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OPTIMIZATION OF CUTTING FORCE, SURFACE ROUGHNESS IN MACHINING OF 2024-T351 ALUMINIUM ALLOY USING BOX–BEHNKEN DESIGN WITH RSM

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ABSTRACT

One of the significant machining operations is Metal cutting. Amongst, Turning is one of the oldest machining processes. Variation during the machining process due to cutting forces, surface roughness, changes, and other disturbances make it highly inefficient for perfection, especially in high quality machining operations where product quality specifications are very restrictive. Therefore, to assure the quality of machined products, reduce costs and increase machining efficiency, cutting parameters must be optimized to minimize various response variables such as cutting forces, surface roughness, etc. for which several optimization methodologies are being analyzed. Optimization of the parameters to provide the best solution to minimize cutting forces, surface roughness have been presented using software optimization techniques. This attempt to optimize can provide insight into the problems of controlling the finishing of machined surfaces, when the process parameters are adjusted to obtain a certain surface finish. Using the optimum combination of these parameters enables minimizing surface roughness and determining quality of machined part. Owing to the significant role that turning operations play in today's manufacturing world, there is a significant need to optimize machining parameters for this operation. Accordingly this paper describes the development of optimization models and their use of machining parameters using Response Surface Methodology (RSM). The main idea of RSM is to use a sequence of designed experiments in an optimal response.

Keywords: Response Surface Methodology, Turning, cutting forces, surface roughness.

1. INTRODUCTION

1.1 2024-T351 Aluminum alloy

The use of light weight materials are very much essential in the present day Automotive world, hence the need for study and design of machines and its parts using light weight materials such as aluminium, titanium, magnesium and their alloys have increased extensively. Aluminium alloys are widely used for demanding structural applications due to good combination of formability, corrosion resistance, weldability and mechanical properties. Hence the present work is about machining of 2024-T351 aluminium alloy at various combinations of process parameters such as speed, feed rate and depth of cut and to determine the effect these parameters on surface quality. Thus the aluminium alloy needs to undergo several machining operations. Variation during the machining process due to cutting forces, surface roughness changes and other disturbances make it highly inefficient for perfection, especially in high quality machining operations where product quality specifications are very restrictive. Therefore, to assure the quality of machining products, reduce costs and increase machining efficiency, cutting parameters must be optimized in real-time according to the actual state of the process. Parameters such as cutting speed, depth of cut and feed have influence on overall success of machining operation. The constituent elements of 2024-T351 aluminum alloy and its weight percentage is presented in below.

Table 1 The alloy composition of 2024-T351 Aluminium alloy

Component	Wt.%
Al	90.7 -94.7
Cr	Max 0.1
Cu	3.8 - 4.9
Fe	Max 0.5
Si	Max 0.5
Ti	Max 0.15
Zn	Max 0.25
Mg	1.2 - 1.8
Mn	0.3 - 0.9
Other ,each	Max 0.05
Other,total	Max 0.15

1.2 Design of experiments

2024-T351 aluminium alloy is used in this experiment. The material was obtained in the form of cylindrical work piece. The experiments were designed by following full factorial design of experiments. Design of experiments is an effective approach to optimize the parameters in various manufacturing related process, and one of the best intelligent tool for optimization and analyzing the effect of process variable over some specific variable which is an unknown function of these process variables. The selection of such points in the design space is commonly called design of experiments (DOE). In this work related to turning of 2024-T351 aluminium alloy, the experiments were conducted by considering three main influencing process parameters such as Speed, Feed rate and Depth of cut at three different levels namely Low, Medium and High. So according to the selected parameters a three level full factorial design of experiments in single block five center points in Box-Benhen were designed and conducted. The level designation of various process parameters are shown in Table 2 and the conditions at which 17 experimental runs were conducted are detailed in Table 3.

