CASE 25

Development of Machining Technology for High-Performance Steel by Transformability

Abstract: In this research we focused on developing cutting technology for difficult-to-cut material. It is an urgent necessity to develop energy-efficient production engineering as well as fuel-efficient automobiles to conserve our energy resources. Among various technical items, improvement in surface roughness and tool life in a gear-cutting process using high-strength steel, which is quite difficult to cut, has been suggested. Instead of cutting the gear itself, test pieces were designed in such a way that the concept of transformability could be applied to develop machining technology.

1. Introduction

Because component parts used for power train or steering systems require high strength and durability, we have secured such requirements by cutting and carburizating low-carbon steel, which is easy to cut. However, since carburization takes approximately 10 hours and lowers productivity, currently, high-frequency heating is used to reduce process time drastically, to 1 minute. Yet high-frequency heating material shows 30 on the Rockwell C scale and is difficult to cut, whereas carburization material is quite easy to cut, with almost zero on the same scale. In this research we focused on developing cutting technology for difficult-to-cut material.

2. Shape to Be Machined

When we develop cutting technology, by paying too much attention to an actual product shape, we tend to digress from our original technological purpose. To avoid this situation and develop accurate and stable machining technology, a development method using the idea of transformability is extremely effective.

Applying the idea of transformability to our research, we pursued cutting conditions with the proportionality

$$y = \beta M \tag{1}$$

where M is a signal factor of input data from a numerically controlled (NC) machine and y is the output of a product dimension corresponding to the input.

As a product shape to be machined, we used an easy-to-measure shape without sticking with a product shape to be manufactured, because our objective was technological development. In addition, to pursue cutting technology robust to the control shaft direction of a cutting machine and to simplify an experimental process by using analogous solid geometry, we selected the model detailed in Figure 1, which depicts the measured points a_1 to a_4, b_1 to b_4, and c_1 to c_4. The signal factors are defined as follows:

Signal factor:

$M_1 \quad M_2 \quad \cdots \quad M_{12} \quad \cdots \quad M_{66}$

Linear distance:

$a_1 - a_2 \quad a_1 - a_3 \quad \cdots \quad a_2 - a_3 \quad \cdots \quad c_3 - c_4$

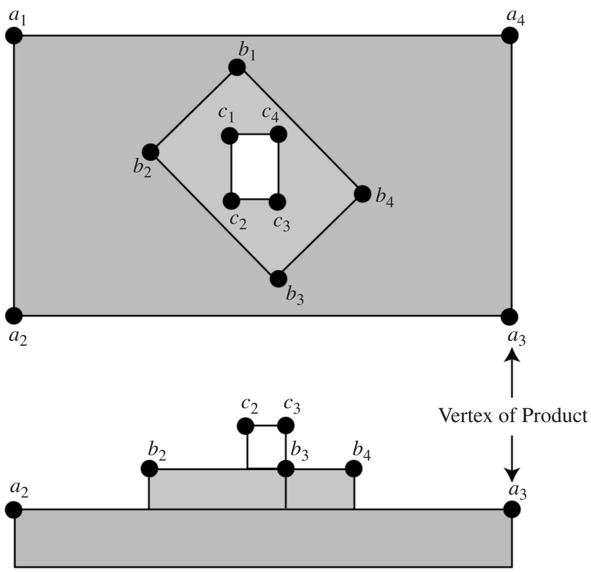

Figure 1
Test piece shape and measured points

A signal factor can be calculated from a coordinate of each vertex of the model shown in Figure 1. This is defined as a linear distance between all possible combinations of two vertices. Now since we have 12 vertices, the number of signal factor levels amounts to 66. By measuring a coordinate (X, Y, Z) of each vertex with a coordinate measuring machine, we computed a linear distance as output.

From our technical knowledge, we chose as control factors, eight factors that affect machining accuracy and tool life. For a noise factor, we picked material hardness and set up maximum and minimum values that were assumed to happen in the actual manufacturing processes. Table 1 summarizes the control and noise factors and levels selected.

