Statistical Analysis of Surface Roughness Using RSM in Hard Turning of AISI 4340 Steel with Ceramic Tool

Asutosh Panda, Sudhansu Ranjan Das and Debabrata Dhupal

Abstract The present study concerns the modeling and optimization of surface roughness in dry hard turning of high-strength low-alloy (HSLA) grade AISI 4340 steel (49 HRC) with coated ceramic tool. For parametric study, the turning operations have been established according to Taguchi L_{27} orthogonal array consisting of an experimental design matrix 3 levels and 3 principal turning parameters (factors) such as, cutting speed, axial feed, and depth of cut. Analysis of sixteen set experimental data with ANOVA showed that axial feed and speed are the most significant controlled cutting parameters for hard turning operation, if the improvement of the machined surface finish is considered. Thereafter, statistical regression model based on response surface methodology has been proposed for correlation of cutting parameters with machined workpiece surface roughness. Finally, optimal cutting conditions with the aim to minimize the surface roughness via desirability function approach of RSM are proposed.

Keywords Hard turning · AISI 4340 steel · Ceramic tool · OA · ANOVA · RSM

1 Introduction

Nowadays in metal cutting-based manufacturing industries, dry hard turning is widely used in machining of hardened steel because of its low cost, high machining efficiency and green environmental protection, and surface finish of hard turned components has greater influence on functionality of product concerning tribological behavior, fatigue strength, and wear as well as corrosion resistance. The cutting mechanism of dry hard turning is different from that of traditional turning because of multi-field coupling effect in machining process. Thus, the above-cited advantages of hard turning (HT) can only be obtained with appropriate selection of process parameters, cutting tool materials and geometry, and cutting environment. A number

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of investigative studies have been carried out for the assessment of various process variables (cutting parameters, tool geometry, workpiece hardness, and environmental conditions) using the statistical approach via analysis of variance (ANOVA) [1–4]. Similarly, researchers have focused on modeling as well as optimization in order to predict and control the result for minimizing surface roughness of various hardened steel materials (AISI D2, D3, D6, 1015, 1045, 4140, 4340, 52100, H11, and H13) during HT process using response surface methodology [5–7], which allowed to enrich the saving cost and time. However, relatively few investigations as well as lack of systematic studies have been executed concerning process modeling and parametric optimization for surface roughness, which is need to be explored for practical improvement in productiveness by hard turning as it is categorical worthy and beneficial for machining industries point of view to achieve their goal. Thus, the present research is focused on parametric study (assessment), process modeling, and optimization of surface roughness during turning hardened HSLA steel (49 HRC) with PVD–TiN coated Al_2O_3–TiCN mixed ceramic tool using Taguchi's OA, analysis of variance, response surface methodology, and desirability function approach.

2 Experimental Procedure

Cylindrical specimens (diameter and length of 90 mm and 220 mm, respectively) made of AISI 4340 steel were turned on a high precision and accuracy CNC lathe (make: Batliboi ltd., model: SPRINT 16TC), having 7.5 kW power capacity and spindle speed varies from 50 to 5000 rpm. High-strength low-alloy (HSLA) grade AISI 4340 steel (49 HRC) was chosen in the experiment because of its hardenability and wide application. For experimentation, PVD coated ceramic with TiN layer, designated as ISO grade CNGA120408 AB2010, having negative rake angle 60, nose radius of 0.8 mm, and approach angle of 950 is used for finish hard turning employing design of experiments. The coated ceramic insert was rigidly held on a ISO-designated tool holder of PCLNL2525M12. The measurements of machined surface for each cutting conditions were acquired from Mitutoyo (Surftest SJ210) roughness tester. The arithmetic mean surface roughness (Ra) was taken at different three positions on the cylindrical surface of test specimen and its mean is taken as final average surface roughness value. Statistical Minitab 16 software has been used for optimization, modeling, normality plot, and surface plot. The schematic view of experimental work and methodology proposed in the current study is presented in Fig. 1.

