

Analysis and Optimization of Machining Process Parameters Using Design of Experiments

Dr. M. Naga Phani Sastry, K. Devaki Devi, Dr, K. Madhava Reddy
Department of Mechanical Engineering, G Pulla Reddy Engineering College, Kurnool, A. p, India.
*navya_2517@yahoo.co.in

Abstract

In any machining process, apart from obtaining the accurate dimensions, achieving a good surface quality and maximized metal removal are also of utmost importance. A machining process involves many process parameters which directly or indirectly influence the surface roughness and metal removal rate of the product in common. Surface roughness and metal removal in turning process are varied due to various parameters of which feed, speed, depth of cut are important ones. A precise knowledge of these optimum parameters would facilitate reduce the machining costs and improve product quality. Extensive study has been conducted in the past to optimize the process parameters in any machining process to have the best product. Current investigation on turning process is a Response Surface Methodology applied on the most effective process parameters i.e. feed, cutting speed and depth of cut while machining Aluminium alloy and resin as the two types of work pieces with HSS cutting tool. The main effects (independent parameters), quadratic effects (square of the independent variables), and interaction effects of the variables have been considered separately to build best subset of the model. Three levels of the feed, three levels of speed, three values of the depth of cut, two different types of work materials have been used to generate a total 20 readings in a single set. After having the data from the experiments, the performance measures surface roughness (Ra) of the test samples was taken on a profilometer and MRR is calculated using the existing formulae. To analyze the data set, statistical tool DESIGN EXPERT-8 (Software) has been used to reduce the manipulation and help to arrive at proper improvement plan of the Manufacturing process & Techniques. Hypothesis testing was also done to check the goodness of fit of the data. A comparison between the observed and predicted data was made, which shows a close relationship.

Key words: Surface Roughness and Metal Removal Rate, Turning, Response Surface Methodology, Aluminium Alloy, Resin.

1. Introduction

The selection of proper combination of machining parameters yields the desired surface finish and metal removal rate the proper combination of machining parameters is an important task as it determines the optimal values of surface roughness and metal removal rate. It is necessary to develop mathematical models to predicate the influence of the operating conditions. In the present work mathematical models has been developed to predicate the surface roughness and metal removal rate with the help of Response surface methodology, Design of experiments. The Response surface methodology (RSM) is a practical, accurate and easy for implementation. The study of most important variables affecting the quality characteristics and a plan for conducting such experiments is called design of experiments (DOE).The experimental data is used to develop mathematical models using regression methods. Analysis of variance is employed to verify the validity of the model. RSM optimization procedure has been employed to optimize the output responses, surface roughness and metal removal rate subjected to turning parameters namely speed, feed, depth of cut and type of material using multi objective function model.

2. Methodology

In this work, experimental results were used for modeling using Response surface methodology, is a practical, accurate and easy for implementation. The experimental data was used to build first order and second order mathematical models by using regression analysis method. These developed mathematical models were optimized by using the RSM optimization procedure for the output responses by imposing lower and upper limit for the input machining parameters speed, feed, depth of cut and type of material.

2.1 Design of Experiments (DOE)

The study of most important variables affecting quality characteristics and a plan for conducting such experiments is called the Design of Experiments.

2.2 Response Surface Methodology (RSM)

Response Surface Methodology is combination of mathematical and statistical technique [30-31], used develop the mathematical model for analysis and optimization. By conducting experiment trails and applying the regression analysis, the output responses can be expressed in terms of input machining parameters namely table speed, depth of cut and wheel speed. The major steps in Response Surface Methodology are:

1. Identification of predominate factors which influences the surface roughness, Metal removal rate.
2. Developing the experimental design matrix, conducting the experiments as per the above design matrix.
3. Developing the mathematical model.
4. Determination of constant coefficients of the developed model.
5. Testing the significance of the coefficients.
6. Adequacy test for the developed model by using analysis of variance (ANNOVA).
7. Analyzing the effect of input machining parameters on output responses, surface roughness and metal removal rate.

