANOVA) was used to validate the developed models and also to predict the effect of selected factors A, B, and C on the response characteristics *Ra*. Optimization of the coded and actual response functions, Ra (A, B, C), subject to constraints as determined by the limits of the factors A, B, and C, was performed as appropriate using a standard optimization technique. The RSM was implemented in the Design-Expert software version 11 environment.

2.6 Experiment plan

The experiment was performed to investigate the effect of input parameters on response. The DOE has a significant effect on the approximate accuracy and cost of the response surface. The experiment of 27 runs was randomized by using DOE. DOE was evaluated as the response to the model fitness. The design data is evaluated by running the 27 samples through turning operation and calculated the measuring value of the surface roughness using a profile-meter. The machining of a cutting parameter is given in Table 3.

2.7 Surface roughness measurement

The experimental setup is shown in Figure 1(a). The final work piece used for measuring the surface roughness is shown in Figure 1(b). The surface roughness of the finished surface is measured by placing the work piece on a rectangular block over a cast-iron surface plate after each cut (Figure 1(c)).

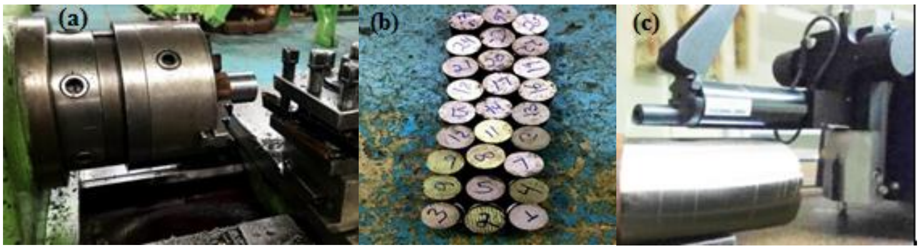

Figure 1 (a) Experimental setups,(b) samples after machined and (c) measuring surface roughness

After the setup was ready, trial cuts were taken, and equipment was calibrated to ensure that the part quality adhered to the quality requirements of the Original Equipment Manufacturer (OEM) and to compare the stability of the machining process to that of the OEMs. The equipment was calibrated by measuring the known diameter of a high-precision spherical ball. Figure 2(c) shows the surface roughness profile, measured on the spherical ball. The stability of the experimental setup was compared to the OEM's recommended specification. Once the stability of the setup was confirmed, the experiments were conducted and the surface roughness was measured at three equally spaced locations around the circumference of the work-piece to obtain the statistically significant data for the test, and then the mean of measurements was calculated. Thus, probable observation errors were kept relatively small.

3. RESULTS AND DISCUSSIONS

After completing the machining operation, the response parameter that is the surface roughness was measured. Statistical analysis was performed on the optimum result obtained for attaining main effects. The experimental study was conducted to evaluate the effect of cutting parameters,
namely cutting speed, feed rate, and depth of cut on the surface quality of EN-8 steel during the turning process. This step determines the effect of various process parameters to achieve desired surface roughness. Table 4 shows the design layout for the turning experiment conducted as well as the response data generated. The experiment was conducted in a controlled environment to minimize errors. The DOE was used to identify the optimum cutting parameters and to identify the most influential parameters.

Table **Error! No text of specified style in document.**. Measured surface roughness at L_{27} full factorial machining parameters

No.	A: Cutting speed (m/min)	B: Feed rate (mm/min)	C: Depth of cut (mm)	Surface roughness (µm)			
				Run 1	Run 2	Run 3	Average
1	220	0.1	1	13.313	13.496	13.261	13.357
2	220	0.1	1.5	7.592	7.629	7.584	7.602
3	220	0.1	2	7.230	7.218	7.422	7.290
4	220	0.2	1	13.977	15.222	10.776	13.325
5	220	0.2	1.5	7.577	7.824	8.868	8.090
6	220	0.2	2	8.252	8.274	8.297	8.274
7	220	0.3	1	14.150	13.335	12.095	13.193
8	220	0.3	1.5	9.368	9.699	9.985	9.684
9	220	0.3	2	9.409	9.250	9.089	9.249

10	292	0.1	1	9.156	9.167	9.015	9.113
11	292	0.1	1.5	7.010	7.015	6.945	6.990
12	292	0.1	2	8.214	8.203	8.160	8.192
13	292	0.2	1	6.916	7.246	6.374	6.845
14	292	0.2	1.5	6.215	6.10	7.379	6.565
15	292	0.2	2	8.083	8.082	8.130	8.098
16	292	0.3	1	7.076	7.106	7.149	7.110
17	292	0.3	1.5	6.853	6.841	6.831	6.842
18	292	0.3	2	11.066	11.075	11.100	11.080
19	375	0.1	1	5.158	4.792	5.316	5.089
20	375	0.1	1.5	7.074	7.021	7.115	7.070
21	375	0.1	2	11.571	11.564	11.515	11.550
22	375	0.2	1	5.496	5.487	5.503	5.495
23	375	0.2	1.5	6.211	6.225	6.220	6.219
24	375	0.2	2	13.524	13.558	13.501	13.528
25	375	0.3	1	5.156	5.139	5.117	5.137
26	375	0.3	1.5	8.936	8.928	8.889	8.918
27	375	0.3	2	14.733	14.698	14.848	14.760

3.1 Data generated from the turning experiment

Data collection plays a significant role in the statistical analysis of any field, as it decides the progression of the analysis to the best or worst. Proper and suitable data collection leads to better results from the analysis. In such a focus, it is very much essential to choose a well suitable data collection technique for the analysis. In this work, Data collection for the turning process is selected for proceeding with RSM design, i.e., a second-order quadratic model. The values predicted using the model in the turning of EN-8 steel using a carbide cutting tool have been shown in Table 5.

