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Tool Wear Optimization of Aluminum Alloy using Response Surface Methodology

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***Abstract* - Aluminium alloys have excellent machining properties compared with other common engineering metals. In this study deals with the Aluminum alloy 5083, the following process parameter the cutting speed, feed rate, depth of cut for the purpose of analysis. Tool wears measurement of great apprehension in machining industries and it affects the surface quality dimensional accuracy and production cost of the material components. The twenty experiments were conducted as per central composite face centered design for turning machining the process of aluminum alloy. Response surface methodology is utilized to developed an effective mathematical models on linear, quadratic and cubic to predict tool wear of the aluminum alloy 5083. A comparison study is made for tabulated values and experimental values for tool wear by using analysis of variance. The model found statistically fit for 95% confidence level.**

Key words - Tool wear, Aluminum alloy, CCD, RSM, ANOVA.

1. INTRODUCTION

Machining operations have been the core of the manufacturing industry since the industrial revolution. The machining parameters (cutting speed, feed rate, depth of cut) accelerate tool wear and it affects the surface finishing. The tool wear is directly related to the machining parameters. Optimum machining parameters, being the objective of this work is planned for turning machines to minimize tool wear in order to improve quality of machined products to improve the tool life. Chelladurai et al., [1] to created an empirical model using artificial neural network model and the model based on a full factorial experimental design to analyze the effect of various cutting speeds, depth of cut, feed rate and flank tool wear. They showed that the vibration increases tool wear and hence it influences the quality of the machining components. Palanikumar [2] developed a Response surface method (RSM) model for GFRP composites to predict the surface roughness. The model uses a CCD based four factors five level rotatable designs to carry out the experimental sequence of investigation and the model was validated using analysis of variance (ANOVA). Response surface methodology is a collection of mathematical and statistical techniques, which are useful for the modeling and analyzing the engineering problems and developing, improving, and optimizing processes. It also has important applications in the design, development, and formulation of new products, as well as in the improvement of existing product designs, and it is an effective tool for constructing optimization models [3].

2. EXPERIMENTAL PROCEDURES:

2.2 Plan of Experiments

An important stage in response surface model generation by RSM is the planning of experiments. The factors which have a significant influence on tool wear of aluminum alloy were identified they are cutting speed, depth of cut, and feed rate of turning machine. Large numbers of trial runs were carried out using aluminum alloy bar to determine tool wear values of turning machining parameters.

Table: 1 Process parameters and their actual values

Factors	Notation	Unit	Factor Level		
			Low	Middle	High
Cutting Speed	S	rpm	300	600	900
Feed rate	F	mm/rev	0.05	0.10	0.15
Depth of cut	D	mm	0.5	1	1.5

2.3 Response surface methodology

Response surface methodology is a collection of mathematical and statistical techniques for empirical model building. By careful design of experiments the objective is optimize a response which is influenced by several independent variables. An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response. The second order mathematical models have been developed predict the tool wear.

$$yi = \beta_0 + \sum_{j=1}^{q} \beta jxj + \sum_{j=1}^{q} \beta jjxj^2 + \sum \sum_{i<j}^{3} \beta ij\, xi\, xj$$

Where y_i is response, i.e., tool wear; x_j represents cutting speed, feed rate depth of cut β_0, β_j, β_{jj}, and β_{ij} represent the constant, linear, quadratic, and interaction terms, respectively. The tool wear obtained from experimental results for different combination of parameters is given as input to the design expert software, and a second order mathematical model (quadratic, linear and cubic) for predicting tool wear is developed.

Tool wear (TW) = $0.18-0.056\times A-0.059\times B-0.059\times C-7.045E^{-003}\times A^2-0.025\times B^2+3.535E^{-003}\times C^2- 0.044\times AB+0.0 \times AC-0.047\times BC$. (Quadratic model)

Tool wear (TW) = $0.19+0.0\times A-0.018\times B+4.667E^{-003}\times C$. (Linear model)

Tool wear (TW) = $0.18-0.060\times A-0.059\times B-0.060\times C-7.879E^{-003}\times A^2-0.025\times B^2+3.535E^{-003}\times C^2\ 0.047\times AB+\ 7.5\ E^{-003}\times AC-0.047\times BC+0.0\times A^2\times B+1.667\ \ 003A^2\times C+0\times A\times\ B^2+5.833E^{-003}$. (Cubic model)

A total of twenty experiments were conducted at different levels of parameters to obtain a machining operation. The values of tool wear obtained from experiments response surface model along with design matrix tabulated.

