Proceedings of the 15th International Conference on Manufacturing Systems – ICMaS
Published by Editura Academiei Române, ISSN 1842-3183

"Politehnica" University of Bucharest, Machine and Manufacturing Systems Department
Bucharest, Romania, 26 – 27 October, 2006

OPTIMUM TOOL GEOMETRY AND PROCESS PARAMETERS PRESCRIBED BY A NEURAL NETWORK MODEL IN THE CASE OF CYLINDRICAL PARTS DEEP-DRAWING

Crina AXINTE

Abstract: *Geometrical inaccuracy of sheet metal parts due to springback are the reason for considerable efforts in the tool and process development. Numerous studies have been carried out in order to find the optimum process parameters and tool geometry so that the resulted parts to be within tolerances. In the present paper, the finite element method coupled to the neural network method are used to get the best relation between process parameters and tool geometry in order to minimize the shape deviations of the formed parts, related to the target geometry.*

Key words: *neural network, cylindrical deep-drawn parts, springback.*

1. INTRODUCTION

One of the considerations regarding the quality of formed parts is dimensional and shape accuracy. The dominate factor that affects the drawparts accuracy is the springback phenomenon. Springback occurs in various forms like bending, twisting, etc. and it is known that many factors affect it, such as material mechanical properties (Young's modulus, yield strength, Bauschinger effect, etc.), tooling geometry (die shape, punch-die clearance, tools radii), process parameters (blankholder force, punch velocity, lubrication condition, etc). Springback can be minimized by proper design of forming process but it cannot be totally eliminated. Therefore, the 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 target of such "activity" is to determine, using FEM simulation, all distortions of the part due to springback and to compensate them by modifying the virtual tools geometry before their construction.

In this paper, an optimization procedure based on the implementation of an artificial neural network model for the springback control, in the case of cylindrical drawn parts, is presented.

In recent years, many research groups have investigated the use of the artificial neural networks to control the springback phenomenon. For example, Yang *et al.* [1], Elkins [2], Forcellese et al. [3] used a neural network to control the springback in a 60 deg. aluminium V-punch air bending process. Ruffini and Cao [4] proposed to use a neural network to control the springback angle in a channel forming process of aluminium sheets, Kinsey *et al.* [5] managed to maintain the springback angle between the given limits using a variable blankholder force whose amplitude and moment of variation on the punch stroke were prescribed by a neural network.

Viswanathan *et al.* [6] took up the Kinsey's experiment but for a different geometry of the part.

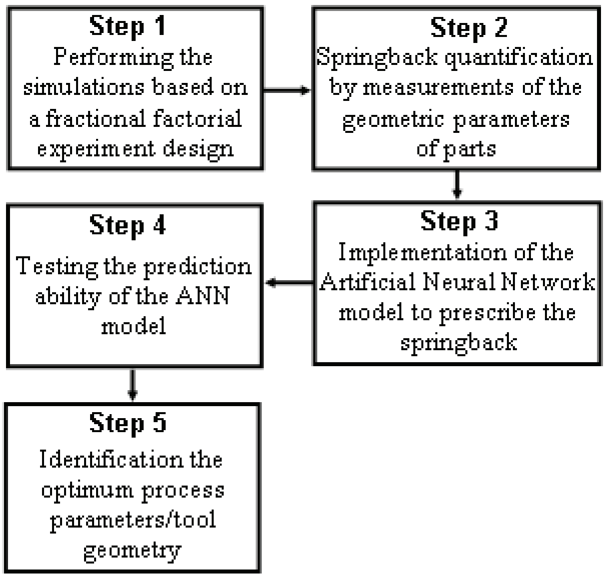

Fig. 1. Implementation of the optimization procedure.

In the case of the present analysis, the optimization procedure assumes the following steps (Fig. 1): firstly, the virtual parts are manufactured and their springback parameters are determined. The obtained results are used as training data for an ANN model, whose effectiveness for springback predicting will be then tested. After the neural network validation, it is used to find the best set of process parameters/tool geometry that leads to a minimum springback.

