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Development of surface roughness prediction model using 2 level full factorial design and to analyze during turning of AISI 1019 steel

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Abstract:
Achieving the desired surface quality is of great importance for the functional behavior of the mechanical parts. Surface roughness is one of the important aspects of surface quality. It has an impact on the mechanical properties of the machined parts. The surface finish of the machined parts is greatly influenced by the cutting tool properties, machining parameters, work piece properties and cutting phenomenon. The proper selection of machining conditions can yield desired surface finish on the machined surface. So it can be achieved by establish empirical relationship between machining condition and surface roughness indicators using design of experiments (DOE). The proposed work will be employed for optimization of machining condition for minimum surface roughness and for maximum material removal rate in turning of AISI 52100 steel. A attempt has also been made to investigate the effect of turning parameters on surface roughness indicators and MRR using 2 level full factorial design.

Key terms: DOE, feed, speed, surface roughness

INTRODUCTION

Manufacturing is the process of converting raw materials into finished products. It encompasses the design and manufacturing of goods, using various production methods i.e. metal casting, forming, shaping, machining etc. The economics of manufacturing has always been a major factor and it has become even more important as the international competition for high quality products and low prices becomes a major issue in worldwide markets. The markets have become multinational and dynamic, the product lines have become extensive and technically complex and the demand by customers for quality has become a commonplace.

Among various manufacturing processes, the machining is considered to be quite important because majority of the finished products requires machining at some stage during their production. In the manufacturing industries, various machining processes like turning, milling, etc. are adopted for removing the material from the workpiece to obtain finished product.

1. Literature review

To identify research gaps, a broad range of research papers have been studied in order to understand the influence of the different machining conditions that affect the surface roughness of machined parts in turning processes. Also, research related to the prediction of surface roughness using different techniques has been studied.

Choudhury and Baradie, 1997 developed surface roughness prediction models for turning EN 24T steel with uncoated carbide inserts utilizing response surface methodology. A factorial design technique has been used to study the effects of the main cutting parameters such as cutting speed, feed, and depth of cut, on surface roughness. The results revealed that response surface methodology combined with factorial design of experiments is a better alternative to the traditional one variable at a time approach for studying the effect of cutting variables on responses such as surface roughness and tool life. This significantly reduces the total number of experiments required.

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.

Abouelatta et al., 2001 developed correlation between surface roughness and cutting vibration in turning free cutting steel with cemented carbide cutting tool. A full

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factorial design has been used for developing surface roughness prediction models in terms of rotational cutting speed, feed rate, depth of cut, tool nose radius, tool overhang, approach angle, work piece length and work piece diameter. It has been concluded from the results that the prediction models that depend on both cutting parameters and tool vibrations are more accurate as compared to those depends on cutting parameters only.

Aslan et al., 2006 studied the optimization of cutting parameters in turning hardened AISI 4140 steel with Al2O3 + TiCN mixed ceramic tool. The Taguchi technique has been employed for obtaining the optimum values of cutting speed, feed rate and depth of cut for minimization of surface roughness and flank wear. The relationship between the input parameters and the responses have been developed using multiple linear regression. The results concluded that the cutting speed is most statistically significant factor that influences the tool wear (with a 30% contribution). As the cutting speed increases, the tool wear decreases. On the other hand only two interactions, cutting speed-feed rate (with a 28 % contribution) and feed rate-axial depth of cut (with a 23 % contribution) have been found significant influence on the surface roughness.

Al-Ahmari , 2007 developed empirical models for tool life, surface roughness and cutting force in terms of cutting speed, feed rate, depth of cut and tool nose radius. The multiple linear regression analysis technique (RA), response surface methodology (RSM) and computational neural networks (CNN) have been used to develop models. The turning tests have been conducted on austenitic AISI 302 steel using carbide inserts. The developed models from the three different techniques have been compared on the basis of percentage relative error. It has been found that the computational neural network models are better than multiple linear regression analysis techniques and response surface models. Also, it has been found that RSM models are better than RA models for predicting tool life and cutting force models.