Table 5**.** Data generated from the turning experiment

Run	Factor 1 A: Cutting speed (m/min)	Factor 2 B: Feed rate (mm/min)	Factor 3 C: Depth of Cut (mm)	Response Surface roughness (µm)
1	220	0.1	1	13.357
2	220	0.1	1.5	7.602
3	220	0.1	2	7.290
4	220	0.2	1	13.325
5	220	0.2	1.5	8.090
6	220	0.2	2	8.274
7	220	0.3	1	13.193
8	220	0.3	1.5	9.684
9	220	0.3	2	9.249
10	292	0.1	1	9.113
11	292	0.1	1.5	6.990
12	292	0.1	2	8.192
13	292	0.2	1	6.845
14	292	0.2	1.5	6.565

15	292	0.2	2	8.098
16	292	0.3	1	7.110
17	292	0.3	1.5	6.842
18	292	0.3	2	11.080
19	375	0.2	1	5.089
20	375	0.2	1.5	7.070
21	375	0.2	2	11.550
22	375	0.1	1	5.495
23	375	0.1	1.5	6.219
24	375	0.	2	13.528
25	375	0.3	1	5.137
26	375	0.3	1.5	8.918
27	375	0.3	2	14.760

On average the minimum surface roughness was found to be 5.089µm whereas the maximum surface roughness is 14.760µm (Figure 2).

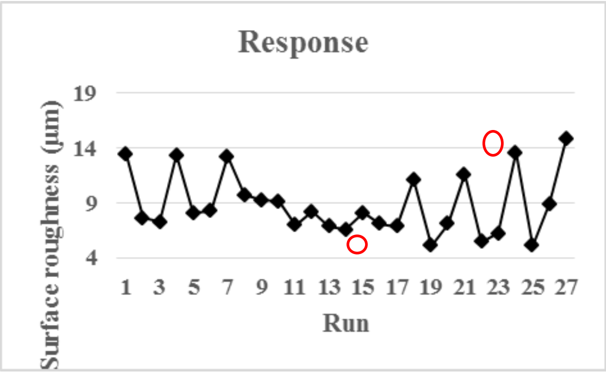

Figure 2 Minimum and maximum surface roughness

3.2 Surface roughness data

This analysis deals with the finding the investigation of cutting parameters on surface roughness in turning the operation of EN-8 steel using cemented carbide cutting tool in turning for the different values of cutting speed, feed rate, and depth of cut. The selection of experimental design was a decision-making process that decides the degree of validity of the desired model in finding optimal cutting parameters. This work was carried out using a Response surface methodology. Central Composite Design (CCD) method comes under the Response surface methodology.

A central composite design is an experimental design, useful in response surface methodology, for creating a second-order (quadratic) model for the response variable. The response surface design is better, as it generates a second-order quadratic model of regression, which is a better predictive model than a first-order quadratic model. In this work, CCD was applied for the experimental investigation.

3.3 Model summary statistics

In the process of model selection, the cubic Model is aliased as the central composite matrix provides too few unique design points to determine all the terms in the cubic model. It's set up only for the quadratic model. Table 6 shows the model summary statistics.

Table 6 Model summary statistics

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	2.81	0.1113	-0.0046	-0.2993	265.23	
2FI	1.50	0.7803	0.7144	0.5995	81.77	
Quadratic	**0.6593**	**0.9638**	**0.9446**	**0.9136**	**17.63**	**Suggested**
Cubic	0.7282	0.9740	0.9325	0.7873	43.42	Aliased

For each source of terms, the quadratic probability Prob > F falls under 0.05. So far, Design-Expert was indicated (via bold highlighting) the quadratic model best – these terms are significant, but adding the cubic order terms will not significantly improve the fit. (Even if they were significant, the cubic terms would be aliased, so they wouldn't be useful for modeling purposes).

3.4 Analysis of variance(ANOVA)

The ANOVA is where the descriptive statistics and statistical tests are presented. In general, look for low p-values to identify important terms in the model. The p-values to determine if the model explains a significant portion of the variance. Table 7 shows ANOVA results for the linear [A, B, C] quadratic [A^2, B^2, C^2] and interactive [(A × B), (A × C), (B×C)] factors. The sum of squares is used to estimate the square of deviation from the mean. Mean squares are estimated by dividing the sum of squares by degrees of freedom. F-value, which is a ratio between the regression mean square and the mean square error, is used to measure the significance of the model under investigation concerning the variance of all the terms, including the error term at the desired significance level. Usually, $F > 4$ means that the change of the design parameter has a significant effect on the response variable. P-value or probability value is used to determine the statistical significance of results at a confidence level. In this study, the significance level of $\alpha = 0.05$ is used, i.e., the results are valid for a confidence level of 95%. Table 7 shows the p-values, the significance levels associated with the F-values for each source of variation. If the p-value is less than 0.05, then the corresponding factor (source) has a statistically significant contribution to the response variable. If the p-value is more than 0.05, then it means the effect of a factor on the response variable is not statistically significant at a 95% confidence level.

Table 7 Analysis of variance results

Source	Sum of Squares	Df	Mean Square	F-value	p-value	Contribution%
Model	6.75	9	21.86	6.74	< 0.0001	21.62
A-Cutting speed	0.97	1	5.3	1.19	0.0528	3.11
B-Feed rate	2.4	1	8.4	19.33	0.0004	7.69
C-Depth of cut	23.84	1	12.07	27.77	< 0.0001	76.36
AB	0.16	1	0.1646	0.3787	0.0564	0.51
AC	0.75	1	127.77	2.97	0.4901	2.40
BC	0.63	1	8.63	1.85	0.7003	2.02
A^2	0.51	1	13.51	3.08	0.3022	1.63
B^2	0.57	1	1.62	3.72	0.0505	1.83
C^2	0.33	1	22.33	0.38	0.8059	1.06
Residual	1.06	17	0.4346			3.40
Total	31.22	26				

The Model F-value of 6.75 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise. P-values less than 0.0500 indicate model terms are significant. In this case, A, B, C, AC, BC, A^2, C^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there're a lot of numerous insignificant model terms (not counting those required to support hierarchy), model reduction may improve the model.

3.5 Parametric influence on surface roughness

Theoretically, surface roughness is a function of feed rate and nose radius. However, in practice, cutting speed, depth of cut, and tool wear also affect surface roughness. Since the inserts used in the experiments have identical nose radius values, the effect of nose radius was not investigated in this study. The effect of tool wear was neglected as a new cutting edge was used for each experiment, and wear did not reach high levels enough to affect the surface roughness.

