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Statistical analysis of surface roughness in turning based on cutting parameters and tool vibrations with response surface methodology (RSM)

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Abstract. In this paper, we present an experimental study to determine the effect of the cutting conditions and tool vibration on the surface roughness in finish turning of 32CrMoV12-28 steel, using carbide cutting tool YT15. For these purposes, a linear quadratic model in interaction of connecting surface roughness (Ra, Rz) with different combinations of cutting parameters such as cutting speed, feed rate, depth of cut and tool vibration, in radial and in tangential cutting force directions (Vy) and (Vz) is elaborated. In order to express the degree of interaction of cutting parameters and tool vibration, a multiple linear regression and response surface methodology are adopted. The application of this statistical technique for predicting the surface roughness shows that the feed rate is the most dominant factor followed by the cutting speed. However, the depth of the cut and tool vibrations have secondary effect. The presented models have some interest since they are used in the cutting process optimization.

Keywords: cutting parameter / surface roughness / analysis of variance (ANOVA) / response surface methodology (RMS) / tool vibration

Résumé. Analyse statistique de la rugosité de surface dans le tournage basée sur les vibrations de l'outil avec la méthodologie de la surface de réponse (RSM). Une étude expérimentale a conduit à déterminer les effets des paramètres de coupe et des vibrations d'outil sur la rugosité de surface en tournage lors de l'usinage de l'acier 32CrMoV12-28 avec un outil en carbure métallique YT15. Un modèle quadratique linéaire avec interaction reliant la rugosité (Ra, Rz) aux différentes combinaisons de régime de coupe et les vibrations de l'outil a été élaboré. La régression linéaire multiple et la méthodologie de la surface de réponse ont permis d'exprimer le degré d'influence de chaque élément du régime de coupe et les vibrations d'outil ; l'application de cette technique statistique pour la prédiction de la rugosité montre que l'avance est le facteur le plus dominant suivi par la vitesse de coupe, alors que la profondeur de passe et les vibrations d'outil ont un effet secondaire. Ce modèle peut présenter un intérêt certain pour l'optimisation du processus de coupe.

Mots clés: paramètres de coupe / rugosité de surface / analyse de variance (ANOVA) / méthodologie de la surface de réponse (RSM) / vibrations d'outil

1 Introduction

The surface quality is an essential consumer's requirement which impacts the performance of machining products. The machined surfaces' characteristics influence the ability of a material to resist the stress, the temperature and the corrosion.

Many factors may affect the roughness in a direct or in an indirect manner. To clarify and understand the influence of parameters on the cutting process, and to propose a mathematical model of the roughness that takes into account the correlations of these parameters, several studies are carried out. In [1] and [2], the surface quality is affected by hardness and machined material properties. It is proved that surface roughness decreases by increasing the workpiece hardness. In [3], the effect of the cutting edge geometry is studied and it is found that a chamfered cutting edge altercates the roughness comparing it to a sharp one. It is shown in [4] that the cutting tool geometry has a significant impact on residual stress; a rounded edge promotes appearance of compressive stresses. Moreover, the tool tip radius has a considerable effect on the surface integrity. In fact, roughness is inversely proportional to radius.

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Vibrations are pointed out to be strongly correlated with surface roughness [5] and the different characteristics of vibration signals are chosen to evaluate surface quality. In [6], it is observed that one of the factors that has a major influence on the machined surface and can deteriorate the quality is the presence of tool vibration during cutting process. Therefore, the effect of machining parameters (cutting speed, feed rate, depth of cut), and cutting tool vibrations on surface roughness parameters are presented. Thomas et al. [7] studied the effect of tool vibration on surface roughness during lathe dry turning process on mild carbon steel samples at different levels of speed, feed, depth of cut, tool nose radius, tool length and work piece length.

In [8], the tool nose radius is the preponderant factor on the surface roughness. The response surface methodology (RSM) is used in order to optimize the effect of tool geometry parameters on the surface roughness in hard turning of AISI 1040 with P25 tool. In [9], the application of response surface methodology is studied by describing the performance of coated carbide tools when turning AISI 1045 steel. The investigated factors are: the cutting speed and feed rate; the response variable is the surface roughness (Ra). ANOVA reveal that feed rate is the most significant factor influencing the investigated response variables. In [10] and [11], empirical models of roughness based on the technique of multiple linear regressions are developed. The former takes into account several factors such as: the feed rate, the hardness of the workpiece, the depth of cut, the cutting speed and their interactions. The study proves the influence of parameters and their importance degrees.

In this paper, our experimental study focuses on the prediction and optimization of the surface roughness in finish turning of 32CrMoV12-28 steel using cutting tool carbide (YT15). Also, we present the effect of machining parameters (cutting speed, feed rate, depth of cut), and tool vibrations (Vy, Vz) on surface roughness (Ra, Rz). Finally, the response surface methodology (RSM) associated with the response optimization technique and composite desirability is adopted for the mathematical models which are developed with 95% confidence level.

The present work is structured as follows: in Section 2 the experimental procedure is detailed. The statistical treatment of the data and the correlations between parameters obtained from the quadratic regression is presented in Section 3. A graphical analysis of the observed values using Minitab 16 is given in Section 4, and optimization of responses in Section 5. Last of all, the conclusion shows the effect of cutting parameters and tool vibrations on the surface roughness using RSM.

