Optimization and Mathematical Modelling of Surface Roughness Criteria and Material Removal Rate when Milling C45 Steel using RSM and Desirability Approach

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ABSTRACT

This work consists of studying the workability of C45 steel in face milling by using coated carbides (GC4040). The objective is to investigate the evolution of surface roughness (Ra, Ry, and Rz) and Material Removal Rate (MRR) according to cutting speed, feed rate, and depth of cut. A full-factorial design (4^3) was adopted in order to analyse the obtained experimental results via both Analysis of Variance (ANOVA) and Response Surface Methodology (RSM) design. The levels of cutting speed were as follows: Vc_1=57 m/min; Vc_2=111 m/min; Vc_3=222 m/min and Vc_4=440 m/min. The ranges of feed rate were fz_1=0.024 mm/tooth; fz_2=0.048 mm/tooth; fz_3=0.096 mm/tooth and fz_4=0.192 mm/tooth. As for the depth of cut levels, they included ap_1=0.2 mm; ap_2=0.4 mm; ap_3=0.6 mm, and ap_4=0.8 mm. To determine mathematical models to make predictions, a statistical analysis of the results by using RSM was applied to obtain the main effects and interactions plot of the answer. Furthermore, a multi-objective optimization procedure for minimizing Ra and maximizing the metal removed rate using the desirability approach was also implemented. Therefore, the developed models can be effectively used to predict the surface roughness criteria and the material removal rate in machining C45 steel. The results indicated that feed rate is a significant factor affecting surface roughness (Ra: 52.37%, Ry: 80.97%, and Rz: 54.96%), followed by cutting speed (Ra: 37.88%, Ry: 12.90%, and Rz: 24.43%). Meanwhile, cutting speed

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and feed rate are the most significant parameters on the MRR with a contribution of 29.5% followed by the depth of cut with 11.62%.

Keywords: *Milling; C45; Modelling; Optimization; Roughness; ANOVA*

Introduction

The manufacturing process, in particular machining, plays an important role in determining the levels of integrity on the surfaces to be produced. In manufacturing industries, different machining processes are used to remove material from the workpiece, and milling is one of the most widely used processes due to its ability to remove material quickly with a surface roughness quality [1]-[2]. In the machining process, modelling, and optimization [3]-[4] are important tasks, allowing the choice of the most convenient cutting conditions in order to obtain desired values in a certain variable, which usually has a direct economic impact such as the machine time or the total cost of operation. The response surface methodology is a general approach to obtaining the maximum value of a dependent (response) variable that depends on several independent (explanatory) variables. This technique combines the Design of Experiments (DOE) and multiple regressions.

Modelling is applied to look at the form of influence like linear, quadratic, or cubic and what mathematical equation it governs, with a given precision, the variation of the phenomenon according to the influential factors. The modelling of response is done by choosing experimental points whose number is at least equal to the sum of the effects, interactions, and quadratic effects. Thus, a matrix of n rows and k columns is defined. Rizvi and Ali [5] presented mathematical modelling and optimization of surface roughness (*Ra*) and Material Removal Rate (MRR) during the machining of AISI 1040 steel in which response optimization that represents the optimal combination of cutting process parameters are observed to be cutting speed of 400 rpm, feed rate of 0.3 mm/rev, and cutting depth of 2.1 mm. Cutting speed is the most significant parameter that affects *Ra*, *Rz,* and MRR. Good agreement was observed by Ghosh et al. [6] between the experimental with predicted *Ra* value for the RSM-PSO technique during modelling and the optimization of cutting parameters for keyway milling operation of C40 steel under wet conditions.

To study the influences of cutting parameters on the surface roughness criteria during face milling AISI 1045 steel, Trung et al. [7] suggested two models of surface roughness prediction, one of which is built on the basis of Johnson transformation and the other is developed according to Response Surface Method (RSM). Palanisamy et al. [8] optimized cutting parameters (*Vc, fz,* and *ap*) and modelled results such as MMR, surface roughness, cutting force, and tool tip temperature using Taguchi-based Gray's Relational Analysis (GRA) and RSM, respectively when machining Incoloy 800H. Surface roughness and MRR are important parameters in the machining process. Bouzid et al. [9] proposed modelling technique of the surface roughness and optimization of cutting parameters to determine the optimal cutting regime by minimizing roughness and maximizing MRR during the machining of AISI 1040 steel. Concerning the machinability of AISI 5140 steel, Kuntoğlu et al. [10] carried out a study to determine the optimal cutting conditions, analysis of vibrations, and surface roughness under different cutting parameters. Using the neural network method, Sureshkumar et al. [11] investigated the influence of cutting parameters (*vc*, *fz*, and *ap*) on surface roughness in milling operation. Modelling and optimization play important roles in choosing the optimum cutting regimes during machining to achieve the desired results [12].

To minimize the surface roughness and maximize the MRR when turning X20Cr13 stainless steel, Bouzid et al. [13] concluded that the optimal values should include a feed rate of 0.08 mm/rev, depth of cut of 0.15 mm and cutting speed of 120 m/min. The experimental study of Pandiyan et al. [14] involved machining AA6351 alloy steel by a CNC machining centre which was evaluated according to RSM with an objective function and optimization methods to find the values of process variables that produce desirable values of the response where mathematical models are developed from the responses obtained and validated. Ozdemir [15] studied the effect of cutting parameters on the machinability of X37CrMoV5-1 hot work tool steel. He found that the feed rate was 95.90% effective on the *Ra* value, whereas the cutting speed and the cutting depth factors were not effective. The *Ra* value increased as the feed rate increased. Factors and ratios affecting the MRR value were determined as 61.70% for feed rate, 27.42% for cutting depth, and 5.04% for cutting speed, respectively.

This paper presents the effect of the cutting regime (*Vc*, *fz*, and *ap*) on surface roughness criteria (*Ra*, *Ry*, and *Rz*) and MRR in face milling of C45 steel using coated carbide (GC4040) inserts.

Materials and Methods

All the tools used to conduct the experiments are presented which consist of a presentation of various equipment that are used to monitor the evolution of the surface roughness during face milling. In addition, the different methods used for planning and the conditions for carrying out the experiments are cited. The experiments necessary for this study were carried out at the Laboratory of Mechanics and Structure (LMS), Department of Mechanical Engineering, University of May 8, 1945 - Guelma.

