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Experimental Investigation And Optimization Of Machining Parameters For Surface Roughness In CNC Turning By Taguchi Method

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Abstract

Medium Carbon Steel AISI 1045 has a wide variety of applications in vehicle component parts & machine building industry. Surface roughness is the main quality function in high speed turning of medium carbon steel in dry conditions. In this study, the effect and optimization of machining parameters (cutting speed, feed rate and depth of cut) on surface roughness is investigated. An L'27 orthogonal array, analysis of variance (ANOVA) and the signal-to-noise (S/N) ratio are used in this study. Three levels of machining parameters are used and experiments are done on STALLION-100 HS CNC lathe. The optimum value of the surface roughness (Ra) comes out to be 0.89. It is also concluded that feed rate is the most significant factor affecting surface roughness followed by depth of cut. Cutting speed is the least significant factor affecting surface roughness. Optimum results are finally verified with the help of confirmation experiments.

Keywords: ANOVA, CNC Turning, Optimization, Surface Roughness, Taguchi Method.

1. Introduction

Quality plays a major role in today's manufacturing market. From Customer's viewpoint quality is very important because the quality of product affects the degree of satisfaction of the consumer during usage of the product. It also improves the goodwill of the company. High speed turning is a machining operation which is done on cnc lathe. The quality of the surface plays a very important role in the performance of dry turning because a good quality turned surface surely improves fatigue strength, corrosion resistance and creep life. Surface roughness also affects on some functional attributes of parts, such as, contact causing surface friction, wearing, light reflection, ability of distributing and also holding a lubricant, load bearing capacity, coating and resisting fatigue. As we know in actual machining, there are many factors which affect the surface roughness i.e. cutting conditions, tool variables and work piece variables. Cutting conditions include speed, feed and depth of cut and also tool variables include tool material, nose radius, rake angle, cutting edge geometry, tool vibration, tool overhang, tool point angle etc. and work piece variable include hardness of material and mechanical properties. It is very difficult to take all the parameters that control the surface roughness for a particular manufacturing process. In a turning operation, it is very difficult to select the cutting parameters to achieve the high surface finish. This study would help the operator to select the cutting parameters.

The work material used for the present study is AISI 1045 medium carbon steel of composition { Carbon (0.43-0.50)%, Silicon (0.2-0.3)%, Magnesium (0.60-0.90)%, Phosphorus (0.05)% Sulphur (0.05)% }. Its tensile strength is (620- 850) Mpa. This Carbon steel is suitable for shafts and machinery parts. It is mostly used in Automobile parts, in gears and machine building industry.

This paper is about experimentally investigating and optimizing the machining parameters for surface roughness in cnc turning by taguchi method. Taguchi's orthogonal arrays are highly fractional designs, used to estimate main effects using few experimental runs only. These designs are not only applicable for two level factorial experiments, but also can investigate main effects when factors have more than two levels. Designs are also available to investigate main effects for some mixed level experiments where the factors included do not have the same number of levels. For example, a four-level full factorial design with five factors requires 1024 runs while the Taguchi orthogonal array reduces the required number of runs to 16 only.
David et al. (2006) described an approach for predicting Surface roughness in a high speed end-milling process and used artificial neural networks (ANN) and statistical tools to develop different surface roughness predictors.

Srikanth and Kamala (2008) proposed a real coded genetic algorithm (RCGA) for finding optimum cutting parameters and explained various issues of RCGA and its advantages over the existing approach of binary coded genetic algorithm (BCGA).

According to Roy, R. K. (2001)., the very intention of Taguchi Parameter Design is for maximizing the performance of a naturally variable production process by modifying the controlled factors.

Experiments were designed using Taguchi method so that effect of all the parameters could be studied with minimum possible number of experiments. Using Taguchi method, Appropriate Orthogonal Array [7, 8] has been chosen and experiments have been performed as per the set of experiments designed in the orthogonal array. Signal to Noise ratios are also calculated for analyzing the effect of parameters more accurately. Results of the experimentation were analyzed analytically and also graphically using ANOVA. ANOVA used to determine the percentage contribution of all factors upon each response individually.

