Modeling and optimization of surface roughness and productivity thru RSM in face milling of AISI 1040 steel using coated carbide inserts

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CHRONICLE

Article history:

Received October 27 2016

Received in Revised Format

December 22 2016

Accepted February 27 2017

Available online

March 1 2017

Keywords:

Face milling

RSM

Optimization

Flank wear

Surface roughness and productivity

ABSTRACT

The aim of this study is to evaluate the impact of factors such as cutting speed, feed rate, and depth of cut on surface roughness and Material Removed Rate (MRR) when machining in dry face milling AISI 1040 steel with coated carbide inserts GC1030 using the response surface methodology (RSM). For this purpose, a number of machining experiments based on statistical three-factor and three-level factorial experiment designs, completed (L27) with a statistical analysis of variance (ANOVA), were performed in order to develop mathematical models and to identify the significant factors of these technological parameters. Multi-objective optimization procedure for minimizing R_a , R_y and R_z and maximizing MRR using desirability approach has been also implemented. The current study was also carried out to investigate the tool life of the inserts. The models found the relationship between the cutting parameters (V_c , f_z and a_p) and the studied technological parameters. It has been found that the cutting speed was the most affecting surface roughness which is due to the geometry of the insert which has a scraping edge and enables to obtain low roughness even at important feed rate, followed by the feed rate and the depth of cut at the end. The optimal combination of cutting parameters were cutting speed of 314 m/min, feed rate of 0.16 mm/tooth and depth of cut of 0.6 mm with a composite desirability of 0.924.

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Nomenclature

V_c	Cutting speed, m/min	<i>ANOVA</i>	Analysis of variance
f_z	feed rate, mm/tooth	<i>df</i>	Degrees of freedom
a_p	depth of cut, mm	<i>SS</i>	Sequential sum of square
a_e	Radial depth of cut, mm	<i>MS</i>	Adjusted mean squares
R_a	arithmetic mean roughness, μm	<i>Cont. %</i>	Contribution ratio, %
R_y	total roughness, μm	<i>P</i>	Probability
R_z	mean depth of roughness, μm	R^2	coefficient of determination
Z	Number of tooth	<i>MRR</i>	Material Removed Rate, mm^3/min
D	Diameter milling cutter, mm	<i>VB</i>	Flank wear, mm.

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1. Introduction

The surface roughness is one of the important performance index. It is also considered as the most useful technological parameters due to its relation to many other mechanical properties such as tool life, capacity of adjustment, wear resistance and tightness (Aouici et al., 2013; Meddour et al., 2015; Bouacha et al., 2014; Panda et al., 2016). Therefore, surface defects play a crucial role in the ability of the part to perform a particular function (Fnides et al., 2013; Bhuyan & Routara, 2016). These defects have either geometrical and/or physico-chemical nature. In the present paper, only the geometrical defects are concerned. In the optimization study of the surface roughness, for the case of face milling of an aluminum alloy mold 6061 -T6 with coated carbide inserts, Kadirgama et al. (2009) found that the RSM was an effective technique for the trends of the surface roughness analysis with respect to different combinations of cutting parameters (cutting speed, feed per tooth, axial and radial depth of cut).

The optimal parameters that could give a good surface in end milling of titanium alloys using the design method of Taguchi has been evaluated by Khairi et al. (2010); the authors used the analysis of variance (ANOVA) for identifying the significant factors affecting roughness. They found that the most significant factors affecting the surface roughness were mainly the cutting speed (V_c), followed by the type of the tool used, the feed rate (f_z) and lastly, the depth of cut (a_p). Doniavi et al. (2007) proved that the application of the analysis of variance (ANOVA) showed that the feed rate and cutting speed were the most significant factors on the roughness contrary to the depth of cut. The authors used the response surface methodology (RSM) to develop an empirical model for the prediction of the roughness by choosing the optimum cutting conditions in hard turning. RSM has been used by Oktem et al. (2005) to create an efficient analytical model for surface roughness in terms of cutting parameters: feed rate, cutting speed, axial depth of cut, radial depth of cut and machining tolerance.