To accomplish the objective of proposed research work, depth of cut, axial feed, and cutting speed are taken as major process variables with an attempt to analyze surface roughness as the only technological response parameter. The different cutting parameters and their values are shown in Table 1. The levels of the parameters were selected based on the recommendation of tool's manufacturer (TaeguTec). Taguchi's orthogonal array (OA) has been established as balanced approach for design of experiments which ensures the all levels of all factors equally and assures accuracy of

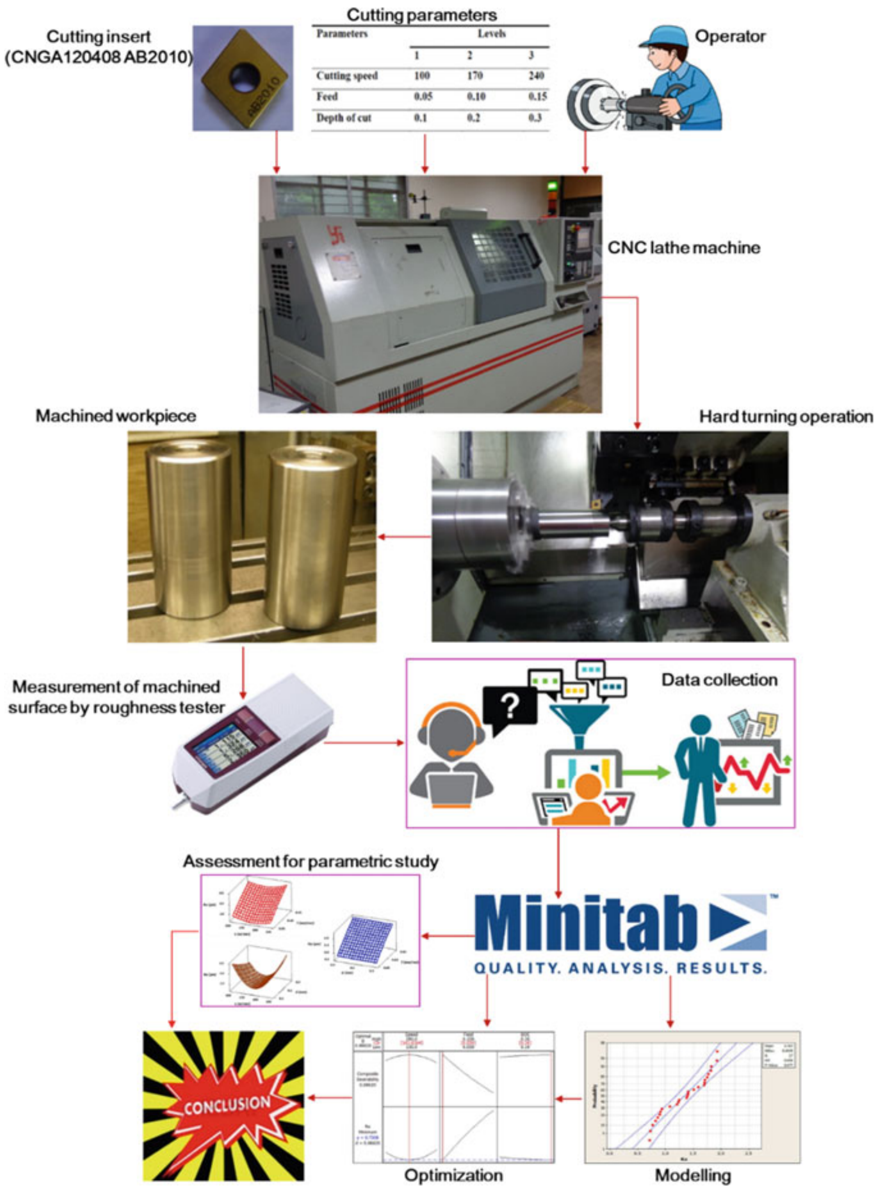

Fig. 1 Schematic of experimental setup and methodology presented

Table 1 Parameters and levels

Parameters	Levels		
	1	2	3
Cutting speed, v (m/min)	100	170	240
Feed, f (mm/rev)	0.05	0.10	0.15
Depth of cut, d (mm)	0.1	0.2	0.3

the statistical model. Hence, employing the selected controllable parameters (three) and levels (three), a well sequential design layout was established based on L27 OA in order to perform the dry longitudinal turning operation (Table 2).

