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SURFACE ROUGHNESS IN AL 7075-T6 USING SHOULDER MILL CUTTER BY RESPONSE SURFACE METHODOLOGY

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Abstract

The present experimental work investigated the effects of cutting parameters on surface roughness in shoulder milling of AL7075-T6 aluminium alloy using a coated solid carbide cutter. Response surface methodology was used to develop a mathematical model to predict surface roughness in terms of cutting speed, feed rate, depth of cut. The objective of this study was to develop a better understanding of the effects of spindle speed, feed rate and depth of cut on the surface roughness then to build a multiple regression model. Such an understanding could provide insight into the problems of controlling the finish of machined surfaces when the process parameters were adjusted to obtain a certain surface finish. Surface roughness value was measured using Mitutoyo Surf test SJ201tester. The adequacy of the model was verified using analysis of variance (ANOVA), and the effect of spindle speed *(V_c)*, feed rate *(f_z)* and depth of cut *(a_p)*, and interactions of all variables predicted the surface roughness values within the confidence limit. The deviation between predicted and measured surface roughness values was within an error band of about 5 per cent.The contour plots were generated to study the effect of process parameters as well as their interactions.

Key Words*:Surface roughness; End Milling; AL7075-T6; RSM;*Mathematical model

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1. Introduction

In manufacturing industries, milling is a fundamental metal-cutting operation and shoulder milling is the most frequent operation encountered, which was employed for making profiles, slots, engraves, contours and pockets in various components. Surface roughness is an important parameter in milling, which decides how the work piece components interact with its assembled parts. Obviously, rough surface will wear more and have high coefficient of friction than smooth surface, hence surface roughness is a good predictor of quality of product. The demands for high quality of product relay on surface roughness urge the industrial automation to focus its attention on the surface finish of the product. Though surface roughness is a prominent parameter, it is expensive to control since the manufacturing cost will increase exponentially with decrease in surface roughness. An effective model to predict the surface roughness becomes essential to ensure the desired quality in shoulder milling.

Surface roughness is an indicator of quality. It is obtained from processed pieces by means of shoulder milling and accurate control of the dynamic variables, such as cutting speed, feed rate and depth of cut.

Oktem et al., (2005) predicted surface roughness model in shoulder milling cutter using RSM and observed that surface roughness was affected by other variables, like the mechanical properties of the material, the geometry of the milling cutter, the number of inserts in the cutter, the run out errors in the inserts and the vibration produced during the process.

Abhang et al., (2011),utilized the regression modeling in turning process by using response surface methodology (RSM) with factorial design of experiments. From the analysis, it was observed that feed rate was the most significant factor on the surface roughness followed by cutting speed and depth of cut at 95% confidence level. Tool nose radius and concentration of lubricants was found to be statistically less significant at 95% confidence level. Furthermore, the interaction of cutting velocity/feed rate, cutting velocity/ nose radius and depth of cut/nose radius were found to be statistically significant on the surface finish because their p-values are smaller than 5%. The predicted surface roughness values of the samples have been found to lie close to that of the experimentally observed values.

Mike et al., (1999), examined a new approach for finish surface prediction in end-milling operations. Through experimentation, the system proved capable of predicting the surface roughness (Ra) with about 90% accuracy. He concluded that the surface roughness (Ra) could be predicted effectively by applying cutting speed, feed rate, depth of cut, and their interactions in the multiple regression models. The multiple regression models could predict the surface roughness (Ra) with average percentage deviation of 9.71% or 90.29% accuracy from training data set.

Kadirgama et al., (2008), was concerned with optimization of the surface roughness when milling Mould Aluminum alloys (AA6061-T6) with carbide coated inserts. The approach was based on Response Surface Method (RSM) and Radian Basis Function Network (RBFN). In this work, the objectives were to find the optimized parameters, and to find out the most dominant variables (cutting speed, federate, axial depth and radial depth). With the model equations obtained, a designer could subsequently select the best combination of design variables for achieving optimum surface roughness. This eventually reduced the machining time and saved the cutting tools. Patel et al. (2012) studied about the influence of various machining parameters like tool speed, tool feed, depth of cut and tool diameter. In his study, experiments were conducted on AL 6351 – T6 material with four factors and five levels and try to find out optimum surface roughness by using taguchi method. This paper attempted to introduce how Taguchi parameter design could be used in identifying the significant processing parameters and optimizing the surface roughness of end-milling operations.

2. Research Design

In this present study, twenty experimental runs were allowed for the estimation of linear, quadratic and two – way interactive effects of the process parameters on the surface roughness to each treatment combination of parameters and corresponding responses were noted.At the end of each run, settings for all parameters were disturbed for the next experiment and the experiments were conducted. The experimental set up was illustrated in the following Figure-1.

