International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-04, Issue-11, Feb 2019

Application of RSM with performance of coated carbide tools for turning operation

Dr. Ashvin J. Makadia

Professor, Darshan Institute of Engineering and Technology, Rajkot, India

Abstract: In this study, a Response surface methodology (RSM) is used for the prediction of surface roughness in a computer numerically controlled (CNC) machine. Experimental investigation was conducted on the CNC machine to obtain the data used for the prediction of surface roughness on AISI 1040 steel. The parameters used in the experiment were cutting speed, feed, depth of cut and tool nose radius. Each of the other parameters such as work piece material, work piece diameter, work piece length and approach angle were taken as constant. This study shows that feed is the dominant factor determining the surface finish followed by nose radius and cutting speed. Finally, the depth of cut has no significant effect on the surface roughness in the studied range, which could be used to improve the productivity. Mathematical models for the surface roughness were developed by using the response surface methodology (RSM).

Keywords: CNC, Nose radius, Response surface methodology, Surface roughness

I. INTRODUCTION

Turning is the primary operation in most of the production processes in the industry. The turning operation produces the components, which have critical features that require specific surface finish. The operators working on CNC machine use their own experience and machining guidelines in order to achieve the best possible surface finish. Unfortunately, surface roughness can be difficult to notice visually and chatter can be obscured by other noises. Due to inadequate knowledge of the complexity and factors affecting on the surface finish in turning operation, an improper decision may cause high production costs and low machining quality. The proper selection of cutting tools and process parameters for achieving high cutting performance in a turning operation is a critical task. Hence a proper estimation of surface roughness has been focus on study for several years. It is necessary to employ theoretical models making it feasible to do predictions in function of operating conditions.

Statistical design of experiments refers to the process of planning the experiments so that appropriate data can be analysed by statistical methods, resulting in valid and objective conclusions [1]. Thiele and Melkote [2] had used a three-factor complete factorial design to determine the effects of work piece hardness and cutting tool edge geometry on surface roughness and machining forces in the finish hard turning of AISI 52100 steel. Mital and Mehta [3] have conducted a survey of surface prediction models developed and factors influencing the surface roughness. They have developed the surface finish models for aluminium alloy 390, ductile cast iron, medium carbon leaded steel, medium carbon alloy steel 4130 and inconel 718 for a wide range of machining conditions defined by cutting speed, feed and tool nose radius. Sundram and

Lambert [4, 5] have developed the mathematical models for predicting the surface roughness of AISI 4140 steel during the fine turning operation using both TiC coated and uncoated tungsten carbide throw away tools. The parameters considered were cutting speed, feed, depth of cut, time of cut, nose radius and types of the tool. Noordin et al. [6] studied the application of response surface methodology in describing the performance of coated carbide tools when turning AISI 1045 steel. The factors investigated were cutting speed, feed and side cutting edge angle. The response variables were surface finish and tangential force. ANOVA revealed that feed is the main factor influencing the response variables investigated. Suresh et al. [7] have developed a surface roughness prediction model for turning mild steel using a response surface methodology to produce the factor effects of the individual process parameters. Surface roughness prediction model has been optimized by using genetic algorithms (GAs). The Taguchi method was used in references [8, 17, 20] to find the optimal cutting parameters for turning operations. Choudhury and Baradie [9] had used RSM and 2^3 factorial design for predicting surface roughness when turning high-strength steel. Munoz and Cassier [10] have developed mathematical model of surface roughness for different types of steel such as AISI 1020, AISI 1045 and AISI-4140. They found that surface finish improves by increasing cutting speed and tool nose radius and by decreasing the feed rate. The depth of cut does not seem to have a significant influence on surface finish. Feng [11] found that feed rate, tool nose radius, work material, speed and the tool point angle have a significant impact on the