Sharma et al., 2008 used regression analysis and artificial neural network to investigate the effect of machining parameters on surface finish and cutting forces. The turning experimentations have been carried out on adamite steel with indexable coated carbide insert (CCMT090304). The regression models and ANN model for cutting force, passive force, feed force and surface roughness have been developed in terms of feed, speed, depth of cut and approaching angle. In addition to this, a comparison between predicted values from ANN model and experimental values has been made on the basis of percentage error. The result revealed that ANN model has good predictive ability with 76.4% accuracy. On the other hand, this study also concluded that cutting force increases with the increase in approaching angle, feed and depth of cut where as it shows a decreasing trend with speed. Surface roughness increased with increases in feed and it shows a negative trend with approaching angle, speed and depth of cut.

Bhattacharya et al., 2008 employed Taguchi's orthogonal array design and analysis of variance (ANOVA) to evaluate the contribution of cutting parameters (cutting speed, feed rate and depth of cut) on three surface roughness namely average surface roughness (R_a), root-mean-square roughness (R_q), and maximum peak-to-valley roughness (R_t or R_{max}) and power consumption. The turning experiments have been conducted on AISI 1045 steel with coated carbide tool (SNMG 120408). The results shows that cutting speed has been found to be the most significant parameter for the surface roughness (R_a, R_q and R_t) with a percent contribution of 83%.The contribution of feed rate has been observed to be 6.9% and 11.4% for roughness parameter R_a and R_q, respectively, and depth of cut was found to be a significant factor for R_t with a contribution of 11.3%. On the other hand, cutting speed has been once again observed to be the most significant factor to reduce the power consumption with a contribution is 77.4%, followed by the depth of cut (13.2%). The feed rate has no significant effect on the power consumption.

Bouchelaghem et al., 2010 used response surface methodology to investigate the wear behaviour of CBN tool during hard turning of AISI D3 (60 HRC).In addition to this, the effect of cutting parameters (feed, speed, depth of cut and nose radius) and tool wear on surface roughness, cutting forces and temperature has also been investigated. It has been concluded from the results that wear phenomenon in CBN inserts takes place due to abrasion process. On the other hand, it has also been found that cutting force increased with the increase of depth of cut while surface roughness increases with increased of feed rate and decreased with the increase of cutting speed.

Tsourveloudis, 2010 developed relationship between surface roughness and critical machining parameters during the turning of Ti6Al4V's. The surface roughness prediction models have been developed in terms of feed rate, turning speed and the cutting depth using response surface methodology (RSM) and the adaptive neuro-fuzzy inference system (ANFIS). The surface roughness prediction ability of these two methodologies has also been compared. It has been observed that the ANFIS predicts surface roughness with less error. On the other hand feed rate has been identified as the most important machining parameter for the surface roughness. In addition to this depth of cut has also been found significant factor.

Chen et al., 2010 developed mathematical models for modeling and analyzing the vibration and surface roughness in the precision turning of A6061-T6 material with a diamond cutting tool. The models have been developed using a D - optimal design based on the response surface methodology in terms of spindle speed, feed rate, cutting depth and status of lubrication. The results revealed that spindle speed and the feed rate have the greatest influence on the longitudinal vibration amplitude. On the other hand, the feed rate and the cutting depth play major roles for the transverse vibration amplitude. In addition to this, best machined surface has been obtained at high spindle speed, low feed rate and low cutting depth with lubrication.

Sahoo and Sahoo, 2011 developed surface roughness prediction models in turning of D2 steel using TiN coated carbide insert. The prediction model has been developed in terms of cutting speed, feed and depth of cut using L_{27} orthogonal array base Taguchi parameter design and response surface methodology. The influence of the machining parameters on the surface finish has also been investigated. The result reveals that feed has been found most significant parameter followed by the depth of cut. The effect of cutting speed has been found insignificant.

2. Research gaps and objectives

In the present work the 2 level full factorial design has been selected to optimize turning parameters for minimum average surface roughness. An effort has also been made to investigate the effect of turning parameters on average surface roughness in turning of AISI 1019 steel. Thus objectives of the present study are:

1. Development of surface roughness prediction model and model for metal removal rate using 2 level full factorial design and to analyze the effect of turning parameters (cutting speed, feed rate, and depth of cut) on surface roughness parameters during turning of AISI 1019 steel .