The main effects of machining parameters are shown in Figure 3. Depth of cut has the greatest effect on surface roughness. The effect of feed rate is very less, and the effect of cutting speed is negligible, as shown in Figure 3. Even after a 900% increase in cutting speed, no considerable change was noticed. An increase in cutting speed improves surface quality. This result supports the argument that high cutting speeds reduce cutting forces, giving a better surface finish[14]. The best surface quality values can be achieved at low feed rates and high cutting speeds. Sahin and Motorcu (2005)[15] also demonstrated that surface roughness increases with an increase in feed rate and decreases with an increase in cutting speed during the cutting of EN-8 steel using a cemented carbide cutting tool.

However, Cetin *et al.* (2011)[16] indicated that the effects of feed rate and depth of cut are more effective than cutting speed on reducing the forces and improving the surface finish.

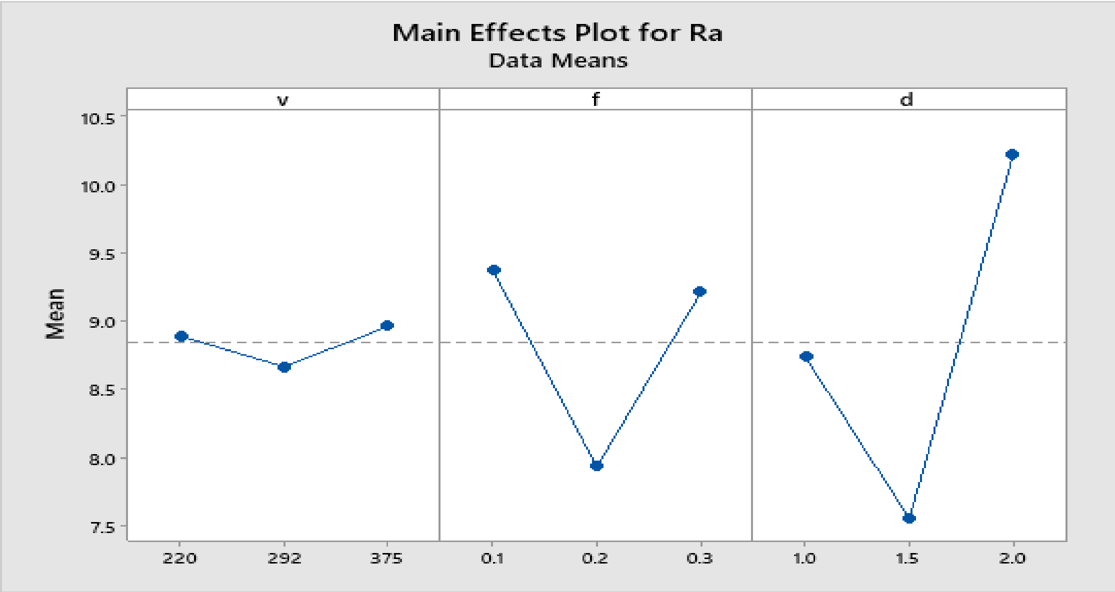

Figure 3 Main effect plot of surface roughness

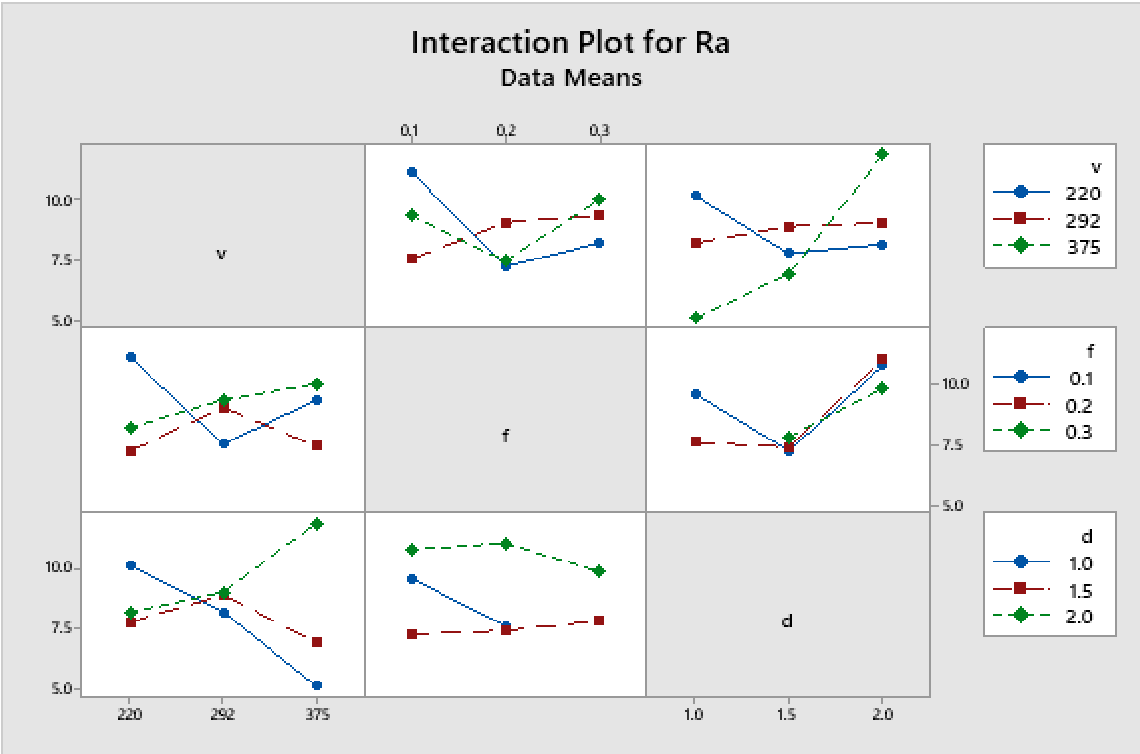

Figure 4 Interaction plot of surface roughness

The interaction plot for surface roughness is shown in Figure 4. This figure clearly shows that the surface roughness is high with a variation of feed rate at any depth of cut (row 3 column 2) and any cutting speed (row 1 column 2) as the minimum surface roughness is close to 5 µm for level 1 depth of cut and all levels of feed rate and cutting speed, and the maximum surface roughness is more than 7.5 µm for level 3 depth of cut and all levels of feed rate and cutting speed. The variation of feed rate has a negligible effect on surface roughness for feed rate (row 2 column 3) as the spacing between the lines is very small.

