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MODELING AND OPTIMIZATION OF SURFACE ROUGHNESS IN END MILLING OF ALUMINIUM USING LEAST SQUARE APPROXIMATION METHOD AND RESPONSE SURFACE METHODOLOGY

Imhade P. Okokpujie, O. O. Ajayi, S. A. Afolalu, A. A. Abioye, E.Y. Salawu, M. O. Udo
Department of Mechanical Engineering,
Covenant University, P.M.B 1023, Ota, Ogun State, Nigeria

U. C. Okonkwo
Department of Mechanical Engineering, Nnamdi Azikiwe University,
PMB 5025 Awka, Nigeria

K. B. Orodu
Department of Petroleum Engineering, Covenant University,
P.M.B 1023, Ota, Ogun State, Nigeria

O. M. Ikumapayi
[4]Department of Mechanical and Mechatronics Engineering,
Afe Babalola University Ado Ekiti (ABUAD)

ABSTRACT

In end milling, accurate setting of process parameters is extremely important to obtained enhanced surface roughness (SR). Due to a recent innovation in mechanization made it possible to produce high quality manufacturing products. The perceptions of quality in mechanical products are their physical look that is the surface roughness (SR). The aim of this research work is to develop mathematical expression (M.E) and mathematical model using least square approximation method and Response Surface Methodology (RMS) to predict the SR for end milling of Al 6061 alloy. The process parameters that were selected as predictors for the SR are Spindle speed (V), axial depth of cut (a), feed rate (f) and radial depth of cut (d). 30 samples of Al 6061 alloy were carried out using SIEG 3/10/0010 CNC machines and each of the experimental result was measured using Mitutoyo surface roughness tester and Press-o-firm. The minimum SR of 0.5 µm were obtained at a spindle speed of 2034.608 rpm, feed rate of 100 mm/min, axial depth of cut of 20 mm, and radial depth of cut 1.5 mm. Analysis of variances shows that the most influential parameters was feed rate. After *the predicted SR has been obtained by using the two methods, average percentage deviation was calculated, the result obtained using least square approximation method (that is the mathematical expression) show the accuracy of 99% and Response Surface Methodology (RSM) mathematical model shows accuracy of 99.6% which is viable and appropriate in prediction of SR. When either of these models are applied this will enhance the rate of production.*

Key words: End milling; Minimum Quantity Lubrication (MQL); Response Surface Methodology; Surface Roughness (SR); Optimization.

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1. INTRODUCTION

End Milling is a well-known metal cutting or removing processes. It is a strategy for creating machined surfaces by step by step expelling a fated measure of the work-piece material at a moderate rate of movement of the machine by an end-milling cutter rotating at a relatively high speed [1]. The behavior of the end-milling process is that the tooth removes its split of the stock in the form of small individual chips [2]. It is broadly used in the production industries such are aerospace sectors and automotive, where quality is a significant factor in the manufacturing of slots, pockets and dies. In end milling, the cutting tool revolve on an axis perpendicular to the work material, it is one of the indispensable tools in milling, which have their cutting teeth located on both the end face and the edge of the cutter body [3]. The basic use is that the end mill revolves and makes a plane of a material in the right-and-left direction or a plane of a bottom side of the work-piece. Distinctive mechanical part can be made with the end-milling process. In this case the spindle speed, the radial depth of cut, axial depth of cut and feed rate are very important. These important parameters affect the shapes and the surface roughness of the work-piece materials. Generally, in order to obtain minimum roughness, the radial depth of cut, axial depth of cut, feed rate and the spindle speed must have proper setting [4].

Minimum quantity lubricant (MQL) is the method of applying little quantity of high-quality lubricant directly to the cutting tool / work-piece interface instead of using conventional flood coolants. Minimum quantity lubricant in machining is a better option to completely dry or flood cooling method, which were considered as some of the keys for reducing the amount of lubricant to deal with the environmental pollution, economical and mechanical factors performance. Numerous scholars have recommended the MQL technique in machining process Gaitonde et al. [5], Davim et al., [6]; Machado and Wallbank, [7], Dhar et al. [8] applied this technique in a turning process and found that MQL is better than flood cooling. Silva et al. [9] also used tempered and annealed steel with aluminium oxide grinding wheel to explore and discuss the idea of the MQL in the grinding process. Okonkwo et al [10] carried out Comparative study of dry and MQL conditions where the MQL mixture used is 10% boric acid and base oil SAE 40, which proved that MQL can reduce the surface roughness by 20% when compared with the dry machining. Surface roughness is another important key of machining as the service life of the work piece machined are often affected by surface roughness, nature and extent of residual stresses and presence of surface or subsurface micro-cracks, particularly when that component is used under dynamic loading

Kuttolamadom et al, [11]. Generally, high-quality surface finish is achieved by process of machining, the major causes behind the increase of surface roughness in continuous machining process is as a results of the regular pattern left by the tool-tip on the finished surface, irregular deformation of the auxiliary cutting edge at the tool-tip due to chipping, fracturing and wear, vibration in the machining system, and built-up edge development, this will lead to corrosion of the work piece after machining [12, 22- 25].