3. EXPERIMENTAL STUDY

In the present work, two level full factorial design is applied to determine the optimal turning parameters to achieve minimum surface roughness value for AISI 1019 steel under varying machining conditions.

4.1. CNC turning centre

Turning operations were carried out on Pushkar 200, Make HMT Pvt. Ltd. The CNC machining centre equipped with continuously variable spindle speed up to 5000 rpm, and 15 kW motor drive was used for experimentation. A picture of machining centre is shown in fig. 4.1.

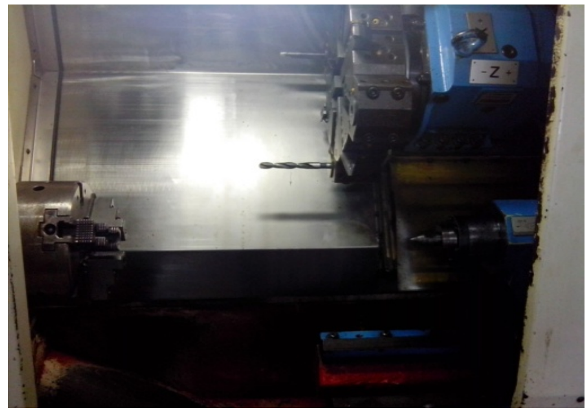

Fig 4.1 picture of machining centre

4.2 Cutting insert

Coated carbide tool performs better than uncoated carbide tools. Because of this reason, commercially used carbide coated carbide Inserts for turning steel was used in this research for turning.

4.3 Work piece

The machining experiments were performed on AISI 1019 steel. All the pieces used in experimentation were 40 mm in diameter and 60 mm in length as shown in Fig 4.2.

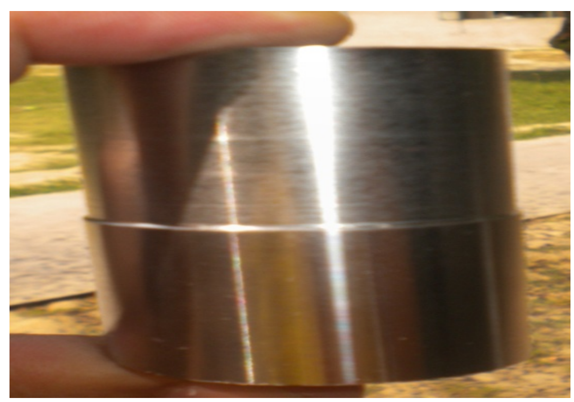

Fig. 4.2 Workpiece after turning

4.4 Surface roughness measurement

In this study, surface roughness of finish-turned work pieces was measured by making use of a portable surface roughness tester (Surf coder SE1200) and the measurements were repeated three times. Cut-off length for roughness measurements was set to be 0.8 mm. Table 4.1 shows the all values of surface roughness.

Table: 4.1 Surface roughness measurement results

Run	Speed (m/ min)	Feed (mm/ rev)	Depth of cut (mm)	Nose Radius (mm)	Roughness (microns)
1	209.46	0.1	0.28	0.4	0.566
2	150	0.21	0.55	0.8	2.296
3	90.54	0.1	0.82	0.4	2.821
4	90.54	0.1	0.28	0.8	2.5
5	150	0.21	0.55	0.4	3.78
6	209.46	0.32	0.82	0.8	4.525
7	150	0.21	0.55	0.4	3.35
8	90.54	0.32	0.28	0.8	8.369
9	90.54	0.1	0.28	0.4	2.745
10	209.46	0.32	0.28	0.4	10.13
11	150	0.21	0.55	0.4	2.513
12	209.46	0.32	0.28	0.8	4.185
13	209.46	0.1	0.82	0.8	0.696
14	150	0.21	0.55	0.8	2.812
15	150	0.21	0.55	0.4	2.34
16	209.46	0.1	0.82	0.4	0.823
17	150	0.21	0.55	0.8	3.022
18	150	0.21	0.55	0.8	2.327
19	209.46	0.1	0.28	0.8	0.544
20	90.54	0.1	0.82	0.8	2.376
21	90.54	0.32	0.82	0.8	6.838
22	150	0.21	0.55	0.4	3.59
23	90.54	0.32	0.82	0.4	7.812
24	90.54	0.32	0.28	0.4	10.492
25	150	0.21	0.55	0.4	2.546
26	150	0.21	0.55	0.8	2.125
27	209.46	0.32	0.82	0.4	8.439
28	150	0.21	0.55	0.8	2.519

5. ANOVA Analysis

Analysis of variance (ANOVA) was conducted on the collected data to investigate the main effect of cutting speed, feed rate, depth of cut, nose radius together with their two-level interaction effect on surface roughness as measured by surface roughness tester.