Machine tools, cutting tools, and tool holder

The machine tool used for these tests included a vertical milling machine from the National Society for the Production of Industrial Machine Tools (PMO), model ALMO with a power of 5 KW (Figure 1) on C45 grade steel specimens machined (65 x 65 x 250 mm) (Figure 2) with three (*Z*=3) GC4040 coated carbide inserts (Figure 3) fixed on a 100 mm diameter milling cutter (Figure 4), where *Z* is the number of insets.

Spindle rotational speeds available on the milling machine (*N*; *rev/min*) are 45; 63; 90; 125; 180; 250; 355; 500; 710; 1000, 1400; 2000. The different feed rates of this machine are in (*Vf; mm/min*): 10; 16; 20, 25; 31.5, 50; 63; 80; 100; 125; 160; 200; 250; 314; 400; 500; 630; 800, with *fz* calculated using the following Equation (1).

$$fz = \frac{Vf}{N * Z} \tag{1}$$

where *Z*: number of inserts (*Z*=3 inserts).

In order to reduce uncertainties due to resumption operations, the roughness was directly measured on the workpiece without dismounting from the lathe using a 2D roughness meter *Sj- 201p* (Mitutoyo) which was selected to measure surface roughness criteria (Figure 5) in the machining direction. The measurements were repeated three times on the surface at three references.

Figure 1: Machine Tools (PMO), model ALMO

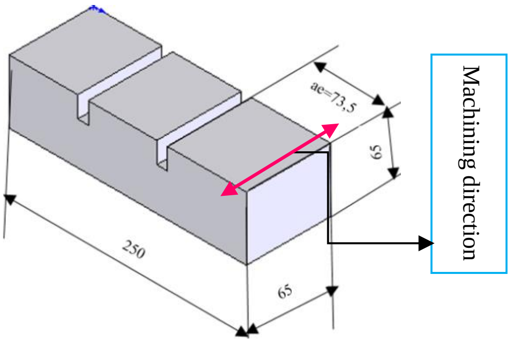


Figure 2: Specimens machined (65 x 65 x 250 mm)

Due to the medium-high carbon content, C45 steel can be welded with some precautions, and it has a low hardenability in water or oil. It is fit for surface hardening gives this steel grade a high hardness of the hardened shell and its chemical composition is shown in Table 1. Concerning the measurement of the roughness, a roughness meter Sj-201p was used.

Figure 3: Insert GC4040

Figure 4: Coromill 245 milling cutter

Figure 5: Roughness meter Sj-201p and roughness measurement method

Table 1: Chemical composition % of C45 steel

Cr + *Mo* + *Ni* = max 0.63							
C	*Si*	*Mn*	*Ni*	*P*	*S*	*Cr*	*Mo*
0.43 - 0.5	max	0.5 - 0.8	max	max	max	max	max

Planning of experiments

To calculate the constants and coefficients of the mathematical models, Minitab and Design-Expert (both software) were used and characterized by Analysis of Variance (ANOVA), multiple regressions, and the RSM. In the current study, the relation between the cutting conditions and the technological parameters is given in Equation (2).

$$Y = \phi(Vc.fz.ap) \tag{2}$$

where *Vc*: cutting speed, *fz*: feed rate, *ap*: depth of cut.

φ is the response function and 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 RSM-based second order mathematical model is given by Equation (3).

$$Y = b_o + \sum_{i=1}^{k} b_i X_i + \sum_{ij}^{k} b_{ij} X_i X_j + \sum_{i=1}^{k} b_{ii} X_i^2 + \varepsilon_{ij} \quad \left(\varepsilon_{ij} = y_{ij} - \overline{y}_{ij}\right) \tag{3}$$

where b_0 is the free term of the regression equation, the coefficients $b_1, b_2, ...,$ b_k and b_{11}, b_{22}, b_{kk} are the linear and the quadratic terms, respectively, while b_{12}, b_{13}, b_{k-1} are the interacting terms. *Xi* represents the input parameters (*Vc, f,* and, *ap*) and ε_{ij} is the error of fit for the regression model. Output surface roughness and MRR are also called response factors.

Multi-factorial method 3 factors and 4 levels (Table 2) were chosen. Cutting parameters were selected based on the chemical composition, tool manufacturer guidelines, and cutting hardness of the workpiece material. Full-factorial design (4^3=64 runs) was selected for the design of experiments and the experimental results are given in Table 3.

Multiple response optimization is a procedure that enables the determination of the independent cutting speed parameters (*Vc, f,* and *fz*) that lead to optimal response results. The desirability function (*DF*) is expressed as Equation (4).

$$Df = \left(\Pi_{n}^{i=1} . d_i^{wi} \right)$$
$$F(x) = -Df \tag{4}$$

where:
Df: desirability function,
di: specific desirability of each of the (*n*) target outputs. It is expressed as a function of the target for each target output.
Wi: the corresponding weighting function.

The MRR in milling operations is the volume of material that is removed per unit time in mm^3/min. The study of this parameter is important since the goal is to manufacture low-cost and high-quality products in a short time. The value of MRR is calculated using the following Equation (5).

$$MRR = ap \times ae \times fz \times Z \times \frac{Vc \times 1000}{\pi \times D} \tag{5}$$

where; *ae* (cutting width)=73.5 mm, *Z*=3 tooths, *D*=100 mm (milling cutter).

Table 2: Factors and levels used in the experiments (multi-factorial method)

Factors	Symbol	Levels			
		Level 1	Level 2	Level 3	Level 4
Cutting speed (m/min)	*Vc*	57	111	222	440
Feed rate (mm/ tooth)	*fz*	0.024	0.048	0.096	0.192
Depth of cut (mm)	*ap*	0.2	0.4	0.6	0.8

Results and Discussion

Statistical data treatments were carried out in two steps. In the first one, the ANOVA and the effect of each factor and its interactions were determined. To achieve this goal, the response surface plots were generated considering two parameters at a time while the third one was kept constant. The second step focused on the modelling aspects using RSM outputs.