2 Experimental procedure

The present work is an attempt to examine the effect of cutting parameters and tool vibrations on surface roughness produced, and to correlate them using response surface methodology (RSM).

2.1 Workpiece and tool materials

The characteristics of 32CrMoV12-28 bar steel material are given in Table 1.

The Turning experiments are carried out in dry conditions by using a universal lathe of type SN 40C with 6.6 kW spindle power. The experiments' setups are shown in Figure 1.

However, for the used cutting tool, it is made of carbide metal elaborated at IRIS/SYRIANA-BATNA carbide unit. Cutting tools and the tool holder characteristics are given in Table 2.

Table 1. Characteristics of the steel 32CrMoV12-28.

Dimension							D = 54 mm				L = 490 mm			
Chemical composition														
%C	%Mn	%Si	%P	%S	%Cu	%AL	%Ti	%Ni	%Cr	%Mo	%V	%Sn	% B	%W
0.27	0.31	0.32	0.015	0.008	0.029	0.007	0.003	0.13	2.96	2.35	0.45	0.032	0.001	0.034

Fig. 1. Experimental equipment.

Table 2. Characteristics of the cutting tool and of the tool holder.

Cutting tool	Tool holder						
Type	Active zone geometry					Type	Section
YT15	X_r $+75°$	λ $-6°$	α $+6°$	γ $-6°$	r 0.8 mm	PSBNR 25* 25K12	25×25

Table 3. Attribution of the levels to the factors.

Level	Cutting speed Vc (m/min)	Feed rate f (mm/rev)	Depth of cut ap (mm)
1 (low)	120	0.08	0.5
2 (medium)	170	0.11	0.75
3 (high)	240	0.16	1

In the experimental design, three process parameters at three levels have led to a total of 27 tests. The process surface roughness (Ra and Rz) produced is obtained from a Surftest 201 Mitutoyo roughness meter.

Three levels are specified for each process parameter as shown in Table 3. Parameter levels are chosen in the recommended cutting tool manufacturer units.

In order to measure the tangential (Vz) and the radial cutting vibration forces (Vy), a dynamic signal analyzer with bidirectional accelerometers is used. The latter is attached to the tool holder.

2.2 Experimental design

Experiments are conducted using the L27 orthogonal array, which has 27 rows corresponding to the number of parameter combinations (26° of freedom), with 13 columns at three levels as given in Table 4 [12].

One test was carried out for each combination resulting in a total of 27 runs [13].

In this work, the relationship between independent input process parameters and output data (process response) is established by applying response surface methodology (RSM). This procedure is composed of six steps [14] which are given as follows:
- define the independent input variables and the desired output responses;
- adopt an experimental design plan;
- perform regression analysis with the quadratic model of RSM;
- perform a statistical analysis of variance (ANOVA) of the independent input variables in order to find parameters which affect the most significantly response;
- determine the situation of the RSM model and decide whether this model needs screening variables or not;
- optimize, conduct confirmation experiment with verifying the predicted surface roughness.

The relationship between inputs, cutting parameters, tool vibration and the output Y is also analyzed. The output Y characterizing the surface roughness is given by Equation (1):

$$Y = H\left(V_c, f, ap, V_y, V_z\right) + e_{ij} \tag{1}$$

where Y is the desired response and H is the response surface. In this particular case, the approximation of Y is proposed by using the fitted second order polynomial regression model called the quadratic model. The quadratic model of Y is given by Equation (2):

$$Y = \alpha_0 + \sum\nolimits_{i=0}^{k} \alpha_i X_i + \sum\nolimits_{i=0}^{k} \alpha_{ii} X_i^2 + \sum\nolimits_{i \prec j}^{k} \alpha_{ij} X_i X_j \tag{2}$$

3 Data analysis results and discussion

The first phase of the statistical treatment of the data is focused with the ANOVA and the effect of the factors and of their interactions. In the second phase, the correlations between parameters are obtained from the quadratic regression. Finally, the results are optimized.

3.1 Statistical analysis

Data analyzed by ANOVA algorithm with the surface roughness aims to quantify the influence of the cutting parameters, and the vibration signals of the result's total variance. Table 5 shows the obtained orthogonal arrays Ra and Rz.

Tables 6 and 7 give the ANOVA results for surface roughness (Ra) and (Rz) data. This analysis is carried out with a significance level of 5%, i.e. for a confidence level of 95%. A low p-value indicates a statistical significance for the source on the corresponding response [15]. The greater the contribution percentage is, the greater the influence of factor on the results also is.

From Table 6, the main contributions are noticed for (Vc) 12.19%, (f) 79.18%, (ap) 2.58%, and for the interaction (Vc × f) 1.32%. The feed rate (f) factor shows a statistical and a physical significance on the surface roughness (Ra). The most significant factor based on the F-value was the effect of feed rate with 21.27 F ratio, effect the interaction of (Vc × Vy) and (Vc × ap).

In the Table 7, all the factors (Vc) 38.36%, (f) 68.99%, (ap) 2.94% and the interactions (f^2) 2.67%, (f × Vy) 1.64% present a statistical and a physical significance on the surface roughness (Rz). The latter is the most significant parameter followed by the other factors and interactions.

