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Effects of Cutting Parameters on Surface Roughness during End Milling of Aluminium under Minimum Quantity Lubrication (MQL)

Okokpujie Imhade P. [1], **Okonkwo Ugochukwu C.**[2]

Department of Mechanical Engineering, Nnamdi Azikiwe University, Awka, Nigeria

Abstract: ***In this study an experimental investigation of effects of cutting parameters on surface roughness during end milling of aluminium 6061 under minimum quantity lubrication (MQL) condition was carried out. The experiments were carried out to investigate surface quality of the machined parameters and to developed mathematical models using least square techniques. Spindle speed (N), feed rate (f), axial depth of cut (a) and radial depth of cut (r) has been chosen as input variables in order to predict surface roughness. The experiment was designed by using central composite design (CCD) in which 30 samples were run in a CNC milling machine. Each of the experimental result was measured using Mitutoyo surface tester. After the predicted surface roughness values have been obtained the average percentage errors were calculated. The mathematical model developed by using least square method shows accuracy of 89.5% which is reasonably reliable for surface roughness prediction. With the obtained optimum input parameters for surface roughness, production operations will be enhanced.***

Keywords: CNC end milling, Minimum quantity lubrication (MQL), Surface roughness, Response surface methodology.

1. Introduction

Milling is a process of generating machined surfaces by progressively removing a predetermined amount of materials from the work-piece at a relatively slow rate of movement by a milling cutter rotating at a comparatively high speed. The characteristic feature of the milling process is that each milling cutter tooth removes its share of the stock in the form of small individual chips. It is of three types which are: Peripheral milling, Face milling and End milling. End milling is one of the most common metal removal operation encountered in industrial process. It is widely used in the manufacturing industries which include the automotive and aerospace sectors, where quality is an important factor in the production of slots, pockets, precision molds, and dies. In end milling, the cutter generally rotates on an axis vertical to the work-piece. It can be tilted to machine tapered surfaces. Cutting teeth are located on both the end face of the cutter and the periphery of the cutter body. The quality of machined surface is characterized by the accuracy of its manufacture with respect to the dimensions specified by the designer. Each type of cutting tool leaves its own individual pattern which therefore can be identified. This pattern is known as surface finish or surface roughness.

The primary function of the MQL in metal machining operations is to serve as a coolant, also as a lubricant thereby reducing friction and tool wear. It is generally agreed that the application of MQL can improve the tool life and results in good surface finish by reducing thermal distortion and flushing away of machined chips. What is perhaps even more important is to ensure proper filtration of the fluid as suspended swarf can cause random deep scratches on the job. Predictive modeling of machining processes is the first and the most 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 suited approach for industrial applications. Ginta et al, (2009) developed an effective methodology to determine the performance of uncoated WC-Co inserts in predicting minimum surface roughness in end milling of titanium alloys Ti-6Al-4V under dry conditions. Central composite design (CCD) of response surface methodology was employed to create an efficient analytical model for surface roughness in terms of cutting parameters: cutting speed, axial depth of cut, and feed per tooth. End milling tests were conducted on Vertical Machining Center (VMC ZPS, Model: MLR 542 with full immersion cutting and under dry condition. They concluded with CCD being a successful technique to predict the surface roughness produced in end-milling of titanium alloy Ti-6Al-4V using uncoated inserts under dry conditions. Linear CCD model proved inadequate while quadratic CCD model is adequate with 95% accuracy. The two developed models indicated that feed is the most predominant cutting condition followed by cutting speed and depth of cut. Interaction effect between cutting speed and feed will also give a high effect on surface roughness values.