Predictive modeling of machining processes is an important step for process control and optimization. A predictive model is an accurate relationship between the independent input variables and dependent output performance measures. There are two well-known approaches to obtain this relationship: the empirical approach and, the fundamental approach involving analytical means. The empirical approach is considered a short-term and practical method, and it is the most suitable approach for industrial applications. Okokpujie and Okonkwo [13] studied the effect of four cutting parameters on Al 6061 alloy machined surface under MQL condition. The numerical mathematical model developed predicted the surface roughness with about 89.5%. Likewise, Ertekin et al. [14] discovered the most significant and standard sensor features for the accuracy of surface roughness in milling process. Matsubara et al [15] also design a model for end-milling by studying the transfer matrix and direction of chips width leading to the origination of the static stiffness. Rashid [16] used multiple regressions and artificial neural network to design a model, the experiment was executed by using full-factorial design. The mathematical model developed by multiple regression method and artificial neural network technique shows the accuracy of 86.7% and 93.58% which is reliable to be used in surface roughness prediction.

Moreover, the accomplishments of some researchers efforts related to the current investigation have been reviewed in the preceding subsections of this work. Progress in evaluation, experimental analysis of modeling and the effects of cutting parameters on SR predictions, as they pertain to end milling process were reviewed. Further efforts aimed at resolving the problems posed by SR is needed and this work aims at making a contribution by providing empirical and numerical study of end-milling through a designed four-factor five-level experiments. The factors considered are the spindle speed, the axial depth of cut, the radial depth of cut and feed rate. This paper presents the application of both Response Surface methodology (RSM) and least square approximation method, to predict the SR for end milling of aluminium alloy machining process. The accuracy of the RSM to predict SR was compared with the least square approximation predicted method and ANOVA was used to carry out the effects of the various factors on SR.

2. EXPERIMENTAL

In this experimental study, AL 6061 material was machined at different cutting size of axial depth of cut of 10, 15, 20, 25 and 30 mm. Method used for the experimental studies is explained as shown in Fig. 1.

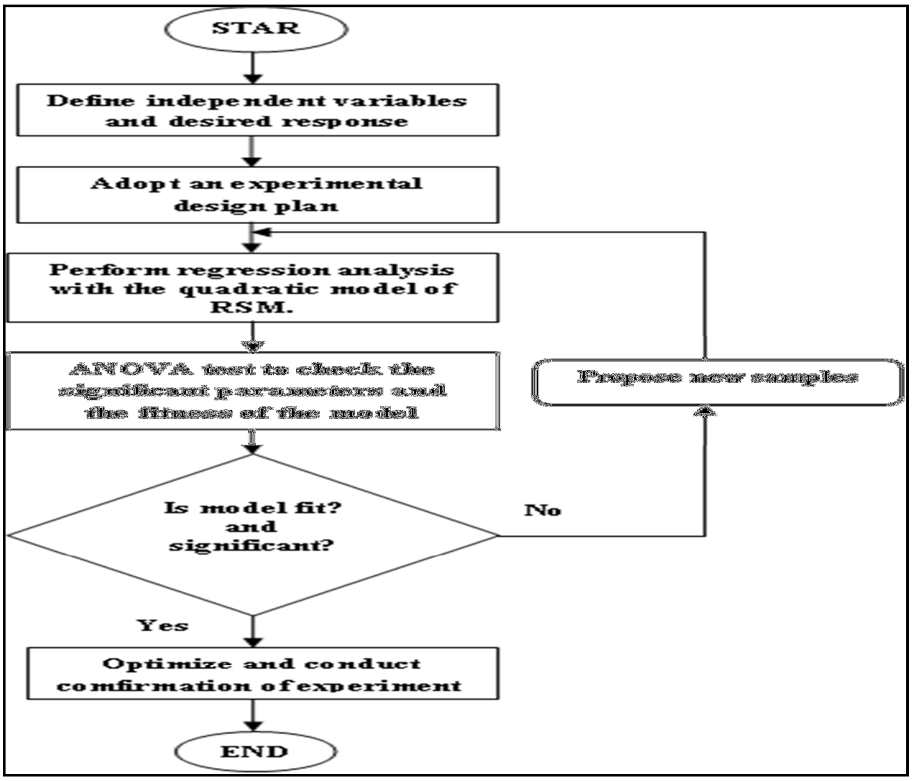

Figure 1 Flow chart of the experimental design

The Al 6061 alloy chemical composition is shown in Table 1. The cutting tools were made of high speed steel (HSS) having a flute 4 and diameter of 12 mm. The Selected machining parameters used for the experiment are presented in Table 2