3. Mathematical Formulation

The first order and second order Mathematical models were developed using multiple regression analysis for both the output responses namely surface roughness and metal removal rate. Multiple regression analysis is a statistical technique, practical, easy to use and accurate. The aim of developing the mathematical models is to relate the output responses with the input machining parameters and there by optimization of the machining process. By using these models, optimization problem can be solved by using Response Surface optimization procedure as multi objective function model. The mathematical models can be represented by

$$Y_i = f\,(v, f, d, m) \tag{1}$$

Where Y_i is the i^{th} output grinding response(R_a and MR), v, f, d, m are the speed, feed, depth of cut and material (Aluminium Alloy and Resin) respectively.
Regression analysis can be represented as follows

$$Y1= Y\text{-}e = b_0x_0+b_1x_1+b_2x_2+b_3x_3 \tag{2}$$

Where Y_1 is first order output response, Y is the measured response and x_1, x_2, x_3 are the input parameters.
The second order polynomial of output response will be given as

$$Y_2=Y\text{-}e= b_0x_0+b_1x_1+b_2x_2+b_3x_3+b_{12}x_1x_2+b_{13}x_1x_3+b_{23}x_2x_3+b_{11}x_{12}+b_{22}x_{22}+ b_{33}x_{32} \tag{3}$$

Where Y2 is second order output response Y is the measured response, b_0, b_1, ----- are estimated by the method of lest squares. The validity of this mathematical model will be tested using F- test, p-test test before going for optimization.

4. Experimental Details

A set of experiments were conducted on Lathe machine to determine effect of machining parameters namely table speed (rpm),feed (mm/rev),depth of cut (mm) and material (Al alloy and Resin) on output responses namely surface roughness and metal removal rate. The machining conditions were listed below. Three levels for first three factors and two for the fourth, taken as categoric are used to give the design matrix by using Response Surface Methodology (RSM) and relevant ranges of parameters as shown in Table 1.cutting tool used for the present work is the High Speed Steel. The selected design matrix with 24 runs to conduct the experiments is shown in the Table 2 along with the output responses, MRR and surface roughness. MRR was calculated as the ratio of volume of material removed from the work piece to the machining time. The surface roughness, R_a was measured in perpendicular to the cutting direction using Profilometer. These results will be further used to analyze the effect of input machining parameters on output responses with the help of RSM and design expert software.

4.1 Machining conditions:

(a) Work piece material: EN 24 steel
(b) Chemical composition: Carbon 0.35-0.45/ Silicon 0.10-0.35/ Manganese 0.45-0.70/ Nickel 1.30-1.80 /Chromium 0.90-1.40/ Moly 0.20-0.35/ Sulphur 0.050 (max)/ Phosphorous 0.050(max) and balance Fe
(c) Work piece dimensions: 155mm x 38mm x 38mm
(d) Physical properties: Hardness-201BHN, Density-7.85 gm/cc, Tensile Strength-620 Mpa
(e) Grinding wheel: Aluminum oxide abrasives with vitrified bond wheel WA 60K5V
(f) Grinding wheel size: 250 mm ODX25 mm widthx76.2 mm ID

5. Development of Empirical Models

In the present study, Empirical models for the output responses, Surface roughness (Ra), Metal removal rate (MRR) in terms of input machining parameters in actual factors were developed by using the RSM [23-27]. The developed models are further used for optimization of the machining process. The regression coefficients of the developed model are determined from the regression analysis. The second order models were developed for output responses due to lower predictability of the first order model to the present problem. The following equations were obtained in terms of actual factors individually for aluminium alloy and resin

Surface Roughness:
For aluminium alloy,

$$\mathbf{R_a} = 35.32134822 - 0.011385648s - 0.019427137f - 41.93268705d + 4.67811\text{ E-}7sf - 0.000254967s\,d + 0.108362292fd + 2.3633\text{ E-}06s^2 - 0.000398249f^2 + 19.48317581d^2$$

For resin,

$$\mathbf{R_a} = 33.08948639 - 0.011833057s - 0.018043056f - 38.56288148d + 4.67811\text{ E-}07sf - 0.000254967sd + 0.10836229f\,d + 2.3633\text{ E-}06\,s^2 - 0.000398249\,f^2 + 19.48317581\,d^2$$

Metal Removal Rate
For aluminium alloy,

$$\mathbf{MRR} = -1850.976709 + 0.594459933\,s + 7.533431572\,f + 2481.309721\,d - 0.000694198\,s\,f - 0.49934073\,s\,d + 8.93648226\,f\,d$$