3. Assignment of Factors and Levels to Orthogonal Array and Data Analysis

As illustrated in Table 2, each control factor was allocated to an L_{18} orthogonal array, and signal and noise factors were assigned to an outer array. Based on this, we conducted 18 experiments. Finally, we obtained the results shown in Table 3. Using them, we implemented data analysis as follows.

Total variation:

$$S_T = 70.992^2 + 84.607^2 + \cdots + 10.955^2 = 150{,}021.740385 \qquad (f = 132) \tag{2}$$

Linear equations:

$$L_1 = (71.000)(70.992) + (84.599)(84.607) + \cdots + (11.000)(10.958) = 125{,}043.939335 \tag{3}$$

$$L_2 = (71.000)(70.991) + (84.599)(84.607) + \cdots + (11.000)(10.955) = 125{,}040.360611 \tag{4}$$

Effective divider:

$$r = (2)(71.000^2 + 84.599^2 + \cdots + 11.000^2) = 250{,}146.969846 \tag{5}$$

Variation of proportional term:

Table 1
Factors and levels

Factor	Level 1	2	3
Control factors			
A: cutting direction	Up	Down	—
B: cutting speed (m/min)	Slow	Standard	Fast
C: feeding speed (m/min)	Slow	Standard	Fast
D: tool material	Soft	Standard	Hard
E: tool rigidity	Low	Standard	High
F: twisting angle (deg)	Small	Standard	Large
G: rake angle (deg)	Small	Standard	Large
H: depth of cut (mm)	Small	Standard	Large
Noise factor			
N: material hardness	Soft	Hard	—

Table 2
Layout of control factors and results of analysis (dB)

No.	Factor *A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	SN Ratio	Sensitivity
1	1	1	1	1	1	1	1	1	31.41	−0.0022
2	1	1	2	2	2	2	2	2	39.70	0.0058
3	1	1	3	3	3	3	3	3	39.68	0.0028
4	1	2	1	1	2	2	3	3	9.25	0.0730
5	1	2	2	2	3	3	1	1	44.56	−0.0001
6	1	2	3	3	1	1	2	2	42.02	0.0020
7	1	3	1	2	1	3	2	3	33.75	0.0057
8	1	3	2	3	2	1	3	1	44.59	0.0003
9	1	3	3	1	3	2	1	2	19.18	0.0114
10	2	1	1	3	3	2	2	1	42.80	0.0011
11	2	1	2	1	1	3	3	2	30.55	0.0145
12	2	1	3	2	2	1	1	3	26.41	0.0166
13	2	2	1	2	3	1	3	2	25.86	0.0148
14	2	2	2	3	1	2	1	3	35.24	0.0056
15	2	2	3	1	2	3	2	1	42.52	0.0022
16	2	3	1	3	2	3	1	2	41.01	−0.0009
17	2	3	2	1	3	1	2	3	2.63	0.1801
18	2	3	3	2	1	2	3	1	39.30	0.0025

Table 3
Results of experiment 1 (mm)

Noise Factor	Signal Factor M_1 a_1–a_2 71.00	M_2 a_1–a_3 84.599	···	M_{66} c_3–c_4 11.000
N_1	70.992	84.607	···	10.958
N_2	70.991	84.607	···	10.955
Total	141.983	169.214	···	21.913

$$S_\beta = \frac{1}{250{,}146.969846}(125{,}043.939335 - 125{,}040.360611)^2$$
$$= 250{,}021.645747 \qquad (f = 1) \tag{6}$$

Variation due to proportional terms:

$$S_{N\beta} = \frac{1}{250{,}146.969846}(125{,}043.939335 - 125{,}040.360611)^2$$
$$= 0.000051 \qquad (f = 1) \tag{7}$$

Error variation:

$$S_e = 250{,}021.740385 - 250{,}021.645747 - 0.000051$$
$$= 0.094587 \qquad (f = 130) \tag{8}$$

