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Application of response surface methodology in describing the performance of mixed ceramic tool when turning AISI 4140 steel

Mohamed Elbah[1,a], Hamdi Aouici[1,2], Ikhas Meddour[1,2], Mohamed Athmane Yallese[1] and Lakhdar Boulanouar[3]

[1] Mechanics and Structures Research Laboratory (LMS), May 8th 1945 University, P.O. Box 401, 24000 Guelma, Algeria
[2] ENST-ex CT siege DG. SNVI, Route Nationale No. 5 Z.I., 16012 Rouiba, Algerie
[3] LRTAPM, Université Badji-Moukhtar, B12, 23000 Annaba, Algérie

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Abstract – Statistical tools, as well as mathematical ones, have been widely adopted and their performance has been shown in different engineering problems where randomicity usually exists. In the realm of engineering, merging statistical analysis into structural evaluation and assessment will be a tendency in the future. As a combination of mathematical and statistical techniques, response surface methodology has been successfully applied to design optimization, response prediction and model validation. The aim of this study was to evaluate the impact of factors such as cutting speed, feed rate, and depth of cut on cutting force components and surface roughness of a mixed ceramic (CC650) cutting tool during the hard turning process of AISI 4140 steel. The experimental results indicate that the proposed mathematical models suggested could adequately describe the performance indicators within the limits of the factors that are being investigated. The depth of cut is the most significant factor that influences the cutting force components and the surface roughness. However, there are other factors that provide secondary contributions to the performance indicators. In the case of surface roughness, the feed rate and the interaction of feed rate and depth of cut provide these contributions whilst for forces components, the feed rate, the interaction of feed rate and depth of cut and the cutting speed provide them.

Key words: Ceramic / hard turning / AISI 4140 / surface roughness / cutting force / RSM

1 Introduction

The machining of hardened steel components (45–70 HRC) has been extensively used to replace the grinding operations due to improvements in the performance of hard tool materials such as ceramics and cubic boron nitride. The possibility of eliminating coolant reduced processing costs and power consumption, improved material properties and productivity, flexibility in producing complex geometric errors, ability to machine thin wall sections, and comparable surface finish are the major benefits of hard turning [1,2]. Hence, hard turning is broadly used in many applications such as tools, dies, gears, cams, shafts, axles, and bearings [3,4]. The surface finish is an important parameter in the machining process. In machining of parts, surface quality is one of the most specified customer requirements. Major indication of surface quality on machined parts is surface roughness. It has formed an important design feature in many situations

Nomenclature

ap	Depth of cut, mm
f	Feed rate, mm.rev^{-1}
Fa	Axial force, N
Ft	Tangential force, N
Fr	Thrust force, N
HRC	Rockwell hardness
PRESS	Predicted residual error sum of squares
R^2	Determination coefficient
R^2_{pred}	Predicted coefficient
R^2_{adj}	Adjusted coefficient
Ra	Surface roughness, μm
SS_{E}	Error sum of squares
SS_{R}	Regression model to the sum of squares
SS_{T}	Total sum of squares
Vc	Cutting speed, m.min^{-1}
α	Clearance angle, degree
γ	Rake angle, degree
λ	Inclination angle, degree
χ	Major cutting edge angle, degree

[a] Corresponding author: elbah_med@yahoo.fr

such as parts subjected to fatigue loads, precision fits, fastener holes, and aesthetic requirements. In addition to tolerance, surface roughness imposes one of the most critical constraints for the selection of machines and cutting parameters in the process planning [1]. So, surface roughness is an important measure of the technological quality of a product and a factor that greatly influences manufacturing cost [5,6].

The response surface methodology (RSM) is a family of statistical techniques for the design, empirical modeling and optimization of processes, where the responses of interest are influenced by several process variables (termed factors) [7, 8]. RSM comprises the following three major components: (i) experimental design to determine the process factor' values based on which the experiments are conducted and data are collected; (ii) empirical modeling to approximate the relationship (i.e. the response surface) between responses and factors; (iii) optimization to find the best response value based on the empirical model. In addition, the above three stage procedure is typically operated in an iterative manner, where the information attained from previous iterations is utilized to guide the search for better response variables.

Related to the problem concerning our work, several works have been previously done using the RMS method as a tool for design of experiments in various area including metal cutting: milling process [9], grinding process [10], turning process [11], drilling processes [12], but also other processes like vibration process [13].

Hessainia et al. [14] used design of experiments for studying and minimizing the surface roughness (Ra) during machining of 42CrMo4. The process factors chosen were cutting speed, feed rate, depth of cut and tool vibration. These factors were optimized using response table and response graph, normal probability plot, interaction graphs and analysis of variance (ANOVA). In their discussion of results, the authors concluded that the feed rate has greater influence followed by cutting speed on surface roughness (Ra). The product of feed rate ($f \times f$) has more influence compared to other interaction of Ra. Based on the analysis, an empirical equation was developed to determine the surface roughness that was valid for the chosen factors only. The surface finish of the hard turning of AISI 52 100 was studied using Taguchi's design method by Azizi et al. [15]. The machining characteristics were investigated based on surface roughness and cutting force. The machining parameters were optimized using ANOVA. Simple regression method was employed. An empirical model was developed to determine the percentage of improvement in surface roughness and cutting force. Kirby et al. [16] developed the prediction model for surface roughness in turning operation. The regression model was developed by a single cutting parameter and vibrations along three axes were chosen for in-process surface roughness prediction system. By using multiple regression and Analysis of Variance (ANOVA) a strong linear relationship among the parameters (feed rate and vibration measured in three axes) and the response (surface roughness) was found. The authors demonstrated that spindle speed and depth of cut might not necessarily have to be fixed for an effective surface roughness prediction model. Doniavi et al. [17] used response surface methodology (RSM) in order to develop empirical model for the prediction of surface roughness by deciding the optimum cutting condition in turning. The authors showed that the feed rate influenced surface roughness remarkably. With the increase in feed rate surface roughness was found to be increased. With increasing in cutting speed the surface roughness decreased. The analysis of variance was applied which showed that the influence of feed and speed were more in surface roughness than depth of cut. Davim and Figueira [18] performed statistical analysis to study the influence of cutting speed and feed rate on specific cutting pressure, and surface roughness in hard turning of AISI D2 cold work tool steel with conventional ceramic inserts. Feng and Wang [19] have developed a statistical regression technique for surface roughness in terms of process parameters that includes hardness, feed, point angle, depth of cut, and spindle speed in finish turning.Choudhury and El-Baradie [20] had used RSM and 2^3 factorial designs for predicting surface roughness when turning high-strength steel. Thiele and Melkote [21] had used a three-factor complete factorial design to determine the effects of workpiece hardness and cutting tool edge geometry on surface roughness and machining forces.