Table 4. Orthogonal array L_{27} (3^{13}) of Taguchi.

	Vc	f	ap	Interactions									
$L_{27}(3^{13})$	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

Table 5. Design layout and experimental results.

Run	Coded factors			Actual factors			Response variables			
	X_1	X_2	X_3	Vc (m/min)	f (mm/rev)	ap (mm)	Ra (μm)	Rz (μm)	Vy (m/s^2)	Vz (m/s^2)
1	–1	–1	1	120	0.08	1	2.345	11.68	2.393	1.184
2	1	0	1	240	0.11	1	2.515	12.11	5.372	1.394
3	1	0	0	120	0.11	0.75	2.695	12.605	3.765	1.329
4	–1	0	–1	120	0.11	0.5	2.66	12.595	3.41	1.227
5	–1	–1	–1	120	0.08	0.5	2.34	11.535	3.521	1.941
6	1	1	0	240	0.16	0.75	2.785	12.995	5.434	1.527
7	1	–1	0	240	0.08	0.75	2.145	9.09	3.101	1.897
8	0	–1	0	170	0.08	0.75	2.325	10.89	3.328	1.059
9	–1	1	1	120	0.16	1	3.305	14.76	3.269	1.449
10	0	–1	1	170	0.08	1	2.34	11.6	5.809	1.304
11	–1	1	–1	120	0.16	0.5	2.99	13.58	4.07	1.429
12	0	1	0	170	0.16	0.75	2.985	13.495	2.75	1.403
13	1	–1	1	240	0.08	1	2.3	9.77	4.989	3.562
14	1	–1	–1	240	0.08	0.5	1.955	8.69	2.59	1.02
15	1	1	–1	240	0.16	0.5	2.735	12.88	3.414	0.943
16	1	0	–1	240	0.11	0.5	2.475	11.73	3.23	1.734
17	–1	0	1	120	0.11	1	2.735	12.855	3.414	0.943
18	0	0	0	170	0.11	0.75	2.54	12.385	3.614	1.384

Table 5. (continued).

Run	Coded factors			Actual factors			Response variables			
	X_1	X_2	X_3	Vc (m/min)	f (mm/rev)	ap (mm)	Ra (μm)	Rz (μm)	Vy (m/s^2)	Vz (m/s^2)
19	0	–1	–1	170	0.08	0.5	2.305	10.65	3.269	1.449
20	1	0	0	240	0.11	0.75	2.5	11.93	5.119	2.769
21	1	1	1	240	0.16	1	2.79	13.04	3.379	2.052
22	0	0	1	170	0.11	1	2.585	12.41	4.225	2.441
23	0	1	–1	170	0.16	0.5	2.8	13.18	3.41	1.551
24	–1	–1	0	120	0.08	0.75	2.342	11.635	5.809	1.304
25	0	0	–1	170	0.11	0.5	2.525	12.155	4.36	1.668
26	0	1	1	170	0.16	1	2.99	14.275	3.115	1.013
27	–1	1	0	120	0.16	0.75	3.235	14.555	3.521	1.641

Table 6. Analysis of variance for the surface roughness (Ra) results.

Source	DF	SeqSS	Adj SS	Adj MS	*F*-value	*p*-value	cont%
Vc	1	0.32875	0.00632	0.006321	2.07	0.200	12.19
f	1	2.13538	0.06481	0.064806	21.27	0.004	79.18
ap	1	0.06969	0.00123	0.001232	0.40	0.548	2.58
Vy	1	0.00330	0.00306	0.003060	1.00	0.355	0.12
Vz	1	0.01837	0.00002	0.000019	0.01	0.939	0.68
Vc*Vc	1	0.00229	0.00504	0.005038	1.65	0.246	0.08
f*f	1	0.01499	0.00000	0.000003	0.00	0.977	0.55
ap*ap	1	0.00296	0.00466	0.004663	1.53	0.262	0.10
Vy*Vy	1	0.00620	0.00666	0.006662	2.19	0.190	0.22
Vz*Vz	1	0.00039	0.00028	0.000284	0.09	0.770	0.01
Vc*f	1	0.01981	0.01606	0.016056	5.27	0.061	0.73
Vc*ap	1	0.00412	0.03006	0.030059	9.86	0.020	0.15
Vc*Vy	1	0.01063	0.03894	0.038936	12.78	0.012	0.39
Vc*Vz	1	0.00154	0.00059	0.000589	0.19	0.675	0.05
f*ap	1	0.01168	0.02033	0.020335	6.67	0.042	0.43
f*Vy	1	0.03564	0.02349	0.023495	7.71	0.032	1.32
f*Vz	1	0.00004	0.00033	0.000330	0.11	0.753	0.00
ap*Vy	1	0.00111	0.00094	0.000945	0.31	0.598	0.04
ap*Vz	1	0.00745	0.00351	0.003512	1.15	0.324	0.27
Vy*Vz	1	0.00418	0.00418	0.004183	1.37	0.286	0.15
Error	6	0.01828	0.01828	0.003047			0.67
Total	26	2.69680					100

Based on *F*-value, the same result is obtained for the feed rate with 9.19F ratio.

According to the obtained results, the most significant factor on surface roughness evolution is the feed rate. Based on [13], [16], [17], however, it can realize the weak effect of vibration on the surface roughness evolution.