2. THE OPTIMIZATION PROCEDURE

2.1. Numerical simulations

Finite element analysis was used to simulate both, the cylindrical deep-drawing process (by using the software ABAQUS/Explicit) and the unloading phase (by using the software ABAQUS/Standard). A three dimensional axis-symmetric model was used in simulation. Only a quart of the model was solved due to the symmetry conditions (Fig. 2). The blank was considered deformable

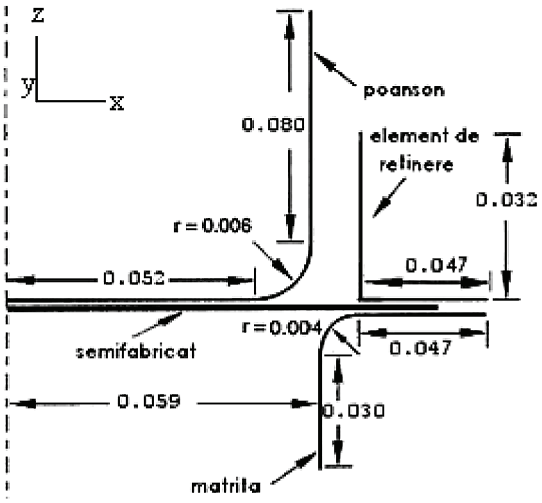

Fig. 2. Geometrical model used in simulations.

with a planar shell base while the tools were considered analytical rigid. The stress-strain curve of the material (FEPO 5MBH steel) 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 simulations were performed accordingly to a factorial plan of experiments. The profile of the virtual parts was obtained by post-processing, into CAD software, the coordinates of nodes representing the geometry of the formed parts.

2.2. Implementation of the ANN model

The utilization of the artificial neural network in order to find the optimum relation between the process parameters, tools geometry and springback parameters in the case of cylindrical drawn parts assumed the following four steps (Fig. 3).

2.2.1. Data collection

The 27 combinations of the process parameters established according to a fractional factorial experiment design were used as input data for the neural network and the values of the springback parameters resulted from the 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.

2.2.2. Choice of the ANN model

Within the input layer, five neurons – respectively the five analyzed process parameters (R_p, R_d, F, j, s) (Fig. 4)

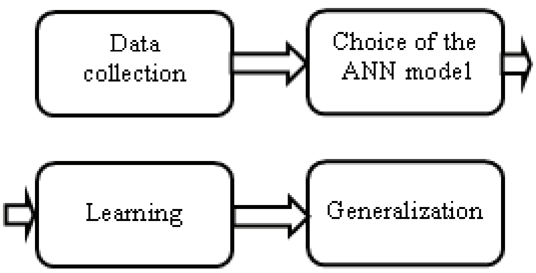

Fig. 3. Main steps for the ANN implementation.

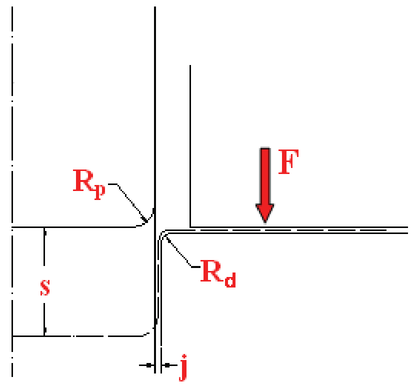

Fig. 4. The process parameters.

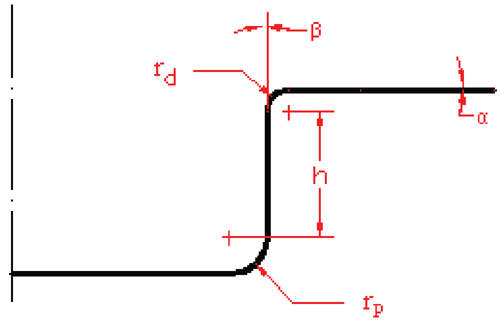

Fig. 5. The geometric parameters of part.

were used; within the output layer, five neurons – respectively the five analyzed geometric parameters of the part (r_p, r_d, α, β, h) (Fig. 5) were also used. The number of the neurons within the hidden layer must be chosen so that the square means error to the end of the training process to be minimum.

2.2.3. The learning process

The learning process was based on the back propagation algorithm. This algorithm works as its name suggests: after the propagation of an input through the network, the error (difference between the real and the desired output) is calculated and it is propagated back through the net while the weights are adjusted in order to make the error smaller.