Table: 2 Experimental values of tool wear

S.no	Cutting Speed (rpm) (A)	Feed rate (mm/min) (B)	Depth of Cut (mm)(C)	Experimental Tool Wear (TW)
1	300	0.05	0.5	0.18
2	900	0.05	0.5	0.21
3	300	0.15	0.5	0.24
4	900	0.15	0.5	0.21
5	300	0.05	2	0.24
6	900	0.05	2	0.26
7	300	0.15	2	0.21
8	900	0.15	2	0.19
9	300	0.1	1.25	0.21
10	900	0.1	1.25	0.21
11	600	0.05	1.25	0.22
12	600	0.15	1.25	0.21
13	600	0.1	0.5	0.22
14	600	0.1	2	0.23
15	600	0.1	1.25	0.22
16	600	0.1	1.25	0.22
17	600	0.1	1.25	0.215
18	600	0.1	1.25	0.22
19	600	0.1	1.25	0.22
20	600	0.1	1.25	0.22

3. RESULTS AND DISCUSSION

3.1 Analysis of variance

Analysis of variance is the separation of variance ascribable to one group of causes from the variance ascribable to other group. It is nothing but an arithmetical procedure used to express the total variation of data as the sum of its non- negative components. Typically however the one-way ANOVA is used to test for differences among at least three groups, since the two-group case can be covered by a t-test. When there are only two means to compare, the t-test and the F-test are equivalent. General quadratic model is used to determine the influence of cutting speed, feed rate and depth of cut on tool wear.

Table: 3 ANOVA for quadratic model

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F
Model	0.005428	9	0.000603	63.03378	< 0.0001
A	0.001196	1	0.001196	125.0164	< 0.0001
B	9.48E-06	1	9.48E-06	0.990784	0.3430
C	0.002792	1	0.002792	291.7909	< 0.0001
A2	0.000137	1	0.000137	14.26663	0.0036
B2	1.15E-05	1	1.15E-05	1.202494	0.2985
C2	0.000174	1	0.000174	18.18587	0.0017
AB	0.00125	1	0.00125	130.6413	< 0.0001
AC	0	1	0	0	1.0000
BC	0.0032	1	0.0032	334.4418	< 0.0001
Residual	9.57E-05	10	9.57E-06		
Lack of Fit	7.48E-05	5	1.5E-05	3.592727	0.0934
Pure Error	2.08E-05	5	4.17E-06		
Cor Total	0.005524	19			

Table: 4 ANOVA table for linear model

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F
Model	0.00074	3	0.000247	0.825015	0.4991
A	0	1	0	0	1.0000
B	0.00025	1	0.00025	0.836164	0.3741
C	0.00049	1	0.00049	1.638882	0.2187
Residual	0.004784	16	0.000299		
Lack of Fit	0.004763	11	0.000433	103.9182	< 0.0001
Pure Error	2.08E-05	5	4.17E-06		
Cor Total	0.005524	19			

Table: 5 ANOVA table for cubic model

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F
Model	0.005488	13	0.000422	70.98726	< 0.0001
A	1.5E-05	1	1.5E-05	2.528979	0.1629
B	9.35E-06	1	9.35E-06	1.572812	0.2564
C	0.002554	1	0.002554	429.4654	< 0.0001
A2	4.74E-06	1	4.74E-06	0.797454	0.4062
B2	1.15E-05	1	1.15E-05	1.934713	0.2136
C2	0.000174	1	0.000174	29.25955	0.0016
AB	3.5E-06	1	3.5E-06	0.58888	0.4720
AC	4.76E-05	1	4.76E-05	8.01199	0.0299
BC	0.0032	1	0.0032	538.0892	< 0.0001
A3	0	0			
B3	0	0			
C3	0	0			
A2B	0	1	0	0	1.0000
A2C	0.00001	1	0.00001	1.681529	0.2424
AB2	0	1	0	0	1.0000
AC2	0	0			
B2C	0	0			
BC2	0	0			
ABC	5E-05	1	5E-05	8.407643	0.0273
Residual	3.57E-05	6	5.95E-06		
Lack of Fit	1.48E-05	1	1.48E-05	3.563636	0.1177
Pure Error	2.08E-05	5	4.17E-06		
Cor Total	0.005524	19			

The Model F-value of 63.03 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant.

In this case A, C, A^2, C^2, AB, BC are significant model terms for quadratic model table 3. The "Model F-value" of 0.83 implies the model is not significant relative to the noise. There is a 49.91 % chance that a "Model F-value" this large could occur due to noise. In this case there are no significant model terms for linear model table 4. The Model F-value of 70.99 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case C, C^2, AC, BC, ABC are significant model terms for cubic model table 5. Each observed value is compared with the predicted value calculated from the model in Figure 1. These figure illustrate that the developed model are adequate and predicted results are in good agreement with the measured data as the residuals are close to the diagonal line [16].