Table.5.1: ANOVA for selected factorial model

Source	Sum of squares	df	Mean Square	F Value	P value	
Model	16.58424159	9	1.842693511	60.46849	< 0.0001	S
A-Cutting Speed	2.745291035	1	2.745291035	90.08747	< 0.0001	
B-Feed Rate	11.81534662	1	11.81534662	387.7238	< 0.0001	
C-Depth of Cut	1.1649E-06	1	1.1649E-06	3.82E-05	0.9951	
D-Nose Radius	0.405288592	1	0.405288592	13.29966	0.0018	
AB	1.265590811	1	1.265590811	41.53071	< 0.0001	
AC	0.06718322	1	0.06718322	2.204636	0.1549	
AD	0.07426776	1	0.07426776	2.437117	0.0359	
BC	0.089807855	1	0.089807855	2.947069	0.1032	
BD	0.121464533	1	0.121464533	3.985892	0.0412	
Residual	0.548525073	18	0.030473615			
Lack of Fit	0.242808112	8	0.030351014	0.992781	0.4941	NS
Pure Error	0.305716961	10	0.030571696			
Cor Total	17.13276667	27				

Std. Dev.	0.17		**R-Squared**	0.9680
Mean	1.07		**Adj R-Squared**	0.9520
C.V. %	16.32		**Pred R-Squared**	0.9197
PRESS	1.37		**Adeq Precision**	29.401

As per the result in the Table 5.1, the model F value of 60.8649 depicts that the model generated is significant. Also the variables that are A, B, C, D has certain values of P value. As per the rule if the P value of the parameters is less than 0.05, whereas the P value of C, which is depth of cut has a P value greater than 0.5. This suggests that the effect on the roughness from the depth of cut is not significant and is negligible.

<u>The final empirical models in terms of coded factors were presented as follows</u>:

Ln (Roughness)= 1.07 – (0.41*A) + (0.86*B) –(2.698E – 004 * C) – (0.12 * D) + (0.28 * A * B) + (0.065 *A * C) – (0.068 *A * D) – (0.075 *B *C) – (0.087 * B* D) (5.1)

The Fig.5.1, shows the half normal plot, the extreme right side factor has the highest effect on the response, however as the dots corresponding to the particular factor comes nearer and nearer to the line, it shows these value affects the least.

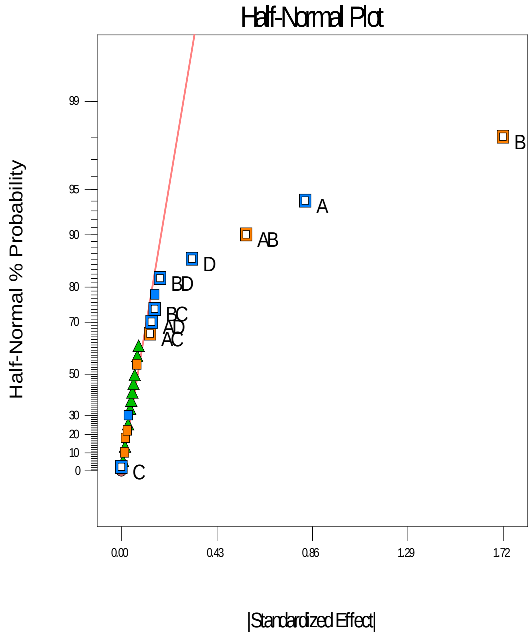

Fig.-5.1: A half normal plot shows the effectiveness of the factors

The value at the right extreme has the strongest effect on the roughness and keeps on decreasing as it comes nearer and nearer to the line. It can also be understood in the Fig5.2, which shows the of effectiveness rank wise. The graph is between t-value and rank of factors.

