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Prediction of springback in the air V-bending of metallic sheets

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Abstract. Springback is a critical phenomenon in design and analysis of sheet metal forming process of metallic sheets. An accurate prediction of elastic recovery of material allows to design forming tools which take into account springback compensation. Springback is influenced by many factors including mechanical properties of material, friction conditions, temperature and geometry of bending die. In this paper, the investigations are focused on the analysis of an intelligent air bending process using an artificial neural network (ANN). The air bending experiments were carried out in a designed semi closed 90° V-shaped die. The tests were conducted on three grades of sheet metals: aluminium 1070, brass CuZn37 and deep-drawing quality steel sheet DC04. The results of experimental tests were used as a training set for back-propagation learning of a multilayer artificial network built in Statistica Neural Network program. For all materials tested, an increase of the springback coefficient is observed when the bend angle increases. The results of neural prediction are in a good agreement with the experiments. The correlation coefficient of ANN prediction to the experimental results is equal to about 0.99.

1. Introduction

Elastic recovery of material called springback is one of the main phenomena which influences the quality of the drawpieces formed in sheet metal forming process [1]. The accuracy and quality of sheet metal formed parts depend on the contact phenomena in sheet-tool interface and quality (wear) of the tools surface [2-5]. To control springback, there exist two main techniques: geometry-based compensation and mechanics-based reduction [6]. The geometry-based compensation can guarantee the shape accuracy of the drawpiece by performing the modifications of the tools [7]. These modifications are performed based on the measurements of the springback of a real part using digital image correlation methods or based on the results of finite element-based simulations. The other method is overbending of the sheet material. In the mechanics-based methods the sheet metal is subjected to additional tension stresses which reduce the springback. It is possible by choosing the appropriate trajectory of blankholder force variation [8].

There are many simple tests which allow the fast prediction of springback of metallic sheets. In this paper the air V-bending process is applied which allows to achieve different angles. Three main groups of parameters are influenced the springback phenomenon: geometrical, material and technological. As

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the bending radius increases, the springback angle increases considerably, while with an increase of thickness the springback angle decreases (Fig. 1). The springback angle decreases slightly with an increase of the sheet width. An increase of the yield stress causes an increase of the springback angle. Pre-strengthened materials, due to the greater value of plasticizing stresses, spring more than annealed materials. Since the increase in the deformation speed causes an increase in the value of the yield stress, it also causes an increase in the value of the springback angle. The effect of temperature is reversed.
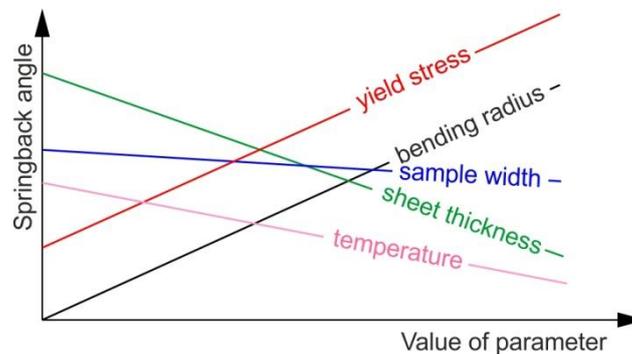

Figure 1. Effect of selected parameters on the springback angle.

Many studies were devoted to the development of a neural network control system for the development of an intelligent bending process. Şenol et al. [9] used ANN to predict the springback amount of stainless steel sheets through experiment based networks. It is observed that ANN can be applied effectively to determine springback in the air bending process. Jamli et al. [10] process the nonlinear elastic recovery using ANN. It was found that this approach is able to perform pattern recognition after plastic deformation. In the other work, Jamli et al. [11] processed the experimental results of monotonic loading, unloading, and reloading through a back propagation network that is able to do a direct mapping of elastically-driven change after the plastic forming. Song and Yu [12] developed a neural network for identification of residual deflection of a T-section beam after springback. The results indicate that the proposed approach could achieve an allowable straightness error. Gisario et al. [13] analysed the springback in sheet metal bending by laser-assisted bending. Multilayer perceptrons were proposed to improve the matching between the numerical and experimental data. Kazan et al. [14] developed the prediction model of springback in wipe-bending process using ANN approach. The neural networks were trained using the data of numerical simulations using finite element method (FEM). Li and Lu [15] used the radial basis function (RBF) ANN to study the springback and tensile strength in age forming of 2A97 aluminium alloy. It was found that prediction accuracy of the RBF ANN model is higher than that of the regression model. Pathak et al. [16] used the results of finite element analyses as input to ANN and gets several relevant outputs for springback compensation. Dilan et al. [17] proposed ANN-based intelligent control algorithm pipeline to eliminate the effects of variation of physical properties of sheet metals on bending. Fu et al. [18] combined three methods; FEM, genetic algorithm and ANN for optimizing the multiple step incremental air-bending of metallic sheets. Inamdar et al. [19] developed an ANN model of springback prediction based on the backpropagation of error. It was found that accuracy of predictions depended more on the number of training patterns used than on the ANN architecture.