 DOI : 10.18231/2454-9150.2019.0055

observed surface roughness using the fractional factorial experimentation approach. Paulo Davim [12] found that the cutting speed has greater influence on the roughness followed by the feed and depth of cut has no significant influence on surface roughness. Lee et al. [13, 15] have developed a system for measuring surface roughness of turned parts through computer vision system. Sahin and Motorcu [14] used 2^3 factorial design for the development of surface roughness model for turning of mild steel with coated carbide tools. Ozel T. et al. [16, 18, 26] have used models for predicting the surface roughness with ceramic wiper inserts. Paulo Davim et al. [19, 21] used ANN to develop the surface roughness model for different cutting conditions. Petropoulos et al. [22] had used multi regression analysis and ANOVA for statistical study of surface roughness in turning of PEEK composite. Galanis and Manolakos [23] used 2^3 full factorial design for AISI 316L steel with three variables named feed, speed and depth of cut for application of femoral head. Tsourveloudis NC [24] used response surface methodology (RSM) and fuzzy logic system through the Adaptive Neuro-Fuzzy Inference System (ANFIS) for Ti6Al4 V titanium alloy. Asilturk and Cunkas [25] have developed artificial neural networks (ANN) and multiple regression approaches used for the surface roughness of AISI 1040 steel. Stavropoulos et al. [27, 28] have used machining technologies for micro cutting processes. Makadia and Nanavati [29, 30,31] used RSM for optimization of machining parameters for AISI 410 steel, Mild Steel and Aluminium. Neseli S et al. [32] used optimization of tool geometry parameters for turning operations based on RSM for AISI 1040 steel. Kini and Chincholkar [33] have used two level full factorial design to study the effect of machining parameters on surface roughness and material removal rate in finish turning of glass fibre reinforced polymers. Davidson MJ et al. [34] used RSM to study the effect of main flow forming parameters such as the speed of the mandrel, the longitudinal feed and amount of coolant used on surface roughness of flow formed AA6061 tube. Lalwani DI et al. [35] used RSM for investigations of cutting parameters influence on cutting forces and surfaces finish in hard turning of MDN250 steel. Gaitonde VN et al. [36] used (3^3) full factorial design for the analysis of machinability during hard turning of cold work tool steel (AISI D2) using Response Surface Methodology. Ramesh S et al. [37] used Taguchi method to study the effect of cutting parameters on the surface roughness in turning of titanium alloy using RSM.

The aim of the present study has been, therefore to develop the surface roughness prediction model of AISI 1040 steel with the aid of statistical method using coated carbide cutting tools under various cutting conditions. By using response surface methodology and (3^4) full factorial design of experiment, first and second-order models have been developed with 95% confidence level.

II. METHODOLOGY

Since there are a large number of variables controlling the process, some mathematical models are required to represent the process. However, these models are to be developed using only the significant parameters influencing the process rather than including the all parameters. In order to achieve this, statistical analysis of the experimental results will have to be processed using the analysis of the variance (ANOVA). ANOVA is a computational technique that enables the estimation of the relative contributions of each of the control factors to the overall measured response. In the present work, only the significant parameters will be used to develop mathematical models using response methodology. These models would be of great use during the optimization of the process variables. RSM methodology is practical, economical and relatively easy for use. The experimental data was utilized to build mathematical model for first and second-order model by regression method. The purpose of developing the mathematical models is to understand the combined effect of the involved parameters and to facilitate the optimization of the machining process.

Response surface methodology is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which response of interest is influenced by several variables and the objective is to optimize the response. The following relationship is used for representing the mathematical models.

$$y = \emptyset\,(v, f, d, r) + \varepsilon \tag{1}$$

Where y is the turning response, $\emptyset$ is the response function and v, f, d and r are the cutting speed, feed, depth of cut and nose radius and 'ε' is the error which is normally distributed with zero mean according to the observed response. Taylor's tool life equation in metal cutting and a functional relationship between surface roughness and the independent variables under investigation could be postulated:

$$R_a = C v^n f^m d^p r^q \varepsilon \tag{2}$$

Where R_a is the surface roughness (μm), $v, f, d,$ and r are the cutting speed (m/min), feed (mm/rev), depth of cut (mm) and tool nose radius(mm) respectively and c, n, m, p and q are constants and ε is a random error. Eq. (2) can be written as a linear combination of the following form in order to facilitate the determination of constants and parameters, the mathematical models were literalized by performing logarithmic transformation.

$$Ln\, R_a = ln\, C + n\, ln\, V + m\, ln\, f + p\, ln\, d + q\, ln\, r + ln\, \varepsilon \tag{3}$$

 DOI : 10.18231/2454-9150.2019.0055

Which may represent the following linear mathematical model:

$$\hat{\eta} = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \qquad (4)$$

where $\hat{\eta}$ is the true response of the surface roughness on logarithmic scale, x_0 =1 (a dummy variable) x_1, x_2, x_3 and x_4 are logarithmic transformations of speed, feed rate, tool nose radius and depth of cut. The linear model of Eq. (4) in terms of the estimated response can be written as:

$$Y_1 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 \qquad (5)$$

where Y_1 is the estimated response of the surface roughness on a logarithmic scale and y is the measured response on a logarithmic scale. In this equation 'ε' is the experimentally random error and the b values are the estimates of the β parameters. If this model is not sufficient to represent the process, then the second order model will be developed.

