

Research Article

Design of Experiments for optimization of Cutting Parameters for Turning of AA7075aluminium alloy

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Abstract

The manufacturing cost can be minimized by reducing the machining cost through optimization of machining environment by optimizing the machining parameters like cutting speed, feed and depth of cut, etc. The production cost can be reduced by reducing the lead time and proper selection of machine tools, cutting tools material, tool geometry and cutting parameters. They govern the economics of machining operations. Thus, attempts have been made to carry out experimental investigation using Taguchi method and regression analysis mainly to find and correlate the technological factors to the economics of machining process. The Taguchi method is systematic application of design and analysis for experiments. It is an effective approach to produce high quality products at relatively low cost. Therefore Taguchi method is used to investigate the multiple performance characteristic in the turning operation. Regression analysis gives a quantitative measure of effect of each factor on the response, i.e. the surface roughness of the work piece. This document gives a brief introduction on design of experiments and the various types of methods used for the same. For this study, turning parameters for AA7075aluminium are taken into consideration. 27 experiments were carried out on a CNC lathe and using Taguchi's L27 array.

Keywords: Taguchi method, ANOVA, Regression analysis, factors.

Introduction

In the industry, a variety of activities, such as, developing new products, maintain, control and improve the ongoing manufacturing process; improving the existing designs, maintaining and repairing products are done.

Since experimentation is a frequent task in all these activities, the engineers end up using statistics regardless of their background in it. Therefore, the issue is not whether they use statistics or not, but how good they are at it. The aim of this paper is to stimulate the engineering community to implement efficient techniques to experimentation, the Design of Experiments, in order to tackle quality problems in key processes that they deal with every day, by doing minimum possible number of experimental trials and optimizing the processes.

We understand as Lye states, the Design of Experiments (DoE) as a methodology for systematically applying statistics to experimentation. It involves a series of tests in which purposeful changes are made to the input variables (factors) of a product or process so that one may identify their effects on the changes in the response. DoE provides a cost-effective and time-saving method to understand and optimize products and the involved processes.

In the following section, we briefly explain the importance of DoE. Moreover, we included a brief explanation of the activities needed and tools which can be used for each step.

Common DOE Terms and Concepts

The most commonly used terms in the DOE methodology include: controllable and uncontrollable input factors, responses, hypothesis testing, blocking, replication and interaction.

Controllable input factors, or x factors, are those input parameters that are in complete control of the designer and can be modified in an experiment or process.

Uncontrollable input factors are those parameters that cannot be changed or controlled by the designer. These factors need to be recognized to understand their effects on the *Responses*, or output.

The responses, are the elements of the process outcome that gauge the desired effect.

The controllable input factors can be altered so as to optimize the output. The relationship between the factors and responses is shown in Figure 1

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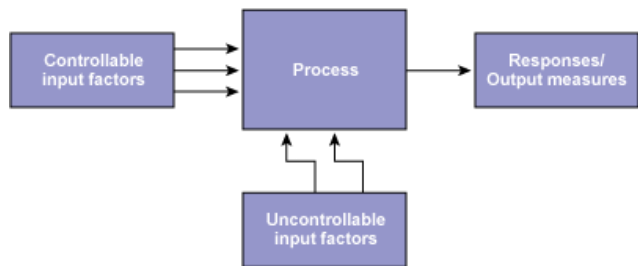


Figure 1: Process Factors and Responses

Methods of Design of Experiments

1. One Factor Designs
2. Factorial Designs
3. General Full Factorial Designs
 - Two Level Full Factorial Designs
 - Two Level Fractional Factorial Designs
 - Plackett-Burman Designs
 - Taguchi’s Orthogonal Arrays
 - Response Surface Method Designs
 - Reliability DOE
 - ANOVA Method
 - Regression Analysis

Experimental work

The aluminium alloy AA7075 finds a wide range of applications in the field of manufacturing and has very significant applications in the aerospace field.

The objective of the present investigation is to find the effect of cutting parameters on AA7075 aluminium alloy workpiece on its surface roughness (Smaller-the-better) by employing Taguchi’s orthogonal array design and Regression analysis.

This will help us identify which is the most dominating predictor, so that by controlling its value near optimum, better surface finish can be achieved. The experiments will be carried out taking AA7075 as the work piece material with carbide tool in the turning operation on CNC lathe machine

We present a case where surface roughness acts as the output parameter and the factors are speed, feed and depth of cut with each parameter having 3 levels. We have used MINITAB 17 and MS Office 2016 Excel to perform the Taguchi and Regression analysis respectively.