In this paper, the ANN is used to build a model of springback prediction of three grades of materials. The experimental results of air V-bending test were used to training the ANN. The results of ANN modeling by Statistica Neural Network program are verified by results of experimental investigations.

2. Material

Three grades of materials were used as test specimens: aluminium 1070, brass CuZn37 and deep-drawing quality steel sheet DC04. The V-bending tests were conducted on 40 mm x 110 mm specimens cut along the rolling direction of the sheet. The thickness of specimens was 2 mm. The mechanical properties of the sheet metals (Table 1) have been determined through uniaxial tensile tests conducted according to EN ISO 6892-1:2016 standard [20]. Three samples were tested for each material. The average values of three mechanical parameters are determined using the formula:

$$X_{av} = \frac{X_0 + 2X_{45} + X_{90}}{4}$$

(1)

where: X – the mechanical parameter, the subscripts denote the orientation of the sample with respect to the rolling direction of sheet.

The values of the strain hardening parameters K and n in Hollomon law ($\sigma = K \cdot \varepsilon^n$) are determined from the logarythmic true stress – true strain plot by linear regression.

Table 1. The selected mechanical properties of the tested sheet*

Material	E (GPa)	$R_{p0,2}$ (MPa)	R_m (MPa)	A_{50} (%)	K (MPa)	n
1070	64.5	118.7	127.3	8.94	155.0	0.048
CuZn37	107.5	285.9	382.7	25.4	609.0	0.174
DC04	151.4	187.0	322.5	46.2	559.6	0.218

* E – Young's modulus, $R_{p0,2}$, yield stress, R_m – ultimate tensile stress, A_{50} – elongation, K – strain hardening coefficient, n – strain hardening exponent

3. Experimental procedure

V-bending tests were carried out in experimental stand with a semi closed 90° V-die (Fig. 2). The flat specimens with dimensions of 110×40×2 mm were cut in the rolling direction. During the tests, three parameters were measured: bending force P_B, punch bend depth under loading u_l and punch bend depth under unloading u_u (Fig. 3).

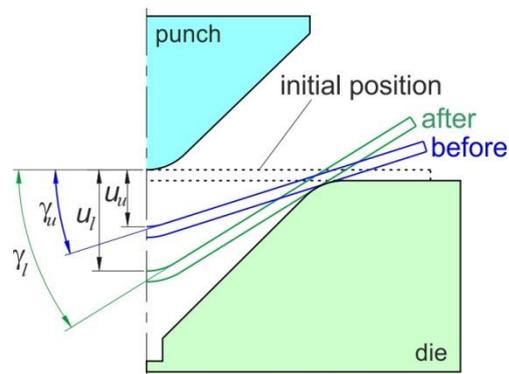**Figure 2.** The experimental setup.

Figure 3. The schematic of measurement of springback.

The values of these parameters were registered by QuantumX Assistant V.1.1 program for processing the signals of both force and punch stroke transducers. Three experiments were carried out for each specimen material. The springback coefficient K_s is defined as a ratio of specimen bend angle under unloading γ_u and specimen bend angle under loading γ_l (Fig. 3) according to the following formulae:

$$K_s = \frac{\gamma_u}{\gamma_l}$$

(2)

4. ANN Modeling

Multilayer networks named multilayer perceptrons (MLP) with a suitable number of hidden layers and neurons are theoretically sufficient to approximate any nonlinear function [21]. To build an accurate ANN, it is necessary to prepare the training set consisting of input signals and the corresponding values of output signal (springback coefficient). The following input sets of variables were assigned as input signals: yield stress of material, Young's modulus, punch bend depth under unloading and punch bend depth under loading. For the purpose of the use to keep an independent check on the progress of the training algorithm from all observations was random separated a validation set which contains 10% of all training samples.