3 Results and Discussion

3.1 Analysis of Surface Roughness

Experimental results by Taguchi OA are analyzed by employing analysis of variance which involves statistical treatment to access the significance as well as determines the percentage of contribution of each process variables (v, f, d) against a stated level of confidence (here, 95%) on the response under consideration (here, surface roughness Ra). Here, P-value indicates the influence of the factor on Ra as: significant if $P \leq 0.05$, and insignificant if $P > 0.05$. The ratio of factor-mean-square to the error-mean-square called Fisher's ratio (F) determines significant parameter affecting quality characteristic comparing the F-test value of the parameter with the standard F-table value at the 0.05 significance level. ANOVA for surface roughness has been illustrated in Table 3. From the analysis, it is illustrated that feed is the most effective variable, revealing significant contribution (80.05%) on surface roughness (Ra) as its P-value is under 0.05 and over F-value (4.46). The next parameter based on F-value is the cutting speed with 27.54 for Ra and its contribution on Ra is 13.56%. The depth of cut (d) does not have any noticeable effect on Ra (0.76% only). Also, the interaction of cutting variables like cutting speed-feed ($v*f$), feed-depth of cut ($f*d$), and cutting speed-depth of cut ($v*d$) do not exhibit any statistical imprint on the observed surface roughness. Respectively, their contributions are (0.96, 1.47, and 1.23% to Ra) and the error associated with the ANOVA is 1.97% for Ra.

Three dimension (3D) effect plots for surface roughness Ra is shown in Fig. 2. It was found that with increase in feed, Ra increased resulting degradation of surface finish predominantly (see, Fig. 2a). This phenomenon may be attributed to the following reasons: (1) neglecting the effect of BUE formation and tool flank wear [1], (2) increase in axial feed leads to increase in thrust force which in turn induces vibration followed by heat generation [8], and (3) as feed increases, the plowing action becomes predominant thereby forming deeper and broader helicoid furrows on machined surface due to insert's nose profile and workpiece-tool movements [9].

Table 2 Experimental design and results

Test no.	Coded values			Actual settings			Surface roughness Ra (μm)
	v	*f*	*d*	*v* (m/min)	*f* (mm/rev)	*d* (mm)	
1	1	1	1	100	0.05	0.1	0.854
2	1	1	2	100	0.05	0.2	0.643
3	1	1	3	100	0.05	0.3	0.843
4	1	2	1	100	0.1	0.1	0.951
5	1	2	2	100	0.1	0.2	1.188
6	1	2	3	100	0.1	0.3	1.073
7	1	3	1	100	0.15	0.1	1.569
8	1	3	2	100	0.15	0.2	1.620
9	1	3	3	100	0.15	0.3	1.596
10	2	1	1	170	0.05	0.1	0.829
11	2	1	2	170	0.05	0.2	0.762
12	2	1	3	170	0.05	0.3	0.629
13	2	2	1	170	0.1	0.1	0.914
14	2	2	2	170	0.1	0.2	0.955
15	2	2	3	170	0.1	0.3	0.928
16	2	3	1	170	0.15	0.1	1.361
17	2	3	2	170	0.15	0.2	1.382
18	2	3	3	170	0.15	0.3	1.463
19	3	1	1	240	0.05	0.1	0.516
20	3	1	2	240	0.05	0.2	0.631
21	3	1	3	240	0.05	0.3	0.573
22	3	2	1	240	0.1	0.1	0.629
23	3	2	2	240	0.1	0.2	0.705
24	3	2	3	240	0.1	0.3	0.788
25	3	3	1	240	0.15	0.1	1.071
26	3	3	2	240	0.15	0.2	1.267
27	3	3	3	240	0.15	0.3	1.427