Arokiadass et al, (2011) also studied the influence of four machining parameters including spindle speed (N), feed rate (f), depth of cut (d), and various percentage weight of silicon carbide (S) on surface roughness (Ra). The response surface methodology was employed to establish the mathematical relationship between the response and the various process parameters. The result they obtained shows that the quadratic model is statistically significant for analysis of surface roughness. The value of R is 99.85 %, which indicates that the developed regression model is adequately significant at a 95% confidence level. Their model also indicated that the feed rate was the most dominant parameter on surface roughness followed by spindle speed and %weight of SiC. Depth of cut has less influence on surface roughness. They also concluded that the regression model is well fitted with the observed values and high correlation that exists between fitted values and observed values.

2. Materials and Methods

The work piece material used for the study is a rectangular 6061Aluminium blocks of 2000mm×50mm×5mm. Method used for the experimental investigations is explained thus:

- Preparation of the vertical CNC milling machine system ready for performing the machining operation, Cutting of the work piece of the aluminium 6061 rectangle plate into different sizes of 10, 15, 20, 25 and 30mm. A total of 30 pieces, for MQL condition
- Fixing of the high speed steel (HSS) end milling cutter of 12mm diameter on the spindle taper of the machine
- Mounting the work piece, clamped on a vice mounted on top of the table of the machine
- Creating CNC part programs on CNC professional software for tool paths, with specific commands using different levels of spindle speed, feed rate, axial depth of cut and radial depth of cut, taking reference for Y axis, and Z axis then performing end milling operation.
- After each machining the surface roughness of the work piece was measured with the press-o-firm and mitutoyo surface tester

Detailed information on chemical composition of the 6061 Aluminium is provided in table 1, and details of the experimental outlay, only up-milling cutting mode was investigated.

Table 1: Chemical Composition of Al-6061

Element	Mg	Fe	Si	Cu	Mn	V	Ti	AL
Weight %	1.08	0.17	0.63	0.32	0.52	0.01	0.02	Remainder

Table 2: Details of the Experimental Outlay

Exp. Runs	Material	Mql Cutting Condition	Cutting Tool	Input Parameters	Response Parameters
1 to 30	Al-6061 alloy	10% boric acid + base oil SAE 40	High speed steel	Cutting speed	Surface Roughness
				Feed rate	
				Axial depth of cut	
				Radial depth of cut	

The experiment was performed on SIEG 3/10/0010 table top CNC machine vertical milling centre. The vertical milling centre has three (3) planes namely x, y and z planes.

Response surface methodology (RSM) was employed in the experimental design using second-order rotatable central composite design. By considering all the factorial corner points, some of the central replicates and all the axial points second-order rotatable central composite design requires between 25 to 33 experimental runs depending on the number of the central replicates considered while a full factorial design will require 5^4= 625 experimental runs. This explains the choice of second-order rotatable central composite design which tremendously reduces needed number of experimental runs for the MQL cutting conditions, which doubles the calculated number of experimental runs. The design expert 9.0.1 was used in analysis and presentation of results. The response surface methodology (RSM) is the procedure for determining the relationship between the independent process parameters with the desired response and exploring the effect of these parameters on responses, including six steps (Chiang 2008). These are in the order;

- Define the independent input variables and the desired responses with the design constants.
- Adopt an experimental design plan.
- Perform regression analysis with the quadratic model of RSM.
- Calculate the statistical analysis of variance (ANOVA) for the independent input variables in order to find which parameter significantly affects the desired response.
- Determine the situation of the quadratic model of RSM and decide whether the model of RSM needs screening variables or not.
- Optimize and conduct confirmation experiment and verify the predicted performance characteristics.

In the current study, the relationship between the cutting conditions and the technology parameters aspect is given as (*Sabahudin et al, 2011*).

$$Y = \varphi (N, f, a, r), \quad (1)$$

Where Y is the desired machinability aspect and φ is the response function. The approximation of Y is proposed by using a non-linear (quadratic) mathematical model, which is suitable for studying the interaction effects of process parameters on machinability characteristics. In the present work, the RMS-based second order mathematical model is given by

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \quad (2)$$

Where β_o is the free term of the regression equation, the coefficients, β_1, β_2, β_3 and β_4 values are the estimates of corresponding 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.

