Cutting Parameters Effects on Surface Roughness During End Milling of Aluminium 6061 Alloy Under Dry Machining Operation

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Abstract: ***In this project an experimental investigation of the cutting parameters effects on surface roughness during end milling of aluminium 6061 under dry machining operation was carried out. The experiments were carried out to investigate surface quality of the four machined parameters and to developed mathematical models using least square approximation techniques. Spindle speed (N), axial depth of cut (a) radial depth of cut (r) and feed rate (f), 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 Press-o-firm and 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 approximation method shows accuracy of 91% 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, Surface roughness, and Response surface methodology

1. Introduction

The importance of control and optimization of surface roughness cannot be overemphasized when considered against the backdrop of role of surface roughness in the measurement of surface dimensional accuracy and integrity. Obtaining a good surface quality is very important in every engineering component design or fabrication. Good surface finish has some influence in mechanical properties such as fatigue behaviour, wear, corrosion, lubrication, and electrical conductivity. Therefore measurement of surface finish and characterization also plays an important part in the prediction of a machining performance. One way to check if a machined material has good quality is through the measurement of its surface roughness.

Milling is a process of generating machined surfaces by progressively removing a predetermined amount of material or stock from the work-piece at a relatively slow rate of movement or feed 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.

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.

Dimensional inaccuracy of a machined surface may be classified into two, namely; surface location error and surface roughness. Surface location error is due to tool compliance that causes it to deflect under action of cutting forces leading to the cutting edges of the tool being deviated from the intended location and profile. Research on surface location error of end-milling process is already fairly well-developed. About three decades ago Fujii et al (1979) correlated surface error with the cutting forces. Three years later Kline et al (1982) predicted surface accuracy of end-milling by summing up the cutting forces generated on the chip load elements and mimicking the end mill as a slender cantilever beam.

A few years later Matsubara et al (1987) developed a theoretical model for accuracy of end-milling by investigating the transfer matrix and instantaneous chip thickness leading respectively to derivation of the static stiffness of the end mill and the instantaneous cutting forces. Budak and Alintas (1994) presented a model that highlighted dependence of surface accuracy on the cutting parameters. Insperger et al. (2006) generated both the stability diagram and the surface location error diagram and discussed the selection of optimal spindle speed considering both diagrams. Surface roughness is the inherent irregularities left by a single-point tool like turning tool or milling tool on a machined surface. Surface roughness is noted by Field et al (1989) as cited that surface roughness is predominantly considered as the most important feature of practical engineering surfaces due to its crucial influence on the mechanical and physical properties of a machined part. The roughness of a machined surface is an indication of relative vibration between the tool and work piece during a machining operation as the work of Peigne et al. (2004) in which they studied the effects of the cutting vibratory phenomena and their impacts on the surface roughness of the machined surface suggests.

The parameters of machining process are expected to affect this relative vibration thus have effects on component surface roughness. The obvious machining parameters of a machining process such as end-milling are the spindle speed, the axial depth of cut, the radial depth of cut and the feed rate. These are the most easily controlled parameters of the machining process being at the disposal of the operator to choose or to vary continuously in process. Other parameters include tool geometry (given in terms of tool angles like rake angle, flank or tool relief angle, notch angle), tool and work piece material and tool wear. Tool wear being a tribological phenomenon develops with progression of machining and then causes progressive increase in surface roughness.

Surface roughness has been attributed to cutting conditions, tool geometry and mechanical stiffness. Various other studies have considered the behavior of surface roughness under different tool-work-piece material combinations and experiments. Kishawy et al. (2005) studied the effect of flood coolant, and dry cutting, on tool wear, surface roughness and cutting forces.
A study of the surface integrity produced by end mill tool using a Taguchi orthogonal array has been presented by Mantle and Aspinwall (2001), Wang and Chang (2004) analyzed the influence of cutting conditions and tool geometry on surface roughness of slot end milling operation. Feasibility study and development of an in-process based recognition system to predict the surface roughness of machined parts in the end milling process has been presented by Tsai et al. (1999) Similarly, Ertekin et al. (2003) has identified the most influential and common sensory features for dimensional accuracy and surface roughness in CNC milling operations.

