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OPTIMIZATION METHODS FOR THE SPRINGBACK CONTROL

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ABSTRACT
Springback is one of the most important phenomenons that affect the accuracy of the sheet metal parts. In order to obtain tight tolerances for the formed parts it is highly recommended to use such process parameters/tool geometry that allow a significantly diminishing of the springback amount. In this sense, good results could be obtained by applying some methods and techniques of optimization. The solution proposed within this paper assumes the application of two optimization procedures, based on the LMECA and Neural Networks methods, in order to find an optimal relation between the amount of springback and the tool geometry/forming parameters. The analysis is made in the case of cylindrical deep-drawn parts.
Keywords: springback, optimization procedure, cylindrical drawn parts

1. INTRODUCTION
Sheet forming processes are widely used in order to fabricate different sheet metal structures in many industries, e.g. automotive, aerospace, alimentary industry, etc. One of the considerations regarding the quality of formed parts is dimensional and shape accuracy, which is mainly affected by the springback phenomenon. Springback can be minimized by proper design of forming process but it cannot be totally eliminated. Therefore, tools correction or change of process parameters should be considered with respect the drawparts accuracy. To accomplish this goal, avoiding the expensive trial-error approach specific to the experimental tests, the optimization procedures based on the FEM simulation are currently used.
The solution proposed within this paper assumes the application of an optimization procedure, based on the LMECA and Neural Networks methods, in order to find an optimal relation between the amount of springback and tool geometry/forming parameters (fig.1). The analysis is made in the case of cylindrical deep-drawn parts.

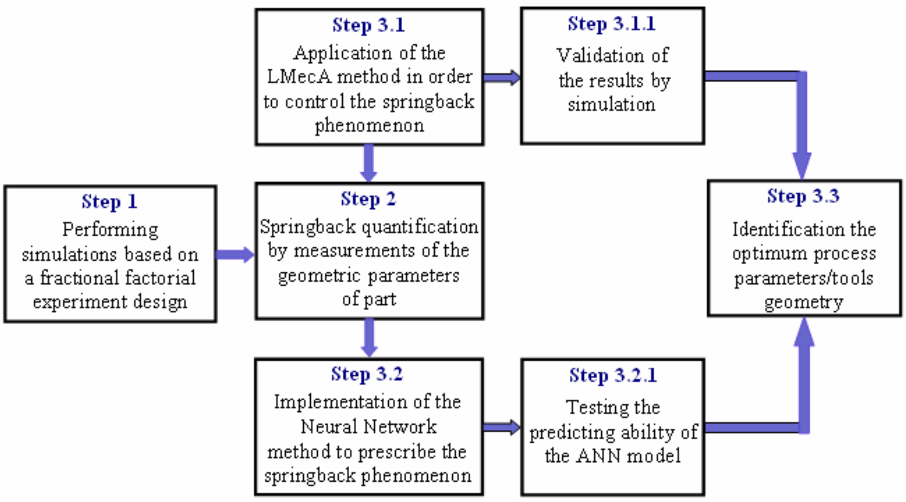


Fig.1 Optimization procedure

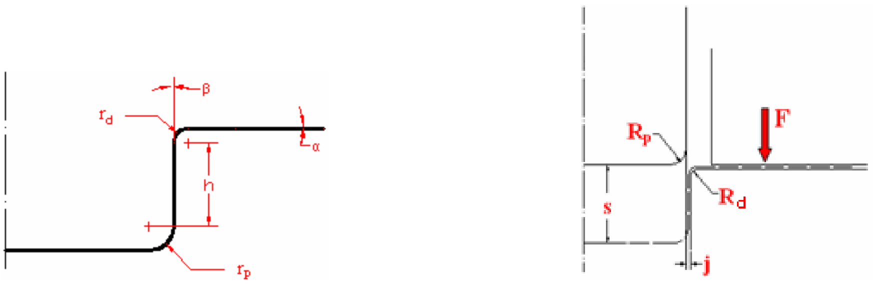
2. IMPLEMENTATION OF THE OPTIMIZATION METHODS INTO THE SPRINGBACK CONTROL

2.1 Implementation of the LMecA method

The method elaborated by the research team of the Applied Mechanic Laboratory from Savoie University, France, in order to reduce the springback of an aluminum V-bending part, is based on the Taguchi optimization strategy and consists in the following six stages: 1.Definition of the parameters that characterize the geometric deviations of the part. 2. Selection of the process parameter which can influence the geometry of the part, and their range of variation to test. 3. Choice of a polynomial model and construction of an experiment design. 4. Performing the simulations defined by the experiment design and measurement of the geometrical defects on the obtained virtual parts. 5. Calculation of the coefficients of polynomial models and verification of the models. 6. Optimization of the process parameters in order to obtain the desired geometric parameters of the formed parts [1].