For resin,

$$\mathbf{MRR} = -737.3687931 + 0.464291611\,s - 4.961102928\,f + 856.649045\,d - 0.000694198\,s\,f - 0.499340729\,s\,d + 8.93648226\,f\,d$$

Analysis of variance (ANOVA) is employed to test the significance of the developed models. The multiple regression coefficients of the second order model for surface roughness and metal removal rate were found to be 0.8411 and 0.9911 respectively. The R^2 values are very high, close to 1, it indicates that the second order models were adequate to represent the machining process. The "Pred RSquared" of 0.8027 is in reasonable agreement with the "Adj R-Squared" of 0.8967 in case of surface roughness. The "Pred R-Squared" of 0.9498 is in reasonable agreement with the "Adj R-Squared" of 0.9666 in case of MRR.

The Model F-value of 26.09 for surface roughness and The Model F-value of 84.51 for metal removal rate implies the model is significant. The analysis of variance (ANOVA) of response surface quadratic model for surface roughness and metal removal rate were shown in Table 3 and Table 4 respectively. Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. S/N ratio of 8.415 &32.54 for surface roughness and MRR indicates an adequate signal. This model can be used to navigate the design space. The *P* value for both the models is lower than 0.05 (at 97% confidence level) indicates that the both the models were considered to be statistically significant. The Plot of Predicted versus actual response for surface roughness and MRR are shown in **figure 1** and show that the models are adequate without any violation of independence or constant assumption.

6. Interpretation of Developed Models

The detailed main effects and interaction effects for both the outputs are discussed in the following sections. It should be noted that if a particular parameter does not influence the output during the course of evaluation, it gets eliminated.

6.1 Effect of process parameters on surface roughness (Ra)

The effect of process parameters on output response, surface roughness is shown in figs 5 to 7. From Fig. 5, it is observed that increase in wheel speed tends to improve the finish. With carbide tools particularly, slow speed is not at all desirable since it means wastage of time and money and tools wear out faster. Fig. 6 shows the effect of table speed on roughness. As the table speed increases, finish gets poorest because the tool marks show on the work piece. The effect of depth of cut on surface roughness is shown in Fig. 7. It is noted from Fig. 7, that the increase in depth of cut makes the finish poor. Hence smaller values of table speed and depth of cut and larger value of wheel speed must be selected in order to achieve better surface roughness during the process.

6.2 Effect of Process parameters on MRR

The effect of process parameters on output response, surface roughness is shown in Figs 11 to 13. From Fig. 11, it is observed that increase in wheel speed tends to increase the MRR; where as the other two machining parameters are kept at its mid value. It is observed from the direct effects, depth of cut plays more vital role on MRR than other two parameters. Material removal rate in machining process is an important factor because of its vital effect on the industrial economy. Increasing the table speed, wheel speed and depth of cut, leads to an increase in the amount of Material removal rate. But the most influential factors are table speed, and depth of cut. The highest value of MRR is obtained at the extreme range of the input parameters in all the interaction plots. Also the MRR increases gradually with the depth of cut.

7. Optimization of the Problem

Optimization of machining parameters increases the utility for machining economics; a Response Surface Optimization is attempted using DESIGN EXPERT software for individual machining parameters in turning. Table 6 shows the RSM optimization results for the surface roughness and MRR parameters in turning. It also includes the results from confirmation experiments conducted with the optimum conditions individually in case of Aluminium alloy and resin. The desirability values for the two combinations show the conformity to the optimality (desirability should be nearer to 1).

8. Results

The optimum results for the output responses namely surface roughness and Metal removal rate in terms of machining parameters namely speed, feed, depth of cut and material type on CNC lathe machine using DESIGN EXPERT software were determined and presented in Table 6.The confirmation experiments were conducted and there is in good agreement between predicted and experimental values. It is found that the error in prediction of the optimum conditions is about 3 to8%. Thus the response optimization predicts the optimum conditions fairly well.