Table 1 THE CHEMICAL COMPOSITION OF AL-6061 ALLOY

Alloy	Si	Fe	Cu	Mn	Mg	Cr	Zn	Ti	Al
6061	0.8	0.75	0.32	0.52	1.09	0.04	0.25	0.15	Balance

TABLE 2 SELECTED MACHINING PARAMETERS USED FOR THE EXPERIMENT

S/N	Factor	Notation	Levels				
			-2	**-1**	**0**	**1**	**2**
1.	Spindle speed [rpm]	V	1000	1500	2000	2500	3000
2.	Feed rate [mm/min]	f	100	150	200	300	500
3.	Axial depth of cut [mm]	a	10	15	20	25	30
4.	Radial depth of cut [mm]	d	0.5	1	1.5	2.0	2.5

This investigation applied RSM in the experimental design using central composite design (CCD) which required 30 experimental runs depending on the central replicates considered. The analysis and presentation of results was done by design expert 9.0.1. The RSM was used to determine the correlation between the process parameters and the response parameter. This was design to evaluate the effect of four factors on the SR. Five levels were selected for each process parameters as shown in Table 2. The parameters levels were selected within the specification given by the manufacturer of the cutting tools. The adequate number of experimental runs for four-factor five levels for C.C.D is 30 runs.

In this present study, the correlation between the responses parameters and the input parameters was given as [17]:

$Y = \varphi$ (V, f, a, d) (1)

Where, Y = desired machine-ability aspect and φ = response function. The estimation of Y is planned by using a non-linear mathematical model, which is appropriate for studying the interaction effects of process parameters on machine-ability characteristics. In the study, the RMS-based second order mathematical model is given as

$$Y = \beta_0 + \beta_1 x_2 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + e \quad (2)$$

Where, β_0 = free term of the regression equation, the coefficients, β_1, β_2, β_3 and β_4 =*The* estimated of corresponding values of the parameters, x_1, x_2, x_3, x_4 are logarithmic transformation of factors: spindle speed, cutting feed, axial dept of cut and radial depth of cut, respectively, and the e is the error term.

3. MATHEMATICAL MODELS

The experiments were carried out in MQL lubrication condition. A mathematical expression was modeled for the response parameter, which is surface roughness (SR). The relationship between the surface roughness and cutting process parameters is represented in equation (3) [17].

$SR = K.V^x.f^y.a^z.d^{zr}$ (3)

Where, K is constant, and x, y, z and zr are the power equations. Equation (3) can be represented in mathematical form as follows:

$$\log SR = \log K + \mathrm{x}.\log V + \mathrm{y}.\log f + z.\log a + \mathrm{zr}.\log d \quad (4)$$

The introduction of a replacement gets the following expression:

$$\mathrm{Y} = \log SR, \beta_0 = \log K, \mathrm{x}_1 = \log V, \mathrm{x}_2 = \log f, \mathrm{x}_3 = \log a, \mathrm{x}_4 = \log d, \mathrm{x} = \beta_1 \quad (5)$$

Therefore, $10^{\beta_0} = \mathrm{k}$ (6)

Linear model developed from the equation is represented as follows:

$$Y = \beta_0 + \beta_1 x_2 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + e \quad (7)$$

Where, x_1, x_2, x_3, x_4, are base-10 logarithmic transformation of factors: spindle speed, feed rate, axial depth of cut and radial depth of cut and β values are the estimates of corresponding parameter.

Table 3 Experimental Result for the Surface Roughness

S/N	Spindle speed(rpm)	Feed rate (mm/min)	Axial depth of cut(mm)	Radial depth of cut(mm)	Surface roughness (µm)
1	-1	-1	1	1	0.94
2	1	-1	1	1	0.85
3	1	1	1	-1	1.02
4	-1	1	-1	1	1.11
5	-1	-1	-1	1	0.92
6	0	0	0	2	1.10
7	-1	-1	-1	-1	0.90
8	0	0	0	0	1.01
9	-1	-1	1	-1	0.88
10	2	0	0	0	0.51
11	0	2	0	0	1.16
12	1	1	1	1	1.10
13	0	-2	0	0	0.50
14	1	1	-1	-1	0.98

S/N	Spindle speed(rpm)	Feed rate (mm/min)	Axial depth of cut(mm)	Radial depth of cut(mm)	Surface roughness (µm)
15	0	0	2	0	1.00
16	0	0	0	-2	0.88
17	0	0	0	0	1.08
18	1	-1	-1	1	0.93
19	1	-1	-1	-1	0.74
20	0	0	0	0	1.08
21	-2	0	0	0	1.12
22	1	1	-1	1	1.07
23	-1	1	1	1	1.14
24	0	0	-2	0	0.92
25	0	0	0	0	0.96
26	-1	1	-1	-1	1.06
27	-1	1	1	-1	1.04
28	1	-1	1	-1	0.60
29	0	0	0	0	1.01
30	0	0	0	0	1.01