Many of other researchers (Kevin et al., 2003; Huang et al., 2001) used the technique of multiple linear regressions to develop a comprehensive empirical model of roughness taking into account several factors such as the feed rate, the hardness of the workpiece, the depth of cut, the cutting speed and their interactions. Recently, Koblouti et al. (2016) analyzed and optimized the influence of coating material of cutting tool and machining parameters on surface roughness, in dry turning of AISI 52100 steel. It is observed that a lower surface roughness value is achieved using the PVD (TiCN/TiN) coated insert compared to the uncoated tool. Aouici et al. (2016) investigated and analyzed the surface roughness of different cutting materials in machining AISI H11. The ANOVA result confirmed that multiple linear regression models predict the surface roughness parameter with a confidence level of 95%.

John (2013) used desirability approach to optimize the advantage characteristics of carbonitrided bushes. The results proved that the optimum combination was found through the use of different methods. Mohapatraa et al. (2017) used two multi objective optimization methods for MRR and surface quality comparison of optimization techniques for MRR and surface roughness in the wire EDM process for gear cutting. He investigated the comparison of the wire EDM phenomenon using the Taguchi quality loss function and the hybrid optimization method. Tebassi et al. (2016) studied how to optimize surface quality, cutting forces and productivity when machining Inconel 718. RSM Box-Cox profiles have been investigated to find mathematical models followed by a desirability approach to optimize R_a , cutting forces, f_z and a_p .

In the current study, different combinations of material-process and tool have been investigated with the integration of the wear analysis. It intends to study the impact of machining conditions on the surface roughness based on the methodology of response surface for face milling of the AISI 1040 steel with coated carbide insert. Multi-objective optimization procedure allowed minimizing R_a , R_y and R_z and maximizing MRR using desirability approach has been also approved and the tool life of the inserts were calculated.

2. Experimental procedures

2.1. Equipments and materials

In this study, the machining experimental tests are performed under dry conditions using a vertical milling machine (FV 1.5) of the company PMO (Almo) running at 5 KW.

The workpiece material used in this investigation is a commercially available AISI 1040 steel grade with the following dimensions: 405mm X 73mm X 73mm. equivalent with the nuance C35 (NF EN 10027-1) at a better aptitude for the heat treatments. As for parts, they are fairly subjected to shocks and requiring good resistance, they were: gears, endless screw, axes, pinions, nuts and bolts, forging mill (levers, Arbors.....). The chemical composition and mechanical properties are given respectively in Table 1 and Table 2.

Table 1

Chemical composition of AISI 1040 steel on %

C	S	Mn	P	Si	Mo
0.37- 0,44	=< 0.035	0.50- 0,80	=< 0.035	0.40 maxi	=< 0.10

Table 2

Mechanical characteristics of AISI 1040 steel

Rm, N/mm ²	Re, N/mm ²	A, %	Hardness
530/580	260/320	16/17	mini 54 HRC

Coated carbide inserts with PVD applied unique -layer TiAlN coating of 3.5 micrometer thickness were employed for the machining experiments.- ISO tool designation GC1030 (R245-12 T3-EPL) from Sandvik Coromant tool manufacturer - The specification of the inserts was wiper edge length (scraping edge) BS = 2.1 mm (Fig. 1). This insert presents first choice in end milling and for sticky materials, e.g. low-carbon steel.

The milling cutter used in this experiment was a CoroMill 245 cutter which has a capacity for 5 inserts designed and provided by Sandvik Coromant (R245-100Q32-12L). Fig. 1 shows the geometry of the cutting inserts and the milling cutter used for all experiments.

A 2D roughness meter Sj- 201p (Mitutoyo) was selected to measure surface roughness criteria (Ra: The arithmetic average roughness, Ry: The total roughness and Rz: height of irregularities). It consisted of a diamond point (probe) with a 5 μ m radius and moves linearly on the working surface. The length examined was 4.0 mm with a basic cut-off of 0.8 mm, these measurements were repeated three times. The average value of these results was calculated. All roughness measurements have been obtained directly on the tool machine without disassembling the workpiece. On the other hand the analysis of the surface roughness was done using both profiles and 3D topographies of the generated surfaces (Alti surf 500). (See Fig. 1).