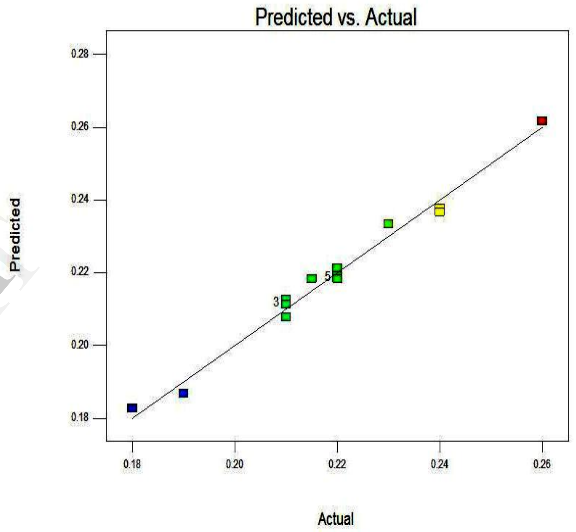

Figure: 1 Correlation graph

3.2 Analysis of response surface graphs cubic model

Response surfaces were developed for the empirical relationship, taking two parameters in the 'X' and 'Y' axis and response in 'Z' axis. The response surfaces clearly indicate the optimal response point. The response of tool wear of the surface plots showing the effect of input parameters taken on tool wear. The different colored surfaces show that the value of tool wear obtained for the corresponding values of input parameters.

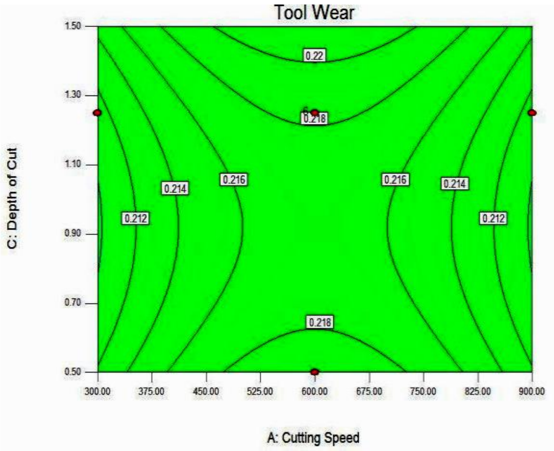

Figure: 2 Contour plot (Effect of depth of cut and cutting speed on tool wear)

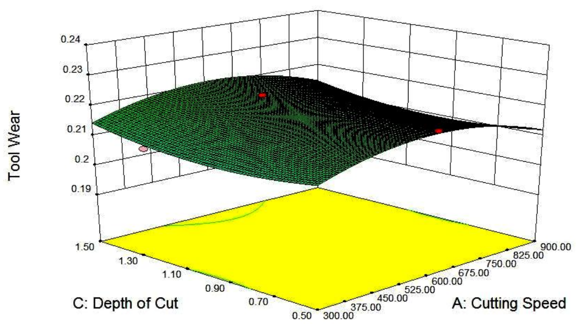

Figure: 3 Response surface due to interaction of depth of cut and cutting speed on tool wear

Figure 2 & 3 represent the three dimensional response surface plots for the response tool wear obtained from the regression model. The response surface graphs for the tool wear between depth of cut and cutting speed, it can be seen from this figure that tool wear increases with decrease of cutting speed and increase of depth of cut. It is inferred that tool wear conditions of high cutting speed and low depth of cut produce low tool wear. On the other hand high depth of cut and high feed rate produce high tool wear. So the combination of decrease in depth of cut and high cutting speed leads to decreasing of tool wear.

CONCLUSION

Experiments were conducted on turning machine using aluminum alloy 5083, the data tool wear was collected under different turning machining conditions for various combination of cutting speed, feed rate, and depth of cut environment. RSM provides a large amount of information with a small amount of experimentation. The RSM based tool wear model in terms of cutting speed, feed rate, and Depth of cut environment was developed by means of the experimental database as per central composite face centered design of experiments. The quadratic, linear and cubic models are developed using RSM were reasonable accurate and can be used for prediction within the limits of the factors investigated. The second order quadratic model was used to predict tool wear values for experimental value by response surface methodology. A comparison study is made for tabulated values and experimental values for tool wear by using analysis of variance the model is statistically fit found on 95% confidence level.

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