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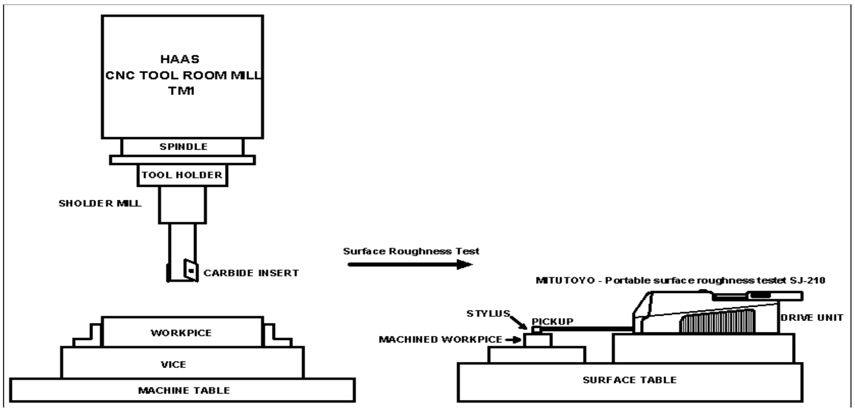

Figure1Experimental Setup

The following machines and equipments were used for the purpose of conducting the experiments:
1. Vertical Haas Milling machine
2. Mitutoyo SJ201 Surftester
3. Shoulder mill Cutting Tool with 2 inserts (Carbide)
4. Work piece material AL 7075-T6

Mitutoyo SJ201 Surftester is a surface roughness measuring device which is provided with exchangeable diamond stylus of radius of 5μ, which sensing the horizontal and vertical deflection from any surface gives roughness value. As shown in figure-2, it has a graphic LCD display which directly gives a surface roughness value of measured surfacein terms of R_a.Mitutoyo SJ201 surf tester is given in Figure-2.

Figure2 Surface Roughness testing device (Mitutoyo SJ201 Surftester)

2.1. Components of Experimental Design

There are three aspects of the process that were analyzed by a designed experiment:

Factors or inputs to the process-Factors were classified as either controllable or uncontrollable variables. The controllable variables referred to throughout the material as factors. People were generally considered a Noise Factor - an uncontrollable which caused variability under normal conditions, but one could control it during the experiment using blocking and randomization.

Levels or settings of each factor- The difference between the values for each level were uniform.

Response or output of the experiment-This wasthe parameter upon which the experimenter was focused. Important outcomes were measured and analyzed to determine the factors and their settings that provided the best overall outcome

2.2. Response Surface Methodology

In statistics, response surface methodology (RSM) explored the relationships between several explanatory variables and one or more response variables. The method was introduced by G. E. P. Box and K. B. Wilson in 1951. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. According to Box and Wilson suggestionsa second-degreepolynomial model was used to do this experiment.

2.3. Development of Design Matrix

A Box-Wilson Central Composite Designcontained an imbedded factorial or fractional factorial design with center points that was augmented with a group of `star points' that allow estimation of curvature. If the distance from the center of the design space to a factorial point was ±1 unit for each factor, the distance from the center of the design space to a star point was ±**α** with |**α**| > 1. The precise value of **α** depended on certain properties desired for the design and on the number of factors involved. A central composite design always contained twice as many star points as there were factors in the design. The star points represented new extreme values (low and high) for each factor in the design.

To maintain rotatability, the value of **α** depended on the number of experimental runs in the factorial portion of the central composite design:

α = [Number of factorial runs] $^{1/4}$ For full factorial, **α = [2^{k}] $^{1/4}$.**

Table 1 gives the Components of central composite second order rotatable design**.**

Table 1 Components of Central Composite Second Order Rotatable Design

No of x-variables k	Number of points in 2^{k} factorial	Star	Center	Total N	Value of Á
3	*8*	*6*	*6*	*20*	*1.682*
4	16	8	7	31	2.000
5	16	10	6	32	2.000
6	32	12	9	53	2.378

The following Table -II illustrates the process parameters and their levels.