In this paper, data of factorial design for the four responses (feed force, thrust force, tangential force and surface roughness) when turning AISI 4140 are used to predict the machinability models using RSM. The obtained machinability models are compared against each other using the relative error analysis, descriptive statistics and hypothesis testing. Three machining parameters were considered (cutting speed, feed rate and depth of cut). Therefore, this paper presents the following contributions.

2 Experimental procedure

2.1 Material, workpiece and tool

The material used in the experiment was AISI 4140 steel in the form of round bar 75 mm in diameter and 400 mm in length. The chemical composition and mechanical properties are listed in Table 1. The workpiece is hardened to 60 HRC. Its hardness was measured by a digital durometer DM2-D 390. It is of 72 mm in diameter and it is machined under dry conditions. The lathe used for machining operations is TOS TRENCIN; model SN40C, spindle power 6.6 kW.

The cutting tool used was CC650, a mixed alumina ($Al_2O_3 \sim 70\%$)-based ceramic with titanium carbide (TiC $\sim 30\%$). According to ISO standard, the tool is designated as CNGA120408 S01525, rhomboid (manufacturer: Sandvik). The insert was rigidly attached to a tool holder of ISO designation of PCBNR2525M12. The combination of the insert and the tool holder provided 80° cutting edge angle, −6° rake angle and −6° clearance angle.

The three components of the cutting forces; feed force (Fa), thrust force (Fr) and tangential force (Ft), were

Table 1. Chemical composition and mechanical properties of AISI 4140 steel.

Composition		Mn	Si	Cr	Cu	Al	Ti
(Wt %)	0.43	0.79	0.24	1.10	0.02	0.025	0.004
Mechanical properties	Yield strength MPa		Tensile strength MPa		Elasticity modulus GPa		Thermal conductivity W.mK^{-1}
	415–483		500–655		∼210		42.6

recorded using a standard quartz dynamometer (Kistler 9257B) allowing measurements from –5 to 5 kN. Instantaneous roughness criteria measurements (Ra), for each cutting condition, are obtained by means of a Mitutoyo Surftest 201 roughness meter. The length examined is 2.4 mm with a basic span of 3. The measured values of Ra are within the range 0.05 to 40 μm. Absolute roughness is directly measured on the same turned part, without disassembling, in order to reduce uncertainties due to resumption operations. The measurements are repeated 3 times at 3 reference lines equally positioned at 120°.

2.2 Experiments design

Response surface methodology (RSM) is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response [5–7]. It is a sequential experimentation strategy for empirical model building and optimization.

By conducting experiments and applying regression analysis, a model of the response to some independent input variables can be obtained. Based on the model of the response, a near optimal point can then be deduced. RSM is often applied in the characterization and optimization of processes. In RSM, it is possible to represent independent process parameters in quantitative form as:

$$Y = \varphi(Vc, f, ap) \tag{1}$$

where φ is the response function. The approximation of Y is proposed by using a non-linear (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:

$$Y = a_0 + \sum_{i=1}^{k} b_i X_i + \sum_{i,j}^{k} b_{ij} X_i X_j + \sum_{i=1}^{k} b_{ii} X_i^2 \tag{2}$$

where b_0 is the free term of the regression equation, the coefficients $b_1, b_2, \ldots b_k$ and $b_{11}, b_{22}, \ldots b_{kk}$ are the linear and the quadratic terms respectively; while $b_{12}, b_{13}, \ldots b_{k-1}$ are the interacting terms. Xi represents input parameters (Vc, f, and ap). The output surface roughness (Ra) and cutting force components (Fa, Fr and Ft) are also called the response factors. The experimental plan is developed to assess the influence of cutting speed (Vc), feed rate (f) and depth of cut (ap) on three components force (Fa, Fr and Ft) and surface roughness (Ra).

The other factors such as type of abrasive, workpiece, dry, and cutting tool were constant. Three levels are defined for each cutting variable as given in Table 2. The variable levels are chosen within the intervals recommended by cutting tool manufacturer. Three cutting variables at three levels led to a total of 27 tests.

The response surface method is a sequential process and its procedure can be summarized as shown in Figure 1.

Data were processed for Equation (1) using Design Expert 8.0.7 program including ANOVA to obtain the interaction between the process variables and the response. The quality of the fit of polynomial model was expressed by the coefficient of determination R^2, and its statical

Table 2. Assignment of the levels to the factors.

Level	Cutting speed Vc (m.min^{-1})	Feed rate f (mm.rev^{-1})	Depth of cut ap (mm)
1	85	0.08	0.1
2	115	0.11	0.2
3	150	0.14	0.3

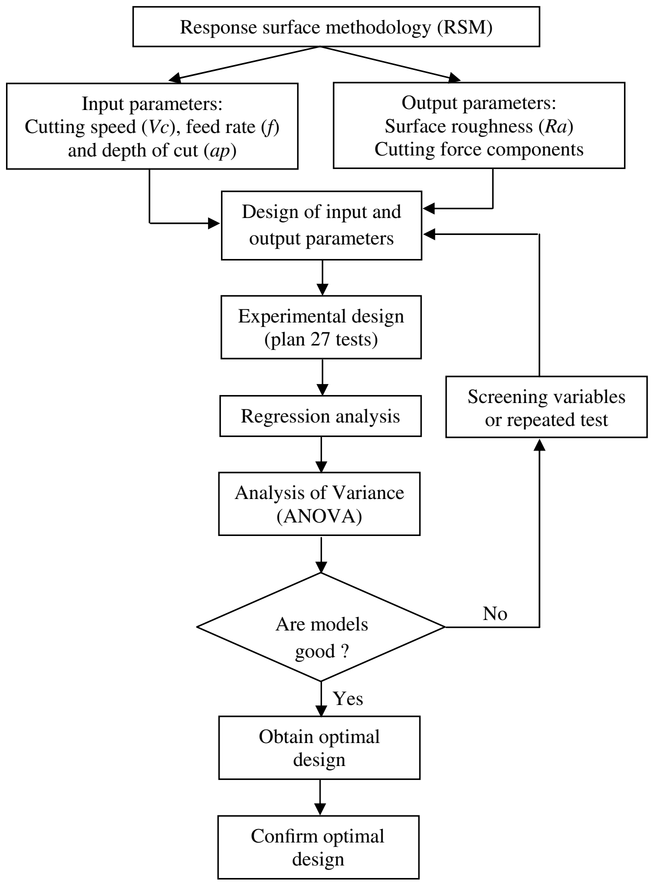


Fig. 1. Procedure of response surface methodology.

