

A study for minimum root mean square surface roughness during the turning of AISI 316 L stainless steel

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Abstract:

Machining parameters such as cutting speed, feed rate and depth of cut play a vital role in machining the given work piece to the required shape. These have a major effect on the quality of production, cost of production and production rate; Turning is the most common process associated with the production of cylindrical shapes because of its simplicity, rapidity and economy. However, it is one of the most complex cutting processes.

Roughness is often a good predictor of the performance of mechanical components, since irregularities in the surface may form nucleation sites for cracks or corrosion. The purpose of the metal cutting process is not only to shape machine components but also to manufacture them so that they can achieve their functions according to geometric, dimensional and surface considerations. (Abhang et al.2011) There are machining processes such as turning, milling, drilling, shaping, slotting, grinding etc. In the present work, turning process has been taken up for the selection of cutting parameters for minimum Rq : root-mean-square roughness

An attempt has also been made to investigate the effect of turning parameters on surface roughness parameters. As, the turning process is the most productive process, the study is expected to be quite beneficial. Ferrous metals are widely used in manufacturing industries. Among the various ferrous materials the AISI 316 L stainless steel is quite popular main engineering materials in various industries.

The aim of present study is to develop surface roughness prediction models using response surface methodology (RSM) based on centre composite rotatable design (CCRD).

Key point: feed, speed depth of cut, FCD, CCRD, RSM, DOE

INTRODUCTION:

The challenge of modern machining industries is mainly focused on the achievement of high quality, in terms of work piece dimensional accuracy, surface finish, high production rate, less wear on the cutting tools, economy of machining in terms of cost saving and increase the performance of the product with reduced environmental impact. Root mean square Surface roughness plays an important role in many areas and is a factor of great importance in the evaluation of machining accuracy .The response surface method is statistical tool, adopted experimentally to investigate influence of surface roughness by cutting parameters such as cutting speed, feed and depth of cut. The response surface surface method helps to select or to determine the optimum cutting conditions for turning process. Many researchers developed many mathematical models to optimize the cutting parameters to get lowest surface roughness by turning process. The variation in the material hardness,

alloying elements present in the work piece material and other factors affecting root mean square surface finish.

Empirical models in terms of machining parameters and response can be developed using various techniques such as factorial design, Taguchi method, response surface methodology (RSM), artificial neural networks (ANN) etc. Each of the techniques has its own advantages and disadvantages.

The RSM has been used in the present work due to following advantages:

1. Numbers of trials required for experimentation are reduced.
2. Optimum value of the machining parameters can be determined.
3. Assessment of experimental error and pure error can be made.
4. Qualitative estimation of parameter can be made.
5. Inference regarding the effect of parameters on the response can be made.

2. LITERATURE REVIEW

2.1 INTRODUCTION

A review of various published literature on any specific topic is the first important step to be taken to get,

- Knowledge about the state of art.
- Familiarity with the established methods and procedures of conducting work
- To stop duplication of work & wastage of old time.

2.2 REVIEW OF LITERATURE

Nian et al., (1999) used Taguchi method to optimize multiple performance characteristics including tool life, cutting force and surface finish in turning of S45C steel bars by using tungsten carbide tool. The orthogonal array, multi-response signal-to-noise ratio and analysis of variance have been employed to study the performance characteristics in turning operations. Three cutting parameters namely, cutting speed, feed rate and depth of cut were optimized for maximum tool life, minimum cutting force and maximum surface finish. It has been found that the Taguchi method provides a simple, systematic and efficient methodology for the optimization of the cutting parameters.

Ghani et al., (2002) experimentally investigated the effect of speed, feed and depth of cut on tool life, surface finish and vibration during turning of nodular cast iron using ceramic tool. Numbers of cutting test have been conducted to verify the change in surface finish of the work piece due to increased tool wear. Also, the effects of vibration on the flank wear in the direction of main cutting force and radial cutting force have been investigated. The results revealed that the tool life of the alumina ceramic inserts has been found unsatisfactory. On the other hand, Variation in surface finish with the progression of the flank wear under all cutting conditions has been found almost constant.