8. Conclusions

In this study, aluminum and resin work pieces were produced by machine-turning, which is an important form of metal fabrication. The surface quality and metal removal rate of the work piece were analyzed and the potential effects of variables such as cutting speed, feed and depth of cut with two different work pieces mentioned above (Aluminium alloy and resin) on these dependent variables were investigated. A plan of experiments has been prepared from design of experiments in order to test the influence of cutting speed, feed rate, depth of cut and material type on the output parameters. The obtained data have been statistically processed using Response Surface Method (central composite design). The empirical models of output parameters are established and tested through the analysis of variance to validate the adequacy of the models. It is found that the surface roughness and MRR parameters greatly depend on work piece materials. A response surface optimization is attempted using DESIGN EXPERT software for output responses in turning. The following summary of results was extracted:

1. Experimental and statistical methods were used. The parameters determined at the experimental design stage and the parameters necessary for improving dimensional precision of the work piece were consistent. Thus, the study was successfully completed. In short, independent variables estimated for the dependent variables solved the problem.
2. The minimum surface roughness value was 1.18 µm for Aluminium alloy and2.295 for resin.
3. The maximum metal removal rate was found to be 1377.83mm^3/min for Aluminium alloy and 182.899 mm^3/min for resin.
4. Confirmatory experiment have been conducted which proved the efficiency of the models with negligible percentage errors.
5. The study determined appropriate cutting parameters to optimal performance measures. The Response Surface optimization method was successfully applied in the study. Machining parameters such as surface roughness was minimized and metal removal rate was maximized for the considered aluminium alloy and resin; process performance was enhanced and product quality was improved.

11. References

M. Janardhan and A. Gopala Krishna, “Multi-Objective Optimization 0f Cutting Parameters for Surface Roughness and Metal Removal Rate in Surface Grinding Using Response Surface Methodology”, International Journal of Advances in Engineering & Technology, March 2012. IJAET ISSN: 2231-1963.

Poornima And Sukumar, “Optimization of Machining Parameters in CNC Turning of Martensitic Stainless Steel Using RSM And GA”, International Journal of Modern Engineering Research (IJMER), Vol.2, Issue.2, Mar.-Apr. 2012 Pp-539-542 Issn: 2249-6645, Www.Ijmer.Com .

Ramo´ n Quiza Sardin˜, Marcelino Rivas Santana, Eleno Alfonso Brindis, “Genetic algorithm-based multi-objective optimization of cutting parameters in turning processes”, Engineering Applications of Artificial Intelligence 19 (2006) 127–133, www.elsevier.com.

Atul Kumar, Dr. Sudhir Kumar, Dr. Rohit Garg, “Statistical Modeling Of Surface Roughness In Turning Process”, International Journal of Engineering Science and Technology (IJEST), ISSN : 0975-5462 Vol. 3 No. 5 May 2011

Ashok kumar Sahoo and Bidyadhar Sahoo, “Surface roughness model and parametric optimization in finish turning using coated carbide insert: Response surface methodology and Taguchi approach”, International Journal of Industrial Engineering Computations 2 (2011) 819–830.

E. Daniel Kirby, “A Parameter Design Study in a Turning Operation Using the Taguchi Method”, *the Technology Interface/Fall 2006*

Smruti Ranjan Sahoo, “Prediction of machining parameters for optimum Surface Roughness in turning SS 304”, B.Tech Thesis, National Institute of Technology, Department of Mechanical Engineering, Rourkela, 2010-2011.

T.G.Ansalam Raj, “Analysis And Optimization Of Machining Process Using Evolutionary Algorithms”, Doctoral Thesis, Cochin University Of Science And Technology, Kochi, August 2011.

Montegomery. D. C., 1991, Design and Analysis of experiments, Wiley, India.

Response Surface Methodology, Raymonds.H.Mayres & Douglas.E.Montgomery, Second Edition,John Whiely Publishers.

Authors' information

First A. K. Devaki Devi, is presently working as Assistant Professor in G Pulla Reddy Engineering College, Kurnool, Andhra Pradesh, INDIA. She completed her M. Tech in Advanced Manufacturing Systems in 2011. She is presently pursuing her doctorate in manufacturing systems.

Second A. Dr. M. Naga Phani Sastry, is presently working as Assiociate Professor in G Pulla Reddy Engineering College, Kurnool, Andhra Pradesh, INDIA. He acquired Doctorate for being worked on design optimisation of machine elements.

Third A. Dr. K. Madhava Reddy, is presently working as Professor in G Pulla Reddy Engineering College, Kurnool, Andhra Pradesh, INDIA. He acquired Doctorate for being worked on Reliability Based Robust Design of machine elements.