The error associated to the response Ra is approximately 0.67% and the error for the response Rz is 1.46%.

To make the difference between significant factors by using ANOVA, several hypotheses should be satisfied. The residuals are determined by evaluating the following equation [18]:

$$e_{ij} = Y_{ij} - \hat{Y}_{ij} \tag{3}$$

Where e_{ij} is the residual. The normality assumption may be checked by constructing the normal probability plot of the residuals. If the underlying error distribution is normal, the plot will look like a straight line as given in Figure 2a and b. Since the *p*-value is larger than 0.05, it is concluded that normal assumption is valid [19]. The other two assumptions are shown valid by means of plot of residuals versus fitted values. This plot is illustrated in Figure 3a and b. The structure less distribution of dots above and below the **ABSCISSA** shows that the errors are independently distributed and the variance is constant, Montgomery and Runger [20].

Table 7. Analysis of variance for the surface roughness (Rz) results.

Source	DF	SeqSS	Adj SS	Adj MS	*F*-value	*p*-value	cont%
Vc	1	10.4673	0.6186	0.61862	3.93	0.095	38.36
f	1	39.5242	1.4455	1.44546	9.19	0.023	68.99
ap	1	1.6836	0.0092	0.00920	0.06	0.817	2.94
Vy	1	0.8749	0.0007	0.00068	0.00	0.950	1.53
Vz	1	0.0506	0.0055	0.00546	0.03	0.858	0.09
Vc*Vc	1	0.0681	0.0081	000810	0.05	0.828	0.12
f*f	1	1.5286	0.1879	0.18789	1.19	0.316	2.67
ap*ap	1	0.0319	0.0127	0.01266	0.08	0.786	0.05
V y*V y	1	0.0290	0.0473	0.04726	0.30	0.603	0.05
Vz*Vz	1	0.1309	0.0023	0.00233	0.01	0.907	0.23
Vc*f	1	0.4033	0.0874	0.08737	0.56	0.484	0.70
Vc*ap	1	0.1112	0.2469	0.24686	1.57	0.257	0.19
Vc*Vy	1	0.2316	0.4766	0.47658	3.03	0.132	0.40
Vc*Vz	1	0.0007	0.0459	0.04590	0.29	0.609	0.00
f*ap	1	0.1779	0.1035	0.10353	0.66	0.448	0.31
f*Vy	1	0.9376	0.6286	0.62855	3.99	0.093	1.64
f*Vz	1	0.0022	0.0291	0.02911	0.18	0.682	0.00
ap*Vy	1	0.0466	0.0337	0.03365	0.21	0.660	0.08
ap*Vz	1	0.0292	0.0368	0.03682	0.23	0.664	0.05
Vy*Vz	1	0.0085	0.0085	0.00847	0.05	0.824	0.01
Error	6	0.9442	0.9442	0.15736			1.64
Total	26	57.2821			100		

3.2 Regression equations

The initial analysis of the responses obtained from RSM includes all parameters and their interactions. The obtained equations are as follows:

$$\begin{aligned} Ra &= 0.7086 - 7.65 \times 10^{-3} Vc + 14.75 f + 1.05 ap \\ &\quad + 5.18 \times 10^{-1} Vy + 5.57 \times 10^{-2} Vz + 1.0 \\ &\quad \times 10^{-5} Vc^2 + 8 \times 10^{-1} f^2 - 5.08 \times 10^{-1} ap^2 \\ &\quad - 4.08 \times 10^{-2} Vy^2 + 4.96 \times 10^{-2} Vz^2 - 2.42 \\ &\quad \times 10^{-2} Vc.f - 5.17 \times 10^{-3} Vc.ap + 2.05 \\ &\quad \times 10^{-3} Vc.Vy + 4.98 \times 10^{-4} VcVz + 5.202 f.ap \\ &\quad - 2.09 f.Vy + 5.63 \times 10^{-1} f.Vz - 9.17 \\ &\quad \times 10^{-2} apVy + 2.40 \times 10^{-1} apVz - 1.46 \\ &\quad \times 10^{-1} Vy.Vz \end{aligned} \tag{4}$$

$$\begin{aligned} Rz &= 2.27511 - 3.1210^{-2} Vc + 98.17 f + 3.58 ap \\ &\quad + 1.73 Vy + 1.20 Vz + 1.32 \times 10^{-5} Vc^2 \\ &\quad - 211.57.f^2 + 8.38 \times 10^{-1} ap^2 - 1.08 \times 10^{-1} Vy^2 \\ &\quad + 1.42 \times 10^{-1} Vz^2 + 5.64 \times 10^{-5} Vc^2 - 211.57.f^2 \\ &\quad + 8.38 \times 10^{-1} ap^2 - 1.08 \times 10^{-1} Vy^2 + 1.42 \\ &\quad \times 10^{-1} Vz^2 + 5.64 \times 10^{-2} Vc.f - 1.48 \\ &\quad \times 10^{-2} Vc.ap + 7.17 \times 10^{-3} Vc.Vy - 4.39 \\ &\quad \times 10^{-3} Vc.Vz + 11.73\mathrm{f}.ap - 10.85\mathrm{f}.Vy + 5.28\mathrm{f}.Vz \\ &\quad - 5.47 \times 10^{-1} ap.Vy - 7.77 \times 10^{-1} ap.Vz - 2.08 \\ &\quad \times 10^{-1} Vy.Vz \end{aligned} \tag{5}$$