Rech et. al. (2003) studied surface integrity in finish hard turning of case hardened steel. Roughness, residual stresses and white layers of surface integrity were functions of machining parameters. The main aim of this work was to study the influence of feed rate, cutting speed and tool wear on the effects induced by hard turning. Case hardened 27MnCr5 gear cone brakes and to point out the technical limitation in mass production. Results revealed that Tin coating substantially improves the surface integrity of hard turned surfaces.

Noordin et. al. (2004) deals with the study of a multilayer tungsten carbide tool on turning AISI 1045 steel using response surface methodology (RSM). The factors investigated were cutting speed, feed and the side cutting edge angle (SCEA) of the cutting edge. Tangential force and surface roughness were the response variables.

Cutting tests were performed with constant depth of cut and under dry cutting conditions. The feed is the most significant factor that influences the surface roughness and the tangential force. However there are other factors that provide secondary contributions to the performed indicators. In the case of surface roughness, the SCEA² and the interaction of feed and SCEA provides these contributions whilst for tangential force, the SCEA², the interaction of feed and SCEA; and the cutting speed provides them.

Sahin et. al. (2005) in their paper predicted surface roughness model for turning of mild steel with coated carbide tools. The model was developed in terms of cutting speed, feed rate and depth of cut, using response surface methodology (RSM). First order and second order model predicting equation for surface roughness have been developed using response surface methodology. The results clearly indicated that the feed rate and cutting speed was main influenced factor on the surface roughness. It increased with increasing the feed rate but decreased with increasing the cutting speed and the depth of cut. Depth of cut was found to be more insensitive than the cutting speed.

Dhar et. al. (2006) made experimental investigation in the role of cryogenic cooling by liquid nitrogen jet in turning of AISI 4037 steel at industrial speed-feed combination by coated carbide insert on cutting temperature, tool wear, surface finish and dimensional deviation. The result was compared with machining as soluble oil or coolant and dry machining. The results of the present work indicate substantial benefit of cryogenic cooling on dimensional deviation, surface finish and tool life and showed that cryogenic cooling by liquid nitrogen jets provided better surface finish, higher dimensional accuracy and lesser tool wear as compared to wet and dry machining. That might be attributed mainly to the favorable change in chip tool interaction and reduction in cutting zone temperature. Further is was evident that machining with soluble oil cooling failed to provide any significant improvement in tool life , rather surface finish deteriorated.

Davim et. al. (2007) developed surface roughness using artificial neural network (ANN) also to investigate the effect of various cutting conditions during turning of free machining steel. L27 orthogonal array with three levels is applied for each of the factors in order to develop the knowledge base for artificial neural network (ANN) training. 3D surface plots were generated using ANN model to study the interaction effect of cutting conditions on surface roughness parameters. The analysis revealed that cutting speed and feed rate had more

effect in reducing the surface roughness, while the depth of cut had the least effect.

Ozel et. al. (2007) in their study investigated the modeling of surface finish and tool flank wear in turning of AISI D2 steel with ceramic wiper inserts. Multi linear regression models and neural network models have been developed for predicting surface roughness and tool flank wear. Experimental results indicated that surface roughness Ra values as low as 0.18 - 0.2 μm should be easily attained with wiper inserts. Results showed that neural network models are suitable to predict the tool wear and surface roughness patterns for a range of cutting conditions should be used in intelligent process planning for hard turning.

Prajapati (2013) used full factorial method for optimization of machining parameters in turning of SS 316 on surface roughness and material removal rate. The turning parameters evaluated was cutting speed, feed rate, and depth of cut. Machining test was carried out with PVD coated ceramic insert with 0.8 mm nose radius and 80° negative rhombic angles. L27 orthogonal array and analysis of variance were employed to find the effective cutting parameters on surface roughness and material removal rate. The obtained results indicated that the optimal combination of low feed rate and low depth of cut with high cutting speed is beneficial for reducing machining force so surface roughness is decreased when high cutting speed, low feed rate and low depth of cut, similarly volume of material removed can be achieved better when machining was done at high depth of cut and high feed rate.