2. Taguchi method

Traditional experimental design methods are very complicated and difficult to use. Additionally, these methods require a large number of experiments when the number of process parameters increases [16, 17, 18]. In order to minimize the number of tests required, Taguchi experimental design method, a powerful tool for designing high-quality system, was developed by Taguchi. This method uses a design of orthogonal arrays to study the entire parameter space with small number of experiments only. Taguchi recommends analyzing the mean response for each run in the inner array, and he also suggests to analyze variation using an appropriately chosen signal-to-noise ratio (S/N). There are 3 Signal-to-Noise ratios of common interest for optimization of static problems:

(I) SMALLER-THE-BETTER:

$$\frac{S}{N} = -10\log\left(\frac{\sum Yi^2}{n}\right)$$

(II) LARGER-THE-BETTER:

$$\frac{S}{N} = -10\log\left(\sum \frac{1}{yi^2}\right)/n)$$

(III) NOMINAL-THE-BEST:

$$\frac{S}{N} = 10\log\left(\frac{y^2}{s^2}\right)$$

Here Yi is the ith observed value of the response, n is the no. of observations in a trial, y is the average of observed values (responses) and s is the variance. Regardless of category of the performance characteristics, the higher S/N ratio corresponds to a better performance. Therefore, the optimal level of the process parameters is the level with the highest S/N value. The statistical analysis of the data is performed by analysis of variance (ANOVA) [9, 10] to study the contribution of the factor and interactions and to explore the effects of each process on the observed value.

3. Design of experiment

In this study, three machining parameters were selected as control factors, and each parameter was designed to have three levels, denoted 1, 2, and 3 (Table 1). The experimental design was according to an L'27 array based on Taguchi method, while using the Taguchi orthogonal array would markedly reduce the number of experiments. A set of experiments designed using the Taguchi method was conducted to investigate the relation between the process parameters and response factor. Minitab 16 software is used to optimization and graphical analysis of obtained data

Table 1 Turning parameters and levels

Symbol	Turning parameters	Level 1	Level 2	Level 3
V	**Cutting speed(m/min)**	175	220	264
F	**Feed rate(rev/min)**	0.1	0.2	0.3
D	**Depth of cut(mm)**	0.5	1.0	1.5

4. Experimental details

Medium Carbon Steel (AISI 1045) of Ø: 28 mm, length: 17 mm were used for the turning experiments in the present study. The chemical composition, mechanical and physical properties of AISI 1045 can be seen in Tables 2 and 3, respectively. The turning tests were carried out to determine the surface roughness under various turning parameters. STALLION-100 HS CNC lathe used for experimental investigations.

Table 2 Chemical composition of Medium Carbon Steel (AISI 1045)

Element	Percentage
Carbon	(0.43-0.50)%
Silicon	(0.2-0.3)%
Magnesium	(0.60-0.90)%
Phosphorus	(0.05)% max.
Sulphur	(0.05)% max.

Table 3 Mechanical and Physical properties of Medium Carbon Steel (AISI 1045)

Property	Value
Yield strength (Mpa)	(300-450)
Tensile strength (Mpa)	640
Hardness (HB)	170-210
Density(g/cm³)	7.85
Poisson's Ratio	0.27-0.30
Elongation	14% min.
Modulus of elasticity (Mpa)	205

5. Results and discussion

5.1 Experiment results and Taguchi analysis

In high speed turning operation, surface roughness is an important criterion. The purpose of the analysis of variance (ANOVA) is to investigate which design parameter significantly affects the surface roughness. Based on the ANOVA, the relative importance of the machining parameters with respect to surface roughness was investigated to determine the optimum combination of the machining parameters.

A series of turning tests are conducted to assess the effect of turning parameters on surface roughness in turning of AISI 1045. Experimental results of the surface roughness for turning of AISI 1045 with different turning parameters are shown in Table 4. Table 4 also gives S/N ratio for surface roughness. The S/N ratio for each experiment of L'27 was calculated using smaller the better approach. The objective of using the S/N ratio as a performance measurement is developing products and process insensitive to noise factor.