In the case of the cylindrical deep-drawn parts, five geometric parameters were analyzed in order to quantify the effects of springback, respective: radius of connection between the part flange and part sidewall (r_d), radius of connection between the part bottom and part sidewall (r_p), angle of the flange (α), inclination angle of the part sidewall (β) and height of the part sidewall (h) (fig.1,a).

The process parameters chosen to investigate their influence on the springback intensity were as follows (fig. 1, b): blankholder force (F), punch-die clearance (j), punch stroke (s), punch radius (Rp) and die radius (R_d). These parameters and their domain of variation (table 1) was chosen according to the results of an initial simulation and based on their probable influence on the part geometry.



a. analyzed geometric parameters of part *b. investigated process parameters*

Fig. 1 Investigated parameters

Table 1 Tested parameters and their field of variation

Parameter	Initial value	Minimum value (-1)	Maximum value (+1)
Punch radius **(R_p)**	6 mm	5 mm	7 mm
Die radius **(R_d)**	4 mm	3 mm	5 mm
Blankholder force **(F)**	45 kN	40 kN	90 kN
Punch-die clearance **(j)**	1 mm	1 mm	1.5 mm
Punch stroke **(s)**	30 mm	30 mm	32 mm

In order to establish a relation between the process parameters and springback intensity, two types of mathematical models can be used:

- a polynomial model of first degree:

$$Y = a_0 + a_1x_1 + a_2x_2 + \ldots + a_nx_n + a_{12}x_1x_2 + \ldots + a_{n-1,n}x_{n-1}x_n \quad (1)$$

- a polynomial model of the second degree,

$$Y = a_0 + a_1x_1 + a_2x_2 + \ldots + a_nx_n + \ldots + a_{11}x_1^2 + \ldots + a_{nn}x_n^2 + a_{12}x_1x_2 + \ldots + a_{n-1,n}x_{n-1}x_n \quad (2)$$

In each of the two models, Y represents the followed values (r_d, r_p, α, β, h), x_1 … x_n represent the values of the input parameters that must be optimized (R_p, R_d, F, j, s) and x_ix_j represent the interactions between the considered factors.

Initially it started with a factorial design to identify a linear dependence between the part and process parameters. In order to determine the coefficients a_0, a_1, a_2 ….a_n corresponding to each function, for the five analyzed factors, sixteen numerical experiments were needed to carry out. The result of each simulation was a file of nodes, representing the nodes of the virtual part mesh, after the tools removing. These files were post treated in order to measure the geometric part parameters. The assumption of linearity of the output with the input was then verified by testing the model in the center of the field (see table 1), i.e. when the reduced centred variables are equals to (0). Because the model was not enough precise (some differences could be observed between the results of the two modalities of determination: simulation and linear functions), a second experiment design (another ten additional simulations), was used and together with the first one, it allowed to identify a quadratic model. This model was also tested by performing a simulation that had as input data the centered values of process parameters (**R_p**= 6mm, **R_d**= 4mm, **F** = 65kN, **j** = 1.25mm and **s** = 31mm). The results are given in table 2.

Table 2 Comparison of the results

	R_p’	R_d’	F’	j’	s’	Values obtained with quadratic model	Values obtained from simulation	Errors
r_p	0	0	0	0	0	6.378	6.416	-0.038
r_d	0	0	0	0	0	4.417	4.462	-0.045
α	0	0	0	0	0	0.501	0.535	-0.034
β	0	0	0	0	0	0.593	0.539	0.054
h	0	0	0	0	0	19.899	19.625	0.274

From the above presented results, very small differences between the values obtained from the two modalities of determination could be observed; in consequence, the quadratic model was used to determine the optimum process parameters which allow to obtain an improved geometry of the formed part. The principle of optimization consists in minimizing a function equal to the squared sum of deviation between the real and the desired output:

$$\Phi = (r_p - 6)^2 + (r_m - 4)^2 + (\alpha - 0)^2 + (\beta - 0)^2 + (h - 20)^2 \qquad (3)$$

This function has several local minima. The Excel solver was used to seek them. In the field of study, defined by the value (-1) and the value (+1) of the process parameters, none of these minima is equal to zero. In other words, it is not possible to obtain the five wished values for the part parameters simultaneously. The lowest minimum on this field is given in table 3.