Observation Table

Sr. No.	Speed	Feed	Depth of Cut	Exp Ra Value
1	1000	0.2	0.5	2.438540904
2	1000	0.2	0.75	3.142944439
3	1000	0.2	0.1	4.067643457
4	1000	0.3	0.5	8.560703533
5	1000	0.3	0.75	7.234474691
6	1000	0.3	0.1	8.554097832
7	1000	0.4	0.5	11.71799225
8	1000	0.4	0.75	12.72130303
9	1000	0.4	0.1	12.63970297

10	1500	0.2	0.5	3.724905058
11	1500	0.2	0.75	3.070225462
12	1500	0.2	0.1	3.231031893
13	1500	0.3	0.5	8.679648588
14	1500	0.3	0.75	7.431278907
15	1500	0.3	0.1	8.455950526
16	1500	0.4	0.5	11.99131292
17	1500	0.4	0.75	11.99598845
18	1500	0.4	0.1	11.95708638
19	2000	0.2	0.5	3.551191785
20	2000	0.2	0.75	3.707784828
21	2000	0.2	0.1	4.017493684
22	2000	0.3	0.5	8.78025255
23	2000	0.3	0.75	8.060589926
24	2000	0.3	0.1	7.808546681
25	2000	0.4	0.5	12.20706987
26	2000	0.4	0.75	13.59852148
2	2000	0.4	0.1	11.74646989
7				

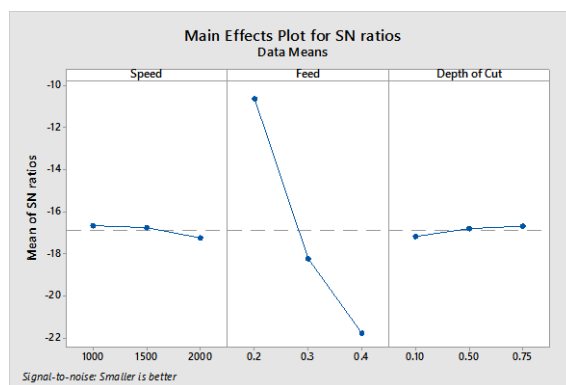
Taguchi Method

Table 1: Taguchi analysis

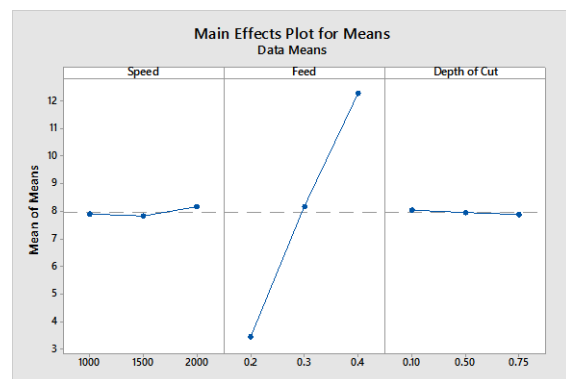
Level	Speed	Feed	Depth of cut
1	-16.65	-10.63	-17.16
2	-16.76	-18.23	-16.79
3	-17.24	-21.78	-16.68
Delta	0.58	11.15	0.48
Rank	2	1	3

Interpretation

Response Table for Signal to Noise Ratios



Graph 1



Graph 2

Regression Method

Summary Output

Table 2: Regression Analysis

Regression Statistics	
Multiple R	0.9891043
R Square	0.9783274
Adjusted R Square	0.9755005
Standard Error	0.5828153
Observations	27

ANOVA

	df	SS	MS	F	Significance F
Regression	3	352.665	117.5551	346.0828	2.852E-19
Residual	23	7.8124	0.33967		
Total	26	360.4781			

Table 3: ANOVA and Regression Coefficients

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	5.58900142	0.622737018	8.974898	5.64631E-09	6.877231	4.300772
Speed	0.000266724	0.000274742	0.970818	0.341738581	0.000302	0.000835
Feed	44.23538097	1.373708781	32.201426	1.23001E-20	41.393648	47.077114
Depth of Cut	0.25622425	0.41897725	0.611547	0.546835362	1.122945	0.610496

