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A study of surface roughness during the end milling of AISI-1020 steel using partial factorial design

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Abstract:

End Milling is the most efficient and creative manufacturing method for roughing and finishing large surfaces of metallic parts. End milling process has been studied by many researchers. The main research subjects are cutting forces, surface roughness, search of optimal parameters and tool wear. An area of great interest is the optimization of cutting parameters, for the selection of the optimal cutting parameters for end milling operation.

The current study presents an approach to the determination of the optimal cutting parameters to create minimum surface roughness levels in the end milling of AISI-1020 steel.

In present study the fractional factorial design technique is used to optimize the process parameter in end milling of AISI-1020 steel with tungsten coated end mill inserts. The parameters taken for the study are cutting speed (rpm), feed rate (mm/tooth), depth of cut (mm) and coolant condition. Out of these four parameter the coolant used is a categorical parameter rest has numeric value. Two level of 2^{4-1} fractional factorial designs of eight runs was selected for conducting the experiments. The mathematical models were developed from the data generated. The graphical analysis through various plots for surface roughness plots also implemented.

1. INTRODUCTION

Milling may be defined as a machining process for removing excess material from a work piece with a rotating cutting tool. The rotating cutting tool called the "Milling cutter" is a multiple point tool having the shape of a solid of revolution with cutting teeth arranged(equally spaced) either on the periphery or on end face or on both.

A end mill consists of a cutter body (with the appropriate machine taper) that is designed to hold multiple disposable carbide or ceramic tips or inserts, often golden in color. End milling is the milling of surface that are perpendicular to the cutter axis. End milling produce flat surface and machine work to the required length. In end milling the feed can be either horizontal or vertical.

1.1: SURFACE ROUGHNESS MEASUREMENT

Surface roughness, often shortened to roughness, is a measure of the texture of a surface. It is quantified by the vertical deviations of a real surface from its ideal form. If these deviations are large, the surface is rough; if they are small the surface is smooth. Roughness is typically considered to be the high frequency, short wavelength component of a measured surface. Roughness plays an important role in determining how a real object will interact with its environment. Rough surfaces usually wear more quickly and have higher friction coefficients than smooth surfaces. Roughness is often a good predictor of the performance of a mechanical component, since irregularities in the surface may form nucleation sites for cracks or corrosion.

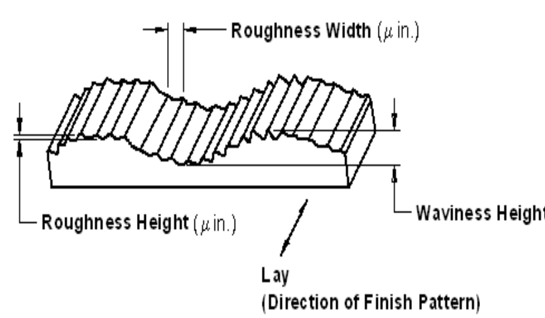

Fig.1.7: Close view of irregularities on the surface

Surface roughness is the measure if the finer surface irregularities in the surface texture. These are the result of the manufacturing process employed to create the surface. Surface roughness Ra is rated as the arithmetic average deviation of the surface valleys and peaks expressed in micro inches or micro meters.

Inspection and assessment of surface roughness of machined work pieces can be carried out by means different measurement technique.

- Direct measurement method

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- Comparison based technique
- Non contact method

2. LITERATURE SURVEYED

2.1 Introduction

Literature identifies that there are several studies, which have been contributed by many researchers and engineers regarding the optimization of machining characteristics in milling.

Dae Kyun Baek at el. (2001) developed a surface roughness model for optimization of feed rate in face milling of AISI 1041 using Korea Tungsten M 115 SP 04 R/L-10 inserts. The surface roughness model was developed considering cutter insert run out errors and the feed rate of the cutting tool and the optimal feed rate was obtained by solving the objective function with a bisection method.

P.G. Benardos and G.C. Vosniakos (2002) used neural network modeling approach for the prediction of surface roughness in CNC face milling of Aluminum . The data used for checking of the networks performance derived from experiments conducted on a CNC milling machine according to the principles of Taguchi design. The factors considered were the depth of cut, the feed rate per tooth, the cutting speed, the engagement and wear of the cutting tool, the use of cutting fluid and the three components of the cutting force. It is found that ANNs are a powerful tool, easy-to-use in complex problems.