2.3 RESEARCH GAPS AND OBJECTIVES

In the present work the response surface methodology based on centre composite rotatable design has been selected to investigate the effect of turning parameters for minimum surface roughness parameters. An effort has also been made to optimize the turning parameters for minimum surface roughness parameters in turning of AISI 316 L stainless steel. Thus objectives and the steps of the present study are:

1. Development of root mean square surface roughness prediction models using RSM based on CCRD.
2. Optimization of cutting parameters for minimum root mean square surface roughness parameters i.e. R_q , in turning of AISI 316 L stainless steel.

3. EXPERIMENTAL STUDY

This chapter presents the experimental set up i.e. details of CNC turning Centre, cutting tool, work piece, surface roughness and material removal rate measurement. A design matrix based on RSM based on CCRD method has also been developed.

3.1 MACHINE TOOL

Turning operations was carried out on a computer numerical control (CNC) lathe machine (Pushkar 200) of Hindustan machine tools Ltd.



Figure 3.1: Controller of CNC Lathe machine

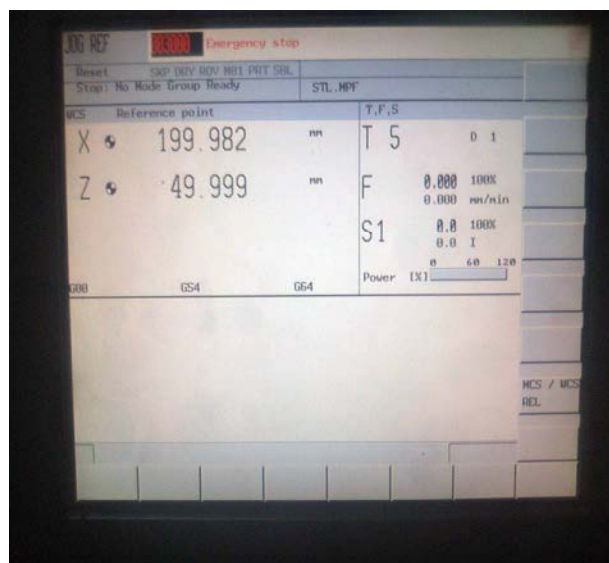


Figure 3.2: CNC part programmer

CNC lathe is one of the most versatile and widely used machine tool. Figure 3.1 shows the control panel of machine and figure 3.2 shows the CNC part programmer.

3.2 CUTTING TOOL

In this study, TIN coated carbide tool single point cutting tool is used. Its specification and geometry are as shown in fig 3.3

Tool material: TIN coated carbide

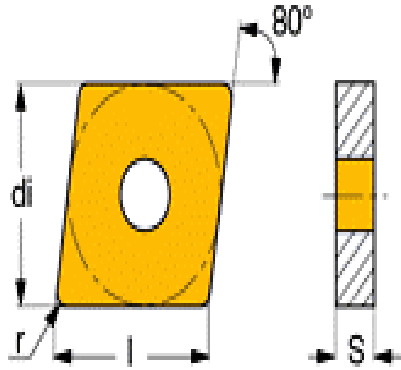


Figure 3.3: Cutting tool

3.3 WORK PIECE

The machining experiments were performed on AISI 316 L stainless steel. The AISI 316 L stainless steel pieces of length 40 mm and diameter 30 mm size has been used as a work piece material for the present experiments. The AISI 316 L stainless steel has good corrosion resistance properties. It has various applications like manufacturing of camshafts, fasteners, gears, and chains/chain pins.

3.4 PREPARATION OF SPECIMENS

The AISI 316 L stainless steel rod of the length of 1080 mm and diameter of 30 mm size is mounted on the power hacksaw machine tool and specimens of the length 40 mm and diameter of 30 mm size are cut.



Figure 3.5: AISI 316 L stainless specimen after turning operation

The rod used for cutting the specimens is mounted on the machine. The final dimension of the specimens after cutting is of Ø30 X 40 mm. Figure 3.5 shows the specimen after turning operations.

3.5 DESIGN OF EXPERIMENT

Number of experiments required, mainly depends on the approach adopted for design of experiment. In this study, the design suggested by CCRD has been implemented for

the experiments. The machining parameters and their levels are shown in table 3.1.

Table 3.1 Factors and levels of independent variables according to response surface methodology.