Table 3: Experimental data for C45 steel

Runs	Factors			Responses			
	Vc; m/min	*fz*; mm/tooth	*ap*; mm	*Ra*; µm	*Ry*; µm	*Rz*; µm	*MRR*; mm^3/min
1	57	0.024	0.2	4.071	7.928	5.85	192.13
2	57	0.024	0.4	4.155	8.224	6.12	384.26
3	57	0.024	0.6	4.218	7.788	5.99	576.39
4	57	0.024	0.8	4.26	9.132	6.295	768.52
5	57	0.048	0.2	5.265	9.592	7.705	384.26
6	57	0.048	0.4	5.312	9.8	7.705	768.52
7	57	0.048	0.6	5.417	9.46	7.295	1152.78
8	57	0.048	0.8	5.68	9.216	7.09	1537.04
9	57	0.096	0.2	6.163	10.116	8.845	768.52
10	57	0.096	0.4	6.394	11.244	9.51	1537.04
11	57	0.096	0.6	6.541	9.252	9.795	2305.56
12	57	0.096	0.8	6.583	10.144	10.08	3074.08
13	57	0.192	0.2	7.234	11.956	9.03	1537.04
14	57	0.192	0.4	7.318	11.728	10.31	3074.08
15	57	0.192	0.6	7.465	12.18	9.075	4611.12
16	57	0.192	0.8	7.381	11.376	10.69	6148.16
17	111	0.024	0.2	3.365	6.864	4.895	374.15
18	111	0.024	0.4	3.365	5.64	5.205	748.3
19	111	0.024	0.6	3.386	5.736	5.01	1122.44
20	111	0.024	0.8	3.659	6	4.8	1496.59
21	111	0.048	0.2	3.785	7.152	5.225	748.3
22	111	0.048	0.4	3.848	7.248	5.32	1496.59
23	111	0.048	0.6	4.29	7.44	5.035	2244.89
24	111	0.048	0.8	4.079	6.588	4.655	2993.19
25	111	0.096	0.2	5.31	7.956	5.415	1496.59
26	111	0.096	0.4	5.415	7.968	5.605	2993.19
27	111	0.096	0.6	5.436	8.004	5.89	4489.78
28	111	0.096	0.8	5.562	8.976	6.175	5986.37
29	111	0.192	0.2	6.528	10.86	7.79	2993.19
30	111	0.192	0.4	6.612	11.076	7.98	5986.37
31	111	0.192	0.6	6.843	12.84	8.835	8979.56

32	111	0.192	0.8	6.885	12.756	9.025	11972.74
33	222	0.024	0.2	2.653	5.2	4.04	748.3
34	222	0.024	0.4	2.821	5.128	4.035	1496.59
35	222	0.024	0.6	3.184	4.84	4.32	2244.89
36	222	0.024	0.8	3.389	5.28	4.7	2993.19
37	222	0.048	0.2	4.31	7.224	5.32	1496.59
38	222	0.048	0.4	4.31	7.968	5.415	2993.19
39	222	0.048	0.6	4.31	8.34	5.7	4489.78
40	222	0.048	0.8	4.394	7.008	4.985	5986.37
41	222	0.096	0.2	5.478	10.656	6.555	2993.19
42	222	0.096	0.4	5.415	8.004	5.7	5986.37
43	222	0.096	0.6	5.562	8.868	6.175	8979.56
44	222	0.096	0.8	5.457	8.232	5.985	11972.74
45	222	0.192	0.2	6.99	12.48	8.455	5986.37
46	222	0.192	0.4	6.032	11.784	8.455	11972.74
47	222	0.192	0.6	6.053	12.984	9.12	17959.1
48	222	0.192	0.8	6.948	11.4	8.265	23945.4
49	440	0.024	0.2	1.092	4.716	2.945	1483.11
50	440	0.024	0.4	1.113	4.932	3.04	2966.22
51	440	0.024	0.6	1.197	5.808	3.23	4449.33
52	440	0.024	0.8	1.218	5.688	3.325	5932.44
53	440	0.048	0.2	2.596	4.28	3.515	2966.22
54	440	0.048	0.4	2.575	3.836	3.515	5932.44
55	440	0.048	0.6	2.68	4.312	3.99	8898.66
56	440	0.048	0.8	3.159	5.412	3.8	11864.8
57	440	0.096	0.2	3.352	7.98	6.08	5932.44
58	440	0.096	0.4	3.394	7.968	5.7	11864.8
59	440	0.096	0.6	3.373	8.436	5.795	17797.3
60	440	0.096	0.8	3.394	8.172	5.795	23729.7
61	440	0.192	0.2	4.549	10.656	7.505	11864.8
62	440	0.192	0.4	4.57	10.404	7.695	23729.7
63	440	0.192	0.6	4.612	10.992	7.885	35594.6
64	440	0.192	0.8	4.612	10.608	5.89	47459.5

Modelling using RSM technique

ANOVA analysis

ANOVA is useful for understanding the influence of given input parameters from a series of experimental results by the method of designing experiments for machining processes, and it also helps to provide an interpretation [16]. Essentially, it partitions the total variation in an experiment into components attributable to the factors controlled and the errors generated. The statistical significance of the fitted quadratic models is assessed by *p*-values and *F*-values from the ANOVA.

In ANOVA Tables 4, 5, and 6, the *p*-value is the probability (ranging from 0 to 1). If the *p*-value is greater than 0.05, the parameter is insignificant; if the *p*-value is less than 0.05, the parameter is significant. The squared sum (SS) is used to estimate the square of the deviation from the general mean (Equation 6).

$$SS_f = \frac{N}{N_{nf}} \sum_{i=1}^{N_{nf}} (\overline{y}_i - \overline{y})^2 \tag{6}$$

where:
$\overline{y}$: the average response,
$\overline{y}_i$: average of the measured responses for each level *i* of the *F*-factor,
N: the total number of trials,
N_{nf}: the number of levels of each f factor.

The squared mean (MS) is calculated by dividing the squared sum by the number of degrees of freedom (Equation 7).

$$MS_i = \frac{SS_i}{dl_i} \tag{7}$$

The *F*-Value is used to check the compatibility of the mathematical model on the grounds that the calculated *F*-Values must be greater than the tabulated *F* (*F*-Table) (Equation 8).

$$F_i = \frac{MS_i}{MS_e} \tag{8}$$

where MS_e is the mean squared sum of the errors.