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 DRY 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 as shown in fig 1
- 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, slot-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*	*Cutting Tool*	*Input Parameters*	*Response Parameters*
1to 30	Al-6061 alloy	High speed steel	Cutting speed	Surface Roughness
			Feed rate	
			Axial depth of cut	
			Radial depth of cut	

The experiment was performed on SIEG 3/10/0016 table top CNC machine vertical milling centre. The vertical milling centre has three (3) planes namely x, y and z planes as shown in figure 1.

Figure 1: Experimental setup for the dry end milling operation

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 Dry 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

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

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 4. 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 Dry cutting condition. Percentage improvement in surface roughness expected to be occasioned by Dry 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.

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

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

$$\text{InR}_a = \text{In K} + \text{x.In N} + \text{y.In f} + \text{z.In a+zr.Ina} \quad (4)$$

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:

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

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

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 DRY 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	1.12
14	2	1	-1	1	1	0.95
8	3	1	1	1	-1	1.17
11	4	-1	1	-1	1	1.27

9	5	-1	-1	-1	1	1.1
24	6	0	0	0	2	1.21
1	7	-1	-1	-1	-1	1.08
25	8	0	0	0	0	1.2
5	9	-1	-1	1	-1	1.04
18	10	2	0	0	0	0.61
20	11	0	2	0	0	1.31
16	12	1	1	1	1	1.26
19	13	0	-2	0	0	0.58
4	14	1	1	-1	-1	1.13
22	15	0	0	2	0	1.16
23	16	0	0	0	-2	1.03
26	17	0	0	0	0	1.17
10	18	1	-1	-1	1	1.05
2	19	1	-1	-1	-1	0.84
27	20	0	0	0	0	1.18
17	21	-2	0	0	0	1.28
12	22	1	1	-1	1	1.22
15	23	-1	1	1	1	1.29
21	24	0	0	-2	0	1.15
30	25	0	0	0	0	1.19
3	26	-1	1	-1	-1	1.26
7	27	-1	1	1	-1	1.24
6	28	1	-1	1	-1	0.75
29	29	0	0	0	0	1.13
28	30	0	0	0	0	1.15

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:

$\sum x_1 = 227.2231$ $\sum x_1x_2 = 1212.728$
$\sum x_2 = 160.1149$ $\sum x_1x_3 = 674.6051$
$\sum x_3 = 89.06798$ $\sum x_1x_4 = 80.53167$
$\sum x_4 = 10.6339$ $\sum x_1Y_i = 17.2375$
$\sum Y_i = 2.355666$ $\sum x_2x_3 = 475.3713$
$\sum x_1^2 = 1722.695$ $\sum x_2x_4 = 56.75883$
$\sum x_2^2 = 857.8118$ $\sum x_2Y_i = 13.8149$
$\sum x_3^2 = 266.1206$ $\sum x_3x_4 = 31.56074$
$\sum x_4^2 = 7.136489$ $\sum x_3Y_i = 6.929026$
$\sum x_4Y_i = 1.315218$

$30\beta_0 + 227.2231\beta_1 + 160.1149\beta_2 + 89.06798\beta_3 + 10.6339\beta_4 = 2.355666$

$227.2231\beta_0 + 1722.695\beta_1 + 1212.728\beta_2 + 674.6051\beta_3 + 80.53167\beta_4 = 17.2375$

$160.1149\beta_0 + 1212.728\beta_1 + 857.8118\beta_2 + 475.3713\beta_3 + 56.75883\beta_4 = 13.8149$

$10.6339\beta_0 + 80.53167\beta_1 + 56.75883\beta_2 + 31.56074\beta_3 + 7.136489\beta_4 = 6.929026$

$89.06798\beta_0 + 674.6051\beta_1 + 475.3713\beta_2 + 266.1206\beta_3 + 31.56074\beta_4 = 1.315218$