Table 3. Experimental results for feed force, thrust force, tangential force and surface roughness.

No.	Machining parameters			Response factors			
	ap (mm)	f (mm.rev^{-1})	Vc (m.min^{-1})	Fa (N)	Fr (N)	Ft (N)	Ra (μm)
1	0.1	0.08	80	13.85	38.62	43.61	0.33
2	0.1	0.08	115	12.72	49.11	44.55	0.37
3	0.1	0.08	150	13.48	58.36	46.75	0.39
4	0.1	0.11	80	12.07	56.38	49.97	1.01
5	0.1	0.11	115	18.51	77.49	45.00	1.12
6	0.1	0.11	150	18.33	69.43	58.09	1.15
7	0.1	0.14	80	18.38	65.58	65.02	1.36
8	0.1	0.14	115	16. 74	77.56	56.70	1.36
9	0.1	0.14	150	25.49	97.23	67.92	1.50
10	0.2	0.08	80	33.13	86.45	70.05	0.73
11	0.2	0.08	115	33.37	101.37	81.49	0.70
12	0.2	0.08	150	47.65	117.38	84.35	0.64
13	0.2	0.11	80	43.95	100.85	107.99	0.76
14	0.2	0.11	115	44.90	134.83	97.18	0.49
15	0.2	0.11	150	49.77	143.31	108.48	0.61
16	0.2	0.14	80	42.05	120.59	122.94	0.75
17	0.2	0.14	115	61.83	151.87	129.00	0.76
18	0.2	0.14	150	65.36	182.02	119.41	0.64
19	0.3	0.08	80	63.84	137.3	114.48	0.44
20	0.3	0.08	115	74.20	177.77	117.60	0.40
21	0.3	0.08	150	75.46	193.10	116.86	0.38
22	0.3	0.11	80	75.55	175.53	152.68	0.56
23	0.3	0.11	115	86.64	202.27	146.04	0.53
24	0.3	0.11	150	85.22	203.28	151.86	0.51
25	0.3	0.14	80	77.96	192.26	191.43	0.55
26	0.3	0.14	115	92.80	220.53	182.51	0.56
27	0.3	0.14	150	108.79	245.97	167.57	0.64

significance was checked by the F-test in the same program. The optimum values of the selected variables were obtained by solving the regression equation and by analyzing the response surface contour plots [22].

To prove the usability of a primary model, its adequacy is checked mainly by three criteria. The first R^2 criterion measures the amount of variation around the mean explained by the model [15]:

$$R^2 = \frac{SS_\mathrm{R}}{SS_\mathrm{T}} = 1 - \frac{SS_\mathrm{E}}{SS_\mathrm{T}} \quad (0 \le R^2 \le 1) \tag{3}$$

with $SS_\mathrm{T} = SS_\mathrm{E} + SS_\mathrm{R}$ the total sum of squares, where, SS_E is the error sum of squares and the SS_R is regression model to the sum of squares. A value of R^2 close to1.0 is always preferred but does not imply an adequate model at all times because R^2 always increases with additional parameters, even non-significant ones. Therefore, an adjusted R^2 criterion can be used as a supplementary evaluation since it often decreases with the augmentation of non-significant parameters:

$$R^2_\mathrm{adj} = 1 - \frac{SS_\mathrm{E}/(n-p)}{SS_\mathrm{T}/(n-1)} = 1 - \frac{n-1}{n-p}(1-R^2) \quad (0 \le R^2_\mathrm{adj} \le 1) \tag{4}$$

where $p = k + 1$. An RS model is well fitted with the samples if both R^2 and R^2_adj are close to 1.0 with slight difference. However, a well-fitted model does not always accurately predict the responses of the unseen values of input parameters. Hence a third criterion R^2_pred measuring the amount of variation in new data is also considered:

$$R^2_\mathrm{pred} = 1 - \frac{PRESS}{SS_\mathrm{T}} \quad (0 \le R^2_\mathrm{pred} \le 1) \tag{5}$$

where PRESS denotes the predicted residual error sum of squares and measures how the model fits the samples. In practice, R^2_pred should also be close to 1.0 and a difference within 0.2 between R^2_adj and R^2_pred is acceptable for an RS model. Besides above three criterion indices, some plots such as the normal probability of internally studentized residuals versus predicted values or runs should also be checked [23, 24].

3 Results and discussion

Table 3 shows all the values of the response factors, surface roughness and cutting force components. The surface roughness (Ra) was obtained in the range of (0.3–1.50) μm, feed force (Fa), thrust force (Fr) and tangential force (Ft) were obtained in range of (12.7–108.79) N, (38.6–245.97) N and (43.61–191.43) N, respectively.

Table 4. ANOVA result for feed force (Fa).

Source	Sum of squares	DF	Mean square	F-value	Prob.	Cont. %	Remarks
Model	21 676.1124	9	2408.45693	142.149377	<0.0001		Significant
Vc	752.900185	1	752.900185	44.4368719	<0.0001	3.455	Significant
f	1103.87342	1	1103.87342	65.1516401	<0.0001	5.065	Significant
ap	19 397.5065	1	19 397.5065	1144.85894	<0.0001	89.010	Significant
$Vc \times f$	140.472137	1	140.472137	8.29079667	0.0104	0.645	Significant
$Vc \times ap$	127.5312	1	127.5312	7.5270105	0.0139	0.585	Significant
$f \times ap$	159.845556	1	159.845556	9.43423395	0.0069	0.733	Significant
Vc^2	2.49615	1	2.49615	0.1473251	0.7059	0.011	No significant
f^2	70.017094	1	70.017094	4.13247427	0.0580	0.321	No significant
ap^2	37.95135	1	37.95135	2.23992411	0.1528	0.174	No significant
Error	288.033396	17	16.943141				
Total	21 964.1458	26				100	

SD = 412	$R^2 = 0.9869$
Mean = 4857	R^2 Adjusted = 0.9799
Coefficient of variation = 8.48	R^2 Predicted = 0.9671
Predicted residual error of sum of squares (PRESS) = 722.4	Adequate precision = 38.223

3.1 Statistical analysis

The results from the cutting force components (Fa, Fr and Ft) and the surface roughness (Ra) experimented as per the experimental plan are tabulated in Table 3. For the checking of the goodness of fit of the quadratic model obtained in this study, the test for significance of the regression model, the test for significance on individual model coefficients need to be performed. The analysis of ANOVA is usually applied to summarize the above tests performed.

