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SPRINGBACK AND ITS EFFECTS ON THE PART ACCURACY

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ABSTRACT

Springback is a serious problem in manufacturing of sheet metal components. In order to reduce as much as possible its baleful effects on the part accuracy and farther on the part assembly, it is necessary to know how this phenomenon is influenced by the different variable of the forming process. The purpose of the present work is to quantify the springback intensity in the case of drawn parts made from different materials, in order to apply an optimization method that allow to compensate its effects.

Keywords: springback, part material, optimization method

1. INTRODUCTION

The forming of sheet metal into a desired and functional shape is a process which requires a detailed prediction of springback in order to avoid the contingent assembly problems of the resulted parts. Springback is reported in the literature to be influenced by different variable of the forming process like process parameters, material properties, tools geometry. By controlling these factors, we will be able to control the springback as well, in order to obtain the desired accuracy of the formed parts.

The increased use of the simulation techniques has created possibilities to optimize the parameters of the forming process avoiding the expensive trial-error approach specific to the experimental tests. This development, together with the increased speed in computer technology, has opened possibilities for obtaining virtual parts within tight tolerances, in a shorter time. Another advantage of the sheet-metal-forming simulations is represented by the animated presentation of the results, witch allow to follow the entire sheet metal forming process.

In this paper, the simulation of cylindrical deep-drawing process, in the case of two different materials: FEPO 5MBH steel and SOLDUR steel respectively, is presented. After the springback quantification, an optimization method base on the ANN models will be applied in order to find an optimal relation between the amount of springback and the parameters of the deep-drawing process.

2. METHODOLOGY AND CONDITIONS OF SIMULATION

Determination by simulation of the springback intensity in the case of cylindrical deep-drawn parts consisted in the following steps:

- first, the cylindrical cups were obtained by simulation of the deep drawing process into ABAQUS/Explicit;
- second, the import the forming results into ABAQUS/Standard program was performed in order to simulate the unloading phase (obtaining the parts’ springback);
- the parts profile was then determined on the base of displacements resulted after deep drawing and springback;
- the above resulted profiles were measured with a CAD software and compared with the nominal shape, in order to quantify the springback.

A three dimensional model was used for the simulations. Only a quart of the model was solved using symmetry conditions (fig. 1). The blank was considered deformable with a planar shell base while the tools were considered analytical rigid. Thus, numerical integration (Gaussian with 5 integration points

through the thickness) was involved only for the work-piece material. The stress-strain curve of the materials was implemented point by-point rather than using a curve fit equation. A slave-master concept was used for the contact problem to impose penalty regularization.
The geometrical parameters of part profile whose variation was investigated in order to quantify the amount of springback, and their nominal values are presented in figure 2.

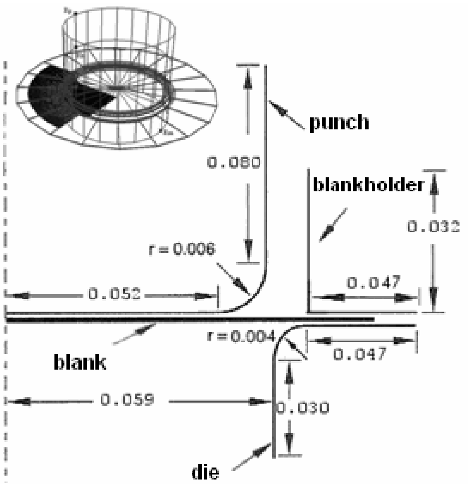

Figure 1. The geometrical model

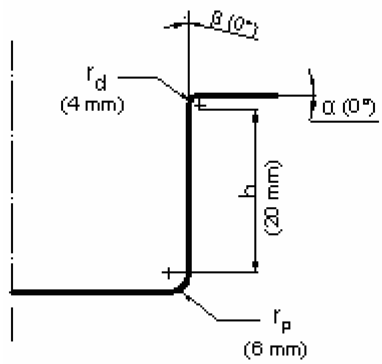

Figure 2. Geometrical parameters of part and their nominal values

3. SIMULATION RESULTS

The simulation of deep-drawing process was performed based on a factorial plan of experiments. The process parameters chosen to investigate their influence on the springback intensity were as follows: blankholder force (F), punch-die clearance (j), punch stroke (s), punch radius (Rp) and die radius (R_d). The results of simulations are presented in table 1 and table 2 respectively.