The experimental plan is developed to assess the influence of spindle speed (N), feed rate (f), axial depth of cut (a) and radial depth of cut (r) on the surface roughness parameters (R_a). Five levels were allocated for each cutting variable as given in table 3. The variable levels were chosen within the intervals recommended by cutting tool manufacturer. Four cutting variables at five levels led to a total of 30 tests for each condition.

Table 3: Factor levels to be used in the experimental design

Variable	Levels				
	-2	-1	0	1	2
Spindle speed [rpm]	1000	1500	2000	2500	3000
Feed rate [mm/min]	100	150	200	300	500
Radial depth of cut [mm]	0.5	1	1.5	2.0	2.5
Axial depth of cut[mm]	10	15	20	25	30

Mathematical model of surface roughness was built for MQL cutting condition. Percentage improvement in surface roughness expected to be occasioned by MQL was thereafter quantified. Furthermore, optimization of the arising model was carried out to determine the coordinate of minimum surface roughness.

The required number of experimental points for four-factor in the C.C.D with one replication of factorial and axial parts having, factorial design is = $2^f = 2^4 = 16$, the axial point or star point is = 2×f = 2×4 = 8, where f= number of factors, the center point chosen for this experiment is 6, which is = 16+8+6 = 30. Therefore the thirty experiments are carried out according to the blocked central composite design (CCD).

3. Mathematical Models

The relationship between the surface roughness and cutting independent variables can be represented by the following equation (Sabahudin et al, 2011).

$$R_a = K.N^x.f^y.a^z.r^{zr} \quad (3)$$

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

$$InR_a = In\ K + x.In\ N + y.In\ f + z.In\ a + zr.In\ a \quad (4)$$

The constant and exponents K, x, y, z, zr can be determined by least squares method. The introduction of a replacement gets the following expression:

$$Y = InRa,\ \beta_0 = InK,\ x_1 = InN,\ x_2 = Inf,\ x_3 = In\ a,\ x_4 = Inr,\ x = \beta_1,\ y = \beta_2,\ z = \beta_3,\ zr = \beta_4 \quad (5)$$

Therefore, $e^{\beta 0}$ = K (6)

Linear model developed from the equation can be represented as follows:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \quad (7)$$

Where, x_1, x_2, x_3, x_4, are 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 parameters.

Table 4: Experimental result for MQL environment

Std	Run	Factor 1 A: Spindle speed(rpm)	Factor 2 B: Feed rate (mm/min)	Factor 3 C: Axial depth of cut(mm)	Factor 4 D: Radial depth of cut(mm)	Factor 5 E: Surface roughness (Ra)(μm)
13	1	-1	-1	1	1	0.94
14	2	1	-1	1	1	0.85
8	3	1	1	1	-1	1.02
11	4	-1	1	-1	1	1.11
9	5	-1	-1	-1	1	0.92
24	6	0	0	0	2	1.1
1	7	-1	-1	-1	-1	0.9
25	8	0	0	0	0	1.01
5	9	-1	-1	1	-1	0.88
18	10	2	0	0	0	0.51
20	11	0	2	0	0	1.16
16	12	1	1	1	1	1.1
19	13	0	-2	0	0	0.5
4	14	1	1	-1	-1	0.98
22	15	0	0	2	0	1
23	16	0	0	0	-2	0.88
26	17	0	0	0	0	1.08
10	18	1	-1	-1	1	0.93
2	19	1	-1	-1	-1	0.74
27	20	0	0	0	0	1.08
17	21	-2	0	0	0	1.12
12	22	1	1	-1	1	1.07
15	23	-1	1	1	1	1.14
21	24	0	0	-2	0	0.92
30	25	0	0	0	0	0.96
3	26	-1	1	-1	-1	1.06
7	27	-1	1	1	-1	1.04
6	28	1	-1	1	-1	0.6
29	29	0	0	0	0	1.01
28	30	0	0	0	0	1.01