Transform above equations into matrix form

$$\left\{\begin{matrix} 30 & 227.2231 & 160.1149 & 89.06798 & 10.6339 \\ 227.2231 & 1722.695 & 1212.728 & 674.6051 & 80.53167 \\ 160.1149 & 1212.728 & 857.8118 & 475.3713 & 56.75883 \\ 10.6339 & 80.53167 & 56.75883 & 31.56074 & 7.136489 \\ 89.06798 & 674.6051 & 475.3713 & 266.1206 & 31.56074 \end{matrix}\right.$$

Solving the above equations to get the coefficient for, β_0, β_1, β_2, β_3 and β_4 yields

$\beta_0 = 0.8212$
$\beta_1 = -0.3586$
$\beta_2 = 0.3819$
$\beta_3 = -0.0389$
$\beta_4 = 0.1409$

From equation 3.7a, $K = e^{0.8212}$

Therefore, K = 2.2732
And from equation 3.7, x = - 0.3586, y = 0.3819, z = -0.0389and zr = 0.1409
Finally, the mathematical model of surface roughness (3.5) is:

$$R_a = 2.2732.N^{-0.3586}.f^{0.3819}.a^{-0.0389}.r^{0.1409}$$

Hence, the mathematical model of dry condition is

$$R_a = \frac{2.2732.f^{0.3819}.r^{0.1409}}{N^{0.3586}.a^{0.0389}} \quad (9)$$

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Table 5: Comparison between Actual Data and Predicted Data (Dry 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	1.12	1.09	2.82
2	2500	150	25	2	0.95	0.91	4.61
3	2500	300	25	1	1.17	1.07	8.47
4	1500	300	15	2	1.27	1.45	-13.91
5	1500	150	15	2	1.1	1.11	-0.93
6	2000	200	20	2.5	1.21	1.14	5.74
7	1500	150	15	1	1.08	1.01	6.77
8	2000	200	20	1.5	1.2	1.06	11.56
9	1500	150	25	1	1.04	0.99	5.09
10	3000	200	20	1.5	0.61	0.92	-50.44
11	2000	500	20	1.5	1.31	1.51	-14.96
12	2500	300	25	2	1.26	1.18	6.28
13	2000	100	20	1.5	0.58	0.81	-40.43
14	2500	300	15	1	1.13	1.09	3.32
15	2000	200	30	1.5	1.16	1.04	9.94
16	2000	200	20	0.5	0.92	0.91	1.18
17	2000	200	20	1.5	1.17	1.06	9.29
18	2500	150	15	2	1.05	0.92	11.96
19	2500	150	15	1	0.84	0.84	0.19
20	2000	200	20	1.5	1.18	1.06	10.06
21	1000	200	20	1.5	1.28	1.36	-6.31
22	2500	300	15	2	1.22	1.2	1.27
23	1500	300	25	2	1.29	1.42	-9.94
24	2000	200	10	1.5	1.12	1.09	2.65
25	2000	200	20	1.5	1.19	1.06	10.81
26	1500	300	15	1	1.26	1.31	-4.13
27	1500	300	25	1	1.24	1.29	-3.73
28	2500	150	25	1	0.75	0.82	-9.58
29	2000	200	20	1.5	1.13	1.06	6.08
30	2000	200	20	1.5	1.15	1.06	7.71