Error variance:

$$V_e = \frac{0.094587}{130} = 0.005944$$
$$= 0.000728 \tag{9}$$

Total error variance:

$$V_N = \frac{0.094587 + 0.000051}{131}$$
$$= 0.000722 \tag{10}$$

Now V_N is smaller than V_e, so we calculated the SN ratio using the equation below:

SN ratio:

$$\eta = 10 \log \frac{1}{250{,}146.969846}\left(\frac{250{,}021.645747 - 0.000728}{0.000728}\right)$$
$$= 31.41 \text{ dB} \tag{11}$$

Sensitivity:

$$S = 10 \log \frac{250{,}021.645747 - 0.000728}{250{,}146.969846}$$
$$= -0.0022 \text{ dB} \tag{12}$$

We summarized these results in Table 2. Additionally, using these results, we created Table 4 as a level-by-level supplement table regarding the SN ratio and sensitivity. Further, we plotted the factor effects in Figure 2.

4. Estimation of Optimal Configuration and Prediction of Effects

Selecting levels for a higher SN ratio, we obtained the following optimal configuration: $A_1B_1C_3D_3E_1F_3G_2H_1$. To estimate the SN ratio of the optimal configuration using factors B, D, F, and H, which have large differences from the average grand total of SN ratios, we calculated its process average as

$$\eta = B_1 + D_3 + F_3 + H_1 - 3T$$
$$= 35.09 + 40.89 + 38.68 + 40.86 - (3)(32.80)$$
$$= 57.24 \text{ dB} \tag{13}$$

On the other hand, the estimation of the process average of the initial configuration $A_1B_2C_2D_2E_2F_2G_2H_2$ was as follows:

$$\eta = B_2 + D_2 + F_2 + H_2 - 3T$$
$$= 33.24 + 34.93 + 30.91 + 33.05 - (3)(32.80)$$
$$= 33.73 \text{ dB} \tag{14}$$

Comparing the two SN ratios, we noticed that we could obtain a gain of more than 23 dB from the initial configuration and reduce the variance to 1/220.

Table 4
Supplementary table of the SN ratio and sensitivity (dB)

	SN Ratio			Sensitivity		
Control Factor	**1**	**2**	**3**	**1**	**2**	**3**
A: cutting direction	33.79	31.81	—	0.0110	0.0263	—
B: cutting speed	35.09	33.24	30.08	0.0065	0.0162	0.0332
C: feeding speed	30.68	32.88	34.85	0.0153	0.0344	0.0063
D: tool material	22.59	34.93	40.89	0.0465	0.0076	0.0018
E: tool rigidity	35.38	33.91	29.12	0.0047	0.0162	0.0350
F: twisting angle	29.82	30.91	38.68	0.0353	0.0166	0.0040
G: rake angle	32.97	33.90	31.54	0.0051	0.0328	0.0180
H: depth of cut	40.86	33.05	24.49	0.006	0.0079	0.0473
Average		32.80			0.0186	

Next, using factors *B*, *D*, *E*, *F*, and *H*, which have large differences from the average grand total of sensitivity, we estimated the sensitivity at the optimal configuration as

$$\begin{aligned} S &= B_1 + D_3 + E_1 + F_3 + H_1 - 4T \\ &= 0.0065 + 0.0018 + 0.0047 + 0.0040 + 0.0006 \\ &\quad - (4)(0.0186) \\ &= -0.0568 \text{ dB} \end{aligned} \tag{15}$$

Using the definition $S = 10 \log \beta^2$, we can compute the coefficient of proportionality: $\beta = 0.9935$. For the initial configuration, we estimated the following sensitivity:

$$\begin{aligned} S &= B_2 + D_2 + E_2 + F_2 + H_2 - 4T \\ &= 0.0162 + 0.0076 + 0.0162 + 0.0166 + 0.0079 \\ &\quad - (4)(0.0186) \\ &= -0.0099 \text{ dB} \end{aligned} \tag{16}$$

This value can be converted into $\beta = 0.9989$.

