CASE 40

Optimization of a Deep-Drawing Process

Abstract: In this study we attempt to reduce production cost for deep-drawn products by minimizing the number of processes through optimization of manufacturing conditions for deep drawing.

1. Introduction

In general, a manufacturing process to form from sheet metal a cylindrical container with a bottom is called a *drawing process,* (Figure 1). In most cases, a deep-drawn product is rarely formed in a single process but is stamped with the required depth in multiple processes. To reduce production cost for deep-drawn products, we minimize the number of processes through optimization of manufacturing conditions for deep drawing.

A drawing defect (i.e., a crack) is caused by partial strain concentration following uneven stretch of a material under an inappropriate forming condition. Ideal stamping is considered as forming any shape with uniform stretch and no cracks in the material. In a deep-drawing process, we obtain the required depth through multiple drawing processes. In the processes following process 2, the rate of drawing is regarded to decrease, compared with that in process 1, under the influence of work hardening. Therefore, since we need to evaluate deep drawing in the processes after process 2, as a signal factor the number of drawings was selected. At each drawing, we measured material thickness and defined a logarithmized value of the ratio of the before and after drawing thickness as an output, y. That is, setting the number of drawings to a signal factor, M, and a logarithmized value of the initial thickness, Y_0, and after-drawing thickness, Y, to the following output, we regarded a zero-point proportional equation of y and βM as a generic function:

$$y = -\log \frac{Y}{Y_0} \tag{1}$$

In addition, since a product should be formed with uniform thickness, we selected a measurement of product thickness, N (five points) as a noise factor to determine a condition with minimal variability.

2. SN Ratio and Sensitivity

Table 1 shows the data of experiment 1 in the L_{18} orthogonal array. The calculations for the SN ratio and sensitivity follow.

Total variation:

$$S_T = 0.021^2 + \cdots + 0.061^2 = 0.025325 \qquad (f = 15) \tag{2}$$

Effective divider:

$$r = 1^2 + 2^2 + 3^2 = 14 \tag{3}$$

Linear equations:

$$L_1 = (1)(0.021) + (2)(0.029) + (3)(0.057) = 0.250$$

$$L_2 = (1)(0.021) + (2)(0.026) + (3)(0.058) = 0.247$$

$$L_5 = (1)(0.023) + (2)(0.027) + (3)(0.061) = 0.260 \tag{4}$$

Variation of proportional term:

$$S_\beta = \frac{(L_1 + \cdots + L_5)^2}{5r} = 0.024816 \qquad (f = 1) \tag{5}$$

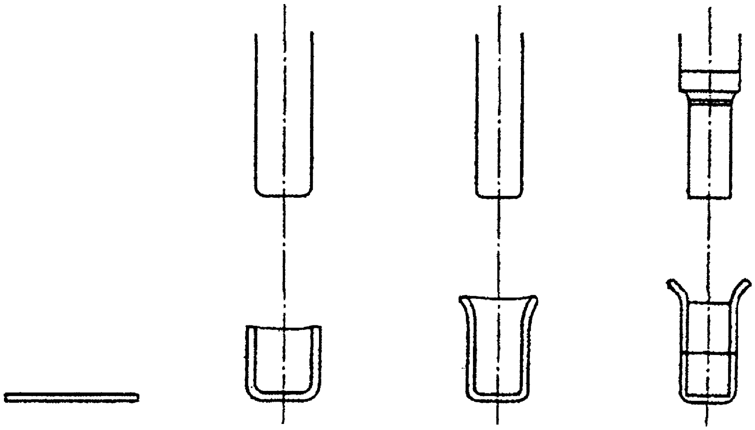

Figure 1
Deep-drawing process

Variation of differences between proportional terms:

$$S_{N\beta} = \frac{L_1^2 + \cdots + L_5^2}{r} - S_\beta = 0.000079 \qquad (f = 4) \tag{6}$$

Error variation:

$$S_e = S_T - S_\beta - S_{N\beta} = 0.00043 \qquad (f = 10) \tag{7}$$

Error variance:

$$V_e = \frac{S_e}{10} = 0.000043 \tag{8}$$

Total error variance:

$$V_N = \frac{S_{N\beta} + S_e}{14} = 0.000036 \tag{9}$$

SN ratio:

$$\eta = 10 \log \frac{(1/5r)(S_\beta - V_e)}{V_N} = 9.88 \text{ dB} \tag{10}$$

Sensitivity:

Table 1
Measured data of experiment 1 in the L_{18} orthogonal array (converted)

Noise Factor	Signal Factor M_1 1	M_2 2	M_3 3	Linear Equation
N_1	0.02	0.03	0.06	L_1
N_2	0.02	0.03	0.06	L_2
N_3	0.02	0.04	0.06	L_3
N_4	0.02	0.03	0.06	L_4
N_5	0.02	0.03	0.06	L_5

$$S = 10 \log \frac{1}{5r} (S_\beta - V_e) = -34.51 \text{ dB} \quad (11)$$

3. Optimization Configuration and Results of Confirmatory Experiment

As control factors, we selected the seven factors shown in Table 2 and allocated them to an L_{18} orthogonal array. Figure 2 shows the response graphs. Based on these graphs, we determined $B_1C_3D_1E_3F_1G_2H_3$ as the optimal configuration. On the other hand, as a comparative configuration, we chose $B_2C_1D_3E_2F_3G_3H_1$, leading to the worst SN ratio. For these optimal and comparative configurations, a confirmatory experiment was conducted. Table 3 shows estimations of the SN ratio and sensitivity. Considering all of the above, we concluded that the gains in SN ratio and sensitivity have good reproducibility.