From equation (7), by minimizing the residual sum of the squares,

$$S_r = \sum_{i=1}^{n} [Y_i - (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4]^2 \qquad (8)$$

Solving the minimization, the resulting equations are as follows

$N\beta_0 + \beta_1\sum x_1 + \beta_2\sum x_2 + \beta_3\sum x_3 + \beta_4\sum x_4 = \sum Y_i$ (9)

$\beta_0\sum x_1+\beta_1\sum x_1^2+\beta_2\sum x_1x_2+\beta_3\sum x_1x_3+\beta_4\sum x_1x_4=\sum x_1 Y_i$ (10)

$\beta_0\sum x_2+\beta_1\sum x_1x_2+\beta_2\sum x_2^2+\beta_3\sum x_2x_3+\beta_4\sum x_2x_4=\sum x_2 Y_i$ (11)

$\beta_0\sum x_3+\beta_1\sum x_1x_3+\beta_2\sum x_2x_3+\beta_3\sum x_3^2+\beta_4\sum x_3x_4=\sum x_3 Y_i$ (12)

$\beta_0\sum x_4+\beta_1\sum x_1x_4+\beta_2\sum x_2x_4+\beta_3\sum x_3x_4+\beta_4\sum x_4^2=\sum x_4 Y_i$ (13)

Due to the fact that the surface roughness from the experiment has been established, the analysis for the multiple regressions using equations (9 - 13) was done to obtain the regression coefficient and the sum of values calculated for x_i, has the following result:

$\sum x_1= 98.6817$ $\sum x_1x_2= 228.7346$
$\sum x_2= 69.5370$ $\sum x_1x_3= 127.2384$
$\sum x_3= 38.6817$ $\sum x_1x_4= 15.1892$
$\sum x_4= 4.6182$ $\sum x_1Y_i= 3.3643$
$\sum Y_i= 1.0580$ $\sum x_2x_3= 89.6605$
$\sum x_1^2=324.9204$ $\sum x_2x_4= 10.7053$
$\sum x_2^2= 161.7933$ $\sum x_2Y_i= 2.6862$
$\sum x_3^2=50.1934$ $\sum x_3x_4= 5.9527$
$\sum x_4^2=1.3460$ $\sum x_3Y_i= 1.3524$
$\sum x_4Y_i=0.2308$

Substituting all the sums of values into the simultaneous equation is as follows

$30\beta_0+98.68\beta 1+69.53\beta_2+38.68\beta_3+4.61\beta_4 = -0.8719$

$98.68\beta_0+324.92\beta_1+228.73\beta_2+127.23\beta_3+15.18\beta_4=-2.97$

$69.53\beta_0+228.73\beta_1+161.79\beta_2+89.66\beta_3+10.70\beta_4= -1.77$

$38.68\beta_0+127.23\beta_1+89.66\beta_2+50.19\beta_3+5.95\beta_4= -1.12$

$4.61\beta_0+15.18\beta_1+10.70\beta_2+5.95\beta_3+1.34\beta_4 = -0.044$

Transform above equations into matrix form

$$\begin{pmatrix} 30 & 98.6817 & 69.5370 & 38.6817 & 4.6182 \\ 98.6817 & 324.9204 & 228.7346 & 127.2384 & 15.1892 \\ 69.5370 & 228.7346 & 161.7933 & 89.6605 & 10.7053 \\ 38.6817 & 127.2384 & 89.6605 & 50.1934 & 5.9527 \\ 4.6182 & 15.1892 & 10.7053 & 5.952725 & 1.3460 \end{pmatrix} \begin{Bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{Bmatrix} = \begin{Bmatrix} -0.8719 \\ -2.9793 \\ -1.7748 \\ -1.1287 \\ -0.0443 \end{Bmatrix}$$

Solving the above equations to get the coefficient for, β_0, β_1, β_2, β_3 and β_4 yields,
$\beta_0 = 0.1893$, β_1 = -0.3500, β_2 =0.4012, β_3 = -0.0144
β_4 = 0.1399
From equation (6), $K = 10^{0.1893}$
Therefore, K = 1.5463
Therefore from equation (5),
x = -0.3500, *y* =0.4012, *z* =-0.0144 and zr = 0.1399
Finally, mathematical expression (M.E) of respond parameter (SR) is:
$SR = 1.5463.V^{-0.3500}.f^{0.4012}.a^{-0.0144}.d^{0.1399}$