Column (Cont%) of the ANOVA table shows the contribution of factors (in percent) to the total variance, indicating the degree of percent effect on response (Equation 9).

$$Cont.\% = \frac{SS_f}{SS_T} \times 100 \tag{9}$$

The coefficient of determination (R^2), defined as the ratio of explained variation to total variation, is a measure of the goodness of fit (Equation 10).

$$R^2 = \frac{\sum (y_i - \overline{y})^2}{\sum (\overline{y}_i - \overline{y})^2} \tag{10}$$

ANOVA results for response surface criteria (*Ra, Ry,* and *Rz*)

To determine the influence of any given input parameter from a series of experimental results by DOE for the machining process, the statistical method of ANOVA was used to properly interpret the experimental data [4]. The coefficient of determination R^2 is an important criterion that is defined as the ratio of the explained variation to the total variation and is a measure of the degree of adjustment. R^2 (adj) is an average measure explained by the model, adjusted for the number of terms in the model, and the obtained results are analysed using Design Expert 12.

Tables 4 to 6 show the results of the analysis of variance for *Ra, Ry,* and *Rz,* respectively. This analysis was performed for *p*-values of less than 0.05 (95% reliability or better). Table 4 summarizes the results of the analysis of variance for the surface roughness criterion *Ra,* and it is noted that the most important factor affecting the criterion of surface roughness *Ra* is the feed rate (*fz*) with a contribution of 52.37%. The increase in feed rate generates furrows which become deeper and wider with each increase in the feed rate. The cutting speed has a contribution of 37.88% and it is the second most influential factor. In the third position, it goes to the effect of product *fz***fz* with a contribution of 4.40%. The depth of cut (*ap*) effect is insignificant, but we do not take it into account because its reliability does not exceed 8%. We also neglect the interactions of $fz \times ap$, $ap \times Vc$, and $Vc \times fz$ as well as the effects of products Vc^2, and ap^2 because they are not important.

Table 5 summarizes the results of the ANOVA analysis for the roughness criterion, *Ry*. It is noted that the feed rate contributes the greatest effect with 80.97%, then the cutting speed has a contribution of 12.90%, followed by the interaction of combined parameter $Vc \times fz$ with a contribution of 1.55%. Regarding the depth of cut, interactions, and effects of products have a low contribution. Referring to Table 6, the feed rate and the cutting speed are the two most important factors contributing to the effect of the roughness *Rz*, with contributions of 42.01%, and 24.44%, respectively, followed by fz^2, and Vc^2 with contributions of 13.44%, and 3.56%, while the other factors are insignificant.

Main effects and interactions

Figures 6, 7, and 8 represent the main effects plot in which the differences between the average responses of one or more factor levels were examined. This is a major effect when different levels of a factor affect the response. The main effects plot shows a plot of the mean response for each factor level connected to a line. The main effects plot shows that feed rate is the most influential factor as it exhibits the greatest trend for roughness criteria (*Ra*, *Ry*, and *Rz*) as a function of feed rate, followed by cutting speed, and finally, the effect of depth of cut, which does not affect significantly with respect to cutting speed and feed rate as shown in the main effects diagram of *Ra, Ry,* and *Rz*.

Table 4: Analysis of variance for *Ra*

Source	*Df*	*SS*	*MS*	*F*	*P*	*Cont.%*	Remarks
Regression	9	163.255	18.1395	119.761	0.000000	95.22%	Significant
Vc	1	64.952	0.8116	5.358	0.024458	37.88%	Significant
fz	1	89.783	17.1105	112.967	0.000000	52.37%	Significant
ap	1	0.584	0.0014	0.009	0.924464	0.34%	Insignificant
Vc×Vc	1	0.235	0.2354	1.554	0.217919	0.13%	Insignificant
fz×fz	1	7.546	7.5464	49.823	0.000000	4.40%	Significant
ap×ap	1	0.075	0.0746	0.493	0.485825	0.04%	Insignificant
Vc×fz	1	0.001	0.0009	0.006	0.939487	0.000%	Insignificant
Vc×ap	1	0.020	0.0199	0.131	0.718424	0.01%	Insignificant
fz×ap	1	0.059	0.0591	0.390	0.534957	0.03%	Insignificant
Error	54	8.179	0.1515				
Total	63	171.435					

Table 5: Analysis of variance for *Ry*

Source	*Df*	*SS*	*MS*	*F*	*P*	*Cont.%*	Remarks
Regression	9	330.787	36.7541	36.5299	0.00001	85.89%	Significant
Vc	1	49.689	49.689	49.387	0.001298	12.90%	Significant
fz	1	271.373	271.373	269.72	0.00001	80.97%	Significant
ap	1	0.0761	0.0761	0.0757	0.78432	0.024%	Insignificant
Vc×Vc	1	1.806	1.806	1.7948	0.18595	0.46%	Insignificant
fz×fz	1	1.415	1.415	1.4065	0.24083	0.36%	Insignificant
ap×ap	1	0.029	0.029	0.0292	0.864882	0.007%	Insignificant
Vc×fz	1	6.003	6.003	5.9665	0.017883	1.55%	significant
Vc×ap	1	0.368	0.368	0.3653	0.548103	0.09%	Insignificant
fz×ap	1	0.011	0.011	0.0113	0.915879	0.002%	Insignificant
Error	54	54.331	1.0061				
Total	63	385.118					

Table 6: Analysis of variance for *Rz*

Source	*Df*	*SS*	*MS*	*F*	*P*	*Cont.%*	Remarks
Regression	9	210,334	23,370	31,877	0,000000	84.16	Significant
Vc	1	61,072	14,607	19,924	0,000041	24.44	Significant
fz	1	105,001	36,898	50,329	0,000000	42.01	Significant
ap	1	0,252	0,485	0,662	0,419384	0.1	Insignificant
Vc×Vc	1	8,895	8,895	12,133	0,000990	3.56	Significant
fz×fz	1	33,583	33,583	45,807	0,000000	13.44	Significant
ap×ap	1	0,217	0,216	0,295	0,588814	0.087	Insignificant
Vc×fz	1	0,638	0,638	0,870	0,354900	0.26	Insignificant
Vc×ap	1	0,633	0,632	0,863	0,356959	0.26	Insignificant
fz×ap	1	0,042	0,041	0,057	0,811982	0.017	Insignificant
Error	54	39,589	0,733				
Total	63	249,923					

DF: degree of freedom; *SS*: sum of squares; *MS*: adjusted mean squares.