3.6 Validation of the proposed predictive models

The results obtained from the proposed predictive modeling techniques of RSM are shown in Table 8. The relative percentage error between the fitted values predicted and the experimental values of the surface roughness are computed using the following equation.

$$Relative\ Error\ (\%) = \frac{[Predicted\ value\ -\ Experimental\ value]}{\text{Experimental Value}} X100$$

Table 8 Predicted values and relative errors for modeling techniques of RSM for surface roughness

Experiment No. Experiment	Surface roughness (µm)		Relative Error (%)
	Experimental	Predicted	
1	13.357	12.891	3.489
2	9.113	8.508	6.639
3	5.495	5.821	5.933
4	13.325	12.497	6.214
5	13.193	12.319	6.625
6	6.845	6.737	1.578
7	5.137	5.603	9.071
8	5.089	5.43	6.701
9	7.11	7.453	4.824
10	6.99	7.164	2.489
11	7.602	7.832	3.026
12	6.565	6.294	4.128
13	7.07	7.576	7.157
14	8.09	7.548	6.700
15	9.684	8.916	7.931
16	6.842	7.287	6.504
17	8.918	8.365	6.201
18	6.219	6.837	9.937
19	8.098	7.653	5.495
20	7.29	7.414	1.701
21	11.55	11.67	1.039
22	14.76	14.54	1.491
23	8.274	7.806	5.656
24	13.528	12.368	8.575
25	8.192	7.928	3.223
26	11.08	10.499	5.244
27	9.249	10.065	8.823

Table 8 and Figure 5 show the relative errors for the modeling techniques.

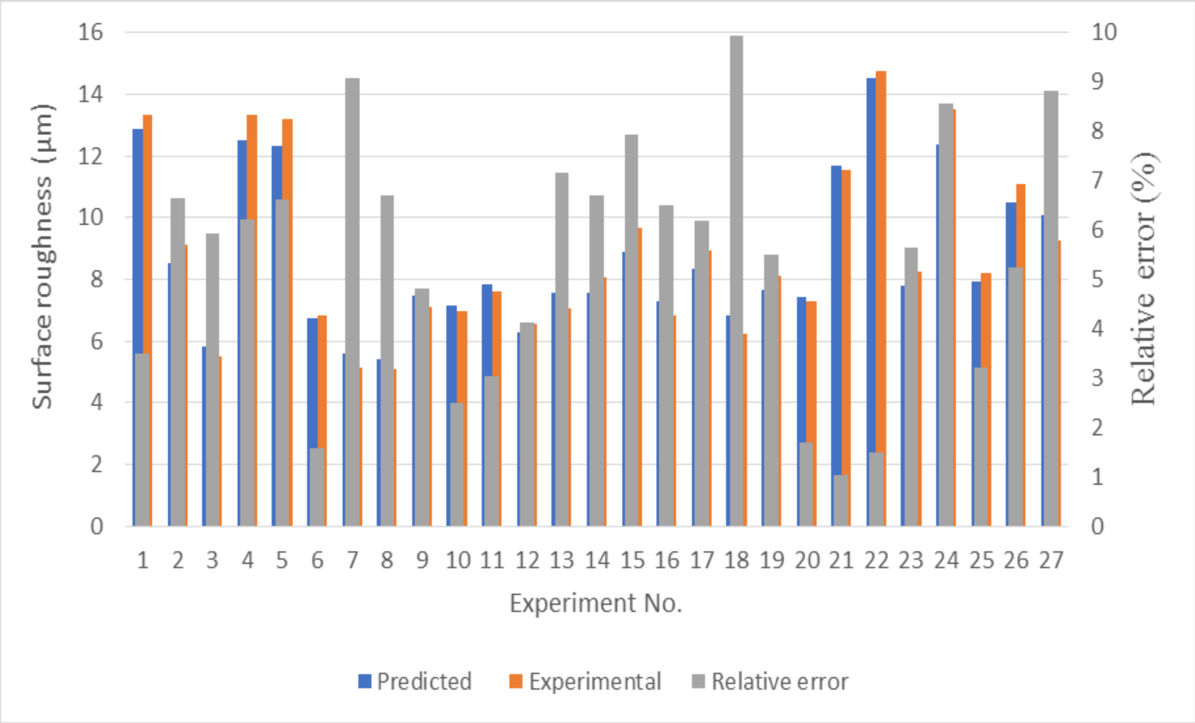

Figure 5 Deviation of surface roughness predicted values from the experimental values

The maximum relative error of 9.937% is obtained and which is caused by measurement error and accuracy of profile-meter used.

3.7 Surface roughness optimization using response surface methodology

After developing predictive models to predict the surface roughness, the next logical step is surface roughness optimization concerning cutting conditions. The selection of optimum cutting conditions has always been a challenge in machining. Low surface roughness values can be achieved by adjusting cutting conditions with the help of appropriate optimization methods. Therefore, the process parameters are defined in the standard optimization format to be solved by optimization algorithms. The response optimization parameters and starting values are given in table 9 and 10.The optimal response plot is generated using MINITAB software.

Response Optimization: Ra

Table 9 Parameters

Response	**Goal**	**Lower**	**Target**	**Upper**	**Weight**	**Importance**
Ra	Target	4.5801	5.089	14.76	1	1

Table 10 Starting values

Variables	**v(m/min)**	**f(mm/min)**	**d(mm)**
Settings	260.15	0.1	1.202

Desirability is simply a mathematical method to find the optimum. Desirability is an objective function that ranges from zero external of the limits to one at the goal. The numerical optimization finds a point that maximizes the desirability function. The desirability of 1.00 means the goals were simple to reach and better results may be available. Consider thinking about producing the goals harder or adding new criteria for less critical responses and even factors. The final goal is not to maximize the desirability value. The factor settings that result in the highest desirability scores point to over there is an island of acceptable outcomes. It is quite possible for over there to be multiple islands (local optima) to explore. The optimized solution is as shown in table 11.