These models are reduced by eliminating terms that have no significant effect on the responses. The estimated regression coefficients for Ra and Rz using data in uncoded units are presented in Tables 8 and 9. The final models are given as follows:

$$\begin{aligned} Ra &= 0.7086 + 14.75 f - 5.17 \times 10^{-3} V_c.ap + 2.05 \\ &\quad \times 10^{-3} V_c.V_y + 5.202 f.ap - 2.09 f.V_y \end{aligned} \tag{6}$$

$$R_z = 2.27511 + 98.17 f \tag{7}$$

Equations (6) and (7) present a good agreement, greater than 95% in the fit values. However, these mathematical models can help in the prediction of the surface roughness at any zone of the experimental domain [21], [22].

The analysis of variance is performed to examine the null hypothesis given in Tables 10 and 11. The result indicates that the estimated model by the regression procedure is significant at the alpha level of 0.05.

The sum of R^2 is computed to check the adjustment quality. The value of R^2 for preacher in the models is respectively 99.32 % for (Ra) and 98.35% for (Rz) from response's variation. The adjusted R^2 for preachers' numbers in the models are 97.06% and 92.86% for (Ra) and (Rz) respectively. These numbers express that the data are well fitted.

Thus, Figure 4a and b shows that the predicted values of the surface roughness parameters (Rz) and (Ra) are very close to those recorded experimentally.

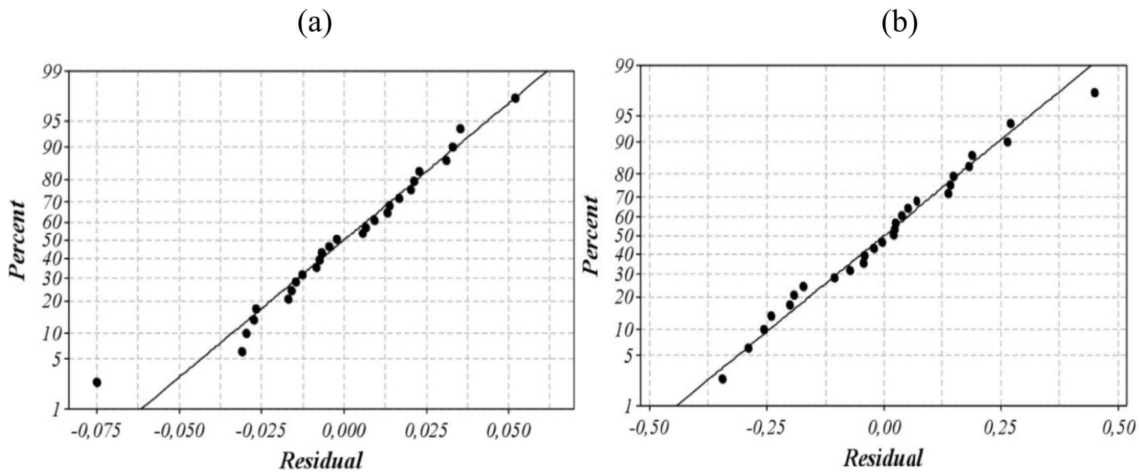

Fig. 2. Normal probability plot of residuals for Ra (a) and Rz (b).

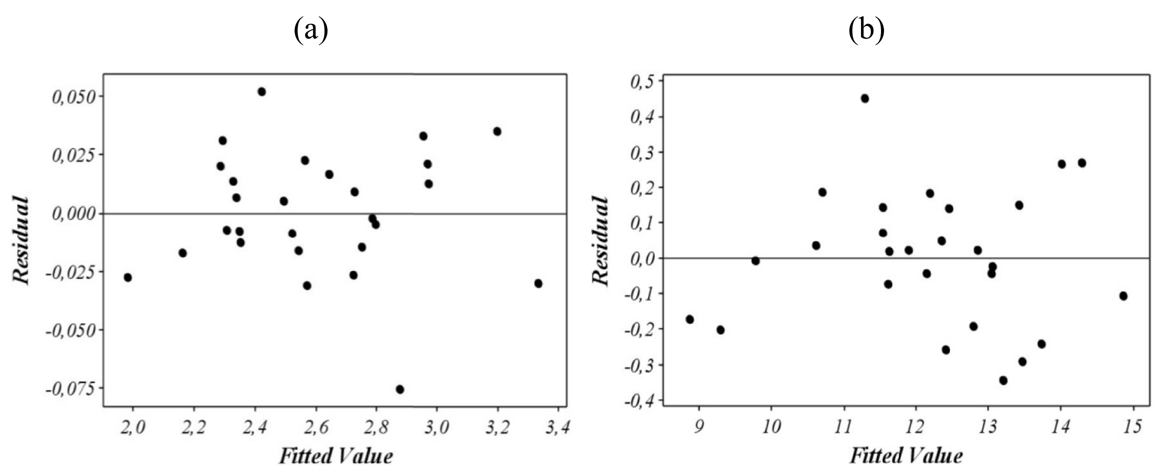

Fig. 3. Plot of residuals versus the order of the data for Ra (a) and Rz (b).

Table 8. Coefficients for regression analysis, response Ra.