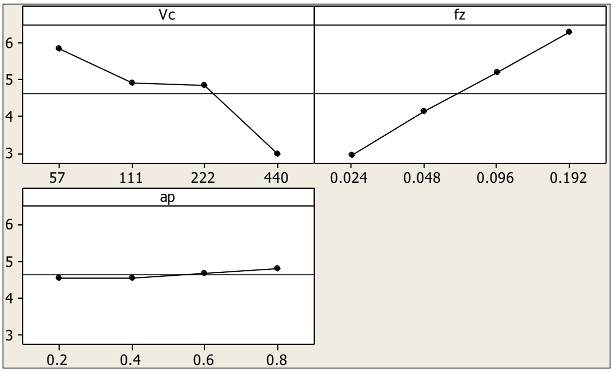


Figure 6: Main effects plot for *Ra*

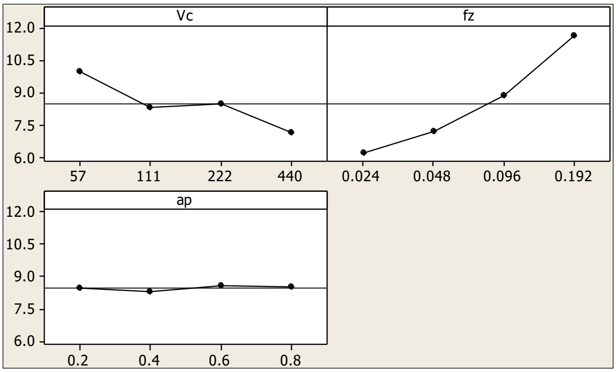


Figure 7: Main effects plot for *Ry*

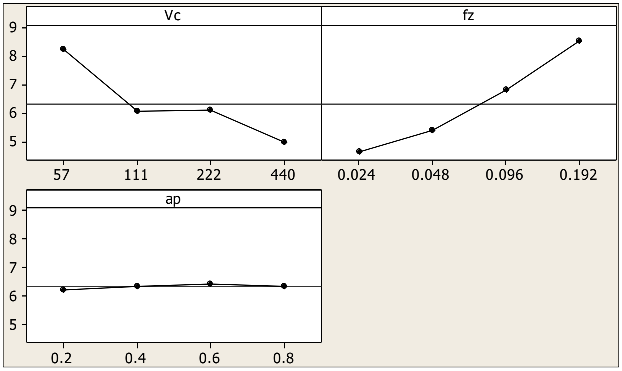


Figure 8: Main effects plot for *Rz*

Figures 9, 10, and 11 show the interaction diagram in which parallel lines indicate the absence of interaction between the two segments: the greater the difference in slope between the lines, the greater the degree of interaction. However, the interaction plot does not indicate whether the interaction is statistically significant. It appears from the interaction diagrams (*Ra*, *Ry*, and *Rz*) that the interaction of the cutting conditions does not have a significant impact on the surface roughness criteria (*Ra*, *Ry*, and *Rz*) except in the case of the interaction between the cutting speed and the feed rate in the two diagrams of *Ry* and *Rz*. We, therefore, notice a small convergence of the roughness values *Ry* when the feed rates are high. Moreover, the roughness values of *Rz* are approachable when the feed rate increases, especially when *fz*=0.096 mm/tooth.

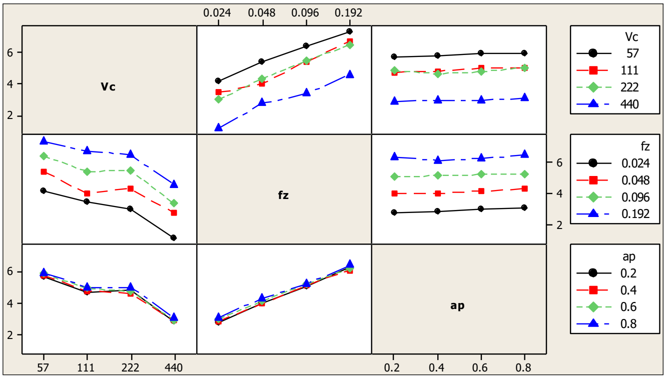


Figure 9: Interaction plot for *Ra*

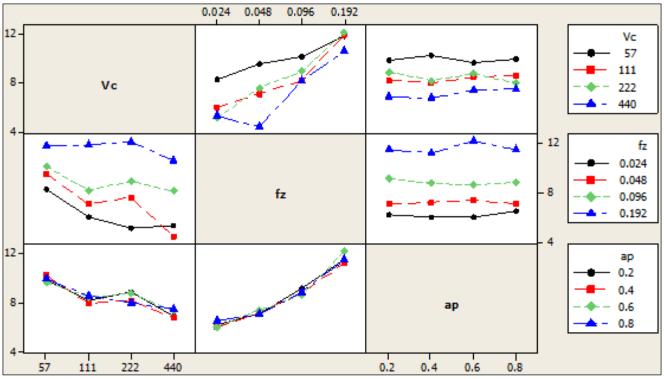


Figure 10: Interaction plot for *Ry*

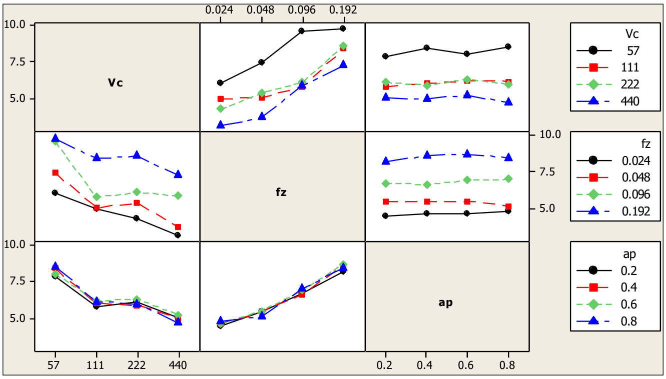


Figure 11: Interaction plot for *Rz*

Regression equations

The relationship between input parameters and performance measurements (outputs) is modelled by quadratic regression using Minitab 16 software. The regression equations are obtained together with determination coefficients (R^2). The arithmetic mean roughness (*Ra*) model and coefficients of determination are given in Equation (11).

$$\begin{aligned} Ra &= 3.0909 - 0.004458\, Vc + 46.4462\, fz - 0.124696\, ap - \\ & 4.109\times 10^{-6}\, Vc^2 - 0.000392 Vc\times Fz - 0.000537084\, Vc\times ap \\ & -121.033\, fz^2 - 2.11146\, fz\times ap + 0.853516\, ap^2 \\ R^2 &= 95.23\% \quad , \quad R^2(adj) = 94.43\% \end{aligned} \tag{11}$$