The 15.23 dB gain obtained from the confirmatory experiment was converted into an antilog value of 33.37, which implies that we can reduce the variability to 1/33.37 (1/5.58) of the initial value. In actuality, the standard deviation under the optimal configuration is decreased to 1/7.07 of the counterpart under the comparative configuration. Because of large gains and good reproducibility, reduction in the number of drawing processes can be expected under the optimal configuration.

On the other hand, sensitivity, S, indicates the degree of influence for displacement of thickness at the bottom of a product. As the sensitivity becomes larger, the rate of change becomes larger and the thickness at the bottom becomes smaller, causing cracks more often. Therefore, a smaller value of sensitivity is advantageous to drawing.

4. Economic Benefits under the Optimal Configuration Based on the Loss Function

This product has a much larger tolerance in dimensions compared with the actual standard deviation. Thus, even if we minimize the variability and lower the standard deviation, we cannot expect much benefit through the loss improvements as a whole. In contrast, even if the variability increases to some extent, less production cost through reduction in the number of drawing processes can mitigate the total loss. Then we reduce the production cost by integrating drawing processes under the optimal configuration. By applying the optimal configuration and unifying processes, we lowered the number of processes by 40%. Consequently, we arrived at considerably less production cost.

The production cost for one deep-drawn product is 8.5 yen. All products that exceed the tolerance have been discarded. The loss that occurs to a

Table 2
Control factors and levels

Control Factor	Level 1	2	3
A: error	—	—	—
B: punch type	A	B	C
C: dice type	A	B	C
D: clearance	Small	Mid	Large
E: blank holder force	Small	Mid	Large
F: lubricant type	Company A	Company B	Company C
G: knockout pressure	Small	Mid	Large
H: material type	A	B	C

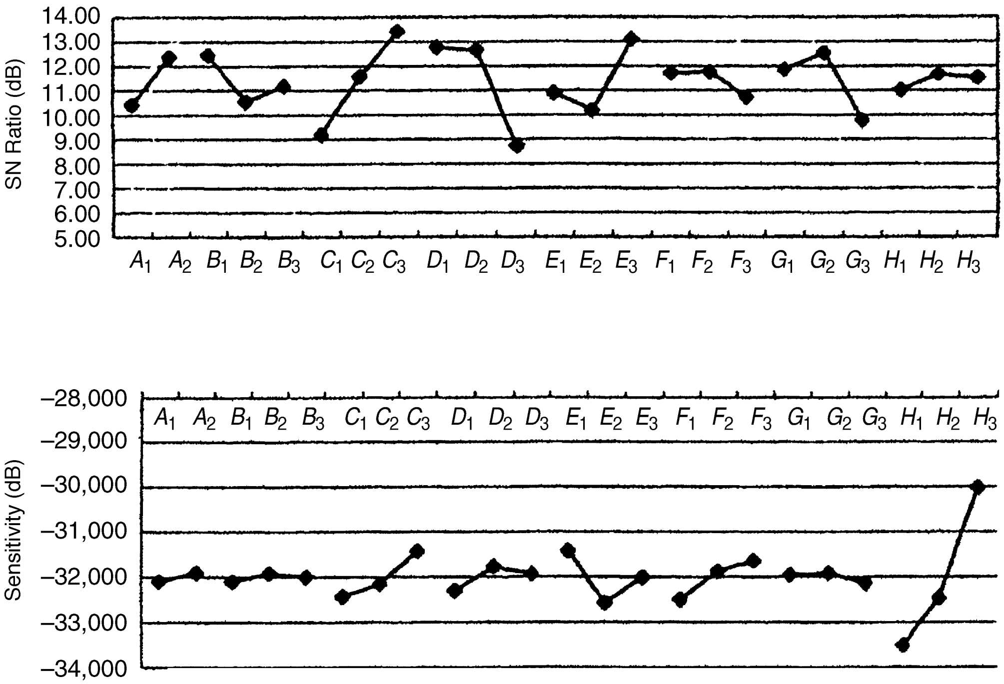

Figure 2
Response graphs

customer in this case is defined as A_0 yen. The production cost that has to date amounted to 8.5 yen/product can be reduced to 4 yen under the optimal configuration. The improvement is calculated as follows.

Loss function:

$$L = \frac{A_0}{\Delta^2}\ \sigma^2 + \text{product cost} \tag{12}$$

Under the current configuration:

$$L = \frac{8.5}{0.2^2}\,(0.0032^2) + 8.5 = 8.502 \tag{13}$$

Under the optimal configuration:

$$L = \frac{8.5}{0.2^2}\,(0.0068^2) + 4 = 4.01 \tag{14}$$

Table 3
Estimation and confirmation of SN ratio and sensitivity

	SN Ratio		Sensitivity	
Configuration	**Estimation**	**Confirmation**	**Estimation**	**Confirmation**
Optimal	19.13	18.63	−34.47	−30.26
Current	2.17	3.40	−30.26	−30.79
Gain	16.96	15.23	−4.21	−1.41

Thus, the improvement expected per product is 8.502 yen − 4.01 yen = 4.49 yen. As we produce 30,000 units/day and 600,000 units/year, we have the following benefit:

$$(4.49 \text{ yen})(600{,}000 \text{ units})(12 \text{ months}) = 32{,}400{,}000 \text{ yen}$$

As a result of applying the optimal configuration, we can improve approximately 30 million yen on a yearly basis through streamlined production with no increased variability.

Reference

Satoru Shiratsukayama, Yoshihiro Shimada, and Yasumitsu Kawasumi, 2001. Optimization of deep drawing process. *Quality Engineering*, Vol. 9, No. 2, pp. 42–47.

This case study is contributed by Satoru Shiratsukayama.