Hence, the M.E is

$$SR = \frac{1.5463.f^{0.4012}.d^{0.1399}}{V^{0.3500}.a^{0.0144}} \qquad (14)$$

Statistical Analysis of Variance: A model for response surface was designed and analyzed using design expert software. Table 4 shows the result of the ANOVA used to analyzed the effects of the process parameters on the SR. Tables 5 show the statistical analysis of the process parameters on SR

TABLE 4 RESULT OF THE ANALYSIS OF VARIANCE

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob > F	
Model	0.25	18	0.014	44.69	< 0.0001	Significant
A - Spindle Speed	6.838E-004	1	6.838E-004	2.19	0.0166	
B - Feed Rate	0.010	1	0.010	32.80	0.0001	
C - Axial Depth of Cut	1.336E-004	1	1.336E-004	0.43	0.5264	
D - Radial Depth of Cut	1.996E-003	1	1.996E-003	6.40	0.0280	
AB	0.022	1	0.022	70.01	< 0.0001	
AC	8.498E-005	1	8.498E-005	0.27	0.6122	
AD	1.529E-005	1	1.529E-005	0.049	0.8289	
BC	1.046E-003	1	1.046E-003	3.35	0.0943	
BD	1.435E-003	1	1.435E-003	4.60	0.0552	
A^2	0.016	1	0.016	51.63	< 0.0001	
B^2	0.026	1	0.026	83.19	< 0.0001	
C^2	9.294E-004	1	9.294E-004	2.98	0.1124	
ABC	1.517E-003	1	1.517E-003	4.86	0.0497	
ABD	2.532E-003	1	2.532E-003	8.11	0.0159	
A^2B	0.013	1	0.013	42.53	< 0.0001	
AB^2	0.017	1	0.017	55.68	< 0.0001	
B^2C	1.774E-003	1	1.774E-003	5.68	0.0363	
B^3	3.906E-003	1	3.906E-003	12.51	0.0047	
Residual	3.434E-003	11	3.122E-004			
Lack of Fit	1.472E-003	6	2.453E-004	0.62	0.7097	not significant
Pure Error	1.962E-003	5	3.924E-004			
Cor Total	0.25	29				

ANOVA was used to determine the adequacy of the mathematical model developed in Table 4. In this study, the preferred level of confidence used was 95%. The 44.69 F-value implies that the model is fit, significant and adequate, the "Prob > F" Values of less than 0.05 indicate that the model terms are significant. In this experiment, A, B, D, AB, A^2, B^2, ABC, ABD, A^2B, AB^2, B^2C, and B^3 are

Significant, the "Prob > F" Values great than 0.10 indicate that the model terms are not significant. 0.62 of the "Lack of Fit F-value" implies the Lack of Fit is not significant relative to the pure error. Non-significant lack of fit is good, the model need to be fit to predict accurately.

Table 5 STATISTICAL ANALYSIS OF EXPERIMENTAL RESULT

Std. Dev.	0.018	R - Squared	0.9865
Mean	-0.029	Adj. R-Squared	0.9644
C.V. %	60.79	Adeq. Precision	25.994

The R-Square was 0.9865 which showed that 98.65 % of the observed variability in the SR could be determined by the independent variables which are the spindle speed, feed rate, axial depth of cut, and radial depth of cut. The Adeq accuracy is 25.994 which certain that the correlation coefficient between the experiential value of the dependent variable (SR) and the predicted value based on the regression model was Normal.

Hence, equation (15) shows the mathematical model for RSM.

$$SR = 0.30 - 0.018V + 0.45f + 0.030d + 0.77Vf - 1.08V^2 - 0.42f^2 + 0.10Vfa - 0.13Vfd - 1.91V^2f + 0.93Vf^2 - 0.30f^2a - 0.27f^3 \quad (15)$$

In the process of examining the SR mechanism in detail, the machined surface is observed and measured using press-o-firm and Mitutoyo surface roughness tester. Fig. 2 – 5, explained the various effects the four process parameters have on the SR, as the spindle speeds increases from 1000 rpm to 3000 rpm the SR reduces where the color change from green to blue, as the feed rate increases from 100 mm/min to 500 mm/min the SR increases, that why the color also change from green to red. In general the color variation help to explain the various cutting parameters effect on the SR. From Fig. 5, it is seen that the SR is high when the feed rate was increased to 500 mm/min. This was due to the increased in vibration and heat generated between work piece and cutting tool. As the feed rate was increased, their becomes discontinuity in the chips formation as a result of the chips been deposited between work piece and cutting tool which lead to the increase in the coefficient of friction and vibration there by result to increase surface roughness of the work piece. This result is in line with the result gotten by Arokiadass et al. [18] and Nwoke et al. [22], in their research where surface roughness increases as a result of the increased of feed rate. From Fig. 3 due to the increase spindle speed lead to increase of the cutting force which helps to eliminate the built-up edge tendency, it also reduces chip fracture and hence the roughness decreases, it is clear that the SR is low at a high spindle speed 2000 rpm. These findings is in line with the result obtained by Korkut Donertas [19], Ezugwu et al, [20] and Sabahudin et al [21] in related studies.

