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METHODS OF OPTIMISATION OF SHEET METAL FORMING PROCESSES CONCERNING THE REDUCTION OF SPRINGBACK

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ABSTRACT

The final form of the parts in sheet metal forming, especially in U bending, is highly affected by the springback occurring when the material is set free of the forming constraints. Numerous studies aiming to control this phenomenon are conducted and there is still a degree of incertitude concerning the intensity of springback. As the analytical methods are not accurate, due to the complexity of the factors intervening, the development of the finite element methods proved to be a valuable tool. Still there are numerous differences between the results from the real physical tests and the results from simulations especially when it comes to estimation of springback. The present paper aims to propose a method that can be effective in reducing the springback with exemplification on U bended sheet metal parts.

KEYWORDS: springback, metal forming, response surface.

1. INTRODUCTION

Forming simulation technologies have developed lately offering a powerful tool for the design engineers to develop more robust products with higher quality and performance characteristics. Still there are numerous differences between the results from the real physical tests and the results from simulations especially when it comes to estimation of springback. These discrepancies come from inappropriate finite element models or from the inherent variations of the forming parameters.

Li et al [1] proposed an explicit finite element method in conjunction with the orthogonal regression analysis for the prediction of springback. Choi and Kim [2] used an optimization method that relies on a mesh-free nonlinear analysis and continuum based design sensitivity analysis. Lee and Yang [3] have used explicit time integration method for the simulation of forming, implicit time integration for springback stage and the factors influencing springback have been evaluated quantitatively using Taguchi method. Pourboghrat and Chu [4,5] have developed a robust method for predicting springback and sidewall curvature in U bending operations using moment-curvature relationships derived for sheets undergoing plane-strain stretching, bending and unbending deformations using a membrane finite element solution. Ruffini and Cao [6] proposed a neural network control system for springback reduction in a channel section stamping process. Tan et al [7] used an approach consisting in finite element method analysis model to predict the value of the objective function and an evolutionary algorithm optimization procedure.

Response surface methodology (RSM) is used as an alternative method [8,9] for replacing a complex model by an approximate one based on results calculated at various points in the design space. RSM are well established for physical processes as documented by Myers and Montgomery [8].

Jansson et al. [10] evaluated the use of linear and quadratic approximating response surfaces as metamodels in reliability assessment of sheet metal forming process using the Monte Carlo simulation technique.

The present paper aims to propose a method using RSM that can be effective in the reduction of springback with exemplification on U bending.

2. MODELISATION PRINCIPLES

Considering a plane stress state and transverse anisotropy of the material, yielding condition according to Hill criterion is written as:

$$\phi = \sigma^T P \sigma - \overline{\sigma}^2 = 0 \qquad (1)$$

where σ represents the strain-stress uniaxial extension curve. The matrix P depends on the mean planar isotropy coefficient which is defined by the three anisotropy coefficients (r_0, r_{45}, r_{90}).

The stress–strain rate relationship is derived from the associated flow rule and Hill's anisotropic yield criterion. The assumption of the proportional loading allows to analytically integrate the strain rate to obtain a total constitutive law:

$$\begin{Bmatrix} \sigma_{xx} \\ \sigma_{yy} \\ \sigma_{xy} \end{Bmatrix} = \frac{2}{3}\frac{\bar{\sigma}}{\bar{\varepsilon}} \begin{bmatrix} FG & F & 0 \\ F & FH & 0 \\ 0 & 0 & FK \end{bmatrix} \begin{Bmatrix} \varepsilon_{xx} \\ \varepsilon_{yy} \\ \varepsilon_{xy} \end{Bmatrix} \qquad (2)$$

with

$$F = \frac{r(2+r)}{(1+2r)},\ G = H = \frac{1+r}{r},\ K = \frac{1}{r} \qquad (3)$$

The equivalent strain $\bar{\varepsilon}$ is given by

$$\bar{\varepsilon} = \sqrt{\frac{2}{3}F\left(G\varepsilon_{xx}^2 + 2\varepsilon_{xx}\varepsilon_{yy} + H\varepsilon_{xx}^2 + 2K\varepsilon_{xy}^2\right)} \qquad (4)$$

The mechanical properties of the material (Soldur 340) are presented in table 1.

