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The Optimal Selection of Cutting Parameters in Turning Operation

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Abstract

This paper has focused on the optimization of the cutting parameters for turning operation based on the Taguchi method. Four cutting parameters, namely, cutting speed, feed, depth of cut and nose radius are optimized with consideration of the surface roughness. The design and analysis of experiments are conducted to study the performance characteristic. The effects of these parameters on the surface roughness have been investigated using the signal-to-noise (S/N) ratio, analysis of variance (ANOVA). The experiments have been performed using coated tungsten carbide inserts without any cutting fluid. Experimental results illustrate the effectiveness of this approach.

Key Words: Optimization, Taguchi Method, Cutting Parameter, Surface Roughness, Design of Experiment, Signal-to-Noise Ratio, Analysis of Variance.

1. Introduction

Turning is a machining process for the generation of external surfaces of revolution by the relative motion between a cutting tool and a workpiece. An important characteristic in determining the quality of parts produced by turning process is the surface roughness of the parts, because it has very significant impact on wear, friction, lubrication, and the ability to hold coating.

A large number of theoretical and experimental studies on the surface roughness of machined parts have been reported.[1,2,3] These studies have shown that the cutting conditions significantly influence the roughness of machined parts.

In order to achieve an economic objective of the cutting process, optimal cutting conditions have to be determined. Although one can generally determine the desirable cutting conditions based on experience or handbook data, it does not ensure that the data obtained will be optimal or near optimal for that particular machining operation. In the past, several optimization methods for turning operations have been proposed.[4,5,] To determine the optimal cutting parameters, in most of these researches, the mathematical models based on a large amount of machining data have to be formulated to associate the cutting parameters with machining performance. Optimization algorithms are then applied to the models for solving the optimal cutting parameters. However, the experiments were conducted by changing a single cutting parameter while the others needed to be fixed. It resulted in increasing the numbers of the experiments and the optimal combination of the variable cutting parameters cannot be usually obtained. It has been shown by this study that the Taguchi method to parameter design can greatly simplify the optimization analysis procedure for the selection of the optimal cutting parameters in tuning operations.

2. The Taguchi Method to Parameter Design

In the Taguchi method, the objective of the parameter design is to find the settings of a product or the process design parameters that minimize the average quadratic loss, that is, the average squared deviation of the response from its target value.[6,7]

A loss function is defined to calculate the deviation between the experimental and desired values. The loss function can be written as the following quadratic form.

$$L(y) = k(y - T)^2 \qquad (1)$$

where $L(y)$ is a loss function. k, y and T are cost coefficient, value of performance characteristic and target value, respectively. The value of the loss function is further transformed into a signal-to-noise (S/N) ratio. While there are many different types of the S/N ratio, three of them are considered as a standard and are generally applicable when the performance characteristic can be classified as the

Table 1. Levels of independent variables

Levels	Low	Center	High
Coding	1	2	3
Feed f (mm/rev)	0.1	0.2	0.4
Speed V (m/min)	72	120	200
Nose radius r_ε (mm)	0.4	0.8	1.2
Depth of cut a_p (mm)	0.5	1	2

lower-the-better, the higher-the-better, and the nominal-the-better in the analysis of the S/N ratio.

To obtain the optimal machining performance, the lower-the-better performance characteristic for surface roughness should be taken. The S/N ratio can be written as:

$$S/N = -10 \log \left[\frac{1}{n} \sum_{i=1}^{n} y_i^2 \right] \qquad (2)$$

The S/N ratio for each level of process parameters is computed based on the S/N analysis. Furthermore, a statistical analysis of variance (ANOVA) is conducted to identify which process parameters are statistically significant in the surface roughness. With the S/N and ANOVA, the optimal combination of the process parameters can be predicted.

3. Experimental Design

3.1 Experiment procedure

In order to achieve the objectives of the investigation, an experiment was designed to collect surface roughness data. The cutting experiments were conducted on a NC lathe, using coated tungsten carbide inserts (CNMG). The workpiece material was SM45C, 48 mm in diameter and 250 mm in length. The cutting experiments were performed without cutting fluids. The cutting parameters were tabulated in Table 1. Three levels were selected for each of these parameters.

3.2 Surface roughness measurements

The machined surface roughness was measured using the surface measuring instrument (SURFTEST SV • 600, Mitutoyo). The arithmetic average values, R_a, were obtained from random locations on the circumference of each sample. The values measured from the machined surface are listed in Table 2.