It is also observed that the surface roughness decreases as cutting speed increases (refer, Fig. 2c). This can be attributed to intense elastic deformation and squeezing effect within workpiece-tool junction area at slower cutting speeds as compared to higher speeds, reported by Tang et al. [10]. Another possible explanation is that the heat dispersed by chip is much lesser than that absorbed by the turned surface at low cutting speed which is manifested as higher surface roughness Ra. Aouici et al. [11] also obtained similar results. As the cutting speed rises, the tool chip contact duration decreases thereby subsiding the BUE resulting improvement in surface finish,

Table 3 Analysis of variance (ANOVA) for surface roughness criteria (Ra)

Source	DOF	Seq SS	Adj SS	Adj MS	*F*	*P*-value	*C* (%)
v (cutting speed)	2	0.41872	0.41872	0.20936	27.54	<0.000	13.56
f (feed)	2	2.47242	2.47242	1.23621	162.63	<0.000	80.05
d (depth of cut)	2	0.02335	0.02335	0.01167	1.54	0.273	0.76
v*f	4	0.02960	0.02960	0.00740	0.97	0.473	0.96
v*d	4	0.04558	0.04558	0.01139	1.50	0.290	1.47
f*d	4	0.03812	0.03812	0.00953	1.25	0.363	1.23
Error	8	0.06081	0.06081	0.00760			1.97
Total	26	3.08859					100

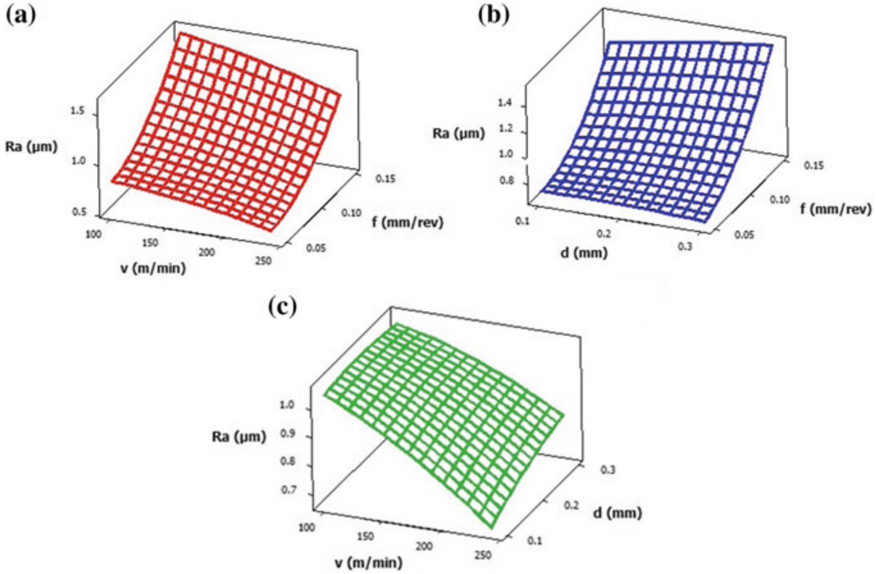

Fig. 2 Surface plots of surface roughness, Ra

in accordance with the previous study [2]. The depth of cut is not very sensitive to influence the surface roughness of turned surfaces; nevertheless, Ra increases slightly with increase in depth of cut (Fig. 2b) for harder material mainly due to chatter, as revealed by Naigade et al. [12].