1.3 Box–Behnken design

Box–Behnken design was chosen for the experimentation in turning of 2024-T351 Aluminium Alloy because it proposed suitable quadratic model for three level designs. According to one block of five center points of Box– Behnken design (BBD) 17 runs (five center points per block) were carried out. BBDs are response surface designs, specially made to require only three levels, coded as −1, 0, and +1.This procedure creates designs with desirable statistical properties but, most importantly, with only a fraction of the experiments required for a three-level factorial. Because there are only three levels, the quadratic model is appropriate. The Box–Behnken design is an independent quadratic design in that it does not contain an embedded factorial or fractional factorial design. In this design, the treatment combinations are at the midpoints of edges of the process space and at the center. These designs are rotatable (or near rotatable) and require three levels of each factor. The designs have limited capability for orthogonal blocking compared to the central composite designs. The geometry of this design suggests a sphere within the process space such that the surface of the sphere protrudes through each face with the surface of the sphere tangential to the midpoint of each edge of the space. The 17 runs of experimental data recorded for 2024-T351 Aluminium Alloy were shown in Table 3.

Table 2 Level designation of process parameters

Parameters	**Level 1**	**Level 2**	**Level 3**
Cutting speed(m/min)	100	150	200
Feed rate(mm/rev)	0.05	0.08	0.1
Depth of cut(mm)	0.25	0.63	1

By taking the above said parameters as input parameters, the parameters evaluated are cutting forces(Fx, Fz) are measured by using Kistler dynamometer in Newton and surface roughness (Ra) is measured in surface roughness tester in micro meter.

Table 3 Experimental output for surface roughness, cutting forces at varying input parameters

Runs	Cutting speed (m/min)	Feed rate(mm/rev)	Depth of cut(mm)	Cutting forces (Fx)N	Cutting forces (Fz)N	Surface roughness(Ra)µm
1	150	0.05	1.00	22.35	21.07	1.62
2	100	0.08	1.00	13.13	23.38	1.87
3	150	0.08	0.63	17.52	15.41	1.39
4	200	0.10	0.63	19.01	12.76	2.1
5	150	0.08	0.63	13.26	14.7	1.78
6	150	0.08	0.63	15.65	17.13	1.56
7	200	0.05	0.63	13.8	20.92	1.15
8	150	0.10	0.25	12.38	15.81	2.31
9	100	0.05	0.63	20.69	18.26	1.59
10	150	0.05	0.25	14.49	24.15	1.23
11	200	0.08	0.25	18.46	29.59	1.85
12	150	0.10	1.00	10.19	14.55	1.5
13	200	0.08	1.00	12.45	26.69	1.24
14	100	0.10	0.63	1.83	9.45	1.98
15	100	0.08	0.25	7.82	25.47	1.82
16	150	0.08	0.63	14.86	15.7	1.54
17	150	0.08	0.63	16.64	18.84	1.32

2. MATHEMATICAL MODEL FOR AA2024-T351

The mathematical relationship for correlating of the responses are cutting forces, surface roughness and the considered process variables were obtained from the coefficients resulting from the Design expert software output. The regression equations are

Fx = +44.04838-0.21609* speed-698.53333 * feed+43.93000* depth of cut+4.81400 * speed * feed-0.15093* speed * depth of cut-262.66667 * feed * depth of cut →(1)

Fz = +37.57339 – 0.35224 * speed+ 798.53667* feed - 65.01444*depth of cut+ 0.13000*speed*feed- 0.010800* speed *depth of cut+48.53333* feed* depth of cut+1.27580E-003*speed^2* 6716.80000*feed^2+47.90756*depth of cut^2 →(2)

Ra = +0.25990-5.20000E-003 * speed+14.70000 * feed+3.39333 *depth of cut+0.11200* speed * feed-8.80000E-003*speed * depth of cut-32.00000 *feed*depth of cut →(3)