The maximum height of the profile (*Ry*) model is given below in Equation (12). Its coefficient of determination is R^2=85.89%.

$$\begin{aligned} Ry &= 7.80398 - 0.0158878\, Vc + 36.463\, fz - 0.928013\, ap \\ & + 1.138\times 10^{-5}\ \ Vc^2 + 0.032419\, Vc\times fz + 0.002308\, Vc\times ap \\ & - 52.4124\, Fz^2 + 0.924819\, fz\times ap + 0.535938\, ap^2 \\ R^2 &= 85.89\% \end{aligned} \tag{12}$$

The mean of the third point height (*Rz*) model is given below in Equation (13). Its coefficient of determination is R^2=84.95%.

$$\begin{aligned} Rz &= 5.66873 - 0.0190703\, Vc + 36.5371\, fz + 2.17619\, ap \\ & + 2.52746\times 10^{-5}\ \ Vc^2 + \ 0.0113375\, Vc\times fz - \\ & 0.00303\, Vc\times ap - 77.2339\, fz^2 + 2.09941\, fz\times ap - 1.455\, ap^2 \\ R^2 &= 84.16\% \end{aligned} \tag{13}$$

Models are reduced by eliminating terms with no significant effect on the responses, and they are given by Equation (14) and Equation (15).

$$Ra = 3.46201 - 0.00686135\, Vc + 45.309\, fz - 121.033\, fz^2 \quad R^2 = 94.66\% \tag{14}$$

$$Ry = 7.4366 - 0.00891901\, Vc + 25.2762\, fz + 0.0324191\, fz \times Vc \quad \text{with } R^2 = 84.93\% \tag{15}$$

$$Rz = 6.10858 - 0.0195655\, Vc + 39.9393\, fz + 2.52746 \times 10^{-5} Vc^2 - 77.2339\, fz^2 \quad R^2 = 84.19\% \tag{16}$$

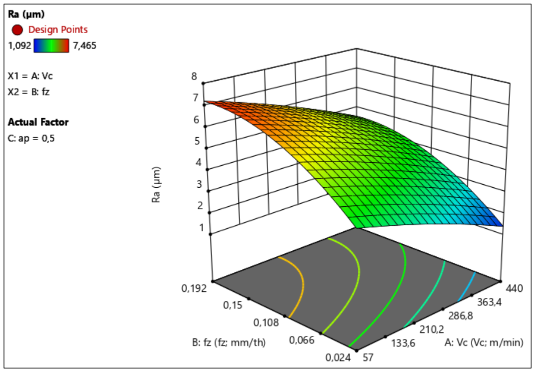
Response surface and contour plots of *Ra, Ry,* and *Rz*

Response surfaces (as shown in Figures 12, 13, and 14) show that the feed rate has the greatest effect and that each reduction in the feed rate reduces the surface roughness parameters significantly, followed by the cutting speed with a significant effect, while the depth of cut is minimally affected.

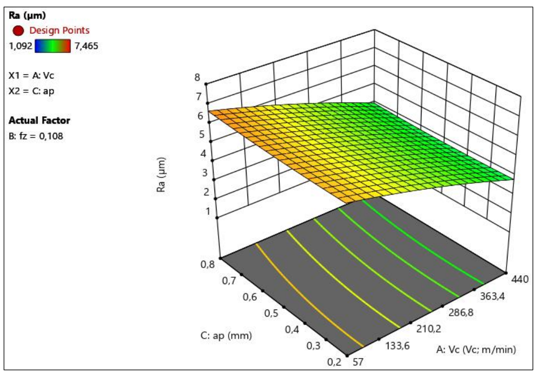
These graphs (Figures 12, 13, and 14) also show that high roughness criteria require a high feed rate (0.192 mm/tooth) and low cutting speed (57 m/min), while low roughness criteria require a low feed rate (0.024 mm/tooth) and high cutting speed (440 m/min). Therefore, the best roughness is achieved by applying a small feed rate and a high cutting speed.

Model verification was performed using residual analysis. The coloured dots indicate the surface roughness value. The curves of the normal probability of *Ra*, *Ry*, and *Rz* are presented in Figures 15 to 17. It is clear that the residuals are very close compared to the straight line of normality, which implies that the errors are normally distributed. Thus, the already obtained mathematical models can be used to predict surface roughness.

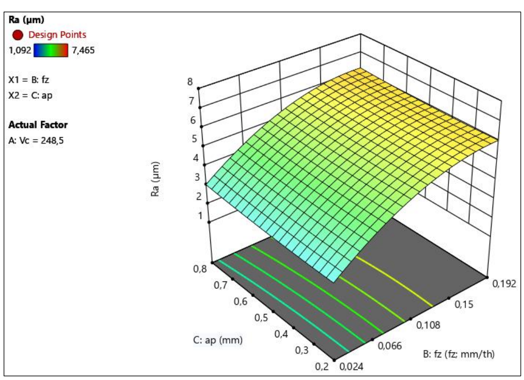
Table 7 shows the results of the *ANOVA* analysis for the MRR. It is noted that all factors (*fz, Vc*, and *ap*) and interactions (*fz*×*ap*, *ap*×*Vc*, and *Vc*×*fz*) have no significant effect; thus, the feed rate and the cutting speed are the two important factors contributing to the effect of the MRR with contributions of 29.69% and 29.09%, respectively. The interaction (*Vc*×*fz*) has a contribution of 14.87%, followed by the depth of cut with a contribution of 11.62% of the total effect, while the interactions (*fz*×*ap* and *ap*×*Vc*) have low contributions (5.94% and 5.82%), respectively.