Table 11 Optimized solution

Solution	v (m/min)	f (mm/min)	d (mm)	Ra Fit (µm)	Composite Desirability
1	375	0.287879	1	5.09575	0.999302

The value is completely dependent on how closely the lower and upper limits are set relative to the actual optimum. The goal of optimization is to locate a good set of conditions that will meet all the goals, not to get to a desirability value of 1.0. The optimal machining parameters are given in table 12.

Table 12 Optimal machining parameters

Variable	v (m/min)	f (mm/min)	d (mm)
Setting	375	0.287879	1

Optimal machining parameters obtained are cutting speed of 375 m/min at a feed rate of 0.287 mm/min and 1 mm depth of cut. The optimized surface roughness is given in table 13.

Table 13 Optimized surface roughness

Response	Fit	SE Fit	95% CI	95% PI
Ra	5.10	3.76	(-2.83, 13.02)	(-4.72, 14.91)

The optimized surface roughness obtained is (Ra) 5.10 µm. The desirability value is 0.9993, which is very close to 1.0. The response optimization for surface roughness is given in table 14.

Table 14 Response optimization for surface roughness

Response	Goal	Optimum Combination			Lower	Target	Upper	Predicted	Desirability
		v (m/min)	f (mm/min)	d (mm)					
Ra	Min	375	0.287	1	5.089	5.089	14.76	5.10	0.9993

Figure 6 shows the surface roughness optimization plots for parameters v, f, and d. Each column of the graph corresponds to a factor. Each row of the graph corresponds to the response. Each cell of the graph shows how the response changes as a function of one of the factors, while all other factors remain fixed. The numbers displayed at the top of a column show the current factor level settings and the high and low settings of a factor in the experimental design.

The current optimal parameter settings are: cutting speed of 375 m/min, the feed rate of 0.287 mm/min Furthermore, the depth of the cut of 1 mm for achieving the minimum surface roughness. The composite desirability (D) is displayed in the upper left corner of the graph. The label above composite desirability refers to the current setting and changes interactively with the factor settings. The optimal response plot is generated using MINITAB software. The vertical lines inside the graph represent current optimal parametric settings. The horizontal dotted lines represent the current response values.

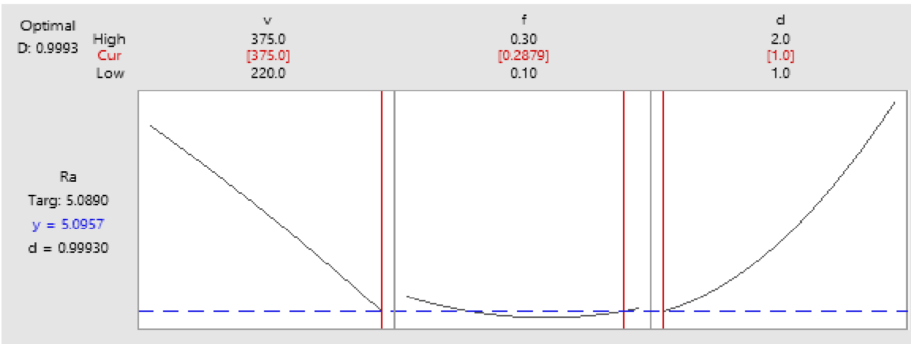

Figure 6 Response optimization plot for surface roughness

3.8 Combined effect

The combined effect of feed rate and cutting speed on surface roughness is as shown in Figure 7.

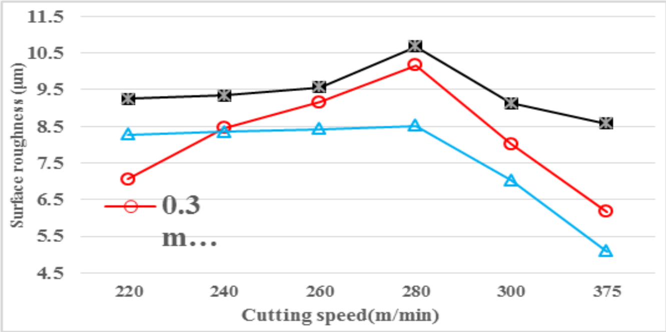

Figure 7 Combined effects on surface roughness

Figure 7 shows 3 different combined effect feed rates and the minimum result is found at 0.2 feed rate, at 375 cutting speed, and Min Ra = 5.089µm.

3.9 Interaction contour plot

The 2D, 3D surface, and contour plots for the respective cutting parameters and surface roughness are shown in Figures 8, 9 and 10. However, this plot is useful to find the optimum values of cutting speed and feed rate at a particular value of surface roughness and depth of cut. These 3D surface plots can be used for estimating the surface roughness values for any suitable combination of the input parameters, namely cutting speed, feed rate, and depth of cut.

Figure 8 shows the surface and contour plots for surface roughness at 1 mm depth of cut. It is observed that the surface roughness increases with decreases in cutting speed at a slower feed rate and decreases with an increase in feed rate. While at a higher feed rate, the surface roughness decreases with an increase in cutting speed.