Table 1. Material properties

Material orientation	Young Modulus MPa	Yield strength MPa	Uniform elongation %	Total elongation %	Anisotropy coefficient r
0°	198000	306	18	34.7	0.82
45°	200000	360	17.5	44.1	0.77
90°	200000	375	18	26.1	0.81

3. RESPONSE SURFACE DESIGN FORMULATION

Response surface models (RSM) are used to evaluate the functions describing the relationship among some influencing factors and the process results. RSM provides an approximate relationship between a true response Y_t and n design variables, which is based on the observed data from the process or system. We suppose that the true response Y_t can be written as:

$$Y_t = F(x_1, x_2, \ldots, x_n) \qquad (5)$$

where the variables x_1, x_2, . . . x_n are expressed in natural units of a measurement, and so are called the natural variables. The experimentally obtained response Y_t differs from the expected value y due to random error. Because the form of the true response function F is unknown and perhaps very complicated, we must approximate it. y can be written as:

$$y = F(\varsigma_1, \varsigma_2, \ldots, \varsigma_n) + \varepsilon \qquad (6)$$

where ε denotes the random error, which includes measurement error on the response and the variables ς_1, ς_2, . . . ,ς_n are the coded variables of the natural variables. We treat ε as a statistical error, often assuming it to have a normal distribution with mean zero and variance σ^2. In many cases, the approximating function F of the true response y is normally chosen to be either a first-order or a second-order polynomial model, which is based on a Taylor series expansion.

An important task is to distribute the experimental points appropriately in the region of interest, i.e. selecting a "design of experiments" (DOE). A popular DOE in structural analysis, that allows the user to determine how many function evaluations that should be used, is the D-optimality criterion (DOPT) [8]. The DOPT tries to scatter the evaluations as much as possible in the design space.

Unlike standard classical designs such as factorials and fractional factorials, D-optimal design matrices are usually not orthogonal and effect estimates are correlated. D-optimal designs are straight optimizations based on a chosen optimality criteria and the model that will be fit. The optimality criterion used in generating D-optimal designs is one of maximizing |X'X|, the determinant of the information matrix X'X.

This optimality criterion results in minimizing the generalized variance of the parameter estimates for a pre-specified model. As a result, the optimality of a given D-optimal design is model dependent. That is, the experimenter must specify a model for the design before a computer can generate the specific treatment combinations for the design. Given the total number of treatment runs for an experiment and a specified model, the computer algorithm chooses the optimal set of design runs from a candidate set of possible design treatment runs. This candidate set of treatment runs usually consists of all possible combinations of various factor levels that one wishes to use in the experiment.

For this research the following design variables were considered: the blankholder force (BHF), the die radius (R_d) and the punch radius (R_p) within the variation limits presented in table 2.

Table 2. The variables of the DOE

Parameters	Minimum value (-1)	Maximum value (+1)
A: Blankholder force F [kN]	40	200
B: Punch profile radius R_p [mm]	10	12
C: Die profile radius R_m [mm]	5	6

The objective function is the maximum opening distance of the final part formulated as follows:

$$F = \max \|d_i\| \quad (7)$$

where d_i represents the difference between the positions of each node of the mesh before and after springback (fig. 1). The above relation may be written as:

$$F = \sqrt{\sum_{i=1}^{n_d} \left(x_i^2 + y_i^2 + z_i^2\right)} \quad (8)$$

where x_i, y_i and z_i are the components of d_i in a Cartesian reference system and n_d is the number of nodes of the mesh.

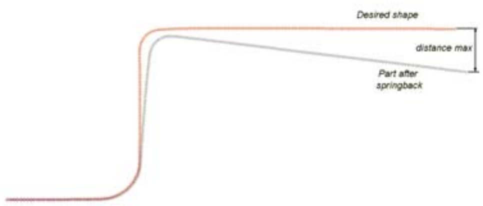

Fig.1. The opening distance

4. RESULTS

The experimental plan contained 20 simulations, presented in table 3 together with the obtained responses.

A quadratic form was initially considered for the objective function. This was evaluated according to the standard errors and Ri-squared values (a coefficient of determination) that indicate the possibility that the model is significant and may lead to proper results. The variation of standard error of the design in process variable space is indicated in figure 2.

The analysis of variance (ANOVA) shows the significance of the chosen variables and the influence upon the objective function and in combination with the diagnostic plots offers information about the correctitude of the entire model.

Table 3. Experimental plan and results

Factor 1 **A: BHF** kN	Factor 2 **B: Rp** mm	Factor 3 **C: Rd** mm	Response 1 **Opening** mm
135.03	10.81	6	90.34
40	12	6	80.29
48.25	12	5.5	74.50
40	10.8	5.4	193.61
200	12	6	25.68
200	12	6	25.68
40	12	5	68.23
98	11.24	5	136.83
40	12	6	80.29
40	10	6	95.96
135.83	12	5.4	94.32
200	10	5	34.03
200	11.26	5.63	13.55
97.01	10	5	14.80
140	10.76	5.39	85.67
200	10	5.65	41.36
40	12	5	68.23
200	11.28	5	42.52
40	10	6	95.96
135.83	12	5.4	94.32