Table 2Process Parameters and their Levels

Parameters	Units	Levels -1.682	-1	0	1	1.682
Cutting speed (V_c)	m/min	1500	2000	2500	3000	3500
Feed rate (f_z)	mm/tooth	0.06	0.07	0.08	0.09	0.10
Depth of cut (a_p)	mm	0.5	1	1.5	2	2.5

From Table 1, for k=3, 4, 5, 6. Note that with 3 x-variables, the size of the experiment is reduced by using a half-replicate of the 2^{k} factorial. With a half replicate, α becomes [2 ^{k}]$^{1/4.}$ This assumes that the experiment is to be completely randomized. If the different treatment combinations are applied one after another, the order in this sequence should be randomized. All process parameters in the intermediate levels (0) constituted the center points and the combination of each parameter at either its highest value (+1.682) or lowest (-1.682) with other parameters of the intermediate levels (0) constituted the star points. Table2shows the process parameters and their levels as we selected and Table 3 gives design matrix for the required parameters as it was taken in the present study.

Table 3Design Matrix

Trial number	Design matrix: Cutting speed (m/min) V_c	Feed rate (mm/tooth) f_z	Depth of cut (mm) a_p
1	-1	-1	-1
2	1	-1	-1
3	-1	1	-1
4	1	1	-1
5	-1	-1	1
6	1	-1	1
7	-1	1	1
8	1	1	1
9	-1.682	0	0

10	1.682	0	0
11	0	-1.682	0
12	0	1.682	0
13	0	0	-1.682
14	0	0	1.682
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
20	0	0	0

2.3.1.Tool Specification (Shoulder Mill)

Material - Carbide
Diameter - 20 mm
Overhang length - 62 mm
Number of inserts- 2
Corner radius - 0.8 mm
Insert thickness - 3.5 mm
Insert length - 10 mm
Insert width - 6.35 mm

2.3.2.Work Piece

The work piece material was Aluminium Alloy of grade 7075T6. Specimens of size 50 mm lengths, 30 mm width, 25 mm height were cut from long rectangular bar. 20 specimens of similar dimensions were cut and punched with specimen no. for identification Shown in Figure3.

Figure3 Specimen of AL 7075-T6 Qty : 20Nos.

The subsequent Table 4 gives the experimental results for average surface roughness.

Table 4 Experimental results for average surface roughness

Experiment number	Control factors			Average value of Surface roughness (µm) Ra
	Cutting speed (m/min) V_c	Feed rate (mm/tooth) f_z	Depth of cut (mm) a_p	
1	-1	-1	-1	0.389
2	1	-1	-1	0.3423
3	-1	1	-1	0.173
4	1	1	-1	0.4452
5	-1	-1	1	0.6792
6	1	-1	1	0.7831
7	-1	1	1	0.399

8	1	1	1	0.9267
9	-1.682	0	0	0.276
10	1.682	0	0	0.644
11	0	-1.682	0	0.4963
12	0	1.682	0	0.4231
13	0	0	-1.682	0.3019
14	0	0	1.682	0.8537
15	0	0	0	0.265
16	0	0	0	0.2871
17	0	0	0	0.282
18	0	0	0	0.2871
19	0	0	0	0.2639
20	0	0	0	0.2595

2.4. Development of Mathematical Model

A procedure based on regression was used for the development of a mathematical model and to predict the surface roughness (Montgomery and Peck., 2005). The response surface function representing surface roughness can be expressed as $Y = F\ (V_c,\ f_z,\ a_p)$ and the relationship selected was a second order response surface for k factors was given by Eq. (1.1).

$$Y = b_o + \sum_{i=1}^{k} b_i X_i + \sum_{i,j=0,i\neq j}^{k} b_{ij} + \sum_{i=1}^{K} b_{ii} X^2_i \qquad (1.1)$$

Where $b_o$was the free term of the regression equation. The coefficients b_1, b_2, b_3, b_4 and $b_5$were linear terms. The coefficients b_{11}, b_{22}, b_{33}, b_{44} and b_{55}were quadratic terms and the coefficients b_{12}, b_{13}, b_{14}, b_{15}, b_{23}, b_{24}, b_{25}, b_{34}, b_{35} and b_{45} were interaction terms (Montgomery and Peck 2005). The values of the coefficients of the polynomial were calculated by regression with the help of Eqs. (1.2) through (1.5).

$$b_o = 0.142857(\Sigma Y) - 0.035714\Sigma\Sigma X_{ii} Y \qquad (1.2)$$

$$b_i = 0.04167\Sigma(X_i Y) \qquad (1.3)$$

$$b_{ii} = 0.03125\Sigma(X_{ii} Y) + 0.00372\Sigma\Sigma(X_{ii} Y) - 0.035714\Sigma Y \qquad (1.4)$$

$$b_{ij} = 0.0625\Sigma(X_{ij}) \qquad (1.5)$$

Statistical software package, (MINITAB - 14) was used to calculate the values of these coefficients as shown in the Figure 4.

