OPTIMIZATION OF SURFACE ROUGHNESS AND FLATNESS IN END MILLING OF ALUMINIUM ALLOY AL 6063-T6

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ABSTRACT

The objective of present work is to study the influence of spindle speed, feed rate, axial depth of cut and radial depth of cut on surface roughness and flatness of end milled workpieces of Aluminium alloy Al 6063-T6 and to develop a model for their optimal selection. Second-order mathematical models have been developed using Response Surface Methodology (RSM) based on the machining data obtained by end milling of workpieces of Al 6063-T6 on a CNC milling machine. The milling experiments were designed using Design-Expert software, based on 4-factor, 5-level Central Composite Design (CCD). Surface roughness and flatness were measured using a roughness tester and a coordinate measuring machine (CMM) respectively. The developed models have been validated using verification experiments.

KEYWORDS: *Central Composite Design, Desirability Function, End Milling Process, Flatness, Optimization, Response Surface Methodology and Surface Roughness.*

I. INTRODUCTION

Manufacturing industries attempt to make high quality products at lower cost to remain competitive in the market. The products may be made using various manufacturing methods, such as machining, etc. End milling is among the most common machining processes used to make planar surfaces with faster material removal and good surface quality. Flatness and average surface roughness (Ra) are specified respectively to control the geometry and surface texture of milled planar surfaces, which is necessary to ensure their adequate functioning. The computer numerically controlled (CNC) machines provide better dimensional and geometrical accuracies and surface finish along with higher productivity. Such benefits are achievable only by programming them with optimum values of parameters governing the process. The optimal selection of parameters, using analytical or experimental methods, thus become an important research area in machining. Analytical methods use numerical or mathematical models of machining processes to analyse them through computer simulation. Experimental methods examine the effect of the parameters that are considered to be important through experiments. Experimentation based optimization of end milling parameters is considered in the present research.

Ghani et al. [1] used the Taguchi method to optimize the parameters in end milling of hardened steel AISI H13 with TiN coated P10 Carbide inserted tool under semi-finishing and finishing conditions. High cutting speed, low feed rate and low depth of cut have been found to yield lower cutting forces and better surface finish. Wang and Chang [2] performed an experimental study on surface roughness in slot end milling of Aluminium alloy 2014-T6 and found that dry-cut roughness was reduced by using the cutting fluids. They concluded that the cutting speed, feed rate, concavity and axial relief angles as the significant factors affecting the dry-cut roughness and feed rate and concavity angle as the significant factors affecting the coolant-cut roughness. Reddy and Rao [3] used surface roughness prediction model for selecting the optimum tool geometry and cutting conditions in end milling of medium carbon steel with carbide coated solid end milling cutters. Surface roughness has been found to be influenced by cutting speed, feed, radial rake angle and tool nose radius. They used Genetic Algorithm (GA) to optimize the analytical models developed for obtaining the best surface quality.

Ryu et al. [4] carried out series of tests to verify the surface generation model in end milling and concluded that surface texture is determined by the combination of tool geometry and the cutting conditions. Kromanis and Krizbergs [5] developed a 3D surface roughness prediction model for end milling using regression analysis and showed that cutting speed had little influence on form and surface roughness is more influenced by cutting speed, depth of cut and feed rate. Gopalsamy et al. [6] used Taguchi method to optimally select the process parameters for end milling of hardened steel by taking cutting speed, feed rate, depth of cut and width of cut as input parameters and tool life and surface finish as output parameters and concluded cutting speed as the important parameter. Moshat et al. [7] used the entropy measurement technique to optimize the parameters in CNC milling to achieve a better surface finish, used as quality attribute, and higher Material Removal Rate (MRR), used as a productivity related performance index. Taguchi method was used to optimize the multiple objectives that were merged into an equivalent single quality index called grey relation grade.

Raju et al. [8] investigated the effect of spindle speed, feed rate and depth of cut on surface roughness in end milling of Aluminium alloy Al 6061 using HSS and carbide tools under dry and wet conditions to determine the best combination of parameters for achieving lower roughness using GA, supported with multiple regression analysis. Rao et al. [9] used Taguchi method to optimize the surface quality in damper inserted end milling. Analysis of Variance (ANOVA) tests were performed to identify the key factors affecting the surface roughness. Optimal cutting conditions were determined by seeking the best surface roughness and signal-to-noise (SN) ratio. Chahal [10] studied the effect of milling parameters on the surface roughness of end milled hardened die steel (H13) workpieces with the objective of optimization using Taguchi method. Milling was performed using the four fluted, solid carbide end mill cutting tool under finishing conditions. An increased spindle speed and depth of cut and decreased feed rate were shown to yield lower surface roughness. Also, the surface roughness was shown to be mainly affected by feed rate. Mahesh and Rajesh [11] presented a fuzzy logic integrated Taguchi approach for simultaneously minimizing surface roughness and maximizing the MRR in CNC end milling of 7000 series Aluminium alloy. The cutting speed, feed rate and depth of cut and tool nose radius have been taken as parameters for optimization. The fuzzy logic system took SN ratios of surface roughness and MRR as input and produced a multi-response performance index (MRPI) as output. Based on ANOVA, tool nose radius and depth of cut were identified as the factors influencing the surface roughness and MRR.