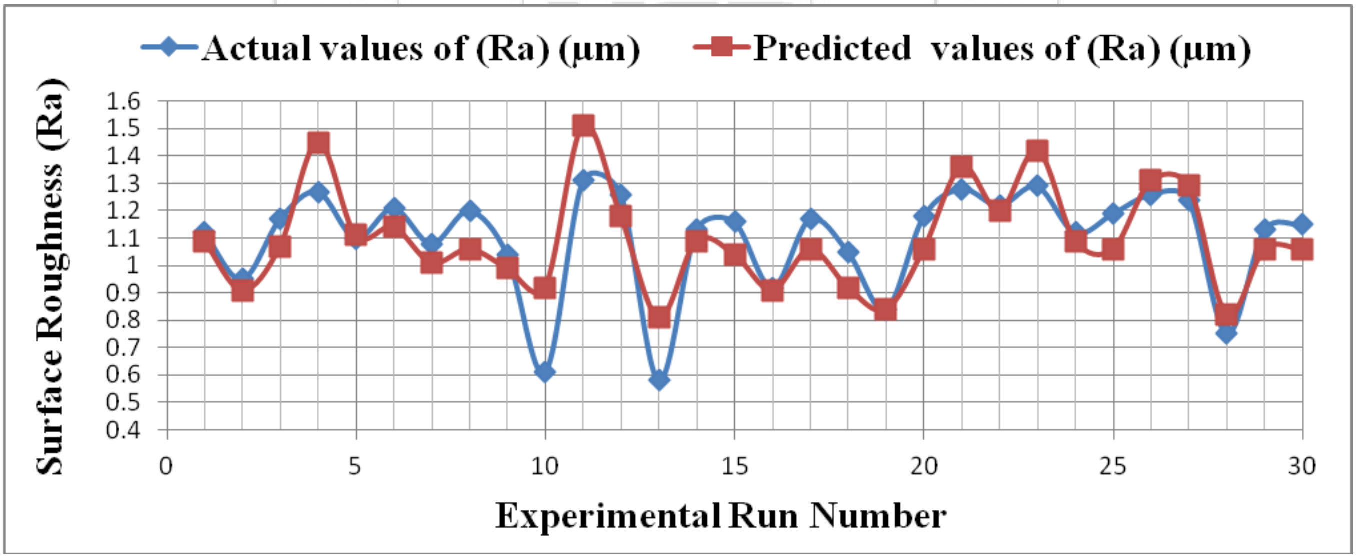

Figure 2: Actual and Predicted Values of the Surface Roughness for Dry Condition

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:

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

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 $\bar{\varphi} = \frac{280.16}{30}$

= 9.34%

The result of average percentage deviation ($\bar{\varphi}$) showed that the training data set (n=30) was 9.34%. This means that the statistical model could predict the surface roughness (Ra) with about 91% 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 DRY Condition

The effects of cutting parameters on surface roughness in end milling of aluminium were investigated using plots of the results obtained in DRY 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 cutting parameters effect on surface roughness.

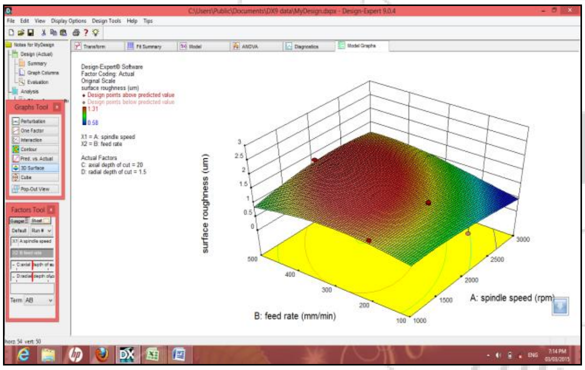

Figure 3: Surface Roughness Plot for Spindle Speed vs Feed Rate in DRY Condition

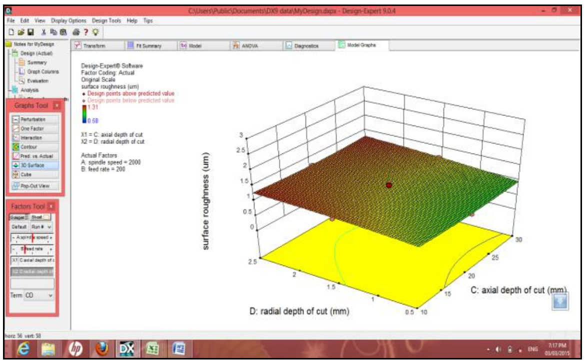

Figure 4: Surface Roughness Plot for Axial Depth of Cut vs Radial Depth of Cut in DRY Condition

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

Spindle speed: it can be seen from figure 3 and 4 that there are indeed and interaction which has nonlinear on a general note, 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. It can be seen in figure 3 that, as the feed rate is increased from 100 to 500mm/min the surface roughness also increased from 0.58µm to 1.31µm, 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 6061 alloy in DRY environments. Through experimentation, the system proved it is capable of predicting the surface roughness (Ra) with about 91% accuracy in DRY 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 Dry 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.
- 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.
- From the experimental values of table 5, 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 0.58µm.

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