Symbol	Cutting parameters	Unit	Levels				
			-α	-1	0	+1	+α
A	Cutting speed	m/min	100	140.5	200	259.4	300
B	Feed rate	mm/rev	0.10	0.20	0.35	0.50	0.60
C	Depth of cut	mm	0.10	0.20	0.35	0.50	0.60

Complete design layout for experiments is summarized in table 3.2 and experimental results are summarized in table 3.6. This demonstrates a total of 20 runs required for complete experimentation. Twenty experiments constitute 2³ factorial point, six centre point and six axial points.

Table 3.2 Complete design layout

Run	Factor 1A: Cutting Speed	Factor 2 B: Feed rate	Factor3 C: Depth of cut	R _q (µm)
1	140.54	0.20	0.20	2.554
2	259.46	0.20	0.20	2.359
3	140.54	0.50	0.20	7.036
4	259.46	0.50	0.20	5.782
5	140.54	0.20	0.50	2.477
6	259.46	0.20	0.50	2.334
7	140.54	0.50	0.50	6.173
8	259.46	0.50	0.50	4.735
9	100	0.35	0.35	4.786
10	300	0.35	0.35	2.550
11	200	0.1	0.35	1.332
12	200	0.6	0.35	8.136
13	200	0.35	0.1	3.811

14	200	0.35	0.6	3.676
15	200	0.35	0.35	3.777
16	200	0.35	0.35	3.954
17	200	0.35	0.35	4.318
18	200	0.35	0.35	4.096
19	200	0.35	0.35	4.311
20	200	0.35	0.35	4.369

3.6 MEASUREMENT OF SURFACE ROUGHNESS

In this research, a portable surface roughness tester (Model No TR 210 manufactured by Beijing TIME High Technology Ltd. Beijing City, China) has been used to measure surface roughness indicators of finished work pieces.

4. ANALYSIS FOR R_q (ROOT MEAN SQUARE VALUE OF SURFACE ROUGHNESS)

4.1 Fit Summary

After the examination of fit summary as shown in table 4.1, output results that the quadratic model for R_q is statistically significant therefore it would be used for further analysis.

Table 4.1 Fit summary for roughness parameter R_q

Source	Sum of Squares	Degree of freedom	Mean Square	F Value	p-value Prob > F	
Linear	3.2611	11	0.2964	8.6806	0.01	
2FI	2.1578	8	0.2697	7.8978	0.01	
Quadratic	0.7349	5	0.1469	4.3037	0.06	Sugge
Cubic	0.0627	1	0.0627	1.838	0.23	Alias
Pure Error	0.1707	5	0.0341			

Table 4.2 represents the ANOVA table for the reduced quadratic model for root mean square value of surface roughness parameter (R_q) by selecting the backward elimination procedure to automatically reduce the terms that are not significant.

4.2 Reduce ANOVA Table

Table 4.2 Reduce ANOVA table for quadratic model for R_q

Source	Sum of Squares	Degree of freedom	Mean Square	F Value	p-value Prob > F
Model	52.409	4	13.102	90.694	< 0.0001
A-	3.374	1	3.374	23.353	0.0002
B-feed	47.403	1	47.403	328.126	< 0.0001
AB	0.692	1	0.692	4.791	0.0462
B^2	0.940	1	0.940	6.507	0.0191
Residual	2.167	15	0.144		
Lack of Pure Cor	1.996	10	0.200	5.845	0.0943
Std. Mean	0.380			R-Squared	0.960
	4.138			Adj R-Squared	0.950
C.V. %	9.184			Pred R-Squared	0.915
PRESS	4.657			Adeq Precision	32.774

It shows that the value of “Prob. > F” for model is 0.0001 which is less than 0.05, that indicates the model is still significant after elimination, which is desirable as it indicates that the terms in the model have a significant effect on the response. In the same manner, The value of “Prob. > F” for main effect of speed and feed, and two-level interaction of speed and feed, and second-order effect of feed are less than 0.05 so these terms are significant model terms. The value of “Prob. > F” for lack-of-fit is 0.0960, which is greater than 0.05 that indicate that lack of fit is insignificant. If the model does not fit the data well, this will be significant. The non-significant lack of fit is desirable.