3. RESULTS & DISCUSSION

Table 4. ANOVA for Response Surface 2FI Model
Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	354.08	6	59.01	17.77	< 0.0001	significant
A-speed	51.26	1	51.26	15.43	0.0028	
B-feed	98.84	1	98.84	29.76	0.0003	
C-depth	2.84	1	2.84	0.86	0.3766	
AB	144.84	1	144.84	43.60	< 0.0001	
AC	32.04	1	32.04	9.64	0.0111	
BC	24.26	1	24.26	7.30	0.0222	
Residual	33.22	10	3.32			
Lack of Fit	22.42	6	3.74	1.39	0.3924	not significant
Pure Error	10.79	4	2.70			
Cor Total	387.29	16				

The Model F-value of 17.77 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, B, AB, AC, BC are significant model terms. Values greater than 0.1000 indicate the model terms are not significant.
If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model.

The "Lack of Fit F-value" of 1.39 implies the Lack of Fit is not significant relative to the pure error. There is a 39.24% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good -- we want the model to fit.

Table 5 ANOVA for Response Surface Quadratic Model
Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	461.52	9	51.28	30.65	< 0.0001	significant
A-speed	22.45	1	22.45	13.41	0.0080	
B-feed	126.64	1	126.64	75.69	<0.0001	
C-depth of cut	10.88	1	10.88	6.50	0.0381	
AB	0.11	1	0.11	0.063	0.8088	
AC	0.16	1	0.16	0.098	0.7633	
BC	0.83	1	0.83	0.49	0.5045	
A^2	42.83	1	42.83	25.60	0.0015	
B^2	74.20	1	74.20	44.35	0.0003	
C^2	191.10	1	191.10	114.21	<0.0001	
Residual	11.71	7	1.67			
Lack of Fit	0.88	3	0.29	0.11	0.9512	notsignificant
Pure Error	10.84	4	2.71			
Cor Total	473.23	16				

The Model F-value of 30.65 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, B, C, A^2, B^2, C^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant.If there are many insignificant model terms (not counting those required to supporthierarchy),model reduction may improve your model.

The "Lack of Fit F-value" of 0.11 implies the Lack of Fit is not significant relative to the pure error. There is a 95.12% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good -- we want the model to fit.

Table 6**. ANOVA for Response Surface 2FI Model**
Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	1.43	6	0.24	9.10	0.0014	significant
A-speed	0.11	1	0.11	4.03	0.0725	
B-feed	0.66	1	0.66	25.18	0.0005	
C-depth of cut	0.12	1	0.12	4.57	0.0582	
AB	0.078	1	0.078	2.98	0.1147	
AC	0.11	1	0.11	4.15	0.0691	
BC	0.36	1	0.36	13.71	0.0041	

Residual	0.26	10	0.026			
Lack of Fit	0.14	6	0.023	0.72	0.6593	notsignificant
Pure Error	0.13	4	0.032			
Cor Total	1.70	16				

The Model F-value of 9.10 implies the model is significant. There is only a 0.14% 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 B, BC are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to supporthierarchy),model reduction may improve your model.

The "Lack of Fit F-value" of 0.72 implies the Lack of Fit is not significant relative to the pure error. There is a 65.93% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good – we want the model to fit.

Table 7

Factor	**Name**	**Level**	**Low Level**	**High Level**	**Std. Dev.**	**Coding**
A	**speed**	**150.00**	**100.00**	**200.00**	**0.000**	**Actual**
B	**feed**	**0.075**	**0.050**	**0.100**	**0.000**	**Actual**
C	**depth of cut**	**0.63**	**0.25**	**1.00**	**0.000**	**Actual**

Table 8 99% of Population

Response	**Prediction**	**Std Dev**	**S E Mean**	**95% CI low**	**95% CI high**	**SE Pre**	**95% PI low**	**95% PI high**	**95% TI low**	**95% TI high**
Fx	14.3959	1.82255	0.442033	13.411	15.3808	1.87539	10.2173	18.5745	6.11592	22.6758
Fz	16.356	1.29354	0.578488	14.9881	17.723	1.417	13.0053	19.7067	9.27202	23.44
Ra	1.63824	0.162064	0.0393063	1.55066	1.72582	0.166762	1.26667	2.00981	0.901968	2.37454.