$$Y_2 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + b_{11} x^2 + b_{22} x_2^2 + b_{33} x_3^2 + b_{44} x_4^2 + b_{12} x_1 x_2 + b_{23} x_2 x_3 + b_{14} x_1 x_4 + b_{24} x_2 x_4 + b_{13} x_1 x_3 + b_{34} x_3 x_4 \qquad (6)$$

where Y_2 is the estimated response on a logarithmic scale and b values, i.e. b_0, b_1, b_2, b_3, b_4,. are to be estimated by the method of least squares. In present study, the parameter of Eqs. 5 and 6 have been estimated by using a Minitab-14 computer package.

III. EXPERIMENTATION

The design of experiments has a major effect on the number of experiments needed. Therefore it is essential to have a proper design of experiments. A full factorial design was selected in this work so that all the interactions between the independent variables can be investigated, though it was required to conduct large number of experiments. In this study, four cutting parameters namely cutting speed, feed, depth of cut and nose radius are selected for the experimentation. The ranges of each parameter were set at three different levels based on industrial practice (Table 1). Based on (3^4) full factorial designs, a total number of 81 experiments are carried out. Due to large number of experiments, result table is not shown. The variables were coded by taking into account the capacity and the limiting cutting conditions of the CNC machine. The coded values of the variables to be used in Eqs. (5) and (6) were obtained from the following transforming equations:

$$x_1 = \frac{\ln v - \ln 250}{\ln 250 - \ln 220} \qquad (7)$$

$$x_2 = \frac{\ln f - \ln 0.15}{\ln 0.15 - \ln 0.10} \qquad (8)$$

$$x_3 = \frac{\ln r - \ln 0.8}{\ln 0.8 - \ln 0.4} \qquad (9)$$

$$x_4 = \frac{\ln d - \ln 0.6}{\ln 0.6 - \ln 0.3} \qquad (10)$$

Where x_1 is the coded value of is cutting speed (v), x_2 is the coded value of feed (f), x_3 is the coded value of nose radius (r) and x_4 is the coded value of depth of cut (d).

All the experiments were carried out on Jobber X_L model made by Ace designer CNC lathe machine with variable spindle speed 50-3500 rpm and 7.5 KW motor drive was used for machining tests. Surface finish of the work piece material was measured by Surf test model No. SJ-400 (Mitutoyo make).The surface roughness was measured at three equally spaced locations around the circumference of the work pieces to obtain the statistically significant data for the test. In the present work, the work piece material was the AISI 1040 steel. This material is used for the manufacturing of the gear box shaft. Mechanical property of the material is given in Table 2. In this study, ceramic inserts (supplied by Ceratizit) with ISO code (TNMG160404 EN-TMF, TNMG 160408 EN-TM and TNMG 160412 EN-TM) and different nose radius (60^0 triangular shaped inserts) were used. The inserts were mounted on a commercial tool holder having the following geometry: rake angle = - 6^0, Clearance angle = 6^0, side cutting angle = 60^0.

IV. RESULT AND DISCUSSION

In this paper, experimental work was conducted to determine the effect of tool geometry and the cutting parameters on the surface finish during the turning of AISI 1040 steel. The tool geometry was the tool nose radius and the cutting parameters used in this experiment were feed, cutting speed and depth of cut. ANOVA was performed to find the statistical significance of the process parameters and their interactions. Though, the experiments were conducted using full factorial design, replication of the experiments with each combination could not be carried out due to the limitations of experimental resources. Accordingly, it was assumed that the four and three factor interactions were not present and the corresponding sum of square and degree of freedom were taken as residual to conduct the ANOVA.

4.1 FIRST ORDER MODEL

In order to understand the turning process, the experimental results were used to develop the mathematical models using response surface methodology (RSM). In this work, a commercially available software package was used for the computation work. The proposed first order model developed from the above functional relationship using RSM method is as follows:

 DOI : 10.18231/2454-9150.2019.0055

$$Y_1 = 1.35494 - 0.20852\ x_1 + 0.46574\ x_2 - 0.50963\ x_3 + 0.03944\ x_4 \quad (11)$$

$$Ra = 2.63574 - 0.00695062v + 9.31481f - 1.27407r + 0.131481d \quad (12)$$

Eq. (12) is derived from the Eq. (11) by substituting the coded variables of x_1, x_2 x_3 and x_4 in terms of $ln\ v$, $ln\ f$, $ln\ r$ and $ln\ d$.