For the wear tests, the cutting speed Vc and the feed rate fz have been considered as the parameters showing more influence on this phenomenon (Patel et al., 2006; Richetti et al., 2004; Da Silva et al., 2011; Aouici et al., 2014). For lows and intermediates cutting speed and feed rate, the wear occurs at a much longer length of cut corresponding of 120000 mm (300 machining pass). Subsequently, it was important to take severe cutting conditions, such as Vc = 439.6 m/min (n = 1400 rpm); fz = 0.114 mm/tooth (Vf = 800 mm/min); ap = 0.6 mm. The tool life rejection criterion was flank wear, VB = 0.3 mm. Flank wear was measured at various intervals at the end of each pass (i.e., after cutting tool moves along a complete length of a workpiece). Relevant images of the worn tools were selected and captured with the microscope (Standard gage- Visual 250) equipped with (Visual Gage 2.2.0) software (Fig. 1).

Fig. 1. Illustration of measured surface roughness and tool wear

2.2. Experiment design

Cutting experiments are planned using statistical three-level full factorial experimental design and conducted considering three cutting parameters: cutting speed (V_c), feed rate (f_z), depth of cut (ap). Overall 33 = 27 tests are carried out. Low–middle–high level of cutting parameters in cutting space for three-level full factorial experimental design is shown in Table 3.

Table 3

Low–middle–high levels of cutting parameters in three-level full factorial design of experiment

Factors	Symbol	Levels		
		Level 1	Level 2	Level 3
Cutting speed (m/min)	V_c	78	157	314
Feed rate (mm/ tooth)	f_z	0.04	0.08	0.16
Depth of cut (mm)	ap	0.2	0.4	0.6

2.3. Response surface methodology

The response surface methodology (RSM) (Bouazid et al., 2014a; Aouici et al., 2014; Hessainia et al., 2015; Bhaumik & Maity, 2017; Nayak et al., 2017) is both a statistical and a mathematical technique that is useful for modeling and analyzing problems in which responses can be affected by several variables.

ANOVA tables show the DF, SS, MS, F-VAL, P-VAL in addition to the percentage contribution of each factor and the coefficients of regression mathematical models estimated for Ra, Ry, Rz criteria and MRR, the aim is to analyze the main effect as well as the interactions (Fnides et al., 2009). To calculate constants and coefficients of mathematical models, the Minitab software has been used and characterized by the Analysis of Variance: ANOVA, multiple regression and Response Surface Methodology (RSM). In the current study, the relationship between the cutting conditions and the technology parameters is given by Eq. (1).

$$Y = \phi(Vc, fz, ap), \quad (1)$$

where Y is the desired machinability (roughness, forces, etc.) and ϕ is the response function. The approximation of Y is proposed by using a General Regression with interaction terms, which is suitable for studying the main effects of process parameters on machinability characteristics.

3. Results and discussion

In Table 4, the experimental values of different criteria surface roughness (Ra, Ry, and Rz) and the Material Removed Rate are shown. These values were obtained by using various combinations of elements of the cutting regime elements (cutting speed, feed per tooth and depth of cut) according to 33 full factorial design.

Table 4
Experimental data for AISI 1040 steel

Runs	Factors			Responses			
	Vc, m/min	fz, mm/tooth	ap, mm	Ra, μm	Ry, μm	Rz, μm	MRR, mm^3/min
1	78	0.04	0.2	2.23	13.84	12.18	730
2	78	0.04	0.4	2.29	15.12	12.22	1460
3	78	0.04	0.6	2.32	14.86	12.66	2190
4	78	0.08	0.2	2.37	12.93	12.22	1460
5	78	0.08	0.4	2.4	15.83	12.83	2920
6	78	0.08	0.6	2.42	16.05	13.09	4380
7	78	0.16	0.2	2.58	16.82	13.65	2920
8	78	0.16	0.4	2.6	18.67	14.61	5840
9	78	0.16	0.6	2.62	20.55	15.47	8760
10	157	0.04	0.2	1.5	7.89	7.47	1460
11	157	0.04	0.4	1.54	8.16	7.64	2920
12	157	0.04	0.6	1.55	8.17	7.92	4380
13	157	0.08	0.2	1.59	8.56	7.68	2920
14	157	0.08	0.4	1.6	8.57	7.74	5840
15	157	0.08	0.6	1.61	9.3	8.28	8760
16	157	0.16	0.2	1.62	9.84	7.86	5840
17	157	0.16	0.4	1.64	10.22	8.62	11680
18	157	0.16	0.6	1.65	11.04	9.38	17520
19	314	0.04	0.2	0.5	3.27	2.73	2920
20	314	0.04	0.4	0.48	3.71	3.01	5840
21	314	0.04	0.6	0.51	2.85	3.05	8760
22	314	0.08	0.2	0.55	2.92	3.81	5840
23	314	0.08	0.4	0.6	3.32	3.14	11680
24	314	0.08	0.6	0.62	3.77	3.3	17520
25	314	0.16	0.2	0.65	3.7	3.36	11680
26	314	0.16	0.4	0.76	3.35	3.74	23360
27	314	0.16	0.6	0.82	4.83	4.17	35040

