Journal of Materials Processing Technology 147 (2004) 321–327

Journal of Materials Processing Technology

www.elsevier.com/locate/jmatprotec

Sensitivity analysis of a deep drawing process for miniaturized products

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Received 6 March 2002; received in revised form 20 February 2003; accepted 26 November 2003

Abstract

Deep drawing is a widely used sheet metal forming technique, and its successful implementation has been a subject of research since many years. It has undergone many developments, one of the important ones being the application of numerical modeling techniques, like the finite element method (FEM) to simulate the process. Although deep drawing has been a subject of research for many years, there is still not much data available on deep drawing of miniature components, which find extensive application in electronics industry.

The deep drawing process is affected by many material and process parameters, like the strain-hardening exponent, plastic strain ratio, friction and lubrication, blank holder force, presence of drawbeads, punch velocity, etc. This paper aims at identifying the important parameters that affect the deep drawing process and quantitatively studying the effect of these parameters on the deep drawing operation for components of similar shape but different sizes. Thus, establishing a correlation between the size of a component and the effect of the parameters on the deep drawing of the component.

The study consists of a plane strain analysis of bell shaped geometry. Taguchi's robust design technique [Quality Engineering Using Robust Design, Prentice-Hall, New Jersey, 1989, p. 145] has been used to design the experiments using the maximum thinning strain developed in the walls as the quality characteristic.

Since carrying out actual experiments is both expensive and time consuming, computer modeling has been used to simulate the experiments. A FEM-based program, SHEET-S, developed by Wagoner and co-workers [Int. J. Meth. Eng. 30 (8) (1990) 1471] has been used for this purpose.

Keywords: FEM analysis; Deep drawing process; Forming process sensitivity

1. Robust design technique

Robust design is an engineering methodology for improving productivity during research and development by aiding the determination of optimum settings of control parameters so that the process becomes insensitive to the noise factors, thus enabling the production of high quality products at a low cost [3].

This methodology consists of three major steps:

1. planning the experiment,
2. performing the experiment,
3. analyzing and verifying the results.

The first step, i.e., 'planning the experiments' consists of identifying the main function of the process, its failure modes, noise factors (factors which are difficult or expensive to control), testing conditions, quality characteristics (characteristic of the quality of output), control factors (factors which can be easily controlled), and objective function to be optimized. The testing conditions should be chosen such that they capture the effect of the important noise factors. The two factors, which influence the quality characteristic, are

(i) noise factors,
(ii) control factors.

Robust design methodology aims at maximizing the signal-to-noise (S/N) ratio which thus forms the objective function; i.e., minimization of sensitivity to noise factors. The S/N ratios are derived from quadratic loss functions [4] (cf. [3]). The most commonly used S/N ratios are

(i) Nominal the 'best' type: in this type the objective function is targeted to have a non-zero and finite value:

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0924-0136/$ – see front matter © 2003 Published by Elsevier B.V.
doi:10.1016/j.jmatprotec.2003.11.023

$$\eta = 10 \log \frac{\mu^2}{\sigma^2} \tag{1}$$

where

$$\mu = \frac{1}{n} \sum y_i, \qquad \sigma^2 = \frac{1}{n-1} \sum (y_i - \mu)^2$$

(ii) Smaller the 'better' type: in such type of problems zero is the desired value of the function:

$$\eta = -10 \, log \left(\frac{1}{n} \sum y_i^2 \right) \tag{2}$$

(iii) Larger the 'better' type: larger the better type function is desired to have as large value as possible:

$$\eta = -10 \log \left(\frac{1}{n} \sum \frac{1}{y_i^2} \right) \tag{3}$$

The objective function, η, for any of the above approach, and the parameters are related by the following linear model:

$$\eta(A_i B_j C_k D_l) = \mu + a_i + b_j + c_k + d_l + e \tag{4}$$

where μ is the overall mean—that is, the mean value of η for all the experimental region; a_i, b_j, c_k, d_l the deviations from μ caused by setting factor A at level A_i, B at the level B_j, C at level C_k, and D at level D_l, respectively; while e the error of the additive approximation. In addition, in all the above equations, the y_i is the magnitude of the quality characteristic and n is the number of observations under different noise conditions. In this work, all the analysis are performed using smaller the better type approach.

It is important to select control factors, which influence a distinct aspect of the basic phenomenon affecting the quality characteristic, otherwise there is a possibility of interaction among these factors. For each factor, usually two or three levels (settings) are chosen, sufficiently apart so that a wide region is covered. Selecting three levels reduces curvature effects (Fig. 1), and therefore is always preferred.

The experiment can be designed in an efficient way to study the effect of several control factors simultaneously, by using orthogonal arrays, which exhibit many benefits. First, the conclusions arrived at from such experiments are valid over the entire experimental region spanned by the control factors and their settings. Second, there is a large saving in the experimental effort. Third, the data analysis is very easy. An orthogonal array for a particular robust design project can be constructed from the knowledge of the number of control factors, their levels, and the desire to study specific interactions. Also taken into account are the physical difficulties in conducting the experiment, like difficulty in changing the level of control factors. Taguchi and Keikakuho [5] have tabulated 18 basic orthogonal arrays that are called standard orthogonal arrays. The number of rows of an orthogonal array represents the number of experiments, while the number of columns represents maximum number of factors that can be studied using that array. The interaction table associated with a standard array shows in which columns the interaction is confounded with for every pair of columns of the array. Thus, it can be used to determine which column should be kept empty in order to estimate a particular interaction. The optimum level of a factor is the one, which gives the maximum value of η (objective function or the S/N ratio).

After determining the optimum conditions and predicting the response under these conditions, it is necessary to conduct a "confirmation experiment", at the optimum parameter settings, comparing the observed value of η with the prediction. If the observations are drastically different from the prediction then we say the additive model is not valid for the system and that a strong interaction exists between the various parameters of the system.

The analysis of results is done using analysis of variance (ANOVA) which gives the relative contribution of the effect of each factor on the objective function or the sensitivity of objective function to a particular factor.

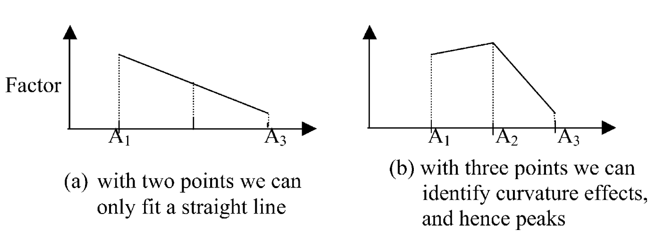

Fig. 1. Linear and curvature effects of a factor.

2. Planning the experiment

2.1. Component geometries studied

The four geometries studied are depicted in Fig. 2(a)–(d). The thickness of the blank used in all the four cases was 0.2 mm. In addition a simulation was also carried out using a 2.0 mm thick blank for the geometry depicted in Fig. 2(d). The punch used is a channel type of punch to simulate plane strain conditions. Hence, the third dimension, i.e. in Z-axis will not affect the strain path.

2.2. Quality characteristics and objective function

The quality characteristic measured was the maximum thinning strain developed in the walls of the component during the deep drawing. Since the lesser the thinning strain is the better it is, so the objective function used was $\eta = -10 \log(\text{thinning})^2$.

2.3. Control factors and their levels

Although there are many factors like punch velocity, blank holder force, strain-hardening exponent, strain rate hardening exponent, lubrication and friction, presence of drawbeads, etc. which affect the deep drawing process, the ones