Predictor	Coefficient Seq.SS	SE Coefficient	T	Prob
Constant	0.7086	0.9694	0.73	0.492
f	14.751	6.754	2.18	0.072
Vc*ap	–0.005174	0.001648	–3.14	0.020
Vc*Vy	0.002049	0.000573	3.57	0.012
f*ap	5.202	2.014	2.58	0.042
f*Vy	–2.0986	0.7558	–2.78	0.032

Table 9. Coefficients for regression analysis, response Rz.

Predictor	Coefficient Seq.SS	SE Coefficient	T	Prob
Constant	2.275	6.966	0.33	0.755
f	98.17	48.53	2.02	0.090

4 Surface plot

In order to investigate the influence of machining parameters on the surface roughness (Ra) and (Rz), a graphical analysis is done on the observed values using Minitab 16. The plots of surface responses based on the response surface methodology are presented. Figure 5a shows that the surface roughness (Ra) decreases as the cutting speed increases. As the feed increases, the cutting speed combination, as expected, decreases. Thus, it produces better surface roughness. Figure 5b shows that a cutting speed of around 240 m/min gives the lowest surface finish. For a lower depth of cut (Ra), value is almost constant. Figure 5c shows that the feed has the highest impact on the surface roughness (Ra). However, Figure 5e illustrates the surface roughness (Rz) versus cutting speed and feed rate. The latter has the most significant effect on surface roughness. Figure 5f shows that a cutting speed of around 240 m/min gives the lowest surface finish. When the depth of cut is in the highest levels, the (Rz) value reduces. Figure 5g shows that the feed has the highest impact on the surface roughness (Rz). Figure 5d and h reveals the effect of vibration amplitudes in the main and

Table 10. ANOVA table for the fitted models Ra.

Source	DF	Seq ss	AdjSS	Adj MS	*F*-value	Prob	Remarks
Regression	20	2.67851	2.67851	0.133926	43.95	0.000	Adequate
Residual error	6	0.1828	0.1828	0.003047			
Total	26	2.69680					
R^2							99.32
R^2adjusted							97.06

Table 11. ANOVA table for the fitted models Rz.

Source	DF	Seq ss	AdjSS	Adj MS	*F*-value	Prob	Remarks
Regression	20	56.3379	56.3379	2.81690	17.90	0.001	Adequate
Residual error	6	0.9442	0.9442	0.15736			
Total	26	57.2821					
R^2							98.35%
R^2adjusted							92.86%

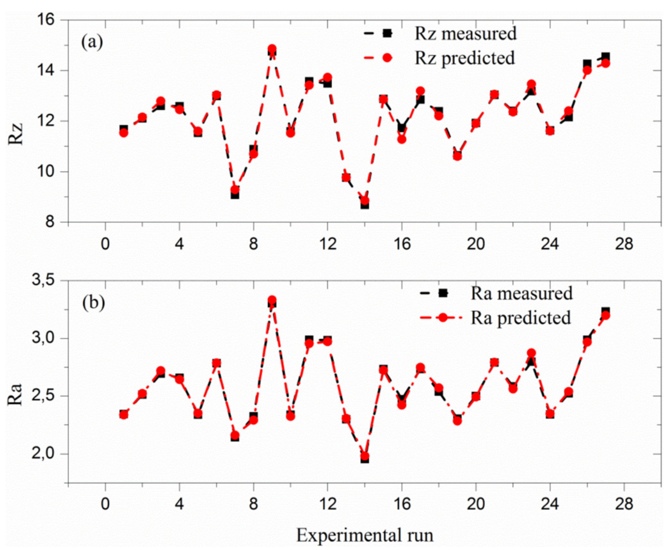

Fig. 4. Comparison between measured and predicted values for surface roughness: (a) Rz, (b) Ra.

tangent direction of the cutting force with the surface roughness Ra and Rz, respectively. It shows that the amplitude of the vibration signals (Vz and Vy) have a secondary effect on the surface roughness. The cutting conditions are well adapted.

5 Response optimization

RSM is a helpful mathematical and statistical technique for the modelling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response [19]. A useful technique for surface roughness optimization is the exploitation of the RSM technique and that for an optimum cutting parameters and tool vibrations. The goal is to minimize the surface roughness (Ra) and (Rz). To solve this problem of design parameters, an objective function *F(X)*, is given as follows [23]:

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

$$F(X) = -DF$$

where d_i the desirability defined for the i^{th} is targeted output and w_i is d_i weights. For various goals of each targeted output, the desirability d_i is defined in different forms. If a goal is to reach a specific value of T_i, the desirability d_i is given by:

$$d_i = 0 \text{ if } Y_i \le Low_i,$$

$$d_i = \left[\frac{Y_i - Low_i}{T_i - Low_i}\right] \text{ if } Low_i \le Y_i \le T_i \tag{9}$$

$$d_i = \left[\frac{Y_i - High_i}{T_i - High_i}\right] \text{ if } T_i \le Y_i \le High_i,$$

$$d_i = 0 \text{ if } Y_i \ge High_i$$

For the purpose of finding a maximum, the desirability is represented as follows:

$$d_i = 0 \text{ if } Y_i \le Low_i,$$

$$d_i = \left[\frac{Y_i - Low_i}{High_i - Low_i}\right] \text{ if } Low_i \le Y_i \le High_i \tag{10}$$