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

We have

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

Solving the minimization, the resulting equations are as follows

$n\beta_0 + \beta_1\sum x_1 + \beta_2\sum x_2 + \beta_3\sum x_3 + \beta_4\sum x_4 = \sum Y_i$

$\beta_0\sum x_1 + \beta_1\sum x_1^2 + \beta_2\sum x_1x_2 + \beta_3\sum x_1x_3 + \beta_4\sum x_1x_4 = \sum x_1Y_i$

$\beta_0\sum x_2 + \beta_1\sum x_1x_2 + \beta_2\sum x_2^2 + \beta_3\sum x_2x_3 + \beta_4\sum x_2x_4 = \sum x_2Y_i$

$\beta_0\sum x_3 + \beta_1\sum x_1x_3 + \beta_2\sum x_2x_3 + \beta_3\sum x_3^2 + \beta_4\sum x_3x_4 = \sum x_3Y_i$

$\beta_0\sum x_4 + \beta_1\sum x_1x_4 + \beta_2\sum x_2x_4 + \beta_3\sum x_3x_4 + \beta_4\sum x_4^2 = \sum x_4Y_i$

Since the surface roughness from the experiment has been established, the analysis for the multiple regressions using equations above are done to obtain regression coefficient and the sum values calculated for x_i, with the following results:

$\sum x_1$= 227.2231 $\sum x_1x_2$= 1212.728

$\sum x_2$= 160.1149 $\sum x_1x_3$= 674.6051

$\sum x_3$= 89.06798 $\sum x_1x_4$= 80.53167

$\sum x_4$= 10.6339 $\sum x_1Y_i$= -15.7963

$\sum Y_i$= -2.00772 $\sum x_2x_3$= 475.3713

$\sum x_1^2=1722.695$ $\sum x_2x_4= 56.75883$
$\sum x_2^2= 857.8118$ $\sum x_2Y_i= -9.41013$
$\sum x_3^2=266.1206$ $\sum x_3x_4= 31.56074$
$\sum x_4^2=7.136489$ $\sum x_3Y_i= -5.98435$
$\sum x_4Y_i=-0.23536$

Substituting all the sums values into the simultaneous equation of linear system as follows

$30\beta_0 + 227.2231\beta_1 + 160.1149\beta_2 + 89.06798\beta_3 + 10.6339\beta_4 = -2.00772$

$227.2231\beta_0 + 1722.695\beta_1 + 1212.728\beta_2 + 674.6051\beta_3 + 80.53167\beta_4 = -15.7963$

$160.1149\beta_0 + 1212.728\beta_1 + 857.8118\beta_2 + 475.3713\beta_3 + 56.75883\beta_4 = -9.41013$

$10.6339\beta_0 + 80.53167\beta_1 + 56.75883\beta_2 + 31.56074\beta_3 + 7.136489\beta_4 = -5.98435$

$89.06798\beta_0 + 674.6051\beta_1 + 475.3713\beta_2 + 266.1206\beta_3 + 31.56074\beta_4 = -0.23536$

Transform above equations into matrix form

$$\begin{pmatrix} 30 & 227.2231 & 160.1149 & 89.06798 & 10.6339 \\ 227.2231 & 1722.695 & 1212.728 & 674.6051 & 80.53167 \\ 160.1149 & 1212.728 & 857.8118 & 475.3713 & 56.75883 \\ 10.6339 & 80.53167 & 56.75883 & 31.56074 & 7.136489 \\ 89.06798 & 674.6051 & 475.3713 & 266.1206 & 31.56074 \end{pmatrix} \begin{Bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{Bmatrix} = \begin{Bmatrix} -2.000772 \\ -15.7963 \\ -9.41013 \\ -5.98435 \\ -2.3536 \end{Bmatrix}$$

After completing the solution for the matrix form, the regression coefficients estimated were;