5. Confirmatory Experiment

We performed confirmatory experiments for both the optimal and initial configurations. Measured data and calculation procedures are tabulated in Table 5. We expressed sensitivity by the value of β. Consequently, we confirmed a dramatic improvement in machining accuracy, almost 20 dB, and at the same time verified that the gains and absolute values have high reproducibility. This 20 dB indicates that the standard deviation of accuracy decreases to $\frac{1}{10}$.

On the other hand, the sensitivity for the optimal configuration in the confirmatory experiment turns out to be $\beta = 0.9939$. Therefore, using the following equation, we can compute an NC input data, *M*, when actual products are produced:

$$M = \frac{y}{\beta} = \frac{y}{0.9939} = 1.0061y$$

where y is defined as product size.

6. Research Process

This example began with the following requests from a manager and engineer in charge of developing cutting technology: to coach them on the Taguchi method in developing cutting technology for high-strength steel; and to focus on two evaluation characteristics, surface roughness of a gear after it is machined and tool life.

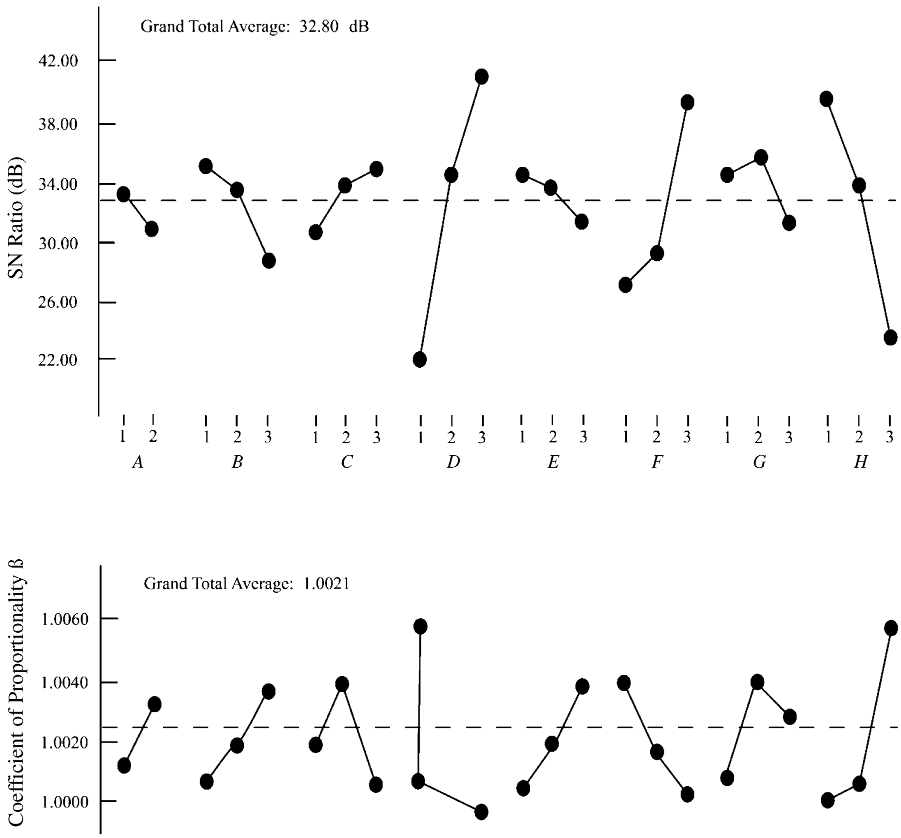

Figure 2
Response graphs of the SN ratio and coefficient of proportionality β

Table 5
Results of estimation and confirmatory experiment (dB)

	SN Ratio		Sensitivity	
Configuration	**Estimation**	**Confirmation**	**Estimation**	**Confirmation**
Optimal	57.24	54.09	0.9935	0.9939
Current	33.73	34.71	0.9989	0.9992
Gain	23.51	19.38	—	

Although their main goal was technological development, they were particularly interested in the gear as a product. Therefore, the original evaluation characteristics were quality characteristics (objective characteristics) of surface roughness and tool life through actual machining of the product.