Table 4 EXPERIMENTAL RESULT AND CORRESPONDING S/N RATIO

Ex. No.	CS (m/min)	F (mm/ rev)	D (mm)	SR, Ra(µm)	S/N Ratio
1	175	0.1	0.5	1.46	-3.28
2	175	0.1	1.0	1.24	-1.86
3	175	0.1	1.5	1.25	-1.93
4	175	0.2	0.5	1.88	-5.48
5	175	0.2	1.0	2.20	-6.84
6	175	0.2	1.5	1.91	-5.62
7	175	0.3	0.5	3.35	-10.50
8	175	0.3	1.0	3.48	-10.83
9	175	0.3	1.5	3.15	-9.96
10	220	0.1	0.5	1.17	-1.36
11	220	0.1	1.0	1.09	-0.74
12	220	0.1	1.5	0.88	1.11
13	220	0.2	0.5	1.93	-5.71
14	220	0.2	1.0	1.83	-5.24
15	220	0.2	1.5	1.76	-4.91
16	220	0.3	0.5	3.14	-9.93
17	220	0.3	1.0	3.00	-9.54
18	220	0.3	1.5	3.01	-9.57
19	264	0.1	0.5	1.23	-1.79
20	264	0.1	1.0	1.02	-0.17
21	264	0.1	1.5	0.95	0.44
22	264	0.2	0.5	1.80	-5.10
23	264	0.2	1.0	1.74	-4.81
24	264	0.2	1.5	1.63	-4.24
25	264	0.3	0.5	3.00	-9.54
26	264	0.3	1.0	2.95	-9.39
27	264	0.3	1.5	2.71	-8.65

Table 5 ANOVA Table for Surface roughness

Variable Factors	DF	SS	MS	F	P	Contribution
CS	2	0.496	0.248	28.83	0.000	2.71 **
F	2	17.426	8.713	1011.42	0.000	95.23 ***
D	2	0.177	0.088	10.28	0.006	0.96*
CS * F	4	0.048	0.012	1.41	0.313	0.26
CS * D	4	0.036	0.009	1.05	0.440	0.19
F * D	4	0.043	0.010	1.26	0.360	0.23
E	8	0.068	0.008			0.37
T	26	18.297				

Where
CS-Cutting Speed,
F-Feed Rate,
D-Depth Of Cut,
SR-Surface Roughness,
E-Error,
T-Total,
DF-Degree of Freedom,
SS-Sum of Squares,
MS-Mean of Squares,
F-a statistical parameter,
P-Percentage

Here *** & ** represents most significant and significant parameters and * as less significant.

S/N Ratio of Surface Roughness is calculated by :

$$\frac{S}{N} = -10\log\left(\frac{(\Sigma Yi^2)}{n}\right)$$

Here yi is the ith observed value of the response , n is the no. of observations in a trial.