$\beta_0 = 0.4324$
$\beta_1 = -0.3496$
$\beta_2 = 0.4013$
$\beta_3 = -0.0144$
$\beta_4 = 0.1398$

From equation 6, K= $e^{0.4324}$

Therefore, $K = 1.5409$

And from equation 5, x = -0.3496, y =0.4013, z =-0.0144 and zr = 0.1398

Finally, mathematical model of surface roughness for MQL is:

$Ra = 1.5409.N^{-0.3496}.f^{0.4013}.a^{-0.0144}.r^{0.1398}$

Hence, the mathematical model of MQL condition is

$$R_a = \frac{1.5409.\,f^{0.4013}.\,r^{0.1398}}{N^{0.3498}.\,a^{0.0144}} \qquad (9)$$

Table 5: Comparison between Measure Data and Predicted Data (MQL Condition)

Exp No.	Spindle speed (rpm)	Feed Rate (mm/min)	Axial depth of cut (mm)	Radial depth of cut (mm)	Surface Roughness (Ra) (μm)	Predicted values(Ra) (μm)	Percentage deviation (φ_i)
1	1500	150	25	2	0.94	0.93	0.11
2	2500	150	25	2	0.85	0.78	7.60
3	2500	300	25	1	1.02	0.94	7.70
4	1500	300	15	2	1.11	1.25	-12.54
5	1500	150	15	2	0.92	0.95	-2.81
6	2000	200	20	2.5	1.1	0.99	10.33
7	1500	150	15	1	0.9	0.86	4.61
8	2000	200	20	1.5	1.01	0.92	9.07
9	1500	150	25	1	0.88	0.85	3.15
10	3000	200	20	1.5	0.51	0.79	-56.27
11	2000	500	20	1.5	1.16	1.32	-14.36
12	2500	300	25	2	1.1	1.04	5.71
13	2000	100	20	1.5	0.5	0.69	-39.07
14	2500	300	15	1	0.98	0.95	3.23
15	2000	200	30	1.5	1	0.91	8.69
16	2000	200	20	0.5	0.88	0.79	10.49
17	2000	200	20	1.5	1.08	0.92	14.96
18	2500	150	15	2	0.93	0.79	14.93
19	2500	150	15	1	0.74	0.72	2.96
20	2000	200	20	1.5	1.08	0.92	14.96
21	1000	200	20	1.5	1.12	1.17	-4.48
22	2500	300	15	2	1.07	1.04	2.34
23	1500	300	25	2	1.14	1.24	-8.77
24	2000	200	10	1.5	0.92	0.93	-0.82

Exp No.	Spindle speed (rpm)	Feed Rate (mm/min)	Axial depth of cut (mm)	Radial depth of cut (mm)	Surface Roughness (Ra) (µm)	Predicted values(Ra) (µm)	Percentage deviation (φ_i)
25	2000	200	20	1.5	0.96	0.92	4.34
26	1500	300	15	1	1.06	1.13	-6.96
27	1500	300	25	1	1.04	1.12	-8.22
28	2500	150	25	1	0.6	0.71	-18.81
29	2000	200	20	1.5	1.01	0.92	9.07
30	2000	200	20	1.5	1.01	0.92	9.07

