Optimisation of Machining Parameters in Hard Turning by Desirability Function Analysis Using Response Surface Methodology

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Abstract. In this study, the effects of cutting speed, feed rate and depth of cut on surface roughness in the hard turning were experimentally investigated. AISI 4140 steel was hardened to (56 HRC) .The cutting tool used was an uncoated AL_2O_3/TiC mixed ceramics which is approximately composed of 70% of AL_2O_3 and 30% of TiC. Three factor (cutting speed, feed rate and depth of cut) and three-level factorial experiment designs completed with a statistical analysis of variance (ANOVA) were performed. Mathematical model for surface roughness was developed using the response surface methodology (RSM) associated with response optimization technique and composite desirability was used to find optimum values of machining parameters with respect to objectives surface roughness. The results have revealed that the effect of feed is more pronounced than the effects of cutting speed and depth of cut, on the surface roughness. However, a higher cutting speed improves the surface finish. In addition, a good agreement between the predicted and measured surface roughness was observed. Therefore, the developed model can be effectively used to predict the surface roughness on the machining of AISI 4140 steel with in 95% confidence intervals ranges of conditions studied.

Keywords: Hard turning, Surface roughness prediction, Response surface methodology (RSM), Ceramic tool, ANOVA, desirability.

1 Introduction

The surface roughness of machined parts is a significant design specification that is known to have considerable influence on properties such as wear resistance and fatigue strength. The quality of the surface is a factor of importance in the evaluation of machine tool productivity. Hence it is important to achieve a consistent tolerance and surface finish. When surface finish becomes the main criteria in the quality control department, the productivity of the metal cutting operation is limited by the surface quality. According to (Palanikumar.k et al 2008) and

M. Chouchane et al. (eds.), *Design and Modeling of Mechanical Systems - II*,
Lecture Notes in Mechanical Engineering, DOI: 10.1007/978-3-319-17527-0_8

(Thomas TR 1981)**,** surface finish can be characterised by various parameters. The various roughness height parameters such as arithmetic average roughness average (Ra), maximum height of peaks (Rp), root mean square (Rq), maximum height of the profile (Rt) and mean of the third point height (R3z) can be closely correlated. The present study uses average roughness (Ra) for the characterisation of surface roughness, being that used most widely in the industry for specifying surface roughness. Response Surface Method (RSM) is an empirical modeling approach for determining the relation ship between various process parameters and the responses with the various desired criteria, by means of which we can further search the significance of these process parameters on the coupled responses. It is a sequential experimentation strategy for building and optimizing the empirical model. Therefore, RSM is a collection of mathematical and statistical procedures that are useful for the modeling and the analysis of problems in which response of demand is affected by several variables and the objective is to optimize this response (Montgomery D C 2001). Through using the design of experiments and applying regression analysis, the modeling of the desiring response to several independent input variables can be gained. Consequentially, the RSM is utilized to describe and identify with a great accuracy, the influence of the interactions of different independent variables on the response when they are varied simultaneously. In addition, it is one of the most widely used methods to solve the optimization problem in the manufacturing environments as studied by (York Puri A B et al 2005)**,** (Ozcelik B et al 2005)**]** Most of the previous investigators have studied the effect of cutting variables such as speed, feed and depth of cut using response surface methodology has been widely reported in literature ((Choudhury L A 1997)**,** (Arbizu I P et al 2003)**,** (Dabnun M A 2003)**,** (Sahin Y et al 2003)**,** (Cakir M C et al 2009)**,** (Hessainia Z et al 2013)**,** (Kribes N et al 2012)**).** In this paper, an experimental contribution that focuses on prediction and optimization of surface roughness during hard turning of AISI 4140 steel with **Al_2O_3 + TiC mixed** ceramic tool, using response surface methodology is presented. The ANOVA involve the effects of cutting parameters (cutting speed, feed rate and depth of cut).

2 Experimental Procedure

2.1 Equipment and Materials

The goal of this experimental work was to investigate the effects of cutting parameters on surface roughness, and to establish a correlation between them. In order for this cutting speed, feed rate and depth of cut were chosen as process parameters.

The work material was AISI 4140 steel in the form of round bars with 74mm in diameter and 380mm in length. The work material was hardened and tempered to 56 HRC. Chemical composition of work material is as follows: 0.42% C; 0.25% Si, 0.08% Mn; 0.018% S; 0.013% P; 0.021% Ni; 0.022% Cu; 1.08% Cr; 0.004% V; 0.209% Mo; 96.95% Fe.