3.3 Orthogonal array experiment

The orthogonal array is a method of set-up experiments that only requires a fraction of the full factorial combinations. An important characteristic of the design is that it will require a small number of experiments without losing the reliability of experiment results.[8]

Table 2 illustrates the standard form of an orthogonal array that describes the level setting for each of the four factors that is to be used for the 27 trial runs. The 27 combinations were randomized for removing the experimental bias, and the experimental replications were conducted in order to increase the reliability of the experimental results. In this paper, the effect of interactions between factors has also been taken into account. The symbols in this table, such as A, B, C, and D, are used to depict the control factors, while A×B and A×C depict the interaction between the control factors. The symbol e indicates errors.

4. Determination of Optimal Cutting Parameters

4.1 Signal-to-noise (S/N) ratio

As mentioned earlier, there are three types of performance characteristic. Regardless of the types of characteristic, the larger the S/N ratio, the better. The larger S/N ratio corresponds to the better performance characteristic. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio.

Table 3 shows the signal-to-noise ratio response by Eq. (2), in which the S/N ratio for control factors under the each of three levels are listed. The interaction matrices are developed for factors A×B and A×C as shown in Table 4 and 5, respectively. The S/N response graphs can also be plotted in conjunction with the S/N response table in Figure 1 and the interaction graph between control factors is shown in Figure 2.

Figure 1 reveals that factors A and C are more significant than factors B and D. The A_1 (low) level appears to be the best choice for factor A since it corresponds to the highest average S/N ratio. Similarly, the S/N analysis for factor B suggests that B_3 (high) level is recommended level. In Figure 2, the interaction of all three lines at several locations reveals some strong interaction effects between the two factors. From the graph, in fact, there is an optimal combination of two factors in which the best performance characteristic can be obtained. Since the further study of the interaction A×B suggests that A_1B_3 can be the preferred combination from the interaction matrix and graph. The result is as same as that based on individual effect.

For factor C, the S/N analysis reveals that C_2 is close to C_3. However, from the interaction

Table 2. Experiment design for an $L_{27}(3^{13})$ orthogonal array

Symbol		A	B	A × B	A × B	C	A × C	A × C	e	D	e	e	e	e	Response (μm)		S/N (db)
Factor		f	V			r_ε				a_p							
level	1	0.1	72			0.4				0.5							
	2	0.2	120			0.8				1							
	3	0.4	200			1.2				2							
No.	run order	1	2	3	4	5	6	7	8	9	10	11	12	13	1	2	
1	17	1	1	1	1	1	1	1	1	1	1	1	1	1	2.01	2.02	-6.09
2	19	1	1	1	1	2	2	2	2	2	2	2	2	2	1.53	1.45	-3.47
3	24	1	1	1	1	3	3	3	3	3	3	3	3	3	0.98	1.07	-0.22
4	23	1	2	2	2	1	1	1	2	2	2	3	3	3	1.08	1.02	-0.43
5	2	1	2	2	2	2	2	2	3	3	3	1	1	1	1.77	1.79	-5.01
6	27	1	2	2	2	3	3	3	1	1	1	2	2	2	2.99	2.85	-9.31
7	18	1	3	3	3	1	1	1	3	3	3	2	2	2	1.16	1.22	-1.51
8	8	1	3	3	3	2	2	2	1	1	1	3	3	3	0.59	0.60	4.51
9	7	1	3	3	3	3	3	3	2	2	2	1	1	1	0.67	0.70	3.28
10	1	2	1	2	3	1	2	3	1	2	3	1	2	3	3.04	3.06	-9.69
11	20	2	1	2	3	2	3	1	2	3	1	2	3	1	1.86	1.85	-5.37
12	22	2	1	2	3	3	1	2	3	1	2	3	1	2	4.46	4.58	-13.10
13	13	2	2	3	1	1	2	3	2	3	1	3	1	2	3.57	3.43	-10.88
14	5	2	2	3	1	2	3	1	3	1	2	1	2	3	1.78	1.71	-4.84
15	6	2	2	3	1	3	1	2	1	2	3	2	3	1	2.00	1.74	-5.46
16	25	2	3	1	2	1	2	3	3	1	2	2	3	1	2.98	2.99	-9.50
17	12	2	3	1	2	2	3	1	1	2	3	3	1	2	1.85	1.84	-5.32
18	14	2	3	1	2	3	1	2	2	3	1	1	2	3	1.31	1.26	-2.18
19	4	3	1	3	2	1	3	2	1	3	2	1	3	2	18.23	18.75	-25.34
20	3	3	1	3	2	2	1	3	2	1	3	2	1	3	7.45	6.18	-16.71
21	26	3	1	3	2	3	2	1	3	2	1	3	2	1	4.78	4.56	-13.38
22	15	3	2	1	3	1	3	2	2	1	3	3	2	1	13.98	13.74	-22.84
23	16	3	2	1	3	2	1	3	3	2	1	1	3	2	6.57	6.37	-16.22
24	11	3	2	1	3	3	2	1	1	3	2	2	1	3	4.23	4.27	-12.57
25	21	3	3	2	1	1	3	2	3	2	1	2	1	3	16.02	16.97	-24.35
26	9	3	3	2	1	2	1	3	1	3	2	3	2	1	6.80	6.98	-16.73
27	10	3	3	2	1	3	2	1	2	1	3	1	3	2	4.13	4.14	-12.33
															T=-245.05		