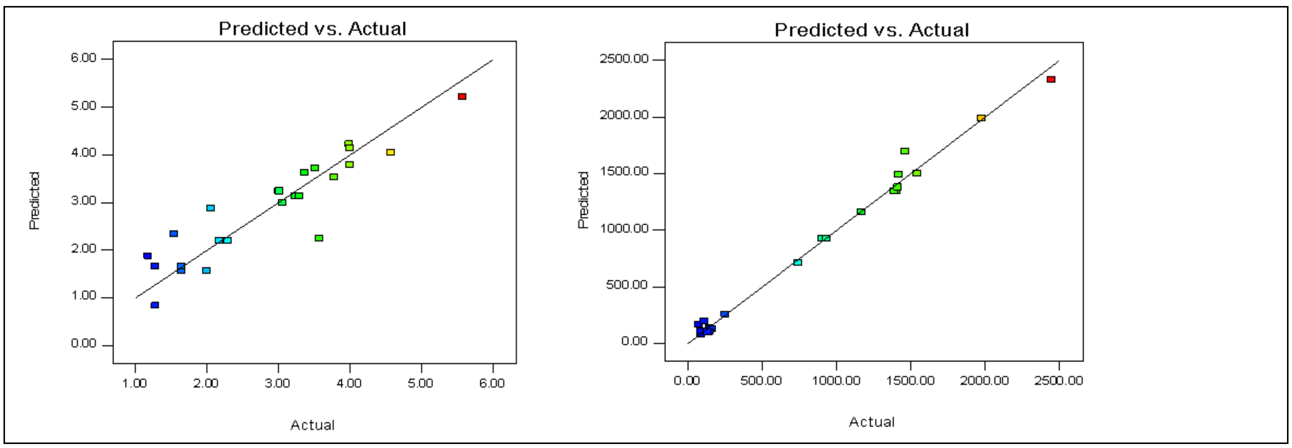
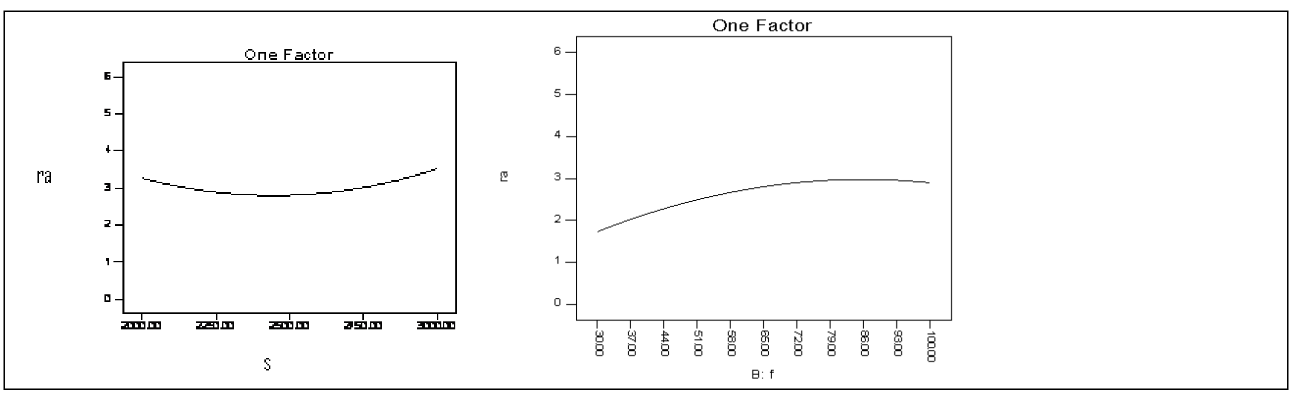