The result shows that the feed has the most significant effect on the surface roughness, followed by the nose radius and finally cutting speed. Simply, this equation indicates that the surface roughness decreases with increasing nose radius and cutting speed and surfaces roughness increases with increasing feed rate. This can also be seen in the graph of main effect plot for roughness of Fig.1.

Also, regression coefficients for the surface roughness for first order model is shown in Table 3. From table it is obvious that feed, nose radius and cutting speed play an important role for the first order model and the 'p' factor is less than 0.01 which means that the confidence level is over 99%. And 'p' factor for the depth of cut is 0.321 which means that the depth of cut has no significant effect on the surface roughness. The multiple regression coefficient of the first order model was found to be 0.8050. This shows that the first order can explain the variation to the extent of 80.50 %.

4.2 SECOND ORDER MODEL

In order to see whether a second order model can represent better than the first order or not, a second order model was developed. The second order surface roughness model thus developed is given as below:

$$Ra = 1.358 - 0.0777109v + 12.557f - 3.18009r - 0.821605d + 0.000135v^2 + 41.8519f^2 + 1.78935r^2 + 0.137860d^2 - 0.0175926vf + 0.00506944vr + 0.00274691vd - 14.791fr - 0.72222fd - 0.00925926rd \quad (13)$$

The result shows that feed has the most significant effect on the surface roughness, followed by nose radius and cutting speed. It has been seen that the 'p' values for the model is less than 0.05 which indicates that model is significant and the terms in the model have a significant effect on the response. In the same way, some square terms like (d^2) and interaction terms ($v*f$), ($v*d$), ($f*d$) and ($r*d$) have not significant effect on the response (Table 4).

By selecting the backward elimination procedure to automatically reduce the terms that are not significant, the result for the reduced quadratic model for surface roughness is shown in Table 5. The result indicated that the model is still significant. However, the main effect of feed (f), cutting speed (v), nose radius (r) and second order effect of v^2, f^2, r^2 and two level interaction of ($v*r$) and ($f*r$) are the significant model terms. The interaction term ($v*f$) is added to support hierarchy

Eq. 14 shows the final quadratic model for the surface roughness after backward elimination procedure. Finally, the multiple regression co efficient of the second order model was found to be 0.9596. This means that second order can explain the variation to the extent of 95.96%. Since the difference between first order and second order is 15.46 %, so it can be concluded that second order is adequate to represent the turning process for turning of AISI 1040 steel.

$$Ra = 11.5007 - 0.0760628\ v + 12.9907\ f - 3.18565\ r + 0.000135391\ v^2 + 41.8519 f^2 + 1.78935\ r^2 - 0.0175926\ v\ f + 0.00506944\ v\ r - 14.7917\ f\ r \quad (14)$$

The 3 D surface graphs for the surface roughness are shown in Figs. 2, 3 and 4. It can be observed from Fig.2 that for a given cutting speed and depth of cut the surface roughness sharply decreases with increasing nose radius and increases with increasing feed rate. It can be observed from Fig. 3 that the depth of cut has not much significant effect on the surface roughness. From Fig.4, it can be seen that surface roughness decreases with increasing nose radius and with increasing cutting speed. Finally, the minimum surface roughness results with the combination of low feed rate, high nose radius and high cutting speed.

4.3 VRRIFICATION TEST

In order to verify the accuracy of the model developed, four confirmation run experiments were performed given in Table 6. The test conditions for the confirmation test were so chosen that they be within the range of the levels defined previously. The predicted values and the associated experimental values were compared. The error percentage is within permissible limits. So, the response equation for the surface roughness predicted through RSM can be use to successfully predict the surface roughness values for any combination of the feed rate, tool nose radius, cutting speed and depth of cut within the range of the experimentation performed.

V. CONCLUSION

This paper presents the finding of experimental investigations in to the effect of cutting speed, feed, tool nose radius and depth of cut on the surface roughness when turning AISI 1040 steel.

 DOI : 10.18231/2454-9150.2019.0055

ISSN : 2454-9150 Vol-04, Issue-11, Feb 2019

1. The results revealed that the feed is the most significant factor affecting the surface roughness with 51.32% contribution of model.
2. Tool nose radius and cutting speed are significant factors on the surface roughness with 16.23% and 7.18% contribution of model.
3. Depth of cut has no significant effect on the surface roughness. It can be used to improve productivity.
4. Second order surface roughness model (with backward elimination) has been found to represent the turning process very well. This model would be helpful in selecting the cutting conditions and tool geometry for required surface roughness. This can also be used for optimization of the turning process.