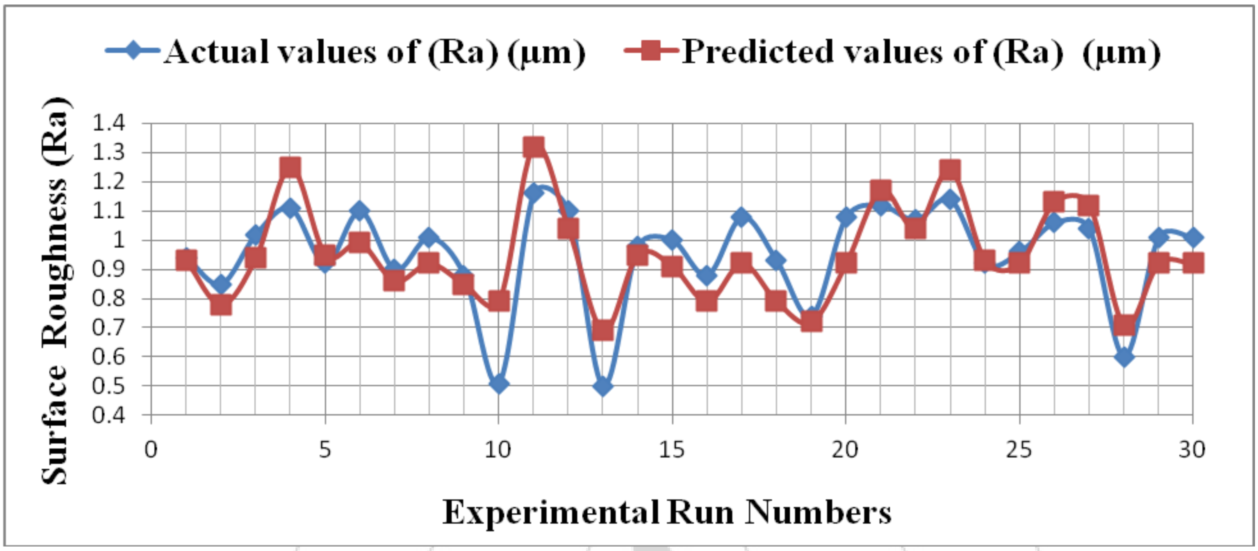

Figure 2: Actual and Predicted Values of the Surface Roughness in MQL Condition

Similarly, the actual values gotten from the experiment and the predicted values obtained from the developed mathematical model are depicted in figure 2. It can be seen that they have good agreement. Quantitatively, In order to judge the accuracy of the experimental developed mathematical models, percentage deviation φ_i and average percentage deviation $\bar{\varphi}$ were used. The percentage deviation φ_i is stated thus:

$$\varphi_i = \frac{\left| Ra_{(e)} - Ra_{(m)} \right|}{Ra_{(e)}} \text{ x } 100\% \qquad (10)$$

Where φ_i: percentage deviation of single sample data, $Ra_{(e)}$: measured, $Ra_{(e)}$: predicted $Ra_{(m)}$ generated by a multiple regression equation.

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

$$\varphi_i = \frac{\sum_{i=1}^{n}\varphi_i}{n} \qquad (11)$$

Where $\bar{\varphi}$: average percentage deviation of all sample data
n: the size of sample data.

For training data $\bar{\varphi} = \frac{316.43}{30} = 10.54\%$

The result of average percentage deviation ($\bar{\varphi}$) showed that the training data set (n=30) was 10.54%. This means that the statistical model could predict the surface roughness (Ra) with about 89.5% accuracy of the training data set. For a full test on the model created on the training data, table 6 shows the predicted value for surface roughness and percentage deviation from the measured or actual Ra values.

4. Effects of Cutting Parameters on Surface Roughness under MQL Condition

The effects of cutting parameters on surface roughness in end milling of aluminium were investigated using contour plots of the results obtained in MQL conditions. The graphical evaluation was obtained by plotting surface roughness values against the various cutting parameters (axial depth of cut, radial depth of cut, spindle speed and feed rate). Surface roughness values are simultaneously plotted against two cutting parameters while keeping the other two constant. Figures 3-4 show the experimental results obtained from the effect of cutting parameters on surface roughness.