Figure1: Comparison of Predicted and actual values for Ra and MRR



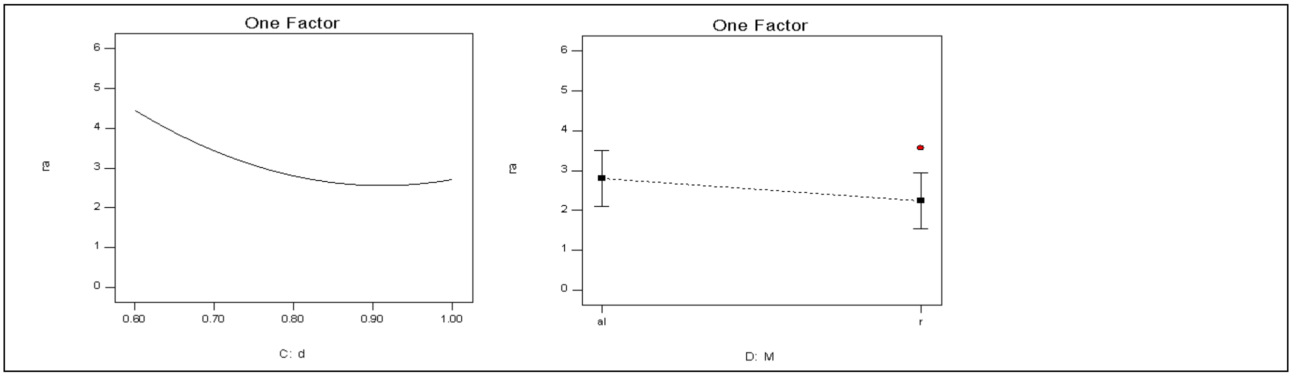


Figure2: Main Effects Plot for Surface Roughness

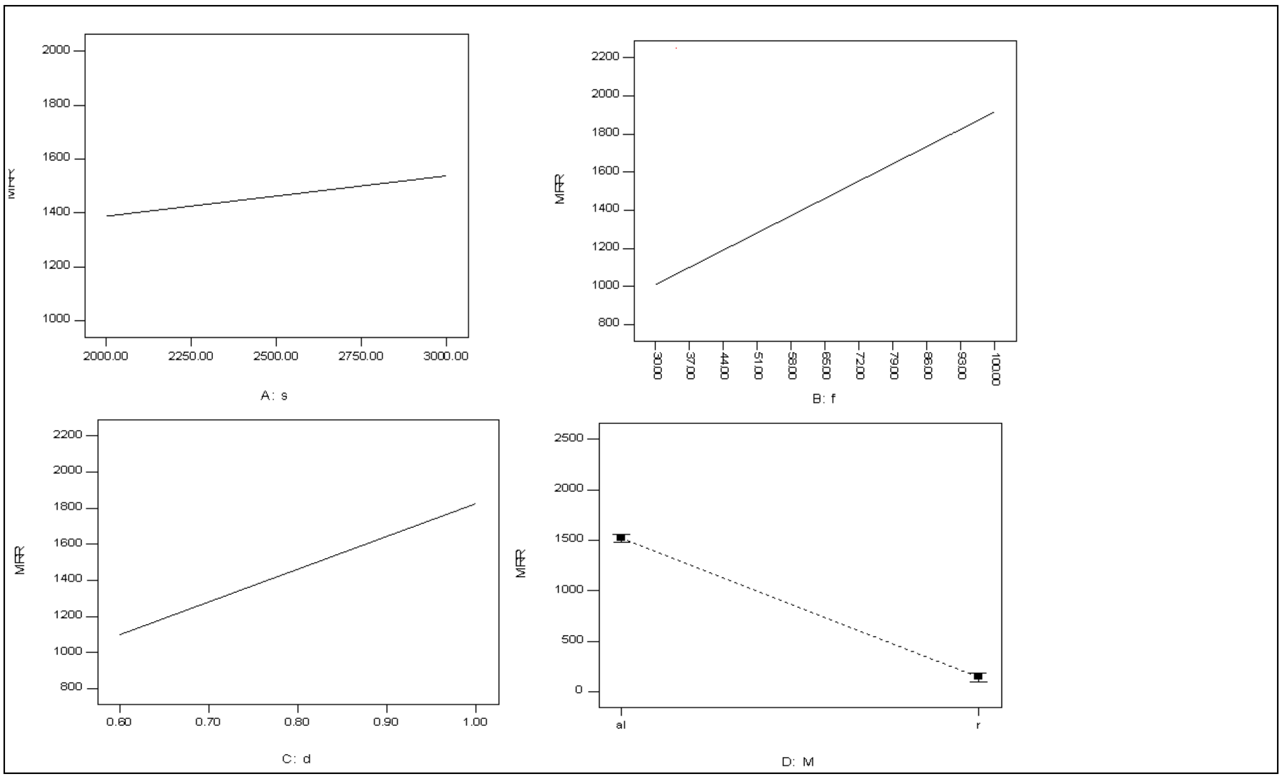