Fig 5.2 and 5.3 are describing the mechanism of error. It can be seen that the points are following evenly on the straight line that shows the errors are evenly distributed.

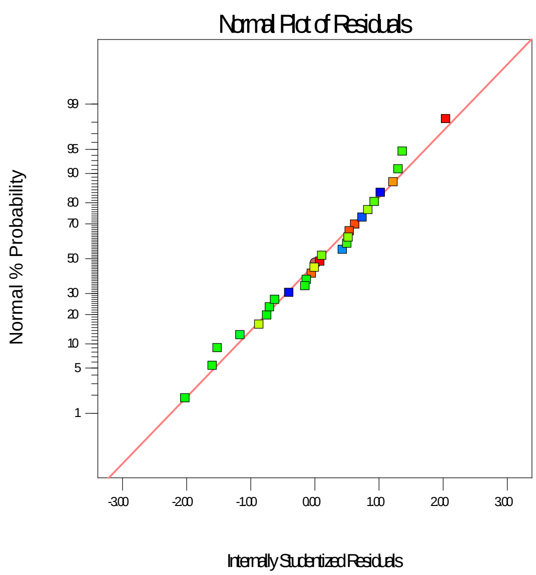

Fig.-5.2: Normal probability plot for surface roughness

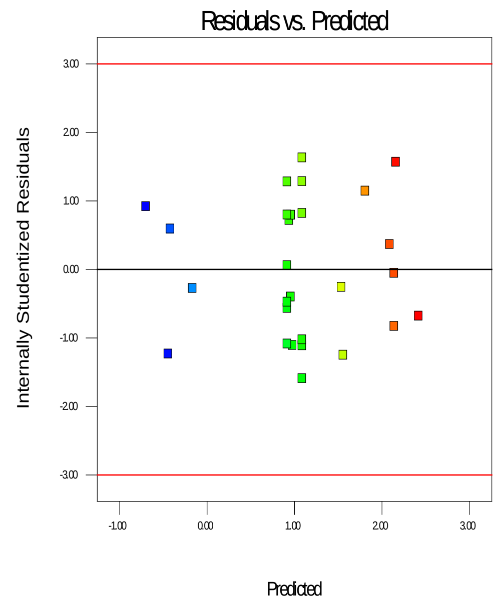

Fig.-5.3: Plots of Residual vs Predicted response for the surface roughness in turning operation

Fig.-5.4 and 5.5 shows the behavior pattern of surface roughness with increase and decrease in the Cutting speed, in minimum nose radius and maximum nose radius (0.4mm & 0.8). These figures are showing the sole effect of these factors on the roughness. The dotted points are showing the design points.

- It is seen that the surface roughness decreases with the cutting speed in turning operation.