3.1. Analysis of variance (ANOVA)

3.1.1. Analysis of variance (ANOVA) for R_a , R_y and R_z

In the 1930 this method was developed by Sir Ronald Fisher. ANOVA is a statistically objective based decision-making tool for detecting any differences in average performance of groups of items tested (Eyup et al., 2006). The analysis of variance (ANOVA) of the criteria surface roughness R_a , R_z and R_y respectively indicated in Tables (5-7). These numbers show that the cutting speed (V_c) is the most influential factor on the surface roughness followed by the feed rate (f_z) and finally the depth of cut (ap) with a negligible contribution. The contribution of (V_c) on R_a , R_y and R_z are respectively 96.05%, 86.75% and 92.21%, for feed per tooth (f_z) it was 1.5%, 3.52% and 1.88%, finally the depth of cut (ap) with contributions of 0.10%, 0.95% and 0.49%. We have noted, on the contrary, of what is known that the effect of the cutting speed is superior to the feed rate, which is due to the geometry of the insert which has a scraping edge, which enables to obtain low roughness even at important feed rate, as Khairi et al. (2010) had found.

Table 5

Analysis of variance for the surface roughness R_a

Source	DF	SS	MS	F	P	Cont%
Regression	6	14.4889	2.4148	118.613	0.0000	97.26%
V_c	1	14.2278	1.3353	65.591	0.0000	95.51%
f_z	1	0.2167	0.0188	0.925	0.3477	1.4%
ap	1	0.0338	0.0000	0.001	0.9786	0.2%
V_c*f_z	1	0.0049	0.0049	0.243	0.6273	0.032%
V_c*ap	1	0.0018	0.0018	0.089	0.7688	0.012%
f_z*ap	1	0.0039	0.0038	0.191	0.6667	0.026%
Error	20	0.4072	0.0203			
Total	26	14.8961				

Table 6

Analysis of variance for the surface roughness R_y

Source	DF	SS	MS	F	P	Cont%
Regression	6	715.982	119.330	45.3023	0.0000	93.14%
V_c	1	666.773	24.694	9.3746	0.0061	86.74%
f_z	1	27.724	5.458	2.0719	0.1655	3.60%
ap	1	7.540	1.277	0.4848	0.4942	0.98%
V_c*f_z	1	9.344	9.344	3.5474	0.0742	1.21%
V_c*ap	1	2.668	2.668	1.0128	0.3262	0.34%
f_z*ap	1	1.933	1.933	0.7338	0.4018	0.25%
Error	20	52.682	2.634			
Total	26	768.663				

Table 7

Analysis of variance for the surface roughness R_z

Source	DF	SS	MS	F	P	Cont%
Regression	6	430.403	71.7338	66.5546	0.0000	95.23%
V_c	1	416.738	25.2347	23.4128	0.0001	92.20%
f_z	1	8.502	0.7966	0.7391	0.4001	1.88%
ap	1	2.247	0.1756	0.1629	0.6907	0.49%
V_c*f_z	1	1.462	1.4619	1.3563	0.2578	0.32%
V_c*ap	1	0.586	0.5856	0.5433	0.4696	0.13%
f_z*ap	1	0.868	0.8680	0.8054	0.3801	0.19%
Error	20	21.556	1.0778			
Total	26	451.959				