Figure 3: Main Effects Plot for Surface Roughness

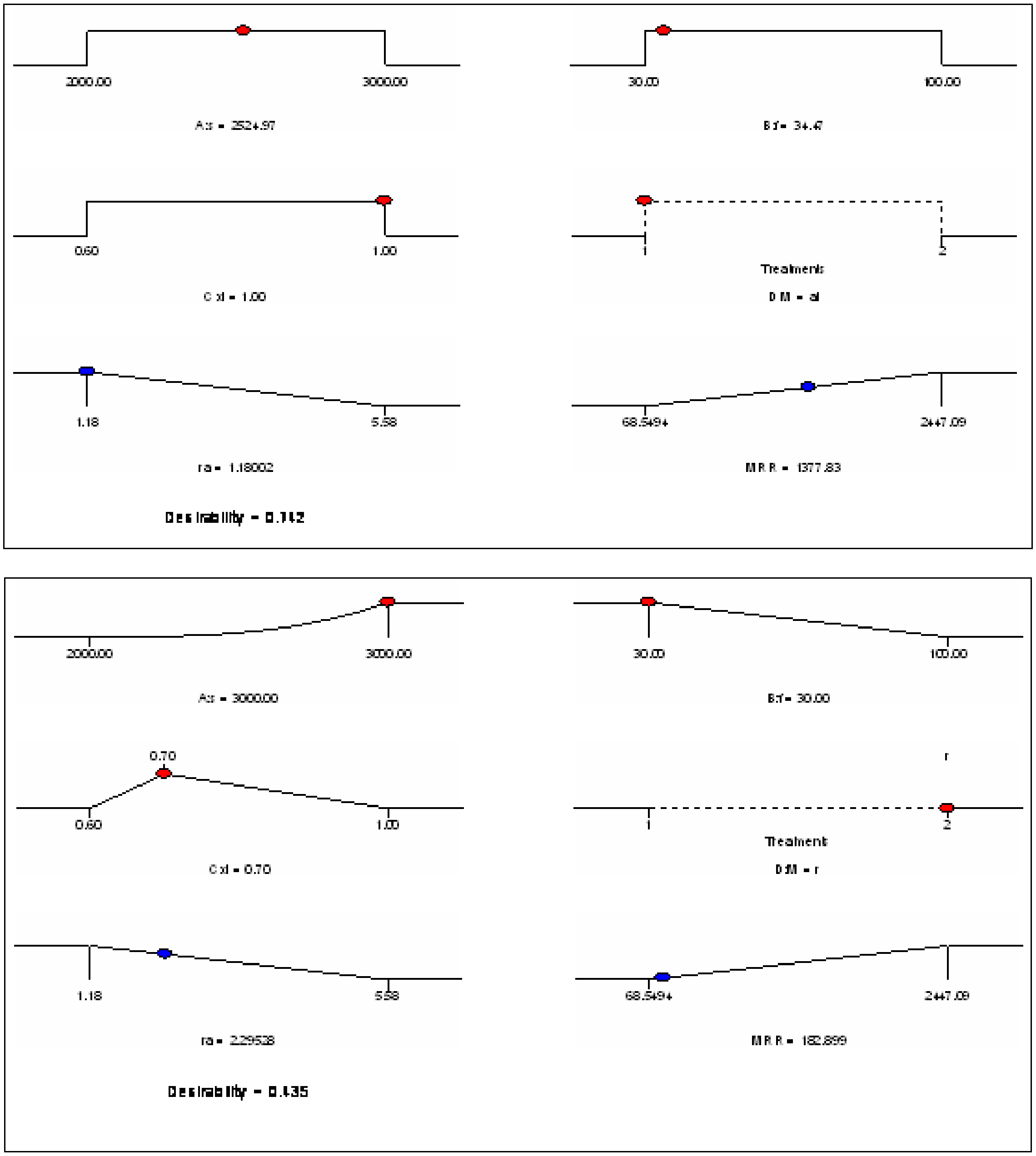


Figure 4: ramped views showing graphical representation of optimal outputs.