REFERENCES

[1] Montgomery D (2001) Design and Analysis of Experiments. 5th edn, John Wiley, New York.

[2] Thiele JD, Melkote SN (1999) Effect of cutting edge geometry and work piece hardness on surface generation in the finish hard turning of AISI 52100 steel. J Mater Process Technol 94: 216-226

[3] Mittal A, Mehta M (1988) Surface finish prediction models for fine turning. Int J Prod Res 26(12):1861–1876

[4] Sundaram RM, Lambert BK (1981) Mathematical models to predict surface finish in fine turning of steel, Part 1. Intl J Prod Res 19(5):547–556

[5] Sundaram RM, Lambert BK (1981) Mathematical models to predict surface finish in fine turning of steel, Part 2. Int J Prod Res 19(5):557–564

[6] Noordin MY, Venkatesh VC Sharif S, Elting S, Abdullah A (2004) Application of response surface methodology in describing the performance of coated carbide tools when turning AISI 1045 steel. J Mater Process Technol 145:46–58

[7] Suresh PVS, Rao PV, Deshmukh SG (2002) A genetic algorithmic approach for optimization of surface roughness prediction model. Int J Mach Tools Manuf 42 :675–680

[8] Yang WH, Tarng YS (1998) Design optimization of cutting parameters for turning operations based on Taguchi method. J Mater Process Technol 84:112–129

[9] Choudhury IA, El- Baradie MA (1998) Tool life prediction model by design of experiments for turning high strength steel. J Mater Process Technol 77:319–326

[10] Munoz-Escalona P, Cassier Z (1998) Influence of critical cutting speed on the surface finish of turned steel. Wear 218: 103-109

[11] Feng C-X (2001) An experimental study of the impact of turning parameters on surface roughness In: Proceedings of the 2001, Industrial Engineering Research Conference, Paper No. 2036.Dallas,TX,May 2001

[12] Paulo Davim J (2001) A note on the determination of optimal cutting conditions for surface finish obtained in turning using design of experiments. J Mater Process Technol 116:305–308

[13] Lee BY, Tarng YS (2001) Surface roughness inspection by computer vision in turning operations. Int J Mach Tools Manuf 41: 1251–1263

[14] Sahin Y, Motorcu AR (2005) Surface roughness model for machining mild steel with coated carbide tool. Mater Des 26:321–326. doi:10.1016/j.matdes.2004.06.015

[15] Lee BY, Yu S, Juan H (2004) The model of surface roughness inspection by vision system in turning. Mechatronics 14:129–141

[16] Ozel T, Karpat Y, Figueira L, Paulo Davim J (2007) Modeling of surface finish and tool flank wear in turning of AISI D2 steel with ceramic wiper inserts. J Mater Process Technol 189: 192–198

[17] Kirby ED, Zhang Z, Chen JC, Chen J (2006) Optimizing surface finish in a turning operation using the Taguchi parameter design method. Int J Adv Manuf Technol (2006) 30: 1021–1029 DOI 10.1007/s00170-005-0156-0

[18] Grzesik W, Wanat T (2006) Surface finish generated in hard turning of quenched alloy steel parts using conventional and wiper ceramic inserts. Int J Mach Tools Manuf 46: 1988–1995RI

[19] Paulo Davim J, Gaitondeb VN, Karnik SR (2008) Investigations into the effect of cutting conditions on surface roughness in turning of free machining steel by ANN models. J Mater Process Technol 205: 16–23

[20] Lan TS, Wang MY (2009) Competitive parameter optimization of multi-quality CNC turning. Int J Adv Manuf Technol 41:820–826 DOI 10.1007/s00170-008-1495-4

[21] Karayel D (2009) Prediction and control of surface roughness in CNC lathe using artificial neural network. J Mater Process Technol 209:3125-3137

[22] Petropoulos G, Mata F, Paulo Davim J (2008) Statistical study of surface roughness in turning of peek composites. Mater Des 29 :218–223

[23] Galanis NI, Manolakos DE (2010) Surface roughness prediction in turning of femoral head. Int J Adv Manuf Technol 51:79–86 DOI 10.1007/s00170-010-2616-4

[24] Tsourveloudis NC (2010) Predictive Modeling of the Ti6Al4V Alloy Surface Roughness. J Intell Robot Syst 60:513–530DOI 10.1007/s10846-010-9427-6

[25] Asilturk I, Cunkas M (2011) Modeling and prediction of surface roughness in turning operations using artificial neural network and multiple regression method. Expert Syst Appl 38 :5826–5832

[26] Correia E, Paulo Davim J (2011) Surface roughness measurement in turning carbon steel AISI 1045 using wiper inserts. Measurement 44:1000–1005

[27] Stavropoulos P, Salonitis K, Stournaras A, Pandremenos J, Paralikas J, Chryssolouris G (2007) Experimental Investigation of Micro-milling Process Quality. 40th CIRP International Seminar on Manufacturing Systems, Liverpool, U.K.