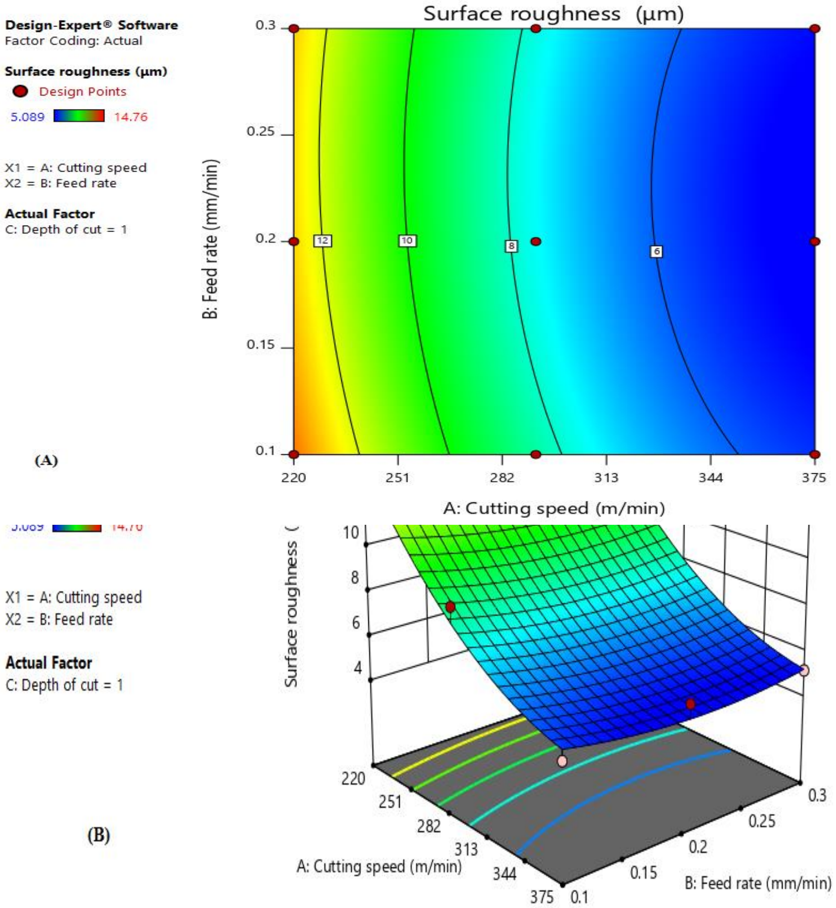

Figure 8 Surface and contour plot of Ra for varying cutting speed and feed rate at 1 mm depth of cut (A) 2D view and (B) 3D view

Figure 9 shows the surface and contour plots for surface roughness at a cutting speed of 375 m/min. It reveals that surface roughness increases with an increase in depth of cut, and feed rate has a less significant effect. Figure 10 shows the surface and contour plots for surface roughness at a feed rate of 0.287 mm/min. At a minimum depth of cut and maximum cutting speed, the surface roughness is minimum. At a maximum depth of cut maximum cutting speed, the surface roughness is high. At a minimum depth of cut and minimum, cutting speed surface roughness is maximum.

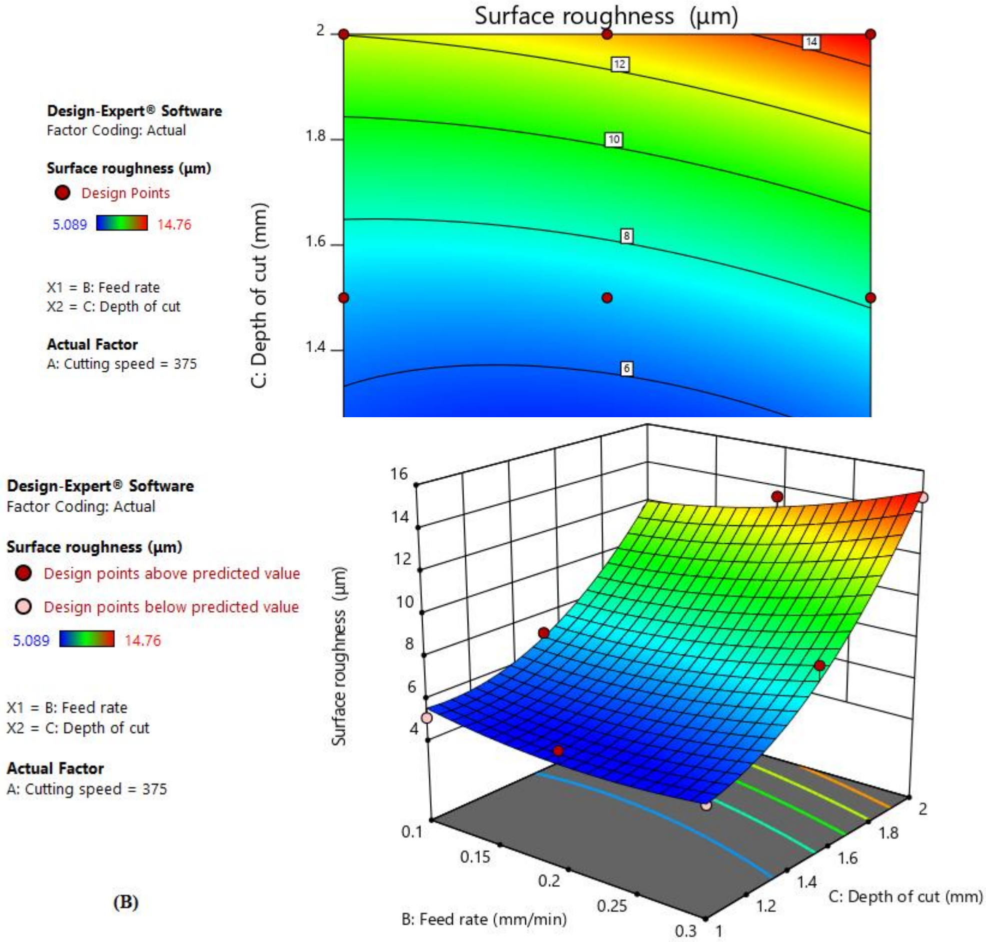

Figure 9 Surface and contour plot of Ra for varying feed rate and depth of cut at 375 m/min cutting speed (A) 2D view and (B) 3D view