Table 1. The results of simulations for FEPO 5MBH steel

R_p	R_d	F	j	s	r_p	r_d	α	β	h
5	3	40	1	30	5.613	3.673	0.928	0.252	20.654
5	3	40	1.5	32	5.648	3.388	0.742	1.192	22.922
5	3	90	1	32	5.608	3.388	0.742	1.192	22.964
5	3	90	1.5	30	5.589	3.525	0.938	1.565	20.619
5	5	40	1	32	5.548	5.399	0.618	0.261	20.926
5	5	40	1.5	30	5.738	5.536	0.523	1.342	18.750
5	5	90	1	30	5.589	5.456	0.185	0.368	18.923
5	5	90	1.5	32	5.662	5.396	0.627	1.304	20.849
7	3	40	1	32	7.503	3.494	1.031	0.158	20.912
7	3	40	1.5	30	7.499	3.385	0.909	1.443	18.944
7	3	90	1	30	7.558	3.350	0.909	1.443	18.984
7	3	90	1.5	32	7.594	3.396	0.728	1.424	30.947
7	5	40	1	30	7.443	5.437	0.476	0.348	16.978
7	5	40	1.5	32	7.525	5.437	0.306	1.382	18.910
7	5	90	1	32	7.485	5.494	0.313	0.348	18.971
7	5	90	1.5	30	7.560	5.524	0.444	1.784	16.833
6	4	65	1.25	31	6.416	4.462	0.535	0.539	19.625
4.28	4	65	1.25	31	4.793	4.307	0.801	0.831	21.799
7.72	4	65	1.25	31	8.402	4.457	0.709	1.378	18.017
6	2.28	65	1.25	31	6.535	3.31	0.674	0.949	21.082
6	5.72	65	1.25	31	6.627	6.176	0.088	1.116	18.151
6	4	22	1.25	31	6.545	4.355	0.58	0.107	20.049
6	4	108	1.25	31	6.661	4.446	0.58	0.818	19.808
6	4	65	0.82	31	6.528	4.34	0.406	1.197	18.336
6	4	65	1.68	31	6.696	4.439	0.538	1.971	19.808
6	4	65	1.25	29.28	6.626	4.45	0.612	0.859	21.606
6	4	65	1.25	32.72	6.701	4.439	0.528	1.844	19.803

Table 2. The results of simulations for SOLDUR steel

R_p	R_d	F	j	s	r_p	r_d	α	β	h
5	3	40	1	30	5.732	3.405	0.986	0.1265	20.813
5	3	40	1.5	32	5.738	3.471	1.202	0.891	22.543
5	3	90	1	32	5.6845	3.452	0.869	0.109	22.7515
5	3	90	1.5	30	5.7055	3.6155	0.895	1.1935	20.579
5	5	40	1	32	5.6865	5.5135	0.551	0.018	20.6415
5	5	40	1.5	30	5.648	5.3305	0.6735	0.612	18.849
5	5	90	1	30	5.608	5.368	0.6865	0.0735	18.8845
5	5	90	1.5	32	5.753	5.432	0.444	0.571	20.701
7	3	40	1	32	7.5275	3.601	1.1225	0.2075	20.7185
7	3	40	1.5	30	7.776	3.509	1.1415	0.874	18.342
7	3	90	1	30	7.603	3.382	0.75	0.2265	18.989
7	3	90	1.5	32	7.7615	3.55	1.304	1.047	20.4825
7	5	40	1	30	7.526	5.396	0.4225	0.1355	16.8575
7	5	40	1.5	32	7.6095	5.442	0.577	0.9605	18.8015
7	5	90	1	32	7.61	5.3995	0.494	0.1835	18.844
7	5	90	1.5	30	7.541	5.2965	0.364	1.38	16.892
6	4	65	1.25	31	6.696	4.468	0.963	0.397	19.701
4.28	4	65	1.25	31	5.036	4.472	0.739	0.2195	21.325
7.72	4	65	1.25	31	8.4965	4.443	0.784	0.577	17.803
6	2.28	65	1.25	31	6.6325	3.35	0.9	0.5825	20.794
6	5.72	65	1.25	31	6.7915	6.1595	0.541	0.48	17.9525
6	4	22	1.25	31	6.862	4.4385	0.772	0.221	19.4475
6	4	108	1.25	31	6.74	4.4155	0.706	0.534	19.695
6	4	65	0.82	31	6.481	4.383	0.566	0.186	20.051
6	4	65	1.68	31	6.878	4.405	1.019	1.178	19.3095
6	4	65	1.25	29.28	6.924	4.387	0.664	0.3205	17.848
6	4	65	1.25	32.72	6.659	4.415	1.068	0.333	21.499