Dikshit et al. [12] used Response Surface Methodology (RSM) to study the influence of cutting speed, feed per tooth, axial depth of cut and radial depth of cut during ball-end milling of Al 2014-T6 under dry conditions. Based on a quadratic model for the prediction of force components, they found the cutting forces to increase with an increase in feed per tooth and axial depth of cut but decrease with increase in cutting speed. The radial depth of cut has been found to have significant effect on the cutting force components. Mahesh et al. [13] developed a predictive model to study the effect of radial rake angle of end milling cutters by considering spindle speed, feed rate, axial depth of cut and radial depth of cut as the parameters. The RSM provided the optimal surface roughness values and a GA model provided the optimum cutting parameters for achieving the minimum surface roughness. Karabulut [14] investigated the influence of feed rate, cutting speed and depth of cut on surface roughness and cutting forces while milling of AA7039/Al2O3 metal matrix composites using uncoated carbide insert tools using Taguchi method. Artificial neural networks (ANN) and regression analysis were used to predict the cutting force and surface roughness. ANN was reported to be able to predict surface roughness and cutting force with a mean squared error equal to 2.25% and 6.66% respectively. In another different attempt, Tammineni and Yedula [15] investigated the influence of cutting speed, feed and depth of cut for the optimization of surface roughness and flatness in end milling of Aluminium 1050 workpieces using solid end milling cutters of 12 mm diameter. Minitab Software has been used in the design and analysis of experimentation.

The foregoing discussions reveal that mostly surface roughness has been optimized using different tools such as the Taguchi method, Fuzzy Logic, GA, ANOVA, etc. The MRR or tool life or cutting forces has been combined with surface roughness in some cases. Design of Experiments (DoE) tools, such as RSM, have also been shown as powerful tools for modelling and studying the influence of controlling factors. Apart from these, machining of Aluminium alloys has been shown to be an

important area of research with applications in high technology areas. Further, the literature reveals only few studies on combined surface roughness and flatness in end milling. All of these motivated the authors to attempt the optimization of parameters in end milling of Aluminium alloy Al 6063-T6. Spindle speed, feed rate, axial depth of cut and radial depth of cut have been considered as the input parameters to achieve minimum values of surface roughness and flatness. Mathematical models have been developed using RSM to determine the optimal machining parameters in order to achieve the desired objective. Central Composite Design (CCD) has been used in the design of experiments for generating the machining data for modelling. The end milling was performed using a 10 mm diameter HSS end mill cutter. Surface roughness and flatness of milled workpieces were measured respectively using a surface roughness tester and a coordinate measuring machine (CMM). Finally, few validation experiments were performed to explore the feasibility of the proposed approach.
Remainder of the paper is organized as follows. Section II presents some theoretical topics relevant to the present work and Section III describes about the methodology used in the proposed work. Section IV discusses about the experimental details of the present work. Section V presents and discusses the results obtained using the proposed approach and finally the concluding remarks are presented in Section VI.

II. SOME RELEVANT THEORETICAL TOPICS

2.1. Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a collection of statistical techniques that are useful for modelling and analysis of problems in which one or more responses of interest are influenced by several input variables. The objective is to find a relationship between the responses and input variables and to optimize the responses. A brief description of RSM is presented below.
If there are two input factors x_1 and x_2 and the process yield (y) is a function of the levels of x_1 and x_2, they can be related as shown in Eq. (1).

$$y = f(x_1, x_2) + \varepsilon \tag{1}$$

Here, ε represents the noise or error observed in the response variable y and x_1 and x_2 are the independent variables or factors. If we denote the expected response by $E(y) = f(x_1, x_2) = \eta$, then the response surface represented by

$$\eta = f(x_1, x_2) \tag{2}$$

where, η is a called as *true response surface*. Then the approximating function is a first order model as in Eq. (3).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \tag{3}$$

If there is a curvature in system, then the approximating function is a second order model as shown in Eq. (4).

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum\sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \tag{4}$$

If there are n observations, y can be represented in matrix form as in Eq. (5).

$$y = x\beta + \varepsilon \tag{5}$$

The RSM is a very useful tool for quality and productivity improvement in industries in order to discover some functional relationship between the responses and several input variables governing the system being considered.