Table 3 optimum values of tools and process parameters

	R_p [mm]	R_d [mm]	F [kN]	j [mm]	s [mm]	r_p [mm]	r_d [mm]	α [°]	β [°]	h [mm]
Values resulted from optimization	5.56	3.62	48	1	31.90	6.122	3.988	0.328	0.411	19.936

In order to validate the optimization algorithm a new simulation was performed, using as input data the optimized process parameters and tool geometry. The results of quadratic optimization, of finite element simulation and the nominal values of the geometrical parameters of part are compared in table 4.

Table 4 Comparative analysis of the results

	R_p	R_d	F	j	s	r_p [mm]	r_d [mm]	α [°]	β [°]	h [mm]
Values resulted by using initial tools design	6 [mm]	4 [mm]	45 [kN]	1 [mm]	30 [mm]	6.522	4.602	0.528	0.784	17.69
Values resulted from quadratic model	5.56 [mm]	3.62 [mm]	48 [kN]	1 [mm]	31.90 [mm]	6.122	3.988	0.328	0.411	19.936
Values resulted from simulation						6.105	4.062	0.286	0.405	20.122
Nominal values						6.000	4.000	0.000	0.000	20.000

A good concordance between the estimated values by minimizing the function Φ and that obtained from simulation could be observed. Also, the accuracy of part obtained by using the optimized parameters is much improved compared to that obtained by using the initial tools geometry.

2.2 Implementation of the Neural Network method

The utilization of an artificial neural network in order to find the optimum relation between the process parameters, tools geometry and springback parameters assumed the following four steps: 1.Data collection, 2. Choice the ANN model, 3.Network training, 4. Generalization.

The values of the process parameters established according to the fractional factorial experiment design applied to the LMecA method (quadratic optimization) were used as input data for the neural network while the values of the springback parameters resulted from simulations were used as their associated targets.

A two-layer neural network with a sigmoid activation function between the input and hidden layers and a linear activation function between the hidden and the output layers was used. Within the input layer, five neurons - respectively the five process parameters (R_p, R_d, F, j, s) were used; within the output layer, five neurons - respectively the five analyzed geometric parameters of the part (r_p, r_d, α, β, h) were also used. The number of the neurons (five) within the hidden layer was chosen so that the mean square error to the end of the training process to be minimum.

The training process was based on the backpropagation algorithm and its correctness was monitored by using a cross validation criterion (a data set of 15% from the total inputs of the network was used).

For the generalization phase of the network, a data set of 25% from the total inputs was given to it. The outputs prescribed by the neural network were compared with the desired outputs. By analyzing the obtained results, a good concordance between the desired outputs and the prescribed ones could be observed and, accordingly, the chosen ANN model was validated. This model was then tested for different combinations of process/tools parameters (without have defined the target values of these inputs) in order to find the optimum ones which allow to obtain an improved accuracy of part. Good results reported to the nominal geometry of the parts were obtained for the following set of tools /process parameters: **R_p = 5.5 mm; R_d = 3.4 mm; F = 49 kN; j = 1 mm; s = 30.3 mm.**

In order to validate the optimization procedure, a simulation has been performed using as input data the above set of parameters and the obtained results were compared with the nominal geometry of the part (table 5).

Table 5 Comparative analysis of the results

	R_p	R_d	F	j	s	r_p	r_d	α	β	h
Values prescribed by the ANN model	5.5 [mm]	3.4 [mm]	49 [kN]	1 [mm]	30.3 [mm]	6.078	4.034	0.425	0.491	20.076
Values resulted from simulation						6.022	3.996	0.391	0.366	20.192
Nominal values						6.000	4.000	0.000	0.000	20.000

By analysing the above results, a good agreement between the nominal geometry of part and that resulted from simulation could be observed. In consequence, the previous mentioned set of process parameters can be considered as optimum.

3. CONCLUSIONS

- An optimization procedure based on the LMecA method and Neural Network method, respectively, was applied.
- By applying the LMecA method, the deviations of the geometrical parameters of part reported to the nominal profile decreased as follows: with 78.5% for r_p, with 88.3% for r_d, with 94.8% h, with 54.2% for α and with 51.7% for β.
- By applying the Neural Network method, the deviations of the geometrical parameters of part reported to the nominal profile decreased as follows: with 95.4% for r_p, with 99.2% for r_d, with 91.8% h, with 74.1% for α and with 46.7% for β.
- By analysing the above presented results, it can be stated that both optimization methods could be successfully used to control the springback phenomenon in the case of cylindrical drawn-parts.

4. REFERENCES

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