The contributions of interactions ($V_c \times f_z$, $V_c \times a_p$ and $f_z \times a_p$) are respectively (0.032%, 0.012%, 0.026%), (1.21%, 0.34%, 0.25%) and (0.32%, 0.13%, 0.19%) on R_a , R_y and R_z . The main effect diagram shows that the cutting speed has the most influential factor on the criteria surface roughness R_a since it has the greatest slope, followed by the feed per tooth and finally the effect of depth of cut does not have a significant impact compared to cutting speed and feed (Fig. 2a). It is clear from Fig. 2b that interactions diagrams of cutting parameters have no significant effects on criteria surface roughness (R_a) because the lines do not intersect.

Fig. 2. Main plot effects and interactions plot for R_a (a, b), MRR (c, d)

3.1.2. Analysis of variance (ANOVA) for MRR

The Material Removed Rate in milling operations is the volume of material/metal that is removed per unit time in mm^3/min . The study of this parameter is important: the goal is to manufacture low cost, high quality products in short time (Fnides et al., 2013; Bouzid et al., 2014a). The value of Material Removed Rate was calculated by the following Eq. (2).

$$MRR(\text{mm}^3/\text{min}) = a_p(\text{mm}) \times a_e(\text{mm}) \times f_z(\text{mm/tooth}) \times Z \times \frac{V_c(\text{m/min}) \times 1000}{\pi \times D(\text{mm})} \quad (2)$$

Table 8

Analysis of variance for Material Removed Rate

Source	DF	SS	MS	F	P	Cont%
Regression	6	1560921559	260153593	224.149	0.0000000	98.53%
Vc	1	487424660	46421396	39.997	0.0000036	30.76%
fz	1	487425867	46252592	39.851	0.0000037	30.76%
ap	1	284331756	35432272	30.529	0.0000208	17.94%
Vc*fz	1	139264189	139264189	119.991	0.0000000	8.79%
Vc*ap	1	81237643	81237643	69.995	0.0000001	5.13%
fz*ap	1	81237644	81237644	69.995	0.0000001	5.13%
Error	20	23212508	1160625			
Total	26	1584134067				

Table 8 shows the results of the analysis of variance (ANOVA) for the Material Removed Rate, the analysis (ANOVA) shows that the cutting speed and the feed per tooth are the most significant factors. For their contributions are 30.76 % for both parameters, followed by the depth of cut with a contribution of 17%. All of the interactions ($V_c \times f_z$, $V_c \times a_p$ and $f_z \times a_p$), have significant effects on the Material Removed Rate. Respectively, their contributions are 8.79%, 5.13% and 5.13%. For the main effects plot, we see that the three parameters (V_c , f_z and a_p) have some influences on the Material Removed Rate (Fig. 2c). Fig. 2d shows the interaction plot of cutting parameters for MRR.

3.2. Modeling of R_a , R_y , R_z and MRR

Regression analysis is used to investigate and model the relationship between a response variable and one or more predictors. RSM is a combination of mathematical and statistical techniques which is useful for the modeling and analysis of the problem. It determines the suitable approximation for the true functional relationship between the response and the set of independent variables (Myers et al., 2002) and it is commonly approximated by polynomial functions where models are obtained by conducting small number of experiments using design of experiment (Sahoo et al., 2014). According to Hessainia et al. (2013); Bouzid et al. (2014b), the correlations between the factors and the performance measures were modeled by linear regressions. Mathematical models were developed using the multiple regression method. R_a , R_y , R_z and MRR are successively given by Eqs. (3- 6), their coefficients of determination R^2 are respectively 97.27 %, 93.15%, 95.23% and 98.53%.