2.2. Desirability Function Analysis (DFA)

Desirability Function Analysis (DFA) is one of the most widely used methods for optimization of multi-response characteristics. DFA converts the multi-response characteristics into single response characteristics. Individual desirability index is calculated first for the respective responses using Eq. (6) for maximization problems and Eq. (7) for minimization problems. A larger value of desirability index is preferred for maximization problems while a smaller value of desirability index is preferred for minimization problems.

$$d_i(x) = \begin{cases} 0 & y_i(x) < L \\ \left[\dfrac{y_i(x) - L}{T - L} \right]^r; & L \le y_i(x) \le T \\ 1 & y_i(x) > T \end{cases} \quad (6)$$

$$d_i(x) = \begin{cases} 1 & y_i(x) < T \\ \left[\dfrac{U - y_i(x)}{U - T} \right]^r; & T \le y_i(x) \le U \\ 0 & y_i(x) > U \end{cases} \quad (7)$$

where, L is the minimum allowable value or lower limit, T is the satisfactory or target value and U is the maximum allowable value or upper limit of the response $y_i(x)$, and r is an arbitrary constant (called the weight), usually taken as 1.0 in practice. The overall desirability function $D(x)$ is then calculated using Eq. (8), where m is the number of responses to be optimized. The maximum desirability value for optimized parameters varies from 0.0 to 1.0.

$$D(x) = [d_1(x) \times d_2(x) \times d_3(x) \times ... \times d_m(x)]^{1/m} \quad (8)$$

III. METHODOLOGY USED

The methodology used in the present work is shown in Figure 1. It begins with cutting of workpieces of desired size (100×20×20 mm). Experimental design is then carried out using the Central Composite Design (CCD). The experimental design provides the necessary settings for the selected parameters for each experiment. End milling of workpieces was then performed on the CNC milling machine using the parameters computed in the previous step. End milling was followed by the measurement of desired performance attributes, viz. surface roughness (Ra) and flatness, using the measuring devices mentioned earlier. The measured data is then used to develop second order models for optimizing the desired parameters, subsequently validated through the validation experiments.

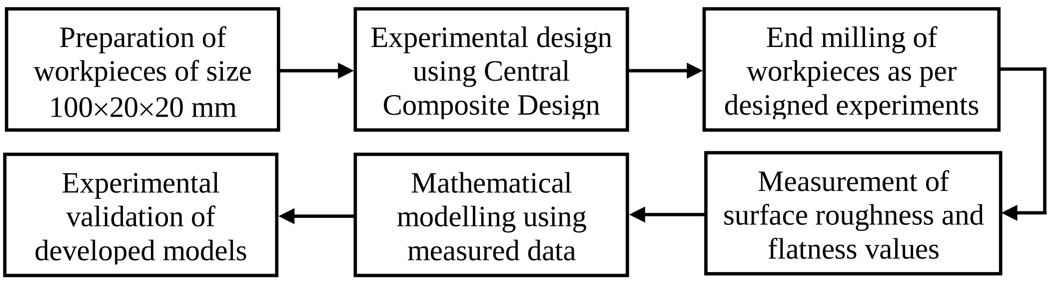

Figure 1. Methodology used

IV. EXPERIMENTAL DETAILS

4.1. Workpiece Material

Aluminium alloy Al 6063-T6 is used in the present research work as it has widespread applications in aerospace and marine industries, etc. Table 1 shows the chemical composition of this alloy. The stock material is cut into workpieces of 100×20×20 mm size (Figure 2) for experimental purposes.

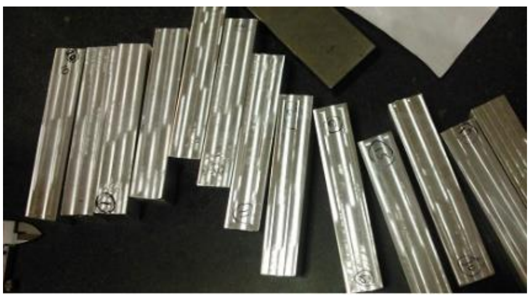

Figure 2. Workpieces of Aluminium alloy Al 6063-T6

Table 1. Chemical Composition (in Weight %) of Aluminium alloy Al 6063-T6

Si	Fe	Cu	Mg	Mn	Cr	Zn	Ti	Al
0.600	0.340	0.090	0.880	0.090	0.092	0.095	0.092	97.721

4.2. Details of Equipment and Cutting Tools used

Table 2 shows the technical details of EMCO Concept Mill 105 (Figure 3) used in the present work. End milling experiments (Figure 4) were performed using ϕ10 mm HSS end mill cutters. Workpieces were mounted onto the machine table to provide maximum rigidity. Surface roughness was measured with a portable surface roughness tester (Mitutoyo Surftest SJ201) and flatness was measured using a DEA make CMM (Figure 5). Flatness evaluation has been carried out using the least squares method.