3.2 *Prediction of Optimal Performance*

From the ANOVA analysis (Table 3), two cutting parameters (feed and speed) were found significant and obtained the lowest surface roughness at feed of 0.05 mm/rev (level-1) and cutting speed of 240 m/min (level 3). Optimal performance of Ra when two most significant factors are at their best level, i.e., at $f_1 v_3$ level, then

$$\mu_{\text{Ra}} = \overline{f}_1 + \overline{v}_3 - \overline{T}_{\text{Ra}} = (0.6978 + 0.8452) - 1.006$$
$$= 0.537\ \mu\text{m} \quad (\overline{T}_{\text{Ra}} = 1.006 \text{ from Table 2})$$

Confidence interval (CI) for surface roughness (Ra) is calculated with the help of following equation

$$\text{CI} = \sqrt{\frac{F_{95\%;(1,\,\text{DF error})} \times V_{\text{e}}}{\eta_{\text{eff}}}} \tag{1}$$

where

$$\eta_{\text{eff}} = \frac{\text{Number of trials}}{1 + \text{degrees of freedom corresponding to that level}} = \frac{27}{1+2+2} = 5.4$$

$F_{95\%;(1,8)} = 5.32$ and $V_{\text{e}} = 0.0076$ (from Table 3)

Hence, $\text{CI}_{\text{Ra}} = \sqrt{\frac{5.32 \times 0.0076}{5.4}} = 0.086\ \mu\text{m}$

The best optimal range of Ra is predicted as, $\left[\mu_{\text{Ra}} - \text{CI}_{\text{R}_\text{a}}\right] \le \mu_{\text{Ra}} \le [\mu_{\text{Ra}} + \text{CI}_{\text{Ra}}]$ i.e. $0.451 \le \mu_{\text{Ra}} \le 0.623\ \mu\text{m}$.

3.3 Empirical Modeling for Surface Roughness

Empirical modeling can be described as compilation of mathematical function and statistical approach for the analysis and modeling of numeric problems which are connected with design of experiments as well as least square error fitting. The output responses are resolved by various input parameters and the major objective is to obtain the relation between the output response (here, Ra) and the input variables (here, v, f, d) studied. Predictive mathematical model for response, Ra is expressed using regression analysis named response surface methodology (RSM) with uncoded unit at 95% confidence level taking into consideration of L27 orthogonal array experimental result data set. From the surface roughness model Eq. (2), it is noticed that coefficient of determinations (experimental and adjusted) are $R^2 = 96.4\%$ and R^2 (adj) = 94.5%, respectively.

$$\begin{aligned}\text{Ra} = {} & 1.1259 - 0.9467d - 5.6443f - 0.0003v - 1.6222d^2 + 61.6444f^2 - 0.000v^2 \\ & + 10.6500f * d + 0.0052v * d - 0.0095v * f\end{aligned} \tag{2}$$

The R^2 value is very close to unity, which ensures the excellence of fit for the model with greater statistical significance. Additionally, normal probability plot has

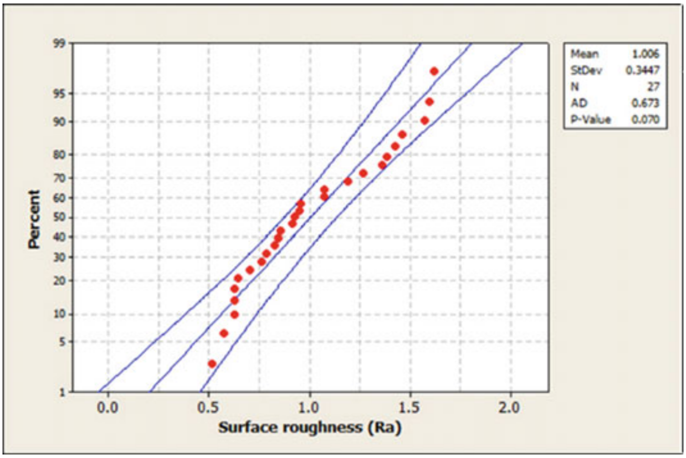

Fig. 3 Normal probability plot for Ra

been displayed for surface roughness as shown in Fig. 3, which ensures that the residuals distributed fairly approach to a straight line indicating the errors are dispersed normality that implies to good correlation between measured and predicted values. With *P*-value (0.07) complimented by Anderson-Darling test is over significance level value (0.05), which confirms the adequacy of model due to favorable reception of null-hypothesis.