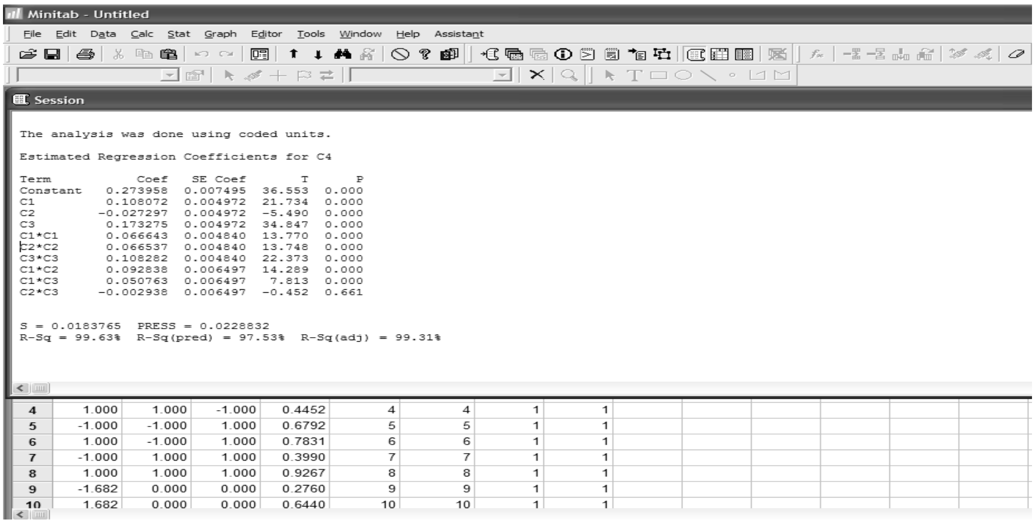

Figure 4 Output of MiniTab 14 Software

An initial mathematical model was developed using the coefficients obtained from the above equations. The mathematical model was as follows:

Surface roughness Ra $= 0.273958 + 0.108072\, V_c - 0.027297 f_z + 0.173275 a_p + 0.066643\, V_c^2 + 0.066537\, f_z^2 + 0.108282\, a_p^2 + 0.092838\, V_c f_z + 0.050763\, V_c a_p - \mathbf{0.002938\, f_z\, a_p}$ (1.6)

2.5. Testing the Coefficients for Significance

The value of the regression coefficients gave an idea as to what extent the control parameters affected the response quantitatively. The less significant coefficients were eliminated along with the responses with which they were associated without sacrificing much of the accuracy. This was done by using student's t – test (Yang et al., 1993) and by finding p-value. According to this test, when the calculated value of t corresponding to the coefficient exceeded the standard tabulated value for the probability criterion kept at 0.75, the coefficient became significant. Also, if the p-value of the coefficient was less than 0.05, then the coefficient became significant. Otherwise, it remained insignificant. The final mathematical model was developed using only the significant coefficients.

The coefficients which had p-value greater than 0.05 were eliminated. The final mathematical model as determined by the above analysis is given by Eq. (1.7).

Surface roughness Ra $= 0.273958 + 0.108072\, V_c - 0.027297 f_z + 0.173275 a_p + 0.066643\, V_c^2 + 0.066537\, f_z^2 + 0.108282\, a_p^2 + 0.092838\, V_c f_z + 0.050763\, V_c a_p$ (1.7)

2.6.Checking the Adequacy of the Developed Model

The adequacy of the model was tested using the analysis of variance techniques (ANOVA). As per the ANOVA technique by Sudhakaran, R (2012), it was desired that the calculated value of the F-ratio of the model developed should not exceed the standard tabulated value of the F-ratio for a desired level of confidence (say 95%), Also, if the calculated value of the R-ratio of the model developed exceeded the standard tabulated value of the R- ratio for the desired level of confidence (say 95 %), then the model could be considered to be adequate within the confidence limit shown in Table 5. The Table 5 illustrates the adequacy of the model.It is evident from the following Table -5 that the model is adequate.

Table 5 Adequacy of the Model

Response	**Factors**	**Lack of Fit**	**Pure Error**	**F-ratio**		**R-ratio**		**Whether model is adequate**
				Model	Standard	Model	Standard	
Surface roughness	8	6	0.001	2.754	4.95	719.627	4.82	Adequate

3. Results and Discussions

The Table 6 shows the comparison of measured and predicted surface value with % error.