Too large number of input variables may cause noisy data and increase the input data required for accurate training of the ANN. So, only basic inut variables were selected for the analysis. The algorithm built in *Statistica Neural Networks* program confirmed of importance of all selected input variables. The optimal network structure was found by *Intelligent Problem Solver* (*IPS*) built-in *Statitica Neural Networks.* The objective of *IPS* analysis was to find the network architecture that ensures the smallest value of standard deviation ratio (S.D. ratio) in connection with a high value of Pearson's correlation coefficient R [22]. The ANN (MLP 4 :4-7-1:1) has four neurons in input layer, eight neurons in hidden layer and one neuron in output layer The back propagation algorithm was selected to train the ANN. To prevent overlearning, the learning process was stopped when the value of verification root mean square error [22] for validation set was stopped dropping.

5. Results

The regression statistics for the ANN anlysed are shown in Table 2. The good quality of the MLP is confirmed by high value of correlation for both data sets. According to the Manual of Statistica Neural Networks Software [22] the very good model of the ANN is characterized by S.D. ratio value in the range of 0 and 0.1. S.D. ratio is computed as the ratio of error of standars deviation and standard deviation of output variable. The low value of S.D. ratio indicates a good ability of neural network to generalize data which were not involved in the network learning process.

Table 2. Regression statistics of MLP 4 :4-7-1:1 network

Set	Data mean	Data S.D.	Error mean	Error S.D.	S.D. ratio	Correlation
Training	0.8692083	0.1132947	0.0003097	0.0114139	0.1007451	0.9949153
Verification	0.8053333	0.1089694	-0.002782	0.0102202	0.09379	0.9999171

With an increase in the value of punch bend angle under loading γ_l the value of springback coefficient nonlinearly increases (Fig. 4). For the small values of bend angle, the material is mainly subjected to the action of elastic deformation and springback coefficient increases very fast. In the next stage of bending, the sheet is subjected to the impact of plastic deformation and its strength increases as a result of strain hardening phenomenon.
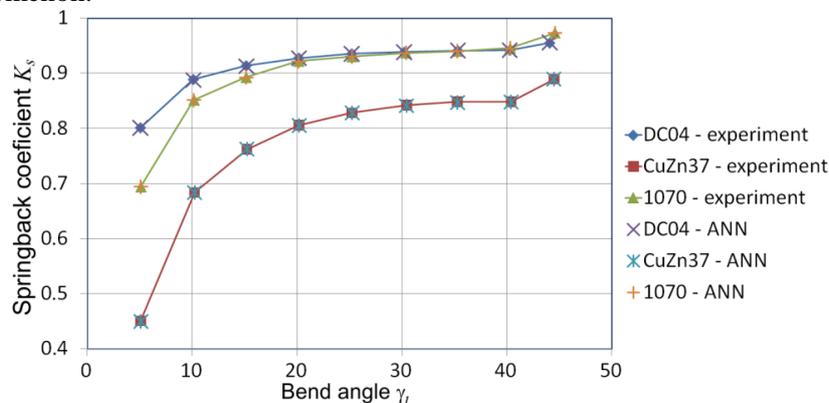

Figure 4. Effect of bending angle on springback coefficient.

Then the value of springback coefficient stabilizes and after bending to the angle of 45°, it slightly increases. This is related to the increased resistance of deformation after the surface of the sheet is contacted with the lateral surfaces of the die. Although the tested sheets differed significantly in terms of the value of mechanical properties, the neural network matched perfectly to the experimental data (Fig. 4). It is confirmed by the value of correlation coefficient whose value is close to 1 (Table 2).

6. Summary
Springback is defined as a geometrical change of the element shape after the forming process and unloading. Elastic recovery of material is one of the main problems in the forming process of drawpieces with a complex shape. By application of the artificial neural networks, it is possible to accurately predict the sheet metal springback coefficient. Furthermore, based on the neural model results, we can create the database of springback coefficient based on the experimental tests of different both grades of material and sheet thickness. After collecting a sufficiently large knowledge base, it is possible to predict the behavior of sheets with known mechanical properties without the need to carry out time-consuming experimental research.

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