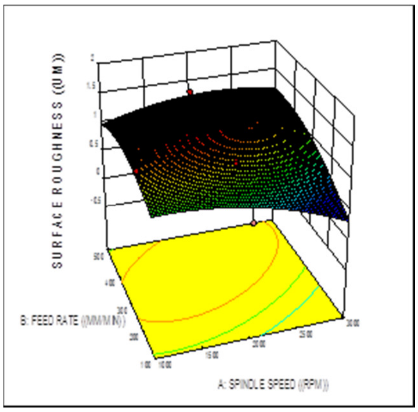

Figure 2 Effects of spindle speed and feed rate on the surface roughness

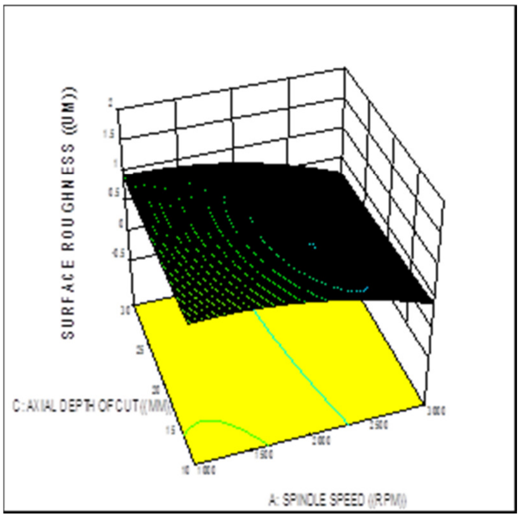

Figure 3 Effects of spindle speed and axial depth of cut on the surface roughness

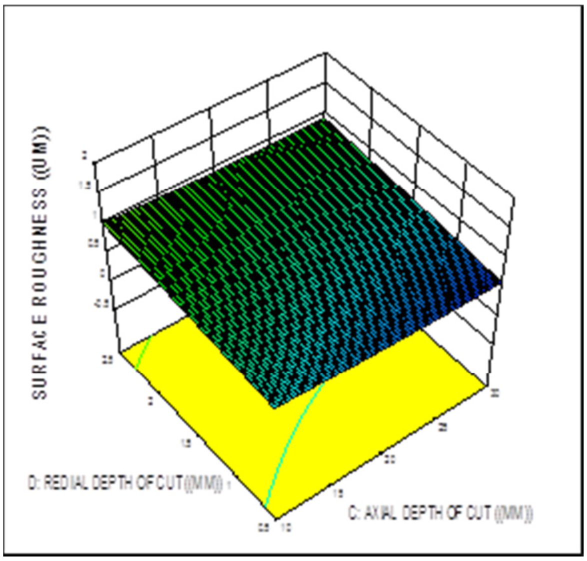

Figure 4 Effects of redial depth of cut and axial depth of cut on the surface roughness

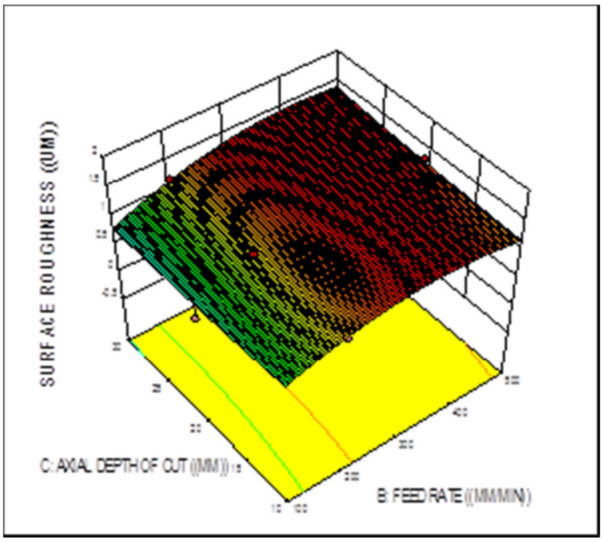

Figure 5 Effects of feed rate and axial depth of cut on the surface roughness.

Fig. 4 shows the 3D plot of surface roughness against radial depth of cut and axial depth of cut, increasing the radial depth of cut will slightly increase the SR, this is as a result of increase in the vibration in the point of contact between the cutting tool and the work piece and increasing axial depth of cut lead to slight reduction of the surface roughness due to the implemental of the minimum quantity lubrication (MQL). This is supported by observation.