Since it seemed that this plan would not be successful, I asked them various questions about previous technical trials. They confessed that they had not made any significant achievement in over one year of development before consulting with me. In addition, I answered their questions about why their efforts to date had failed, as follows: Their original evaluation characteristics, surface roughness and tool life, were related not to features to measure cutting functions but to superficial phenomena. Furtherm, even if material characteristic or material hardness were changed, development of a technology for smoothly cutting material would enable us to smooth surface roughness by improving surface evenness and prolonging tool life.

Although the engineer suggested measuring the machining and consumption powers, I recommended applying the idea of transformability instead because we wondered how we could measure them. Afterward, when they started to make a new experimental plan, they asked me to identify the key point in applying transformability. I suggested the following key points:

- The shape to be machined should be easy to measure.
- The shape to be machined can be assigned many signal factors with a wide range of levels.
- We should implement technological development using a test piece in place of a real product.
- The shape of the test price should have a geometry similar to that of the product so that it can also be analyzed.
- After completing generic technological development, we should apply the technology to a gear.

The underlying idea is that once we are able to cut a line smoothly, we will be able to cut a surface. In other words, we cannot cut a surface without being able to cut a line. As a result, we devised the model shape shown in Figure 3.

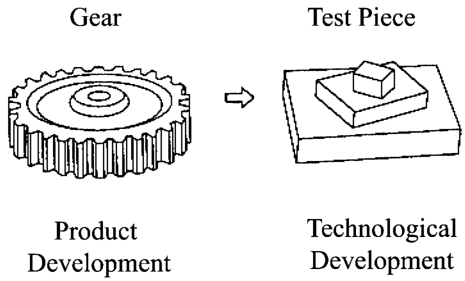

Figure 3
Final product and test piece

Since the original plan focused mainly on a gear, the idea was to cut a gear directly in the actual production process and to use quality characteristics such as surface roughness and tool longevity as evaluation characteristics. Indeed, this type of procedure could be used to improve quality to some extent if we take steady steps for a long time; however, we would encounter the following serious problems:

- We could not survive in fierce competition because we would take too much time.
- A technology applicable only to a particular product demands that the same technological development be repeated each time a specification is changed.

Therefore, instead of a real product shape, we tackled a test piece to develop the cutting technology.

Nonetheless, we anticipate the following questions:

1. *Did you use machining lubricant in this experiment?* We did not use it because we assumed that if we succeeded in developing a technology to cut material smoothly without lubricant, we could cut even more smoothly in actual production processes.

2. *Looking at the experimental results in the orthogonal array, we see a great difference, ranging from 2.6 to 44.5 dB. Taking into account that the average grand total is 32.8 dB, don't the SN ratios of experiments 4 and 17 seem extraordinarily small?* We set control factor levels as well as selected material hardness as a noise factor within as large a range as possible. As a consequence, we made a difference between a good condition and a bad condition for a tool standout.

Therefore, we regarded this experiment as quite meaningful.

3. *Although you prove that a technological development has good results, can you expect that the result will hold true for a real product?* Because we obtained the result by using proportionality between various input signals regarding all directions *x*, *y*, and *z* and product sizes, we are confident that this method can work for any types of model shapes. Yet absolute values of the SN ratio of a test piece may not be consistent with those of an actual product. Even in this case, we ask readers to confirm the results because you can obtain good reproducibility of gain.

Reference

Kenzo Ueno, 1993. Machining technology development for high performance steel to which concept of transformability is applied. *Quality Engineering*, Vol. 1, No. 1, pp. 26–30.

This case study is contributed by Kenzo Ueno.