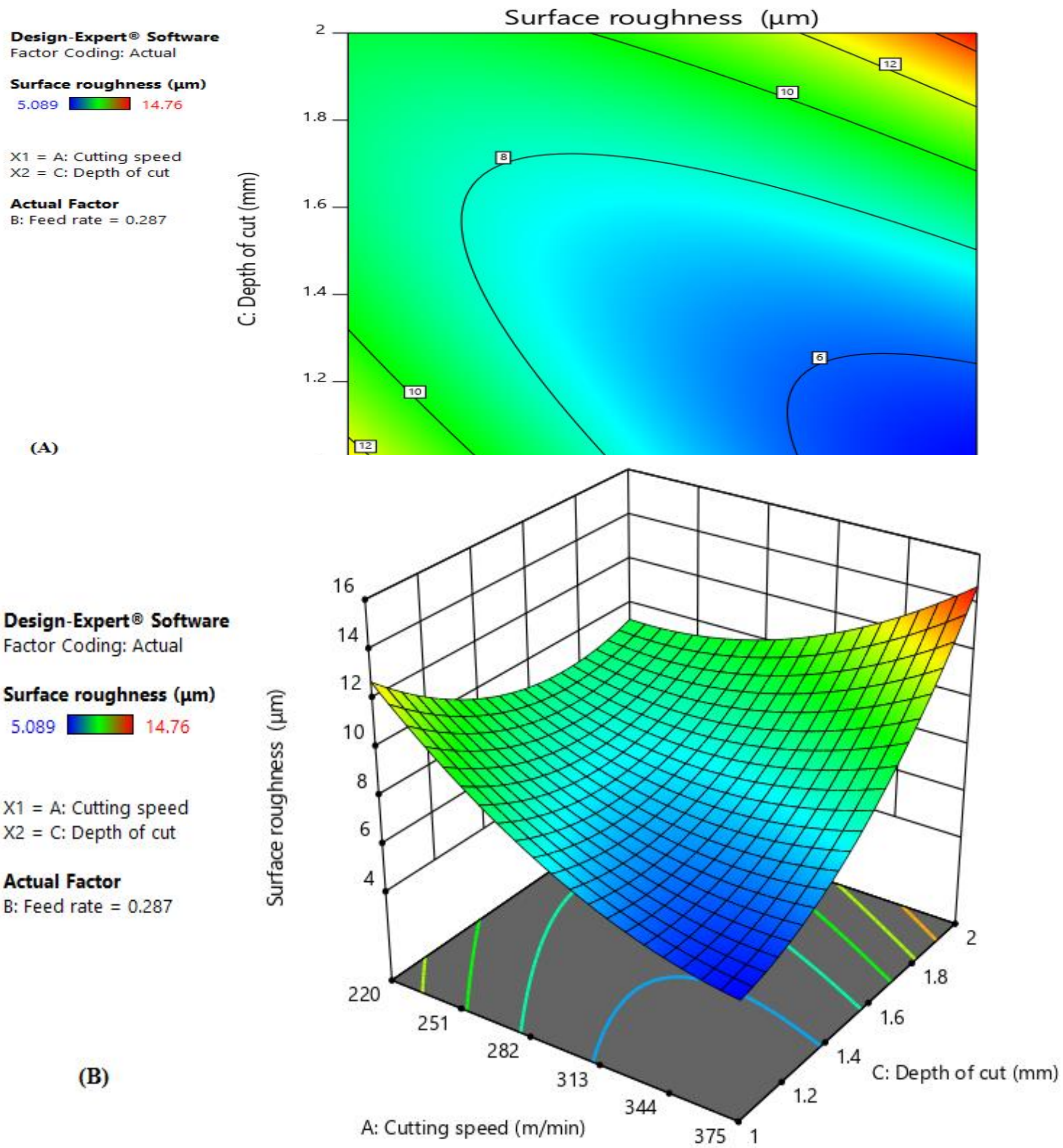

Figure 10 Surface and contour plot of Ra for varying cutting speed and depth of cut at 0.287 mm/min feed rate (A) 2D view and (B) 3D view

3.10 Predicted values

Predicted values of surface roughness from the developed mathematical model and the experimental values are shown in Figure 11 and Table 15. The comparison of predicted and measured values shows that the predicted values of the surface roughness are very close to measured values.

The mathematical model for the surface roughness prediction based on the experimental results given in Table 15 is developed using equation (7). The developed mathematical model to predict Ra is:

$$Ra = 41.4 - 0.075\ v - 9.6\ f - 30.3\ d - 0.000028\ v^2 + 45\ f^2 + 4.39\ d^2 - 0.027\ v*f + 0.0625\ v*d + 0.1\ f*d \quad (7)$$

Table 15 Experimental and predicted values of surface roughness

Experiment No.	**Surface roughness (µm)**	
	Experimental	**Predicted**
1	13.357	12.891
2	9.113	8.508
3	5.495	5.821
4	13.325	12.497
5	13.193	12.319
6	6.845	6.737
7	5.137	5.603
8	5.089	5.43
9	7.11	7.453
10	6.99	7.164
11	7.602	7.832
12	6.565	6.294
13	7.07	7.576
14	8.09	7.548
15	9.684	8.916
16	6.842	7.287
17	8.918	8.365
18	6.219	6.837
19	8.098	7.653
20	7.29	7.414
21	11.55	11.67
22	14.76	14.54
23	8.274	7.806
24	13.528	12.368
25	8.192	7.928
26	11.08	10.499
27	9.249	10.065

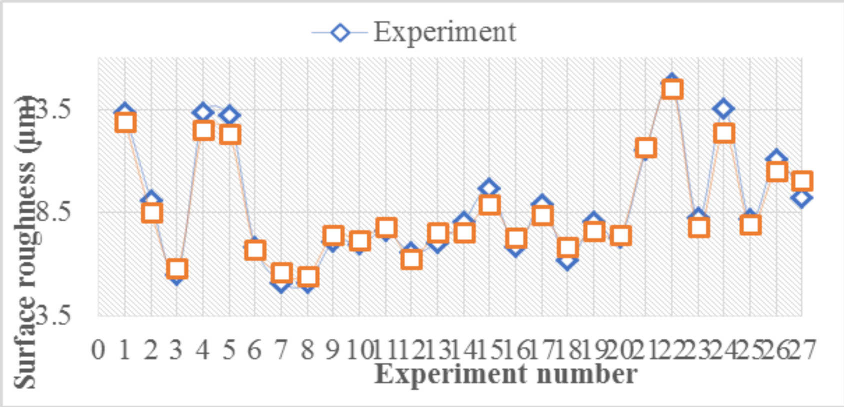

Figure 11 Experimentally measured and predicted values of surface roughness

3.11 Parameter optimization

The surface roughness (Ra) is an undesirable and uncontrollable quality characteristic of a turning process. As such, they are to be minimized to improve product quality subject to constraints determined by the design limits of the process variables. Figure 10, therefore, gives the optimum setting of cutting speed of 375 m/min at a feed rate of 0.287 mm/min and 1 mm depth of cut. These would be required to minimize Ra to a value of 5.10 µm with the desirability of 0.9993, all within the selected design space. This is confirmed by the contour and surface plots of the figures are Figures 8, 9, and 10. The results of optimum parameters is shown in the figure 12.