Figure 6 Machined Surface at Speed 2000rpm, Feed 500mm/Min, Radial D.O.C 1.5mm and Axial D. O. C 20mm

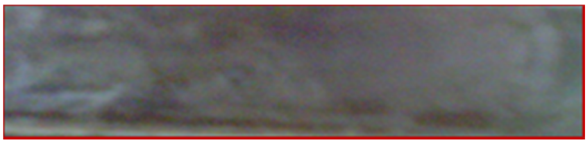

Figure 7 Machined Surface at Speed 2000rpm, Feed 100mm/min, Radial D.O.C 1.5mm and Axial D.O.C 20mm

Fig. 6 and 7 shows the image of the Al 6061 work-piece surface at different stages of machining, in Figure 6 the feed rate was increase to 500 mm/min when the spindle speed 2000 rpm, radial depth of cut 1.5 mm and axial depth of cut 20 mm are kept constant and the surface roughness obtained was 1.16 μm, which is the highest surface roughness in this investigation and the minimum surface roughness 0.5 μm occur when the feed rate was reduce to 100 mm/min, at this same constant value of the radial, axial depth of cut and spindle speed as shown in Fig. 7.

A. Analysis and Validation of Results

In order to determine the accuracy of the mathematical expression and the mathematical model developed from experimental results, percentage deviation φ_i and average percentage deviation $\overline{\varphi}_i$were used. The percentage deviation φ_i is stated thus, Okokpujie and Okonkwo [13]:

$$\varphi_i = \left(\frac{S_{a(m)} - S_{a(e)}}{S_{a(e)}}\right) \times 100\,\% \qquad (16)$$

Where, φ_i : is the sample data of percentage deviation

$Sa_{(e)}$: the experimental values of the surface roughness

$Sa_{(m)}$: predicted surface roughness generated by mathematical models.

Similarly, the average percentage deviation $\overline{\varphi}_i$ is stated thus:

$$\overline{\varphi}_i = \frac{\sum_{i=1}^{n} \varphi_1}{n} \qquad (17)$$

Where, $\overline{\varphi}_i$: is the percentage deviation average for all the experimental data, n: is the numbers of the experimental run. For a full test on the model created on the data, Table 6 shows the experimental values and the predicted values for surface roughness and percentage deviation

TABLE 6 Comparison between Actual Data and Predicted Data for Both M.E and RSM

S/N	Spindle speed (rpm)	Feed Rate (mm/min)	Axial depth of cut(mm)	Radial depth of cut(mm)	Surface Roughness (Ra) (μm)	Predicted values(Ra) (M.E)(μm)	Predicted values(Ra) (RSM)(μm)	Percentage deviation for Ra(e)-Ra(M.E)	Percentage deviation Ra(e)-Ra(RSM)
1	1500	150	25	2	0.94	0.93	0.93	-1.06	-1.06
2	2500	150	25	2	0.85	0.78	0.82	-8.23	-3.52
3	2500	300	25	1	1.02	0.94	1.02	-7.84	0.00
4	1500	300	15	2	1.11	1.24	1.12	11.71	0.90
5	1500	150	15	2	0.92	0.95	0.93	3.26	1.08
6	2000	200	20	2.5	1.10	0.98	1.15	-10.9	4.54
7	1500	150	15	1	0.90	0.85	0.89	-5.55	-1.11
8	2000	200	20	1.5	1.01	0.91	1.01	-9.90	0.00
9	1500	150	25	1	0.88	0.85	0.90	-3.40	2.27
10	3000	200	20	1.5	0.51	0.79	0.51	54.90	0.00
11	2000	500	20	1.5	1.16	1.33	1.16	14.65	0.00
12	2500	300	25	2	1.10	1.03	1.11	-6.36	0.90
13	2000	100	20	1.5	0.50	0.69	0.50	38.00	0.00
14	2500	300	15	1	0.98	0.94	0.99	-4.08	1.02
15	2000	200	30	1.5	1.06	0.91	1.00	-14.15	-5.66
16	2000	200	20	0.5	0.88	0.78	0.90	-11.36	2.27
17	2000	200	20	1.5	1.08	0.92	1.01	-14.81	-6.48
18	2500	150	15	2	0.93	0.79	0.95	-15.05	2.15
19	2500	150	15	1	0.74	0.72	0.72	-2.70	-2.70
20	2000	200	20	1.5	1.08	0.92	1.01	-14.81	-6.48
21	1000	200	20	1.5	1.12	1.17	1.13	4.46	0.89
22	2500	300	15	2	1.07	1.04	1.06	-2.80	-0.93
23	1500	300	25	2	1.14	1.24	1.13	8.77	-0.87
24	2000	200	10	1.5	0.81	0.93	0.92	14.81	13.58
25	2000	200	20	1.5	0.96	0.92	1.01	-4.16	5.20
26	1500	300	15	1	1.06	1.13	1.05	6.60	-0.94
27	1500	300	25	1	1.04	1.13	1.06	8.65	1.92
28	2500	150	25	1	0.60	0.71	0.62	18.33	3.33
29	2000	200	20	1.5	1.01	0.92	1.02	-8.91	0.99
30	2000	200	20	1.5	1.01	0.92	1.02	-8.91	0.99