Figure 3. EMCO CNC Milling Machine

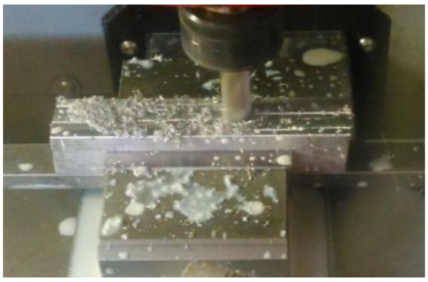

Figure 4. End milling in progress

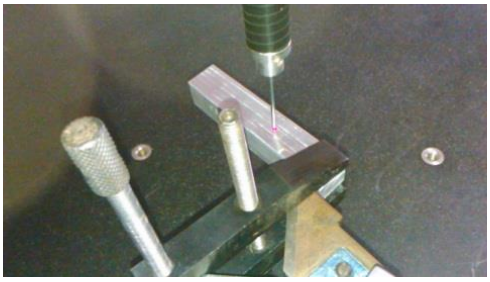

Figure 5. Flatness measurement using the coordinate measuring machine (CMM)

Table 2. Technical Specifications of EMCO Concept End Mill 105

Speed range, rpm	150 - 5000
Maximum tool diameter × length, mm	55 × 50
Positioning range (X × Y × Z), mm	200 × 150 × 250
Table dimensions (L × W), mm	420 × 125
Feed range, mm/min	0.3 - 3.0

4.3. Milling Parameters

The parameters considered in this work and their levels and values (Table 3) are as given below.
(a) *Spindle speed*: the rotational frequency of the machine spindle.
(b) *Feed rate*: the rate with which the workpiece being milled advances under the revolving cutter.
(c) *Axial depth of cut*: the thickness of the layer of workpiece removed in a single pass.
(d) *Radial depth of cut*: the amount of work surface engaged by the cutting tool in the radial direction.

Table 3. Parameters and their Values at different Levels

S#	Parameters	Level 1	Level 2	Level 3	Level 4	Level 5
1	Spindle speed, rpm	1000	1500	2000	2500	3000
2	Feed rate, mm/min	50	70	90	110	130
3	Axial depth of cut, mm	0.25	0.3	0.35	0.4	0.45
4	Radial depth of cut, mm	2	3	4	5	6

4.4. Experimental Design

The number of experiments will be decided by the selected design methodology, viz. full or fractional factorial design. A carefully designed fractional factorial experimentation may be able to provide an accuracy similar to that of full factorial at lesser expense and hence more often used in the experiments based optimization methods. Central Composite Design (CCD) based fractional factorial design [16] approach is used in the present work. The design values of parameters, selected using the Design Expert software, and the corresponding measured responses are shown in Table 4. A total of 30 different experiments were carried out.

Table 4. Input Parameters and Corresponding Output Responses

S#	Spindle speed (rpm)	Feed rate (mm/min)	ADOC (mm)	RDOC (mm)	Ra (μm)	Flatness (μm)
1	1500	70	0.3	3	0.33	0.009
2	2500	70	0.3	3	0.15	0.009
3	1500	110	0.3	3	0.37	0.012
4	2500	110	0.3	3	0.29	0.005
5	1500	70	0.4	3	0.35	0.011
6	2500	70	0.4	3	0.20	0.007
7	1500	110	0.4	3	0.38	0.009
8	2500	110	0.4	3	0.31	0.011
9	1500	70	0.3	5	0.38	0.023
10	2500	70	0.3	5	0.23	0.018
11	1500	110	0.3	5	0.38	0.022
12	2500	110	0.3	5	0.31	0.015
13	1500	70	0.4	5	0.41	0.021
14	2500	70	0.4	5	0.26	0.022
15	1500	110	0.4	5	0.43	0.023
16	2500	110	0.4	5	0.33	0.022
17	1000	90	0.35	4	0.36	0.012
18	3000	90	0.35	4	0.13	0.010
19	2000	50	0.35	4	0.28	0.015
20	2000	130	0.35	4	0.40	0.021
21	2000	90	0.25	4	0.32	0.020
22	2000	90	0.45	4	0.37	0.018
23	2000	90	0.35	2	0.31	0.002
24	2000	90	0.35	6	0.40	0.024
25	2000	90	0.35	4	0.36	0.016
26	2000	90	0.35	4	0.27	0.019
27	2000	90	0.35	4	0.32	0.022
28	2000	90	0.35	4	0.35	0.021
29	2000	90	0.35	4	0.26	0.018
30	2000	90	0.35	4	0.30	0.016

4.5. Mathematical modelling using Response Surface Methodology (RSM)

A second order mathematical model has been developed using the Design Expert software, based on experimental data. The model is checked for significance by Analysis of Variance (ANOVA), which is a collection of statistical models used to analyse the differences between group means and their associated procedures, such as *variation* among and between groups. A continuous response variable and at least one categorical factor with two or more levels are needed to perform ANOVA. The results of ANOVA on surface roughness is shown in Table 5 and that of flatness is shown in Table 6. The R-squared, Adj. R-squared and Pred. R-squared values are shown in Table 7.