Table 1: Levels of independent control factors

S.No.	Input factor	symbol	Range of factors	
			min	**max**
1	Speed (rpm)	s	2000	3000
2	Feed (mm/rev)	f	30	100
3	Depth of cut(mm)	d	0.6	1
4	Material (categoric)	m	Al	r

Table 2 Experimental observations

Run	Speed A:s rpm	Feed B:f mm/rev	Depth of cut C:d mm	Material D:m	Surface roughness R_a microns	Metal Removal Rate MRR mm^3/min
1	2500	56	1	al	1.54	1461.86685
2	2000	30	1	r	1.65	161.697621
3	3000	30	0.754	r	1.18	68.549388
4	2000	30	0.801218	al	2.29	933.390204
5	2000	100	0.6	al	3.99	1413.10541
6	2500	100	0.6	al	4	1415.18061
7	3000	58	0.832706	al	3	1542.06676
8	3000	100	0.6	r	3.23	120.27972
9	2000	100	1	al	4.58	2447.08995
10	3000	59	0.6	al	5.58	1166.52812
11	3000	30	1	al	2	1406.98772
12	2500	65	0.8	r	3.57	146.046452
13	2500	100	1	r	3.51	251.230251
14	2000	100	0.846	r	3.02	106.902357
15	3000	100	0.6	r	3.3	128.292572
16	3000	100	0.805478	al	3.36	1977.93538
17	3000	58	1	r	3.06	163.977437
18	2500	30	0.6	al	4	739.018088
19	2500	30	0.932	r	1.28	83.6340723
20	3000	30	1	al	1.65	1388.62509
21	2000	30	1	r	1.28	157.171717
22	2000	30	0.801218	al	2.17	902.292769
23	2000	30	0.6	r	3.78	85.7484502
24	2500	74	0.638	r	2.06	142.347568

Table 3 ANOVA for Response Surface Quadratic Model of Ra

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	26.35247	13	2.027113465	4.072587	0.0161 significant
s	0.00343	1	0.00343414	0.006899	0.9354
f	5.193041	1	5.193041235	10.43311	0.0090
d	3.743536	1	3.743536316	7.52097	0.0207
M	1.694704	1	1.694704893	3.40475	0.0948
sf	0.000667	1	0.000667092	0.001340	0.9715
sd	0.005508	1	0.005508487	0.011066	0.9183
sm	0.187601	1	0.187601179	0.376901	0.5530
fd	5.774464	1	5.774464545	11.60123	0.0067
fm	0.009111	1	0.009111988	0.018306	0.8951
dm	1.565137	1	1.565137016	3.144450	0.1066

s^2	1.433995	1	1.433995833	2.880980	0.1205
f^2	0.781212	1	0.781212606	1.569501	0.2388
d^2	2.594529	1	2.594529007	5.212558	0.0455
Residual	4.977458	10	0.497745828		
Lack of Fit	4.838108	6	0.806351381	23.14607	0.0045 significant
Pure Error	0.13935	4	0.0348375		
Cor Total	31.32993	23			

Table 4 ANOVA for Response Surface Quadratic Model of MRR

Source	**Sum of Squares**	**df**	**Mean Square**	**F Value**	**p-value Prob > F**
Model	11930552.07	10	1193055.207	145.45352	< 0.0001 **significant**
s	24703.16835	1	24703.16835	3.0117322	0.1063
f	783857.4457	1	783857.4457	95.565423	< 0.0001
d	528267.101	1	528267.101	64.404655	< 0.0001
m	9457633.216	1	9457633.216	1153.0447	< 0.0001
sf	1479.166472	1	1479.166472	0.1803353	0.6780
sd	21309.6792	1	21309.6792	2.5980087	0.1310
sm	16016.68949	1	16016.68949	1.9527041	0.1857
fd	42662.68995	1	42662.68995	5.2013003	0.0401
fm	750567.0703	1	750567.0703	91.506765	< 0.0001
dm	380561.5434	1	380561.5434	46.396861	< 0.0001
Residual	106630.0598	13	8202.312289		
Lack of Fit	105935.5966	9	11770.62184	67.796954	0.0005 **significant**
Pure Error	694.4631606	4	173.6157902		
Cor Total	12037182.13	23			

Table 6: RSM optimization for output responses

s	**f**	**d**	**m**	**R_a model**	**R_a exp**	**% error in R_a**	**MRR model**	**MRR exp**	**% error in MRR**	**Desirability**
2524.97	34.47	1.00	al	1.18	1.2	1.69	1377.83	1371.56	0.23	0.74
3000	30	0.7	r	2.295	2.35	2.3	182.899	180.10	1.5	0.73