Experimental Investigation of AISI 1015 Steel Plate in Milling by Response Surface Methodology

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ABSTRACT - *In the present study, response surface methodology has been applied to determine the significant cutting parameters leading to minimum surface roughness (Ra), and maximum material removal rate (MRR) in milling operation on AISI1015. The second order mathematical models in terms of machining parameters were developed for surface roughness, and MRR prediction using response surface methodology (RSM) on the basis of experimental results. Solid carbide tool of 20 mm diameter is used to machine AISI 1015 plate of 10mm thickness on VMC. The model selected for optimization has been validated with F-test. The adequacy of the models on all responses has been established with Analysis of variance (ANOVA).*

KEYWORDS: Milling, Response Surface Methodology, Optimization

1. INTRODUCTION

Milling is the process of machining flat, curved or irregular surface by feeding the workpiece against a rotating cutter containing a number of cutting edges.

The selection of efficient machining parameters is of great concern in manufacturing industries, where economy of machining operations plays a key role in the competitive market. Many researchers have dealt with the optimization of machining parameters. The RSM is a dynamic and foremost important tool of Design of Experiment (DOE) where in the relationship between process output(s) and its input decision variables, it is mapped to achieve the objective of maximization or minimization of the output properties. RSM was successfully applied for prediction and optimization of cutting parameters.

Roughness plays an important role in determining how a real object will interact with its environment. Although roughness is usually undesirable, it is difficult and expensive to control during manufacturing. Decreasing roughness of a surface will usually exponentially increase its manufacturing costs. This often results in a trade-off between the manufacturing cost of a component and its performance in application.

2. EXPERIMENT DETAILS

The work material selected for machining was AISI 1015 Steel which has wide range of application in industry viz. rivets, screws, panels, ship plates, boilers plates, fan blades, valves, cam shaft gear, crank shafts, connecting rods, railway axles, tubes of bicycles forged, cold-headed or cold-formed parts which are low strength with wear resistant and hard surfaces. The steel plates with 10 mm thickness were used for machining. The hardness of AISI 1015 steel was 15 HRc. The chemical composition of test specimen of AISI1015 carbon steel is shown in table 1

Table 1. Chemical Composition of AISI 1015 steel

C	Mn	Cr	Ni	Mo	S	P	si
0.178	0.60	0.04	0.03	0.002	0.019	0.020	0.19

3. DESIGN OF EXPERIMENTS

In our study we have used Response Surface Methodology for design of experiment. Various cutting parameters are considered in milling operation which is responsible for surface roughness, but according to literature review speed, feed and depth of cut are most important and significant parameters. In the present study these are selected as design factors while other parameters have been assumed to be constant over the experimental domain. A central composite design is selected for the experimentation. It is the most widely used experimental design for the modeling a second - order response surface. A randomized experimental run has been carried out to minimize the error due to machining set-up. The levels of cutting parameters for the experiments have been listed in Table 2.

Table 2. Machining parameters and their levels

Factors	Levels				
	-1.68	-1	0	+1	+1.68
Speed (V), m/min	25.909	30	36	42	46.0908
Feed (f), mm/rev	0.06591	0.1	0.15	0.2	0.23409
Depth of Cut (D), mm	0.6591	1	1.5	2	2.3409

Experiments have been carried out according to the experimental plan based on central composite second order design. Experimental plan consists of experiment standard order and un-coded values of the process parameters and observed responses are shown in Table 3.

Table 3.Experimental design matrix with un-coded values and observed responses

Run Order	V	f	D	Ra	MRR ex
1	+1	-1	-1	2.303	31.25
2	-1	+1	+1	3.180	16.67
3	0	0	0	2.587	31.25
4	0	-1.68	0	1.907	41.10
5	0	0	0	2.500	57.14
6	0	0	0	2.654	60.00
7	-1	-1	-1	3.206	7.69
8	0	0	+1.68	2.594	31.25
9	-1	+1	-1	2.448	16.48
10	+1	+1	-1	2.609	28.57
11	0	0	-1.68	2.885	80.00
12	-1	-1	+1	2.674	31.25
13	0	0	0	2.505	29.70
14	0	0	0	2.603	27.59
15	+1	+1	+1	2.884	31.25
16	+1	-1	+1	1.853	31.25
17	-	0	0	3.133	40.00
18	+1.6	0	0	2.602	28.57
19	0	0	0	2.480	58.52
20	0	+1.68	0	2.689	13.70

3.1 Mathematical Model Development for Surface Roughness:

After conducting the experiment to develop the mathematical model and find significant factor for surface roughness, Response Surface regression and analysis of variance is done by using miniTAB.