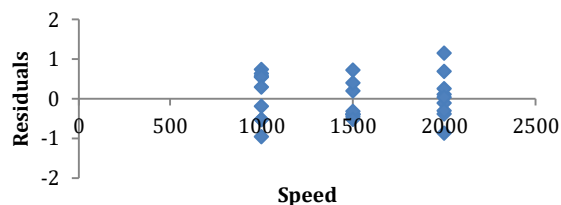
Table 4: Residual Output

Obs. No.	Predicted Experimental Ra Value	Residuals	Standard Residuals
1	3.3967	-0.9581	-1.7479
2	3.3326	-0.1897	-0.3460
3	3.4992	0.5685	1.0370
4	7.8202	0.7405	1.3508
5	7.7562	-0.5217	-0.9517
6	7.9227	0.6314	1.1518
7	12.2438	-0.5258	-0.9592
8	12.1797	0.5416	0.9880
9	12.3463	0.2935	0.5353
10	3.5300	0.1949	0.3555
11	3.4660	-0.3958	-0.7220
12	3.6325	-0.4015	-0.7325
13	7.9536	0.7261	1.3245
14	7.8895	-0.4583	-0.8360
15	8.0561	0.3999	0.7295
16	12.3771	-0.3858	-0.7038
17	12.3131	-0.3171	-0.5784
18	12.4796	-0.5225	-0.9532
19	3.6634	-0.1122	-0.2047
20	3.5994	0.1084	0.1978
21	3.7659	0.2516	0.4590
22	8.0869	0.6933	1.2648
23	8.0229	0.0377	0.0688
24	8.1894	-0.3809	-0.6949
25	12.5105	-0.3034	-0.5535
26	12.4464	1.1521	2.1017
27	12.6130	-0.8665	-1.5808

Table 5: Probability Output

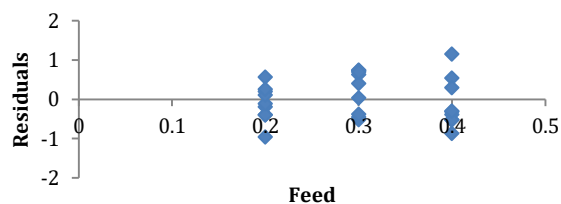
Percentile	Experimental Ra Value
1.851851852	2.438540904
5.555555556	3.070225462
9.259259259	3.142944439
12.96296296	3.231031893
16.66666667	3.551191785
20.37037037	3.707784828
24.07407407	3.724905058
27.77777778	4.017493684
31.48148148	4.067643457
35.18518519	7.234474691
38.88888889	7.431278907
42.59259259	7.808546681
46.2962963	8.060589926
50	8.455950526
53.7037037	8.554097832
57.40740741	8.560703533
61.11111111	8.679648588
64.81481481	8.78025255
68.51851852	11.71799225
72.22222222	11.74646989
75.92592593	11.95708638
79.62962963	11.99131292
83.33333333	11.99598845
87.03703704	12.20706987
90.74074074	12.63970297
94.44444444	12.72130303
98.14814815	13.59852148