The cutting tests were conducted in dry conditions using a universal lathe type SN40 with 6,6KW spindle power.

The cutting tool used was uncoated AL2O3 + TiC mixed ceramic which is approximately composed of 70% of AL2O3 and 30% of TiC. Mixed ceramic tool, type SNGA120408T01020 was clamped onto a tool holder with a designation of PSBNR 25×25K12, its geometry is as follows -6° rake angle, 6°clearance angle, -6° inclination angle and 75° approach angle, nose radius of 0.8mm.

Surface roughness measurements were performed by using a Surftest 201 Mitutoyo with a cut-off length of 0,8mm and sampling length of 5mm. (Fig 1)

Fig. 1 (a) Surftest 201 Mitutoyo, (b) Expérimental configuration for measuring surface roughness

Three levels were specified for each of the factors as indicated in Table 1. A randomized schedule of runs was created using the design of experiment shown in Table 2.

Table 1 Attribution of the levels to the factors

Level	Cuttingspeed, *Vc* (m/min)	Feed rate, *f* (mm/rev)	Depth of cut, *ap* (mm)
1 (low)	90	0.08	0.15
2 (medium)	120	0.12	0.30
3 (high)	180	0.16	0.45

2.2 Design of Experiments

The response surface methodology (RSM) is a procedure for determining the relationship between the independent process parameters with the desired response and exploring the effect of these parameters on responses, including six steps (Gained V N et al 2009).

These are, (1) define the independent input variables and the desired responses with the design constants, (2) adopt an experimental design plan, (3) perform regression analysis with the quadratic model of RSM, (4) calculate the statistical analysis of variance (ANOVA) for the independent input variables in order to find which parameter significantly affects the desired response, then, (5) determine the situation of the quadratic model of RSM and decide whether the model of RSM needs screening variables or not and finally, (6) optimize and conduct confirmation experiment and verify thes predicted performance characteristics.

In the current study, the relationship between the inputs, called the cutting conditions such as cutting speed (Vc), feed rate (f) and depth of cut (ap) and the out put Y define as a machinability aspect for cutting forces and surface roughness is given as:

$$Y = F(Vc, f, ap) + e_{ij} \tag{1}$$

Where Y is the desired machinability aspect and F is proposed by using a nonlinear quadratic mathematical model, which is suitable for studying the interaction effects of process parameters on machinability characteristics.

In the present work, the RMS based second order mathematical model is given by [15]:

$$Y = a_o + \sum_{i=1}^{3} a_i X_i + \sum_{i=1}^{3} a_{ii} X_i^2 + \sum_{i \angle j}^{3} a_{ij} X_i X_J \tag{2}$$

Table 2 Design layout and experimental results(Hessainia Z 2014)

Run	Coded factors			Actual factors			Surface roughness (μm)		
	X_1	X_2	X_3	Vc (m/min)	f (mm/rev)	ap (mm)	Observed Value	Predicted Value	% Error
01	-1	-1	1	90	0.08	0.45	0.43	0.44	-2.32
02	1	0	1	180	0.12	0.45	0.49	0.49	0.00
03	1	0	0	90	0.12	0.30	0.66	0.64	3.03
04	-1	0	-1	90	0.12	0.15	0.64	0.62	3.12
05	-1	-1	-1	90	0.08	0.15	0.39	0.39	0.00
06	1	1	0	180	0.16	0.30	0.53	0.52	1.88
07	1	-1	0	180	0.08	0.30	0.32	0.31	3.12
08	0	-1	0	120	0.08	0.30	0.35	0.34	2.85
09	-1	1	1	90	0.16	0.45	0.78	0.77	1.28
10	0	-1	1	120	0.08	0.45	0.37	0.36	2.70
11	-1	1	-1	90	0.16	0.15	0.72	0.72	0.00
12	0	1	0	120	0.16	0.30	0.63	0.62	1.58
13	1	-1	1	180	0.08	0.45	0.34	0.33	2.94
14	1	-1	-1	180	0.08	0.15	0.30	0.30	0.00
15	1	1	-1	180	0.16	0.15	0.51	0.50	1.96
16	1	0	-1	180	0.12	0.15	0.46	0.46	0.00

Table 3 (*continued*)