F. Dweiri at el. (2003) used adaptive neuro fuzzy inference proposed the modeling to predict the effect of machining variables spindle speed, feed, depth of cut, no. of flutes on surface roughness for down milling on alumic-79. It was found that fuzzy modeling proved effective in modeling such complex system. Further, it was also found that four flutes cutter give better surface finish than two flutes cutter.

Ming-Yung Wang and Hung-Yen Chang (2004) experimental studied the surface roughness in end milling of AL2014-T6 using two fluted end mills. The parameters considered were the cutting speed, feed, depth of cut, concavity and axial relief angles of the end cutting edge of the end mill. Surface roughness models for both dry cutting and coolant conditions were developed using the response surface methodology (RSM). It has been found that the dry-cut roughness was reduced by applying cutting fluid. The significant factors affecting the dry-cut model were the cutting speed, feed, concavity and axial relief angles; while for the coolant model, they were the feed and concavity angle.

Hasan oktem et al. (2005) developed an approach for determination of the best cutting parameters leading to minimum surface roughness in end milling of an aluminium 7075-T6 by Al TiN PVD coated tool. Optimization is done by coupling neural network and genetic algorithm. Cutting parameters such as cutting speed, feed, axial–radial depth of cut, and machining tolerance are selected. It has been found that a good correlation is obtained between the value of surface roughness predicted by the GA and that of surface roughness obtained from experimental measurements.

Julie. Z. Zhang at el. (2006) studied the Taguchi design method to optimize surface quality in a CNC end milling of aluminum by coated carbide inserts. The independent variables are cutting speed, feed rate, depth of cut, tool wear and temperature range. It has been found that taguchi method gives optimal values of cutting conditions for good surface finish with minimum number of experiments.

Savas and Ozay, (2007) developed an approach for optimization of cutting parameters for minimum surface roughness using genetic algorithm in the tangential turn-milling process. The experimental studies was carried out on cylindrical workpieces of SAE 1050 steel using end-milling cutter of high speed steel. The effect of cutting parameters (depth of cut, workpiece speed, tool speed and feed rate) on surface roughness has also been investigated. It was inferred from the analysis of result that as depth of cut and feed rate increased, the surface roughness also increased.

Wen-Hsien Ho at el. (2009) proposed an adaptive network-based fuzzy inference system (ANFIS) with the genetic learning algorithm is used to predict the workpiece surface roughness for the end milling of 6061 aluminium alloy using four flute HSS cutter. The independent variables taken are speed, feed, depth of cut. It has been found that the optimal values given by hybrid Taguchi-genetic learning algorithm approach outperforms the ANFIS methods given in the Matlab toolbox.

Kadirgama et al., (2010) used response ant colony optimization (RACO) approach for optimum surface roughness in milling of mould aluminium alloys 6061-T6. The approach is based on response surface method (RSM) and ant colony Optimization (ACO). The empirical surface roughness model was developed in terms of cutting speed, feed, axial depth and radial depth. The good prediction ability of the model has been found that's indicating the effectiveness of the model based on ACO combine with RSM.

Kakati et al., (2011) used artificial neural network (ANN) to establish the relationship between the surface roughness and the input cutting parameters (i.e., spindle speed, feed, and depth of cut) in end milling of aluminium alloy with carbide tool. The feed forward back propagation algorithm used for modeling purpose. The results revealed that the spindle speed has inversely effect on surface roughness while it has been increased as feed rate and depth of cut increases.

Parmar and Makwana, (2012) used artificial neural networks to develop surface roughness prediction model in end milling of mild steel with carbide tool. The prediction model was developed in term of spindle speed, feed and depth of cut using MATLAB. The result shows that the prediction based on an ANN model is quite closer to the experimental results. The average prediction error for data set was found to be 3.5% and maximum prediction error was 8.743766%.

2.2 GAPS IDENTIFIED

On the basis of the literature surveyed, it has been observed that,

- Not much work has been reported on optimizing end milling process on AISI-1020 steel by tungsten coated triangular insert end mill cutter using factorial design technique.
- It is also observed that not much literature exists on using the coated end mill cutter.