matrix and graph, the interaction exists between factors A and C, and the interaction affects the performance characteristic. Therefore, further analysis of the interaction indicates A_1C_2 as the preferred combination since it corresponds to the highest average S/N ratio.

Finally, factor D appears to have little significance with respect to the S/N ratio. The D_2 (medium) level is recommended level. In summary, from the S/N response table, S/N response graphs, and the interaction graph, the recommended levels are:

A_1, B_3, C_2, D_2

As a result, based on the S/N analysis, the optimal cutting parameters are the feed rate at level 1, the cutting speed at level 3, nose radius at level 2, and the depth of cut at level 2.

4.2 Analysis of variance

Analysis of variance (ANOVA) is used to find each control factor's contribution to the response. ANOVA uses a mathematical technique known as the sum of squares to quantitatively examine the deviation of the control factor effect response average from the overall experimental mean response. This is referred to a variation between the control factors. The significance of the individual control factors is quantified by comparing the variances between the control factor effects against the variance in the experimental data due to random experimental error and the effects of unrepresented interactions.

Table 4. A×B Interaction Matrix

	B1	B2	B3
A1	-3.26	-4.92	2.09
A2	-9.39	-7.06	-5.67
A3	-18.5	-17.2	-17.8

Table 5. A×C Interaction Matrix

	C1	C2	C3
A1	-2.68	-1.32	-2.08
A2	-10	-5.17	-6.91
A3	-24.2	-16.6	-12.8

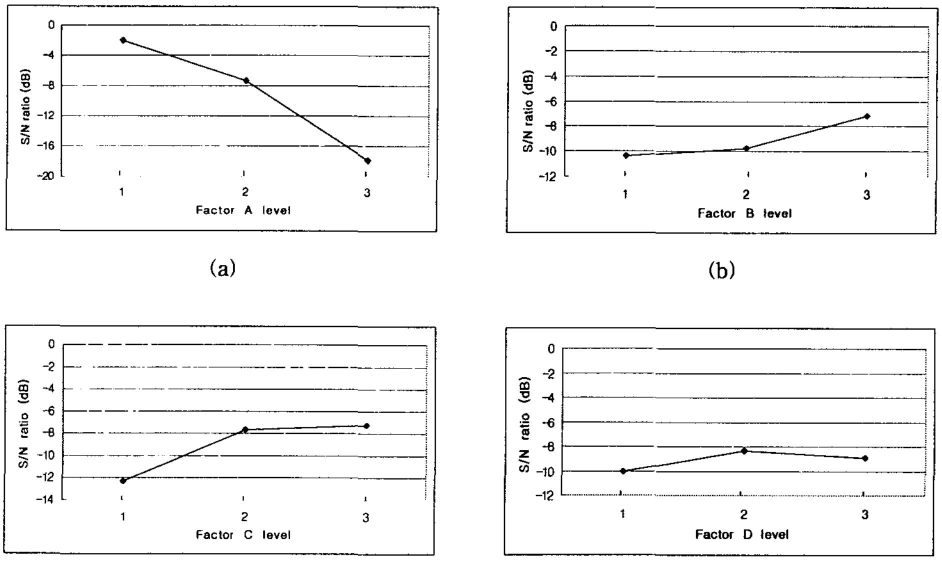
Table 6 shows the results of ANOVA. It can be found that the feed rate and nose radius are dominant cutting parameters associated with the surface roughness. This is expected because it is well known that the theoretical surface roughness is primarily a function of the feed for a given nose radius and varies as the square of the feed.[1] In addition, Table 6 shows that the main effect of cutting speed and the interaction between feed and nose radius are moderate. The change of the depth of cut in the range given by Table 1 shows an insignificant effect on the defined performance characteristic.