Table 5. ANOVA for the prediction of Surface Roughness (Ra)

Source	Sum of Squares	Degrees of Freedom	Mean Square	F value	P value Prob. > F
Model	0.15	14	0.010	16.81	< 0.0001 ***significant***
A	5.356E-005	1	5.356E-005	0.087	0.7722
B	4.640E-004	1	4.640E-004	0.75	0.3992
C	1.074E-003	1	1.074E-003	1.74	0.2066
D	1.960E-004	1	1.960E-004	0.32	0.5811
AB	6.006E-003	1	6.006E-003	9.75	0.0070
AC	6.250E-006	1	6.250E-006	0.010	0.9211
AD	6.250E-006	1	6.250E-006	0.010	0.9211
BC	5.625E-005	1	5.625E-005	0.091	0.7667
BD	1.406E-003	1	1.406E-003	2.28	0.1516
CD	5.625E-005	1	5.625E-005	0.091	0.7667
A^2	7.524E-003	1	7.524E-003	12.21	0.0033
B^2	1.417-003	1	1.417E-003	2.30	0.1502
C^2	1.953E-003	1	1.953E-003	3.17	0.0953
D^2	3.281E-003	1	3.281E-003	5.33	0.0357
Residual	9.242E-003	15	6.161E-004		
Lack of Fit	8.417E-004	10	8.417E-005	0.050	0.999 ***not significant***
Pure Error	8.400E-003	5	1.680E-003		
Cor. Total	0.15	29			

Table 6. ANOVA for the Prediction of Flatness

Source	Sum of Squares	Degrees of Freedom	Mean Square	F value	P value Prob. > F
Model	9.980E-004	14	7.128E-005	12.82	0.0001 ***significant***
A	1.154E-005	1	1.154-005	2.07	0.1703
B	2.975E-008	1	2.975E-008	5.349E-003	0.9427
C	7.065E-006	1	7.065E-006	1.27	0.2774
D	3.319E-005	1	3.319E-005	5.97	0.0274
AB	1.562E-006	1	1.562-006	0.28	0.6038
AC	1.806E-005	1	1.806E-005	3.25	0.0916
AD	5.625E-007	1	5.625E-007	0.10	0.7548
BC	5.062E-006	1	5.062E-006	0.91	0.3551
BD	5.625E-007	1	5.625E-007	0.10	0.7548
CD	3.062E-006	1	3.062E-006	0.55	0.4695
A^2	1.063E-004	1	1.063E-004	19.12	0.0005
B^2	1.312E-006	1	1.312E-006	0.24	0.6341
C^2	2.679E-008	1	2.679E-008	4.817E-003	0.9456
D^2	5.917E-005	1	5.917E-005	10.64	0.0053
Residual	8.342E-005	15	5.561E-006		
Lack of Fit	5.208E-005	10	5.208E-006	0.83	0.6257 ***not significant***
Pure Error	3.133E-005	5	6.267E-006		
Cor. Total	1.081E-003	29			

A model F-value of 16.81 (Table 5) implies that the selected model is significant. There is only 0.01% chance that an F-value this large could occur due to noise. Model term values greater than 0.100 indicate that they are not significant. There is a 99.99% chance that lack of fit this large could occur due to noise. A model F-value of 12.82 (Table 6) implies that the model is significant. There is 62.57% chance that a lack of fit F-value this large could occur due to noise. The non-significant lack of fit is also good in both cases. The regression equations obtained from Design Expert software, in terms of actual factors, are given in Eq. (9) and Eq. (10).

Table 7. R-Squared, Adj. and Pred. R-Squared for the responses

Parameters	Roughness	Flatness
R-Squared	0.9401	0.9229
Adj. R-Squared	0.8842	0.8509
Pred. R-Squared	0.8902	0.6808

<u>Surface Roughness (Ra):</u> $R_1 = 0.89346 - 4.0625e{-5} * A - 3.05729e{-3} * B - 2.11875 * C - 0.038854 * D + 1.9375e{-6} * AB + 2.5e{-5} * AC + 1.25e{-6} * AD - 1.875e{-3} * BC - 4.6875e{-4} * BD + 0.0375 * CD - 6.625e{-8} * A^2 + 1.79688e{-5} * B^2 + 3.375 * C^2 + 0.010938 * D^2$ (9)

<u>Flatness:</u> $R_2 = -0.014867 + 1.88542e{-5} * A + 2.44792e{-5} * B - 0.17188 * C + 0.01599 * D - 3.125e{-8} * AB + 4.25e{-5} * AC - 3.75e{-7} * AD + 5.625e{-4} * BC - 9.375e{-6} * BD + 8.75e{-3} * CD - 7.875e{-9} * A^2 - 5.46875e{-7} * B^2 + 0.0125 * C^2 - 1.46875e{-3} * D^2$ (10)

In the above equations, *A* stands for spindle speed, *B* stands for feed rate, *C* stands for axial depth of cut or ADOC and *D* stands for radial depth of cut or RDOC.