Tables 4–7 show these results of ANOVA, respectively, for Fa, Fr, Ft and Ra. This analysis was out for a 5% significance level, i.e., for a 95% confidence level. The last column of tables shows the factor contribution (percentage; Cont. %) on the total variation, indicating the degree of influence on the result.

Table 4 shows the ANOVA table for response surface quadratic model for feed force (Fa). The model F-value of 142.149 implies that the model is significant.There is only a 0.01% chance that a "model F-Value" could occur due to noise. The value of Prob. in Table 4 for the model is less than 0.0001 which indicates that the model is significant, which is desirable as it indicates that the terms in the model have a significant effect on the response. In the same manner, the main effects of cutting speed (Vc), feed rate (f), depth of cut (ap) and the product of cutting speed and feed rate ($Vc \times f$), cutting speed and depth of cut ($Vc \times ap$) and feed rate and depth of cut ($f \times ap$) are significant model terms. The interactions $Vc \times Vc$, $f \times f$ and $ap \times ap$ do not present any significant contribution on the obtained feed force.

The other important coefficient R^2 in the resulting ANOVA table is defined as the ratio of the explained variation to the total variation and is a measure of the degree of fit. When R^2 approaches to unity, the better response model fits the actual data. The value of R^2 calculated in Table 4 for this model is over 0.95 and reasonably close to unity, which is acceptable. It denotes that about 95% of the variability in the data is explained by this model. It also confirms that this model provides an excellent explanation of the relationship between the independent factors and the response.

The resulting ANOVA table for the quadratic model for thrust force is shown in Table 5. The model F-value of 204.78 implies that the model is significant. Results from Table 5 indicate that the model is still significant. However the main effect of cutting speed (Vc), feed rate (f) and depth of cut (ap) and the two level interactions of cutting speed and feed rate ($Vc \times f$), cutting speed and depth of cut ($Vc \times ap$) and feed rate and depth of cut ($f \times ap$) are the significant model terms. The R^2 value is high, close to 1, which is desirable. The Pred. R-Squared of 0.9771 is in reasonable agreement with the Adj R-Squared of 0.9860. The adjusted R^2 value is particularly useful when comparing models with different number of terms. Adequate Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. Our ratio of 49.861 indicates an adequate signal. So, this model can be used to navigate the design space.

From the analysis of influence on the feed force (Ft) is summed up in Table 6. It can be indicated that the model is still significant. However the main effect of feed rate (15.269%), depth of cut (80.233%) and the two level interactions of feed rate and depth of cut (2.552%) and the product (1.331%) have statistical significances on Ft, in particular the depth of cut factor. The cutting speed and the interactions $Vc \times f$, $Vc \times ap$, $Vc \times Vc$ and $ap \times ap$ do not present any statistical significance on the tangential force (Ft).

The R^2 value is high, close to 1, which is desirable. The Pred. R-Squared of 0.9636 is in reasonable agreement with the Adj R-Squared of 0.9796. The adjusted R^2 value is particularly useful when comparing models with different number of terms. Adequate Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. Our ratio of 39.932 indicates an adequate signal. So, this model can be used to navigate the design space.

Table 5. ANOVA result for thrust force (Fr).

Source	Sum of squares	DF	Mean square	F-value	Prob.	Cont. %	Remarks
Model	90669.8938	9	10074.4326	204.779112	<0.0001		Significant
Vc	6522.10764	1	6522.10764	132.57237	<0.0001	7.196	Significant
f	8630.79014	1	8630.79014	175.434746	<0.0001	9.523	Significant
ap	73509.3373	1	73509.3373	1494.19598	<0.0001	81.104	Significant
$Vc \times f$	230.806401	1	230.806401	4.6915128	0.0448	0.255	Significant
$Vc \times ap$	441.896033	1	441.896033	8.98225044	0.0081	0.488	Significant
$f \times ap$	281.20101	1	281.20101	5.71586462	0.0287	0.310	Significant
Vc^2	192.515585	1	192.515585	3.91319014	0.0643	0.212	No significant
f^2	759.204359	1	759.204359	15.4320546	0.0011	0.838	Significant
ap^2	67.6256463	1	67.6256463	1.37460046	0.2572	0.075	No significant
Error	836.341918	17	49.1965834				
Total	91506.2358	26				100	
SD = 7.01				R^2 = 0.9909			
Mean = 128.76				R^2 Adjusted = 0.9860			
Coefficient of variation = 5.45				R^2 Predicted = 0.9771			
Predicted residual error of sum of squares (PRESS) = 2094.81				Adequate precision = 49.861			

Table 6. ANOVA result for tangential force (Ft).

Source	Sum of squares	DF	Mean square	F-value	Prob.	Cont. %	Remarks
Model	51 243.4661	9	5693.71845	139.446333	<0.0001		Significant
Vc	3.32549067	1	3.32549067	0.08144545	0.7788	0.006	No significant
f	8139.17876	1	8139.17876	199.338734	<0.0001	15.269	Significant
ap	42 767.8569	1	42 767.8569	1047.43866	<0.0001	80.233	Significant
$Vc \times f$	174.912248	1	174.912248	4.28382115	0.0540	0.328	No significant
$Vc \times ap$	110.777633	1	110.777633	2.7130837	0.1179	0.208	No significant
$f \times ap$	1360.3513	1	1360.3513	33.316716	<0.0001	2.552	Significant
Vc^2	286 307 852	1	28.6307852	0.70120397	0.4140	0.054	No significant
f^2	709.433135	1	709.433135	17.3749106	0.0006	1.331	Significant
ap^2	9.91591852	1	9.91591852	0.24285333	0.6285	0.019	No significant
Error	694.1252	17	40.8308941				
Total	51 937.5913	26				100	
SD = 6.39				R^2 = 0.9866			
Mean = 101.46				R^2 Adjusted = 0.9796			
Coefficient of variation = 6.30				R^2 Predicted = 0.9636			
Predicted residual error of sum of squares (PRESS) = 1891.59				Adequate precision = 39.932			

The same procedure is applied to deal with the other response, surface roughness (Ra), and the resulting ANOVA for the quadratic model is shown in Table 7. The value of Prob. in Table 7 for this model is also less than 0.05 (i.e. $\alpha = 0.05$, or 95% confidence) and indicates that the model is considered to be statistically significant.