$$R_a = 2.65599 - 0.00726733 \times V_c + 1.70439 \times f_z - 0.012765 \times a_p - 0.00273646 \times V_c \times f_z + 0.000505119 \times V_c \times a_p + 1.47321 \times f_z \times a_p \quad (3)$$

$$R^2 = 97.27 \%, \quad R^2 (\text{adj}) = 96.45\%, \quad R^2 (\text{pred}) = 94.77\%$$

$$R_y = 13.3783 - 0.0315938 \times V_c + 29.1751 \times f_z + 3.76226 \times a_p - 0.120222 \times V_c \times f_z - 0.0196253 \times V_c \times a_p + 32.8423 \times f_z \times a_p \quad (4)$$

$$R^2 = 93.15\%, \quad R^2 (\text{adj}) = 91.09\%, \quad R^2 (\text{pred}) = 87.33\%$$

$$R_z = 13.1258 - 0.0319381 \times V_c + 11.1464 \times f_z + 1.39511 \times a_p - 0.0475516 \times V_c \times f_z - 0.00919462 \times V_c \times a_p + 22.0089 \times f_z \times a_p \quad (5)$$

$$R^2 = 95.23\%, \quad R^2 (\text{adj}) = 93.80\%, \quad R^2 (\text{pred}) = 91.28\%$$

$$MRR = 7927.21 - 43.31 \times V_c - 84934.4 \times Fz - 19818 \times ap + 464.12 \times V_c \times f_z + 108.295 \times V_c \times ap + 212917 \times f_z \times ap \quad (6)$$

$$R^2 = 98.53\%, \quad R^2 (\text{adj}) = 98.10\%, \quad R^2 (\text{pred}) = 94.79\%$$

These equations can be used to calculate the R_a and MRR from cutting parameters. For Residuals plot for R_a : normal probability plot, A Histogram of the Residuals, Residuals Versus Fitted Values and Residuals Versus Order of Data are represented respectively in Fig. 3a, Fig. 3b, Fig. 3c and Fig. 3d. We notice a goodness of model fit in regression and ANOVA and the normality assumption is valid.

Finally, the curves in Figs. (4-5) are used to compare the predicted values (provided by the model) of the criteria surface roughness R_a , and Material Removed Rate with the experimental values in order to evaluate the fit of the model. The analysis showed a good correlation between the two curves (Sahoo et al., 2014). The experimental and predicted values are very close to each other. Thus, the developed mathematical models can effectively be utilized for prediction of surface roughness.

Fig. 3. Residual plots for Ra **Fig. 4.** Comparison between the predicted (pre) and measured (exp) values for Ra **Fig. 5.** Comparison between the predicted (pre) and calculated (exp) values for MRR

3.3. Response surface and contour plots of R_a and MRR

RSM determines the suitable approximation for the true functional relationship between the response and the set of independent variables (Barua et al., 2010). The 3D response surface (Fig. 6) shows that the increase in the cutting speed decreases the criteria surface roughness R_a by increasing against the feed per tooth and increasing the surface roughness. Depth of cut has a small influence. Therefore, the better roughness are obtained by applying a low feed per tooth and a high cutting speed. These figures were obtained using response surface methodology according to their mathematical models. On the other hand, contour graphs (Fig. 7) allow visualizing the response surface and establishing the response values. It shows the relationship between a responses value (R_a) and the factors (V_c , f_z and a_p) from a model equation. The points having the same response are joined to generate the contour lines of constant responses. The (3D) response surface plot of the Material Removed Rate MRR according to the factors of the experiment is shown in Fig. 8. This figure shows that the slope of the feed per tooth (f_z) and the cutting speed (V_c) are higher, implying that these factors have an important influence on the Material Removed Rate followed by the depth of cut (a_p). On the other hand, the contour graphs (Fig. 9) allow visualizing the response surface and establishing the response values.

Fig. 6. Response surface for R_a as a function of (V_c , f_z), (V_c , a_p) and (a_p , f_z)

Fig. 7. Contour plot of $Ra = f(V_c, f_z, a_p)$

3.4. Multi-response optimization using desirability approach

Optimization methods have to be used to obtain the optimum machining conditions for milling operations using surface roughness and Material Removed Rate as responses. During the optimization process, the aim is to minimize the criteria surface roughness Ra , Rz and Ry and Maximize the MRR. The desirability approach is a popular method that assigns a “score” to a set of responses and chooses factor settings that maximize that score and it is an objective function that ranges from zero outside of the limits of one at the goal. The numerical optimization finds a point that maximizes the desirability function. The characteristics of a goal may be altered by adjusting the weight or importance. For several responses and factors, all goals get combined into one desirability function (Aman et al., 2008). To resolve this type of parameter design problem, an objective function, $F(x)$, is defined as follows Eq. (7) (Myers et al., 2002; Bouzid et al., 2014a; Routara et al., 2009).

$$DF = \left(\prod_{i=1}^n d_i^{w_i} \right)^{\sum_{j=1}^{1/n} w_j} \quad (7)$$

$$F(x) = -DF$$

where d_i is the desirability defined for the i^{th} targeted output and w_i is the weighting of d_i . For various goals of each targeted output, the desirability d_i can be defined in different forms.