(a)

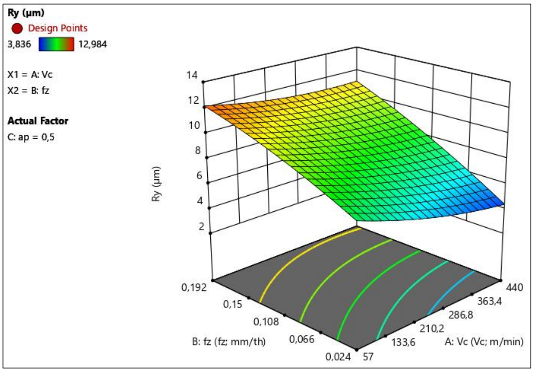


(b)

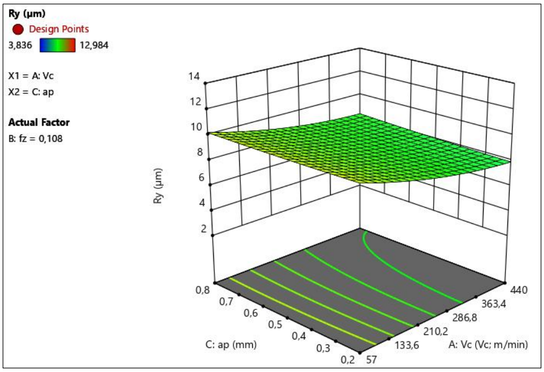


(c)

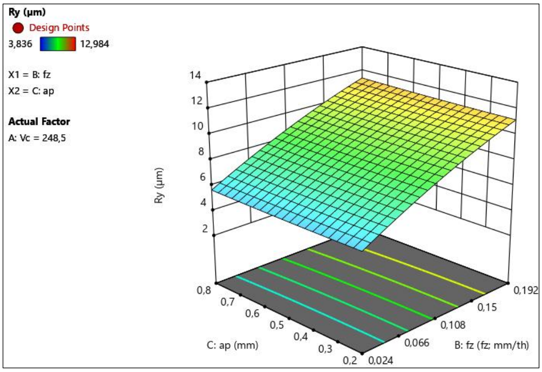
Figure 12: Response surface for *Ra* as a function of (a) *Vc, fz,* (b) *Vc, ap,* and (c) *ap, fz*



(a)

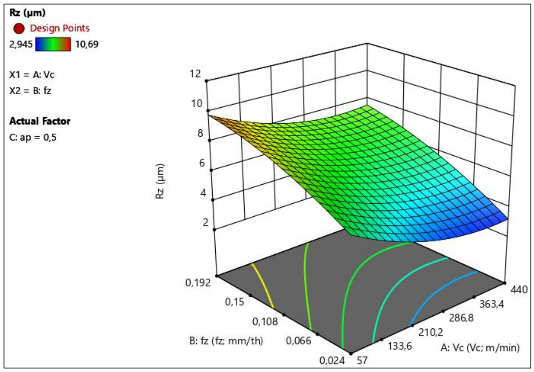


(b)

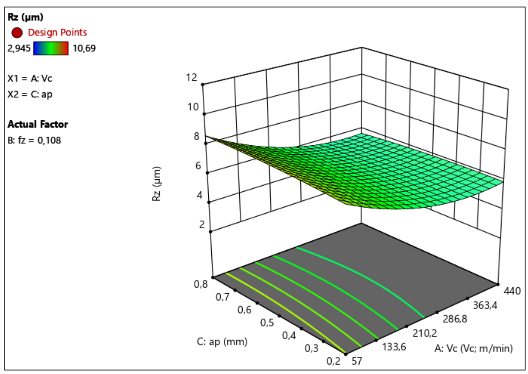


(c)

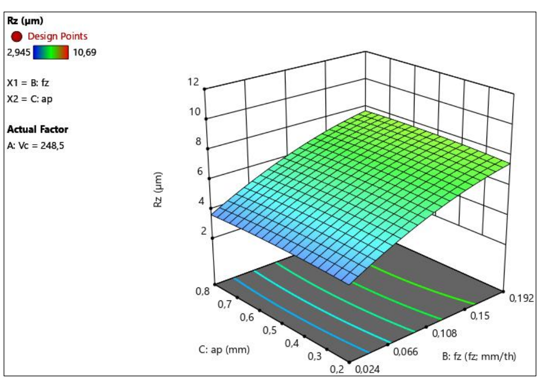
Figure 13: Response surface for *Ry* as a function of (a) *Vc, fz,* (b) *Vc, ap,* and (c) *ap, fz*



(a)



(b)



(c)

Figure 14: Response surface for *Rz* as a function of (a) *Vc, fz,* (b) *Vc, ap,* and (c) *ap, fz*

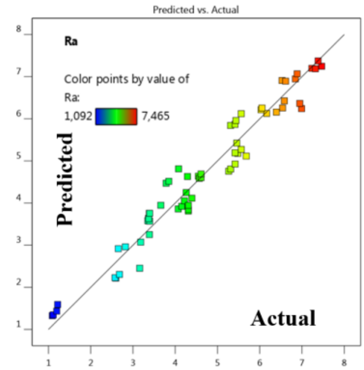


Figure 15: Normal probability of *Ra*

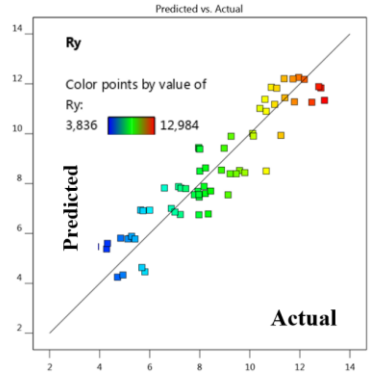


Figure 16: Normal probability of *Ry*

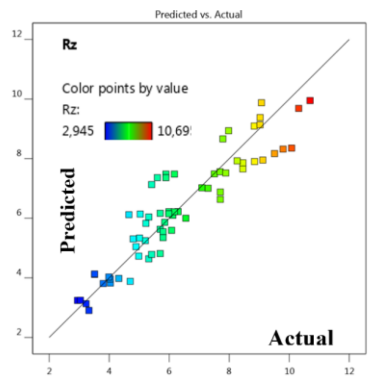


Figure 17: Normal probability of *Rz*

Table 7: Analysis of variance for *MRR*

Source	*DF*	*SS*	*MS*	*F*	*P*	*Cont.%*	Rem.
Regr.	9	4595454514	510606057	195,7	0,000	97.03%	Significant
Vc	1	1377709478	40774922	15,63	0,000	29.09%	Significant
fz	1	1406419728	42101246	16,14	0,000	29.69%	Significant
ap	1	550338006	15201146	5,829	0,020	11.62%	Significant
*Vc*fz*	1	704162218	704162218	70,00	0,999	14.87%	Insignificant
*Vc*ap*	1	275541693	275541693	105,6	0,809	5.82%	Insignificant
*fz*ap*	1	281283390	281283390	107,8	0,999	5.94%	Insignificant
Error	54	140831875	2607998				
Total	63	4736274157					

Main effects and interactions of MRR

For the main effects, the diagram in Figure 18 illustrates that the depth of cut has almost a constant effect between all levels, while the increase in feed rate and speed of cut produces a simple increase in the effect between their levels. Figure 19 indicates the interactions for MMR. From these diagrams, the interactions of the three cutting parameters (*fz*×*ap*, *ap*×*Vc*, and *Vc*×*fz*) have no significant impact on the material removal rate. The mathematical model can be reduced as follows: MRR= *f* (*Vc, fz,* and *ap*).