The R² value is equal to 0.96 or close to 1, which is desirable. The adjusted R² value is equal to 0.95. The result shows that the adjusted R² value is very close to the ordinary R² value. Adequate precision value is equal to 32.774; A ratio greater than 4 is desirable which indicates adequate model discrimination.

4.3 DIAGNOSIS OF ASSUMPTIONS OF ANOVA FOR REDUCE ROOT MEAN SQUARE VALUE OF SURFACE ROUGHNESS MODEL

To check the assumption of normal distribution, the normal probability plot of the residuals for reduce root

mean square value of surface roughness model is shown in figure.4.1. The figure displays that the residuals generally fall on a straight line implying that the errors are distributed normally.

Fig.4.2 represents residuals versus the predicted root mean square value of surface roughness plot for reduce model. The figure shows that there is no obvious pattern and it shows unusual structure. This implies that there is no reason to suspect any violation of the independence or constant variance assumption.

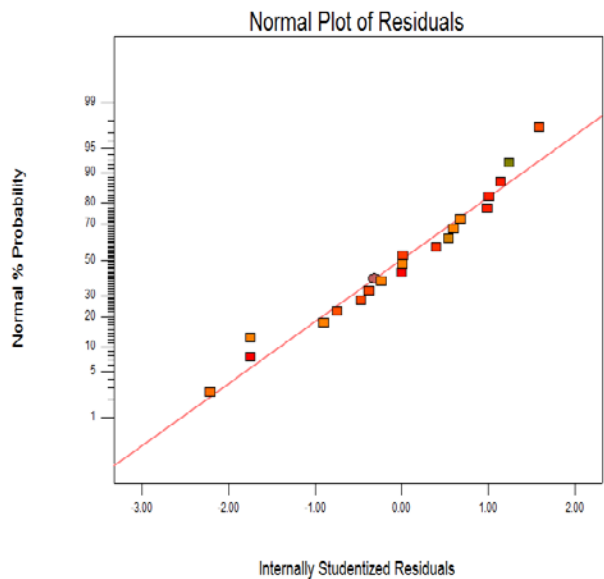


Fig.4.1 Normal probability plot of residuals for Rq data using reduce model

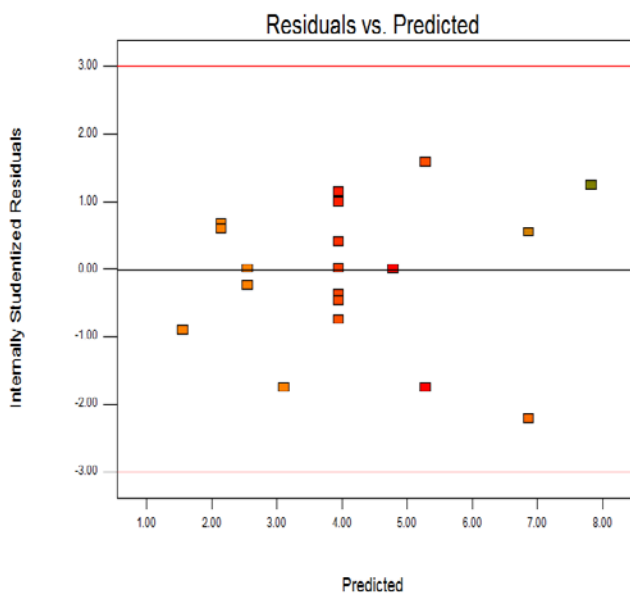


Fig 4.2 residuals versus the predicted Rq plot using reduce model

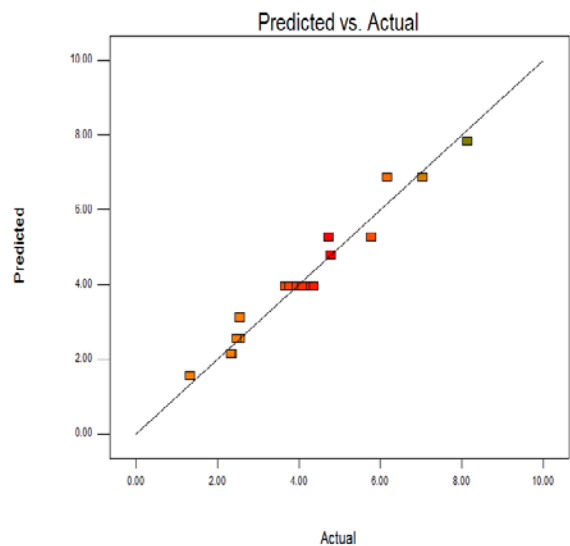


Fig.4.3 Plot of predicted vs. Actual response for Rq data using reduce model

A graph of the predicted root mean square value of surface roughness values versus the actual root mean square value of surface roughness values using reduce model is shown in Fig.4.3. The figure reveals that all the data points split evenly by the 45 degree line.