4 Optimization of Surface Roughness Using RSM

In this study, with the goal to minimize the surface roughness, desirability function analysis of RSM is utilized for response optimization which is basically employed to determine the best parametric arrangement for single and multi-objective optimizations. This optimization unit looks for a combination of parameter levels that concurrently fulfill the necessities placed on each and every one of the responses, and parameter trying to set up the suitable model. Performance of the optimization procedure adopted is given by composite desirability index through gradient algorithm. It is the weighted geometric average of individual desirability indices for different responses in the range 0–1. If the value of desirability lies nearer to zero, the response would be absolutely rejected. On the other hand, if its value approaches unity, the response would be acknowledged. Optimum cutting speed, axial feed, and doc during hard turning of AISI 4340 steel obtained using RSM technique (see, Fig. 4) are 240 m/min, 0.0556 mm/rev, and 0.10 mm, respectively, for corresponding estimated minimum surface roughness (Ra) 0.5451 μm, is approaching good predictive ability as the percentage of error about 4.8% when it is compared with the experimental value (refer, Table 4).

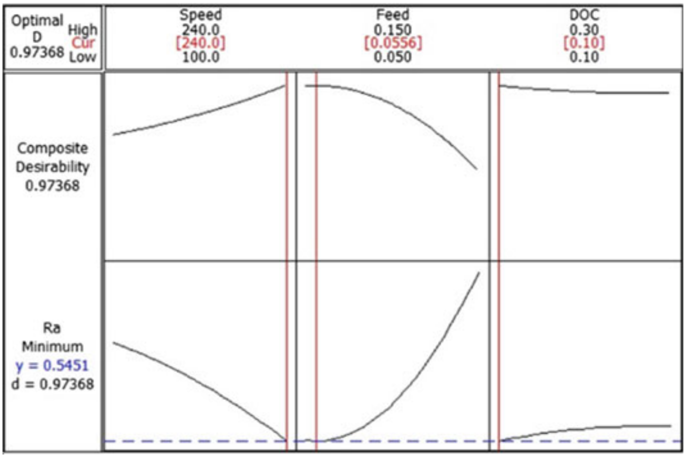

Fig. 4 Optimization plot for Ra

Table 4 Summary of confirmation experiments and comparison of results

Optimal control parameters			Surface roughness, Ra (μm)		Error (%)
V	*f*	*d*	Predicted	Experimental	
240 m/min	0.0556 mm/rev	0.1 mm	0.545 μm	0.52 μm	4.8

5 Conclusions

Based on experimental findings, modeling, and optimization in finish dry hard turning (FDHT) of HSLA steel utilizing PVD–TiN coated mixed (Al_2O_3–TiCN) ceramic tool, machined surface quality of HSLA steel with coated ceramic insert produced roughness within 1.6 μ and can be comparable with cylindrical grinding. Surface roughness was highly emulated by the feed (Ra: 80.05%) followed by the cutting speed (Ra: 13.56%), which well agrees with ANOVA results. Increase in feed the surface roughness increases, but the opposite is seen with cutting speed. The predicted optimal range of surface roughness criteria (Ra) at 95% CI level is $0.451 \leq \mu_{Ra} \leq 0.623$ μm. Empirical model developed for response such as surface roughness has R^2 value close to unity. This ensures the excellence of fit for the model with greater statistical significance. The normal probability plots ensures that the residuals distributed fairly near to a straight line indicating that the errors are dispersed in normality and implying that the sources associated with the model are significant. Anderson–Darling test for model show adequate, as *P*-value is more than 0.05 at 95% confidence level.

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