2.3: PROBLEM STATEMENT

The cutting parameter such as cutting speed, feed rate and depth of cut are the most important factor has to be considering in end milling operation. The wrong selection of combination cutting parameter will lead to the bad cutting condition e.g. vibration that effect the poor surface finish. Different work piece material with different property and microstructure give different effect to the cutting tool performance. The main objectives of this research are to carry out the experiment techniques and then analyzing the result obtained. The two main objectives of present research are-

- Metal removal rate
- Surface roughness

3.: EXPERIMENTAL SET UP AND PLAN

3.1: DESIGN OF EXPERIMENT

The design of experimentation has a significant role on the number of experiments needed. Therefore cutting experiments have to be designed in this study a 2 level fractional factorial were performed to obtain the metal removal rate and surface roughness values. A total number of 24 experiments are conducted at 2 levels for the four input variables speed, feed, depth of cut and coolant condition.

3.2.: MATERIAL AND TOOL USED

AISI-1020 steel plate having 16mm thickness was used in this research work. The milling cutter used for machining having 2 cutting inserts made from tungsten carbide (coated). The dimensions of tool were-:

Cutter diameter ---- 20 mm
Size of inserts ---- triangular
Nose radius ---- 0.6 mm

3.3: MACHINE USED FOR EXPERIMENT

In present work, vertical computer numerical control (CNC) milling machine is used. The end milling operation was carried out on a (LEADWELL V 60 Machining center, Taiwan). The CNC Milling equipped with continuously variable spindle speed up to 8000 rpm, and 18.5KW motor drive was used for machining test. The cutter used for this operation with 50 mm diameter.

3.4 : SELECTION OF PARAMETERS AND THEIR LEVELS

Selected parameters and their working range has been shown in the Table 3.1.

Table 3.1: Process parameter with levels

Name	Units	Type	Minimum	Maximum
Speed	m/min	Numeric	100	200
Feed	mm/tooth	Numeric	0.05	0.15
Depth of cut	mm	Numeric	0.6	3
Coolant		Categorical	on	off

3.5: OBSERVATION TABLE

The observed values surface roughness are tabulated in Table 3.2

Table 3.2: Observed values of surface roughness

Std	A:Speed (m/min)	B:Feed (mm/tooth)	C:Depth of cut (mm)	D:Coolant	Surface roughness (microns)
1	100	0.05	0.6	off	1.14
2	100	0.05	0.6	off	1.11
3	100	0.05	0.6	off	1.15
4	200	0.05	0.6	on	0.69
5	200	0.05	0.6	on	0.74
6	200	0.05	0.6	on	0.75
7	100	0.15	0.6	on	1.25
8	100	0.15	0.6	on	1.32
9	100	0.15	0.6	on	1.31
10	200	0.15	0.6	off	1.23
11	200	0.15	0.6	off	1.22
12	200	0.15	0.6	off	1.2
13	100	0.05	3	on	1.24
14	100	0.05	3	on	1.22
15	100	0.05	3	on	1.23
16	200	0.05	3	off	1.3
17	200	0.05	3	off	1.27
18	200	0.05	3	off	1.34
19	100	0.15	3	off	1.79
20	100	0.15	3	off	1.86
21	100	0.15	3	off	1.72
22	200	0.15	3	on	1.24
23	200	0.15	3	on	1.28
24	200	0.15	3	on	1.23

3.6: MEASUREMENT OF SURFACE ROUGHNESS

The surface roughness of machined specimen has measured using a piezoelectric type instrument Model no. TR-100, manufactured by TIME Company shown as fig 3.1.

Fig. 3.1: The SR-Tester

4. MATHEMATICAL MODELING

4.1 Introduction

The complete results of the 24 experiments performed as per the experimental plan were input into the Design Expert 8.0.7.1 software for further analysis.

4.2 ANOVA for surface roughness prediction model

4.2.1 Diagnosis of assumptions of ANOVA

The analysis of variance (ANOVA) is commonly used to perform test for (1) significance of the regression model, (2) significance on individual model coefficients, and (3) lack of fit of model. This analysis is based on two assumptions: (1) the variables are normally distributed and (2) homogeneity of variance.

To check the assumption of normal distribution, the normal probability plot of the residuals is shown in fig.4.1.The normal probability plot indicates whether the residuals follow a normal distribution or not.

The fig.4.2 represents residuals versus the predicted response plot for surface roughness. It tests the assumption of constant variance. The plot should be a random scatter.