[28] Stavropoulos P, Salonitis K, Stournaras A, Pandremenos J, Paralikas J, Chryssolouris G (2007) Tool Condition Monitoring in Micro-Milling - A Critical Review, (ICMR 07), 5th International Conference on Manufacturing Research, Leicester, U.K.324-328

 DOI : 10.18231/2454-9150.2019.0055

[29] Makadia AJ, Nanavati JI (2013) Optimization of machining parameters for turning operations based on response surface methodology, Measurement 46: 1521-1529.

[30] Makadia AJ, Nanavati JI (2013) Optimization of tool geometry and cutting parameters for turning operations based on response surface methodology, Proceeding of the International Conference on Advances in Materials Processing and Characterization (AMPC 2013) Anna University, Chennai, India, pp. 885-890.

[31] Makadia AJ, Nanavati JI (2013) Optimizing Surface Finish in Turning Operation by Factorial Design of Experiments, Proceedings of the International Conference on Advanced Engineering Optimization Through Intelligent Techniques, (AEOTIT), S.V. National Institute of Technology, Surat – 395 007, Gujarat, India, pp. 67-71.

[32] Neseli S, Yaldız S, Turkes E (2011) Optimization of tool geometry parameters for turning operations based on the response surface methodology, Measurement 44: 580–588.

[33] Kini MV, Chincholkar AM (2010) Effect of machining parameters on surface roughness and material removal rate in finish turning of ± 300 glass fibers reinforced polymer pipes, Mater. Des. 31: 3590–3598.

[34] Davidson MJ, Balasubramanian K, Tagore GRN (2008) Surface roughness prediction of flow-formed AA6061 alloy by design of experiments, J. Mater. Process. Technol. 202: 41–46.

[35] Lalwani DI, Mehta NK, Jain PK (2008) Experimental investigations of cutting parameters influence on cutting forces and surface roughness in finish hard turning of MDN250 steel, J. Mater. Process. Technol. 206: 167–179.

[36] Gaitonde VN, Karnik SR, Luis Figueira, Davim JP (2009) Analysis of Machinability During Hard Turning of Cold Work Tool Steel (Type: AISI D2), Mater. Manuf. Process. 24: 1373–1382.

[37] Ramesh S, Karunamoorthy L, Palanikumar K (2012) Measurement and analysis of surface roughness in turning of aerospace titanium alloy (gr5) , Measurement 45: 1266–1276.

Table 1 Factors and levels for response surface study

Factors	Symbol	Level-1	Level-2	Level-3
Speed (m/min)	v	220	250	280
Feed (mm/rev)	f	0.1	0.15	0.2
Depth of cut (mm)	d	0.3	0.6	0.9
Nose radius (mm)	r	0.4	0.8	1.2

Table 2 Mechanical properties

Material properties	AISI 1040 STEEL
Physical density	7.85 g/cm^3
Mechanical hardness, Rockwell B	92
Tensile strength, ultimate	600 MPa
Tensile strength, yield	350 MPa
% of elongation	20

Table 3 Estimated Regression Coefficients for Roughness (First order)

Term	Coef	SE Coef	T	P
Constant	1.35494	0.03226	42.007	0.000
Cutting speed (V)	-0.20852	0.03950	-5.278	0.000
Feed (f)	0.46574	0.03950	11.790	0.000
Nose radius(r)	-0.50963	0.03950	-12.901	0.000
Depth of cut (d)	0.03944	0.03950	0.998	0.321

S = 0.290297 PRESS = 7.35914
R-Sq = 81.48% R-Sq (pred) = 78.72% R-Sq (adj) = 80.50%

Table 4 Estimated Regression Coefficients for Roughness (Second order)