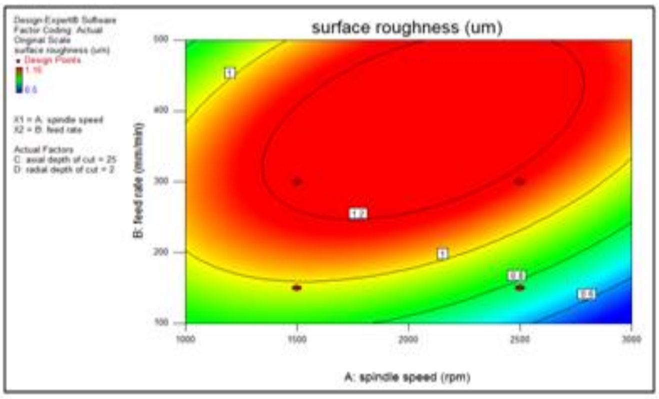

Figure 3: Surface Roughness Contour Plot for Spindle Speed vs Feed Rate in MQL Condition

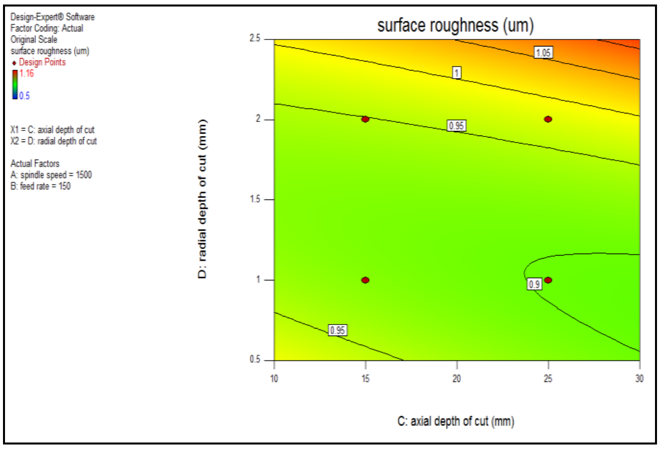

Figure 4: Surface Roughness Contour Plot for Axial Depth of Cut vs Radial Depth of Cut in MQL Condition

Following conclusions can be deduced from figure 3 and figure 4.

Spindle speed: An increase in spindle speed increases the cutting force and eliminates the built-up edge (BUE) tendency. At low spindle speed (rpm), the unstable larger BUE is formed and also the chips fracture readily producing the rough surface. As the spindle speed (rpm) increases, the BUE vanishes, chip fracture decreases, and hence, the roughness decreases. These findings were in line with observations made by Tosun and Mesut (2010); Korkut and Donertas (2007) in related studies. Feed rate: An increase in feed rate significantly increases the surface roughness. Increasing feed rate increases vibration and heat generated, which courses an increase in surface roughness. As the feed rate is increased, chips become discontinuous and are deposited between work piece and tool leading to increased coefficient of friction and more interruption resulting in poor surface finish. This finding is also supported by *Arokiadass et al (2011)*. Radial depth of cut: increasing the radial depth of cut will slightly increase the surface roughness. Axial depth of cut: it has no significant effect on the surface roughness. This is supported by observation.

5. Conclusion

Experimental work is carried out on aluminium metal in MQL environments. Through experimentation, the system proved it is capable of predicting the surface roughness (Ra) with about 89.5% accuracy in MQL environment. The important conclusions drawn from the present research are summarized as follows:

- The quadratic second order models developed to predict the surface roughness value for the MQL cutting condition could provide predictive values for surface roughness pretty close to the actual values by applying the values of the control parameter on the model.
- In the order of influence, spindle speed is the most significant effect on the surface roughness, followed by feed rate. However radial depth of cut has little effect on the surface roughness and axial depth of cut has no significant effect on the surface roughness.
- From the experimental values of table 4, the optimum or minimum surface roughness during cutting process occurs at spindle speed of 2000rpm, feed rate of 100mm/min, axial depth of cut 20mm and radial depth of cut 1.5mm for these conditions, the minimum surface roughness was 0.50µm.
- Interaction effect between spindle speed and feed rate also possesses a major effect over the surface roughness, followed by axial depth of cut and radial depth of cut.

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