4.4 ROOT MEAN SQUARE VALUE OF SURFACE ROUGHNESS PREDICTION MODELS

Final root mean square value of surface roughness prediction model in terms of coded Factors:

$$R_q = 3.95 - 0.5 * A + 1.86 * B - 0.29 * A * B + 0.26 * B^2$$

Final root mean square value of surface roughness prediction model in terms of actual factors:

$$R_q = 0.36 + 0.00328 * \text{Cutting speed} + 10.87 * \text{Feed} - 0.033 * \text{Cutting speed} * \text{Feed} + 11.87 * \text{Feed}^2$$

4.5 EFFECT OF CUTTING PARAMETERS ON SURFACE ROUGHNESS (Rq)

Effect of cutting speed on root mean square value of surface roughness at feed rate (0.35 mm/rev) and depth of cut (0.35 mm) is shown in fig. 4.4. The result shows that the root mean square value of surface roughness decreases as the cutting speed increases because as the cutting speed increases, temperature during cutting also increases, which softens the material to enhance the cutting performance leading to reduced root mean square value of surface roughness.

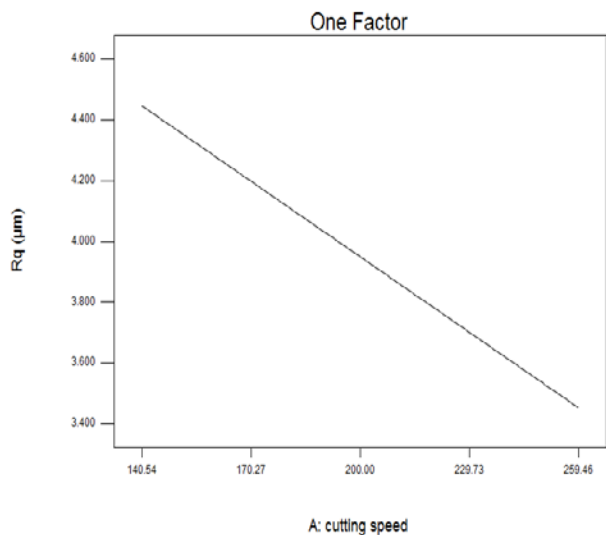


Fig. 4.4 Plot between root mean square value of roughness and cutting speed at feed (0.35 mm/rev) and depth of cut (0.35 mm)

Influence of feed on root mean square value of surface roughness at constant cutting speed (200 m/min) and constant depth of cut (0.35 mm) is shown in fig. 4.5 The root mean square value of roughness increases as the feed increases. This is due to the fact that at higher feed rate, tool traverses the work piece too fast, resulting in deteriorated surface quality.