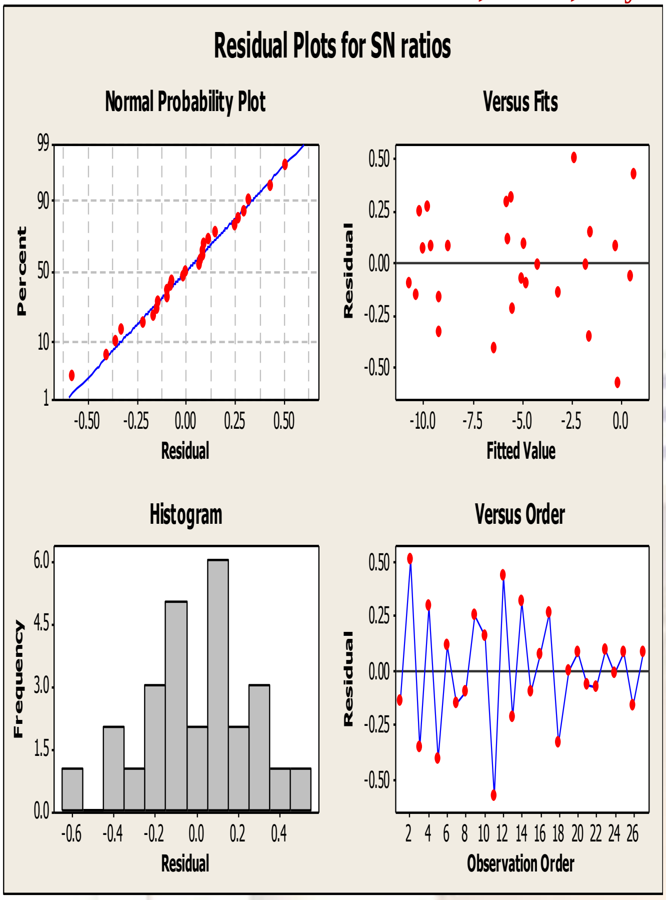

Fig 1: Residual analysis of Surface Roughness of first degree polynomial equation