$$d_i = 1 \text{ if } Y_i \ge High_i$$

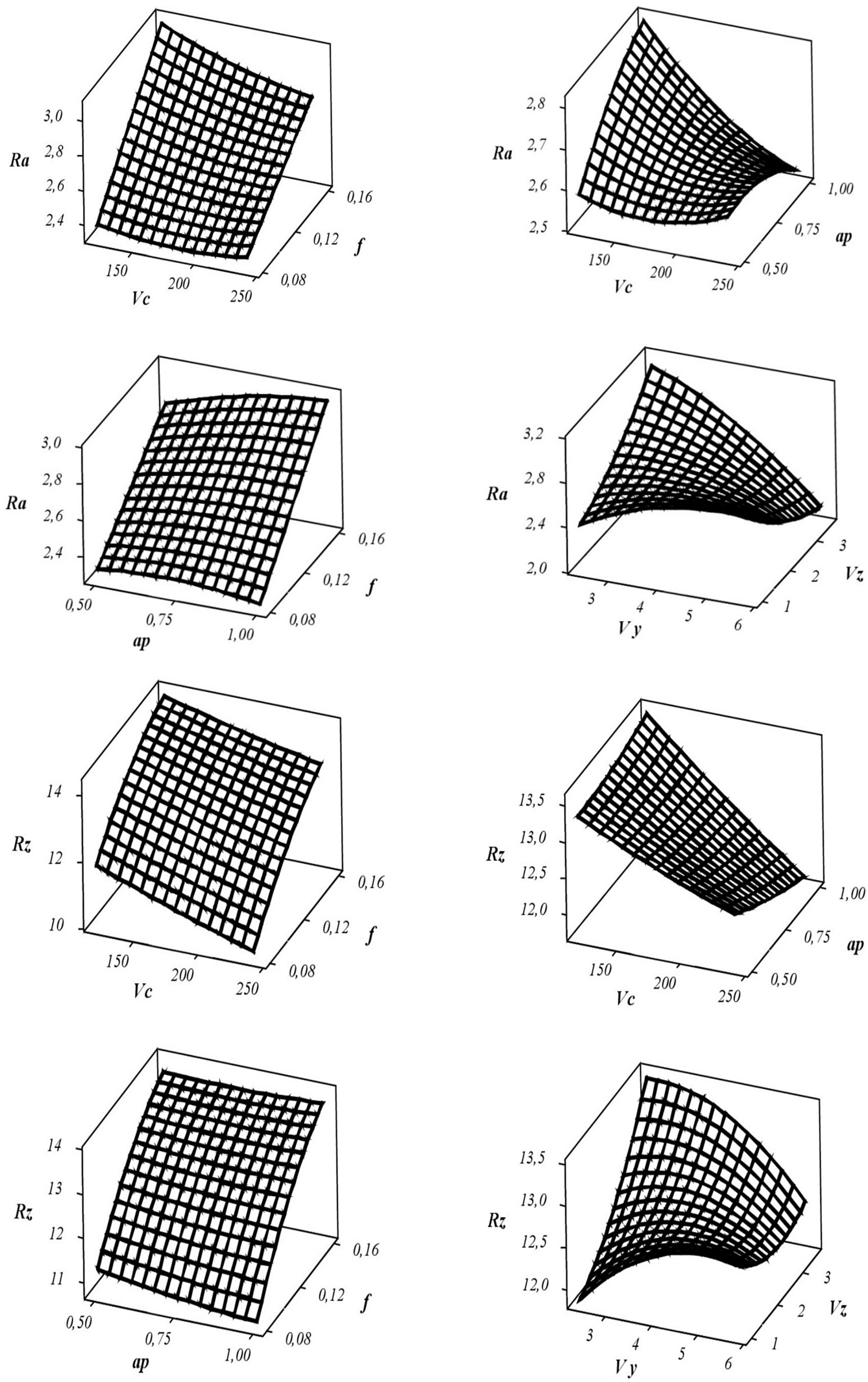

Fig. 5. Response surface plots of surface roughness Ra and Rz according to change of Vc, f, ap and Vy, Vz.