Fig. 8. Response surface for MRR as a function of (Vc, fz), (Vc, ap) and (ap, fz)

Fig. 9. Contour plot of $MRR = f(Vc, fz, ap)$

The constraints used during the optimization process are summarized in Table 9. The optimal solutions are reported in Table 10 in order to decrease the desirability level. Fig. 10 and Table 10 show the optimization results. Values of optimal cutting parameters are found to be as follows: $V_c = 314$ /min, $f_z = 0.16$ mm/tooth and $a_p = 0.6$ mm. The optimized criteria surface roughness and Material Removed Rate are as follows: $R_a = 0.709548$, $R_y = 3.79162$, $R_z = 3.69408$ μm and $MRR = 32804.9$ mm^3/min . Figs. 11, 12 and 13 present respectively the contour plot, response surface and the bar graph of composite desirability for the cutting conditions and the responses together with a combined desirability = 0.924.

Table 9

Constraints for optimization of machining parameters

Constraints	Goal	Lower limit	Upper limit
V_c , m/min	In range	78	314
f_z , mm/tooth	In range	0.04	0.16
a_p , mm	In range	0.2	0.6
R_a , μm	Minimize	0.48	2.62
R_y , μm	Minimize	2.85	20.55
R_z , μm	Minimize	2.73	15.47
MRR , mm^3/min	Maximize	730	35040

Table 10Response optimization for surface roughness and MRR

N ^{ber}	V_c , m/min	f_z , mm/tooth	a_p , mm	R_a , μm	R_y , μm	R_z , μm	MRR , mm^3/min	Desirability
1	314.000	0.160	0.600	0.710	3.792	3.694	32804.878	0.924
2	314.000	0.160	0.600	0.709	3.787	3.690	32722.181	0.924
3	313.999	0.160	0.596	0.709	3.780	3.686	32607.955	0.923
4	314.000	0.159	0.600	0.707	3.777	3.681	32551.972	0.923
5	313.994	0.158	0.600	0.706	3.770	3.676	32430.457	0.923
6	313.997	0.160	0.593	0.709	3.771	3.680	32459.469	0.923
7	313.999	0.160	0.591	0.708	3.766	3.677	32377.561	0.922
8	314.000	0.156	0.600	0.702	3.743	3.653	31993.905	0.921

Fig. 10. Ram function graph for surface roughness and Material Removed Rate

Fig. 11. Contour plot of Composite desirability for Ra, Ry, Rz and MRR

Fig.12 Response surface of Composite desirability for Ra, Ry, Rz and MRR

Fig. 13. 3D bar graph of desirability for Ra, Ry, Rz and MRR

3.5 Flank wear effect on cutting length and roughness

Fig. 14 shows the evolution of the flank wear (VB) and the maximum flank wear (VBmax) according to the cutting length L_c . The value of wear shown in the curve is the average of the five cutting inserts. The results obtained show that the wear goes through three steps. In the first step the flank wear is relatively accelerated, reaching $VB = 0.147$ mm for a cutting length $L_c = 6684$ mm (501 sec); this is explained by the first commissioning of cutting tool, which favors the coating removal and elimination of the asperities at the cutting edges. The second step is the normal wear period, during which the tool travels a total cutting length $L_c = 29960$ mm (2247 sec), it reaches a wear $VB = 0.32$ mm. Beyond this point, the temperature in the contact area of the active portion will increase more and more, which promotes the acceleration of the wear mechanism until $VB_{max} = 0.72$ mm with $L_c = 34000$ mm (2551 Sec). Therefore, the tool loses its cutting qualities then its change becomes indispensable. The tool wear behaviors were also pointed out by Khrais et al. (2007). Excellent scraping edge -line gives it a greater resistance to wear. In the first zone, the results of the Fig. 15 show a significant increase in the surface roughness R_a of the order of $0.6 \mu\text{m}$, for a flank wear ($VB = 0.147$ mm) after a cutting length $L_c = 6684$ mm (501 Sec). In the second zone corresponding to the normal wear phase, there has been a certain stability of the roughness R_a , which is of the order of $0.75 \mu\text{m}$ with a flank wear $VB = 0.32$ mm, after a total cutting length $L_c = 29960$ mm (2247 Sec), this can be explained by the built up edge on the cutting inserts increasing the curvature radius of the cutting edge and then minimize the depth of the furrows dug on the