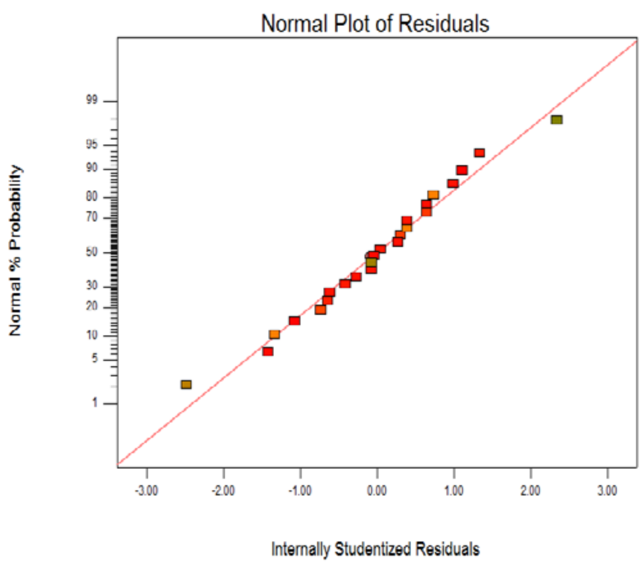

Fig. 4.1 Normal probability plot of residuals

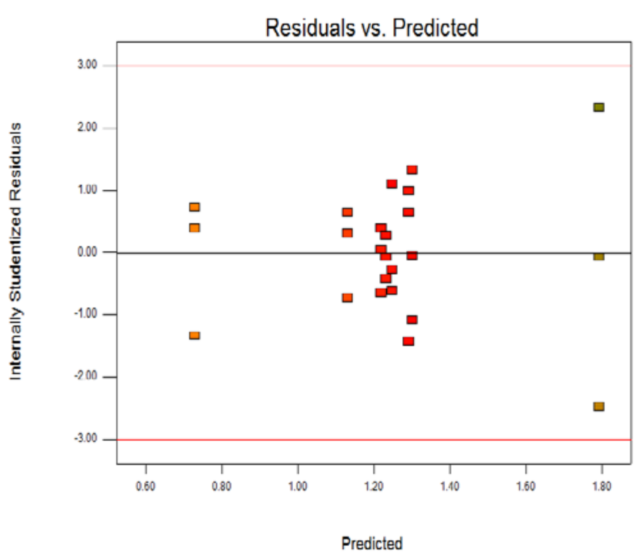

Fig. 4.2 Plot of residuals v/s predicted response

A graph of the actual response values versus the predicted response values is shown in fig.4.3. It helps detect a value, or group of values, that are not easily predicted by the model.

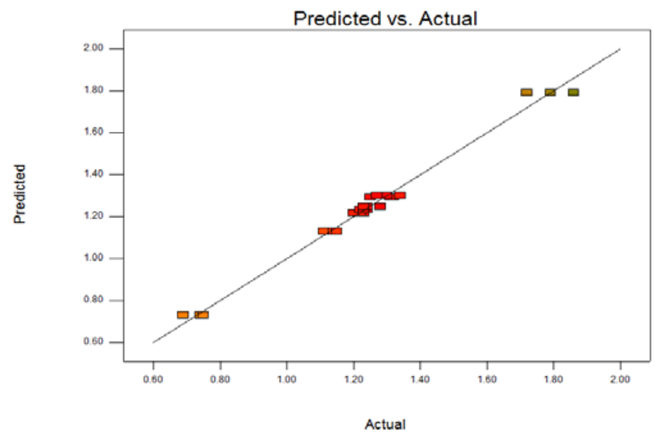

Fig. 4.3 Plot of predicted v/s actual response

4.2.2 ANOVA analysis and development of surface roughness prediction model

The ANOVA test for response surface model for surface roughness is summarized in Table 4.1. This analysis was carried out for a significance level of α = 0.05, i.e. for a confidence level of 95%.