Response Surface Regression: Ra versus V, f, D

For each term in the model, there is a coefficient. Using these coefficients we have construct an equation representing the relationship between the response and the factors. For the Surface Roughness (Ra) and Metal Removal Rate (MRR), regression equations are:

$$\begin{aligned} SurfaceRoughness(Ra) &= 12.11 - 0.3325V \\ &- 24.47f - 1.789D + 0.003097V*V \\ &- 35.9f*f + 0.265D*D + 0.662V \\ &*f - 0.0157V*D + 9.94f*D \end{aligned} \quad (1)$$

$$\begin{aligned} (MRR) &= 241.3 - 6.65V - 327f \\ &- 112.5D + 0.0511V*V - 273f \\ &*f + 15.79D*D + 7.13V*f \\ &+ 1.789V*D + 66.6f*D \end{aligned} \quad (2)$$

R2 and adjusted R2 represent the proportion of variation in the response that is explained by the model. R2 (R-Sq) describes the amount of variation in the observed responses that is explained by the model.

For a given milling experiment, 94.17% of the variation in surface roughness and 96.6% is explained by model.

Adjusted R2 is a modified R2 that has been adjusted for the number of terms in the model. If we include unnecessary terms, R2 can be artificially high. Unlike R2, adjusted R2 may get smaller when you add terms to the model. For the given experimental data, the adjusted R2 is 88.92% for surface roughness. For the given experimental data, the adjusted R2 93.53% for metal removal rate.

3.2 Model Validation:

Normal Plot of the Residuals:

This graph plots the residuals versus their expected values when the distribution is normal. The residuals from the analysis should be normally distributed. In practice, for balanced or nearly balanced designs or for data with a large number of observations, moderate departures from normality do not seriously affect the results.

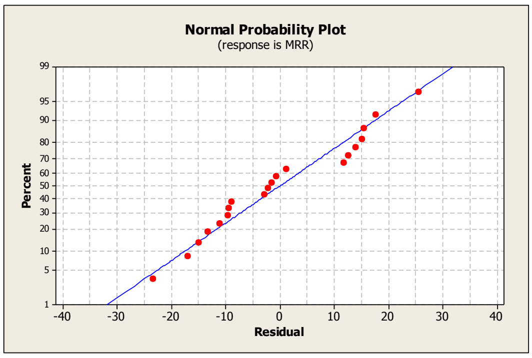

Fig. 1 Normal plot of the residuals for MRR

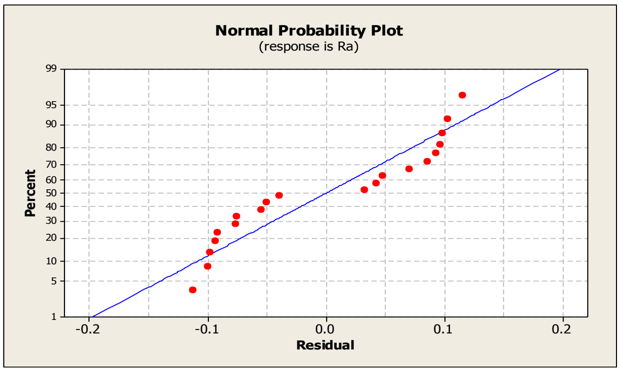

Fig.2: Normal plot of the residuals for Ra

For MRR as well as Surface Roughness data, the residuals generally appear to follow the straight line (Figure. 1 and Figure. 2). Therefore, the given design is well balanced and no evidence of non normality, skewness, outliers, or unidentified variables exists.

Residual versus fits:

This graph plots the residuals versus the fitted values. The residuals should be scattered randomly about zero.

Based on the plot for both MRR and Surface Roughness (Fig. 3 and Fig. 4), the residuals appear to be randomly scattered about zero. Therefore, constant variation is observed between residuals and fitted values and no evidence of non constant variance, missing terms, outliers, or influential points exist.

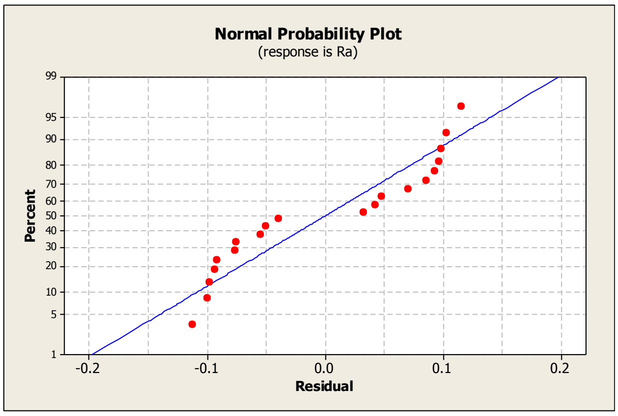

Fig.3 : A graph of residuals versus fits for MRR

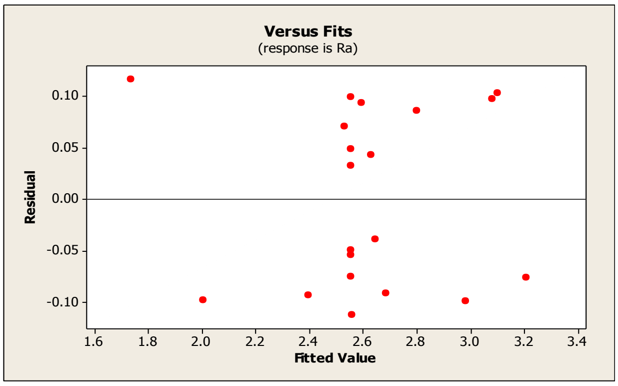

Fig.4: A graph of residuals versus fits for Ra

Residuals versus Order Plot:

This graph plots the residuals in the order of the corresponding observations. The plot is useful when the order of the observations may influence the results, which can occur when data are collected in a time sequence or in some other sequence, such as geographic area. This plot can be particularly helpful in a designed experiment in which the runs are not randomized.