4. APPLICATION OF THE OPTIMIZATION PROCEDURE

In order to determine the optimum process parameters in a shortest time, an optimization method based on the utilization of an artificial neural network model was implemented.

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 (table 3 and table 4, respectively).

Table 3. Comparative analysis of the results in the case of FEPO 5MBH steel

Desired outputs					Values prescribed by the ANN model				
r_p	r_d	α	β	h	r_p	r_d	α	β	h
6.626	4.450	0.612	0.859	21.606	6.615	4.759	0.518	1.046	21.181
7.558	3.350	0.909	1.443	18.984	7.506	3.893	0.744	1.113	18.501
4.793	4.307	0.801	0.831	21.799	5.060	4.378	0.713	0.654	21.655
7.594	3.396	0.728	1.424	20.947	7.326	3.557	0.698	1.564	20.801
5.589	3.525	0.938	1.565	20.619	5.692	3.595	0.856	1.310	21.141
5.608	3.388	0.742	1.192	22.964	5.533	3.659	0.665	0.856	22.291
7.485	5.494	0.313	0.348	18.971	7.297	5.488	0.302	0.612	18.289

Table 4 Comparative analysis of the results in the case of SOLDUR steel

Desired outputs					Values prescribed by the ANN model				
r_p	r_d	α	β	h	r_p	r_d	α	β	h
5.738	3.471	1.202	0.891	22.543	6.161	3.238	0.968	0.585	21.839
7.5275	3.601	1.1225	0.2075	20.7185	6.934	3.802	1.015	0.406	20.944
7.776	3.509	1.1415	0.874	18.342	7.438	3.704	0.972	1.015	18.972
5.732	3.405	0.986	0.1265	20.813	5.715	3.568	0.801	0.315	21.610
6.924	4.387	0.664	0.3205	17.848	6.623	4.409	0.661	0.459	18.582
7.7615	3.55	1.304	1.047	20.4825	7.370	3.763	1.072	1.133	20.114
5.036	4.472	0.739	0.2195	21.325	5.468	4.650	0.706	0.076	21.668

By analyzing the obtained results, a good concordance between the desired outputs and those prescribed by the ANN model 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 sets of tools/process parameters:

- in the case of FEPO 5MBH steel: ***R_p = 5.5 mm; R_d = 3.4 mm; F = 49 kN; j = 1 mm; s = 30.3 mm.***
- in the case of SOLDUR steel: ***R_p = 5.2 mm; R_d = 3.6 mm; F = 42 kN; j = 1 mm; s = 27 mm***

In order to validate the optimization procedure, two simulations have been performed using as input data the above sets of parameters and the obtained results were compared with the nominal geometry of part (table 5) .

Table 3 Comparative analysis of the results

	FEPO 5MBH steel									
	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 simulations						6.022	3.996	0.391	0.366	20.192
	SOLDUR steel									
	R_p	R_d	F	j	s	r_p	r_d	α	β	h
Values prescribed by the ANN model	5.2 [mm]	3.6 [mm]	42 [kN]	1 [mm]	27 [mm]	5.878	4.006	0.611	0.422	19.720
Values resulted from simulations						6.005	4.079	0.405	0.398	20.082
Nominal values						6.000	4.000	0.000	0.000	20.000

6. CONCLUSIONS

- Material springback generated deviations of geometrical parameters of the part from the theoretical profile.
- An optimization procedure based on the neural network method coupled with the finite element analysis was applied in order to find the best relation between the parameters of cylindrical deep-drawing process and the springback parameters.
- The optimization procedure conducted to a considerable increasing of the part accuracy, fact that is encouraging in using further the artificial neural networks models to control the springback phenomenon in the case of sheet-metal-forming processes.

7. REFERENCES

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