An especially attention should be paid to the learning phase correctness because a lower error, however, does not always mean a better network. It is possible to overstrain a network. This happens when the network starts “memorizing” the training patterns, so that it is not able to generalize anymore.

There are many graphic instruments to monitor how the network is well learning. One of the simplest methods is to observe how the cost, which is the square difference between the network output and the desired response, changes over training epochs. This graph of the output error versus training epochs is called learning curve. The learning curve decreases exponentially to zero or a small constant when the learning process works well (the network overstrain not occurs); otherwise the learning curve will rise. Very useful in this sense is to set aside a small percentage of the training data and to use it for cross validation, which is a highly recommended

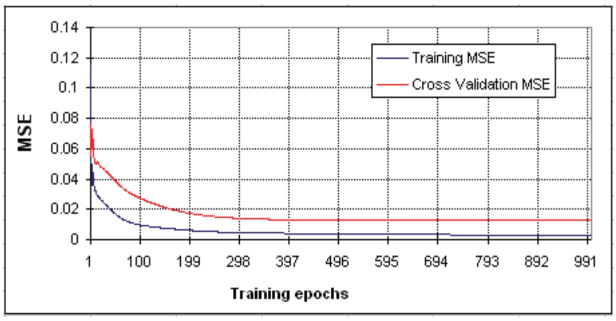

Fig. 6. MSE/Training epochs.

criterion for stopping the training of a network. One should monitor the error in the training set and the validation set, respectively. When the error in the validation set increases, the training should be stopped. The goal of the stop criterion is to maximize the network generalization.

In the case of the present analyses, a cross validation data set of 15% from the total inputs of the network was used, the validation process being repeated for different numbers of hidden neurons to determine which network provided the lowest validation mean square error. For the chosen ANN model, the optimum number of the hidden neurons was set to 5. In Fig. 6 the learning curves for the training data and the cross validation data, respectively are presented in the case of using 5 neurons in the hidden layer.

By analyzing the above diagram it could be seen that the chosen ANN model leads to an adequate variation of the learning curve; as consequence, the model will be used to the next functional phase of the neural network.

2.2.4. Generalization

After training, the best test for a network performance, however, is to prescribe correct outputs for that it has not yet seen. In the case of the present analyses, a data set of 25% from the total inputs was given to the network.

In Fig. 7 and Table 1 respectively, a comparative analysis of the desired outputs and the outputs prescribed by the neural network is presented.

By analyzing the above diagrams and the data presented in the Table below, a good concordance between the desired outputs and the prescribed ones could be observed; as a consequence the neural network is validated.

2.3. Identification of the optimum process parameters and tool geometry

In order to find the best set of parameters that lead to the diminishing of the springback intensity, the above validated network will be tested for different combinations of process parameters and tool geometry. The neural network should prescribe the outputs for different inputs without have defined the target values of these inputs. Good results reported to the nominal geometry of the parts were obtained for the following set of process parameters and tool geometry: $R_p = 5.5$ mm; $R_d = 3.4$ mm; $F = 49$ kN; $j = 1$ mm; $s = 30.3$ mm.