Table 4.1 Resulting ANOVA table for surface roughness

Source	Sum of Squares	Degree of freedom	Mean Square	F-Value	p-value Prob > F
Model	1.755	6	0.292	245.659	< 0.0001
A-Speed	0.338	1	0.338	284.296	< 0.0001
B-Feed	0.502	1	0.502	421.444	< 0.0001
C-Depth of cut	0.543	1	0.543	456.137	< 0.0001
D-Coolant	0.334	1	0.334	280.320	< 0.0001
AB	0.030	1	0.030	25.288	0.0001
AD	0.008	1	0.008	6.472	0.0210
Residual	0.020	17	0.001		
Lack of Fit	0.0001	1	0.000	0.083	0.7773
Pure Error	0.020	16	0.001		
Cor Total	1.775	23			
Std. Dev.	0.0345		R-Squared		0.989
Mean	1.2429		Adj R-Squared		0.985
C.V. %	2.7760		Pred R-Squared		0.977
PRESS	0.0403		Adeq Precision		57.065

Table shows that the value of "Prob. > *F*" for model is 0.0001 which is less than 0.05, that indicates the model is significant, 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 cutting speed, feed, depth of cut, coolant and two-level interaction of cutting speed and feed, cutting speed and coolant, are less than 0.05 so these terms are significant model terms. The value of "Prob. > *F*" for lack-of-fit is 0.7773 which is greater than 0.05 and it indicates the insignificant lack of fit..

The R^2 value (the measure of proportion of total variability explained in the model) is equal to 0.989 or close to 1, which is desirable. The adjusted R^2 value is equal to 0.985. The result shows that the adjusted R^2 value is very close to the ordinary R^2 value. Adequate precision value is equal to 57.065; a ratio greater than 4 is desirable which indicates adequate model discrimination.

The regression model for surface roughness in terms of coded factors is shown as follows:

$$(Surface\ roughness) = 1.24 - 0.12 * A + 0.14 * B + 0.15 * C - 0.12 * D - 0.035 * A * B - 0.018 * A * D$$

(4.1)

While, the equations 4.2 and 4.3 is the empirical model in terms of actual factors for coolant off and coolant on conditions respectively

$$(Surface\ roughness) = 0.906 - 0.0015 * Cutting\ speed + 4.3 * Feed + 0.125 * Depth\ of\ cut - 0.0035 * Cutting\ speed * Feed$$

(4.2)

$$(Surface\ roughness) = 0.742 - 0.0033 * Cutting\ speed + 4.3 * Feed + 0.125 * Depth\ of\ cut - 0.0035 * Cutting\ speed * Feed$$

(4.3)

4.3 Contribution of milling parameters on surface roughness

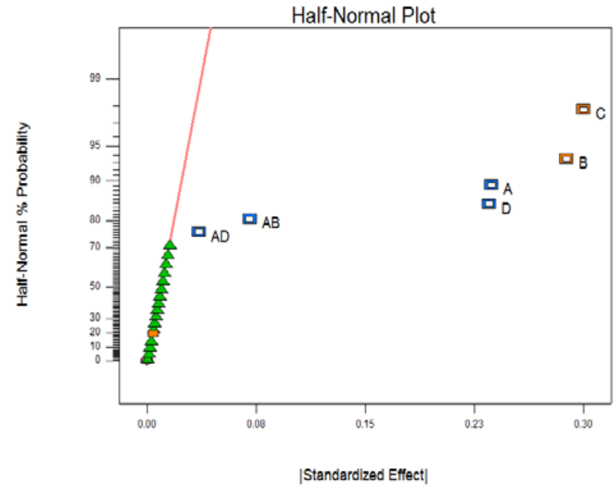

Fig.4.4: A half normal plot shows the effectiveness of the factors

The fig.4.4, 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.

The value at the right extreme has the strongest effect on the surface roughness and keeps on decreasing as it comes nearer and nearer to the line.

4.4 Effect of end milling parameters on surface roughness

4.4.1 Effect of cutting speed on surface roughness

Influence of cutting speed on surface roughness at coolant off and coolant on condition is shown in fig. 4.5 and 4.6 respectively.

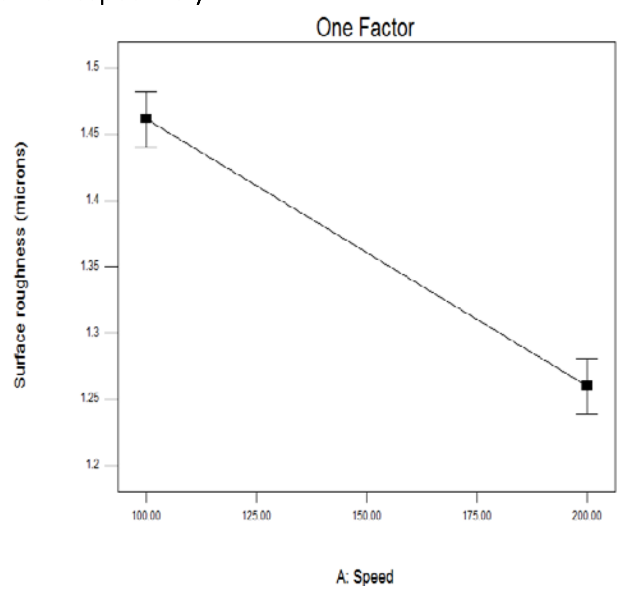

Fig. 4.5 Plot between roughness & cutting speed at feed (0.1mm/tooth), depth of cut (1.8 mm) and coolant off condition