Term	Coef	SE Coef	T	P	(%) contribution
Constant	1.00481	0.04356	23.068	0.000	

 DOI : 10.18231/2454-9150.2019.0055

Cutting speed(V)	-0.20852	0.01778	-11.726	0.000	7.18
Feed(f)	0.46574	0.01778	26.190	0.000	51.32
Nose radius(r)	-0.50963	0.01778	-28.658	0.000	16.23
Depth of cut(d)	0.03944	0.01778	2.218	0.030	0.99
Cutting speed(v)*Cutting speed(v)	0.12185	0.03080	3.956	0.000	1.98
Feed(f)*Feed(f)	0.10463	0.03080	3.397	0.001	6.10
Nose radius(r)*Nose radius(r)	0.28630	0.03080	9.295	0.000	3.47
Depth of cut(d)*Depth of cut(d)	0.01241	0.03080	0.403	0.688	0.47
Cutting speed(v)*Feed(f)	-0.02639	0.02178	-1.212	0.230	0.71
Cutting speed (v)*Nose radius (r)	0.06083	0.02178	2.793	0.007	1.32
Cutting speed(v)*Depth of cut(d)	0.02472	0.02178	1.135	0.260	0.75
Feed(f)*Nose radius(r)	-0.29583	0.02178	-13.583	0.000	1.56
Feed(f)*Depth of cut(d)	0.01083	0.02178	0.497	0.621	0.45
Nose radius(r)*Depth of cut(d)	-0.00111	0.02178	-0.051	0.959	0.32
Error					7.15

S = 0.130677   PRESS = 1.68446

R-Sq = 96.74% R-Sq (pred) = 95.13% R-Sq (adj) = 96.05%

Table 5 Estimated Regression Coefficients for Roughness (Second order/backward elimination)

Term	Coef	SE Coef	T	P
Constant	1.01309	0.03885	26.076	0.000
Cutting speed (v)	-0.20852	0.03885	-11.594	0.000
Feed (f)	0.46574	0.01798	25.896	0.000
Nose radius (r)	-0.50963	0.01798	-28.337	0.000
Cutting speed (v)*Cutting speed (v)	0.12185	0.03115	3.912	0.000
Feed (f) *Feed (f)	0.10463	0.03115	3.359	0.001
Nose radius (r)*Nose radius (r)	0.28630	0.03115	9.191	0.000
Cutting speed (v) *Feed (f)	-0.02639	0.02203	-1.198	0.235
Cutting speed (v) *Nose radius (r)	0.06083	0.02203	2.762	0.007
Feed (f)*Nose radius (r)	-0.29583	0.02203	-13.431	0.000

S = 0.132160   PRESS = 1.59571
R-Sq = 96.41% R-Sq (pred) = 95.38% R-Sq (adj) = 95.96%

Table 6 Verification test

Sr. No.	Speed (v)	Feed (f)	Nose radius (r)	Depth of cut (d)	Experimental (Ra)	Predicted (Ra)	Error (%)
1	220	0.12	0.4	0.5	1.82	1.7650	3.0
2	260	0.15	0.8	0.7	0.99	0.9570	3.3
3	275	0.18	1.2	0.8	0.93	0.8776	5.6
4	280	0.14	0.8	0.8	0.88	0.8426	4.2

 DOI : 10.18231/2454-9150.2019.0055

International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-04, Issue-11, Feb 2019

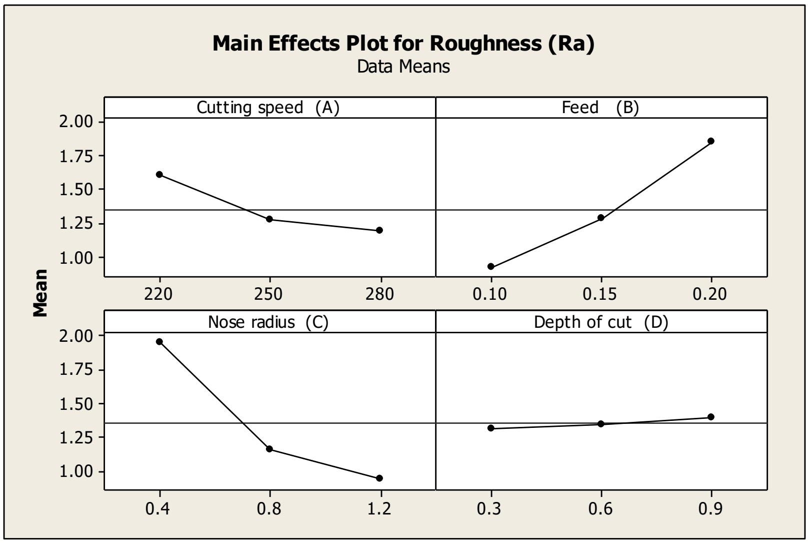

Fig. 1 Main Effects Plot for Roughness (Ra)