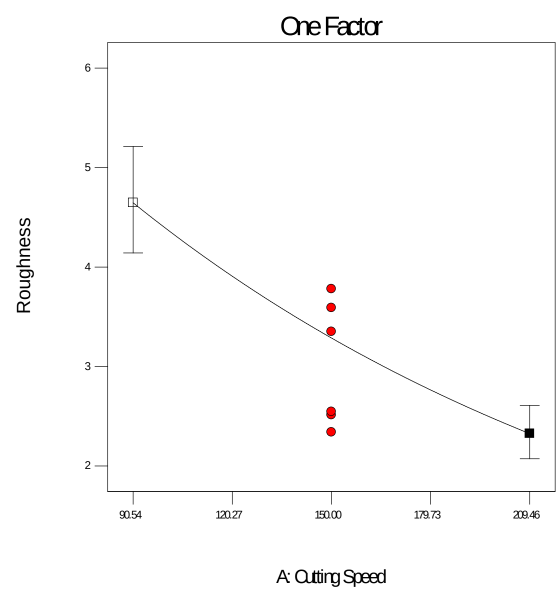

Fig.-5.4. Plot of Roughness vs Cutting speed at nose radius 0.4

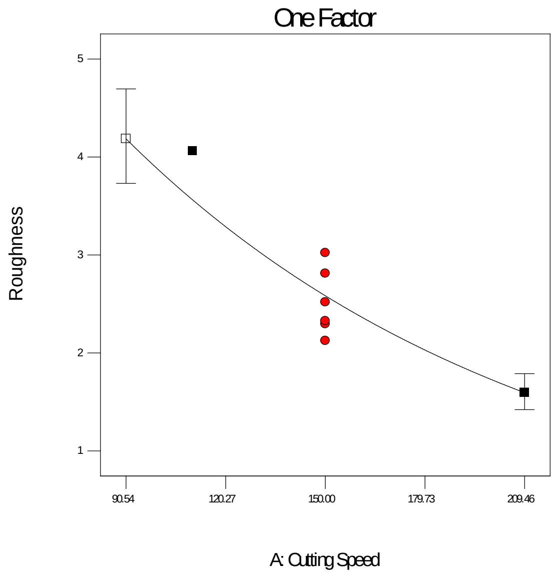

Fig.-5.5. Plot of Roughness vs Cutting Speed at nose radius 0.8

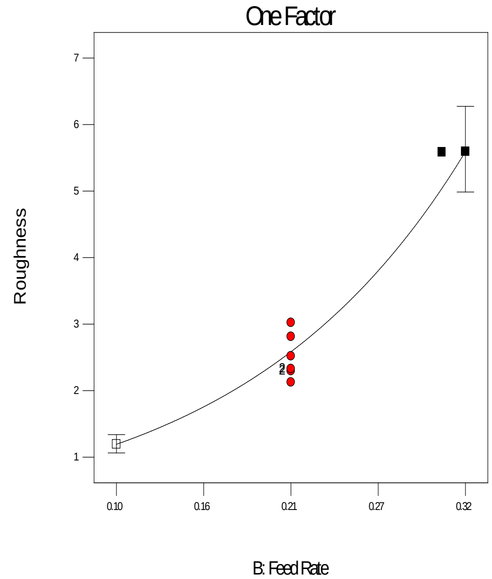

Fig.5.7: Plot of Feed rate vs Roughness at nose radius maximum (0.8mm)

The Fig.5.6 and 5.7 shows the relation between surface roughness and feed rate at nose radius minimum and maximum This effect is solely due to the feed rate on roughness in the turning operation. It is seen that there is no significant effect on the roughness pattern in either of the nose radius.

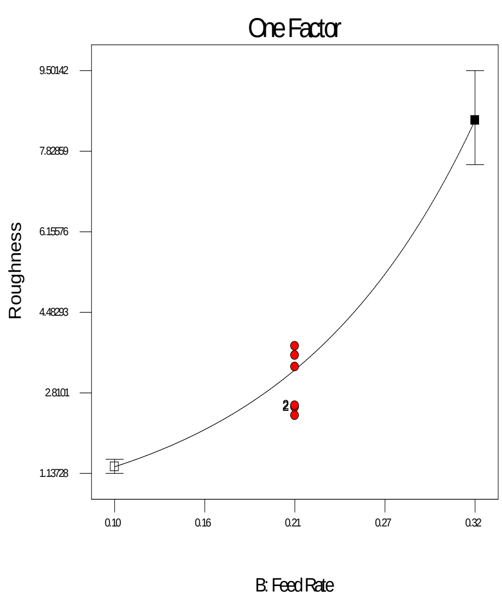

Fig 5.6: Plot of Feed rate Vs. Roughness at min nose radius (0.4mm)

The next fig.5.8 shows the relation between nose radius and the surface roughness. It can be seen that with increase in the nose radius of tool used for the turning operation, the surface roughness decreases.