The model F-value of 6.860 implies that the model is significant. The value of Prob. in Table 7 for the model is 0.0004 which indicates that the model is significant, which is desirable as it indicates that the terms in the model have a significant effect on the response.

The significant model terms include the main effect of factor f (feed rate), factor ap (depth of cut) and interaction effect of factor $f \times ap$ (feed rate and depth of cut). The other model terms cannot be regarded as significant effect due to their "Prob. > F" values greater than 0.05. These insignificant model terms can be removed.

According to the results in ANOVA, a sensitivity analysis for the design factors in the surface roughness is performed and shown in the last column (Tab. 7). From the results of percent contribution for each significant design factor, the front two significant design factors in the surface roughness are factor depth of cut (44.39%) and factor feed rate (30.729%), and the interaction effect of factor, feed rate and depth of cut (17.962%).

3.2 Regression equations

The relationship between the factors and the performance measures were modeled by quadratic regression. The regression equations obtained were as follows.

The feed force model (Fa) is given by Equation (6) with a determination coefficient (R^2) of 98.69%.

$$\begin{aligned} Fa = {} & -14.377 - 0.096Vc + 202.346f + 44.994ap \\ & + 1.563Vc \times f + 0.931Vc \times ap + 584.423f \times ap \\ & - 0.0005Vc^2 - 1316.872f^2 + 251.5ap^2 \end{aligned} \quad (6)$$

Table 7. ANOVA result for surface roughness (Ra).

Source	Sum of squares	DF	Mean square	F-value	Prob.	Cont. %	Remarks
Model	2.18304893	9	0.24256099	6.86033192	0.0004		Significant
Vc	3.141E-05	1	3.141E-05	0.00088837	0.9766	0.001	No significant
f	0.77708889	1	0.77708889	21.9783389	0.0002	30.729	Significant
ap	1.12257123	1	1.12257123	31.7495865	<0.0001	44.390	Significant
$Vc \times f$	0.00424808	1	0.00424808	0.120148	0.7331	0.168	No significant
$Vc \times ap$	0.0108	1	0.0108	0.30545548	0.5877	0.427	No significant
$f \times ap$	0.45422308	1	0.45422308	12.8467526	0.0023	17.962	Significant
Vc^2	0.00253519	1	0.00253519	0.07170243	0.7921	0.100	No significant
f^2	0.13884615	1	0.13884615	3.92697396	0.0639	5.490	No significant
ap^2	0.01851852	1	0.01851852	0.52375768	0.4791	0.732	No significant
Error	0.60106959	17	0.03535703				
Total	2.78411852	26				100	
SD = 0.19					R^2 = 0.7841		
Mean = 0.71					R^2 Adjusted = 0.6698		
Coefficient of variation = 26.39					R^2 Predicted = 0.4619		
Predicted residual error of sum of squares (PRESS) = 1.5					Adequate precision = 8.919		

The thrust force model (Fr) is given by Equation (7) and the determination coefficient (R^2) is 99.09%.

$$\begin{aligned} Fr = &-134.25 + 0.990Vc + 1193.348f + 209.025ap \\ &+ 2.006Vc \times f + 1.733Vc \times ap + 775.149f \times ap \\ &- 0.0046Vc^2 - 4336.316f^2 + 335.722ap^2 \end{aligned} \quad (7)$$

The tangential force model (Ft) is given by the following Equation (8). Its coefficient of determination is 98.66%.

$$\begin{aligned} Ft = &-95.865 - 0.0045Vc + 1387.99f + 409.292ap \\ &- 1.748Vc \times f - 0.868Vc \times ap + 1704.914f \times ap \\ &+ 0.0017Vc^2 - 4191.769f^2 - 128.555ap^2 \end{aligned} \quad (8)$$

The roughness Ra model is given below in Equation (9). Its coefficient of determination (R^2) is 78.41%.

$$\begin{aligned} Ra = &-0.761 - 0.0033Vc + 25.123f + 0.580ap \\ &+ 0.008Vc \times f - 0.0085Vc \times ap - 31.143f \times ap \\ &+ 1.678 \times 10^{-5}Vc^2 - 58.642f^2 + 5.555ap^2 \end{aligned} \quad (9)$$

Figures 2 and 3 show the cutting forces components (Fa, Fr and Ft) and surface roughness (Ra) values obtained by experimentation and the values predicted by the quadratic model for mixed ceramic. It is clear that the predicted values are very close to the experimental readings. The adequacy of the quadratic model is verified using the analysis of variance (ANOVA). At a level of confidence of 95%, the model is checked for its adequacy. As shown in Table 6, the model is adequate owing to the fact that the P-values of lack-of-fit are not significant. This implies that the model could fit and it is adequate

3.3 Effect of machining parameters on surface response factors

The three-dimension surface plots were drawn to illustrate the main and interactive effects of the independent variables on the dependent one. These graphs (Figs. 4 to 7) were obtained by fixing one variable at middle level (Tab. 2) while varying the remaining two variables and predicting the response variables (Fa, Fr, Ft and Ra).

Figure 4 presents the effect of the feed rate and cutting speed on the feed force. Clearly, the cutting speed has a similar influence to that of the feed rate on the feed force. An increase of cutting speed results in an increase in the feed force, but with less effect when feed rate approaches 0.16–0.20 rev.min^{-1}.

Results of the combined effects of depth of cut and cutting speed on the thrust force (Fr) are presented in Figure 5. For dry condition, Figure 5 shows clearly that the thrust force increases significantly with depth of cut and cutting speed and the highest value occurs at highest depth of cut and highest cutting speed. It can be also observed that the Fr behaves linearly with depth of cut and nonlinearly with cutting speed.The increased depth of cut increases thrust force. As the depth of cut is increased, the cutting edge length in contact with the workpiece increases. This means that the working zone is out of the tool-nose radius [25].

The influence of depth of cut and feed rate on the tangential force (Ft) is presented in Figure 6. Both surface and contour plots show clearly a substantial linear increase of the Ft with depth of cut and a slight nonlinear increase with the feed rate. This figure shows that as the feed rate and the depth of cut increase the tangential force increases because of the sheared chip cross section that is getting larger together with the volume of the deformed metal. Therefore, the workpiece material becomes more resistant to shearing and there should be much effort applied to remove the chip. This trend is similar as results were reported by Aouici [26] when turning AISI H11 steel (52 HRC) using CBN7020 tool.