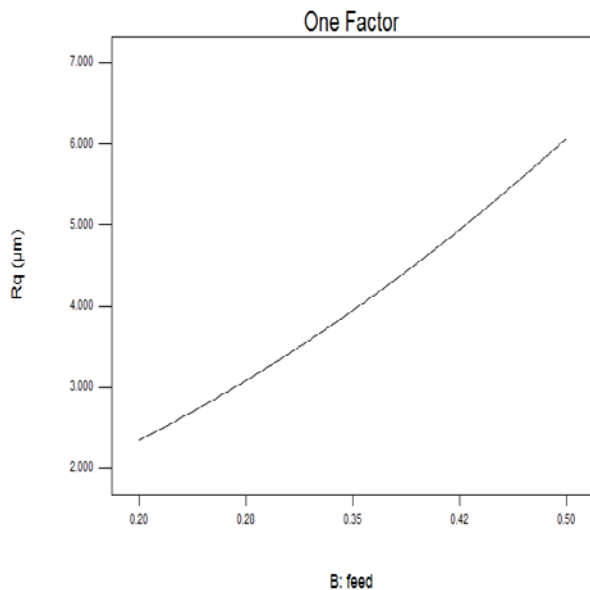
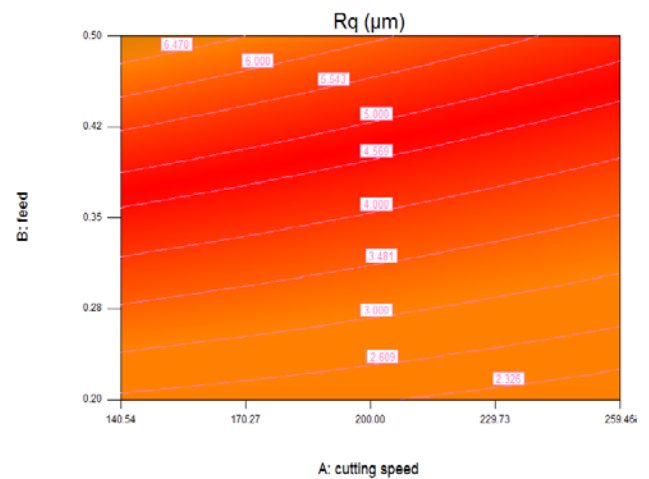


Fig. 4.5 Plot between feed and root mean square value of surface roughness at constant cutting speed (200 m/min) and constant depth of cut (0.35 mm)

The contour plot for the response root mean square value of surface roughness parameter (Rq) at 0.35 mm depth of cut is shown in fig. 4.6.



4.6 Rq contour in feed-speed plane at depth of cut 0.35mm

It is clear from the plot that at constant speed, the root mean square value of surface roughness increases as the feed rate increases. Also, at constant feed rate, the root mean square value of surface roughness decreases as the cutting speed increases resulting in better surface quality. The 3D surface graph for root mean square value of surface roughness Rq is shown in fig 4.7 and the curve have curvilinear profile in accordance to the quadratic model fitted. From the graph it is clear that as the cutting speed increases root mean square value of surface roughness decreases, on the other hand as feed increases root mean square value of surface roughness increases.

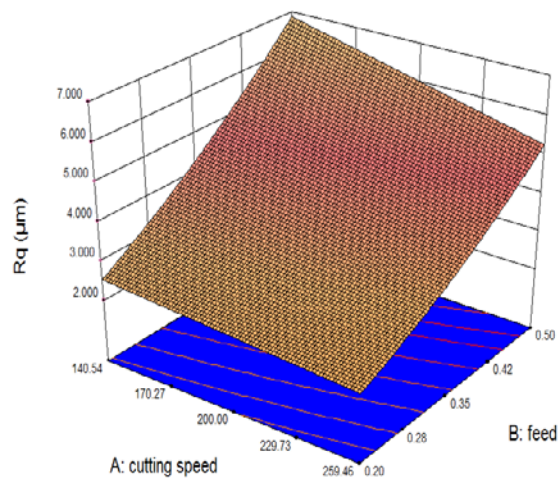


Fig. 4.7 3D surface graph for surface roughness parameter Rq at depth of cut 0.35mm

From the both plot 4.17 to 4.20, it is clear that the minimum root mean square value of surface roughness (Rq) is achieved at low level of feed (0.20 mm/rev.) and high level of cutting speed (259.46 m/min).

5. CONCLUSION

The important conclusions drawn from the present work are summarized as follows:

1. Out of three parameters, feed seems to be the most significant and influential machining parameter that affect the root mean square surface roughness R_q followed by cutting speed.
2. The depth of cut has insignificant influence on the root mean square surface roughness parameters.
3. The mathematical models developed clearly show that root mean square surface roughness increases with increasing the feed but decreases with increasing the cutting speed.
4. The results of ANOVA and the confirmation runs verify that the developed mathematical models for root mean square surface roughness parameters shows excellent fit and provide predicted values of surface roughness that are close to the experimental values, with a 95 per cent confidence level.
5. The minimum surface roughness R_q (2.146 microns), have been obtained at cutting speed 259.46 m/ min and feed 0.20 mm/rev.

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