17	-1	0	1	90	0.12	0.45	0.68	0.66	2.94
18	0	0	0	120	0.12	0.30	0.54	0.54	0.00
19	0	-1	-1	120	0.08	0.15	0.33	0.32	3.03
20	1	0	0	180	0.12	0.30	0.47	0.47	0.00
21	1	1	1	180	0.16	0.45	0.55	0.54	1.81
22	0	0	1	120	0.12	0.45	0.56	0.56	0.00
23	0	1	-1	120	0.16	0.15	0.62	0.61	1.61
24	-1	-1	0	90	0.08	0.30	0.41	0.41	0.00
25	0	0	-1	120	0.12	0.15	0.51	0.52	-1.96
26	0	1	1	120	0.16	0.45	0.64	0.65	-1.56
27	-1	1	0	90	0.16	0.30	0.74	0.75	-1.35

Where ao is constant, ai, aii, and aij represent the coefficients of linear, quadratic and cross product terms, respectively. Xi reveals the coded variables that correspond to the studied machining parameters. The coded variables Xi,i = 1,2,3 are obtained from the following transformation equations.

$$X_1 = \frac{Vc - Vco}{\Delta Vc} \quad (3)$$

$$X_2 = \frac{f - fo}{\Delta f} \quad (4)$$

$$X_3 = \frac{ap - apo}{\Delta ap} \quad (5)$$

Where X1, X2 and X3 are the coded values of parameters Vc, f and ap respectively. Vco, fo and apo at zero level. ΔVc, Δf and Δap are the values of Vc, f, and ap, respectively.

3 Data Analysis Results and Discussion

The plan of the experiment was developed for assessing the influence of the cutting speed (*Vc*), feed rate (*f*) and depth of cut (*ap)* on the surface roughness (*Ra*). Table 2 illustrates the experimental results for *Ra*.

The ANOVA table in this study shows that all these five factors are significant well with p-value equal to zero. The variance ratio, denoted by F in ANOVA tables, is the ratio of the mean square due to a factor and the error mean square. In robust design F ratio can be used for qualitative understanding of the relative factor effects. A large value of F means that the effect of that factor is large compared to the error variance. So, the larger value of F, the more important that factor i influencing the response. In present study, the most significant factor was feed rate with 353.27 F ratio and importance most of other factors based on the F was quadratic effect of feed rate, interaction effect of cutting speed and feed rate, quadratic and effect of cutting speed, respectively. The percentage of each factor contribution (P) on the total variation thus indicating the degree of influence on the result. After analyzing, it may be observed that the *f* factors (P ≈ 67.32%), the *Vc* (P ≈ 22.02 %) and the interaction *Vc*×*Vc* (P ≈ 2.32%), *f*×*f* (P ≈ 4.09%) also have considerable influence on the surface roughness, especially the feed rate factor this is a good agreement with the previous researchers' works ((Choudhury L A 1997), (Arbizu I P et al 2003), (Dabnun M A 2003), (Sahin Y et al 2003), (Cakir M C et al 2009)). The *ap* factor, the interactions of *ap*×*ap* and *Vc*×*ap* do not present significative percentages of contribution on the obtained surface roughness (*Ra*).

Design of Experiments

Estimated regression coefficients for surface roughness using data in uncoded units are shown in Table 4. The quadratic model of response equation in terms of actual factors for surface roughness (*Ra*) is given below in Eq. (6).

$$\begin{aligned} Ra &= -0.0438 - 6.4\times10^{-4} Vc + 14.508 f + 1.44\times10^{-1} ap \\ &+ 2.51\times10^{-5} Vc^2 - 36.805 f^2 - 1.71\times10^{-2} Vc\times f \end{aligned} \tag{6}$$

R^2 value of the model is 99.5%, which shows that the model can explain 99.5% of total variations in surface roughness.

The percentage error for each experimental run was calculated by the following relation

$$\% error = \frac{\exp erimentalvalue - predictedvalue}{\exp erimentalvalue} \times 100 \tag{7}$$

It is evident from the Table 2 that the error between the experimental value and predicted value is less than 5%.

Table 4 Pearson correlation coefficient of parameters with (Ra)

Parameter	Pearson correlation coefficient
Constant	-0.04382
Vc	-0.00645
f	14.5089
ap	0.14497
Vc×*Vc*	0.00002
f×*f*	-36,8056
Vc×*f*	-0.01716

4 Optimization of Response

One of the most important aims of experiments related to manufacturing is to achieve the desired surface roughness of the optimal cutting parameters (Palanikumar K et al 2006), (Hessainia Z et al 2013). To this end, the response surface optimization is an ideal technique for determination of the best cutting parameters combination in turning.