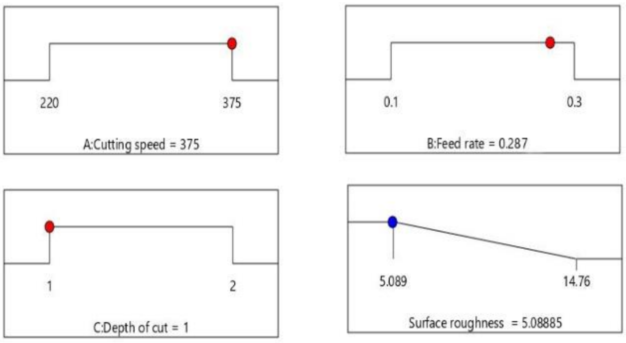

Figure 12 Results of parameter optimum

3.12 Experimental confirmation

The confirmation experiments were performed to facilitate the verification of the obtained feasible optimal machining parameters (v = 375 m/min, f = 0.287 mm/rev and d = 1 mm) for the surface roughness. The results of the confirmation run for the response Ra are listed in Table 16. The error between the predicted and the confirmation results is 3.403%.

Table 16 Confirmation results for surface roughness

Optimum cutting parameters			**Surface roughness (µm)**					**Validation error (%)**
v **(m/min)**	***f*** **(mm/min)**	**d (mm)**	**Experimental**				**Predicted**	
			Run 1	**Run 2**	**Run 3**	**Average**		
375	0.287	1	5.10	5.118	5.122	5.113	4.939	3.403

The comparison of predicted and measured values shows that the predicted values of the surface roughness are very close to measured values and the same result was reported by Girish Kant (2016)[17].

4. CONCLUSION

The research presents an investigation of cutting parameters on surface roughness for the turning operation of EN-8 steel. It has been found that the predictive model provides optimum machining parameters. The results of the proposed model provide improvement in surface roughness over the best experimental run. It has been observed that the depth of cut is the main influencing machining parameter for the minimization of surface roughness by the feed rate and the cutting speed. The 3D surface and contour plots designed during the study can be used for choosing the optimal machining parameters to gain specific values of surface roughness these can be used by the machine tool manufacturers to provide the range of cutting speeds, feed rate, and depth of cut for a particular application. RSM is the best modeling as it learns the best fit of models. It has better performance in optimization and enhancement of surface finish. Confirmations experiments carried out using the optimum machining parameters show that the developed predictive and optimization model can be used for turning of EN - 8 steel within 3.403% error. The minimum value of surface roughness obtained is 5.113µm. Optimal cutting conditions for turning operation o EN-8 steel for better surface finish of 5.113 µm was found to be 1mm, 375m/min, and 0.287mm/min for depth of cut, cutting speed, and feed rate respectively.

REFERENCES

1. Sahoo, P., Optimization of Turning Parameters for Surface Roughness using RSM and GA, Advances in Production Engineering and Management, Vol. 6, No. 3, 2011, 197–208.
2. *ASME/ANSI B46.1 (1985) Surface texture (surface roughness, waviness and lay). ASME, New York.*
3. Aggarwal, A., Singh, H., Kumar, P., & Singh, M. (2008). Optimizing power consumption for CNC turned parts using response surface methodology and Taguchi's technique—a comparative analysis. *Journal of materials processing technology*, *200*(1-3), 373-384.
4. Bhattacharya, A., Das, S., Majumder, P., and Batish, A. (2009). Estimating the effect of cutting parameters on surface finish and power consumption during high-speed machining of AISI 1045 steel using Taguchi design and ANOVA. *Production Engineering*, *3*(1), 31-40.
5. Bhushan, R. K. (2013). Optimization of cutting parameters for minimizing power consumption and maximizing tool life during machining of Al alloy SiC particle composites. *Journal of Cleaner Production*, *39*, 242-254.
6. *Fratila, D., & Caizar, C. (2011). Application of Taguchi method to selection of optimal lubrication and cutting conditions in face milling of AlMg3. Journal of Cleaner Production, 19(6-7), 640-645.*
7. *Hanafi, I., Khamlichi, A., Cabrera, F. M., Almansa, E., & Jabbouri, A. (2012). Optimization of cutting conditions for sustainable machining of PEEK-CF30 using TiN tools. Journal of Cleaner Production, 33, 1-9.*
8. *Montgomery, D. C. (2017). Design and analysis of experiments. John wiley and sons.*
9. *Myers, R. H., Montgomery, D. C., and Anderson-Cook, C. M. (2016). Response surface methodology: process and product optimization using designed experiments. John Wiley and Sons.*
10. *Kassab, S. Y., and Khoshnaw, Y. K. (2007). The effect of cutting tool vibration on surface roughness of workpiece in dry turning operation. Engineering and Technology Journal, 25(7), 879-889.*
11. *Selvam, M. D., and Senthil, P. (2016). Investigation on the effect of turning operation on surface roughness of hardened C45 carbon steel. Australian Journal of Mechanical Engineering, 14(2), 131-137.*
12. *Metals4u.co.uk. 2020. EN-8 Mild Steel Properties | Technical Information | Metals4u - Ideas & Advice | Metals4u. [online] Available at: <https://www.metals4u.co.uk/blog/EN8-mildsteel#:~:text=EN-8%20or%20080m40%20can%20be%20tempered%20at%20a,%C2%B0F1580%20%C2%B0F%29%20then%20it%20is%20cooled%20in%20air.> [Accessed 18 January 2020].*
13. Box, G. E., and Draper, N. R. (1987). *Empirical model-building and response surfaces*. John Wiley and Sons.
14. *Sarıkaya, M., & Gullu, A. (2014). Taguchi design and response surface methodology-based analysis of machining parameters in CNC turning under MQL. Journal of Cleaner Production, 65, 604-616.*
15. *Sahin, Y., and Motorcu, A. R. (2005). Surface roughness model for machining mild steel with coated carbide tool. Materials and design, 26(4), 321-326.*
16. Cetin, M. H., Ozcelik, B., Kuram, E., and Demirbas, E. (2011). Evaluation of vegetable based cutting fluids with extreme pressure and cutting parameters in turning of AISI 304L by Taguchi method. *Journal of Cleaner Production*, *19*(17-18), 2049-2056.
17. *Kant, G. (2016). Prediction and optimization of machining parameters for minimizing surface roughness and power consumption during turning of AISI 1045 steel.*