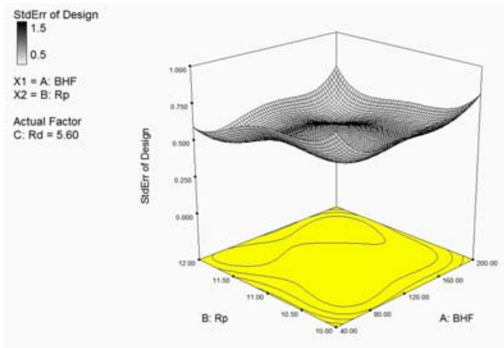

Fig. 2. Standard error of the quadratic model

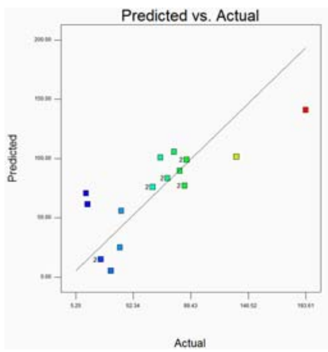

Fig. 3. Predicted vs. actual values of the quadratic model

According to ANOVA the quadratic model is not significant and the diagnostic plot in figure 3 indicates a large scattering of the predicted values.

The second approach considered a cubic model for the objective function. ANOVA showed it is a significant model and also indicated the significant terms of the cubic function (fig. 4). The objective function had the following form in terms of coded factors:

$$\begin{aligned} Opening = {} & 115.76 - 95.68A + 26.5B + 0.83C + \\ & + 0.64AB - 21.04AC - 19.34BC - 7.01A^2 \\ & - 51.88B^2 - 15.13A^2B + 3.21A^2C + 89.58AB^2 \end{aligned} \quad (8)$$

Model	35990.92	11	3271.90	443.14	< 0.0001	significant
A-BHF	13284.43	1	13284.43	1799.23	< 0.0001	
B-Rp	573.63	1	573.63	77.69	< 0.0001	
C-Rd	1.33	1	1.33	0.18	0.6830	
AB	2.34	1	2.34	0.32	0.5891	
AC	618.64	1	618.64	83.79	< 0.0001	
BC	392.05	1	392.05	53.10	< 0.0001	
A^2	101.03	1	101.03	13.68	0.0061	
B^2	6093.28	1	6093.28	825.27	< 0.0001	
A^2B	63.22	1	63.22	8.56	0.0191	
A^2C	10.94	1	10.94	1.48	0.2583	
AB^2	3201.04	1	3201.04	433.54	< 0.0001	
Residual	59.07	8	7.38			
Lack of Fit	59.07	3	19.69			
Pure Error	0.000	5	0.000			
Cor Total	36049.98	19				

The Model F-value of 443.14 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise.

Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case A, B, AC, BC, A^2, B^2, A^2B, AB^2 are significant model terms.

Fig. 4. ANOVA of the cubic model of RSM

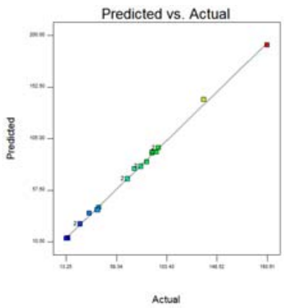

Fig.5. Predicted vs. actual values for the cubic model

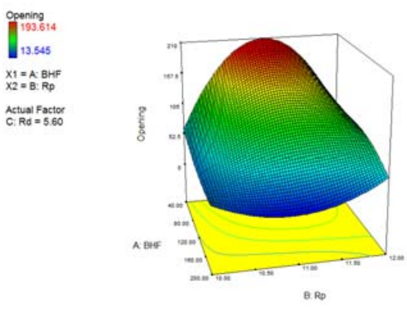

Fig. 6. Response surface of the cubic model

The diagnostic plot shows a very good coincidence among the predicted and the actual values of the model (fig. 5). The graph of the cubic model of the response surface is illustrated in fig. 6.

The optimization process was effected and the proposed values are: BHF=199.2kN, Rp=11.75mm, Rd=6mm with an estimated value of the opening of 12.85mm and a standard error mean of 2.37%.

To verify the proposed solution a new simulation was carried and the result for the opening was 13.12mm, meaning a 2.10% error compared to the estimated value.

5. CONCLUSIONS

A new method for the optimization of the sheet metal forming process has been presented and applied in the case of the channel forming benchmark (U-bending test). This method is based on response surface methodology and D-optimality criterion.

The most important three process parameters were taken into consideration: the blankholder force, the die profile radius and the punch profile radius. The objective function to be minimized was a measure of springback that expressed the deviation from the designed form.

The study included the use of quadratic and cubic functions of the response surface. The result showed that the cubic form of the functions provided more accurate results in predicting the amount of springback for a given combination of process parameters.

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