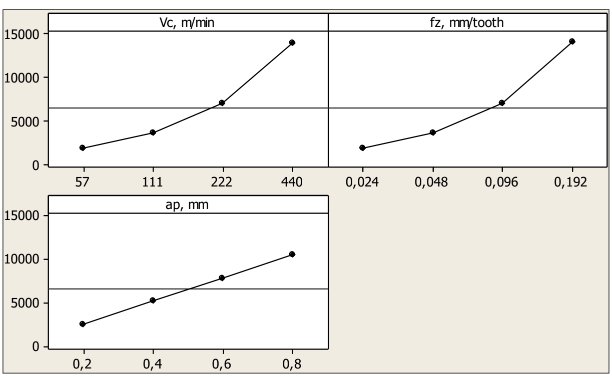


Figure 18: Main effects plot for *MMR*; mm^3/min

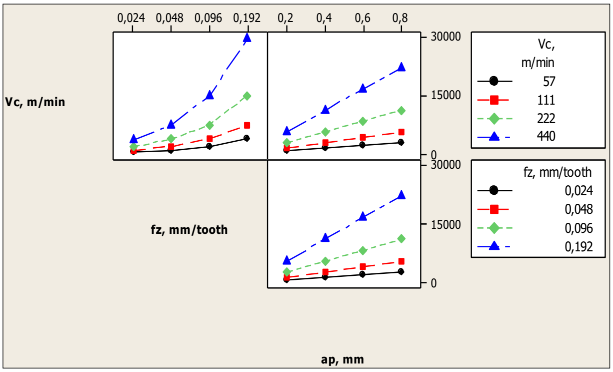


Figure 19: Interaction plot for *MMR*, mm3/min

Regression equations

The material removal rate RMM model is given below in Equation (17).

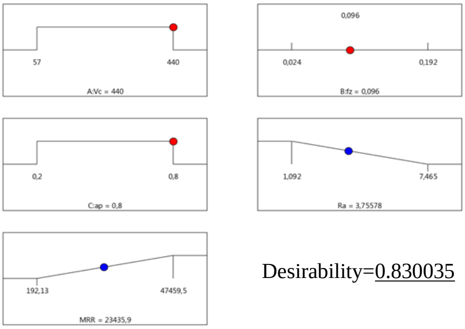
$$MRR=6557{,}07 - 31{,}6003\ Vc - 72856{,}3\ fz - 13114{,}1\ ap + 351{,}115\ Vc\times fz + 63{,}2007\ Vc \times ap + 145713\ fz\times ap \qquad (17)$$

$$R^2 = 97.03 \ , \ Adjusted\ R^2 = 96{,}71\%$$

Multi-response optimization *Ra* and *MRR* using desirability approach.

Optimization methods were used to obtain the optimum machining conditions for milling operations using surface roughness and MRR as responses.

In order to decrease the level of desirability, Figure 20 and Table 8 show the optimization results (minimize *Ra* and maximize MRR). Values of optimal cutting parameters were found to be as follows: *Vc*=440 m/min, *fz*=0.096 mm/tooth, and *ap*=0.8 mm. The optimum surface roughness and MRR were as follows: *Ra*=3.756 µm and *MRR*=23435.874 mm^3/min with combined desirability=0.830035.



Desirability=0.830035

Figure 20: Ramp function graph for surface roughness and *MRR*

Table 8: Response optimization for surface roughness and MRR

Number	*Vc*	*fz*	*ap*	*Ra*	MRR	Desirability
1	440.00	0.096	0.800	3.756	23435.874	0.830035
2	440.00	0.096	0.792	3.749	23206.315	0.828512
3	440.00	0.096	0.769	3.732	22543.256	0.825466
4	440.00	0.096	0.717	3.695	21067.795	0.814805
5	439.99	0.096	0.710	3.690	20845.963	0.813282
6	440.00	0.096	0.704	3.687	20686.579	0.811759
7	440.00	0.096	0.688	3.677	20220.899	0.808713
8	440.00	0.096	0.626	3.642	18445.980	0.79196
9	440.00	0.096	0.548	3.608	16194.432	0.767592

Conclusions

In this work, it studied the effects of these parameters such as feed rate, cutting speed, and depth of cut on roughness criteria (*Ra*, *Ry*, and *Rz*) with Material Removal Rate (MRR) while face milling C45 steel using a GC4040 cutting insert. Based on the experimental results, the following conclusions can be drawn:

i. The ANOVA analysis of the surface roughness criteria reveals that the feed rate (*fz*) has a significant effect on the different surface roughness criteria (*Ra*, *Ry*, and *Rz*) with contributions of 52.37%, 80.97 %, and 54.96%, followed by the cutting speed (*Vc*) with contributions of 37.88%, 12.90%, and 24.43% on each *Ra*, *Ry*, and *Rz*, respectively, while the effect of depth of cut is negligible.

ii. The contour plots in this work enabled us to visualize the response surface in two dimensions, and these two methods make it possible to compare the influence of factors on the response.

iii. The mathematical model of the MRR was the most representative model because its coefficient of determination R^2 was 97.03%, followed by the model of *Ra*, *Ry*, and *Rz* with 95.23%, 85.89%, and 84.95%, respectively. Producing very good ratios, it shows that the studied surface roughness criteria and MRR are mainly related to each response of the cutting parameters (*Vc*, *fz*, and *ap*) which is close to 100%.

iv. Values of optimal cutting parameters are found to be as follows: *Vc*=440 m/min, *fz*=0.096 mm/tooth, and *ap*=0.8 mm. The optimum surface roughness and MRR are as follows: *Ra*=3.756 µm and MRR=23435.874 mm^3/min with a combined desirability=0.830035.

Contributions of Authors

The authors confirm the equal contribution in each part of this work. All authors reviewed and approved the final version of this work.

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Conflict of Interests

All authors declare that they have no conflicts of interest

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