Speed Residual Plot



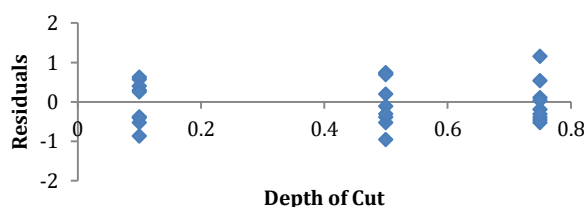
Graph 3

Feed Residual Plot

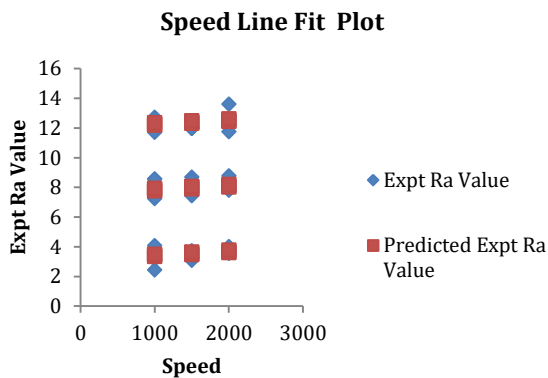


Graph 4

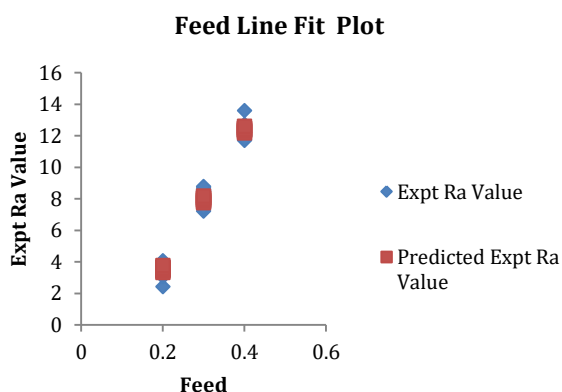
Depth of Cut Residual Plot



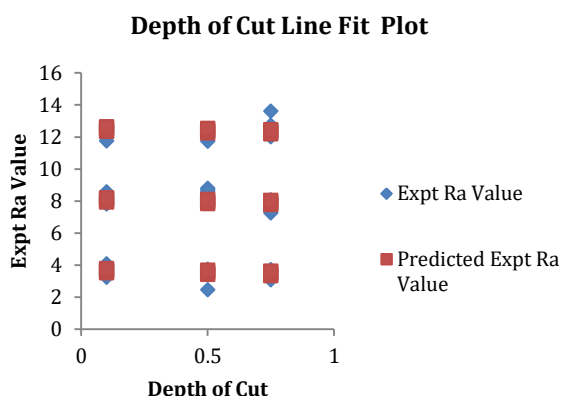
Graph 5



Graph 6



Graph 7



Graph 8

Graphs 1 and 2 are obtained from MINITAB 17. Graphs 3-8 are obtained from MS Office 2016 Excel. The interpretations of the graphs are discussed in the subsequent sections.

Results and discussion

1. Taguchi Outputs:

- From the Table 1, it is clear that the parameter 'feed' is ranked 1, followed by 'speed' and then 'depth of cut'.

- From graph 1 and 2, it is clear, that level 2 of speed, level 1 of feed and level 3 of depth of cut are found to be attributing minimum value of surface roughness, which is the optimum condition for this experiment.
- Hence optimum levels of parameters are, 1500 rpm speed, 0.2 mm/s feed and 0.75 mm depth of cut.

2. Regression analysis outputs

- The 'Proportion of variance' ie. R square as found in table 2, has value 0.9783274, which is very close to 1.0.
- This shows, the function very closely predicts the observed data.
- The "F value" statistics test the overall significance of the regression model. From table 3, its value is 346.0828, which is quite a large number, proving the data and its analysis is well co-related.
- Extremely low P-values in table 3, prove the same.
- From table 3, the regression equation is found as,

$$\begin{aligned}
 \text{Surface Roughness} &= (-5.58900142) + (0.000266724) \times (\text{Speed}) + (44.23538097) \times (\text{Feed}) \\
 &+ (-0.25622425) \times (\text{Depth of cut})
 \end{aligned}$$

- From the regression equation too, it is evident that the Feed is the most dominating parameter. This result matches with the result from Taguchi analysis.
- The graph 3,4 and 5 signify that the residuals are very close to 0 and hence the errors between regression estimated value and actual experimental values are very negligible.
- From figures 6, 7 and 8, it is evident that for almost all the values of all three parameter, the predicted Ra values are fitting very closely with the experimentally obtained values.
- Thus from both the analyses, it can be concluded that the Feed is the most dominant parameter and its value needs to be kept low to get lower values of surface roughness.
- Both the methods were found to be very effective for the data analysis.

Conclusion

- Trial and error has been avoided using TAGUCHI'S technique of design of experiments, utilizing orthogonal arrays the number of tests involved generally i.e., by trial and error has been reduced considerably. Individual effect of each parameter is calculated.
- It is clearly found that the feed has maximum impact on the surface roughness (as seen from Table. 1), and hence just by changing feed value, lower surface finish can be obtained.
- Quantization of effect of each predictor on the response.
- From regression analysis, the coefficients of each parameter are obtained. The regression equation makes it clear, that 1 unit increase in speed will

cause surface roughness increase by 0.000266724, 1 unit of increase in feed causes very significant increment in surface roughness by 44.2358097, and 1 unit of increase in depth of cut, reduces surface roughness by 0.25622425. It makes it clear yet again, that feed is the most dominant factor.

- Optimization of Turning parameters
The optimized values of turning parameters to obtain minimum surface roughness have been obtained. They are as follows;
Speed = 1500 rpm
Feed = 0.2 mm/sec
Depth of cut = 0.75 mm

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