4. RESPONSE SURFACE METHODOLOGY

Use of many methods has been reported in the literature to solve optimization problems for machining parameters. These methods include various nomograms, graphical methods, performance envelope, linear programming, Lagrangian multipliers, geometric programming, dynamic programming, and artificial intelligence. In statistics, response surface methodology (RSM) explores 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 set of designed experiments to obtain an optimal response. By this technique, the cause and effect relationships between true mean responses and input control variables influencing the responses are determined and represented as a two or three dimensional hyper surface.

RSM enables to (i) determine the factorial levels that will simultaneously satisfy a set of desired specifications. (ii) Determine the optimum combination of factors that yield a desired response and describes the response near the optimum. (iii) Determine how a specific response is affected by changes in the level of factors over the specified levels of interest. In this paper, work is done to develop a mathematical model for correlating the interactive and higher order influences of various turning parameters on surface roughness at various locations during the turning phenomena using RSM.

5. ANALYSIS OF EXPERIMENTAL

Studies were carried out to analyze the effect of various process variable on cutting forces, surface roughness for a turning operation, based on the equation developed through experimental observations and response surface methodology. Figures below show the effect of cutting speed, feed rate, and depth of cut on cutting forces (Fx, Fz), surface roughness .

3D Graphs for Fx

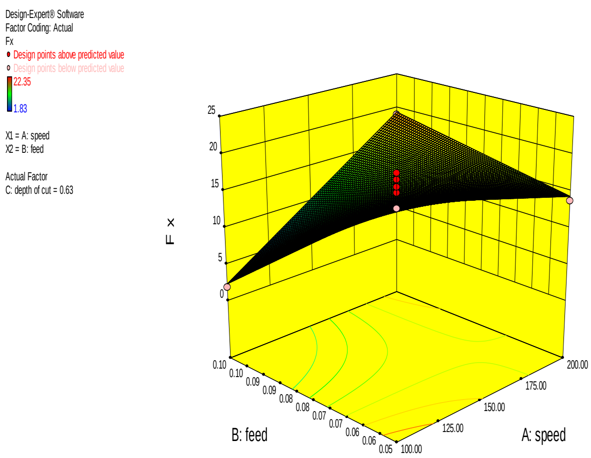

Figure 1

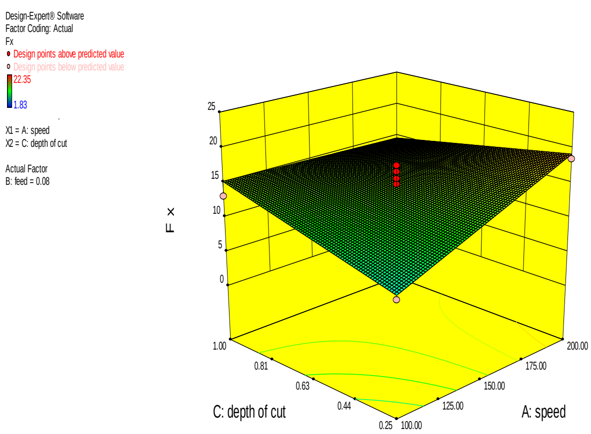

Figure 2

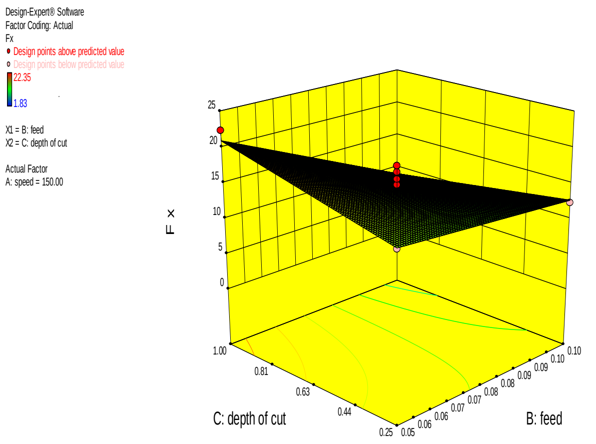

Figure 3

3D Graphs for Fz

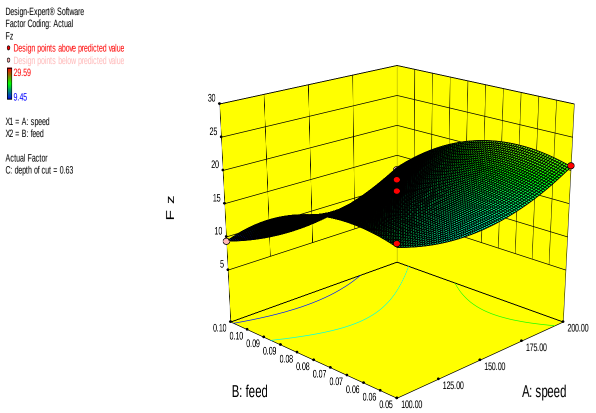

Figure 4

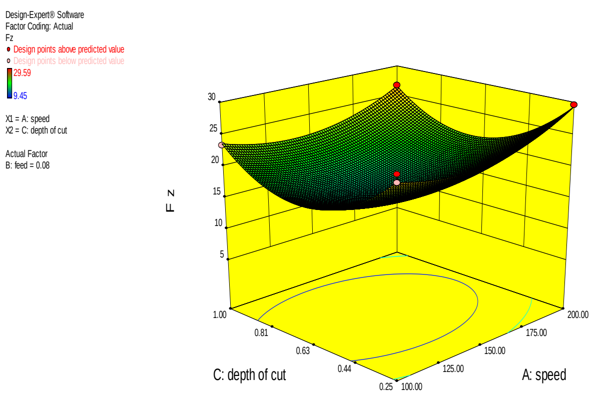

Figure 5

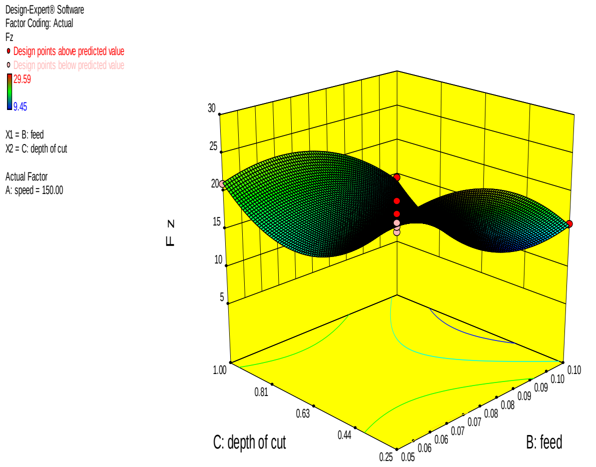

Figure 6

3D Graphs for Ra

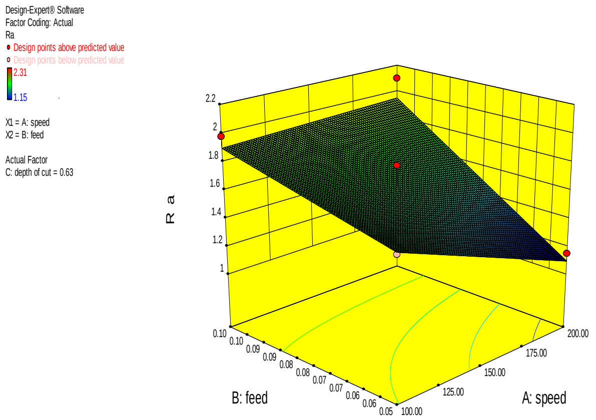

Figure 7

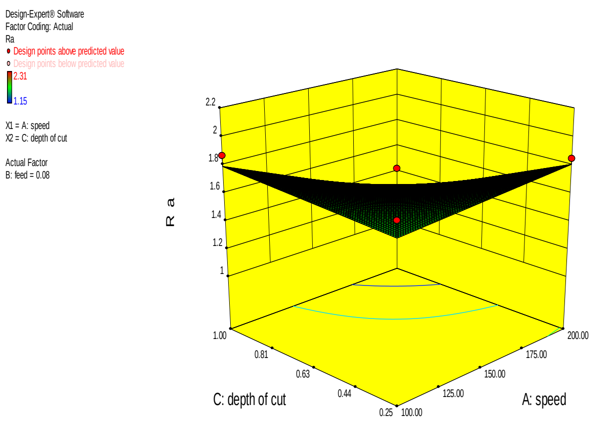

Figure 8

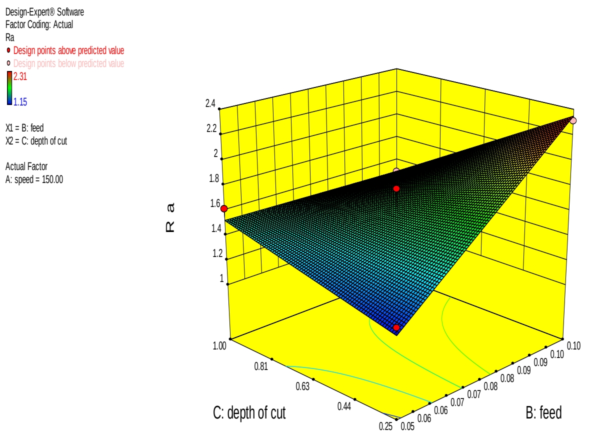

Figure 9

6. OPTIMIZATION OF PARAMETERS

This involves an optimality search model, for the various process variables conditions for maximizing the responses after designing of experiments and determination of the mathematical model with best fits. The optimization is done numerically and the desirability and response cubes are plotted. The parameters for the turning operations were determined using Response Surface Methodology