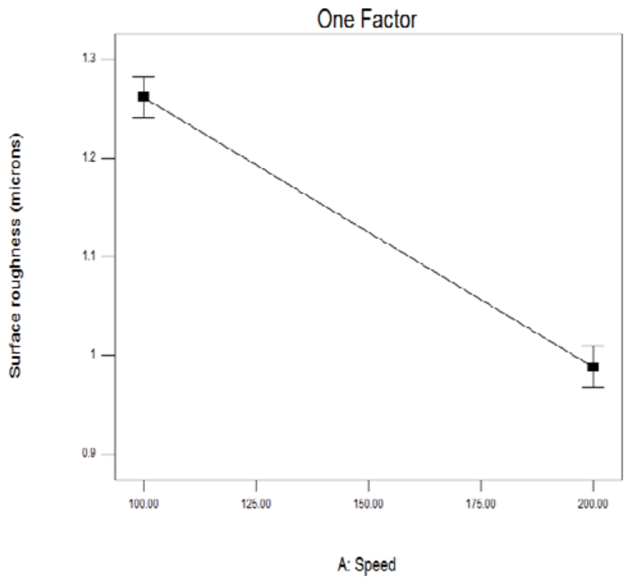

Fig. 4.6 Plot between roughness & cutting speed at feed (0.1mm/tooth), depth of cut (1.8 mm) and coolant on condition

The result shows that the surface roughness decreases as the cutting speed increases from 100 mm/min to 200 m/min because as the cutting speed increases, temperature during cutting also increases, which soften the material to enhance the cutting performance leading to reduced surface roughness.

4.4.2 Effect of feed rate on surface roughness

Influence of feed on surface roughness at constant at coolant off and coolant on conditions is shown in fig. 4.7 and 4.8 respectively.

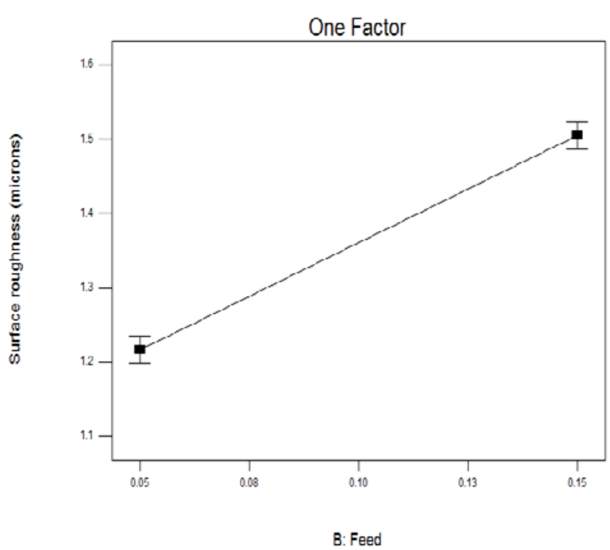

Fig. 4.7 Plot between feed and surface roughness at constant cutting speed (150 m/min) constant depth of cut (1.8 mm) and coolant off condition