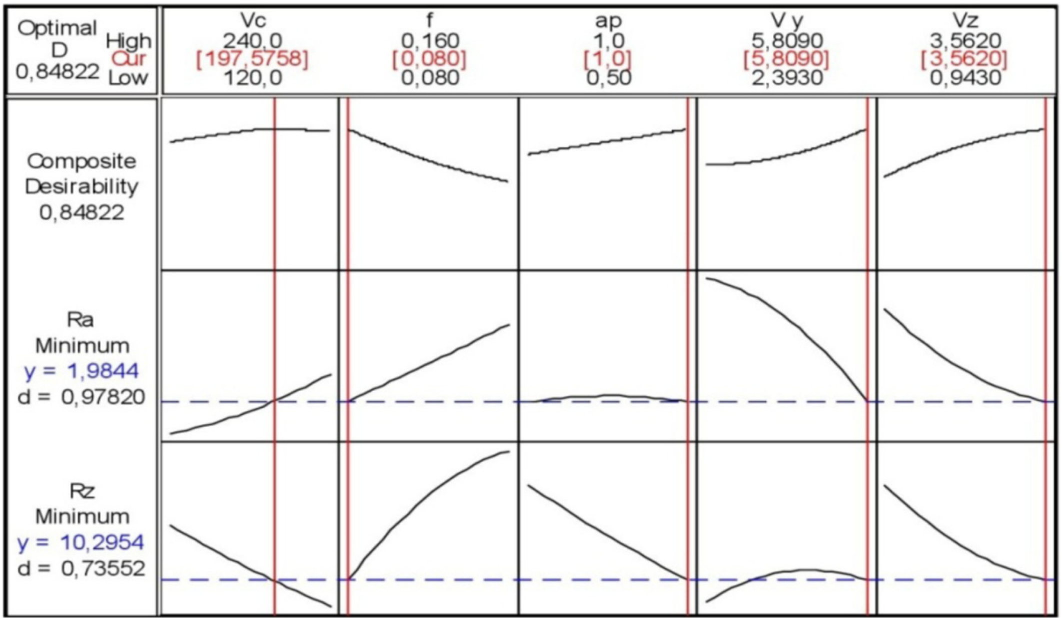

Fig. 6. Response optimization plot for surface roughness parameter component.

Table 12. Response optimization for the surface roughness parameters.

Parameters	Goal	Optimum combination					Lower	Target	Upper	Predicted response
		Vc (m/mn)	f (mm/rev)	Ap (mm)	Vy (m/s^2)	Vz (m/s^2)				
Ra (μm)	Min	197.57	0.080	1	5.80	3.56	1.955	1.955	3.305	1.9844
Rz (μm) Min		197.57	0.080	1	5.80	3.56	8.690	8.690	14.76	10.2954
Ra desirability = 0.98										
Rz desirability = 0.73										
Composite desirability = 0.85										

For the purpose of finding a minimum, the desirability is given by:

$$d_i = 1 \text{ if } Y_i \geq Low_i,$$

$$d_i = \left[\frac{High_i - Y_i}{High_i - Low_i}\right] \text{ if } Low_i \leq Y_i \leq High_i \qquad (11)$$

$$d_i = 0 \text{ if } Y_i \geq High_i$$

where the Y_i is the found value of the i$^{\text{th}}$ output during optimization processes; the Low_i and the $High_i$ are, respectively, the minimum and the maximum values of the experimental data for the i$^{\text{th}}$ output. From Equation (8), w_i is set to one since the d_i is equally important in this study. The DF is a combined desirability function [23], the objective is to select an optimal setting to minimize $F(x)$. The results are illustrated in Figure 6 and Table 12.

6 Conclusion

The obtained conclusions after the experimental study in finish turning of 32CrMoV12-28 steel using carbide cutting tool YT15 are given as follows:

– Response surface methodology (RSM) combined with the factorial design of experiment is useful for predicting machined surface roughness. Only a small number of experiments are required to generate helpful information exploited for predicting roughness equations.
– The Statistical analysis (ANOVA) have shown that the most influent factors on the evolution of the surface roughness are feed rate(f) and cutting speed (Vc) with the influences (79.18% and 12.19%) respectively on Ra, and (68.99% and 38.36%) respectively on Rz.
– Feed rate causes a primary contribution compared to the other working parameters and influences significantly on the surface roughness evolution. According to the surface roughness model (Ra), the interaction between cutting

speed (Vc) and tool vibration in radial cutting force direction (Vy), and between cutting speed (Vc) and depth of cut (ap) provide a secondary contribution to the model.
– The Surface roughness model (Rz), demonstrates that the feed rate furnishes a primary contribution and influence significantly the surface roughness. The interaction between (f) and (Vy) provides secondary contribution to the model.
– From equations (4–7): vibrations have a secondary effect on the cut surface roughness.
– The correlations' coefficients of the quadratic model (RMS) are respectively 99.32% and 98.35% for (Ra) and (Rz) models. The ANOVA shows that both models are valid at a high significance.
– According to the surface roughness optimization, a good surface roughness can be achieved when the cutting speed and the depth of cut are set at a high level in the experimental area (197.57 m / rev, 1 mm), feed rate at a low level in the experimental range (0.08 mm/tr), and tool vibrations are set at a high level in the experimental area (Vy = 5.8090, Vz = 3.5620).

Nomenclature

a_ii	Quadratic term
a_j	Coefficients of linear terms
a_ij	Cross-product terms
Adj MS	Adjusted mean squares
Adj SS	Adjusted sum of squares
ANOVA	Analysis of variance
ap	Depth of cut (mm)
DF	Degrees of freedom
f	Feed rate (mm/rev)
PC%	Percentage contribution ratio (%)
Ra	Arithmetic average of absolute roughness (μm)
Rz	Average maximum height of the profile (μm)
R^2	Determination coefficient
RSM	Response surface methodology
r	Nose radius
Seq SS	Sequential sum of squares
Vc	Cutting speed (m/min)
Vy	Acceleration in radial cutting force (m/s^2)
Vz	Acceleration in tangent cutting force (m/s^2)
X_r	Major cutting edge angle (°)
X_i	Coded machining parameters
Y_{ij}	Corresponding observation of the runs
$\hat{Y}_{ij}$	Fitted value
α	Clearance angle (°)
γ	Rake angle (°)
λ	Cutting edge inclination angle (°)

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