Figure 7 shows the combined effect of cutting speed and feed rate on the surface roughness at constant depth of cut. It is evident from the figure that the effect of feed rate is more significant than that of the cutting speed at

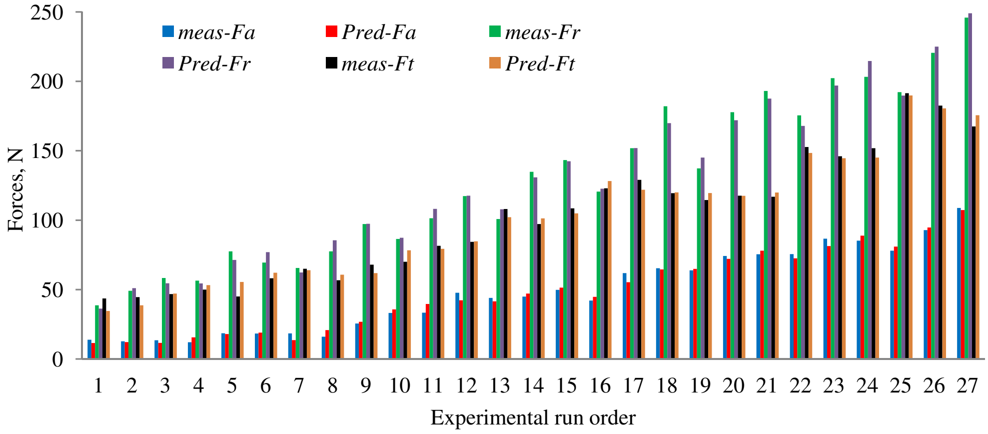


Fig. 2. Comparison between measured and predicted values for cutting force components.

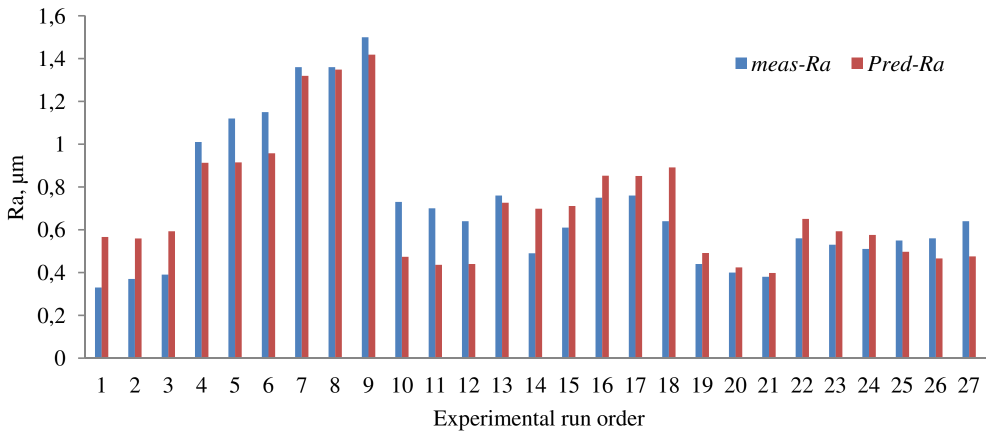


Fig. 3. Comparison between measured and predicted values for surface roughness.

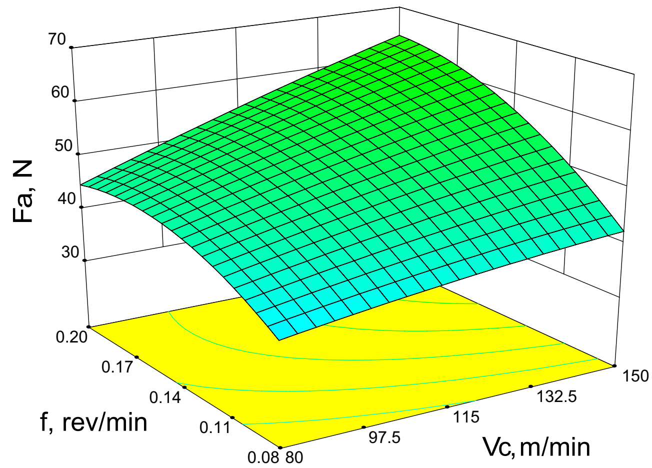


Fig. 4. The response surface of feed force according to change of feed rate and cutting speed.

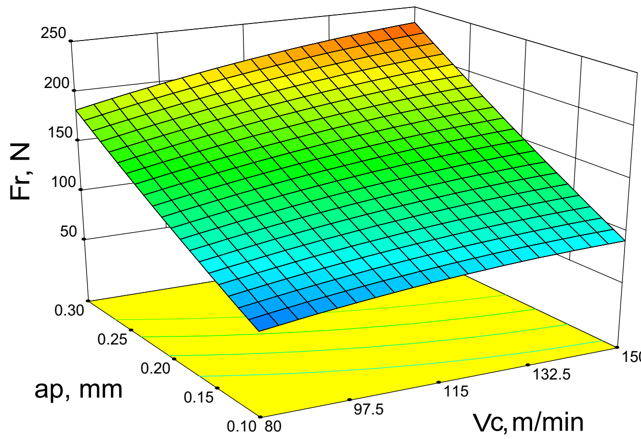


Fig. 5. The response surface of thrust force according to change of depth of cut and cutting speed.

constant depth of cut.This is because the increased feed rate increases cutting forces. As the feed rate is increased, the region of sheared chip increases, since resistance to material rupture is higher and hence requires larger efforts for chip removal [25]. From the contour plot we can easily predict the surface roughness and when both combined effect increases the surface roughness value increases substantially.

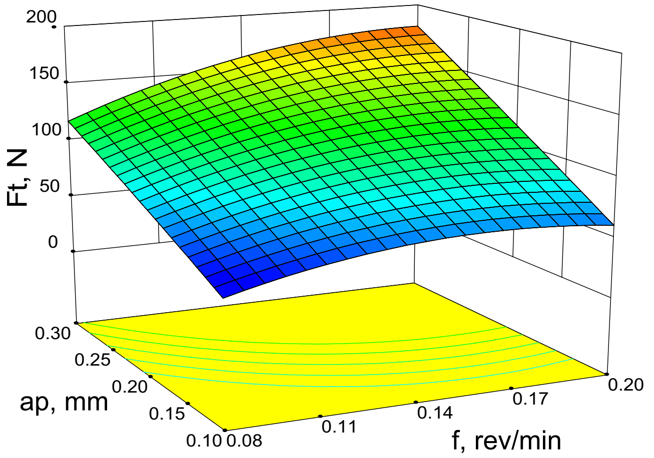


Fig. 6. The response surface of tangential force according to change of depth of and feed rate.