and the optimum condition obtained is listed in Table 6. The optimal levels for turning of 2024-T351 aluminium alloy in center lathe to obtain minimum cutting forces, surface roughness are possible at a cutting speed of 150 m/min, depth of cut of 0.63 mm and feed rate of 0.08 mm/rev.

Table 9 optimal parameters for the turning operations

Number	Speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Desirability
1	150	0.08	0.63	1.000

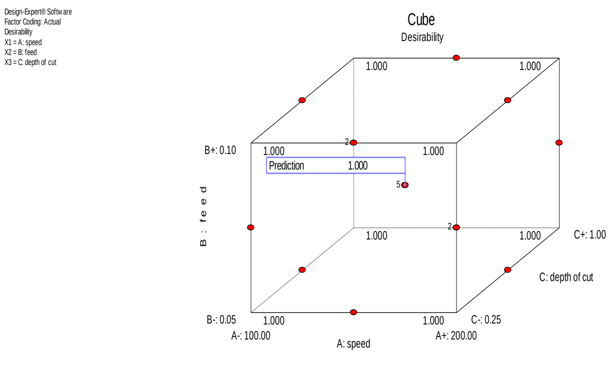

Figure 10

7. CONCLUSION

By the mathematical modeling results the obtained conclusions can be drawn as follows:

1. The mathematical models were developed based on RSM, utilizing the practical data obtained from turning experiments conducted on a center lathe turning machine.

2. 2. The optimal control variables have been found using one of the new optimization techniques namely Response surface Methodology.

3. When turning is performed at a cutting speed of 150 m/min, depth of cut of 0.63 mm and feed rate of 0.08 mm/rev predict cutting forces can be achieved.

Hence, this article represents not only the use of RSM for analyzing the cause and effect of process parameters on responses, but also on optimization of the process parameters themselves in order to realize optimal responses.

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