4.3 Verification tests

An important step in an experiment is the

Table 3. Signal-to-noise ratio response

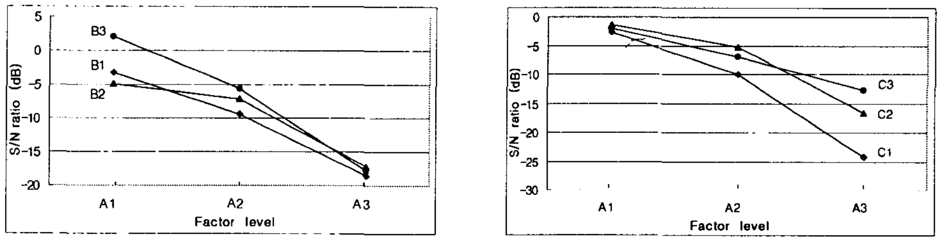
	1	2	3	4	5	6	7	8	9	10	11	12	13
Symbol	A	B	A×B	A×B	C	A×C	A×C	e	D	e	e	e	e
Level 1	-2.03	-10.4	-8.71	-9.37	-12.3	-8.71	-6.87	-9.55	-10	-9.25	-8.71	-10.1	-9.01
Level 2	-7.37	-9.73	-10.7	-9.68	-7.68	-8.04	-10.8	-7.88	-8.34	-9.19	-9.80	-9.33	-10.8
Level 3	-17.8	-7.13	-7.81	-8.17	-7.25	-10.5	-9.55	-9.79	-8.87	-8.79	-8.71	-7.82	-7.39
Max-Min	15.8	3.25	2.89	1.52	5.04	2.44	3.93	1.92	1.69	0.47	1.09	2.26	3.45



(a) (b)

(c) (d)

Fig. 1 Signal-to-noise ratio response graphs



(a) (b)

Fig. 2 Interaction graphs for (a) A×B (b) A×C

verification of the results. Verification tests are used to check the results of the parameter optimization experiment and demonstrate the optimum performance. In order to verify the results, a predicted S/N ratio based on the optimum configuration, usually, is compared with an actual ratio and the consistence of two results will be verified. The general form of the predictive equation can be written as follows:

$$\hat{y} = \bar{y} + \sum_{j=1}^{m} (\bar{y}_j - \bar{y}) \tag{3}$$

where $\bar{y}$ is the overall experimental average S/N ratio for the orthogonal array, $\bar{y}_j$ is the average S/N ratio for optimum factors, and m is the number of the factors and the interactions that significantly affect the performance characteristic. The predicted value obtained from equation (3) is 4.52 and the actual value is 4.73,

Table 6. Analysis of variance

Source	Sum of Squares	DOF	Mean Square	F_0	F(0.05)
A	1163.12	2	581.56	55.19	4.1
B	53.21	2	26.61	2.53	4.1
C	140.4	2	70.2	6.66	4.1
D	13.35	2	6.68	0.63	4.1
A×B	50.9	4	12.73	1.21	3.48
A×C	101.27	4	25.32	2.4	3.48
e	105.36	10	10.54		
T	1627.63	26			

which is close to each other. The recommended settings can be implemented.

5. Conclusions

In this study the optimization of cutting parameters for turning operation based on Taguchi method has been proposed. The effects of the cutting parameters on the surface roughness were also investigated by using the analysis of variance. It shows that the effect of feed and nose radius on the surface roughness was very significant and the interaction of the two factors was also found to be statistically significant. It has been found that the Taguchi method to parameter design provides a simple, systematic, and efficient methodology for the optimization of the cutting parameters. As a result, from the practical viewpoint, the parameter design of the Taguchi method seems to be the most suitable approach to determine the optimal cutting parameters for turning operations.

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