Table 6Comparison of Measured and Predicted surface roughness value with % Error

Experiment number	Control factors			Surface roughness (µm) Ra		% Error
	Cutting speed (m/min) V_c	Feed rate (mm/tooth) f_z	Depth of cut (mm) a_p	Observed value	Predicted value	
1	-1	-1	-1	0.389	0.404971	-3.94374
2	1	-1	-1	0.3423	0.333913	2.511732
3	-1	1	-1	0.173	0.164701	5.038828
4	1	1	-1	0.4452	0.464995	-4.25704
5	-1	-1	1	0.6792	0.649995	4.493111
6	1	-1	1	0.7831	0.781989	0.142074
7	-1	1	1	0.399	0.409725	-2.61761
8	1	1	1	0.9267	0.913071	1.492655
9	-1.682	0	0	0.276	0.280722	-1.68216
10	1.682	0	0	0.644	0.644276	-0.0429
11	0	-1.682	0	0.4963	0.508113	-2.32487
12	0	1.682	0	0.4231	0.416286	1.636887
13	0	0	-1.682	0.3019	0.288853	4.516955
14	0	0	1.682	0.8537	0.87175	-2.07052
15	0	0	0	0.265	0.273958	-3.26984
16	0	0	0	0.2871	0.273958	4.797086
17	0	0	0	0.282	0.273958	2.935486
18	0	0	0	0.2871	0.273958	4.797086
19	0	0	0	0.2639	0.273958	-3.67137
20	0	0	0	0.2595	0.273958	-5.27745

3.1.Direct Effects of Variables

Figure 5 shows the direct effect of depth of cut n surface roughness

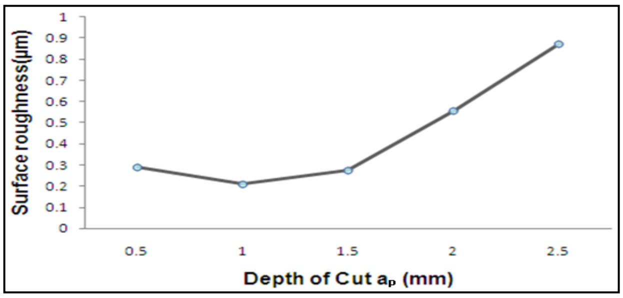

Figure 5Direct Effect of Depth of Cut on surface roughness

Figure 6 illustrates the direct effect of feed rate on surface roughness

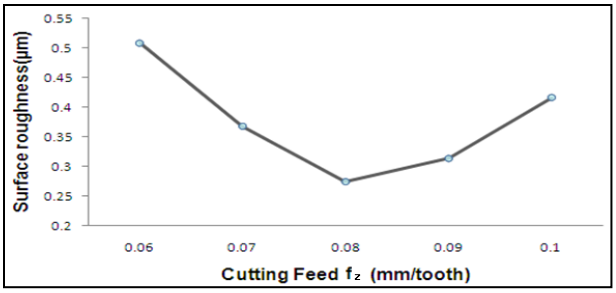

Figure 6 Direct Effect of Depth of Cut on surface roughness

Figure 7 shows the Direct Effect of Depth of Cut on surface roughness

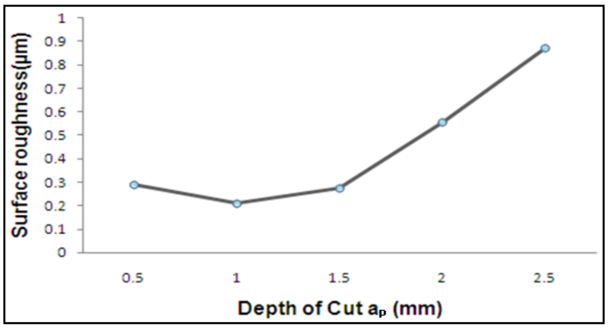

Figure 7 Effect of Depth of Cut on surface roughness

4. Conclusions

The experimental runs was conducted using central composite design and the second order quadratic equation had been developed to predict the values of surface roughness in terms of cutting speed, cutting feed, depth of cut and it is compared with the observed experimental values which helped to evaluate the accuracy of the surface roughness model and found the model parameters were under control.

The following conclusions were arrived from the investigation,

- An empirical relationship was developed to predict the surface roughness of AL7075-T6 alloy at 95% confidence level, incorporating shoulder milling process and process parameters.
- Response surface methodology used to develop a mathematical model to predict surface roughness in terms of cutting speed V_c, feed rate f_z, and depth of cut a_p.
- The deviation between predicted and measured surface roughness values was within an error band of about 5%.
- The model indicated that the cutting speed and feed rate was the most dominant parameter on surface roughness followed by depth of cut.
- The most important interactions, that effect surface roughness of machined surfaces, were between the cutting speed and cutting feed, and between cutting speed and depth of cut.
- The mathematical model developed in this work from the experimental data can be employed to control the machining parameter and achieve the desired surface roughness in shoulder milling.

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