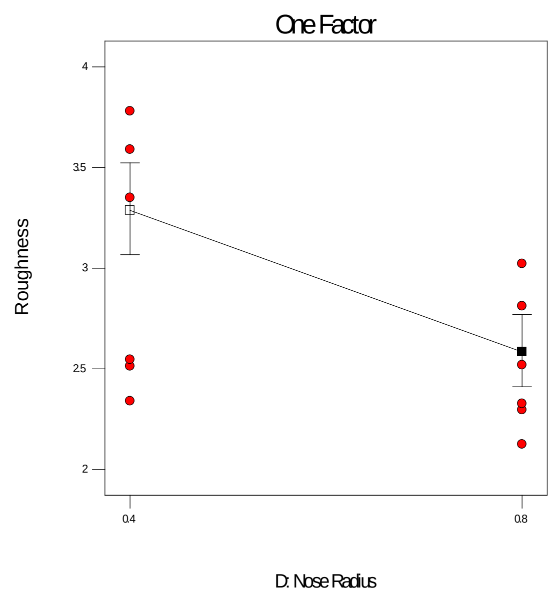

Fig.5.8; Plot of Nose radius of tool Vs. Roughness

Fig.5.9 shows the 3-D curve of roughness vs. Cutting speed and Feed rate. It can be clear from the diagram how the roughness is changing with the change in both the cutting speed as well as feed rate at the same time.

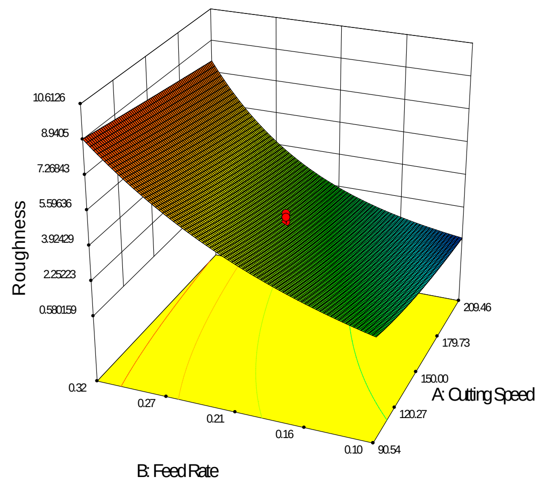

Fig.5.9. Roughness Vs A and B.

It can be seen that as the feed rate increasing, from left to right the roughness is also increasing. Whereas, the cutting speed increase the roughness is decreasing. The slope is high, that is the increase in the roughness is steeper in this case when nose radius is 0.4 mm.

Fig. 5.10 shows the same graph pattern but the condition there is that nose radius has been increased to 0.8 mm. In this case the increase in the roughness is not at much high rate in comparison to lower nose radius. However, the roughness still shows the same behavior of increment with feed rate and decrement with the increase in the cutting speed but the rate is low.

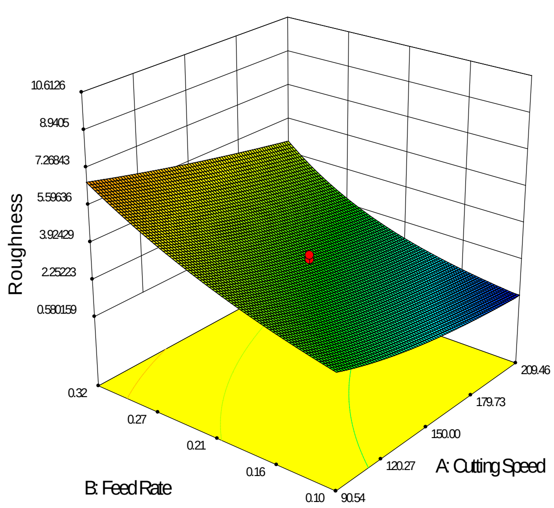

Fig.5.10 Plot of roughness vs. feed rate and cutting speed.

This behavior of the roughness gives the idea about the effect of various factors on the roughness. By keeping these behavioral patterns, the roughness can be optimized with the best possible combination value of the factors.

6. Conclusion

From the analysis of all the graphs and models generated by the software Design Expert, we have to following conclusion:-

- If the cutting speed is high roughness decreases at all the feed rate what we have taken in the model range and at all the nose radius in our range.
- If the nose radius is increased the roughness is decreased within all the permissible range of values of all the factors but at too little feed rate the roughness has shown increase, although it was too little but it has increased.
- When we increase the feed rate the roughness also increases at all the values of factors within the permissible range of model.
- When cutting speed and nose radius interact together, the roughness also decreases. It may be due to combined effect of the speed as well as nose radius as both alone also cause the roughness to decrease.
- When feed rate and nose radius interact together the roughness tend to increase. However, at too low feed rate at 0.10 mm/rev the roughness is almost increasing with the nose radius.

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