machined surface that improves the surface roughness, the furrows are deeper and broader as the feed rate increases. The Fig. 16 illustrates the morphology of the flank wear from one of cutting inserts at different states.

Fig. 14. Flank wear curves when machining at a 439.6m/min and a feed per tooth of 0.114 mm

Fig. 15. Flank wear effect on roughness when machining at a 439.6m/min and a feed per of 0.114 mm tooth

Fig. 16. Micrograph of insert after different machining times

To visualize the furrows, a representative example of 3D image of milling surface is envisioned by means of isometric view Fig. 17. In the third zone, which begins from $VB = 0.32$ mm is noted that the roughness takes an upward curve again after a certain stability. We noted that until $VB_{max} = 0.6$ mm, the surface roughness $Ra < 0.7 \mu\text{m}$ (Yallese et al., 2009).

Fig. 17. 3D surface topography for (Ra)

4. Conclusions

The face milling tests of the AISI 1040 steel, using the coated carbide insert GC1030 has been investigated in order to develop statistical models of surface roughness criteria. These models were obtained using multiple linear regression and response surface methodology. The evaluation of coefficients of determination and mathematical models allowed us the examination of the influence degree of the various cutting parameters (cutting speed, feed per tooth and depth of cut) on different roughness criteria (R_a , R_y , R_z) and on the Material Removed Rate during the face milling process.

From the results and the analysis obtained, it can be concluded that the:

- 1) Cutting speed (V_c) has a significant impact on various criteria roughness studied (R_y , R_z and R_a) with contributions of 95.51%, 86.74% et 92.20% respectively, this is due to the geometry of the insert which has a scrapping edge which enables to obtain low roughness even at important feed rate.
- 2) Cutting speed (V_c) and the feed per tooth (f_z) are the most influential parameters on the Material Removed Rate with a contribution of 30.76% followed by depth of cut with 17.94%.
- 3) The analysis of the results shows that the mathematical model of the Material Removed Rate was the most representative model because its coefficient of determination R^2 was 98.53%, followed by the model of R_a with R^2 of 97.67%, followed by the model R_y with 95.23% and R_z was the last model with 93.15%.
- 4) The experimental and predicted values were very close to each other; the developed mathematical models could be effectively utilized in face milling.
- 5) Based on the response surface optimization and the composite desirability method of RSM, the optimal cutting parameters of AISI 1040 steel with coated carbide tool have been found to be as follows: $V_c = 314$ m/min, $f_z = 0.16$ mm/tooth and $a_p = 0.6$ mm. The optimized responses are $R_a = 0.709548$, $R_y = 3.79162$, $R_z = 3.69408$ μm and $\text{MRR} = 32804.9$ mm^3/min , with a composite desirability of 0.924.
- 6) At $V_c = 439.6$ m/min, $f_z = 0.114$ mm/tooth and $a_p = 0.6$ mm. The tool life of the insert is 2247 sec with total cutting length $L_c = 29960$ mm.
- 7) We noted that until $VB_{\text{max}} = 0.6$ mm, the surface roughness $R_a < 0.7$ μm

Acknowledgments

This work was achieved in the laboratory LMS (Guelma University, Algeria). The authors would like to thank the Algerian Ministry of Higher Education and Scientific Research (MESRS) and the Delegated Ministry for Scientific Research (MDRS) for providing financial support through CNEPRU Research Project, Code: 0301520080027 (University 08 May 1945, Guelma).

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