4.6. Optimization of Cutting Parameters

Table 8 shows the constraints and range for the inputs parameters used in the optimization of selected responses. The desirability values corresponding to the optimal parameters is shown in Table 9.

Table 8. Parameter and constraints settings for optimization of responses

Name	Goal	Lower limit	Upper limit	Weights*	Importance
Spindle speed	Is in range	1000	3000	1	3
Feed rate	Is in range	50	130	1	3
Axial depth of cut	Is in range	0.250	0.450	1	3
Radial depth of cut	Is in range	2	6	1	3
Surface roughness	Minimize	0.130	0.430	1	3
Flatness	Minimize	0.002	0.024	1	3

** Both upper and lower weights*

Table 9. Optimum desirability parameters

Spindle speed (rpm)	Feed rate (mm/min)	ADOC (mm)	RDOC (mm)	Ra (µm)	Flatness (µm)	Desirability Value
2499	83.98	0.343	3.275	0.216	0.011	0.783

V. RESULTS AND DISCUSSION

Parameter optimization for end milling of Aluminium alloy Al 6063-T6 has been considered in the present work. Four parameters, viz. spindle speed, feed rate, axial depth of cut and radial depth of cut, have been considered to optimize the surface roughness and flatness of end milled surfaces. End milling has been done on an EMCO CNC Milling machine and the surface roughness (R_a) and flatness were measured respectively using Mitutoyo Surftest SJ201 and DEA make CMM. The results obtained are presented and discussed in the subsections below. In the discussions below, ADOC refers to axial depth of cut and RDOC refers to radial depth of cut.

5.1. Surface Roughness (Ra)

The average height of roughness (R_a), the most commonly evaluated surface roughness parameter for 2D surface profiles, is considered present work as one of the output parameters for optimization. The variation of R_a with various input parameters considered are discussed below. The holdup values, as applicable, for spindle speed, axial depth of cut, radial depth of cut and feed rate have been observed to be 2351.35 rpm, 0.414865 mm, 5.99998 mm and 129.996 mm/min respectively.
Figure 6 shows the graph of variation of *Ra* with spindle speed and feed rate keeping the axial depth of cut and radial depth of cut constant at hold values. Minimum *Ra* value has been observed with minimum feed rate of 50 mm/min and high spindle speed of 3000 rpm whereas the maximum *Ra* has been observed at maximum feed rate with minimum spindle speed. It may be due to the fact that unstable larger built-up-edges (BUE) are formed at low spindle speeds and the chips fracture readily producing a rougher surface. The variation of *Ra* with spindle speed and axial depth of cut, while keeping the feed rate and radial depth of cut constant is shown in Figure 7. Under these conditions, increase in axial depth of cut and keeping spindle speed low lead to non-uniform increase in the *Ra* values. On the other hand, keeping the axial depth of cut low and spindle speed high results in lower *Ra* values.
Holding the spindle speed and feed rate as constant, variation of *Ra* with radial depth of cut and axial depth of cut follows a pattern as shown in Figure 8. Under these conditions, *Ra* values increase with increasing radial and axial depth of cuts and vice versa. The variation of *Ra* with feed rate and axial depth of cut, while keeping the spindle speed and radial depth of cut constant is shown in Figure 9. The *Ra* values increase with increasing feed rate and axial depth of cut and decrease with decreasing feed rate and axial depth of cut but a little sharply in this case.