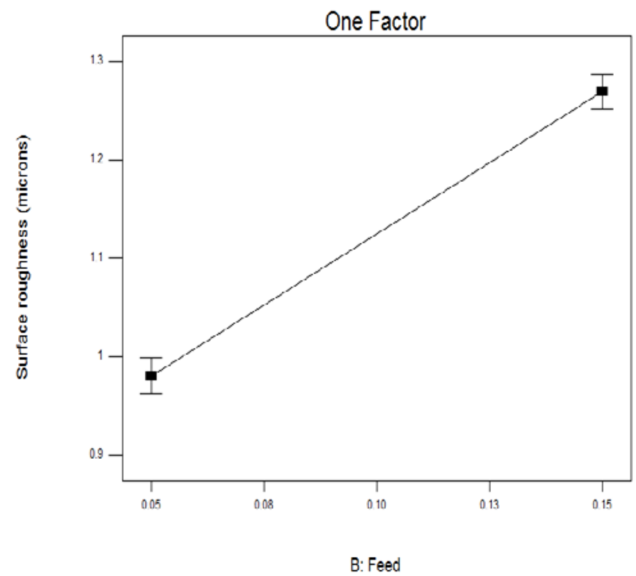

Fig. 4.8 Plot between feed and surface roughness at constant cutting speed (150 m/min) constant depth of cut (1.8 mm) and coolant on condition

The figures show the effect of feed rate on surface roughness. The roughness increases as the feed rate increases. This is due to the fact that at higher feed rate, tool traverses the work piece too fast, resulting in deteriorated surface quality and also high feed increase the chatter, which leads to higher surface roughness.

4.4.3 Effect of depth of cut on surface roughness

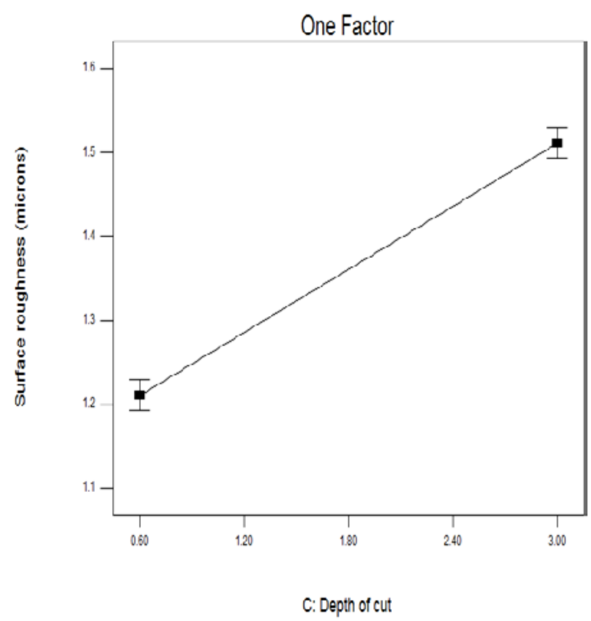

Fig. 4.9 Plot between depth of cut and surface roughness at constant cutting speed (150 m/min), constant feed rate (1.8 mm/tooth) and coolant off condition

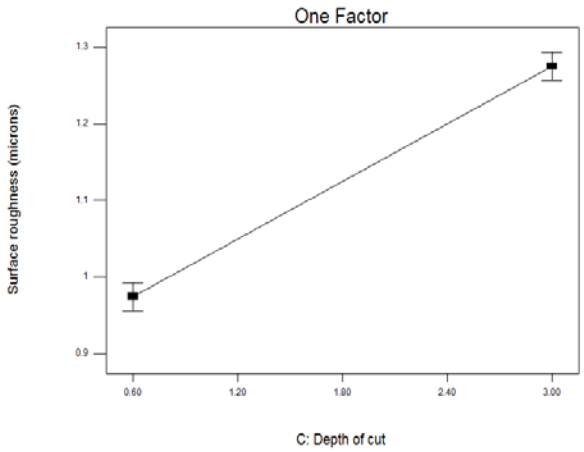

Fig. 4.10 Plot between depth of cut and surface roughness at constant cutting speed (150 m/min), constant feed rate (1.8 mm/tooth) and coolant on condition

Influence of depth of cut on surface roughness at coolant off and coolant on conditions is shown in fig. 4.9 and 4.10 respectively. It is clear from the plots that as the depth of cut increases the value of surface roughness also increases. This is due to the fact that at higher depth of cut, vibration of tool increases, resulting in deteriorated surface quality

4.4.4 Effect of coolant on surface roughness

Influence of coolant condition on surface roughness at cutting speed 150 m/min, feed 0.1 mm/tooth and depth of cut 0.18 mm is shown in fig. 4.11. It is clear from the plot that with the application of coolant, the surface roughness decreases. This is due to the fact that cutting with coolant on condition, decrease the friction between the tool and workpiece, resulting in good surface finish.