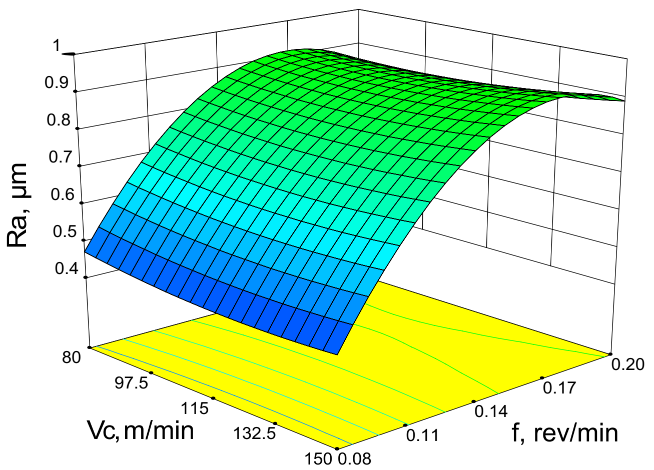


Fig. 7. The response surface of surface roughness according to change of cutting speed and feed rate.

3.4 D surface topography

The 3D surface profiles of the hard turned surfaces along the feed direction are shown in Figure 8. It must be noted that the both 3D profiles have represented pure roughness values, i.e. the turned surface topography in Figures 8a and 8b shows well-defined peaks and valleys, this is mainly because when the turning operation process uses a single cutting edge. The analysis of the effect of feed rate on surface roughness (Fig. 8) shows that this parameter has a very significant influence, because its increase generates helicoid furrows for the result tool shape and helicoid movement tool-workpiece. These furrows are deeper and broader as the feed rate increases. For this reason, we must employ weak feed rate during turning.

4 Optimization of cutting conditions

We consider that the optimal manufacturing conditions for machining hot work steel (AISI4140) are those minimizing the values of cutting force components (Fa, Fr and Ft) and surface roughness (Ra) during the hard turning process. The goals and the parameter ranges defined for the optimization process are summarized in Table 8.

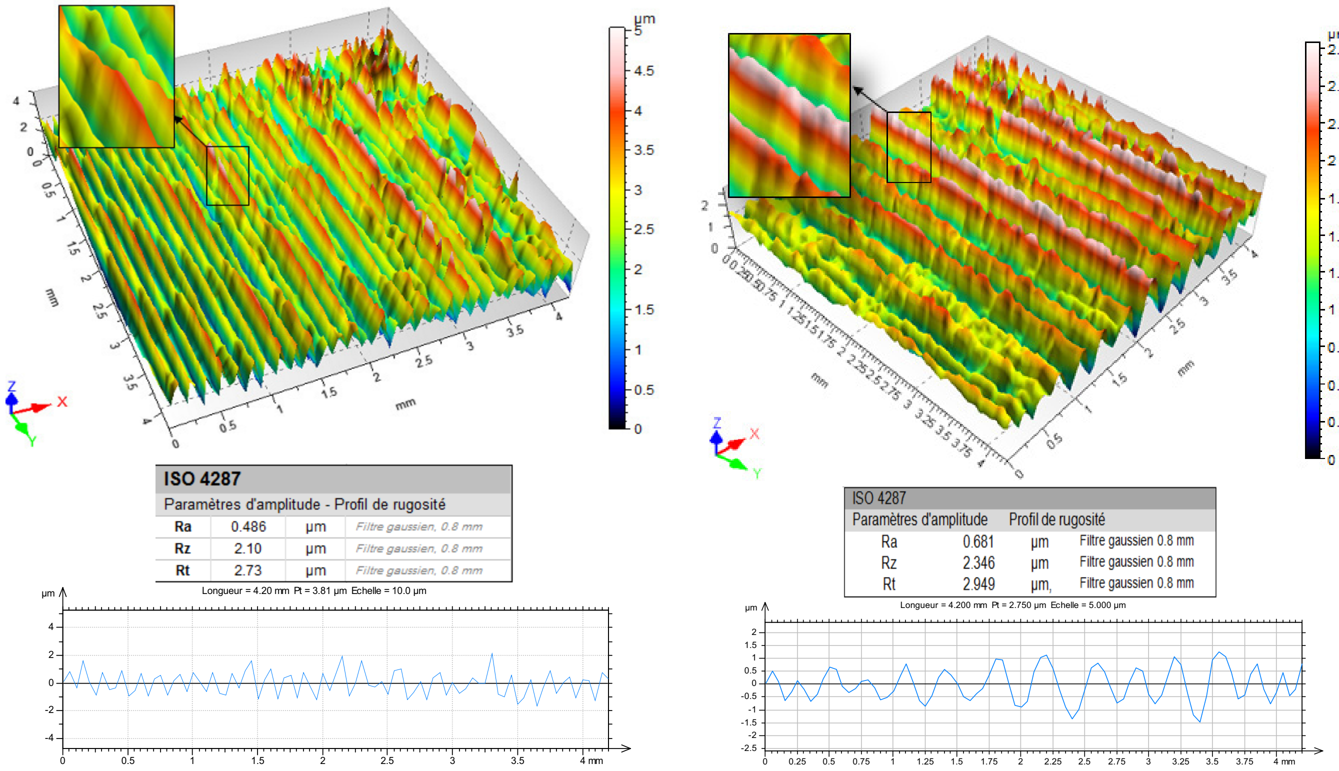
Table 9 shows the RSM optimization results (cutting force components (Fa, Fr and Ft) and surface roughness (Ra) in order of decreasing desirability level. The optimized surface roughness (Ra) and cutting force components (Fa, Fr and Ft) are (0.556–0.563) μm, [(11.655–12.176; (38.620–50.883) and 34.850–38.543)] N, respectively.