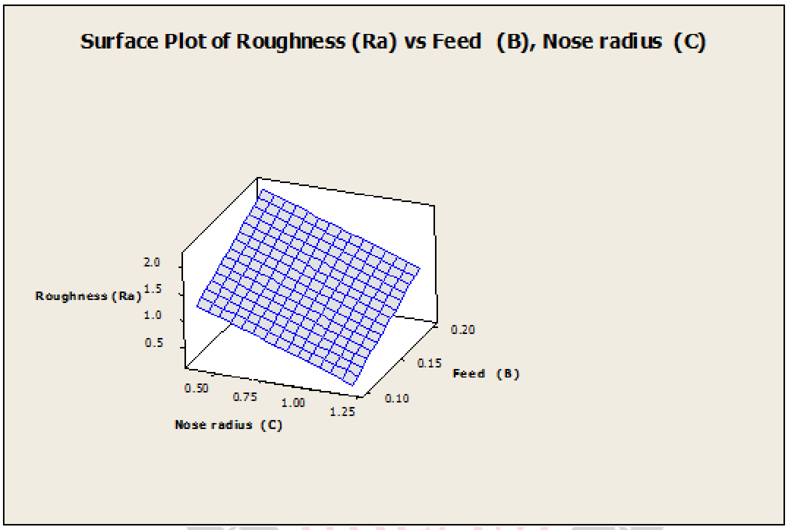

Fig. 2 3 D surface graph Nose radius Vs Feed

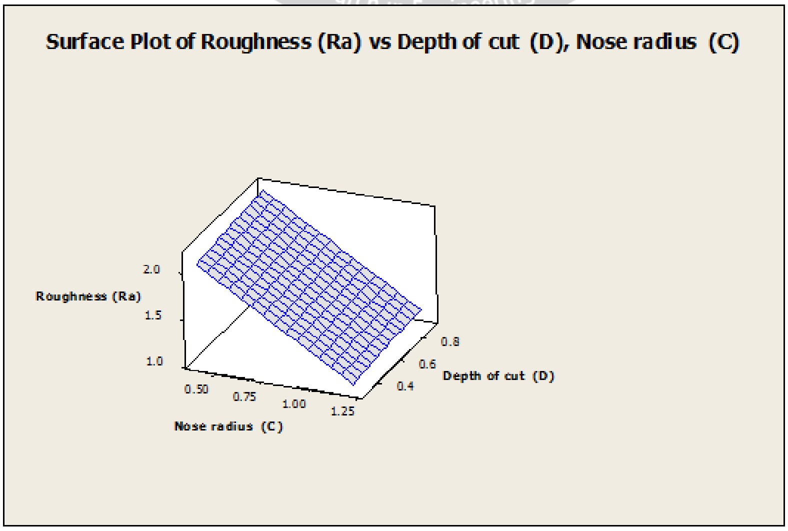

Fig. 3 3 D surface graph Nose radius Vs Depth of cut

 DOI : 10.18231/2454-9150.2019.0055

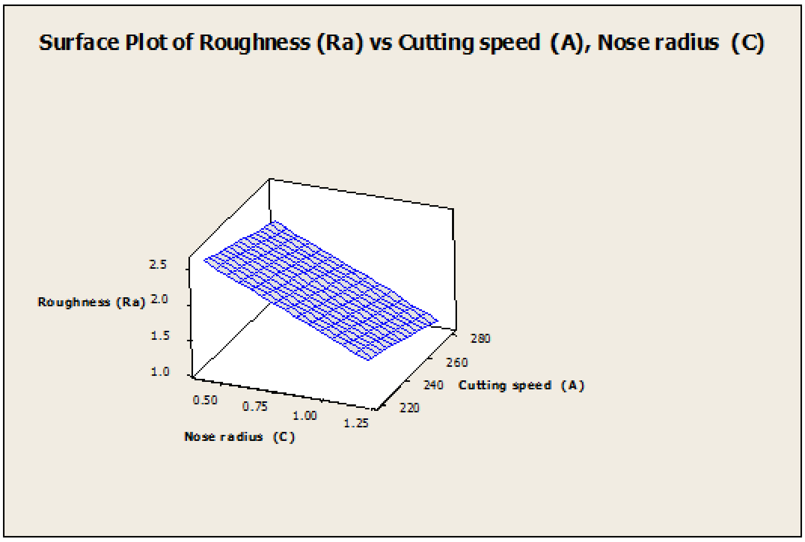

Fig. 4 3 D surface graph Nose radius Vs cutting speed

 DOI : 10.18231/2454-9150.2019.0055