Here, the goal is to minimize surface roughness (Ra). To resolve this type of parameter design problem, an objective function, F(x), is defined as follows:

$$DF = \left(\prod_{i=1}^{n} d_i^{wi} \right)^{\frac{1}{\sum_{j-1}^{n} wi}} \quad F(x) = -DF \tag{8}$$

$$F(x) = -DF$$

Where di is the desirability defined for the i th targeted output and wi is the weighting of di.

For a goal to search for a minimum, the desirability can be defined by the following formulas:

$$
\begin{aligned}
&di = 1 \quad \text{if} \quad Y_i \le Low_i \\
&di = \left[\frac{Highi_i - Y_i}{High_i - Low_i} \right] \quad \text{if} \quad Low_i \le Y_i \le High_i \\
&di = 0 \quad \text{if} \quad Y_i \ge High_i
\end{aligned} \tag{9}
$$

Where the Yi is the found value of the i th output during optimization processes; the Lowi and the Highi are, respectively, the minimum and the maximum values of the experimental data for the i th output. In Eq. (9), wi is set to one since the di is equally important in this study. The DF is a combined desirability function (Myers R H et al 2002), and the objective is to choose an optimal setting that maximizes a combined desirability function DF, i.e., minimizes F(x).

RSM optimization result for surface roughness parameter (Ra) is shown in Figure 2 and Table 5 are found to be cutting speed of 156.36 (m/min), feed rate of 0.08 (mm/rev) and depth of cut of 0.15 (mm). The optimized surface roughness parameter is Ra = 0.28 µm.

Table 5 Response optimization for surface roughness parameters

Paramaters	Goal	Optimum combination			Lower	Target	Upper	Predicted reponse
		Vc (m/mm)	*f* (mm/rev)	*ap* (mm)				
Ra (µm)	Minimum	156.36	0.08	0.15	0.30	0.30	0.78	0.28
Desirability = 1								
Composite desirability = 1								

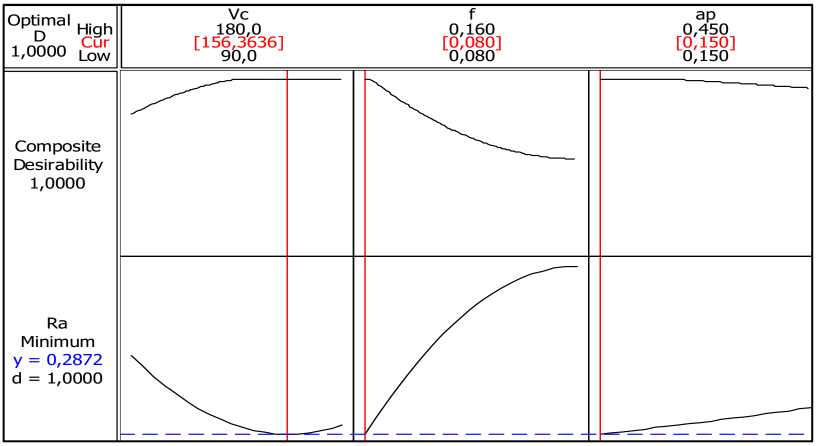

Fig. 2 Response optimization plot for surface roughness parameter components

5 Conclusion

In this paper, the application of RSM on the hard turning of AISI 4140 steel with Al2O3/TiC mixed ceramic tool had carried out the mathematical model of the surface roughness (Ra) so as to investigate the influences of machining parameters, for finding optimum value the following conclusions of research are as follows.

The analysis of machining parameters using RSM technique has the advantage of investigating the influence of each machining parameter on the value of surface roughness.

The surface roughness increases with the increase of feed rate and almost decreases with the increase of cutting speed.

The best surface roughness was achieved at the lower feed rate and the highest cutting speed.

Surface roughness model: the feed rate provides primary contribution and influence most significantly on the surface roughness with 67.32% contribution in the total variability of model whereas cutting speed has a secondary contribution of 22.02% in the model. Quadratic effect of feed rate, interaction effect of cutting speed and feed rate, quadratic effect of cutting speed provide secondary contribution and account for 4.09%, 2.34% and 2.32%, respectively. in the total variability of model.

The results of ANOVA and the conducting confirmation experiments have proved that the mathematical model and predict value of surface roughness which is close to those readings recorded experimentally with a 95% confident interval.

Using response optimization show that the optimal combination of machining parameters are cutting speed of 156.36 m/min, feed rate of 0.08 mm/rev, depth of cut of 0.15 mm. The optimized surface roughness parameter is Ra = 0.28 µm.

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