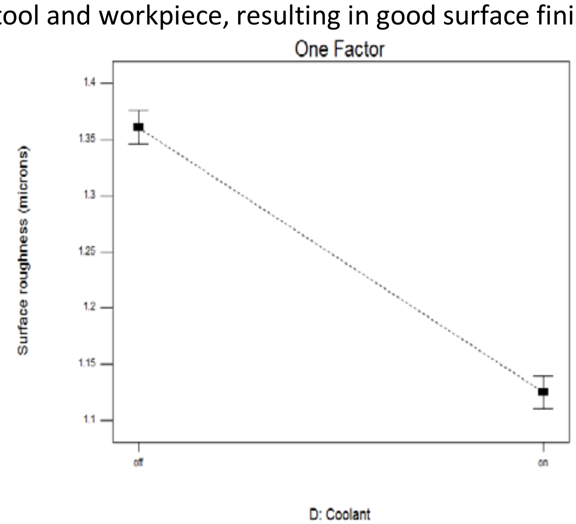

Fig. 4.11 Plot between coolant condition and surface roughness at constant cutting speed (150 m/min), constant feed rate (1.8 mm/tooth) and depth of cut 1.8 mm

4.4.5 3D plots for surface roughness

The figures 4.12 and 4.13 show the 3 D plots for surface roughness. From the all 3D plots it is clear that surface roughness increases with increase in feed rate and decreases as increase in cutting speed. The minimum surface roughness is achieved at low feed and higher value of cutting speed.

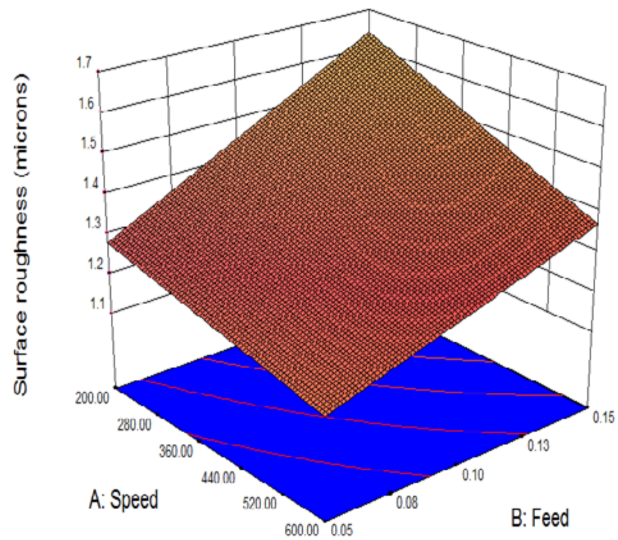

Fig.4.12 3D plot between cutting speed and feed at coolant is off

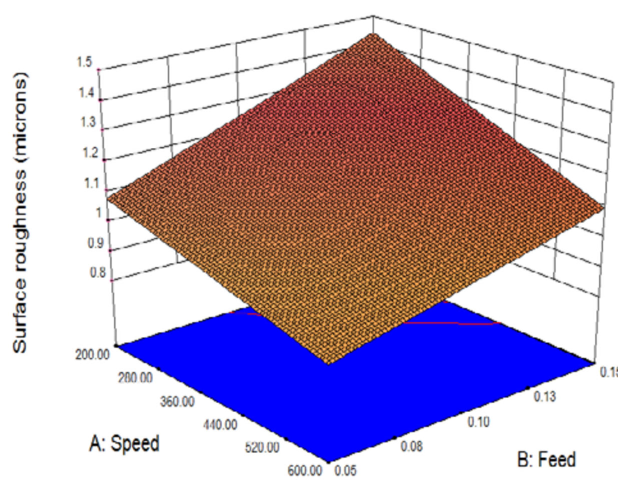

Fig.4.13 3D plot between cutting speed and feed at coolant is on

From the all plots it is clear that surface roughness increases with increase in feed rate, depth of cut and decreases as increase in cutting speed with the application of coolant. The minimum surface roughness is achieved at low feed, low depth of cut , higher value of cutting speed with coolant on condition.

5. CONCLUSION

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

- Out of four variables, depth of cut contributes the highest effect on surface roughness, followed by feed, cutting speed and coolant.
- The established equations clearly show that surface roughness increased with increasing the feed and depth of cut but decreased with increasing the cutting speed under wet condition.
- Minimum surface roughness is achieved at higher level of speed, low level of feed, low level of depth of cut and with the use of coolant.
- Surface roughness decrease under wet condition and increase under dry condition.

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