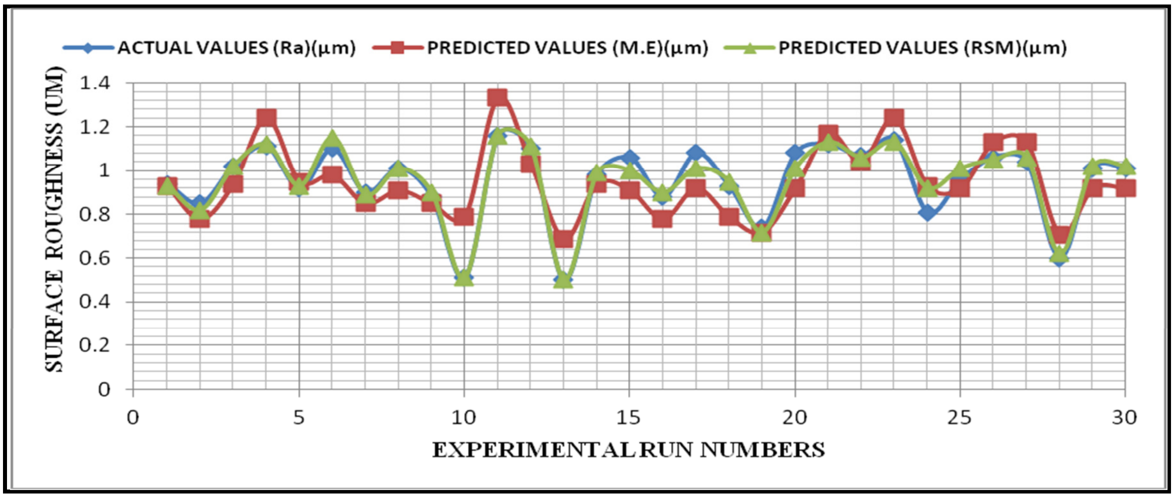

Figure 8 comparison plot of actual value, predicted values (M.E) and predicted values (RSM) of the surface roughness (SR)

Similarly, the actual values from the experiment and the predicted values obtained from the developed mathematical expression (M.E) from least square approximation method and the developed mathematical model from the Response surface methodology are shown in Fig. 8. It can be seen and observed that they have good agreement quantitatively; the accuracy of the models developed was tested using equation (17) and (18).

For data M.E $\overline{\varphi}_i = \left[100 - \left[\frac{29.16}{30}\right]\right]\% = 99\%$

For data RSM $\overline{\varphi}_i = \left[100 - \left[\frac{12.28}{30}\right]\right]\% = 99.6\%$

The result from the average percentage deviation ($\overline{\varphi}_i$) showed that M.E = 99% and RMS = 99.6%. This means that the mathematical expression predict the surface roughness (SR) with 99% accuracy and the mathematical model developed from RSM predicted the SR with 99.6% accuracy. For the full test created on the data, Table 6 shows the predicted values for both M.E and RSM for SR and their percentage deviation from the measured or actual SR values.

B. Optimization analysis

The aim of this research work is not for the investigation of the factor over the response alone, but also to indentify the area of impact where the SR reaches its minimum value. The optimization analysis of the process parameters was carried out using RSM technique where desirability was determined, that is to investigate if all the parameters are within their working range or not as the desirability is equal to 1, it was concluded that the parameters are within their working range. The result for the optimization is shown in Table 7

Table 7 Surface roughness optimal value of the process parameters

Parameters	Optimum value
N/(rpm)	2034.608
f/(mm/min)	100
a/mm	20
r/mm	1.5

Surface roughness: 0.50μm

4. CONCLUSIONS

The aim of this research was to provide an effective and perfect way to predict surface roughness in CNC end milling. In this study both least square approximation method and RSM was employed to develop a mathematical model (M.M) and mathematical expression (M.E) for surface roughness prediction. The result of average percentage deviation is 99% for M.E and 99.6% for RSM, showing that the prediction accuracy was about 99% and 99.6%. That means the mathematical expression and the model developed is reliable to predict surface roughness with acceptable accuracy range based on previous research, the following findings were observed.

- Response Surface Methodology model provided better accuracy prediction of the surface roughness in end milling process than the least square approximation method.
- From investigation the minimum surface roughness of 0.5 μm during the end milling operation occur at a spindle speed of 2034.608 rpm, feed rate of 100 mm/min, axial depth of cut of 20 mm, and radial depth of cut 1.5 mm respectively.

- Feed rate and spindle speed has great significant effect on the surface roughness in end milling of Al-6061 alloy, followed by radial Depth of cut and axial depth of cut has less significant effect on surface roughness.

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