5 Confirmation experiments

In confirmation of the second-order (quadratic model) response surface model, verification tests were conducted at the optimal conditions (Tests 1 and 2) that were determined by the RMS method and one selected condition (Test 3) that was not carried out in Table 3. In Test 3, the same depth of cut of 0.3 mm, feed rate of 0.11 mm.rev^{-1} and cutting speed 115 m.min^{-1} were used. The data from the confirmation runs and their comparisons with the predicted designed cutting forces (Fa, Fr and Ft) and surface roughness (Ra) are listed in Table 10. Figure 9 presented the test result, it can be observed that the calculated error is small. The error between experimental and predicted values for Fa, Fr, Ft and Ra are lain within 0.008 to 4.130%, 0.002 to 2.838%, 0.003% to 2.856 and –11.698 to 0.179% respectively. All the experimental values for the confirmation run are within the 95% prediction interval. Obviously, the second-order response model was very useful for predicting the machining responses.

6 Conclusion

This paper presents the findings of an experimental investigation into the effect of cutting speed, feed rate and depth of cut on the cutting force components (Fa, Fr and Ft) and surface roughness (Ra) when turning AISI 4041 steel. The ANOVA revealed that depth of cut and feed rate are the most significant factor influencing the response variables investigated. The feed rate and depth of interaction factors provided secondary contribution to the responses investigated. Additionally, the cutting speed also provided secondary contribution to the feed force and thrust force. The comparison of experimental and predicted values of surface roughness and cutting force components shows that good agreement has been achieved between them. Therefore, the developed model can be recommended to be used for predicting surface roughness and cutting force components. The confirmation tests showed that the error between experimental and predicted values of cutting force components (Fa, Fr and Ft) and surface roughness are within 0.008 to 4.130%, 0.002 to 2.838%, 0.003% to 2.856 and –11.698



(a) (b)

Fig. 8. 3D-topography plot of the mixed ceramic for; (a) $f = 0.08$ mm.rev^{-1} and (b) $f = 0.14$ mm.rev^{-1}.

Table 8. Constraints for optimization of cutting conditions.

Condition	Goal	Lower limit	Upper limit	Importance
Cutting speed, Vc (m.min^{-1})	Is in range	8	150	***
Feed rate, f (mm.rev^{-1})	Is in range	0.08	0.14	***
Depth of cut, ap (mm)	Is in range	0.10	0.3	***
Feed force Fa (N)	Minimize	12.72	108.79	*****
Thrust force Fr (N)	Minimize	38.62	245.97	*****
Tangential force Ft (N)	Minimize	43.61	191.43	*****
Surface roughness (Ra)	Minimize	0.33	1.50	*****

Table 9. Optimization results.

Solution No.	Vc (m.min^{-1})	f(mm.rev^{-1})	ap (mm)	Fa (N)	Fr (N)	Ft (N)	Ra (μm)	Desirability
1	82.22	0.08	0.10	12.070	38.620	35.708	0.561	0.9490
2	84.13	0.08	0.10	11.655	38.622	34.850	0.563	0.9486
3	86.53	0.08	0.10	11.716	39.871	34.991	0.561	0.9475
4	89.17	0.08	0.10	12.069	41.819	35.746	0.558	0.9462
5	92.39	0.08	0.10	11.881	42.779	35.507	0.559	0.9450
6	103.89	0.08	0.10	12.099	47.567	36.874	0.556	0.9401
7	108.71	0.08	0.10	12.149	49.211	37.588	0.557	0.9380
8	114.44	0.08	0.10	12.176	50.883	38.543	0.558	0.9357

Table 10. Confirmation experiment.

Exp. No.	Designing parameters			For regression equations		
	Vc (m.min^{-1})	f (mm.rev^{-1})	ap (mm)	Exp.	Predict.	Error %
Feed force (Fa)						
1	82.22	0.08	0.1	12.070	11.571	4.130
2	103.89	0.08	0.1	12.099	12.098	0.008
3	115	0.11	0.30	86.640	81.29	0.061
Thrust force (Fr)						
1	82.22	0.08	0.1	38.620	37.524	2.838
2	103.89	0.08	0.1	47.567	47.566	0.002
3	115	0.11	0.30	202270	19695	2.630
Tangential force (Ft)						
1	82.22	0.08	0.1	35.708	34.688	2.856
2	103.89	0.08	0.1	36.874	36.873	0.003
3	115	0.11	0.30	14604	14459	0.992
Surface roughness (Ra)						
1	82.22	0.08	0.1	0.561	0.564	–0.534
2	103.89	0.08	0.1	0.557	0.556	0.179
3	115	0.11	0.30	0.530	0.592	–11.698

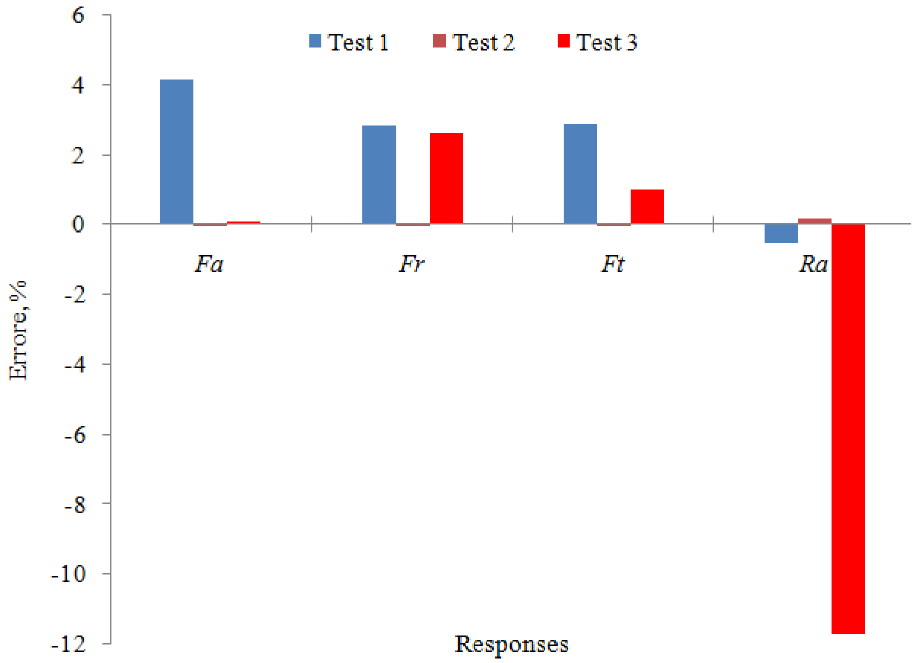


Fig. 9. Verification results for the machining responses comparing response surface model with experiments.

to 0.179% respectively. The results of ANOVA and the validation experiments confirm that the developed mathematical model shows excellent fit and predicted values are very close to experimental values.

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