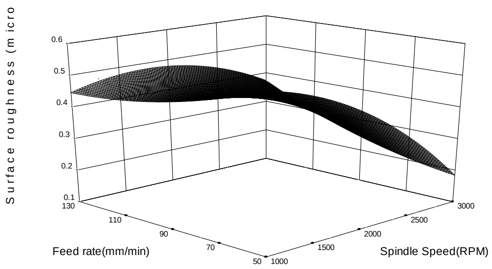

Figure 6. R_a vs feed rate and spindle speed

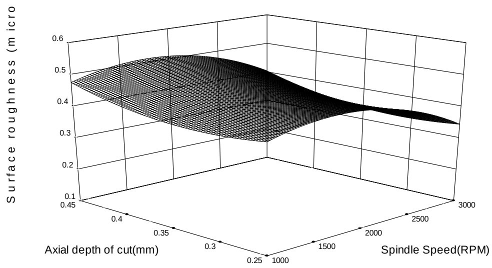

Figure 7. R_a vs ADOC and spindle speed

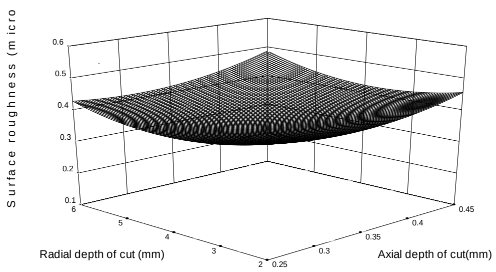

Figure 8. R_a vs RDOC and ADOC

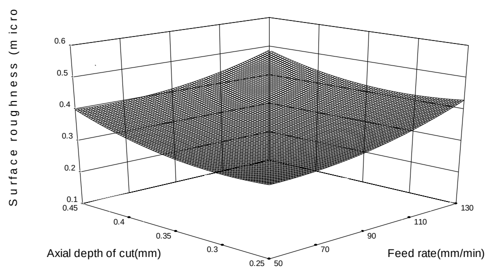

Figure 9. R_a vs ADOC and feed rate

The variation of *Ra* with radial depth of cut and feed rate is shown in Figure 10. The other parameters, viz. spindle speed and axial depth of cut have been kept constant at hold values. It is seen that an increase in radial depth of cut increases the *Ra* value non-uniformly at high feed rates and a decrease in radial depth of cut decreases the *Ra* value non-uniformly at low feed rates. Figure 11 shows the influence of spindle speed and radial depth of cut on *Ra* with the feed rate and axial depth of cut kept constant at holding values. In this case, the *Ra* value increases with increasing radial depth of cuts with lower spindle speeds and decreases with decreasing values of radial depth of cut while keeping the spindle speeds higher.

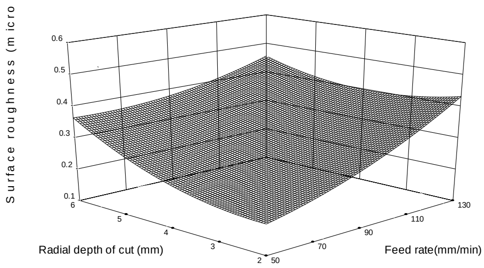

Figure 10. R_a vs RDOC and feed rate

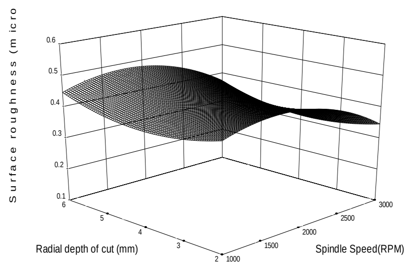

Figure 11. R_a vs RDOC and spindle speed

5.2. Flatness (F)

Flatness may be defined as a condition wherein all elements of a surface lie in a plane. The flatness control is a geometric tolerance that limits the amount of flatness error a surface is allowed. Flatness may be measured, for example, using a coordinate measuring machine (CMM). Though there are many methods to calculate the flatness error, the least squares method is considered in the present work owing to its simplicity, uniqueness and sound mathematical basis. In Figures 12 to 17, letter F is used to denote flatness error. The variation of flatness with input parameters considered are discussed below. The spindle speed, axial depth of cut, radial depth of cut and feed rate of 2567.57 rpm, 0.414865 mm, 5.99998 mm and 129.996 mm/min respectively are taken to be holdup values.

The variation of F with axial depth of cut and feed rate is shown in Figure 12. The spindle speed and radial depth of cut have been kept constant at hold values. Minimum flatness error has been observed with lower axial depth of cut and higher feed rate, while maximum flatness error has been observed with higher axial depth and lower feed rate. Figure 13 shows the influence of axial depth of cut and spindle speed on F with the feed rate and radial depth of cut kept constant at hold values. In this case, the F values increase with higher axial depth of cut with medium spindle speed while lower F values can be observed at higher spindle speeds with lower axial depth of cuts.

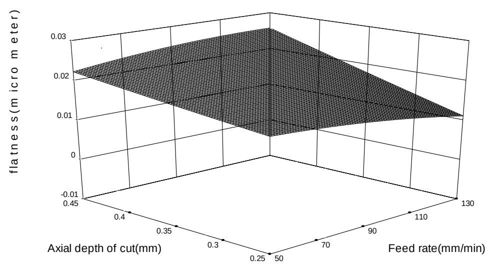

Figure 12. F vs ADOC and feed rate

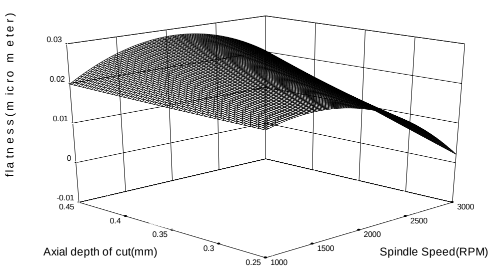

Figure 13. F vs ADOC and spindle speed

Holding the radial depth of cut and axial depth of cut as constant, variation of F with spindle speed and feed rate follows a pattern as shown in Figure 14. It may be observed that minimum flatness error is induced with lower feed rates and higher spindle speeds. On the other hand, it may be observed that the maximum flatness error is induced at higher feed rates and spindle speeds ranging between 2000 to 2500 rpm. The variation of F with radial depth of cut and axial depth of cut, while keeping the spindle speed and feed rate at the hold values is shown in Figure 15. It may be observed from this figure that minimum flatness error is resulting from minimum axial and radial depth of cut and maximum flatness error occurs with maximum values of these parameters.