For the given MRR and Surface Roughness data, the residuals appear to be randomly scattered about zero [Fig.5 and Fig. 6]. Therefore, no evidence exists that the error terms are correlated with one another. Hence given model is accurately defined for MRR & Surface Roughness analysis.

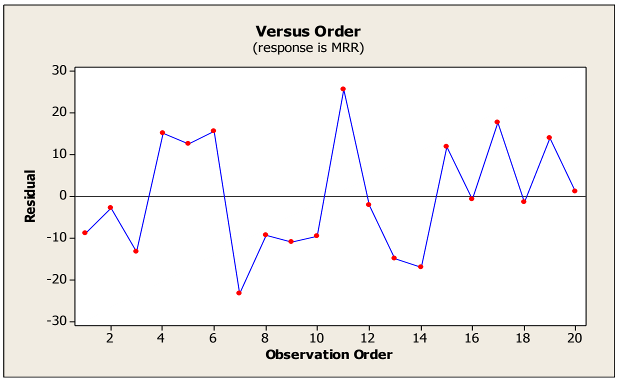

Fig.5: Residuals versus observation order (MRR)

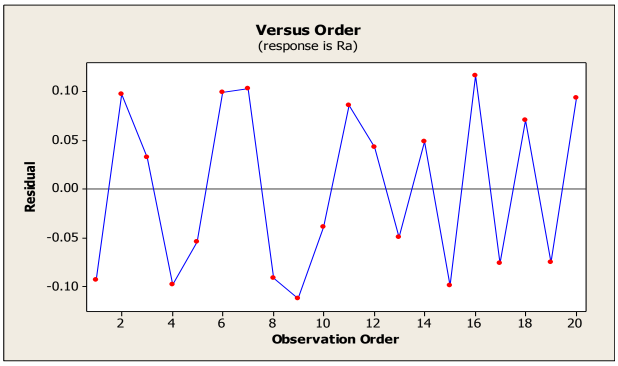

Fig.6 Residuals versus observation order (Ra)

3.3 Analysis of Variance:

The analysis of variance (ANOVA) and the F-ratio test have been performed to check the adequacy of the models as well as the significance of the individual model coefficients. Table.4. presents the ANOVA table for the second order model proposed for Ra given in equation 6.

It can be appreciated that the P-value is less than 0.05 which means that the model is significant at 95% confidence level. Also the calculated value of the F-ratio is more than the standard value of the F-ratio for Ra, and MRR. It means the model is adequate at 95% confidence level to represent the relationship between the machining response and the machining parameters of the milling process. Similarly, analysis of variance is carried out for all the response models as given in equations 7. The calculated F- values of the lack-of-fit for different response parameters are very much lower than the tabulated value of the F -distribution found from the standard table at 95% confidence level. It implies that the lack-of-fit is not significant relative to pure error. Therefore, the developed second-order regression models for two responses are adequate at 95% confidence level. These models can be used to navigate the design space.

4. CONCLUSIONS:

In this work, response surface methodology have been utilized for establishing optimum milling parameters leading to minimum surface roughness and maximum MRR during milling of AISI1015 with different cutting condition. Milling parameters cutting speed, feed rate and depth of cut are used to conduct experiments. A response surface methodology was used to develop surface roughness and MRR quadratic model. The following conclusions are drawn within the experimental domain:

- The three levels central composite design designs can be employed easily for developing mathematical models for predicting surface roughness and MRR parameters within the workable region of control process parameters in milling operations.
- RSM can be applied successfully in analyzing effect of process parameters on different output parameters.
- It is identified that lower cutting speed, lower feed rate and lower depth of cut leads to minimized surface roughness.
- It is identified that higher cutting speed, higher feed rate and higher depth of cut leads to maximized MRR.

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Table 4: Analysis of Variance for Ra

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	2.20783	0.245314	17.95	0.000
Linear	3	0.99252	0.330841	24.21	0.000
V	1	0.55491	0.554909	40.60	0.000
f	1	0.42182	0.421823	30.86	0.000
D	1	0.01579	0.015792	1.16	0.308
Square	3	0.38760	0.129201	9.45	0.003
V*V	1	0.17915	0.179147	13.11	0.005
f*f	1	0.11612	0.116125	8.50	0.015
D*D	1	0.06306	0.063064	4.61	0.057
2-Way Interaction	3	0.82770	0.275901	20.19	0.000
V*f	1	0.31601	0.316012	23.12	0.001
V*D	1	0.01767	0.017672	1.29	0.282
f*D	1	0.49402	0.494018	36.14	0.000
Error	10	0.13668	0.013668	**	**
Lack-of-Fit	5	0.11242	0.022485	4.64	0.059
Pure Error	5	0.02425	0.004851	**	**
Total	19	2.34451	**	**	**