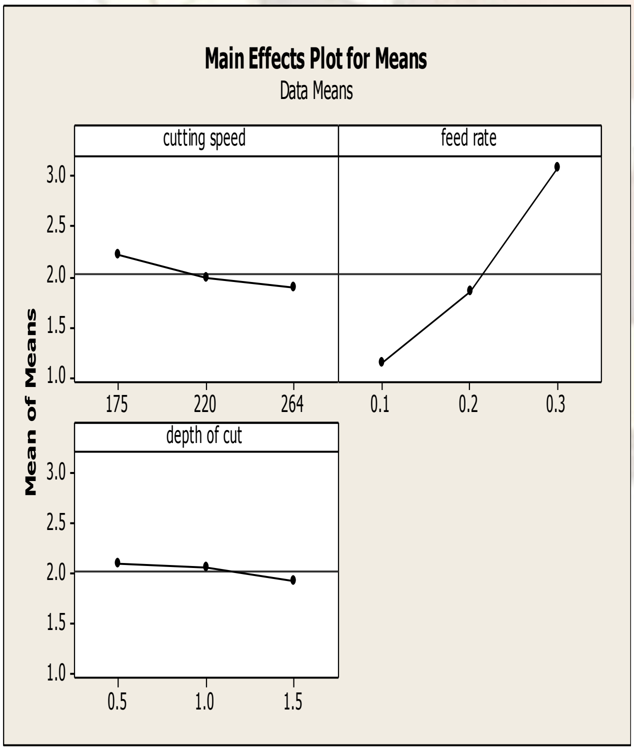

Fig 2: Effect of turning parameters on Material removal rate

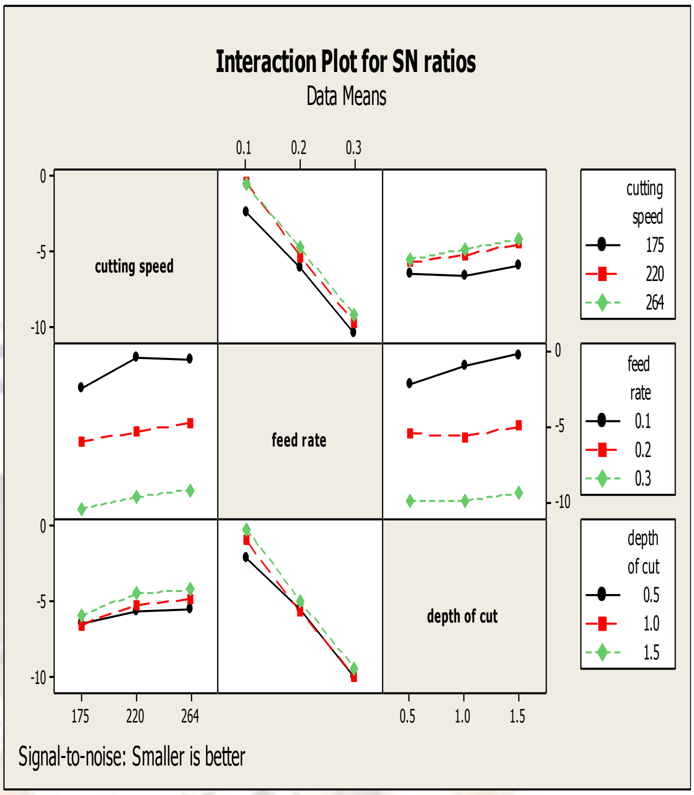

Fig 3: Interaction Plot for S/N Ratios of Surface Roughness

From the ANOVA table it is clear that maximum contribution factor is feed rate having percentage contribution up to 95.23%. After that second main contribution is of cutting speed. Hence the individual ranking of these three parameters on the average value of means of Surface roughness:-

Table 6 Mean values of process parameters for material removal rate

Level	Cutting speed (CS)	Feed rate (F)	Depth of cut (D)
1	2.213	**1.143**	2.107
2	1.979	1.853	2.061
3	**1.892**	3.088	**1.917**
Rank	2	1	3

5.2 Predictive Equation and Verification

The predicted value of Surface roughness at the optimum levels [13, 14] is calculated by using the relation given as:

$$\check{n} = nm + \sum_{i=1}^{o}(nim - nm)$$

Where ň is the predicted value of the surface roughness after optimization, nm is the total mean value of surface roughness for every parameter, nim is the mean surface roughness at optimum level of each parameter and o is the number of main machining parameters that affects the response parameter.

By applying this relation, the predicted value of surface roughness at optimum conditions is obtained:-

ň Ra = **2.028 + [(1.892-2.028) + (1.143-2.028) + (1.917-2.028)]**

ň Ra = **0.89 µm**

The effectiveness of this parameter optimization is verified experimentally. This requires the confirmation run at the predicted optimum conditions. The experiment is conducted at the predicted optimum conditions and the average of the response is comes out to be 0.93 µm. The error in the predicted and experimental value is only 4.4%, so good agreement between the experimental and predicted value of response is obtained. Because the percentage error is less than 5%, it confirms that the results have excellent reproducibility. The results show that using the optimal parameter setting (V3F1D3) the lower surface roughness is achieved. Table 7 shown below shows that optimal values of surface roughness lie between the optimal range.

Table 7 Optimal values of machining and response parameters

CP	OV	OL	POV	EOV	OR
CS	264	V3-F1-D3	0.89	0.93	0.89 < Ra > 0.93
F	0.1				
D	1.5				

Where,
CP-Cutting Parameters
OV-Optimal Values of Parameters
OL-Optimum Levels of Parameters
POV-Predicted Optimum value
EOV-Experimental Optimum Value
OR-Optimum Range of Surface Roughness

5.3 Results

The effect of three machining parameters i.e. Cutting speed, feed rate and depth of cut and their interactions are evaluated using ANOVA and with the help of MINITAB 16 statistical software. The purpose of the ANOVA in this study is to identify the important turning parameters in prediction of Surface roughness. Some important results comes from ANOVA and plots are given below:

5.3.1 Surface Roughness

It has been found that feed rate is the most significant factor for surface roughness and its contribution is 95.23% . The best results for Surface roughness would be achieved when AISI 1045 medium carbon steel work piece is machined at cutting speed of 264 m/min, depth of cut of 1.5 mm, feed rate of 0.1 mm/rev. With 95% confidence interval, feed rate affects the surface roughness most significantly.

6. Conclusion

The current study was done to study the effect of machining parameters on the surface roughness. The following conclusions are drawn from the study:

1. The Surface roughness is mainly affected by feed rate and cutting speed. With the increase in feed rate the surface roughness also increases & as the cutting speed decreases the surface roughness increases.
2. From ANOVA analysis, parameters making significant effect on surface roughness are feed rate and cutting speed.
3. The parameters taken in the experiments are optimized to obtain the minimum surface roughness possible. The optimum setting of cutting parameters for high quality turned parts is as :-
   - i) Cutting speed i.e. 264 m/min.
   - ii) Feed rate i.e. 0.1 mm/rev.
   - iii) Depth of cut should be 1.5 mm.

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