The variation of F with radial depth of cut and feed rate is shown in Figure 16. The other parameters, viz. spindle speed and axial depth of cut have been kept constant at respective hold values. It is seen that an increase in radial depth of cut and feed rate increases the F value almost linearly. Radial depth of cut appears to be more influencing parameter in this case. Figure 17 shows the influence of spindle speed and radial depth of cut on F with the feed rate and axial depth of cut kept constant at their respective holding values. Minimum F value has been observed at minimum spindle speed and radial depth of cut and maximum F value has been observed at maximum radial depth of cut and medium spindle speed (2000-2500 rpm).

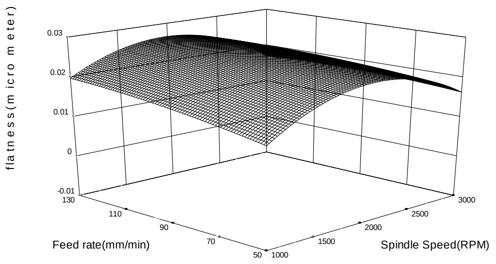

Figure 14. F vs feed rate and spindle speed

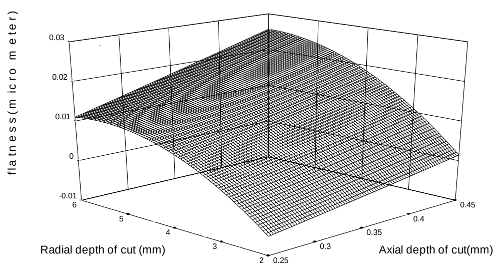

Figure 15. F vs RDOC and ADOC

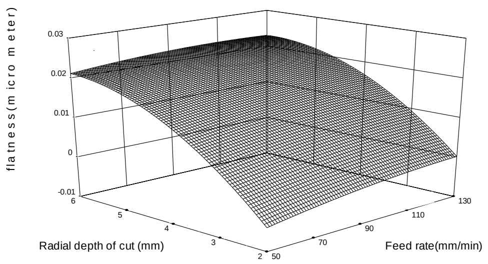

Figure 16. F vs RDOC and feed rate

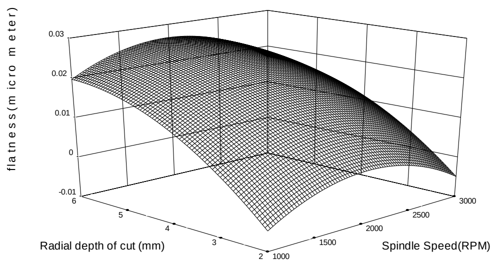

Figure 17. F vs RDOC and spindle speed

5.3. Experimental Validation

Two new experiments have been performed randomly for validation purposes. The results obtained based on the selected parameter values using the prediction model and actual experiments are shown in Table 10 below. The absolute average error between experimental and predicted values for selected parameter settings is calculated as 5.56% for surface roughness and as 5.51% for flatness, which are quite low. Based on these results, it may be concluded that the proposed model predicts the output parameters well.

Table 10. Validation Experiment and Results

S#	Spindle speed, rpm	Feed rate, mm/min	ADOC, mm	RDOC, mm	Roughness (*Ra*), µm			Flatness, µm		
					Pred.	Exp.	% Err.	Pred.	Exp.	% Err.
1	1600	100	0.3	3	0.344	0.360	4.45	0.0124	0.0130	4.61
2	2900	80	0.4	4	0.140	0.150	6.67	0.0131	0.0140	6.42

VI. CONCLUSIONS AND FUTURE SCOPE

In the present work, Aluminium alloy Al 6063-T6 workpieces have been end milled using a CNC milling machine. Four end milling parameters, viz. spindle speed, feed rate, axial depth of cut and radial depth of cut have been considered for optimization. Milling experiments were designed using central composite design (CCD) and the flatness and surface roughness values have been measured. The response surface methodology (RSM) model has been used for optimization. Based on this work, the following conclusions are arrived at:

1) The surface roughness and flatness values predicted from the proposed model compares well with the values obtained experimentally.
2) Feed rate is the dominant parameter and surface roughness increases rapidly with increase in feed rate and decrease with increase in cutting speed. An increase in either the feed rate or axial depth of cut increases the surface roughness, while an increase in the spindle speed decreases the surface roughness. In case of flatness, significant changes are caused by depth of cut, i.e. radial depth of cut and also axial depth of cut.

3) Minimum surface roughness of 0.216 μm and flatness of 0.011 μm were observed at a spindle speed of 2450 rpm, feed rate of 84 mm/min, axial depth of cut of 0.343 mm and radial depth of cut of 3.275 mm with a desirability of 0.783.

Optimization of more output responses by considering additional input parameters may be taken up as future research. Similar studies may also be performed using other materials of engineering importance.

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