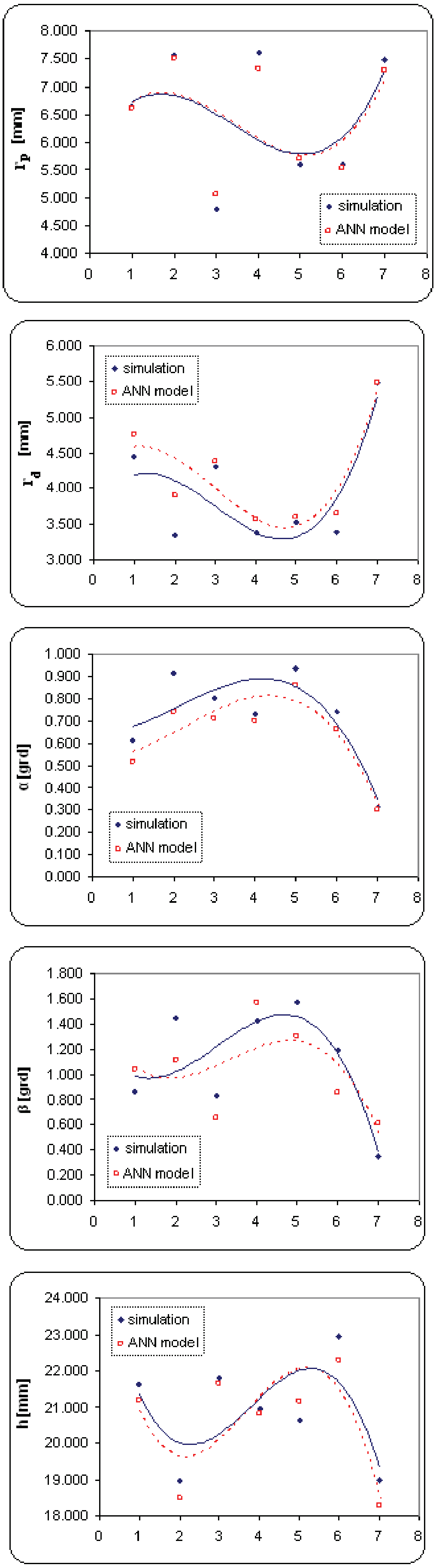

Fig. 7. Comparative analysis of the desired/prescribed outputs.

Table 1

Comparative analysis of the results

Desired outputs					Outputs 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

To validate the neural network method, 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. In Table 2 the comparative analysis of the results is presented.

By analyzing the above results, a good agreement between the nominal values of the geometric parameters of part and those resulted from the simulation that used as input data the process parameters prescribed by the neural network could be observed. As consequence, it can be considered as optimum the previous mentioned set of process parameters/tool geometry. Based on these results, an optimized geometry of tools was designed, whose utilization, in conjunction with the optimized process parameters allowed to obtain an improved accuracy of the formed part (Table 2).

3. CONCLUSIONS

An optimization procedure based on the neural network method was applied in order to find the best relation between the parameters of cylindrical deep-drawing process and the springback parameters.

The geometrical parameters of the cylindrical parts profile whose variation was investigated in order to quantify the amount of springback were as fallows: the radius of connection between the part flange and part sidewall (r_d), the radius of connection between the part bottom and part sidewall (r_p), the angle of the flange (α), the inclination angle of part sidewall (β) and the height of part sidewall (h).

The process parameters used in simulation in order to investigate their influence on the springback intensity were as follows: the blankholder force (F), the punch-die clearance (j), the punch stroke (s), the punch radius (R_p) and the die radius (R_d).

Table 2

Comparative analysis of the results

	r_p	r_d	α	β	h
Values prescribed by the ANN model	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 applying the optimization procedure, the deviations of geometrical parameters of the virtual 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.

The optimization procedure based on the utilization of neural network method conducted to a considerable increasing of the part accuracy.

REFERENCES

[1] Yang, M. *et al.* (1992). *Development of control system using neural network combined with deformation model for an intellingent V-bending process of sheet metals*, Proceeding of Japan/USA Symposium on Flexible Automation, ASME, vol. 2.

[2] Elkins, K. L. (1994). *On-line angle control for small radus air bending*, Camegie Mellon University, UMI Disertation Services, Ph.D. thesis.

[3] Forcellese, A. *et al.* (1997). *Springback control in an air bending process by neural network*, Proc. III Convegno AITEM.

[4] Ruffini, R., Cao, J. (1998). *Using neural network for springback minimization in a channel forming process*, Developments in sheet metal stamping, SAE Paper 98M-154, SP-1322.

[5] Kinsey *et al.* (2000). *Consistent and minimal springback using stepped binder force trajectory and neural network control*, Journal of Engineering Materials and Technologies, vol. 122.

[6] Viswanathan, V. *et al.* (2000). *Experimental implementation of neural network springback control for sheet metal forming*, Journal of Engineering Materials and Technologies.

[7] Axinte, C. (2006). *Theoretical and experimental researches concerning the springback phenomenon in the case of cylindrical deep-drawn parts*, Ph.D. Thesis.

Author:

Crina AXINTE, Assistant professor, University of Bacău, Faculty of Engineering, E-mail: `crina.axinte@gmail.com`